Import Uses and Domestic Value Added in Chinese Exports:
What can we learn from Chinese micro data?*
(web version)

Shunli Yao
University of International Business and Economics &
Institute for Applied International Trade
shunliyao@yahoo.com

Hong Ma
Tsinghua University
mahong@sem.tsinghua.edu.cn

Jiansuo Pei
University of International Business and Economics
jspei@amss.ac.cn

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Abstract

Proportionality assumption is often used to allocate intermediate imports into various domestic uses in the construction of input-output tables. This paper explores two rich Chinese micro datasets on trade and production and finds that considerable firm heterogeneity exists which potentially invalidates the proportionality assumption. Considering the issues of proprietary rights in processing trade, trading agency and domestic content requirement in exports, it further estimates boundaries of Chinese domestic value added share (DVS) in exports. Given the wide range of possible DVSs, the paper speculates a firm survey project to obtain additional information on import uses to narrow the scope of DVS estimates.

JEL codes: F14, F61, C81
Key words: micro data, import uses, firm heterogeneity

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I. Introduction

Estimating the economy-wide and sectoral domestic value added in exports requires an input-output table (IOT) with good information on import uses. Normally, statistical agencies do not compile this information at sectoral level. The IOT experts either break the data on total import uses or make inference from available but limited micro data. In so doing, they often explicitly rely on the proportionality assumption to assign imported inputs into different sectors, or implicitly resort to the proportionality assumption when making generalization of the import uses patterns by a sample of firms. However, this assumption is hardly valid in reality, because individual sectors normally do not have the same patterns of import uses as the overall economy, and firms are heterogeneous and they often behave differently in international trade (Bernard *et al*, 2007). As a result, these approaches tend to lead to biased estimates, as shown by the micro data work at the US Bureau of Census (Feenstra and Jensen, 2012) and the micro data work for Germany (Winkler and Milberg, 2009). Meanwhile, IOT based trade-related estimates are sensitive to the structure of import matrix, such as for emission estimation in Dietzenbacher *et al* (2012) and for vertical specialization (VS)[1] estimation in Yang *et al* (2013).

Therefore, when the WTO and OECD launched the "Made in the World Initiative" in 2011 to promote the world-wide research on domestic value added share (DVS) estimation and to enhance the understanding of the global value chain, they pointed out that "the key challenges in the immediate future concern the quality of trade statistics and the assumptions made to allocate imports to users," and linking traders to the manufacturers will form an important part of the work (Ahmad, Escaith, Miroudot, Webb and Yamano, 2011). In addition to the joint TEC (Trade by Enterprise Characteristics) project with Eurostat, OECD's exercise with Turkish micro data is another attempt to reveal the patterns of firm heterogeneity in trade and production and based on that, to improve trade in value added measures (Ahmad and Araujo, 2011).

There are two threads of methodologies to estimate China's DVS in exports under

[1] The term is borrowed from Hummels et al (2001) and defined as the value of imported intermediates in exports.

an IOT framework: one relies on assumptions or optimization programming to derive key coefficients, and the other is based on real data to obtain these coefficients. The former includes Dean *et a*l (2011) and Koopman *et al* (2012) that split the officially published Chinese 2007 IOT into processing and normal trade parts in their modified Chinese IOT. When further splitting this modified IOT produced by Koopman *et al* (2012) into different ownership of producers, Ma *et al* (2013) also incorporates micro firm level data and other real data. Still, it falls into the former category given the complexity of the IOT structure after two rounds of splitting and the lack of import uses information in the micro data, to be shown in this paper.

On the other hand, Chinese National Bureau of Statistics (NBS) follows the latter approach. When compiling China's 2007 input-output table, for the first time, NBS researchers use firm survey to prepare the import uses coefficients. Recently, in updating the IOT and also as China's response to the WTO/OECD "Made in the World Initiative," import uses matrices from two sources are to be used. While the NBS will keep the previous 2007 matrix, the Chinese General Administration of Customs has started their own independent firm survey on import uses. The approaches by the two agencies are quite different. NBS has jurisdiction over enterprise production data collection, and its survey is an added module to their exiting annual survey on above-scale industrial production enterprises. On the other hand, the Customs are responsible to manage the customs clearance documents provided by firms doing international trade. It is based on this firm level trade data that the Customs conduct the survey.

The two agencies are trying to reach the same goal from different starting points and on different routes. The two micro datasets have rich information on firm's production, financial positions and trade. Combined, they would be able to provide much needed information on firms' import uses. However, the two threads of similar work are independent of each other. According to the work plan, Customs will only provide its aggregated import uses matrix to NBS who will in turn compare it with its own aggregate import uses matrix and make necessary adjustments for the final one used in its next IOT.

Surveys are costly. Without exhausting the existing micro data, surveys would not be efficient and even worse, could lead to aggregation bias if they are not based on samples representative of Chinese firms' trade and production patterns. In that case, the proportionality assumption is implicitly applied.

Needless to say, the ideal approach is to make best use of existing micro data on trade and production. Upward *et al* (2012) made the first attempt to do so in estimating China's DVS in exports. However, their work suffers several flaws. First, they made a strong assumption that production for domestic sale uses the same level of imported inputs as export production, whereas in fact, production for domestic sale normally has lower level of foreign content than export production because of the domestic content requirement.

Secondly, they did not differentiate the two sub-modes of processing trade: processing with imported materials (PWIM) and processing and assembly with provided imported materials (P&A). The main difference between PWIM and P&A is the proprietary rights of foreign materials. Under PWIM, they belong to the Chinese firms and firm's outputs include the values of the foreign inputs. But under P&A, foreign firms own the proprietary rights of imported materials throughout the whole production process, and firm's outputs do not include their values.

Thirdly, they ignored the trading agency issue and treated the import and export data in the firm level trade dataset as used or produced by the same firms. In fact, they could be resold to other production firms or produced by other firms but only handled for international trade by the firms in the dataset.

Finally, they did not consider the imported inputs embodied in domestic inputs. Conceptually, the estimated DVS in exports in Upward *et al* (2012) are derived from the *direct* VS effect, i.e., based on only foreign inputs directly used in the firms' production, not including those embodied in domestic inputs purchased by the firms. Therefore, their DVS numbers are not conceptually comparable to those generated by an IOT, which are based on the estimation of the *total* effect of VS.

Despite the above problems, Upward *et al* (2012) represent the right direction to pursue the micro data work to estimate the Chinese DVS in exports. This paper follows this direction. Specifically, like Upward *et al* (2012), we combine the two micro datasets used respectively and independently by NBS and the Customs: (a) the firm and product level customs trade data; and (b) industrial production data for all state-owned enterprises and non-state enterprises with 5 million yuan or more annual sales. We identify the production enterprises that also do international trade by linking (a) and (b).

Based on this, the paper tries to reveal the patterns of Chinese firm heterogeneity as reflected in trade and production by examining various indicators constructed with the two micro datasets and other statistics. The firm heterogeneity in trade and production justifies further exploration of the micro data in import uses and DVS estimation. With appropriate treatment of the problems in Upward *et al* (2012) identified above, this paper provide various estimates of DVS boundaries.

The paper has five sections. Section II evaluates the methodologies used by NSB and Customs in estimating import uses. It points out the sampling problems and lack of consideration of both production and trade patterns in conducting their respective firm surveys on import uses. Section III explores the merged micro data. It constructs various measures on firm exposure to international trade, particularly on firms' imports of intermediate inputs, to illustrate not only the within-sample but also between-sample firm heterogeneity. Section IV estimates Chinese DVSs in exports based on various samples pulled from the micro data population, as well as on the aggregate commodity level trade data. It provides DVS lower and upper boundaries and associated confidence level. Section V concludes with a speculation of a firm survey project to improve the VS/DVS estimation.

