Revenue, Variety and Productivity in China's Export Sector

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Abstract

In this paper I argue by empirical test that it is the underlying export variety that helps to explain the strong correlation between China's provincial export revenue and productivity. The empirical model maps export varieties into provincial GDP function with multiple sectors by price index theory. Employing a panel data that covers all 31 executive districts of mainland China from 1998 to 2005, I find that export varieties, via export revenue, significantly affect export productivity: it accounts for 44.1% of interprovincial TFP differences and 36.6% of within-province TFP growth; a 10% increase in export variety leads to a 1.4% productivity growth in China.

Keywords: Export Variety; Price Index; Total Factor Productivity

JEL Classification: F14; O47; R11

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1 Introduction

Since the "Open Door Policy" from 1983, China's export has experienced a rapid real growth at an average rate of 20% per year. During this period China has also emerged to be one of the fastest growing economies. As a result, economists usually characterize China as a so called "export-led" economy. Furtehrmore, though the interprovincial productivity difference in mainland China[1] before 1983 was small, it has been strikingly enlarged sicne then. Interestingly, provinces that export more (relative to its regional GDP) usually have a higher productivity. Figure 1 plots the export share (export revenue to GDP) with average wage in all Chinese provinces in 2005. Evidently, it shows that there exists a significantly positive correlation between export and productivity approximated by labor productivity. (i.e. average wage)

Although traditional trade literature has discussed intensively the positve correlation between export and productivity, they seem far from enough to fully explain such phenomenon in China's provinces for two reasons. First, productive factors (i.e. labor and capital) are supposed to be mobile across provinces whereas they are assumed to be immobile in traditional literature that focuses on country-wise studies. Second, traditional literature typically deems productivity development as the cause of export boom, however, in the "export-led" economies such as China, the causality may actually be the reverse. In this paper, I argue by empirical test that it is the underlying export variety that helps to explain the positive correlation between export

[1] They include the four municipalities directly under the Central Government. (i.e. Beijing, Shanghai, Tianjing, and Chongqing)

and productivity.

The hypothesis that expansion of export varieties could boost exporting country's productivity is based on the assumption of diminishing technical rate of substitution (i.e. concavity of production possibility frontier (PPF), see figure 2). Intuitively, marginal productivity of productive factors in general is diminishing, thus producing more varieties will have a processing gain from production than concentrating on producing existing varieties since the average marginal productivity is higher if there are more varieties to produce. Empirically, the link between export variety and productivity has been found by Feenstra et al (1999) for South Korea and Taiwan, and by Funke and Ruhwedel (2001, 2002, 2005) for OECD, East Asian countries, and East European transition economies. Particularly, based on the monopolistic competition model with endogenous technology, Feenstra and Kee (hereafter FK)(2008) test the effects of sectoral export variety on country productivity. By analyzing a panel data containing 48 countries (developed and developing) across 20 years, they found that the total increase in export variety accounts for a 3.3% average productivity growth in the exporting countries from 1980-2000.

The theoretical interaction between export variety and productivity also leads to another interesting question: can we identify the direction of causality between export variety and productivity in various cases? In fact, many economists have analyzed, although not explicitly proposed, possible answers. In a standard MC model, whether a variety (firm level) can be exported depends on two key factors: own productivity and initially irreversible investment (costs from trade barriers as well as investment cost for marketing, promotion, etc.). Holding the initial investment constant, productivity increases export variety in an obvious way: if more and more firms' productivity exceeds the threshold where the operational profit just covers the initial investment, more and more varieties will be exported. Likewise, holding the infrastructural productivity or productivity distribution constant, a decrease in trade barriers can also lead to more export varieties and higher aggregate productivity because of the self-selection of efficient/productive firms to the world market. For example, Melitz (2003) develops a dynamic industry model with heterogeneous firms and shows that more exposure to trade will cause market reallocation in favor of the more productive firms and thus contribute to an increase in productivity (also see Bernard and Jensen (1999), Delgado et al (2002)). From these analyses, one can expect that in developed open economies with intensive R&D activities, productivity would more likely be one of the fundamental sources of export variety expansion as well as economic growth; whereas in developing economies in the process of liberalizing trade export may lead economic and productivity growth.

This paper analyzes the effects of China's exports on its interprovincial productivity variation and growth by examining provincial export variety and revenue, which has been relatively lightly researched. This paper has three major contributions and improvement to existing literature. First of all, exploring the provincial data enables me to obtain a more accurate estimation for the country-specific effect of trade variety on productivity: a key (implicit) assumption in existing panel study that use country level data is that the export elasticities of substitution between varieties within the same sector are the same across countries. For example, it is assumed that the output elasticities of substitution in agricultural sector should be the same in both US and China. Apparently, it is too strong an assumption. While using all Chinese provincial data, I can obtain "China-specific" output elasticities of substitution without assuming identical elasticities across countries. Second, by Hausman test, I confirm the hypothesis that China is an "export-led" economy: the export variety *exogenously* accounts for interprovincial productivity difference and growth rather than the endogenous variety assumption that is typically made in existing literature. (see, amongst many others, Arkolakis, Demidova, Klenow, Rodríquez-Clare (2008)) This finding is consistent with the results of Kwan and Kwok (1995) that exports are exogenous in explaining China's economic growth (and thus productivity). Third, a lot of empirical literature uses the U.S. data, but employing Chinese export data makes the results more reliable: an important assumption in the empirical price-factor GDP function is that the prices and production factors are all given, i.e., exogenous. For example, FK (2008) employ the U.S. import data to approximate the exports of 48 countries including the major developed ones. However, it is very likely that the prices are actually endogenous in some industries where the developed countries may have monopolistic power. For instance, electronic products import from Japan and machines from Germany. Furthermore, the U.S. itself is the largest open economy in the world suggesting that it has monopsonistic power over many of its imports. As a result, if monopoly dominates, estimates of the elasticities of productivity on export varieties tend to be overstated; while if monopsony dominates, the estimates tend to be understated. On the contrary, though China is a large economy, most of its exports are characterized as low value-added and easy-to-substitute.[2] In other words, Chinese exports mainly face competitive markets with very elastic demand. As a result, most Chinese exporters are price takers to a large extent.

The rest of the paper will be organized in three parts. Section 2 summarizes the mechanism of how the underlying export variety, via export revenue, affects productivity in export sectors, mainly borrowing from the methods discussed in FK (2004).[3] Then I describe the dataset and estimate a system of equations relating sectoral shares and adjusted total factor productivity (TFP) to export variety. In section 3, I present the results of estimation well as hypothesis tests to show the validity of the estimation method and the robustness of these results that are based on various constraints imposed in the model. Finally, section 4 concludes that export variety accounts for 44.1% of the variation of interprovincial export productivity in level and 36.6% of within-province export productivity growth. Overall, at the sample mean, a 10% increase in export varieties of all exporting sectors leads to a 1.4% increase in China's export productivity.

[2] For example, by 2005 the top three markets where Chinese exports occupy the largest world shares are textiles (35%), footwears (60%), and toys (40%) which are easily found in Wal-Mart but not in luxury franchise stores.

[3] Although FK (2008) is the revised version of FK (2004), the 2008 version is based on a "Melitz-type" model where the export variety is assumed to be endogenously affected by productivity. However, China is an "export-led" economy which suggests export may exgenously explain productivity. Therefore I borrow FK's method in 2004 version where variety endogeneity is not asuumed though it is tested.

2 The Empirical Model

2.1 Price Index Theory and Product Variety

Feenstra (1994) derives an exact price index from a CES (constant elasticity of substitution) aggregate good allowing both variety and taste changes in existing varieties. This index can also apply for several goods or even industries as long as they are still CES aggregates.

