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1 The Anatomy of China's Export Growth

Mary Amiti and Caroline Freund

1.1 Introduction

China's real exports increased by more than 500 percent over the last fifteen years. As a result, in 2004, China overtook Japan as the world's third largest exporter, just behind Germany and the United States. This paper decomposes this stunning export growth along various dimensions. In particular, how has China's export structure changed? Has the export sector become more specialized, focusing on particular types of goods, or has it diversified as it has grown? Are China's exports becoming more skill-intensive? How important are new goods in export growth? The answers to these questions have important implications for the global welfare consequences of China's export expansion and for future growth of China's export sectors.

Our analysis shows that China's export structure has transformed dramatically since 1992. There has been a significant decline in the share of agriculture and soft manufactures, such as textiles and apparel, with growing shares in hard manufactures, such as consumer electronics, appliances, and computers. However, a large component of this export growth in machinery has been due to growth in processing trade—the practice of assembling duty-free intermediate inputs. These inputs are generally of high-skill

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content, originating in countries such as the United States and Japan (see Dean, Fung, and Wang 2007). Thus, on the surface, it appears that China is dramatically changing its comparative advantage, yet a closer examination reveals that it is continuing to specialize in labor-intensive goods. We find that the labor intensity of China's exports remains unchanged once we account for processing trade. Further, exports remained highly concentrated in a small fraction of goods—though the particular goods have changed. These patterns are consistent with traditional trade theories, which place specialization and comparative advantage at the center of trade growth.

More recent trade theories emphasize the gains from trade as importing countries access new product varieties. For example, Broda and Weinstein (2006) find that 30 percent of U.S. import growth between 1972 and 2001 was in new varieties (the extensive margin) and that China was the largest contributor to growth in these U.S. varieties; however, most of this growth was in the earlier period from 1972 to 1988. Other papers highlight a strong positive correlation between the number of export varieties a country produces and its living standard (see Funke and Ruhwedel 2001). Hummels and Klenow (2005) find that larger and richer countries export more varieties of goods, using data for 1995. This finding is suggestive that a large portion of China's export growth would be associated with exports of new varieties. However, our analysis of China's export growth patterns between 1997 and 2005 shows that most of its export growth was actually in existing varieties (the intensive margin). This large growth in the intensive margin is also supportive of predictions consistent with traditional theories with an important role for terms-of-trade effects, where the welfare gains for importing countries arise through lower import prices. As China increases its supply of existing varieties on world markets, this is likely to exert downward pressure on world prices of these goods. Indeed, between 1997 and 2005, average prices of goods exported from China to the United States fell by an average of 1.5 percent per year, whereas the average prices of these products from the rest of the world to the United States increased, on average, by 0.4 percent per year.[1]

The rest of the paper is organized as follows. Section 1.2 describes the data. Section 1.3 examines the reallocation of exports across industries. Section 1.4 looks at the skill intensity of exports. Section 1.5 examines whether there has been increased diversification or specialization as exports have grown. Section 1.6 decomposes export growth into the intensive and extensive margins. Section 1.7 compares China's export prices to the United States to those from the rest of the world. Section 1.8 concludes.

1. This is a Törnqvist chain-weighted price index using HS ten-digit goods that China exported during this period.

1.2 Data

The most disaggregated export data available for China is at the Harmonized System (HS) eight-digit level, from China Customs Statistics, which includes 8,900 product codes. The trade data are in current U.S. dollars, which we deflate by the U.S. Consumer Price Index (CPI; base year 1992) to generate a constant dollar series. Summary statistics for China's exports are presented in table 1.1, showing that China's real exports to the world increased by 500 percent between 1992 and 2005, from US$84.94 billion to US$525.48 billion. Its share of exports to the United States increased from 10 percent to 21 percent over the sample period. To check for the accuracy of the China export data, we also use data on U.S. imports from China, from the U.S. Bureau of the Census, Foreign Trade Division. This data also has the advantage of being available at an even higher level of disaggregation, at the HS ten-digit, which includes 18,600 product categories.

As there were major reclassifications in the international HS six-digit classifications in 1996 and 2002, in some cases we aggregate the data up to HS six-digit codes and convert them to the same HS six-digit classifications used in 1992 to avoid problems related to reclassification of codes. This reduces the number of product codes for China's world exports to 5,000 products. To examine broader export patterns we divide the data into Standard International Trade Classification (SITC) one-digit codes, which include agriculture (SITC 1 to 4), chemicals (SITC 4), manufactured materials (SITC 5), manufactured materials (SITC 6), machinery (SITC 7) and miscellaneous manufacturers (SITC8).

Table 1.1 **Summary statistics: trade data for China**

	1992	1995	1997	1999	2001	2003	2005
Total exports							
$U.S. billions	84.94	136.50	160.34	163.81	211.19	334.53	525.49
Total processing exports							
$U.S. billions	39.92	67.92	87.59	93.23	117.04	184.56	287.24
Share (%)	0.47	0.50	0.55	0.57	0.55	0.55	0.55
Exports to U.S. (Chinese data)							
$U.S. billions	8.59	22.67	28.70	35.25	43.08	70.59	112.34
Share (%)	0.10	0.17	0.18	0.22	0.20	0.21	0.21
Exports to U.S. (U.S. data)							
$U.S. billions	25.73	41.79	54.87	68.73	81.17	116.32	167.91

Source: China Customs Statistics.

Note: Deflated using 1992 U.S. Consumer Price Index.

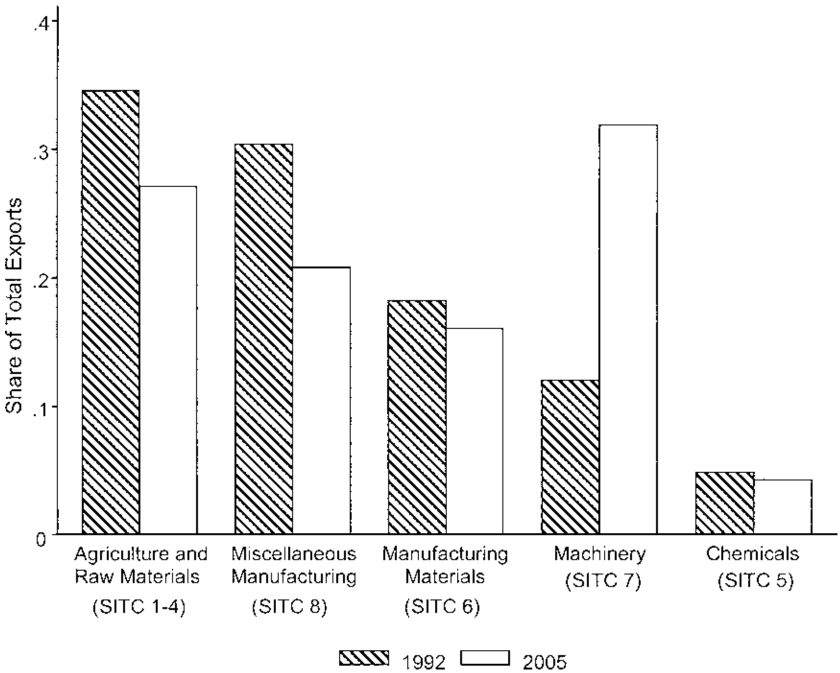

Fig. 1.1 Reallocation of exports across SITC one-digit industries

Note: Column headings include the following industries:

SITC 1–4: Beverages, tobacco, raw materials, mineral fuels, oils, and fats.

