We analyse Chinese manufactured export performance mainly focusing on four time points: (i) 1980 (just after the 1978 economic reforms were introduced, which is our comparator period), (ii) 1990 and 2000 (chosen as intermediate, relatively recent dates for further comparison) and (iii) finally 2003, which is the most recent year for which data for China is available to us. We analyse a matrix of product-industry groupings, subdivided according to technology characteristics, including high technology, medium technology and low technology categories, using SITC 3-digit level industry codes as a proxy for export industries. In this analysis, trade indices such as Balassa’s revealed comparative advantage (RCA) index, and other variants, are used to analyse the relative strengths of the Chinese manufacturing based export sectors, including the revealed symmetric comparative advantage (RSCA) index. Proudman and Reading’s (2000) modification of the Balassa’s index is expanded to carry out a graphical pre-test and graphical analysis of the broad trends in industrial change in Chinese exports. Detailed regression analysis on the RSCA indices is used to further analyse structural change. The stability of the RCA indices is examined making use of suitable Wald tests. Our results point towards substantial industrial restructuring in China’s manufactured exports industries.

JEL codes: F14, L6

Keywords: China, industrial structural transformation, manufacturing, exports, comparative advantage

Work in progress. All comments welcome.
1 Introduction

China’s economy has shown rapid growth based on closer integration with the world economy, especially in China’s post-1978 period. In China’s post-Mao period, liberalisation of markets, greater reliance on price based signals and more incentives based structures have engendered large investible surpluses which have been channelled into investments for Chinese manufacturing based industries, as a part of the process of decentralised planning practised in China. This has contributed to the strengthening of China’s manufactured based exports which have shown rapid growth across a number of industries.

This paper is an empirical study which aims to assess structural change for manufacturing based exports from China, based on an analysis of 140 SITC industries and product groupings, while explicitly taking into account the technology characteristics of exporting industries. By an examination of trade data, the structural changes emergent in China’s manufactured exports can be deduced. We analyse manufactured export performance for China at four time points: (i) 1980, which is just after the 1978 economic reforms were introduced at the Third Plenum of the 11th Congress of the Chinese Communist Party (our comparator period), (ii) 1990 and 2000 are chosen intermediate, relatively recent dates which are used for comparison with Chinese performance in the pre-reform period, and (iii) finally 2003, which is the most recent year for which disaggregated manufactured export data for China is available to us.

We analyse a matrix of product-industry groupings, which are subdivided according to technology characteristics, including high technology, medium technology and low technology categories, using SITC 3-digit level industry codes as a proxy for export industries. In this analysis, trade indices such as Balassa’s revealed comparative advantage (RCA) index, and other variants commonly employed in the literature are used to analyse the relative strengths of the Chinese manufacturing based export sectors, including the revealed symmetric comparative advantage (RSCA) index. Proudman and Reading’s (2000) modification of the Balassa’s index is expanded to carry out a graphical pre-test and graphical analysis of the broad trends in industrial change in Chinese exports. Detailed regression analysis on the RSCA indices is used to further analyse structural change. Thereafter, the stability of the RCA indices is examined, as well as the process of their intertemporal evolution by making use of suitable Wald tests.

This analysis enables us to examine the export performance of Chinese manufactured based export industries in the selected product-industry groupings in detail. We are also able to assess the prospects for growth of particular Chinese manufactured export industries in groupings with different technology parameters. We thus use a range of econometric and statistical techniques to provide a detailed analysis of Chinese manufactured based export performance for a recent and up-to-date data set, to understand such trends in a meaningful manner. In Section 2 we present the main theoretical underpinning which inform our empirical analysis. Section 3 provides a brief description of the data set and technology categories used. Section 4 outlines our methodology and formal definitions of the key trade indices we use in our empirical analysis. We present our empirical results, based on both our graphical approach and our econometric analysis, in Section 5. Section 6 concludes.
2 The Main Theory

Standard postulated from classical trade theory and Ricardian ideas about comparative advantage imply that gains from exchange maximise welfare and that free trade enhances economic prosperity. Ricardo (1819) theorises this based on cost and technological differences while the Heckscher (1919)-Ohlin (1967)-Samuelson (1948) theoretical framework considers factor endowments and factor price differentials to explain this difference. Comparative advantage is a concept which has been used extensively in empirical research. A central idea underlying much of international trade theory remains the commodity pattern of comparative advantage. Even though comparative advantage is defined in terms of relative autarkic price relationships that are not observable in post-trade equilibria which leads to the notion of comparative advantage facing a measurement problem, this concept is widely employed. This problem arises because trade statistics reflect post-trade positions. In Ballance et al. (1987) a simple theoretical framework for understanding the notion of comparative advantage is outlined. Economic conditions (EC) in the various trading countries ultimately determine the international pattern of comparative advantage (CA). From this emergent pattern of CA, in turn, the pattern of trade, production and consumption (TPC) among countries is governed. Indices which are constructed from post-trade variables (such as TPC) can be employed to estimate comparative advantage and they are termed as ‘revealed’ comparative advantage (RCA) indices. The aforementioned causal indices are linked as follows [Ballance et al. (1987: 157)]:

\[ EC \rightarrow CA \rightarrow TPC \rightarrow RCA \] (1)

If we consider a two-country, two factor, two-product world, the application of this ‘model’ is straightforward, with deterministic relationships between CA and TPC. However, once we generalise to a world in which there are more than two countries, products or factors, the deterministic links between TPC and CA break down (Drabicki and Takayama, 1979). Deardoff (1980) presents a theoretical analysis which strongly supports the use of such methods in empirical work. Deardoff (1980) shows that under relatively general conditions there is a negative correlation between net exports and relative autarkic prices. This implies that there are limits to the extent to which the pattern of trade may depart from that identified in the deterministic specification of the model specified in equation 1. As a result, we can conclude that while comparative advantage may not be precisely measurable, indices based on real world post-trade observations may ‘reveal’ much about the underlying pattern of comparative advantage.

