Global Productivity Distribution and Trade in Processed Food Industries

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Introduction

Recent research in international economics has identified large levels of intra-industry reallocation of market shares and resources (Aw, Chung, and Roberts, 2000; Pavcnik, 2002; Bernard and Jensen, 2004). Melitz (2003) and Helpman, Melitz, and Yeaple (2004) suggest that the intra-industry reallocation results from trade liberalization in the presence of firm heterogeneity. The presence of large and persistent differences in capital and skill intensity, size, and productivity among firms in the same, narrowly defined industries has been well documented (Bernard and Jensen, 1999; Helpman, 2006; Bernard *et al.* 2007). Given such heterogeneity, the seminal contribution of Melitz (2003) demonstrates the role of international trade as a catalyst for resource reallocation within an industry. More specifically, exposure to trade in a country induces not only its high-productivity firms to enter foreign markets but also its low-productivity firms to exit the domestic market. The consequences include a reallocation of resource and market share to high-productivity firms and a shift in the industry's productivity distribution to the right, which increases its average productivity. Empirical evidence on such trade-liberalization effects on firms and industries can be found in Aw, Chung, and Roberts (2000), Pavcnik (2002) and Bernard and Jensen (2004). The latter study reports that as much as 40 percent of the productivity growth in the U.S. manufacturing industries can be attributed to the intra-industry reallocation effect.

The objective of this article is to investigate the impact of trade liberalization on the productivity and spatial distribution of global processed food industries. The primary reason for choosing the processed food industries is that the possibility of low-productivity firms' death and resource shifts in favor of high-productivity firms have important consequences for developing countries' employment, wages and income. Agriculture and processed food industries account for up to 60 percent of developing countries' GDP and employment. Although these industries have been subject to tariff reductions in the 1994 Uruguay Round Agreement on Agriculture, few studies have analyzed the resulting spatial reallocation of market shares and resources.[1] We build on Melitz's (2003) and Helpman, Melitz, and Yeaple's (2004) firm-heterogeneity model to investigate the trade liberalization-productivity distribution linkage in a cross-country setting. Our extension considers heterogeneity across countries and tests the hypothesis that the global productivity distribution shifts to the right following multilateral trade liberalization.[2] We also examine the consequent intra-industry redistribution of market shares and resources among countries.

Our empirical analysis includes 1993-2000 data from 34 countries (11 high-income, 23 low-income) on 5 processed food industries, defined on the basis of ISIC (Revision 3) 4-digit classification. We employ a value-added function allowing for country-, industry-, and time-specific effects to estimate total factor productivity (TFP) levels, assuming variable returns to scale (Harrigan, 1999). The productivity distribution of each industry is approximated by nonparametric kernel density estimation (Sala-i-Martin, 2006; Beaudry, Collard, and Green, 2005; Jones, 1997). We then employ

[1] Under URAA, developed countries are to cut agricultural tariffs by 36% during six years following 1994 and developing countries are to reduce their agricultural tariffs by 24% during a ten-year period.

[2] Although we suppress firm differences within a country, i.e., overlook the existence of high-productivity firms inside low-productivity countries, the fact that such countries have the greatest concentration of low-productivity firms remains valid.

quantile regression techniques to quantify the effects of trade liberalization on the global productivity distribution in each industry. Our results suggest global productivity distribution shifts to right with liberalized international trade. Moreover, countries with faster productivity growth benefit from trade liberalization by acquiring larger global market shares and resources.

Conceptual Framework

We draw on the firm-heterogeneity model of Melitz (2003) and Helpman, Melitz, and Yeaple (2004) to investigate the shifts in the global productivity distribution and the intra-industry consequences of trade reform. For this purpose, we first illustrate their monopolistic competition framework, where firms differ in productivity levels. In equilibrium, an industry's productivity distribution and its resource allocation depend on trade exposure. Then, we generalize these results for the cross-country setting.

A continuum of firms produce differentiated goods in the same industry. Each firm manufactures a differentiated variety due to monopolistic competition. With a constant-elasticity-of-substitution (CES) utility function of the Dixit-Stiglitz type, the demand function of firm *i*'s variety is $x_i = Ap_i^{-\varepsilon}$, where x_i is the quantity and p_i is the price, A is a measure of the demand level, and $\varepsilon = 1/(1-\alpha) > 1$ is the demand elasticity.[3] Firm *i* draws its productivity, θ_i, only after it incurs a fixed entry cost, f_E. Upon observing its draw, a firm decides whether or not to produce. If it chooses to produce, it then bears fixed production cost, f_D. If the firm chooses to export, it has to

[3] This form of demand function is derived from a CES utility function. $A = E / \int_{i \in I} p(i)^{1-\varepsilon} di$, where E is total expenditure on these differentiated goods, $p(i)$ is the consumer price of variety *i*, and I is the set of available varieties.

bear the additional fixed cost of f_X per foreign market. The latter allows for high-productivity firms' self-selection into foreign markets (Bernard and Jensen, 1999). Helpman, Melitz, and Yeaple (2004) indicate that f_X can be considered as the costs of forming a distribution and servicing network in a foreign country. In addition, an iceberg trade cost, τ, which includes transportation costs and trade barriers, is incurred for the shipment of every variety between any two countries, i.e., $\tau > 1$ units are shipped for one unit to arrive.

Let c_i / θ_i be the *i*-th firm's variable production cost per unit of output, where c_i measures the cost of resources, which equals the wage rate when labor is the only input into production. When serving the domestic market, firm *i* maximizes its profit by charging a price $p_i = c_i / \alpha\theta_i$, yielding an operating profit $\pi_D^i = \theta_i^{\varepsilon-1} c_i^{1-\varepsilon} B - f_D$, where $B = (1-\alpha)A\alpha^{\varepsilon-1}$. On the other hand, firm *i* can acquire additional operating profits from exporting to a foreign country ℓ, $\pi_X^i = \tau^{1-\varepsilon}\theta_i^{\varepsilon-1} c_i^{1-\varepsilon} B^{\ell} - f_X$, where $B^{\ell} = (1-\alpha)A^{\ell}\alpha^{\varepsilon-1}$. The model is solved by setting π_D^i and π_X^i to zero each, and ensuring free entry, i.e., expected value of a firm equals the fixed entry costs (f_E). The equilibrium distribution of productivity in the industry is characterized by the cut-off productivity levels θ_D and θ_X to break-even in domestic and foreign markets, respectively. Moreover, the higher the average industry profits, the larger is the domestic-market productivity cut-off θ_D (Melitz, 2003).

