Positioning in Global Value Chains: World Map and Indicators. A new dataset available for GVC analyses

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Abstract

Recently, a strand of the international trade literature has developed measures of the positioning of countries and industries in GVCs using the global Input-Output tables. These measures allow scholars from different research fields to conduct qualitative and quantitative analyses on GVCs, at the aggregate and sectoral level and inform policymaking. To compute these indicators, a common approach is to consider the extent to which a country-industry pair sells its output for final use to consumers worldwide or instead sells intermediate inputs to other producing sectors in the world. Following this approach, we compute and make available to scholars a new dataset of GVC positioning indicators at the country-industry level based on the most used global Input-Output tables (WIOD, OECD, EORA, ADB). Specifically, we compute two popular measures: 1) a measure of distance or *upstreamness* of a production sector from final demand, which was developed by Fally (2012), Antràs et al. (2012), and Antràs and Chor (2013, 2018); 2) a measure of distance or *downstreamness* of a given sector from the economy's primary factors of production (or sources of value-added), originally proposed by Fally (2012). These indicators are "ready-to-use" and can be freely downloaded from this Journal. We also provide an international comparison, by sectors and countries, of these indicators and their evolution over time. Lastly, to illustrate the possible use of such measures, we test their effects on productivity by country and sector worldwide.

Keywords: Global Value Chain, positioning indicators, upstreamness, downstreamness, country-sector analysis, data.

JEL codes: D57, F14

1. Introduction

Over the last decades, the world economy experienced a radical transformation through a significant fragmentation in the production of goods and services and a deeper international division of labour, resulting in larger returns from specialisation. This transformation has been called the "Age of Global Value Chains" (World Bank, 2020, Antràs and Chor, 2021). Global value chains (GVCs) have had remarkable effects also on development via changes in income, productivity, and poverty (World Bank, 2020). Even small countries with limited capacities or resources have a chance to participate in GVCs and benefit from global trade since GVCs allow countries to join existing supply chains instead of building them (Minten et al., 2009; Baldwin, 2012, Cattaneo et al., 2013; Swinnen and Vandeplas, 2014; Swinnen, 2016).

Recently, scholars have developed various indicators to map and measure the degree of involvement of countries and sectors in GVCs (see, among others, Hummels et al., 2001; Johnson and Noguera, 2012; Koopman, Wang and Wei, 2014; Borin et al., 2021). Another strand of this specialized literature (see Fally, 2012; Antràs et al., 2012; Antràs and Chor, 2013; Fally and Hillberry, 2015; Miller and Temurshoev, 2017; Wang et al., 2017; Alfaro et al., 2019) looks instead at the country and/or sectoral positioning within GVC, that is whether a given country (or industry) is specialised in relatively upstream activities or whether its positioning is more proximate to final demand. Such notions of production staging are important and should be included in the economic models of GVCs, for example, to model productivity differences or geography or firm organisational decisions (see Antràs and Chor, 2022, for details).

Using the global Input-Output tables, with information on the various entries, it is now possible to compute the implied upstreamness or downstreamness of specific industries and countries. Together with the GVCs participation indicators, these positioning measures help enrich and complete empirical analyses on GVCs and inform policymaking.

This paper aims to review and compute the most common GVC positioning indicators used in the empirical literature and provide scholars with a new global dataset of upstreamness and downstreamness measures for the largest number of countries – including most developing countries – and sectors and for the longest time span. Specifically, we provide GVC positioning indicators for all the economies and industries included in the most used Inter-Country Input Output tables, i.e. EORA dataset (189 countries and 26 sectors) for the period 1990-2015, the ADB MRIO database (63 countries and 56 sectors) for the period 2007-2019, WIOD Long Run dataset (25 countries and 23 sectors) for the period 1965-2000, OECD TiVA dataset (66 countries and 45 sectors) for the period 1995-2018, WIOD (43 countries and 56 sectors) for the period 2000-2014. The vast and comprehensive database on positioning we provide complements the already available database on GVC participation measures by the World Bank WITS (Borin et al., 2022). Using these new measures, scholars can investigate the evolution of GVC positioning over time, at both the country and industry levels, and provide an international comparison. The key added value of this work is that researchers working on the topic of GVC and belonging to different research disciplines – economic sociology, international economics, economic geography, international political economy, supply chain management and international business – will benefit from these ready-to-use indicators, without necessarily getting into technicalities and performing matrix calculations.

Specifically, we compute two measures: 1) a measure of distance or *upstreamness* of a production sector from final demand, which was developed by Fally (2012), Antras et al. (2012), and Antras and Chor (2013, 2019). This measure captures the average number of production stages by pegging the endpoint of the sequence at final consumption, which enables us to measure the distance to final demand of a product (or a country) along the production chains; 2) a measure of distance or *downstreamness* of a given sector (or a country) from the economy's primary factors of production (or sources of value-added), originally proposed by Fally (2012). This measure is based on a country-industry pair's use of intermediate inputs and primary factors of production. We also provide an international comparison, by sectors and countries, of these indicators and their evolution over time. To the best of our knowledge, this is the first work that computes GVC positioning indicators for such a large set of countries and sectors and makes them freely available to scholars.

We also provide some descriptive statistics, by sectors and countries, of these indicators and their evolution over time. Lastly, in order to illustrate the possible use of these indicators, following Constantinescu et al., (2017); Gal and Witheridge (2019), Montalbano and Nenci (2022), we test the effects of GVC positioning indicators on productivity by country and sector worldwide.

The structure of the paper is as follows. Section 2 illustrates the approach and data used to construct the GVC indicators, Section 3 presents some stylised facts, Section 4 explains the empirical analysis and comments on the outcomes, and Section 5 concludes. An on-line Appendix makes available to scholars the GVC indicators computed at the country, sectoral and country-sectoral level.

2. Measuring GVCs positioning: the upstreamness and downstreamness indicators

To compute the upstreamness or downstreamness of specific industries and countries a common approach is to consider the extent to which a country-industry pair sells its output for final use to consumers worldwide or instead sells intermediate inputs to other producing sectors in the world. A sector that sells disproportionately to final consumers would appear to be downstream in value chains. In contrast, a sector that sells little to final consumers is more likely to be upstream in value chains.

Following this approach, in this work, we have computed two measures of GVC positioning that are the most popular in the literature. The first indicator is a measure of distance or upstreamness of a production sector from final demand, which was developed by Fally (2012), Antras et al. (2012) and Antras and Chor (2013).[1] Fally's model, as well as the variation proposed by Antràs and others (2012), captures the average number of production stages by

[1] Though the arguments used to develop the index differ in Fally (2012) and Antràs and Chor (2013), Antràs et al. (2012) emphasize that the resulting indexes are equivalent.

pegging the endpoint of the sequence at final consumption, which enables us to measure the *distance to the final demand* of a sector along the production chains. More specifically, this measure (labelled U in Antras and Chor, 2019 and given the same name in our dataset) aggregates information on the extent to which "an industry in a given country produces goods that are sold directly to final consumers or that are sold to other sectors that themselves sell disproportionately to final consumers. A relatively upstream sector is thus one that sells a small share of its output to final consumers and instead sells disproportionately to other sectors that themselves sell relatively little to final consumers (Antras and Chor, 2019). Building on these ideas, final goods can be considered one step away from demand, inputs directly used to produce final goods are two steps away from demand, inputs used to produce inputs are three steps away from demand, and so on. Furthermore, this count is weighted by the share of the value of output at each production stage in total output. The U indicator can assume values equal to or greater than 1: larger values are associated with relatively higher levels of upstreamness of the output originating from one sector.

