Skill-based functional specialization in trade: an input–output analysis of multiscalar value chains in Brazil

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**ABSTRACT**
Sophisticated spatial labour markets can promote better opportunities for functional upgrading in value-added trade. This paper estimates the skill-based functional specialization in Brazilian labour factor content in trade in value-added (LTiVA), considering different geographical scales. We combined an interregional input–output model for Brazilian states with occupational data to identify the skill intensity embedded in LTiVA based on the hypothetical extraction method (HEM) technique. Our findings show that the largest Southeastern economic area specializes in highly sophisticated functions, while the rest of the country embodies low skills in value-added trade for domestic and global trade levels. Furthermore, the results reveal a central role for the São Paulo state governing the subnational value chains and reinforcing the international uneven spatial functional division pattern at the subnational level.

**KEYWORDS**
skill-based division of labour, functional specialization, labour factor-content trade, trade in value-added (TiVA), value-added exports

**JEL** F60, R12, R15, R23

**HISTORY** Received 26 March 2021; in revised form 11 May 2022

1. **INTRODUCTION**

The global value chain (GVC) literature recognizes the international division of labour as a relevant source for functional upgrading, focusing on trade in value-added (TiVA) measures (Audretsch et al., 2011; Bacolod & Blum, 2010; Brunelle & Polèse, 2008; del Prete et al., 2018; Duranton & Puga, 2005; Zhong et al., 2021). However, despite economic geography location models pointing out the interplay between the spatial division of labour and regional economic development, the role of skills-based location assets and the implication for regional functional upgrading is understudied. Moreover, the value-added (VA) trade literature does not explicitly include the location of subnational skills to understand the quality of linkages across production networks (Ezcurra & Rodríguez-Pose, 2014; Mudambi et al., 2018; Mudambi & Puck, 2016; Verbeke & Asmussen, 2016).

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\(^\text{b}\)Supplemental data for this article can be accessed online at https://doi.org/10.1080/17421772.2022.2081714.

This article has been corrected with minor changes. These changes do not impact the academic content of the article.
This study analyses the skill-based functional specialization of value chains in Brazil, considering both interregional and international VA measures. The paper’s contribution is twofold. First, we extend the GVC analysis of TiVA by including an explicit subnational dimension to estimate the VA labour factor content embedded in subnational and international trade levels. Incorporating a multiscalar approach provides a broader picture of value chains’ territoriality (Mudambi & Puck, 2016), allowing a better understanding of the unbalanced regional development pattern in Brazil. Second, we expand the analysis of the role of the spatial divisions of labour to account for the regional skill-based assets embodied in bilateral VA trade flows. Combining an occupational dataset at the regional level with a TiVA footprint analysis, we identify hierarchies of compensation for local labour factor content assets in VA trade and functional upgrading opportunities across and within value chains.

The study assesses the regional sources of specialization within value chains regarding labour-related territorial assets in Brazil’s tradable activities, considering both subnational and international TiVA spatial levels. Brazil is a singular case study for this type of analysis due to its considerable regional inequalities, an unequal composition of skill intensity among subnational labour markets and territorial disadvantages related to potential functional upgrading opportunities. The country’s large size (population, area, gross domestic product – GDP) and the diversity of natural resources can induce diverse location patterns of sophisticated skill-based labour factor content in value-added trade (LTiVA). First, there is a spatial concentration of economic activity in Southeastern Brazil, mainly São Paulo and Rio de Janeiro, which have dense economic spaces in terms of labour markets (Dietzenbacher et al., 2014; Imori, 2015). Second, peripheral states are generally specialized in exploiting natural resources (Gerefifi et al., 2005; Guilhoto et al., 2015; Haddad & Araújo, 2021; Lee et al., 2018), and potential less knowledge-intensive regional labour markets (das Neves Júnior, 2018). Hence, both aspects deal with the uneven geography of skill-based LTiVA within the country, which is relevant to understanding their functional upgrading specialization potential at the subnational and global trade levels.