The principal hypothesis that we test relates to our three technological classifications which are LT, MT and HT (low, medium and high technology, respectively). As would be expected from basic Heckscher-Ohlin type ideas and the impact of learning by doing effects over time, we argue that if learning by doing occurs and skills upgradation takes place over two time periods for a given country (say \( t_1 \) and \( t_2 \)), we should then observe greater export shares for MT and HT exports as compared to LT based exports for an economy such as China. Provided a sufficiently long period of time, we would expect to see a movement upwards in terms of increasing technological sophistication of exports, which reflects learning by doing and experience effects[Young (1991)]. Consequently, over time, the share of HT export as a proportion of the total should rise, as should the share of MT exports and we should observe a smaller share for LT exports. As a result, with economic maturity we expect that:
where Prop LT is the proportion of LT based exports, Prop MT is the proportion of MT based exports and Prop HT is the proportion of HT based exports. Equation 2 is consistent with a growth process as a result of which we would observe greater growth in HT as compared to growth in MT and LT, and greater growth in MT as compared to LT. For instance, if we detect the largest possible gain for HT exports, that would be indicative of the highest level of upward movement in terms of technological sophistication of manufactured exports, and so on for the other groups. As a result, we investigate the hypothesis that learning by doing effects occur over time and skills upgradation occur over time, which should lead to a process of upgradation in terms of technology content of manufactured exports, which would be manifested in a increasing shares for high technology (HT) exports, as compared to medium technology (MT) and low technology (LT) exports, and increasing shares for medium technology exports as compared to low technology exports [see also, Sharma and Panagiotidis (2005) and Sharma and Dietrich (2007)]. Such phenomena have been observed for the case of other East Asian economies such as Korea and Taiwan [see Lall (2001)].

3 Data, Technology Sectors and Industries Employed

In this paper, we analyse manufacturing based export performance for 140 industries / product groupings at the three digit level of Standard Industrial Trade Classification (SITC) for China between 1980 and 2003. Standard Industrial Trade Classification (SITC) based export data has been used, which is available from the UNCTAD Handbook of Trade Statistics: 2005 and the largest number of usable manufactured export industries available are included (totalling 140 for China’s case). In the literature, the three digit level of SITC codes are conventionally understood to represent industry-level exports, and we follow this convention in this study also. Data obtained from the UNCTAD Handbook of Statistics 2005 itself collates data made available by national statistical agencies for China. An examination of trade data allows us to deduce the structural changes emergent in Chinese manufactured exports.

We analyse a matrix of product-industry groupings, which we subdivide into high technology (HT), medium technology (MT) and low technology (LT) categories and SITC product codes are used as a proxy for export industries [OECD (1994), Pavitt (1984) and Lall (2001)].\(^1\) We carry out detailed analysis for the HT, MT and LT sectors (and, of course, for the manufacturing sectors chosen as a whole as well). It is, of course, possible to refine these categories further by defining sub-categories (for instance, high-technology export sectors can be classified into two sub-sectors, the first encompassing a ‘higher’ technology definition than the second one), such subgroups are not always practically useful owing to the limited number of industries available and possible serious consequences arising through small-sample biases and general loss of degrees of freedom while undertaking statistical and econometric analysis. Consequently, in this paper we adopt a relatively aggregative approach or parsimonious approach.

\(^1\)The industries chosen for analysis as well as the technology groups are in listed in an Annexe to this paper.
4 METHODOLOGY

4 Methodology

4.1 Measuring trade specialisation

In this paper, we begin by estimating three ‘revealed’ comparative advantage indices.\(^2\) For any group of reference countries, the Balassa Index basically measures normalised export shares, where the normalisation is with respect to the exports of the same industry in the group of reference countries. Consequently [Hinloopen and van Marrewijk (2001: 4)], if \(X^A_j\) is country \(A\)’s export value of industry \(j\), \(X^{ref}_j\) is industry \(j\)’s export value for the group of reference countries, and we define \(X^i = \sum_j X^i_j\) for \(i = A, \text{ref}\), then country \(A\)’s Balassa Index (\(BI\)) of revealed comparative advantage for industry \(j\), \(BI^A_j\), equals:

\[
BI^A_j = \frac{X^A_j / X^A}{X^{ref}_j / X^{ref}}
\]  

(3)

If \(BI^A_j\) exceeds 1, country \(A\) is said to have a comparative advantage in industry \(j\), since this industry is more important for country \(A\)’s exports than the exports of reference countries. The Balassa Index, \(BI\), is thus based on observed trade patterns. It measures a country’s exports of a commodity relative to its total exports and relative to the corresponding export performance of a set of countries.

