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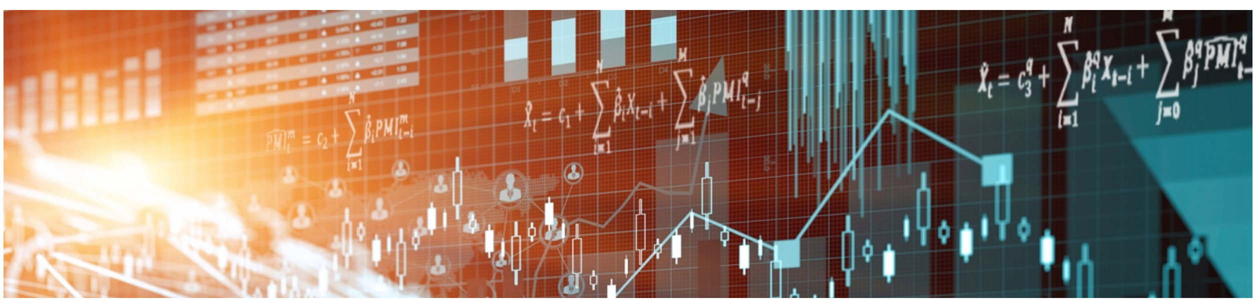
Product Sophistication and the Slowdown in Chinese Export Growth



by Mark Kruger, Walter Steingress and Sri Thanabalasingam

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Bank of Canada Staff Discussion Paper 2017-15

November 2017

Product Sophistication and the Slowdown in Chinese Export Growth

by

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ISSN 1914-0568

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Acknowledgements

We would like to thank Gino Cateau, Michael Francis, Christopher Hajzler, Daniel Trefler, Xiaodong Zhu and seminar participants at the Bank of Canada and the Banque de France for helpful comments and suggestions. We also thank Alexander Lam for excellent research assistance. Any remaining errors and omissions are our own.

Abstract

Chinese real export growth decelerated considerably during the last decade. This paper argues that the slowdown largely resulted from China moving to a more sophisticated mix of exports: China produced more sophisticated goods over which it had pricing power instead of producing greater volumes of less sophisticated products. Indeed, we show that the share of highly sophisticated products in Chinese exports increased steadily over time and that Chinese exports became less price sensitive, suggesting increased pricing power. Further, a decomposition of China's market share gains shows that China continues to gain market share despite exporting products with higher-than-average world prices. China's continuous gain in global export market share suggests that its export machine is far from broken.

Bank topics: International topics; Exchange rates; Development economics
JEL codes: F14, F17, O10

Résumé

La croissance des exportations réelles de la Chine a décéléré de façon significative au cours des dix dernières années. Notre analyse démontre que ce ralentissement s'explique en grande partie par la présence de biens plus sophistiqués dans les exportations chinoises. En effet, la Chine a produit des biens plus sophistiqués pour lesquels elle est en mesure d'imposer ses prix au lieu de fabriquer de grands volumes de biens moins sophistiqués. En fait, nous montrons que la part des produits très sophistiqués parmi les exportations chinoises a augmenté continuellement au fil du temps, et que les exportations de la Chine sont devenues moins sensibles aux mouvements des prix, phénomène qui indiquerait une capacité accrue du pays d'imposer ses prix. Lorsqu'on décompose les gains de parts de marché de la Chine, on constate qu'ils se poursuivent même si les prix des produits exportés sont plus élevés que la moyenne internationale. La hausse constante des parts de marché de la Chine tend à montrer que la machine à exporter du pays est loin d'être en panne.

Sujets : Questions internationales ; Taux de change ; Économie du développement
Codes JEL : F14, F17, O10

1 | Introduction

When China joined the World Trade Organization (WTO) in December 2001, the world economy opened to Chinese exports as trade barriers were relaxed. As a result, Chinese export volumes grew rapidly—more than 25 per cent per year, on average, from 2002 to 2007. However, since 2011, China's real export growth has slowed to about 6 per cent, on average. While the slowdown in global demand in the aftermath of the financial crisis explains part of China's weak export performance, it does not account for all of the moderation. Indeed, a standard export regression controlling for competitiveness and foreign demand significantly overestimates Chinese export growth in the post-crisis period.[1]

In this paper, we explore whether China's move to a more sophisticated export mix has played a role.[2] In particular, following Kwan (2002) and Hausmann, Hwang and Rodrik (2007), we construct product and export sophistication indices and calculate China's sophistication gap relative to the frontier, i.e., the country with the most-sophisticated exports. When we account for export sophistication in our regression, the under-prediction disappears, and China's move toward the frontier can explain much of the export slowdown. The intuition here is straightforward and is derived from the convergence hypothesis. In the same way that the growth literature predicts that a country's rate of gross domestic product (GDP) growth will be faster the further it is from the steady state given by the neoclassical growth model (Barro and Sala-i-Martin 1992), our results suggest that as a country's sophistication gap diminishes, there is less scope for catch-up, and export growth will decelerate.

Even though increased sophistication results in slower growth in export volume, countries moving up the value chain benefit from producing more finely differentiated goods over which they have more pricing power. This, to some extent, compensates for the loss in export volume. Indeed, our results show that Chinese exports became less price sensitive, suggesting that pricing power increased over time.

To strengthen the argument that China indeed upgraded its export mix, we look for industry-level evidence of the changing nature of the export basket. We examine whether Chinese exports become less price sensitive, both within and across industries. Based on industry-level US import data, our results show that changes in the export basket of goods are driven by both

[1] The post-crisis period refers to the period after the global financial crisis of 2008-2009.

[2] Sutton and Trefler (2016) suggest that endogenous factors—higher domestic wages and production costs—provide the impetus for a country to upgrade its export mix.

cross-industry specialization and within-industry upgrading. The share of highly sophisticated products in Chinese exports does increase over time, and we find that more-sophisticated goods are generally less price sensitive. Moreover, we also find some evidence of within-industry upgrading as price elasticities decreased for 11 of 19 manufacturing industries over time. This potentially provides the scope for greater markups.

The changes in the mix of export products have implications for Chinese competitors in global markets. When looking at the evolution of China's share of global exports, we find that China continues to out-compete other countries and gain share at a fairly constant rate. Upgrading the product mix toward more differentiated products enables China to gain market share despite charging higher prices. A decomposition of market share gains shows that more than half of the increase in the recent past comes from prices rather than quantities. A second decomposition provides evidence that China continues to gain market share despite exporting products with higher-than-average world prices. China's continuous gain in global export market share suggests that its export machine is far from broken.

The rest of the paper is organized as follows: Section 2 presents the stylized facts based on the aggregate export data. In section 3, we use industry-level, US import data to shed light on changes that may have contributed to the slowdown in Chinese export growth. Section 4 focuses on changes in Chinese export market share, and section 5 concludes.

