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Functional upgrading in China’s export processing sector

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Functional Upgrading in China's Export Processing Sector*

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Abstract

Functional upgrading occurs when a firm acquires more sophisticated functions within an existing value chain. In this paper, we analyze if there is evidence of this type of upgrading in China's export processing regime by investigating dynamics in the relative prevalence of Import & Assembly (IA) versus Pure Assembly (PA) processing trade over the period 2000-2013. Firms in both regimes provide similar manufacturing services to foreign companies, but IA firms also conduct the sophisticated tasks of quality control, searching, financing and storing imported materials. Consistent with a trend of functional upgrading, we show that the share of IA trade in total processing trade has increased rapidly during the period 2000-2006, both overall and within product categories. Furthermore, we find that this trend has gone hand in hand with improvements in a sector's labor productivity and unit values. Against expectations, we find that this process has slowed down notably during the period 2006-2013.

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1. INTRODUCTION

China's integration in global value chains (GVCs) has since long captured the imagination of trade and development economists. From the onset of its reforms and associated opening up to the global economy in the early eighties, China has made the attraction of labor-intensive export processing activities a key element of its export-led development strategy (Naughton, 2006). Abundant supplies of low-cost labor as well as an undervalued currency contributed to China's comparative advantage in low-skilled export processing activities (Hanson, 2012).

Decades of rapid economic growth highlight the success of this strategy, but now threatens to undermine China's traditional position as labor-intensive export assembler in GVCs. The country's comparative advantage in low-skilled manufacturing has been gradually eroded by rising labor costs, especially in the coastal provinces, and by currency appreciation (Ceglowski and Golub, 2012). If exports are to contribute to future growth, it is believed that export processing firms in China will have to move up the value chain and specialize in more capital- and skill-intensive activities (Lin and Chang, 2009). This is particularly important if China is to avoid the middle-income trap and gain a comparative advantage producing more sophisticated goods and activities.

There are three ways that China's export processing sector can upgrade its export activities: by specializing in more capital- and skill-intensive industries (*industry upgrading*), by moving to more capital- and skill-intensive product lines within industries (*quality or product upgrading*), or by shifting towards more capital- and skill-intensive tasks within product lines (*functional upgrading*).[1] Recent empirical work already provides evidence for the first two types. Consistent with *industry upgrading*, Amiti and Freund (2010) show that the composition of China's processing exports has rapidly shifted towards more skill-intensive industries, whereas Rodrik (2006) and Schott (2008) demonstrate that China's export mix increasingly overlaps with that of developed countries. In line with *quality upgrading*, Wang and Wei (2010) show that the unit values of Chinese processing exports have risen over time as processing firms have moved into more sophisticated product lines within industries.[2]

In this paper we investigate whether we can also find evidence for *functional upgrading* in China's export processing sector. Humphrey and Schmitz (2002) define functional upgrading as a firm's acquisition of new and more sophisticated functions within an existing value chain that are more capital- or skill-intensive. This type of upgrading is difficult to measure with traditional trade and production data since information on the type of value chain activities that export processing

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[1] Export success can also result from *process upgrading*, i.e. producing the same products more efficiently. Sustained productivity growth can lower variable costs and boost a country's global market share and there is ample evidence this has happening for China, see Brandt et al. (2012). Even though this can require investment in process innovations, it does not represent "upgrading" in terms of international trade which we focus on specifically.

[2] While industry and product (quality) upgrading are in principle distinct processes, the extent they can be separated empirically depends on the detail in the industry and product classifications used.

firms conduct is not typically collected. Instead, we propose to measure functional upgrading by analyzing trends in the relative prevalence of two types of export processing trade in China: Pure Assembly (PA) and Import & Assembly (IA).[3] Under both regimes, firms in China provide manufacturing services to foreign companies using imported inputs. Under IA, however, firms have the extra responsibility of searching, obtaining, performing quality control, and paying for the imported intermediates prior to conducting their manufacturing functions. These additional value chain functions generally require more sophisticated competencies related to the governance of supply relationships, inventory management and quality control management (Bair and Gereffi, 2001; Ponte and Sturgeon, 2014). In line with this, Manova and Yu (2016) provide evidence that, controlling for firm characteristics, industry fixed effects and province fixed effects, IA-type firms are more capital-intensive, material-intensive, productive and pay higher average wages than PA-type firms. We thus propose to measure functional upgrading in China's export processing regime by analyzing dynamics in the share of IA-type export processing within a product category's total processing trade.[4]

We conduct the empirical analysis in three steps. First, we investigate whether the prevalence of IA-type export processing has increased significantly over the 2000-2013 period. Previewing our empirical results, we show that China's export processing sector has embarked on rapid functional upgrading both overall and within product categories during the pre-crisis period 2000-2006. However, we also show that functional upgrading slowed down considerably after 2006. Given China's ongoing transition from an investment, export, and assembly-driven economy to one that places greater emphasis on services and innovation, this slow-down was unexpected. The short time period following the Great Recession makes it impossible to ascertain whether it represents a temporary or a more structural change.

Next, we evaluate the drivers of functional upgrading by investigating for which sectors, regions, or ownership types the shift toward IA-type export processing was most pervasive. We find that functional upgrading was particularly strong in sectors where upstream industries previously experienced above average export growth. Such growth makes the information advantage in local sourcing more valuable and thus it is not surprising that Chinese partners in export processing relationships gain more responsibilities. We further show that functional upgrading was particularly strong for State-Owned Enterprises (SOEs) which are gradually catching up to private and foreign-invested firms. Firms located in inner provinces have also been functionally upgrading faster than those in coastal provinces, again reflecting a catching-up process. This functional convergence between firms of different ownership types or located in different regions mirrors a similar convergence in productivity.

Finally, we analyze to what extent functional upgrading goes hand in hand with broader improvements in a sector's economic performance. We show that stronger than average growth in

[3] In the next section we provide additional details on the nature of the PA-IA distinction.
[4] We acknowledge that this is only one of several ways to measure functional upgrading.

a sector's IA share is correlated with stronger than average growth in a sector's labor productivity. This pattern does not hold for total factor productivity, suggesting that functional upgrading is associated with capital deepening. Growth in a sector's IA share is strongly correlated with growth in a sector's unit values, suggesting a link between functional upgrading and quality upgrading. Finally, we find only very weak evidence of a relationship between functional upgrading and industry upgrading which we measure from the compositional shift of exports towards more sophisticated industries within a broader sector. While we need to be careful in interpreting the direction of causality, these results suggest that functional upgrading may well enhance export processing firms to integrate into more sophisticated GVCs both within and across industries.

Our work is related to several literatures. We build on studies in the field of GVC governance which have relied on case study evidence to demonstrate the existence of functional upgrading. Bair and Gereffi (2001) document how Mexican-owned companies producing jeans in Torreon (Mexico) have over time upgraded from being low-end maquila assemblers to full-package manufacturers responsible for acquiring the inputs and coordinating all parts of the production process (purchase of textiles, cutting, garment assembly, laundry and finishing, packaging and distribution). Sturgeon and Lee (2005) illustrate that Taiwanese contract manufacturers in the electronics industry have over time extended their activities beyond assembly to include product redesign for manufacturability, component purchasing, test routine development, global logistics, distribution, and after-sales services and repair. Pavlinek and Zenka (2011) document that assemblers in the Czech automotive industry have over time become increasingly involved in R&D activities. Specifically focusing on the Chinese automotive industry, Brandt and Van Biesebroeck (2006) further illustrate how a change in the responsibility for sourcing decisions induced a shift towards local suppliers. This shift proved a vital element for foreign multinationals to withstand the cost competition from local Chinese firms that took advantage of the supply chain nurtured by Western firms. Our study complements this body of work by going beyond case study findings and providing systematic evidence of a similar process of functional upgrading in China's export processing sector both within and across industries.

Our paper also relates to several papers that have exploited the distinction between PA and IA-type export processing. Feenstra and Hanson (2005) and Fernandes and Tang (2012) have focused on the difference in the allocation of control rights over the imported inputs between the two regimes and have developed property-rights models to explain the choice of IA-type processing over PA-type processing. The former paper finds that IA-type processing is more prevalent in higher-income Chinese regions which have more efficient courts and thicker supply markets. The latter paper shows that the share of foreign-owned processing plants in total trade is positively associated with an industry's skill intensity under the IA-type processing trade regime. Dai, Maitra and Yu (2016) and Manova and Yu (2016), then again, suggested that IA-type firms should have larger fixed costs of exporting and higher working capital requirements than PA-type firms since they need to actively obtain and pay for imported materials as well as search for clients. Consistent with these propositions, the former paper finds empirical evidence that IA-type firms are typically more productive than PA-type firms. The latter article shows that IA-type firms are less credit constrained and that, controlling for industry and province fixed effects, they are more capital-intensive, material-intensive, productive and pay higher average wages than PA-type firms. Our findings complement the cross-sectional analysis in those papers by showing that the prevalence of IA-type processing has systematically changed over time, and by exploring the factors that have driven these dynamics.

Finally, our paper is related to recent empirical work that uses the factor-endowments model to explain patterns of intra-industry upgrading. Schott (2004), Hummels and Klenow (2005) and Hallak and Schott (2011) show that, within narrowly defined product categories, countries with a higher GDP per capita and a greater skill intensity systematically specialize in higher-quality product lines. Our results complement these findings by showing that export processing firms in higher-income regions in China specialize at an even-more fine-grained level than previously established: they specialize in more sophisticated value chain activities even within product categories .

