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Impact of Global Value Chains on Wage in Snake and Spider Configurations: An Empirical Analysis based on WIOD Countries

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Abstract:
Whether and why one should 'join a snake or a spider global value chain (GVC)' is a debate that has received little attention in economic literature. In this paper, we try to compare the effects of the GVCs on wage in both configurations between working skill categories across many countries and industries. The aim pursued is to show which GVC generates better wage in a particular context –especially at skill, country development or industrial level. To distinguish spider from snake, we use the mean value of the weighted average number of border crossing (ABC) proposed by Muradov (2016) and its variant indexed by the UIBE Research Institute of GVC (RIGVC of UIBE). The sample is a panel data of 36 countries selected from the World Input-Output Database (WIOD), spanning 10 years (2000-2009) and 9 industries. By employing the Hausman-Taylor technique, we found that in general, GVCs bring positive gains to workers of all skill categories. These effects tend to be higher for high-skill workers and for those engaged in snake GVCs. Furthermore, the impacts appear more significant in snake for workers in developed countries. On the other hand, these effects are stronger only in spider in developing countries. At industry level, the pair snake-manufacturing display more significant estimates. These findings are meant to inform policymakers on the choice of GVCs. In fact, joining a GVC may require a minutious understanding of its configuration.

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Introduction

Today, almost every country has joined one or many global value chains (GVCs). In order to guarantee higher value added and thereby achieve better gains, most policy-oriented treatments of these GVCs emphasize the importance of workers skill and countries absorptive capabilities (e.g. Rodrik, 2018). Thus, many now advocate that developing nations must imitate advanced ones to upgrade their educational systems or further, improve their business environment in order to make fuller use of the GVCs. Some general questions that surround these propositions are whether the participation in the GVCs is in fact associated with better trade gains, especially wage, and whether higher skill guarantee higher wage in the same context.

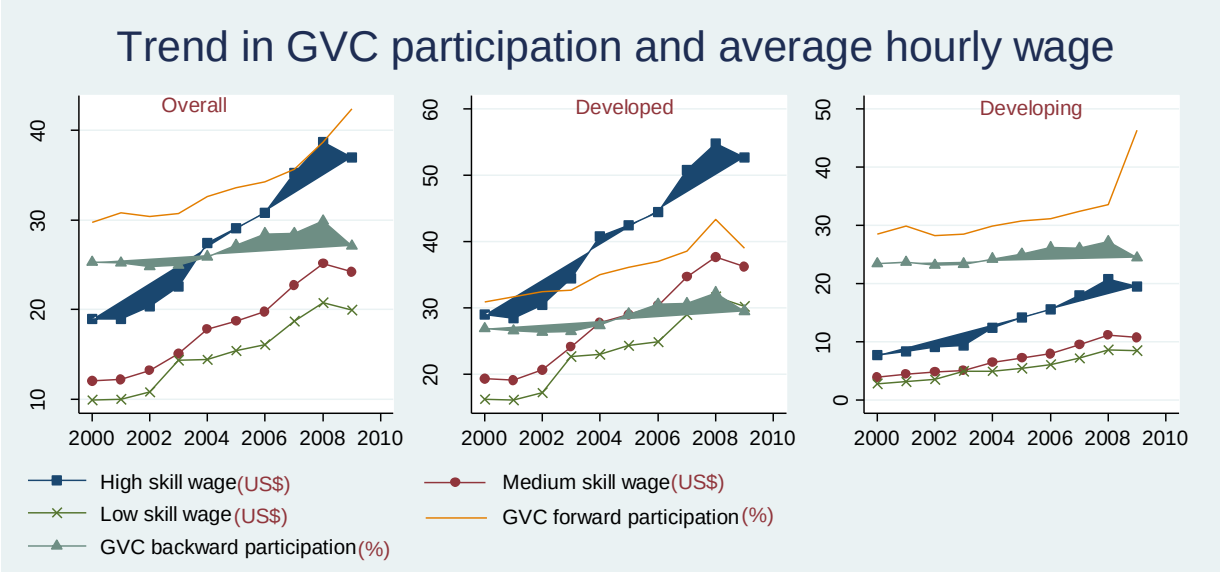

Figure 1: Trend in GVCs and hourly wage across skill categories

Statistics show that the trends in wages across skills follow a quite similar pattern. There is clear evidence that wages have increased across different skill categories within the decade 2000-2009. All the trends including GVCs participations show a slight decline after 2008 except for the forward-based GVCs. This decline might be due to the effects on the aftermaths of the global financial crisis which led to a retraction of investment and international financial capital flows overall. The good news however, is that, following an overall increase in GVCs practices, wages for different skill categories have been increasing too. The drawbacks on the other hand, are the increasing pace of wage gaps between the three skill groups. The gap between skills and across countries is increasing and there is no sign of improvement. Considering the figure in the major grouping regions, the wage gaps tend to reduce between low and medium skills than between high and low skills; they tend to be higher in developing countries. There are possibilities that these figures vary also across industries and across GVC configurations. Although the literature provides some conjectures on these points, the complexity in the GVCs leaves ground for further debates in terms of empirical analysis.

In their recent work to study the determinants of wage inequality, Lopez-Gonzales et al. (2015) adhered to previous literature and proposed that wage is, in practice, affected by the intensity of GVC participation or offshoring; level of countries development; financial flows; technology; and domestic policies such as employment legislation or education. While our

work tends to build on these propositions, further aspects have been considered. Changes in GVCs practices are not only complex but also dynamic phenomena, so are susceptible to be rapidly affected by spatial and temporal shocks. One reason behind such complexity is that GVCs take many different forms: some are sequential in nature (snakes), others are not (spiders) (Baldwin and Venables, 2013; Lee and Yi, 2017; Diakantoni et al. (2017)). Blanchard et al. 2017 suggest that this variety in the structure of GVCs can greatly frustrates policy analysis, since these important modeling details make it difficult to obtain general lessons or predictions for policy. Our work contributes to the literature by addressing some of these concerns. The main contribution is to analyze empirically how workers' wages are affected within/across skill levels, within/across countries following "snake" or "spider" configuration.

Literature Review

By definition, a global value chain (GVC) follows a snake configuration when the final product is a result of value added from parts to parts by multiple producers arranged on multiple stages in a sequential pattern within and across different countries. By contrast, in a spider structure, parts are simultaneously produced by different producers and shipped to a hub for final assembly or components production. Therefore, snake GVCs are longer in nature and spiders' are wider (figure 2).

