Competition, Markups, and the Gains from International Trade

Online Appendix

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Contents

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This appendix is organized as follows. In Appendix A we provide more details on our data and on alternative methods for inferring markups and for inferring producer-level productivity. In Appendix B we provide further details of the robustness experiments mentioned in the main text as well as related sensitivity analysis. In Appendix C we provide further details on three more substantial extensions of our benchmark model, namely: (i) a dynamic model with endogenous capital accumulation and labor supply, (ii) asymmetric countries that differ in size and/or economy-wide productivity, and (iii) a free-entry model with an endogenous number of competitors per sector.

A Data

A.1 Data description and product classification

We use the Taiwan Annual Manufacturing Survey. Our sample covers the years 2000 and 2002–2004. The year 2001 is missing because in that year a separate census was conducted. The dataset we use has two components. First, an *establishment*-level component collects detailed information on operations, such as employment, expenditure on labor, materials and energy, and total revenue. Second, a *product*-level component reports information on revenues for each of the products produced at a given establishment. Each product is categorized into a 7-digit Standard Industrial Classification created by the Taiwanese Statistical Bureau. This classification at 7 digits is comparable to the detailed 5-digit SIC product definition collected for US manufacturing establishments as described by Bernard, Redding and Schott (2010). Panel A of Table A1 gives an example of this classification while Panel B reports the distribution of 7-digit sectors within 4- and 2-digit industries. Most of the products are concentrated in the Chemical Materials, Industrial Machinery, Computer/Electronics and Electrical Machinery industries.

A.2 Firm-level moments

The Taiwanese manufacturing sector is dominated by single-establishment (single-plant) firms. In our data, 98% of firms are single-plant firms and these firms account for 92% of total manufacturing sales. Consequently, whether we choose firms or plants as our unit of analysis makes little difference for our analysis. As reported in Table A2, our key micro and sectoral concentration moments are very similar whether we use firms or plants. We use plant-level data for our benchmark model because it is the natural unit of analysis at which to measure a producer's production technology.

A.3 Alternative markup estimates based on IO methods

In our model, as is standard in the trade literature, labor is the only factor of production and a producer's inverse labor share *is* its markup. But in comparing our model's implications for markups to the data, it is important to recognize that, in general, factor shares differ across producers not only because of markup differences but also because of differences in the technology with which they operate. To control for this potential source of heterogeneity, we use modern IO methods to purge our markup estimates of the differences in technology that surely exist across Taiwanese manufacturing industries.

Controlling for heterogeneity in producer technology. To map our model into micro-level production data, we relax the assumptions of a single factor of production and constant returns to scale. In particular, we follow De Loecker and Warzynski (2012) and assume a *translog* gross production function

$$\log y_i = \alpha_l \log l_i + \alpha_k \log k_i + \alpha_m \log m_i + \alpha_{ll}(\log l_i)^2 + \alpha_{kk}(\log k_i)^2 + \alpha_{mm}(\log m_i)^2 + \alpha_{lk}(\log l_i \log k_i) + \alpha_{lm}(\log l_i \log m_i) + \alpha_{km}(\log k_i \log m_i) + \log a_i \,,$$

where l_i denotes labor, k_i denotes physical capital, m_i denotes material inputs and a_i is physical productivity. The translog specification serves as an approximation to any twice continuously differentiable production function in these inputs and allows the elasticity of output with respect to any variable input, say labor, to differ across firms within the same sector.

We estimate this translog specification for each 2-digit Taiwanese industry, giving us industry-specific coefficient estimates. Let $e_{l,i}$ denote the elasticity of output with respect to labor

$$e_{l,i} := \frac{\partial \log y_i}{\partial \log l_i} = \alpha_l + 2\alpha_{ll} \log l_i + \alpha_{lk} \log k_i + \alpha_{lm} \log m_i \,. \tag{1}$$

Cost minimization then implies that producer i sets

$$\frac{W l_i}{p_i y_i} = \frac{e_{l,i}}{\mu_i} \,. \tag{2}$$

Thus variation in labor input cost shares across producers may be due to either variation in markups μ_i or to variation in output elasticities $e_{l,i}$. We use data on labor input cost shares and production function estimates of $e_{l,i}$ to back out markups μ_i from (2).

Controlling for simultaneity. As is well-known, a key difficulty in estimating production functions is that input choices l_i, k_i, m_i will generally be correlated with true productivity a_i. We follow De Loecker and Warzynski (2012) and apply 'control' or 'proxy function' methods inspired by Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg, Caves and Frazer (2006) to deal with this simultaneity.

More specifically, we write the measurement equation for the translog production function as

$$\log y_{it}^d = \alpha_l \log l_{it} + \alpha_k \log k_{it} + \alpha_m \log m_{it} + \alpha_{ll}(\log l_{it})^2 + \alpha_{kk}(\log k_{it})^2 + \alpha_{mm}(\log m_{it})^2 + \alpha_{lk}(\log l_{it} \log k_{it}) + \alpha_{lm}(\log l_{it} \log m_{it}) + \alpha_{km}(\log k_{it} \log m_{it}) + \log a_{it} + \tilde{\epsilon}_{it} \,,$$

where y_{it}^d is output in the data and where $\tilde{\epsilon}_{it}$ is IID noise.

Our approach to estimating the production function closely follows the procedure in Ackerberg, Caves and Frazer (2006) (and in particular we follow their timing assumptions that rationalize a mapping from a firm's capital k_{it}, labor l_{it} and productivity a_{it} to its demand for materials). To be specific, we:

1. Write the so-called *control function* as

$$m_{it} = f(k_{it}, l_{it}, a_{it})\,,$$

where, as is standard in the literature, we assume that this function can be inverted to uniquely determine a level of productivity associated with a given configuration of observed inputs, so that we can write

$$\log a_{it} = g(k_{it}, l_{it}, m_{it})\,.$$

We can then write the conditional mean of measured log output as

$$\begin{aligned} h(k_{it}, l_{it}, m_{it}) = {} & \alpha_l \log l_{it} + \alpha_k \log k_{it} + \alpha_m \log m_{it} + \alpha_{ll}(\log l_{it})^2 + \alpha_{kk}(\log k_{it})^2 + \alpha_{mm}(\log m_{it})^2 \\ & + \alpha_{lk}(\log l_{it} \log k_{it}) + \alpha_{lm}(\log l_{it} \log m_{it}) + \alpha_{km}(\log k_{it} \log m_{it}) \\ & + g(k_{it}, l_{it}, m_{it})\,, \end{aligned}$$

so that log output in the data is simply

$$\log y^d_{it} = h(k_{it}, l_{it}, m_{it}) + \tilde{\epsilon}_{it}\,,$$

and we can estimate the conditional mean function $h(\cdot)$ by high-order polynomials. Given the nonparametric function $g(\cdot)$ on the right-hand-side of the conditional mean, no structural parameters of production function can be identified at this stage. The purpose of this representation is to isolate the measurement/transitory shock component $\tilde{\epsilon}_{it}$ which is orthogonal to all inputs at time t.

2. Let $\boldsymbol{\alpha} := (\alpha_l, \alpha_k, \alpha_m, \alpha_{ll}, \alpha_{kk}, \alpha_{mm}, \alpha_{lk}, \alpha_{lm}, \alpha_{km})$ denote the parameters of the production function and let $\widehat{h}_{it}(\boldsymbol{\alpha}) := \widehat{h}(k_{it}, l_{it}, m_{it}, \boldsymbol{\alpha})$ denote the fitted values for some candidate parameter vector $\boldsymbol{\alpha}$. This implies an estimate of log productivity

$$\begin{aligned} \widehat{a}_{it}(\boldsymbol{\alpha}) = \widehat{h}_{it}(\boldsymbol{\alpha}) & - \alpha_l \log l_{it} - \alpha_k \log k_{it} - \alpha_m \log m_{it} - \alpha_{ll}(\log l_{it})^2 - \alpha_{kk}(\log k_{it})^2 - \alpha_{mm}(\log m_{it})^2 \\ & - \alpha_{lk}(\log l_{it} \log k_{it}) - \alpha_{lm}(\log l_{it} \log m_{it}) - \alpha_{km}(\log k_{it} \log m_{it})\,, \end{aligned}$$

Estimating the parameters $\boldsymbol{\alpha}$ then depends on specific parametric assumptions about the data generating process for a_{it} and in particular on how it evolves over time. As in standard literature, we assume that log productivity follows a flexible AR(1) process

$$\widehat{a}_{it}(\boldsymbol{\alpha}) = \phi(\widehat{a}_{it-1}(\boldsymbol{\alpha})) + \zeta^a_{it}(\boldsymbol{\alpha})\,,$$

where $\phi(\cdot)$ is a second-order polynomial.

3. Use GMM to estimate the parameter vector $\boldsymbol{\alpha}$. As in the dynamic panel literature, we exploit the sequential exogeneity condition that $\zeta^a_{it}(\boldsymbol{\alpha})$ is uncorrelated with a vector of lagged input variables, specifically

$$\begin{aligned} \mathbf{z}_{it} := \Big[& \log l_{it-1}\,, \log k_{it}\,, \log m_{it-1}, \\ & (\log l_{it-1})^2\,, (\log k_{it})^2\,, (\log m_{it-1})^2, \\ & (\log l_{it-1} \log k_{it})\,, (\log l_{it-1} \log m_{it-1})\,, (\log k_{it} \log m_{it-1}) \Big]\,. \end{aligned}$$

Note that, as is standard in this literature, capital enters without a lag since it is assumed to be pre-determined.

With estimates of the production function parameters $\widehat{\boldsymbol{\alpha}}$ in hand, we then use data on inputs k_{it}, l_{it}, m_{it} to calculate estimated output elasticities for each input $\widehat{e}_{l,i}, \widehat{e}_{k,i}, \widehat{e}_{m,i}$, as in (1), and then use the optimality condition (2) to recover estimated 'inverse markups' $\widehat{1/\mu_i}$.

Production function estimates. In Table A3, we report the median output elasticities and returns to scale for each of 21 Taiwanese manufacturing industries along with the inter-quartile range of output elasticities across producers within the same industry. Several points are worth noting: First, there is modest variation in output elasticities either within or across industries. For example, the 25th percentile of $\widehat{e_{l,i}}$ within industries is typically around 0.15 while the 75th percentile is typically around 0.4 with the standard deviation of median $\widehat{e_{l,i}}$ across industries being 0.04. Second, the median returns to scale within each industry is very close to 1 for almost all industries. In addition, the variation in returns to scale across producers within an industry is small, with the 25th percentile around 0.98 and the 75th percentile around 1.04. Third, the ranking of capital intensity across industries is intuitive, with Petroleum, Chemical Material, Computer, Machinery Equipment the most capital intensive, and Wood, Leather, Motor Vehicle Parts, Apparel the least.

Markup estimates. Given these estimates of $\widehat{e_{l,i}}$ for each producer for each industry, we recover $\widehat{1/\mu_i}$ from (2). Panel A of Table A4 reports summary statistics of the distribution of markups obtained in this way. The estimated markups are highly dispersed, the 95th percentile markup is nearly 2.5 times the median markup and the 99th percentile markup is nearly 5 times the median. We also report the sector-level counterparts of these markup statistics; in accordance with the model, we measure sector-level markups as the revenue-weighted harmonic average of producer markups within a given sector. The sector-level markups are similarly dispersed.

Panel B of Table A4 reports the coefficient we obtain from regressing the De Loecker and Warzynski (2012) measured inverse markups $\widehat{1/\mu_i}$ on observed market shares ω_i using samples of single-product and multi-product producers. The market share coefficient is in a tight range around -0.66 to -0.69 across these regressions.