2 | Assessing Chinese Export Dynamics

To analyze Chinese real export growth over time, we estimate the following standard regression:

$$d \log X_{Chn,t} = \alpha + \beta_1 d \log REER_{Chn,t} + \beta_2 d \log F_{Chn,t} + CNY + e_{Chn,t} \,, \qquad \textbf{(1)}$$

where

- $X_{Chn,t}$ is Chinese exports in real terms;
- $REER_{Chn,t}$ is China's broad real effective exchange rate (REER) index as compiled by the Bank for International Settlements;
- $F_{Chn,t}$ is foreign demand for Chinese products, defined as the average of China's main trading partners' industrial production, weighted by their share of Chinese exports at time *t*;

- CNY represents Chinese New Year dummy variables—each dummy controls for the month in which the New Year took place; and
- $e_{Chn,t}$ is the error term.

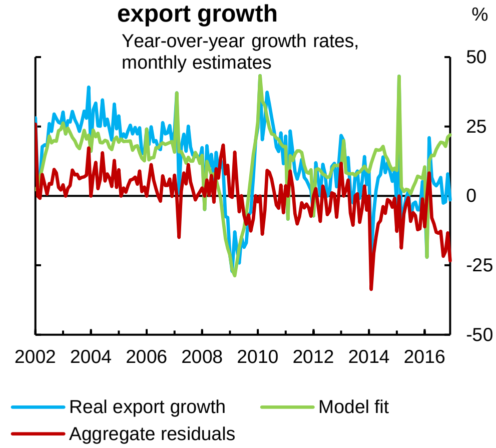
Exports, the real effective exchange rate and foreign demand are expressed as monthly year-over-year growth rates.

The results in column 1 of Table 1 show that the coefficients in our equation have the expected signs and magnitudes. A one-percentage-point appreciation of the REER reduces Chinese export growth by 0.83 percentage points, and a one-percentage-point increase in foreign demand increases exports by 1.45 percentage points. While foreign demand and the REER capture the dynamics of Chinese real export growth quite well, we find that the constant explains a large part of the export growth. Our estimate implies that, absent changes in foreign demand and competitiveness, Chinese exports would grow, on average, at 12.6 per cent over the sample period. This large constant is an artifact of China's accession to the WTO and captures the one-time increase in exports associated with increased market access.

Figure 1a compares actual and predicted export growth. We observe that at the beginning of the period, our regression estimates underestimate export growth, while we overestimate toward the end of the sample period. Indeed, from 2015 onward, the model over-predicted Chinese export growth by around 10 percentage points. These results suggest that the errors are trended. To investigate this point further, Figure 1b plots the error term of equation 1 together with a linear trend and 90 per cent confidence interval. Note that the linear time trend is downward sloping.

Figure 1a: Actual and predicted real export growth

Year-over-year growth rates, monthly estimates

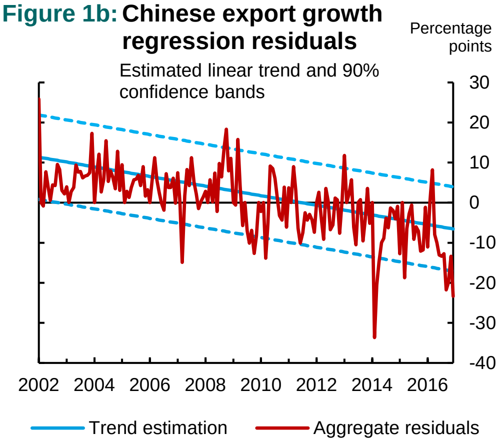


Sources: China Customs via Haver Analytics, Bank of Canada calculations

Last observation: Dec. 2016

Figure 1b: Chinese export growth regression residuals

Estimated linear trend and 90% confidence bands



Note: The confidence bands are at the 90% level.

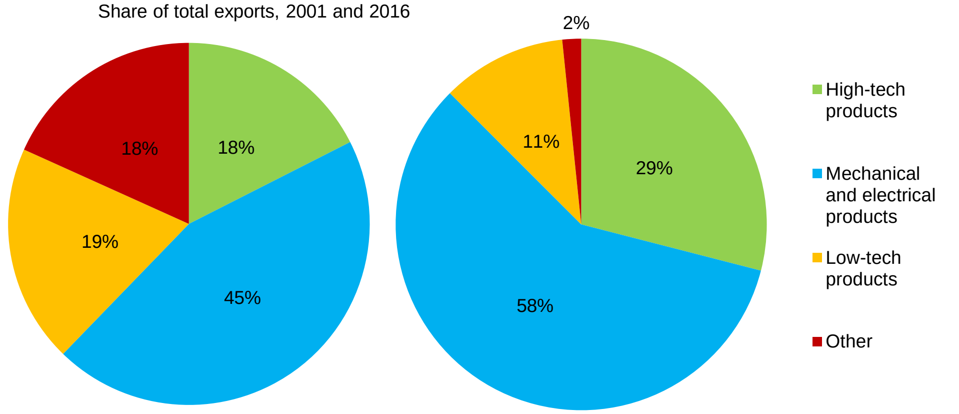
Source: Bank of Canada calculations

Last observation: Dec. 2016

A potential cause of the trend in the estimation errors might be time-variant price elasticities. Our base model imposes a time-constant relationship between relative prices and export growth. However, changes in the type of products exported may change this elasticity. For example, if China upgrades the quality of its products and produces more-sophisticated goods, export volumes may react significantly less to price changes. A high-level look at China's export mix suggests that there has, indeed, been a shift from lower-tech products, such as clothing, footwear and toys, to high-tech goods, such as computers, telecommunications equipment and electronics. The share of high-tech products in China's global exports was roughly a fifth in 2001, and it rose to almost a third by 2006 (Figure 2).[3]

Figure 2: Composition of Chinese exports

Share of total exports, 2001 and 2016



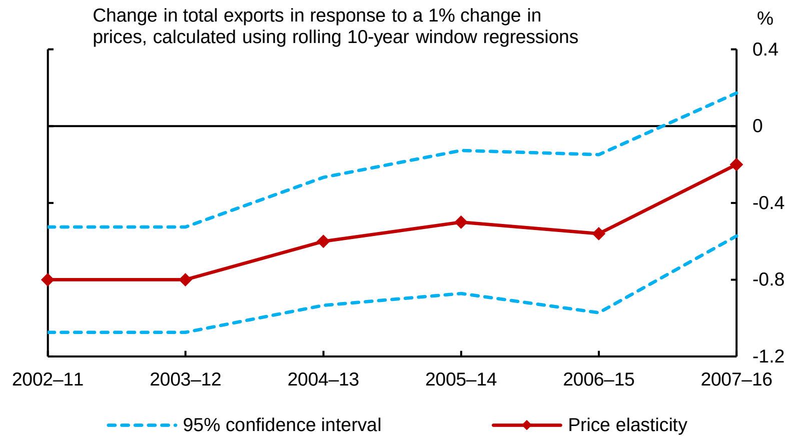
Source: China Customs via Haver Analytics

Last observation: 2016

[3] High-tech goods are as defined by Chinese Customs. They consist of electronics, computers and telecommunications, and aerospace, among other products. Low-tech goods consist of footwear, toys, garments and clothing accessories.

This rapid transformation in China's export basket suggests the aggregate price elasticity might be quite different from a decade ago. To test this prediction, we run the base model specification in rolling 10-year window regressions over a 15-year sample period (2002–16). The price elasticity (the parameter β_1 in our base model) for each window with its 95 per cent confidence band is plotted in Figure 3, which clearly shows a trend of increasing inelasticity.