II. NSB and Customs methodologies in estimating import uses

2.1 DVS estimation without import uses information

What can we know about the Chinese DVS in exports if we do not know the information on import uses? Table 1 shows several estimates based on public data. When talking about DVS in exports, one may be quick to think it as a country's net exports in goods and services, or its current account balances. It is true, only if imports used for final domestic consumption replaced the same amount of domestic resources that would otherwise be used for the same domestic production but instead were allocated to export production. This is a strong assumption. More often than not, imports for final domestic use are not perfect substitutes for goods or services in export sector, and this proxy overestimates the foreign content in exports or underestimates the DVS in exports. In other words, it could be treated as the lower bound of the real DVS in exports. As shown in Table 1, this measure of lower bound DVS (Total DVS1_lower) is between 8.2%~25.3% over 2001-10, and 25.3% for 2007.

Furthermore, with breakdown of Chinese foreign trade into normal and processing trade, the numbers readily available from major Chinese government websites, we could treat processing imports as the only imported intermediates used for exports to obtain an estimate of lower bound VS, 26.4%~37.5% over 2001~10 and 30.3% for 2007, which translates into an upper bound of DVS in exports, 69.7%, for 2007 (Total DVS2_upper in Table 1).

In short, with the data on current account balances and the Chinese trade statistics alone, we can at best estimate only the range of Chinese DVS in exports, 25.3~69.7% for 2007. To narrow down the lower and upper boundaries, we need to explore other data sources, which is the focus of the remaining part of the paper.

2.2 Recent Chinese IOT Development

As a tool of central planning, Chinese IOTs traditionally had a domestic focus when the country was closed to the outside world before 1978. The treatment of international trade in the IOTs was minimal, assuming that domestic and imported goods are identical. With China increasingly opening up to foreign trade and investment, this assumption was later relaxed so that domestic and imported goods were treated as differentiated products. Pioneered by Chen *et al* (2001) and continued in Chen *et al* (2012), the structure of Chinese IOT has undergone dramatic change in the past decade to reflect the unique feature of Chinese foreign trade: about half of the country's foreign trade is under the processing trade regime. The separation of processing trade, normal trade and domestic production in the Chinese IOT is justified by the theory of firm heterogeneity (Melitz, 2003). The structure for China's tripartite IOT for analyzing processing trade is illustrated in Appendix 1.

The new IOT has a very rich trade structure and requires more information to fill in the coefficients, including the import uses matrices which are crucial to estimating DVS in exports. In addition to the "proportionality assumptions" made to draw the numbers for the coefficients, firm survey has also been conducted, and the scope of the survey is expanding from NSB's limited attempt to the Customs' systemic implementation. Though not adopted by this paper, surveys on import uses by the two agencies serve as a background for our analysis of the combined production and trade micro datasets on import uses.

2.3 NSB methodology

When compiling China's 2007 benchmark IOT, the NBS relied on the Annual Survey of Industrial Production (ASIP) to do the import uses survey. The ASIP is a survey with a production focus and normally does not cover very much trade information except for firm's total exports. The import uses survey is a separate module attached to the regular questionnaire.

The survey targeted about 10,000 above-scale production enterprises located mainly in the Yangtze River Delta (1,100 in Shanghai, 1,100 in Zhejiang, 1,300 in Jiangsu and 1,300 in Guangdong). For processing import uses, the survey covered mainly the foreign-funded enterprises (FFEs). For production for normal exports and FFE's production for domestic use, FFEs were again the only type of firms by ownership that were covered by the survey. Domestic firms were only selected for survey on other production matrices.

The NBS firm survey for import uses and other input-output coefficients is the first step towards using micro information as a supplement to the proportionality assumption approach. But aggregation bias may occur when the firm survey info is used to generate sectoral information on import uses, for the following reasons:

(a). the survey was mainly conducted in Yangtze River Delta region. The samples under-represent the firms in Guangdong and has no representation for firms in China's northern coastal region, which have very close trade relation with Japan and Korea. In terms of trade volume, the three regions each accounts for roughly 1/3.

(b). Domestic firms also export, and they behave differently from FFEs in international trade. But they were not covered in export survey, neither processing nor normal export survey.

(c). NBS does not have access to detailed firm level trade statistics. Therefore, the NBS sampling was not based on prior knowledge on the distribution of firm's various trade characteristics, such as products, customs regime, firm size and ownership, trading partner, etc.

2.4 The Customs methodology

The Chinese Customs is a partner in the ongoing global value chain project coordinated by the Chinese Ministry of Commerce as a response to the WTO/OECD "Made in the World Initiative." They are planning the firm survey on import uses for preparation of import uses matrix at sectoral level. As the government agency responsible for border control of goods movement, the agency is at the unique administrative position to approach traders in identifying the domestic uses of imports.

Unlike the NBS survey that targeted the production firm, the Customs survey targets trading companies. Selection of companies and goods are based on the 2010 import volume. Specifically, for non-processing imports, companies at the top 60% percentile 2010 imports are selected together with the goods they imported. This sampling exercise leads to the selection of 1,734 traders and 343 8-digit HS commodities. For processing imports, roughly 10,000 enterprises are included with 300 8-digit HS goods. The survey questionnaire asks traders to classify their imports into two broad categories: intermediates and final use. For intermediates, the questionnaire asks further classification into 65 sectors. A copy of the questionnaire is listed in Appendix 2.

The biggest problem with the Customs approach is that trading companies normally are not end users of the imports. Therefore, they are not in a position to give answers to the questionnaire and the Customs firm survey could lead to aggregation bias at the sectoral level. Though there is a plan to eventually combine the Customs import uses matrix with the NBS matrix to produce the final one, this would not necessarily help.

2.5 Micro data approach: what can we do and can't do?

At the firm level, the Custom statistics have the same variables as those in the commodity level trade statistics. Together with the firm production data, they raise the hope to estimate firm level IOTs. However, the following problems hamper our efforts to do so:

a). The production enterprise data contains only total input use, but not its breakdown into domestic or foreign sources, or into different sectors.

b). The production enterprise data, normally without an import uses module, does not have import information and only has total exports. There is detailed import and export information in the firm trade dataset, but the trading companies may resell the imports to other production firms and may also help export products made by other firms.

c). Neither of the two datasets has inter-firm transaction information in either inputs or final products.

As a result, with the current Chinese firm level data, it is difficult to give a precise DVS estimate. However, with rich information, it could be used to reveal the stylized patterns of firms' trade and production and serve as the basis for sensible assumptions and for efficient and unbiased survey design. This motivates Section III.

III. Chinese micro data and firm heterogeneity

3.1 Chinese micro datasets and their matching

We use two sets of 2007 Chinese firm level data: (a) The Customs data has product level transaction information for 236,505 trading companies, which is the population of firm level trade statistics; and (b) The Annual Survey on Industrial Production (ASIP) data has 336,768 enterprises, -- all are SOEs and other enterprises with annual sales more than 5 million yuan and covers 95% industrial output and 98% industrial exports, approximately the whole population of the Chinese industrial enterprises.

