NOTE

PRODUCT CYCLES IN U.S. IMPORTS DATA

Chong Xiang*

Abstract—In this paper, I construct product-level U.S.-manufacturing-imports data for new products. I show that consistent with product cycles, the North’s new-products exports to the United States, relative to its old-products exports, grow faster than the South’s for over a decade; then the South catches up with the North, and this pattern is reversed. This finding holds up in parametric, nonparametric, and semiparametric estimations, and only when new products are properly identified and old products within the same industries are used as controls. There is also evidence that product cycles become shorter over time and they are technology related.

I. Introduction

PRODUCT cycles (Vernon, 1966) suggest that time could be a source of comparative advantage: once a new product becomes technologically feasible (e.g., CT scanners), it is initially produced and exported by the North; later, the production of this same product moves to the South. A large theoretical literature examines how product cycles relate to trade patterns (Krugman, 1979), innovation (Grossman & Helpman, 1991), and skill premium (Thoenig & Verdier, 2004). Early empirical work on product cycles (surveyed in Deardorff, 1984) shows correlations between export performance and innovation. In more recent work,1 Feenstra and Rose (2000) report that developed countries export products earlier to the United States than developing countries, which they interpret as evidence for product cycles. While these studies examine issues related to product cycles, in the data many non-product-cycle forces affect the North’s and South’s trade patterns differently. Over time, the North and South have experienced different growth rates of GDP and range of exported products (Broda & Weinstein, 2006), different paces and paths of trade liberalization (Subramanian & Wei, 2007), and perhaps different changes in fixed trade costs, factor endowments, and productivities. Controlling for these non-product-cycle forces remains challenging.

In this paper, I identify new products in U.S.-manufacturing-imports data by manually matching the product descriptions to Xiang’s (2005) list of newly produced manufacturing products in the United States. I then construct, by industry, the South’s new-products exports to the United States, relative to its old-products’ production from the North to the South. A large theoretical literature examines how product cycles relate to trade patterns (Krugman, 1979), innovation (Grossman & Helpman, 1991), and skill premium (Thoenig & Verdier, 2004). Early empirical work on product cycles (surveyed in Deardorff, 1984) shows correlations between export performance and innovation. In more recent work,1 Feenstra and Rose (2000) report that developed countries export products earlier to the United States than developing countries, which they interpret as evidence for product cycles. While these studies examine issues related to product cycles, in the data many non-product-cycle forces affect the North’s and South’s trade patterns differently. Over time, the North and South have experienced different growth rates of GDP and range of exported products (Broda & Weinstein, 2006), different paces and paths of trade liberalization (Subramanian & Wei, 2007), and perhaps different changes in fixed trade costs, factor endowments, and productivities. Controlling for these non-product-cycle forces remains challenging.

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1 See also Cantwell (1995) and Gagnon and Rose (1995).

shows the summary statistics of the logs of positive import values of new products for at least one year. Table 1 and the other 106 countries are in the South (example Mexico, Indonesia). More details on the matching and data construction are in the appendix. The 31 countries whose average real per capita GDP for 1972 to 1996 exceeds $7,000 are in the North (e.g., Spain, the United Kingdom), and the other 106 countries are in the South (example Mexico, Indonesia). More details on the matching and data construction are in the online appendix.

Among the 399 four-digit mSIC manufacturing industries, 243 have positive import values of new products for at least one year. Table 1 shows the summary statistics of the logs of $G_{otk}$, $G_{otk}$, $G_{ntk}$, and $G_{otk}$ and the relative exports ratio, $\ln\left(\frac{G_{otk}}{G_{otk}}\right)$. Figure 1 plots the new-products shares in U.S. imports for 1972 to 2001. Consistent with expectations, the plot shows an upward trend, starting at about 4% in 1972 and reaching about 10% in 2001. The average new-products import share is 6.95% for 1972 to 1988 but 9.33% for 1989 to 2001. The average new-products share in U.S. imports for 1972 to 2001. Consistent with expectations, the plot shows an upward trend, starting at about 4% in 1972 and reaching about 10% in 2001. The average new-products import share is 6.95% for 1972 to 1988 but 9.33% for 1989 to 2001.