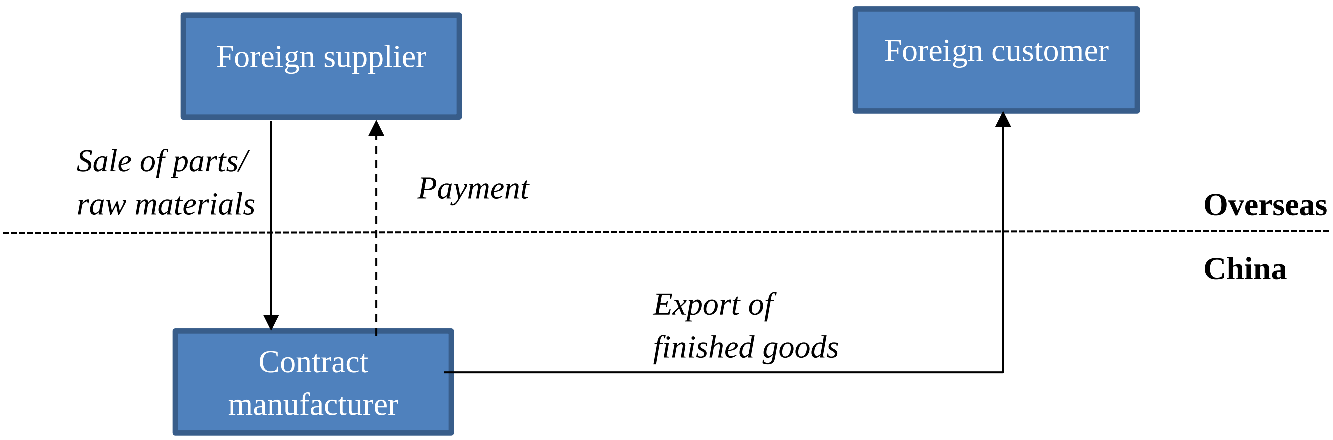
The remainder of the paper consists of five sections. Section 2 discusses functional upgrading. The data and estimation methods are described in Sections 3 and 4. Section 5 contains the results from the empirical analysis and in Section 6 we discuss the implications and conclusions.

2. PURE ASSEMBLY VERSUS IMPORT & ASSEMBLY

China's processing trade regime is a customs system that was installed in the mid-eighties in order to both attract foreign direct investment and promote exporting. Under the regime, firms are granted an exemption from duties on imported raw materials and other intermediate inputs as long as they are used solely for export purposes. Unlike in many other developing countries, China's concessionary provisions rapidly expanded outside of strictly policed export processing zones (Naughton, 2006). Currently, firms are allowed to conduct processing trade anywhere in China as long as they have received the Processing Trade Approval Certificate (Defever and Riano, 2014). As a result, China's processing trade regime has turned into an important albeit slightly declining part of its overall trade performance.

A key distinction in the data that we seek to exploit is between two broad types of processing trade: Import & Assembly (IA) and Pure Assembly (PA). IA refers to business activities in which a manufacturer in China purchases and pays foreign exchange for imported materials free of import duty and VAT (see Figure 1). It then performs manufacturing functions and exports the finished products to an overseas party (not necessarily the same as the input supplier) with the compensation of foreign exchange collected. This processing model is often referred to as contract manufacturing (KPMG, 2016).

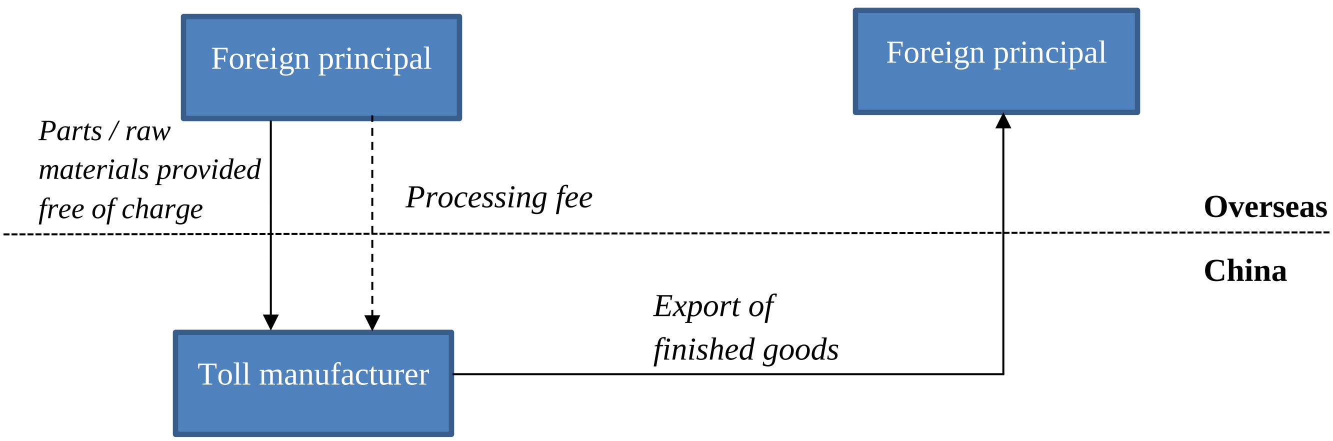
Figure 1: Import & Assembly (Contract Manufacturing Model)



Source: Adapted from KPMG (2016)

PA refers to business activities in which the manufacturer in China receives materials from a foreign principal free of charge (see Figure 2). It performs its manufacturing functions as per the requirements of the foreign principal and then exports the finished goods to the foreign principal. The operating enterprise will only be compensated by the overseas party with a processing fee which is typically calculated as a mark-up on processing costs. This processing model is often referred to as toll manufacturing (KPMG, 2016).

Figure 2: Pure Assembly (Toll Manufacturing Model)



Source: Adapted from KPMG (2016)

Manufacturers in IA and PA share the common feature that they perform manufacturing services to third-party companies which are located overseas. There exist a number of key differences between the two processing models however. First, the contract manufacturers (IA-type firms) have the responsibility of searching and obtaining the imported materials themselves prior to conducting the manufacturing activity, whereas a toll manufacturer (PA-type) passively receive orders and materials from its foreign client and export all the processed goods to this foreign principal. Second, contract manufacturers need to pay for the imported raw materials and parts, whereas toll manufacturers receive them from their foreign trading partners free of charge. Third, to comply with the more complex regulations and approval processes of IA compared to PA, contract manufacturers are required to make greater investments in inventory storages and management than toll manufacturers (Feenstra and Hanson, 2005).

Previous studies have pointed out that these differences imply that IA-type firms need to cover higher fixed exporting costs (Dai, Maitra and Yu, 2016), require more working capital (Manova and Yu, 2016) and entail control rights over the imported inputs (Feenstra and Hanson, 2005; Fernandes and Tang, 2012) compared to PA-type firms. In this paper, we add that the supplementary value chain tasks that contract manufacturers have of actively selecting suppliers, orchestrating the supplier network, managing inventory and product quality, governing control rights, and searching clients require a set of additional competencies than those needed for simple toll manufacturing (see also Bair and Gereffi, 2001; Ponte and Sturgeon, 2014). This is in line with Manova and Yu's (2016) empirical finding that, controlling for industry, province, ownership fixed effects and firm size, a Chinese firm's share of PA exports in processing exports was negatively correlated to its productivity, capital intensity, material intensity and average wage per worker in the year 2005.

Consistent with Humphrey and Schmitz's (2002) definition of functional upgrading, we thus propose that an export processing firm which moves from conducting PA-type to IA-type processing trade within a fine-grained product category is functionally upgrading since it takes on new, more sophisticated tasks in the value chain which it did not perform before. At a more aggregate level, if over time the share of production of a particular product that is conducted under the PA-type declines and the share produced under the IA-type increases, we consider the industry to be functionally upgrading.

3. DATA

To capture trends in the export processing sector, we take advantage of a dataset compiled by the *General Administration of Customs of the People's Republic of China* for the period 2000-2013. The database contains detailed information on the universe of processing trade transactions which are aggregated to the firm-product-country-year level.[5] It reports both export value (in US$) and quantity at the HS 8-digit level. Given that we observe the ownership type of each firm (SOE, private, foreign or other) and the province firms are located in, we can perform the analysis not

[5] In the initial period (2000-2006) the underlying information is even available at the monthly level, but we always aggregate to the annual level.

only at the product level, but also disaggregated further, additionally distinguishing effects by ownership or location.

For each of the firm-product-country-year observations, it is indicated according to which trade regime the transaction is conducted. While the original data contains a large number of trade-regime categories, many of them account for only a tiny fraction of the total trade volume. We collapse them into three exhaustive types: Ordinary trade (OT) and two forms of processing trade (PT), Import & Assembly trade (IA) and Pure Assembly trade (PA).[6] The key dependent variable in the empirical analysis is the share of Import & Assembly trade in processing trade: IA/(IA+PA).

We face a measurement problem in that information on the trade regimes comes from two separate variables available for different sub-periods. The first variable is available in full detail for 2000-2006, while it only identifies a transaction as OT or PT (without distinguishing between IA and PA) for 2007-2009. The second variable is available for the 2007-2009 and 2011-2013 periods, but has missing information for almost 65% of observations (with an outlier of 80% in 2008). This variable does not identify any of the transactions as straightforward ordinary trade, which is the dominant trade regime in the first variable, but distinguishes between the two forms of processing trade. As we observe both variables in the 2007-2009 period, we know that the missing information is dominated by ordinary trade transactions, but it does include some processing trade as well.

As long as the missing PT transactions in the second variable are not systematically biased towards the IA or PA type, this measurement problem will not influence the analysis as we only calculate the IA share within PT. However, given that the IA share over the 2000-2006 and 2007-2013 sub-periods are constructed from different variables, we will include a control variable for the post-2007 period in any regression to capture a possible effect of this change in measurement.