The second measure, originally proposed by Fally (2012), is based on a country-industry pair's use of intermediate inputs and primary factors of production. It captures the distance or downstreamness of a given sector from the economy's primary factors of production (or sources of value-added). According to this measure (labelled D), an industry in each country is downstream if its production process embodies a larger value of intermediate inputs relative to its use of primary factors of production. Conversely, if an industry relies disproportionately on value-added from primary factors of production, then this industry is relatively upstream. The D indicator can assume values equal to or greater than 1: larger values are associated with relatively higher levels of downstreamness of an industry.[2]

We calculated the positioning indicators by using the intermediate use matrix (Z), the final demand matrix (FD) and the value-added matrix (VA). Following Antràs *et al* (2012) and Antràs and Chor (2019), we first perform a "net inventory" correction. This correction consists of imputing N_i^r changes in inventories in country i, sector r, to each Z_{ij}^{rs} intermediates sold by country i sector r to country j sector s, and FD_{ij}^r final goods in sector r sold by i to j, by applying a multiplicative factor equal to $Y_i^r/(Y_i^r - N_i^r)$ where Y_i^r is the gross output in sector r in country i and is computed as follows:

[2] In addition, following Antras and Chor (2019), we have also calculated simpler versions of these two measures of GVC positioning. The first one (labelled F/GO) reduces the indicator in Antras et al. (2012) to the share of a country-industry's output that is sold directly to final consumers. A lower value of this ratio is associated with a higher upstreamness from final use. The second one (called VA/GO) reduces the Fally (2012) measure of distance from value-added to the share of a country-industry's payments accounted for by payments to primary factors. Large values of this measure are associated with lower downstreamness or higher upstreamness.
These simpler versions of the two measures of GVC positioning are also available upon request from the authors.

$$Y_i^r = \sum_{s=1}^{S} \sum_{j=1}^{J} Z_{ij}^{rs} + \sum_{j=1}^{J} FD_{ij}^r \quad [1]$$

In order to measure sectoral upstreamness, we adopt the U_i^r index by Antràs and Chor (2013). Since $Y_i^r = \sum_{s=1}^{S} \sum_{j=1}^{J} a_{ij}^{rs} Y_j^s + FD_i^r$ (where $a_{ij}^{rs} = Z_{ij}^{rs}/Y_j^s$ is the dollar amount of sectors r's output from country i needed to produce one dollar worth of industry s's output in country j), by iterating such identity, we can express industry r's output in country i as an infinite sequence of terms as follows:

$$Y_i^r = FD_i^r + \sum_{s=1}^{S} \sum_{j=1}^{J} a_{ij}^{rs} FD_j^s + \sum_{s=1}^{S} \sum_{j=1}^{J} \sum_{t=1}^{S} \sum_{k=1}^{J} a_{ij}^{rs} a_{jk}^{st} FD_k^t + \cdots \quad [2]$$

As in Antràs and Chor (2019) we compute the weighted average position of each country/sector pair by multiplying each term by its respective production-staging distance from final use plus one and dividing everything by Y_i^r. This means that the first term in equation (2), representing the production stage destinated to final consumption, is multiplied by 1, the second term in equation (2), representing the production stage one step before the completion of final good, is multiplied by 2, and so on.
Building on such identity, the upstreamness index can be expressed as follow:

$$U_i^r = 1 * \frac{FD_i^r}{Y_i^r} + 2 * \frac{\sum_{s=1}^{S} \sum_{j=1}^{J} a_{ij}^{rs} FD_j^s}{Y_i^r} + 3 * \frac{\sum_{s=1}^{S} \sum_{j=1}^{J} \sum_{t=1}^{S} \sum_{k=1}^{J} a_{ij}^{rs} a_{jk}^{st} FD_k^t}{Y_i^r} + \cdots \quad (3)$$

It can be shown that in matrix notation this corresponds to:

$$U = [I - A]^{-2} FD_i^r \oslash [I - A]^{-1} FD_i^r \quad (4)$$

Where A is J*S, J*S matrix of the a_{ij}^{rs}s whereas $\oslash$ refers to an elementwise division.

At for downstreamness, following Antràs and Chor (2013), we adopt the D_j^s measure. Since $Y_j^s = \sum_{r=1}^{S} \sum_{i=1}^{J} Z_{ij}^{rs} + VA_j^s = \sum_{r=1}^{S} \sum_{i=1}^{J} b_{ij}^{rs} Y_i^r + VA_j^s$ (where $b_{ij}^{rs} = Z_{ij}^{rs}/Y_i^r$ is the share of sectors r's output in country i that is used in industry s in country j), and $Y_j^s = VA_j^s + \sum_{r=1}^{S} \sum_{i=1}^{J} b_{ij}^{rs} VA_i^r + \sum_{r=1}^{S} \sum_{i=1}^{J} \sum_{t=1}^{S} \sum_{k=1}^{J} b_{ki}^{tr} b_{ij}^{rs} VA_k^t + \cdots$, analogously to the upstreamness case, we compute downstreamness as follows:

$$D_j^s = 1 * \frac{VA_j^s}{Y_j^s} + 2 * \frac{\sum_{r=1}^{S} \sum_{i=1}^{J} b_{ij}^{rs} VA_i^r}{Y_j^s} + 3 * \frac{\sum_{r=1}^{S} \sum_{i=1}^{J} \sum_{t=1}^{S} \sum_{k=1}^{J} b_{ki}^{tr} b_{ij}^{rs} VA_k^t}{Y_j^s} + \cdots \quad (5)$$

In equation (4) each element is multiplied by the production stage distance from primary factors plus one and divided by country *s* gross output in sector *j*. In matrix notation:

$$D = [I - B]^{-2} VA_j^s \oslash [I - B]^{-1} VA_j^s \quad [6]$$

Where B is J*S, J*S matrix of the b_{ij}^{rs} whereas $\oslash$ refers to an elementwise division.

3. Data sources

Multi-Region Input-Output (MRIO) tables provide a comprehensive map of international transactions of goods and services in a large dataset that combines the national input-output tables of various countries at any given time with trade data. As these tables contain information on supply–use relations between industries and across countries, we can identify the vertical structure of international production sharing and measure cross-border value flows for a country or region (Inomata, 2017). In what follows, given our interest in global analysis, we focus on the EORA26 data, as it is the only source that covers the entire global economy, and on the ADB MRIO database, which is the most up-to-date open-access dataset (up to 2020. In addition, we provide an open access to positioning measures also for WIOD Long Run, WIOD and OECD TiVA dataset - both in Excel and Stata format – here: (to be done).

The EORA dataset (to be cut or put in appendix)
The EORA Global Supply Chain Database (Lenzen et al, 2012; and Lenzen et al, 2013) provides a set of both national and global input-output tables, covering a very large number of countries for complete time series. EORA combines different types of data, such as: i) input–output tables and main aggregates data from national statistical offices, ii) National Accounts Main Aggregates and Official Data, iii) and international trade data. Each MRIO table represents the structure of the global economy; it contains a complete account of monetary transactions between the industry sectors of 189 countries from 1990 to 2015. Because each country has a different economic structure, most of EORA's countries are represented by different table formats and at a different sectoral level, ranging from 26 to 500 sectors per country. The strategy of heterogeneous sector classification and table type was chosen so that the EORA MRIO could incorporate maximum sector detail overall.[3]

Eora is available in several formats. "Eora26" is a simplified model where all countries have been aggregated to a common 26-sector classification -according to the International Standard Industrial Classification of Economic Activities (ISIC Rev.3) that is consistent across all

[3] To build EORA, compilers merged and reconciled multiple, often conflicting, data sources into a single balanced MRIO. The EORA database contains MRIO tables from the national statistics offices of all countries that create them. For the other countries, for which there is no official IO table, they are estimated by constructing a proxy input–output table combining other macro-economic data for these countries with a template input–output structure based on an average of the Australia, Japan, and United States tables. For this reason, EORA compilers point out that the values in EORA should be understood as the mean value with an associated confidence interval. This confirms the suitability of this dataset for global assessments aimed at identifying long-run elasticities holding on average and *ceteris paribus*. Furthermore, some important assumptions characterize these tables, such as the "proportionality assumption" (that assumes identical trade shares for all input purchasing industries) and the "production assumption" (which says that because of the aggregation level, each industry grouping produces all its different outputs using a single production function). Notwithstanding its limitations, EORA data has already been successfully used by many researchers, including Caliendo et al. (2015), Kowalski et al. (2015), Cerdeiro (2016), Feenstra (2017), Balié et al. (2019a, 2019b), Slany (2019), Montalbano and Nenci (2022), as well as by many institutions (see, for instance, reports by the European Commission, the IMF, the World Bank, and the UN).