Columns 2 and 3 of table 2 list the new-products export shares by the North and South (to the United States) by broad industries for 1990. They are highly correlated (0.88–0.92) with the new-products shares in U.S. domestic output (Xiang, 2005), in column 4, but have negative and insignificant correlation (~0.17) with the vertical specialization shares of northern countries of HIY 2001, which are in column 5. The latter result alleviates the concern that the use of gross import values rather than value-added systematically biases the new-products export shares. Columns 6 and 7 report the export shares of Zhu’s (2005) product-cycle goods. Since Zhu’s identification is country specific (e.g., steel could be a product-cycle good for Mexico but not for Thailand), it could reflect offshoring and vertical specialization. Indeed, Zhu’s (2005) measures for the North (column 6) are positively correlated with the vertical specialization shares of HIY 2001 (0.41 with a 10% p-value). In comparison, my new products are not country specific (e.g., arrows are an old product for every country), and they have negative and insignificant correlation (~0.075 for the South and ~0.29 for the North) with Zhu (2005). Additional correlation exercises are in the appendix.

III. Framework

In this section I describe the setup and outline the results of my model, which is fully developed in the appendix. There are three countries: the North, the South, and the United States. Preferences are two tier. The upper tier is Cobb-Douglas over Dixit-Stiglitz monopolistically competitive industries, which correspond to the mSIC industries in my data. Each industry has horizontally differentiated varieties, as in Krugman (1979), and consumers obtain a constant elasticity of substitution subutility from them. Each variety corresponds to one product-by-country in my data (e.g., 8 mm Color Video Recorders exported from the North are one variety).

At the beginning of period 1 (1972 to 2001 in my data), new products become technologically feasible for industry $k$, and they correspond to the SIC manual new products in my data. New products do not drive old products extinct as they are imperfect substitutes; for example, Automatic Teller Machines are a new product in my data and Coin and Currency Handling Machines an old product in the same industry. In this framework, the product cycle hypothesis implies that the North’s new-products exports to the United States, relative to the South’s, decrease initially and then increase, tracing out a U-shape within period 1 with the bottom at T. A large T suggests a large technology gap between the North and the South, in the sense that the South’s diffusion process for new products is slow relative to the North’s, and it takes the South longer to catch up with the North in terms of exporting new products to the United States.

I show that the product cycle hypothesis can be tested parametrically as

$$
\ln\left(\frac{G_{otk}}{G_{otk}}\right) = f_k + \gamma_1 t + \gamma_2 t^2 + \gamma_3 \ln\left(\frac{\tau_{otk}}{\tau_{otk}}\right) + \epsilon_{notk}.
$$

The dependent variable is relative-exports ratio, $t$ is time, $f_k$ industry fixed effects, the $\gamma$’s variable trade costs, and $\epsilon_{notk}$ the error term. The product cycle hypothesis implies $\gamma_2 > 0$, $\gamma_1 < 0$, and $T = -\gamma_1/2\gamma_2$. $\gamma_3 < 0$ since variable trade costs impede trade. The nonparametric and semiparametric versions of regression equation (1) are

$$
\ln\left(\frac{G_{otk}}{G_{otk}}\right) = f_k + m(t) + \gamma_3 \ln\left(\frac{\tau_{otk}}{\tau_{otk}}\right) + \epsilon_{notk}.
$$

Product cycles imply that the function $m(.)$ has a U-shape. As compared with equation (1), equation (2) allows for a more flexible functional form.