Figure 1 depicts π_D^i and π_X^i for the case in which $B = B^{\ell}$. In this figure, both profit functions are increasing: high-productivity firms achieve larger profits in both domestic sales and exports than low-productivity firms. The profit function π_D^i is steeper than π_X^i due to trade cost τ. Figure 1 shows that firms with productivity level lower than θ_D will exit the industry, because they gain negative profits from either domestic sales or exports. Firms with intermediate productivities, between θ_D and θ_X, will attain the highest profits by serving only domestic markets. High-productivity firms, with $\theta > \theta_X$, serve both domestic and foreign markets.

Now consider the two-fold effects of multilateral trade liberalization, which proportionally reduces trade costs τ for all countries. The first is the increase in profits from exporting due to the reduction in trade cost. Firms that had productivity levels just below the cutoff θ_X now find exports profitable. Alternatively, the profit function π_X^i rotates to the left, reducing the export-productivity cut-off to $\theta_X' < \theta_X$. Consequently, more firms become exporters and each firm expands its exports, which are referred to as changes in the extensive and intensive margins, respectively. The second effect is on firm profits in the domestic market. The higher average industry profit due to export market opportunities, made possible by trade reform, increases the break-even productivity in the domestic market, $\theta_D' > \theta_D$. In figure 1, this effect rotates π_D^i to the right. In other words, changes in extensive and intensive margins, the death of low-productivity firms and increased export activity, respectively, reallocate market shares to high-productivity firms. Bernard and Jensen (2004) find that as much as 40 percent of the productivity growth in U.S. manufacturing industries is attributed to this intra-industry resource reallocation effect.

Claim

Trade liberalization induced exit of low-productivity firms truncates from below an industry's productivity distribution and increases average industry productivity.

Proof

Suppose that firms draw their productivity from a raw productivity distribution $G(\theta)$.

Firms that draw a productivity level above θ_D produce, and therefore, the equilibrium cumulative productivity distribution is: $F(\theta) = P(\Theta \leq \theta \mid \Theta \geq \theta_D) = \dfrac{G(\theta) - G(\theta_D)}{1 - G(\theta_D)}$,

which implies the truncated probability density function (pdf) is $f(\theta) = \dfrac{g(\theta)}{1 - G(\theta_D)}$,

where $g(\theta)$ is the pdf of $G(\theta)$.

By definition, the cumulative density of the *p*-th quantile of the truncated distribution, θ^p, is $F(\theta^p) = \dfrac{G(\theta^p) - G(\theta_D)}{1 - G(\theta_D)} = p$, where $p \in [0,1]$, which yields $G(\theta^p) = p + (1-p)G(\theta_D)$. As trade liberalization raises θ_D and $G(\theta_D)$, $G(\theta^p)$ rises, leading to an increase in θ^p. That is, any quantile value of the truncated distribution rises with the increase of domestic cutoff θ_D, and therefore, the whole truncated productivity distribution shifts to the right.

The mean of the truncated distribution $F(\theta)$ is defined as $E(\theta) = \dfrac{\int_{\theta_D}^{+\infty} \theta g(\theta) d\theta}{1 - G(\theta_D)}$.

The first derivative of $E(\theta)$ with respect to θ_D is:

$$\frac{dE(\theta)}{d\theta_D} = \frac{[\int_{\theta_D}^{+\infty} \theta g(\theta) d\theta]'[1-G(\theta_D)] + g(\theta_D)\int_{\theta_D}^{+\infty} \theta g(\theta) d\theta}{[1-G(\theta_D)]^2}$$

$$(1) \qquad = \frac{g(\theta_D)[\int_{\theta_D}^{+\infty} \theta g(\theta) d\theta + G(\theta_D)\theta_D - \theta_D]}{[1-G(\theta_D)]^2} \quad .$$

$$= \frac{g(\theta_D)}{1-G(\theta_D)} \cdot [E(\theta) - \theta_D]$$

$$> 0$$

That is, trade liberalization increases the industry's average productivity by forcing the low-productivity firms to exit. *Q.E.D.*

The impact of trade liberalization on global productivity distribution can also be shown by figure 2. In figure 2, $G(\theta)$ is the raw productivity distribution from which firms draw their productivity. However, only firms with productivity levels above domestic cutoff θ_D can make positive profit and thus, operate in the market, which yields a truncated productivity distribution with a mean of E_1. Trade liberalization increases the domestic cutoff to θ_D', forcing the low-productivity firms to exit the industry, and thus, improving the average productivity of the surviving firms to E_2. As a result, trade liberalization raises the industry average productivity even if the raw productivity distribution does not change. This increase is in addition to the shift in the raw productivity distribution, $G(\theta)'$, in figure 2, arising from factors such as the industry's research and development investment, infrastructure or international technology transfers. Given the new raw distribution, the average industry productivity will then shift to E_3.

Our application of the model to processed food industries treats each country as a firm. That is, we work with heterogeneity across countries than that in the intra-country dimension and explore resource reallocation within an industry, but across countries. By suppressing firm differences within a country, we may be overlooking high-productivity firms inside low-productivity countries, but it does not diminish the fact that such countries have the greatest concentration of low-productivity firms. Moreover, few studies have access to internationally comparable cross-country, firm-level databases with a time series (Tybout, 2000).

Econometric Framework and Procedure

In our empirical application, we estimate total factor productivity (TFP) from an econometric specification of a value-added function (Miller and Upadhyay, 2002; Harrigan, 1999; Bernard and Jones, 1996). Details of the assumed value-added structure, which permits variable returns-to-scale, are provided in Appendix I. The approach in Appendix I allows hypothesis tests about the robustness of cross-country TFP measures (Miller and Upadhyay, 2002; Bernard and Jones, 1996; Baumol, Nelson, and Wolff, 1994; Ark and Pilat, 1993). The internationally comparable database described in the next section permits cross-country comparisons of TFP levels.