Suppose there exist $i = 1, \ldots.., R$ regions. Each region i can produce I_t^i set of product varieties at time t. The quantity of each type of variety produced in region i in period t is denoted by q_t^i. The aggregate output of region i, Q_t^i, is characterized by a CES function of the output of each specific variety produced in that region:

$$Q_t^i = f(q_t^i, I_t^i) = \left(\sum_{j=I_t^i} a_j (q_{jt}^i)^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)}, \quad a_j > 0,\ i = 1, ..., R. \quad (1)$$

where a_j is the unknown quality parameter for variety q_{jt}^i, and $\sigma < 0$ is the elasticity of substitution between variety and thus the PPF is concave.

As demonstrated in Feenstra (1994) the ratio of aggregate price levels associated with the CES production function can be evaluated by the product of the Sato(1976)-Vartia(1976) price index of goods that are common, $I_t \equiv (I_t^a \cap I_t^b) \neq \varnothing$, and by terms reflecting the revenue share of "unique" goods. The log form is given by:

$$ln\frac{P_t^a}{P_t^b} = \sum_{i \in I_t} w_j(I_t) \ln\left(\frac{P_{jt}^a}{P_{jt}^b}\right) + (\frac{1}{\sigma - 1}) \ln\left(\frac{\lambda_t^a(I_t)}{\lambda_t^b(I_t)}\right), \quad a, b = 1, .., m. \quad (2)$$

where P_t^i is the aggregate price level ($i = a, b$), and the weights $w_j(I_t)$ are constructed from the revenue shares in the two regions:

$$w_j(I_t) = \left(\frac{s_{jt}^a - s_{jt}^b}{\ln s_{jt}^a(I_t) - \ln s_{jt}^b(I_t)}\right) / \sum_{i \in I_t} \left(\frac{s_{jt}^a - s_{jt}^b}{\ln s_{jt}^a(I_t) - \ln s_{jt}^b(I_t)}\right) \quad (3)$$

$$s_{jt}^i(I_t) \equiv p_{jt}^i q_{jt}^i / \sum_{j \in I_t} p_{jt}^i q_{jt}^i, \;\; for\ i = a, b, \quad (4)$$

$$\lambda_t^i(I_t) = \frac{\sum_{j \in I_t} p_{jt}^i q_{jt}^i}{\sum_{j \in I_t^i} p_{jt}^i q_{jt}^i} = 1 - \frac{\sum_{j \in I_t^i, j \notin I_t} p_{jt}^i q_{jt}^i}{\sum_{j \in I_t^i} p_{jt}^i q_{jt}^i} \;\; for\ i = a, b, \quad (5)$$

where s_{jt} measures the revenue share of variety j relative to all the varieties that are common in county a and b at period t, and $\lambda_t^i(I_t)$ is the revenue share of common varieties ($j \in I_t$) to total varieties ($j \in I_t^i$).

The first term on the right hand side of (2) is the traditional price index, which only captures the weighted average of the price ratios for varieties in the common set I_t, in other words, it ignores the effect of variety and quality change. The second term is Feenstra's correction term, which reflects changes in product variety given that the quality of the same variety is invariant. Given (2), we can easily tell that a new product variety produced in region a will cause the price ratio on the left to increase because the new product variety induce a more efficient allocation among productive factors (processing gain from production) such that the price index, measured as (maximized) the unit revenue of the aggregate goods, increases.

2.2 Revenue and Variety

The ideal definition for a variety is a market-based firm-brand such as Honda Civic and Ford Focus. In micro-level studies researchers often use the market-based survey data to study the variety effect on welfare or productivity. (see, for example, Blonigen and Soderbery (2009)). However, survey data has a serious limitation in data coverage: it can only cover one or a few industries for a few years. Therefore survey data can not satisfy macro-level studies which need data on a much boarder scope of economy (i.e. export industries). Researchers usually rely on trade data (such as SITC or HTS data system) to carry out their macro-level studies and typically adopt the Armington definition that a variety is a country-good pair. (see, amongst many others, Broda and Weinstein (2006)). For example, the beer produced in France and the beer produced in Britain are treated as two varieties of the product "beer". Since this paper uses provincial level data, a natural modification of the Armington type variety is that a variety is a province-good pair. That is, Shanghai-beer and Beijing-beer are two varieties of beer.

In fact, defining a variety as a province-good pair can help to greatly simplify the eq(2). Assume b as (mainland) China and a is a province. Then it follows $I_t = I_t^a \cap I_t^b = I_t^a$. Furthermore, the prices of common varieties produced in both a province (a) and China (b) are the same since they are the prices of unique varieties. For example, a common variety, shanghai-beer that is produced in both Shanghai and China, refers to the same (unique) variety since no other provinces in China can produce shanghai-beer. Hence, the first term on the right hand side of eq(2) disappears (it is zero!) and $\lambda_t^a(I_t) = 1$.Then eq(2) can be simplified as:

$$ln \frac{P_t^a}{P_t^b} = (\frac{1}{1-\sigma}) \ln \left(\lambda_t^b(I_t) \right), \quad a = 1, .., R. \tag{6}$$

where R=31 is the total number of provincial executive regions in mainland China.

Eq(6) reveals that the exact price ratio in an industry/sector of a province with respect to the counterpart of the whole nation is a simple function the ratio of their corresponding sales revenue as the variety effect on exact price can be fully captured by its sales revenue. Therefore a new variety introduced in province a will lead an increase in $\lambda_t^b(I_t)$ and thus an increase in the provincial exact price level. (to its national counterpart) Furthermore, eq(6) has a very good empirical implication: to study the variety effect on industry/sector exact price level, we do not need disaggregate variety data (i.e. HTS-8 or HTS-10 level data) in that industry/sector, what we need is just the revenue data of that industry/sector! (i.e. HTS-2 or HTS-4) This implication is very important: China only has HTS-4 level export data prior to 2002, but this approach allows me to empirically study the export variety effect even for years prior to 2002 without highly disaggregate date.

2.3 GDP Function with Export Variety

As is common in empirical GDP work, I assume the GDP function of a region follows a translog functional form where there are N+1 (N export sectors and one non-traded sector) and M types of production factors:

$$\ln G_t^i(P_t^i, V_t^i) = \alpha_0^i + \beta_0^t + \sum_{n=1}^{N+1} \alpha_n \ln P_{nt}^i + \sum_{k=1}^{M} \beta_k \ln v_{kt}^i + \frac{1}{2} \sum_{m=1}^{N+1} \sum_{n=1}^{N+1} \gamma_{mn} \ln P_{mt}^i \ln P_{nt}^i$$

$$+ \frac{1}{2} \sum_{k=1}^{M} \sum_{l=1}^{M} \delta_{kl} \ln v_{kt}^i \ln v_{lt}^i + \sum_{n=1}^{N+1} \sum_{k=1}^{M} \phi_{nk} \ln P_{nt}^i \ln v_{kt}^i, \quad i = 1, ..., R. \tag{7}$$

Notice that in a panel data regression setting, α_0^i and β_0^t refer to region and time fixed effects respectively. To satisfy the properties of homogeneity in prices and endowments as well as symmetry, I impose the following restrictions:

$$\gamma_{mn} = \gamma_{nm}, \sum_{n=1}^{N+1} \alpha_n = 1, \sum_{n=1}^{N+1} \gamma_{mn} = \sum_{n=1}^{N+1} \phi_{nk} = 0,$$

$$\delta_{kl} = \delta_{lk}, \sum_{k=1}^{M} \beta_k = 1, \sum_{k=1}^{M} \delta_{kl} = \sum_{k=1}^{M} \phi_{nk} = 0, \tag{8}$$

From (7), the share of sector n is given by the derivative of $\ln G_t^i(P_t^i, V_t^i)$ with respect to $\ln P_{nt}^i$:

$$s_{nt}^i = \alpha_n + \sum_{m=1}^{N+1} \gamma_{mn} \ln P_{mt}^i + \sum_{k=1}^{M} \phi_{nk} \ln v_{kt}^i, \qquad n = 1, ..., N+1. \tag{9}$$