countries covered (see Table A1 in the Appendix). Specifically, EORA26 merged and reconciled multiple data sources into a single balanced and symmetric product-by-product MRIO where 189 countries have been aggregated to a common 26-sector classification over panel data for the period 1990-2015.[4] This allows to track the impacts of international production and supply chains, spanning multiple sectors in multiple countries. They can be used to measure how countries and sectors participate in GVCs, and several features of GVC linkages (Antràs, 2020). In the empirical exercise, we focus on the "Eora26" version, given the need to compare across countries.[5]

The ADB dataset (to be cut or put in appendix)
The ADB multi-region I-O database (ADB MRIO) has been developed by the Asian Development Bank. It is basically an extension of the WIOD and includes five additional Asian economies - Bangladesh, Malaysia, Philippines, Thailand and Vietnam - for the years 2000 and 2007-2019. Notably, the data provided for these countries are derived from estimations produced by researchers and do not refer to official statistics.

Tables A1-A4 in the Appendix shows the countries and sectors available in the dataset (to be updated).

4. Descriptive statistics

In this section, we map the evolution of positioning of countries and sectors over time, highlighting some key descriptive patterns.

Figure 1 provides an overview of how GVCs have evolved for the world economy as a whole reporting the country-level measures of both upstreamness (U) and downstreamness (D). In line with the evidence provided by Antràs and Chor (2019), the evolution of countries' measures of upstreamness and downstreamness is highly correlated over time (pairwise correlation is 0.63). This is not a surprise since these two indicators actually measure the same phenomenon pointing to two different endpoints of the value chain. This empirical evidence is consistent with the assumption that GVCs are getting longer as a result of a rise in cross border intermediate sales and purchases caused by an increase in the inter-country network complexity effects (Miller and Temurshoev, 2017; Wang at al., 2017; Antràs and Chor, 2018). The overall picture thus suggests that GVCs have become more complex since the average global production chain "length" from primary factors to a specific country and onward from

[4] Although data are available since 1990, our analysis focuses on the period 1995-2015 to exclude the period of the transition to market economies of former Eastern bloc.

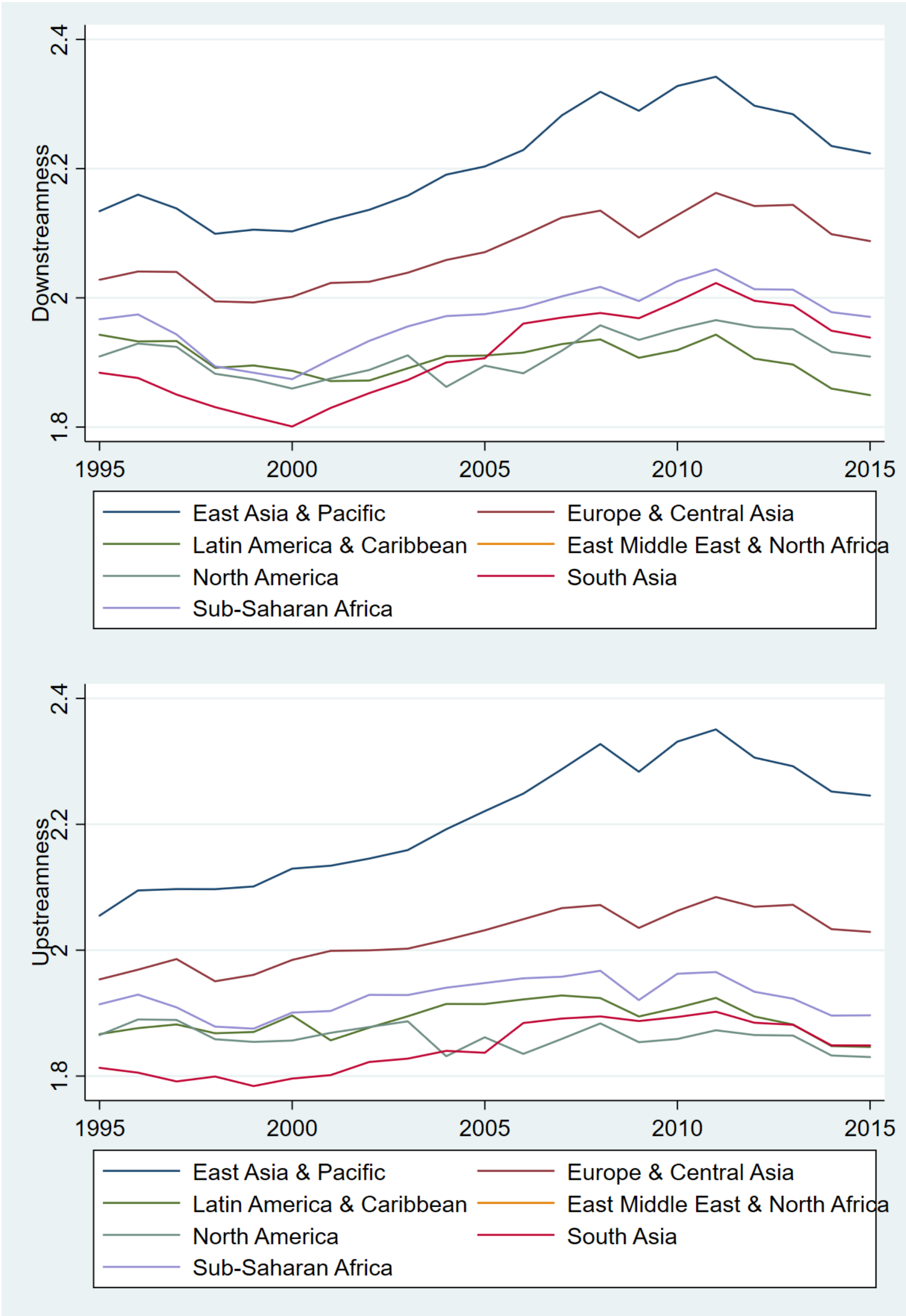
[5] Due to some inconsistencies in the Eora data, Sudan and Zimbabwe are not included in the database.

that country to final demand, have both increased (Antràs & Chor, 2018), reaching a peak in 2011. Following the macroeconomic dynamics, both measures rise at the turning of the century and decreased in 2009 – probably as a consequence of the 2007-08 worldwide financial crises. At the end of the observed period both measures register a value that is slightly higher than that reported in 1995. This is overall around two stages away from each endpoint.

Figure 1 - GVC Positioning over time (world average)

Source: authors' elaboration using EORA26 data.