With industry- and country-specific time-series data on TFP levels, we can estimate each industry's global productivity distribution for each year using a nonparametric kernel density function (Sala-i-Martin, 2006; Beaudry, Collard, and Green, 2005; Jones, 1997). We follow the convention in the literature to use the bandwidth $w=1.059\sigma n^{-1/5}$, where σ is the standard deviation of log-TFP, and n is the number of observations. For each productivity distribution, we then approximate its first moment and p-th percentiles (p = 10, 25, 50, 75, and 90). Thus for each industry, we use time-series estimates of percentiles to capture the shifts of productivity distribution.

In the previous section, we showed how trade liberalization shifts global productivity distribution to the right, resulting in higher average industry productivity. The latter is due to the truncation from below of the productivity distribution, which forces the low-productivity firms to exit the industry. To empirically identify the effect of trade liberalization on the industry's productivity distribution, we specify the estimated first moment and alternative percentile values as a function of a measure of trade liberalization:

$$PROD_{jt} = \beta_{0\,jt} + \beta_1 LOGTRADE_{jt} + \beta_2 YEAR_t + \mu_{1\,jt}\,, \tag{2}$$

where $PROD_{jt}$ denotes the estimated first moment or any of the five quantiles in industry j at period t; $LOGTRADE_{jt}$ denotes log of aggregate trade value in industry j at period t, a measure of industry j's degree of trade liberalization.[4] Thus, the coefficient β_1 indicates the effect of trade liberalization on productivity distribution, and we expect its estimate to take a positive sign. As indicated in figure 2, productivity distribution may also shift over time due to non-trade-liberalization factors, which we capture in two alternative ways. The first is the use of the intercepts, $\beta_{0\,jt}$, which allow for productivity to vary across industries and time due to differences in production technologies, institutional environment, or other unobserved heterogeneity. We therefore include two-way fixed and random effects in equation (2), and employ Hausman test to choose

[4] We considered two alternatives for $LOGTRADE_{jt}$. Employing the one-period lag of global trade value we find significant effects of trade liberalization on the 10^{th} and 25^{th} percentile productivity, and the first moment of productivity distribution in the industry-fixed-effect specifications. However, a Hausman test suggested that current trade value and the industry's productivity growth are not simultaneously determined. We also use trade share of output as an alternative measure of the degree of trade liberalization in an industry. Again, we find that the 10^{th} and 25^{th} percentile productivity are significantly improved by trade share of output. These results are consistent with the expected exit of low-productivity firms, which we discuss in the Results section.

between the two estimators. The other approach we use is to introduce a time-trend, $YEAR_t$, to account for the effect on productivity distribution of these non-trade-liberalization factors. The term μ_{1jt} in equation (2) represents a random disturbance term.

In our application to the cross-country setting, trade liberalization should reallocate market share and resources to high-productivity countries within an industry. For each industry, we use the difference between a country's productivity and the estimated global average to measure the former's relative productivity status. That is, $PRODIFF_{ijt} = PROD_{ijt} - PROD_{jt}$, where $PROD_{ijt}$ is country *i*'s productivity in industry *j* at period *t*, $PROD_{jt}$ is industry *j*'s productivity average. In other words, $PRODIFF_{ijt}$ is country *i*'s productivity relative to the industry average in time *t*. Then, a country's higher productivity relative to the global average should induce global resource and market shares in its direction. Let $GSHARE_{ijt}$ be the indicator of country *i*'s global market share or resource share in industry *j* at period *t*, where the market share is measured by global value-added share and global output share, and the resource share is measured by global capital share and global labor share. Thus, $\Delta GSHARE_{ijt}$ denotes the annual growth rate of $GSHARE_{ijt}$ from the previous year:

(3) $$\Delta GSHARE_{ijt} = ln\, GSHARE_{ij,t} - ln\, GSHARE_{ij,t-1}.$$

To capture the reallocation of market shares and resources due to trade liberalization, we specify $\Delta GSHARE_{ijt}$ as follows:

(4) $$\Delta GSHARE_{ijt} = \gamma_0 + \gamma_1 \Delta PRODIFF_{ijt} + \gamma_2 YEAR_t + \mu_{2ijt},$$

where $\Delta PRODIFF_{ijt}$ denotes the annual growth rate of country *i*'s productivity relative to that of the industry average productivity; $YEAR_t$ denotes a time-trend; and μ_{2ijt} is a random disturbance term. With the shift of productivity distribution, market shares and resources are reallocated toward more productive countries. We therefore expect the estimate of γ_1 to take a positive sign. As in equation (2), we consider fixed- and random-time effects in equation (4). Given the growth-growth specification, the cross-country and –industry heterogeneity cancel out in equation (4).

Data

The United Nations Industrial Development Organization's (UNIDO) Industrial Statistical Database (INDSTAT4 2005) provides cross-country data on manufacturing industry value-added, employment, gross fixed capital formation, and output. Data on 5 processed food industries, based on ISIC (Revision 3) 4-digit classifications in 34 countries from 1993 to 2000, are taken from INDSTAT4.[5] Among the 34 countries, 11 are developed (Austria, Denmark, Finland, Ireland, Italy, Japan, Norway, Portugal, Spain, United Kingdom, United States), and 23 are developing economies (Columbia, Cyprus, Ecuador, Eritrea, Ethiopia, India, Indonesia, Iran, Jordan, Korea, Kuwait, Malawi, Malaysia, Malta, Mexico, Mongolia, Oman, Panama, Singapore, Sri Lanka, Thailand, Tunisia, Turkey). Data for some countries are available only in selected years, so data classified at ISIC Revision 2 are used to complete the series. In U.S. industries, correspondences between ISIC Revision 2 and Revision 3 are taken from U.S. Bureau of

[5]Although there are 17 ISIC 4-digit processed food industries, we chose only 5 due to data availability. Most statistical studies implementing kernel density estimators use at least 25 observations in each time period to capture the underlying (productivity) distribution and its moments.