This approach has several limitations. For example, the Balassa Index’s value is asymmetric since it varies from one to infinity for commodities (or industries) in which a country has a revealed comparative advantage, but only from zero to one for commodities (or industries) with a comparative disadvantage, with a (weighted) average of 1.0. Consequently, if the mean of the Balassa Index is higher than the median, then the distribution of \(BI\) will be skewed to the right [Ferto and Hubbard (2003: 2)]. In a useful study, Hinloopen and van Marrewijk (2001) investigate the distribution of the Balassa Index for export performance of similar countries to a third market using European Union (12 countries) and Japan’s trade data, analysing the EU-12 as a group, and individual countries as well, between 1992 and 1996. They find that in all cases the Balassa index was found to be very skewed with a median well below one, a mean well above one, and a monotonically declining density function. Hinloopen and van Marrewijk (2001) conclude that analysing annual rather than monthly trade flows, or pooling values of the Balassa Index was seen to have only a mild influence on the distribution. The widely used criterion ‘\(BI > 1\)’ to identify sectors with an RCA was found to select one-third of the exporting industries. Nevertheless, the distribution of \(BI\) was found to differ considerably across countries, making comparisons across countries problematic. Dalum et al. (1998: 427) observe that a skewed distribution violates the assumption of normality of the error term in the regression analysis, which makes the \(t\)-statistics unreliable. Also, the use of the Balassa Index in regression analysis gives much more weight to values above one, as compared to observations below one.

In order to address the skewness problem, Dalum et al. (1998) formulate a revealed symmetric comparative advantage index (\(RSCA\)) which is:

\[
RSCA = \frac{BI - 1}{BI + 1}
\]  

(4)

\(^2\)For a more detailed discussion of the merits of various trade indices and their process of definition and development, please see Sharma and Dietrich (2007).
The values of the RSCA lie between [-1, +1] and avoid the problem of having to deal with zero values in logarithmic transformations of the Balassa index [when an arbitrary constant is not added to a (zero) BI value]. The main advantage of this approach is that it attributes changes below unity the same weight as changes above unity. But the main drawback is that forced symmetry does not necessarily imply normality in the error terms and it may hide some of the BI dynamics [Ferto and Hubbard (2003)].

A problem with the BI includes the fact that the arithmetic mean of the Balassa Index across sectors is not necessarily equal to one [Proudman and Redding (2000)]. The numerator of equation 3 is unweighted by the share of total exports accounted for by a product group, while the denominator is a weighted sum of export shares of all commodities. As a result, if a country’s trade pattern is described by high export shares in a few sectors which account for a small share of exports to the reference market, this implies high values for the numerator of the Balassa Index and low values for the denominator. This leads to a mean value of BI above one for a given country. Furthermore, average values of BI may change over time, hence misleading conclusions may be drawn about a country’s average extent of specialisation based on the Balassa Index. To address this issue, Proudman and Redding (2000) propose an alternative RCA measure where a country’s export share in a given product group is divided by its mean export share in all product groups, so that, for exports in the jth sector from country A, there being n sectors in all, we have:

$$BPR^A_j = \frac{X^A_j}{\frac{1}{n} \sum_j (X^A_j / \sum_A X^A_j)}$$

(5)

The mean value of this normalised BI given by BPR in equation 5 is constant and equal to one. BPR thus normalises the BI measure by its cross-section mean in order to abstract from changes in the average extent of specialisation. Ferto and Hubbard (2003: 3) point out that the normalised BI index (i.e. the BPR index) loses its consistency with respect to the original BI, because it may display the opposite status when BI value falls in the range between one and its mean.

Proudman and Redding (2000) also use a method of graphical analysis to assess the evolution of the BPR Index (given in equation 5) over time. In their method, industries are first ordered in terms of increasing values of moving averages of the BPR Index over a period of time and deviations of the BPR index from the value of 1 are graphed. By using such figures, information concerning intra-distribution dynamics is revealed. If patterns of internationalisation in a given economy exhibit persistence, one would expect the distribution of the BPR index to remain similar across successive time periods. Industries with high values in one period of time (initial time period) would also have high RCA values in the end period. A complete absence of specialisation corresponds to an equal share of exports in all sectors which implies that we would observe a BPR index value of 1 in all sectors with zero standard deviation. If an economy were increasingly specialising in a subset of industries, one would observe BI (or its proxy such as the BPR index) systematically increasing in specific sectors and systematically decreasing in others. The distribution of a revealed comparative advantage index would therefore exhibit an increasing mass at extreme values of the RCA index.
### 4.2 Analysing industrial structural transformation

It is a well known stylised fact that technological accumulation and the pattern of industrial comparative advantage often remain fairly stable over time, for firms in any given national industry, especially if sunk costs and long gestation period are involved. In order for revealed comparative advantage to show such persistence patterns, it would be reasonable to suppose that RCA indices and transforms such as the RSCA indices would also remain fairly stable over time. If the RSCA index is calculated for a national group of firms at two different points in time, then these two sectoral distributions of revealed symmetric comparative advantage should be positively correlated with one another. However, since the nature of innovative activity changes over time, the degree of correlation is likely to fall, the further apart are the two groups of years under consideration. We can employ a Galtonian (1889) regression model which is a statistical technique for bivariate distributions. This approach was originally used by Hart and Prais (1956), who used it to analyse size distributions of firms. Other context within which this technique has been used include Cantwell (1989) for technological innovations in industry, by Hart (1976) and Creedy (1985) for income distribution in the UK, and by Sutcliffe and Sinclair (1980) for the case of seasonality of tourist arrivals in Spain.\(^3\)