SITC 5: Chemicals, dyes, pharmaceuticals, and perfumes.

SITC 6: Leather, rubber, cork and wood products, textiles, metallic and nonmetallic manufactures.

SITC 7: Industrial machinery, office machinery, telecommunications equipment, electrical machinery, transportation equipment.

SITC 8: Prefabricated buildings, furniture, travel goods, clothing, footwear, professional and scientific equipment.

1.3 Reallocation across Industries

China has experienced big changes in its export composition. It has moved from the first stage of agriculture and apparel to more sophisticated manufactured goods. Figure 1.1 shows this by plotting the export share of each one-digit SITC sector in 1992 and 2005. Rapid export growth has been associated with a move out of agriculture and apparel into the machinery and transport sectors. In figure 1.2, we focus on changes within the manufacturing sector. In particular, we look at how trade shares have adjusted in all major two-digit SITC sectors, where major is defined as accounting for at least 3 percent of exports in 1992 or 2005. There is a notable move out of

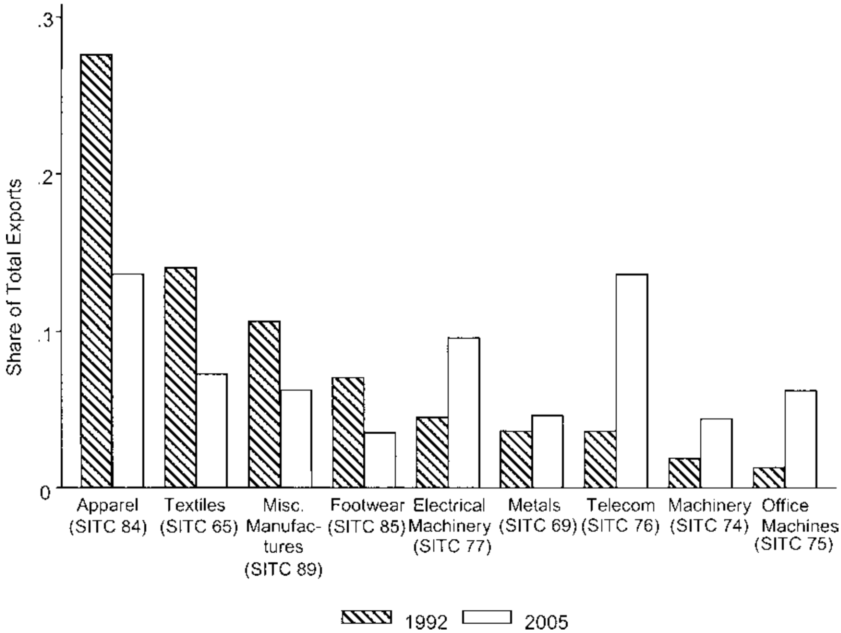

Fig. 1.2 The reallocation of manufacturing exports across major two-digit sectors

Notes: A sector is defined as major if the sector's share of total trade is above 3 percent in 1992 or 2005. These sectors account for about 70 percent of manufacturing exports.

apparel, textiles, footwear, and toys and into electrical machinery, telecom, office machines, and, to a lesser extent, metals.

The strongest overall export growth has been in machinery (SITC 7), and within this broad category, it is telecoms, electrical machinery, and office machines that have experienced the highest growth and make up the largest shares within machinery. The question arises whether China is producing most of the value added of these capital intensive goods or if China is just assembling duty-free imported inputs for export. This practice is known as processing trade and does account for an increasingly large share of China's exports, from 47 percent in 1992 to 55 percent in 2005. According to Dean, Fung, and Wang (2007), imported inputs account for between 52 to 76 percent of the value of processing exports. Figure 1.3 graphs total exports of two-digit machinery categories as a share of total manufacturing exports, in descending order for 2005, and the lighter bars show the portion that is classified as processing trade by China Customs Statistics. This figure reveals that most of the high export growth in machinery is indeed processing trade; thus, only a small share of this growth is likely to be due to high value added production in machinery in China.

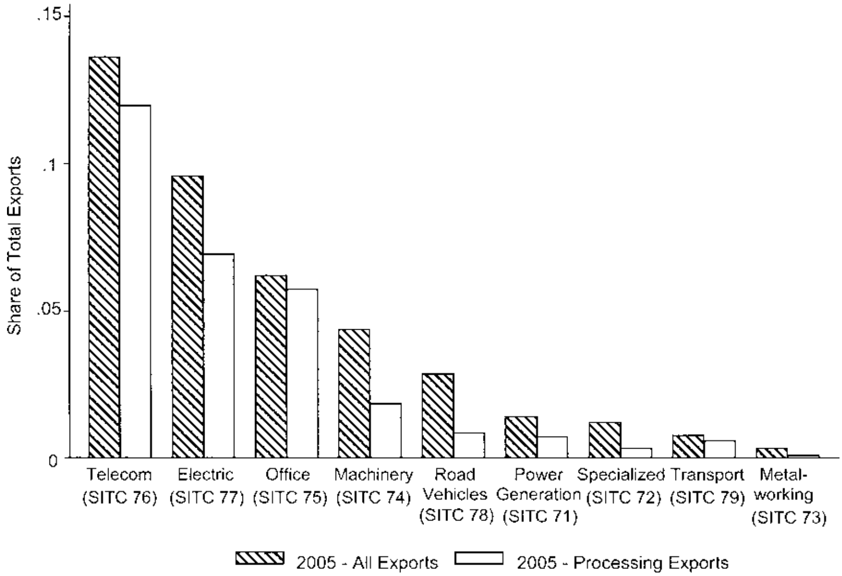

Fig. 1.3 Machinery exports and processing trade

Note: Column headings include the following industries:

SITC 71: Boilers, turbines, internal combustion engines, and power generating machinery.

SITC 72: Agricultural machinery, civil engineering and contractors' equipment, printing and bookbinding machinery, and textile and leather machinery.