Census; we assume this correspondence is applicable to every nation.[6] As data availability varies by country and industry, we have an unbalanced data panel. Except for employment, which is expressed in labor units, production data are measured in INDSTAT4 in current local currencies. To render them internationally comparable, we first convert cross-country and -industry data to constant 2000 local currencies by using the corresponding price index from the World Bank's 2005 World Development Indicators (WDI). We then convert them to constant 2000 U.S. dollars by using the purchasing power parity (PPP) conversion factors from 2005 WDI.[7]

With data on annual gross fixed capital formation, we construct capital stock as a function of past investment flows, following the standard perpetual inventory equation with declining-balance depreciation (Crego *et al.* 1998; Hall *et al.* 1988):

$$(5) \qquad K_t = (1-d)K_{t-1} + I_t ,$$

where I_t is gross fixed capital formation in year t, K_t is capital stock at end of year t, and d is depreciation rate.[8]

Bilateral trade data, expressed in nominal U.S. dollars, come originally from the COMTRADE database (United Nations) and are reclassified into ISIC (Revision 3) 4-

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[6] Some countries' data are available for certain years in both revisions. These data enable us to test the average difference between the data reported in Revision 3 and those converted, from the U.S. industry correspondences, from Revision 2 to Revision 3. Results of t-tests indicate that none of the data differences in value-added, output, employment, or gross fixed capital formation is significantly different from zero at the 5% significance level. Hence, we apply to other countries the U.S. correspondences between the two revisions.

[7] Manufacturing value-added price index and output price index are computed as the ratio of current to constant manufacturing value added; and gross-fixed-capital-formation price index is computed as the ratio of current to constant gross fixed capital formation in the aggregate economy.

[8] We follow Hall *et al.*'s (1988) procedure to obtain base-year capital stock data. Given that I_{t0} is base-year investment, initial capital stock K_{t0} equals $I_{t0}/(d+g)$, where g is pre-sample annual growth rate of new capital. Country-specific pre-sample capital growth rates are derived as the average annual growth rates of gross fixed capital formation in the aggregate economy during the 10-year pre-sample period (2005 WDI). We set the depreciation rate (d) at 8% per year.

digit-level industries. We adopt country-specific import and export price indexes from WDI and convert them to constant 2000 U.S. dollars.[9]

Results and Discussion

Estimates of the determinants of country-level TFP, equation (I.3), are presented in table 1. Log of capital per unit labor is significant at the 1% level and indicates the elasticity of value added with respect to capital is 0.250. The statistically insignificant coefficient of the log of employment (-0.024) suggests food industries exhibit constant returns to scale. Earlier studies have found mixed evidence of scale economies in processed food industries. For instance, focusing on aggregate processed-food industry data, Chan-Kang, Buccola, and Kerkvliet (1999) find modest scale economies in the U.S. food processing industry, while Gopinath (2003) finds significant scale diseconomies in 13 OECD countries. The elasticity of value-added with respect to employment, implicit in the coefficients of employment and capital per unit labor in table 1, is 0.726 (equation I.3). Processed food industries appear, that is, to be labor intensive, consistent with earlier analysis (e.g., Melton and Huffman, 1995; Gopinath, 2003).

Cross-country and -industry TFP estimates are derived for each year with the estimates in table 1 using equation I.4 in appendix I. An F-test rejects, at the 1% level, the null hypothesis of identical technologies across countries [F(33, 1050), 45.70]. Thus, TFP estimates show significant variation in level and growth rate across countries, among which the U.S. is the technological leader in each of the five processed food industries.

[9] The import (export) price index is calculated as the ratio of current to constant imports (exports) of goods and services in the aggregate economy.

Previous studies have found U.S. TFP levels in most processed food industries to be high as well (Harrigan, 1997; Chan-Kang, Buccola, and Kerkvliet, 1999; Gopinath, 2003).

With cross-country, -industry, and -time TFP levels, we employ kernel density techniques to approximate the global productivity distributions for each food industry in every time period. Densities are computed using a Gaussian kernel at each estimating point. Cumulative density then allows estimation of alternative percentile values, and first and second moments of the distribution. Table 2 presents the mean and standard deviation of each industry's productivity distribution in 1993 and 2000. In all the five food industries, industry average productivity has risen during 1993-2000, and the average annual growth rate varies between 0.2 and 2.9 percent.

The estimates of equation (2), i.e., effects of trade liberalization on productivity distribution, are reported in table 3. Four sets of estimates are presented: industry-fixed effects; industry-random effects; industry- and time-fixed effects; and industry- and time-random effects. In most cases, the Hausman tests favor fixed-effects estimators as indicated by the chi-squared test statistics in table 3. In addition, F tests indicate evidence of time-specific effects. Hence, the following discussion focuses on the estimates with industry- and time-fixed effects.

The second column in table 3 corresponds to the trade-effects on the mean of the global productivity distribution. An industry's average productivity increases by 0.465 percent for every 1 percent increase in its global trade and this effect is statistically significant at the 1 percent level. Both industry- and time-specific effects are significant in the mean regression at the 1 and 10 percent levels, respectively. The R^2 of 91.3 percent suggests that our model well explains the variation in the mean of the global productivity distribution. The positive effect of an industry's global trade value on its average productivity is robust across four alternative estimation techniques reported in table 3. However, the random-effects estimates of global trade effects on average industry productivity is about half of those from fixed-effect models. In general, our results are consistent with the firm-heterogeneity models that predict an increase in an industry's average industry productivity following trade liberalization. It is likely that low-productivity firms are forced to exit and, most probably, in low-productivity (developing) countries.

The third to the seventh columns in table 3 report the estimates of trade liberalization's effects on the various measures of global of productivity distribution, i.e., 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles. Except in the case of the 90^{th} percentile, our estimates show that the measures of global productivity distribution are positively and significantly affected by an increase in global trade. The elasticity of productivity with respect to global trade ranges from 0.300 to 0.715. Noteworthy is the elasticity of percentile productivity with respect to the global trade declines with the increase of quantiles, suggesting that facing trade liberalization, productivity improvement is faster in low-productivity countries than in their high-productivity counterparts. The latter result is consistent with the literature on productivity convergence. Earlier studies have found global productivity convergence in manufacturing industries. For example, Bernard and Jones (1996) indicate during 1970-1987, productivity convergence has taken place in manufacturing industry of 14 OECD countries with an annual convergence rate of 1.68%. Gopinath (2003) also finds evidence of productivity convergence in food industry among 13 OECD countries during the period of 1975-1995. Furthermore, the high-percentile productivity, e.g., 90th, may better respond to technological investments than trade liberalization.