We also report moments for *projected markups*. These are moments of the inverse of the fitted values from the regression of $\widehat{1/\mu_i}$ on ω_i which we normalize by setting the intercept equal to its theoretical value (the markup level does not affect allocations in our benchmark model). These projected markups are less dispersed, the 95th percentile sectoral markup is about 1.5 times the median and the 99th percentile is about 2.5 times the median.

Implications for the gains from trade. When we calibrate the model to match this regression of $\widehat{1/\mu_i}$ on ω_i (along with our usual targets) we obtain $\gamma = 10$, $\theta = 1.28$ (very similar to their benchmark values of 10.5 and 1.24 respectively), along with similar values for the other parameters

($\xi_x = 4.53$ vs 4.58, $\xi_z = 0.56$ vs 0.51, $\zeta = 0.043$ vs 0.043, $f_d = 0.004$ vs 0.004, $f_x = 0.211$ vs 0.203, $\tau = 1.128$ vs 1.129, and $\rho = 0.93$ vs 0.94). Given the very similar calibrated parameter values, it is not then surprising that this version of the model, calibrated to the alternative markup estimates, also implies very similar gains from trade. Specifically, it implies total gains from trade of 12% of which 1.8% are pro-competitive gains, very similar to the benchmark values of 12.4% and 2%. Thus we conclude that these alternative markup estimates lead to similar conclusions about the gains from trade.

A.4 Nonparametric productivity distribution

We now show how to use our model to recover the exact nonparametric distribution of producer-level productivity $a_i(s)$ given data on producer market shares $\omega_i(s)$. This procedure uses the structure of the model, but makes no parametric assumptions about the distribution of productivity.

The main idea is fairly intuitive: we simply back out for each producer and sector the productivity draws that are needed to rationalize that producer's and sector's relative size. To do this, begin by recalling that for producer i in sector s the inverse markup is given by

$$\frac{1}{\mu_i^{\mathrm{H}}(s)} = \frac{\gamma - 1}{\gamma} - \left(\frac{1}{\theta} - \frac{1}{\gamma}\right) \omega_i^{\mathrm{H}}(s)\,, \tag{3}$$

and that we can write the market share $\omega_i^{\mathrm{H}}(s)$ as

$$\omega_i^{\mathrm{H}}(s) = \frac{p_i^{\mathrm{H}}(s)^{1-\gamma}}{\sum_i p_i^{\mathrm{H}}(s)^{1-\gamma} + \tau^{1-\gamma}, \sum_i p_i^{\mathrm{F}}(s)^{1-\gamma}}$$

or

$$\omega_i^{\mathrm{H}}(s) = \frac{p_i^{\mathrm{H}}(s)^{1-\gamma}}{\sum_i p_i^{\mathrm{H}}(s)^{1-\gamma}} \times \frac{\sum_i p_i^{\mathrm{H}}(s)^{1-\gamma}}{\sum_i p_i^{\mathrm{H}}(s)^{1-\gamma} + \tau^{1-\gamma} \sum_i p_i^{\mathrm{F}}(s)^{1-\gamma}}\,,$$

or

$$\omega_i^{\mathrm{H}}(s) = \tilde{\omega}_i^{\mathrm{H}}(s) \times \left(1 - \omega^{\mathrm{F}}(s)\right),$$

where $\tilde{\omega}_i^{\mathrm{H}}(s)$ is producer i's share of sales among only domestic firms in sector s and $1 - \omega^{\mathrm{F}}(s)$ is the share of spending on domestic firms in that sector. Both of these terms come directly from the data. The first term can be written

$$\tilde{\omega}_i^{\mathrm{H}}(s) = \frac{\left(\mu_i^{\mathrm{H}}(s)/a_i(s)\right)^{1-\gamma}}{\sum_i \left(\mu_i^{\mathrm{H}}(s)/a_i(s)\right)^{1-\gamma}} \tag{4}$$

where we simply use the definition of the markup to write $p_i^{\mathrm{H}}(s) = \mu_i^{\mathrm{H}}(s)W/a_i(s)$. Thus, given parameter values γ and θ, we can use an iterative procedure to recover the $a_i(s)$ of domestic producers that exactly rationalizes the observed market share data $\omega_i^{\mathrm{H}}(s)$ and $1 - \omega^{\mathrm{F}}(s)$. The iterations are as follows:

1. Given data on $\omega_i^{\mathrm{H}}(s)$ and $\omega^{\mathrm{F}}(s)$, calculate $\mu_i^{\mathrm{H}}(s)$ and $\tilde{\omega}_i^{\mathrm{H}}(s)$ from (3) and (4).

2. Guess productivities $a_i^0(s)$. Then update the guess $a_i^0(s) \to a_i^1(s)$ by iterating on the mapping

$$a_i^{k+1}(s) = \left(\frac{1}{\tilde{\omega}_i^{\mathrm{H}}(s)} \frac{\mu_i^{\mathrm{H}}(s)^{1-\gamma}}{\sum_i \left(\mu_i^{\mathrm{H}}(s)/a_i^k(s)\right)^{1-\gamma}} \right)^{\frac{1}{1-\gamma}}, \qquad k = 0, 1, \ldots$$

and iterate on this until convergence.

To further compute $z(s)$, we repeat this argument at the sectoral level. Specifically, we use

$$\omega_i^{\mathrm{H}}(s) = \left(\frac{p_i^{\mathrm{H}}(s)}{p(s)} \right)^{1-\gamma},$$

thus

$$p(s) = \left(\sum_i \left(\frac{\mu_i^{\mathrm{H}}(s)}{x_i(s) z(s)} \right)^{1-\gamma} \right)^{\frac{1}{1-\gamma}} =: \frac{\Xi^{\mathrm{H}}(s)}{z(s)},$$

where we have already recovered $\Xi^{\mathrm{H}}(s)$ in the previous within-sector iteration, that is

$$\Xi^{\mathrm{H}}(s) = \left(\sum_i \left(\frac{\mu_i^{\mathrm{H}}(s)}{x_i(s)} \right)^{1-\gamma} \right)^{\frac{1}{1-\gamma}}.$$

Finally, note that the sectoral share $\omega(s) = (p(s)/P)^{1-\theta}$, thus we can again use an iterative procedure to find $z(s)$ using observed data of sectoral expenditure shares

$$\omega(s) = \frac{(\Xi^{\mathrm{H}}(s)/z(s))^{1-\theta}}{\int_0^1 (\Xi^{\mathrm{H}}(s)/z(s))^{1-\theta}\, ds}.$$

Since we are primarily interested in the tail properties of the recovered nonparametric productivity distribution, we calculate standard measures of the tail exponent of the recovered distribution and compare this summary statistic to its counterpart in our benchmark model, i.e., our original Pareto shape parameter.

Specifically, to estimate the tail exponent implied by the recovered distribution we follow Gabaix and Ibragimov (2011) and run a log-rank regression. The basic idea is that for any power law distributed randomly distributed data, we have

$$\log(r - \bar{r}) = \text{constant} - \xi_x \log X_{(r)} + \text{noise}$$

where r is the ranking of observation $X_{(r)}$. The slope coefficient $\widehat{\xi}_x$ then corresponds to the Pareto shape parameter. Gabaix and Ibragimov suggest using the correction $\bar{r} = 1/2$ to reduce small-sample bias, but our results are almost identical when we use $\bar{r} = 0$. Our estimate implies a shape parameter $\hat{\xi}_x = 3.46$ with a standard error 0.02.

We apply the same regression to sectoral productivity[1] $Z_{(r)}$, and find an estimate $\widehat{\xi}_z = 0.27$ with a standard error 0.01. Both cases indicate that, if anything, the nonparametric productivity distribution is fatter tailed than our benchmark Pareto distribution (which has $\xi_x = 4.58$ and $\xi_z = 0.51$). Our benchmark results are thus conservative in the sense that, if anything, we somewhat understate the amount of misallocation in the data.

[1]We leave out the bottom 25% of sectoral observations, these look more lognormal and our interest here is in the right tail of the distribution. We find $\widehat{\xi}_z = 0.14$ if we include all sectoral observations.

B Robustness experiments and sensitivity analysis

Here we provide further details of the robustness experiments reported in the main text along with related sensitivity analysis. Unless stated otherwise, for each experiment we recalibrate the trade cost τ, export fixed cost f_x, and correlation parameter ρ so that the Home country continues to have an aggregate import share of 0.38, fraction of exporters 0.25 and trade elasticity 4, as in our benchmark model. The full set of parameters used for each experiment are reported in Table A5. The target moments and the moments implied by each model are reported in Table A6. The gains from trade and statistics on markup dispersion for each model are reported in Table A7.

B.1 Alternative model with correlated $x_i(s), x_i^*(s)$

For this experiment (which we refer to in the main text as our *alternative model*), we allow for cross-country correlation in both sectoral productivity draws and in idiosyncratic producer-level productivity draws. Specifically, we assume $H_Z(z, z^*) = \mathcal{C}_Z(F_Z(z), F_Z(z^*))$ and $H_X(x, x^*) = \mathcal{C}_X(F_X(x), F_X(x^*))$ both linked via a Gumbel copula but with distinct correlation coefficients, ρ_z and ρ_x. As in the benchmark model, we choose the sectoral correlation ρ_z so that the model implies a trade elasticity of 4. We choose the cross-country correlation in idiosyncratic draws ρ_x so that the model reproduces the cross-sectional relationship between domestic producer concentration and import penetration that we see in the data, i.e., that sectors with high import penetration are also sectors with relatively high concentration amongst domestic producers. As shown in the last row of Table A6, our benchmark model implies a mild association, the slope coefficient in a regression of sector import penetration on sector domestic HH indexes is 0.14, a bit low relative to the 0.21 in the data. To match this regression coefficient, the preferred model needs a slight amount of cross-country correlation in in idiosyncratic draws, $\rho_x = 0.05$ (with a correspondingly slightly lower correlation in sectoral draws, $\rho_z = 0.93$). This version of the model otherwise fits the data about as well as the benchmark model. As shown in Table A7, it implies slightly larger pro-competitive gains from trade.

B.2 Labor wedges

For this experiment we assume there is a distribution of producer-level labor market distortions that act like labor input taxes, putting a *wedge* between labor's marginal product and its factor cost. Specifically, we assume a producer with productivity a faces an input tax

$$t(a) := \frac{a\tau_l}{1 + a\tau_l},$$

and pays $(1 + t(a))W$ for each unit of labor hired. The price a Home producer with productivity $a_i(s)$ sets in its domestic market is then

$$p_i^{\mathrm{H}}(s) = \left(\frac{\varepsilon_i^{\mathrm{H}}(s)}{\varepsilon_i^{\mathrm{H}}(s) - 1}\right) \frac{1 + t(a_i(s))}{a_i(s)} W\,, \tag{5}$$

where $\varepsilon_i^{\mathrm{H}}(s) > 1$ is the demand elasticity facing the firm in its domestic market, which satisfies the same formula as in the main text.

We calibrate the sensitivity parameter τ_l so that our model matches the ratio of the average producer labor share to the aggregate labor share that we observe in the data. In the data, the average producer labor share is 1.35 times the aggregate labor share. This requires $\tau_l = 0.001$, implying that the labor taxes and productivity are positively related, albeit weakly so. As shown in Table A7, the gains from trade and the pro-competitive gains from trade are quite similar to the benchmark model.

B.3 Heterogeneous tariffs

For this experiment we assume that in each sector s there is a distortionary tariff $t(s)$, common to every firm in that sector. For simplicity we assume that the tariff revenues are rebated lump-sum to the representative consumer.