Figure 3: China's price elasticity over time, total exports

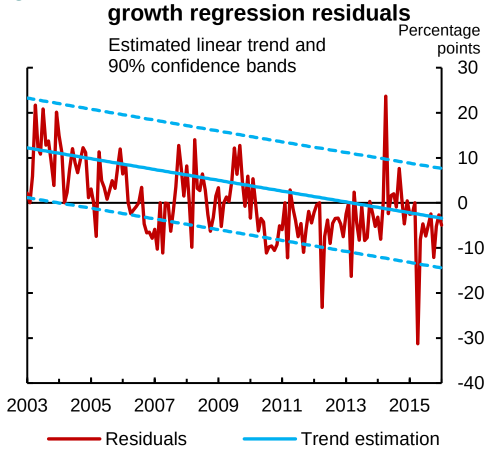


Source: Bank of Canada calculations

Last observation: 2016

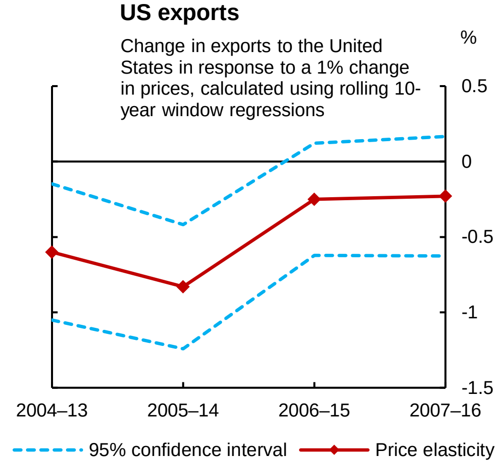
To shed further light on the changes in the Chinese export product mix, we use monthly, disaggregated, industry-level data from the United States import registry. The key advantage of the US import data is that they provide a matching of monthly, industry-specific trade and production information, which is useful for disaggregated analysis. To check whether the 20 per cent of Chinese exports that go to the United States are representative of the overall trend in Chinese exports, we test whether the observed patterns in the aggregate Chinese export data are also present in the US import data. The US data do indeed exhibit the same trends in the errors and the price elasticity as we found in the aggregate data (Figure 4).

Figure 4a: China to United States export growth regression residuals



Source: Bank of Canada calculations Last observation: Dec. 2016

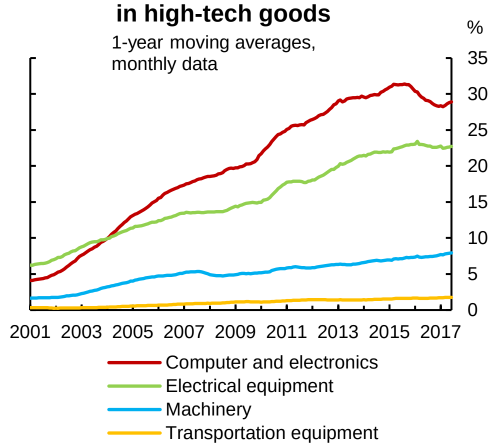
Figure 4b: China's price elasticity over time, US exports



Source: Bank of Canada calculations Last observation: 2016

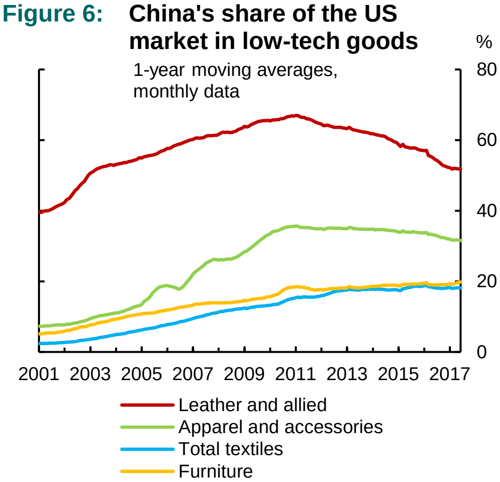
Next, we exploit the US industry-level data and plot the Chinese market share of eight manufacturing industries over the period from 2001 to 2016.[4] Figure 5 shows that since 2010 China has been broadly gaining market share in the following industries: machinery, computer and electronics, electrical equipment and, to a lesser extent, transportation equipment. These are generally considered to be higher-tech industries. On the other hand, since 2010 China has been losing market share in lower-tech industries such as textiles, apparel and accessories, leather and furniture (see Figure 6). These industry-specific results suggest that changes in the type of products China exports may be at the root of the decline in Chinese export growth. In the next section, we test this idea more rigorously.

Figure 5: China's share of the US market in high-tech goods



Sources: US Census Bureau, Bank of Canada calculations Last observation: Dec. 2016

Figure 6: China's share of the US market in low-tech goods



Sources: US Census Bureau, Bank of Canada calculations Last observation: Dec. 2016

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[4] For each industry, we calculate China's share of the US market as imports from China divided by US absorption. Absorption is defined as US sales minus exports plus imports.

3 | Analyzing Structural Changes in Chinese Exports

As discussed above, the observed decline in the price elasticity of Chinese exports could be due to a change in the type of products that China exports. One metric to capture such changes is the export sophistication index developed by Kwan (2002) and utilized by Francis, Painchaud and Morin (2005). This index tries to measure the income level of a country's exports so as to assess their productivity based on the hypothesis that richer countries produce more-sophisticated products. Thus, the higher the import expenditure share on goods from rich countries, the more sophisticated the product or industry is.

Inspired by Kwan, we first construct a product sophistication index for each three-digit NAICS code manufactured good (see Table 2) as follows:

$$PS_k = \sum_{i=1} w_{ik} (GDPpc_i / GDPpc_{US}), \qquad \textbf{(2)}$$

where

- PS_k is the sophistication of good *k*,
- $w_{ik} = IMP_{i,k} / IMP_{US,k}$ is the ratio of imports of good *k* from country *i* to total US imports of that product in 2002,
- $GDPpc_i$ is purchasing power parity (PPP) adjusted GDP per capita of country *i* in 2002, and
- $GDPpc_{US}$ is PPP-adjusted GDP per capita of the United States in 2002.

Our analysis differs from Kwan (2002) in a couple of ways. First, he looked at sophistication at a global level, while we confine our analysis to the US market. Second, we fix the product sophistication index to the initial year (i.e., 2002) to capture potential endogeneity concerns that arise because as China enters more sophisticated products, the product sophistication index will naturally decline.

Having calculated the sophistication of each product, we follow Kwan (2002) in calculating China’s export sophistication index as follows:

$$ES_{Chn,t} = \sum_{k=1}^{K} w_{Chn,k,t} PS_k, \qquad \textbf{(3)}$$

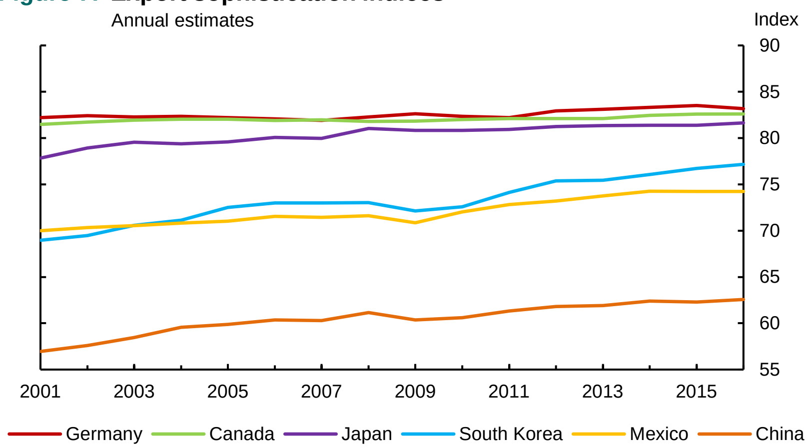
where

- $ES_{Chn,t}$ is China's export sophistication index, and
- $w_{Chn,k,t}$ is good *k*'s share of total US imports from China at time *t*.