To investigate whether functional upgrading is related to other types of improvements in a sector's economic performance, we construct three performance proxies that have been used in the literature. First, we measure a sector's productivity by aggregating the firm-level productivity estimates for China's manufacturing sector from Brandt, Van Biesebroeck and Zhang (2012) to the industry level and merge them into the trade dataset using an HS (6-digit) – CIC (4-digit) concordance table. We use both labor and total factor productivity.[7]

[6] Because of their ambiguous nature we drop the following trade categories entirely: (a) Donations and gifts from other countries and international organizations, (b) Other oversea donations, (c) Compensation trade, (d) Sale by consignment, (e) Exports for contracted projects with foreign countries, (f) Leasing trade. The following categories were assigned to ordinary trade: (a) Small scale trade on border, (b) Barter trade, (c) Other trade, (d) Air transport. Finally there are 7 categories which are clearly related to processing trade, e.g. Bonded Warehouse, Equipment import for export processing zone, etc., but do not specify whether they are of the IA or PA type. We use them to calculate total processing trade, but do not count them as either IA nor PA. Note that the largest 3 (unambiguously identified) categories account for at least 95% of trade.

[7] In the NBS firm-level data, no distinction is made between firms that are engaged in processing or ordinary trade and we use all firms to construct industry-level productivity. That is not a problem for our analysis as we are

Second, we measure a sector's upgrading in product quality following Hallak (2006) as the relative unit value within narrowly defined product categories (at the 8-digit HS level). We compute the log-price as the ratio of export value (X) to export quantity (Q), either for products i or for product-destinations ic, i.e. $\ln(X_{it}/Q_{it})$ or $\ln(X_{ict}/Q_{ict})$, and include product or product-destination dummies in the regression to normalize the unit values and identify the coefficients solely from variation over time.

Third, we measure industry upgrading from the composition of China's exports across products of different sophistication within a broader sector which is measured building on a method pioneered by Rodrik (2006) and Hausmann et al. (2007). In a first step we measure for each detailed (8-digit HS) product category its sophistication ($PRODY_i$) as the weighted average of the GDP per capita (Y_j) of the countries where China sourced its imports from in 2000:

$$PRODY_i = \sum_j \frac{M_{ij}}{\sum_j M_{ij}} Y_j$$

The weight, $M_{ij}/\sum_j M_{ij}$, is the share of China's imports in 2000 of product i that originate from country j. A highly sophisticated product is one that China imported predominantly from high-income countries. In a second step, we construct for broader sectors, using 2-digit or 4-digit HS categories, the average sophistication of China's export bundle using the time-varying export shares, $X_{it}/\sum_{i\in S} X_{it}$, as weights to aggregate the time-invariant $PRODY_i$ measure over all products i in sector S:

$$SOPH_{st} = \sum_{i\in S} \frac{X_{it}}{\sum_{i\in S} X_{it}} PRODY_i$$

This variable will increase over time if China's exports of more sophisticated products grows more rapidly than exports of less sophisticated products, all within the same sector.

4. EMPIRICAL SPECIFICATIONS

We investigate three aspects of the functional upgrading process. First we ask whether it is indeed happening, i.e. does Import & Assembly processing trade become relatively more important over time? Second, is the observed upgrading process most pronounced for industries, firm types, or locations where we expect it to happen most? Third, is functional upgrading happening simultaneously with an increase in a sector's economic performance more generally? Note that in each of the three specifications that follow we have denoted the parameter of interest by α.

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interested in the overall evolution in an industry or product category. We use the shift in processing trade from PA to IA merely as a proxy measure for functional upgrading, not because we are interested in these specific groups of firms.

For the first two questions we use as our dependent variable S_{it}, the share of IA-type processing exports in total processing exports for product i and period t, and investigate whether this share has increased over time. Specifically, we estimate the following regression:

$$S_{it} = \delta_i + \alpha\ time_t + Z_{it}\gamma + \epsilon_{it}, \tag{1}$$

where δ_i are product-fixed effects, $time_t$ is a linear time trend, Z_{it} are control variables (the share of exports by foreign firms and a dummy for the post-2006 period), and ϵ_{it} is a stochastic error term. A positive and significant coefficient on $time_t$ would suggest that China's export processing sector has been systematically upgrading functionally across sectors.

Note that the results need to be interpreted as an equilibrium outcome in the product market. It might involve existing relationships being restructured and individual firms changing the type of export regime they use, but changes at the firm level are not strictly necessary. Changes at the extensive margin, i.e. entry of new Chinese firms or the establishment of new commercial relationships, might be as important as firm-level changes. Even a change in relative market shares between continuing firms trading in different regimes can contribute to the estimated time trend. We would interpret each of these three changes as evidence of functional upgrading at the industry level. Hence, we measure at the product level how the relative importance of IA-type trade has evolved over time.[8]

Next, we evaluate for which industries, firm ownership types, or locations functional upgrading was most pervasive. The objective is to investigate whether the trend towards functional upgrading was strongest for the type of transactions where we would a priori most expect it. We use the same dependent variable as in equation (1), but now interact the time trend with different observable characteristics X. To control for persistent differences between observables we also include the interaction variable uninteracted in the regression:

$$S_{ikt} = \delta_i + \ \beta\ time_t + \gamma\ X_k + \alpha_k\ (time_t\ .X_k) + \epsilon_{ikt}. \tag{2}$$

The k subscript refers to the additional dimensions of the data we bring to the analysis in the three alternative analyses: industry, ownership type, or location. We aggregate the underlying firm-level information to the ik level in each year, e.g. product by ownership type. A positive and significant coefficient on the interaction term $time_t\ .X_k$ would suggest that functional upgrading is particularly pervasive for a certain observable.

Third, we analyze whether functional upgrading in the export processing sector is related to an improvement in a sector's economic performance. We introduced in the data section three proxies

[8] In an extreme case, some firms engaged in PA might stop their activities in China and move production to lower-wage countries. If firms producing the same products using the IA-type of processing trade continue their activities in China we would also measure this as upgrading as the relative importance of IA has increased. Note, however, that this appropriately reflects the composition of activities that are now (still) carried out in China.

Y_{it} for a sector's economic performance. They are used as dependent variables, while the IA-share is now used as explanatory variable, to estimate the following regression:

$$Y_{it} = \delta_i + \beta \, time_t + \alpha \, S_{it} + \epsilon_{it}. \quad (3)$$

The product-fixed effect controls for the average value of the Y-type proxy and IA share for each product. The β coefficient measures the average speed of Y-type performance improvement over the full sample. A positive coefficient on the variable S_{it} would indicate that Y-type improvements in economic performance and functional upgrading are happening simultaneously, increasing for the same products. Note that we are picking up a correlation and that we cannot make an inference on causality in either direction from these regressions.

5. RESULTS

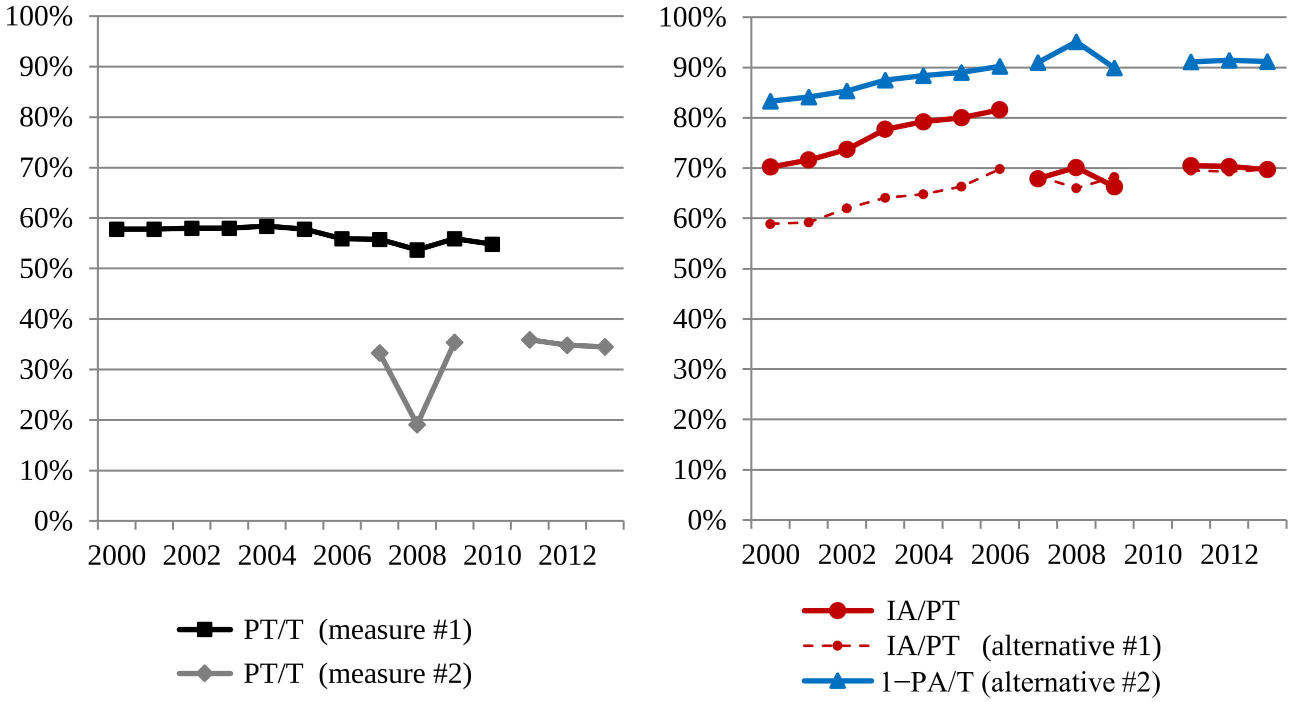
5.1 Trends over time

We first investigate whether China's processing exports have overall been shifting towards IA-type processing trade between 2000 and 2013. It has been documented before that the importance of the export processing trade regime has been surprisingly resilient to China's reduction of import tariffs (Brandt and Morrow, 2017). The stronger relationship with foreign clients, compared to the ordinary trade regime, apparently is providing enduring benefits that go beyond access to duty-free inputs. However, if Chinese export processing firms are upgrading in the type of functions they perform in these relationships, we would expect the IA share of processing trade to become relatively more important over time.

