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BY

BYRON S. GANGNES, ALYSON C. MA
AND ARI VAN ASSCHE

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2424 MAILE WAY, ROOM 540 • HONOLULU, HAWAII 96822
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Global Value Chains and Trade Elasticities

Byron S. Gangnes, University of Hawaii at Manoa

Alyson C. Ma, University of San Diego

Ari Van Assche, HEC Montréal*

Abstract

Previous studies have argued that global value chains (GVCs) have increased the sensitivity of trade to external business cycle shocks. This may occur either because GVC trade is concentrated in durable goods industries, which are known to have high income elasticities (a *composition effect*), or because, within industries, GVC trade has a higher income elasticity than regular trade (a *supply chain effect*). Using Chinese trade data across customs regimes and industries during the period 1995-2009, we find evidence for the former, but not the latter.

Key words: global value chains, trade elasticities, supply chain effect, composition effect

JEL: F1, F4

* Corresponding author. HEC Montréal, Department of International Business, 3000 Chemin de la Côte-Sainte-Catherine, Montréal (Québec), Canada H3T-2A7. Phone: (514)340-6043. Fax: (514)340-6987. E-mail: ari.van-assche@hec.ca.

1. Introduction

Did the emergence of global value chains (GVCs) induce a rise in the elasticity of trade with respect to external business cycle shocks? Could this help explain the collapse of trade during the Great Recession of 2008-2009? Recent studies have highlighted two possible channels through which GVCs may amplify the elasticity of trade to income. On the one hand, Bems et al. (2010) and Eaton et al. (2010) suggest that GVCs have primarily emerged in durable goods sectors, therefore altering the composition of trade. Since durable goods sectors have higher income elasticities, this has made aggregate trade more sensitive to foreign income shocks (a *composition effect*).

On the other hand, Alessandria et al. (2010) argue that characteristics inherent to the structure of global supply chains may cause income elasticities in GVC trade to be higher than for regular trade (a *supply chain effect*). Global supply chains require firms to hold disproportionately large inventories of imported inputs. During economic downturns, firms draw down these inventories to maintain production while suspending new purchases of imported inputs. The disproportionate falloff in upstream imports within GVCs can lead to a heightened sensitivity of trade to foreign income shocks.

The relative importance of these two channels remains an unsettled matter (Altomonte and Ottaviano, 2009). Decomposing these two effects requires data that distinguish between GVC trade and regular trade, which are difficult to come by. In this paper, we address this issue by exploiting a dataset covering China's trade by customs regime. Using a variant of the workhorse export-demand model, we evaluate the existence of a *composition effect* and *supply chain effect* in Chinese exports.

2. Processing versus ordinary trade

To distinguish between GVC trade and regular trade, we use a dataset from the *General Administration of Customs of the People's Republic of China* for the years 1995-2009. Unlike standard trade data, this dataset provides information on the customs regime under which trade occurs. Specifically, it distinguishes between trade under China's processing (PT) regime and ordinary trade (OT) regime. The two regimes differ in terms of tariff treatment and the ability of firms to sell on the domestic market. Under the *PT regime*, firms enjoy duty-free importation of inputs that are used in production, but face restrictions on selling to the domestic market. Under the *OT regime*, firms face duties on imported inputs but can sell their output locally.

Due to the rules of the PT regime, firms use it almost exclusively if they heavily rely on imported inputs and export their products, i.e. if they are part of GVCs. Firms that use the OT regime, in contrast, have more extensive domestic value chains. Two stylized facts back this up. First, processing exports embody less than half as much domestic value added as ordinary exports (Koopman et al. 2012). Second, in 2009, foreign-invested enterprises dominate processing trade with an exports share of 84.1%, while Chinese firms dominate ordinary trade with an export share over 70%.

GVC trade has gained importance in China's exports. As shown in Table 1, the share of processing exports in Chinese exports has increased from 37.7% in 1995 to 51.3% in 2009. These processing exports are heavily concentrated in rapidly growing durable goods sectors. In 2009, processing exports accounted for 63.6% of durable goods exports, but only 26.9% of non-durable goods exports. As a consequence, the composition of Chinese exports has shifted both to durable goods and GVC trade. Disentangling these two phenomena may help understand the determinants of China's trade volatility.

[Table 1 about here]

3. Data and methods

To estimate China's trade elasticities, we build on the workhorse export-demand model, which relates the demand for exports to foreign income and relative prices (Goldstein and Kahn 1985). We modify the standard export demand equation by adding a supply-side variable to take into account the effect of rapid productivity improvements in China (Chinn 2010):

$$\Delta \ln x_{rkt} = \alpha + fe_{rk} + \beta \Delta \ln rgdp_{rkt} + \gamma \Delta \ln rer_t + \delta \Delta \ln sup_t + \varepsilon_{rkt} . \quad (1)$$

Here x_{rkt} is real exports under customs regime r in industry k and at time t ; fe_{rk} are industry-regime fixed effects; $rgdp_{rkt}$ is real foreign income under regime r in industry k and at time t ; rer_t is the Chinese RMB's real exchange rate; and sup_t is a supply-side variable. To avoid spurious results due to non-stationary regressors, we estimate the equation in differenced logarithms (approximately growth rates).¹

¹ An alternative approach is to estimate the model in a cointegration framework. In a panel setting, however, estimation of cointegrating relationships is complicated by heteroskedasticity and potential cross-sectional dependence (Bai et al. 2009). In our case, the very short available time series makes evaluation and treatment of these issues difficult.

