Vertical Spillovers in Global Value Chains

By Swapnika Rachapalli *

Participation in global value chains (GVCs) is an important driver of economic growth and prosperity, especially for developing economies. The fragmentation of production processes has enabled firms, and thereby countries, to specialize in small parts of the value chain and improve efficiency (World Bank, 2019). It is however important that countries not become trapped in the production of specialized inputs, but to expand their production capabilities so as to capture more value in the global production process. In this paper, I ask whether export demand shocks to certain products in a country enable them to improve their capabilities in other vertically related products in the value chain.

Using country-level trade data, I find that countries' expand production of a product in response to export shocks to other products upstream and downstream in the value chain. This suggests that getting integrated into GVCs by specializing in certain stages of production initially can facilitate expansion into more stages enabling countries to add more value over time. Let us take the example of the following value chain: Cotton Yarn → Cotton Fabric → Cotton Shirts; Cotton yarn is used to make cotton fabric which is in turn used to make cotton shirts.[1] The results in this paper suggest that a country becomes better in supplying cotton fabric (stage two) to the world if it were to experience a demand shock to either its upstream products, i.e. cotton yarn (stage one), or its downstream products, i.e. cotton shirt (stage three). These potential vertical spillovers from export market access contribute to the well established trade and firm productivity/innovation literature (see Shu and Steinwender 2019) by emphasizing how export market access for a product can improve a country's comparative advantage in other products in the value chain.

I. Data

I use two primary data sources: one for constructing input-output (I-O) linkages between products, and another for trade data that forms the basis of the analysis. I describe them briefly below.

I-O Linkages: For the purpose of defining vertical relationships between two products, I make use of the I-O table constructed in Rachapalli (2021) by aggregating firm-level data on outputs produced and inputs used to produce them from the Indian Annual Survey of Industries (ASI) for the manufacturing sector for 2003-2009. Products in the Indian data are classified according to the Annual Survey of Industries Commodity Classification (ASICC) which contains ∼6,000 product codes. Of these, 3,971 products are used as inputs and 4,433 products are produced as outputs in my constructed I-O table. The I-O table provides the value of input flows from one product to another for every product pair. For each product p, I then obtain the set of products that are immediately upstream, $U(p)$, and the set of products that are immediately downstream, $D(p)$. Suppose the the flow of materials from product p to p' is given by $M_{pp'}$, then,

$$U(p) \equiv \{p' : M_{p'p} > 0\}\,, \tag{1}$$

$$D(p) \equiv \{p' : M_{pp'} > 0\}\,. \tag{2}$$

An advantage of using the Indian data to construct I-O linkages is the disaggregated level of product detail that allows one to classify a given product as either an input or as an output to another product exclusively. In most publicly available national

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[1] This example is directly taken from the input-output table constructed in Rachapalli (2021).

I-O tables that represent input flows between aggregated industries a large share of industry pairs have materials flowing in both directions.[2]

Trade Data: Primary data for this paper is taken from the CEPII BACI trade database which provides bilateral trade flows at the Harmonized System (HS) 6-digit level for 200 countries (Gaulier and Zignago, 2010). I employ a series of sample selection criterion which results in a final sample of 70 countries.[3] The analysis is carried out for the time period 1996-2018. I construct a crosswalk from the 1992 HS classification that the trade data is reported at to ASICC, and bring all trade data to ASICC level.[4]

II. Revealed Comparative Advantage

The paper has two sets of empirical results. First, I show that countries are likely to have revealed comparative advantage (RCA) in a product if they also have RCA in products that are upstream (inputs) or downstream (outputs) to that product. Second, I find that the RCA of a product can improve over time if the country experiences exogenous demand shocks to its inputs or outputs.

Following Hidalgo et al. (2007), the measure of country i's RCA in product p in year t is constructed as

$$\text{RCA}_{ipt} = \frac{X_{ipt}}{\sum_p X_{ipt}} \Bigg/ \frac{\sum_i X_{ipt}}{\sum_i \sum_p X_{ipt}}, \tag{3}$$

where X_{ipt} is the value of total exports of product p by country i in year t. This measure captures whether a country exports more of product p relative to the world's export of the product compared to all other products, thereby giving a proxy for its comparative advantage in the product (RCA>1). The RCA of upstream and downstream products of p are further constructed as the weighted average of the RCA of each product in the corresponding set with input shares and output shares as weights respectively. Formally, they are defined as follows:

$$\text{RCA}_{iU(p)t} = \sum_{p' \in U(p)} s^I_{p'p} \text{RCA}_{ip't}, \tag{4}$$

$$\text{RCA}_{iD(p)t} = \sum_{p' \in D(p)} s^O_{pp'} \text{RCA}_{ip't}, \tag{5}$$

$$s^I_{p'p} = \frac{M_{p'p}}{\sum\limits_{p' \in U(p)} M_{p'p}}, s^O_{pp'} = \frac{M_{pp'}}{\sum\limits_{p' \in D(p)} M_{pp'}}.$$