In Figure 3 we show the aggregate evolution for the importance of different trade regimes. In panel (a), the black solid line indicates the evolution of the share of all processing trade in total exports. It gradually declines from 58% in 2000 to 55% in 2010. As discussed in the data section, the trade regime indicator we have to rely on in the later part of the sample does not identify ordinary trade transactions. If we assign all transactions with missing information to the ordinary trade category we see the PT share continues its gradual decline from 2009 to 2013 (indicated by the dark grey line in Figure 3). Based on the information in the three years we observe the breakdown between PT and OT for both measures (2007-2009), we can see that the absolute level is not comparable between the two measures. As the switch to the alternative series is unavoidable if we want to cover the entire sample period to 2013, we include an indicator variable for the post-2007 period in all regressions.

Figure 3. Evolution of different trade-category shares

(a) Evolution of processing trade share (PT/T) (b) Evolution of IA trade share (IA/PT)



Note: Exports under different trade regimes are summed over all HS 8-digit products by year before calculating the ratios. The breakdown of processing trade is not observed in 2010. The following trade categories are used:
- Total trade equals the sum of ordinary trade and processing trade (T = OT + PT)
- Processing trade equals the sum of Import & Assembly trade and Pure Assembly trade (PT = IA + PA).
The alternative #1 series only uses the subset of products with a share strictly between 0% and 90% in 2000-2006.

The dependent variable in the empirical analysis is the fraction of each product's processing trade (PT) exports that is conducted under the Import & Assembly (IA) regime. We illustrate the evolution of this ratio in panel (b) on the right. The primary measure is shown with a red solid line. As a reminder that this ratio is constructed from a different variable over the 2000-2006 and the 2007-2013 periods, the connecting line is interrupted in 2007.[9] The vertical drop in this series underscores that we will need to include a post-2007 dummy in all regressions to capture the break in measurement. The IA share increases from 70% in 2000 to 82% in 2006 and fluctuates around 70% thereafter. From 2007 to 2013, the IA share only grows by 2%.

As a robustness check, we show two alternative series for the IA share in the same panel. Both series confirm that in the first half of the sample period the aggregate pattern is consistent with functional upgrading, but at the onset of the Great Recession in 2008 this process becomes less pronounced. For the first alternative measure (shown with a dashed red line) the numerator and

[9] Given that detailed data is missing in 2010, there is a second break in the series.

denominator are calculated only over the subset of products where the IA share is strictly positive but below 90% prior to 2006, such that there is still some growth potential. This approach is similar as the one followed by Evans and Harrigan (2005) to avoid including products with binding quotas in their analysis. This share starts from a lower level, but shows a similar increase between 2000 and 2006 and is indistinguishable in the later period.

The second alternative measure (shown with a solid blue line) calculates the share of all exports not accounted for by Pure Assembly processing trade, which includes not only IA-type processing trade, but also ordinary trade. With the exception of 2008, when there is the most missing information, this share rises monotonically from 83% in 2000 to 91% in 2013. The type of trade where the Chinese partner has the least control and is performing the fewest skill-intensive tasks is becoming less important, in relative terms, over the sample period.

A first step to understand what drives the increase in the IA/PT ratio (y_t) shown in Figure 3, is to decompose the aggregate change into three terms as follows:

$$\Delta y_t = \sum_i w_{it}\, y_{it} - \sum_i w_{it-k}\, y_{it-k} = \underbrace{\sum_i w_{it-k}\, \Delta y_{it}}_{\text{within}} + \underbrace{\sum_i \Delta w_{it}\, y_{it-k}}_{\text{between}} + \underbrace{\sum_i \Delta w_{it}\, \Delta y_{it}}_{\text{covariance}}$$

Different products, defined at the 2-digit or 4-digit level of the HS classification, are indexed by i. The aggregate IA/PT ratio at time t for the entire economy equals the weighted sum of the IA/PT ratios y_{it} over all product groups, where the weights w_{it} are total processing trade for each observation. The change of this aggregate over k years can be decomposed into the contributions of three terms: (1) the within-industry change in the ratio, (2) the change in importance between groups with different ratios, and (3) the covariance between the change in the ratio and the share.

As the IA/PT measure is calculated differently up to 2006 and from 2007 onwards, it is natural to calculate the changes separately over the 2000-2006 and 2007-2013 periods. The results of this exact decomposition are reported in Table 1 for both levels of product aggregation. The aggregate ratio increased by 11.4% cumulatively over the first six year period and by 1.8% over the second period.

Using the more aggregate (2-digit) product classification, the within term accounts for two thirds of the increase in the earlier period and in the later period it even accounts for the entire change. A large part of the aggregate increase has to be understood as operating within product groups and not only the result of a compositional change. Even without weighting we find a large increase in the average IA-share, as the vast majority of product groups experience an increase. By construction, the within term makes a smaller contribution when we define product groups more narrowly at the 4-digit level. But even in this case the within group change accounts for an important share of the aggregate change in the two periods, respectively 47% and 83%.

[Table 1 about here]

The between term will make a positive contribution if groups that have an above-average ratio gain in weight, i.e. account for a larger share of processing trade, at the expense of groups with a below-average ratio. The results in column (2) indicate that this is indeed the case in the first period, and using the more detailed product groupings also in the second period. A shift in composition over time towards products that already had a high IA/PT ratio at the start, contributes to the aggregate change.

Finally, the covariance term makes a negative contribution in most cases. On average, product groupings that increase their IA/PT ratio do not at the same time increase their trade weight. The two changes tend not to go hand in hand, although the absolute magnitudes of the contribution of the covariance term is not that large.

To provide further insights into the type of products that are responsible for the largest change, we list in Table 2 the 2-digit product groups that make the largest contributions to the within-term. For 2000-2006 we report the ten largest. Some of these, such as "Electrical machinery & equipment (HS 85)" see a moderate increase in the ratio, but have a very large trade weight. Some other groups, such as "Toys, games, sporting goods (HS 95)" do not carry a large weight, but see a very large increase in the ratio. The two product group that enter the top-5 in the 2007-2013 period, but were not in the top-10 in the first period, saw an increase in their ratio that was 5 to 10 times larger than the aggregate increase.

[Table 2 about here]

In order to control in a flexible way for confounding differences at the product level, we report in Table 3 the estimation results of equation (1) that includes fixed effects. The first panel contains the growth rate of the IA share in total processing exports using different controls in the three columns. Column (1) are the results for a simple OLS regression without controls, except for the post-2007 indicator to account for the difference in measurement of the dependent variable. The estimate indicates that the IA share grows by almost one half of a percentage point per year, consistent with the pattern in Figure 3.

[Table 3 about here]

The results in column (2) include a full set of product-fixed effects (at the HS 8-digit level). The point estimate is slightly higher which indicates that changes in the product mix of China's exports obscures the functional upgrading trend to some extent. Column (3) reports the results when we estimate equation (1) using product-year-destination observations and include product-destination interaction fixed effects.[10] The point estimate rises further to 0.8 percentage points. Within a given product-destination pair, the IA share increase on average by 10.4 percentage points over the entire sample period, indicative of strong functional upgrading. The aggregate increase is

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[10] The i subscript in equation (1) now indexes product-country observations.

less pronounced because Chinese exports are gradually reoriented to product categories and export destinations where the IA-type of trade is less common.

Given that the dependent variable was estimated from different underlying data in the 2000-2006 and 2007-2013 periods, we also estimated a specification where we allowed the time trend to differ over the two sub-periods – reported in the second panel of Table 3. As could be expected from the aggregate trend in Figure 3, functional upgrading is much stronger in the earlier period. When controlling for the product-destination composition, the annual increase in the IA share averages 1.5 percentage points per year in the period from 2000 to 2006. The increase in the later period is still positive and statistically highly significant, but it slows down to less than half the growth rate in the initial period. Moreover, the increase is now almost entirely masked by the compositional change. The estimate without controls in column (1b) is barely positive. Only when product-destination fixed effects are included, in column (3b), can we detect functional upgrading in the second half of the sample period.

In the next two panels we show robustness checks to verify whether the above finding is robust to measurement problems. In the third panel we omit any products or product-country observations that already achieved an IA share of at least 90% at any time before 2007. Our concern is that some products simply have little room for growth in their IA share, leading to a deceleration in the growth rate by construction. This does not seem to be the case. The growth rates in the later period are only marginally, and statistically insignificantly higher when we exclude those products. It is not surprising as the aggregate evolution in Figure 3 already showed that the re-classification of the series in 2007, discretely lowered the IA share, leaving ample room for growth in the later period.

Finally, in the fourth panel we use a different dependent variable, namely the fraction of exports not traded under the most basic Pure Assembly regime. For the initial period, the positive and significant point estimates are similar in size to those in the second panel. As China lowered its import tariffs substantially surrounding its entry into the WTO (see for example Brandt, Van Biesebroeck, Wang and Zhang, 2017), it could be expected that processing trade would become less important. The shift away from Pure Assembly trade would then not only go towards Import & Assembly trade, but also towards more ordinary trade. The similar magnitudes of the estimated effects using this alternative variable suggests that the processing trade regime proved attractive even after China's WTO accession.

Once again, it turns out to be important to control for product-destinations to gauge the full extent of functional upgrading. In the later period, the point estimates are negative in the first two columns, but again positive in column (3d) when we control for product-destination interactions. The reason is that Chinese firms often start exporting less sophisticated products or to less developed economies and only when they are successful in those markets do they enter more advanced product and destination markets. The upgrading cycle in terms of the type of activities that Chinese firms are responsible for, moving from PA to IA (and then to OT), seems to start afresh when new markets are entered. Compositional improvements in terms of product and destination markets go hand in hand with functional regress, at least temporarily.