Our findings allow a better understanding of the role of the location decisions (Bade & Nerlinger, 2000; Duranton & Puga, 2005; Zahran et al., 2020), the subnational productive integration (Coe et al., 2008; Gerefifi, 2005; Meng et al., n.d., 2013; Meng & Yamano, 2017) and the geography of skill-based assets for enhancing functional upgrading at a regional level (Atienza et al., 2018; Boschma et al., 2014; Johnson & Noguera, 2012). Special attention is given to the role of skill-based content on direct knowledge and innovation transfers at different geographical and firm-size scales, allowing us to build a detailed picture of Brazilian regional patterns of sophisticated labour integration networks. The economic geography literature has not considered the capabilities of large economic structures in transforming skill content into competitiveness. We contribute by including the regional skill levels for functional upgrading in production networks (Brunelle & Polèse, 2008).

The remainder of the article is structured as follows. Section 2 provides the background on the regional skill-based sources of specialization. Section 3 details the empirical strategy used to combine input–output (IO) data and an occupational dataset to measure the LTiVA. Afterwards, we explain the skill-intensity indicator and break down the regional VA procedures considering different geographical scales. Finally, the fourth section shows our main findings and policy implications.

2. REGIONAL SKILL-BASED SOURCES OF TRADE SPECIALIZATION

The perspective commonly used to analyse trade specialization is focused on the industrial level, which generally disregards the fact that companies carry out different stages of their value chain at different locations, which involves differences in how the labour factor is used and where it is located (Timmer et al., 2019). As the regional competitiveness has been viewed at the level of
functions performed within (and between) industries rather than the entire industry or the product levels, the content (quality) of production factors used by local economies is relevant to understanding local endowments and deepening the knowledge regarding new measures of sources of specialization. As pointed out by Bernard et al. (2017), the industrial classification by final economic activities disregards the occupational requirements for labour factors revealed in the differentials of wage income contribution to local VA (Szymczak & Wolszczak-Derlacz, 2021). Conversely, the value chain literature has been developed from trade measures based on VA, showing that geography is a relevant source for accounting for local endowments in trade competitiveness (Beverelli et al., 2019; Hummels et al., 2001; Johnson & Noguera, 2012, 2017; Koopman et al., 2011, 2014; Los et al., 2015, 2016).

Therefore, throughout the value chain, geographical fragmentation requires regions to carry out different production stages, which, in turn, involve the heterogeneous use of labour sophistication and, subsequently, uneven opportunities to benefit from the production and trade integration (Arif, 2021). The composition of labour markets structures, in terms of occupational characteristics, can shed light on essential sources of regional specialization from the occupational and skills approach as a source of economic development opportunities (Amador & Cabral, 2009, 2016; Bacolod et al., 2009; Cabral et al., 2009). This perspective is in line with the growing literature on the ‘factor content’ of tradable goods and services (Bohn et al., 2021; Hartmann et al., 2019; Meng et al., n.d.; Wang et al., 2020), which have shown the influence of the relative local assets on the value chain position of regions (Yeung, 2021).

Moreover, the fragmentation of stages of production within the same value chain implies using different skills in different locations, depending on their local assets’ endowment (particularly labour endowment). From this perspective, two regions may be specialized in the same industry but performing different functions in the value chains, which usually demand different skills from the regional labour force. In this regard, local structures of labour markets can shed light on essential sources not related to the industry mix but their functional specialization.¹ The need for this functional perspective – complementary to the sectoral one – has been acknowledged since Massey’s conceptualization of the regional divisions of labour (Massey, 1984, 2007). The labour requirements are diverse across space, and regions with greater skills and industrial capabilities can be highlighted by analysing the implicit content of skills incorporated in each value chain stage into the trade (Timmer et al., 2019). These spatial patterns of functional specialization have a direct influence on regional development opportunities.

By incorporating the factor-content and skills perspective, this study includes an occupational and skill-based approach to compute the effects of the differentiation of tradable goods and services arising from labour factor sophistication embedded in both production and trade (Pahl & Timmer, 2019; Phillips, 2016; Timmer et al., 2019). We further distinguish the interregional and international final demand destinations in terms of VA traded (Amador & Cabral, 2017; Horvát et al., 2020; Hoseini, 2020; Koopman et al., 2014; Los et al., 2016; Miroudot & Ye, 2019). When analysing the degree of labour sophistication embedded in regional VA, we further go beyond the explanation of the regional specialization sources in which the heterogeneous degrees of industrial capacities across space could demand different requirements in terms of skills in labour production factors (Guan et al., 2020; Szymczak & Wolszczak-Derlacz, 2021; Tian et al., 2019).