Figure 1 plots the average probability that a country has comparative advantage in product p conditional on the country having comparative advantage in some other products, denoted by $S(p)$. The conditional probability is defined as

$$\phi_{p|S(p)} = \frac{\sum_i \mathbb{I}(\text{RCA}_{ipt}, \text{RCA}_{iS(p)t} > 1)}{\sum_i \mathbb{I}(\text{RCA}_{iS(p)t} > 1)}, \tag{6}$$

where the function $\mathbb{I}()$ takes value 1 if the condition inside the parenthesis is true. The figure plots the conditional probability for three different sets of $S(p)$ - Upstream products $U(p)$, Downstream products $D(p)$, and 100 iterations of a randomly matched product.[5] The figure shows that on average, countries that are good at producing either upstream inputs (like yarn) or downstream outputs (like shirts) also have a comparative advantage in producing the focal product (like fabric). In other words, countries are more likely to co-produce inputs and outputs compared to two randomly chosen products.

[2]For example, in the 2007 US I-O table 15% of all product pairs linked with input flows are round-about links. In the above constructed Indian I-O table this number is only 5.5%. I drop product pairs that have material flows in both directions from the analysis including diagonal links.

[3]See online appendix for the sample selection criteria employed.

[4]See Rachapalli (2021) for more details on the construction of the I-O table and the crosswalk.

[5]In each iteration k, for every country and year a focal product is randomly matched with another product p', after which the the conditional probability $\phi^{(k)}_{p|p'}$ is calculated. The figure plots the average of this value over 100 iterations.

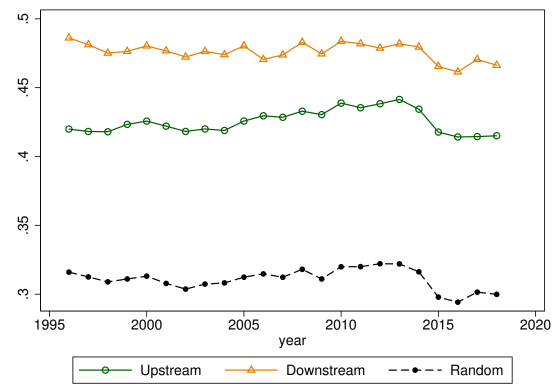

FIGURE 1. CONDITIONAL PROBABILITIES OF CO-PRODUCTION

Note: Figure plots the probability of a country having comparative advantage in a product conditional on the country having comparative advantage in that product's upstream product set, downstream product set, or a randomly matched product as defined in equation 6.

III. Testing for Vertical Spillovers

In the rest of the paper, I explore if countries' comparative advantage in products improves in response to increased exports of vertically related products to the rest of the world. I estimate the following regression specification to explore this relationship.

$$\ln(\text{RCA}_{ipt}) = \alpha + \alpha^O \ln(X_{ip(t-s)}) + \alpha^U \ln(X_{iU(p)(t-s)}) + \alpha^D \ln(X_{iD(p)(t-s)}) + \mathbf{Z}_{ipt}\delta + \epsilon_{ipt}, \tag{7}$$

where $X_{ip(t-s)}$, $X_{iU(p)(t-s)}$, and $X_{iD(p)(t-s)}$ are s-period lagged values of own product exports and the weighted averages of upstream and downstream exports respectively.[6] $\mathbf{Z}_{ipt}$ represents the different sets of fixed effects (FEs). α^O is the elasticity of a product's RCA to changes in its own exports, while α^U and α^D are the elasticities with respect to upstream and downstream exports. I estimate the above regression specification using an instrumental variable strategy by using plausibly exogenous variation in export demand for products in different countries.

Including own product exports, $X_{ip(t-s)}$, serves two purposes. First, it gives us a benchmark estimate to compare the cross product spillover effects to. Second, it addresses the concern of correlated export shocks across products within the same value chain. In the cotton value chain example with cotton fabric (stage 2) as the focal product, increased foreign demand for fabrics can result in increased demand for the input to produce fabric, namely cotton yarn. Then, the RCA of cotton fabric improves due to cotton fabric experiencing a demand shock, and may not be a result of the demand shock experienced by cotton yarn. Explicitly controlling for own product export shocks that are potentially correlated with demand for its inputs or outputs allays such concerns.