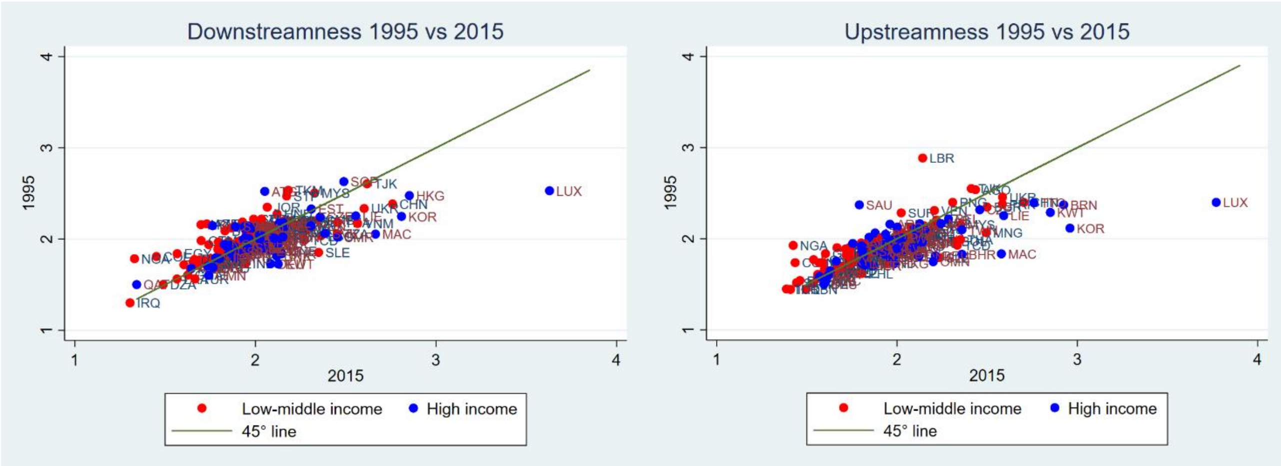
Figure 2- GVC Positioning by region over time



Source: authors' elaboration using EORA26 data.

Further details are provided in *Figure 2* showing the evolution of D and U reported in the previous figure by world regions. The trend over time is quite similar for all the regions although with different magnitudes. East Asian and Pacific countries are those that experience the highest level of involvement in GVC, in particular for the upstreamness metrics. On the other hand, while Southern Asian countries reported in 1995 the lowest values of both downstreamness and upstreamness, they show the best performance in climbing the ladder overtaking the North American economies at the end of the period.

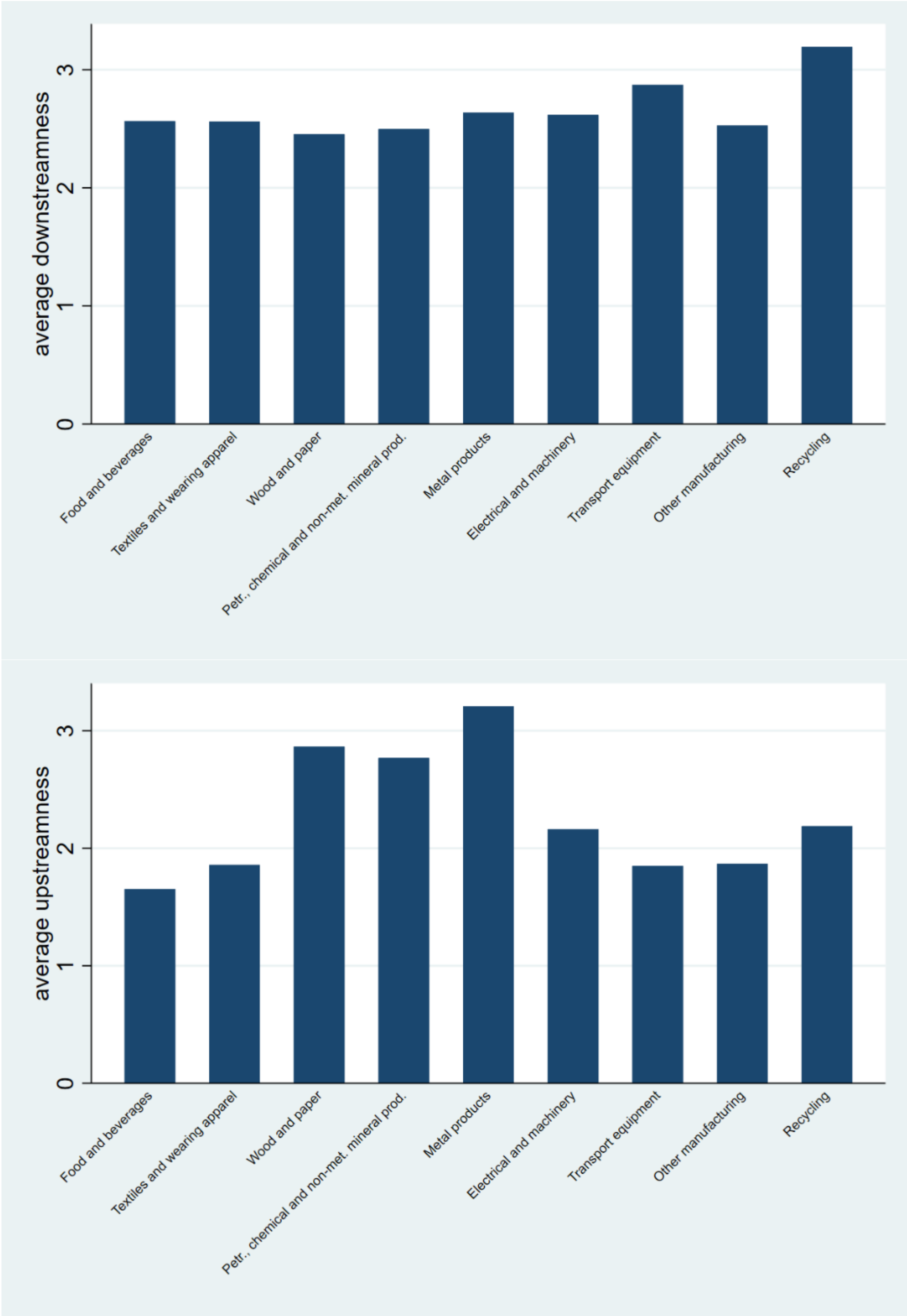
Figure 3 - GVC Positioning measures by income group and their correlation over time – 1995 and 2015.



Source: authors' elaboration using EORA26 data.

Figure 3 shows the plot of D and U metrics at the beginning and at the end of the period under scrutiny. Looking at the position of countries with respect to the 45 degrees line, it is possible to identify which countries have changed most their relative position in the GVC. Both D and U plots show that, in general, more advanced economies have shifted their production towards more 'extreme' sectors: most of the countries below the 45° line – thus those countries which have experienced an increase in the positioning metrics – are high income. On the opposite, most of the countries beyond the 45° line are low-middle income economies, suggesting that such countries have shifted towards less upstream and less downstream sectors.

Figure 4 - GVC Positioning by sector (world average, 1995-2015)



Source: authors' elaboration using EORA26 data.

Figure 4 finally reports the overall levels of the two measures of positioning for each industrial sector considered in EORA26 dataset (see Table A2 in the Appendix for the descriptions of sectors). *Recycling*, as expected, is the most downstream sector, with a value higher than 3 while *Metal products* sector is the most upstream one. High degree of downstreamness is found for transport equipment (D index slightly lower than 3) whereas all the other sectors have D values higher than 2.5. *Figure 4* shows high levels of upstreamness also for *Wood and paper* as well as *Petroleum, chemical and non-metal mineral products*, two sectors usually involved the first stages of global value chains. On the other hand, sectors such as *Food and beverage*, *Textile and wearing apparels* and *Transport equipment* result to be relatively upstream sectors.

