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Domestic Value Added in Exports: Theory and Firm Evidence from China[†]

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China has defied the declining trend in domestic content in exports in many countries. This paper studies China's rising domestic content in exports using firm- and customs transaction-level data. The approach embraces firm heterogeneity and hence reduces aggregation bias. The study finds that the substitution of domestic for imported materials by individual processing exporters caused China's domestic content in exports to increase from 65 to 70 percent in the period 2000–2007. Such substitution was induced by the country's trade and investment liberalization, which deepened its engagement in global value chains and led to a greater variety of domestic materials becoming available at lower prices. (*JEL* F13, F14, L14, O19, O24, P31, P33)

> *"Production processes are more and more fragmented… The nature of trade has changed, but our trade data have not… Many goods are assembled in China, but their commercial value comes from the numerous countries… We want to know the value added by each country in the production process of final goods."*
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> —Pascal Lamy, WTO Director General, "Made in the World" Initiative (2011)

Over the past two decades, increasing global production fragmentation has allowed exporting firms to rely less on domestic inputs for production. Indeed, research finds

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that domestic content in exports has been declining in most countries. China is an intriguing exception.[1] What caused China to defy the declining trend in domestic content in exports in most countries, despite its deep engagement in global value chains? There are several possible answers to this question with conflicting implications. The rising domestic content could reflect the changing composition of Chinese exports, suggesting that China has shifted its comparative advantage toward the industries with high domestic content. It could also be a result of its increasing domestic production costs, which would imply that the country has become less competitive. Yet another possible answer is that it could be due to the gradual substitution of domestic for imported materials by its exporters. This would imply that China has become more competitive, particularly in the intermediate input sectors. Understanding the determinants of China's rising domestic content in exports can provide important development policy insights for other countries.

This paper uses customs transaction-level data merged with firm survey data to measure and analyze China's rising domestic content in exports, or the *ratio of domestic value added in exports to gross exports* (DVAR). Our transaction-level data cover the universe of Chinese exporters during the period 2000–2007, allowing us to construct firm, industry, and aggregate DVARs over time to study their evolution. The recent burgeoning literature on measuring industry and aggregate DVARs relies on input-output (IO) tables. While using IO tables has the advantage of capturing IO linkages within and across countries, the presence of firm heterogeneity may result in significant aggregation biases in the estimates of the DVAR. Our ground-up approach embraces firm heterogeneity by measuring industry and aggregate DVARs as the weighted averages of the underlying firms' DVARs.[2] This unique methodology further allows us to compute bootstrapped standard errors for our aggregate estimates, which are then used to perform statistical tests on the rising trend. Finally, we use the customs data merged with manufacturing firm survey data to examine whether changes in export composition, firms' production costs, and material shares are responsible for China's rising DVAR.

Our DVAR estimates confirm existing studies that China's DVAR has been rising, but are higher than previous estimates. Specifically, we find that the DVAR of China's aggregate exports increased from 65 percent to 70 percent between 2000 and 2007, with similar magnitudes of increases in the country's bilateral exports to its major trading partners. The increase in the aggregate DVAR is statistically significant and confirms the upward trend found in Koopman, Wang, and Wei (2012)—henceforth, KWW12—which adopts an IO table-based approach. However, our DVAR estimate for processing exports is significantly higher than those of KWW12.

The finding that our DVAR estimates are higher than those of KWW12 exemplifies that ignoring firm heterogeneity may lead to downward aggregation bias in the IO table-based approach. Samples that are used to construct IO tables often consist

[1] Koopman, Wang, and Wei (2012) find that China's DVAR rose between 2002 and 2007. Johnson and Noguera (2014), using the GTAP IO tables, show that from 1970 to 2009, the DVAR of all countries in their sample are declining, except for the Republic of Korea and Indonesia.

[2] Ahmad et al. (2013) also allow firm heterogeneity to affect the estimates of a country's aggregate DVAR. They use firm-level data to generate indicators by exporter status, which are then used to refine IO-table based estimates of domestic value added in exports from Turkey.

mainly of large firms.[3] Given that large firms tend to have a lower DVAR due to their high import-to-sales ratios, oversampling large firms in the construction of IO tables can lead to lower estimates of the aggregate DVAR.[4] To illustrate this point, we conduct a decomposition exercise. In particular, we show how our DVAR estimate can be lowered to a level that is not statistically different from that of KWW12, just by using a sample that includes only those large firms that satisfy the sample selection criteria behind the construction of the Chinese IO tables. This suggests that aggregation bias driven by firm heterogeneity alone is sufficient to explain the wedge between our estimates.

What has caused the rise in China's aggregate DVAR? Our firm-level regressions reveal that it is mainly driven by individual processing exporters substituting domestic for imported materials, both in terms of volume and varieties. Other factors, such as rising production costs due to higher wages, changing composition of Chinese exports toward the high-DVAR industries, or churning of firms with different DVARs, cannot explain the upward trend during the sample period.

We also find that the substitution of domestic for imported materials was induced by the country's trade and foreign direct investment (FDI) liberalization since the early 2000s. To guide our empirical analysis, we build a model featuring a translog cost function, which permits an estimation of the time-varying elasticity of substitution between domestic and foreign input varieties to study how various government policies may affect a country's DVAR. We find that for China, increasing FDI and declining input tariffs have led to a greater variety of domestic materials becoming available at lower prices during the sample period. For the entire processing sector and for most industries within that sector, imported and domestic materials are gross substitutes, with the estimated elasticity of substitution ranging between 1.9 and 6.6. These large elasticities explain why lower prices of domestic materials can result in such significant increases in the DVAR at the firm and thus the aggregate level in China.

Despite its simplicity, our methodology can be applied widely. In its basic form, our methodology can be used directly to measure the DVAR of processing exporters that operate in many export-oriented industries deeply embedded in global value chains.[5] Furthermore, with additional assumptions, our methodology can be applied to constructing the DVAR for countries that have little dependence on processing exports.[6]

Our paper is related to several strands of literature. It relates to the literature on measuring value-added trade.[7] In particular, our DVAR estimates complement the IO table-based estimates, by incorporating firm heterogeneity and thus minimizing aggregation bias. This paper is also related to the literature on the effects of trade and

[3] See the *Handbook of Input-Output Table Compilation and Analysis* (United Nations 1999).

[4] Recent research by Amiti, Itskhoki, and Konings (2014) and Blaum, Lelarge, and Peters (2014) shows that larger firms tend to have a higher import-to-sales ratio.

[5] The industries of garment, shoes, and toys in Bangladesh, Cambodia, Dominican Republic, and Mauritius, as well as the electronics industry in Malaysia, Thailand, and Vietnam are some of the examples.

[6] In research in progress, we apply our current methodology to construct the DVAR for a wide range of countries, where we obtain matched importer-exporter customs transaction data from the World Bank's Exporter Dynamics Database (Cebeci et al. 2012). Preliminary results, based on Bangladesh, Guatemala, Madagascar, and Morocco, show an upward trend in the DVAR of these countries' aggregate exports.

[7] This literature starts with Hummels, Ishii, and Yi (2001) to use industry input-output (IO) tables to calculate the value added to exports ratios for many countries. Recent related work includes Antràs, Fally, and Hillberry (2012); Johnson and Noguera (2012, 2014); Koopman, Wang, and Wei (2012, 2014); Antràs and Chor (2013); De la Cruz et al. (2013); and Johnson (2014).

FDI liberalization on domestic product varieties.[8] Our results confirm existing findings that the reduction in input tariffs and increased presence of FDI in downstream sectors could lead to an expansion of the variety of domestic intermediate inputs. Finally, our paper contributes to the literature on international production sharing and global value chains,[9] as well as the studies on China's increasing engagement in the global economy.[10] Our results speak to both bodies of work by showing that China's rising DVAR is due to the substitution of domestic for imported materials. Such substitution indicates that the country is relying less on imports and becoming more competitive in intermediate input sectors. This suggests that China has been moving up the value chains, and thus may have significant implications for world trade and the global economy, given its sheer size.[11]

The paper proceeds as follows. Section I defines our measures of firm DVAR. Section II shows how we use firms' DVAR to compute industry and aggregate DVARs, and analyze their patterns. We also discuss the associated aggregation biases in the standard IO table-based approach, extend our methodology to include the nonprocessing sector, and calculate the DVAR of China's aggregate exports in this section. Section III presents the pattern of firm DVAR. Section IV develops a simple model to theoretically and quantitatively study the determinants of firm DVAR. Section V concludes. In the online Appendix, we describe our datasets and the construction of the main variables, such as the number of upstream varieties, import varieties, and industry exchange rates. A theoretical model that features a Cobb-Douglas production function is also presented there.

I. Defining Firm-Level Domestic Value Added

We use two micro datasets in this paper: Chinese customs transaction-level trade data from 2000 to 2007, and the Annual Surveys of Industrial Firms from the National Bureau of Statistics (NBS) of China over the same period. Readers are referred to the online Appendix for details.[12] For the ease of exposition, we first focus on processing exporters, which are required by law to sell all their outputs abroad and

[8] Goldberg et al. (2010) studies the impact of trade liberalization of India on its export variety. Kee (2015) shows that the increased presence of FDI in the garment sector of Bangladesh caused a greater variety of domestic materials to become available which led to product scope expansion and productivity gains in domestic garment firms.

[9] See Feenstra (1998) for a review of the early literature on foreign outsourcing. More recent work includes, among others, Baldwin (2014), which postulates how participating in a global supply chain should be viewed as a new strategy of industrialization; and Timmer et al. (2014), which summarizes the main findings in the literature on global value chains.

[10] Johnson and Noguera (2012) show that the US-China trade imbalance in 2004 is 30 to 40 percent smaller when trade is measured in value added. Autor, Dorn, and Hanson (2013) show that increasing Chinese imports causes significantly suppressed job creation, lower wages, lower labor market participation, and higher unemployment in the United States. Pierce and Schott (2015) find that US industries with the larger decline in tariffs against imports from China experienced the slower employment growth, lower job creation, and higher job destruction.

[11] These findings are consistent with a recent paper by Constantinescu, Mattoo, and Ruta (2015), who suggest that China's structural transformation may be an important reason for the recent global trade slowdown, as China is relying less on foreign materials, thanks to its increasingly competitive domestic intermediate input industries.

[12] We employ the procedures commonly used to organize these data. We remove trade intermediaries, identified by the methods proposed by Ahn, Khandelwal, and Wei (2011), in the customs data. We also remove import and export transactions with China itself. As pointed out by Liu (2013), China's re-imports from itself accounted for about 9 percent of its total imports. These abnormal trade flows could arise from tax and transport cost saving incentives.

may import materials free of duties.[13] In Section C of the online Appendix, we will extend our methodology to study nonprocessing exports and thus aggregate exports of China.

Let us first define the main variable of interest: *domestic value added in exports* (DVA), starting from the accounting identity of a firm's total revenue. A firm's (i) total revenue (PY_i), by definition, consists of the following components: profits, (π_i), wages (wL_i), cost of capital (rK_i), cost of domestic materials $(P^D M_i^D)$, and cost of imported materials $(P^I M_i^I)$:

$$PY_i \equiv \pi_i + wL_i + rK_i + P^D M_i^D + P^I M_i^I. \tag{1}$$

Some domestic materials may embody foreign content, while some imported materials may embody domestic content. Let us denote the foreign content in domestic materials and domestic content in imported materials by δ_i^F and δ_i^D, respectively. Then $P^D M_i^D$ can be written as the sum of δ_i^F and a part that constitutes purely domestic content, q_i^D. Likewise, $P^I M_i^I$ can be written as the sum of δ_i^D and a part that constitutes purely foreign content, q_i^F:

$$P^D M_i^D \equiv \delta_i^F + q_i^D, \quad \text{and} \quad P^I M_i^I \equiv \delta_i^D + q_i^F.$$

Similar to the concept of a country's gross domestic product, we define the DVA of a firm as the total value of domestic goods and services embodied in the firm's output. In other words, a firm's DVA equals the sum of its profits, wages, rental costs of capital, and both direct or indirect domestic materials purchased:[14]

$$DVA_i \equiv \pi_i + wL_i + rK_i + q_i^D + \delta_i^D. \tag{2}$$

For a processing firm that exports all its output and imports some of its intermediate inputs and capital equipment, its export (EXP_i) equals its revenue, while its import (IMP_i) equals the costs of imported materials, $P^I M_i^I$, and imported capital, δ_i^K. Thus, (1) implies

$$\begin{aligned} EXP_i &= DVA_i + IMP_i - \delta_i^D + \delta_i^F - \delta_i^K \Rightarrow \\ DVA_i &= (EXP_i - IMP_i) + (\delta_i^D - \delta_i^F + \delta_i^K). \end{aligned} \tag{3}$$

[13] China's Customs regulates processing trade under several regimes, with pure assembly (PA) and import and assembly (IA) being the two main types. The main difference between these two regimes lies in the allocation of control rights of the imported inputs. In the PA regime, a foreign firm supplies components to a Chinese assembly plant and retains ownership and control over the imported inputs throughout the production process. In the IA regime, a Chinese assembly plant imports components of its own accord and retains control over their use. Readers are referred to Feenstra and Hanson (2005) for a more detailed description of the two regimes. While this distinction will not affect our DVAR estimates, it may affect the way one should model firm sourcing decisions. See Fernandes and Tang (2012), which exploits these regulatory differences to study the organizational form of offshoring. Later on we will report regression results separately for the two types of processing.

