Product Cycles in U.S. Imports Data

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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 U.S., relative to its old-products exports, grow faster than the South's for over a decade, and then the South catches up with the North and this pattern is reversed. This finding holds up in parametric, non-parametric and semi-parametric 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.

Keywords: product cycle; new product;

JEL Classification: F1, O1.

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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 and Helpman 1991), and skill premium (Theonig and Verdier 2004). Early empirical work on product cycles (surveyed in Deardorff 1984) shows correlations between export performance and innovation. In recent work[1] Feenstra and Rose (2000) report that developed countries export products earlier to the U.S. than developing countries, which they interpret as evidence for product cycles. While these studies examine issues related to product cycles, in the data there are many non-product-cycle forces that 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 and Weinstein 2006), different paces and paths of trade liberalization (Subramanian and Wei 2006), and may also experience 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 (2005)'s list of newly-produced-manufacturing products in the U.S. I then construct, by industry, the South's new-product exports (to the U.S.) relative to the North's, normalized by the South's old-product exports relative to the North's, a variable I call relative-exports ratio. Product cycles imply that the relative-exports ratio displays a U-shape over time, falling initially as the North pulls ahead of the South in terms of exporting new products to the U.S., and rising later as the South catches up with the North. The non-

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

product-cycle forces, however, do not affect the change of relative-exports ratio over time if they have symmetric impacts on new and old products within the same dis-aggregated industries. I find strong evidence that the relative-exports ratio displays a U-shape, and this finding holds up in parametric, non-parametric and semi-parametric estimations. I also find evidence that product cycles are technology-related and they become shorter over time.

The latter result complements the product-*life*-cycle literature in management (Bass 1969), which examines the introduction, growth and then obsolescence of specific product-models (e.g. IBM 286-CPU 16-bit PC). Some in the literature argue that product-*life*-cycles become shorter over time (Qualls et al. 1981, von-Corswant and Fredriksson 2002) but others disagree (Bayus 1994). Both sides mainly use data from surveys/anecdotes or specific industries/products. In comparison I systematically study the new products for the whole manufacturing sector, use the old products within the same industries as controls, and examine the migration of new-products' production from the North to the South.

My paper is distinct from Zhu (2005), who examines the general-equilibrium effects of new products and identifies product z as a "product-cycle good" for country c if c switches from importing z from the U.S. to exporting z to the U.S., even if z itself is an old product (e.g. the North makes CT scanners, a new product, and the production of furniture, an old product, moves to the South in general equilibrium). I show that Zhu (2005)'s measures are uncorrelated with mine but positively correlated with the vertical-specialization measures of Hummels, Ishii and Yi (1999) (HIY 1999). The latter result is consistent with Zhu (2005)'s acknowledgement that her measures could reflect offshoring. I also show that if new products were identified using year-to-year changes in product codes, instead of my matching process, there would be no evidence for product cycles.

II. Data

I start with Feenstra, Romalis and Schott (2002), who report values of U.S. manufacturing imports by product by source country by year for 1972-2001. Each product has a description and a numerical code. For 1972-1988 the codes are 7-digit TS (Tariff-System-of-the-United-States) and for 1989-2001 they are 10-digit HS (Harmonized-System). I then use the list of manufactured products newly produced in the U.S. during 1972-1987, which Xiang (2005) identifies by comparing the 1972 and 1987 SIC-manuals (Standard-Industrial-Classification-manuals). I classify the products in the imports-data into new and old by manually matching their descriptions to the names of the SIC-manual-new-products. New imports-data-products are those whose descriptions match SIC-manual-new-products names; e.g. "Exercise Rowing Machines", TS 7352055 and HS 9506910020, matches the SIC-manual-new-product "rowing machines". The un-matched imports-data-products are old; e.g. "Arrow and Arrow Parts", HS 9506990520.