The price a Home producer with productivity $a_i(s)$ sets in its domestic market is then

$$p_i^{\mathrm{H}}(s) = \frac{1}{1-t(s)}\left(\frac{\varepsilon_i^{\mathrm{H}}(s)}{\varepsilon_i^{\mathrm{H}}(s)-1}\right)\frac{W}{a_i(s)}\,, \tag{6}$$

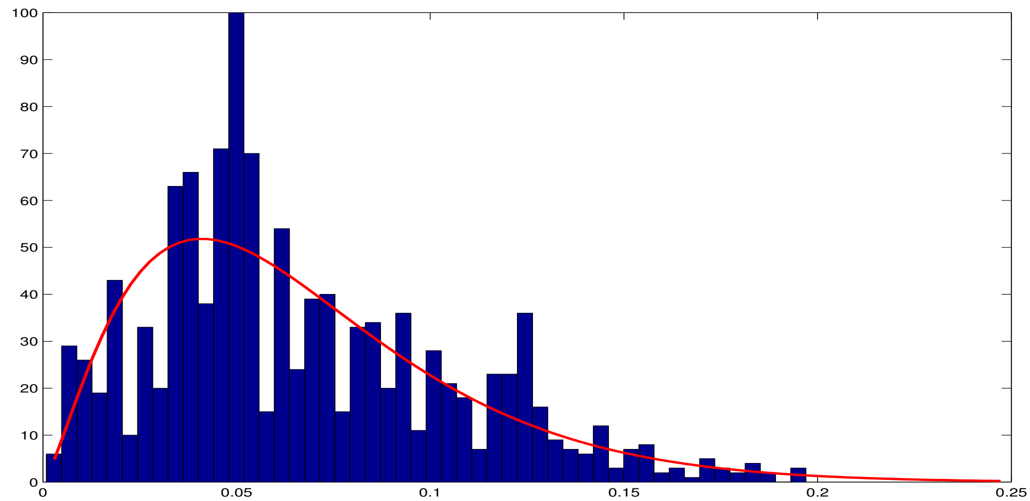
We assume that the tariffs $t(s) \in [0,1]$ are drawn IID beta(a,b) across sectors. We estimate the parameters of this beta distribution by maximum likelihood using detailed tariff data for Taiwanese 7-digit manufacturing sectors. The maximum likelihood point estimates are $a = 2.3$ and $b = 35$, implying a quite skewed distribution with mean tariff of $a/(a+b) = 0.062$ and a standard deviation of $\sqrt{ab/((a+b)^2(a+b+1))} = 0.039$. Figure 1 plots the empirical histogram of tariffs in the Taiwanese data against the density function of a beta distribution with these parameters. As reported in Table A7, the total gains from trade are somewhat larger than in the benchmark while the pro-competitive gains are unchanged.

B.4 Bertrand competition

For this experiment we re-solve the model under the assumption that producers compete by simultaneously choosing prices (Bertrand) rather than simultaneously choosing quantities (Cournot). This changes the model set-up in only one way. The demand elasticity facing producer i in sector s is no longer a harmonic weighted average, of θ and γ but is instead a simple arithmetic weighted average, $\varepsilon_i(s) = \omega_i(s)\theta + (1-\omega_i(s))\,\gamma$. With this specification the results are similar to the benchmark. The Bertrand model implies somewhat lower markup dispersion than the Cournot model but also implies a larger change in markup dispersion when opening to trade — and hence a larger reduction in misallocation.

One problem with the Bertrand model is that it implies a negative correlation between domestic sectoral concentration and domestic import penetration, i.e., in the Bertrand model highly concentrated sectors tend to have low import penetration, the opposite of what we see in the data.

Figure 1: Distribution of tariff rates $t(s)$ across 7-digit Taiwanese manufacturing sectors



B.5 Role of γ

For our benchmark calibration procedure we obtain $\gamma = 10.5$. To see what features of the data determine this value, we have recalibrated our model with a range of alternate values for γ.

For example, with a much lower value of $\gamma = 5$ we find that the model cannot produce a trade elasticity of 4 — even setting $\rho = 0.999$ (effectively perfect correlation) gives a trade elasticity of only 3.59. In addition, as shown in the last few rows of Table A6, with $\gamma = 5$ the model also implies too much intraindustry trade, too little import share dispersion, and too strong an association between sector import shares and size. At the other extreme, with a much higher value of $\gamma = 20$, the model can better match the trade elasticity and facts on intraindustry trade and import share dispersion, but now produces too weak an association between sector import shares and size as well as too strong an association between sector concentration and import penetration.

In short, low values like $\gamma = 5$ and high values like $\gamma = 20$ are at odds with key features of the data. In trying to match these moments, our calibration procedure selects the value $\gamma = 10.5$. Importantly, as shown in Table A7, our model's implications for the gains from trade do not change dramatically even for these extreme values of γ. For example, with $\gamma = 5$ the model implies that the total gains are 16.6% of which 2.7% are pro-competitive gains. With $\gamma = 20$ the model implies that total gains are 11.8% of which 1.4% are pro-competitive gains.

B.6 No fixed costs

For this experiment, we solve our model assuming that fixed costs are zero, $f_d = f_x = 0$. In this version of the model, all producers operate in both markets. Thus the number of domestic producers in each country in sector s is just given by the geometric draw $n(s)$ for that sector.

As shown in Table A7, this version of the model yields almost identical gains from trade as the benchmark. Shutting down these extensive margins makes little difference because the typical firm near the margin of operating or not is very small and has negligible impact on the aggregate outcomes.

B.7 Gaussian copula

For this experiment we resolve the model using a Gaussian copula to model the cross-country correlation in sectoral productivity draws, specifically

$$\mathcal{C}(u, u^*) = \Phi_{2,r}(\Phi^{-1}(u), \Phi^{-1}(u^*)) \tag{7}$$

where $\Phi(x)$ denotes the CDF of the standard normal distribution and $\Phi_{2,r}(x, x^*)$ denotes the standard bivariate normal distribution with *linear* correlation coefficient $r \in (-1, 1)$. To compare results to the benchmark Gumbel copula, we map the linear correlation coefficient into our preferred Kendall correlation coefficient, which for the Gaussian copula is $\rho = 2 \arcsin(r)/\pi$. To match a trade elasticity of 4 requires $\rho = 0.99$, up from the benchmark 0.94. As shown in Table A7, this version of the model yields very similar results to our benchmark model. In this sense, the functional form of the copula per se does not seem to matter much for our results, instead, as discussed at length in the main text, it is the amount of correlation ρ in cross-country productivity draws that matters.

B.8 Uncorrelated $n(s), n^*(s)$

For this experiment, for each sector s we independently draw $n(s)$ producers for the Home country and $n^*(s)$ producers for the Foreign country (each drawn from the same geometric marginal distribution as in the benchmark model). With independent draws for $n(s), n^*(s)$ we find that the model cannot produce a trade elasticity of 4, even setting $\tau(\rho) = 0.999$ (effectively perfect correlation) gives a trade elasticity of 2.99. As a consequence of this lower trade elasticity, this version of the model implies very large total gains from trade.

As shown in the last row of Table A6, with independent draws for $n(s), n^*(s)$ the model implies too strong an association between sector concentration and import penetration relative to the data.

B.9 5-digit sectors

For this last robustness experiment, we recalibrate our model to 5-digit rather than 7-digit data. The second-last column of Table A6 reports the 5-digit counterparts of our usual 7-digit moments in the Taiwanese data while the last column of Table A6 reports the model moments when calibrated to this 5-digit data.

At this higher level of aggregation there is less concentration in sectoral shares than there is at the 7-digit level and hence there is less measured misallocation. The productivity losses due to markups are 6.2%, down from the 7% for our benchmark model calibrated to 7-digit data. The total gains from trade remain about the same as in our benchmark but since there is less measured misallocation, the pro-competitive effects are weaker, contributing 0.5% down from our benchmark

2%. Thus, consistent with our earlier results, we see that the pro-competitive gains from trade are smaller when product market distortions are small.

To maintain comparability with our other results, for this experiment we have kept the across-sector elasticity fixed at $\theta = 1.24$, which is arguably quite high for 5-digit data.[2] With a lower value for θ (e.g., with Cobb-Douglas $\theta = 1$) measured misallocation is higher and the pro-competitive gains from trade are correspondingly higher also.

B.10 Experiments with N competitors per sector

To further highlight the role of cross-country correlation in sectoral productivity draws, we have solved a simplified version of our model with the following structure: a fixed number of producers N per sector (the same in both countries), no fixed costs of operating (so all N producers operate), and either perfectly dependent cross-country draws $\rho = 1$ or perfectly independent cross-country draws, $\rho = 0$. We compare autarky to *free trade* — i.e., no net trade costs, $\tau = 1$, and no fixed costs of exporting $f_x = 0$.

Panel A of Table A8 shows results for the case of *no idiosyncratic* productivity draws, $x_i(s) = 1$ for all i, s. Now consider the case $N = 1$, so that under autarky there is a single monopolist in each sector. In this case there is no misallocation in autarky (there is neither within-sector nor across-sector markup dispersion). Now with free trade there are two producers in each sector (in this sense, it is as if the country size doubles). The effects on misallocation now crucially depend on the cross-country correlation in sectoral productivity. If sectoral productivity draws are independent across countries, then typically one producer gains market share at the expense of the other, and, crucially, this pattern varies across sectors depending on the particular pairs of productivity draws. This creates markup dispersion and hence with free trade there is misallocation whereas there was no misallocation in autarky. Thus the gains from trade will be less than if markups were constant (i.e., aggregate productivity increases by less than first-best productivity). By contrast, if sectoral productivity draws are perfectly correlated across countries, then the two producers (who have equal productivity) split the market between them and this happens exactly the same way in each sector, hence in this case trade does not lead to misallocation. Put differently, $\rho = 1$ perfectly *mitigates* the increase in misallocation that would otherwise happen.

Notice that the extent of misallocation created when sectoral productivity draws are independent is *decreasing* in N — and steeply decreasing in N at that. With independent draws and $N = 1$, free trade creates productivity losses of 16.4% relative to the first-best, with $N = 2$ the losses are much smaller, 0.9% and with $N = 10$ the losses are down to 0.02%.

Panel B of Table A8 shows the same exercise but now *with idiosyncratic* productivity draws, as in the benchmark model. We again see that for low N opening to trade creates misallocation and that this misallocation is mitigated by correlated sectoral productivity draws. By the time we get to $N = 10$ (which is similar to our benchmark model, which has a median of about 10 producers per sector per country), opening to free trade reduces misallocation if sectoral draws are correlated.

[2] A 5-digit sector in Taiwan best corresponds to a 4-digit sector in the US.

C Extensions

Our benchmark model makes several stark simplifying assumptions: (i) labor is the only factor of production and is in inelastic supply, (ii) the two countries Home and Foreign are symmetric at the aggregate level, and (iii) there is an exogenous number of competitors per sector. Here we provide further details on extensions of our benchmark model that relax these assumptions. Since the main text already discusses the results from these extensions at some length, here we focus on recording additional details that were omitted from the main text to save space.

C.1 Capital accumulation and elastic labor supply

In the benchmark model, the only source of pro-competitive gains from trade is changes in markup *dispersion*. Changes in the *level* of the aggregate markup μ have no welfare implications. But with capital accumulation and/or elastic labor supply, the aggregate markup μ acts like a distortionary wedge affecting investment and labor supply decisions, and, because of this, a reduction in the aggregate markup increases welfare beyond the increases associated with a reduction in markup dispersion.