Within industrial structural transformation and evolution of revealed comparative advantage, the correlation between the sectoral distribution of the RSCA index at time \(t_2\) and at an earlier time period \(t_1\) is estimated through the simple cross-section regression represented by:

\[
RSCA_{t2}^{t2}jA = \alpha_j + \beta_j RSCA_{t1}^{t1}jA + \varepsilon_{jA}
\]

where superscripts \(t1\) and \(t2\) describe the initial year and the final year (for analysis), respectively. The dependent variable, RSCA at time \(t2\) for sector \(j\) in country \(A\), is tested against the independent variable which is the value of the RSCA in the initial year \(t1\). \(\alpha\) and \(\beta\) are standard linear regression parameters. Equation 6 is estimated for a given country. In this analysis it is assumed that the regression is linear and that the residual \(\varepsilon_{jA}\) is stochastic \([\varepsilon_{jA} \sim N(0, \sigma)]\) and independent of \(RSCA_{t1}^{t1}jA\) (independent identically distributed or iid). If \(\beta = 1\), this suggests an unchanged pattern of RSCA between periods \(t1\) and \(t2\). If \(\beta > 1\), the country tends to be more specialised in product groups in which it already specialised, and it is less specialised in those industries where initial specialisation is low for a graphical derivation of these ideas, see Cantwell (1989)]. In other words, the initial specialisation of the country is strengthened. If \(0 < \beta < 1\), then commodity groups with low (negative) initial RSCA indices grow over time, and/or groups with high (positive) initial RSCA indices decline. The special case where \(\beta < 0\) indicates a change in the sign of the index. As Dalum et al. (1998) point out, \(\beta > 1\) is not a necessary condition for growth in the overall specialisation pattern. This is valid if the cross-industry RSCA index at each point in time approximately conforms to a normal distribution.

By employing such an analysis of the RSCA distribution, we facilitate a simple test of changes in the degree of revealed symmetric comparative advantage. The degree of revealed symmetric comparative advantage in a country can be measured by the variance of its RSCA index, which shows the extent of the dispersion of the distribution around the mean. Pavitt (1987) used the standard deviation of an analogous concept, the

\(^3\)See also, Brasili et al. (2000).
revealed technological advantage (RTA) index as a measure of such specialisation. Such analysis can be extended to the preceding RSCA regression analyses, where the standard deviation of the RSCA index can be identified as a measure of such revealed symmetric comparative advantage. The procedure for estimating changes in the variance of the distribution over time follows from Hart (1976) and Cantwell (1989). Taking equation 6, if the variance of the RSCA index at time $t_2$ is denoted by $(\sigma_{t_2})^2$ then:

$$ (\sigma_{t_2})^2 = \beta_j^2 (\sigma_{t_1})^2 + \sigma_{\varepsilon}^2 $$

(7)

where $\beta_j^2$ is the square of the regression coefficient (from equation 6), $\sigma_{t_1}^2$ is the variance of the RSCA index at time $t_1$ and $\sigma_{\varepsilon}^2$ is the variance of the error term. The coefficient of determination $R_j^2$ is given by:

$$ R_j^2 = 1 - \left( \frac{(\sigma_{\varepsilon})^2}{(\sigma_{t_2})^2} \right) = \left( (\sigma_{t_2})^2 - \sigma_{\varepsilon}^2 \right) \left( \frac{1}{(\sigma_{t_2})^2} \right) $$

(8)

Combining equations 7 and 8 gives us:

$$ (\sigma_{t_2})^2 - \sigma_{\varepsilon}^2 = \beta_j^2 (\sigma_{t_2})^2 = R_j^2 (\sigma_{t_2})^2 $$

(9)

Equation 9 can be rewritten to show the relationship between the variance of the two distributions as follows:

$$ (\sigma_{t_2})^2 / (\sigma_{t_1})^2 = \beta_j^2 / R_j^2 $$

(10)

This can be simplified to:

$$ \sigma_{t_2} / \sigma_{t_1} = |\beta_j| / |R_j| $$

(11)

$R_j$ is the square root of the coefficient of determination, obtained from the regression, and $\sigma^2$ is the variance of the dependent variable. From equation 11 we can see that the degree of trade specialisation rises when $\beta_2 > R_2$, and it falls when $\beta_2 < R_2$. A high variance of the distribution of RSCA indices over time indicates a high variance in specialisation or narrow degree of specialisation, while a low variance indicates that the country has a broad range of technological advantage/specialisation or a low variance of specialisation. Using the estimated regression values, the extent of specialisation rises if $|\beta_j / R_j| > 1$, whereas if $|\beta_j / R_j| < 1$, specialisation decreases.

We can interpret the estimated coefficient ($\hat{R}$) as a measure of the mobility of industries up and down the RSCA distribution. If we observe a high value of $\hat{R}$, it indicates that the relative position of industries is little changed, while a low value indicates that some industries are moving closer together and others further apart, quite possibly to the extent that the ranking of industries changes. The magnitude of $(1 - \hat{R})$ thus measures what is described by Cantwell (1989) as the ‘mobility effect’. The ‘mobility effect’ would capture the tendency of the rankings of the firm export specialisation altering over time. On the other hand, the ‘Galtonian’ effect would capture any tendency of reversion towards the mean for the distribution as a whole. It may well be that even where the regression effect suggests a fall in the degree of specialisation due to a proportional move in industries towards the average ($\beta < 1$), that is outweighed by the mobility effect, due to changes in the proportional position between industries ($\beta > R$).

---

4 Pavitt built upon the work of Soete (1980 and 1987) who initially analysed the variance of RTA indices.

5 Analogously, the extent of specialisation rises where $|\hat{\beta}_j| > |\hat{R}_j|$, and it falls where $|\hat{\beta}_j| < |\hat{R}_j|$. 