5. An empirical test

Finally, we provide an empirical test to investigate the relationship between productivity and GVCs positioning indicators by country and sector worldwide. This is just an example of how the indicators computed in this work can be used, among many other alternatives. To this end, we adopt a standard macro version of the reduced form of the constant returns to scale Cobb-Douglas production function with labor and capital, augmented with indicators of GVCs positioning. This approach is similar to other studies that estimate the performance of other indicators of export performance (Constantinescu et al., 2019; Gal and Witheridge, 2019; Montalbano et al., 2018; Montalbano and Nenci, 2020). Specifically, we express the sectoral value-added in country *c*, industry *j* and year *t* ($VA_{cj,t}$) as a function of capital ($K_{cj,t}$), labor ($L_{cj,t}$) and a technology shifter (A_j). We assume that the latter is driven in part by a range of trade-related determinants ($\boldsymbol{\omega_1}$,$\boldsymbol{\omega_2}$,…., $\boldsymbol{\omega_n}$), including trade and GVC performances. Since we cannot identify export and GVC performances separately because of collinearity, here we focus our test on the presence of linear correlation between *changes* in GVC positioning and the corresponding *changes* in the country/sectoral productivity over time, net of the full range of unobserved country time-varying determinants, such as, for instance, absolute and relative convergence, labor market and other institutional country dynamics, structural and time-varying differences in trade flows and policies, time-varying differences in technology across countries, and other possible country time-varying differences/confounders. These are all captured by a set of country-time fixed effects. By introducing sector-time fixed effects, we also control for any sectoral time varying differences across sectors. By introducing country-sector fixed effects, we also control for structural time-invariant sectoral differences across countries. By dividing productivity and factors of production by labor and taking logs, we derive the following reduced equation to be estimated:

$$\theta_{cjt} = \alpha_{ct} + \beta_1 k_{cjt} + \beta_2 pos_{cjt} + \eta_{jt} + \omega_{cj} + \varepsilon_{cjt} \qquad (5)$$

where θ_{cjt} is the country/sectoral value added per worker in year *t*; k_{cjt} is a measure of country/sectoral capital intensity and pos_{cjt} is a measure of GVC positioning (alternatively, upstreamness and downstreamness). This latter represents our key variable of investigation. α_{ct}, η_{jt}, ω_{cj} are country-time, sector-time, and country-sector effects, respectively, whereas ε_{cjt} is the error component.

Since we are interested in the dynamics of the relationship between GVC positioning and economic performance, we employed here estimation techniques that are able to isolate the relationship between *changes* in explanatory variables and *changes* in the dependent one. In this respect, the use of panel data and an appropriate set of fixed effects restricts the identification to the *within-variance* of the country sectoral variables. Although the use of panels coupled with our empirical strategy can control for a wide set of observable and unobservable determinants as well as likely self-selection due to unobserved common factors driving GVC positioning via productivity improvements, we also lag positioning variables by one period to avoid further risk of endogeneity (in line with Constantinescu et al., 2019). Furthermore, we clustered standard errors by country to control for possible further error correlation bias. By interacting our GVC measures with income and geographical areas, we could also test for heterogeneity by country clusters.

Table 1 shows the outcomes of our baseline estimates. The various columns correspond to alternative specifications controlling for a specific set of fixed and time effects. The coefficients of our baseline equation are significant also when we propose the most constrained identification strategy allowing only for country-sector-time variations (columns 5-6 in *Table 1*). This is consistent with the narrative that distance from final markets matters in determining value added prospects. We find a negative association between changes in country/sector value added and value chain positioning both for our upstreamness and dowstreamness indicators.

Table 1: Baseline estimates. OLS estimates

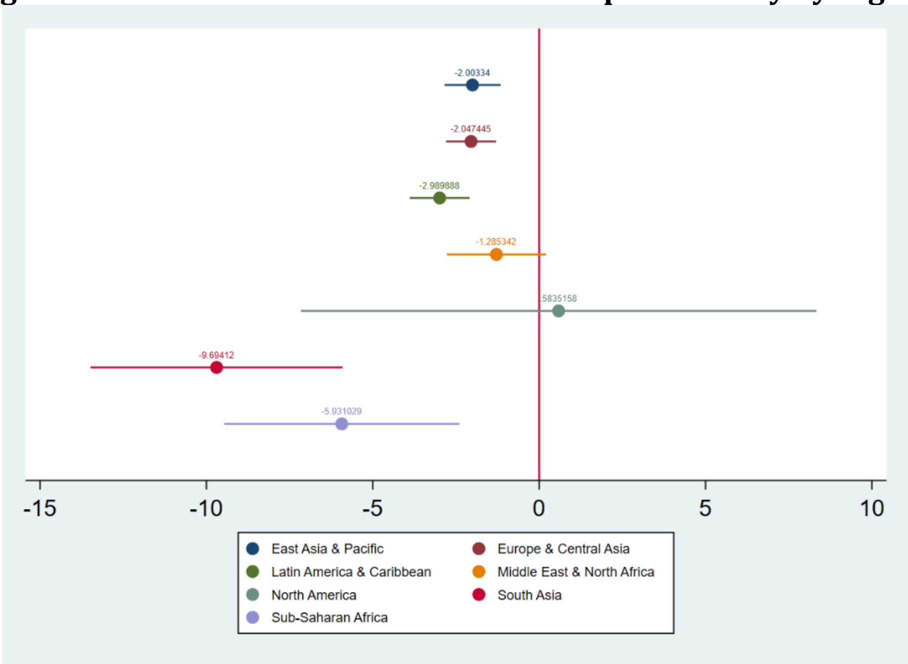
DepVar: Labor Productivity (ln)	(1)	(2)	(3)	(4)	(5)	(6)
Capital stock per employee (ln)	0.181***	0.112***	-0.001	-0.000	0.046**	0.045**
	(0.041)	(0.040)	(0.022)	(0.022)	(0.018)	(0.018)
Downstreamness (ln, t-1)	-1.284***		-1.115**		-1.319***	
	(0.342)		(0.492)		(0.426)	
Upstreamness (ln, t-1)		0.448***		-0.103		-0.710**
		(0.108)		(0.344)		(0.304)
Constant	-3.343***	-4.324***	-1.977***	-2.948***	-2.177***	-2.851***
	(0.389)	(0.338)	(0.453)	(0.312)	(0.396)	(0.290)
R^2	0.63	0.63	0.95	0.95	0.97	0.97
N	7,614	7,548	7,598	7,532	7,598	7,532
Country-Year FEs	YES	YES	YES	YES	YES	YES
Country-Sector FEs	NO	NO	YES	YES	YES	YES
Sector-Year FEs	NO	NO	NO	NO	YES	YES

As for downstreamness, our results suggest that sectors relatively downstream in the global value chain are characterised – *ceteris paribus* – by weaker labor productivity performances. This can be motivated by the fact that focusing our analysis on manufacturing, we are cutting the right end of the standard "smile curve," thus recording a general robust negative association between downstreamness and value added performances.

When controlling for the full set of fixed effects (including sectoral ones in particular), also the coefficient associated with upstreamness is negative. This is largely expected. Although not directly comparable, U and D are not measuring opposite features – in fact Antràs and Chor (2019) show that the two measures are correlated over time.[6] As shown by Miller and Temurshoev (2017), U captures a sort of "output upstreamness" of a certain sector in a certain country, while D captures "input downstreamness" of the same sector. On the other hand, when excluding sector-specific fixed effects, the sign associated to upstreamness' coefficient turns positive. This indicates that moving upstream (increasing the sectoral levels of U), positively affects intersectoral labor productivity heterogeneity and negatively affects intrasectoral one, at the same time. Furthermore, upstreamness is a general feature that combines very different situations of countries and sectoral specialisations ranging from raw inputs to the most sophisticated ones. Finally, since GVCs have become more complex, meaning that the average global production chain "length" from primary factors to a specific country and onward from that country to final demand has increased (Antras and Chor, 2019), it is reasonable that both measures are negatively correlated with the country/sectoral performance, as shown in our estimates controlling for the full set of fixed effects. However, the idea that it is possible to identify a general relationship between positioning and performance that is independent of the characteristics of the specific value chains and/or geographical context is somehow heroic. Note that in the most constrained specifications, also country and sectoral time-varying heterogeneity is filtered out from the estimated coefficients. We acknowledge that this kind of heterogeneity is a key component of the narrative behind the structural and time-varying difference in GVC position across countries and sectors worldwide. To dig deeper into this important issue, we run below a set of separated estimates by industry and geographical areas. *Figures 7-8* confirm the general negative association between downstreamness and performance, although associated with heterogeneous patterns across sectors and geographical areas. As expected, *Figures 9-10* show more mixed evidence, especially when we look at the geographical patterns of upstreamness, showing a robust positive association only in the case of SSA.