In table 3, F tests suggest the presence of industry-specific effects in each of the five percentile regressions, and that of time-specific effects in the 50th, 75th and 90th percentile equations. In these percentile regressions, the R^2 ranges from 58.1 to 95.5 percent. Note that our results are robust across the two fixed-effect estimates, with and without time-specific effects. Except for 10th and 90th percentile productivity regressions, Hausman tests favor fixed effects in other equations. In general, our results suggest that the shifts in global productivity distribution, especially the left-tail, are strongly influenced by the increase in global trade in processed food industries.

We present the results of reallocation of market shares and resources, due to the shift of the global productivity distribution, in table 4. Three sets of estimates are reported: with time-fixed effects, time-random effects, and a time-trend. In the following, we focus on the results from the model with time-fixed effects, given their statistical significance. Note, however, the effects of relative productivity do not vary much across the three specifications reported in table 4.[10] Reallocation of market shares is measured by the annual growth rate in a country's global value-added share and its global output share. For every 1 percent growth in a country's productivity relative to the global average, its share in global value-added increases by 1.112 percent, and that in global output increases by 0.606 percent. Both of these effects are significant at the 1 percent level, confirming our claim that market shares will be reallocated toward high-

[10] Fixed- and random-effects models yield the same coefficients on annual growth rate of relative productivity, and so, the Hausman statistics are close to zero in all four equations. Though F tests favor time-specific effects, using a time-trend instead does not change the coefficient on growth rate of relative productivity in any of the four equations.

productivity countries. Note that our estimation of equation (4) explains 76.2 percent of the variation in global value-added share, and 36.7 percent of the variation in global output share.

The reallocation of production resources associated with the shift of productivity distribution, captured using annual growth rate in a country's global labor share and global capital share, is presented in the last two columns of table 4. Global labor share of a country increases by 0.173 percent for every 1 percent growth in its productivity relative to the global average. So, employment in processed food industries shifts due to relative productivity differences. However, growth in a country's relative productivity does not significantly affect its global capital share in our results. The latter may arise if processed food industries are labor-intensive or capital's mobility is restricted. For instance, the gain from productivity growth may not be enough to release capital, whose returns may be bounded between salvage value and average market return on other investments.

Summary and Conclusions

In this article, we investigate the effects of trade liberalization on the global productivity distribution in processed food industries. For this purpose, we extend firm-heterogeneity models of international trade to a cross-country setting. The extension suggests that multilateral trade liberalization induces intra-industry reallocation of market shares and resources. In particular, export market opportunities raise average industry profits, which in turn, increases the minimum productivity required to break-even in domestic markets. Thus, low-productivity firms are forced to exit an industry, while resources and market shares are reallocated to high-productivity firms. Our application of the model to processed food industries considers heterogeneity across countries than that in the intra-country dimension. The macro focus allows us to explore reallocation of resources away from countries that have the greatest concentration of low-productivity firms in a given industry.

Data on 5 processed food industries in 34 developed and developing nations are assembled to estimate, through a value-added equation, cross-country and cross-industry productivity levels. Estimates indicate significant cross-country variation in productivity levels, with U.S. as the productivity leader in each of the five food industries. For each industry, we approximate the global productivity distribution in each year by using a nonparametric kernel density estimator. We then employ quantile regression techniques to estimate the effects of trade liberalization on the global productivity distribution. More specifically, the first moment and alternative percentile values are used to represent the shifts of the global productivity distribution. We find that our estimates of trade-liberalization effects on such measures of global productivity distribution to be robust across alternative econometric specifications. The results suggest that trade liberalization significantly boosts an industry’s average productivity and shifts to the right most of the percentile values of the global productivity distribution. Moreover, countries with faster productivity growth relative to the global average increase their shares of global value-added, output, and labor. The latter confirms the intra-industry reallocation of market shares and resources to high-productivity countries.

Since the early of 1990s, multilateral trade liberalization has greatly deepened the global integration of processed food production. Our study examines the evolution of global productivity distribution in processed food industries, its response to trade liberalization, and the intra-industry reallocation of market shares and resources among countries. Ceteris paribus, our results suggest that a liberalized trade regime can improve industry average productivity, and thus, the income and welfare of an economy. However, low-productivity countries - regardless of their comparative advantage- face significant adjustments to employment and income following trade liberalization.