Taking the difference of any province i with that of the comparison region $*$ (i.e. the whole country), we can map export variety variable λ into the empirical GDP function as well as the share equations with minimal computation:

$$\begin{aligned} s_{nt}^i - s_{nt}^* &= \sum_{k=1}^{M} \phi_{nk} (\ln v_{kt}^i - \ln v_{kt}^*) + \sum_{m=1}^{N} \frac{\gamma_{mn}}{(1-\sigma_m)} \ln \lambda_{mt}^{i*} \\ &\quad + \gamma_{N+1,n} (\ln P_{N+1,t}^i - \ln P_{N+1,t}^*). \end{aligned} \tag{10}$$

and

$$\begin{aligned} & lnG_t^i(P_t^i, V_t^i) - lnG_t^i(P_t^*, V_t^*) - \sum_{k=1}^{M} \frac{1}{2} (s_{kt}^i + s_{kt}^*)(\ln v_{kt}^i - \ln v_{kt}^*) \\ & \qquad - \frac{1}{2} (s_{N+1t}^i + s_{N+1t}^*)(\ln P_{N+1t}^i - \ln P_{N+1t}^*) \\ = \; & \alpha_0^i + \sum_{n=1}^{N} \frac{1}{2} (s_{nt}^i + s_{nt}^*) \frac{\ln \lambda_{nt}^*}{(1-\sigma_n)} \end{aligned} \tag{11}$$

where the price difference of tradable goods (sector 1 to N) has been substituted by the variety variable $\ln \lambda_{nt}^*$ according to eq(6). Without the loss of generality, I normalize $\alpha_0^* = 0$. The left hand side of (8) can be interpreted as the productivity difference between province i and the country

$*$ (the average productivity of all provinces): it is the difference of GDP net of the differences in factor endowments and prices in nontraded goods. The remaining difference is the productivity differences in export sectors due to export variety shown on the right.

2.4 Data and Estimating Equations

With equations (10) and (11), we can estimate the parameters of interest such as the elasticity (σ_n) of substitution between different varieties within an export sector, the relative price effects on the sector shares (γ_n), as well as the effects of relative endowments on industry shares and productivity.

The dataset covers all 31 provincial level executive districts in mainland China. However, due to data availability, it is an unbalanced panel dataset with 17 of the provinces starting from 1998 while the rest start no later than 2002 and all series end in 2005. This dataset contains 193 observations for each regression. All of the data was obtained from corresponding national or provincial statistical yearbooks.

Since variety in this paper is defined as a province-good pair, λ^*_{nt} is then the ratio of provincial export revenue to its national counterpart for export sector n at time t.

I assume there are three factors of production: Labor, Capital, and (arable) Land. Labor and Land (as well as nominal GDP) are directly reported by China Statistical Yearbooks (1999-2006). Capital is constructed by the perpetual inventory method using real investment of the whole nation as well as the 31 provinces across the 8 years. Real investment is obtained by deflating the gross domestic capital formation of the whole nation as well as 31 provinces with their respective GDP deflators. All the data on gross capital formation and GDP deflators are obtained from China Statistical Yearbooks as well. In addition, I construct the base year capital stock using an infinite sum of series of investment prior to the first year (1998), assuming that the average growth rate of investment of the first 7 years is a good proxy for the investment prior to the first year. Note that all the three productive factors are reported as year-end input rather than initial endowment in the statistical yearbooks. Therefore there is no interprovincial factor mobility problem.

I aggregate up all the export goods into 7 sectors: agriculture, wood & paper, textile & clothing, chemicals & plastics, mining & metals, machinery[4], and food & beverage[5]. The value-added of these sectors is obtained from the corresponding provincial statistical yearbooks (1999−2006), which are used to compare with the corresponding regional GDP to construct the sector shares. The nontraded goods price is obtained by taking an equally-weighted average of the Education, Health Care & Child Care, and Rental for Housing price indices. The regional labor share in GDP, s^i_{Lt}, is constructed by comparing the labor income to the corresponding regional GDP.

Here I use each of the 31 provinces as a specific "region", i.e. $i = 1, ..., 31$, and China as a whole as the comparison region $*$. By applying the homogeneity constraints on productive factors (i.e. $\sum_{n=1}^{3} s^i_{nt} = 1$) and prices (i.e. $\sum_{m=1}^{8} \gamma_{mn} = 0$), we can rewrite (9) and (10) as follows:

[4] Including transportation equipments and electronic products.

[5] Including tobacco.

$$
\begin{aligned}
s^i_{nt} &= \delta_{nt}+\phi_{Ln}(\ln \ell^i_t - \ln \ell^*_t) + \phi_{Kn}(\ln k^i_t - \ln k^*_t) \\
&\quad + \sum_{m=1}^{7} \gamma_{mn}(\frac{\ln \lambda^{i*}_{mt}}{(1-\sigma_m)} - (\ln P^i_{8,t} - \ln P^*_{8,t})) + \varepsilon^i_{nt}, \\
n &= 1, ..., 7. \qquad (12a)
\end{aligned}
$$

$$
\begin{aligned}
Adj.TFP^i_t &\equiv lnG^i_t(P^i_t, V^i_t) \\
&\quad -\frac{1}{2}(s^i_{Lt} + s^*_{Lt})(\ln \ell^i_t - \ln \ell^*_t) - \frac{1}{2}(1 - (s^i_{kt} + s^*_{kt}))(\ln k^i_t - \ln k^*_t) \\
&\quad -\frac{1}{2}(\ln T^i_t - \ln T^*_t) - \sum_{n=1}^{7} \frac{1}{2}(s^i_{nt} + s^*_{nt})(\ln P^i_{8t} - \ln P^*_{8t}) \\
&= \alpha^*_t + \ \alpha^i_0 + \beta_k(\ln k^i_t - \ln k^*_t) + \beta_8(\ln P^i_{8t} - \ln P^*_{8t}) \\
&\quad + \sum_{n=1}^{7} \frac{1}{2}(s^i_{nt} + s^*_{nt})\frac{\ln \lambda^*_{nt}}{(1-\sigma_n)} + \varepsilon^i_t \qquad (12b)
\end{aligned}
$$

where $\ln(\ell_t) = \ln(L_t/T_t)$ and $\ln(k_t) = \ln(K_t/T_t)$. If the homogeneity constraint in prices is not violated, β_8 in (9b) should be equal to unity, whereas β_k in (9b) represents the negative value of the share of Land in GDP.[6] Note, the output shares of the comparison country (China), appearing as s^*_{nt} in (7), are measured as year fixed effects, δ_{nt} in (9a); whereas China's national (log) GDP, $lnG(P^*_t, V^*_t)$, in equation (8) is treated as a year-fixed effect, α^*_t in the regression function (9b). In summary, I will regress the panel data for seven sectoral share equations (with year-fixed effects only) and a TFP

[6] In fact, β_k should be $\beta^i_{kt} \ = 1 - \frac{1}{2}(s^i_{Lt} - s^*_{Lt}) - \frac{1}{2}(s^i_{Kt} - s^*_{Kt})$, which is a random parameter. For the sake of simplicity, we assume the relative labor share and the relative capital share do not change for different regions and across periods so that we treat β_k as a time- and region-invariant parameter.

equation (with both region and time fixed effects).

Furthermore, with the estimated parameters, the regional estimated productivity is given by (13):

$$Est.TFP_t^i = Adj.TFP_t^i - \hat{\alpha}_t^* - \hat{\beta}_k(\ln k_t^i - \ln k_t^*) + \hat{\beta}_8(\ln P_{8t}^i - \ln P_{8t}^*)$$

$$= \hat{\alpha}_0^i + \sum_{n=1}^{N} \frac{1}{2}(s_{nt}^i + s_{nt}^*)\frac{\ln \lambda_{nt}^*}{(1-\hat{\sigma}_n)} + \hat{\varepsilon}_t^i \tag{13}$$

Due to the cross equation restrictions on $1/(1-\sigma_n)$ and γ_{mn}, and the multiplicative nature of these parameters, I use nonlinear system estimation for the seven share equations (12a) and one TFP equation (12b). The optimal estimates for these parameters are derived by minimizing the variance-covariance matrix of the residuals in the full system of the regression equations.