Location and agglomeration economies theories establish that skills influence productivity and, consequently, influence competitiveness, economic development and value creation at a regional level (Achtenhagen et al., 2013; Atienza et al., 2020; Taguchi, 2018). Knowledge and human capital are approaches consolidated in the literature. However, little attention has been paid to regional differences in value chain networks. In this light, creating value within a production chain requires a greater content of skills, which translates into higher remuneration for the labour factor. Thus, in this study, we consider that the composition of income
(i.e., the VA) attributed to the labour production factors is a relevant measure to understand the differences between the local use of factor content.

Therefore, our contribution is in computing the skills content of the occupations used in the production process to generate the local VA. It should be noted that the occupations performed by workers are treated here as standardized in terms of their skill requirements. So, in terms of remuneration and location of occupations, the differentials will identify any differences between regions (details are in the next section). In this regard, the literature that supports this argument points out that skills are intrinsic to the performance of a particular occupation or function within the production process (Acemoglu & Autor, 2011; Boschma et al., 2014; Castellacci et al., 2020; Ehab & Zaki, 2021). The skill-based perspective introduces an element of differentiation concerning purely occupational (Arif, 2021; Bignebat & El Hadad-Gauthier, 2021; Lee & Yi, 2018; Sturgeon & Gereffi, 2012), schooling (Cheng et al., 2015) or task-based (Acemoglu & Autor, 2011; Grossman & Rossi-Hansberg, 2012; Marcolin et al., 2019; Miroudot & Ye, 2020) functional approaches because it is based on the requirements for carrying out a given occupation in the formal labour market.

Understanding the contribution of labour factor skills to VA trade is further potentially significant for regions, given that relative local endowments can have different influences on the production integration linkages (Azzoni & Haddad, 2018; Haddad et al., 2020; Haddad & Araújo, 2021). This is helpful to policymakers because the relative subnational endowments can have different influences in relation to domestic and international trade and regarding the potential benefits of regional integration in complex production networks, with considerable implications for the formulation of regional development policies based on the VA produced and incorporated in the subnational territories.

3. METHODOLOGY

3.1. Measurement of TiVA at different skill-intensity levels

In order to estimate VA flows at different geographical scales, we adopt the demand-driven concept typical of the second and third generations of trade statistics, whether interregional or international flows levels (Meng et al., 2017). Our approach allows accounting for the degree of connectedness across domestic-based value chains and trade for global exports from the subnational perspective, which has been ignored in most literature on GVC. We extend the hypothetical extraction method (HEM) initially proposed by Los et al. (2016) for an interregional input–output (IRIO) system, with $R$ subnational regions (labelled $r$ or $s$) and $m$ exogenous rest of world ($m = RoW$) region destinations, $N$ industries (labelled $i$ or $j$), and $C$ final demand uses (domestic regions and foreign destination), following the approach suggested by Haddad et al. (2020). Therefore, the standard IO model can be expressed as follows:

$$x = Ax + Y$$

$$x = (I - A)^{-1} Y = BY$$

where $x$ is the $(NR \times 1)$ vector of gross output; $B = (I - A)^{-1}$ is a $(NR \times NR)$ Leontief’s inverse matrix; $I$ is the $(NR \times NR)$ identity matrix; $A$ is a $(NR \times NR)$ matrix with input coefficients $(a_{ij})$; and $Y$ is $(NR \times C)$, with $n$ different subnational regions and rest of the world (RoW) as a column vector in final demand. As a block matrix, this relationship is given by:

$$\begin{bmatrix}
    x^1 \\
    \vdots \\
    x^R \\
\end{bmatrix} =
\begin{bmatrix}
    B^{11} & \cdots & B^{1R} \\
    \vdots & \ddots & \vdots \\
    B^{R1} & \cdots & B^{RR} \\
\end{bmatrix}
\begin{bmatrix}
    y^{11} & \cdots & y^{1R} & y^{1RoW} \\
    \vdots & \ddots & \vdots & \vdots \\
    y^{R1} & \cdots & y^{RR} & y^{RRoW} \\
\end{bmatrix}$$

$$i$$

where $\mathbf{x}$ is the vector of gross output; $\mathbf{B}$ is the Leontief’s inverse matrix; $\mathbf{A}$ is the input–output matrix with input coefficients $(a_{ij})$; and $\mathbf{y}$ is the vector of final demand.
where $i$ is a summation vector; $y_{ij}^r$ is a $N$-dimensional vector of final deliveries from region $r$ to region $s$ and $y^r_{n\text{RoW}}$ represents the exports vector with demand from each region $r$ to the foreign destinations.