To merge the two datasets by firm name and other identifying information produces the linked dataset, which is a subset of each of the two datasets. This is a standard exercise that has been done by researchers working on Chinese micro data. They may differ in specific matching criteria but with the similar strategy and therefore produce the similar overall results. In this paper, the matching exercise only includes trade data with non-zero exports and excludes those with zero exports but non-zero imports. This is a shortcoming for research on import uses. In term of firm size, firms in the matched dataset do both production and direct trade that tend to be large and medium (L&M), while the non-matched are generally small. Key summary statistics of the matching exercise for this paper are presented in Table 2.

Among the 336,768 firms in the ASIP dataset and the 236,505 firms in the trade dataset, only 65,545 firms are successfully matched, accounting for 19.5% or 27.7% of the two datasets respectively. The shares are small, but they account for 82.9% of the total 79,103 exporting ASIP firms. In terms of trade volume, the matched firms handle 35.1% and 27.8% of the total exports for the two datasets respectively. Because the ASIP dataset does not have the import variable, we can only see they account for 16.9% of the total imports for the trade dataset, lower than the same export share. The output and sales variables only appear in the ASIP dataset and they are almost the same in value, 40~41 trillion yuan in total and 21~22 trillion yuan for exporting ASIP. Therefore, the L&M firms produce and sell about 18.5% and 34.5% of the whole and exporting ASIP firms' sale/output respectively.

There are several reasons that a large number of firms in the two datasets are not matched, in addition to the lack of accurate identification information. Among the 80.5% of the total ASIP firms and the 17.1% of the exporting ASIP firms that are not matched, they either do not export or do not export directly, and therefore their names do not show up in customs registry. As for the 72.3% of the firms in the trade dataset that are not matched, they could be pure trading companies with no production at all, or they could be production firms but are not included into ASIP dataset.

Under L&M dataset, there are two subsets that are used in this paper. The subset "L&M ASIP exp>0" represents the firms whose exports in the production data are also positive. The last row in Table 2 shows a subset of the matched data with positive imports (L&M with imp>0). This is the dataset Upward *et al* (2012) work on in estimating China's DVS in exports. Because it is the smallest sample in terms of firm number, its representativeness of the whole population is in doubt and firm heterogeneity within and cross samples deserves careful scrutiny if the aggregate DVS is to be derived from it.

3.2 Firm heterogeneity in trade and production patterns

We construct indicators to show the patterns of firm heterogeneity in trade and production. We compare various measures of trade and production intensity to illustrate the large variations across different types of firms and across sectors.

For L&M firms, they have two export values, one from the trade data and the other from production data. Because of the trading agency problem with the trade data, export value in the production data is more reliable as the real exports produced by the firm. However, as the production data only have total exports with no HS identification and also to be consistent throughout this paper, we instead use the export information from the trade dataset unless otherwise specified, while mindful of the trading agency problem.

The intermediates include two parts: processing imports are treated as intermediates; and intermediates under normal imports are identified with the Broad Economic Categories (BEC) classification developed by the United Nations Statistics Division. Because of the existence of two sub-modes of processing imports, two different definitions are adopted for imported intermediates under processing imports in estimating DVS. One defines all processing imports as intermediates, and the other only includes PWIM. To be consistent, the second definition is adopted when firms' input and output are used in estimating DVS together with import data, as the P&A imports are not counted as input and not part of the output either.

Use of imported intermediates and exports breakdown by firm type (Table 3)

Trade intensity by ownership is shown in Table 3. The shares of intermediate imports in processing exports are listed in the first panel. Comparing the shares in the L&M samples and in the population of trade statistics, collective enterprises, wholly foreign funded enterprise and joint ventures behave similarly, whereas state-owned enterprises and private firms show significant differences, possible indication of a high concentration of pure trading companies among state-owned trading enterprises and the prevalence of small private firms in China's processing trade sector, -- both are not included in the L&M samples. In both the population and the L&M samples, only wholly foreign funded enterprises have higher than average shares.

In the second panel in Table 3, normal imports of intermediates defined by BEC as a share of normal exports are listed, showing large differences between the L&M samples and the population for all types of firms. Therefore, L&M samples are not representative of the population for this indicator either. Foreign firms (wholly foreign funded firms and joint ventures) and state-owned enterprises have higher than average shares in both the population and the L&M samples[2].

In terms of the share of processing exports in total exports shown in the right two panels in Table 3, foreign firms (wholly foreign funded firms and joint ventures) have the highest share, and they are even more so in the L&M samples (86% and 65% respectively), far ahead of the closest state-own enterprises (34%).

Distribution of export shares in output (Table 4)

Both "other exporting ASIP" and "L&M ASIP exp>0" samples have the same export variable from the production dataset, but not the export variable from trade dataset, simply because the "other exporting ASIP" is not matched with the trade data. Therefore, we can only use the export value in the production data to make comparison of export intensity in the two samples. The advantage of using the export value from the production data is that it is the real export produced by the firm, and we can reasonably expect the export shares in total output lie somewhere in [0,1]. In Table 4, weighted averages (or sectoral average) and cross firm simple averages of the export shares in total output are reported for the two samples. Also reported are the differences between the weighted average and cross firm simple average within a

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[2] The higher shares for the state-owned companies are either because some of the traditional state trading companies have diversified their operations into production business and therefore are kept in the L&M dataset, or because import of primary resources is often conducted by state-owned production enterprises with overseas investment.

sample, an indicator of within sector variations, under DIFF, and the differences between the weighted average between thee two samples, an indicator of cross sample variations, under W. A. DIFF. The sectors are indexed by the China Industrial Classification (CIC) system developed by NBS (Appendix 3).

Visual inspection of the numbers shows there are large variations both within and cross the two samples and within sectors in both samples. The lower panel of the table gives the summary statistics of export intensity measures. For “other exporting ASIP” firms, tobacco (CIC 16) and the furniture (CIC 21) sectors have the lowest (4.2%) and the highest (74.9%) export intensities respectively. For the “L&M ASIP exp>0” sample, the “artwork and other manufacturing” sector (CIC 42) carries the highest export share (82.0%), and the tobacco sector still ranks the lowest (1.5%). The cross sectors standard deviations of export intensity for the two samples are 18.4% and 19.8% respectively.

In terms of within sector variations, DIFF is a rough proxy, as it reflects the skewness of firm export intensity distribution in a sector. In the “other exporting ASIP” sample, the sector with the highest negative skew is the sector “processing of petroleum, coking, and nuclear fuel (CIC 25)” (-6.1) and the largest positive skew happens in the sector “electrical machinery and equipment (CIC 39)” (DIFF=26.2). In the “L&M ASIP exp>0” sample, the largest negative skew is in the sector “communication, computers and other electronic equipment (CIC 40)” (DIFF=-5.7), while the largest positive skew is in the sector “paper and paper products (CIC 22)” (DIFF=19.8). Overall, both samples are positively skewed, implying that firms with higher outputs tend to export smaller shares. But it is more pronounced in the first sample.

In terms of cross sample variations, the overall share in second sample is 4.2% higher than that in the first sample. It can be 17.3% higher in the sector “electrical machinery and equipment (CIC 39)” and 21.1% lower in the sector “processing of petroleum, coking and nuclear fuel (CIC 25).”

Intermediate Import Intensity for L&M (Tables 5&6)

As discussed earlier in this sub-section, when constructing the measures of a firm's import intensity in output or input, differentiation between PWIM and P&A matters. Imports under P&A account for 17% of processing imports in the L&M dataset, which is not trivial. We adopt the second definition of intermediate import under processing import that only includes PWIM for Table 5 and Table 6.