Figure 7 shows China's sophistication index along with those of other top exporters to the United States. The most-sophisticated exporters are Germany, Canada and, increasingly, Japan. Mexico and South Korea have both made gains in export sophistication since 2001, with South Korea outpacing Mexico in recent years. China has steadily become more sophisticated over the sample period but continues to lag the other exporters.

Figure 7: Export sophistication indices

Annual estimates



Source: Bank of Canada calculations

Last observation: 2016

Next, we compare China's export sophistication index to that of the country that sends the most-sophisticated products, on average over the sample period, to the United States:

$$Gap_{Chn,t} = ES_{Chn,t} / \max(ES_j)\,. \quad \textbf{(4)}$$

The idea here is that the country with the highest export sophistication index represents the technological frontier. The gap gives an indication of the distance between China and the frontier. Of the major exporters to the United States, Germany has the most-sophisticated exports, on average, over the sample period. Figure 8 plots the evolution of the sophistication gap between China and Germany over time. We observe that during the last 16 years China upgraded its product mix by exporting more-sophisticated products. While at the beginning of the period China's average product sophistication was around 70 per cent of Germany's sophistication, this ratio continuously increases over time to above 75 per cent in 2016. China has been converging with Germany at a somewhat slower rate than Korea and about as fast as Mexico.

Figure 8: China's export sophistication gap with Germany

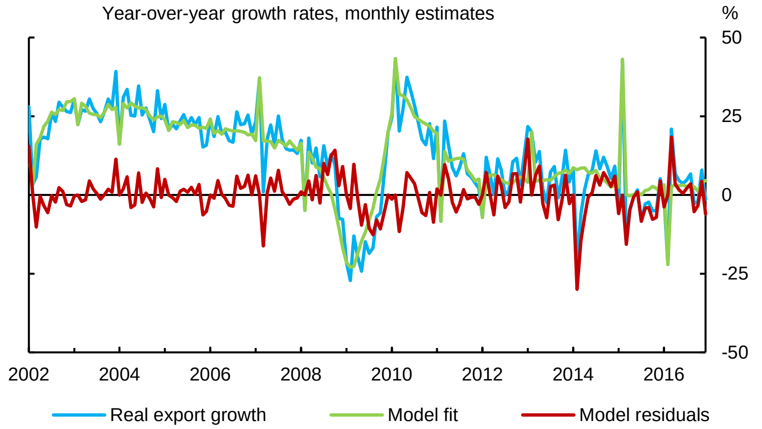
We include the gap in our aggregate regression to represent the change in the mix of Chinese exports:

$$d\log X_{Chn,t} = \alpha + \beta_1 d\log REER_{Chn,t} + \beta_2 d\log F_{Chn,t} + \beta_3 Gap_{Chn,t} + CNY + e_{Chn,t}\,. \quad \textbf{(5)}$$

Column 2 of Table 1 presents the results. Including the gap improves the fit of the equation. Moreover, the coefficient on the real effective exchange rate falls from -0.83 in the baseline model to -0.21. This implies that the gap measure is negatively correlated with the competitiveness measure ($d\log REER_{Chn,\,t}$) and hence captures part of the ongoing changes in China's supply of exports. On the other hand, the coefficient on the demand elasticity (β_2) does not change significantly. Furthermore, unlike the base model, the downward trend in residuals disappears under this specification.

Next, we include the square of the gap term in equation 5 to capture any non-linear relationship between the gap and export growth. The gap-squared variable is significant at the 1 per cent level, and we find the contribution of the gap, its squared term and the constant to be broadly similar to that from equation 5. The results are presented in column 3 of Table 1 and Figure 9.

Figure 9: **Chinese export growth model results**



Sources: China Customs via Haver Analytics, Bank of Canada calculations Last observation: Dec. 2016

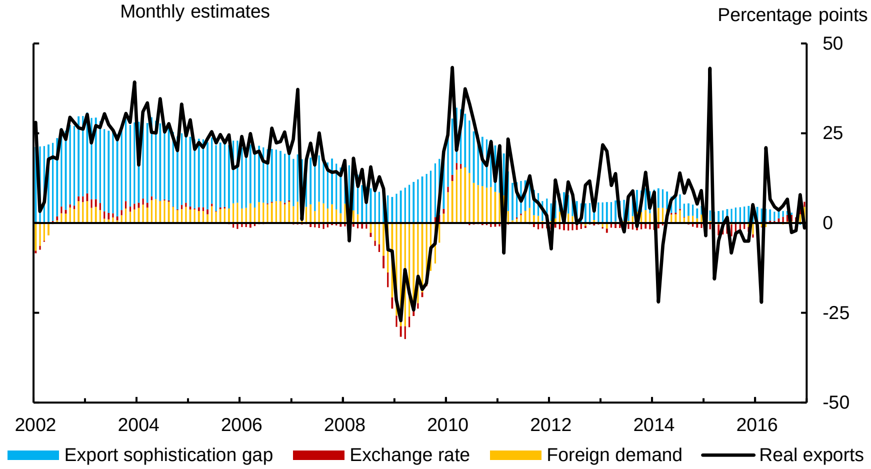
We then calculate the contribution of each variable in equation 5 to overall real export growth. Given that the theory of convergence suggests that export growth depends on the distance to the technological frontier, we combine the contribution of the constant with the level of the gap and its square into a single factor. Figure 10 shows the results. This equation suggests that changes in the Chinese export product mix — the gap — contribute the most to the slowdown in Chinese export growth. The gap was a missing variable in our baseline regression; excluding it led to the large constant and the declining trend in the errors. As Chinese products become more sophisticated and approach the technological frontier, export growth of 20 per cent is increasingly difficult to maintain. Convergence toward the frontier implies that the returns to production factors diminish, and overall productivity growth will inevitably slow down. At the end of the sample period, the contribution of the gap to export growth is negative but relatively small. Thus, going forward, at the current level of export sophistication, changes in competitiveness and foreign demand will be the main determinants of Chinese export growth.

A prominent explanation for the rapid growth in Chinese exports since China's accession to the WTO in 2002 is the steady decline in Chinese trade costs. For this reason, we include the change in average trade costs of manufacturing that China faces in its export markets as an additional control variable.[5] Column 4 of Table 1 presents the result. Note that, contrary to our expectations, average trade costs do not have a significant impact on Chinese export growth. One potential explanation is that the constructed trade costs from the World Bank cover only

[5] Data on trade costs comes from the Trade Costs Dataset provided by the World Bank. The data set contains estimates of bilateral trade costs in agriculture and manufactured goods for the 2002–15 period. It is built on trade and production data collected in 178 countries. Symmetric bilateral trade costs are computed using the Inverse Gravity Framework (Novy 2013), which estimates trade costs for each country pair using bilateral trade and gross national output.

one part of total trade costs. An additional source of trade costs not covered by the data is non-tariff barriers, which are difficult to quantify.

