Heckscher-Ohlin: Evidence from virtual trade in value added*

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Abstract

The fragmentation of production chains across borders is one of the most distinctive feature of the last 30 years of globalization. Nonetheless, our understanding of its implications for trade theory and policy is only in its infancy. We suggest that trade in value added should follow theories of comparative advantage more closely than gross trade, as value-added flows capture where factors of production, e.g. skilled and unskilled labor, are used along the global value chain. We find empirical evidence that Heckscher-Ohlin theory does predict manufacturing trade in value-added, and it does so better than for gross shipment flows. While countries exports across a broad range of sectors, they contribute more value-added in techniques using their abundant factor intensively.

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1 INTRODUCTION

The second unbundling, or the fragmentation of production chains across borders, is one of the most distinctive feature of the last 30 years of globalization (Baldwin, 2011). Nonetheless, our understanding of its implications for trade theory and policy is only in its infancy. One explanation for this delay is the only-recent release of input-output matrices that cover the whole world and allow for a better understanding of the location of production across global value chains.

One implication of global value chains is that 'Made in China' no longer means 'Made in China'. Koopman et al. (2008) estimate that the share of domestic content in China exports is about 50%. One recurring example is that of Apple's iPad, 'Made in China' but with Chinese labor accounting for only about 3% of its value added. Gross trade figures, e.g. Chinese exports of iPads, are hence no perfect guide to understand where value addition occurs. They also imply a 'double-counting' of value added, as the value added embedded in parts and components is counted when both intermediates and final goods cross borders. The 'double-counting' means that trade data overstates the domestic value-added content of exports (see Figure 1).

Economists have thus recently focused on capturing the value-added content of trade (Johnson and Noguera, 2012). Extracting the value-added embedded in exports allows us to trace where factors of production are used. For example, it allows us to identify that China's electronics exports embed wages paid to Chinese labor and profits pocketed by US wholesalers. It elucidates the paradox that labor-abundant China apparently exports capital-intensive and sophisticated products (Krugman, 2008). When looking at trade in value added, we find that China actually exports only unskilled labor embedded in iPads. Another example is that of Boeing's Dreamliner. While it is 'Made in the USA', it embeds value from a long list of countries.

We suggest that trade in value added should follow theories of comparative advantage more closely than gross trade. The reason is that it tells you where factors of production, e.g. skilled and unskilled labor, are used. As Daudin et al. (2011) notes, only a value-added trade measure can answer the question 'who produces for whom in the world economy?'. Value-added trade thus offers a new lens to test for theories of comparative advantage. Do skill-abundant countries export skill-intensive products? Or rather, do skill-abundant countries export skill-intensive value-added? Previous tests of comparative advantage theories based on factor endowments include Romalis (2004) (and extensions in Morrow, 2010; Regolo, 2013), who shows that the US imports more skill-intensive products from skill-abundant countries, Chor (2010) who explains industry trade flows using Heckscher-Ohlin (HO) and other sources of comparative advantage, and Trefler and Zhu (2010), who tests for factor content predictions (the standard Heckscher-Ohlin-Vanek (HOV) test) in the presence of traded intermediates.

In this paper we combine Chor (2010) and Johnson and Noguera (2012) to provide novel evidence for Heckscher-Ohlin theory. The Heckscher-Ohlin prediction is that countries will export goods whose production uses its abundant factor intensively. But, as Leamer (1987, p.985) points out, the theoretical prediction is properly interpreted to refer to value added, not gross output. We thus expect that the value-added trade patterns fit the Heckscher-Ohlin prediction better than gross trade patterns as they capture precisely the location of production factors. We mimic the gravity regression setting of Chor (2010), who tested for different sources of comparative advantage, but including value-added trade rather than gross trade data on the left-hand side. In doing so we generalize the approach of Davis and Weinstein (2001), Trefler and Zhu (2010) and others to test for Heckscher-Ohlin-type predictions to a framework with bilateral trade costs.[1] In robustness checks we also do HOV tests à la Trefler and Zhu (2010), as well as graphical analysis à la Romalis (2004), both of which strengthen our argument.

We thus add to a resurgence of papers that decompose the factor content of trade to

[1] Davis and Weinstein (2001) modify the standard HOV test and use a gravity framework to account for trade costs and estimate the factor content of demand for tradables.

test for factor proportions theory, e.g. Egger et al. (2011) and Fisher (2011) who show that it is important to take into account international differences in technology, which depends largely on variation in labor requirements across countries (Nishioka, 2012). Our paper is also in line with Fisher and Marshall (2013) who insist that the factor content of trade in labor is not an exchange of person-years, but trade in value added attributed to a worker.

We find empirical evidence that HO theory does predict manufacturing trade in value-added, and it does so better than for gross shipment flows. The paper proceeds as follows. In the next section we describe the data and present our empirical strategy. A third section presents the results and a fourth concludes.

2 DATA AND EMPIRICAL STRATEGY

We use data from the World Input-Output Database (WIOD). It provides international input-output tables for 40 countries, 34 sectors, from 1995 to 2009 (Timmer, 2012). This data allows us to compute the value added embedded in final imports as the sale value of a product equals to the cost of intermediate inputs plus value added. Here value added refers to payments to primary inputs such as different types of labor. For example we can identify where the workers involved into Chinese electronics were employed, by sector and by nation. It would most likely involve skilled labor in the US who designed and market the product, as well as workers in Taiwan that produced the parts and components, as well as other inputs from the chemical and metal industries in other countries. By tracking down the whole process until the sales value equals the sum of value added components, we can trace the value added by industry and country. Computing value-added exports is straightforward using matrix algebra (see Johnson and Noguera, 2012):

$$VA = F(I - B)^{-1}X$$

where VA is a $(NJ, 1)$ vector (N countries and J sectors) that collects the value-added generated in country o and sector j, and embodied final demand; F is a (NJ, NJ) diagonal matrix with the ratio of *direct* value-added to gross output for each country and sector on the diagonal, $(I - B)^{-1}$ is the (NJ, NJ) Leontief inverse - it estimates the amount of intermediates per US$ of final output after all rounds of intermediate shipments across sectors and countries. X is the $(NJ, 1)$ vector of gross shipments for final demand - where N here denotes the set of destination countries.

Trade in value added may be direct (embodied in bilateral gross trade shipments) or indirect (traveling through intermediate shipments that cross multiple borders) - see Figure 2 for an illustrative example. We label the total value added trade as 'Virtual VA trade'.

Figure 3 shows the difference between trade in value added and in gross terms for China. One clear observation is that the contribution of China in global value-added trade is smaller than in gross terms. Overall, China gross trade with other Asian countries and with the EU and the US include more foreign than Chinese value added. The difference in the two flows is even bigger in China's exports to Asia, as many of those are parts that will be re-exported to the US or the EU and thus embedded in China's value-added exports to the US and EU. Figure 4 shows that China's top export sectors in value-added terms are different from those in gross terms. While electric equipment remains on top, plastics, transport equipment (cars), and leather fall out of the top 10. One explanation is that most of the leather exported from China embeds value added in, say, Ethiopia, and plastic exports embed oil from Indonesia. Mining and agriculture enter the top 10 in value-added terms. The case of mining is of particular importance as it provides some *prima facie* evidence of how trade in value-added can better capture factor abundance forces. Whilst China is abundant in primary inputs that are specific to the the mining sector (e.g. rare earths), gross trade figures suggest Chinese mining products are not a major export sector - not least, because of protectionist trade and industrial policies. In value-added terms, where we are able to include the input-ouput linkages between the mining and other manufacturing sectors, we observe that indeed China exports a lot of value-added generated in the mining industry, as factor abundance theories would suggest. To provide a concrete example, while China doesn't export rare earths, it embeds them in electronic exports. Mining thus accounts for a large share of value-added exported through this type of supply chain linkages.