### Table 1.—Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Observations</th>
<th>Mean</th>
<th>STD</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln(S.\ New\ Prod.\ Exports)$</td>
<td>4,478</td>
<td>14.7724</td>
<td>3.24125</td>
<td>3.49144</td>
<td>23.9105</td>
</tr>
<tr>
<td>$\ln(S.\ Old\ Prod.\ Exports)$</td>
<td>5,204</td>
<td>17.6755</td>
<td>2.68252</td>
<td>5.88934</td>
<td>24.0913</td>
</tr>
<tr>
<td>$\ln(S.\ New\ Prod.\ Exports)$</td>
<td>4,602</td>
<td>16.2359</td>
<td>2.69163</td>
<td>3.76782</td>
<td>23.4074</td>
</tr>
<tr>
<td>$\ln(S.\ Old\ Prod.\ Exports)$</td>
<td>5,252</td>
<td>18.8072</td>
<td>2.65539</td>
<td>7.37657</td>
<td>25.3599</td>
</tr>
<tr>
<td>Relative exports ratio, $\ln\left(\frac{\text{Notk}}{\text{Nntk}}\right)$</td>
<td>4,419</td>
<td>-0.403</td>
<td>1.67934</td>
<td>-10.627</td>
<td>8.9966</td>
</tr>
</tbody>
</table>

**Figure 1.—Shares of New Products in U.S. Manufacturing Imports**

![Shares of New Products in U.S. Manufacturing Imports](image-url)
for time but does not produce a point estimate for the bottom of the U-shape, $T$. Therefore, these two equations are complementary.

IV. Estimation Results

Figure 2 illustrates why I have relative exports ratio as the dependent variable in equations (1) and (2) rather than the ratio of new-products exports, $\ln(G_{ntk}/G_{ntk})$. The left panel of figure 2 plots the average $\ln(G_{ntk}/G_{ntk})$ across industries, weighted by average new-products imports by industry over time for 1978 to 2001. The plot shows that the South’s new-products exports grow faster than the North’s throughout the 1978–2001 period, which could be consistent with product cycles or many non-product-cycle factors (e.g., faster economic growth and more trade liberalization for the South). The right panel of figure 2 plots the weighted average of $\ln(G_{olk}/G_{olk})$, and shows that

\[ \text{Table 2.—New-Products Export Shares by Industry} \]

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>Food, Beverages &amp; Tobacco</td>
<td>0.035</td>
<td>0.071</td>
<td>0.122</td>
<td>0.172</td>
<td>0.220</td>
<td>0.195</td>
</tr>
<tr>
<td>Textiles, Apparel &amp; Leather</td>
<td>0.092</td>
<td>0.092</td>
<td>0.112</td>
<td>0.271</td>
<td>0.058</td>
<td>0.099</td>
</tr>
<tr>
<td>Wood Products &amp; Furniture</td>
<td>0.051</td>
<td>0.016</td>
<td>0.076</td>
<td>0.198</td>
<td>0.035</td>
<td>0.073</td>
</tr>
<tr>
<td>Paper, Paper Products &amp; Printing</td>
<td>0.050</td>
<td>0.037</td>
<td>0.100</td>
<td>0.188</td>
<td>0.135</td>
<td>0.318</td>
</tr>
<tr>
<td>Industrial Chemicals</td>
<td>0.014</td>
<td>0.014</td>
<td>0.076</td>
<td>0.266</td>
<td>0.110</td>
<td>0.335</td>
</tr>
<tr>
<td>Drugs &amp; Medicines</td>
<td>0.103</td>
<td>0.101</td>
<td>0.131</td>
<td>0.166</td>
<td>0.070</td>
<td>0.380</td>
</tr>
<tr>
<td>Petroleum &amp; Coal Products</td>
<td>0.001</td>
<td>0.001</td>
<td>0.028</td>
<td>0.436</td>
<td>0.260</td>
<td>0.298</td>
</tr>
<tr>
<td>Rubber &amp; Plastic Products</td>
<td>0.143</td>
<td>0.141</td>
<td>0.183</td>
<td>0.254</td>
<td>0.045</td>
<td>0.150</td>
</tr>
<tr>
<td>Non-Metallic Mineral Products</td>
<td>0.033</td>
<td>0.029</td>
<td>0.040</td>
<td>0.141</td>
<td>0.027</td>
<td>0.247</td>
</tr>
<tr>
<td>Iron &amp; Steel</td>
<td>0.000</td>
<td>0.000</td>
<td>0.015</td>
<td>0.227</td>
<td>0.280</td>
<td>0.345</td>
</tr>
<tr>
<td>Non-Ferrous Metals</td>
<td>0.014</td>
<td>0.001</td>
<td>0.035</td>
<td>0.299</td>
<td>0.100</td>
<td>0.290</td>
</tr>
<tr>
<td>Metal Products</td>
<td>0.041</td>
<td>0.045</td>
<td>0.108</td>
<td>0.194</td>
<td>0.020</td>
<td>0.165</td>
</tr>
<tr>
<td>Non-Electrical Machinery</td>
<td>0.156</td>
<td>0.106</td>
<td>0.111</td>
<td>0.208</td>
<td>0.180</td>
<td>0.530</td>
</tr>
<tr>
<td>Electrical Machinery</td>
<td>0.584</td>
<td>0.547</td>
<td>0.359</td>
<td>0.215</td>
<td>0.080</td>
<td>0.280</td>
</tr>
<tr>
<td>Transport Equipment</td>
<td>0.016</td>
<td>0.009</td>
<td>0.086</td>
<td>0.232</td>
<td>0.190</td>
<td>0.640</td>
</tr>
<tr>
<td>Professional Goods</td>
<td>0.132</td>
<td>0.097</td>
<td>0.191</td>
<td>0.190</td>
<td>0.020</td>
<td>0.280</td>
</tr>
<tr>
<td>Other Manufacturing</td>
<td>0.198</td>
<td>0.100</td>
<td>0.078</td>
<td>0.209</td>
<td>0.010</td>
<td>0.110</td>
</tr>
</tbody>
</table>