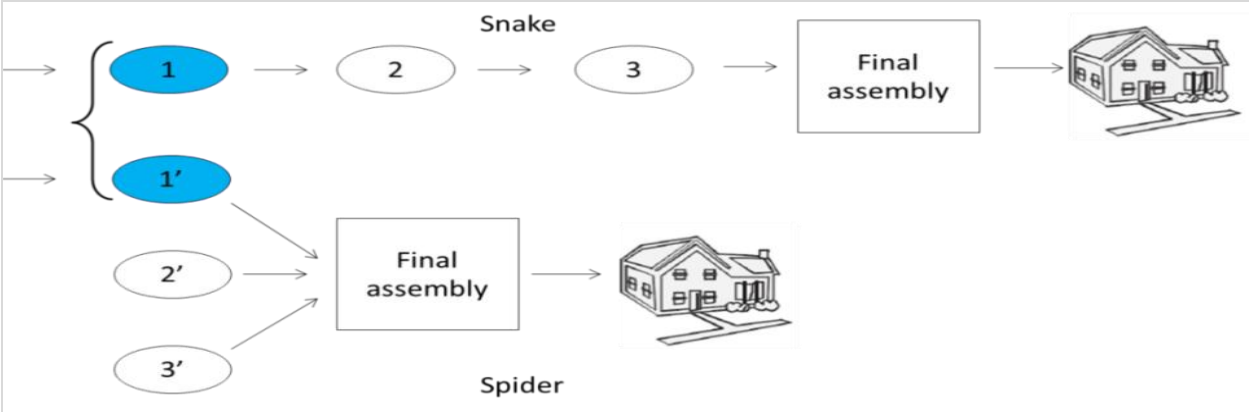

Figure 2: Snake and spider GVCs architecture
Source: Adapted from Baldwin and Venables (2013)

Regardless of their configurational structure, opinions in the literature are largely supportive of the importance for countries of being or becoming part of these GVCs because in practice, they can lead to better specialization, facilitate access to 'cheaper' inputs for production, bring export gains to economies, transfer technologies, create jobs and increase individuals' earnings and more. But in reality, these outcomes may not be straightforward because of the complexity of the GVCs. The GVCs take several forms; some are sequential; others are organized within firms, are arm's length; feature bilateral bargaining over prices; allow for market-determined prices; are bilateral, or involve many countries. This is why in general; GVCs may not affect everyone in similar way. In previous literature, some authors advanced that low-skilled workers are more exposed to wage drops or job losses due to offshoring, mainly resulting from declining demand for unskilled labor in developed countries (Feenstra & Hanson 1996; Feenstra & Hanson 1999). More recent works however, shift their support to the importance of a proper distinction between configurational aspects (Baldwin and Venables, 2013; Antràs and Chor, 2013) and skills and tasks difference (Hummels et al. 2014;

Autor 2015). The insights from trade-in-tasks models of international trade (Grossman & Rossi-Hansberg 2008; Baldwin & Robert-Nicoud 2007) suggesting that the outcome of offshoring practices depends on the nature of the tasks performed are also supported, in later literature by empirical evidences, especially pointing out that when low skill tasks are offshored, wage loss will be felt only at the source by low-skilled workers and vice-versa for high-skilled workers. Furthermore, these insights tend to be consistent with Hummels et al. (2014). When these authors used matched Danish worker-firm data, they find that offshoring tends to increase high-skilled wages and decrease low-skilled wages but again, that these effects of offshoring vary across tasks. For them, workers who perform routine tasks suffer the most from job loss. Besides these insightful studies, the literature has not clearly addressed the question of how wage varies when the GVCs take different forms. While some theories propose that trade costs have more detrimental effects on the expansion of snake GVCs (Diakantoni et al, 2017; Lee and Yi, 2017), there is still lacks of empirical evidence, and moreover how these changes occur across countries and industries.

Theoretical review and hypotheses development

Our work focuses on aforementioned gap by reviewing and extending the model of Grossman and Rossi-Hansberg (2008). The model allows us to express wage functions across countries and to compare them in different configurations using the logic in Diakantoni et al. (2017) and Lee and Yi (2017). The determinants from the framework are used to analyze empirically the impact of GVCs participation on wages in both snake and spider structures. Putting these authors' ideas together, it can be proposed that:

When parts offshoring is subject to trade and offshoring costs at border crossing, wage tends to be lower in the downstream for workers engaged in snake GVCs.

To prove this, we can assume a world of two distinct countries N and S. Any good produced in the world results in shared tasks between N and S. Firms in N offshore a skill category of tasks. Assume N is skill abundant and that only parts of low skill tasks $k \in [0,1]$ are offshored. Domestic and foreign wage are respectively w_N and w_S. To simplify, assume N has comparative advantage in producing parts and S has comparative advantage in assembling. On the basis that assembly is relatively uncompetitive in N; low skill wage can be expressed as:

$$w_N = w_S \beta(k)$$

Where, $\beta(k) \geq 1, k \in [\bar{k}, 1]$ is the part-specific offshoring cost in all industries and assumed strictly increasing in task k. The fraction $\bar{k} = 1 - k$ is performed in N and the remaining k is the amount of tasks offshored overseas. The market is assumed competitive. Considering the whole production chain, firms' optimal choices of intensity θ_l and θ_h, the optimal offshoring of low skill tasks k, and the market relative price p_N, we have:

$$p_N \leq w_N \theta_l (1-k) + w_S \theta_l k + W_N \theta_h$$

The quantities θ_l and θ_h are respectively the unit of low-skilled (l) and high-skilled (h) workers supplied in the production of a good. By substituting for w_S, the above becomes:

$$p_N \leq w_N \theta_l \Lambda(k) + W_N \theta_h \text{ where } \Lambda(k) \equiv 1 - k + \frac{k}{\beta(k)}$$

There is equality if all industries are active. Taking the high skill wage W_N as given, the low skill wage function can be expressed as:

$$w_N = \frac{p_N - W_N\theta_h}{\theta_l \Lambda(k)}$$

When market clears in the labor market, labor supply in N in the production of a good is given by:

$$\theta_l = \frac{L}{1-k} \quad and \quad \theta_h = H$$

This market-clearing condition highlights the fact that offshoring leverages the domestic factor supply; i.e. that an expansion in k is like an increase in L. By substitution, the wage function can be rewritten as:

$$w_N = \frac{p_N - W_N H}{L(1-k)^{-1}\Lambda(k)}, k \in [0, \bar{k}]$$

By definition, the denominator of the wage function is positive. Ceteris paribus, w_N is increasing in terms of trade $(\partial w_N / \partial p_N \geq 0)$, decreasing in overall labor supply, $(\partial w_N / \partial H \leq 0, \partial / \partial L \leq 0)$ and decreasing in the amount of low skill tasks offshored $(\partial w_N / \partial k \leq 0)$. The latter –the labor supply effect – is basically captured by the forward linkage participation to GVC and its effect on low-skilled workers at home i.e. in N. The differential of the last term in the denominator $(\partial w_N / \partial \Lambda(k)$, known as the productivity effect (Grossman and Rossi-Hansberg, 2008) is also positive.

As in Diakantoni et al (2017), when trade is costly, there exists $T = \beta(k) + t$ which is the sum of offshoring cost and the other trade frictions borne on the part of a good during border-crossing from N to S and to final consumer. Therefore:

$$w_S = \frac{w_N}{T(k)} \leq \frac{w_N}{\beta(k)} \leq w_N$$

If we pose t^1 and t^2 the cumulative trade frictions, $\beta^1(k)$ and $\beta^2(k)$ the offshoring costs, w_S^1 and w_S^1 the wage levels in the respective cases of snake and spider GVCs such that $\beta^1(k) \geq \beta^2(k)$, $t^1 = xt^2, x \geq 1$, then:

$$w_S^1 = \frac{w_N}{\beta^1(k) + xt^2}, w_S^2 = \frac{w_N}{\beta^2(k) + t^2}, \text{implying:}$$

$$w_S^1 \leq w_S^2$$

As proposed, when parts offshoring are subject to trade and offshoring costs at border crossing, wage tends to be lower in the downstream for workers engaged in snake GVCs. The factor parameter x recalls the magnification effect of trade cost as parts cross multiple borders (Yi, 2003, 2010). Based on this demonstration and the findings discussed in previous literature, the following hypotheses are put forward.

Hypothesis one (H1): Participation in GVCs increases wage level regardless of workers skill category. In fact, the literature is largely supportive of GVCs positive gains for everyone (Baldwin and Nicoud, 2007; Lee and Yi, 2017).