As shown in Table 5, in overall Chinese materials production, for every 100 yuan output, there are 17.3 yuan foreign inputs. The highest share (49.5%) goes to the sector "waste recycling and processing (CIC 43)," while the lowest (0.3%) is still in the tobacco sector (CIC 16). Though overall skewness is insignificant, for the sector "waste recycling and processing (CIC 43)," it has the highest negative skew (-28.3%), and for the sector "communication, computers and other electronic equipment (CIC 40)," it comes with the highest positive skew (7.3%), an indication of large within sector variations. The standard deviations for cross sector weighted and simple averages are 9.8% and 13.2% respectively, an indication of large across sector variations.

All shares in the left panel are positive and smaller than 100. But with breakdown into various percentiles, the samples show quite a few numbers greater than 100, strong evidence of the importing agency problems. It is most prevalent in the sector "waste recycling and processing (CIC 43)," as at least 25% of firms in this sector run importing agency business. Importing agency evidences also show up in other eight sectors at 99 percentile, including "food processing (CIC 13)," "leather, fur and feather products (CIC 19)", "timber and wood processing (CIC 20)," "chemical fibers (CIC 28)," "plastics (CIC 30)," "smelting and pressing of ferrous and non-ferrous metals (CIC 32 and 33)" and "communication, computers and other electronic equipment (CIC 40)."

Table 6 reports an alternative measure of intermediate import intensity: share of intermediate import in total inputs. As input is a portion of output, this measure can better expose the extent of importing agency problem. A simple comparison between the weighted averages and the cross firm simple averages of the intermediate import share in the two tables shows that numbers in Table 6 are all bigger than the corresponding numbers in Table 5, with overall weighted average 22.8% and overall simple average 59.0%.

With this measure, importing agency problems appear to be more evident: there are three sectors whose simple averages of shares across firms are greater than 1, including textile and clothing (CIC 18), furniture (CIC 21) and plastics (CIC 30), whereas none in Table 5. While the sector “waste recycling and processing (CIC 43)” still has the highest weighted average share and seemingly the largest number of firm (at least 25%) doing importing agency business among all sectors, numbers in the breakdown panel in Table 6 show that four more sectors, plastics (CIC 30), “smelting and pressing of ferrous and non-ferrous metals (CIC 32 and 33)” and “communication, computer and other electronic equipments (CIC 40),” have 5% firms doing importing agency business, and at the 99th percentile, additional 24 sectors have evidences of doing importing agency business. If we consider the possibility that firms with shares lower than 100 may also engage in importing agency business, the true extent of pure importing would be higher than that suggested by the sectors and firms with larger than 100 ratios. It is worth noting that firms with import intensity larger than 100 are not necessarily more misleading in reporting true imports of their own use than firms with lower import intensity measures. For example, a firm that imports 110% of its total input may actually have 80% for its own use and 30% for resale, while another firm with 60% import may use 30% for its own production and resell the remaining 30%. This suggests that the importing agency problem can not be solved simply by dropping those records with import intensity larger than 100.

Comparison between the max, min and standard deviations on the left corner of the two tables suggests that both cross and within sector variations are more pronounced for the intermediate import and total input ratios.

Summary results: cross and within samples variations (Table 7)

Firm heterogeneity can be revealed in many ways. To put things in perspective, Table 7 assembles some of the previous aggregate measures together with shares of value-added in output with breakdown by firm ownership and size.

For import intensity, large discrepancies exist between domestic and foreign firms: foreign firms’ import shares are higher. There are some differences cross firm size, but more differences within the same size group for the share of imported input in total input, as shown by the difference between the weighted and simple averages.

For export intensity, domestic and foreign firms behave differently: foreign firms' export shares are higher. Compared to the "L&M ASIP exp>0" sample, firm size matters more for the "other exporting ASIP" sample where larger firms tend to export smaller share of total output.

Value-added share in total output (va/output) is a new indicator. While the aggregate measures in the two samples are quite similar, they can differ as much as 6.3%~58.6% at sector level, as shown in Table 7 and its annex.

In summary, the existence of firm heterogeneity is extensive and the issues of proprietary rights in processing imports and trading agency are real. These will complicate the efforts to estimate the DVS in Chinese exports.

IV: Estimating DVS: boundaries and confidence

Proportionality assumption on domestic and export production

Proportionality assumption regarding import uses means two things: (1) imports are proportionally allocated among different sectors; and (2) within each sector, they are further proportionally allocated between domestic and export production. If the importing agency problem could be solved so that the import data truly reflects the amount of intermediate imports used in a firm's production, then L&M dataset would be able to remedy the first problem. So the importing agency issue is a focus of the paper. As for the second problem, unfortunately, firm level data alone is of little help, as it does not contain information on how firms split intermediate imports between domestic and export production.

When Hummels *et al* (2001) first employ IOTs to estimate VS, they assume equal percentage of foreign input in domestic output and exports. Upward *et al* (2012) retain this assumption in estimating China's VS. Working on a dataset similar to L&M, Upward *et al* (2012) distinguish processing and normal trade and apply this assumption to normal trade only. That is, within normal trade, imports are allocated to domestic and export production proportional to domestic output and normal exports.

This assumption is over-simplified but still acceptable. However, when they actually do the calculation, they use the following formula to determine the ratio of intermediate import in domestic output and normal exports,

$$r^{uwz} = \frac{M^{bec}}{Y - X^{p}} \qquad (1)$$

where "uwz" represents the initials of the last names of the three authors of Upward *et al* (2012). This is problematic, because imports for processing and assembly ($M^{p\&a}$) in trade dataset are included only in X^p but not in Y. Therefore, the denominator in the above formula gives a lower value of domestic output and normal exports, or a higher share of foreign content in domestic output and normal exports. Because $M^{p\&a}$ accounts for 17.0% and 24.2% of L&M processing imports and total processing imports respectively, and they are not a trivial amount. As such, mistreatment of $M^{p\&a}$ in the above formula can not be ignored.

Imports for processing and assembly and lower VS boundary

This paper corrects this problem and modifies the above formula by deducting $M^{p\&a}$ from processing exports when calculating the ratio of normal intermediate imports defined by BEC (M^{bec}):

$$r = \frac{M^{bec}}{Y - (X^{p} - M^{p\&a})} = \frac{M^{bec}}{DN} \qquad (2)$$

where DN represents domestic output and normal exports.