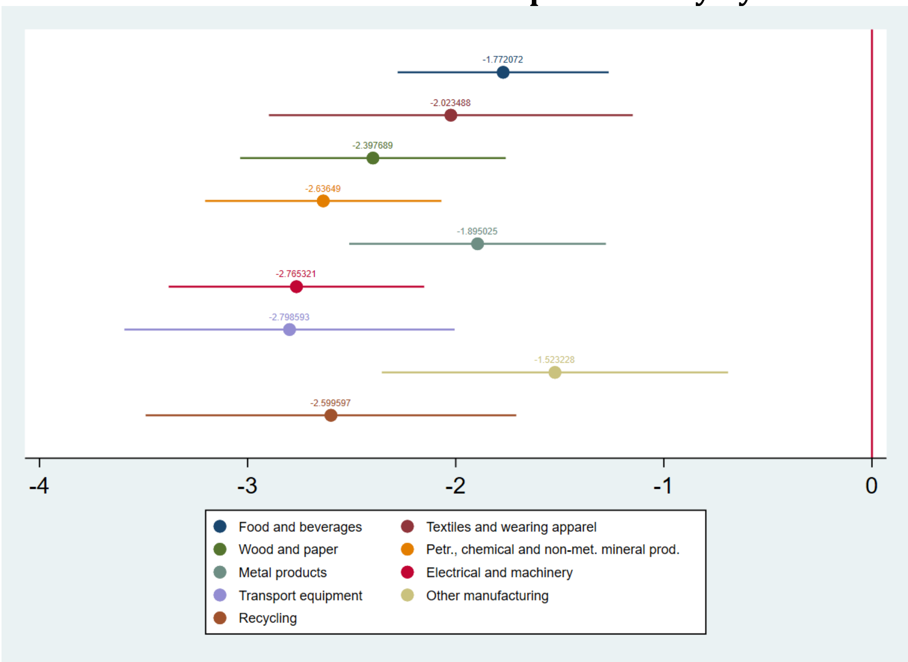
[6] Antras and Chor (2019) investigate in depth the pattern of co-movement between these two GVC positioning measures.

Figure 7 – Elasticities between D and labor productivity by region.



Source: OLS estimates by region using EORA26 and UNIDO data. D is considered with 1-year lag. The figure shows the coefficient as well as 95% confidence intervals.

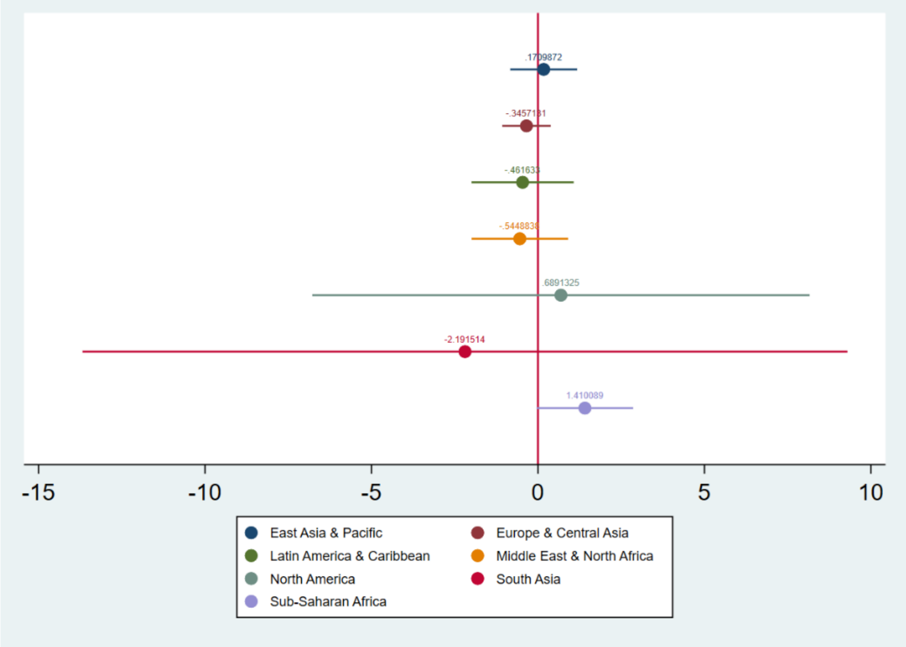
Figure 8 – Elasticities between D and labor productivity by industrial sector.



Source: OLS estimates by sector using EORA26 and UNIDO data. D is considered with 1-year lag. The figure shows the coefficient as well as 95% confidence intervals.

Figure 7 confirms that the elasticity between downstreamness and labor productivity is negative for all regions, apart from North America where it is statistically non different from zero. Although the value is about -2 for East Asia, Central Asia and Latin America, it reaches -*5.9* in the case of Sub-Saharan African countries and *-9.7* for South Asian countries. *Figure 8* looks at the elasticities between D and labor productivity by sector. It also confirms a statistically significant negative coefficient for all the sectors considered. In this case, the estimated elasticities range between *-1.5* and *-2.8* with *Transport equipment* and *Electrical and machinery* being the sectors with the highest values in absolute value.

Figure 9 – Elasticities between U and labor productivity by region.

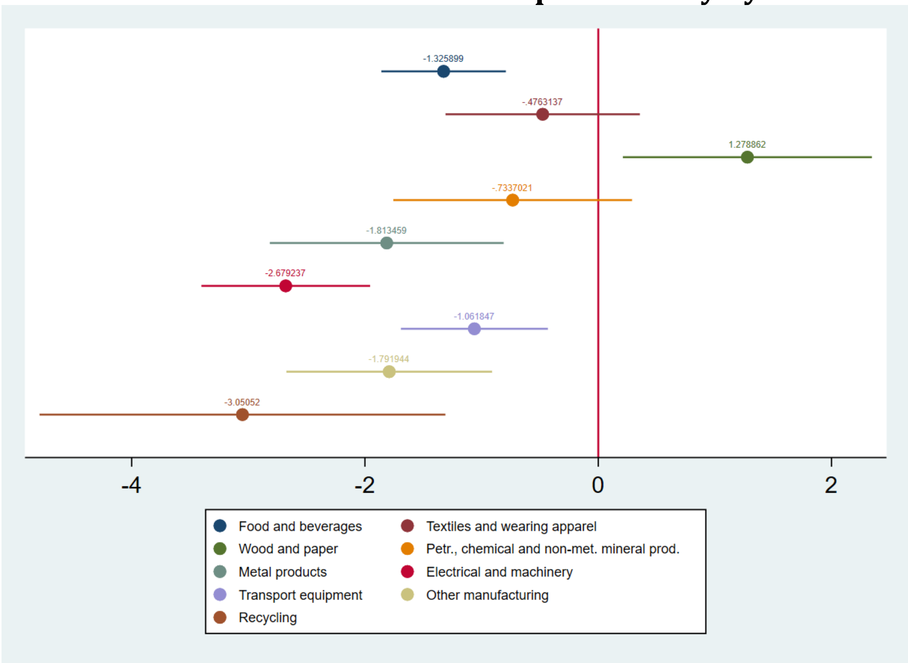


Source: OLS estimates by region using EORA26 and UNIDO data. U is considered with 1-year lag. The figure shows the coefficient as well as 95% confidence intervals.

Figure 9 shows that only for Sub-Saharan African economies the relationship between upstreamness and labor productivity is positive. For such countries, a 1 % increase in the U metrics is associated with a 1.41 % increase in labor productivity. All the other economies have coefficients that are statistically non-different from zero, reflecting the mixed evidence shown in *Table 1*.

Analysing the relationship between U and labor productivity by industrial sector as reported in *Figure 10* it is possible to assert that only *Wood and paper* sector shows a positive and statistically significant elasticities, with value equal to 1.28. Negative but statistically non different from zero are the coefficients estimated for *Textile and wearing apparel* and *Petroleum, chemical and non-metal mineral products*. All the other sectors have negative values, in particular the *Recycling* sector.

Figure 10– Elasticities between U and labor productivity by industrial sector.



Source: OLS estimates by sector using EORA26 and UNIDO data. U is considered with 1-year lag. The figure shows the coefficient as well as 95% confidence intervals.