The matching took over two years of work. As compared with the literature, it does not identify new products through year-to-year changes in the numerical codes, which are noisy for two reasons: a given product description may have different codes in different years, and previously unused codes may represent changes in U.S. tariff or quota. In addition, the matching process finesses the change of product classification from TS to HS in 1989 in the imports data. By using the same standards, the SIC-manual-new-products, to designate new products pre-1989 and post-1989, the matching process produces the same *set* of new products pre-1989 and post-1989. For each 4-digit mSIC manufacturing industry k in year t, I aggregate across individual products and across source countries to calculate the U.S. imports of new products from the North and South, G_{ntk} and G_{ntk}^*, plus those of old products from the North and South, G_{otk} and

G_{otk}^*. The 31 countries whose average real per-capita-GDP in 1972-1996 exceeds $7,000 are the North (e.g. Spain, the U.K.), and the other 106 countries are the South (e.g. Mexico, Indonesia). More details of the matching and data construction are in the Appendix.

Among the 399 4-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_{ntk}, G_{ntk}^*, G_{otk} and G_{otk}^*, and the relative-exports ratio, $\ln(\frac{G_{ntk}^*}{G_{otk}^*} / \frac{G_{ntk}}{G_{otk}})$. Figure 1 plots the new-products shares in U.S. imports for 1972-2001. 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 1972-1988 but 9.33% for 1989-2001.

Columns 2-3 of Table 2 list the new-products export shares by the North and South (to the U.S.) 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), which are in column 4, but have negative and insignificant correlation (–0.17) with the vertical-specialization shares of Northern countries of HIY 1999, 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 6-7 report the export shares of Zhu (2005)'s "product-cycle goods". Since Zhu (2005)'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 (2005)'s measures for the North (column 6) are positively correlated with the vertical-specialization shares of HIY 1999 (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 U.S. 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 sub-utility from them. Each variety corresponds to one product-by-country in my data (e.g. "8 mm Colored Camcorders" imported from the North are one variety).

At the beginning of Period 1 (which corresponds to 1972-2001 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; e.g. "Automatic Teller Machines" are a new product in my data and "Coin and Currency Handling Machines" an old product of the same industry. In this framework the product-cycle-hypothesis implies that the North's new-products exports to the U.S., relative to the South's, decreases initially and then increases, 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 U.S.

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

$$\ln\left(\frac{G^{*}_{ntk}}{G^{*}_{otk}} / \frac{G_{ntk}}{G_{otk}}\right) = f_k + \gamma_1 t + \gamma_2 t^2 + \gamma_3 \ln\left(\frac{\tau^{*}_{ntk}}{\tau^{*}_{otk}} / \frac{\tau_{ntk}}{\tau_{otk}}\right) + \varepsilon_{notk}. \quad (1)$$

The dependent variable is relative-exports ratio, t is time, f_k industry fixed effects, the τ's variable trade costs and ε_{notk} the error term. The product-cycle-hypothesis implies $\gamma_2 > 0$, $\gamma_1 < 0$, and $T = -\dfrac{\gamma_1}{2\gamma_2}$. $\gamma_3 < 0$ since variable trade costs impede trade. The non-parametric and semi-parametric versions of regression (1) are

$$\ln(\frac{G^*_{ntk}}{G^*_{otk}} / \frac{G_{ntk}}{G_{otk}}) = f_k + m(t) + \gamma_3{}' \ln(\frac{\tau^*_{ntk}}{\tau^*_{otk}} / \frac{\tau_{ntk}}{\tau_{otk}}) + \varepsilon_{notk}{}'. \qquad (2)$$

Product cycles imply that the function *m*(.) has a U-shape. As compared with (1), (2) allows for a more flexible functional form for time, but does not produce a point estimate for the bottom of the U-shape, *T*. Therefore, (1) and (2) are complementary.

IV. Estimation Results

Figure 2 illustrates why I have relative-exports ratio as the dependent variable in (1) and (2) rather than the ratio of new-products exports, $\ln(\frac{G^*_{ntk}}{G_{ntk}})$. The left-panel of Figure 2 plots the average $\ln(\frac{G^*_{ntk}}{G_{ntk}})$ across industries, weighted by average new-products imports by industry over time, for 1978-2001.[2] The plot shows that the South's new-products exports grow faster than the North's throughout 1978-2001, 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 $\ln(\frac{G^*_{otk}}{G_{otk}})$, and shows that similar to the left-panel, the South's old products exports grow faster than the North's throughout 1978-2001. This suggests that Figure 2 is driven by non-product-cycle factors.[3] These factors, however, are

[2] The U.S. imports-data for 1972-1977 is noisy (see the Appendix). Results are similar using 1972-2001 (Table 3).