Export production often uses more foreign inputs than domestic production. This can be seen from trade intensity measures by ownership breakdown in Table 3 and Table 7, where FFEs have higher shares of intermediate import in normal exports, total input and total output. Because FFEs dominate Chinese foreign trade in both imports and exports, a link can be established that export production have higher shares of foreign intermediates than domestic production. Also considering that domestic content requirement is normally imposed on FFEs for domestic production, a lower bound of VS exists as a result of this policy. In fact, the proportionality assumption regarding the import uses among domestic and export production, as reflected in above equation, can be regarded as the lower bound:

$$VS^{lower} = M^{p} + \frac{M^{bec}}{Y - (X^{p} - M^{p\&a})} X^{n} = M^{p} + r \cdot X^{n} \qquad (3)$$

Trading agency problem

Imports and exports in the above equations mean to be the actual imports used as inputs by the firms and the actual exports produced by the firms. Because of trading agency problem, trade volume from the trade dataset does not meet this requirement at the firm level. However, since the L&M data already screened out the pure trading companies, production firms doing trading agency business are more likely to deal with firms in the same sector. Based on this assumption, we first sum up the variables across firms within a sector and then proceed to estimate sectoral VS using that formula. By so doing, we neutralize the trading agency problem among firms within a sector, but we also risk introducing aggregation bias. This can be illustrated by the following equations:

$$VS_{i}^{lower} = M_{i}^{p} + \frac{M_{i}^{bec}}{DN_{i}} \cdot X_{i}^{n} \qquad (4)$$

$$VS^{lower} = \sum M_{i}^{p} + \frac{\sum M_{i}^{bec}}{\sum DN_{i}} \cdot \sum X_{i}^{n} \qquad (5)$$

$$VS^{lower} - \sum VS_{i}^{lower} = \sum \left(\frac{X_{i}^{n}}{DN_{i}} - \frac{\sum X_{i}^{n}}{\sum DN_{i}^{n}} \right) \cdot M_{i}^{bec} \qquad (6)$$

Therefore, the two approaches may generate different sectoral VS, as the right hand side of equation (6) is not always zero. Referring to Table 4, though it is not exact the same export intensity measures as that in the above equation, they do suggest that both within and between sector variations could be large. This potential bias can also occur when estimation is done at the whole manufacturing level. The lower bound of VS thus should be treated with less confidence[3].

Upper VS boundary

After having the estimation of lower bound of VS with less confidence above, we

[3] Less confidence on the lower bound of VS is also due to lack of an exact minimum for domestic content requirement.

now turn to the upper bound VS estimation. As exports use more intermediate imports than domestic production, the upper limit of VS can be achieved by assuming all intermediate imports are used for export production:

$$VS^{upper} = M^{p} + M^{bec} \quad (7)$$

In contrast to the lower bound VS, the upper bound VS estimates are invariant of the level of analysis, commodity or sectoral level. It is not subject to the constraint of the domestic content requirement either. As a result, the confidence level is high for it, as long as we are confident with BEC definition of intermediates[4].

Results and discussions[5]

Sectoral and whole manufacturing shares of VS (VSS) over two samples “L&M imp>0” and “L&M” are reported in Table 8. The lower bound of VSS is converted into upper bound of DVS via the following formula:

$$DVS = 1 - \frac{VS}{X} = 1 - VSS \quad (8)$$

Cross all sectors, DVS upper bounds are 61.0% and 67.2% for the respective two samples. Among all sectors, DVSs in CIC sectors “food and beverage products (CIC 14 and 15)”, “furniture (CIC 21)”, “petroleum and coking processing (CIC 25)” and “non-metalic mineral products (CIC 31)” are among the highest, because these domestic sectors are not as much globalized as the sectors with the lowest DVSs, such as “communication, computer and other electronic equipments (CIC 40)” and “waste recycling and processing (CIC 43)”. The DVS patterns are consistent with import intensity patterns shown in Table 6, where sectors with higher DVSs tend to have lower intensity of intermediate imports, and vice versa.

Comparing the two data samples, DVSs in L&M are consistently higher than those in the “L&M imp>0” sample, simply because the former dataset has records with zero imports. Firms that do not import intermediates may buy from other production firms that are also in importing agency business. This is another example that sampling matters in DVS estimation and trading agency problem deserves careful

[4] According to Timmer *et al* (2012), 14% of BEC codes can be both final goods and intermediates.
[5] We do not attempt to compare the numerical results with those from other studies because our methodology is based on a set of different concepts, which make them uncomparable.

treatment.

Table 9 reports the aggregate DVSs, both lower and upper bounds, for overall and normal trade estimated with different datasets and intermediate definitions. Some of the numbers are drawn from previous tables. The numbers in italics are the estimates with less confidence in part due to firm heterogeneity issue as discussed earlier about equation (6)[6]. As a reminder, Table 9 also lists the shares of processing & assembly imports in total processing imports for the three datasets affected by the proprietary rights issue. Taking into consideration of this issue helps improve the confidence in the GVC upper bounds in the three datasets.

Clearly, the range of DVS estimates varies depending on the data scope and the associated definitions of intermediates. For overall DVS, both lower and upper bounds are estimated with confidence and the true value could be anywhere in the range [38.9, 69.7]. For normal trade, the DVS could be anywhere in a much wider range [37.3, 96.3].

What have we learned from our DVS estimation results? First of all, DVS estimates are sensitive to data samples. Cross sample variations for lower and upper DVS bounds as well as the ranges of possible DVS are significant, especially when compared to the overall DVS estimates. This suggests none of the samples appears to be representative of the population.

Secondly, as reflected by the wide ranges of possible GVC values, DVS estimates are sensitive to assumptions on import uses. It is quite intuitive, as the import uses across sectors and across domestic and export production directly allocate the flow of foreign intermediates within a country, and ultimately determine the sectoral and overall DVSs. It is also in line with previous findings in IOT literature, e.g., Dietzenbacher *et al* (2012 and Yang *et al* (2013).

Given the uncertainties surrounding the true DVS numbers, it is natural and logical to speculate about a firm survey project on import uses that aims to obtain additional information for better DVS estimation.

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[6] VS is first estimated at sector level and then summed up across sectors. For VS estimation with the whole commodity trade data in the last row of Table 9, there is no link between production output and trade data and estimation can only be done with data summed up over the whole database.

V. Conclusion

It is true that assumptions have to be made in one way or another to estimate the DVS with an IOT, but they can not be made pervasively. This paper does not estimate the exact true DVS value because we do not make arbitrary assumptions. Instead, we take stock of the possible estimates, and in so doing, we clarify several conceptual issues that help improve the methodology in the literature. We leave a wide range for possible DVS estimates and only expect them to be narrowed down by future firm survey work.

Though firm level data has rich information that could be used to correct the bias in import uses matrix caused by proportionality assumption in IOT development, realization of its potentials is hampered by several factors, mainly, the non-representative samples and trading agency problems. Thus, firm survey shall follow the following steps:

First, identify the small production firms from firm level trade data. This could be done by first screening the non-matched small trading firms and then tracking them through firms' contact information to verify their production status. Together with these small trade and production firms, dataset L&M can be expanded to include large, medium and small firms (LMS).

Second, select a sample of firms from LMS to be covered by the survey. The questionnaire shall include the questions on the amount of imports for own use and exports produced by trade regime and the amount split between domestic production and export production, among others.

Of course, various other aspects of the firm distribution shall also be considered, such as ownership, sector, location and trading partners.

Firms can answer questions regarding direct import uses, but it is difficult for firms to know the uses of imports embodied in domestic inputs. Probably, this is the only area that needs an assumption.

References

Ahmad, N. and S. Araujo, 2011, "Using Trade Microdata To Improve Trade In Value Added Measures: Proof of Concept Using Turkish Data," OECD

Ahmad, N., H. Escaith, S. Miroudot, C. Webb and N. Yamano, 2011, "Trade in Value-added: Concept, Methodologies and Challenges," OECD/WTO

Chen, Xikang, Leonard K. Cheng, K. C. Fung, Lawrence J. Lau, 2001, "The Estimation of Domestic Value-Added and Employment Induced by Exports: An Application to Chinese Exports to the United States," http://www.stanford.edu/~ljlau/Presentations/Presentations/010618.pdf

Chen, X., Leonard K. Cheng, K.C. Fung, Lawrence J. Lau, Yun-Wing Sung, K. Zhu, C. Yang, J. Pei, Y. Duan, 2012, "Domestic value added and employment generated by Chinese exports: A quantitative estimation," *China Economic Review*, vol 23: 850-864

Dean, Judith, K.C. Fang and Zhi Wang, 2011, "Measuring Vertical Specialization: The Case of China," *Review of International Economics*, 19(4):609-625.