SITC 73: Lathes, machines for finishing and polishing metal, soldering equipment, metal forging equipment, and metal foundry equipment.

SITC 74: Heating and cooling equipment, pumps, ball bearings, valves for pipes, and nonelectrical machines.

SITC 75: Typewriters, photocopiers, and data processing machines.

SITC 76: Television receivers, radio receivers, and sound recorders.

SITC 77: Equipment for distributing electricity, electro-diagnostic apparatus, and semiconductors.

SITC 78: Automobiles, trucks, trailers, and motorcycles.

SITC 79: Railroad equipment, aircraft, ships, boats, and floating structures.

1.4 Skill Content of Export Growth

China's export bundle is very different now from what it was in the early 1990s. Rodrik (2006) and Schott (2006) highlight the increasing sophistication of China's exports, as demonstrated by an export pattern that more closely resembles high-income countries than would be expected given its income level. To see whether this increased sophistication has been associated with an increase in the overall skill content of its exports, we rank industries from low- to high-skill intensity on the horizontal axis of figure 1.4 and plot the cumulative export share on the vertical axis. Because indus-

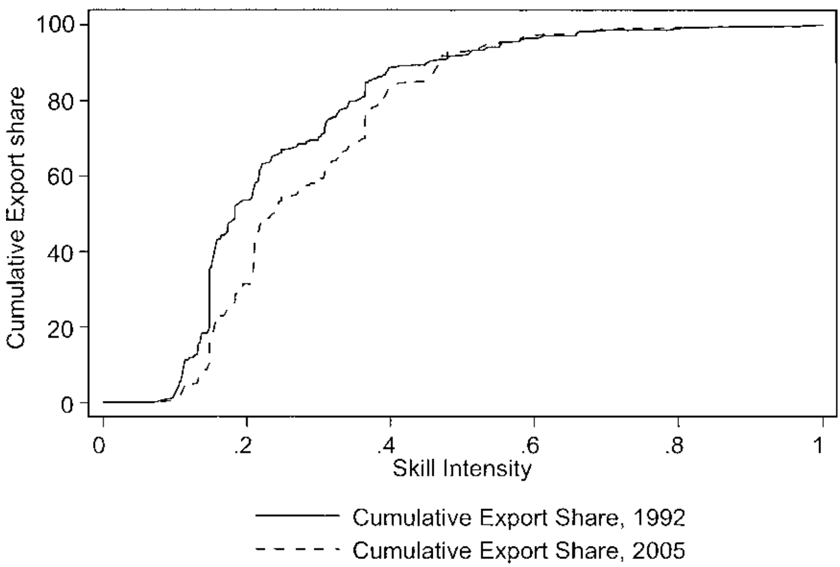

Fig. 1.4 Skill intensity of China's manufacturing exports

Notes: Data uses HS six-digit classifications. The skill intensity is measured as the ratio of nonproduction workers to total employment from the Indonesian manufacturing census at the five-digit ISIC level for 1992.

try skill-level data for China were unavailable, we based the skill-intensity ranking on information from Indonesia, another emerging market that is likely to have similar technologies.[2] The skill intensity is measured as the ratio of nonproduction workers to total employment from the Indonesian manufacturing census at the five-digit International Standard Industrial Classification (ISIC) level for 1992. In figure 1.4, the shift of the curve to the right indicates that the skill content of China's exports has increased over the sample period. For example, in 1992, 20 percent of the least skill-intensive industries produced 55 percent of China's export share. By 2005, the export share that these industries produced fell to 32 percent.[3]

However, given the high share of processing trade in China, an increase in the skill content of China's exports could be due to China importing intermediate inputs with higher skill content that it then assembles for exporting. We assess this possibility by plotting the cumulative of export shares against the skill intensity with nonprocessing manufacturing exports only. That is, we exclude any exports that have been classified as processing trade. From

2. Zhu and Trefler (2005) measure changes in the skill content of exports for all countries using U.S. industry-level skill data to rank the skill intensity of industries, assuming no factor intensity reversals. Our results also hold using U.S. skill data.

3. This approach only gives an indication of shifts between industries; thus, we cannot say if there has been any skill upgrading within an industry.

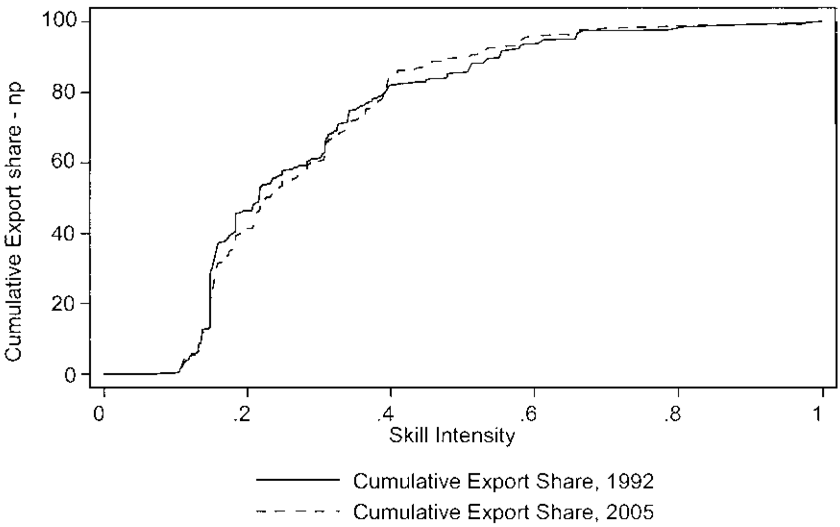

Fig. 1.5 Skill intensity of China's manufacturing exports excluding processing trade

Notes: Data uses HS six-digit classifications. The skill intensity is measured as the ratio of nonproduction workers to total employment from the Indonesian manufacturing census at the five-digit ISIC level for 1992.

figure 1.5, we see that there is hardly any shift in the curve indicating no change in the skill content of China's nonprocessing exports.

Processing exports make up a large share of China's manufacturing exports and by excluding processing exports, we are excluding around 54 percent of China's manufacturing exports (see table 1.1). Although imported inputs account for a large share of the value of processing exports, there still remains a significant amount of value added in China in processing exports, and there could be a shift in the skill content within that portion. To examine this possibility, we compare the change in the skill content of imported manufacturing inputs for processing trade to the skill content of imported inputs for nonprocessing trade in figures 1.6 and 1.7. Using U.S. industry skill data to rank the skill intensity of imports, we find a much larger increase in the skill content of processed imports than of nonprocessing imports. Of course, this rise in the skill content of processing imports does not rule out the possibility that the Chinese value added has become more skill-intensive, too.