[3] Consistent with this conclusion, the Appendix shows that regressing $\ln(G^*_{ntk} / G_{ntk})$ on the regressors of (1) doesn't provide evidence for product cycles.

swept out of the relative-exports ratio, $\ln(\frac{G^*_{ntk}}{G^*_{otk}} / \frac{G_{ntk}}{G_{otk}})$, 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 1978-2001. All standard errors are bootstrapped with a cluster-by-year structure. I weight the observations by the average import values over 1978-2001 since the observations with low import values are more likely to be subject to measurement errors (Besedes and Prusa 2006). I measure variable trade costs as the difference between cif and fob values divided by fob values. Column 1 reports the results of regression (1). The coefficients of t and t^2 are -0.290 and 0.0086 and both are significant. This shows that the relative-exports ratio displays a U-shape over 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 1972-2001, 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 (1). I construct relative-exports ratio for each Northern country and the South, re-estimate (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 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 mis-measure $\ln(\frac{G^*_{ntk}}{G^*_{otk}} / \frac{G_{ntk}}{G_{otk}})$ and bias the results of (1). Since one cannot back out value-added as in HIY 1999 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 1978-2001. The results are similar. The Appendix reports additional robustness exercises for (1).

Figures 3a-3b report the results of regression (2), obtained following di Giovanni and Levchenko (2010). In Figure 3a the estimation is non-parametric, without the variable-trade-cost variable. The solid line plots the predicted-value of relative-exports ratio. The dashed lines plot the upper- and lower-bounds of the 95% confidence interval, obtained via bootstrapping. They show a clear U-shape, consistent with product cycles. For comparison I generate the predicted values of relative-exports ratio using the parametric estimation of column 2, Table 3, and plot it in Figure 3a (dotted line). The non-parametric 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 relative-exports ratio by year and plot it in Figure 3a (small circles). This pattern is consistent with both non-parametric and parametric estimates. Figure 3b is similar to 3a, but the estimation is semi-parametric, with the variable-trade-cost variable, whose coefficient estimate of -0.567 is similar to column 1, Table 3. The vertical axis is 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 re-estimate regression (1) for the randomized sample. Performing these exercises 1000 times I obtain 1000 estimates of the coefficients of t, t^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 t^2 are essentially zero 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 1973-1988.[4] This alternative new-products variable, ng_code, has a small correlation of 0.14 with my new-products variable, ng_match, consistent with the section-II discussions that changes in numerical codes are a noisy measure. I then calculate relative-exports ratio using ng_code, estimate regression (2) for 1978-1988, and plot the estimates and their bounds in Figure 4 (dotted lines). For comparison the solid lines plot the same estimates and bounds except that the relative-exports ratio is based on ng_match. The crosses and circles are 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 and 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 1969-1987. I then identify the peak-mention-years and calculate its average by 4-digit mSIC industries. Of the 243 new-products industries 93 have average-peak-years above 1979.5, the mid-point of 1972-1987, and I call these late-vintage industries. They are 46.3% of the new products' trade values, more concentrated in the 2-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 more 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

[4] To go beyond 1988 one has to map TS product-codes to HS product-codes, which is very difficult.

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 35-38, redo the estimations of columns 1-2 of Table 4, and report the results in columns 3-4. Columns 3-4 are very similar to columns 1-2, consistent with the hypothesis that product cycles are technology-driven.

V. Conclusion

To conclude, I construct product-level U.S.-manufacturing-imports data for new products. I find that one, the relative-exports ratio shows a U-shape over time, consistent with product cycles; two, the industries with late-vintage new products reach the bottom of the U-shape more quickly, suggesting that product cycles become shorter over time; and three, 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 doesn’t distinguish the causes and channels of product cycles, which seems 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 et al. 1990), Southern imitation (Grossman and Helpman 1991), or standardization (Acemoglu et al. 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.