For the dependent variable, we use Chinese annual exports, disaggregated by customs regime (PT versus OT) and the twelve sectors identified in Table 1. Note that our degree of industry disaggregation is finer than those adopted in other studies. Cheung et al. (2012) disaggregate Chinese exports into primary and manufacturing exports; whereas, Aziz and Li (2008) distinguish between seven industries. We deflate exports by using the U.S. Bureau of Labor Statistics price deflator for U.S. imports from non-industrial countries (Thorbecke and Smith, 2010).

For our foreign income measure, we use the export-weighted real GDP of the OECD countries, where weights equal the share of Chinese exports destined for each country in year t . We obtained the real GDP data from the IMF's *International Financial Statistics*.

Due to the poor coverage of export prices for China, we use the IMF's CPI deflated trade-weighted index of the RMB against a broad basket of currencies as a measure for rer_t (Cheung et al., 2012).

Finally, for our supply-side variable, we use China's total factor productivity growth, obtained from the Conference Board's Total Economy Database.

To investigate variations in trade elasticities across sectors and regimes, we estimate the following encompassing export demand equation:

$$\begin{aligned} \Delta \ln x_{rkt} = & \alpha + f e_{rk} + \beta_1 \Delta \ln rgdp_{rkt} + \beta_2 \Delta \ln rgdp_{rkt} * dur_k + \\ & \beta_3 \Delta \ln rgdp_{rkt} * proc_r + \beta_4 \Delta \ln rgdp_{kt} * dur_k * proc_r + \gamma_1 \Delta \ln rer_t + \\ & \gamma_2 \Delta \ln rer_t * dur + \gamma_3 \Delta \ln rer_t * proc_r + \gamma_4 \Delta \ln rer_t * dur_k * proc_r + \delta \Delta \ln sup_t + \varepsilon_{rkt}. \end{aligned} \quad (2)$$

$Proc_r$ is a dummy variable that takes a value of 1 if trade occurs under the PT regime, and 0 otherwise; dur_k is a dummy that equals 1 for durable goods, and 0 otherwise. To distinguish between durables and non-durables, we follow Engel and Wang (2011) (see Table 1).

There will be evidence of a *composition effect* if $\beta_2 > 0$. In that case, the income elasticity of exports is higher for durables than for non-durables. There will be evidence of a *supply chain effect* if $\beta_3 > 0$ or $\beta_4 > 0$. This would indicate that, within industries, the income elasticity of processing exports is larger than for ordinary exports.

4. Results

We present our regression results in Table 2. All regressions are estimated with a single lag of each independent variable to allow for the possibility of gradual adjustment of

exports to income and exchange rate movements and to eliminate first-order serial correlation from regression residuals. In all equations, we compute standard errors that are robust to heteroscedasticity and autocorrelation within panels.

[Table 2 about here]

Columns 1 and 2 present our estimates for equation (1). Overall, the export equation appears to do a reasonable job of describing Chinese exports, with estimates that are within the range of previous studies (e.g. Cheung et al. 2012). The income elasticity is positive and significant with an impact effect of 1.1 when $\Delta \ln tfp_t$ is excluded and 1.4 when it is included. The price elasticity is negative and significant, with a cumulative effect of contemporaneous and one-period-lagged values ranging from 1.5 to 1.7. Total factor productivity growth exerts only a small effect on exports, presumably because the industry-regime fixed effects capture much of trend growth in exports.

Columns 3 and 4 report the estimates of equation (2). In line with the *composition effect*, we find that the coefficient on $\Delta \ln RGDP * dur$ is positive and significant. In our preferred specification in column 4, the size of the coefficient is 3.4, indicating that the income elasticity of durable goods exports is more than four times as large as the income elasticity of non-durable goods exports (0.7). There is no evidence that durable goods exports have a different price elasticity than non-durable goods exports, or that they have a different relationship with TFP growth.

The estimates in Columns 3 and 4 suggest that there is no evidence of a *supply chain effect*. The coefficients on $\Delta \ln rgdp_{kt} * proc_r$, on $\Delta \ln rgdp_{kt} * proc_r * dur_k$ and on their one-year lags are insignificant across both specifications. This suggests that, within sectors, processing exports do not have statistically different income elasticities than ordinary exports. There is also no evidence that processing exports have different price responsiveness than non-processing exports.

Our central results are robust to alternative econometric specifications. The results are unaffected by the inclusion of a lagged dependent variable as regressor; the inclusion of year fixed effects; or the exclusion of lagged independent variables. Similarly, the results are invariant to two alternate supply side variables: China's relative productivity, measured by the Chinese real GDP per capita relative to the U.S. output per man hour in the nonfarm business sector and China's fixed asset investment to GDP ratio.