Figures 5 and 6 similarly display the case of Japan exports. Japan's value-added exports to the US and EU are larger, not smaller, than its gross exports. This may reflect the more upstream position of Japan in global value chains than China. Japanese value-added is embedded in China's and other Southeast Asian countries exports of electronics to the US and the EU, and hence does not show up in the gross trade of Japan with those destination markets. When we look at the sectoral breakdown (Figure 6), services such as finance, inland transport, and wholesale do not appear as top-10 gross exports but do make the list for value-added exports as they are embedded in Japan's sophisticated exports. This pattern is again indicative of HO forces being at work more in value-added than in gross trade statistics, insofar as services such as finance use skilled labor intensively (and Japan being relatively skill-abundant).

WIOD also provides data on factor use and payments - three types of labor (high-skilled, medium-skilled and low-skilled) and capital. We follow Timmer et al. (2014) and merge the low and medium categories in an 'unskilled' aggregate. The factors are Unskilled labor (L_{US}) and High-skilled labor (L_{HS}). We do not focus on physical capital as it is constructed as a residual and is thus not as precisely-measured as human capital endowments. Moreover we follow Wood (1994) and think of it more as a traded good rather than an endowment - see also Caselli and Feyrer (2007) for corroborative evidence.

We regress virtual VA exports and gross exports on relative endowments interacted with relative intensities. Formally, we estimate the following model:

$$\ln(VA)_{odit} = \alpha_{dit} + \sigma_{ot} + \beta_1 \ln(\frac{l_{hs}}{l_{us}})_{oit} + \beta_2 \ln(\frac{l_{hs}}{l_{us}})_{oit} \times \ln(\frac{L_{hs}}{L_{us}})_{ot} + \varepsilon_{odit}$$

where α_{dit} and σ_{ot} are importer-industry-year and exporter-year dummies. L stands for labor, hs for skilled and us for unskilled types. Lower-case letters are for intensities, upper-case endowments. In the cross-section specification, the time subscript drops out. We mimic the specification of Chor (2010), but focus on relative skill abundance and (possibly country-varying) skill intensity as the only comparative advantage source of trade specialization in value added and gross terms.[2]

The coefficient of interest, β_2, is identified within destination country and industry from variation in relative skill endowments and intensity across country of origin (for gross trade) and country where value-added is created (for value-added trade). The country of origin dummies further control for all determinants of trade that shift exports from country o. The HO logic suggests that, for a given market d and industry i, trade should be higher from skill-abundant countries, if they use skill intensively in industry i. Our prediction is that β_2 is positive and significant, even more so for value-added exports than for gross exports.

3 RESULTS

When we focus on manufacturing sectors our prediction is confirmed. Countries export more skilled-intensive value-added if they are relatively skill abundant. The coefficient on the interaction of relative skill intensity ($\frac{l_{hs}}{l_{us}}$) and relative skill endowment ($\frac{L_{hs}}{L_{us}}$) is positive and significant in all 3 specifications. This is true both in the cross section, i.e. the 1995-2009 average (Table 1) and the panel (Table 2). In the second specification (column 2), we add terms that capture the relative capital abundance and intensities, on top of the skill terms. While we find no effect for capital intensity, this additional term does not alter the coefficients on the skill terms. As we mentioned earlier, physical capital is constructed as a residual and

[2] We estimated also extended specifications of our baseline regression in (1) adding other potential sources of comparative advantage (e.g. the quality of institutions and contract intensity), similarly to Chor (2010). The estimates of the HO interaction coefficient are similar, while other comparative advantage forces have no robust effect across specifications.

is thus not as precisely-measured as human capital endowments. Adding gravity controls (column 3) as in Chor (2010) does not alter the results either.

These results are all the more interesting when compared to those with gross exports on the left-hand side (Columns 4-6). Indeed, we find no indication of Heckscher-Ohlin forces significantly affecting gross manufacturing trade patterns. These contrasting results are illustrated in Figure 7. The latter plots the elasticities estimated in columns 1 and 4 of Table 1. For a country with relatively high skill abundance, such as South Korea, a 10% increase in skill intensity corresponds to an increase in VA exports of about 4%. For a country with relative skill scarcity, such as India, a 10% increase in skill intensity corresponds to a decrease in VA exports of about 5%. This is exactly in line with countries exporting along their comparative advantage. When looking at gross exports, we do not find such clearly differing elasticities at the opposite end of the skill abundance distribution.

When looking at services and total trade (Tables 3, 4, 5, and 6) we find no significant difference between gross and virtual VA flows. This is illustrated in Figure 8. While the results still lean more in favor of Heckscher-Ohlin forces when looking at services in value-added terms, we find no significant difference between the 2 types of flows. This difference between services and manufacturing may be explained by the fact that is it mostly in manufacturing that global value chains have emerged.

In what follows we do HO tests à la Trefler and Zhu (2010), as well as figures à la Romalis (2004), to strengthen our argument. Figure 9 is inspired by Figure 1 in Romalis (2004), which gave the example of Germany's and Bangladesh's exports to the US. It showed that US imports from Germany, where the average adult has more than ten years of education, accounted for larger shares of US imports in skill-intensive commodities. Imports from Bangladesh, on the other hand, were concentrated in commodities that require little skilled labor. This illustrated the quasi-Heckscher-Ohlin prediction that, once controlling for transport costs and allowing for monopolistic competition, countries abundant in skilled labor capture larger shares of US imports in skill-intensive products. Figure 9 provides a similar picture for US imports, both in gross and VA terms, from China, Germany, Japan and Mexico. The horizontal axis measures the US skill-intensity of each sector, the vertical axis the share of US imports. The figure highlights the contrasts between China and Japan as well as between Germany and Mexico. For Japan and Germany, countries with skill endowments similar to the US, the estimated share of US imports does not vary much across skill intensities. For China and Mexico, skill-scarce countries relative to the US, there is a clear downward trend suggesting that their exports account for smaller shares in skill-intensive sectors. But what is most interesting is that the differences in import shares across sectors are even bigger when trade is measured in VA terms. In other words, VA trade is more sensitive to skill intensity. This confirms our previous results, namely that the HO prediction is stronger when trade is measured in value added.

Trefler and Zhu (2010) offer a test for factor content predictions (HOV) in the presence of traded intermediates. They compute the labor content of net exports across 40 countries, F, accounting for trade in intermediate inputs, and show that the latter is positively correlated with relative labor endowments, defined as $V - sV_w$, where V is the country's endowment, s is the country's share of world's consumption, and V_w the world's endowment. Trefler and Zhu (2010)'s Figure 1 focuses on the Vanek prediction for labor. In Figure 10 we look more precisely at the unskilled-labor content of net exports, and compare the cases of unskilled labor embedded in gross trade and via intermediates that can travel through many industries and countries ('F gross trade' vs. 'F VA trade'). More precisely, each observation of 'F gross trade' equals: $f_{ct} = \sum_i a_{cit}X_{cit} - \sum_{o \neq c}\sum_i a_{oit}X_{ocit}$, where $a_{cit}X_{cit}$ equals the unskilled labour content of total country c's gross exports X (a being the unskilled input requirement) and $a_{oit}X_{ocit}$ is the unskilled labour embedded in gross imports of country c coming from country o - the unskilled labour requirements are hence specific to the origin country o. Each observation of 'F VA trade' equals instead net trade in unskilled labor taking into account all the possible input-output linkages - using the Leontief inverse $(I - B)^{-1}$ (see also Trefler and Zhu, 2010, p. 197). As in Trefler and Zhu (2010) we normalize F and $V - sV_w$ by $s^{\frac{1}{2}}\sigma$ where σ^2 is the cross-country variance of the residuals: $(F - V + sW_w)$.