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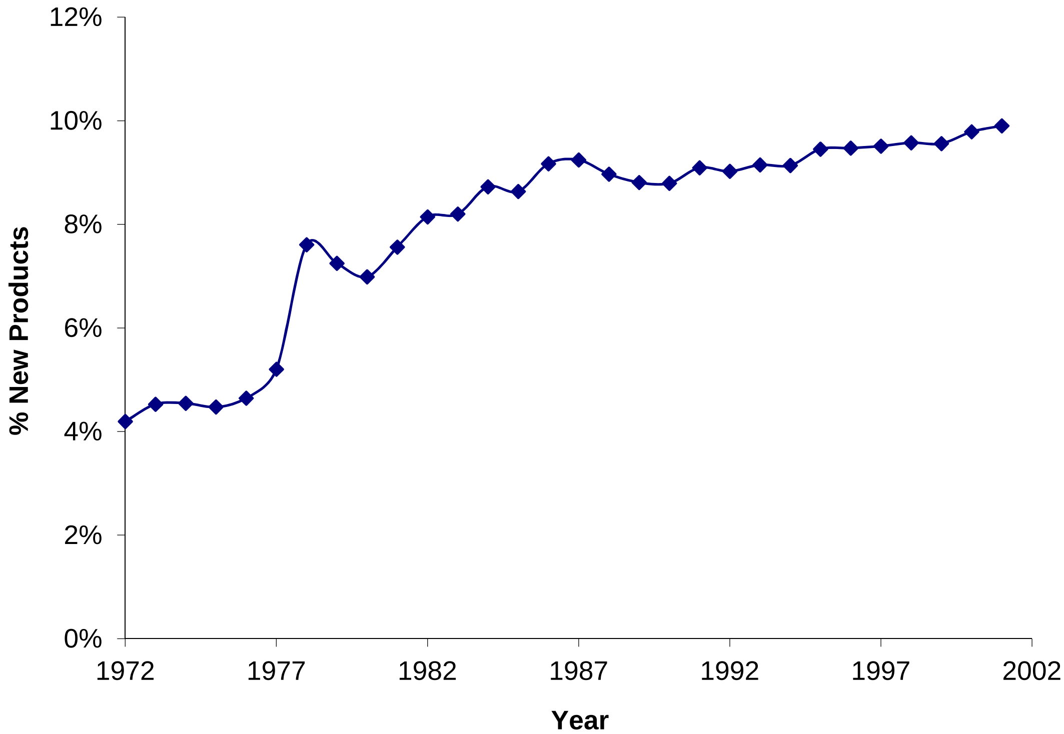