Figure 1. Profits from Domestic Sales and from Exports

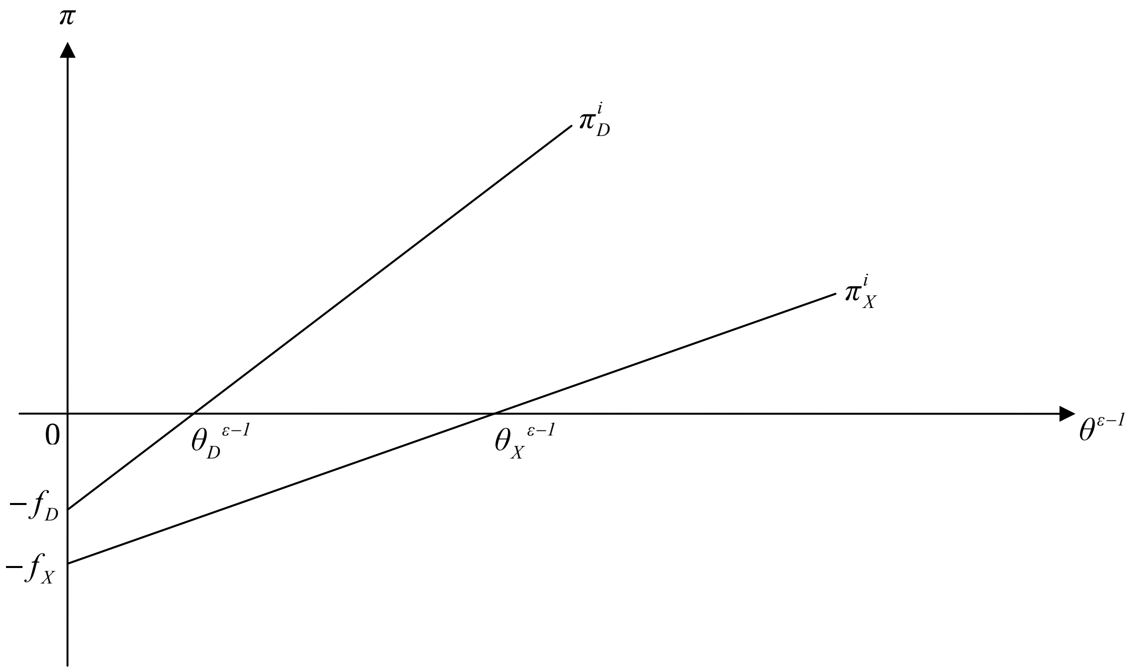

Figure 2. Global Productivity Distribution with Trade Liberalization

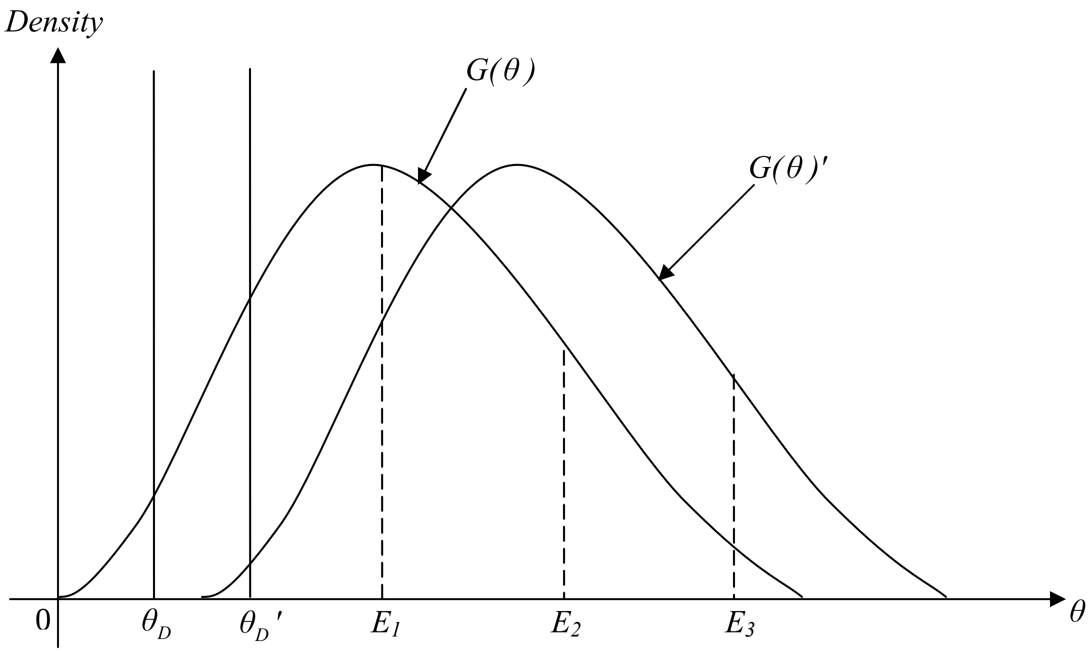

Table 1. Estimates of the Value-Added Equation
(Dependent Variable: Log of Value-Added Per Worker, 1993-2000)

Independent Variable		
Log of capital per labor	0.250***	(11.51)
Log of employment	-0.024	(-1.38)

Country-Specific Intercepts			**Industry-Specific Intercepts**			**Time-Specific Intercepts**		
Austria	8.456***	(24.36)	1511	-0.232***	(-4.85)	1993	-0.098	(-1.57)
Colombia	8.991***	(26.46)	1512	-0.411***	(-7.67)	1994	-0.077	(-1.30)
Cyprus	8.174***	(25.87)	1513	-0.459***	(-9.21)	1995	-0.009	(-0.16)
Denmark	8.429***	(24.07)	1514	0.081*	(1.67)	1996	-0.025	(-0.41)
Ecuador	6.785***	(19.44)	1520	----		1997	0.061	(1.02)
Eritrea	7.143***	(21.87)				1998	-0.011	(-0.19)
Ethiopia	7.103***	(24.84)				1999	-0.021	(-0.35)
Finland	8.295***	(24.28)				2000	----	
India	7.626***	(21.42)						
Indonesia	7.742***	(21.78)						
Iran	8.080***	(21.91)						
Ireland	8.575***	(24.19)						
Italy	8.558***	(22.82)						
Japan	8.838***	(23.87)						
Jordan	7.714***	(25.23)						
Korea	8.617***	(23.61)						
Kuwait	7.852***	(24.94)						
Malawi	6.023***	(18.01)						
Malaysia	8.193***	(23.93)						
Malta	8.189***	(26.29)						
Mexico	8.029***	(21.62)						
Mongolia	5.685***	(15.73)						
Norway	8.186***	(23.41)						
Oman	7.573***	(21.45)						
Panama	8.004***	(25.23)						
Portugal	7.748***	(21.95)						
Singapore	7.975***	(24.37)						
Spain	8.504***	(23.53)						
Sri Lanka	7.909***	(27.24)						
Thailand	7.913***	(20.62)						
Tunisia	7.319***	(20.45)						
Turkey	8.736***	(25.11)						
United Kingdom	8.623***	(23.81)						
United States	9.225***	(24.16)						

$R^2 = 0.998$

$N = 1097$

F test: H_0: $b_{0c} = b_0 \quad \forall c$ F (33, 1050)=45.70*** Reject H_0

*** indicates significance at 1%; * indicates significance at 10%; numbers in parentheses are t-statistic of the coefficients. Dummy variables of ISIC 1520 and year 2000 are dropped to avoid perfect multicollinearity.

Table 2. Descriptive Statistics, 1993 and 2000: Mean and Standard Deviation of Global Productivity Distributions in Processed Food Industries

Industry and ISIC code	Mean of log-TFP 1993	Mean of log-TFP 2000	Annual growth rate (%)
1511 Processing/preserving of meat	7.687	7.739	0.7
	(0.85)	(0.90)	
1512 Processing/preserving of fish	7.759	7.848	1.3
	(0.65)	(0.76)	
1513 Processing/preserving of fruits and vegetables	7.767	7.778	0.2
	(0.85)	(0.81)	
1514 Vegetable and animal oils and fats	7.796	8.002	2.9
	(0.82)	(0.94)	
1520 Dairy products	8.015	8.101	1.2
	(0.90)	(0.78)	

Numbers in parentheses are standard deviation.