Setup. To illustrate this, we solve a simple dynamic extension of our benchmark model. Specifically, we suppose the representative consumer has intertemporal preferences $\sum_{t=0}^{\infty}\beta^t U(C_t, L_t)$ over aggregate consumption C_t and labor L_t, that capital is accumulated according to $K_{t+1} = (1-\delta)K_t + I_t$, and that individual producers have production function $y = ak^{\alpha}l^{1-\alpha}$. We then have a standard two-country representative consumer economy with aggregate production function $Y_t = A_t K_t^{\alpha}\tilde{L}_t^{1-\alpha}$ where A_t is aggregate productivity (TFP) as in the main text and where $\tilde{L}_t$ is aggregate employment net of fixed costs.

Aggregate markup distortions. Using the representative consumer's optimality conditions for capital accumulation and labor supply and the firms' optimal input demands gives the equilibrium conditions

$$U_{c,t} = \beta U_{c,t+1}\Big(\frac{1}{\mu_{t+1}}\alpha\frac{Y_{t+1}}{K_{t+1}} + 1 - \delta\Big)\,, \tag{8}$$

and

$$-\frac{U_{l,t}}{U_{c,t}} = \frac{W_t}{P_t} = \frac{1}{\mu_t}(1-\alpha)\frac{Y_t}{\tilde{L}_t}\,, \tag{9}$$

where μ_t is the aggregate markup as in the main text. High aggregate markups thus act like distortionary capital and labor income taxes and reduce output relative to its efficient level.

Parameterization. To quantify the additional welfare effects of changes in the aggregate markup, we solve this version of the model assuming utility function $U(C, L) = \log C - L^{1+\eta}/1+\eta$ and assuming discount factor $\beta = 0.96$, depreciation rate $\delta = 0.1$ and output elasticity of capital $\alpha = 1/3$. We report results for various elasticities of labor supply η. We start the economy in autarky and then compute the transition to a new steady-state corresponding to the Taiwan benchmark. We measure the welfare gains as the consumption compensating variation taking into account the dynamics of consumption and employment during the transition to the new steady-state.

Results. The first column of Table A9 shows what happens in a standard model with constant markups if TFP increases by 10.4%, i.e., the benchmark increase in first-best TFP. Physical capital, output, and consumption all increase by 15.7%, i.e., by $1/(1-\alpha) = 1.5$ times the increase in TFP. Aggregate labor does not change because utility is log in consumption so that the income and substitution effects implied by the change in TFP exactly cancel out. The measured welfare gain is slightly less than the long-run increase in aggregate consumption because we take the transitional dynamics into account.

The next column shows the corresponding results in our model with variable markups but where we hold the aggregate markup unchanged. Thus TFP increases by 12.4% because in addition to the first-best 10.4% there are now pro-competitive gains of 2%. Aggregate labor is again constant because of log utility and because the aggregate markup is held fixed. Thus the additional gains here are entirely because capital accumulation magnifies the TFP gains.

The remaining columns show results when we also allow the aggregate markup to change, falling by 2.9% from autarky to the new steady-state. We report results for various choices of the Frisch elasticity of labor supply $1/\eta$. If labor supply is inelastic, so the fall in the aggregate markup affects capital accumulation alone, welfare increases by 18%. This gain is larger than the 17% we had when only TFP changes and the additional gain of 1% is entirely due to the effect of the change in the aggregate markup and hence this extra 1% is entirely due to pro-competitive effects, making for a total pro-competitive gain of 3.5%. Elastic labor supply magnifies these gains yet further. With a Frisch elasticity of 1, the pro-competitive gains rise to 3.6% (as shown in Table A9, the size of the pro-competitive gains are not sensitive to a Frisch elasticity in the range 0.5 to 2). In short, we see that with elastic factor supply the relative importance of the pro-competitive effects is larger than in our benchmark model.

C.2 Asymmetric countries

Our benchmark model assumes trade between two symmetric countries. We now relax this and consider trade between countries that differ in size and/or productivity.

Setup. Let L, L^* denote Home and Foreign labor forces and let $\bar{A}, \bar{A}^*$ denote Home and Foreign economy-wide productivity — that is, Home producers now have technology $y_i(s) = \bar{A}a_i(s)l_i(s)$ and Foreign producers have $y_i^*(s) = \bar{A}^*a_i^*(s)l_i^*(s)$. We normalize $L = 1$ and $\bar{A} = 1$ and consider various L^* and $\bar{A}^*$.

In our benchmark model, aggregate symmetry implied that the wage in each country was the same so that by choosing the Home wage as numeraire we simply had $W = W^* = 1$ along with symmetric price levels $P = P^*$ and symmetric productivities $A = A^*$ so that the real wage in both countries was $1/P$ and the aggregate (economy-wide) markup in both countries was $\mu = PA$.

We continue to choose the Home country wage as numeraire, $W = 1$, but with asymmetric countries now have to solve for the Foreign wage W^* in equilibrium. Intuitively, W^* has to adjust to ensure that trade between the two countries is balanced. With asymmetric countries, the equilibrium price levels P, P^* and aggregate productivities A, A^* likewise differ across countries. We then have Home real wage $1/P$ and aggregate markup $\mu = PA$ and Foreign real wage W^*/P^* and aggregate markup $\mu^* = P^*A^*/W^*$.

Parameterization. We consider $L^* = 2$ and $L^* = 10$ times as large as Home, holding economy-wide productivity the same in both countries, and then consider $\bar{A}^* = 2$ and $\bar{A}^* = 10$ times as great as Home productivity, now holding the labor force the same in both countries. For each of these four experiments, we recalibrate the model so that, *for the Home country*, we reproduce the degree of openness of the Taiwan benchmark — in particular, we choose the proportional trade cost τ, export fixed cost f_x, and correlation parameter ρ so that the Home country continues to have an aggregate import share of 0.38, fraction of exporters 0.25 and trade elasticity 4. Table A10 reports the full set of parameters used for each experiment, Table A11 reports the target moments and their model counterparts for both Home and Foreign countries for each experiment, and Table A12 reports the gains from trade and statistics on markup dispersion for both Home and Foreign countries for each experiment. In addition to our usual aggregate statistics, in Table A12 we also report the relative real wage expressed as the real wage of Foreign to Home, that is $(W^*/P^*)/(W/P) = (A^*/A)/(\mu^*/\mu)$.

C.3 Free entry

We now discuss in somewhat greater detail a version of our model with *free entry* and an endogenous number of competitors per sector. We assume that entry is not directed at a particular sector: after paying a sunk entry cost, a firm learns the productivity with which it operates, as in Melitz (2003), as well as the sector to which it is assigned. We also assume that there are no fixed costs of operating or exporting in any given period. Instead, we assume that a firm's productivity is drawn from a discrete distribution which includes a mass point at zero.

Setup. The productivity of a firm in sector $s \in [0, 1]$ is given by a world component, common to both countries, $z(s)$, and a firm-specific component. In addition, we assume a *gap*, $u(s)$, between the productivity with which a firm produces for its domestic market and that with which it produces in its export market. Greater dispersion in $u(s)$ reduces the amount of head-to-head competition between Home and Foreign producers, lowers the aggregate trade elasticity, and thus has the same role as reducing the correlation between sectoral productivity draws in our benchmark model.

Specifically, let $u(s)$ denote the productivity gap of Home producers in sector s and $u^*(s)$ denote the productivity gap of Foreign producers in sector s. There is an unlimited number of potential entrants. To enter, a firm pays a sunk cost f_e that allows it to draw (i) a sector s in which to operate and (ii) idiosyncratic productivity $x_i(s) \in \{0, 1, \bar{x}\}$. A Home firm in sector s with idiosyncratic productivity $x_i(s)$ produces for its domestic market with overall productivity $a_i^{\mathrm{H}}(s) = z(s)u(s)x_i(s)$

and produces for its export market with overall productivity $a_i^{*\mathrm{H}}(s) = z(s)x_i(s)/\tau$ where τ is the gross trade cost. Similarly, a Foreign firm in sector s with idiosyncratic productivity $x_i^*(s)$ produces for its domestic market with overall labor productivity $a_i^{*\mathrm{F}}(s) = z(s)u^*(s)x_i^*(s)$ and produces for its export market with overall productivity $a_i^{\mathrm{F}}(s) = z(s)x_i^*(s)/\tau$.

Sector types. Sectors differ in the probability that any individual entrant assigned to that sector draws a particular productivity $x_i(s)$. To simplify computations, we assume a finite number of sector *types* $k = 1, ..., K$. A sector type is a *pair* $\Omega_1(k), \Omega_2(k)$ where Ω_1 denotes the probability that an entrant is *successful*, i.e., that it draws $x_i(s) > 0$, and Ω_2 denotes the probability that a successful entrant draws *high productivity* $x_i(s) = \bar{x}$. We write $\nu(k)$ for the measure of sectors of type k with $\sum_k \nu(k) = 1$.

The special case of a single sector type, $K = 1$, is of particular significance since it implies that there is *no* cross-country correlation in productivities, since in this case the probability that a successful entrant gets a high productivity draw $\bar{x}$ is the same in all sectors and such draws are IID across producers. In the more general case with heterogeneous sector types, $K > 1$, there *is* cross-country correlation in productivities since the sector *type* k is the same for both countries so that producers in a sector with high $\Omega_2(k)$ have a common high probability of drawing $\bar{x}$, irrespective of which country they are located in. We think of these sectoral differences as being primarily technological in nature and thus invariant across countries.

Timing. The timing of entry is as follows:

1. An entrant draws a sector and thus implicitly a type $k \in \{1, ..., K\}$. The type k determines both the probability of any individual entrant drawing a particular productivity realization as well as the distribution of other competitors it will face.

2. The entrant draws a random variable that determines whether it is successful (with probability $\Omega_1(k)$) and can thus begin operating, or whether it exits (with probability $1 - \Omega_1(k)$).

3. Successful entrants then draw their productivity type. With probability $\Omega_2(k)$ a successful entrant becomes a high-productivity producer (with $x_i(s) = \bar{x}$), while with probability $1 - \Omega_2(k)$ they become a low-productivity producer (with $x_i(s) = 1$).

Now let N be the measure of producers that actually enter. Recall that we assume entrants are uniformly distributed across sectors. Then since the total measure of sectors is 1, the number of successful entrants who produce in a sector of type k is a binomial random variable with a success probability $\Omega_1(k)$ and N trials. For each sector $s \in [0, 1]$, let $k(s)$ denote that sector's type and let $n(s)$ denote the resulting number of producers. Likewise let $n_1(s)$ and $n_2(s)$ denote the number of low-productivity producers ($x_i(s) = 1$) and high-productivity producers ($x_i(s) = \bar{x}$). Given the realization of $n(s)$, $n_2(s)$ is a binomial random variable with a success probability of $\Omega_2(k(s))$ and $n(s)$ trials. Finally, let $n_1^*(s)$ and $n_2^*(s)$ denote the number of Foreign producers of each type that produce in sector s

To summarize, any individual sector s is characterized by (i) the number of competitors of each productivity type, $n_1(s), n_2(s), n_1^*(s), n_2^*(s)$, (ii) the common productivity component of all producers (both Home and Foreign) operating in that sector, $z(s)$, (iii) the productivity advantage of Home producers relative to importers in the Home market, $u(s)$, and (iv) the productivity advantage of Foreign producers relative to Home exporters in the Foreign market, $u^*(s)$.