The homogeneity constraints in endowments and prices (for each of the eight equations) and the symmetry constraint in cross price effects (for the seven sectoral share equations) will also be tested.

3 Estimation Results and Hypothesis Tests

3.1 Estimation Results

3.1.1 Ordinary Least Square Regressions

Table 1 presents the results of the nonlinear system of share equations (12a) with the TFP equation (12b), estimated by iterative Nonlinear Ordinary Least Square Regressions (NOLS). All the homogeneity constraints on prices and endowments as well as the symmetric constraints on cross-price effects are imposed in the share equations, and the last column shows the estimated coefficients of the provincial productivity equation.

The upper part of table 1 reports γ_{mn}, which are the partial price effects on the share of sectors in the columns due to export variety changes in the rows. Particularly, the diagonal shows the own-price effects which are all positive and significant. That is to say, the underlying supply curves of these sectors are positively sloped. The lower part of table 1 shows the Rybczynksi effects of endowments on the industry shares. For example, an increase in capital relative to land (significantly) hurts the agriculture and food & beverage industries but benefits the chemical & plastics, mining & metals, and machinery industries. On the other hand, an increase in the labor endowments relative to land (significantly) benefits agriculture, wood & paper but hurts chemical & plastics, mining & metals, and machinery.

The upper part of column (8) presents the NOLS estimates of $1/(1-\sigma_n)$ for each industry in the row. According to the assumption, the elasticities (σ_n) among outputs should be strictly negative. In other words, the expected estimates of $1/(1-\sigma_n)$ should be between zero and one. As shown in the upper part of column (8), all the estimates are significant and fall in the range of zero to one. The ranking of export sectors according to their implied elasticities of substitution are: wood & paper (-0.235), machinery (-0.748), textile & garments (-1.322), chemical & plastics (-1.390), agriculture (-1.621), mining & metals (-4.882), and food & beverage (-8.025).

The lower part of column (8) presents the effects of the capital-land ratio and nontraded goods prices on adjusted TFP. As predicted in the model, the coefficient on the capital-land ratio should be negative of the value of the land share in GDP. That is, our estimate, -0.083, implies that the estimated share of land in China's GDP is about 8.3%. However, the estimated coefficient on nontraded goods price is significantly less than unity which suggests a violation of the homogeneity assumption on prices.[7]

However, our NOLS method might have two potential problems. First of all, for a system of simultaneous regression equations there may be correlation between the error terms of these equations. That is, the error terms of the seven sectoral share equations (12a) might be correlated as these export sectors may compete for the same resources. For example, the Rybczynksi suggests that an increase in one productive factors may cause an expansion in some sectors that use this factor intensively but a contraction in some other sectors. Ignoring the correlation problem will cause the estimates to be less efficient as the variance of estimation is not at a minimum. If there is cross-equation correlation among the error terms, a seemingly unrelated re-

[7] The violation of homogeneity constraint in prices in TFP equation does not affect the rest of the estimations since I did not impose it in TFP equation.

gression (SUR) can yield more efficient estimates (Zellner, 1962). Secondly, endogeneity might be a problem since in our adjusted TFP equation (12b) productivity can also affect export variety. That is, a simultaneity problem may arise since productivity growth may help some products gain comparative advantage over their international counterparts so that they become new exported varieties (for example, Melitz (2003), Ghironi and Melitz (2005)). Ignoring this potential endogeneity problem, if any, will cause the estimates to be biased. To overcome the endogeneity problem, I use a nonlinear two stage least square (N2SLS) method to derive unbiased estimates based on sufficient valid instrumental variables (IVs) which affect productivity only via export variety.

To check the validity of our estimates of NOLS, I compare them to those of SUR and N2SLS respectively in the following two subsections.[8]

3.1.2 Iterative Seemingly-Unrelated Regressions

Table 2 presents the results estimated by SUR. The results reveal that both the partial price effects on the share of industries and the Rybczynksi effects of endowments are very similar to those estimated by NOLS. The similarity also appears in column (8) except that the coefficients on Textile & Garments and Wood & Paper are above unity, but not significantly.

[8] Though the SUR and N2SLS can be combined into a N3SLS (so called "full information estimation" in theory), we choose to check for these two problems separately for the following reasons: First of all, if the estimates of NOLS were not robust, I wish to find out the main causes: SUR, endogeneity, or both. Secondly, when only one or none of the problem seriously exists in our regression system, the empirical estimates of N3SLS may be much less efficient than those of NOLS. (I discuss this empirical efficiency issue in the following subsection) Thus, even if there were significant difference between N3SLS and NOLS, we could not tell whether it is because of the SUR/endogeneity problem or just the inefficient estimation of N3SLS.

Even though SUR is a theoretically more efficient estimation method than OLS, a number of empirical studies reveal that this superiority is ambiguous in practice. (for example, Srivastava and Giles, 1987; Maeshiro, 1980; Heien, et al., 1998). Indeed, the closer the error covariance comes to being spherical, the more likely it is that OLS estimates will be superior. Therefore, the overall similarity between the estimates of NOLS and SUR is not surprising, it may result from the fact that residuals of the sectoral share equations do not have strong correlation. Thus, after considering the potential SUR problem, we still can confidently retain estimates of NOLS.[9]

3.1.3 Two Stage Nonlinear Least Square Regressions

As for the endogeneity problem, the key task is to find enough (at least as many as the endogenous variables to be replaced) valid IVs. Many economists (e.g. Eaton and Kortum, 2002; Melitz, 2003) have suggested various IVs such as tariff, transport costs and distance as these trade costs can only affect productivity through export variety. However, since all Chinese provinces face the same tariffs (except the so called "Special Economic Zones") against their exports, only IVs concerning transportation costs and distance will be useful here. Therefore, in order to find enough IVs, I also consider market demand and supply factors.

[9] Strictly speaking, a reliable test for the correlation of error terms should be done before we can retain estimate results of NOLS. To test the correlation of error terms, many studies directly test for the zeros in off-diagonal error covariance matrix. (for example, Breusch and Pagan, 1980; Kariya,1981; Shiba and Tsurumi, 1988). However, most of the tests are only justified under asymptotic arguments. Thus standard multivariate likelihood-based asymptotic tests are unreliable in finite samples, in the sense that test sizes deviate from the nominal significance levels for related simulation evidence (Dufour and Khalaf, 1998). Since the overall similarity between estimates of NOLS and SUR, doing any (unreliable) test for SUR problem seems unnecessary in our study.

Besides all the included exogenous variables (except for the price index of nontraded goods), I find seven excluded IVs along three dimensions in addition to the land difference. They are weighted distance, road density, seaboard dummy, and border dummy for geography; lagged population density, and lagged CPI for market demand; and the policy dummy for market supply. All the relevant data except for the dummies and distance are available from provincial and national statistical yearbooks.

With respect to the distance IVs, since the export destinations are all over the world, I have to use a weighted distance to approximate the real trade distance facing each province. First of all, I assume that all Chinese exports will be shipped to the following five destinations: Hong Kong (Hong Kong, Macao, Taiwan), Singapore (South-east, South, and West Asia and Oceania), Tokyo (North-east Asia), Los Angeles (west hemisphere), and Amsterdam (Europe and Africa). Then I measure the distance between the capital of each province to the five destinations with the distance weights approximated by the export shares of those regions represented by the five destinations.