Hypothesis two (H2): GVCs have higher impact on wage for low-skilled workers in countries that rely more on backward integration. In practice, developing countries are often assumed labor abundant, thus tend to have comparative advantage is tasks $k \in [\bar{k}, 1]$. An increase in k implies more demand for low-skilled workers in countries located in the midstream through downstream of the value chain. An increase in the demand for their skill may lead to an increase in their marginal return to skill.

Hypothesis three (H3): Analogously to H2, GVCs have higher impact on wage for high-skilled workers in countries that are specialized in forward integration. An increase in k tends to create more demand for high-skilled workers in countries located in the farther upstream of the value chain. An increase in the demand for their skill leads to an increase in their marginal return to skill too.

Hypothesis four (H4): The marginal effect on wages is higher in spider GVCs as compared with snake ones. This may occur due to cascading trade cost effect as we previously demonstrated and following Diakantoni et al. (2017). Spider GVCs are short in nature, at most two border-crossings which may lower trade costs. In snake GVCs, the impact of cascading transaction costs is amplified as intermediate goods are further processed by importing countries and then re-exported.

Hypothesis five (H5): Trade cost is detrimental to workers wage, especially for those working in the farther downstream of the value chain. This logic can explain why wage may be lower in snake GVCs as we demonstrated.

Data, evidence and discussion

Our data –defined in this section – spans multiple years. And the GVCs, as discussed in the literature, involve many countries and industries. This requires appropriate models for panel data analysis.

The data

The sample used for our study is limited to 10 years (2000-2009) because the WIOD data on wages at high and low skill levels is available only from 1995 to 2009. The range 1995-1999 has been dropped to ensure reliability in matching older classification of 35 industries for the period 1995-2011 with the new classification of 56 industries for the period 2000-2014. In total, 9 industries –see table below – were selected based on the max values of their average propagation length (APL).

Table 1: List of industries

Sector of Activity	Industry code (WIOD)	Description
Primary sector	B	Mining and quarrying
Manufacturing	C19	Manufacture of coke and refined petroleum products
	C20	Manufacture of chemicals and chemical products
	C22	Manufacture of rubber and plastic products
	C28	Manufacture of machinery and equipment n.e.c.
Services	D35	Electricity, gas, steam and air conditioning supply
	G46	Wholesale trade, except of motor vehicles and motorcycles
	H49	Land transport and transport via pipelines
	J62_J63	Computer programming, consultancy and related activities; information service activities

Table 2: Descriptive statistics

Variable	Observation	Mean	Std. Deviation	Minimum	Maximum
Hourly wage (low skill)	3,240	15.05765	14.54396	0.012779	96.75867
Hourly wage (high skill)	3,240	27.9191	24.53285	0.0294526	186.0996
APL	3,240	1.754723	0.1522971	1.235895	2.442423
ABC	3,230	1.357259	0.1096271	1.080179	1.807063
GVC (Part)	3,240	0.0474387	0.1676453	-0.5410286	2.954952
GVC (Back)	3,240	0.2669658	0.1592415	0.0264583	0.8529686
GVC (Forw)	3,240	0.3427106	0.4758177	0.0314792	21.78981
Lab (Prod-HS)	3,240	2228.288	41270.38	0	2310255
Lab (Prod-LS)	3,240	1364.629	4962.018	0	107943.5
Lab (Supp)	3,240	0.0522681	0.3293843	-0.941153	14.69545
Price (Outp)	3,240	83.05263	22.15944	5.557	270.022
DEV	3,240			0	1
OECD	3,240			0	1
EU24	3,240			0	1
FDI (Open)	3,240	5.346742	8.189626	-5.670921	87.44259
H_Skill	3,240	0.1124175	0.1857693	0.0000616	0.9916272
L_Skill	3,240	0.0998184	0.1816156	0.0000491	0.9885724
Tarif (Rate)	3,240	3.516713	3.530132	1.31	26.51

Note: Given the scale of the mean values of the dependent variables we decide to take the log of the variables Lab (Prod-LS) and Lab (Prod-HS).

The econometric model

The basic relationship between wage and GVCs can be expressed in econometric terms as:

$W_{ij,t} = \mathbf{x}'_{ij,t}\boldsymbol{\beta} + \mu_{ij,t}$ where $\mu_{ij,t} = \mathbf{z}'_{ij}\boldsymbol{\alpha} + \varepsilon_{ij,t} = c_{ij} + \varepsilon_{ij,t}$

The dependent $W_{ij,t}$ is the observed average hourly wage in country i, paid to workers in industry j in year t. We exclude the intercept, so there are K GVCs-related variables in $\mathbf{x}_{ij,t}$. The heterogeneity or individual effect is $\mathbf{z}'_{ij}\boldsymbol{\alpha}$, with $\mathbf{z}_{ij}$ containing a constant term and a set of group-specific variables which may be observable such as countries' membership to advanced economies, and unobservable, such as workers' ability and trade policies that contribute to wage differences as well.

The Variables Specification

We follow our theoretical framework and the description in the literature to specify the key variables that contribute to changes in wage in a GVC configuration. In the rest of our discussion, wage at different skill levels is used as dependent variable. Employee's wage for each skill category is computed following OECD's definition which suggests that labor compensation per hour worked is the compensation of employees in national currency divided by total hours worked by employees. Based on this definition:

$$w_z = \frac{(Labor\ Compensation)_z}{H_z}, \text{z} = \text{low skill, high skill; H} = \text{number of hours worked}$$

GVC participation index

To calculate the GVC participation index, Koopman et al. (2014) define a position index that characterizes the relative upstreamness of a country in particular industry.

$$P_{ij} = ln(1 + F_{ij}) - ln(1 + B_{ij})$$

This means that countries with a larger position index are relatively more upstream, i.e., they contribute more value added to other countries exports than other countries contribute to theirs.

Country's backward participation in the GVCs

Countries' backward linkage refers to the "Foreign value added content of exports (FVAX)". This is the 'Buyer' perspective or sourcing side in GVCs, where an economy imports intermediates to produce exports (Hummels et al. 2001; Wang et al. 2014).

$$B_{ij} = \frac{FVA_{ij}}{E_i}$$

Country's forward participation in the GVCs

Forward participation to GVCs corresponds to the indicator "Domestic value added sent to third economies (DVAX)". It captures the domestic value added contained in inputs sent to third economies for further processing and export through the value chain (Hummels et al. 2001; Wang et al. 2014).

$$F_{ij} = \frac{DVA_{ij}}{E_i}$$

Number of border crossing

Following the logic of the average propagation length (APL), Muradov (2016) suggests that the index can be obtained by weighting the cumulative number of border crossing $1 + 2 + 3 + \cdots + n$ by the share of direct and indirect exports at each successive tier in the cumulative exports at all tiers. Thus:

$$ABC = 1 \times \frac{E^Y_{direct} + E^M_{direct}}{E_{cumul}} + 2 \times \frac{E^Y_{indirect}\ to\ 2^{nd}TP + E^M_{indirect}\ to\ 2^{nd}TP}{E_{cumul}} + 3 \times \frac{E^Y_{indirect}\ to\ 3^{rd}TP + E^M_{indirect} to\ 3^{rd}TP}{E_{cumul}} + \cdots + n \times \frac{E^Y_{indirect}\ to\ n^{th}TP + E^M_{indirect}\ to\ n^{th}TP}{E_{cumul}}$$

Where: ABC is the weighted average number of border crossing, E^Y is the exports of final products, E^M the exports of intermediate products and TP the tier partner. In order to parse spider from snake, we use the mean value of ABC which is 1.357259. This leads to a dummy variable:

$$Structure\ Dummy = \begin{cases} 1\ if\ \ ABC \geq 1.357259 \rightarrow snake \\ 0\ if\ \ ABC < 1.357259 \rightarrow spider \end{cases}$$

Trade cost

We use tariff rate defined as the average of effectively applied rates weighted by the product import shares corresponding to each partner country.