We find a positive and significant relationship between net exports of unskilled labor and relative unskilled-labor endowments, as well as a high R-squared around 0.9, wether we account for global value chains or not. Yet the slope coefficient is much larger under a VA-trade scenario, at 0.1176 vs. 0.0015, suggesting that HO effects are stronger when we account for global value chains. The difference is even starker when we look at the variance ratio $\frac{Var(F)}{Var(V-sV_w)}$ (or, as Trefler, 1995 coined it, the 'missing trade' statistics) as a more specific measure of fit. While it is very low in the 'F VA trade' specification (0.01), it is still much larger than under the gross-trade scenario, where it is practically zero. The consistently higher trade in unskilled labor that we obtain when we consider global value chains has a clear intuition. The unbundling of production across borders expands the possibilities to trade and hence for factors of production to 'travel' through traded intermediates. What's more, this higher trade in factors is positively correlated with factor abundance, as the higher slope coefficient in the 'F VA trade' suggests.

When we remove the China and India outliers, as in the bottom panel of Figure 10, we find a similar difference in coefficients and a large difference in R-squared, at 0.92 when we take global value chains into account, and at 0.67 when we don't. This confirms our previous result that HO forces are all the more relevant when we take global value chains into account, i.e. when we look at virtual VA trade, rather than gross trade, and here specifically when we compare virtual flows of unskilled labor to the flows of unskilled labor embedded in gross trade. As before, trade in unskilled labor through global supply chains is much larger than trade in unskilled labour through gross trade.

4 CONCLUSION

Tests of the Heckscher-Ohlin theory have come a long way since Leontief's paradox, i.e. the observation in 1953 that the US, a capital abundant country, was importing mostly capital-intensive goods, and since Bowen et al. (1987) claimed that net factor exports are no better predicted by measured factor abundance than by a coin flip. While many studies have followed and claimed that the theory performed (more or less) badly empirically, we find empirical evidence that it does predict manufacturing trade in value-added, and it does so better than for gross shipment flows. Countries exports ‘value’ that they produce using their abundant factor intensively. As Nishioka (2012) noted, the bulk of world factor content of trade does not arise from specialization across goods, but rather via specialization in abundance-inspired techniques. One note of caution is that when we look at total trade, we do not find any statistical difference between VA and gross flows. This may be because global value chains are still mostly national. The spread of global value chains should make HO theory more, rather than less, relevant.

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Table 1: Manufacturing trade - Cross-section

	(1)	(2)	(3)	(4)	(5)	(6)
	Virtual VA			Gross exports		
$\ln\left(\frac{l_{hs}}{l_{us}}\right) \times \ln\left(\frac{L_{hs}}{L_{us}}\right)$	0.309***	0.339***	0.339***	0.167	0.159	0.159
	(0.0800)	(0.0918)	(0.0945)	(0.112)	(0.129)	(0.132)
$\ln\left(\frac{l_{hs}}{l_{us}}\right)$	0.642***	0.560***	0.560**	0.222	0.109	0.109
	(0.209)	(0.215)	(0.221)	(0.266)	(0.283)	(0.290)
$\ln\left(\frac{k}{l_{us}}\right) \times \ln\left(\frac{K}{L_{us}}\right)$		-0.00931	-0.00931		0.0155	0.0155
		(0.0297)	(0.0302)		(0.0335)	(0.0344)
$\ln\left(\frac{k}{l_{us}}\right)$		0.272**	0.272**		0.137	0.137
		(0.125)	(0.127)		(0.138)	(0.142)
Log(distance)			-0.717***			-0.981***
			(0.0508)			(0.0678)
Same cty			2.029***			2.186***
			(0.195)			(0.238)
Share border			0.490***			0.655***
			(0.0918)			(0.113)
Common lang			0.0300			0.0501
			(0.0918)			(0.110)
Colony			0.158*			0.302***
			(0.0891)			(0.110)
Legal			0.187***			0.256***
			(0.0432)			(0.0510)
FTA			0.393***			0.506***
			(0.0919)			(0.123)
Obs	25,520	25,520	25,520	25,520	25,520	25,520
R^2	0.671	0.674	0.854	0.575	0.577	0.807

All regressions include importer-industry and exporter dummies. Two-way clustered standard errors by exporter-industry and country-pair are in parenthesis. Significant at: *10%, **5%, ***1% level.

Table 2: Manufacturing trade - Panel

	(1)	(2)	(3)	(4)	(5)	(6)
	Virtual VA			Gross exports		
$\ln\left(\frac{l_{hs}}{l_{us}}\right) \times \ln\left(\frac{L_{hs}}{L_{us}}\right)$	0.285***	0.307***	0.307***	0.170*	0.164	0.164
	(0.0674)	(0.0752)	(0.0776)	(0.0950)	(0.107)	(0.110)
$\ln\left(\frac{l_{hs}}{l_{us}}\right)$	0.577***	0.507***	0.507***	0.236	0.145	0.145
	(0.174)	(0.177)	(0.182)	(0.220)	(0.232)	(0.238)
$\ln\left(\frac{k}{l_{us}}\right) \times \ln\left(\frac{K}{L_{us}}\right)$		-0.00686	-0.00686		0.0132	0.0132
		(0.0263)	(0.0268)		(0.0294)	(0.0302)
$\ln\left(\frac{k}{l_{us}}\right)$		0.235**	0.235**		0.123	0.123
		(0.110)	(0.112)		(0.121)	(0.124)
Log(distance)			-0.816***			-1.095***
			(0.0427)			(0.0566)
Same cty			1.945***			2.080***
			(0.202)			(0.246)
Share border			0.439***			0.595***
			(0.0867)			(0.107)
Common lang			0.0374			0.0593
			(0.0948)			(0.112)
Colony			0.112			0.252**
			(0.0898)			(0.110)
Legal			0.172***			0.238***
			(0.0440)			(0.0516)
FTA			0.0966			0.180**
			(0.0604)			(0.0758)
Obs	382,440	382,440	382,440	382,440	382,440	382,440
R^2	0.669	0.672	0.843	0.566	0.567	0.783

All regressions include importer-industry-year and exporter-year dummies. Two-way clustered standard errors by exporter-industry and country-pair are in parenthesis. Significant at: *10%, **5%, ***1% level.