Export performance of a country across products in different stages of the value chain are potentially endogenous resulting from common supply/technology shocks to the value chain. In order to establish causality I instrument upstream and downstream exports using plausibly exogenous shocks to foreign demand to these products. Following Chor, Manova and Yu (2021), exports X_{ipt} are instrumented by a projected growth rate in foreign demand for that country's product p between $t-1$ and t. Specifically, I use a weighted average of the year-on-year growth rate in the foreign country j's import demand for product p from the rest of the world (excluding the

[6]See equations 4-5 for the weights used to aggregate upstream and downstream variables.

focal country), M^{-i}_{jpt}. The formula used is

$$(8)\quad X^{IV}_{ipt} = X_{ip(t-1)} \left(1 + \sum_j s^x_{ijpt_0}\, g^{m_{-i}}_{jpt}\right),$$

$$s^x_{ijpt_0} = \frac{X_{ijpt_0}}{X_{ipt_0}}, \quad g^{m_{-i}}_{jpt} = \frac{M^{-i}_{jpt} - M^{-i}_{jp(t-1)}}{M^{-i}_{jp(t-1)}},$$

where $s^x_{ijpt_0}$ is the share of exports from i to j in the first period that country i exports product p in the sample, and $g^{m_{-i}}_{jpt}$ is the growth rate in foreign country j's demand for product p from the rest of the world. Using the above described export instrument, I construct instruments for upstream and downstream exports as follows:

$$(9)\qquad X^{IV}_{iU(p)t} = \sum_{p' \in U(p)} s^I_{p'p} X^{IV}_{ip't},$$

$$(10)\qquad X^{IV}_{iD(p)t} = \sum_{p' \in D(p)} s^O_{pp'} X^{IV}_{ip't}.$$

I report the baseline results and results from a placebo exercise here. Additional results, including fist stage estimates and heterogeneity across time and products, are presented in the online appendix.

A. *Baseline Results*

Table 1 reports the IV results for 3-period lagged explanatory variables with different sets of FEs. Column (1) includes country×product FEs which controls for potential persistence of attributes of a specific product in a specific country over time, and product×year fixed effects, which controls for any common product trends across countries. These FEs absorb the product normalization in the RCA measure, and hence column (1) estimates are elasticities of a product's export share in a country's total exports. Column (2) includes country×product and country×year FEs which controls for common country trends across different products' RCA. This subsumes the country normalization in the RCA measure, which leaves the share of a country's exports in total world exports of a product. The results in this column show that a 10% increase in own exports increases a country's share in total world exports by 2.88%, while the upstream and downstream effects are 0.23% and 0.21% respectively.

Finally, in column (3), I control for all three sets of FEs. Column (4) reports more conservative standard errors clustered two-way at product and year level. In all specifications, own export elasticity is high compared to cross product elasticities. However, the cross product elasticities are substantial and meaningful quantitatively. The effect of upstream export shock is 6.7% - 8.4% that of own exports, and the effect of downstream export shock is 2.7% - 7.3% that of own exports effect.

B. *Placebo Test*

In order to allay any other concerns regarding the IV estimates picking up spurious correlation, I conduct the following placebo test. For each product p, I randomly match a product p' from the set of all products in the sample. I proceed to then incorrectly use the upstream and downstream exports of product p' (and their corresponding export instruments) in place of product p's upstream and downstream exports respectively.[7] The idea behind the randomization exercise is to check whether a country's RCA in a particular product improves in response to randomly chose upstream and/or downstream products.

I repeat this randomization exercise 100 times, and obtain the IV estimates from the baseline specification using 3-period lagged explanatory variables. Figure 2 plots the histogram of the estimates obtained from 100 iteration of the placebo exercise, as well as the estimates from column (3) in Table 1 for reference. The placebo estimates for both upstream and downstream exports are centered around zero. This shows that a country's comparative advantage in a product does not respond to export shocks in any random product, but specifically to other vertically related products within the value chain.

[7]The product randomization is kept consistent within every country-year pair, i.e. for a given focal product, the same random product gets matched for every country and year.