Others

Many other variables are used as controls in our analysis. These variables include labor productivity, labor supply, price level, skill level and country dummies –as described in Table 11 of appendix.

The benchmark regression model

First, following the econometric model as above specified, we run the following benchmark regression:

$$W_{ij,t} = \alpha_{ij} + \beta_1 GVC(Part)_{ij,t} + \beta_2 GVC(Back)_{ij,t} + \beta_3 GVC(Forw)_{ij,t} + \beta_4 ABC_{ij,t} + \beta_5 Log(Prod - LS)_{ij,t} + \beta_6 Log(Prod - HS)_{ij,t} + \beta_7 Lab(Supp)_{ij,t} + \beta_8 TOT_{ij,t} + \beta_9 DEV_{ij} + \beta_{10} OECD_{ij} + \beta_{11} EU24_{ij} + \varepsilon_{ij,t}$$

Where α_{ij} and $\beta_k, k = 1,2, \dots, 11$ are the parameters to be estimated

Table 3: Results of the benchmark regression

Independent variables	$\hat{\beta}_{ij}$	Dependent variable: hourly wage					
		Pooled OLS		Random effects		Within Fixed effects	
		Low skill	High skill	Low skill	High skill	Low skill	High skill
GVC (Part)	$\hat{\beta}_1$	0.476	-2.939	10.16***	12.06***	14.79***	18.87***
		(1.810)	(3.214)	(2.264)	(3.812)	(2.584)	(4.262)
GVC (Back)	$\hat{\beta}_2$	4.638***	6.494**	22.85***	30.58***	32.73***	43.19***
		(1.608)	(2.855)	(2.414)	(4.112)	(3.195)	(5.270)
GVC (Forw)	$\hat{\beta}_3$	-0.802	-0.858	-1.365***	-1.674**	-1.901***	-2.482***
		(0.550)	(0.977)	(0.396)	(0.661)	(0.424)	(0.700)
ABC	$\hat{\beta}_4$	5.123***	10.07***	21.14***	50.50***	29.08***	67.75***
		(1.777)	(3.155)	(2.726)	(4.618)	(3.286)	(5.419)
Log (Prod-LS)	$\hat{\beta}_5$	1.859***	2.699***	2.266***	3.917***	2.828***	4.593***
		(0.151)	(0.267)	(0.261)	(0.449)	(0.383)	(0.632)
Log (Prod-HS)	$\hat{\beta}_6$	2.008***	4.222***	0.417	1.946***	-0.601	0.834
		(0.142)	(0.253)	(0.274)	(0.472)	(0.421)	(0.695)
Lab (Supp)	$\hat{\beta}_7$	-1.861***	-2.867***	-0.381	-0.112	-0.400	-0.0629
		(0.493)	(0.875)	(0.273)	(0.451)	(0.277)	(0.457)
TOT	$\hat{\beta}_8$	0.0481***	0.0783***	0.0722***	0.147***	0.0608***	0.125***
		(0.00801)	(0.0142)	(0.00669)	(0.0112)	(0.00715)	(0.0118)
DEV	$\hat{\beta}_9$	11.21***	15.71***	11.46***	14.78***		
		(0.433)	(0.769)	(1.080)	(1.933)		
OECD	$\hat{\beta}_{10}$	-0.389	0.864	-0.617	0.157		
		(0.579)	(1.027)	(1.446)	(2.582)		
EU24	$\hat{\beta}_{11}$	4.739***	5.511***	2.608**	1.338		
		(0.436)	(0.774)	(1.059)	(1.888)		
Incremental F Test (Ha)		N/R	N/R	N/A	N/A	Yes	Yes
LM Test (Ha)		N/R	N/R	Yes	Yes	N/A	N/A
Hausman test (Ha)		N/A	N/A	N/R	N/R	Yes	Yes
Observations		2,894	2,894	2,894	2,894	2,894	2,894
R^2		0.573	0.564	N/A	N/A	0.344	0.418
Country×Industries		N/A	N/A	322	322	322	322

Standard errors are in parentheses, stars represent significance levels (*** p<0.01, ** p<0.05, * p<0.1). N/A = non-applicable, N/R = not reported. Ha= alternative hypothesis

The results from the benchmark regression and the necessary tests performed are in favor of the fixed effects (FE). These results are very general. Yet, one can remark that some variable's coefficients meet our predictions. For instance, $\hat{\beta}_1$ and $\hat{\beta}_2$ are positive and statistically significant at 1% level for both skill categories. This indicates that GVC participation tends to increase wage of workers regardless of their skill level. Another remark is the difference in the coefficient magnitude, which suggests that although the effects are same, the scope of the impact is much higher for high-skilled workers. Results display $\hat{\beta}_3 < 0$ across both skill categories. Note that the variable GVC(Part) is a log transformed version of the forward GVC

index. In this sense, we can say that forward participation is having a non-lineal effect on wages at each skill level. Having the coefficient $\hat{\beta}_4 > 0$ may imply that wages are higher in snake GVCs. This finding contradicts H_4, but needs to be further explored and validated in next sections. Another point in this phase is that the FE model has omitted three coefficients – $\hat{\beta}_9, \hat{\beta}_{10}$ and $\hat{\beta}_{11}$. As the option on using pooled OLS and RE are excluded, we turn to a new approach in the following section with a model that can generate similar results to FE, but that can at the same time accommodate the use our time-invariant dummies (DEV, OECD and EU24) and help to solve problems, if there are any, related to possible multicollinearity and endogeneity.

Extended RE: The Hausman and Taylor instrumental variables estimator

We are aware that multicollinearity can cause biases to the estimates and mislead our inferences. To deal with this case, we instrument the predictor which is been caused by one or more other variables in the model. Our approach is embedded in the Hausman and Taylor methodology (hereafter HT, 1981). After instrumenting a predictor with valid proof that it is being caused by one or other variables in the model, we use it as an endogenous variable while considering its predictor as instruments in the new model. Let's recall our basic model:

$$W_{ij,t} = \mathbf{x}'_{ij,t}\boldsymbol{\beta} + \mathbf{z}'_{ij}\boldsymbol{\alpha} + \varepsilon_{ij,t}$$

In this part, we use the HT method that allows us to account for biases in the RE model while accommodating omission and multicollinearity issues in the FE's. The main assumption of this method is that the explanatory variables that are correlated with u_{ij} can be identified within the basic model, in which case:

$$W_{ij,t} = \mathbf{x}'_{1ij,t}\boldsymbol{\beta}_1 + \mathbf{x}'_{2ij,t}\boldsymbol{\beta}_2 + \mathbf{z}'_{1ij}\boldsymbol{\alpha}_1 + \mathbf{z}'_{2ij}\boldsymbol{\alpha}_2 + \varepsilon_{ij,t} + u_{ij}$$

Where the coefficient vectors $\boldsymbol{\beta} = \left(\boldsymbol{\beta}'_1, \boldsymbol{\beta}'_2\right)'$ and $\boldsymbol{\alpha} = \left(\boldsymbol{\alpha}'_1, \boldsymbol{\alpha}'_2\right)'$. The set $\mathbf{x}_{1ij,t}$ are K_1 time-varying variables that are uncorrelated with u_{ij}; $\mathbf{x}_{2ij,t}$ are K_2 time-varying and correlated with u_{ij}; $\mathbf{z}_{1ij}$ are L_1 time-invariant and uncorrelated with u_{ij}; and $\mathbf{z}_{2ij,t}$ are L_2 time-invariant and correlated with u_{ij}. Based on these specifications, we can now understand that the likely presence of $\mathbf{x}_2$ and $\mathbf{z}_2$ is what causes the bias in the random effects model. The strategy proposed by Hausman and Taylor is to use information already contained in the model to instrument for the problematic variables $\mathbf{x}_2$ and $\mathbf{z}_2$. Test results for identification and selection of the endogenous and instrumental variables are shown in appendix (Table 4).