Wei and Wang, in chapter 2, also examine how the sophistication of China's goods have changed over time. They use two measures. The first is an index of how different China's export structure is from the export structure of industrial countries (using the Group of Three [G3] to represent industrial countries), which they refer to as a disimilarity index. If China's export

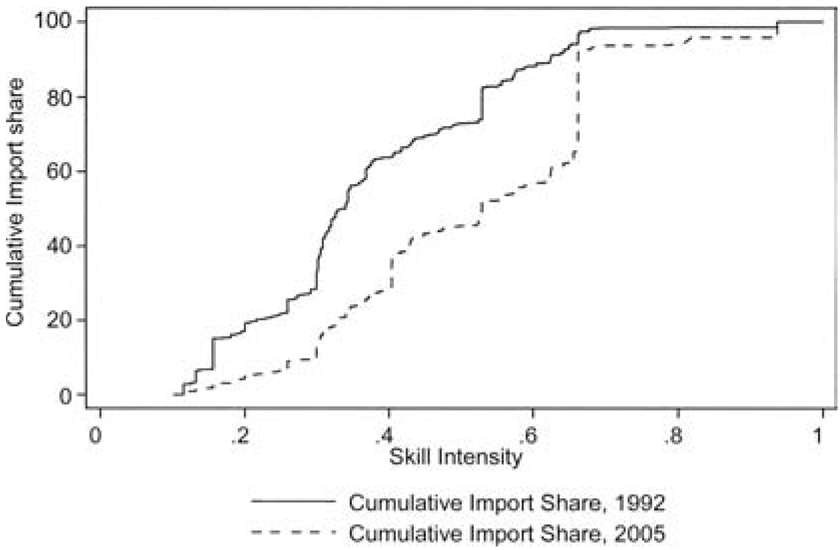

Fig. 1.6 Cumulative import share and skill intensity, processing trade

Notes: Data uses HS six-digit classifications. The skill intensity is measured as the ratio of nonproduction workers to total employment for U.S. four-digit SIC industries in 1992.

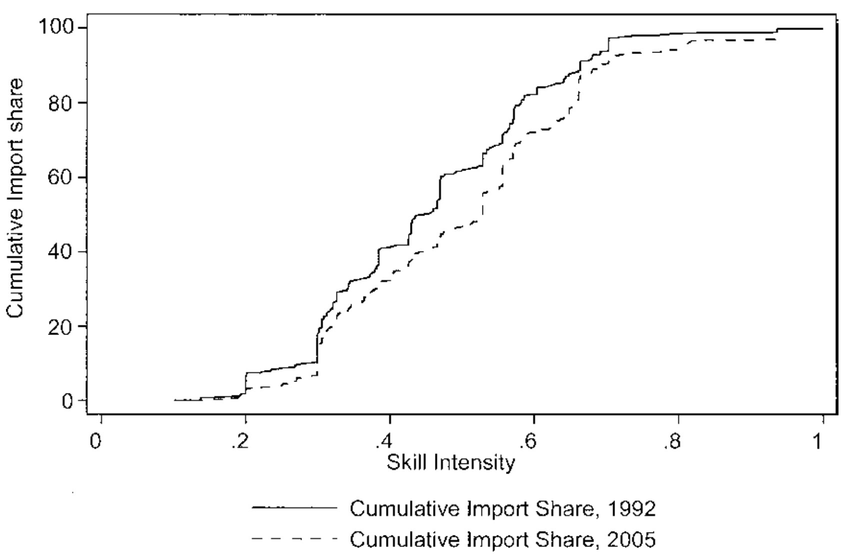

Fig. 1.7 Cumulative import share and skill intensity, nonprocessing trade

Notes: Data uses HS six-digit classifications. The skill intensity is measured as the ratio of nonproduction workers to total employment for U.S. four-digit SIC industries in 1992.

structure becomes more similar to industrial countries', this is interpreted as China's exports becoming more sophisticated. The second is an index of the average value of China's exports, using unit value data. An increase in the average unit value of exports is interpreted as exporting higher-quality or more-sophisticated goods. They examine how the two indexes have changed for seventy-nine cities in China and the determinants of the changes. With respect to the disimilarity index, they find that increased processing trade has not contributed to making regional export patterns more similar to industrial country patterns. However, with respect to unit values, they find strong evidence that processing trade has contributed to higher unit values, especially processing exports in high-tech zones. The unit value results support our conclusions, but the dissimilarity results do not.[4] One possibility is that the unit value index is closer to our measure of skill intensity, as high unit value industries are likely to be more skill-intensive. Together, the results imply that processing trade has contributed to higher unit value and higher skill-intensity goods being exported from China.

1.5 Diversification versus Specialization

We have seen that snapshots of China's export sector taken in 1992 and 2005 look very different, with the increased churning from agriculture and textiles into machinery, electronics, and assembly. As a result of this transformation, China's exports may have become more specialized or more diversified. Traditional trade theory highlights the combination of increased trade and specialization as a key factor in promoting higher living standards. Imbs and Warziarg (2003), however, find that countries tend to diversify production as they grow from low levels of income and that they only begin to specialize once they reach a relatively high level of income. This is consistent with countries moving from exploiting natural resources to developing new industrial sectors as they grow. Hausmann and Rodrik (2003) argue that in the early stage of development, more entrepreneurship and potentially greater diversification may help producers identify the sectors in which it is a competitive producer.

We examine whether China's exports display increased or decreased specialization in figure 1.8 by plotting the inverse cumulative export shares for all products at the HS six-digit level. A shift to the left of the curve would indicate increased specialization. Looking across all products, it appears

4. One issue with the dissimilarity index is that regional export shares can divert from industrial country export patterns at the same time as China's total gross exports become more similar to industrial countries. For example, assume processing industries are overall similar to G3 export structure but tend to be geographically specialized, for example, flat screens in one area, computers in another, and so on. Then increasing processing trade in a given region could pull you away from OECD structure, while increasing processing trade overall will pull China as a country toward OECD structure.