Production and pricing. The rest of the model is essentially identical to the benchmark model in the main text. For example, the final good is a CES aggregate of sector inputs

$$Y = \left(\int_0^1 y(s)^{\frac{\theta-1}{\theta}}\, ds\right)^{\frac{\theta}{\theta-1}} ,$$

while sector output is a CES aggregate of the production of the various types of producers in each sector, which we now write

$$y(s) = \left(n_1(s) y_1^{\mathrm{H}}(s)^{\frac{\gamma-1}{\gamma}} + n_2(s) y_2^{\mathrm{H}}(s)^{\frac{\gamma-1}{\gamma}} + n_1^*(s) y_1^{\mathrm{F}}(s)^{\frac{\gamma-1}{\gamma}} + n_2^*(s) y_2^{\mathrm{F}}(s)^{\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}} ,$$

where γ is, as earlier, the elasticity of substitution within a sector and θ is the elasticity of substitution across sectors. Since there are no fixed costs of exporting or selling domestically, all $n(s)$ producers operate in sector s.

As in the benchmark model, the markup a firm charges is a function of the number of competitors of each productivity it competes with. For example, in its domestic market a Home firm with idiosyncratic productivity $x_i(s)$ in sector s has markup

$$\mu_i^{\mathrm{H}}(s) = \frac{\varepsilon_i^{\mathrm{H}}(s)}{\varepsilon_i^{\mathrm{H}}(s) - 1} ,$$

where

$$\varepsilon_i^{\mathrm{H}}(s) = \left(\omega_i^{\mathrm{H}}(s)\frac{1}{\theta} + \left(1 - \omega_i^{\mathrm{H}}(s)\right)\frac{1}{\gamma}\right)^{-1} ,$$

and where $\omega_i^{\mathrm{H}}(s)$ denotes their market share in their domestic market

$$\omega_i^{\mathrm{H}}(s) = \left(\frac{\frac{\mu_i^{\mathrm{H}}(s)}{z(s)x_i(s)u(s)}}{p(s)}\right)^{1-\gamma} .$$

Similarly, a Home firm with idiosyncratic productivity $x_i(s)$ in sector s has export market share

$$\omega_i^{*\mathrm{H}}(s) = \left(\frac{\frac{\mu_i^{*\mathrm{H}}(s)}{z(s)x_i(s)}}{p^*(s)}\right)^{1-\gamma} .$$

Given the markups, the Home price of the sector s composite satisfies

$$\begin{aligned} p(s)^{1-\gamma} = {} & n_1(s)\mu_1^{\mathrm{H}}(s)^{1-\gamma}\left(z(s)u(s)\right)^{\gamma-1} + n_2(s)\mu_2^{\mathrm{H}}(s)^{1-\gamma}\left(z(s)u(s)\bar{x}\right)^{\gamma-1} \\ & + \tau^{1-\gamma} n_1^*(s)\mu_1^{\mathrm{F}}(s)^{1-\gamma} z(s)^{\gamma-1} + \tau^{1-\gamma} n_2^*(s)\mu_2^{\mathrm{F}}(s)^{1-\gamma}\left(z(s)\bar{x}\right)^{\gamma-1} , \end{aligned}$$

and the Foreign price of the sector s composite satisfies

$$p^*(s)^{1-\gamma} = \tau^{1-\gamma} n_1(s) \mu_1^{*\mathrm{H}}(s)^{1-\gamma} z(s)^{\gamma-1} + \tau^{1-\gamma} n_2(s) \mu_2^{*\mathrm{H}}(s)^{1-\gamma} \left(z(s)\bar{x}\right)^{\gamma-1} \\ + n_1^*(s) \mu_1^{*\mathrm{F}}(s)^{1-\gamma} \left(z(s)u^*(s)\right)^{\gamma-1} + n_2^*(s) \mu_2^{*\mathrm{F}}(s)^{1-\gamma} \left(z(s)u^*(s)\bar{x}\right)^{\gamma-1} .$$

Expected profits of a potential entrant. We now compute the expected profits of a firm that contemplates entry. Such a firm has an equal probability of entering any one of the sectors. Recall that sectors differ in

$$\lambda = (\Omega_1, \Omega_2, u, u^*, z, n_1, n_2, n_1^*, n_2^*) ,$$

where z, u, u^* are all independent random variables. Let $F(\lambda)$ denote the distribution of producers over λ and let $\pi_1(\lambda), \pi_2(\lambda)$ denote respectively the profits of an entrant with idiosyncratic productivity $x = 1$ and $x = \bar{x}$ in sector λ. Since a potential entrant is equally likely to enter any sector, its expected profits are

$$\pi_e = \int \Omega_1(\lambda) \Big[(1 - \Omega_2(\lambda)) \pi_1(\lambda_1(\lambda)) + \Omega_2(\lambda) \pi_2(\lambda_2(\lambda)) - W f_e(\lambda) \Big] \, dF(\lambda) ,$$

where $\lambda_1(\lambda)$ is equal to λ except that n_1 is replaced by $n_1 + 1$ and $\lambda_2(\lambda)$ is equal to λ except that n_2 is replaced by $n_2 + 1$ — i.e., a potential entrant *recognizes* that its entry, if successful, will change the number of producers and thus alter the industry equilibrium by changing the price $p(s)$ and $p^*(s)$ of that sector's composite in both countries.

This expression says that the expected profits conditional on entering a sector λ are given by $\Omega_1(\lambda)$, the probability of successful entry into that sector, times the expected profits conditional on entry, which in turn depend on the probability of getting the higher productivity draw, $\Omega_2(\lambda)$. This expression also reveals why we simplify the productivity distribution for this free-entry version of the model: the distribution $F(\lambda)$ is a high-dimensional object which we can only integrate accurately when we use the simpler productivity distribution assumed here.

Free entry condition. Expected profits π_e are implicitly a function of N, the measure of entrants — since N characterizes the Binomial distribution of the number of producers of each type in a given sector — as well as the trade cost τ, which determines how much the producer is making from its export sales as well as how much competition it faces from Foreign producers. We pin down the measure of entrants N in equilibrium by setting

$$\pi_e(N, \tau) = 0 ,$$

for any given level of the trade cost τ.

Notice here that we implicitly allow the fixed cost of entering, to vary with the sector to which a producer is assigned. More specifically, we assume that the fixed cost is proportional to the sector's productivity, $f_e(s) = f_e \times z(s)^{\theta-1}$ for some constant $f_e > 0$. Sectoral profits are homogeneous of degree 1 in $z(s)^{\theta-1}$ so this assumption simply implies that the fixed cost scales up with the profits of the sector to which the entrant is assigned.

Model with collusion: setup. We also report in text results based on a model in which all high-productivity producers from a given country and sector are able to *collude* and maximize joint profits. We assume that producers in a fraction of sectors collude, while the rest face the same problem as that described above.

Consider the problem of the colluding Home producers selling in Home. They choose their price to maximize joint profits

$$n_2(s)\left[p_2^{\mathrm{H}}(s)y_2^{\mathrm{H}}(s) - Wl_2^{\mathrm{H}}(s)\right],$$

taking as given the inverse demand curve

$$p_2^{\mathrm{H}}(s) = \left(\frac{y_2^{\mathrm{H}}(s)}{y(s)}\right)^{-\frac{1}{\gamma}} \left(\frac{y(s)}{Y}\right)^{-\frac{1}{\theta}} P,$$

and recognizing that

$$y(s) = \left(n_1(s)y_1^{\mathrm{H}}(s)^{\frac{\gamma-1}{\gamma}} + n_2(s)y_2^{\mathrm{H}}(s)^{\frac{\gamma-1}{\gamma}} + n_1^*(s)y_1^{\mathrm{F}}(s)^{\frac{\gamma-1}{\gamma}} + n_2^*(s)y_2^{\mathrm{F}}(s)^{\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}}.$$

The optimal markup is now given by

$$\frac{1}{\mu_2^{\mathrm{H}}(s)} = \frac{\gamma-1}{\gamma} - \left(\frac{1}{\theta} - \frac{1}{\gamma}\right) n_2(s)\omega_2^{\mathrm{H}}(s),$$

and now reflects the overall sectoral share $n_2(s)\omega_2^{\mathrm{H}}(s)$ of the colluding producers, not each individual producer's share in isolation.

Parameterization. We continue to set $\gamma = 10.5$ and $\theta = 1.24$ as in our benchmark model to allow comparability of results. We again choose the trade cost, τ, to match Taiwan's import share of 0.38. We assume the productivity gaps $u(s), u^*(s)$ are IID logormal with variance σ_u^2 and choose the dispersion to match a trade elasticity of 4.

We consider two variants of the model, (i) with a single sector type $K = 1$ (and hence two probabilities Ω_1, Ω_2) and (ii) with heterogeneous sector types, that, as we will see, does a better job of matching the dispersion in concentration we see in the data. For the latter we have found that allowing for 3 values for $\Omega_1(k)$ and another 3 values for $\Omega_2(k)$ works reasonably. In this case, we have to determine these 6 values plus $8 = 3^2 - 1$ values for the measures $\nu(k)$ of each sector type. For both variants, we choose the entry cost f_e, the productivity advantage of type 2 producers $\bar{x}$, and the distribution of $\Omega_1(k), \Omega_2(k)$ across sectors targeting the same set of concentration moments we targeted for the benchmark model. Finally, we choose the dispersion of sectoral productivity $z(s)$ to match the amount of concentration in output and employment across sectors. Specifically, we assume a Pareto distribution of $z(s)$ and choose the shape parameter to match the fraction of value added (employment) accounted for by the top 1% and 5% of sectors.

Table A13 reports the full set of parameters used for each free-entry experiment, Table A14 reports the target moments and their model counterparts, and Table A15 reports the gains from trade and statistics on markup dispersion for each free-entry experiment.

Single sector type: results. With a single sector type, $K = 1$, the free-entry model implies total gains of 6.3% of which 1.9% is due to pro-competitive effects. The free-entry model implies less misallocation in autarky than in the benchmark model but also implies a greater reduction in misallocation when the economy opens to trade, misallocation relative to autarky falls by just under a half. As shown in Table A14, this version of the model is not able to reproduce the amount of dispersion in concentration that we see in the data. As a consequence, as shown in Table A15, this version of the model also implies very little dispersion in sectoral markups as compared to the data.

Heterogeneous sector types: results. By allowing sectoral differences in the probability of a successful entrant drawing the high-productivity $\bar{x}$, the model is more dispersion in concentration and hence more dispersion in sectoral markups. We have found that, as shown in Table A14, with nine sector types the model does a considerably better job of matching the facts on dispersion in sectoral concentration. This version of the model implies total gains of 6.9% of which 1.2% is due to pro-competitive effects. Nonetheless, this version of the model still produces too little dispersion in sectoral markups — the key source of misallocation in the model. For example, the ratio of the 95th percentile of markups to that of the median is equal to only 1.17 in the model, much lower than the 1.50 in the data.

To better match the dispersion in sectoral markups, we turn to the extension with *collusion* outlined above. With collusion the model produces considerably more dispersion in sectoral markups. For example, when 25% of sectors collude, the ratio of the 95th to the median markup increases from 1.17 to 1.31, still smaller than in the data but now considerably more than in the nine sector model without collusion. With 25% collusion, the model implies total gains of 11.6% of which 4.3% is due to pro-competitive effects. Thus this version of the model implies total gains about the same as the benchmark but gives a much larger share to the pro-competitive effect. In short, we again see that the pro-competitive gains from trade are large when product market distortions are large to begin with.

References

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer, "Structural Identification of Production Functions," 2006. UCLA working paper.

Bernard, Andrew B., Stephen J. Redding, and Peter Schott, "Multiple-Product Firms and Product Switching," *American Economic Review*, March 2010, *100* (1), 70–97.

De Loecker, Jan and Frederic Warzynski, "Markups and Firm-Level Export Status," *American Economic Review*, October 2012, *102* (6), 2437–2471.