5.2 Interactions with observables

We next evaluate if there are industries, ownership types, or regions for which functional upgrading is more pervasive.

<u>Variations across industries</u>

We first verify whether we see more functional upgrading in product categories where upstream industries have experienced above average export growth. If upstream suppliers are becoming more competitive on the export market, this could provide opportunities for export processing firms that rely on their inputs to take on a more important role in GVCs.

To construct a proxy for the competitiveness of suppliers, we follow Acemoglu, Johnson and Mitton (2009) and Alfaro and Charlton (2009) and use information from the Chinese input-output table (for the year 2002) to identify the relative importance of different sectors as input providers. Specifically, we calculated a weighted average of each sectors' past export growth using as weight for each (upstream) sector the fraction of the downstream sector's input that it provides. This weighted average of lagged *suppliers' export growth* provides a measure that captures the increased capability of the average input supplier to provide quality inputs.

At the fairly aggregate level of the Chinese input-output table—it only counts 80 industrial sectors—many sectors source a sizeable fraction of their inputs from within their own sector. As a result, the measure described above will be correlated with a sector's own export success. Given that there are likely to be alternative channels that can explain a link between own-sector export success and functional upgrading, we also show results that separate out the own-sector effect. We split the first measure into two separate lagged export growth variables: The first captures the own-sector growth, while the second one aggregates only over strictly upstream sectors.[11]

The results in Table 4 are all estimated at the product-year level and include product-fixed effects in the regressions. We find a positive coefficient on the time trend in all four specifications, confirming that the IA share in processing exports has increased over the entire 2000-2013 period and even more strongly over the 2000-2006 sub-period. The positive coefficients on the export growth of suppliers further indicate that industries with strongly performing suppliers on average have larger IA shares than industries whose suppliers are not showing strong export growth. It is notable that *upstream suppliers' export growth* is more strongly correlated with a high IA share than *own-sector export growth.*

[Table 4 about here]

[11] We adjust the weights such that they still sum to one and the coefficient estimates are comparable between both specifications.

Finally we discuss the coefficient of interest, the α_k coefficient in equation (2) for the interaction between time and own or upstream sector export growth. It measures whether the time trend in the evolution of the IA share, our measure of functional upgrading, is larger in sectors with suppliers that recently showed a strong export performance. The evidence shows this to be the case in the initial period from 2000 to 2006. The point estimate indicates that a sector whose suppliers enjoyed export growth that was 10% faster than average, experienced annual growth in its IA share that was 0.23 percentage points faster than the average, i.e. growing a rate of 1.97% rather than 1.74% per year. There is no difference in the point estimates when we distinguish between the effects of a strong export growth performance of the own sector or upstream suppliers.

Over the full sample period, however, the support for this pattern disappears. All three coefficients of interest in columns (3) and (4), on the interactions of time with export growth of all suppliers, export growth of upstream suppliers, or own-sector export growth, are not statistically significant anymore. Over the full period, high export growth of suppliers is still associated with a high level of the IA share, but not systematically with a growing IA share.

We show results separately for the later period (2007-2013) in panel (a) of Table A.1 in the Appendix. The sign on every coefficient is the same as in the earlier period, but all magnitudes are smaller. Export growth of suppliers is still significantly associated with growth in the IA share, but the coefficients become statistically insignificant if we allow for effects of different magnitudes for suppliers in own and other sectors.

Variations across firm types

We next explore which type of export processing firms have been functionally upgrading most. For this purpose, we divided firms into five exhaustive categories according to their official registration type: (1) state-owned domestic firm (*SOE*); (2) privately-owned domestic firm (*private*); (3) foreign-invested firm (*foreign*); (4) firm of mixed-ownership (*mixed*), which is a heterogeneous group of collectively owned firms and several types of joint ventures; and (5) firms that switched ownership at some point during the sample period.[12,13]

We used either a single intercept for each ownership type in the regression and added product-fixed effects, for the results in columns (1) and (3) of Table 5, or allowed the intercept for firms of different ownership types to vary across products, for the results in columns (2) and (4). Inclusion of these fixed effects implies that the coefficients are again identified from within-product variation. The time variable is normalized to be zero in the year 2000, which gives the coefficients

[12] *SOE* includes the NBS registration types 110, 120, 141, 142, 143 and 151; *Private* captures 171, 172, 173 and 174; *Foreign* includes 210, 220, 230, 240, 310, 320, 330 and 340; *Mixed* captures the remaining categories.

[13] While non-negligible, the fifth category of firms that switch ownership contains 11.2% of all firms and is not that large to compromise the representativeness of the other categories. Over the entire sample period, only 2.7% of mixed firms (which is by far the largest group of firms) switch ownership, 4.4% of SOEs, 14.1% of foreign firms, and 26.4% of private firms (mostly towards mixed).

on the uninteracted ownership variables the interpretation of the initial IA share in 2000 for each firm type.

The results on the uninteracted ownership categories in columns (1) and (3) indicate that the initial ranking of ownership types by increasing IA share is *SOE* (the excluded category, captured by the intercept), *private* (the intercept plus the coefficient on the private firm dummy), *mixed*, *foreign* and *ownership-switchers*. The difference between the *mixed* and *foreign-owned* firms is not statistically significant and the order switches for the initial and the full sample period. This ranking is not unexpected. State-owned firms are least likely to engage in the Import & Assembly type of processing trade and foreign firms or mixed-ownership firms, which contain various types of joint ventures, the most.

[Table 5 about here]

The differences are quite large. In the first year, almost two thirds of processing trade exports of SOEs are of the Pure Assembly type variety, which overall accounts for only 40% of processing trade in that year. The group of firms with the second lowest share, private firms, already uses the IA organizational form for 62% of trade. This share is even 76% for the group of ownership-switchers. This group accounts for one fifth of all observations in the sample, but almost half of all trade. Only a small fraction of the ownership changes involve state-owned firms; they should certainly not be interpreted as reflecting a privatization process.[14]

With only a few exceptions the interactions between time and the ownership type follow the reverse pattern of the initial ranking based on the uninteracted coefficients. In three of the four columns, (1), (3), and (4), SOEs are found to be functionally upgrading more quickly than any other type of firms. Especially over the full sample period, the increase in the IA share for SOEs is very rapid, growing by 2.3 or 1.9 percentage points per year. Another pattern that is very robust is the small change in IA share for foreign firms. They start out with a relatively high share in 2000, estimated at 70% or 64%, but three of the four time trends are estimated not statistically different from zero for foreign firms.

For some of the other categories, the evolution of the IA share differs between the 2000-2006 period or over the full sample. For private firms it is estimated to be increasing over the initial period, but decreasing over the full period. The reverse pattern hold for ownership-switchers. Note that the initial difference between private firms and SOE is estimated larger using only the initial period than using the full period and this coincides with a larger difference in growth rate (higher for SOEs) over the initial than the full period. A similar pattern holds for firms with mixed

[14] Note that both coefficients, the intercept and the time trend, are estimated very precisely for firms switching ownership. It suggests that it is not a residual category, subject to a wide variety of experiences, but a group that share a systematic pattern in the evolution of their relative use of IA trade: a very high rate in 2000 which even builds over the 2000-2006 period, but then converges rapidly to the average usage by 2013.

ownership: the difference with SOEs in 2000 is estimated larger over the initial period than over the full period, but this coincides with a more negative time trend for the initial period.

Overall, these patterns suggest convergence between firm types in the use of the IA form of trade. Ownership categories with low initial shares tend to see relatively higher rates of growth in IA trade. Lagging firms, most notably SOEs but to some extent also privately-owned domestic firms, gradually catch up to foreign-invested firms. Differences between types are smaller in the even-numbered columns where we allow for flexible intercepts, but the ordering of growth rates across the categories is consistent with the more restricted specification reported in the odd-numbered columns. Using the estimates over the full sample period in column (3) we find that the average IA shares over the five ownership categories vary widely from 37% to 78% in 2000, but this range narrows tremendously to between 58% and 66% in 2013.[15]

In panel (b) of Table A.1 in the Appendix we show separate results for the later period (2007-2013). The strong increase in the IA share for SOEs that we discussed above lead to a more than complete convergence in IA share for SOEs by 2007. After 2007 they do not show any further increase. Firms switching industries, the group with highest IA share in 2007, also did not experience any further trend growth after 2007. Private, mixed-ownership, and foreign-owned firms had slightly lower IA share than these other groups in 2007 and they did continue to enjoy growth in IA share. These results for 2007-2013 thus confirm the overall tendency towards convergence.

Variations across regions

We finally explore in which regions functional upgrading is most prevalent. All else equal, we expect the process to be stronger in more developed economic regions as firms are likely to have more opportunities to develop advanced capabilities. To evaluate this prediction, we used the classification of Chinese provinces as coastal or non-coastal and calculated the IA shares for each product-year separately for the two locations.[16] The presence of product-fixed effects implies we are still exploiting intra-industry variation.

The results in Table 6 again suggest convergence, as was the case for results by firm type, but now the patterns in the two regions are converging. While the IA-type of export processing is indeed more common in the coastal provinces in 2000, their advantage is not large, with the average at most 3% higher. The coefficient on the time trend is always estimated to be higher for the inland than for the coastal region. The higher rate of functional upgrading, as indicated by the difference in the two time trends, combined with a small coefficient on the Coast dummy implies

[15] Note that these regressions are not weighted by trade volumes. Given that the sample average of the IA share in 2013 (which is 70%) is outside the range of the average shares across ownership categories, it must be the case that the IA-type of trade is more popular among high volume traders than the PA-type.

[16] The standard classification for the 11 coastal provinces are Beijing, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin and Zhejiang.

that inland firms are catching up rapidly. Depending on whether one extrapolates from the coefficients in columns (1), (2), or (3), the gap would be eliminated in six to ten years.