Table 3: Services trade - Cross-section

	(1)	(2)	(3)	(4)	(5)	(6)
	Virtual VA			Gross exports		
$\ln\left(\frac{l_{hs}}{l_{us}}\right) \times \ln\left(\frac{L_{hs}}{L_{us}}\right)$	0.109***	0.109***	0.109***	0.0693*	0.0964**	0.0964**
	(0.0342)	(0.0349)	(0.0375)	(0.0388)	(0.0411)	(0.0443)
$\ln\left(\frac{l_{hs}}{l_{us}}\right)$	0.181**	0.201**	0.201**	0.0724	0.144	0.144
	(0.0778)	(0.0816)	(0.0883)	(0.0940)	(0.101)	(0.109)
$\ln\left(\frac{k}{l_{us}}\right) \times \ln\left(\frac{K}{L_{us}}\right)$		0.00662	0.00662		-0.0198	-0.0198
		(0.0104)	(0.0112)		(0.0134)	(0.0144)
$\ln\left(\frac{k}{l_{us}}\right)$		-0.0709	-0.0709		0.0110	0.0110
		(0.0549)	(0.0584)		(0.0602)	(0.0653)
Log(distance)			-0.564***			-0.280***
			(0.0461)			(0.0739)
Same cty			4.340***			6.728***
			(0.163)			(0.249)
Share border			0.347***			0.572***
			(0.0857)			(0.112)
Common lang			0.0571			0.108
			(0.0836)			(0.123)
Colony			0.210**			0.351***
			(0.0870)			(0.108)
Legal			0.205***			0.218***
			(0.0394)			(0.0487)
FTA			0.198**			0.207
			(0.0812)			(0.126)
Obs	27,200	27,200	27,200	27,200	27,200	27,200
R^2	0.644	0.644	0.882	0.377	0.377	0.739

All regressions include importer-industry and exporter dummies. Two-way clustered standard errors by exporter-industry and country-pair are in parenthesis. Significant at: *10%, **5%, ***1% level.

Table 4: Services trade - Panel

	(1)	(2)	(3)	(4)	(5)	(6)
	Virtual VA			Gross exports		
$\ln\left(\frac{l_{hs}}{l_{us}}\right) \times \ln\left(\frac{L_{hs}}{L_{us}}\right)$	0.0983***	0.0982***	0.0982***	0.0647*	0.0889**	0.0889**
	(0.0316)	(0.0323)	(0.0347)	(0.0359)	(0.0377)	(0.0407)
$\ln\left(\frac{l_{hs}}{l_{us}}\right)$	0.161**	0.175**	0.175**	0.0680	0.130	0.130
	(0.0706)	(0.0736)	(0.0796)	(0.0848)	(0.0906)	(0.0976)
$\ln\left(\frac{k}{l_{us}}\right) \times \ln\left(\frac{K}{L_{us}}\right)$		0.00591	0.00591		-0.0191	-0.0191
		(0.00924)	(0.00999)		(0.0125)	(0.0134)
$\ln\left(\frac{k}{l_{us}}\right)$		-0.0582	-0.0582		0.0165	0.0165
		(0.0471)	(0.0504)		(0.0543)	(0.0588)
Log(distance)			-0.648***			-0.371***
			(0.0398)			(0.0620)
Same cty			4.290***			6.675***
			(0.169)			(0.264)
Share border			0.307***			0.530***
			(0.0818)			(0.106)
Common lang			0.0608			0.112
			(0.0870)			(0.126)
Colony			0.162*			0.300***
			(0.0872)			(0.105)
Legal			0.194***			0.207***
			(0.0401)			(0.0481)
FTA			-0.0863*			-0.0957
			(0.0523)			(0.0747)
Obs	408,000	408,000	408,000	408,000	408,000	408,000
R^2	0.645	0.645	0.870	0.374	0.375	0.707

All regressions include importer-industry-year and exporter-year dummies. Two-way clustered standard errors by exporter-industry and country-pair are in parenthesis. Significant at: *10%, **5%, ***1% level.

Table 5: Total trade - Cross-section

	(1)	(2)	(3)	(4)	(5)	(6)
	Virtual VA			Gross exports		
$\ln\left(\frac{l_{hs}}{l_{us}}\right) \times \ln\left(\frac{L_{hs}}{L_{us}}\right)$	0.207***	0.197***	0.197***	0.205***	0.217***	0.217***
	(0.0301)	(0.0321)	(0.0335)	(0.0392)	(0.0417)	(0.0433)
$\ln\left(\frac{l_{hs}}{l_{us}}\right)$	0.370***	0.325***	0.325***	0.448***	0.446***	0.446***
	(0.0768)	(0.0798)	(0.0833)	(0.0970)	(0.102)	(0.106)
$\ln\left(\frac{k}{l_{us}}\right) \times \ln\left(\frac{K}{L_{us}}\right)$		0.00321	0.00321		-0.0185	-0.0185
		(0.0115)	(0.0119)		(0.0154)	(0.0159)
$\ln\left(\frac{k}{l_{us}}\right)$		0.0510	0.0510		0.108	0.108
		(0.0544)	(0.0563)		(0.0668)	(0.0692)
Log(distance)			-0.638***			-0.620***
			(0.0466)			(0.0645)
Same cty			3.222***			4.530***
			(0.177)			(0.215)
Share border			0.416***			0.612***
			(0.0877)			(0.102)
Common lang			0.0434			0.0789
			(0.0861)			(0.0949)
Colony			0.185**			0.328***
			(0.0874)			(0.0941)
Legal			0.196***			0.237***
			(0.0401)			(0.0432)
FTA			0.292***			0.352***
			(0.0835)			(0.112)
Obs	52,720	52,720	52,720	52,720	52,720	52,720
R^2	0.653	0.653	0.859	0.503	0.504	0.757

All regressions include importer-industry and exporter dummies. Two-way clustered standard errors by exporter-industry and country-pair are in parenthesis. Significant at: *10%, **5%, ***1% level.

Table 6: Total trade - Panel

	(1)	(2)	(3)	(4)	(5)	(6)
	Virtual VA			Gross exports		
$\ln\left(\frac{l_{hs}}{l_{us}}\right) \times \ln\left(\frac{L_{hs}}{L_{us}}\right)$	0.189***	0.180***	0.180***	0.182***	0.193***	0.193***
	(0.0275)	(0.0293)	(0.0306)	(0.0356)	(0.0374)	(0.0389)
$\ln\left(\frac{l_{hs}}{l_{us}}\right)$	0.329***	0.288***	0.288***	0.388***	0.384***	0.384***
	(0.0684)	(0.0706)	(0.0735)	(0.0854)	(0.0893)	(0.0926)
$\ln\left(\frac{k}{l_{us}}\right) \times \ln\left(\frac{K}{L_{us}}\right)$		0.00401	0.00401		-0.0164	-0.0164
		(0.0103)	(0.0107)		(0.0142)	(0.0147)
$\ln\left(\frac{k}{l_{us}}\right)$		0.0444	0.0444		0.0992	0.0992
		(0.0478)	(0.0496)		(0.0603)	(0.0625)
Log(distance)			-0.730***			-0.722***
			(0.0398)			(0.0538)
Same cty			3.155***			4.451***
			(0.184)			(0.230)
Share border			0.371***			0.561***
			(0.0834)			(0.0962)
Common lang			0.0489			0.0853
			(0.0895)			(0.0988)
Colony			0.138			0.277***
			(0.0879)			(0.0931)
Legal			0.184***			0.222***
			(0.0410)			(0.0436)
FTA			0.00189			0.0374
			(0.0546)			(0.0676)
Obs	790,440	790,440	790,440	790,440	790,440	790,440
R^2	0.652	0.652	0.847	0.495	0.495	0.731

All regressions include importer-industry-year and exporter-year dummies. Two-way clustered standard errors by exporter-industry and country-pair are in parenthesis. Significant at: *10%, **5%, ***1% level.