Gabaix, Xavier and Rustam Ibragimov, "Rank −1/2: A Simple Way to Improve the OLS Estimation of Tail Exponents," *Journal of Business and Economic Statistics*, 2011, *29* (1), 24–39.

Levinsohn, James and Amil Petrin, "Estimating Production Functions using Inputs to Control for Unobservables," *Review of Economic Studies*, April 2003, *70* (2), 317–342.

Melitz, Marc J., "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, November 2003, *71* (6), 1695–1725.

Olley, G. Steven and Ariel Pakes, "The Dynamics of Productivity in the Telecommunications Equipment Industry.," *Econometrica*, November 1996, *64* (6), 1263–1297.

Table A1: Data Description and Product Classification

Panel A: An Example of Product Classification

3-digit	314: computers and storage equipment
5-digit	31410 - computers
7-digit	3141000 - mini-computer
	3141010 - work-station
	3141021 - desktop computer
	3141022 - laptop computer
	3141023 - notebook computer
	3141024 - palmtop computer
	3141025 - pen-based computer
	3141026 - hand held computer
	3141027 - electronic dictionary

Panel B: Distribution of Sectors and Industries

2-digit	4-digit	7-digit (sector)
textile	16	76
apparel	10	39
leather	4	33
lumber	6	15
furniture	4	12
paper	6	23
printing	3	4
chemical materials	7	152
chemical products	9	83
petroleum	2	12
rubber	3	16
plastics	7	34
clay/glass/stone	18	47
primary metal	14	99
fabricated metal	14	65
industrial machinery	29	163
computer/electronics	11	136
electronic parts	6	72
electrical machinery	11	125
transportation	12	99
instruments	7	70

Table A2: Plant-Level and Firm-Level Concentration

	Plant	Firm
Within-sector concentration, domestic sales		
mean inverse HH	7.25	7.02
median inverse HH	3.92	3.85
mean top share	0.45	0.45
median top share	0.40	0.40
Distribution of sectoral shares, domestic sales		
mean share	0.04	0.04
median share	0.005	0.004
p75 share	0.02	0.02
p95 share	0.19	0.19
p99 share	0.59	0.58
std dev share	0.11	0.11
Across-sector concentration		
p10 inverse HH	1.17	1.28
p50 inverse HH	3.73	3.85
p90 inverse HH	13.82	14.36
p10 top share	0.16	0.16
p50 top share	0.41	0.40
p90 top share	0.92	0.88
p10 number producers	2	3
p50 number producers	10	11
p90 number producers	52	56

	Plant	Firm
Size distribution of sectors based on domestic sales		
fraction sales by top 0.01 sectors	0.26	0.27
fraction sales by top 0.05 sectors	0.52	0.53
fraction wages (same) top 0.01 sectors	0.11	0.15
fraction wages (same) top 0.05 sectors	0.32	0.36
Size distribution of producers based on domestic sales		
fraction sales by top 0.01 firms	0.41	0.41
fraction sales by top 0.05 firms	0.65	0.65
fraction wages (same) top 0.01 producers	0.24	0.32
fraction wages (same) top 0.05 producers	0.47	0.56

Table A3: Production Function Estimates

		Panel A: Output Elasticity With Respect to…									Panel B: Returns to Scale			
		Labor			Capital			Materials						
TW SIC 2	Sector	median	iqr		median	iqr		median	iqr		median	iqr		#Obs
11	Textile	0.27	0.17	0.39	0.04	0.02	0.06	0.69	0.57	0.79	1.00	0.98	1.02	5982
12	Apparel	0.26	0.11	0.43	0.03	0.00	0.06	0.68	0.56	0.80	0.97	0.92	1.03	3790
13	Leather	0.30	0.21	0.39	0.02	0.01	0.03	0.66	0.59	0.74	0.98	0.96	1.01	4585
14	Wood	0.30	0.27	0.34	0.01	0.00	0.01	0.69	0.64	0.74	1.00	0.99	1.01	4765
15	Paper	0.23	0.13	0.34	0.05	0.03	0.07	0.70	0.61	0.78	0.98	0.96	1.00	4919
16	Printing	0.35	0.24	0.46	0.05	0.03	0.07	0.62	0.52	0.73	1.03	1.01	1.05	7744
17	Petroleum	0.20	0.07	0.37	0.10	0.03	0.17	0.68	0.53	0.83	0.99	0.95	1.04	3337
18	Chemical Material	0.30	0.21	0.41	0.08	0.04	0.13	0.63	0.55	0.70	1.02	0.98	1.06	6860
19	Chemical Prod	-0.11	-0.24	0.04	0.18	0.06	0.28	0.86	0.77	0.95	0.94	0.85	1.03	706
20	Pharmaceutical	0.33	0.22	0.43	0.04	0.01	0.06	0.64	0.53	0.75	1.00	0.98	1.03	3424
21	Rubber	0.29	0.20	0.39	0.05	0.03	0.07	0.66	0.58	0.74	1.00	0.97	1.03	23813
22	Plastic	0.23	0.09	0.37	0.05	0.04	0.07	0.73	0.59	0.87	1.01	0.98	1.04	8041
23	Non-metallic Mineral	0.41	0.30	0.53	0.09	0.04	0.14	0.52	0.43	0.61	1.03	0.97	1.08	7693
24	Basic Metal	0.30	0.20	0.41	0.05	0.03	0.06	0.67	0.57	0.77	1.02	0.99	1.04	35622
25	Fabricated Metal	0.29	0.19	0.41	0.04	0.03	0.05	0.66	0.56	0.76	1.00	0.98	1.02	52159
26	Electronic Parts and Components	0.30	0.17	0.42	0.07	0.03	0.11	0.63	0.53	0.73	0.99	0.96	1.03	6772
27	Computer, Electronic, Optical Prod	0.34	0.23	0.44	0.10	0.06	0.13	0.62	0.51	0.72	1.05	1.02	1.07	8723
28	Electrical Equipment	0.25	0.10	0.42	0.06	0.03	0.09	0.69	0.55	0.83	1.00	0.97	1.04	11316
29	Machinery and Eqiupment	0.28	0.20	0.37	0.08	0.05	0.11	0.67	0.60	0.73	1.03	1.01	1.04	12708
30	Motor Vehicle and Parts	0.38	0.27	0.48	0.03	0.01	0.06	0.57	0.47	0.67	0.97	0.90	1.06	3923
31	Transportation Equipment and Parts	0.31	0.20	0.42	0.04	0.01	0.06	0.65	0.56	0.74	1.00	0.98	1.01	10288
	Overall	0.30	0.19	0.41	0.05	0.03	0.07	0.66	0.56	0.75	1.01	0.98	1.03	239067

Table A4: Alternative Markup Estimates

Panel A: Markup Dispersion

	DLW	Projected
Unconditional markup distribution		
p75/p50	1.24	1.01
p90/p50	1.74	1.04
p95/p50	2.46	1.08
p99/p50	4.84	1.33
std dev log	0.38	0.06
Across-sector markup distribution		
p75/p50	1.30	1.10
p90/p50	1.99	1.31
p95/p50	2.81	1.56
p99/p50	4.56	2.58
std dev log	0.41	0.20

Panel B: Inverse Markup Regressions

Regression of DLW inverse markups on market shares	
multi-product	-0.69
	[0.01]
single-product	-0.66
	[0.02]

Table A5: Parameters for Robustness Experiments

		Benchmark	Alternative	Labor wedges	Tariffs	Bertrand	Low γ	High γ	No fix costs	Gauss. copula	n(s),n*(s)	5-digit
Main parameters												
γ	within-sector elasticity of substitution	10.5	10.5	10.5	10.5	10.5	5	20	10.5	10.5	10.5	10.5
θ	across-sector elasticity of substitution	1.24	1.24	1.24	1.24	1.24	1.20	1.25	1.24	1.24	1.24	1.24
ξ_x	pareto shape parameter, idiosyncratic productivity	4.58	4.58	4.58	4.58	4.53	4.58	4.58	4.58	4.58	4.58	5.70
ξ_z	pareto shape parameter, sector productivity	0.51	0.51	0.51	0.51	0.56	0.51	0.51	0.51	0.51	0.51	0.51
ζ	geometric parameter, number producers per sector	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.020
f_d	fixed cost of domestic operations	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0	0.004	0.004	1e-7
f_x	fixed cost of export operations	0.203	0.060	0.065	0.055	0.110	1.35	0.040	0	0.070	0.065	0.049
τ	trade cost	1.129	1.129	1.129	1.055	1.132	1.080	1.138	1.136	1.129	1.170	1.130
ρ	kendall correlation for sectoral draws	0.94	0.93	0.93	0.94	0.91	1.00	0.92	0.95	0.99	1.00	0.91
Additional parameters / moments												
	kendall correlation for idiosyncratic draws	0	0.05	0	0	0	0	0	0	0	0	0
	sensitivity of labor wedge to productivity	0	0	0.001	0	0	0	0	0	0	0	0
	mean tariff	0	0	0	0.062	0	0	0	0	0	0	0
	std dev tariffs	0	0	0	0.039	0	0	0	0	0	0	0

Table A6: Moments implied by Robustness Experiments

	Data	Autarky	Benchmark	Alternative	Labor wedges	Tariffs	Bertrand	Low γ	High γ	No fix costs	Gauss. copula	n(s),n*(s)	5-digit Data	5-digit Model
Within-sector concentration, domestic sales														
mean inverse HH	7.25	17.20	4.30	16.12	16.22	16.08	2.85	10.00	14.91	16.10	14.75	4.55	14.97	13.22
median inverse HH	3.92	5.06	3.79	3.92	4.00	3.91	2.31	7.97	2.84	3.93	3.91	3.86	7.98	5.67
mean top share	0.45	0.37	0.46	0.44	0.43	0.44	0.61	0.31	0.52	0.44	0.44	0.46	0.30	0.36
median top share	0.40	0.33	0.41	0.40	0.40	0.41	0.59	0.25	0.49	0.40	0.40	0.41	0.25	0.33
Distribution of sectoral shares, domestic sales														
mean share	0.04	0.03	0.05	0.03	0.03	0.03	0.06	0.04	0.04	0.00	0.03	0.05	0.01	0.02
median share	0.005	0.004	0.005	0.004	0.004	0.004	0.004	0.015	0.004	0.000	0.004	0.006	0.002	0.003
p75 share	0.02	0.01	0.03	0.01	0.01	0.01	0.03	0.04	0.01	0.00	0.01	0.03	0.01	0.01
p95 share	0.19	0.17	0.27	0.18	0.17	0.18	0.40	0.16	0.28	0.00	0.19	0.25	0.06	0.09
p99 share	0.59	0.41	0.59	0.50	0.49	0.50	0.87	0.41	0.67	0.09	0.51	0.60	0.22	0.32
std dev share	0.11	0.08	0.12	0.09	0.09	0.09	0.16	0.08	0.13	0.03	0.10	0.12	0.05	0.06
Across-sector concentration														
p10 inverse HH	1.17	2.00	1.70	1.72	1.79	1.75	1.13	2.20	1.25	1.80	1.81	1.52	2.14	2.41
p50 inverse HH	3.73	5.06	3.79	3.92	4.00	3.91	2.31	7.97	2.84	3.93	3.91	3.86	6.09	5.67
p90 inverse HH	13.82	10.70	7.66	8.83	9.02	8.64	5.19	20.56	5.68	8.67	8.38	8.47	16.38	12.58
p10 top share	0.16	0.18	0.24	0.21	0.20	0.21	0.32	0.12	0.27	0.21	0.22	0.22	0.14	0.17
p50 top share	0.41	0.33	0.41	0.40	0.40	0.41	0.59	0.25	0.49	0.40	0.40	0.41	0.30	0.33
p90 top share	0.92	0.58	0.75	0.73	0.73	0.74	0.94	0.55	0.89	0.73	0.71	0.80	0.63	0.60
p10 number producers	2	3	3	3	3	3	3	3	2	2	3	3	5	6
p50 number producers	10	18	16	17	17	17	13	17	10	15	16	16	36	36
p90 number producers	52	64	47	55	56	55	36	58	27	52	48	47	138	127
Size distribution sectors, domestic sales														
fraction sales by top 0.01 sectors	0.26	0.21	0.21	0.21	0.19	0.21	0.15	0.12	0.26	0.21	0.17	0.20	0.24	0.19
fraction sales by top 0.05 sectors	0.52	0.31	0.32	0.33	0.30	0.33	0.27	0.22	0.38	0.32	0.29	0.32	0.51	0.31
fraction wages (same) top 0.01 sectors	0.11	0.22	0.22	0.22	0.12	0.23	0.15	0.13	0.27	0.22	0.16	0.19	0.11	0.19
fraction wages (same) top 0.05 sectors	0.32	0.32	0.33	0.34	0.21	0.34	0.27	0.23	0.39	0.33	0.27	0.31	0.32	0.30
Size distribution producers, domestic sales														
fraction sales by top 0.01 producers	0.41	0.36	0.33	0.40	0.37	0.40	0.33	0.19	0.43	0.84	0.38	0.32	0.41	0.42
fraction sales by top 0.05 producers	0.65	0.66	0.61	0.72	0.70	0.73	0.70	0.42	0.75	1.00	0.70	0.60	0.65	0.73
fraction wages top 0.01 producers	0.24	0.32	0.31	0.36	0.26	0.37	0.31	0.17	0.41	0.81	0.33	0.29	0.24	0.38
fraction wages top 0.05 producers	0.47	0.61	0.57	0.68	0.62	0.69	0.67	0.39	0.71	1.00	0.65	0.55	0.47	0.69
Import dispersion statistics														
coefficient, share imports on share sales	0.81	--	0.55	0.65	0.54	0.59	0.51	1.13	0.37	0.56	1.12	0.63	0.81	0.44
index import share dispersion	0.38	--	0.26	0.24	0.25	0.24	0.44	0.08	0.38	0.23	0.15	0.43	0.28	0.34
index intraindustry trade	0.37	--	0.45	0.49	0.47	0.48	0.31	0.74	0.33	0.48	0.63	0.33	0.41	0.40
coefficient, import penetration on domestic HH	0.21	--	0.14	0.23	0.22	0.21	-0.18	0.14	0.45	0.12	0.11	0.66	0.32	0.28