Figure 10: Contributions to Chinese real export growth
Monthly estimates



Source: Bank of Canada calculations

Last observation: Dec. 2016

3.1 | Why would China move up the value chain?

The results in the previous section create a puzzle. Why would China produce more-sophisticated products if it means weaker real export growth? According to the theory outlined by Sutton and Trefler (2016), early on in the development process, countries produce relatively unsophisticated goods and compete mainly on price. Since relatively unsophisticated products are fairly homogeneous, the ability to produce at a low price can result in large market share gains. However, as real incomes—and by extension unit costs of production—start to rise, continuing to compete on prices in relatively unsophisticated goods becomes more difficult as margins are squeezed.

One strategy for maintaining margins in the face of increasing production costs is to improve export mix, since more sophisticated goods provide increased product differentiation and greater pricing power. However, this export-upgrading process is costly, as a country needs to acquire the new technologies and distribution channels. Because of these high transition costs, it may not be optimal for every country to move up the value chain. As a result, the number of countries capable of producing highly sophisticated goods decreases with the level of technology. Having fewer competitors reduces competitive pressures, improves pricing power and increases markups. The more sophisticated product mix will be less sensitive to price changes and result in a lower price elasticity of exports. Overall, this theory provides a coherent explanation of the stylized facts outlined in section 2.

Next, we provide further empirical evidence consistent with the theory outlined by Sutton and Trefler (2016). More specifically, we test whether China's increasingly sophisticated product mix has been accompanied by a lower price elasticity of exports. There are two potential channels through which this effect might work. First, over time, the mix of exports could shift to goods that are more sophisticated and less price elastic. Second, within a given industry, products become more differentiated, and their price elasticity may decrease over time.

To test the across-industry implications, we run the following specification for each of the 19 manufactured goods at the NAICS three-digit level:

$$d\log X_{Chn,US,t} = \alpha + \beta_1 d\log relpri_{Chn,US,k,t} + \beta_2 d\log realabs_{US,k,t} + e_{Chn,,t}\,, \qquad \textbf{(6)}$$

where

- $d\log X_{Chn,US,t}$ is real growth of Chinese exports to the United States of product *k* in year-over-year terms;
- $d\log relpri_{Chn,US,k,t}$ is the year-over-year change of Chinese import prices, relative to changes in the US prices, for each three-digit NAICS product *k* at time *t*;
- $d\log realabs_{US,k,t}$ captures the year-over-year changes in US demand for product *k* and is defined as US absorption deflated by the producer price index (PPI) of product *k*;[6] and
- $e_{Chn,t}$ is the error term.

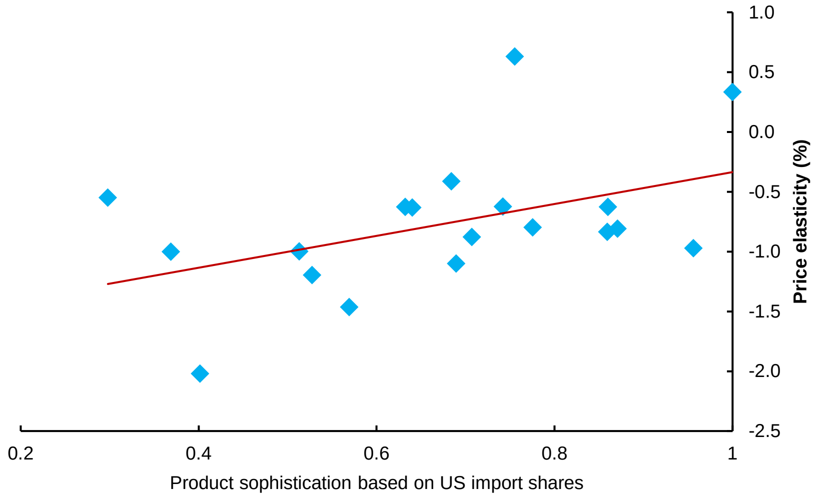
Before discussing the results of regression 4, we want to point out that the US Bureau of Labor Statistics does not provide bilateral, industry-specific price indexes. For this reason, we construct a unit-value-based, industry-specific US import price index for Chinese goods using detailed monthly import data. More precisely, we first calculate year-over-year changes in unit values for imported products from China at the 10-digit Harmonized System (HS) level by month beginning in 2002. We follow Gaulier et al. (2008) and aggregate the 10-digit HS unit value changes into weighted three-digit NAICS chained Tornqvist price indexes. We then divide these Chinese import price series by their US PPI equivalent, giving us a relative China-United States price index in domestic currency for each industry *k* at time *t*. Results from the regressions across products are shown in the first three columns of Table 3. Apart from chemical products and primary metal products, all the regressions show a negative sign for β_1, and, except for petroleum and coal products, all of the regressions show a positive sign for β_2.

[6] US absorption is US production plus imports minus exports.

In general, these results show that as China's relative price of product *k* increases, export growth of that good to the United States falls, and as the US demand for good *k* rises, exports increase. Figure 11 plots the estimated β_1 coefficient for each three-digit NAICS industry against the product sophistication index defined above. It shows that as export sophistication increases across products, the price elasticity of the product falls. Thus, to some extent, China can gain pricing power even as export growth slows.

Figure 11: Export sophistication and price elasticities

Comparison by 3-digit NAICS manufacturing industry



Sources: China Customs via Haver Analytics, Bank of Canada calculations

In addition to producing a more sophisticated mix of goods, China might also be upgrading its products within given industries. This would also have the effect of increasing pricing power. In the following regression, we test whether the price elasticity has declined in the post-financial crisis period for each industry *k*:

$$\begin{aligned} d\log X_{Chn,US,t} &= \alpha + \beta_1 d\log relpri_{Chn,US,k,t} + \beta_2 d\log realabs_{US,k,t} \\ &\quad + \beta_3 d_{crisis} * d\log relpri_{Chn,US,k,t} + \beta_4 d_{crisis} + e_{Chn,US,t} \end{aligned}, \qquad \textbf{(7)}$$

where

- d_{crisis} is a dummy to identify the post-crisis period, which we have defined as the period beginning in 2011.