[14] Note that while some firms may have foreign capital in its ownership, the returns to this foreign capital are still included in its DVA in exports. This is because the service of these capital is rendered within the country's borders. Moreover, a firm's DVA contains domestic materials produced by other firms and is therefore larger than its own value added by definition.

Equation (3) shows that we may use $EXP_i - IMP_i$ to measure a processing firm's DVA after adjusting for δ_i^D, δ_i^F, and δ_i^K. For China, KWW12 and Wang, Wei, and Zhu (2014) find that δ_i^D is very close to 0 for processing exports.[15] Moreover, in our current dataset, processing firms' imports of capital are recorded separately from material imports, implying $\delta_i^K = 0$.[16] Thus, the only necessary adjustment here is to remove foreign content in domestic materials, δ_i^F, which causes $EXP_i - IMP_i$ to overestimate DVA_i in exports. From (3), firm i's *ratio of domestic value added in exports to gross exports* (DVAR) depends only on the share of imported materials in total revenue $\left(P^I M_i^I / PY_i\right)$ with adjustments for δ_i^F / EXP_i:

$$DVAR_i \equiv \frac{DVA_i}{EXP_i} = 1 - \frac{P^I M_i^I}{PY_i} - \frac{\delta_i^F}{EXP_i} \tag{4}$$

$$= 1 - \frac{P^M M_i}{PY_i} \frac{P^I M_i^I}{P^M M_i} - \frac{\delta_i^F}{EXP_i}, \tag{5}$$

$$\text{where} \quad P^M M_i = P^D M_i^D + P^I M_i^I.$$

Without firm-level information on δ_i^F / EXP_i, we refer to KWW12 for the industry estimates for 2007 and impute the estimates backward for each industry-year between 2000 and 2007, using the weighted average of the growth rates of the number of ordinary (nonprocessing) importers across upstream industries.[17] These industry estimates range from 0.4 to 5.7 percent, which we use to proxy for δ_i^F / EXP_i in (4) to construct a firm's DVAR.[18]

Equation (5) shows that, once we control for the share of materials in total revenue $P^M M_i / PY_i$, factors that do not affect the share of imported materials in total materials will not affect a firm's DVAR. This is an accounting identity, independent of the choice of production functions. It highlights that in order to understand a

[15] Based on the Global Trade Analysis Project (GTAP) multicountry IO tables, Koopman, Wang, and Wei (2014) estimate that the domestic content embedded in imported materials accounted for 0.7 percent of China's ordinary exports in 2004, and essentially 0 for its processing exports. Using the IO tables from the World Input-Output Database (WIOD), Wang, Wei, and Zhu (2014) update these estimates and show that the domestic content embedded in imports used by Chinese exporters $\left(\frac{\delta_i^D}{EXP_i}\right)$ increased from 0.1 percent in 1995 to 1.3 percent in 2007. They also show that these estimates can vary widely across sectors, ranging from 2.5 percent for the Chemical Products sector to 0.2 percent for the Leather and Footwear sector. Unfortunately, such estimates are not available separately for processing and ordinary exports. Nevertheless, given the low estimated domestic content in imported materials at the aggregate level, adjusting for it is unlikely to have a significant effect on both the levels and the trends of our aggregate DVAR estimates. Our approach therefore may underestimate the DVAR for sectors that use imported material with high domestic content. Given that our DVAR estimates for most sectors are already higher than the existing estimates based on IO tables, accounting for returned domestic content in imports will only strengthen our point that the existing estimates are subject to a downward aggregation bias.

[16] The Chinese customs data record material and capital imports separately from a firm's total imports, in a category called "Equipment for Processing Trade" (code number = 20). We thank a referee for pointing this out.

[17] The rationale is that the net entry of ordinary importers, stimulated by China's continuous trade liberalization, may increase the supply of intermediate inputs that embody more foreign content. This assumption is grounded on the findings in Brandt et al. (2015), which shows that while the cost share of imports in total materials has been stable, the aggregate import share has increased substantially due to a large entry of new importers since China's accession to the World Trade Organization (WTO) in late 2001.

[18] Table A7 in the online Appendix reports the estimates of δ_i^F / EXP_i by industry-year. Notice that our approach does not double count DVA as long as we exclude indirect trade between processing firms and focus on measuring DVA of the processing trade regime. We need additional assumptions to deal with the double-counting issue when we measure DVA for nonprocessing and aggregate exports.

firm's DVAR, one should focus on the determinants of the share of imported materials in total materials. In Section IV, we will develop a simple but general model that features a translog cost function to formally study these determinants.[19]

II. From Firm DVAR to Industry and Aggregate DVAR

Inferring the DVAR of an industry or aggregate exports from firms' DVAR is straightforward. If firms only engage in direct trading (i.e., do not import or export for other firms) and only produce in one industry, then we can compute the DVAR of industry j as follows:

$$(6)\qquad DVAR_j = 1 - \frac{\sum_{i \in \Omega_j} IMP_i}{\sum_{i \in \Omega_j} EXP_i} = \sum_{i \in \Omega_j} \frac{EXP_i}{\sum_{i \in \Omega_j} EXP_i} \frac{EXP_i - IMP_i}{EXP_i}$$

$$= \sum_{i \in \Omega_j} \frac{EXP_i}{\sum_{i \in \Omega_j} EXP_i} DVAR_i,$$

where Ω_j is the set of firms in industry j. Industries are defined according to the industry classification by the United Nations.[20] By construction, the DVAR of industry j is a weighted average of the DVAR of all firms in industry j with weights equal to the export shares of the firms. Likewise, we can sum up all industry imports and exports first and then compute the DVAR of aggregate exports as follows:

$$(7)\qquad DVAR = 1 - \frac{\sum_j \sum_{i \in \Omega_j} IMP_i}{\sum_j \sum_{i \in \Omega_j} EXP_i} = \sum_j \sum_{i \in \Omega_j} \frac{EXP_i}{\sum_j \sum_{i \in \Omega_j} EXP_i} DVAR_i.$$

Similar to an industry's DVAR, the aggregate DVAR constructed based on (7) is a weighted average of the DVAR of all firms, with weights reflecting the export shares of the firms.[21]

While our ground-up approach is appropriate for inferring the aggregate DVAR, there are two caveats. The first caveat is about multi-industry exporters, for whom the allocation of imported materials (IMP_{ij}) to the production of output in different

[19] To show that our main theoretical results are not specific to the functional form choice, we also solve for a model that features a Cobb-Douglas production function in the online Appendix.

[20] See http://unstats.un.org/unsd/tradekb/Knowledgebase/HS-Classification-by-Section for the UN industry classification. There are originally 20 sectors in the UN list. Sectors 1–3, which are agricultural sectors, are excluded since we cannot match most of the transactions to the manufacturing survey data. Sector 5 (Mining) and Sector 19 (Arms and Ammunition) are excluded for the same reason. Examples of a sector include Chemical Products (HS2 = 28–38), Textiles (HS2 = 50–63), Footwear and Headgear, etc. (HS2 = 64–67), and Machinery, Mechanical, and Electrical Equipment (HS2 = 84–85).

[21] In reporting the aggregate DVAR, we first aggregate firm DVARs to the industry level. To make sure that the industry-level analysis, particularly the between-and-within analysis, is not driven by potential noises due to merging the customs data with the firm data, we use industry weights based on the export value of single-industry exporters in the customs dataset.

industries (EXP_{ij}) is generally unobservable in the data, making the inference of an industry's DVAR based on (6) impossible. Thus, we only use the subset of single-industry exporters to infer industry DVARs.[22]

The second caveat relates to processing exporters importing indirectly through other firms in China. Under the current customs regulations in China, processing firms can legally sell imported materials to other firms and benefited from tariff exemption, as long as the buyers are also registered processing firms. Complicating this problem is that such transactions are not confined within the same industry or geographic location.[23] The transactions of imported materials between two processing firms in the domestic economy appear to be widespread according to our data.

This practice of indirect importing certainly impacts the way we construct the firm-level and industry-level DVAR. In particular, for those firms that import more than their needs, which we call excessive importers, using (4) may underestimate their DVARs and in the extreme case result in negative DVARs.[24] On the other hand, for those firms that buy imported materials from other processing firms locally, which we call excessive exporters, using (4) may overestimate their DVARs, and in the extreme case bias the DVARs toward 1. To address the issue of indirect importing, we first use balance-sheet data to identify both the excessive importers and exporters.

We define excessive importers as those firms that import more than their total material costs as recorded in the NBS Annual Survey of Industrial Firms (2000–2007), given that total material costs should equal to the sum of imported materials and domestic materials.[25] These excessive importers import more than their total materials and are dropped from our sample. To identify excessive exporters, we first identify all registered ordinary (nonprocessing) exporters that only export in a single industry. Unlike processing exporters, ordinary exporters are not required by China's Customs to sell all outputs abroad. They can use imported materials to produce for both domestic and foreign sales. In addition, ordinary exporters need to pay import tariffs and thus should have less incentive to import materials. The DVAR of ordinary exporters should be on average higher than that of processing exporters in the same industry. Thus, we use the twenty-fifth percentile of ordinary exporters' DVARs as an upper bound for processing exporters' DVAR, and identify all processing firms that have a DVAR higher than this cutoff as excessive exporters. Our firm-level regression results below are robust to using higher percentiles of ordinary firms' DVAR as filters.

[22] Nevertheless, since the construction of the firm-level DVAR is not restricted by the multi-industry concerns, we will also include multi-industry exporters in the firm-level regressions below.

[23] See "Regulations Concerning Customs Supervision and Control over the Inward Processing and Assembling Operation" (China's Ministry of Commerce 1990). For example, a shoe processing exporter may import leather and sell it to a handbag processing exporter.

[24] In the raw data, about 10 percent of the single-industry firms have negative net exports.

[25] Without a common firm identifier shared by the two datasets, we use firm names to merge the customs transaction data with the NBS Annual Surveys of Industrial Firms. For rare cases that have duplicate firm names, we use the firm's address to improve the merging. See Ma, Tang, and Zhang (2014) for details about the merging procedures. Tables A2 and A3 in the online Appendix present the representation of the merged and filtered samples, relative to the original customs sample. In terms of the number of exporters, about 39 percent of the single-industry processing exporters from the customs datasets can be merged with the NBS data, and about 22 percent survive our filters that remove excessive importers and exporters. In terms of export value, our final sample covers over 46 percent of exports based on the original customs data.

Table 1—Issues and Assumptions or Solutions

	Issues	Assumptions or solutions
1	Domestic content in imported materials.	Negligible according to KWW12.
2	Imported content in domestic materials.	Lower DVAR by 1.5 to 5.7 percent, computed based on KWW12
3	Firms import capital equipment.	Remove equipment from firm imports.
4	Firms buy imported materials from firms.	Drop excessive exporters.
5	Firms sell imported materials to other firms.	Drop excessive importers.
6	Multi-industry firms hinder the calculation of industry DVAR.	Restrict the sample to single-industry firms.