Table A7: Gains from Trade and Markup Distributions implied by Robustness Experiments

	Data	Benchmark	Alternative	Labor wedges	Tariffs	Bertrand	Low γ	High γ	No fix costs	Gauss. copula	n(s),n*(s)	5-digit
TFP loss autarky, %	--	9.0	9.1	8.8	9.0	4.6	4.9	11.3	8.9	9.8	10.4	6.8
TFP loss Taiwan, %	--	7.0	6.7	6.8	6.9	2.1	2.3	9.9	6.9	7.2	7.8	6.2
gains from trade, %	--	12.4	12.0	12.2	14.6	13.8	16.6	11.8	11.8	11.6	26.6	12.3
pro-competitive gains, %	--	2.0	2.4	2.0	2.0	2.5	2.7	1.4	2.0	2.6	2.6	0.5
trade elasticity	4.00	4.00	4.00	4.00	4.00	4.00	3.59	4.00	4.00	4.00	2.99	4.00
import share	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38
fraction exporters	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	1.00	0.25	0.25	0.25
average/aggregate labor share	1.35	1.16	1.17	1.35	1.17	1.09	1.07	1.23	1.19	1.20	1.16	1.14
aggregate markup	--	1.31	1.31	1.30	1.34	1.21	1.37	1.32	1.31	1.34	1.31	1.27
Unconditional markup distribution												
p75/p50	1.01	1.02	1.01	1.01	1.03	1.00	1.02	1.00	1.00	1.01	1.02	1.00
p90/p50	1.03	1.09	1.05	1.05	1.11	1.01	1.05	1.09	1.00	1.06	1.08	1.02
p95/p50	1.06	1.18	1.12	1.12	1.17	1.04	1.10	1.20	1.00	1.13	1.15	1.06
p99/p50	1.27	1.51	1.39	1.38	1.44	1.21	1.28	1.57	1.03	1.42	1.45	1.22
Across-sector markup distribution												
p75/p50	1.10	1.08	1.08	1.08	1.09	1.06	1.06	1.09	1.08	1.08	1.07	1.05
p90/p50	1.27	1.24	1.23	1.23	1.23	1.18	1.18	1.28	1.24	1.23	1.19	1.16
p95/p50	1.50	1.42	1.43	1.43	1.44	1.31	1.53	1.38	1.43	1.42	1.31	1.27
p99/p50	2.34	1.71	1.67	1.68	1.73	1.78	1.60	1.88	1.71	1.58	1.61	1.54

Table A8: Fixed N Experiments

Panel A: No Idiosyncratic Productivity Draws

	Autarky	Free trade $\rho = 1$	Free trade $\rho = 0$		Autarky	Free trade $\rho = 1$	Free trade $\rho = 0$
N=1				**N=2**			
TFP loss, %	0	0	16.4	TFP loss, %	0	0	0.9
import share	0	0.5	0.5	import share	0	0.5	0.5
fraction exporters	0	1	1	fraction exporters	0	1	1
trade elasticity	--	1.32	0.57	trade elasticity	--	2.85	0.63
aggregate markup	5.25	1.83	3.48	aggregate markup	1.83	1.38	1.76
domestic markup	5.25	1.83	3.48	domestic markup	1.83	1.38	1.76
import markup	--	1.83	3.48	import markup	--	1.38	1.76
Markup dispersion				*Markup dispersion*			
unconditional	0	0	0.59	unconditional	0	0	0.22
sectoral	0	0	0	sectoral	0	0	0
N=10				**N=20**			
TFP loss, %	0	0	0.02	TFP loss, %	0	0	0.004
import share	0	0.5	0.5	import share	0	0.5	0.5
fraction exporters	0	1	1	fraction exporters	0	1	1
trade elasticity	--	6.83	0.71	trade elasticity	--	7.97	0.66
aggregate markup	1.20	1.15	1.20	aggregate markup	1.15	1.13	1.15
domestic markup	1.20	1.15	1.20	domestic markup	1.15	1.13	1.15
import markup	--	1.15	1.20	import markup	--	1.13	1.15
Markup dispersion				*Markup dispersion*			
unconditional	0	0	0.04	unconditional	0	0	0.02
sectoral	0	0	0	sectoral	0	0	0

Panel B: With Idiosyncratic Productivity Draws

	Autarky	Free trade $\rho = 1$	Free trade $\rho = 0$		Autarky	Free trade $\rho = 1$	Free trade $\rho = 0$
N=1				**N=2**			
TFP loss, %	0	4.6	15.9	TFP loss, %	4.25	6.73	6.01
import share	0	0.5	0.5	import share	0	0.5	0.5
fraction exporters	0	1	1	fraction exporters	0	1	1
trade elasticity	--	1.29	0.55	trade elasticity	--	2.60	0.63
aggregate markup	5.25	1.88	3.55	aggregate markup	1.87	1.47	1.81
domestic markup	5.25	1.88	3.55	domestic markup	1.87	1.47	1.81
import markup	--	1.88	3.55	import markup	--	1.47	1.81
Markup dispersion				*Markup dispersion*			
unconditional	0	0.14	0.59	unconditional	0.13	0.14	0.24
sectoral	0	0	0	sectoral	0.06	0.09	0.12
N=10				**N=20**			
TFP loss, %	8.0	7.8	8.3	TFP loss, %	7.4	7.1	10.5
import share	0	0.5	0.5	import share	0	0.5	0.5
fraction exporters	0	1	1	fraction exporters	0	1	1
trade elasticity	--	4.33	0.65	trade elasticity	--	4.67	0.65
aggregate markup	1.33	1.31	1.34	aggregate markup	1.30	1.28	1.35
domestic markup	1.33	1.31	1.34	domestic markup	1.30	1.28	1.35
import markup	--	1.31	1.34	import markup	--	1.28	1.35
Markup dispersion				*Markup dispersion*			
unconditional	0.11	0.08	0.09	unconditional	0.08	0.06	0.06
sectoral	0.11	0.11	0.11	sectoral	0.12	0.12	0.12

Notes:
N is number of producers per sector per country
No fixed cost of operating, $f_d = 0$
Free trade means $\tau = 1$ (no net trade cost) and $f_x = 0$
Markup dispersion is measured as std dev of log markups

Table A9: Gains from Trade with Capital Accumulation and Elastic Labor Supply

		Variable markups					
			Frisch elasticity of labor supply ($1/\eta$)				
	Standard model	Aggregate markup constant	0	0.5	1	2	Inf
change TFP, %	10.4	12.4	12.4	12.4	12.4	12.4	12.4
change markup, %	0	0	-2.9	-2.9	-2.9	-2.9	-2.9
change C, %	15.7	18.6	19.5	20.7	21.3	21.8	23.0
change K, %	15.7	18.6	23.0	24.2	24.8	25.4	26.6
change Y, %	15.7	18.6	20.1	21.3	21.9	22.5	23.7
change L, %	0	0	0	1.2	1.8	2.4	3.6
change welfare, % (including transition)	14.5	17.0	18.0	18.1	18.1	18.2	18.4
pro-competitive gains, %	0	2.4	3.5	3.6	3.6	3.7	3.9

Other parameters:

α	output elasticity of capital	0.33
β	time discount factor	0.96
δ	capital depreciation rate	0.1

Table A10: Parameters for Asymmetric Countries Experiments

			Larger trading partner		More productive trading partner	
		Benchmark	L*=2L	L*=10L	Abar*=2Abar	Abar*=10Abar
γ	within-sector elasticity of substitution	10.5	10.5	10.5	10.3	10.3
θ	across-sector elasticity of substitution	1.24	1.24	1.24	1.23	1.23
ξ_x	pareto shape parameter, idiosyncratic productivity	4.58	4.58	4.58	4.58	4.58
ξ_z	pareto shape parameter, sector productivity	0.51	0.51	0.51	0.51	0.51
ζ	geometric parameter, number producers per sector	0.043	0.043	0.043	0.043	0.043
f_d	fixed cost of domestic operations	0.004	0.004	0.004	0.004	0.004
f_x	fixed cost of export operations	0.203	0.203	0.203	0.250	0.300
τ	trade cost	1.129	1.245	1.500	1.132	2.660
ρ	kendall correlation	0.94	0.94	0.96	0.86	0.60