Figure 1 Shares of New Products in U.S. Manufacturing Imports

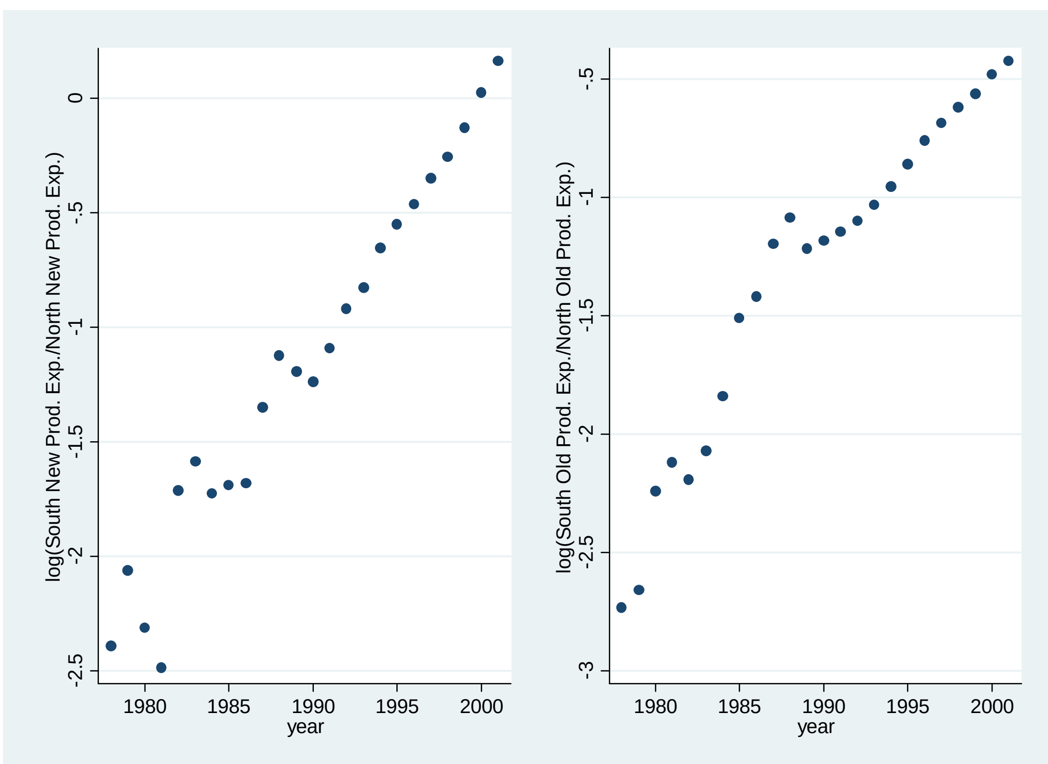

Figure 2 The South's New-Products and Old-Products Exports Relative to the North's