FIGURE 1

Virtual value-added exports vs. exports

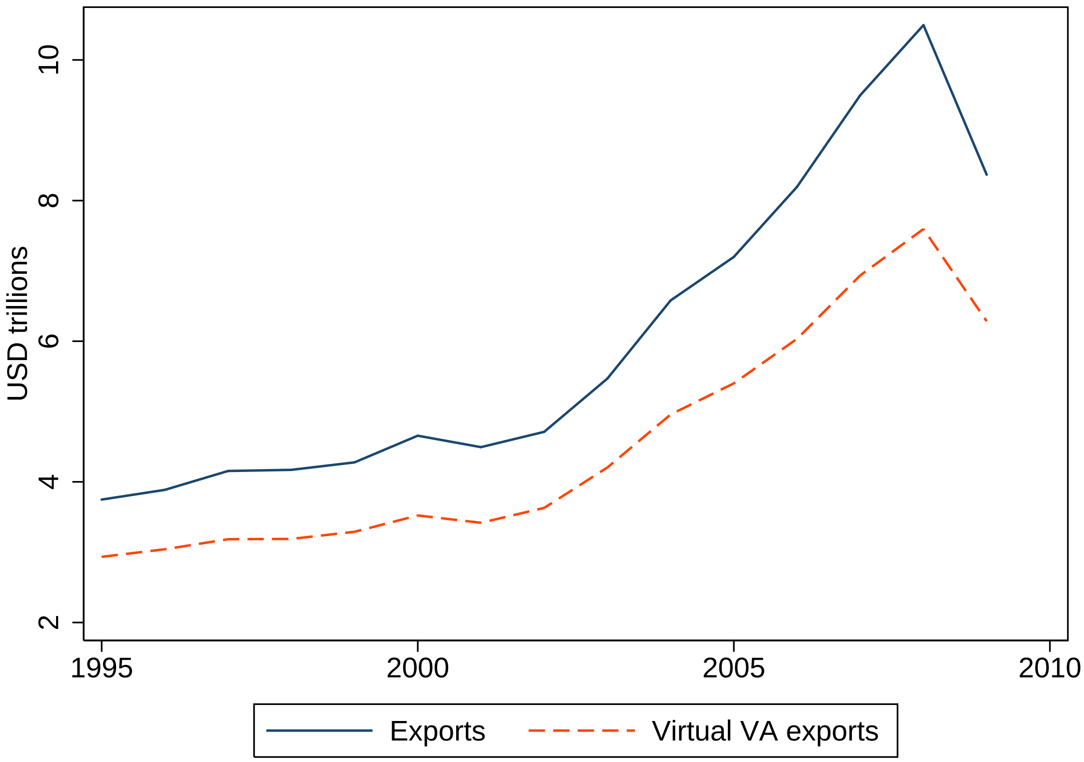


FIGURE 2

Virtual trade in value added

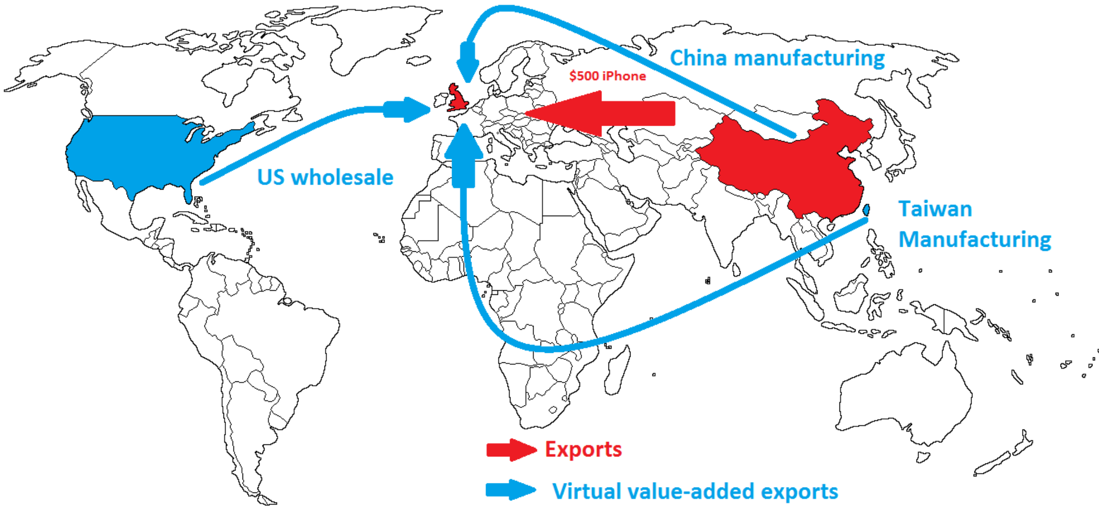


FIGURE 3

China exports and virtual VA exports

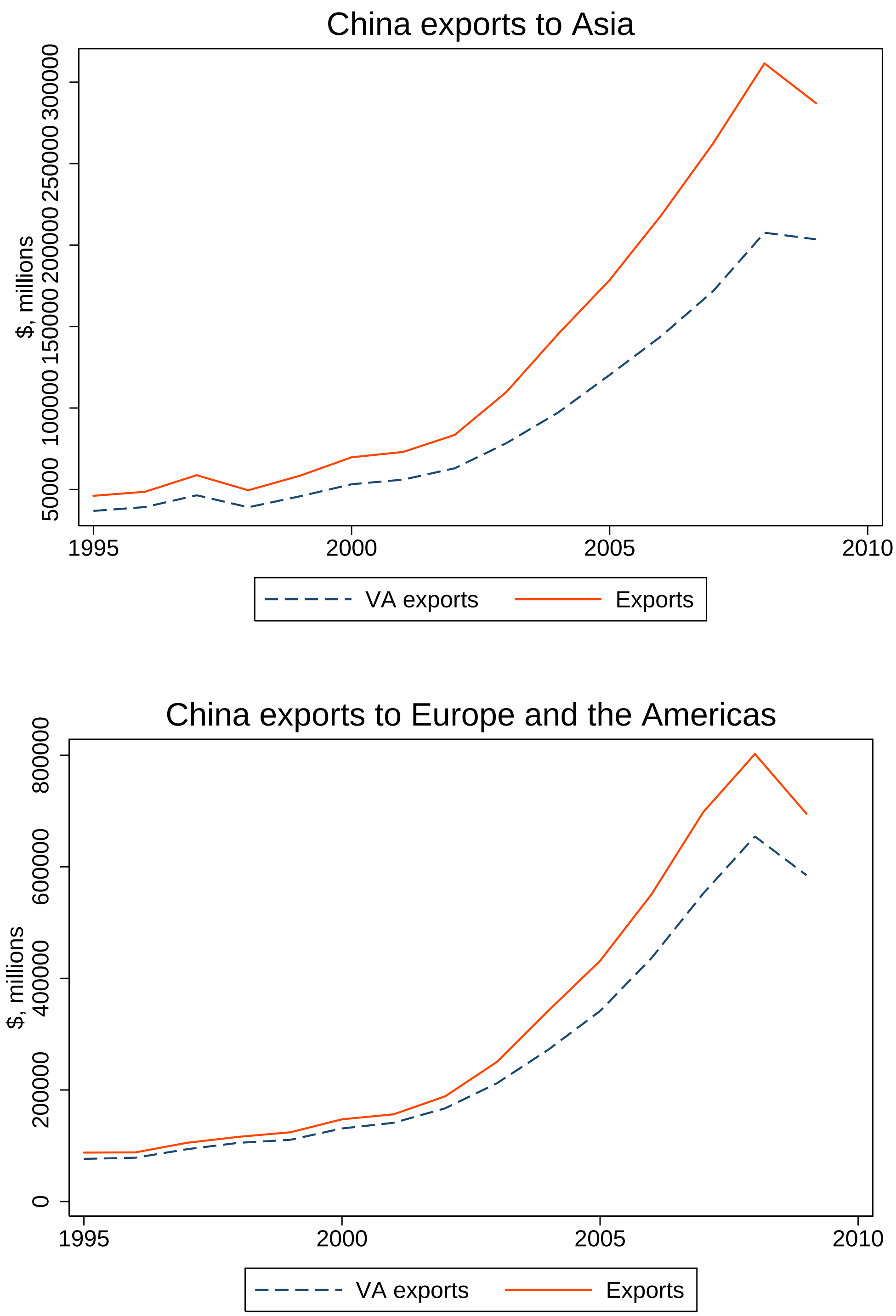