Table 3. Effects on Productivity Distribution

	Dependent Variable					
	Mean	10^{th} Percentile	25^{th} Percentile	50^{th} Percentile (Median)	75^{th} Percentile	90^{th} Percentile
Industry- and Time-Fixed Effects						
Intercept	-3.557	-10.567	-9.095	-2.825	0.942	4.803
	(-1.00)	(-1.03)	(-1.58)	(-0.94)	(0.33)	(0.96)
Log of trade value	0.465***	0.715*	0.674***	0.439***	0.300**	0.155
	(3.17)	(1.68)	(2.83)	(3.53)	(2.53)	(0.75)
F test for industry-fixed effect	F(4, 27) = 38.39***	F(4, 27) = 6.86***	F(4, 27) = 13.64***	F(4, 27) = 46.96***	F(4, 27) = 64.31***	F(4, 27) = 20.74***
F test for time-fixed effect	F(7, 27) = 2.14*	F(7, 27) = 0.84	F(7, 27) = 1.60	F(7, 27) = 3.81***	F(7, 27) = 3.58***	F(7, 27) = 3.60***
R square	0.913	0.581	0.744	0.923	0.955	0.908
N = 40						
Industry- and Time-Random Effects						
Intercept	4.578***	3.103	3.955*	6.142***	6.780***	9.148***
	(2.73)	(1.15)	(1.89)	(3.55)	(4.13)	(3.72)
Log of trade value	0.139**	0.156	0.145	0.076	0.069	-0.012
	(1.99)	(1.39)	(1.66)	(1.06)	(1.01)	(-0.12)
Hausman test	$\chi^2(1)$ = 6.40**	$\chi^2(1)$ = 1.86	$\chi^2(1)$ = 5.69**	$\chi^2(1)$ = 12.84***	$\chi^2(1)$ = 5.72**	$\chi^2(1)$ = 0.86
N=40						
Industry-Fixed Effects						
Intercept	29.712***	59.451*	62.000***	46.910***	14.463	-35.968*
	(2.30)	(1.77)	(3.37)	(4.24)	(1.18)	(-1.74)

Table 3. (Continued)

	Dependent Variable					
	Mean	10^{th} Percentile	25^{th} Percentile	50^{th} Percentile (Median)	75^{th} Percentile	90^{th} Percentile
Log of trade value	0.355***	0.704***	0.633***	0.302***	0.147	0.014
	(3.76)	(2.87)	(4.70)	(3.73)	(1.64)	(0.09)
Time trend	-0.015**	-0.035*	-0.035***	-0.023***	-0.005	0.022*
	(-2.08)	(-1.83)	(3.34)	(-3.68)	(-0.70)	(1.88)
F test for industry-fixed effect	F(4, 33) = 38.16***	F(4, 33) = 9.09***	F(4, 33) = 20.03***	F(4, 33) = 44.08***	F(4, 33) = 43.02***	F(4, 33) = 14.88***
R square	0.880	0.536	0.729	0.891	0.915	0.840
N=40						
Industry-Random Effects						
Intercept	12.90	7.324	28.151	33.831***	2.878	-55.056***
	(0.97)	(0.26)	(1.54)	(2.99)	(0.24)	(-3.10)
Log of trade value	0.190**	0.202	0.305**	0.173**	0.033	-0.171
	(2.14)	(1.28)	(2.64)	(2.26)	(0.41)	(-1.58)
Time trend	-0.005	-0.003	-0.014	-0.015**	0.002	0.034***
	(-0.64)	(-0.17)	(-1.39)	(-2.37)	(0.35)	(3.49)
Hausman test	$\chi^2(2)$ = 26.27***	$\chi^2(2)$ = 7.16**	$\chi^2(2)$ = 22.66***	$\chi^2(2)$ = 25.94***	$\chi^2(2)$ = 9.48***	$\chi^2(2)$ = 3.07
N=40						

*** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%.
Numbers in parentheses are t-statistic of the coefficients.

Table 4. Reallocation of Market Shares and Resources

	Dependent Variable			
	Annual growth rate of global value-added share	Annual growth rate of global output share	Annual growth rate of global labor share	Annual growth rate of global capital share
Time-Fixed Effect				
Annual growth rate of productivity relative to the industry average	1.112*** (43.74)	0.606*** (17.78)	0.173*** (6.19)	-0.038 (-1.16)
F test for time-fixed effect	F(4, 616) = 11.49***	F(4, 608) = 9.43***	F(4, 616) = 12.97***	F(4, 616) = 16.98***
R square	0.762	0.367	0.130	0.111
N	622	614	622	622
Time-Random Effect				
Intercept	-0.039 (-0.94)	-0.009 (-0.18)	-0.179 (-0.37)	-0.043 (-0.72)
Annual growth rate of productivity relative to the industry average	1.112*** (43.78)	0.606*** (17.79)	0.173*** (6.20)	-0.038 (-1.16)
Hausman test	$\chi^2(1) = 0$	$\chi^2(1) = 0.01$	$\chi^2(1) = 0$	$\chi^2(1) = 0.03$
N	622	614	622	622
Time-Trend				
Intercept	-5.215 (-0.55)	6.946 (0.55)	-17.637* (-1.69)	-33.674*** (-2.71)

Table 4. (Continued)

	Dependent Variable			
	Annual growth rate of global value-added share	Annual growth rate of global output share	Annual growth rate of global labor share	Annual growth rate of global capital share
Annual growth rate of productivity relative to the industry average	1.112*** (42.31)	0.605*** (12.27)	0.173*** (5.98)	-0.036 (-1.06)
Time trend	0.003 (0.54)	-0.003 (-0.55)	0.009* (1.69)	0.017*** (2.71)
R square	0.743	0.329	0.059	0.013
N	622	614	622	622

*** indicates significance at 1%; * indicates significance at 10%.
Numbers in parentheses are t-statistic of the coefficients.