1. Conclusions

The common wisdom is that the emergence of GVCs represents a golden opportunity for supporting the ongoing transformations of developing countries. The availability of new indicators of GVCs positioning at the country and sectoral level offered by this work provides an unprecedented opportunity to carry out qualitative and quantitative analyses on different economic aspects related to GVCs. In this work, for the sake of future use by other scholars, we compute and provide access to a new dataset of GVC positioning indicators at the country-industry level, based on the most used global Input-Output tables, i.e. the EORA dataset (189 countries and 26 sectors) for the period 1990-2015, the ADB MRIO database (63 countries and 56 sectors) for the period 2007-2020, the WIOD Long Run dataset (25 countries and 23 sectors) for the period 1965-2000, the OECD TiVA dataset (66 countries and 45 sectors) for the period 1995-2018, the WIOD dataset (43 countries and 56 sectors) for the period 2000-2014.
We are confident that researchers will benefit from this work and use these indicators to refine their analysis of GVCs providing also more detailed information to policymakers.

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Appendix

Table A1: 182 countries included in the EORA database

Afghanistan	Chad	Hong Kong	Monaco	Singapore
Albania	Chile	Hungary	Mongolia	Slovakia
Algeria	China	Iceland	Montenegro	Slovenia
Andorra	Colombia	India	Morocco	Somalia
Angola	Congo	Indonesia	Mozambique	South Africa
Antigua and Barbuda	Congo, the D.R. of the	Iran, Islamic Republic of	Myanmar	Spain
Argentina	Costa Rica	Iraq	Namibia	Sri Lanka
Armenia	Cote D'Ivoire	Ireland	Nepal	Suriname
Aruba	Croatia	Israel	Netherlands	Swaziland
Australia	Cuba	Italy	Netherlands Antilles	Sweden
Austria	Cyprus	Jamaica	New Caledonia	Switzerland
Azerbaijan	Czech Republic	Japan	New Zealand	Syrian Arab Republic
Bahamas	Denmark	Jordan	Nicaragua	Taiwan, Province of China
Bahrain	Djibouti	Kazakhstan	Niger	Tajikistan
Bangladesh	Dominican Republic	Kenya	Nigeria	Tanzania, United Rep. of
Barbados	Ecuador	Korea, DPR of	Norway	Thailand
Belarus	Egypt	Korea, Republic of	Oman	Togo
Belgium	El Salvador	Kuwait	Pakistan	Trinidad and Tobago
Belize	Eritrea	Kyrgyzstan	Palestinian Terr., Occupied	Tunisia
Benin	Estonia	Lao P. D.R.	Panama	Turkey
Bermuda	Ethiopia	Latvia	Papua New Guinea	Turkmenistan
Bhutan	Fiji	Lebanon	Paraguay	USR
Bolivia	Finland	Lesotho	Peru	Uganda
Bosnia and Herzegovina	France	Libyan Arab Jamahiriya	Philippines	Ukraine
Botswana	French Polynesia	Liechtenstein	Poland	United Arab Emirates
Brazil	Gabon	Lithuania	Portugal	United Kingdom
British Virgin Islands	Gambia	Luxembourg	Qatar	United States
Brunei Darussalam	Georgia	Macao	Romania	Uruguay
Bulgaria	Germany	Macedonia, the FYR	Russian Federation	Uzbekistan
Burkina Faso	Ghana	Madagascar	Rwanda	Vanuatu
Burundi	Greece	Malawi	Samoa	Venezuela
Cambodia	Greenland	Malaysia	Sao Tome and Principe	Viet Nam
Cameroon	Guatemala	Maldives	Saudi Arabia	Yemen
Canada	Guinea	Mali	Senegal	Zambia
Cape Verde	Guyana	Malta	Serbia	
Cayman Islands	Haiti	Mauritania	Seychelles	
Central African Rep.	Honduras	Mexico	Sierra Leone	

Table A2: countries included in the ADB database

(…)

Table A3: Eora sector classification

Industry Code	*Sector Description*
1	Agriculture
2	Fishing
3	Mining and Quarrying
4	Food & Beverages
5	Textiles and Wearing Apparel
6	Wood and Paper
7	Petroleum, Chemical and Non-Metallic Mineral Products
8	Metal Products
9	Electrical and Machinery
10	Transport Equipment
11	Other Manufacturing
12	Recycling
13	Electricity, Gas and Water
14	Construction
15	Maintenance and Repair
16	Wholesale Trade
17	Retail Trade
18	Hotels and Restaurants
19	Transport
20	Post and Telecommunications
21	Financial Intermediation and Business Activities
22	Public Administration
23	Education, Health and Other Services
24	Private Households
25	Others
26	Re-export & Re-import

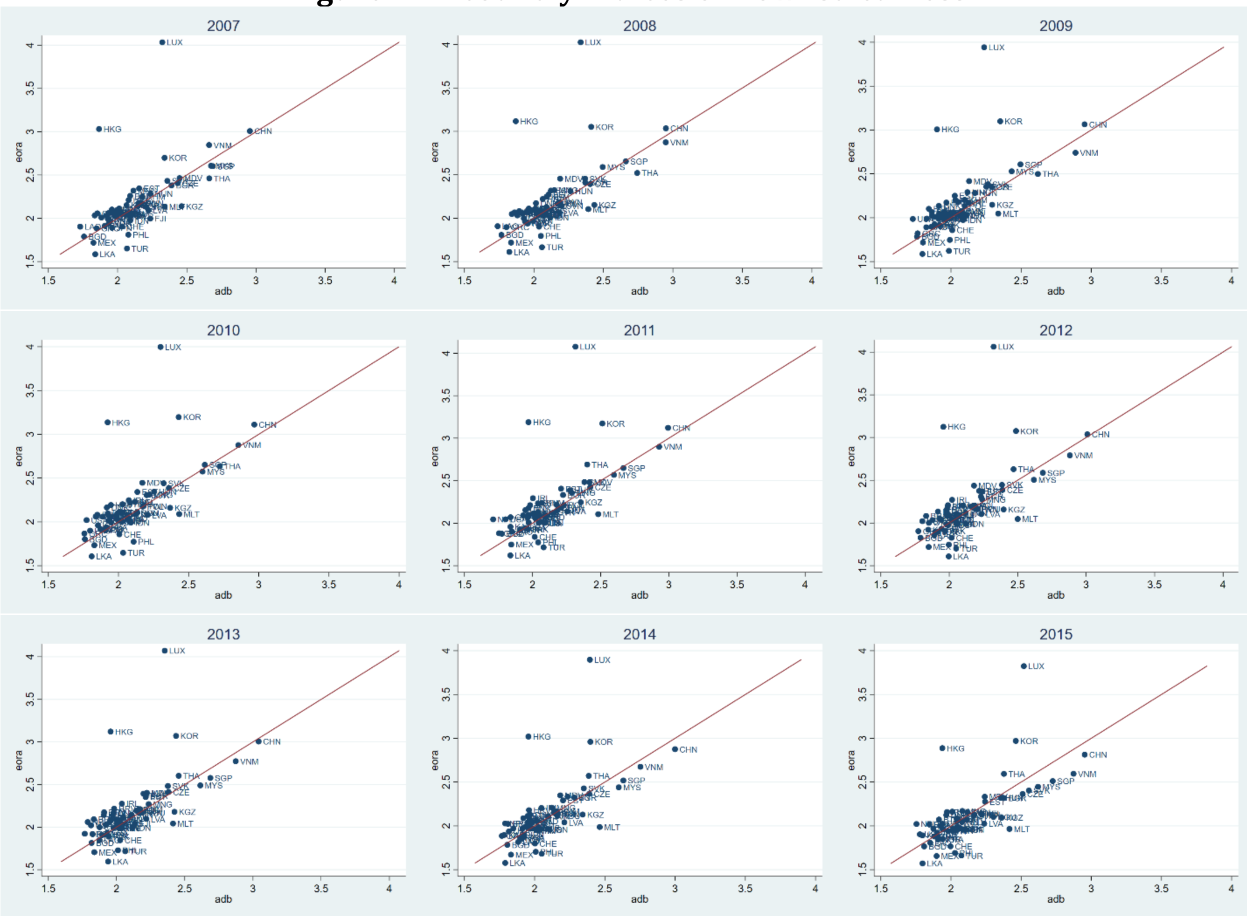
Table A4: ADB sector classification

(insert)

Comparison between datasets

In this section, we provide a comparison of the two datasets. Fig. A1 shows the consistency of our measures of downstreamness in all periods for almost all countries available in both datasets (the data points given by the combination of the same measures for the two datasets lie along the 45 degree line). The relevant exception are Luxembourg, Hong Kong and South Korea that for all periods register higher downstreamness in EORA than in ADB dataset.