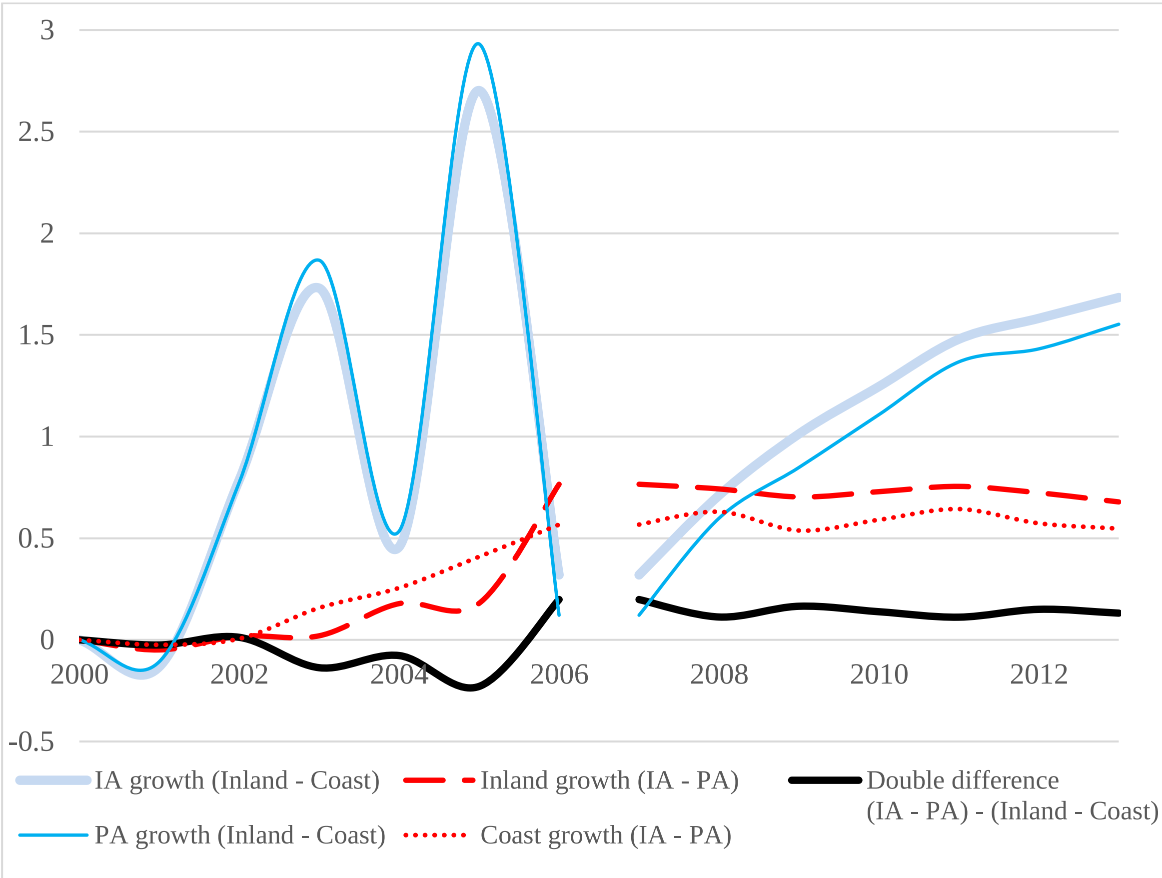
[Table 6 about here]

The catch-up of the inland region can be the result of a faster increase in IA trade than in coastal provinces or it can reflect a slower relative growth rate (or even a decline) for PA trade. Given rising wage rates, Chinese firms face increasing competition from other developing countries for the lowest value added tasks in value chains. The inland provinces are likely to be more at risk from such competition as manufacturing tends to be less advanced there. To investigate these alternative explanations further, we ran product-level regressions separately for four groups, distinguishing simultaneously between both types of trade (IA and PA) and both regions (Inland and Coast). We used log-exports as dependent variable, normalized to 0 in 2000 and re-normalizing the value in 2007 at the level of 2006 to account for the change in the definition of trade types. We used year-dummies to extract average growth rates for the group, while including product-fixed effects.

In Figure 4 we show the relative evolution, i.e. the difference in cumulative growth rates, for pairs defined in two ways, as well as the double-difference in cumulative growth. The red lines compare the evolutions of IA and PA trade separately for the two regions. They confirm the two pattern already shown in Table 6: (i) Both regions experience faster growth of IA than PA trade, as can be seen from the positive values; and (ii) the growth difference is larger for the inland than the coastal provinces, as can be seen from the long-dashed red line being above the short-dashed red line, leading to convergence between the two regions.

The blue lines show the growth differentials in a different way, i.e. showing the difference in growth rates between the two regions separately for either type of trade. In both cases, trade is growing more rapidly in inland than in coastal provinces—again all values are positive—but the difference is very volatile. Overall, we see that thick, light-blue line (for IA-type trade) is above the fine, dark-blue line (for PA-type trade). It is thus not the case that PA activities are leaving the inland provinces, they grow more rapidly than in coastal provinces. It is the relative growth rate in IA activities that is even higher. As a result, the double difference that is depicted by the solid black line is slightly positive over the period.

Figure 4. Differences and double-difference in growth rates for two types of trade and two regions



As a robustness check, we report in columns (4) to (6) of Table 6 the results for a similar analysis, but conducted at the more detailed product-year-province level. We now include product-province interaction fixed effects as controls and estimate whether functional upgrading is related to a province's overall export intensity for a particular product. The X_k variable in equation (2) is now calculated as the total exports across all trade regimes for province k (separately for each product-year).

Over the initial 2000-2006 period, we find that the IA share in 2000 was higher in provinces with a higher export intensity. The interaction term further indicates that functional upgrading was happening more quickly when the export intensity was high. However, over the full 2000-2013 sample period, the uninteracted export intensity remains strongly positive, but the coefficient on the interaction with time turns negative. When we include a separate set of product-location fixed effects for the pre and post-2006 period to control more flexibly for the change in measurement of the dependent variable, in column (6), the interaction coefficient even becomes statistically significant and slightly larger in absolute value at -0.0003.[17] In terms of absolute magnitude, the average time trend in functional upgrading of 0.16% per year implies a 0.08% growth rate for provinces with an export intensity one standard deviation above the mean and 0.24% for provinces one standard deviation below. This again points to convergence, but at a very slow rate.

5.3 Links with economic performance

Finally, we analyze whether the process of functional upgrading in the export processing sector is related to more general improvements in a sector's economic performance. For this analysis we limit the sample to 2000-2006, the period for which we have identified strong functional upgrading. We first investigate the relation with productivity growth, next with quality upgrading, and finally with industry upgrading. In each case we use a different dependent variable and the IA share, the index of functional upgrading, as explanatory variable, as described by equation (3).

<u>Productivity growth</u>

The results in the first two columns of Table 7 evaluate whether functional upgrading in a sector goes hand in hand with stronger than average productivity growth. We use the natural logarithm of a sector's productivity (at the 4-digit CIC level) as the dependent variable: labor productivity in column (1) and total factor productivity in column (2). Each specification includes a time trend to capture the overall trend in China's productivity across industries; product and industry fixed effects allow for product-specific and industry-specific intercepts. We find that labor productivity growth was indeed higher than average in years that the IA share was also above average. The included fixed effects mean that the estimate is identified from changes over time: higher productivity growth goes together with more rapid functional upgrading.[18] This result is consistent with Manova and Yu (2016) who find that value added and productivity are higher for IA-type export processing than for PA-type export processing.

[Table 7 about here]

The results in column (2), however, show an effect with the opposite sign for total factor productivity. Higher functional upgrading is estimated to go together with lower total factor productivity growth. A likely explanation is that functional upgrading is accompanied by capital accumulation and the observed boost to labor productivity is not a shifting out of the production possibilities frontier, but a movement along the frontier. Note as well that the results are silent on causality. It might be the case that functional upgrading *requires* capital accumulation as a facilitator in this process. Alternatively, it might be the case that the different tasks a firm performs

[17] We estimated all regressions over the 2000-2013 period that are reported in the paper using either a simple post-2007 dummy variable or using two separate sets of product-fixed effects for the 2000-2006 and the 2007-2013 sub-periods. Column (6) in Table 6 was the only instance where the statistical significance on the crucial interaction term depended on the specification; the coefficient's sign never changed.

[18] We even find a positive coefficient if we include an interaction term *time**IA share*. It suggests that the labor productivity growth accelerated in sectors and years when firms were functional upgrading most strongly.

after functional upgrading raises capital productivity and *induces* a firm to invest more in capital equipment.

In sum, the evidence that functional upgrading goes hand in hand with productivity growth in a sector is mixed. The accompanying capital deepening leads to opposite effects on labor productivity and total factor productivity.

Quality upgrading

We next verify whether functional upgrading happens simultaneously with an increase in relative unit values within narrowly defined product categories. While this price measure captures several factors, Hallak (2006) shows that product quality differences are the dominant component. An advantage of this variable is that it can be measured easily for all product categories and working at the 8-digit level of detail in product classification should make prices still comparable.

There are a number of reasons why functional upgrading may lead to an increase in unit values. It may be that the extra competencies of contract manufacturers (IA) compared to toll manufacturers (PA) attract foreign clients that specialize in higher-quality product lines. It may also be that the extra value chain activities performed by contract manufacturers lead to higher costs or price-cost margins which generate a price difference between IA and PA. Our empirical analysis can unfortunately not distinguish between these two types of effects.

We conduct the analysis at two different levels. Results in column (3) are for a regression at the product-year level, while in column (4) a unit of observations is a product-year-destination. In either case we include the appropriate fixed effects, as in columns (2) and (3) of Table 3. The latter specification is more flexible as it allows average prices for each product to differ across destinations. It only relies on the correlation between the price deviation from the product-destination specific average and the corresponding deviation in the composition of exports over the PA and IA trade regimes.