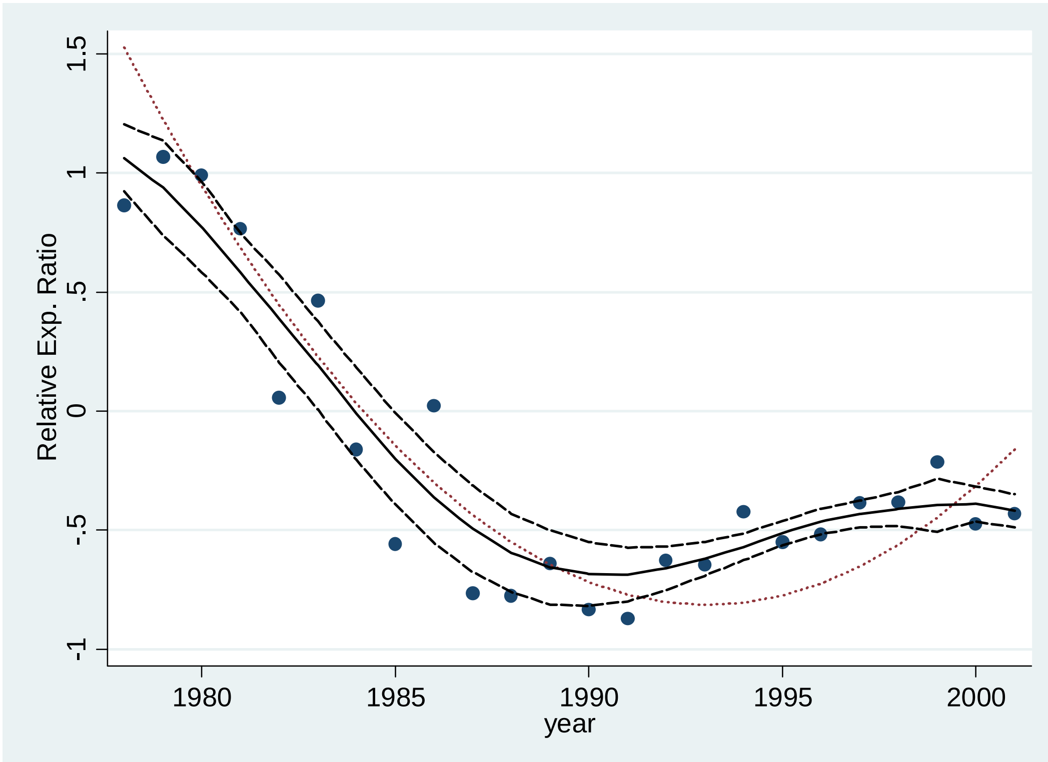

Figure 3a Non-Parametric Fitted Values and Bounds, and Parametric Fitted Values

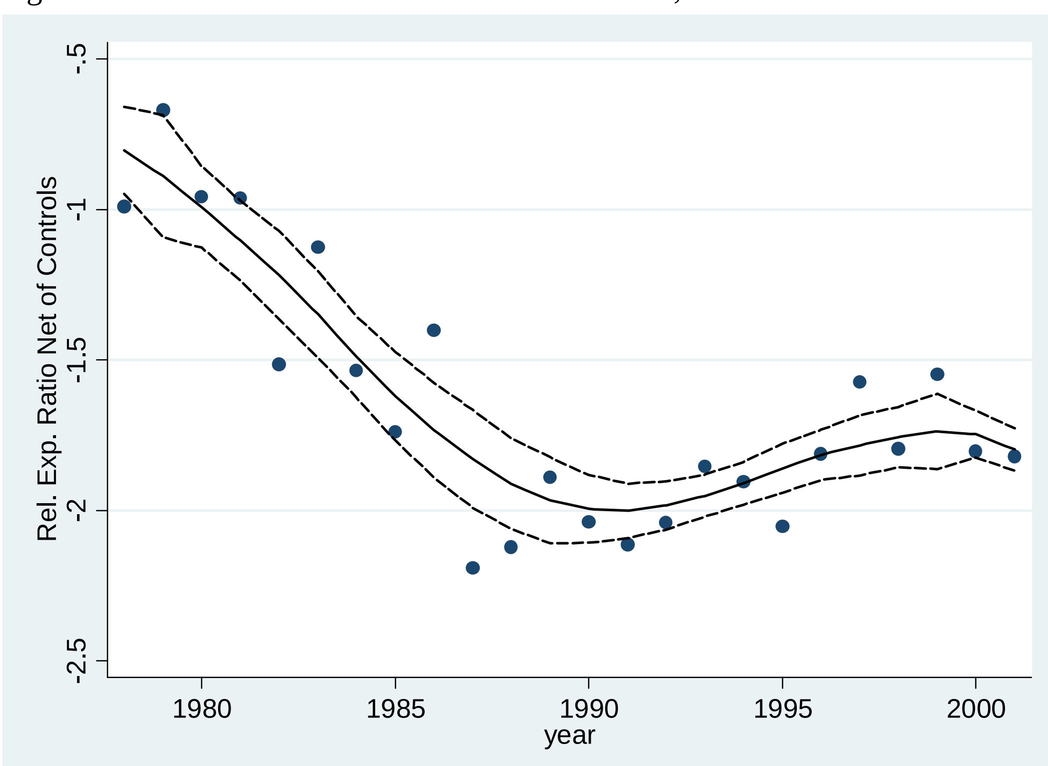

Figure 3b Semi-Parametric Fitted Values and Bounds

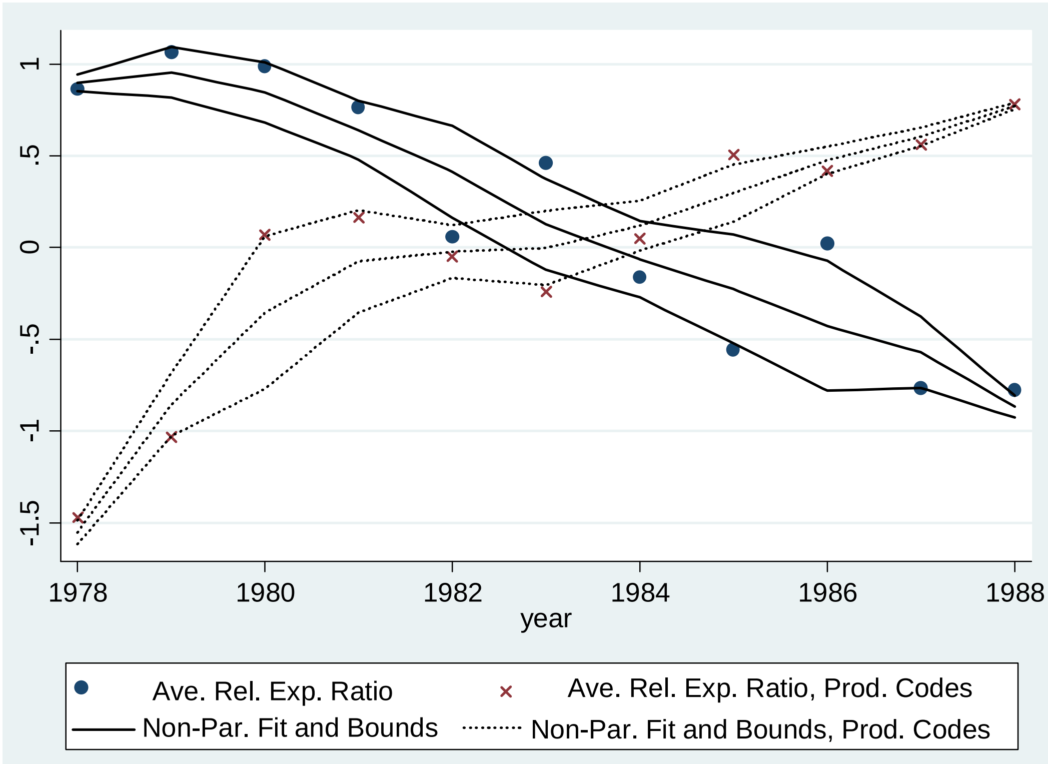

Figure 4 New-Products Measure Based on Year-to-Year Changes in Product Codes

Table 1 Summary Statistics

Variable	Obs.	Mean	Std.	Min	Max
ln(S. New Prod. Exports)	4478	14.7724	3.24125	3.49144	23.9105
ln(S. Old Prod. Exports)	5204	17.6755	2.68252	5.88934	24.0913
ln(N. New Prod. Exports)	4602	16.2359	2.69163	3.76782	23.4074
ln(N. Old Prod. Exports)	5252	18.8072	2.05539	5.73657	25.3599
Relative-Exports Ratio, $\ln(\frac{S_{ntk}}{S_{otk}} / \frac{N_{ntk}}{N_{otk}})$	4419	-0.403	1.67934	-10.627	8.9966

Table 2 New-Products Export Shares by Industry

Industry	(1) New Prods. Imp. Share, N.	(2) New Prods. Imp. Share, S.	(3) New Prod. Outp. Share U.S., Xiang (2005)	(4) Vertical Spec. Share N., HIY 1999	(5) Zhu (2005), N.	(6) Zhu (2005), S.
Food, beverages & tobacco	0.035	0.071	0.122	0.172	0.220	0.195
Textiles, apparel & leather	0.092	0.092	0.112	0.271	0.058	0.099
Wood products & furniture	0.051	0.016	0.076	0.198	0.035	0.073
Paper, paper products & printing	0.050	0.037	0.100	0.188	0.135	0.318