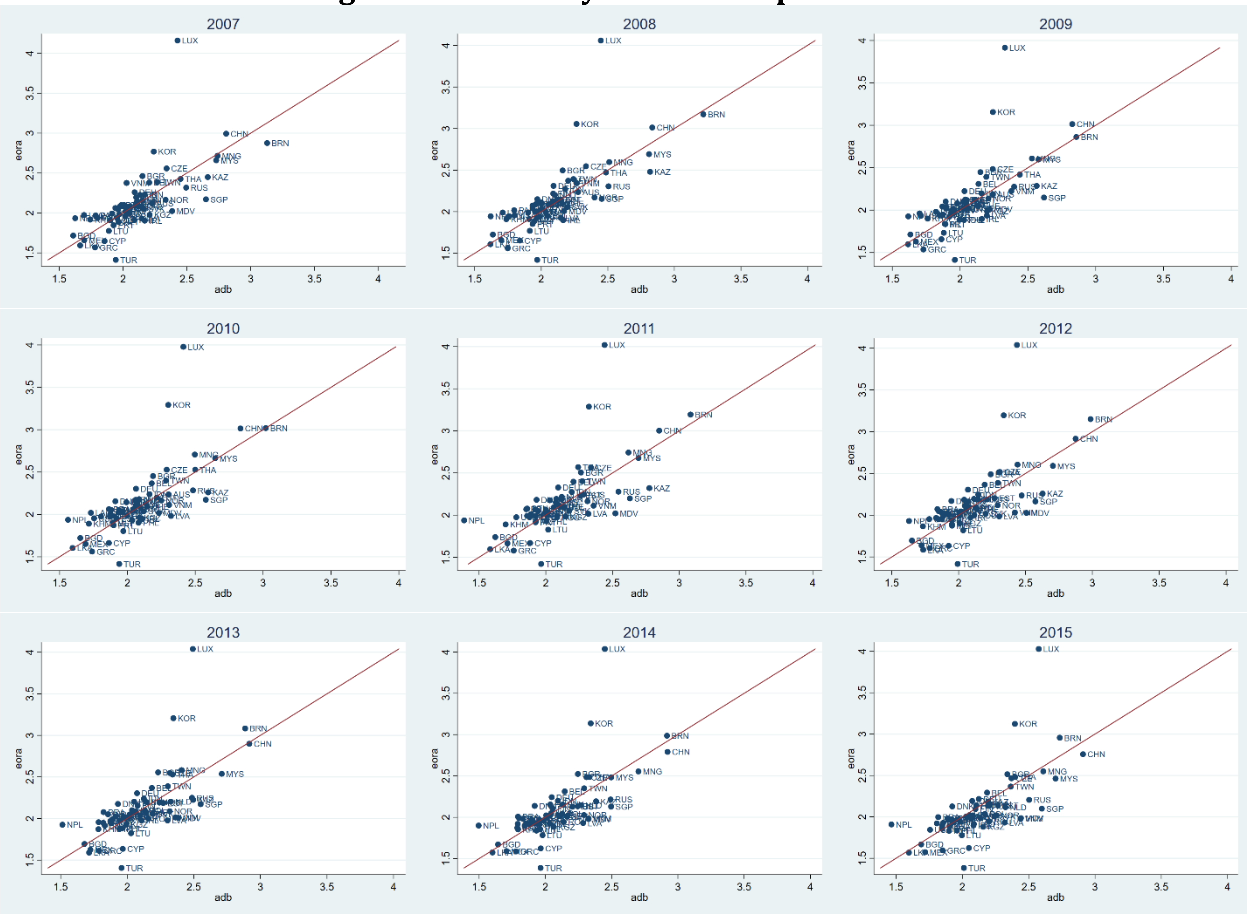
Figure A1 – country indices of Downstreamess



Source: Own computations on Eora 26 and ADB databases. Plots far from the 45° line denote differences in the country indices between the two datasets

A similar outcome is provided by Figure A2 that shows the same graphs for our measures of upstreamness. We can confirm the same pattern for all countries and the same exception only for Luxembourg and South Korea.

Figure A2 – country indices of Upstreamess



Source: Own computations on Eora 26 and ADB databases. Plots far from the 45° line denote differences in the country indices between the two datasets

Table A5: test for comparing positioning indices

		Spearman's rho	p-value	Kendall's tau	p-value	Student's t	p-value
Upstreamness	*2007*	0.725	*0.000*	0.559	*0.000*	0.783	*0.437*
	2008	0.707	*0.000*	0.536	*0.000*	1.375	*0.174*
	2009	0.718	*0.000*	0.548	*0.000*	1.217	*0.228*
	2010	0.713	*0.000*	0.543	*0.000*	1.527	*0.132*
	2011	0.710	*0.000*	0.547	*0.000*	1.402	*0.166*
	2012	0.682	*0.000*	0.515	*0.000*	0.826	*0.412*
	2013	0.691	*0.000*	0.519	*0.000*	0.738	*0.464*
	2014	0.707	*0.000*	0.536	*0.000*	0.095	*0.924*
	2015	0.716	*0.000*	0.545	*0.000*	-1.065	*0.291*
Downstreamness	*2007*	0.799	*0.000*	0.613	*0.000*	1.500	*0.139*
	2008	0.829	*0.000*	0.645	*0.000*	2.102	***0.040***
	2009	0.790	*0.000*	0.604	*0.000*	2.662	***0.010***
	2010	0.781	*0.000*	0.595	*0.000*	2.552	***0.013***
	2011	0.790	*0.000*	0.594	*0.000*	2.475	***0.016***
	2012	0.762	*0.000*	0.574	*0.000*	1.843	*0.070*
	2013	0.774	*0.000*	0.581	*0.000*	2.014	***0.048***

	2014	0.782	*0.000*	0.589	*0.000*	1.301	*0.198*
	2015	0.763	*0.000*	0.571	*0.000*	-0.087	*0.931*
Positioning	*2007*	0.588	*0.000*	0.435	*0.000*	-1.022	*0.311*
	2008	0.616	*0.000*	0.458	*0.000*	-1.153	*0.254*
	2009	0.461	*0.000*	0.337	*0.000*	-2.083	***0.041***
	2010	0.513	*0.000*	0.386	*0.000*	-1.395	*0.168*
	2011	0.478	*0.000*	0.362	*0.000*	-1.223	*0.226*
	2012	0.434	*0.000*	0.324	*0.000*	-1.263	*0.211*
	2013	0.424	*0.001*	0.315	*0.000*	-1.663	*0.101*
	2014	0.472	*0.000*	0.352	*0.000*	-1.544	*0.128*
	2015	0.519	*0.000*	0.373	*0.000*	-1.445	*0.153*

Note: Spearman's and Kendall's ranking tests assume as null hypothesis that countries' ranking obtained with Eora26 and ADB data are independent. Thus, the rankings are comparable if the null hypothesis is rejected. Student t test of equality of means assume as null hypothesis that the mean difference between indices computed with Eora26 and ADB data is equal to zero. The values are statistically non different from zero if the null hypothesis is accepted.