5 Empirical Results

5.1 Graphical analysis

We first employ a technique based on Proudman and Redding’s (2000) approach, and we carry out a graphical analysis of a transform of the Balassa Index (see equation 5) that they propose, to employ a more efficient measure of trade specialisation. We focus on six time points: 1980, 1985, 1990, 1995, 2000 and 2003. Results for only presented for 1985 and 1995 for our graphical analysis to examine additional trends in intervening periods. In the main, trends in our comparator period, 1980-1990, are compared to three additional periods (i) 1990-2000, (ii) 1990-2003 and (iii) 1980-2003. Since China’s economic reforms were initiated in 1978, a comparison of the latter periods (1990 to 2000, 1990 to 2003 and 1980 to 2003) would hopefully be ‘long’ enough to reveal (at least the initial) impact of liberalisation on the structure of China export industries, as against the immediate post-reform decade (1980 to 2000) which would serve as a comparator period and as a period where China economies were greatly influenced by the autarkic policies and import-substituting industrialisation prior to the 1978 reforms. An assumption here, of course, is that the initial and long-term trends are in the same direction. All the figures based on BPR estimations are drawn to the same scale to facilitate visual comparison. Industries are first ordered in terms of increasing values of moving averages of the BPR index over a period of time and deviations of the BPR index from the value of 1 are graphed. Such figures reveal information concerning intra-distribution dynamics. If patterns of internationalisation in a given economy exhibited persistence, one would expect the distribution of the BPR index to remain similar across successive time periods. Industries with high values in one period of time (initial time period) would also have high RCA values in the end period. A complete absence of specialisation corresponds to an equal share of exports in all sectors which implies that we would observe a BPR index value of 1 in all sectors with zero standard deviation. If an economy were increasingly specialising in a subset of industries, one would observe BI (or its proxy such as the BPR index) systematically increasing in specific sectors and systematically decreasing in others. The distribution of a revealed comparative advantage index would therefore exhibit an increasing mass at extreme values of RCA.

The results of our graphical analysis are presented in Figures 1, 2, 3 and 4. For each respective figure, the same scale has been used on the y-axis to facilitate easy comparison. In Figure 1 we can see the results of our analysis for ALL manufactured based exports for China for six years. There is clear visual evidence for industrial structural change. We can see that, over time, more industries exhibit specialisation. This is particularly true over decades: specialisation in the 2000s is more pronounced than specialisation in the 1990s, which is itself higher than for the 1980s. Over time we clearly observe thickening in the right tails. However, 2003 seems to show a degree of despecialisation as compared to 2000, and this may be partly explained by influence of the bursting of the so called ‘dot com bubble’ in 2000 and the resulting fall in demand. The early 2000s also saw mild recession in developed economies. For the case of LT export (Figure 2), there are very similar trends, but we observe more stark changes. For instance, there is evidence of a high degree of specialisation in the 1990s compared to the 1980s, but this

\footnotesize

\textsuperscript{6}Unlike Proudman and Redding (2000), owing to limited data being available and the possibility of loss of several degrees of freedom, we do not employ five yearly moving averages, but we use BPR index values for six time points, the years being 1980, 1985, 1990, 1995, 2000 and 2003.
contrast is especially vivid for 1995 compared with 1980. This growth is sustained until 2000, but there is a fall in the extent of specialisation in 2003.

In Figure 3, we observe evidence for increased specialisation patterns in 2000s for MT exports (especially 2000), but there are spikes for 1990 as well, and falls in specialisation in 2003 as compared to 2000. There is virtually no specialisation in 1985. For the HT sector also, we observe increased specialisation in 2000 and a decline in 2000. There is virtually no specialisation observed in 1985, but the sharpest peaks emerge in 1990. All this visual evidence points towards two things. First, there is a significant and ongoing process of industrial restructuring occurring in Chinese manufactured exports. Secondly, there is strong evidence for increasing specialisation in ALL industries and individually for LT, MT and HT, especially in the 1990s and the year 2000.
Figure 2: China’s Manufactured Exports: LT
Figure 3: China’s Manufactured Exports: MT
Figure 4: China’s Manufactured Exports: HT
5 EMPIRICAL RESULTS

5.2 Regression analysis

We begin our regression analysis by looking at the chosen manufacturing based export sectors as a whole.\(^7\) We employ the revealed symmetric comparative advantage (RSCA) index specified in section 4 and for reasons cited there. Following Hart and Prais (1956), Cantwell (1989), Dalum, Laursen and Villumsen (1998) and Hinloopen and van Marrewijk (2001), regression analysis on the RSCA indices is used to further analyse structural change.\(^8\) We use the specification set out in equation 6, viz.:

\[
RSCA_{t2jA} = \alpha_j + \beta_j RSCA_{t1jA} + \varepsilon_{jA}
\]

As mentioned previously, if \(\beta = 1\), this suggests an unchanged pattern of RSCA between periods \(t1\) and \(t2\). If \(\beta > 1\), the country tends to be more specialised in product groups in which it already specialised, and it is less specialised in those industries where initial specialisation is low. In other words, the initial specialisation of the country is strengthened. From equations 10 and 11 it follows that the pattern of a given distribution remains unchanged when \(\beta = R\). If \(\beta > R\) then the degree of specialisation has grown, while if \(\beta < R\) then the degree of specialisation has decreased.

5.3 Specialisation and despecialisation

Table 1 presents a summary of the results we obtain. Through our analysis [results in Table 1] we are able to examine whether \(\beta\) is greater than, less than or equal to 1. In Table 2 we present some conclusions about specialisation/ despecialisation patterns.