Road density is calculated by dividing total mileage of railway, national highway, and waterway by the provincial area. The lagged population density is measured by dividing the lagged effective provincial population by the provincial area. And effective population is the sum of the rural residents and the triple of urban residents. The idea of "effective population" comes from two reasons: firstly, the annual income of a representative urban resident is triple as high as that of a representative rural resident; secondly, an urban resident is more important for market demand than a rural counterpart because the former has to depend on trade for exchanging goods while the latter is more likely to produce most goods by himself.

The seaboard dummy indicates whether a province has seaboard and the border dummy indicates whether a province shares international borders with the other country. Finally, the policy dummy is assigned to the three provinces having the Special Economic Zones[10] and four municipalities directly under central government. The remaining IVs are directly given.

The geographical IVs are the "classic" exogenous variables in explaining productivity since they may affect productivity via export variety but not the other way round. Likewise, the policy dummy is also a straightforward IV since these policies, which is based on political and geographical concerns, affect tariff which may affect productivity via export variety as well. Since both CPI and effective population density are time series, so they may cointegrate with productivity which is also a time series. A treatment is to use the lags of CPI and effective population density. Intuitively, a current production plan may base on the information in the last period such as last period's prices and number of target consumers. For example, a higher CPI or increase in population density may be treated as a positive signal to producers, and they may find it profitable to create new varieties to compete for the prospering market.

Theoretically, good (excluded) IVs should not only be exogenous with respect to the regressand(s), but also correlate non-trivially with the endoge-

[10] The special economic zones are designed for the "experiments" of China's economic reform. In these zones, tariff and taxes are generally lower and legal procedures on business are simplified. By the year 2006, there are 6 special economic zones: Shenzhen, Zhuhai, Shantou, Xiamen, Pudong, and Hainan. The first three belong to Guangdong province, the rest three belong to Fujian province, Shanghai, and Hainan province respectively.

nous regressors (i.e. the excluded IVs should not be too "weak"). Following the method introduced in Staiger and Stock (1997), empirical studies often adopt the first-stage F-statistic to test for weak instruments to detect the "weak instruments" problem. The rule of thumb to reject the weak IVs hypothesis is that in the first stage (when regressing the endogeous variables on all IVs) the first-stage F-statistics based on the Residual Sum of Sqaures of the OLS with and without the excluded IVs should be larger than 10.

Table 3 presents the results estimated by N2SLS. The results reveal that both the partial price effects on the share of industries and the Rybczynksi effects of endowments are very similar to those estimated by NOLS. The coefficient estimates on export varieties in (12b) change a little bit compared to NOLS. The coefficients on Textile & Garments, wood & paper, and Chemical & Plastics are all above unity, but not significantly so. Furthermore, the fact that the first-stage F-statistics in column (8) are all much larger than 10 shows that the overall IVs are strongly correlate with the export variety variables (λ).

However, we need to be cautious that the estimates of N2SLS may not be more reliable than those of NOLS. After all, if the endogeneity problem is not so serious, NOLS is naturally superior to N2SLS since N2SLS actually replaces the most relevant explanatory variables with less explanatory ones (the IVs). The Hausman Test (Hausman,1978) is widely used to test for potential endogeneity. The null hypothesis is that the regressors in the structural equations are exogenous. Under the null hypothesis, both of the estimates (NOLS and N2SLS) should be consistent, and the difference between these two vectors of parameter estimates should follow a Chi-square distribution with K degrees of freedom (K is number of unknown parameters). If the null hypothesis is not rejected, one can retain the estimates of NOLS; otherwise, the estimates from N2SLS will have to be taken. Column (6) of table 4 reports that the p-value of the statistic is almost unity which means we cannot reject the null hypothesis of no endogeneity. This result is consistent with Kwan and Kwok (1995) that exports are exogenous in explaining China's economic growth (and thus productivity).

3.2 Specification Tests

As the NOLS estimation results are still valid after checking the SUR and endogeneity problems, I proceed to test the overall validity of the restrictions imposed on the system based on the NOLS estimation to check the overall robustness. Recall in section 2, I have imposed the following restrictions. For each of the share equations, homogeneity constraints on prices and endowments are imposed. The homogeneity constraint on endowments is imposed in the GDP function but not the homogeneity constraint on prices due to the possible measurement errors in nontraded good prices. The twenty-one symmetry constraints on the cross-price effects are also imposed on the whole system of equations.

I first test for all the homogeneity constraints one at a time. In each case, I constrain the variance-covariance matrix to be that of the unrestricted model. Conditional on all the accepted homogeneity constraints I further test for the symmetry constraints. This is done by comparing the value of the criterion function of the restricted model to a model with no symmetry constraints.

Table 4 presents the test statistics and the associated p-values for all the hypothesis tests. None of the homogeneity constraints for endowments are rejected, nor are the homogeneity constraints in prices on all industry share equations (except that the constraint on agriculture industry can be rejected at the confidence level of 10%). The only violation of homogeneity constraint in prices is for the TFP equation, which we did not impose in the previous estimation.[11] Given that all the homogeneity constraints on endowments and prices are not rejected, table 5 also reports that the null hypothesis on the 21 symmetry constraints on the seven sectors cannot be rejected either.

In summary, the results of hypothesis testing support my previous specification in terms of the imposed homogeneity constraints on endowment and prices as well as the symmetry constraints on cross-equation prices.

3.3 Productivity Decomposition

To highlight the relationship between export variety and productivity in China, I carry out a panel regressions of the estimated productivity on export variety ($\sum_{n=1}^{7} \frac{1}{2}(s_{nt}^{i}+s_{nt}^{*})\frac{\ln \lambda_{nt}^{*}}{(1-\hat{\sigma}_n)}$) using the estimated parameters obtained in last section. Figure 3 plots the scatter graph. Both variables are averaged over time so actually we plot a "between" regression. From this graph, it is evident that the provincial export variety explains the productivity difference in a significant way.

To highlight the relationship between variety and productivity export

[11] Our estimation results should remain robust as long as the measurement error in non-traded goods is not systematically related to the province productivity or export variety.

sectors in China's provinces, I perform a post-regression decomposition of estimated productivity based on the results in Table 1. Using (13), I compute the variance of estimated provincial TFP as:

$$var(Est.TFP_t^i) = var(\hat{\alpha}_0^i) + var(\sum_{n=1}^{7} \frac{1}{2}(s_{nt}^i + s_{nt}^*) \frac{\ln \lambda_{nt}^*}{(1-\hat{\sigma}_n)})$$

$$+2cov[\hat{\alpha}_0^i, \sum_{n=1}^{7} \frac{1}{2}(s_{nt}^i + s_{nt}^*) \frac{\ln \lambda_{nt}^*}{(1-\hat{\sigma}_n)}] + var(\hat{\varepsilon}_t^i). \tag{14}$$

The first term on the right hand side is the variance of provincial fixed effects, the second is the variance of export varieties, the third is the covariance between these two, and the fourth is the error variance. By removing variance of the fixed effects and the regression error, the "variety-induced" provincial TFP is defined as:

$$\text{Variety-induced } TFP_t^i \equiv \sum_{n=1}^{N} \frac{1}{2}(s_{nt}^i + s_{nt}^*) \frac{\ln \lambda_{nt}^*}{(1-\hat{\sigma}_n)}, \tag{15}$$

In addition, the first order difference of (15) within a province between years reveals the growth decomposition of provincial productivity into two terms, which is the growth of variety induced provincial TFP and the change in regression errors:

$$\begin{aligned} \text{Growth of } TFP_t^i \equiv & \sum_{n=1}^{7} \left(\frac{1}{2}(s_{nt}^i + s_{nt}^*) \frac{\ln \lambda_{nt}^*}{(1-\hat{\sigma}_n)} - \frac{1}{2}(s_{nt-1}^i + s_{nt-1}^*) \frac{\ln \lambda_{nt-1}^*}{(1-\hat{\sigma}_n)} \right) \\ & +(\hat{\varepsilon}_t^i - \hat{\varepsilon}_{t-1}^i). \end{aligned} \tag{16}$$