References

Ark, B.V. and D. Pilat. 1993. "Productivity Levels in Germany, Japan, and the United States: Differences and Causes." *Brookings Papers on Economic Activity: Microeconomics* 0(0): 1-48.

Aw, B.Y., S. Chung, and M.J. Roberts. 2000. "Productivity and Turnover in the Export Market: Micro-level Evidence from the Republic of Korea and Taiwan (China)." *World Bank Economic Review* 14(1):65-90.

Baumol, W.J., R.R. Nelson, and E.N. Wolff. 1994. *Convergence of Productivity: Cross-National Studies and Historical Evidence*. Oxford University Press, Oxford.

Beaudry, P., F. Collard, and D.A. Green. 2005. "Changes in the World Distribution of Output per Worker, 1960-1998: How a Standard Decomposition Tells an Unorthodox Story." *Review of Economics and Statistics* 87(4):741-753.

Bernard, A.B., and C.I. Jones. 1996. "Comparing Apples to Oranges: Productivity Convergence and Measurement across Industries and Countries." *American Economic Review* 86(5):1216-1238.

Bernard, A.B., and J.B. Jensen. 1999. "Exceptional Exporter Performance: Cause, Effect, or Both?" *Journal of International Economics* 47(1):1-25.

Bernard, A.B., and J.B. Jensen. 2004. "Exporting and Productivity in the USA." *Oxford Review of Economic Policy* 20:343-357.

Bernard, A.B., J.B. Jensen, S.J. Redding, and P.K. Schott. 2007. "Firms in International Trade." *Journal of Economic Perspectives* forthcoming.

Chan-Kang, C., S. Buccola and J. Kerkvliet. 1999. "Investment and Productivity in Canadian and U.S. Food Manufacturing." *Canadian Journal of Agricultural Economics* 47(2):105-118.

Crego, A., D. Larson, R. Butzer, and Y. Mundlak. 1998. *A New Database of Investment and Capital for Agriculture and Manufacture*. World Bank, Working Paper No. 2013, Washington D.C.

Gopinath, M. 2003. "Cross-country Differences in Technology: The Case of the Food Processing Industry." *Canadian Journal of Agricultural Economics* 51(1):97-107.

Hall, B.H., C. Cummins, E.S. Laderman, and J. Mondy. 1988. *The R&D Master File Documentation*. National Bureau of Economic Research, Technical Working Paper No. 72, Cambridge, MA.

Harrigan, J. 1997. "Technology, Factor Supplies, and International Specialization: Estimating the Neoclassical Model." *American Economic Review* 87:475-494.

___. 1999. "Estimation of Cross-Country Differences in Industry Production Functions." *Journal of International Economics* 47(2):267-293.

Helpman, E. 2006. "Trade, FDI, and the Organization of Firms." Journal of Economic Literature 44(3):589-630.

Helpman, E., M.J. Melitz, and S.R. Yeaple. 2004. "Export versus FDI with Heterogeneous Firms." *American Economic Review* 94(1):300-316.

Jones, C.I. 1997. "On the Evolution of the World Income Distribution." *Journal of Economic Perspectives* 11(3):19-36.

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

Melton B.E., and W.E. Huffman. 1995. "Beef and Pork Packing Costs and Input Demands: Effects of Unionization and Technology." *American Journal of Agricultural Economics* 77(3):471-485.

Miller, S.M., and M.P. Upadhyay. 2002. "Total Factor Productivity and the Convergence Hypothesis." *Journal of Macroeconomics* 24(2):267-286.

Pavcnik, N. 2002. "Trade Liberalization, Exit, and Productivity Improvement: Evidence from Chilean Plants." *Review of Economic Studies* 69(1):245-276.

Sala-i-Martin, X. 2006. "The World Distribution of Income: Falling Poverty and … Convergence, Period." *Quarterly Journal of Economics* 121(2):351-397.

Tybout, J.R. 2000. "Manufacturing Firms in Developing Countries: How Well Do They Do, and Why?" *Journal of Economic Literature* 38(1):11-44.

United Nations. *UNIDO INDSTAT4 2005 Industrial Statistics Database at the 4-digit level of ISIC (Rev. 3)*, Austria, 2005.

World Bank. *World Development Indicators*, 2005.

Appendix I. Estimation of Cross-Country and –Industry TFP

For country *c* in industry *i* at time *t*, consider real value-added, y_{cit}, as a function of real capital stock k_{cit} and employment level l_{cit}:

(I.1) $$y_{cit} = Z_{cit} \cdot g_{cit}(k_{cit}, l_{cit}),$$

where Z_{cit} is an index of TFP (Hicks-neutral technological change). Assume that function $g_{cit}(k_{cit}, l_{cit})$ has a Cobb-Douglas form, so that an estimable form of equation (I.1) is

(I.2) $$\ln(y_{cit} / l_{cit}) = a_{0cit} + a_1 \ln(k_{cit} / l_{cit}) + \rho \ln l_{cit}$$

where $\rho = a_1 + a_2 - 1$. Equation (I.2) indicates that value added per worker is a function of capital per worker and total employment. The scale elasticity in equation (I.2) is given by $1+\rho$, where ρ indicates how far the value-added function deviates from constant returns to scale.

Since TFP generally varies across countries, industries, and time, the analysis of cross-country and –industry variation in value added per worker should allow for country-, industry-, and time-specific effects. The fixed-effect specification of equation (I.2) with country, industry, and time dummies is thus given by (Miller and Upadhyay 2002):

(I.3) $$\ln(y_{cit} / l_{cit}) = b_{0c} + b_{0i} + b_{0t} + a_1 \ln(k_{cit} / l_{cit}) + \rho \ln l_{cit} + \mu_{cit}$$

where b_{0c} is a country-specific intercept, b_{0i} is an industry-specific intercept, b_{0t} is a time-specific intercept, and μ_{cit} denotes a disturbance term. As a result, the logarithm of TFP of country *c* in industry *i* at period *t* is given as

(I.4) $$\ln TFP_{cit} = \ln(y_{cit} / l_{cit}) - \widehat{a}_1 \ln(k_{cit} / l_{cit}) - \widehat{\rho} \ln l_{cit}.$$