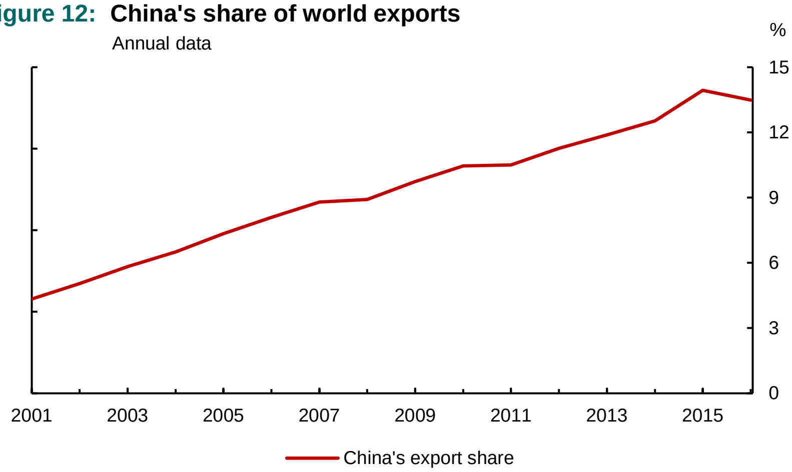
We find that 11 of the 19 manufacturing products experienced a decline in price elasticities over the sample period. Column 5 in Table 3 presents these results; a positive sign on $\boldsymbol{\beta_3}$ indicates a decline in the price elasticity. This provides some evidence that along with a shift to more-sophisticated products, China has also increased quality within products, thereby competing more on quality rather than on price.

Overall, this section relates changes in the mix of Chinese exports to their price elasticity. Consistent with the theory of upgrading toward more-sophisticated products, we document changes within product groups as well as shifts across product groups toward less price elastic goods. In the next section, we show that despite the lower real export growth, China is still rapidly gaining global export market share. However, the source of these gains recently shifted from volumes toward prices.

4 | China's Export Machine Continues to Hum

In addition to an analysis of export growth, an assessment of Chinese export performance can also be made from considering the evolution of China's global export market share. Using information on bilateral quarterly trade flows from the Export Competitiveness Database, we plot the share of total Chinese export sales relative to global export sales, i.e., its export market share (Figure 12). Apart from the slight jump in 2015 and the dip in 2016, China has gained global export market share at a fairly constant rate. This suggests that while Chinese export growth slowed, China has continued to outperform its competitors. In the following paragraphs, we show that this increase in market share is consistent with our previous finding that China upgraded its export model.

Figure 12: China's share of world exports
Annual data



Source: International Monetary Fund via Haver Analytics　　Last observation: 2016

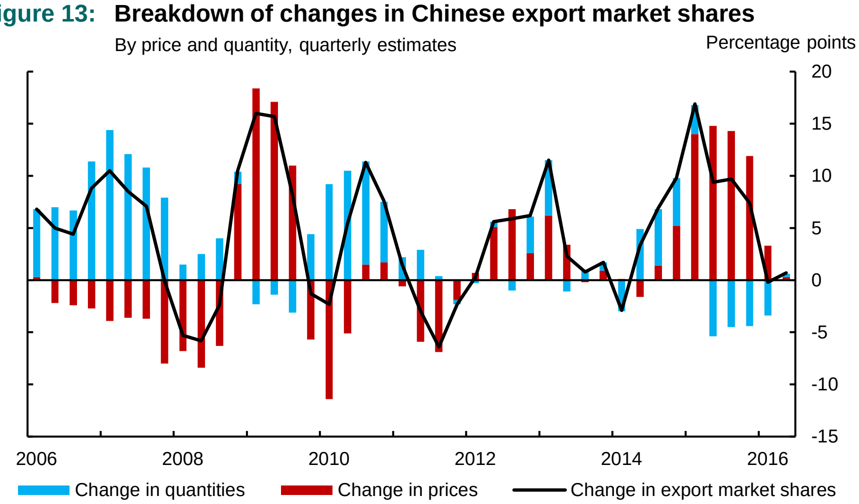
We first employ the shift-share analysis developed by Cheptea, Gaulier and Zignago (2005) to shed light on the origins of Chinese market share gains. This method allows us to distinguish between sectoral and geographical composition of exports as well as price and quantity effects and track their evolution over time. To start with, we decompose the quarterly change in

Chinese export market share into price (trade prices, *P*, are approximated by changes in unit values) and quantity (*Q*) effects to capture their respective roles during the period from 2005 to 2016. The decomposition takes the following form:

$$d\log X_{Chn,t/t-12} - d\log X_{t/t-12} = d\log Q_{Chn,t/t-12} - d\log Q_{t/t-12} + d\log P_{Chn,t/t-12} - d\log P_{t/t-12}, \quad \textbf{(8)}$$

where the differences capture year-to-year Chinese export growth ($d\log X_{Chn,\, t/t-12}$) relative to global export growth ($d\log X_{t/t-12}$) on a quarterly basis. Figure 13 plots the log growth rates for all three series. The analysis confirms that before the 2008 crisis, changes in quantities largely drove China's exports expansion, while Chinese prices generally declined relative to those of its competitors. Except for the crisis period in 2009, this trend continued until the end of 2011. Since 2012, these dynamics have changed. The expansion of quantities decelerated and subsequently turned negative, and prices became the main contributor to the market share growth of Chinese exports. This result is in line with our previous finding that China upgraded its product mix toward less price sensitive products and competed on quality rather than price.

Figure 13: Breakdown of changes in Chinese export market shares



Source: Bank of Canada calculations

Last observation: 2016Q2

To provide further evidence that the Chinese export growth model shifted toward more sophisticated goods, we apply a second shift-share analysis (Cheptea, Gaulier and Zignago 2005) and decompose the changes in China's global export market share into a China-specific effect, a destination-market-specific effect and a product/sector-specific effect. For notational convenience, we denote the exporting country by *i,* the importer by *c*, the product by *k* and the time by *t.* Next, we calculate the mid-point growth rate[7] (g_{ickt}) of the product-specific bilateral

[7] The mid-term growth rate is defined as $g_{ickt} = (X_{ickt} - X_{ickt-1}) / (½(X_{ickt} + X_{ickt-1}))$ where X_{ickt} is the value of exports of product *k* between *i* and *c*.

trade flow and partition the variation of this growth rate into three components using the analysis of variance (ANOVA) methodology. Within this method, we regress the mid-point growth rate on three sets of time-varying fixed effects. The first set consists of time-varying-exporter fixed effects (f_{it}). The dummy variable, f_{it}, equals one for every time-exporter pair and zero otherwise. The second set consists of a time-varying-importer fixed effect (f_{ct}), and the third set consists of a time-varying sector/product-fixed effect (f_{kt}). The last two sets of dummy variables are defined in a similar manner to f_{it}. We estimate the resulting regression by means of a weighted ordinary least squares (OLS) estimation:[8]

$$g_{ickt} = \alpha + \varphi_{it} f_{it} + \beta_{ct} f_{ct} + \gamma_{kt} f_{kt} + e_{ickt} . \qquad \textbf{(9)}$$

The weights are equal to the share of the export value relative to country *i'*s total export at time *t,* (s_{ickt}). Next, we normalize the estimated fixed effects (y_{it}, $\beta_{ct,}$ g_{kt}) to quantify them as deviations from the average growth rates of exports for the overall sample in the data through a least squares estimation.[9] Based on this normalization, we can decompose the growth of country *i*'s export market share as follows:

$$\sum\nolimits_{c,k} s_{ickt} g_{ickt} = \varphi_{it} + \sum_{c,k} s_{ickt} \hat{\beta}_{ct} + \sum_{c,k} s_{ickt} \hat{\gamma}_{kt} . \qquad \textbf{(10)}$$

The first term of the right-hand side of equation 10 is equal to the exporter-specific fixed effect (φ_{it}) and captures any effects that are specific to the exporter; it is orthogonal to importing countries and sectoral issues. This is our measure of Chinese-specific export performance. Examples of such exporter-specific effects are those that are common across all sectors and independent of importers, such as changes in the exporter's exchange rate, its aggregate productivity shocks and the exporter's overall competitiveness. Changes in this factor improve or worsen the competitiveness of all goods exported by a country—China, for example.