FIGURE 4

China virtual value-added exports vs. exports

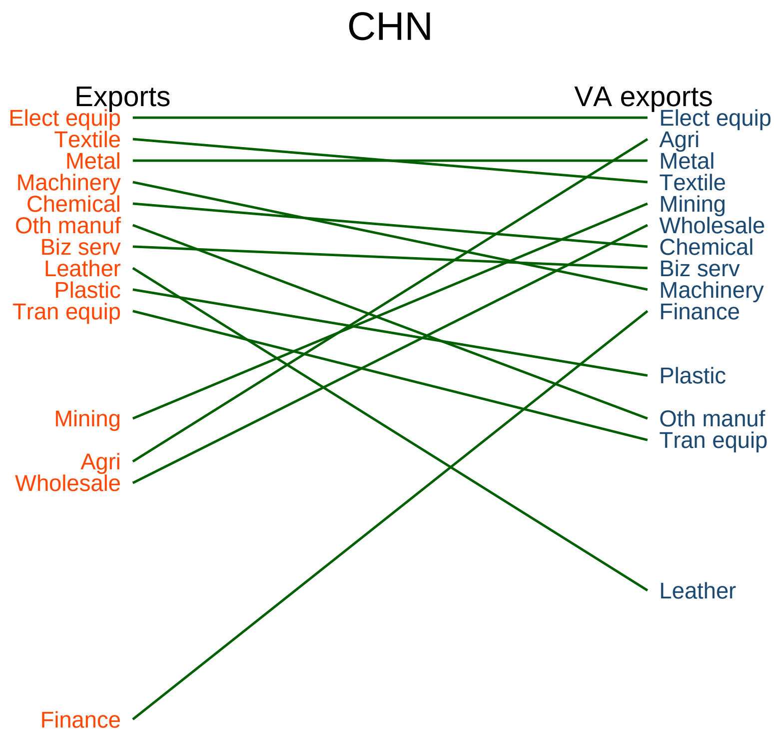


FIGURE 5

Japan exports and virtual VA exports

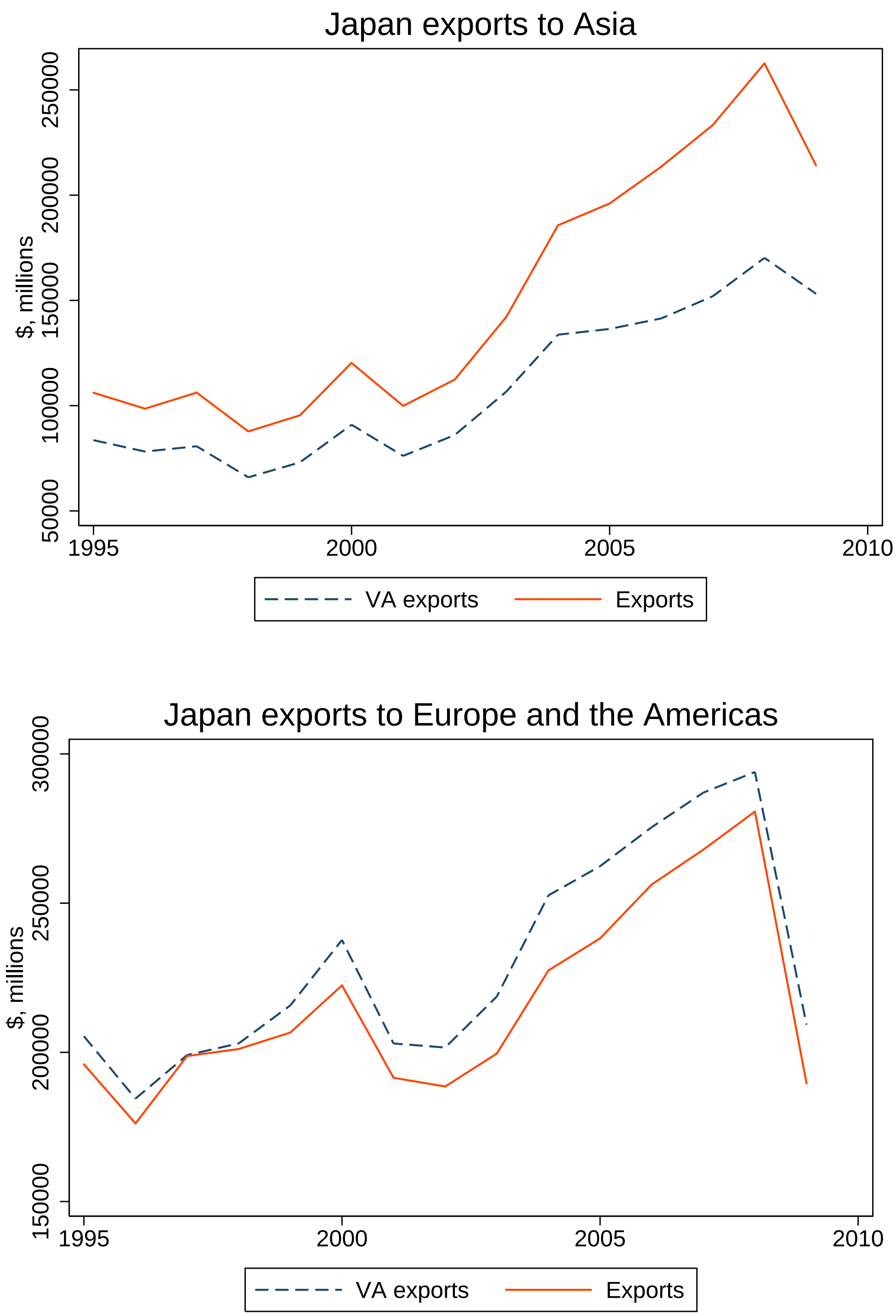


FIGURE 6

Japan virtual value-added exports vs. exports