<table>
<thead>
<tr>
<th></th>
<th>AI</th>
<th>LT</th>
<th>MT</th>
<th>HT</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\beta)</td>
<td>0.8185*</td>
<td>0.7420</td>
<td>0.7252*</td>
<td>0.7211</td>
</tr>
<tr>
<td>(R)</td>
<td>0.6594*</td>
<td>0.6511</td>
<td>0.5393***</td>
<td>0.5620</td>
</tr>
<tr>
<td>(\beta)</td>
<td>0.7873*</td>
<td>0.7527</td>
<td>0.8240*</td>
<td>0.8233</td>
</tr>
<tr>
<td>(R)</td>
<td>0.6461</td>
<td>0.5289***</td>
<td>0.5361</td>
<td></td>
</tr>
<tr>
<td>(\beta)</td>
<td>0.6018*</td>
<td>0.5083</td>
<td>0.6318*</td>
<td>0.6032</td>
</tr>
<tr>
<td>(R)</td>
<td>0.4333**</td>
<td>0.4333**</td>
<td>0.0820</td>
<td>0.1025</td>
</tr>
<tr>
<td>(\beta)</td>
<td>0.7470*</td>
<td>0.6961</td>
<td>0.8489*</td>
<td>0.8150</td>
</tr>
<tr>
<td>(R)</td>
<td>0.5842</td>
<td>0.2654</td>
<td>0.3176</td>
<td></td>
</tr>
</tbody>
</table>

*: For each table, significant at the 99% confidence interval.
**: For each table, significant at the 95% confidence interval.
***: For each table, significant at the 90% confidence interval.

Table 2 indicates evidence for a reduction in specialisation of China’s export industries for all periods considered. This implies that for all categories taken collectively, (and for all periods) there is evidence suggesting declining comparative advantage or despecialisation.

We derive Table 3 from Table 1. A comparison of the value of \(\beta\) with \(R\) is presented in Table 3, using our decision rules. The results obtained are very striking. There is strong evidence indicating increasing specialisation for every period being considered for ALL industries, LT and MT, but not for HT exports. HT exports exhibit despecialisation. These results can be contrasted with the case of India [Sharma and Dietrich (2007)].

\(^7\)We use R 2.5.1 and Sweave for our analysis (www.r-project.org).

\(^8\)The complete regression output is available from the authors.
Table 2: $\beta$ Compared to Unity (AI, LT, MT and HT) (Galtonian ‘reversion to the mean’)

<table>
<thead>
<tr>
<th></th>
<th>AI Result</th>
<th>LT Result</th>
<th>MT Result</th>
<th>HT Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980-1990</td>
<td>$\beta &lt; 1$</td>
<td>$\beta &lt; 1$</td>
<td>$\beta &lt; 1$</td>
<td>$\beta &lt; 1$</td>
</tr>
<tr>
<td>1990-2000</td>
<td>$\beta &lt; 1$</td>
<td>$\beta &lt; 1$</td>
<td>$\beta &lt; 1$</td>
<td>$\beta &lt; 1$</td>
</tr>
<tr>
<td>1980-2003</td>
<td>$\beta &lt; 1$</td>
<td>$\beta &lt; 1$</td>
<td>$\beta &lt; 1$</td>
<td>$\beta &lt; 1$</td>
</tr>
<tr>
<td>1990-2003</td>
<td>$\beta &lt; 1$</td>
<td>$\beta &lt; 1$</td>
<td>$\beta &lt; 1$</td>
<td>$\beta &lt; 1$</td>
</tr>
</tbody>
</table>

D: Despecialisation; I: (Improved) specialisation

Table 3: Comparison of $\beta$ and $R$ Values (AI, LT, MT and HT) (Cantwell’s ‘mobility’ effect)

<table>
<thead>
<tr>
<th></th>
<th>AI Result</th>
<th>LT Result</th>
<th>MT Result</th>
<th>HT Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980-1990</td>
<td>$\beta &gt; R$</td>
<td>$\beta &gt; R$</td>
<td>$\beta &gt; R$</td>
<td>$\beta &lt; R$</td>
</tr>
<tr>
<td>1990-2000</td>
<td>$\beta &gt; R$</td>
<td>$\beta &gt; R$</td>
<td>$\beta &gt; R$</td>
<td>$\beta &lt; R$</td>
</tr>
<tr>
<td>1980-2003</td>
<td>$\beta &gt; R$</td>
<td>$\beta &gt; R$</td>
<td>$\beta &gt; R$</td>
<td>$\beta &lt; R$</td>
</tr>
<tr>
<td>1990-2003</td>
<td>$\beta &gt; R$</td>
<td>$\beta &gt; R$</td>
<td>$\beta &gt; R$</td>
<td>$\beta &lt; R$</td>
</tr>
</tbody>
</table>

D: Despecialisation; I: (Improved) specialisation

5.4 Wald tests

We perform Wald tests to test restriction on the coefficients estimated through equation 6 as follows:

Test 1: Null hypothesis $H_{11} : \beta = 1$ (Alternative: $H_{10} : \beta \neq 1$)

Test 2: Null hypothesis $H_{21} : \beta = R$ (Alternative: $H_{20} : \beta \neq R$)

In Table 4, we test $H_{11}$ using a Wald Test for AI, LT, MT and HT, respectively. An examination of Table 4 shows us that the test results are significant at least at the 90% confidence interval, except for LT export for 1990-2003. We can thus reject the null hypothesis that $\beta = 1$ for all cases considered at least at the 5% significance level. The conclusion is that we do not find evidence to support $H_{11}$, which implies that $\beta$ is statistically different from 1.