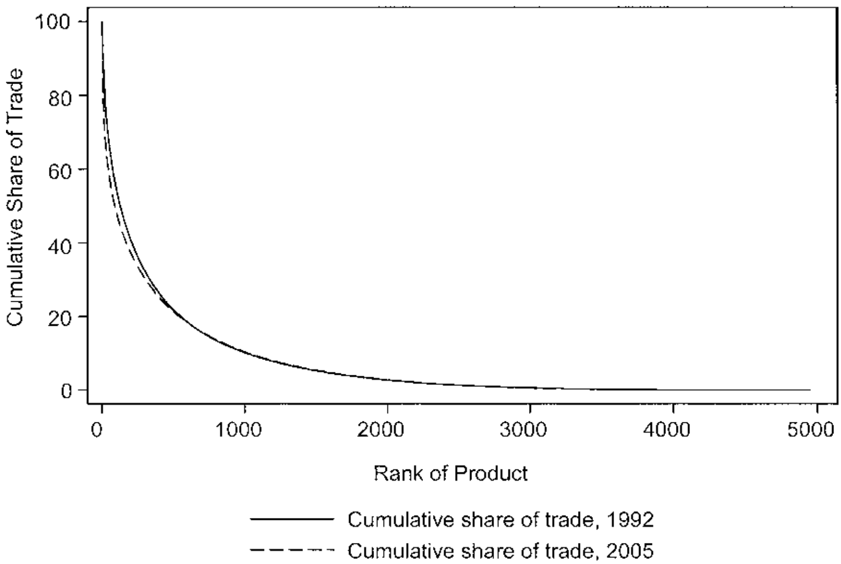

Fig. 1.8 Cumulative share of exports by rank

Notes: Data uses HS six-digit classifications. Rank is largest to smallest by value.

from figure 1.8 that there is hardly any change in the degree of specialization. Yet when we magnify the image of figure 1.8 in figure 1.9, showing the cumulative trade shares when we keep only the largest 500 categories by value, which account for nearly 80 percent of total exports in either of the years, there is a noticeable downward shift in the curve, suggesting there has been an increase in specialization. The pattern is very similar, with a slightly greater increase in specialization, if we only include manufacturing exports.

This finding is confirmed using the Gini coefficient, which is an alternative way to measure changes in specialization, by measuring export equality in each period. It is defined as

$$\text{Gini} \equiv 1 - \frac{1}{n}\sum_{i}(\text{cshare}_{i-1} + \text{cshare}_{i}),$$

where there are n products, i is a product's order (1 is smallest, and n is largest), and cshare_i is the cumulative share of exports of the ith product. The Gini coefficient uses the trapezoid approximation to calculate the area between a 45-degree line and the cumulative distribution, weighting each industry as an equal share of the population of industries ($1/n$). A Gini coefficient of zero indicates that export shares are equally distributed across all industry groups; an increase in the Gini coefficient implies an increase in specialization.

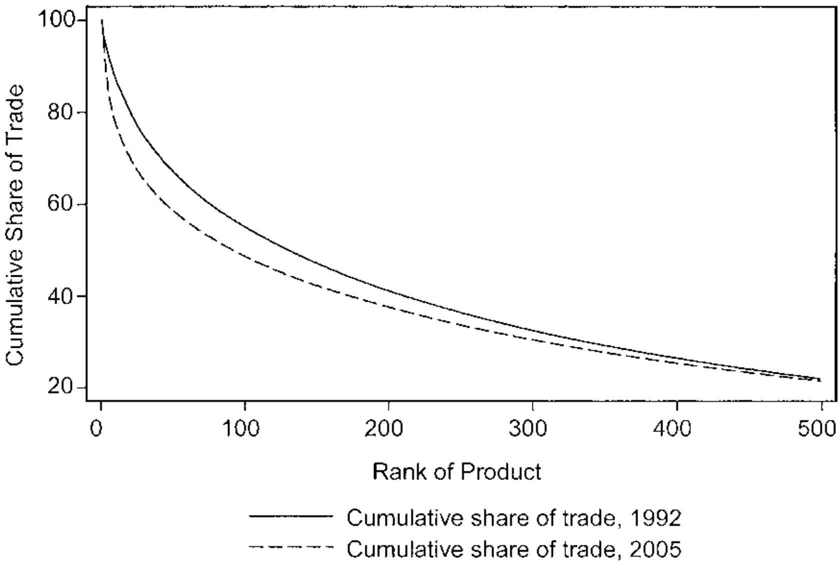

Fig. 1.9 Cumulative share of exports by rank, top 500 products
Notes: Data uses HS six-digit classifications. Rank is largest to smallest by value.

Table 1.2 Gini coefficient for China's exports

Period	All	Top 70%	Top 100
1992	0.85	0.46	0.35
2005	0.86	0.55	0.50

Source: China Customs Statistics and authors' calculations.

Table 1.2 reports the Gini coefficient for 1992 and 2005 for the whole sample of products and some subsamples. The Gini coefficient remained unchanged over the sample period at 0.85 when all products are included. However, when a subsample of the largest goods accounting for 70 percent of exports are included, the Gini coefficient increases from 0.46 to 0.55. Similarly, when we only include the top 100 products, which account for 45 percent of exports in the 1992 period and nearly 50 percent in 2005, the Gini coefficient increased from 0.35 to 0.50. Thus, over the period we see enhanced specialization—a smaller number of products account for an increased size of China's exports—though the bundle of goods exported has changed.

1.6 Intensive versus Extensive Margin

Has the large export growth mainly been in new product varieties or existing varieties? A new variety is generally defined as the export of a new product code, that is, a product code for which there are positive exports one period and zero exports in an earlier period. One of the main problems using this definition is that there have been major reclassifications in the trade data in 1996 and 2002 at the HS six-digit level; thus, a product might be classified as a new variety just because there has been a new product code or previous codes were split. For example, in one year, cherry tomatoes were reclassified into a new product code rather than being part of the tomatoes category. In this case, cherry tomatoes would appear to be counted as a new variety even though they were exported in previous periods. In contrast, flat-screen televisions received a new classification, and these are, in fact, new varieties.

1.6.1 Export Shares

There have been various approaches developed to address these reclassification issues. One approach is to use HS six-digit data concorded to the same 1992 product codes, but in general, these categories might be too aggregated to be able to identify new products: by 1992, China was exporting in over 90 percent of these categories. To examine whether export growth is mainly from new goods with this aggregate data, we follow Kehoe and Ruhl (2009) by splitting exports into deciles by value in 1992 and calculate their share of exports in 2005. If export growth is mainly from new goods, we would expect rapid growth in the bottom deciles, where trade was negligible in 1992. Figure 1.10 shows the share of exports in 2005 that is accounted for by the products falling into each decile. The categories that accounted for the bottom 20 percent of trade by value more than doubled between 1992 and 2005, while the categories in the other deciles contracted or remained constant.[5] This points to a sizable role for the extensive margin as the least-traded goods grew the fastest.

One problem with this method is that exports tend to be concentrated in a small number of categories. This can be clearly seen in figure 1.11, where we divide exports into deciles according to the number of categories of trade in 1992. For example, the 10th decile is the top 10 percent of product categories when products are ranked by value. The distribution in 1992 is highly skewed, reflecting that only 10 percent of categories accounted for nearly 80 percent of trade. The decline in the share of the top decile shows that there was a sizeable reallocation of trade, but it was not the bottom 50 percent of products that gained. Instead, gains in the trade share were in the four deciles just below the top.