The second term represents the importer-specific fixed effect (β_{ct}) weighted by the export shares over all importing countries (s_{ickt}). This market-specific factor is independent of the exporting country and not sector specific. It captures, for example, aggregate demand shocks in the importing country. The market-specific effect also provides a measurement of the capacity to directly export to destination markets with an increasing import demand. For example, if import demand shifts from the euro area to the United States and China exports a large part of its exports to the United States, then the market-specific component will play a bigger role in explaining Chinese export market share growth.

[8] A complete description of the data set can be found at https://mec.worldbank.org/.
[9] See Cheptea, Gaulier and Zignago (2005) for more details.

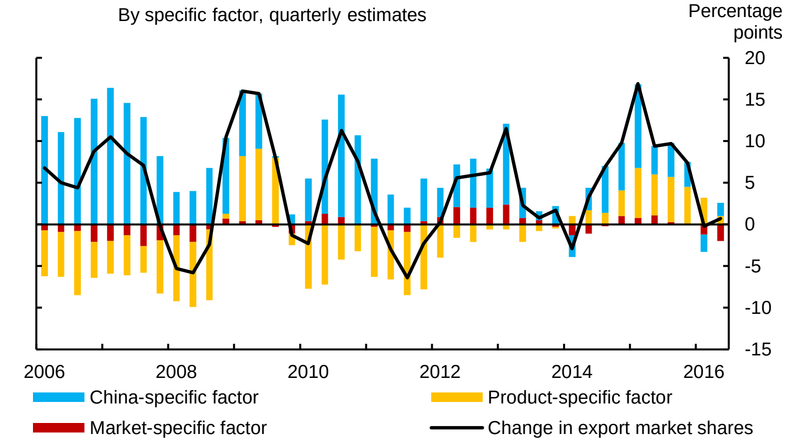
Finally, the third term (γ_{kt}) in equation 10 captures the product-specific effects of exports. The measure abstracts from changes in overall import demand and focuses on changes in the relative importance of products in a country's export basket, for example, the share of less sophisticated products (textiles) relative to more sophisticated products (computers). The product-specific component will have a strong predictive power if China realigns its export product mix in line with products for which there is increased global demand or products whose global prices are rising fastest. If prices or demand rise strongly for highly sophisticated products, and China adjusts its export basket's product mix accordingly, then the explanatory power of this component will be high.

Figure 14 plots this decomposition of the changes in Chinese global export market shares. The average growth rate from the first quarter of 2006 to the second quarter of 2016 was 4.6 per cent with significant cyclical variation after the 2008 crisis as well as in the first quarter of 2015. In addition to the evolution of China's global export market shares, the figure shows the decomposition in the three underlying factors as defined in equation 10. Over the entire sample period, the biggest contributor to Chinese growth in export market shares was the China-specific effect. Potential factors responsible for that strong export growth were a reduction in the overall trade costs and strong overall productivity growth. However, more recently, the contribution of the China-specific effect dropped markedly, while product-specific factors started to play a much more prominent role. On the other hand, the market-specific effect played only a minor role in the growth of Chinese exports.

The large positive contribution of the product-specific factor is in stark contrast to the previous periods when the sectorial composition of Chinese exports was mainly a drag on export market share gains. To exclude the possibility that this effect is entirely driven by demand, we further decompose the product factor into a price and a quantity component. The decomposition (see Figure 15) shows that in the case of China the large positive contribution of product-specific factors is entirely driven by higher prices, while the quantity component contributes negatively to export market share growth over the whole sample period. This suggests that China gained export market shares because it shifted its exports toward products with fast-rising world prices and presents further evidence that China's realignment of its export product composition helped to support gains in global market share. Absent these changes, Chinese export growth might have been much slower.

Figure 14: Breakdown of changes in Chinese export market shares

By specific factor, quarterly estimates

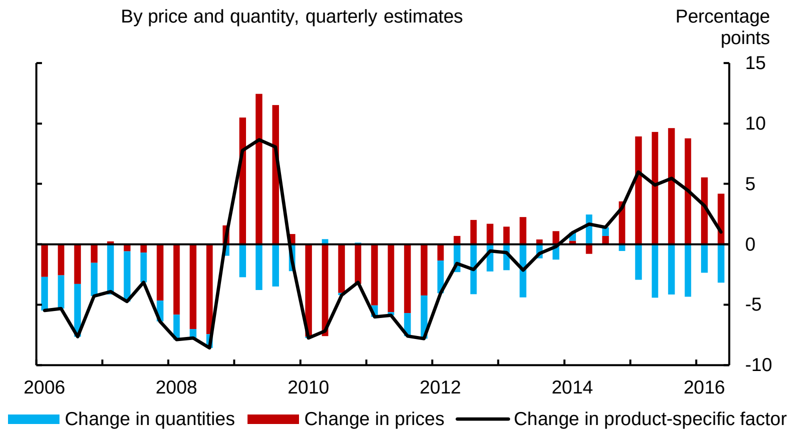


Source: Bank of Canada calculations

Last observation: 2016Q2

Figure 15: Breakdown of changes in Chinese product-specific factors

By price and quantity, quarterly estimates



Source: Bank of Canada calculations

Last observation: 2016Q2

Overall, China continues to gain global export market share at a fairly constant rate. The shift-share analysis highlighted two important changes in the underlying sources of this growth. First, changes in export prices now contribute more, compared to changes in quantities. Second, product specialization is no longer a drag on exports and supports export growth. These two developments are consistent with our argument that China's export model shifted toward more-sophisticated products and that this switch allowed China to gain market share despite slower volume growth.

5 | Conclusion

We began this paper by using a standard export equation to assess the dynamics of Chinese export volumes. The equation fits the data rather well, and the coefficients on the foreign demand and the real exchange rate both had the expected signs. However, we note two anomalies. First, the constant explains a large part of the export growth. We believe that this is an artifact of China's accession to the WTO and that such strong trend growth is unlikely to persist. Second, the residuals are trended, with the equation over-predicting exports at the beginning of the period and under-predicting them at the end. This suggests that there have been structural changes that are not well captured by the standard export equation. These structural changes could be related to China's moving up the value chain, as China's export mix has become less reliant on lower-tech products, such as clothing, footwear and toys, and more reliant on higher-tech products, such as computers, telecommunications equipment and electronics.

To assess how structural changes affected the growth of Chinese export volumes, we calculate export sophistication indices. We then measure how far China has been from the sophistication frontier. We put this gap (and its square) into the standard export equation. These appear to have been missing variables in our baseline regression. Excluding them led to the large constant and the declining trend in the errors.

It does appear puzzling that a country would choose to export more sophisticated goods if this led to slower export volume growth. However, this phenomenon is consistent with the insights from the growth literature that posits that GDP growth will slow as a country approaches the technological frontier and the scope for catch-up is diminished. Moreover, the trade literature suggests that the choice to export more sophisticated products is an endogenous one that depends on a country's costs rising faster than its competitors' as it grows relatively more rapidly.