The variance in the growth rate of provincial TFP in export sectors is therefore the sum of the variance of the growth rate of variety-induced provincial TFP, and the variance of the difference in error terms, along with the covariance between the two terms. Table 5 shows the variance decomposition of provincial export TFP in levels and growth rates. Surprisingly, only 36.3% of the cross-province differences in the export TFP levels are explained by province fixed effects while variety-induced provincial TFP can account for about 44.1% of the provincial export productivity levels. Furthermore, variety-induced TFP and province fixed effects are correlated, jointly contributing nearly 13.8% of the cross-province variation in export TFP levels. Compared to the results from the cross-country literature, our variety-induced TFP can account for a striking proportion of the total export TFP variation.[12] Such a big discrepancy may be attributed to the following two reasons: first, the difference between provinces within a country should be much smaller than that between countries. Secondly, my unbalanced data covers the period from 1998 to 2005 but with more observations in the most recent 4 years (2002−2005) than those prior to 2002. Taking into account that China entered WTO in 2001, freer trade significantly boosted China's economic growth through fast growing exports.[13] Thus my data may contain a strong WTO effect which magnify impact of export variety expansion on export TFP growth. The second column of Table 5 shows the growth decomposition of provincial export productivity. About 36.6% of the

[12] For instance, the variety-induced TFP can account for only 3.3% for OECD countries in FK(2008) while ours account for 44.1%.

[13] According to the national statistical yearbook (1995-2005), the average export growth rate is 29% during 2002-2005 compared to 10% during 1995-2001.

within-province growth in export TFP can be explained by the year-to-year growth in export variety, while the reminder is explained by the change in regression errors and the correlation between the two terms. Again, export variety growth in our estimation can explain much more TFP growth than in the cross-country literature. In any event, export variety nonetheless is important in explaining provincial export productivity differences in both levels and growth rates.

To further illustrate the effects of export variety on productivity in export sectors, according to (13) a 1% increase in the export variety of each sector n would increase provincial export productivity by $\frac{1}{2}(s_{nt}^{i} + s_{nt}^{*})\frac{1}{(1-\hat{\sigma}_n)}$ percent. Thus, at the sample mean, a 10% increase in export varieties of all industries could lead to a 1.4% increase in China's export productivity (as an average of provincial productivity). This effect is significant both statistically and economically.

4 Conclusions

Existing analyses of the export variety effects on export TFP variation and growth have been restricted to cross country studies and mainly to OECD countries. In this paper I study the case for China by estimating the effects of export variety (via export revenue) on provincial export productivity with multiple sectors and introducing export varieties into the provincial GDP function.

Estimating the seven share equations simultaneously with the GDP equation (transformed to become relative provincial productivity) allows us to identify and estimate the elasticity of substitution between export varieties in each sector and then infer the contribution of export variety on provincial productivity in terms of level difference and growth. The resulting elasticity estimates (measuring the degree of contribution) range from a low of -0.235 in the wood & paper sector to a high of –8.025 in the food & beverage sector. The ranking I have obtained seems reasonable except for the wood & paper industry at first blush. Intuitively the contribution in the machinery industry should be the lowest since new variety in this industry generally can collect very high sales revenue. However, considering the fact that China's forest-coverage rate was only 18.21% (only one fourth of the world average) by 2005, the export in wood & paper (for example, furniture in traditional Chinese style) sector is actually highly monopolistic, which may justify the lowest elasticity results. Additionally, the estimation also reveals that the land share in China's GDP is about 8.3%.

I consider the potential problems of correlated error terms in the seven sectoral share equations as well as endogeneity in the adjusted TFP equation. First of all, I conduct a SUR estimation and find that the estimates are very similar to those from NOLS which implies that error term correlation is not a serious problem. Then I use a N2SLS estimation to address the potential endogeneity problem. A Hausman test is applied to test the endogeneity problem of the NOLS estimation. That the p-value statistic is almost unity suggests the null hypothesis of no endogeneity in the system can not be rejected. This result reinforces the hypothesis suggested by many economists that China's (as well as many Southeast Asian countries') exports are exogenous in explaining productivity growth. Then, I check the overall robustness of the NOLS estimation system by testing the specifications in my system. The results of these tests support my previous specifications on homogeneity constraints imposed on endowment and prices as well as the symmetry constraints imposed on cross-equation prices.

Finally, based on the NOLS estimation, I also calculate the impact of export variety differences across provinces on their respective productivity. Surprisingly, export variety explains 44.1% of the total variation in provincial export productivity while the results in previous cross-country studies typically report a much smaller export effect with a fairly big country-fixed effect. The rationale may be that the fixed effect across provinces is much smaller than that across countries, so export variety plays a much more important role in explaining TFP variation. Furthermore, export variety can explain 36.6% of the within-province export productivity growth. At the sample mean, a 10% increase in export varieties of all industries leads to a 1.4% increase in its productivity.

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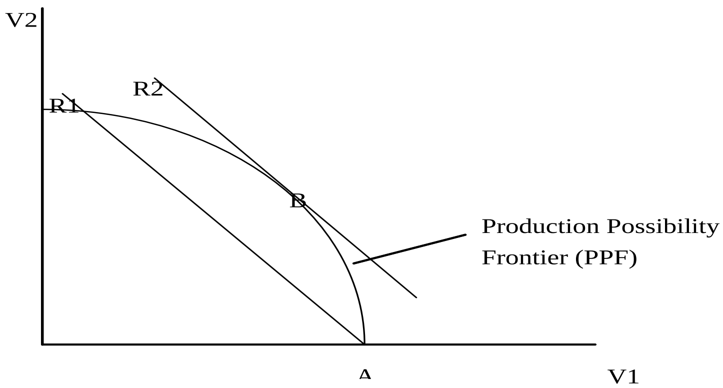
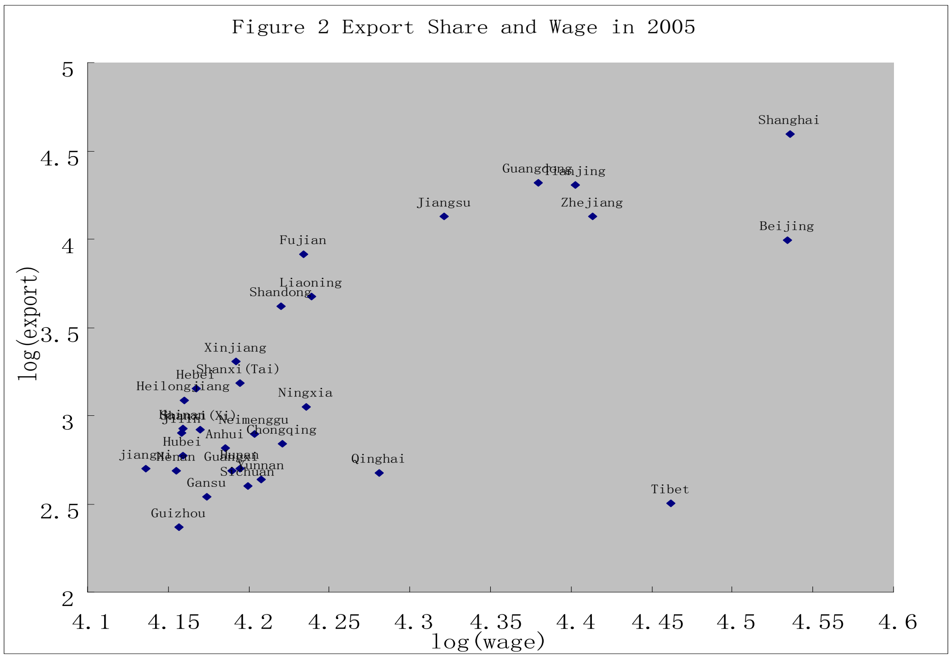
Figure 1. Output Variety and Productivity



Mechanism of Productivity Gain from Output Variety Growth:
Suppose the production function is given by (1), where sigma<0 for outputs. As shown on figure 1, given output prices an increase in output varieties from V1 only to V1 *and* V2, the maximum revenue increases from R1 to R2. It is a productivity gain in processing which is purely due to growth in available varieties.