The U.S. imports data for 1972 to 1977 are noisy (see the appendix). Results are similar using 1972 to 2001 (table 3).
similar to the left panel, the South’s old products exports grow faster than the North’s throughout the 1978–2001 period. This suggests that figure 2 is driven by non-product cycle factors. These factors, however, are swept out of the relative exports ratio, \( \ln \frac{G_{it}}{G_{it}} \), if they affect new and old products within the same industries symmetrically.

Table 3 reports the main results. The dependent variable is relative exports ratio, and the sample period is 1978 to 2001. All standard errors are bootstrapped with a cluster-by-year structure. I weight the observations by the average value of imports for industry \( i \) and time, consistent with product cycles, and that the U-shape reaches its bottom 16.81 years after 1978. Column 2 drops the variable trade cost variable, column 3 uses 1972 to 2001, and the results are similar.

One concern is that cross-country heterogeneity (in, e.g., institutions) within the North and South may bias the results of regression (1). This suggests adding country fixed effects to equation (1). I construct the relative-exports ratio for each northern country and the South, reestimate equation (1) with industry-by-northern-country fixed effects, and report the results in column 4. The coefficients of \( t \) and \( t^2 \) remain significant, their signs are consistent with product cycles, and the estimate \( T = 14.84 \) is similar to column 1. Column 5 is a similar exercise with the relative exports ratio for individual southern countries and industry-by-southern-country fixed effects, and shows similar results. Another concern is that the use of gross values rather than value-added may mismeasure \( \ln \frac{G_{it}}{G_{it}} / \ln \frac{G_{it}}{G_{it}} \) and bias the results of equation (1). Since one cannot back out value-added as in HIY 2001 for product-level trade data, I experiment with dropping the countries whose exports are most likely to be affected by vertical specialization. In column 6, I drop China and Mexico and in column 7 all the countries whose export-to-GDP ratio ever exceeds 50% during 1978 to 2001. The results are similar. The appendix reports additional robustness exercises for equation (1).