One of the benefits of a country's exports becoming more sophisticated is that it will produce more differentiated products over which it can exercise more pricing power and benefit from higher markups. To test whether this occurred in China's case, we examine two channels: changes in China's export mix and changes within product categories. Here we focus on the US market, where we can make use of disaggregated import, demand and price data. Looking across 19 manufacturing industries, we find that increased sophistication is, indeed, associated with lower price elasticities and increased pricing power. Looking within industries, we find that there is also some evidence of decreasing price inelasticity since the crisis, suggesting that China has made within-product-line improvements.

We find supporting evidence for the effect of structural change on export growth from two decompositions of China's global market share. Decomposing changes in market share into price and volume effects, we find that, prior to the crisis, China's export growth had been driven by volumes, but depended more on increased prices thereafter. We then go a step further and decompose the market share changes into a China-specific effect, a geographic market effect and a product effect. We find that, over the entire sample, the China-specific effect was the biggest contributor to export growth. More recently, however, the product effect has become more important, providing evidence that changes in export composition have supported export growth.

In 2010, China became the world's biggest exporter of goods. In 2016, its share of global goods exports was 13 per cent, compared with 9 per cent for the United States and 8 per cent for Germany, which were in second and third place, respectively. It is unrealistic to suppose that from this base, Chinese exports will again grow at the rapid pace recorded after WTO accession. However, what their exports have lost in growth dynamism has been, to some extent, offset by compositional dynamism—in particular, growing sophistication. Given China's distance from the frontier, it is reasonable to assume that this dynamic has not yet fully played out.

References:

Barro, R. J. and X. Sala-i-Martin. 1992. “Convergence.” *Journal of Political Economy* 100 (2): 223–251.

Cheptea, A., G. Gaulier and S. Zignago. 2005. “World Trade Competitiveness: A Disaggregated View by Shift-Share Analysis.” CEPII Working Paper No. 2005-23.

Francis, M., F. Painchaud and S. Morin. 2005. “Understanding China's Long-Run Growth Process and Its Implications for Canada.” *Bank of Canada Review* (Spring): 5–17.

Gaulier, G., J. Martin, I. Méjean and S. Zignago. 2008. “International Trade Price Indices.” CEPII Working Paper No. 2008-10.

Hausmann, R., J. Hwang and D. Rodrik. 2007. “What You Export Matters.” *Journal of Economic Growth* 12: 1–25.

Kwan, C. H. 2002. “The Rise of China and Asia’s Flying-Geese Pattern of Economic Development: An Empirical Analysis Based on US Import Statistics.” The Research Institute of Economy, Trade and Industry Discussion Paper Series 02-E-009.

Novy, D. 2013, “Gravity Redux: Measuring International Trade Costs with Panel Data.” *Economic Inquiry* 51 (1): 101–121.

Sutton, J. and D. Trefler. 2016. “Capabilities, Wealth, and Trade.” *Journal of Political Economy* 124 (3): 826–878.

Tables

Table 1: Real export growth regressions

Variable	**1**	**2**	**3**	**4**
Foreign demand	1.45*** (0.153)	1.55*** (0.121)	1.45*** (0.114)	1.50*** (0.120)
REER	-0.83*** (0.126)	-0.21* (0.118)	-0.24** (0.109)	-0.13 (0.162)
Gap		-4.15*** (0.419)	157.82*** (31.10)	167.98*** (41.57)
Gap-squared			-1.11*** (0.215)	-1.18*** (0.285)
Trade costs				-3.17 (3.02)
Constant	12.58*** (0.741)	315.81*** (30.65)	-5548.20*** (1126.23)	-5933.41*** (1513.89)
Observations	180	180	180	157
R-squared	0.65	0.78	0.81	0.81
Adjusted R-squared	0.61	0.76	0.79	0.78

Note: Chinese New Year dummies included in each regression. ***,**, and * denote statistical significance at the 1%, 5% and 10% level, respectively. Standard errors are shown in parentheses.

Table 2: Sophistication by industry

Industry	Sophistication
Leather & Allied Product Mfg (316)	0.30
Textile Product Mills (314)	0.37
Apparel Mfg (315)	0.40
Misc. Mfg (339)	0.51
Furniture (337)	0.53
Elect Eqpt, Appliance & Component Mfg (335)	0.57
Computer & Electronic Product Mfg (334)	0.63
Non-Metallic Mineral Product Mfg (327)	0.64
Petroleum & Coal Products Mfg (324)	0.68
Textile Mills (313)	0.69
Fabricated Metal Product Mfg (332)	0.71
Plastics & Rubber Products Mfg (326)	0.74
Primary Metal Mfg (331)	0.76
Printing & Related Support Activities (323)	0.78
Wood Product Mfg (321)	0.86
Machinery Mfg (333)	0.86
Transportation Equipment Mfg (336)	0.87
Paper Mfg (322)	0.96
Chemical Mfg (325)	1.00

Note: Industries and three-digit codes are from the NAICS codes

Table 3: Industry regression coefficients

Industry	Constant (Eq.4)	Relative Prices (Eq.4)	Foreign Demand (Eq.4)	β3 in Eq.5
Textile Mills (313)	13.12***	-1.10***	0.96***	-0.04
Textile Product Mills (314)	8.26***	-1.00***	1.00***	-0.45
Apparel Mfg (315)	7.12***	-2.02***	1.23***	0.91***
Leather & Allied Product Mfg (316)	-0.85**	-0.55***	1.19***	-0.21
Wood Product Mfg (321)	7.58***	-0.84***	0.70***	0.27
Paper Mfg (322)	6.28***	-0.97***	0.86***	0.05
Printing & Related Support Activities (323)	7.97**	-0.80***	1.04***	0.79***
Petroleum & Coal Products Mfg (324)	5.81	-0.41**	-1.67	0.51
Chemical Mfg (325)	14.67***	0.33**	0.82***	-1.02***
Plastics & Rubber Products Mfg (326)	7.86***	-0.62***	0.87***	-0.52***
Non-Metallic Mineral Product Mfg (327)	4.38***	-0.63***	1.07***	0.36
Primary Metal Mfg (331)	7.75**	0.62*	1.98***	-0.85
Fabricated Metal Product Mfg (332)	6.34***	-0.88***	1.25***	0.32
Machinery Mfg (333)	7.48***	-0.63***	1.06***	-0.86**
Computer & Electronic Product Mfg (334)	6.87***	-0.63***	1.39***	0.18
Elect Eqpt, Appliance & Comp. Mfg (335)	6.15***	-1.46***	1.24***	0.39
Transportation Equipment Mfg (336)	11.41***	-0.81***	0.83***	0.34
Furniture (337)	5.92***	-1.20***	1.07***	0.33
Misc. Mfg (339)	2.19**	-1.00***	1.35***	-0.85**

Note: ***,**, and * denote statistical significance at the 1%, 5% and 10% level, respectively. Chemical Manufacturing and Primary Metal Manufacturing experienced a decline from a positive coefficient on their relative prices in the pre-crisis period.