Dietzenbacher, Erik, Bart Los, Robert Stehrer, Marcel Timmer and Gaaitzen De Vries, 2013, "The Construction of World Input-Output Tables in the WIOD Project," *Economic Systems Research*, 25: 71-98

Dietzenbacher, Erik, Jiansuo Pei and Cuihong Yang, 2012, "Trade, Production Fragmentation, and China's Carbon Dioxide Emissions," *Journal of Environmental Economics and Management*, 64: 88-101

Feenstra, Robert C. and J. Bradford Jensen, 2012, "Evaluating Estimates Of Materials Offshoring from U.S. Manufacturing," *NBER Working Paper 17916*, Cambridge, MA

Hummels, David, Ishii, Jun, Yi, Kei-Mu, 2001, "The nature and growth of vertical specialization in world trade," *Journal of International Economics* 54, 75–96

Koopman, Robert, Zhi Wang and Shang-jin Wei, 2012, "Estimating Domestic Content in Exports When Processing Trade is Pervasive," *Journal of Development Economics* 99: 178-189

Ma, Hong, Zhi Wang and Kunfu Zhu, 2013, "Domestic Value-added in China's Exports and its Distribution by Firm Ownership," paper presented at the the AEA meetings in San Diego

Marc J. Melitz (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity, *Econometrica*, vol. 71(6), pages 1695-1725.

Timmer, Marcel P. (Eds.), 2012, “The World Input-Output Database (WIOD): Contents, Sources and Methods,” *WIOD Working Paper Nr. 10*, May,

Upward, Richard, Zheng Wang and Jinghai Zheng, 2012, “Weighing China’s export basket: The domestic content and technology intensity of Chinese exports,” *Journal of Comparative Economics*, http://dx.doi.org/10.1016/j.jce.2012.07.004

Winkler, Deborah and William Milberg, 2009, “Errors from the Proportionality Assumption and in the Measurement of Offshoring: Application to German Labor Demand,” SCEPA Working Paper 2009-12, New York: Bernard Schwartz Center for Economic Policy Analysis and Department of Economics, New School for Social Research.

Yang, Cuihong, Erik Dietzenbacher, Jiansuo Pei, Xikang Chen, Kunfu Zhu and Zhipeng Tang (2013). The Bias in Measuring Vertical Specialization: the Effects of Processing Trade in China, conditionally accepted by *Economic Systems Research*

Table 1. Estimates of domestic value added shares in exports without import uses information

Year	CA balances / total exp	Total			L&M firms		
	Total DVS1_lower	Proc imp / proc exp	Proc imp / total exp	Total DVS2_upper	Proc imp / proc exp	Proc imp / total exp	Total DVS3_upper
2001	10.6	63.7	35.3	64.7	64.9	49.2	50.8
2002	11.5	67.9	37.5	62.5	67.9	51.0	49.0
2003	8.2	67.4	37.2	62.8	67.3	51.1	48.9
2004	8.3	67.6	37.4	62.6	69.9	50.6	49.4
2005	16.4	65.8	36.0	64.0	67.9	49.6	50.4
2006	21.6	63.0	33.2	66.8	62.4	44.8	55.2
2007	25.3	59.6	30.3	69.7	57.6	40.5	59.5
2008	24.4	56.0	26.4	73.6			
2009	18.3	54.9	26.8	73.2			
2010	14.7	56.4	26.5	73.5			

Table 2. Summary statistics of the 2007 enterprise and trade data

	Firm numbers	exp	imp	output	sales
ASIP	336,768	7.34	n.a.	40.50	40.00
exporting ASIP	79,103	7.34	n.a.	21.90	21.30
trade data	236,505	9.27	7.27	n.a.	n.a.
L&M (matched)	65,545	2.58	1.23	7.54	7.34
L&M ASIP exp>0	50,277	2.31	1.05	5.95	5.81
L&M imp>0	37,536	2.17	1.23	5.48	5.38

Note: exp, imp output and sales value in trillion yuan

Table 3. Use of imported intermediates and exports breakdown by firm type, 2007

	imported intermediates, %				exp by customs regimes, %			
	for proc exp		for normal exp		proc exp		normal exp	
Firm type	Total	L&M firms	Total	L&M firms	Total	L&M firms	Total	L&M firms
Collective	41.6	41.0	37.8	14.9	24.1	15.4	75.9	84.6
WFFE	63.1	61.9	78.7	52.4	81.8	85.9	18.2	14.1
JV	48.3	46.7	73.7	59.2	59.7	65.5	40.3	34.5
Private	58.7	47.2	25.6	6.4	9.8	14.9	90.2	85.1
SOE	63.4	38.0	104.4	64.3	26.6	34.2	73.4	65.8
All	59.7	57.6	62.7	40.7	50.6	70.4	49.4	29.6
formula	proc imp/proc exp		normal BEC input imp / normal exp		proc exp/total exp		normal exp/total exp	

Table 4: Distribution of export shares (exports/output, %), 2007

	other exporting ASIP			L&M ASIP exp>0			
CIC	Weighted	Cross firm	Diff	Weighted	Cross firm	Diff	W.A. Diff
13	38.8	57.7	18.9	50.1	68.0	17.9	11.3
14	40.1	56.8	16.7	35.2	54.8	19.6	-4.9
15	22.5	46.8	24.3	19.4	38.4	19.0	-3.1
16	4.2	26.4	22.2	1.5	1.5	0.0	-2.6
17	52.3	72.1	19.7	50.8	60.6	9.7	-1.5
18	73.4	83.9	10.4	75.3	79.9	4.6	1.9
19	68.7	84.6	15.9	69.4	78.1	8.7	0.7
20	61.4	71.7	10.3	54.8	69.2	14.4	-6.6
21	74.9	77.8	2.9	77.8	78.8	1.0	2.9
22	31.9	52.7	20.8	30.4	50.2	19.8	-1.5
23	29.4	48.5	19.1	42.6	46.0	3.5	13.1
24	73.7	82.6	8.9	80.5	80.3	-0.2	6.9
25	45.9	39.8	-6.1	24.7	38.2	13.5	-21.1
26	30.8	49.0	18.2	30.5	38.0	7.6	-0.3
27	24.2	35.6	11.4	31.5	41.2	9.7	7.3
28	17.7	33.8	16.1	25.5	34.1	8.6	7.8
29	42.1	60.3	18.1	44.9	58.4	13.5	2.7
30	48.0	67.0	19.0	57.5	64.1	6.6	9.5
31	36.7	59.0	22.3	43.6	59.5	16.0	6.8
32	27.2	44.4	17.2	32.4	38.4	6.0	5.1
33	29.7	38.5	8.8	27.7	37.6	9.9	-2.0
34	52.5	71.9	19.4	60.1	65.1	4.9	7.7
35	33.1	52.6	19.5	39.8	49.1	9.3	6.7
36	26.5	38.1	11.6	38.7	43.6	5.0	12.2
37	30.2	45.4	15.2	40.1	48.1	8.0	9.9
39	36.5	62.7	26.2	53.8	62.3	8.5	17.3
40	55.9	63.4	7.6	71.0	65.3	-5.7	15.1
41	49.4	61.7	12.3	60.5	62.9	2.4	11.1
42	67.6	83.0	15.4	76.1	82.0	5.9	8.5
43	19.3	30.5	11.2	23.0	31.8	8.8	3.7
All	41.5	66.7	25.2	45.6	62.1	16.4	4.2
max	74.9	84.6	26.2	80.5	82.0	19.8	17.3
min	4.2	26.4	-6.1	1.5	1.5	-5.7	-21.1
stdv	18.4	16.9	6.7	19.8	18.3	6.2	7.8

Note: export value is from the production data.