Table 4: Test results from instrumental variable 2SLS estimation

Endogenous	Instruments	Weak identification test	Under-identification test		over-identification test	
		Calculated F-stats against critical	$\chi^2(k)$	P-value	$\chi^2(k-1)$	P-value
GVC(Back)	GVC(Part), Open(FDI) Tarif(Rate)	276.607 against 13.91	653.484, $k = 3$	0.000	4.131, $k = 2$	0.1268
GVC(Forw)	GVC(Part), Tarif(Rate)	4058.224 against 19.93	2237.406, $k = 2$	0.000	2.306, $k = 1$	0.1289
Log(Prod_LS)	L_Skill H_Skill	946.760 against 19.93	1077.988, $k = 2$	0.000	0.141, $k = 1$	0.7071
Log(Prod_HS)	L_Skill H_Skill	787.870 against 13.91	967.329 $k = 2$	0.000	0.002 $k = 1$	0.9659

The general HT/GLS-IV model

In this model, all the variables are included without any distinction on the structure of the GVCs. It is expressed as follows:

$$W_{ij,t} = \alpha_{ij} + \beta_1 GVC(Part)_{ij,t} + \beta_2 GVC(Back)_{ij,t} + \beta_3 GVC(Forw)_{ij,t} + \beta_4 ABC_{ij,t} + \beta_5 Lab(Prod\_LS)_{ij,t} + \beta_6 Lab(Prod\_HS)_{ij,t} + \beta_7 Lab(Supp)_{ij,t} + \beta_8 TOT_{ij,t} + \beta_9 DEV_{ij} + \beta_{10} OECD_{ij} + \beta_{11} EU24_{ij} + \beta_{12} Open(FDI)_{ij,t} + \beta_{13} Hskill_{ij,t} + \beta_{14} L\_Skill_{ij,t} + \beta_{15} Tarif(Rate)_{ij,t} + \varepsilon_{ij,t}$$

Where:

$$GVC(Back)_{ij,t} = a_0 + a_1 GVC(Part)_{ij,t} + a_2 Open(FDI)_{ij,t} + a_3 Tarif(Rate)_{ij,t} + \nu_{ij,t}$$

$$GVC(Forw)_{ij,t} = b_0 + b_1 GVC(Part)_{ij,t} + b_2 Tarif(Rate)_{ij,t} + \zeta_{ij,t}$$

$$Log(Prod\_LS)_{ij,t} = c_0 + c_1 Hskill_{ij,t} + c_2 Lskill_{ij,t} + \xi_{ij,t}$$

$$Log(Prod\_HS)_{ij,t} = d_0 + d_1 Hskill_{ij,t} + d_2 Lskill_{ij,t} + \epsilon_{ij,t}$$

Table 5: Estimates from the general HT model

Independent variables	$\hat{\beta}_{ij}$	Dependent variable: hourly wage			
		HT/GLS-IV		Within FE	
		Low skill	High skill	Low skill	High skill
GVC (Part)	$\hat{\beta}_1$	13.85***	17.69***	14.43***	19.42***
		(2.323)	(3.887)	(2.492)	(4.131)
GVC (Back)	$\hat{\beta}_2$	33.52***	44.89***	33.70***	45.47***
		(2.918)	(4.868)	(3.093)	(5.127)
GVC (Forw)	$\hat{\beta}_3$	-1.722***	-2.225***	-1.805***	-2.460***
		(0.389)	(0.649)	(0.407)	(0.674)
ABC	$\hat{\beta}_4$	23.94***	59.51***	29.18***	70.59***
		(2.982)	(5.014)	(3.302)	(5.475)
Tarif (Rate)	$\hat{\beta}_5$	0.145***	0.236***	0.160***	0.268***
		(0.0483)	(0.0804)	(0.0493)	(0.0818)
Log (Prod-LS)	$\hat{\beta}_6$	4.879***	9.826***	4.960***	9.849***
		(0.473)	(0.789)	(0.499)	(0.827)
Log (Prod-HS)	$\hat{\beta}_7$	-2.516***	-4.166***	-2.728***	-4.407***
		(0.493)	(0.825)	(0.528)	(0.876)
Lab (Supp)	$\hat{\beta}_8$	-0.511*	-0.156	-0.631**	-0.317
		(0.264)	(0.439)	(0.272)	(0.451)
TOT	$\hat{\beta}_9$	0.0498***	0.102***	0.0472***	0.0964***
		(0.00715)	(0.0119)	(0.00744)	(0.0123)
DEV	$\hat{\beta}_{10}$	10.40***	11.90***		
		(1.400)	(2.527)		
OECD	$\hat{\beta}_{11}$	-1.639	-3.323		
		(1.948)	(3.497)		
EU27	$\hat{\beta}_{12}$	3.805***	3.256		
		(1.376)	(2.476)		
Open (FDI)	$\hat{\beta}_{13}$	0.00345	0.00178	-0.00251	-0.00716
		(0.0127)	(0.0211)	(0.0129)	(0.0214)
H_Skill	$\hat{\beta}_{14}$	13.12***	35.85***	15.01***	39.78***
		(3.114)	(5.207)	(3.376)	(5.598)
L_Skill	$\hat{\beta}_{15}$	-17.40***	-47.05***	-13.04***	-40.38***
		(3.173)	(5.302)	(3.419)	(5.668)
Observations		2,780	2,780	2,780	2,780
R^2		N/A	N/A	0.354	0.424
Country×Industries		313	313	313	313

Note 1: We report robust standard errors for FE and asymptotic standard errors for HT in parentheses, stars represent significance levels (*** p<0.01, ** p<0.05, * p<0.1). N/A = non-applicable.

An interesting remark from the results above reveals the majority of the estimates from the HT regression to be similar to those from the FE's. This observation is a strong prerequisite that supports the choice of the HT model. In sections below, we account for wage responses to countries' GVCs participation following different specifications.

Accounting for difference in GVC configurations

The first question here is whether wage changes differently in different configurations and the second is how important is the impact across skills.