In summary, we focus on a subset of single-industry processing exporters that have their $\frac{IMP}{EXP}$ bounded between the two cutoffs:

$$\left(\frac{IMP}{EXP}\right)^{OT}_{(25)} \leq \frac{IMP}{EXP} \leq \frac{P^D M^D + P^I M^I}{EXP}, \tag{8}$$

where $DVAR^{OT}_{(25)} = 1 - \left(\frac{IMP}{EXP}\right)^{OT}_{(25)}$ is the twenty-fifth percentile of the DVAR of ordinary exporters in the same industry.[26] Table 1 summarizes the main issues, assumptions and solutions of our approach to constructing the DVAR at the firm, industry, and aggregate levels.[27]

A. *Movement of the Industry and Aggregate DVAR of Processing Exports*

The final dataset is an unbalanced panel of 17,903 observations for 8,459 single-industry processing exporters over 8 years (2000–2007).[28] Our sample covers a balanced panel of 15 industries throughout the sample period. An advantage of using the micro approach is that we can construct random samples drawn from the firm sample and compute bootstrapped standard errors for our estimates of the aggregate DVAR. Figure 1 shows our benchmark estimates of the DVAR of Chinese processing exports, along with the 95 percent confidence intervals based on 100 randomly drawn samples with replacement. Chinese processing exports' DVAR has been increasing from 46 in 2000 to 55 percent in 2007. Depending on the year, the 95 percent confidence interval is between 5 to 11 percentage points wide, with an average of 7 percentage points over the 8 years in our sample. Most important, based

[26] Table A8 in the online Appendix reports $\left(\frac{IMP}{EXP}\right)^{OT}_{(25)}$ by industry-year. We will check the sensitivity of our regression results by including both excessive importers and exporters in the sample below.

[27] Sometimes, firms have incentives to stock up imported materials when the international prices of commodities are low, particularly in those industries that use a lot of commodities, such as iron, copper, and crude oil, as inputs. Thus, imports may not be fully used to produce goods in the same period. For these firms, the calculation of the DVAR based on (4) may not be accurate. However, there is no easy way to resolve the issue of inventory management. As we will show in the next section, all firm observations with negative DVA are no longer negative once we use (8) to restrict our sample. This suggests that inventory management does not appear to drive our results.

[28] Our sample covers both types of processing trade in China—pure assembly (PA) and import-and-assembly (IA). While we will check the robustness of our regression results below by repeating the analysis separately for the two regimes, it is important to point out that IA accounts for a much larger share of processing, in terms of the volume as well as the number of exporters, compared to PA. In our regression sample, over 90 percent of the observations belong to IA, in which exporters take control and hold ownership over the imported materials. We show in Figure A5 in the online Appendix that even at its peak in 2000, PA never accounts for more than 30 percent of total processing exports, and continuously declined to less than 20 percent by 2007.

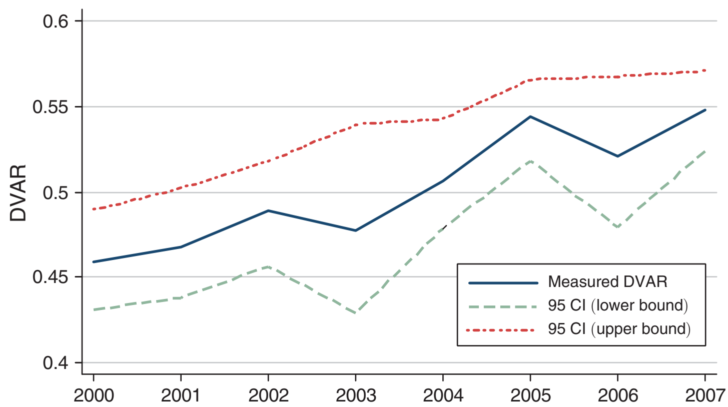

Figure 1. DVAR of Processing Exports (*2000–2007*), with 95 Percent (*Bootstrapped*) Confidence Intervals

on the bootstrapped standard errors, the difference between the DVAR of Chinese aggregate exports in 2007 and that of 2000 is statistically significant, lending strong support for KWW12, who also find an upward trend of similar magnitude based on IO tables and aggregate trade data. Figures A4 and A6 in the online Appendix show similar trends, despite using samples with different cutoffs from (8), and a sample that includes multi-industry firms.

Figure 2 plots the DVAR of processing exports across time for different industries, together with the 95 percent confidence intervals based on 100 random samples drawn with replacement. The DVAR increased for all industries besides two (wood and articles; base metals). For the industries that exhibit an upward DVAR trend, the tight confidence intervals convincingly reject the null hypothesis that the DVAR estimates are the same between 2000 and 2007 (see Table A9 in the online Appendix for details). For wood and articles, and base metals industries, their DVAR are not statistically different between 2000 and 2007. Overall, none of the industries exhibits a declining trend in the DVAR that is statistically significant during the sample period.

The microdata also permit a decomposition of the aggregate trend into between- and within-industry changes. Specifically, the change in the aggregate DVAR (from year $t-1$ to t) can be decomposed according to the following identity:

$$\Delta DVAR_t = \underbrace{\sum_j \overline{w}_{jt}(\Delta DVAR_{jt})}_{within} + \underbrace{\sum_j \left(\overline{DVAR}_{jt}\right)(\Delta w_{jt})}_{between},$$

where $\overline{w}_{jt} = \frac{1}{2}\left(\frac{EXP_{jt}}{EXP_t} + \frac{EXP_{jt-1}}{EXP_{t-1}}\right)$ is the average share of industry j in total exports over year $t-1$ and t, while $\overline{DVAR}_{jt} = \frac{1}{2}\left(DVAR_{jt} + DVAR_{jt-1}\right)$ is the simple average of industry j's DVAR over year $t-1$ and t. Figure 3 shows that the increase in the aggregate DVAR over the sample period is all driven by within-industry increases in the DVAR rather than a between-industry reallocation of resources from the low-DVAR industries to the high-DVAR industries.

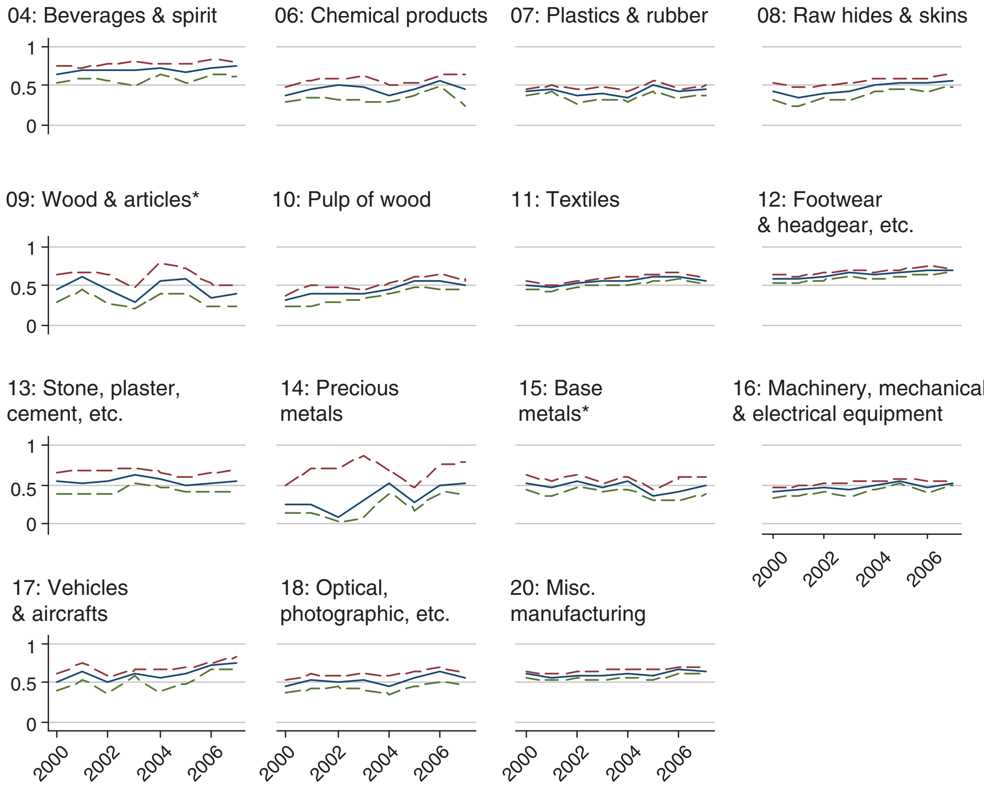

Figure 2. DVAR Trend by Industry with 95 Percent (*Bootstrapped*) Confidence Intervals, 2000–2007

Note: Dashed lines are 95 percent confidence interval; * denotes industries with average DVAR lower in 2007 than 2000.

With these estimates, we further construct the bilateral DVAR with respect to China's major trading partners. For each country-year, we compute the weighted average of the DVAR across industries, with weights equal to each industry's share in total exports to the destination. Figure 4 shows that in all top five trading partners (i.e., the United States, Hong Kong SAR, China, Japan, the Republic of Korea, and Germany), there is a clear upward trend in the bilateral DVAR. In particular, the DVAR of Chinese processing exports to the United States has increased from 0.47 to 0.55 between 2000 and 2007.

B. *Firm Heterogeneity and Aggregation Bias*

How may firm heterogeneity affect the aggregate DVAR estimates? In a nutshell, firm heterogeneity may lead to aggregation bias when the underlying sample used to construct the aggregate DVAR is not representative. This could happen if the following two conditions hold: (i) firm size is used as the sample selection criteria, and (ii) there is a systematic relationship between firm size and import intensity.

The above two conditions may hold in the samples used to construct IO tables in general, and specifically for China. According to the *Handbook of Input-Output*

Figure 3. Decomposing the DVAR Growth into Within- and Between-Industry Growth

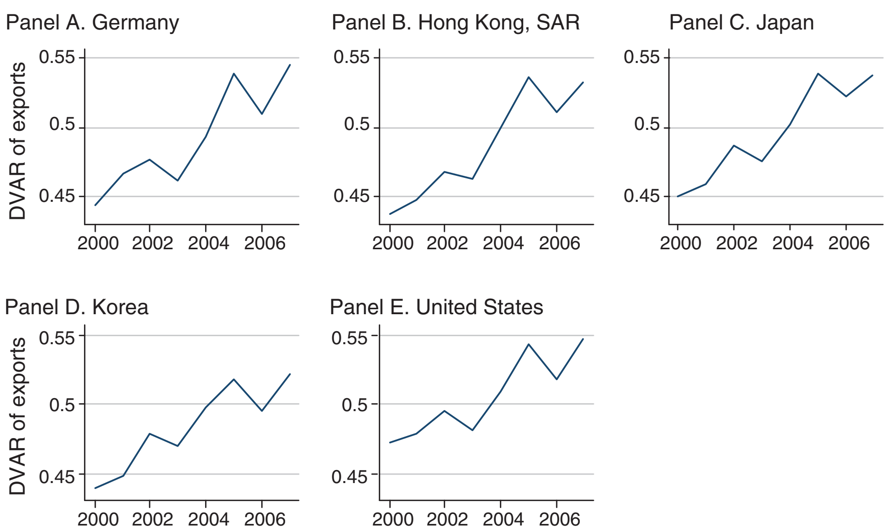

Figure 4. DVAR of China's Exports to Its Top Five Trading Partners

Table Compilation and Analysis (UN 1999, p. 110), the intermediate input consumption and input structure of large establishments could be applied to small establishments, given that they are often not covered by industry statistics. This suggests that small and medium size firms are routinely omitted from the IO table samples, and that the industry import intensities inferred are often based on data of mostly large firms. For China, according to the *National Input-Output Survey Methods of China* (NBS 2007) published by the National Bureau of Statistics of the People's Republic of China, the sample used to construct the IO tables consists of all large firms that have at least 300 million yuan in revenue (about US$38 million during

Table 2—Decomposition Exercise: Firm Heterogeneity and Aggregation Bias

	DVAR of total exports	Number of firms in the sample
1. Census	0.479 (0.021)	3,419
2. Original sample	0.478 (0.023)	2,623
3. KWW12 estimates	0.408	N/A
4. Large firms only	0.453 (0.034)	123

Notes: With the exception of row 3, all numbers are calculated by the authors based on different samples. Bootstrapped standard errors are reported in parentheses.

1: Refers to the 2004 census of manufacturing plants;

2: Restricts the sample in row 1 to the original survey dataset;

3: Is the IO table-based estimate from KWW12;

4: Restricts the sample in row 2 to only firms with total exports larger than 300 million RMB.

the sample period), along with some small- and medium-sized firms sampled with unknown proportions (see item 5 on p. 3 about sample selection and item 4 on p. 27 about size cutoffs). In other words, the sampling method behind the construction of Chinese IO tables is heavily biased toward the very large firms.

Second, recent research by Amiti, Itskhoki, and Konings (2014) and Blaum, Lelarge, and Peters (2014) shows that large firms tend to have a higher import-to-sales ratio. This is also confirmed by our sample of Chinese firms. When we regress a firm's import intensity on firm size (measured by log(sales)), controlling for industry-year fixed effects, we find that doubling firm sales is associated with a 0.5 percentage-point increase in the firm's import intensity (significant at the 1 percent level).[29] Given that firms' import intensity and DVAR are negatively correlated, by omitting the smaller firms, IO tables by construction tend to include firms with a lower DVAR. Such sample selection criteria could cause the aggregate DVAR estimates to be significantly biased downward.