Table 5. Intermediate import in total output, L&M, 2007 (%)

CIC	Weighted Average	Cross firm	Diff	Within L&M p25	p50	p75	p90	p95	p99
13	13.5	11.7	1.8	0.1	1.1	8.8	34.6	54.1	123.1
14	4.8	6.5	-1.6	0.2	1.5	6.3	21.3	32.0	51.9
15	2.3	3.3	-1.0	0.0	0.5	3.0	10.2	18.2	31.6
16	0.3	0.3	0.0	0.3	0.3	0.3	0.3	0.3	0.3
17	9.2	11.1	-1.9	0.1	1.4	12.3	39.2	54.8	81.8
18	10.0	13.4	-3.4	0.1	1.7	16.3	47.2	61.0	84.6
19	15.6	16.2	-0.6	0.4	5.4	21.8	43.3	59.3	101.2
20	11.9	13.9	-2.0	0.2	2.0	12.0	33.4	53.5	129.1
21	8.7	9.4	-0.7	0.1	1.9	11.3	29.4	46.1	66.9
22	19.7	16.6	3.1	2.1	10.2	25.2	42.3	53.7	75.8
23	7.5	9.8	-2.3	0.3	3.2	14.4	29.6	40.2	61.2
24	15.3	16.3	-1.0	0.4	6.9	26.3	45.1	56.6	81.4
25	10.2	10.3	-0.1	0.2	1.5	15.5	28.6	54.2	89.9
26	17.9	17.9	0.0	1.1	7.9	26.1	48.9	61.1	92.7
27	5.8	8.4	-2.6	0.1	1.4	9.9	26.4	36.3	70.9
28	19.9	20.1	-0.2	1.6	11.1	32.4	53.0	61.4	108.8
29	18.9	20.7	-1.9	2.0	12.9	30.3	52.1	64.9	93.0
30	21.9	25.4	-3.5	3.3	15.5	39.2	63.9	77.8	123.2
31	8.9	12.6	-3.6	0.2	2.6	13.5	39.0	54.2	87.6
32	25.0	22.9	2.1	0.1	3.1	36.4	73.6	86.1	169.5
33	13.5	20.5	-6.9	0.1	3.1	20.8	62.9	87.2	125.7
34	13.8	13.6	0.2	0.2	3.1	17.7	44.0	60.9	88.0
35	10.9	10.4	0.5	0.1	1.7	13.2	34.5	49.2	74.1
36	11.1	10.7	0.4	0.2	2.4	13.3	34.5	47.8	79.1
37	13.7	13.2	0.5	0.1	2.7	17.4	41.5	56.7	90.6
39	15.6	15.9	-0.4	0.4	5.2	23.0	45.9	62.9	95.4
40	36.9	29.6	7.3	1.9	15.3	40.8	66.2	80.9	153.0
41	21.4	18.8	2.6	0.4	7.6	29.6	56.0	69.6	99.5
42	10.3	13.9	-3.6	0.1	2.7	15.2	32.7	48.4	81.0
43	49.5	77.9	-28.3	0.8	68.7	110.8	265.4	281.9	281.9
All	**17.3**	**16.1**	**1.1**	0.2	4.3	22.1	47.1	63.4	96.6
max	**49.5**	**77.9**	**7.3**						
min	**0.3**	**0.3**	**-28.3**						
stdv	**9.8**	**13.2**	**5.7**						

Note: PWIM BEC definition is adopted for intermediate import

Table 6. Intermediate import in total input, L&M, 2007 (%)

CIC	Weighted Average	Cross firm	Diff	Within L&M p25	p50	p75	p90	p95	p99
13	18.0	71.3	-53.3	0.1	1.6	11.7	52.2	80.3	184.9
14	6.5	8.8	-2.3	0.3	2.0	8.9	27.6	41.9	73.4
15	3.3	4.7	-1.5	0.0	0.7	4.4	14.9	22.4	45.3
16	1.9	1.9	0.0	1.9	1.9	1.9	1.9	1.9	1.9
17	12.0	19.3	-7.3	0.1	1.9	17.6	53.8	76.3	127.8
18	14.0	204.0	-190.0	0.2	2.6	24.7	67.6	88.4	151.3
19	20.7	40.1	-19.4	0.5	7.3	30.7	62.0	84.6	186.5
20	15.6	34.4	-18.8	0.2	3.0	16.5	44.5	71.3	263.0
21	11.4	144.6	-133.3	0.1	2.5	16.1	43.4	64.2	165.0
22	25.4	25.3	0.1	2.4	13.4	32.5	56.5	69.8	105.7
23	10.3	14.2	-3.9	0.3	4.2	21.0	43.7	51.7	86.0
24	20.2	24.7	-4.5	0.5	9.3	37.0	63.8	80.7	141.6
25	12.6	12.8	-0.2	0.2	1.2	18.9	42.5	63.6	87.3
26	23.5	25.9	-2.4	1.6	10.6	34.5	67.8	84.0	181.8
27	8.3	29.6	-21.2	0.1	1.9	13.5	40.2	53.9	104.1
28	26.1	27.8	-1.8	2.1	13.0	45.9	71.4	93.7	143.2
29	24.9	30.8	-5.9	2.5	17.7	43.9	70.7	84.8	202.0
30	28.5	114.8	-86.3	4.5	21.5	51.9	83.1	103.4	240.0
31	12.5	17.4	-5.0	0.2	3.6	18.2	52.8	74.4	125.4
32	30.8	32.7	-1.9	0.1	4.1	51.1	87.6	109.8	207.1
33	16.9	25.9	-9.0	0.1	4.7	27.1	79.9	105.5	157.4
34	17.9	56.3	-38.4	0.3	4.2	25.0	60.1	81.7	143.6
35	14.5	95.3	-80.8	0.1	2.2	17.8	48.3	70.6	113.2
36	15.0	17.5	-2.5	0.2	3.4	19.7	50.4	73.2	132.8
37	18.0	22.7	-4.7	0.1	3.6	24.0	55.9	77.7	163.2
39	20.1	38.5	-18.4	0.5	7.1	31.1	61.7	81.8	144.7
40	48.0	47.5	0.5	2.7	20.9	54.5	85.8	106.7	278.4
41	29.1	37.7	-8.6	0.6	10.0	43.3	73.6	91.0	134.6
42	13.9	19.6	-5.8	0.1	3.6	21.1	48.5	67.8	113.1
43	66.2	94.4	-28.3	1.1	81.6	116.5	325.3	330.3	330.3
All	**22.8**	**59.0**	**-36.2**	0.3	6.0	30.5	65.0	85.7	163.4
max	**66.2**	**204.0**	**0.5**						
min	**1.9**	**1.9**	**-190.0**						
stdv	**12.8**	**45.0**	**43.9**						