In sum, the results imply that there was a significant reorientation in exports and that the reshuffling of export products during the expansion was mainly in the mid-to-upper rank products. These are products that were in the bottom 20 percent by value but in the mid-to-high range by product

5. Arkolakis (2006) develops a model consistent with this finding.

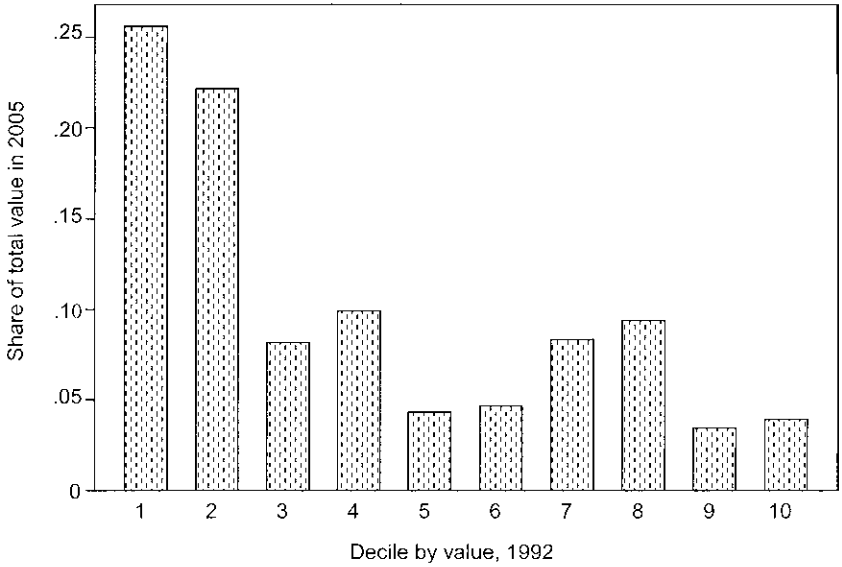

Fig. 1.10 Reallocation of exports by value
Note: Data uses HS six-digit classifications.

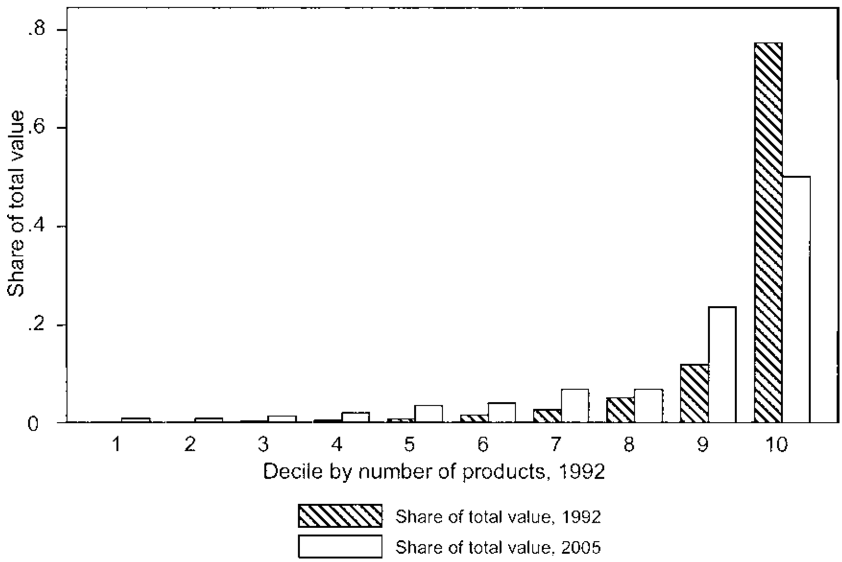

Fig. 1.11 Reallocation of exports by product shares
Note: Data uses HS six-digit classifications.

rank.[6] Taken with the previous results on specialization, this implies that there was a sizable compositional shift over time that led to a more skewed distribution of trade in 2005 as compared with 1992.

1.6.2 Variety Growth

To utilize the more disaggregated trade data at the eight- and ten-digit levels, we examine the contribution of new varieties to export growth using two complementary methods. The first is the Feenstra index of net export variety growth, which provides an indication of the importance of new varieties in trade. The second is a decomposition of export growth into new, disappearing, and existing varieties and offers more information on the magnitude of export creation and destruction. We present the definitions and discuss the strengths and weaknesses of each measure in the following.

Feenstra's (1994) seminal work on measuring import prices incorporating new goods leads to a natural index of variety growth that has been widely used in the literature. Denoting I as the set of varieties available in both periods, $I \subseteq (I_t \cap I_{t-1})$, the Feenstra index of net variety growth is defined as the fraction of expenditure in period $t-1$ on the goods $i \subset I$ relative to the entire set $i \subset I_{t-1}$ as a ratio of the fraction of expenditure in period t on the goods $i \in I$ relative to the entire set $i \in I_t$, minus 1.[7] Let V_{it} be the value of trade at time t in product i ($V_{it} = p_{it}q_{it}$), then

$$(1) \quad \text{Feenstra index of net variety growth} = \frac{\sum_{i \in I} V_{t-1i} / \sum_{i \in I_{t-1}} V_{t-1i}}{\sum_{i \in I} V_{it} / \sum_{i \in I_t} V_{it}} - 1.$$

The index will be equal to zero if there is no growth in varieties relative to the base period and positive if the number of varieties has grown. This measure has the nice feature that if HS trade classifications are split and their share of total trade remains unchanged, the index remains unchanged. However, if growth classifications are split (or reclassified) to a greater extent than shrinking classifications are merged, the index will tend to overstate the extensive margin. A disadvantage of the index for measuring the relative importance of new varieties in export growth is that if there is a lot of churning, with an equal amount of export creation and destruction, it will report net variety growth of nil. To an importer, theory suggests that welfare increases with the number of varieties available, so it is net variety growth that is relevant. To an exporter, however, gross variety changes may be of interest as they provide an indication of how important new goods are to export growth. From the exporter's perspective, the Feenstra index could

6. These figures and the estimates of the extensive and intensive margin are very similar if we use only manufacturing trade.

7. From Feenstra (1994), this is the inverse of the lambda ratio minus 1.

understate the importance of new goods in export growth if there is a lot of creation and destruction.