\footnote{Consistent with this conclusion, the appendix shows that regressing \( \ln (G_{it}/G_{it}) \) on the regressors of equation (1) does not provide evidence for product cycles.}
dashed lines plot the upper and lower bounds of the 95% confidence interval, obtained by bootstrapping. They show a clear U-shape, consistent with product cycles. For comparison, I generate the predicted values of the relative exports ratio using the parametric estimation of column 2, table 3, and plot it in figure 3A (dotted line). The nonparametric and parametric estimates are similar. To illustrate the broad pattern of the data, I calculate the weighted average (same weights as for table 3) of the relative exports ratio by year and plot it in figure 3A (circles). This pattern is consistent with both nonparametric and parametric estimates. Figure 3B is similar to 3A, but the estimation is semiparametric, with the variable-trade-cost variable, whose coefficient estimate of $-0.567$ is similar to column 1, table 3. The vertical axis is the relative exports ratio minus the effects of trade costs and other controls, and again the U-shape is clear.

Now I perform two exercises to verify that if new products had not been properly identified, there would have been no evidence for product cycles. First, following Hanson and Xiang (2004), I randomize the designations of new and old products within each industry and reestimate regression (1) for the randomized sample. Performing these exercises 1,000 times, I obtain 1,000 estimates of the coefficients of $t$, $r^2$, and $T$, plus their standard errors. I report the averages of these estimates and their standard errors in column 8, table 3. The average coefficients for $t$ and $r^2$ are essentially 0, and the average of $T$ has an enormous standard error. Second, I identify new products as the numerical codes that show up for the first time during 1973 to 1987. I then identify the peak mention years and calculate the weighted averages of ng_code-based and ng_match-based relative exports ratios. While the solid lines match the falling arm of the U-shape in figure 3, the dotted lines show the opposite trend. In both exercises, there is no evidence for product cycles when new products are not properly identified.

Some literature conjectures that over time, product cycles become shorter (Puga & Trefler, 2007). I explore whether this is consistent with my data. For every SIC manual new product, I gather the numbers of mentions by year in Factiva, the Dow-Jones news media database, for 1969 to 1987. I then identify the peak mention years and calculate the average by four-digit mSIC industries. Of the 243 new products industries, 93 have average peak years above 1979.5, the midpoint of 1972 to 1987, and I call these late-vintage industries. They are 46.3% of the new products' trade values, more concentrated in the two-digit industry group 36 (electronics) than the other new products industries, and less concentrated in 28 (chemicals), 35 (machinery), 37 (transportation), and 38 (instruments) (see the appendix for details).
I augment regression (1) with the interaction of time and late-vintage dummy. A positive coefficient of the interaction term suggests that the late-vintage industries reach the bottom of the U-shape more quickly than the other new-products industries, consistent with the conjecture that product cycles become shorter over time. Column 2 of table 4 reports the results (column 1 copies column 1 of table 3 as a benchmark). The interaction term has a significant coefficient of 0.119. The late-vintage industries reach the bottom 12.4 years after 1978, while the others do so after 19.2 years.

Most literature hypothesizes that product cycles are technology related. Following Xiang (2005) I restrict my sample to the most R&D-intensive (measured as the private-R&D-expenditure-to-net-sales-ratio) industry groups, 28 and 35 to 38, redo the estimations of columns 1 and 2 of table 4, and report the results in columns 3 and 4. These are very similar to columns 1 and 2, consistent with the hypothesis that product cycles are technology driven.

V. Conclusion

In constructing product-level U.S. manufacturing imports data for new products, I find that the relative exports ratio shows a U-shape over time, consistent with product cycles; the industries with late-vintage new products reach the bottom of the U-shape more quickly, suggesting that product cycles become shorter over time; these results are driven by the most R&D-intensive industry groups, suggesting that product cycles are technology related.

One limitation is that my approach is reduced form and does not distinguish the causes and channels of product cycles, a fruitful area for future research. For example, the South may pick up the production of new products through the expiration of the North’s patents (Segerstrom, Anant, Dinopoulos, 1990), southern imitation (Grossman & Helpman, 1991), or standardization (Acemoglu, Gancia, & Zilibotti, 2010). Finding out which channel is at work may shed light on international technology diffusion and the connection between openness and development. Such future research may benefit from the following two contributions of this paper: the product-level trade data for new products and the estimation strategy of using old products within the same industries as controls.

REFERENCES