Table 1—Baseline Results - IV Estimates

	Dependent Variable: $\ln(\text{RCA}_{ipt})$			
	(1)	(2)	(3)	(4)
$\ln(X_{ip(t-3)})$	0.296^a	0.288^a	0.299^a	0.299^a
	(0.003)	(0.002)	(0.003)	(0.056)
$\ln(X_{iU(p)(t-3)})$	0.020^a	0.023^a	0.025^a	0.025^a
	(0.002)	(0.002)	(0.002)	(0.005)
$\ln(X_{iD(p)(t-3)})$	0.008^a	0.021^a	0.020^a	0.020^a
	(0.002)	(0.002)	(0.002)	(0.003)
Observations	3,347,237	3,347,237	3,347,237	3,347,237
Country × Product FE	Y	Y	Y	Y
Product × Year FE	Y	-	Y	Y
Country ×Year FE	-	Y	Y	Y
F-Stats				
$\ln(X_{ip(t-3)})$	81211	77448	74758	398
$\ln(X_{iU(p)(t-3)})$	35674	33900	31792	277
$\ln(X_{iD(p)(t-3)})$	46971	40895	38167	256
Clustering	Product×Year	Product×Year	Product×Year	Product, Year

Note: Each column reports IV estimates of the regression specification in equation 7 where instruments are defined in equations 9-10. All explanatory variables are 3-period lagged values. Sanderson-Windmeijer F-Stats reported. Standard errors reported in parenthesis are clustered at the product×year level in columns (1)-(3), and at product and year level in column (4). [a] Significance at 1%, [b] Significance at 5%, [c] Significance at 10%.

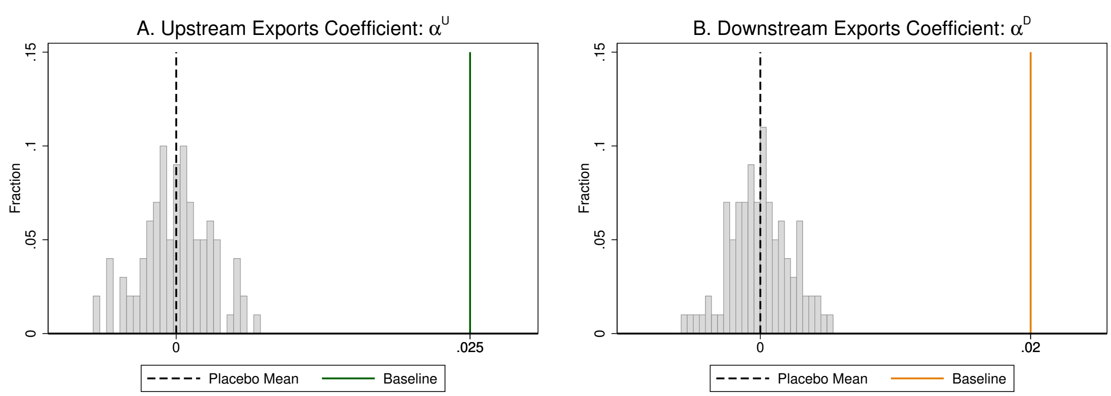

Figure 2. Placebo Test

Note: Figure plots the histograms of the IV estimates from the the placebo exercise described in the text. Each estimate is obtained by randomizing the set of upstream and downstream products that a product is linked to, and running the regression specification in equation 7. Regressions include country×product, product×year, and country×year FEs (specification used in column (3) of table 1). The mean of all the placebo estimates is represented at the dashed line, and the corresponding baseline estimate from column (3) of table 1 is represented at the solid line.

IV. Discussion

What could be driving such cross-product expansion? These spillovers can potentially occur within firms directly linked to the global trade network, or, across firms through buyer-sellers links. Rachapalli (2021) finds that firms exposed to export demand shocks to their products are more likely to introduce new downstream products suggesting a knowledge spillover channel. Ding (2023) finds that increased export demand in one industry increases firm sales of products in other industries suggesting an economies of scope through joint production channel.

Recent work by Amiti et al. (2023) shows that supplying to a "superstar" firm, such as an exporter or an FDI/MNC firm, increases productivity of suppliers consistent with a model of technology transfer between buyers and sellers.[8] Furthermore, other local downstream firms that share common suppliers to these superstar firms can also benefit from productivity improvements spilling downstream (Kee, 2015).

These spillovers could also operate through different channels. Are they a result of improvements in domestic firms' efficiency due to increased access to, or, incentives to adopt/innovate new technologies? Or is it purely an economies of scale story, where demand shocks are translated upstream as input demand shocks and downstream as input supply shocks? These are potential avenues for future research.

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[8] See also Javorcik (2004) and Alfaro-Urena, Manelici and Vasquez (2022) for evidence for FDI and MNC spillovers to upstream suppliers.