Data Source: China Statistical Yearbook 2006.

Figure 3. Provincial productivity versus average export variety

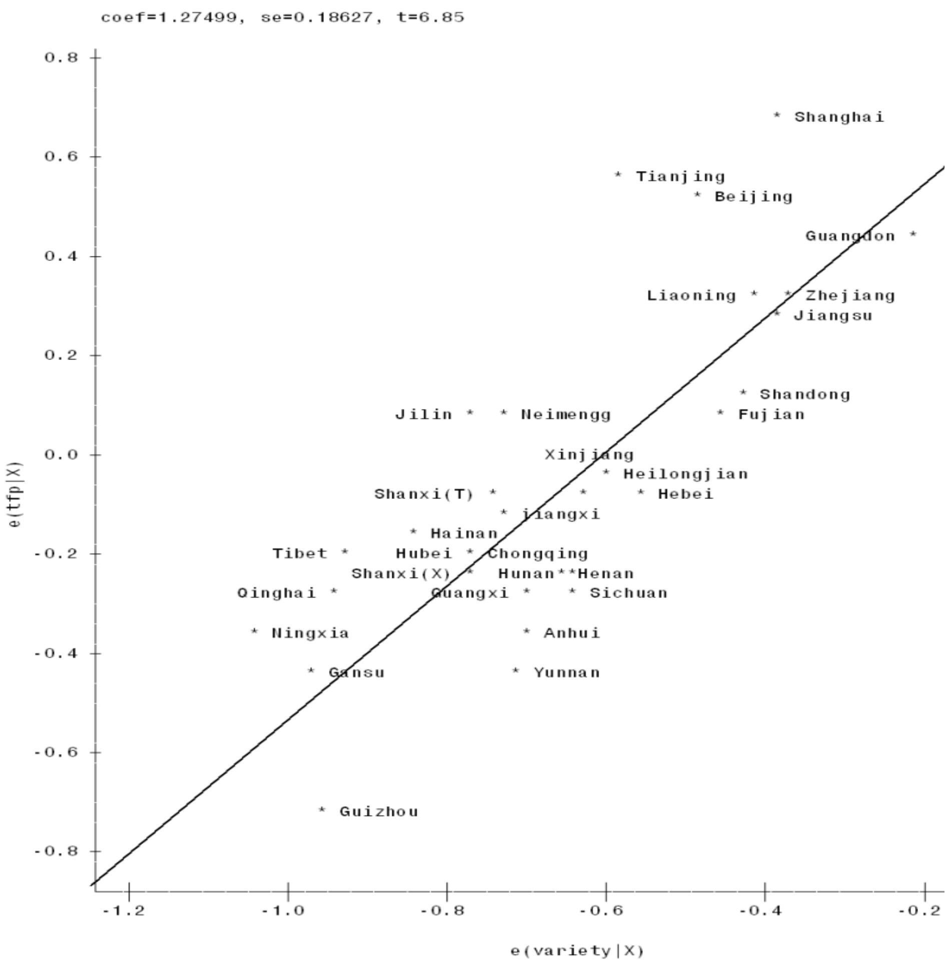


Table 1: Dependent Variables-Industry shares in Column (1) to (7), and adjusted TFP in column (8)
Estimation Method: Non-linear Ordinary Least Squares Regressions
Total system observations: 1544
Observations per equation: 193

Independent Variables	(1) Agriculture	(2) Textile& Garments	(3) Wood &Paper	(4) Chemical &Plastics	(5) Mining& Metals	(6) Machinery & Transportation	(7) Food, Beverage & Tobacco	(8) Adj.TFP
Agriculture	0.023***	-0.010***	0.005***	0.004	-0.022***	-0.016***	0.029***	0.382***
	(0.008)	(0.003)	(0.002)	(0.003)	(0.008)	(0.004)	(0.006)	(0.044)
Textile &	-0.010***	0.016***	0.003***	0.001	-0.004	0.002	-0.021***	0.431***
Garments	(0.003)	(0.006)	(0.001)	(0.002)	(0.005)	(0.002)	(0.007)	(0.140)
Wood &	0.005***	0.003***	0.004***	-0.006***	-0.006**	-0.002***	-0.006***	0.810***
Paper	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.170)
Chemical	0.004	0.001	-0.006***	0.013**	-0.008	0.002	0.016***	0.418***
&Plastics	(0.003)	(0.002)	(0.002)	(0.005)	(0.006)	(0.002)	(0.006)	(0.101)
Mining&	-0.022***	-0.004	-0.006**	-0.008	0.125***	0.003	-0.021*	0.170***
Metals	(0.008)	(0.005)	(0.002)	(0.006)	(0.027)	(0.005)	(0.011)	(0.029)
Machinery&	-0.016***	0.002	-0.002***	0.002	0.003	0.026***	-0.005	0.572***
Transportation	(0.004)	(0.002)	(0.001)	(0.002)	(0.005)	(0.005)	(0.003)	(0.091)
Food,	0.029***	-0.021***	-0.006***	0.016***	-0.021*	-0.005	0.060***	0.111***
Beverage & Tobacco	(0.006)	(0.007)	(0.002)	(0.006)	(0.011)	(0.003)	(0.017)	(0.026)
Capital-Land	-0.059***	-0.002	-0.001	0.010***	0.030***	0.018***	-0.001	-0.083***
Ratio	(0.005)	(0.002)	(0.001)	(0.002)	(0.006)	(0.003)	(0.004)	(0.018)
Labor-Land	0.057***	0.002	0.006***	-0.015***	-0.077***	-0.009**	0.004	
Ratio	(0.007)	(0.003)	(0.001)	(0.003)	(0.008)	(0.004)	(0.006)	
Non-traded								-0.468***
Goods Prices								(0.057)
Year Fixed Effects	YES	NO	YES	YES	YES	YES	NO	YES
Prov. Fixed Effects								YES
R-squared	0.7221	0.4855	0.2033	0.3325	0.5179	0.7638	0.3304	0.9761

Note: For columns (1) to (7), each log of relative export variety coefficient is the partial price effect of the industry in that row on the share of the industry in the column, These are the point estimates of γ_{mn} . Own price effects are underlined. For column (8), each log of the relative export variety coefficient is the point estimate of $1/(1-\sigma_n)$ of the industry in that row.

*, **, and *** indicate significance at 90%, 95% and 99% confidence levels respectively, and White-robust standard errors are in parentheses.

Table 2: Dependent Variables-Industry shares in Column (1) to (7), and adjusted TFP in column (8)
Estimation Method: Iterated Non-linear SUR
Total system observations:1544
Observations per equation: 193