To demonstrate the significant aggregation bias driven by sample selection when the underlying population of firms are heterogeneous in size and import intensity, we conduct the following decomposition exercise relying on China's 2004 firm census data, which covers the universe of all manufacturing firms and is therefore much larger than our original firm survey dataset which only includes manufacturing firms with a minimum 5 million RMB revenue.[30]

The first row of Table 2 shows the aggregate DVAR estimates based on the total population of firms from the manufacturing census in 2004. The estimated DVAR is 0.479. In the next row, we restrict the census sample to include only firms that overlap with our original manufacturing survey. The estimated DVAR dropped slightly to 0.478, which is not statistically different from the previous row. This confirms that sample selection bias is not an issue in our manufacturing survey sample, despite the exclusion of firms with less than 5 million RMB revenue in our sample.[31] Listed in

[29] Results are available upon request.

[30] Unlike our industrial survey dataset, the census dataset does not provide direct information on firms' costs of materials. We follow the guideline of the user manual of the census dataset to compute a firm's cost of materials by subtracting its total sales by its value added. As such, our DVAR estimates based on the census dataset is not directly comparable to the estimates in the previous sections based on the industrial surveys, which provide direct information on firms' costs of materials.

[31] Recall that our sample consists of firms from the Annual Surveys of Industrial Firms, which has sales cutoff of 5 million RMB (about US$600,000) and above, while the 2004 census covers all industrial firms.

row 3 is the IO table-based DVAR estimate of 0.408 from KWW12. Consistent with our results in previous section, the IO table-based DVAR estimate is statistically lower than the DVAR estimates in rows 1 and 2, based on their respective bootstrapped standard errors. In row 4, we further restrict the census sample, according to the sample selection criteria specified in the Chinese IO table manual—firms with over 300 million RMB revenue. The aggregate DVAR estimate drops to 0.453. Not only is the resulting DVAR estimate based on this large firm sample lower than the estimates in rows 1 and 2, it is also not statistically different from the IO table-based estimate by KWW12 in row 3, based on a standard error of 0.034 from bootstrapping with 100 repetitions. This exercise confirms that DVAR decreases when samples that only include larger firms are used, due to firms' heterogeneous input sourcing.

Thus, the result in Table 2 nicely shows that ignoring firm heterogeneity may lead to downward aggregation bias in the IO table-based approach. While there can be many reasons why our firm-based estimates and the IO table-based estimates of KWW12 are different, such as differences in methodology or estimation errors, this decomposition exercise focuses solely on the role of firm heterogeneity in explaining the wedge. Firm heterogeneity matters because firms of different sizes have different import intensities. By restricting the census sample to large firms according to the IO cutoff criteria, we are able to account for the difference between our aggregate DVAR and that of the IO table-based estimate of KWW12.

C. *Extension to Nonprocessing and Aggregate Exports*

The methodology we have developed above is suitable for pure exporters who export all their products, and that the products are produced by using up all the materials they have imported. It requires the condition that no final products or imported materials may leak to the domestic economy. A lot of exporters that engage in global value chains should satisfy this condition, in the form of processing trade, such as garment producers in Bangladesh, Guatemala, and other emerging economies.

However, many exporters are not processing exporters. Unlike processing exporters, nonprocessing exporters do not export all their outputs. In addition, they often use some of their imported materials to produce goods for domestic sales. Thus, the condition that no final output or imported materials leak to the domestic economy is not met. How firms split their imported inputs between production for domestic sales and exports is generally unknown.

To extend our methodology to measure the DVAR of the nonprocessing exporters, we need to make one proportionality assumption at the firm level: the allocation of the firm's inputs to the production for exports is proportional to the share of exports in total sales, which we may infer from our industrial survey data. This assumption is equivalent to assuming that the DVAR is the same between exports and domestic sales of the firms. Our proportionality assumption will likely be nonbinding if firms produce the same products for both the domestic and export markets. In addition, it is considerably less restrictive than the industry-level proportionality assumption commonly made by existing studies, as we still allow firms to be heterogeneous in terms of their shares of exports in total sales.

Thus, the DVA and DVAR of a nonprocessing exporter are

$$DVA_i^O = EXP_i - \left(IMP_i - \delta_i^K + \delta_i^F\right)\left(\frac{EXP_i}{PY_i}\right); \tag{9}$$

$$DVAR_i^O = \frac{DVA_i}{EXP_i} = 1 - \frac{IMP_i - \delta_i^K + \delta_i^F}{PY_i}, \tag{10}$$

where the superscript 'O' stands for ordinary exports. Similar to processing exports, there are transactions between nonprocessing exporters and the rest of the economy. After the adjustment based on the proportionality assumption, we follow the same procedures as outlined in Table 1 to adjust the estimates of the DVAR, similar to what we did for processing exporters. We first obtain imputed δ^F based on the estimates from KWW12. Then we identify imported capital based on the United Nations Broad Economic Categories (BEC) list of capital goods, and adjust for δ_i^K. Finally, we drop excessive importers. However, unlike what we can do for processing exporters that export excessively, there is no corresponding filter we can use to drop the excessive ordinary exporters. Including them in the sample will result in an overestimation of the DVAR of ordinary exports. With this caveat in mind, our approach is transparent and general enough to be applied to estimate the DVAR of different types of exporting firms and thus countries with varying prevalence of processing trade.

We use the ground-up approach to measure the DVAR of Chinese aggregate exports, by taking the weighted average over the DVARs of processing and ordinary exports, with weights equal to the corresponding export shares.[32] As shown in Table 3, the average DVAR of ordinary exports during the sample period is around 0.9, substantially higher than that of processing exports but consistent with similar findings by KWW12. Moreover, the DVAR of ordinary exports has declined slightly between 2000 and 2007, from 0.92 to 0.90. However, given the small decline compared to the much larger increase in the DVAR of processing exports, coupled with the fact that the share of processing exports in China's total exports has been stabilized at around 55 percent throughout the sample period, the DVAR of Chinese aggregate exports increased from 0.65 to 0.70 between 2000 and 2007 (see Figure 5, Table 3, and Figure A7 in the online Appendix). In short, China's DVAR has increased significantly in recent years, almost entirely driven by the rise in the DVAR in the processing export sector.

III. Time-Series Trend of Firm DVAR

In this section, we provide reduced-form evidence of the time-series changes in firms' DVAR and other related variables. A formal analysis of the determinants of China's rising DVAR will be presented in the next section. Given the finding in the previous section that the entire increase in the DVAR is caused by processing

[32] Here we measure the DVAR for single-industry exporters only. As we have done for processing exports, we can also do it for multiple-industry firms as well. The drawback is that excessive processing importers are identified as those that have import-export less the twenty-fifth percentile of the DVAR of ordinary exporters in the same year, but not the same sector-year. These numbers are available upon request.

TABLE 3—DOMESTIC VALUE ADDED RATIO

	Processing (P)			Ordinary (O)	Aggregate (A)
Year	DVAR (Filter 1)	DVAR (Filter 2)	DVAR (Filter 3)	DVAR (Filter 1)	DVAR (Filter 3)
2000	0.487	0.475	0.459	0.924	0.650
2001	0.495	0.488	0.468	0.915	0.652
2002	0.517	0.505	0.488	0.918	0.668
2003	0.502	0.494	0.478	0.914	0.661
2004	0.539	0.531	0.507	0.900	0.674
2005	0.579	0.571	0.544	0.893	0.695
2006	0.565	0.558	0.520	0.904	0.697
2007	0.599	0.587	0.548	0.900	0.701

Notes: Filter 1: Include exporters that have materials > imports, exports >= imports.
Filter 2: Include exporters that satisfy Filter 1 and DVAR < 50th Pct($DVAR_O$).
Filter 3: Include exporters that satisfy Filter 1 and DVAR < 25th Pct($DVAR_O$).
$DVAR_A = \text{Processing\_Shr} \times DVAR_P + (1 - \text{Processing\_Shr}) \times DVAR_O$

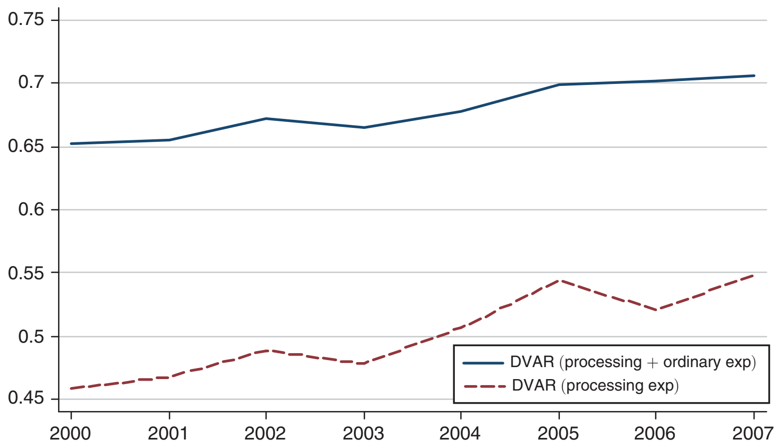

FIGURE 5. DVAR OF CHINA'S AGGREGATE (*Processing* + *Ordinary*) EXPORTS

Note: All firms with materials < imports and exports < imports, and processing firms with DVAR > DVAR (twenty-fifth percentile of Old Exporters) are excluded.

exports instead of ordinary exports, we will focus on providing firm-level evidence based on processing exporters only from this section and on. We start off by estimating the following specification at the firm level:

$$DVAR_{it} = \beta_i + \beta_t + \beta_X \mathbf{X}_{it} + \epsilon_{it}, \tag{11}$$

where i stands for firm, t represents year, and ϵ_{it} is the regression residual. The firm and year fixed effects are β_i and β_t respectively, with the year effect for 2000 dropped to avoid the dummy variable trap. Thus, positive and rising β_ts (i.e., $0 < \beta_t < \beta_{t+1}$, $\forall t > 2000$) will imply a within-firm increase in the DVAR over time.

Control variables in $\mathbf{X}_{it}$ include a firm's material-to-sales ratio, $\left(\frac{P^M M}{PY}\right)_{it}$ and its labor cost (total wages or the ratio of wages to total sales). The inclusion of a firm's $\left(\frac{P^M M}{PY}\right)_{it}$ is to examine whether the firm substitutes between domestic and imported materials, keeping the total material cost share constant, according to (5).

Table 4—Dependent Variable: The Ratio of Domestic Value Added in Exports to Gross Exports (*DVAR*)

Sample	All (1)	All (2)	Dom. private (3)	Foreign (4)	Multiple ind. (5)	Unfiltered (6)
β_{2001}	0.0301	0.0299	0.0764	0.0327	0.0256	0.0268
	(0.007)	(0.006)	(0.080)	(0.006)	(0.005)	(0.005)
β_{2002}	0.0490	0.0493	0.0810	0.0492	0.0466	0.0493
	(0.004)	(0.004)	(0.106)	(0.004)	(0.006)	(0.004)
β_{2003}	0.0657	0.0663	0.190	0.0656	0.0709	0.0681
	(0.008)	(0.008)	(0.078)	(0.008)	(0.005)	(0.005)
β_{2004}	0.0669	0.0674	0.140	0.0677	0.0749	0.0715
	(0.008)	(0.011)	(0.127)	(0.011)	(0.005)	(0.010)
β_{2005}	0.0962	0.0969	0.198	0.0978	0.117	0.101
	(0.007)	(0.009)	(0.124)	(0.008)	(0.005)	(0.010)
β_{2006}	0.135	0.136	0.257	0.136	0.146	0.133
	(0.010)	(0.011)	(0.133)	(0.012)	(0.005)	(0.010)
β_{2007}	0.147	0.147	0.300	0.146	0.161	0.150
	(0.013)	(0.017)	(0.140)	(0.016)	(0.006)	(0.014)
$\left(\frac{P^D M^D + P^I M^I}{PY}\right)_{it}$	−0.0236	−0.0234	0.0190	−0.0230	−0.0207	−0.0108
	(0.007)	(0.008)	(0.060)	(0.010)	(0.006)	(0.004)
$\left(\frac{wL}{PY}\right)_{it}$		−0.0010	0.0522	−0.0010	−0.0040	−0.0032
		(0.016)	(0.155)	(0.017)	(0.009)	(0.006)
Observations	17,903	17,871	858	16,726	28,925	31,965
R^2	0.0729	0.0733	0.104	0.074	0.0955	0.0597

Notes: Firm and year fixed effects are always included. Columns 1 and 2 use the whole sample; columns 3 and 4 include only domestic private and foreign-invested firms, respectively. Column 5 includes firms that operate in multiple industries as well. Column 6 includes single-industry firms that do not satisfy our rules to filter firms that engage in indirect trade. Bootstrapped standard errors, clustered at the industry level, are reported in parentheses.