Table 6: Accounting for difference in GVC configurations overall

Independent variables	$\hat{\beta}_{ij}$	Dependent variable: hourly wage			
		SNAKE		SPIDER	
		Low skill	High skill	Low skill	High skill
GVC (Part)	$\hat{\beta}_1$	28.04***	40.82***	12.51***	22.65***
		(4.303)	(7.080)	(3.595)	(6.123)
GVC (Back)	$\hat{\beta}_2$	46.65***	74.47***	42.04***	59.77***
		(4.675)	(7.693)	(4.100)	(6.913)
GVC (Forw)	$\hat{\beta}_3$	-6.051***	-8.649***	-1.462***	-2.696***
		(1.361)	(2.240)	(0.494)	(0.838)
Tarif (Rate)	$\hat{\beta}_4$	-0.216	-0.375*	0.163***	0.339***
		(0.131)	(0.216)	(0.0511)	(0.0857)
Log (Prod-LS)	$\hat{\beta}_5$	5.070***	10.57***	5.236***	10.82***
		(0.793)	(1.304)	(0.556)	(0.946)
Log (Prod-HS)	$\hat{\beta}_6$	-2.475***	-4.525***	-1.996***	-3.755***
		(0.813)	(1.337)	(0.560)	(0.970)
Lab (Supp)	$\hat{\beta}_7$	-0.727	-1.077	-0.692**	-0.432
		(0.654)	(1.076)	(0.270)	(0.454)
TOT	$\hat{\beta}_8$	0.0675***	0.128***	0.0376***	0.110***
		(0.00962)	(0.0158)	(0.0107)	(0.0179)
DEV	$\hat{\beta}_9$	12.66***	15.92***	5.864***	2.621
		(2.402)	(3.936)	(1.794)	(3.434)
OECD	$\hat{\beta}_{10}$	-4.320	-9.140	-0.947	-0.894
		(3.495)	(5.730)	(2.334)	(4.448)
EU27	$\hat{\beta}_{11}$	3.276	2.932	8.746***	14.22***
		(2.682)	(4.396)	(1.565)	(2.993)
Open (FDI)	$\hat{\beta}_{12}$	0.0236	0.0147	0.00489	0.0508*
		(0.0174)	(0.0287)	(0.0181)	(0.0303)
H_Skill	$\hat{\beta}_{13}$	14.07***	31.89***	-0.146	22.81***
		(4.447)	(7.319)	(4.963)	(8.722)
L_Skill	$\hat{\beta}_{14}$	-12.92***	-32.91***	-20.61***	-64.41***
		(4.760)	(7.832)	(4.657)	(7.937)
Observations		1,248	1,248	1,532	1,532
Country×Industries		182	182	208	208

Note 2: Estimated asymptotic standard errors are given in parentheses, stars represent significance levels (*** p<0.01, ** p<0.05, * p<0.1)

These results suggest that GVCs participation brings gains to everyone as shown by the positive sign of $\hat{\beta}_1$ and its significant level below 1%. We predict the impact from both structures should be positive and that $\hat{\beta}_1^{spider} > \hat{\beta}_1^{snake}$. However, in this general perspective, the marginal effect for workers involved in a snake GVC are higher across skills. Results are

nearly similar for workers in countries that rely more on backward linkages participation. The other coefficients also suggest that the impacts are magnified for both skills when workers are engaged in snake-type GVCs. Another interesting remark is the negative effect of tariff rate which recalls our predictions and the perspective in Lee and Yi (2017). We expected that a reduction in trade cost is causing a reverse impact on offshoring as in Grossman and Rossi-Hansberg. In a specific perspective, Lee and Yi (2017) show that a decrease in trade cost contribute to an expansion of snake-type GVC, which in turn may favor the positive impact on workers' return to skill in that configuration.

Accounting for within skill wage response due to difference in economic development

Does it matter if workers reside in countries that are different based on the level of economic development?

Table 7: Low skill wage response due to difference in economic development

Independent variables	$\hat{\beta}_{ij}$	Dependent variable: hourly wage (Low Skill)			
		DEVELOPED		DEVELOPING	
		Snake	Spider	Snake	Spider
GVC (Part)	$\hat{\beta}_1$	32.56***	-158.5***	-51.45**	8.238**
		(5.642)	(40.87)	(22.55)	(3.896)
GVC (Back)	$\hat{\beta}_2$	37.31***	-95.28***	-16.43	33.56***
		(6.597)	(30.98)	(16.86)	(5.180)
GVC (Forw)	$\hat{\beta}_3$	-7.930***	127.4***	36.03**	-0.993*
		(1.622)	(29.98)	(16.03)	(0.518)
Tarif (Rate)	$\hat{\beta}_4$	-4.580***	-1.571***	0.0421	0.164***
		(0.505)	(0.276)	(0.0802)	(0.0477)
Log (Prod-LS)	$\hat{\beta}_5$	6.130***	5.560***	2.328***	3.237***
		(1.388)	(0.929)	(0.596)	(0.693)
Log (Prod-HS)	$\hat{\beta}_6$	-4.020***	-2.490***	0.0399	-1.386*
		(1.407)	(0.966)	(0.632)	(0.760)
Lab (Supp)	$\hat{\beta}_7$	-0.879	-1.051***	0.0189	2.108**
		(1.005)	(0.298)	(0.530)	(0.936)
TOT	$\hat{\beta}_8$	0.0984***	0.0843***	0.0338***	0.0460***
		(0.0145)	(0.0181)	(0.00846)	(0.0127)
OECD	$\hat{\beta}_9$			2.313	1.869
				(2.134)	(2.102)
EU27	$\hat{\beta}_{10}$	-2.554	7.798***	0.470	6.324***
		(4.594)	(2.492)	(2.303)	(2.159)
Open (FDI)	$\hat{\beta}_{11}$	0.103***	0.0228	-0.0396**	-0.0408
		(0.0233)	(0.0200)	(0.0167)	(0.0363)
H_Skill	$\hat{\beta}_{12}$	21.73***	-3.863	2.894	8.125
		(7.731)	(8.811)	(3.285)	(6.067)
L_Skill	$\hat{\beta}_{13}$	-22.13***	-16.87**	-3.428	-23.61***
		(7.846)	(7.214)	(3.647)	(5.655)
Observations		1,107	483	987	500
Country×Industries		143	70	130	73

Note: Estimated asymptotic standard errors are given in parentheses, stars represent significance levels (*** p<0.01, ** p<0.05, * p<0.1). OECD is omitted because all developed countries in our sample are OECD members.

Table 8: High skill wage response due to difference in economic development

Independent variables	$\hat{\beta}_{ij}$	Dependent variable: hourly wage (High Skill)			
		DEVELOPED		DEVELOPING	
		Snake	Spider	Snake	Spider
GVC (Part)	$\hat{\beta}_1$	51.20***	-120.5*	-110.6**	16.19**
		(8.485)	(63.47)	(52.44)	(7.655)
GVC (Back)	$\hat{\beta}_2$	71.34***	-55.28	-53.63	48.59***
		(9.924)	(48.13)	(39.16)	(10.18)
GVC (Forw)	$\hat{\beta}_3$	-12.31***	104.7**	75.00**	-1.926*
		(2.442)	(46.57)	(37.30)	(1.014)
Tarif (Rate)	$\hat{\beta}_4$	-6.622***	-2.474***	0.00970	0.394***
		(0.759)	(0.428)	(0.187)	(0.0927)
Log (Prod-LS)	$\hat{\beta}_5$	11.06***	10.46***	6.344***	7.614***
		(2.086)	(1.439)	(1.376)	(1.370)
Log (Prod-HS)	$\hat{\beta}_6$	-5.562***	-3.657**	-0.975	-1.994
		(2.115)	(1.496)	(1.456)	(1.534)
Lab (Supp)	$\hat{\beta}_7$	0.571	-0.746	-1.625	1.477
		(1.514)	(0.461)	(1.232)	(1.811)
TOT	$\hat{\beta}_8$	0.154***	0.109***	0.105***	0.142***
		(0.0218)	(0.0281)	(0.0197)	(0.0248)
OECD	$\hat{\beta}_9$			1.379	3.522
				(4.618)	(4.964)
EU27	$\hat{\beta}_{10}$	-2.847	12.52***	-6.711	10.26**
		(6.735)	(3.790)	(4.948)	(5.091)
Open (FDI)	$\hat{\beta}_{11}$	0.104***	0.0746**	-0.0175	0.00754
		(0.0351)	(0.0311)	(0.0389)	(0.0704)
H_Skill	$\hat{\beta}_{12}$	26.86**	5.253	22.56***	31.21**
		(11.62)	(13.59)	(7.622)	(12.43)
L_Skill	$\hat{\beta}_{13}$	-39.50***	-52.00***	-19.33**	-66.00***
		(11.80)	(11.15)	(8.420)	(11.16)
Observations		692	834	562	698
Country×Industries		101	114	82	94

Note: Estimated asymptotic standard errors are given in parentheses, stars represent significance levels (*** p<0.01, ** p<0.05, * p<0.1). OECD is omitted because all developed countries in our sample are OECD members.