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent Variables	Agriculture	Textile& Garments	Wood &Paper	Chemical &Plastics	Mining& Metals	Machinery & Transportation	Food, Beverage & Tobacco	Adj.TFP
Agriculture	0.035***	-0.005***	0.002	-0.010**	-0.030***	-0.017***	0.029***	0.297***
	(0.0106)	(0.002)	(0.0011)	(0.004)	(0.010)	(0.005)	(0.006)	(0.043)
Textile &	-0.005***	0.005***	0.002***	-0.000	0.000	-0.000	-0.008***	1.195***
Garments	(0.002)	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)	(0.253)
Wood &	0.002	0.002***	0.001***	-0.002**	-0.004***	-0.001	-0.001	1.533***
Paper	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.335)
Chemical	-0.010**	-0.000	-0.002**	0.016**	0.013**	0.006**	-0.000	0.286**
&Plastics	(0.004)	(0.001)	(0.001)	(0.007)	(0.005)	(0.003)	(0.003)	(0.115)
Mining&	-0.030***	0.000	-0.004***	0.013**	0.087***	-0.003	-0.005	0.208***
Metals	(0.010)	(0.002)	(0.001)	(0.005)	(0.020)	(0.005)	(0.007)	(0.041)
Mach.&	-0.017***	-0.000	-0.001	0.006**	-0.003	0.036***	-0.007**	0.41***
Transport.	(0.005)	(0.001)	(0.001)	(0.003)	(0.005)	(0.009)	(0.004)	(0.089)
Food,	0.029***	-0.008***	-0.001	-0.000	-0.005	-0.007**	0.037***	0.235***
Beverage & Tobacco	(0.006)	(0.002)	(0.001)	(0.003)	(0.007)	(0.004)	(0.009)	(0.045)
Capital-Land	-0.056***	-0.001	-0.000	0.009***	0.031***	0.018***	-0.002	-0.090***
Ratio	(0.005)	(0.002)	(0.001)	(0.003)	(0.006)	(0.004)	(0.004)	(0.018)
Labor-Land	0.056***	0.002	0.003**	-0.015***	-0.079***	-0.008*	0.006	
Ratio	(0.007)	(0.003)	(0.001)	(0.003)	(0.008)	(0.005)	(0.005)	
Non-traded Goods								-0.470***
Prices								(0.0567)
Year Fixed Effects	YES	NO	NO	YES	YES	YES	NO	YES
Prov. Fixed Effects								YES
R-squared	0.7077	0.4621	0.4916	0.4164	0.4659	0.7487	0.2633	0.9660

Note: For columns (1) to (7), each log of relative export variety coefficient is the partial price effect of the industry in that row on the share of the industry in the column, These are the point estimates of γ_{mn}. Own price effects are underlined. For column (8), each log of the relative export variety coefficient is the point estimate of $1/(1-\sigma_n)$ of the industry in that row.
*, **, and *** indicate significance at 90%, 95% and 99% confidence levels respectively, and White-robust standard errors are in parentheses.

Table 3: Dependent Variables-Industry shares in Column (1) to (7), and adjusted TFP in column (8)
Estimation Method: Two Stage Nonlinear Least Squares Regressions
Total system observations: 1544
Observations per equation: 193

Independent Variables	***(1) Agriculture***	***(2) Textile & Garments***	***(3) Wood & Paper***	***(4) Chemical &Plastics***	***(5) Mining& Metals***	*(6) Machinery*	***(7) Food & Beverage***	(8) **Adj.TFP**	***1st-Stg F-stat.***
Agriculture	**0.0334*****	**-0.019*****	0.0017	**0.0078****	**-0.028****	**-0.0293*****	**0.0513*****	**0.325*****	
	(0.0118)	**(0.0053)**	(0.0012)	**(0.0035)**	**(0.0108)**	**(0.0070)**	**(0.0131)**	**(0.0569)**	**60.18**
Textile & Garments	**-0.0192*****	**0.0330****	-0.0003	**0.0036***	0.0043	0.0023	**-0.044*****	**0.339****	
	(0.0053)	**(0.0144)**	(0.0005)	**(0.0021)**	(0.0054)	(0.0029)	**(0.0168)**	**(0.1390)**	**29.61**
Wood & Paper	0.0017	-0.0003	**0.0017*****	**-0.003*****	**-0.004*****	**-0.0017****	**-0.0022***	**2.470*****	
	(0.0012)	(0.0005)	**(0.0004)**	**(0.0007)**	**(0.0013)**	**(0.0007)**	**(0.0011)**	**(0.4574)**	**46.16**
Chemical &Plastics	**0.0078****	**0.0036***	**-0.003*****	**0.012*****	**-0.011*****	-0.0013	**0.018*****	**0.899*****	
	(0.0035)	**(0.0021)**	**(0.0007)**	**(0.0035)**	**(0.0046)**	(0.0023)	**(0.00479)**	**(0.1806)**	**73.61**
Mining& Metals	**-0.0276****	0.0043	**-0.004*****	**-0.011*****	**0.132*****	0.0093	-0.0175	**0.22*****	
	(0.0108)	(0.0054)	**(0.0013)**	**(0.0046)**	**(0.0306)**	(0.0068)	(0.0129)	**(0.0413)**	**59.10**
Machinery	**-0.0293*****	0.0023	**-0.0017****	-0.0013	0.0093	**0.0497*****	**-0.0129***	**0.413*****	
	(0.0070)	(0.0029)	**(0.0007)**	(0.0023)	(0.0068)	**(0.0123)**	**(0.0071)**	**(0.0940)**	**57.91**
Food & Beverage	**0.0513*****	**-0.044*****	**-0.0022***	**0.0177*****	-0.0175	**-0.0129***	**0.0643****	**0.0621****	
	(0.0131)	**(0.0168)**	**(0.0011)**	**(0.0048)**	(0.0129)	**(0.0071)**	**(0.0302)**	**(0.0252)**	**48.86**
Capital-Land Ratio	**-0.0557*****	**-0.0042***	-0.0005	**0.0129*****	**0.030*****	**0.0174*****	0.0030	**-0.1220*****	
	(0.00566)	**(0.00227)**	(0.0011)	**(0.0026)**	**(0.00634)**	**(0.0036)**	(0.0051)	**(0.0211)**	
Labor-Land Ratio	**0.0555*****	0.0003	**0.0047*****	**-0.018*****	**-0.078*****	**-0.0135*****	0.0012		
	(0.0069)	(0.0028)	**(0.0015)**	**(0.0033)**	**(0.00841)**	**(0.0049)**	(0.0063)		
Non-traded Goods Prices								**-0.5430*****	
								(0.085)	
Year Fixed Effects	YES	YES	YES	YES	YES	YES	NO	YES	
Prov. Fixed Effects								YES	
R-squared	0.7106	0.3942	0.1327	0.2143	0.4575	0.7334	0.2634	0.9639	

Note: For columns (1) to (7), each log of relative export variety coefficient is the partial price effect of the industry in that row on the share of the industry in the column, These are the point estimates of γ_{mn}. Own price effects are underlined. For column (8), each log of the relative export variety coefficient is the point estimate of $1/(1-\sigma_n)$ of the industry in that row.
*, **, and *** indicate significance at 90%, 95% and 99% confidence levels respectively, and White-robust standard errors are in parentheses.

Table 4: Hypothesis Testing

Null Hypothesis	Homogeneity in Endowments	Homogeneity in Prices	Symmetry in Cross Price Effects	Hausman Test OLS vs. N2SLS
Degree of Freedom	1	1	21	139
Critical Value at 95%	3.84	3.84	32.67	167.5
Overall System			7.70 (0.9963)	94.39 (0.9986)
Agriculture	0.13 (0.7145)	3.51* (0.0610)		
Textile & Garments	0.01 (0.9080)	0.10 (0.7486)		
Wood & Paper	0.04 (0.8355)	0.05 (0.8216)		
Chemical &Plastics	0.35 (0.5556)	0.91 (0.3392)		
Mining& Metals	1.68 (0.1947)	0.70 (0.4023)		
Machinery& Transportation	0.95 (0.3297)	0.03 (0.8690)		
Food,Beverage & Tobacco	0.05 (0.8287)	0.84 (0.3587)		
Adj.TFP	0.92 (0.3387)	121.66*** (<.0001)		

Notes: All test statistics are asymptotically Chi-squared distributed with degree of freedom equals number of restrictions. Numbers in parentheses denote p-value of the test statistics.

Table 5: Productivity Decomposition

	Level Decomposition (in % of TFP)	Growth Decomposition (in % of TFP)
Variance of Estimated Province TFP	0.0954 (100)	0.0050 (100)
Variance of Province Fixed Effects	0.0347 (36.3%)	-
Variance of Variety Induced TFP	0.0421(44.1%)	0.0018 (36.6%)
2*Covariance between Province Fixed Effects and Variety Induced TFP	0.0138 (14.4%)	-

Source: Author's calculation based on regression results of Table 1.