Source: Merged NBS and customs data

Labor cost is included to verify the popular claim that increasing labor costs are a main reason behind China's rising DVAR in exports. Controlling for $\left(\frac{P^M M}{PY}\right)_{it}$, if β_ts are positive, significant and rising, while β_Xs are not positive or insignificant, then it implies that the DVAR is rising within firms, due to a substitution of domestic materials for imported materials.

Table 4 presents our baseline results. Bootstrapped standard errors, clustered at the industry level, are used for all the regressions reported in this section. Column 1 shows positive, significant, and increasing year fixed effects, suggesting that firms' DVAR is rising during the sample period. On average, firm DVAR increases by 15 percentage points between 2000 and 2007. This within-firm increase is larger than the 9 percentage-point increase at the aggregate level (see column 4 in Table 3), implying that exiting firms have a higher DVAR than new entrants on average. In other words, the upward trend of the aggregate DVAR of Chinese exports is entirely driven by the rising DVAR among the surviving exporters, not due to the exit of low-DVA firms.[33] Furthermore, by controlling for the firm's $\left(\frac{P^M M}{PY}\right)_{it}$, we confirm that the rising DVAR is due to firms' substitution of domestic for imported materials.

[33] According to Table A10 in the online Appendix, the exiting firms tend to be smaller in terms of sales and exports. Given that firm size and DVAR are negatively correlated, it is not surprising to see that the exiters have

In column 2, we add the firm's wage-to-sales ratio $\left(\frac{wL}{PY}\right)_{it}$ as a control. The insignificant coefficient on $\left(\frac{wL}{PY}\right)_{it}$ supports the prediction based on (4) that once $\left(\frac{P^M M}{PY}\right)_{it}$ is controlled for, labor costs should not have any direct impact on a firm's DVAR. Columns 3 to 5 show the same upward trend for three different samples—domestic exporters only, foreign-invested exporters only, and multi-industry exporters included. In column 6, we repeat the same analysis using an unfiltered sample that includes both excessive importers and exporters. The magnitudes of the estimated year fixed effects are very close to those in column 2 when the filtered sample is used, suggesting that our findings are not driven by the removal of excessive importers and exporters. In summary, we find that the within-firm increase in the DVAR is widespread and it is not driven by sample selection.

The within-firm increase in the DVAR over time should arise from exporters' substituting domestic for imported materials, at both the intensive and extensive margins. To examine this claim, we estimate the following specifications:

$$\left(\frac{P^I M^I}{P^M M}\right)_{it} = \delta_i + \delta_t + \delta_X \mathbf{X}_{it} + \nu_{it}, \tag{12}$$

$$\ln(import\_variety_{it}) = \gamma_i + \gamma_t + \gamma_X \mathbf{X}_{it} + \omega_{it}, \tag{13}$$

where $\left(\frac{P^I M^I}{P^M M}\right)_{it}$ is the share of imported materials in total material cost for firm i in year t, while $\ln(import\_variety_{it})$ stands for the (log) number of import variety, measured by the number of imported HS6-country pairs.[34] Firm fixed effects are denoted by δ_i and γ_i in the respective specifications, while δ_t and γ_t are the year fixed effects, with the year effects for 2000 omitted to avoid the dummy variable trap. Control variables in $\mathbf{X}_{it}$ include firm's wage-to-sales ratio, $\left(\frac{wL}{PY}\right)_{it}$, (log) capital-labor ratio, $\ln\left(\frac{K}{L}\right)_{it}$, and material-to-sales ratio, $\left(\frac{P^M M}{PY}\right)_{it}$. We include these controls to capture the effects of changing labor costs and capital deepening of the firm on imports. The residuals for each of the specifications are ν_{it} and ω_{it}, respectively. If firms are using more domestic materials for imported materials, the year fixed effects are expected to be negative, significant, and declining (i.e., $\delta_t < \delta_{t-1} < 0$ and $\gamma_t < \gamma_{t-1} < 0, \forall t > 2000$).

Column 1 in Table 5 shows that the share of imported materials is gradually declining within firms over time. In particular, firm's $\left(\frac{P^I M^I}{P^M M}\right)_{it}$ dropped by about 17 percentage points on average in 2007 compared to 2000. This result supports our finding that Chinese processing exporters are substituting more domestic materials for imported materials over time. Firm wage-sales ratio and capital-labor ratio do not appear to be related to its import share. The results remain robust when we split the sample into the domestic private and foreign firm samples (columns 2–3) or include multi-industry firms (column 4).

higher DVAR as shown in the table. Furthermore, to the extent that firm size proxies for firm productivity, it is also not surprising that these smaller and thus high-DVAR firms are more likely to exit.

[34] The Harmonized System (HS) classification has changed twice (2002 and 2007) during our sample period. We use the concordance file created by Cebeci et al. (2012) to define a consistent set of varieties over time.

Table 5—Dependent Variable: Share of Imports in Total Materials

Sample	All	Dom. private	Foreign	Multiple ind.
δ_{2001}	−0.0237	0.0538	−0.0241	−0.0200
	(0.010)	(0.047)	(0.011)	(0.006)
δ_{2002}	−0.0278	0.137	−0.0293	−0.0223
	(0.006)	(0.062)	(0.007)	(0.007)
δ_{2003}	−0.0674	0.0761	−0.0695	−0.0678
	(0.007)	(0.067)	(0.007)	(0.007)
δ_{2004}	−0.0837	0.0813	−0.0852	−0.0830
	(0.008)	(0.061)	(0.008)	(0.006)
δ_{2005}	−0.114	0.0483	−0.115	−0.116
	(0.010)	(0.066)	(0.009)	(0.006)
δ_{2006}	−0.155	0.0312	−0.157	−0.144
	(0.011)	(0.081)	(0.009)	(0.007)
δ_{2007}	−0.170	−0.00236	−0.171	−0.154
	(0.017)	(0.086)	(0.013)	(0.007)
$\left(\frac{wL}{PY}\right)_{it}$	0.0336	0.417	0.0328	0.0481
	(0.042)	(0.190)	(0.039)	(0.042)
$\ln(K/L)_{it}$	−0.0035	−0.0252	−0.0040	−0.0040
	(0.003)	(0.030)	(0.003)	(0.003)
Observations	17,831	858	16,688	28,875
R^2	0.0898	0.104	0.0918	0.0896

Notes: Firm and year fixed effects are always included. Column 1 uses the whole sample; columns 2 and 3 include only domestic private and foreign-invested firms, respectively. Column 4 includes firms that operate in multiple industries as well. Bootstrapped standard errors, clustered at the industry level, are reported in parentheses.

Source: Merged NBS and customs data

Consistent with the findings that firms decrease their imports, Table 6 shows negative, significant, and declining year fixed effects, suggesting that on average, processing firms also import fewer input varieties over time. At the sample mean, the number of import varieties decreased by 0.35 log points in 2007 relative to 2000.[35] Other firm-level controls are insignificant. Columns 2 and 3 show that the decline mostly happens for foreign firms but not domestic private firms. The results remain robust to including multi-industry firms in the sample (column 4). Along with the results from the previous tables, we find that firms' average DVAR is rising through substitution of domestic inputs for foreign inputs, at both the intensive (the cost share of imported materials) and extensive margins (import variety).[36]

For processing firms to substitute domestic for imported input varieties, an increased availability of the latter is expected. Unfortunately, data on domestic input variety in China are not available. To examine the phenomenon, we rely on the number of varieties exported by ordinary (nonprocessing) firms as proxies instead. Note

[35] In unreported results, we find that most of the decline is due to firms importing fewer products (HS6) instead of importing from fewer countries.

[36] It is interesting to note that many of the dropped import varieties are parts and components from the neighboring countries, such as parts of refrigerators, computers, and electric conductors from Singapore and Japan; pick-up cartridges from Hong Kong SA, China; iron and steels products from the Republic of Korea; and television cameras from Taiwan, China. Other varieties also include parts of electrical machines from Italy, and cathode-ray tubes from Germany. These observations are consistent with our hypothesis that processing exporters are substituting domestic for imported materials.

TABLE 6—DEPENDENT VARIABLE: ln(*Number of Import Varieties*)

Sample	All	Dom. private	Foreign	Multiple ind.
γ_{2001}	−0.114	−0.208	−0.106	−0.134
	(0.016)	(0.124)	(0.018)	(0.013)
γ_{2002}	−0.110	0.216	−0.0990	−0.128
	(0.016)	(0.284)	(0.016)	(0.016)
γ_{2003}	−0.217	−0.0606	−0.208	−0.240
	(0.029)	(0.419)	(0.026)	(0.016)
γ_{2004}	−0.274	0.186	−0.267	−0.279
	(0.039)	(0.352)	(0.035)	(0.015)
γ_{2005}	−0.342	0.0535	−0.335	−0.360
	(0.046)	(0.367)	(0.045)	(0.016)
γ_{2006}	−0.197	0.122	−0.183	−0.215
	(0.054)	(0.336)	(0.054)	(0.019)
γ_{2007}	−0.351	0.131	−0.344	−0.356
	(0.090)	(0.345)	(0.081)	(0.020)
$\left(\frac{P^D M^D + P^I M^I}{PY}\right)_{it}$	0.0144	−0.106	0.0171	0.0104
	(0.025)	(0.332)	(0.019)	(0.020)
$\left(\frac{wL}{PY}\right)_{it}$	−0.0327	0.899	−0.0374	−0.0608
	(0.038)	(1.033)	(0.054)	(0.059)
Observations	17,871	858	16,726	28,925
R^2	0.0571	0.0609	0.0589	0.0565

Notes: Firm and year fixed effects are always included. Column 1 uses the whole sample; columns 2 and 3 include only domestic private and foreign-invested firms, respectively. Column 4 includes firms that operate in multiple industries as well. Bootstrapped standard errors, clustered at the industry level, are reported in parentheses.

Source: Merged NBS and customs data

that unlike processing exporters, ordinary exporters consist mainly of the indigenous Chinese firms that also sell in the domestic market. Some of these local firms become big and start exporting. By tracking the number of varieties exported by ordinary firms, we are picking up the tip of the iceberg as some of these domestic varieties may not make it to the foreign markets.[37] Nevertheless, the following evidence is insightful. Table A12 in the online Appendix lists 67 products that were imported by processing exporters and were not exported by ordinary exporters in 2000, but were exported by ordinary exporters in 2007. Some of them are important inputs used by large exporters across many industries, accounting for an import value of close to US$392 million. By 2007, not only were these products no longer imported by processing firms, ordinary exporters have started exporting them with a total value of over US$1.55 billion. These results suggest that processing exporters' demand for these imported products may now be met by local suppliers.[38]

[37] We use products produced by ordinary (nonprocessing) exporters to proxy for domestic variety, in the belief that a firm's export product scope is a subset of its domestic product scope. There could be export varieties that were not sold domestically or vice versa. There could also be domestic varieties produced by nonexporters that were not exported. In these regards, our proxy should be considered as a lower bound of domestic variety.

[38] In the last column of Table A12 in the online Appendix, we also report the share of exports by foreign firms for each product in 2007. Out of the 67 products listed in the table, 15 products have over 20 percent of exports by foreign firms in 2007, and 5 products were exported solely by them. These results suggest that foreign firms may have moved into some of the intermediate good sectors in China. These results are also consistent with the

To verify that the decline in import variety is not due to exporters' specialization in their core competencies, we estimate the following specification:

$$\ln(export\_variety_{it}) = \theta_i + \theta_t + \theta_X \mathbf{X}_{it} + u_{it}, \quad (14)$$

where $\mathbf{X}_{it}$ includes $\left(\frac{wL}{PY}\right)_{it}$ and $\left(\frac{P^M M}{PY}\right)_{it}$ as in (11). Dependent variable, $export\_variety_{it}$ is measured by firm i's number of exported HS6-country pairs.[39] Firm fixed effects (θ_i), year fixed effects (θ_t), and other firm controls are included as before. As Table 7 shows, despite the declining cost share of imported materials and decreasing variety, processing firms' export variety is rising over time, particularly after 2002, one year after China joined the WTO.