Industrial chemicals	0.014	0.014	0.076	0.266	0.110	0.335
Drugs & medicines	0.103	0.101	0.131	0.166	0.070	0.380
Petroleum & coal products	0.001	0.001	0.028	0.436	0.260	0.298
Rubber & plastic products	0.143	0.141	0.183	0.254	0.045	0.150
Non-metallic mineral products	0.033	0.029	0.040	0.141	0.027	0.247
Iron & steel	0.000	0.000	0.015	0.227	0.280	0.345
Non-ferrous metals	0.014	0.001	0.035	0.299	0.100	0.290
Metal products	0.041	0.045	0.108	0.194	0.020	0.165
Non-electrical machinery	0.156	0.106	0.111	0.208	0.180	0.530
Electrical machinery	0.584	0.547	0.359	0.215	0.080	0.280
Transport Equipment	0.016	0.009	0.086	0.232	0.190	0.640
Professional goods	0.132	0.097	0.191	0.190	0.020	0.280
Other manufacturing	0.198	0.100	0.078	0.209	0.010	0.110

Notes for Table 2: The industries are the same as in Table 2, HIY 1999, except for Transport Equipment and Electrical Machinery, which are the same as in Table A2, Zhu (2005). Columns 1-2 are for 1990. Column 3 is based on the ng_matching measure of Xiang (2005) for 1992. Column 4 is the simple average across the 9 non-U.S. OECD countries in Table 2, HIY 1999, around 1990. Column 5 is based on the high-income-country measure of Table A2, Zhu (2005) for 1988, and column 6 the simple average of low-income- and middle-income-country measures for 1988.