In Table 5, we test $H_{21}$ using a Wald test for AI, LT, MT and HT, respectively. An examination of Table 5 shows us that the test results are not statistically significant for all the cases and time periods under consideration. We can thus not reject the null hypothesis that $\beta = R$ for all cases considered. The conclusion is that we do not find evidence which would lead to a rejection of $H_{21}$, which tests whether $\beta$ is statistically different from $R$. Results obtained are insignificant for 1980-90 and 1990-2003 (ALL); 1990-2000 and 1990-2003 (LT); and 1980-1990 (MT). They are significant for all other cases.
6 Concluding comments

We examine export data for export industries for China at the 3-digit SITC level for the period 1980-2003, in order to examine the initial effects of China’s trade reforms and market based liberalisation process on the structure of China’s export industries. We employ Proudman and Redding’s (2000) graphical technique in order to visualise the process of industrial change for China. Through both the graphical analysis and our analysis of mean RSCA values, we conclude that China’s export industries are undergoing a process of transformation and evidence suggests that during the post reform period (after 1978), a significant (and perhaps) ongoing process of industrial transition has been happening, which has accompanied the decision by China to liberalise trade and to move from a closed, autarkic economy to becoming an open ‘marketised’ economy. Our graphical pre-test shows vivid signs of patterns of specialisation emerging across all manufactured exports and especially within low technology manufactured exports. These conclusions are consistent with the results of our more formal econometric analysis.

Our results are derived from about twenty three years of the post-reform period and this seems to be a reasonably ‘long’ period to capture the initial effects of a process of industrial transformation and reform in Chines manufactured export industries. That notwithstanding, we know that industrial transformation if often a gradual process and it may well be accompanied by transitional, short-term effects which may well change over time. It seems plausible to expect ceteris paribus, that trends towards strengthening comparative advantage and some industries despecialising, would eventually coincide with some declining firms exiting from the export sector, so that comparative advantage indicators would eventually show a greater rise. As more time elapses and more observations become available, it would become possible to assess this process more completely, especially if steady-state equilibria are exhibited in the technology based subsets that we have examined. Finally, if we assume that China’s long neglected service sector industries begin to show signs of greater growth (in relatively slowly growing information technology sector) and as more data becomes available, it would be possible to ascertain to what extent overall gains in comparative advantage in manufacturing, in terms of specialisation trends, are accompanied with increasing specialisation patterns in the services sector and in medium and high technology manufacturing. In other words, future research using more data could assess empirical evidence relating to the impact of such experience and learning effects, as well as the impact of technology transfers within China, as the economy becomes more open to trade.
References


REFERENCES


[31] Sharma, Abhijit. (2005), Structure and Composition of India’s Exports With Special Reference to India’s Post-Liberalisation Period, PhD thesis (mimeo), Department of Economics: University of Sheffield.


Table 4: Wald Test 1: Null hypothesis: $\beta = 1$

<table>
<thead>
<tr>
<th>Category: All Industries</th>
<th>F-stat</th>
<th>F-stat</th>
<th>Value</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980-1990</td>
<td>8.2494</td>
<td>0.0004129*</td>
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<td></td>
</tr>
<tr>
<td>1990-2000</td>
<td>20.094</td>
<td>2.193e-08*</td>
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<td></td>
</tr>
<tr>
<td>1990-2003</td>
<td>16.467</td>
<td>3.859e-07*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1980-2003</td>
<td>11.01</td>
<td>3.661e-05*</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Category: Low Technology (LT) Industries</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-stat</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td>1980-1990</td>
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<tr>
<td>1990-2000</td>
</tr>
<tr>
<td>1990-2003</td>
</tr>
<tr>
<td>1980-2003</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Category: Medium Technology (MT) Industries</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-stat</td>
</tr>
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<td>-------</td>
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<td>1990-2000</td>
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<tr>
<td>1990-2003</td>
</tr>
<tr>
<td>1980-2003</td>
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</table>

<table>
<thead>
<tr>
<th>Category: High Technology (HT) Industries</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-stat</td>
</tr>
<tr>
<td>-------</td>
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<tr>
<td>1990-2000</td>
</tr>
<tr>
<td>1990-2003</td>
</tr>
<tr>
<td>1980-2003</td>
</tr>
</tbody>
</table>

*: For each table, significant at the 99% confidence interval.
**: For each table, significant at the 95% confidence interval.
***: For each table, significant at the 90% confidence interval.
Table 5: **Wald Test 2: Null hypothesis:** $\beta = R$

<table>
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</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>Probability</td>
<td></td>
</tr>
<tr>
<td>1980-1990</td>
<td>1.4194</td>
<td>0.2454</td>
</tr>
<tr>
<td>1990-2000</td>
<td>16.631</td>
<td>3.38e-07*</td>
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<tr>
<td>1990-2003</td>
<td>12.871</td>
<td>7.494e-06*</td>
</tr>
<tr>
<td>1980-2003</td>
<td>2.4218</td>
<td>0.09253</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Category: Low Technology (LT) Industries</th>
<th>F-stat</th>
<th>F-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>Probability</td>
<td></td>
</tr>
<tr>
<td>1980-1990</td>
<td>11.030</td>
<td>7.66e-05*</td>
</tr>
<tr>
<td>1990-2000</td>
<td>1.6874</td>
<td>0.1931</td>
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<tr>
<td>1990-2003</td>
<td>0.5516</td>
<td>0.5788</td>
</tr>
<tr>
<td>1980-2003</td>
<td>6.3961</td>
<td>0.002935**</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Category: Medium Technology (MT) Industries</th>
<th>F-stat</th>
<th>F-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>Probability</td>
<td></td>
</tr>
<tr>
<td>1980-1990</td>
<td>2.0881</td>
<td>0.1336</td>
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<td>1990-2000</td>
<td>14.080</td>
<td>1.155e-05*</td>
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<td>1990-2003</td>
<td>13.717</td>
<td>1.469e-05*</td>
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<tr>
<td>1980-2003</td>
<td>10.482</td>
<td>0.0001391*</td>
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</table>