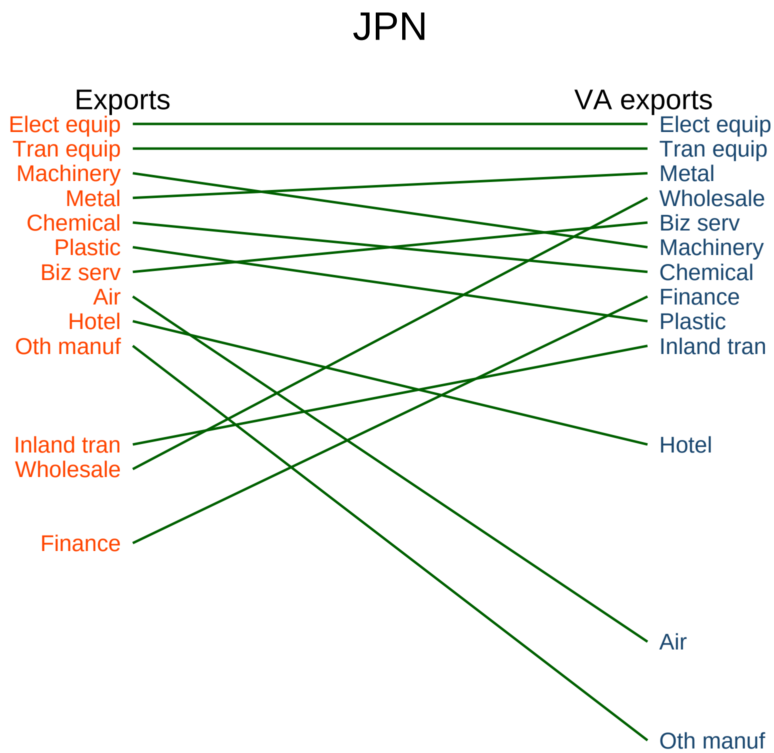
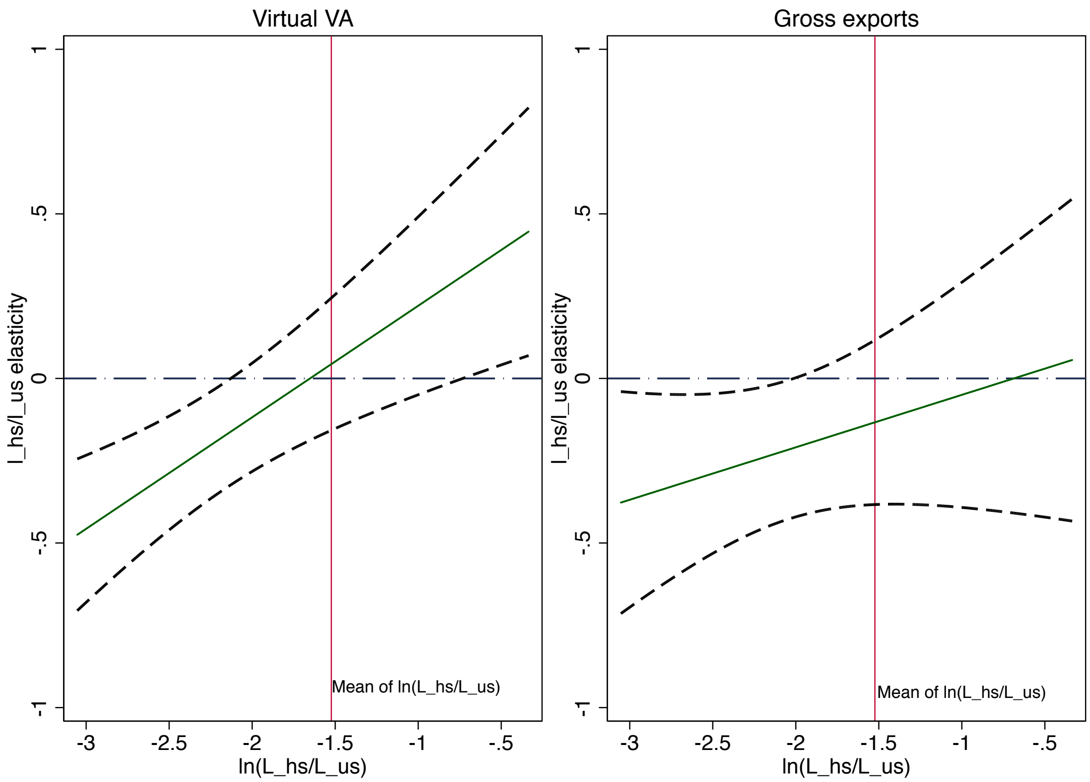


FIGURE 7

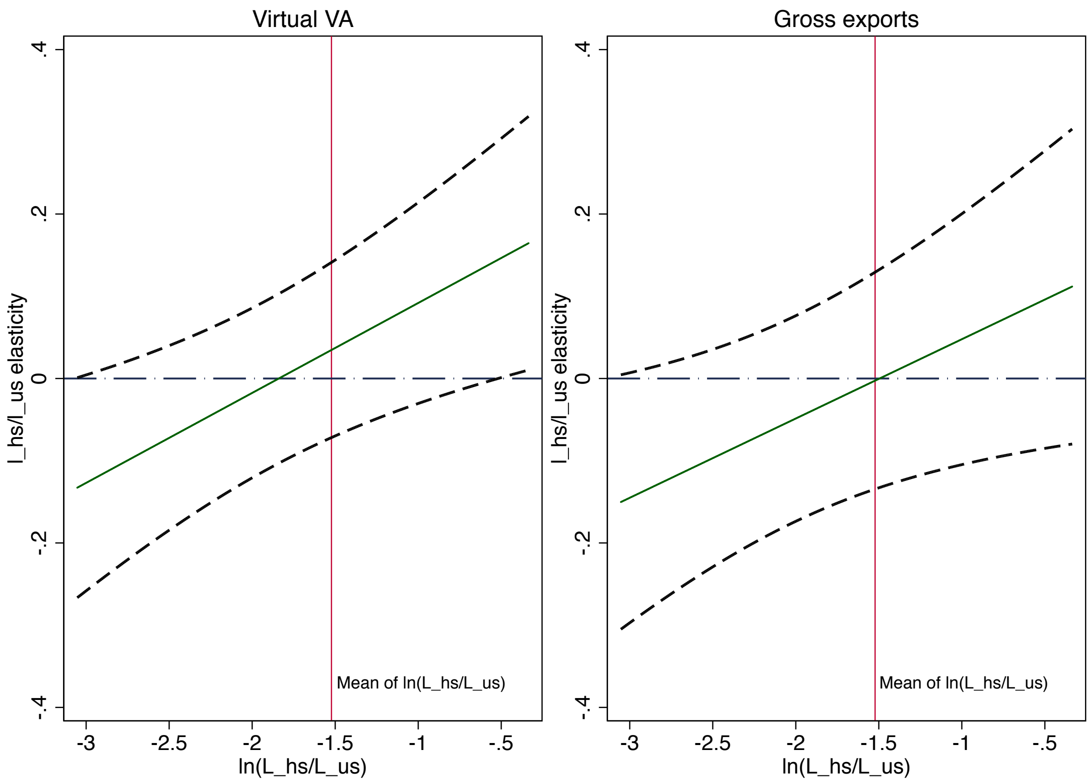
Manufacturing



The solid line is the estimated elasticities. The dashed lines ar 95% confidence intervals.