Results are consistent across both columns and, as expected, stronger in column (4). In either case, higher unit values are strongly associated with periods or destinations with above average growth in the IA share. We can thus conclude that at the same time as China's processing firms were functionally upgrading, i.e. gaining responsibilities for an expanding set of tasks, they were also able to increase the prices they received for their exports on international markets, which we interpret as quality upgrading.

Note again that we do not imply any direction of causation between these two evolutions. In fact, one could equally well estimate the regression by inverting the roles of the unit value and the IA share. In that case, we found that unit values at the product-year level were on average 0.228 log-points higher for IA trade than for PA trade and this difference was even 0.394 if we additionally allow prices to vary by destination. We find that the two evolutions, rising prices and a shift from PA to IA trade, happen simultaneously, but we cannot determine whether ‘one causes the other’ or ‘one is a prerequisite for the other.’[19]

Industry upgrading

Finally, we analyze whether functional upgrading in the export processing sector is related to industry upgrading. In other words, are processing exports disproportionately shifting to more sophisticated products for sectors where the growth in the IA share is also above average? The construction of the dependent variable, a measure of the average sophistication of a sector’s exports, is described in the data section. A highly sophisticated product is a product for which China’s imports in 2000 were primarily sourced from rich countries. The dependent variable is then calculated as a weighted average of the underlying 8-digit products’ sophistication for a broader sector. The results reported in column (5) of Table 7 use the export composition in 2-digit industries, while results in column (6) are for 4-digit industries. This dependent variable will increase over time for a particular industry if China’s exports of more sophisticated products grows more rapidly than exports of less sophisticated products. The regressions evaluate whether the evolution of this average level of sophistication in an industry goes together with functional upgrading, calculated at the corresponding sector level.

The positive estimate on the time trend in column (5) implies that, controlling for cross-industry variation, the average sophistication of China’s industries has increased over time. That is, China is increasingly specializing in products that in 2000 were exported by high GDP per capita countries. At the more disaggregate level, in column (6), the point estimate remains positive, but is much smaller and not statistically significant. The insignificant point estimates on the IA share for both columns does not suggest a link with functional upgrading. Only when we interact the time trend with the IA share, which allows for a differential time trend for products with rapid functional upgrading, do we find positive effects. But even then, the effect is only statistically significant at the 2-digit level. We can thus conclude that the link between functional upgrading and industry upgrading is tenuous at best.

6. CONCLUDING REMARKS

Our paper contributes to the literature by exploring if there is systematic evidence of functional upgrading in China’s export processing sector. By analyzing trends in the relative prevalence of Import & Assembly (IA) versus Pure Assembly (PA), we show that China’s export processing sector has been functionally upgrading over the entire 2000-2013 sample period, but especially strongly up to 2006, with the share of IA-type processing trade consistently increasing both overall as well as within sectors.

We found some evidence that functional upgrading in China’s export processing sector between 2000 and 2006 has gone hand in hand with improvements in a sector’s economic

[19] Studying the exact relationship between these two upgrading processes requires a firm-level analysis.

performance. Above average growth in a sector's IA share goes together with above average growth in labor productivity, but not with total factor productivity growth, which could mean that the effect runs through capital deepening. The link between functional upgrading and industry upgrading is even weaker. In contrast, we find that growth in a sector's IA share is strongly correlated with growth in a sector's unit values, suggesting that functional upgrading is often linked to quality upgrading.

These results are consistent with functional upgrading enhancing export processing firms' economic performance. An alternative interpretation is that improvements in economic performance—productivity growth, industry upgrading, or quality upgrading—have given Chinese firms greater flexibility to start new activities and respond to changes in technology or shifting comparative advantage. In turn this might have facilitated Chinese export processing firms to take on new activities and upgrade functionally. More research is needed to evaluate how firms acquire these additional value chain functions, to what extent it is related to a firm's skill intensity, and which policies can be adopted to further induce functional upgrading.

A surprising finding is that—despite strong evidence of functional upgrading between 2000 and 2006—the process of functional upgrading slowed down considerably between 2007 and 2013. The cause of this slow-down is not entirely clear. Perhaps functional upgrading in the export processing sector has reached a saturation point and for the remaining trade under the PA regime, that form of organization will remain preferable even if China develops further. It is also possible that the dynamics of global value chains have changed post-recession and China's development might even have contributed to such a change. As its weight in the global economy increased, firms increasingly take China's domestic market into account when making decisions on production location and organization. An important implication in any case is that we need to be careful when extrapolating pre-crisis evidence on China's GVC upgrading to after the crisis.

Our analysis has a number of policy implications. First, one factor known to impede foreign lead firms transferring ownership and control functions to firms in developing countries is the contractual implications it entails. The rule of law, contract status, recourse to courts and predictability of regulation are all more important for transactions under the IA-type export processing regime than under the PA-type regime (Feenstra and Hanson, 2005). We thus expect that strengthening the contractual environment would generate a greater willingness among foreign lead firms to transfer further responsibilities to Chinese export processing firms. Second, a foreign firm's willingness to transfer ownership and control functions to Chinese export processing firms also depends on the local firm's capabilities to manage supplier selection and to orchestrate a more significant portion of the supply chain. Promoting entrepreneurship and the development of managerial skills would thus further induce functional upgrading in China's export processing sector.

Our analysis finally points to a few avenues for future research that would be interesting to explore. (1) The first, and most important question our findings raise is what explains the slowdown in functional upgrading? (2) The lack of correlation between total factor productivity growth and functional upgrading, while there is a strong link with labor-productivity growth, suggests a relationship between functional upgrading and capital accumulation that is not previously documented. (3) Some of the interactions between functional upgrading and observable characteristics of exporters suggest a convergence in the importance of the IA-type processing trade across different situations, e.g. by location or ownership type. This might provide some clues to explain the enduring importance of processing trade more generally, as the reduction in import tariffs has lowered its direct benefit in the form of duty-free access to inputs.

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Table 1: Decomposing the aggregate change in functional upgrading

	Aggregate change	Within	Between	Covariance
	(1)	(2)	(3)	(4)
(a) 2-digit HS				
2000-2006	0.114	0.076	0.051	-0.014
2007-2013	0.018	0.018	-0.001	0.001
(b) 4-digit HS				
2000-2006	0.114	0.054	0.071	-0.013
2007-2013	0.018	0.015	0.008	-0.005

Note: Statistics in panel (a) sum over 89 2-digit HS product groups, in panel (b) they sum over 1237 4-digit product groups.

Table 2: Product groups experiencing the most functional upgrading

Rank	2-digit HS code	Description	Weighted change in IA share (1)	Unweighted change in IA share (2)
(a) 2000-2006				
1.	85	electrical machinery & equipment	0.0310	0.1097
2.	95	toys, games, sporting goods	0.0124	0.2577
3.	39	plastics & plastic products	0.0064	0.1986
4.	42	leather, leather goods, travel bags	0.0058	0.2083
5.	94	furniture	0.0049	0.1855
6.	61	apparel & clothing, knitted	0.0033	0.1093
7.	62	apparel & clothing, not knitted	0.0031	0.0420
8.	84	machinery & mechanical appliances	0.0027	0.0175
9.	87	vehicles (excl. railway, tramways)	0.0017	0.1137
10.	72	iron & steel	0.0015	0.1453
(b) 2007-2013				
1.	85	electrical machinery & equipment	0.0096	0.0375
2.	84	machinery & mechanical appliances	0.0063	0.0358
3.	90	optical, photographic, measuring, medical, etc. instruments (and parts)	0.0031	0.0920
4.	27	mineral fuels & oil products	0.0026	0.1821
5.	61	apparel & clothing, knitted	0.0007	0.0140

Table 3: Evidence for functional upgrading

	Dependent variable is the share of import & assembly trade in total processing trade exports		
	(1a)	(2a)	(3a)
Time	0.0050***	0.0056***	0.0084***
	(0.0005)	(0.0005)	(0.0002)
Product FE		Yes	
Product-country FE			Yes
Observations	57,491	57,491	1,031,357

	Dependent variable is the share of import & assembly trade in total processing trade exports		
	(1b)	(2b)	(3b)
Time * 2000-2006 dummy	0.0116***	0.0123***	0.0153***
	(0.0010)	(0.0009)	(0.0004)
Time * 2007-2013 dummy	0.0017***	0.0022***	0.0069***
	(0.0005)	(0.0005)	(0.0002)
Product FE		Yes	
Product-country FE			Yes
Observations	57,491	57,491	1,031,357

Sample limited to product categories with max of dependent var. prior to 2006 < 0.9	Dependent variable is the share of import & assembly trade in total processing trade exports		
	(1c)	(2c)	(3c)
Time * 2000-2006 dummy	0.0105***	0.0125***	0.0126***
	(0.0013)	(0.0013)	(0.0005)
Time * 2007-2013 dummy	0.0023***	0.0028***	0.0072***
	(0.0008)	(0.0007)	(0.0002)
Product FE		Yes	
Product-country FE			Yes
Observations	27,222	27,222	694,581

	Dependent variable is 1 minus the share of pure assembly trade in total exports		
	(1d)	(2d)	(3d)
Time * 2000-2006 dummy	0.0120***	0.0124***	0.0234***
	(0.0006)	(0.0006)	(0.0003)
Time * 2007-2013 dummy	-0.0033***	-0.0023***	0.0055***
	(0.0003)	(0.0003)	(0.0001)
Product FE		Yes	
Product-country FE			Yes
Observations	60,550	60,550	1,328,951

Note: The sample period is 2000-2013. All regressions include an indicator for the post-2007 period to account for measurement differences in the explanatory variable and a variable that measures the share of exports accounted for by foreign-owned firms (not reported). In columns (1)-(2) a unit of observation is a product (HS 8-digit)-year combination; in column (3) it is a product-year-destination. Standard errors indicated in brackets; point estimates are significantly different from zero at the *** 1% level, ** 5% level, * 10% level.