In summary, our results suggest that the domestic content in Chinese processing exports is rising over time. The rise is mainly driven by firms actively substituting domestic for imported materials, but not rising production costs. Chinese exporters have been expanding their product scope while reducing imports, both at the intensive and extensive margins.[40]

IV. Determinants of Firm DVAR

In the rest of the paper, we will focus on studying whether China's trade and FDI liberalization since 2000 could explain its rising DVAR. We first develop a simple model to guide our empirical exploration of the determinants of the rising firm DVAR. This model focuses on the time-series movement of firms' DVAR and thus the aggregate DVAR, and deliberately abstains from explaining the cross-sectional differences in the DVAR.[41]

A. *A Simple Model*

Recall accounting identity (4),

$$DVAR_{it} = 1 - \frac{P_t^I M_{it}^I}{P_{it} Y_{it}} + \varphi_{it} = 1 - \frac{P_t^M M_{it}}{P_{it} Y_{it}} \frac{P_t^I M_{it}^I}{P_t^M M_{it}} + \varphi_{it},$$

assertions of recent studies, such as Autor, Dorn, and Hanson (2013) and Pierce and Schott (2015), that changes in policies in the United States and China may have encouraged foreign firms to offshore production to China, potentially contributing to China's growing competitiveness. That said, the majority of these new export products are actually produced by indigenous domestic Chinese firms. We thank David Hummels for suggesting this exercise.

[39] We also repeat the same analysis using the number of HS6 (without the country dimension) to measure export variety. The results remain robust.

[40] There can be concerns that the regression results are different between the two processing trade regimes, as described in Section III. To this end, we repeat all four sets of regression analyses using the sample of import-and-assembly (IA) and pure-assembly (PA) firms, respectively. As reported in Table A11 in the online Appendix, results remain robust and quantitatively identical to the results reported so far. This is not surprising given that 90 percent of the observations in our sample belong to the IA regime. It is assuring to see that firm DVAR is also increasing within PA exporters. The magnitude of the coefficients on the year fixed effects are similar. Similar trends are also found using this sample for other dependent variables of interest, though the statistical significance may sometimes be smaller due to the much smaller sample of PA firms.

[41] In the online Appendix, we derive a model that features a Cobb-Douglas production function, and show how firm heterogeneity in price-cost margins may lead to a cross-sectional variation in firm DVAR.

TABLE 7—DEPENDENT VARIABLE: ln(*Number of Export Varieties*)

Sample	All	Dom. private	Foreign	Multiple ind.
θ_{2001}	−0.0280	0.138	−0.0233	−0.0272
	(0.022)	(0.223)	(0.012)	(0.021)
θ_{2002}	0.0599	0.318	0.0712	0.0729
	(0.042)	(0.221)	(0.029)	(0.020)
θ_{2003}	0.103	0.479	0.107	0.130
	(0.049)	(0.318)	(0.035)	(0.018)
θ_{2004}	0.124	0.598	0.126	0.161
	(0.056)	(0.267)	(0.039)	(0.016)
θ_{2005}	0.210	0.821	0.210	0.236
	(0.040)	(0.310)	(0.029)	(0.019)
θ_{2006}	0.286	0.945	0.283	0.316
	(0.050)	(0.316)	(0.033)	(0.017)
θ_{2007}	0.275	1.086	0.267	0.306
	(0.046)	(0.338)	(0.030)	(0.022)
$\left(\frac{P^D M^D + P^I M^I}{PY}\right)_{it}$	0.0130	0.182	0.0110	0.0017
	(0.018)	(0.266)	(0.017)	(0.018)
$\left(\frac{wL}{PY}\right)_{it}$	−0.0474	−0.126	−0.0517	−0.0606
	(0.059)	(0.726)	(0.028)	(0.031)
Observations	17,871	858	16,726	28,925
R^2	0.0399	0.121	0.0388	0.0486

Notes: Firm and year fixed effects are always included. Column 1 uses the whole sample; columns 2 and 3 include only domestic private and foreign-invested firms, respectively. Column 4 includes firms that operate in multiple industries as well. Bootstrapped standard errors, clustered at the industry level, are reported in parentheses.

Source: Merged NBS and customs data

where φ_{it} is a well-behaved classical regression error term that captures the unobserved $\frac{\delta_{it}^F}{EXP_{it}}$. Thus, a firm's DVAR depends only on the share of imported materials in total materials, $\left(\frac{P_t^I M_{it}^I}{P_t^M M_{it}}\right)$, once we control for the share of materials in total revenue $\left(\frac{P_t^M M_{it}}{P_{it} Y_{it}}\right)$. Without loss of generality, assuming that the unit material cost function, $P^M\left(P_t^I, P_t^D\right)$, is a translog function of the prices of imported and domestic materials, which is symmetric, homogeneous of degree one and can provide a second-order approximation to any functional form of price aggregates:

$$(15) \qquad \ln P^M\left(P_t^I, P_t^D\right) = \alpha_i + \alpha_{0I} \ln P_t^I + \alpha_{0D} \ln P_t^D + \frac{1}{2}\alpha_{II}\left(\ln P_t^I\right)^2 + \alpha_{ID}\left(\ln P_t^I\right)\left(\ln P_t^D\right) + \frac{1}{2}\alpha_{DD}\left(\ln P_t^D\right)^2.$$

The assumptions of symmetry and homogeneous of degree one imply the following restrictions on the translog parameters:

$$(16) \quad \alpha_{II} < 0; \quad \alpha_{DD} < 0; \quad \alpha_{0I} + \alpha_{0D} = 1; \quad \alpha_{II} + \alpha_{ID} = \alpha_{DD} + \alpha_{ID} = 0;$$

$$\text{and} \quad \alpha_{II} = \alpha_{DD} = -\alpha_{ID} < 0 \Rightarrow \alpha_{ID} > 0.$$

Let m_{it}^I and m_{it}^D be the requirement of imported and domestic materials for producing one unit of total materials M_{it}:

$$m_{it}^k = \frac{M_{it}^k}{M_{it}}, \quad k = I, D.$$

By Shephard's Lemma, the share of imported or domestic materials is the elasticity of the unit material cost function with respect to the price of imported or domestic materials:

$$\frac{\partial P^M\left(P_t^I, P_t^D\right)}{\partial P_t^k} = m_i^k\left(P_t^I, P_t^D\right), \quad \text{for} \quad k = I, D$$

$$\frac{\partial P^M\left(P_t^I, P_t^D\right)}{\partial P_t^k} \frac{P_t^k}{P^M\left(P_t^I, P_t^D\right)} = \frac{P_t^k}{P^M\left(P_t^I, P_t^D\right)} m_i^k\left(P_t^I, P_t^D\right) = \frac{P_t^k M_i^k\left(P_t^I, P_t^D\right)}{P^M\left(P_t^I, P_t^D\right) M_{it}}.$$

Thus, when the unit cost function is translog, the share of imported materials in total materials is a log-linear function of the relative input prices:

$$\text{(17)} \qquad \frac{P_t^I M_{it}^I}{P_t^M M_{it}} = \frac{\partial \ln P^M\left(P_{it}^I, P_{it}^D\right)}{\partial \ln P_{it}^I}$$

$$= \alpha_{0I} + \alpha_{II} \ln P_{it}^I + \alpha_{ID} \ln P_{it}^D$$

$$= \alpha_{0I} - \alpha_{ID} \ln \frac{P_t^I}{P_t^D},$$

where $\frac{P_t^I}{P_t^D}$ is the ratio of the price index of imported input varieties to that of domestic input varieties. From (4), once we control for the share of materials in total sales, $\frac{P_t^M M_{it}}{P_{it} Y_{it}}$, firm DVAR depends only on $\frac{P_t^I}{P_t^D}$ positively (given that $\alpha_{ID} > 0$):

$$\text{(18)} \qquad DVAR_{it} = 1 + \frac{P_t^M M_{it}}{P_{it} Y_{it}} \left(\alpha_{0I} + \alpha_{ID} \ln \frac{P_t^I}{P_t^D}\right) + \varphi_{it}, \forall i, t.$$

Thus, by assuming a translog cost function, we show that the only factor that affects a firm's DVAR is $\frac{P_t^I}{P_t^D}$, after controlling for the share of total material cost in total sales, $\frac{P_t^M M_{it}}{P_{it} Y_{it}}$.[42] Other factors, such as wages, productivity, and other costs of production do not directly enter (18), as long as the share of total materials in total sales is controlled for. We explore three obvious factors that can affect firm DVAR,

[42] Note that it is the firm's total sales in the denominator, not output. Thus, a firm's mark-up, which we do not aim to estimate, is already embedded in the formula.

namely import tariffs facing upstream suppliers, foreign direct investment (FDI), and exchange rates in the next section.

In addition to its flexibility of providing a second order approximation to any cost function, the translog cost function (15) has the advantage of not restricting the elasticity of substitution between domestic and imported materials to be a constant.[43] This modeling flexibility is particularly important since a rising firm DVAR could be driven by a rising elasticity of substitution between imported and domestic input varieties. By using a translog specification, we let the data reveal whether and how the elasticity was changing over the sample period.

Specifically, let σ_t be the elasticity of substitution between domestic and imported materials in year t. According to Blackorby and Russell (1989), the elasticity of substitution between the two variables equals the cross-price elasticity $\left(\varepsilon_t^{ID}\right)$ minus the own price elasticity $\left(\varepsilon_t^{DD}\right)$,

$$\sigma_t = \varepsilon_t^{ID} - \varepsilon_t^{DD}. \tag{19}$$

In this case, using (15), we can express both ε_t^{ID} and ε_t^{DD} as functions of α_{ID} and s_t^D:[44]

$$\varepsilon_t^{DD} \equiv \frac{\partial \ln M_t^D}{\partial \ln P_t^D} = \frac{\alpha_{DD}}{s_t^D} + s_t^D - 1 = \frac{-\alpha_{ID}}{s_t^D} + s_t^D - 1;$$

$$\varepsilon_t^{ID} \equiv \frac{\partial \ln M_t^D}{\partial \ln P_t^I} = \frac{\alpha_{ID}}{s_t^I} + s_t^D,$$

which according to (19) gives

$$\sigma_t = \frac{\alpha_{ID}}{s_t^D\left(1 - s_t^D\right)} + 1 > 1, \tag{20}$$

since $\alpha_{ID} > 0$. We will be able to test these restrictions when we estimate α_{ID} based on (17) and construct σ_t from (20). Note that σ_t could change over time (and across industries) due to changing s_t^D. Before discussing our estimation of σ_t in detail later, let us return to the discussion about the determinants of $\frac{P_t^I}{P_t^D}$ and thus a firm's DVAR.

Exchange Rates.—One obvious factor that could cause firm DVAR to increase is the exchange rate. Define the exchange rate, E_t, as the foreign-currency price of a Chinese yuan. The price of imported materials in yuan is equal to the world price of foreign materials, P_t^{I*}, divided by E_t, i.e., $P_t^I = \frac{P_t^{I*}}{E_t}$. A yuan appreciation (a higher E_t)

[43] This property is in contrast with the case of a constant elasticity of substitution (CES) production function. Readers are referred to the online Appendix for a derivation of a firm's DVAR when the production function is Cobb-Douglas.

[44] See Kee, Nicita, and Olarreaga (2008) for the derivation.

decreases the yuan price of imported materials, possibly lowering firm DVAR according to (18):

$$(21) \qquad \frac{\partial\left(P_t^I/P_t^D\right)}{\partial E_t} < 0 \Rightarrow \frac{\partial DVAR_{it}}{\partial E_t} = \frac{\partial DVAR_{it}}{\partial\left(P_t^I/P_t^D\right)} \frac{\partial\left(P_t^I/P_t^D\right)}{\partial E_t} < 0.$$

Input Tariffs Facing Domestic Input Suppliers.—The relative price of materials could change due to the varying supply of input varieties. We assume that sector-level materials are CES aggregates of different varieties of domestic and imported inputs as follows:

$$M_{it}^D = \left[\sum_{v=1}^{V_t^D} \left(m_{v_i}^D\right)^{\frac{\lambda-1}{\lambda}}\right]^{\frac{\lambda}{\lambda-1}}, \quad M_{it}^I = \left[\sum_{v_i=1}^{V_t^I} \left(m_{v_i}^I\right)^{\frac{\lambda-1}{\lambda}}\right]^{\frac{\lambda}{\lambda-1}}, \quad \lambda > 1,$$

where V_t^D and V_t^I are the numbers of domestic and foreign input varieties available to the firm. Let us assume that the elasticities of substitution, λ, between any two varieties of imported materials, as well as between any two varieties of domestic materials, are constant. The average price of imported and domestic materials can then be expressed as $P_t^D = \left[\sum_{v=1}^{V_t^D}\left(P_{vt}^D\right)^{1-\lambda}\right]^{\frac{1}{1-\lambda}}$ and $P_t^I = \left[\sum_{v=1}^{V_t^I}\left(P_{vt}^I\right)^{1-\lambda}\right]^{\frac{1}{1-\lambda}}$, where P_{vt}^D and P_{vt}^I represent the price of a domestic and a foreign input variety, respectively. An increase in domestic material varieties will raise the relative price of imported materials, which in turn raise firm DVAR:

$$(22) \qquad \frac{\partial P_t^D}{\partial V_t^D} < 0 \Rightarrow \frac{\partial\left(P_t^I/P_t^D\right)}{\partial V_t^D} > 0$$

$$\Rightarrow \frac{\partial DVAR_{it}}{\partial V_t^D} = \frac{\partial DVAR_{it}}{\partial\left(P_t^I/P_t^D\right)} \frac{\partial\left(P_t^I/P_t^D\right)}{\partial V_t^D} > 0.$$

The intuition is similar to the positive effects of an increase in import varieties on aggregate productivity and welfare (e.g., Broda and Weinstein 2006 and Feenstra and Kee 2008).