Whether the dependent is low skill or high skill wage, robust responses with regards to the benchmark are found only in column 1 and column 4 of the tables. This means that the pair developed-snake and the pair developing-spider may be better prospect for wage gains. Snake GVCs cross borders multiple times, implying that, tasks which are once outsourced can potentially return home. This mechanism embodies the possibility to be twice beneficial to workers in developed countries. In contrast, goods in spider cross border at most twice. Parts are often sourced in developed countries and assembled in developing labor-abundant countries with no guaranty of reshoring back home in the form of tasks, but rather as final goods. This may explain why spiders GVCs are more sensitive to low wage in developing countries. The fact that high wages are similarly impacted suggests that high-skilled workers are employed in the farther downstream especially at the services or intangible production stages of the GVCs. This is why, not only $\hat{\beta}_1^{snake} > 0$, but also $\hat{\beta}_2^{snake} > 0$ when the dependent is high skill wage. In column 2 and column 3, key coefficients are displayed with opposite sign, implying that in the same environment, workers' wages in different configurations are indeed affected differently. Moreover, in Table 9 we observe that labor supply has negative effect on low wage in developed countries. In general low skill tasks are offshored from developed countries to be performed in developing ones. Thus, these results are consistent with our wage function given that the coefficients are now positive on wage in developing

countries. Results in Table 10 also show that the same coefficients do not have significant impact on high skill wage. Productivity for low skill in developed country also has positive and highly significant impact on low-skill wages in both configurations. This may recall the notion of productivity effect in Grossman and Rossi-Hansberg (2008). Another relevant result is the positive effect of improvement in terms of trade which is consistent with the relative price effect in Grossman and Rossi-Hansberg (2008). Baldwin and Nicoud (2007) also showed that 'some trade is better than no trade' i.e. trade in tasks can be beneficial for everyone as long as the TOTs are not deteriorating.

Accounting for within skill wage response due to country-industries pair heterogeneity

The question in this part is whether, whilst accounting for difference in structure, the sector of activity plays a role in wage variation within skill level.

Table 9: Low skill wage response due to country-industries pair heterogeneity

Independent variables	$\hat{\beta}_{ij}$	Dependent variable: hourly wage (Low Skill)					
		Mining and quarrying		Manufacturing		Services	
		Snake	Spider	Snake	Spider	Snake	Spider
GVC (Part)	$\hat{\beta}_1$	-75.60	12.43	30.86***	2.560	-144.8**	-244.0***
		(61.70)	(80.51)	(5.460)	(5.471)	(61.61)	(55.15)
GVC (Back)	$\hat{\beta}_2$	-63.52	-11.71	52.73***	29.17***	-80.72*	-158.7***
		(49.38)	(63.35)	(5.876)	(6.574)	(45.84)	(44.46)
GVC (Forw)	$\hat{\beta}_3$	49.44	-6.491	-6.726***	-0.278	145.6***	212.7***
		(41.70)	(51.25)	(1.534)	(0.717)	(49.68)	(44.38)
Tarif (Rate)	$\hat{\beta}_4$	0.0377	0.235	-0.0408	0.416***	-1.777***	0.0878
		(0.324)	(0.205)	(0.146)	(0.101)	(0.569)	(0.0570)
Log (Prod-LS)	$\hat{\beta}_5$	2.007	-0.747	9.825***	12.15***	2.301	3.398***
		(1.864)	(2.075)	(1.256)	(1.281)	(1.426)	(0.646)
Log (Prod-HS)	$\hat{\beta}_6$	0.680	3.825**	-7.918***	-6.257***	0.372	-0.599
		(1.856)	(1.789)	(1.315)	(1.588)	(1.425)	(0.665)
Lab (Supp)	$\hat{\beta}_7$	-1.871	-1.046	0.609	-1.512***	-1.198	-1.197*
		(1.489)	(2.763)	(0.938)	(0.366)	(1.088)	(0.716)
TOT	$\hat{\beta}_8$	0.161***	0.0779*	0.0635***	0.00716	0.000931	0.0258
		(0.0279)	(0.0417)	(0.0111)	(0.0175)	(0.0283)	(0.0157)
DEV	$\hat{\beta}_9$	15.19***	7.937	13.05***	-6.558	10.27**	8.295***
		(4.896)	(9.426)	(3.943)	(4.330)	(4.882)	(1.906)
OECD	$\hat{\beta}_{10}$	-3.078	5.118	-10.20*	-2.339	-0.208	-0.204
		(6.630)	(10.26)	(5.922)	(5.180)	(6.759)	(2.579)
EU27	$\hat{\beta}_{11}$	3.440	9.034	5.614	18.82***	-5.962	4.065**
		(4.877)	(8.756)	(4.405)	(3.725)	(6.419)	(1.726)
Open (FDI)	$\hat{\beta}_{12}$	0.146***	0.283**	-0.0218	-0.0518	0.0187	0.0107
		(0.0472)	(0.125)	(0.0215)	(0.0415)	(0.0313)	(0.0181)
H_Skill	$\hat{\beta}_{13}$	-0.852	-75.26***	27.78***	15.95*	13.21	-3.363
		(9.415)	(18.69)	(6.261)	(8.866)	(19.77)	(13.47)
L_Skill	$\hat{\beta}_{14}$	-0.987	118.8***	-24.19***	-53.11***	-4.066	-3.815
		(10.57)	(41.52)	(7.513)	(8.383)	(8.082)	(5.949)
Observations		250	61	695	545	309	926
Country×Industries		32	11	96	81	55	116