<table>
<thead>
<tr>
<th>Category: High Technology (HT) Industries</th>
<th>F-stat</th>
<th>F-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>Probability</td>
<td></td>
</tr>
<tr>
<td>1980-1990</td>
<td>9.2791</td>
<td>0.002383**</td>
</tr>
<tr>
<td>1990-2000</td>
<td>11.078</td>
<td>0.001110**</td>
</tr>
<tr>
<td>1990-2003</td>
<td>9.6554</td>
<td>0.002018**</td>
</tr>
</tbody>
</table>

*: For each table, significant at the 99% confidence interval.
**: For each table, significant at the 95% confidence interval.
***: For each table, significant at the 90% confidence interval.
Annexe: List of SIC Industries

LOW TECHNOLOGY (LT)
281 Iron ore and concentrates
282 Iron and steel scrap
287 Base metals ores, conc nes
288 Non-ferrous metal scrap nes
289 Prec metal ores, waste nes
323 Briquettes, coke and semi-coke
334 Petroleum products, refined
335 Residual petroleum prdts nes
411 Animal oils and fats
511 Hydrocarbons nes, derivtives
514 Nitrogen-function compounds
515 Organo-inorgan compounds, etc
516 Other organic chemicals
522 Inorg chem elmnt, oxides, etc
523 Other inorganic chemicals
531 Synth dye, natrl indigo, lakes
532 Dyes nes, tanning products
551 Essential oils, perfume, etc
592 Starch, inulin, gluten, etc
661 Lime, cement and building prdts
662 Clay, refractory building prdts
663 Mineral manufactures nes
664 Glass
677 Iron, steel wire, exc w rod
679 Iron, steel casings unworked
611 Leather
612 Leather, etc, manufactures
613 Fur skins tanned, dressed
651 Textile yarn
652 Cotton fabrics, woven
654 Other woven textile fabric
655 Knitted, etc, fabric
656 Lace, ribbon, tulle, etc
657 Spec textile fabrics, products
658 Textile articles nes
659 Floor coverings, etc
831 Travel goods, handbags, etc
842 Men's outwear non-knit
843 Women's outwear non-knit
844 Under garments non-knit
845 Outer garments knit nonelastic
846 Under garments knitted
847 Textile clothing accessoris nes
848 Headgear, non-textile clothing

MEDIUM TECHNOLOGY (MT)
266 Synthetic fibres for spinning
512 Alcohols, phenols, etc
513 Carboxylic acids, etc
533 Pigments, paints, varnishes etc
553 Perfumery, cosmetics, etc
554 Soap, cleansing, etc preps
562 Fertilizers, manufactured
572 Explosives, pyrotechnic prdts
582 Prdts of condensation, etc
583 Polymerization, etc, prdts
584 Cellulose, derivatives, etc
585 Plastic materials nes
591 Pesticides, disinfectants
598 Miscel chemical prdts nes
653 Woven man-made fib fabric
671 Pig iron, etc
672 Iron, steel primary forms
678 Iron, steel tubes, pipes, etc
786 Trailers, non-motor vehicl nes

851 Footwear
642 Paper and paperboard, cut
665 Glassware
666 Pottery
673 Iron, steel shapes, etc
674 Iron, steel univ, plate, sheet
676 Railway rails etc, iron, steel
691 Structures and parts nes
692 Metal tanks, boxes, etc
693 Wire products, non-electric
694 Stell, copper nails, nuts, etc
695 Tools
696 Cutlery
697 Base metal household equip
699 Base metal manufactures nes
821 Furniture and parts thereof
893 Articles of plastic nes
894 Toys, sporting goods, etc
895 Office supplies nes
897 Gold, silver ware, jewellery
898 Musical instruments and parts
899 Other manufactured goods
21 Railway vehicles
23 Ships, boats, etc
812 Plumbg, heatg, lightg equip
822 Photogr and cinema supplies
711 Steam boilers and auxil parts
713 Intern combust piston engines
714 Engines and motors nes
721 Agricult machinry exc tractor
722 Tractors non-road
723 Civil engineering equip, etc
724 Textile, leather machinery
725 Paper etc mill machinery
726 Print and bookbind machy, parts
727 Food machinery, non-domestic
728 Oth machy for spec industries
736 Metal working machy, tools
737 Metal working machinery nes
741 Heating, cooling equipment
742 Pumps for liquids, etc
743 Pumps nes, centrifuges, etc
744 Mechanical handling equipment
745 Non-electr machy, tools nes
749 Non-electr machy parts, acces
751 Office machines
752 Automatic data processing equip
759 Office, adp machy parts, acces
761 Television receivers
764 Telecom equip, parts, acces
771 Electric power machinery nes
774 Electro-medical, xray equip
776 Transistors, valves, etc
778 Electrical machinery nes
524 Radioactive etc materials
541 Medicinal, pharmaceutical prdts
792 Aircraft, etc
871 Optical instruments