Table 4: Relative speed of functional upgrading according to growth in upstream activity

	Dependent variable is the share of Import & Assembly trade in total processing trade exports			
	2000-2006		2000-2013	
	(1)	(2)	(3)	(4)
Time	0.0174***	0.01772***	0.0040***	0.0040***
	(0.0015)	(0.0015)	(0.0005)	(0.0005)
Export growth of suppliers	0.0457***		0.0216***	
	(0.0134)		(0.0043)	
Export growth of own sector		0.0152**		0.0080***
		(0.0067)		(0.0034)
Export growth of upstream sectors		0.0368***		0.0159***
		(0.0127)		(0.0048)
Time * Export growth of suppliers	0.0228***		-0.0015	
	(0.0087)		(0.0017)	
Time * Export growth of own sector		0.0162***		0.0006
		(0.0040)		(0.0010)
Time * Export growth of upstream sectors		0.0169**		-0.0022
		(0.0087)		(0.0016)
Product FE	Yes	Yes	Yes	Yes
Observations	15,419	15,358	48,451	48,390

Note: Regressions in (3)-(4) include an indicator for the post-2007 period to account for measurement differences in the explanatory variable (not reported). A unit of observation is a product (HS 8-digit)-year combination. The growth rate in suppliers' sectors, in columns (1) and (3), is calculated between years *t*-2 and *t* and is a weighted average using input shares from China's 2002 Input-Output table as weight. The results in columns (2) and (4) distinguish between the growth rate in own industry (4-digit CIC), which is sometimes a source of a significant fraction of inputs, and the growth rate in (different) upstream industries. Significantly different from zero at the *** 1% level, ** 5% level, * 10% level.

Table 5: Relative speed of functional upgrading by ownership type

	Dependent variable is the share of Import & Assembly trade in total processing trade exports			
	2000-2006		2000-2013	
	(1)	(2)	(3)	(4)
Constant	0.3356***		0.3698***	
	(0.0073)		(0.0072)	
Private firms	0.2809***		0.1581***	
	(0.0196)		(0.0092)	
Mixed-ownership firms	0.3643***		0.2934***	
	(0.0111)		(0.0095)	
Foreign firms	0.3690***		0.2726***	
	(0.0173)		(0.0126)	
Firms switching ownership	0.4258***		0.4099***	
	(0.0110)		(0.0097)	
Time * SOE	0.0065***	0.0046***	0.0227***	0.0192***
	(0.0017)	(0.0016)	(0.0007)	(0.0007)
Time * Private	-0.0205***	-0.0155***	0.0082***	0.0068***
	(0.0038)	(0.0039)	(0.0007)	(0.0007)
Time * Mixed	-0.0080***	-0.0108***	-0.0034***	-0.0032***
	(0.0018)	(0.0018)	(0.0005)	(0.0006)
Time * Foreign	-0.0040	0.0021	-0.0050***	0.0010
	(0.0033)	(0.0037)	(0.0009)	(0.0010)
Time * Switchers	0.0055***	0.0076***	-0.0148***	-0.0122***
	(0.0012)	(0.0011)	(0.0006)	(0.0006)
Product FE	Yes		Yes	
Product-ownership FE		Yes		Yes
Observations	38,696	38,696	167,296	167,296

Note: The regressions in (3)-(4) include an indicator for the post-2007 period to account for measurement differences in the explanatory variable (not reported). A unit of observation is a product (HS 8-digit)-year-ownership combination. The excluded ownership category is SOEs and the year variables in the interactions are normalized to 0 in the year 2000 such that the constant term captures the average value of the dependent variable for SOEs in 2000. Significantly different from zero at the: *** 1% level, ** 5% level, * 10% level.

Table 6: Relative speed of functional upgrading by location

	Dependent variable is the share of Import & Assembly trade in total processing trade exports					
	Coast or inland			By province		
	2000-2006	2000-2013	2000-2013	2000-2006	2000-2013	2000-2013
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.6104***	0.6442***	0.6386***	0.5851***	0.5941***	0.6273***
	(0.0095)	(0.0050)	(0.0045)	(0.0031)	(0.0030)	(0.0028)
Coast	0.0298***	0.0230***	0.0044			
	(0.0107)	(0.0057)	(0.0055)			
Time * Inland	0.0182***	0.0063***	0.0050***			
	(0.0022)	(0.0005)	(0.0005)			
Time * Coast	0.0131***	0.0039***	0.0044***			
	(0.0010)	(0.0005)	(0.0005)			
Export intensity				0.0191***	0.0103***	0.0213***
				(0.0038)	(0.0017)	(0.0017)
Time				0.0081***	0.0032***	0.0016***
				(0.0010)	(0.0003)	(0.0003)
Time * Export intensity				0.0014***	-0.0001	-0.0003***
				(0.0004)	(0.0001)	(0.0001)
Product FE	Yes	Yes				
Product-Post2007 FE			Yes			
Product-Location FE				Yes	Yes	
Prod-Loc-Post2007 FE						Yes
Observations	28,722	94,544	94,544	54,500	288,389	288,389

Note: The regressions in (2) and (5) include an indicator for the post-2007 period to account for measurement differences in the explanatory variable (not reported). In columns (1) to (3) a unit of observation is a product (HS 8-digit)-year-coast combination, where locations are classified as coastal or not (the 11 coastal provinces include Beijing, Tianjin, and Shanghai). In columns (4) to (6) a unit of observation is a product-year-province combination. Export intensity is measured as the logarithm of total exports at the province-industry (2-digit HS) level. The year variable is normalized to be 0 in 2000 and the export intensity by the sample mean. Significantly different from zero at the: *** 1% level, ** 5% level, * 10% level.

Table 7: Relationship between functional upgrading and industry performance

	(a) Productivity growth		(b) Quality upgrading		(c) Industry upgrading	
Dependent variable:	labor productivity	total factor productivity	unit value ratio		average sophistication of exports	
	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.1549***	0.0089***	0.0444***	0.0407***	0.0024**	0.0005
	(0.0011)	(0.0005)	(0.0013)	(0.0006)	(0.0010)	(0.0004)
IA share	0.0222*	-0.0171***	0.1583***	0.2128***	-0.0317	0.0020
	(0.0135)	(0.0066)	(0.0152)	(0.0050)	(0.0213)	(0.0052)
Product FE	Yes	Yes	Yes	No	Yes	Yes
Industry FE	Yes	Yes				
Product-Country FE			No	Yes		
Observations	17,650	17,104	21,998	185,310	656	5,811

Note: The sample is limited to the 2000-2006 period, but includes all products. The definition of a unit of observation varies by column: in (1)-(2) it is a product (HS 6-digit)-year combination, in (3) it is a product (HS 8-digit)-year combination, in (4) it is a product (HS 8-digit)-country-year combination, in (5) it is a product (HS 2-digit)-year combination, and in (6) it is a product (HS 4-digit)-year combination. Dependent variables are all in logarithms. The dependent variable in columns (5)-(6) is the current export share weighted average of the average GDP/capita of the countries where China sourced imports of the same product in 2000 (see data section for details). Significantly different from zero at the: *** 1% level, ** 5% level, * 10% level.

Appendix

Table A.1: Results for the 2007-2013 period

(a) Extension of Table 4: Functional upgrading and growth in upstream activity

Dependent variable is the share of Import & Assembly trade in total processing trade exports				
	(1)		(2)	
Time	0.0015***	(0.0005)	0.0016***	(0.0005)
Export growth of suppliers	0.0147***	(0.0050)		
Export growth of own sector			0.0069*	(0.0039)
Export growth of upstream sectors			0.0090	(0.0056)
Time * Export growth of suppliers	0.0071**	(0.0032)		
Time * Export growth of own sector			0.0024	(0.0018)
Time * Export growth of upstream sectors			0.0038	(0.0032)
Product FE	Yes		Yes	
Observations	33,032		33,032	

Note: Same analysis as reported in Table 4, but now limited to observations in the 2007-2013 period.

(b) Extension of Table 5: Functional upgrading and ownership type

Dependent variable is the share of Import & Assembly trade in total processing trade exports				
	(1)		(2)	
Constant	0.6666***	(0.0071)		
Private firms	-0.0100	(0.0098)		
Mixed-ownership firms	-0.0273***	(0.0096)		
Foreign firms	-0.0722***	(0.0148)		
Firms switching ownership	0.0096	(0.0100)		
Time * SOE	0.0005	(0.0007)	0.0004	(0.0007)
Time * Private	0.0017**	(0.0007)	0.0016**	(0.0007)
Time * Mixed	0.0042***	(0.0006)	0.0037***	(0.0006)
Time * Foreign	0.0044***	(0.0012)	0.0061***	(0.0013)
Time * Switchers	-0.0002	(0.0007)	-0.0001	(0.0007)
Product FE	Yes			
Product-ownership FE			Yes	
Observations	128,600		128,600	

Note: Same analysis as reported in Table 5, but now limited to observations in the 2007-2013 period.

(c) Extension of Table 6: Functional upgrading and location

Dependent variable is the share of Import & Assembly trade in total processing trade exports				
	Coast or inland		By province	
	(1)		(2)	
Constant	0.6547***	(0.0057)	0.6475***	(0.0010)
Coast	0.0133	(0.0083)		
Time * Inland	0.0025***	(0.0005)		
Time * Coast	0.0009	(0.0006)		
Export intensity			0.0150***	(0.0014)
Time			0.0006*	(0.0003)
Time * Export intensity			-0.0000	(0.0001)
Product FE	Yes			
Product-Location FE			Yes	
Observations	65,822		233,889	

Note: Same analysis as reported in Table 6, but now limited to observations in the 2007-2013 period.