What caused an increase in domestic and imported material varieties? We explore two factors previously explored in the literature. The first factor is China's gradual trade liberalization. Goldberg et al. (2010) show that in India, input tariff liberalization results in domestic firms' expansion of product scope. The main reason is that after trade liberalization, domestic firms have access to cheaper and new imported input varieties. Over our sample period (2000–2007), China experienced a continuous decline in import tariffs and other trade restrictions, which was accelerated after the country's accession to the WTO in December 2001. It is worth noting that such liberalization does not directly affect processing firms, which have always been exempted from tariffs on imported inputs. That said, tariff reduction could have a significant impact on those nonprocessing firms that supply materials to the downstream processing exporters.[45] With access to new, cheaper, or better imported materials after tariff liberalization, nonprocessing firms experience lower production costs and may produce more varieties. Processing exporters in downstream sectors can now purchase these varieties domestically, replacing previously imported input varieties. This substitution at the extensive margin, as we will show below, plays an important role in driving the DVAR of the downstream processing exporters. More formally, let τ_t denote the (average) input tariff of the upstream industries. Tariff reduction may increase domestic input varieties, which in turn raise the relative price of imported materials and thus the DVAR of downstream exporters. These relationships can be expressed as

$$(23)\qquad \frac{\partial V_t^D}{\partial \tau_t} < 0 \Rightarrow \frac{\partial DVAR_{it}}{\partial \tau_t} = \frac{\partial DVAR_{it}}{\partial\left(P_t^I/P_t^D\right)} \frac{\partial\left(P_t^I/P_t^D\right)}{\partial V_t^D} \frac{\partial V_t^D}{\partial \tau_t} < 0.$$

Foreign Direct Investment.—The last factor is related to the rising FDI in the processing sector, as China increased its engagement in global value chains, due to its FDI liberalization since 2000.[46] Participating in global value chains has been proposed to be a new and effective way of industrialization (Baldwin 2012). In particular, Rodríguez-Clare (1996) and Kee (2015) show that more own-industry FDI can increase the demand for domestic materials, raising the supply and quality of domestic material varieties from the upstream industries.[47] Given $\lambda > 1$ in our model, a higher demand by downstream exporters will lower the price of domestic materials, which in turn increase the DVAR for all exporters. More formally, we have

$$(24)\qquad \frac{\partial V_t^D}{\partial FDI_t} > 0 \Rightarrow \frac{\partial DVAR_{it}}{\partial FDI_t} = \frac{\partial DVAR_{it}}{\partial\left(P_t^I/P_t^D\right)} \frac{\partial\left(P_t^I/P_t^D\right)}{\partial V_t^D} \frac{\partial V_t^D}{\partial FDI_t} > 0.$$

The following section will empirically examine how the three factors discussed in this section shape the movement of firm DVAR.

B. *Three-Stage Least Squares Regressions*

Our model shows that factors such as exchange rates, FDI, and upstream input tariffs may raise firms' DVAR, through affecting domestic input varieties and hence the relative price of imported materials. We first empirically establish these channels without imposing the translog cost structure and let the data show the relationship between these variables. In the next section, we will formally estimate the translog parameters to assess how well our highly stylized model may explain firm DVAR.

[45] As long as the imported materials stay inside the processing regime, domestic transactions are still exempted from tariffs.

[46] With China's accession to the WTO in December 2001, the government has committed to a deeper and more comprehensive liberalization to FDI, by revising *the Law on Foreign Capital Enterprises* in October 2000. In particular, the revised law lifted the requirement for foreign enterprises to export the majority of their output.

[47] For example, FDI in the garment industry may increase the demand for domestic textile products and cause the domestic textile industry to increase their product varieties.

We first isolate the part of the within-firm changes in the DVAR that is common across all firms within an industry, given that $\frac{P_{jt}^I}{P_{jt}^D}$ is industry-specific. To this end, we estimate the average within-firm change in the DVAR by industry according to (11) and allow year fixed effects to be industry-specific,

$$DVAR_{it} = \beta_i + \beta_{jt} + \beta_X X_{it} + \epsilon_{it}.$$

The estimated β_{jt}, $\hat{\beta}_{jt}$, captures the average within-firm change in DVAR of each industry j in each year relative to 2000.

We then estimate the following system of three equations using three-stage least squares (3SLS):

$$\hat{\beta}_{jt} = \omega_j^1 + \omega_p^1 \, \Delta \ln\left(\frac{P_{jt}^I}{P_{jt}^D}\right) + \iota_{jt}^1, \tag{25}$$

$$\Delta \ln\left(\frac{P_{jt}^I}{P_{jt}^D}\right) = \omega_j^2 + \omega_E^2 \, \Delta \ln E_{jt} + \omega_v^2 \, \Delta \ln V_{jt}^D + \iota_{jt}^2, \tag{26}$$

$$\Delta \ln V_{jt}^D = \omega_j^3 + \omega_T^3 \, \Delta \, \tilde{\tau}_{kt}^U + \omega_F^3 \, \Delta \ln FDI_{jt} + \omega_E^3 \, \Delta \ln E_{jt} + \iota_{jt}^3, \tag{27}$$

where ω_j^1, ω_j^2, and ω_j^3 stand for industry fixed effects in three different equations, and ι_{jt}^1, ι_{jt}^2, and ι_{jt}^3 are the corresponding error terms.

The first equation uses the change in the price of imported materials relative to domestic materials, $\Delta \ln\left(\frac{P_{jt}^I}{P_{jt}^D}\right)$, to explain the within-firm change in the DVAR that is common across all firms within an industry. The second equation explains how $\Delta \ln\left(\frac{P_{jt}^I}{P_{jt}^D}\right)$ can be caused by the change in the exchange rate, $\Delta \ln E_{jt}$, defined as the increase in the foreign price of the yuan, and the change in domestic upstream variety, $\Delta \ln V_{jt}^D$. The last equation explains how $\Delta \ln V_{jt}^D$ can be caused by the change in own-industry FDI, $\Delta \ln FDI_{jt}$, the change in the average input tariffs facing firms in the upstream industry, $\Delta \, \tilde{\tau}_{kt}^U$, and $\Delta \ln E_{jt}$. We include the exchange rate in (27) to test the hypothesis that a stronger yuan, in addition to affecting import prices directly as specified by (26), may also decrease the demand for domestic inputs as firms may choose to increase imported inputs. The ways that we measure imported input prices, domestic input prices, exchange rates, and domestic upstream variety are discussed in detail in the online Appendix. Our model predicts that $\omega_p^1 > 0$ in (25); $\omega_E^2 < 0$ and $\omega_v^2 > 0$ in (26); $\omega_T^3 < 0$, $\omega_F^3 > 0$, and $\omega_E^3 < 0$ in (27).

Table 8 reports the results. Since $\hat{\beta}_{jt}$ are estimated with errors, bootstrapped standard errors (with 500 repetitions) are used in all equations. Column 1 shows a positive and significant correlation between the relative price index of imported materials, $\frac{P_{jt}^I}{P_{jt}^D}$, and the average within-firm change in the DVAR in the same industry. Column 2 presents the results of (26), which shows that controlling for industry fixed

Table 8—Determinants of the Within-Firm Increase in the DVAR

	$\Delta_{t,00} DVAR_{jt}$ (1)	$\Delta_{t,00} \ln\left(P^I/P^D\right)_{jt}$ (2)	$\Delta_{t,00} \ln\left(V_{jt}^D\right)$ (3)
$\Delta_{t,00} \ln\left(P^I/P^D\right)_{jt}$	0.269		
	(0.026)		
$\Delta_{t,00} \ln\left(E_{jt}\right)$ (RMB appreciation)		1.479	−0.089
		(0.891)	(0.031)
$\Delta_{t,00} \ln\left(V_{jt}^D\right)$		17.108	
		(3.177)	
$\Delta_{t,00} \ln\left(\tilde{\tau}_{jt}^U\right)$			−0.012
			(0.007)
$\Delta_{t,00} \ln\left(FDI_{jt}\right)$			0.017
			(0.002)
Industry fixed effects	Y	Y	Y
Observations	105	105	105
R^2	0.030	0.106	0.006

Notes: $\Delta_{t,00}$ is the operator that subtracts the variable of interest from its corresponding value in 2000. Bootstrapped standard errors (with 500 repetitions) are reported in parentheses. Coefficients are estimated using 3SLS. Columns 1, 2, and 3 are third, second, and first stages, respectively.

effects, upstream variety has a strong and positive influence on the relative price of materials. On the other hand, the estimated coefficient on exchange rate has a wrong sign, but is only marginally significant with a *t*-stat of 1.66. At any rate, given that the average annual change in E_{jt} is close to zero during the sample period, the exchange rate is economically insignificant in affecting the relative price of imported materials. This result suggests that empirically most of the changes in the relative price of materials during the sample period were driven by the expansion of domestic upstream variety and not necessarily due to exchange rate changes. Column 3 reports the estimates of (27). The result shows that all three factors (own-industry FDI, upstream input tariff liberalization, and the exchange rate) are statistically significant in explaining the expansion of upstream domestic variety. In particular, the result that input tariff liberalization in the upstream industry is associated with an expansion of the variety of upstream materials is consistent with the findings by Goldberg et al. (2010). Over our sample period, Chinese ordinary exporters experienced a continuous decline in input tariffs, which was accelerated by the country's accession to the WTO in 2002. From 2000 to 2007, the average input tariff facing suppliers in the upstream sectors declined by about 55 percent. The coefficient of −0.012 implies that the reduction in tariffs is associated with a 0.7 percent increase in domestic input varieties, about one-fifth of the average increase across sectors from 2000 to 2007. It is worth noting again that processing firms are exempted from tariffs for imported materials, so tariff reduction will not affect their production costs directly but only indirectly through other general equilibrium effects in the domestic economy. Tariff reduction leads to an increased supply of input varieties, which in turn lowers the average domestic material price and contribute to the rise in the DVAR of processing exporters. Likewise, the presence of own-industry FDI has a positive impact on the variety of upstream materials, supporting the findings of Rodríguez-Clare (1996) and Kee (2015). Specifically, given that the average FDI stock in an industry is about 1.16 log-point higher in 2007 compared to 2000, the coefficient of 0.017 implies that the increase in FDI in the downstream sectors is associated with a 2 percent increase in domestic input varieties.

Finally, the negative sign on $\Delta \ln E_{jt}$ is consistent with the hypothesis that a stronger Chinese yuan will lead to more imported variety and thus less domestic variety due to import competition. However, during the sample period, the average annual change in E_{jt} is close to zero, implying that the exchange rate plays an economically insignificant role in the expansion of the domestic input market.