Note: see note 2

Table 10: High skill wage response due to country-industries pair heterogeneity

Independent variables	$\hat{\beta}_{ij}$	Dependent variable: hourly wage (High Skill)					
		Mining and quarrying		Manufacturing		Services	
		Snake	Spider	Snake	Spider	Snake	Spider
GVC (Part)	$\hat{\beta}_1$	-133.1	-26.53	36.37***	1.900	-314.3***	-283.1***
		(89.42)	(122.3)	(9.859)	(9.166)	(90.91)	(88.96)
GVC (Back)	$\hat{\beta}_2$	-94.84	-60.86	78.14***	32.33***	-202.1***	-175.0**
		(70.84)	(96.22)	(10.62)	(10.98)	(67.67)	(71.68)
GVC (Forw)	$\hat{\beta}_3$	94.39	23.08	-7.758***	-0.211	289.5***	269.8***
		(60.45)	(77.86)	(2.771)	(1.199)	(73.30)	(71.51)
Tarif (Rate)	$\hat{\beta}_4$	-0.256	0.542*	-0.0540	0.832***	-2.784***	0.151
		(0.468)	(0.311)	(0.263)	(0.169)	(0.838)	(0.0921)
Log (Prod-LS)	$\hat{\beta}_5$	8.338***	-3.461	19.41***	24.76***	3.640*	6.752***
		(2.577)	(3.154)	(2.270)	(2.154)	(2.096)	(1.069)
Log (Prod-HS)	$\hat{\beta}_6$	-2.147	7.481***	-14.22***	-12.46***	2.211	-0.245
		(2.562)	(2.718)	(2.375)	(2.721)	(2.095)	(1.110)
Lab (Supp)	$\hat{\beta}_7$	-0.693	0.314	-0.429	-1.842***	-2.229	-1.296
		(2.142)	(4.193)	(1.695)	(0.614)	(1.604)	(1.162)
TOT	$\hat{\beta}_8$	0.271***	0.229***	0.127***	0.0684**	0.00613	0.0469*
		(0.0399)	(0.0634)	(0.0200)	(0.0291)	(0.0418)	(0.0254)
DEV	$\hat{\beta}_9$	17.87***	11.03	16.92**	-22.33**	14.54**	7.896**
		(5.603)	(14.38)	(6.988)	(8.845)	(6.900)	(3.814)
OECD	$\hat{\beta}_{10}$	-9.042	20.00	-20.96**	-2.194	0.529	-0.596
		(7.589)	(15.66)	(10.52)	(10.68)	(9.602)	(5.114)
EU27	$\hat{\beta}_{11}$	0.829	2.134	7.304	32.53***	-10.49	5.915*
		(5.565)	(13.36)	(7.815)	(7.593)	(9.163)	(3.446)
Open (FDI)	$\hat{\beta}_{12}$	-0.00972	0.316*	0.0174	-0.0449	0.0157	0.0607**
		(0.0689)	(0.190)	(0.0388)	(0.0688)	(0.0462)	(0.0292)
H_Skill	$\hat{\beta}_{13}$	5.797	-103.1***	62.23***	60.95***	22.74	11.83
		(13.19)	(28.39)	(11.31)	(15.44)	(29.13)	(22.29)
L_Skill	$\hat{\beta}_{14}$	-28.46*	175.2***	-52.13***	-148.4***	-7.152	-16.31*
		(14.70)	(63.19)	(13.55)	(14.13)	(11.91)	(9.739)
Observations		250	61	695	545	309	926
Country×Industries		32	11	96	81	55	116

Note: see note 2

In this part, key coefficients namely $\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3$ appear very strong in the pair snake-manufacturing. Results in Table 9 column 3 are consistent with the opinion that demand for low skill workers is often high in the manufacturing sector (Mudambi, 2008). And it is this higher demand that drives up the price for labor. The literature also suggests that highly skilled agents in an economy are employed in the tertiary sector (Aoki and Ando, 2002; Mudambi, 2008). Consequently, their marginal return to skill should be higher in the services too. Here, results show that wage decreases in service sector at both ends of the value chains. But the positive sign of the coefficient $\hat{\beta}_3$ suggest a rather mixed response. For a certain low upstream participation index, the effect is significantly positive, but then becomes negative. This may confirm why $\hat{\beta}_2$ is also negative because it measures the marginal effect of backward participation on wage in service sector. The explanation is that service GVCs generate better wage only in the upstream. Similar results to service appear in both

configurations in the mining and quarrying sector. In a nutshell, only the manufacturing-snake pair tends to display expected and significant results for both skill categories.

Conclusion

This paper provides a side-by-side comparative analysis of GVCs effect on wage in snake and spider configurations. Findings suggest that in general, GVCs participation brings positive gains to everyone. Also, based on our benchmark regression, results showed that wage tends to rise when countries contribute more value added to other countries' exports than other countries contribute to theirs. Similarly participation in the GVCs through backward linkages has positive effect on low-skilled workers wage as expected. But on average, the magnitude of the marginal effect of backward participation tends to be higher for high-skilled workers. At configurational level, there is a marked difference between the results across structures. These effects tend to be higher for workers engaged in snake-type GVCs. Another relevant finding is the impact of trade costs. In fact, tariffs applied as part of trade costs are detrimental to GVCs. This has been translated to negative impact on wages mainly in snake GVCs; showing some consistencies with the literature. It has been demonstrated that longer GVCs are more exposed to trade frictions (Diakantoni et al. 2017; Lee and Yi, 2017).

In practice, these findings imply that a strategic choice of GVCs that a country or a producer enters can make a difference in gains for workers. A strategic choice requires a comprehensive knowledge of the features –especially the length of a given GVC that a firm or a country is linked with. This is a primordial step that can help policymakers in designing appropriate measures for better predictions to shocks associated with cross-country tasks sharing. Based on our findings, developed countries can be advised to specialize more in upstream activities when they are connected to snake GVCs, but should be less dependent on these activities when they are linked to spiders. By contrast, developing nations should focus on spiders in the upstream, but less in snake. The opposite logic may work for downstream stages too. At sectoral level, results pointed out that wage responses to GVCs are more significant in the pair snake-manufacturing. But workers can achieve better gains only if choices of GVCs are accompanied with facilitating trade measures such as reduction in tariffs or other trade frictions at borders.

For future considerations, this paper has some flaws that are relevant to mention. Besides the use of the mean value of ABC to empirically distinguish snake from spider GVCs –which has not yet been used in the literature – our data was also limited to a cluster of 36 WIOD countries, 9 industries and 10 years (2000-2009). Although the findings lead to important policy insights, this sample seems less representative since it is condensed mainly on European and developed countries. As such, further works are needed, first to validate the use of ABC, and by employing more updated data with better coverage worldwide.

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Appendix

Variables	Description	Literature	Source
w_z	Hourly wage by skill categories (high and low)	OECD (2019)	Authors' calculation using SEA
ABC	Weighted average border crossing	Muradov (2016), Wang et al. (2017)	RIGVC_UIBE based on WIOD
GVC (Part)	Relative position of sector j in country i within a given GVC	Koopman et al. (2011)	RIGVC_UIBE based on WIOD
GVC (Forw)	Index of country's forward participation in the GVCs	Hummels (2001), Wang et al. (2017)	RIGVC_UIBE based on WIOD
GVC (Back)	Index of country's backward participation in the GVCs	Hummels (2001), Wang et al. (2017)	RIGVC_UIBE based on WIOD
Lab (Supp)	Labor supply based on number of hour worked	Antras et al (2006)	Own calculation using WIOD
Open (FDI)	Openness to inward FDI or net FDI inflows (%GDP)	Gonzalez and Kowalski (2015)	WDI, World Bank
Tarif (Rate)	Tariff rate as measure for trade costs	Diakantoni et al. (2017)	WDI, World Bank
Lab (Prod-HS), Lab (Prod-LS)	Individual productivity at skill level (high and low)	Antras et al (2006)	Own calculation using WIOD
L_Skill H_Skill	Individual skill level (high and low)	Antras et al (2006)	Own calculation using WIOD
DEV	Membership to developed countries (Yes=1, No=0)	Authors' construct	WDI, World Bank
EU24	Membership to the EU countries (Yes=1, No=0)	Authors' construct	www.gov.uk/eu-eea
OECD	Membership to OECD (Yes=1, No=0)	Authors' construct	www.oecd.org

Note: RIGVC of UIBE = Research Institute of Global Value Chain of the University of International Business and Economics, WIOD = World Input-Output Database, WDI = World Development Indicators. All the WIOD countries were selected except Croatia, Cyprus, Latvia, Luxemburg, Malta, Taiwan and Switzerland due to missing values.

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