Following Timmer et al. (2019), we are interested in disaggregating the content of the labour factor incorporated in production and trade by skills intensity levels. The labour-based domestic value-added (LDVA) of region 1 needed to attend their final demand is given by:

$$\text{LDVA}^1 = \hat{v}_L^1 (I - A)^{-1} Y_i$$  (3)

where $\hat{v}_L^1$ is an $(NR \times NR)$ diagonal matrix with the with the first element ($\hat{v}_{11}^L$) equal to the ratio between labour share of VA and gross output in industries of region 1, and zeros elsewhere like:

$$\hat{v}_L^1 = \begin{bmatrix} \hat{v}_{11}^L & 0 & \cdots & 0 \\ 0 & \ddots & \cdots & \vdots \\ \vdots & \cdots & \ddots & \vdots \\ 0 & \cdots & \cdots & \hat{v}_{NN}^L \end{bmatrix}$$

The elements for other regions are set to 0 since we are interested in 1’s domestic (regional) labour-based value in its trade for other regions or exports (other countries). To measure the LDVA in trade, we follow Los et al. (2016) and Haddad et al. (2020), considering one hypothetical situation, where region 1 does not export to region $n$. The hypothetical LDVA of region 1 and region $r$ is expressed as:

$$\text{LDVA}^{1r} = \hat{v}_L^1 (I - A_r^{1r})^{-1} \bar{Y}^{1r}$$  (4)

where the intermediate inputs and the final demand exchanges between 1 and $r$ are set to 0. The hypothetical matrices $\bar{A}$ and $\bar{Y}$ are defined as follows:

$$\bar{A}^{1r} = \begin{bmatrix} A_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & A_{RR} \end{bmatrix} \quad \text{and} \quad \bar{Y}^{1r} = \begin{bmatrix} y_{11} \cdots 0 \\ \vdots \cdots \vdots \\ y_{R1} \cdots y_{RR} \cdots y_{n\text{RoW}} \end{bmatrix}$$  (5)

For international trade, we follow Haddad et al. (2020), assuming $m$ as exogenously RoW destinations. Therefore, the same logic can be given by the relationship between subnational region 1 and $m = \text{RoW}$, maintaining $A$ as the original input coefficients, as follows:

$$\text{LDVA}^{1\text{Row}} = \hat{v}_L^1 (I - A)^{-1} y^{1\text{Row}}_i$$  (6)

The HEM strategy shows that the LDVA of trade from region 1 is derived as the difference in VA in the actual and counterfactual situations. The bilateral $LTiVA$ from region 1 to region $r$ is:

$$LTiVA^{1r} = \text{LDVA}^1 - \text{LDVA}^{1r}$$  (7)

To complete the trade cycle, we incorporate each region’s gross imports in the interregional system. We assume that imports generate regional VA with local production technology as if they were produced in Brazil (Haddad et al., 2020). This allows us to incorporate foreign markets from the perspective of purchase and the sale of TiVA, accounting for the domestic VA in exports (Haddad & Araújo, 2021).

We then disaggregate $LTiVA$ to measure the functional specialization at the interregional (domestic) and international trade levels. Therefore, following the strategy used by Timmer et al. (2019), we build a $(K \times NR)$ matrix $F$ with the share of labour income (as a part the VA) for $K$ ($k = 1, \ldots 5$) levels of skill intensity in the regional labour market – as a representative of direct use of each set of skill intensity in regional production and trade. A typical element of this matrix ($f^r_{kj}$) denotes the income of all workers of each skill intensity level $k$ in a region $r$. More specifically, we break down the labour content of VA into the $k$ skill-based intensity levels, according to the wage bill distribution to those $k$ levels (see specific details in the next section). To measure the trade in skills from region 1 to region $R$, we replace the diagonal matrix $\hat{v}_L^1$ in
equation (6) with $\hat{f}_k^1$ for estimate the LTiVA for each $k$. The relation is given by:

$$\text{LTiVA}_k^1 = \text{LTiVA}_k - L\text{TiVA}_k^r$$

(8)