Overall, the results presented in Table 8 is consistent with our model, highlighting that the change in firm DVAR is driven by the changes in the relative prices of imported and domestic materials, due to the underlying expansion of domestic input variety, in response to the upstream input tariff liberalization and the increased presence of own-industry FDI in downstream industries.[48]

C. *Quantitative Analysis*

In this section, we estimate our model structurally in order to assess how much of the change in the DVARs at the firm and aggregate levels can be explained by our model. We need to first estimate the translog parameter, α_{ID}. According to (18), a firm's DVAR depends on the share of materials in total sales, $\frac{P_t^M M_{it}}{P_{it} Y_{it}}$, and the translog parameter, α_{ID}, as follows:

$$DVAR_{it} = 1 + \frac{P_t^M M_{it}}{P_{it} Y_{it}} \left(\alpha_{0I} + \alpha_{ID} \ln \left(\frac{P_t^I}{P_t^D} \right) \right) + \varphi_{it}.$$

The partial impact of a change in $\ln\left(\frac{P_t^I}{P_t^D}\right)$ on firm DVAR is

$$\frac{\partial DVAR_{it}}{\partial \ln \left(\frac{P_t^I}{P_t^D} \right)} = \frac{P_t^M M_{it}}{P_{it} Y_{it}} \alpha_{ID}.$$

[48] Per a referee's request, we have also checked whether FDI into upstream sectors could affect the DVAR of downstream industries. To this end, we regress the change in the upstream input variety of an industry on the change in the weighted average of FDI across upstream industries, in addition to all the right-hand side variables included in column 3 of Table 8 (i.e., changes in own-industry FDI, upstream input tariffs, and exchange rates). We find that upstream FDI does not explain the increase in upstream input variety, while all the other variables remain significant and have the same sign as those reported in Table 8. In particular, the coefficient on upstream FDI presence is -0.0038 and is not statistically significant. This finding is consistent with our previous results that most of the new intermediate inputs were produced by indigenous Chinese firms and not foreign firms (see Table A12). Interpreting this result through the lens of our model would suggest that upstream FDI does not affect the relative price of imported materials and hence industry DVAR. However, it is plausible that upstream FDI may have an independent effect on industry DVAR, not through affecting domestic input variety, but that is beyond the scope of our model and paper.

With the estimate of α_{ID} and the actual data on $\frac{P_t^M M_{it}}{P_{it} Y_{it}}$, we can calculate how much of the change in firm and industry DVAR is due to the change in the relative price as predicted by our model:

$$\Delta DVAR_{it} = \frac{P_t^M M_{it}}{P_{it} Y_{it}} \hat{\alpha}_{ID} \, \Delta \ln \frac{P_t^I}{P_t^D}, \tag{28}$$

$$\Delta DVAR_{jt} = \sum_{i \in \Omega_j} \frac{EXP_i}{\sum_{i \in \Omega_j} EXP_i} \Delta DVAR_{it}$$

$$= \left(\sum_{i \in \Omega_j} \frac{EXP_i}{\sum_{i \in \Omega_j} EXP_i} \frac{P_t^M M_{it}}{P_{it} Y_{it}} \right) \hat{\alpha}_{ID} \, \Delta \ln \frac{P_{jt}^I}{P_{jt}^D}, \tag{29}$$

where the change in industry j's DVAR equals the weighted average of the changes in the DVAR of all firms in industry j $(i \in \Omega_j)$, derived from (6), and j subscript is added to the relative price for clarity. In addition, with the estimate of α_{ID}, we can also construct the elasticity of substitution between imported and domestic materials, σ_{jt}, for each industry j and year according to (20). Such estimates allow us to assess the time-series variation in σ_{jt} and examine whether the rise in firm DVAR is driven by an increasing σ_{jt} or not.

To estimate α_{ID}, we estimate the following econometric counterpart of (17):

$$\frac{P_t^I M_{it}^I}{P_t^M M_{it}} = a_i - \alpha_{ID} \ln \frac{P_t^I}{P_t^D} + \xi_{it}, \tag{30}$$

where a_i is the firm fixed effect that subsumes α_{0I} in (17) and ξ_{it} is the residual. In other words, α_{ID} is estimated from the within-firm variation in the relative price between imported and domestic materials. Since the dependent variables are measured with errors, we bootstrap the standard errors (based on 500 randomly drawn samples). Moreover, we use the exchange rate indices, (log) FDI and (log) upstream input tariffs of the sector as the instrumental variables for $\ln \frac{P_t^I}{P_t^D}$.

Table 9 reports the estimated $\hat{\alpha}_{ID}$, firm average share of imported materials in total material cost, and the implied $\hat{\sigma}_{jt}$ for 15 industries and both 2000 and 2007. Estimated $\hat{\alpha}_{ID}$ for all industries and years are positive and the resulting σs are all greater than 1, satisfying the theoretical restrictions specified in (16) and (20). In addition, when the entire sample of firms is used, the F-statistics for the first stage is highly significant with p-value of 0 and thus passing the weak instrument test of Stock and Yogo (2005) by a wide margin.[49] Likewise, across all industries, most of

[49] According to Table 1 of Stock and Yogo (2005), the critical value of the first stage F-statistics for the weak instruments test for three instrumental variables used for one endogenous variable is 13.91, if the bias of the IV estimator is restricted to be no more than 5 percent of the OLS bias.

Table 9—Estimated Elasticity of Substitution between Domestic and Foreign Input Varieties

Industry	s^D_{2000}	s^D_{2007}	α^{IV}_{ID} (SE)	α_{ID} (SE)	$\hat{\sigma}^{IV}_{2000}$	$\hat{\sigma}^{IV}_{2007}$
Whole sample	0.661	0.710	0.376	0.351	2.678	2.826
			(0.019)	(0.017)		
Beverages and spirit	0.921	0.885	0.566	0.553	8.779	6.561
			(0.211)	(0.170)		
Chemical products	0.770	0.722	0.309	0.296	2.745	2.539
			(0.072)	(0.066)		
Plastics and rubber	0.734	0.732	0.175	0.176	1.896	1.892
			(0.058)	(0.069)		
Raw hides and skins	0.603	0.717	0.315	0.403	2.316	2.552
			(0.112)	(0.110)		
Wood and articles	0.620	0.742	0.568	0.283	3.411	3.967
			(0.529)	(0.434)		
Pulp of wood	0.769	0.793	0.506	0.525	3.848	4.083
			(0.180)	(0.183)		
Textiles	0.690	0.771	0.938	0.891	5.385	6.313
			(0.066)	(0.066)		
Footwear and headgear, etc.	0.770	0.771	0.427	0.426	3.411	3.418
			(0.059)	(0.062)		
Stone, plaster, cement, etc.	0.802	0.694	0.121	0.142	1.762	1.570
			(0.121)	(0.154)		
Precious metals	0.664	0.730	0.238	0.202	2.067	2.208
			(0.155)	(0.166)		
Base metals	0.882	0.768	0.292	0.287	3.806	2.639
			(0.091)	(0.118)		
Machinery, mechanical, and electrical equipment	0.571	0.644	0.278	0.273	2.135	2.213
			(0.024)	(0.027)		
Vehicles and aircraft	0.580	0.852	0.405	0.396	2.663	4.212
			(0.069)	(0.076)		
Optical, photographic, etc.	0.713	0.728	0.284	0.286	2.388	2.434
			(0.048)	(0.050)		
Misc. manufacturing	0.691	0.765	0.291	0.335	2.363	2.619
			(0.057)	(0.061)		

Notes: Bootstrapped standard errors (with 500 repetitions) are reported in parentheses. Firm fixed effects are always included when estimating α_{ID}. α_{ID} is estimated using OLS, while α^{IV}_{ID} is estimated using two-stage least squares with instruments including import-weighted exchange rates, upstream input tariffs, and the (log) level of FDI in the same industry. See the online Appendix for the details about these instruments.

the F-statistics are larger than 100 with the minimum first stage F-statistics being 44. Of the 15 industries, the IV estimates of α_{ID} are significant for 12 industries at the 1 percent significance level. The estimated σ_t for the whole sample is 2.68 for 2000 and 2.83 for 2007. Both of them are statistically significant at the 1 percent level. Of the 12 industries for which $\hat{\sigma}_{2007}$ is significantly different from 0, $\hat{\sigma}_{2007}$ ranges from 1.90 for "plastic and rubber (HS2 = 39–40)" to 6.56 for "beverages and spirit (HS2 = 16–24)." Even for the industries for which the estimates are imprecise, the coefficients are positive, implying that the implied σ is larger than 1. In other words, foreign and domestic input varieties are gross substitutes for processing exports in all industries in China. Based on the estimates of σ_{jt} for both 2000 and 2007, we perform simple t-tests and confirm that σ_{jt}s are statistically constant within the sample period and for each industry.[50]

Using these estimates, we can do the following back-of-the-envelope calculations. In 2007, the average (across industries) $\frac{P_t^I}{P_t^D}$ is about 0.419 log-points higher than that of 2000. The estimated average $\hat{\alpha}_{ID}$ for the pooled sample, based on the instrumental variables estimation, is 0.376; while the average (across firms) share of material cost in total sales in 2007 is 0.786. Using (28), the predicted increase in $DVAR_{it}$ is $0.376\times\ 0.786\ \times\ 0.419\ \approx\ 12$ percent, which is not statistically different from 14.7 percent, the estimated within-firm increase in the DVAR from 2000 to 2007 as reported in Table 4.[51] Likewise, the predicted change in industry DVAR is also about 13 percent, according to (29), which explains fully the average increase in the industry DVAR during the sample period. This suggests that our simple translog model of using the relative price of materials (driven by upstream input tariff, FDI, and exchange rates) to explain the firm's and aggregate DVAR fits the data very well.

Let us summarize the main findings of the paper. First, the DVAR of processing firms is increasing within firms across time in our sample and has led to an upward trend in both the industry and aggregate DVAR. Firm entry and exit do not explain the upward trend. Second, such an increase is mainly driven by firms substituting domestic for imported materials. Third, such a substitution is a response to the declining relative prices of domestic to imported materials caused by the expansion of domestic input variety. Fourth, the expansion of domestic input variety is induced by an increasing presence of foreign firms in processing exports and decreasing input tariffs facing upstream suppliers. Fifth, based on the decrease in the relative price of domestic to imported materials, our model explains nearly all of the increase in the firm's and aggregate DVAR from 2000 to 2007.

V. Concluding Remarks

This paper provides micro-level evidence of China's rising *ratio of domestic value added in exports to gross exports* (DVAR). We use China's customs transaction data over the 2000–2007 period to measure a firm's DVAR and show how the increase in firm DVAR might explain the aggregate trend. We find that the drastic increase in the DVAR of Chinese processing exports is observed across all industries and trading partners, and accounts for almost the entire rise in the DVAR of the country's aggregate exports during the period. These findings resonate well with the existing IO table-based studies, such as Koopman, Wang, and Wei (2012).

[50] To assess the time series movement of σ, we test $H_0 : \sigma_{2007} - \sigma_{2000} = 0$. T-tests are performed based on the following variance for σ:

$$\mathrm{var}(\sigma) = \frac{\mathrm{var}(\alpha)}{s^2(1-s)^2},$$

which is derived from (20). We construct the standard errors based on data from both 2000 and 2007. None of the t-statistics is statistically significant. These test statistics are available upon request.

[51] The 95 percent confidence interval of $\Delta\widehat{DVAR}_{it}$ is (11.2 percent, 13.6 percent), which overlaps with (11.3 percent, 18.0 percent), the 95 percent confidence interval of the 2007 fixed effect in Table 4.

We exploit our firm-level data to confirm that the increase in the DVAR not only exists within industries, but also within firms. Neither reallocation of resources across industries nor firm entry and exit contributes to the increase in the DVAR of aggregate exports. Firm-level regressions show that the rising DVAR is due to an active substitution of domestic for imported materials by individual processing exporters. Such substitution is revealed at both the intensive margin, represented by a lower cost share of imported materials, and the extensive margin, manifested by decreasing import varieties. Behind this substitution is a continuous decline in the relative prices of domestic to imported input varieties.

We build a simple model to analyze the time-series determinants of a firm's DVAR and show that during the sample period, the continuous tariff reduction facing upstream firms and the rising FDI since 2000 have contributed significantly to the increase in domestic input varieties and thus the decline in their prices. These micro-level findings provide comprehensive explanations about how Chinese exporters have expanded their activities along global value chains away from the final stages of production. They also highlight that trade and FDI liberalization may actually raise a country's DVAR, through input-output linkages and spillovers that go beyond the targeted industries.

While it is beyond the scope of the current paper, our approach is general enough to examine the micro-foundation and mechanism of a host of interesting economic issues. It can be used to study the relationship between firm DVAR and productivity, and shed light on the desirability for a developing nation to promote high value added exports as a growth strategy. It can also be used to assess the validity of the proposal for emerging markets to "move up the value chains" or to raise the DVAR.

Regarding the last remark, we have started a new project on measuring the DVAR for a wide range of countries, based on the matched importer-exporter customs transaction data from the World Bank's Exporter Dynamic Database. Preliminary results show an upward trend in the DVAR for countries such as Bangladesh, Guatemala, Madagascar, and Morocco. One common trait of these countries is their conducive trade and FDI policies that allow their participation in global value chains, similar to the case of China. This is clearly a promising avenue for future research.

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