Note: PWIM BEC definition is adopted for intermediate import

Table 7. Summary average results (%) by ownership and firm size (employee), 2007

Indicator	Dataset	Average	All	domestic	foreign	<50	[50, 200)	[200, 1000)	>1000
imp input/input	L&M	weighted	22.8	6.3	29.4	28.7	24.6	21.3	23.9
		cross firm	59.0	22.0	71.0	38.0	57.4	69.5	29.7
imp input/output	L&M	weighted	17.3	4.8	22.2	21.6	18.6	16.2	18.2
		cross firm	16.1	5.3	19.6	18.9	15.8	15.4	18.5
exp/output	L&M	weighted	45.6	37.0	59.5	55.0	50.1	50.8	52.5
	ASIP exp>0	cross firm	62.1	51.1	68.9	58.9	60.9	63.8	62.6
	other exp	weighted	41.5	37.5	55.3	62.3	55.6	43.1	32.9
	ASIP	cross firm	66.7	64.3	71.4	70.5	69.4	62.8	46.2
va/output	L&M	weighted	25.9	25.8	26.0	25.7	25.4	26.1	26.0
		cross firm	26.7	25.6	27.4	24.4	26.1	27.6	28.4
	other exp	weighted	27.1	26.9	27.6	24.1	26.6	27.1	27.8
	ASIP	cross firm	28.3	27.5	30.0	23.8	27.5	31.1	31.8

Table 7 Annex: selected sectoral weighted average va/output

CIC		All
16	L&M	97.0
	other exp ASIP	38.4
42	L&M	26.2
	other exp ASIP	32.5
40	L&M	26.0
	other exp ASIP	30.9
26	L&M	26.0
	other exp ASIP	30.7

Table 8. VS share (VSs) and DVS by sector estimated with micro data (%)

	L&M imp>0		L&M	
CIC	VSS_lower	Total DVS4_upper	VSS_lower	Total DVS5_upper
13	32.2	67.8	20.5	79.5
14	11.5	88.5	8.3	91.7
15	8.2	91.8	5.5	94.5
16	56.7	43.3	56.7	43.3
17	23.1	76.9	16.2	83.8
18	27.9	72.1	22.7	77.3
19	35.7	64.3	28.1	71.9
20	24.6	75.4	16.2	83.8
21	12.5	87.5	10.2	89.8
22	56.9	43.1	50.3	49.7
23	26.9	73.1	24.0	76.0
24	23.7	76.3	20.2	79.8
25	16.6	83.4	6.1	93.9
26	49.0	51.0	39.2	60.8
27	19.7	80.3	14.3	85.7
28	51.8	48.2	48.8	51.2
29	39.2	60.8	35.2	64.8
30	55.1	44.9	47.2	52.8
31	17.8	82.2	11.7	88.3
32	72.8	27.2	37.9	62.1
33	50.9	49.1	36.8	63.2
34	23.6	76.4	18.9	81.1
35	22.7	77.3	18.3	81.7
36	29.0	71.0	25.7	74.3
37	30.0	70.0	26.2	73.8
39	35.6	64.4	30.8	69.2
40	66.6	33.4	64.9	35.1
41	42.0	58.0	39.2	60.8
42	30.9	69.1	21.8	78.2
43	88.8	11.2	80.7	19.3
All	**39.0**	**61.0**	**32.8**	**67.2**

Note: Gross output (rather than total sales) is adopted in the denominator.

Table 9. Estimated DVS Boundaries (%)

Data scope and imp input	Total DVS lower	Total DVS upper	Normal DVS lower	Normal DVS upper	note: shares of P&A in PI
CA balances (DVS1)	25.3				
Total PI (DVS2)		69.7			
L&M PI (DVS3)		59.5			
L&M imp>0 PI BEC (DVS4)	50.7	*61.0*	66.9	*94.5*	17.0
L&M PI BEC (DVS5)	58.5	*67.2*	77.8	*96.4*	17.0
Total PI BEC	38.9	*68.0*	37.3	*96.3*	24.2

Appendices

Appendix 1: China's tripartite input-output table for analyzing processing trade

	Intermediate use			Final use		
	D	*P*	*N*	*DFD*	*EXP*	*TOT*
D	$\mathbf{Z}^{DD}$	$\mathbf{Z}^{DP}$	$\mathbf{Z}^{DN}$	$\mathbf{f}^{D}$	0	$\mathbf{x}^{D}$
P	0	0	0	0	$\mathbf{e}^{P}$	$\mathbf{x}^{P}$
N	$\mathbf{Z}^{ND}$	$\mathbf{Z}^{NP}$	$\mathbf{Z}^{NN}$	$\mathbf{f}^{N}$	$\mathbf{e}^{N}$	$\mathbf{x}^{N}$
IMP	$\mathbf{M}^{D}$	$\mathbf{M}^{P}$	$\mathbf{M}^{N}$	$\mathbf{f}^{M}$	0	$\mathbf{x}^{M}$
VA	$(\mathbf{v}^{D})'$	$(\mathbf{v}^{P})'$	$(\mathbf{v}^{N})'$			
TOT	$(\mathbf{x}^{D})'$	$(\mathbf{x}^{P})'$	$(\mathbf{x}^{N})'$			

Notes: *D* = production for domestic use; *P* = production of processing exports; *N* = production of non-processing exports and other production of FIEs; *DFD* = domestic final demand; *EXP* = exports; *TOT* = gross industry outputs (and total imports in the column *TOT*); *IMP* = imports; and *VA* = value added.

Appendix 2: The Customs Import Uses Survey Questionnaire

Commodity code: XXXX.XXXX　　Imports (thousand USD): XXXX　　Proportion: XX.X%

Primary classification	Secondary classification (Input-output sector)		Amount Ratio (%)	Note
Intermediate use	01	Agriculture, forestry, animal husbandry and fishery		
	02	Coal mining and washing industry		
	03	Oil and gas exploration industry		
	…	…		
	…	…		
	…	…		
	…	…		
	…	…		
	…	…		
	…	…		
	…	…		
	65	Public administration and social organizations		
Final use		Final consumption expenditure		
		Capital formation		

Appendix 3: China Industrial Classification

CIC	Description
13	Processing of Food from Agricultural Products
14	Manufacture of Foods
15	Manufacture of Beverages
16	Manufacture of Tobacco
17	Manufacture of Textile
18	Manufacture of Textile Wearing Apparel, Footware and Caps
19	Manufacture of Leather, Fur, Feather and Related Products
20	Processing of timber, manufacture of wood, bamboo, rattan, palm and straw products
21	Manufacture of Furniture
22	Manufacture of Paper and Paper Products
23	Printing, Reproduction of Recording Media
24	Manufacture of Articles For Culture, Education and Sport Activities
25	Processing of Petroleum, Coking, Processing of Nuclear Fuel
26	Manufacture of Raw Chemical Materials and Chemical Products
27	Manufacture of Medicines
28	Manufacture of Chemical Fibers
29	Manufacture of Rubber
30	Manufacture of Plastics
31	Manufacture of Non-metallic Mineral Products
32	Smelting and Pressing of Ferrous Metals
33	Smelting and Pressing of Non-ferrous Metals
34	Manufacture of Metal Products
35	Manufacture of General Purpose Machinery
36	Manufacture of Special Purpose Machinery
37	Manufacture of Transport Equipment
39	Manufacture of Electrical Machinery and Equipment
40	Manufacture of communication equipment, computers and other electronic equipment
41	manufacture of measuring instruments/machinery for cultural activity/office work
42	Manufacture of Artwork and Other Manufacturing
43	Waste Recycling and Processing