Table 3 Main Results

Regressors	(1) Reg. (1)	(2) Reg. (1)	(3) 1972-2001	(4) N. Country FE	(5) S. Country FE	(6) Drop China Mexico	(7) Drop Exp./GDP > 0.5	(8) Random New Prod.
t	-0.290***	-0.319***	-0.147***	-0.054***	-0.086***	-0.309***	-0.328***	-0.001027
	(0.0328)	(0.0362)	(0.0511)	(0.0108)	(0.0181)	(0.0389)	(0.0328)	(0.0038)
t^2	0.00861***	0.0100***	0.00382**	0.0018***	0.0022***	0.00935***	0.00963***	0.0000391
	(0.0013)	(0.0015)	(0.0017)	(0.0004)	(0.0006)	(0.0016)	(0.0012)	(0.0001)
$\ln\left(\frac{\tau^*_{ntk}}{\tau^*_{otk}} / \frac{\tau_{ntk}}{\tau_{otk}}\right)$	-0.852***		-0.852***	-0.410***	-0.374***	-0.862***	-0.744***	-0.6830***
	(0.1960)		(0.1832)	(0.0465)	(0.0544)	(0.2116)	(0.2052)	(0.0045)
T	16.808***	15.962***	19.239***	14.844***	19.904***	16.527***	17.01***	21.55
	(0.8503)	(0.7550)	(2.6805)	(0.8770)	(2.030)	(0.9568)	(0.6587)	(5359.2886)
Industry FE	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Ind. x ctry. FE	No	No	No	Yes	Yes	No	No	No
Obs. No.	4,386	4,419	4,709	72,113	66,198	4,347	4,378	4,386
R^2	0.482	0.38	0.446	0.51	0.79	0.506	0.469	-

Notes for Table 3: *** p<0.01, ** p<0.05, * p<0.1. Bootstrapped standard errors are in the brackets, and the bootstrap sampling reflects the clustered structure (by year) of the data. The dependent variable is relative-exports ratio, $\ln(\frac{G^*_{ntk}}{G^*_{otk}} / \frac{G_{ntk}}{G_{otk}})$. The sample period is 1978-2001 except for column 3, for which it is 1972-2001. The industry-k-year-t observations are weighted by the average value of imports for industry k over the sample period. "Ind. x ctry. FE" means industry x country (Northern countries for column 4 and Southern countries for column 5) fixed effects.

Table 4 Further Explorations

Regressors	(1) Full-Sample	(2) Full-Sample	(3) R&D-Int. Ind. Grps.	(4) R&D-Int. Ind. Grps.
t	-0.290***	-0.335***	-0.400***	-0.442***
	(0.0328)	(0.0334)	(0.0507)	(0.0484)
t x Late-Vintage		0.119***		0.154***
		(0.0215)		(0.0259)
t^2	0.00861***	0.0087***	0.0122**	0.0120***
	(0.0013)	(0.0013)	(0.0021)	(0.0020)
$\ln(\frac{\tau^*_{ntk}}{\tau^*_{otk}} / \frac{\tau_{ntk}}{\tau_{otk}})$	-0.852***	-0.845***	-0.917***	-0.899***
	(0.1960)	(0.1878)	(0.2380)	(0.2119)
T	16.808***		16.418***	
	(0.8503)		(0.9112)	
T Late Vintage		12.361***		12.100***
		(0.8867)		(0.8024)
T Others		19.211***		18.548***
		(1.2582)		(1.3128)
Industry FE	Yes	Yes	Yes	Yes
Obs. No.	4,386	4,386	2,012	2,012
R^2	0.482	0.488	0.411	0.473

Notes for Table 4: *** p<0.01, ** p<0.05, * p<0.1. Bootstrapped standard errors are in the brackets, and the bootstrap sampling reflects the clustered structure (by year) of the data. Column (1) is the same as column (1) of Table 3. The dependent variable is relative-exports ratio, $\ln(\frac{G^*_{ntk}}{G^*_{otk}} / \frac{G_{ntk}}{G_{otk}})$. The sample period is 1978-2001. The industry-k-year-t observations are weighted by the average value of imports for industry k over the sample period. “Late-Vintage” is a dummy that equals 1 if industry k is a late-vintage industry. “T Late-Vintage” (“T Others”) is the time for the late-vintage industries (other new-products industries) to reach the bottom of the U-shape. The R&D-intensive industry groups are SIC 28 (chemicals), 35 (machinery), 36 (electronics), 37 (transportation) and 38 (instruments). They have the highest ratios of private R&D expenditures to net sales among manufacturing industry groups (Xiang 2005).