To get an idea of how important churning is, we also calculate the shares of trade growth due to new, disappearing, and existing goods. The decomposition of trade growth is as follows:

$$(2)\qquad \frac{\sum_i V_{it} - \sum_i V_{it-1}}{\sum_i V_{it-1}} = \frac{\sum_{i\in I} V_{it} - \sum_{i\in I} V_{it-1}}{\sum V_{it-1}} - \frac{\sum_{i\in I^D_{t-1}} V_{it-1}}{\sum V_{it-1}} + \frac{\sum_{i\in I^N_t} V_{it}}{\sum V_{it-1}},$$

where I^D_{t-1} is the set of products that disappeared between $t-1$ and t, and I^N_t is the set of new products available in year t. This is an identity where total growth in trade relative to the base period is decomposed into three parts: (a) the growth in products that were exported in both periods, the intensive margin; (b) the reduction in export growth due to products no longer exported, disappearing goods; and (c) the increase in export growth due to the export of new products. The share of trade growth due to the extensive margin is defined as the new goods share less the disappearing goods. This decomposition provides an estimate of the extent of churning, but it is less robust to reclassifications than the Feenstra index because growth from products that are reclassified for any reason will be attributed to the extensive margin. We report the share of total export growth of each term on the right-hand side of equation (2); hence, by construction, the intensive and extensive margins sum to 1.[8]

Figure 1.12 plots the Feenstra index of net variety growth and the share of trade growth attributed to the extensive margin on an annual basis for China's exports to the United States at the ten-digit level from 1993 to 2005. What is striking about this figure is the large peak in the growth in the extensive margin around 1996, where there were major reclassifications, and in the following year there is a big fall in variety growth using both measures. This likely reflects that some new classifications were used in the middle of 1996, and old classifications were not retired until the following year. Although the

8. Note that there is a direct relationship between the Feenstra index of net variety growth in equation (1) and the decomposition in equation (2). Let the numerator of the first term in the Feenstra index be λ_{t-1} and the denominator λ_t. Then $\lambda_{t-1} = 1 -$ share disappearing • export growth and the denominator is $\lambda_t = 1 -$ share new • export growth/(V_t/V_{t-1}). This highlights how the Feenstra index of net variety growth essentially combines disappearing trade and new trade into one index. For example, consider the U.S. HS ten-digit trade data, line 1 in panel B of table 1.3. Trade growth $(V_t - V_{t-1})/V_{t-1}$ is 168 percent in this period using this data. Because these are shares of trade growth, the value of $(1 - \lambda_{t-1}) =$ share disappearing • export growth $= 0.12 \bullet 1.68 = 0.20$, so $\lambda_{t-1} = 0.80$. To get $(1 - \lambda_t)$, we have share new • export growth/V_t/$V_{t-1} = 0.29 \bullet 1.68/2.68 = 0.18$ (where 2.68 is V_t/V_{t-1}), so $\lambda_t = 0.82$. Thus, the Feenstra index is $(0.8/.82) - 1 = -0.03$.

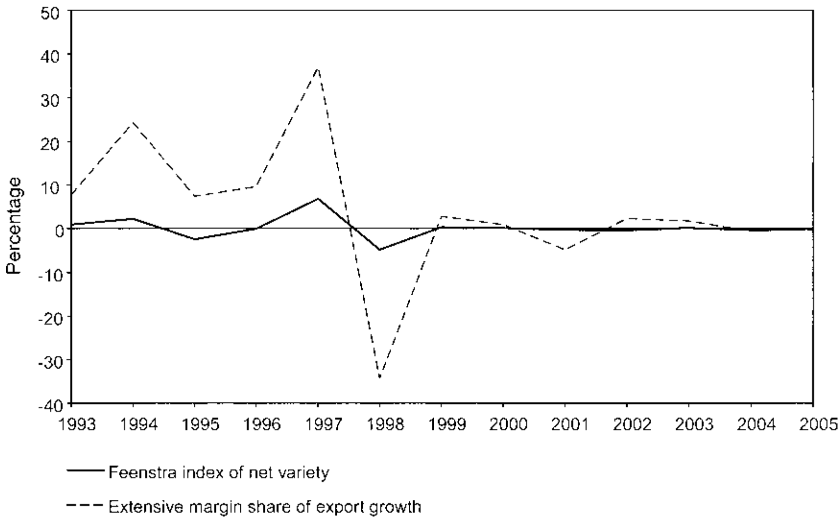

Fig. 1.12 Growth in extensive margin of U.S. Imports from China, 1992–2005
Note: Data uses HS ten-digit U.S. imports from China.

size of the reclassification effect is smaller using the Feenstra index, reclassifications still clearly play an important role in calculations of the extensive margin using both measures.

To measure growth in the extensive margin, it is more insightful to consider changes over a longer horizon because the value of exports in new product codes are generally small when they are first introduced. But if one just compares year-to-year changes, they would no longer be grouped in the new goods category. In order to minimize the reclassification issues, we report the growth in extensive margin from 1997 to 2005 in table 1.3. Using an earlier period as a base yields wide variations in measures, and comparable U.S. and China data give vastly different results. Panel A of table 1.3 shows calculations using China's eight-digit data. In the first row, where we use data on China's exports to the world from 1997 to 2005 in all eight-digit categories, we see moderate net variety growth of 10 percent, with the extensive margin accounting for 26 percent of total export growth. Recalculating the extensive margin with exports only to the United States, in the second row, we see that the magnitudes of the extensive and intensive margins are roughly the same as with total exports. In order to eliminate the potential problem associated with reclassifications that take place from year to year in China's HS eight-digit data, we also calculate the margins for product codes that existed over the whole period. In this case, we find that the growth in exports to the United States accounted for by new varieties falls markedly, to just 2 percent. This implies that part of the large variety growth found with the full sample is likely a result of reclassifications pushing up the

Table 1.3 **Variety growth in China's exports, 1997–2005**

				Share of total export growth from:					
	No. of Codes	Type	Partner	Feenstra	Intensive	New	Disappearing	Extensive	Total export growth (%)
				A: Extensive margin using eight-digit China data					
1.	7,951	All	World	0.10	0.74	0.33	0.07	0.26	187
					[5,501]	[1,624]	[826]		
2.	6,357	All	U.S.	0.11	0.76	0.29	0.05	0.25	243
					[3,641]	[1,980]	[736]		
3.	4,826 (76% of codes)	Exist	U.S.	0.01	0.98	0.02	0.00	0.02	212
					[3,641]	[935]	[250]		
				B: Extensive margin using ten-digit U.S. data					
1.	14,169	All	U.S.	–0.03	0.83	0.29	0.12	0.17	168
					[7,576]	[5,122]	[1,471]		
2.	11,444 (81% of codes)	Exist	U.S.	0.02	0.97	0.03	0.00	0.03	182
					[7,576]	[3,506]	[362]		

Notes: The share of total trade growth from each margin is reported. The extensive margin share is the share of new trade less the share of disappearing trade. The extensive and intensive margin may not sum exactly to 1 because of rounding error. The total number of codes for intensive, new, and disappearing is in brackets.

extensive margin. The existing products codes are likely not to be a random sample because entirely new products—such as a digital camera—will by definition require a new code; thus, this can be taken as a lower bound of the extensive margin.