Table A11: Moments implied by Asymmetric Countries Experiments

	Data	Benchmark		Larger trading partner L*=2L		Larger trading partner L*=10L		More productive trading partner Abar*=2Abar		More productive trading partner Abar*=10Abar	
		Home	Foreign	Home	Foreign	Home	Foreign	Home	Foreign	Home	Foreign
Within-sector concentration, domestic sales											
mean inverse HH	7.25	4.30	4.30	4.29	16.63	4.28	17.08	4.36	16.70	4.46	17.14
median inverse HH	3.92	3.79	3.79	3.79	4.48	3.77	4.93	3.81	4.52	3.86	4.93
mean top share	0.45	0.46	0.46	0.46	0.40	0.46	0.37	0.46	0.40	0.47	0.38
median top share	0.40	0.41	0.41	0.41	0.37	0.41	0.34	0.41	0.36	0.40	0.34
Distribution of sectoral shares, domestic sales											
mean share	0.04	0.05	0.05	0.05	0.03	0.05	0.03	0.05	0.03	0.05	0.03
median share	0.005	0.005	0.005	0.005	0.004	0.005	0.004	0.006	0.004	0.007	0.004
p75 share	0.02	0.03	0.03	0.03	0.01	0.03	0.01	0.03	0.01	0.04	0.01
p95 share	0.19	0.27	0.27	0.27	0.17	0.27	0.16	0.27	0.16	0.28	0.16
p99 share	0.59	0.59	0.59	0.59	0.45	0.58	0.41	0.61	0.45	0.65	0.42
std dev share	0.11	0.12	0.12	0.12	0.09	0.11	0.08	0.12	0.09	0.13	0.08
Across-sector concentration											
p10 inverse HH	1.17	1.70	1.70	1.71	1.98	1.71	2.00	1.57	1.92	1.18	1.98
p50 inverse HH	3.73	3.79	3.79	3.79	4.51	3.77	4.95	3.81	4.56	3.86	4.95
p90 inverse HH	13.82	7.66	7.66	7.61	9.77	7.55	10.57	7.93	10.29	8.38	10.86
p10 top share	0.16	0.24	0.24	0.24	0.19	0.24	0.18	0.23	0.19	0.22	0.18
p50 top share	0.41	0.41	0.41	0.41	0.37	0.41	0.34	0.41	0.36	0.40	0.34
p90 top share	0.92	0.75	0.75	0.75	0.65	0.74	0.59	0.79	0.68	0.92	0.63
p10 number producers	2	3	3	3	3	3	3	3	3	2	3
p50 number producers	10	16	16	16	18	16	18	15	17	13	18
p90 number producers	52	47	47	48	64	48	68	46	64	46	66
Size distribution sectors, domestic sales											
fraction sales by top 0.01 sectors	0.26	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.20
fraction sales by top 0.05 sectors	0.52	0.32	0.32	0.32	0.32	0.32	0.31	0.33	0.32	0.34	0.31
fraction wages (same) top 0.01 sectors	0.11	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.23	0.22
fraction wages (same) top 0.05 sectors	0.32	0.33	0.33	0.33	0.33	0.33	0.33	0.34	0.33	0.35	0.32
Size distribution producers, domestic sales											
fraction sales by top 0.01 producers	0.41	0.33	0.33	0.33	0.38	0.33	0.36	0.33	0.37	0.31	0.36
fraction sales by top 0.05 producers	0.65	0.61	0.61	0.62	0.69	0.62	0.67	0.61	0.69	0.58	0.67
fraction wages top 0.01 producers	0.24	0.31	0.31	0.31	0.35	0.31	0.33	0.30	0.34	0.28	0.32
fraction wages top 0.05 producers	0.47	0.57	0.57	0.57	0.65	0.57	0.63	0.56	0.65	0.53	0.62
Import dispersion statistics											
coefficient, share imports on share sales	0.81	0.55	0.55	0.56	0.66	0.59	0.34	0.43	0.52	0.26	-0.03
index import share dispersion	0.38	0.26	0.26	0.24	0.22	0.22	0.19	0.42	0.39	0.68	0.75
index intraindustry trade	0.37	0.45	0.45	0.40	0.40	0.22	0.22	0.26	0.26	0.01	0.01

Table A12: Gains from Trade and Markup Distributions implied by Asymmetric Countries Experiments

	Benchmark		Larger trading partner				More productive trading partner			
			L*=2L		L*=10L		Abar*=2Abar		Abar*=10Abar	
	Home	Foreign	Home	Foreign	Home	Foreign	Home	Foreign	Home	Foreign
TFP loss autarky, %	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0
TFP loss, %	7.0	7.0	7.3	6.8	7.1	7.5	7.4	7.0	7.5	8.6
gains from trade, %	12.4	12.4	12.0	6.5	12.0	2.2	15.3	8.1	31.9	5.6
pro-competitive gains, %	2.0	2.0	1.7	2.1	1.9	1.4	1.5	1.8	1.5	0.4
trade elasticity	4.00	4.00	4.00	4.19	4.00	4.30	4.00	3.12	4.00	1.30
import share	0.38	0.38	0.38	0.21	0.38	0.05	0.38	0.21	0.38	0.07
fraction exporters	0.25	0.25	0.25	0.11	0.25	0.05	0.25	0.10	0.25	0.03
relative real wage	1	1	1	0.94	1	0.89	1	1.85	1	7.66
average/aggregate labor share	1.16	1.16	1.16	1.17	1.16	1.18	1.16	1.18	1.17	1.19
aggregate markup	1.31	1.31	1.31	1.32	1.31	1.33	1.32	1.33	1.34	1.35
Unconditional markup distribution										
p75/p50	1.02	1.02	1.02	1.01	1.02	1.01	1.02	1.01	1.01	1.01
p90/p50	1.09	1.09	1.09	1.05	1.09	1.05	1.09	1.05	1.06	1.06
p95/p50	1.18	1.18	1.18	1.13	1.18	1.14	1.18	1.13	1.14	1.14
p99/p50	1.51	1.51	1.51	1.42	1.51	1.44	1.51	1.42	1.43	1.45
Across-sector markup distribution										
p75/p50	1.08	1.08	1.08	1.09	1.09	1.10	1.18	1.11	2.14	1.10
p90/p50	1.24	1.24	1.25	1.24	1.27	1.29	1.45	1.24	3.45	1.26
p95/p50	1.42	1.42	1.41	1.47	1.38	1.62	1.56	1.36	3.79	1.45
p99/p50	1.71	1.71	1.69	1.76	1.71	2.07	2.02	1.84	5.07	4.12

Table A13: Parameters for Free Entry Experiments

		A: One type of sector	B: Nine types of sectors				
		Free entry	Free entry	Free entry with collusion			
				15%	25%	35%	50%
Common to all free-entry experiments							
γ	within-sector elasticity of substitution	10.50	10.50	10.50	10.50	10.50	10.50
θ	across-sector elasticity of substitution	1.24	1.24	1.24	1.24	1.24	1.24
Calibrated							
xbar	high productivity draw	1.915	1.915	1.748	1.718	1.638	1.487
f_e	entry cost	0.235	0.242	0.197	0.189	0.183	0.255
σ_u	std dev of log productivity gap, domestic vs. export	0.147	0.175	0.171	0.174	0.135	0.196
τ	trade cost	1.134	1.131	1.127	1.136	1.126	1.133
Ω_1(1)	probability of successful entry	0.097	0.047	0.109	0.158	0.078	0.122
Ω_1(2)		--	0.041	0.013	0.012	0.015	0.028
Ω_1(3)		--	0.293	0.301	0.313	0.281	0.339
Ω_2(1)	probability of high-productivity draw given success	0.173	0.180	0.064	0.154	0.198	0.327
Ω_2(2)		--	0.441	0.098	0.059	0.212	0.126
Ω_2(3)		--	0.421	0.052	0.260	0.170	0.203
ν(1)	fraction of sectors of type (Omega1,Omega2)	1	0.138	0.192	0.097	0.123	0.108
ν(2)		--	0.111	0.119	0.062	0.112	0.188
ν(3)		--	0.146	0.043	0.087	0.086	0.036
ν(4)		--	0.154	0.101	0.118	0.134	0.051
ν(5)		--	0.205	0.087	0.131	0.099	0.067
ν(6)		--	0.029	0.103	0.140	0.099	0.173
ν(7)		--	0.096	0.116	0.087	0.111	0.203
ν(8)		--	0.060	0.141	0.148	0.145	0.165
ν(9)		--	0.061	0.100	0.130	0.091	0.009

Table A14: Moments implied by Free Entry Experiments

	Data	No entry (benchmark)	A: One type of sector Free entry	B: Nine types of sectors Free entry	Free entry with collusion 15%	25%	35%	50%
Within-sector concentration, domestic sales								
mean inverse HH	7.25	4.30	4.38	6.22	6.10	7.71	7.10	7.63
median inverse HH	3.92	3.79	3.69	4.08	4.00	5.51	4.62	5.47
mean top share	0.45	0.46	0.33	0.31	0.37	0.31	0.31	0.30
median top share	0.40	0.41	0.30	0.25	0.33	0.25	0.25	0.25
Distribution of sectoral shares, domestic sales								
mean share	0.04	0.05	0.06	0.06	0.06	0.04	0.05	0.07
median share	0.005	0.005	0.006	0.001	0.014	0.007	0.009	0.021
p75 share	0.02	0.03	0.02	0.05	0.04	0.02	0.05	0.07
p95 share	0.19	0.27	0.31	0.25	0.31	0.19	0.25	0.26
p99 share	0.59	0.59	0.47	0.49	0.52	0.50	0.50	0.50
std dev share	0.11	0.12	0.11	0.11	0.12	0.09	0.10	0.10
Across-sector concentration								
p10 inverse HH	1.17	1.70	2.28	2.03	2.00	1.97	2.00	2.07
p50 inverse HH	3.73	3.79	3.69	4.08	4.00	5.51	4.62	5.47
p90 inverse HH	13.82	7.66	6.29	13.29	14.76	16.60	14.83	15.74
p10 top share	0.16	0.24	0.16	0.08	0.07	0.07	0.08	0.09
p50 top share	0.41	0.41	0.30	0.25	0.33	0.25	0.25	0.25
p90 top share	0.92	0.75	0.57	0.66	0.67	0.69	0.64	0.57
p10 number producers	2	3	13	5	2	2	3	3
p50 number producers	10	16	18	9	15	27	13	12
p90 number producers	52	47	23	51	44	54	51	39
Size distribution sectors, domestic sales								
fraction sales by top 0.01 sectors	0.26	0.21	0.19	0.19	0.19	0.19	0.19	0.19
fraction sales by top 0.05 sectors	0.52	0.32	0.38	0.38	0.38	0.38	0.38	0.38
fraction wages (same) top 0.01 sectors	0.11	0.22	0.19	0.19	0.19	0.20	0.19	0.19
fraction wages (same) top 0.05 sectors	0.32	0.33	0.38	0.38	0.38	0.38	0.38	0.38
Size distribution producers, domestic sales								
fraction sales by top 0.01 producers	0.41	0.33	0.35	0.34	0.33	0.36	0.33	0.28
fraction sales by top 0.05 producers	0.65	0.61	0.62	0.60	0.59	0.63	0.59	0.52
fraction wages top 0.01 producers	0.24	0.31	0.34	0.33	0.31	0.34	0.31	0.27
fraction wages top 0.05 producers	0.47	0.57	0.60	0.58	0.56	0.61	0.56	0.49

Table A15: Gains from Trade and Markup Distributions implied by Free Entry Experiments

		A: One type of sector	B: Nine types of sectors				
		Free entry	Free entry	Free entry with collusion			
	Data			15%	25%	35%	50%
TFP loss autarky, %		3.6	3.4	9.1	9.0	10.2	7.8
TFP loss Taiwan, %		1.9	2.2	4.9	4.6	5.1	5.0
gains from trade, %		6.3	6.9	12.5	11.6	8.1	9.6
pro-competitive gains, %		1.7	1.2	4.2	4.3	5.2	2.8
measure of entrants N, autarky		191	187	136	162	176	114
measure of entrants N, Taiwan		176	168	140	160	171	110
Across-sector markup distribution							
p75/p50	1.10	1.03	1.08	1.05	1.09	1.06	1.06
p90/p50	1.27	1.05	1.14	1.17	1.22	1.14	1.14
p95/p50	1.50	1.07	1.17	1.26	1.31	1.20	1.19
p99/p50	2.34	1.09	1.23	1.48	1.56	1.36	1.35