FIGURE 8

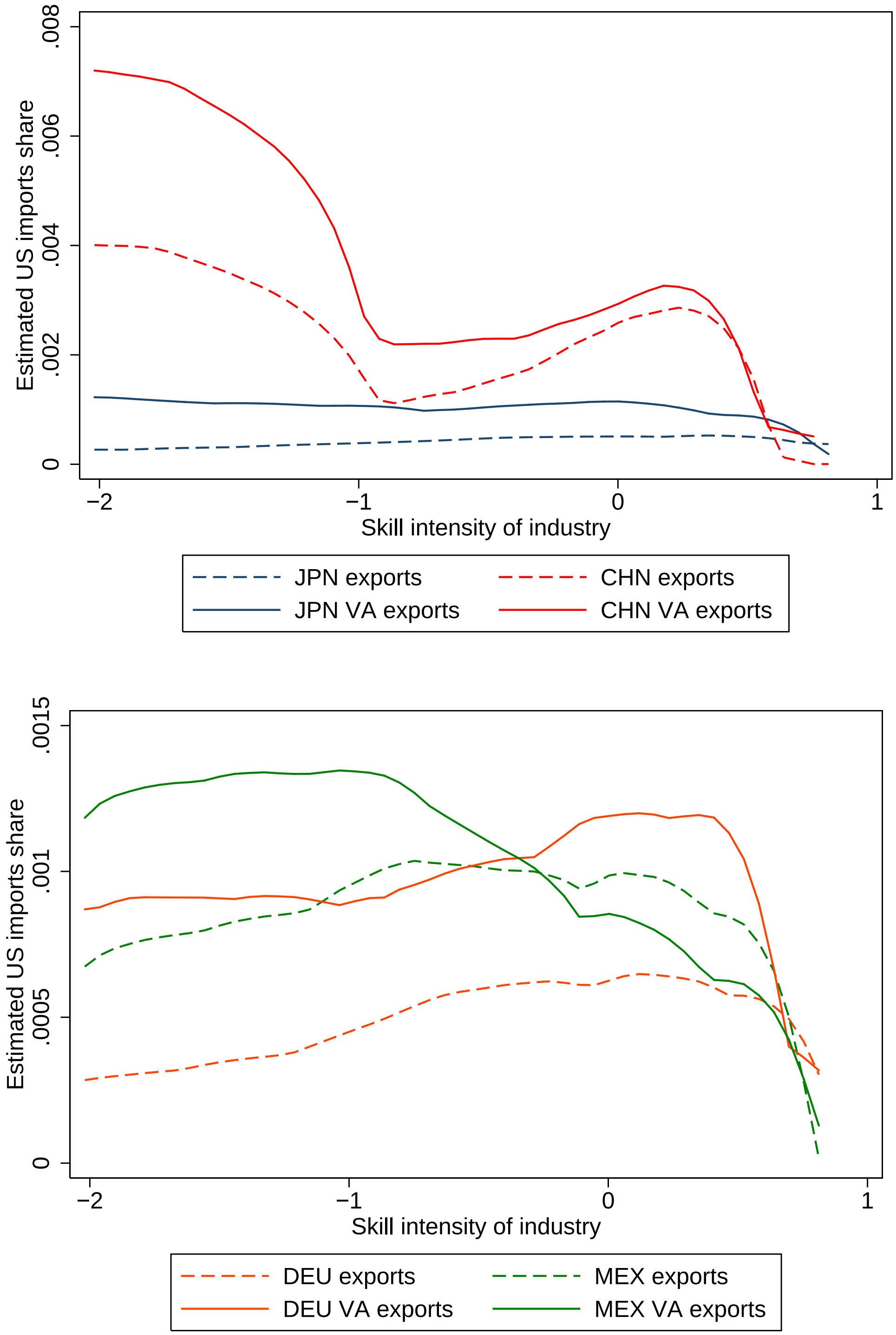
Services



The solid line is the estimated elasticities. The dashed lines ar 95% confidence intervals.

FIGURE 9

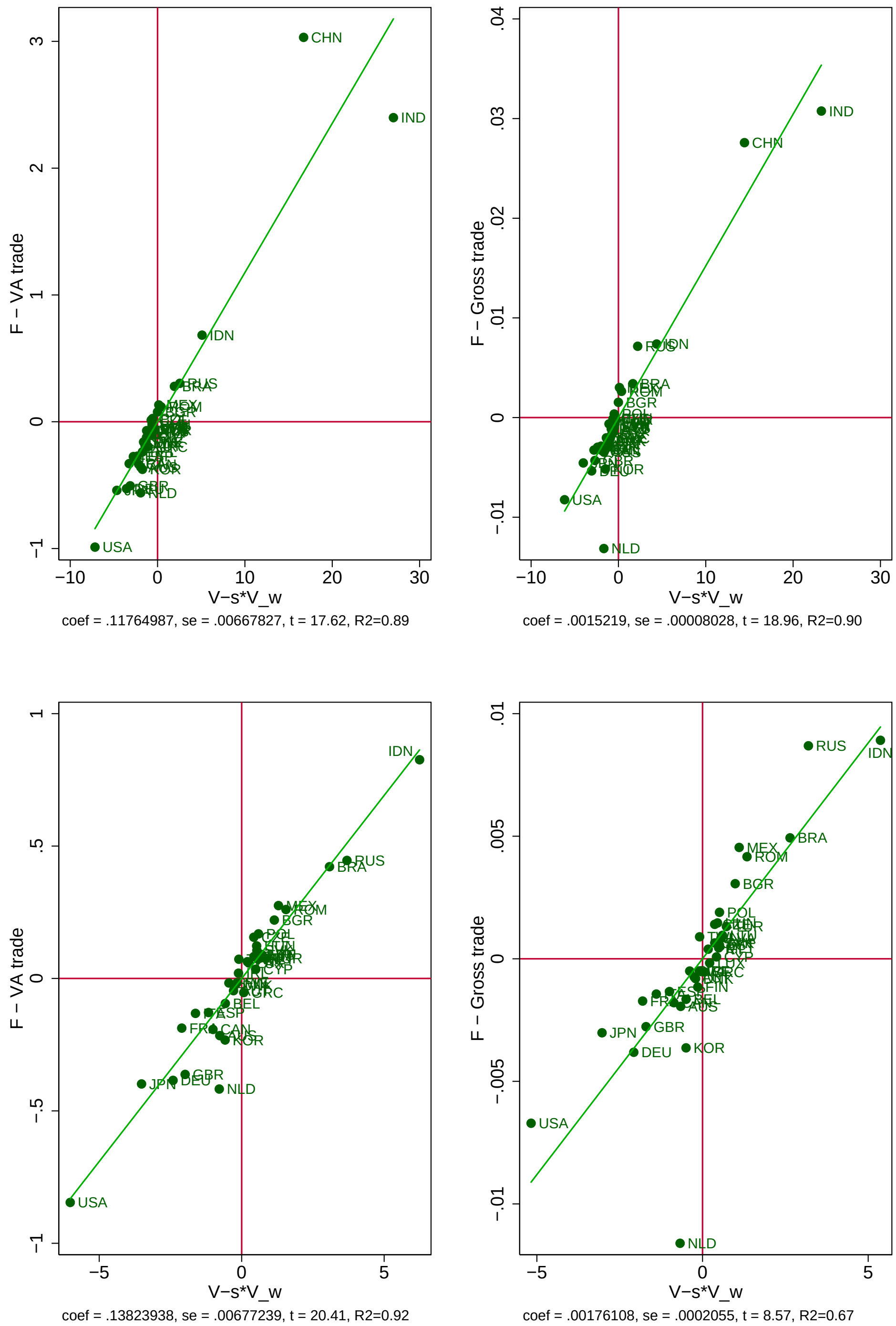
Heckscher-Ohlin effects: VA vs. gross flows (2009)



Note: This figure is inspired by Figure 1 in Romalis (2004).

FIGURE 10

Factor content predictions: Tests à la Trefler and Zhu (2010)



Note: This figure is inspired by Figure 1 in Trefler and Zhu (2010). The bottom panel excludes the CHN and IND outliers.