Panel B of table 1.3 reports the extensive margin using U.S. data at the ten-digit level. The data have more than twice as many codes (over 14,000 for U.S. to China trade), allowing the extensive margin to be larger. Using all of the ten-digit exports from China to the United States, net variety growth is negative and the extensive margin share of trade growth is 17 percent. The smaller value for the extensive margin in the U.S. data, as compared with the China data, is likely a result of there being fewer reclassifications in the United States (81 percent of codes are permanent as compared with 76 percent in the China data). Including only codes that exist between 1997 and 2005, the net variety growth and the extensive margin's share of trade growth are similar, at around 3 percent, and larger than measured using permanent eight-digit codes from the China data. Note that there is still significant growth in the number of new export variety categories, which increased by more than 40 percent, but these new varieties account for a small share of export growth.

Compared to other non-Organization for Economic Cooperation and Development (OECD) countries, China's growth in the extensive margin has been small. Based on the HS ten-digit export data to the United States with all codes included, China ranks 80th out of a total of 133 non-OECD countries using the Feenstra net index of variety measure and 100th using the extensive margin measure.

All of these measures of the extensive margin should be interpreted with caution given that the magnitudes vary considerably depending on whether all product codes are used and whether the base period is before or after the major reclassifications that took place in 1996. The calculations with the more disaggregated U.S. data from 1997 onward indicate that a large portion of China's export growth took place along its intensive margin.

1.7 Export Prices

The large increase in export growth along the intensive margin suggests that China's export growth is likely to put downward pressure on world prices of these goods. Taking the subset of HS ten-digit goods that China exported to the United States between 1997 and 2005, we construct an average export-price index using a chain-weighted Törnqvist index for manufactured goods, defined as follows:

$$\text{Tindex}_t = \prod_i \left(\frac{p_{it}}{p_{it-1}}\right)^{w_{it}}, \text{ where } w_{it} = 0.5 \bullet (\text{share}_{it} + \text{share}_{it-1}),$$

and p_{it} is the unit value, defined as the ratio of the export value from China to the United States of product i at time t to the quantity exported. Note that we only construct export-price indexes to the United States rather than to exports to the world because it is important to have highly disaggregated product-level data to ensure that the units of measurement of quantities are the same within the HS codes. Using more aggregated data, say, at the HS six-digit level runs the risk of having aggregated quantities across different units of measurement. Even at the HS ten-digit level, the quantity data is quite noisy; thus, we clean the data by deleting products with price change of more than 200 percent over this period. After cleaning the data and ensuring that China and the rest of the world export this same subset of products, we are left with 3,800 HS ten-digit product codes within manufacturing. The export-price index for China is weighted by the export value of each of these product codes from China to the United States as a ratio of the total value of these exports, and the export-price index from the rest of the world to the United States is weighted by the export value of each of these same product codes from the rest of the world to the United States as a ratio of total export value of these products.

The Törnqvist export-price index (Tindex) for China between 1997 and 2005 is 0.88, indicating a fall of 12 percent over the period. In contrast, the Tindex for exports of these same HS ten-digit codes from the rest of the world to the United States is 1.03, indicating a 3 percent increase in prices over this period.[9]

The export price decline in China is consistent with a negative terms-of-trade effect, with increased exports pushing down export prices. However, it could also be related to improved productivity in China, declining profit margins, or exchange rate movements.

1.8 Conclusions

This chapter decomposes China's spectacular export growth, of over 500 percent since 1992, along various dimensions. A number of interesting findings emerge. First, churning among different products was significant. China's export structure changed dramatically, with growing export shares in electronics and machinery and a decline in agriculture and apparel. The strongest overall export growth has been in machinery, and within this broad category, telecoms, electrical machinery, and office machines have experienced the highest growth and make up the largest shares within machinery.

Second, despite the shift into these more-sophisticated products, the skill

9. The Fisher price index, which is the square root of the Laspeyres index (that uses base period weights) and the Paasche index (that uses current period weights) gives the same result as the Tindex.

content of China's manufacturing exports remained unchanged once processing trade is excluded. When examining the skill content of China's total manufacturing exports, it looks like there has been an increase over the sample period. However, it turns out that this is mainly due to the increased skill content of imported inputs that are then assembled for export—a practice known as processing trade. This result has implications for other studies that have emphasized the sophistication of China's exports as a potential conduit of China's rapid income growth. We highlight processing trade as the mechanism behind this special feature of China's exports. Of course, there still may be something special about processing trade, perhaps through learning externalities or more growth opportunities in export processing.

Third, export growth was accompanied by increasing specialization. This finding casts some doubt on the notion that export diversification is a key element in export growth. The literature argues that diversification could promote export growth if it makes export discoveries more likely and that it helps alleviate risks associated with shocks to particular sectors. Indeed, traditional thinking highlights trade and specialization, where market forces work to attract resources into the main sectors where relative cost advantages are the greatest.

Fourth, export growth was mainly accounted for by high export growth of existing products (the intensive margin) rather than in new varieties (the extensive margin). Consistent with an increased world supply of existing varieties, we find that China's export prices to the United States fell by an average of 1.6 percent per year between 1997 and 2005, while export prices of these products from the rest of the world to the United States increased by 0.4 percent annually over the same period. Importers have gained from lower prices and from the abundance of products now available in markets around the globe.

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Comment Bin Xu

Amiti and Freund wrote a revealing and stimulating piece on characteristics of China's export dynamics. I summarize their main findings in the following and offer my comments under each of their findings.

Finding 1: The skill content of China's exports increased from 1992 to 2005, but the increase was driven almost entirely by China's processing exports. There was little skill upgrading found in China's nonprocessing exports.

This is a striking result to me. To comment on this result, we need to understand the method used by the authors. The authors first rank China's five-digit International Standard Industrial Classification (ISIC) industries in ascending order of skill intensity. Due to unavailability of relevant Chinese data, the industry skill-intensity ranking is based on Indonesian data. The authors then compute the cumulative export shares of the industries. If a country's cumulative export shares of low-skill industries decrease over time, it is considered as evidence of rising skill content of the country's overall exports. The authors find such a decrease in China's manufacturing exports in the period of 1992 to 2005 but no such a decrease in China's *nonprocessing* manufacturing exports in the same period.

To explain Amiti and Freund's method, let us consider a model of two industries, a low-skill industry 1 and a high-skill industry 2. Denote h_1 and h_2 as skill intensity of exports from 1 and 2, respectively, h_e as skill intensity of total exports, and λ as export share of 1. Then $\lambda h_1 + (1 - \lambda)h_2 = h_e$. By

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