It is interesting to compare these results to previous studies. Aziz and Li (2008), Cheung et al. (2012) and Thorbecke and Smith (2010) find that processing exports have a higher

income elasticity than ordinary exports, which we do not find. A reason for this may be that previous studies have not conducted their analysis at a sufficiently disaggregated sectoral level, therefore inadequately controlling for the composition effect.

5. Conclusion

This paper empirically investigates the channels through which GVCs affect the sensitivity of China's exports to foreign income shocks. Using data across customs regimes and sectors, we find evidence that GVCs increased the income elasticity of Chinese exports through a *composition effect*. GVCs have primarily emerged in durable goods industries, which we find to be four times as sensitive to foreign income shocks as nondurable goods. We find no evidence, however, of a *supply chain effect* in China's exports. Once one controls for industry, Chinese processing exports are not significantly more sensitive to foreign income shocks than China's ordinary exports.

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Table 1: China's exports, by sector, various years

	HS Codes	Share of total exports		Annualized growth rate 1995-2009	Processing exports share	
		1995	2009		1995	2009
DURABLES						
Machinery, electrical	84-85	10.1	43.2	32.2	70.2	77.3
Misc. Manufacturing	90-97	6.5	10.8	23.5	50.2	44.0
Metals	72-83	10.4	6.4	15.1	44.5	19.6
Transportation	86-89	2.1	4.2	25.0	77.8	60.9
Stone and glass	68-71	2.3	2.0	18.0	13.1	20.0
Total durables	68-97	31.4	66.6	25.7	53.9	63.6
NON-DURABLES						
Textiles	50-63	28.8	14.6	13.5	41.8	20.8
Non-manufacturing	01-27	20.5	4.6	7.2	11.4	22.8
Chemical & allied industries	28-38	8.1	4.4	14.1	12.1	17.6
Plastics and rubbers	39-40	1.8	3.2	24.3	58.9	59.9
Footwear and headgear	64-67	3.2	3.1	18.9	56.2	39.1
Wood and wood products	44-49	2.6	1.9	16.7	11.8	31.6
Raw hides, skins, leathers & furs	41-43	3.6	1.6	12.4	62.2	25.5
Total non-durables	01-67	68.6	33.4	13.2	30.3	26.9
Total		100.00	100.00	19.2	37.7	51.3

Source: authors' calculations using China Customs Statistics data

Table 2: Regression Results, 1995-2009

Dependent variable	Exports growth			
	(1)	(2)	(3)	(4)
$\Delta \ln RGDP$	1.127*** [0.312]	1.437*** [0.304]	0.368 [0.417]	0.709* [0.372]
$\Delta \ln RGDP$ (1-lag)	0.475 [0.318]	0.332 [0.322]	0.209 [0.462]	0.211 [0.423]
$\Delta \ln RGDP$ * durable			3.377*** [1.088]	3.404*** [1.006]
$\Delta \ln RGDP$ * durable (1-lag)			0.701 [1.255]	0.282 [1.256]
$\Delta \ln RGDP$ * processing			0.260 [0.583]	-0.260 [0.518]
$\Delta \ln RGDP$ * processing (1-lag)			0.229 [0.622]	0.229 [0.596]
$\Delta \ln RER$	-0.659** [0.266]	-0.095 [0.295]	0.004 [0.333]	0.603 [0.352]
$\Delta \ln RER$ (1-lag)	-1.019*** [0.236]	-1.453*** [0.258]	-1.405*** [0.363]	-1.748*** [0.356]
$\Delta \ln RER$ * durable			0.051 [0.632]	0.024 [0.606]
$\Delta \ln RER$ * durable (1-lag)			-0.776 [0.752]	-0.143 [0.720]
$\Delta \ln RER$ * processing			-0.948 [0.580]	-0.948 [0.580]
$\Delta \ln RER$ * processing (1-lag)			0.684 [0.502]	0.684 [0.446]
$\Delta \ln RGDP$ * processing*durable			-1.850 [1.531]	-1.849 [1.400]
$\Delta \ln RGDP$ * processing*durable (1-lag)			0.268 [2.178]	0.252 [2.307]
$\Delta \ln RER$ * processing*durable			-0.520 [1.37]	-0.520 [1.130]
$\Delta \ln RER$ * processing*durable (1-lag)			0.601 [1.148]	0.599 [1.141]
$\Delta \ln TFP$		0.013*** [0.004]		0.015*** [0.003]
$\Delta \ln TFP$ (1-lag)		-0.015*** [0.004]		-0.015*** [0.004]
Observations	312	312	312	312
Pseudo R-Squared	0.360	0.400	0.413	0.452

Notes: All regression includes a constant and industry-regime fixed effects. Standard errors in brackets are robust to heteroscedasticity and autocorrelation within panels.

*indicates significant at 10%; **significant at 5%; ***significant at 1%.