By disaggregating the labour-content in VA in specific $k$ skill groups, we build a clearer picture of the sophistication of production networks at different geographical scales. Functional and industrial aggregation are consistent with the regional level results, as the sum of the regional LTiVA equals the sum of trade in all $k$ skill levels:

$$\text{LTiVA}_k^1 = \sum_{k,r} \text{LTiVA}_k^r$$

(9)

The analysis to be performed ahead will benefit from some well-known trade-related indicators applied to skill-based specialization. We measure the skill-based specialization in trade as the ratio of two elements: the ratio of the trade flow of each $k$ level of skill-intensity to the total trade in region $r$; and the ratio of the total trade for all skills in region $r$ to the national total (Timmer et al., 2019). The specialization index for each region $r$ is given by:

$$S_r^i = \frac{(\text{LTiVA}_k^i / \sum_k \text{LTiVA}_k^i)}{(\sum_r \text{LTiVA}_k^r / \sum_k \sum_r \text{LTiVA}_k^r)}$$

(10)

Values $> 1$ indicate functional specialization at the specific level $k$ of skill-intensity; values $< 1$ indicate the opposite. This trade specialization indicator allows us to map the interregional and international sophistication of value chains, as measured by the sophistication of labour involved in production.

3.2. Data

We use the 2015 interregional input–output (IRIO) model developed by the Regional and Urban Economics Lab at the University of São Paulo (NEREUS-USP) (Haddad et al., 2017), with 27 regions (26 states, plus the Federal District of Brasilia) and 67 industries. Table 1 presents basic socio-economic information on the Brazilian states. Regional inequalities are pronounced and persistent (Azzoni & Haddad, 2018; Silveira-Neto & Azzoni, 2011). The national economy is dominated by the large economic centres in the Southeast region (São Paulo, Rio de Janeiro, Minas Gerais and Espírito Santo). This central area accounts for just 11% of the territory, but represents 53% of the national GDP and 42% of the population in 2015. These states concentrate on the leading educational and research and development hubs, the financial market, the manufacturing industry and 56% of foreign direct investment (FDI) (Banco do Nordeste, 2016). The Southern states are the second area of economic importance, with 14% of the population, 16% of GDP and above-average per capita income, education and labour quality. The impoverished Northeast region covers nine states, 27% of the population and 15% of GDP in 2017. The sparsely populated North and Midwest regions have large areas, and their economy is based on the exports of natural resources, mainly grains and cattle in the Midwest. Finally, the Northern states specialize in mining activities, except Amazonas, which hosts a sizeable manufacturing area in Manaus, the state capital, as a result of a tax-free import zone.

3.2.1. Occupational data and skills

An occupational database allowed us to measure five skill-intensity levels for the workers of industries and regions. The source of occupational data is the Ministry of Economy’s Annual Social Information Relation (RAIS), a mandatory yearly report filed by all formal businesses in the country. It covers all formal workers and contains demographic characteristics (age,
Table 1. Basic socio-economic indicators at regional level (BRL millions).

| Region | State          | Population | (%) | Gross Regional Product | (%) | Value-added | (%) | Exports | (%) |
|--------|----------------|------------|-----|------------------------|-----|-------------|-----|---------|-----|
| North  | Rondônia       | 1,768,204  | 0.9%| 57,152                 | 0.6%| 32,309      | 0.6%| 3616    | 0.5%|
|        | Acre           | 803,513    | 0.4%| 18,213                 | 0.2%| 12,304      | 0.2%| 104     | 0.0%|
|        | Amazonas       | 3,938,336  | 1.9%| 172,162                | 1.7%| 72,281      | 1.4%| 3563    | 0.5%|
|        | Roraima        | 505,665    | 0.2%| 13,207                 | 0.1%| 9363        | 0.2%| 38      | 0.0%|
|        | Pará           | 8,175,113  | 4.0%| 203,001                | 2.0%| 117,550     | 2.3%| 28,515  | 3.7%|
|        | Amapá          | 766,679    | 0.4%| 17,601                 | 0.2%| 12,680      | 0.2%| 231     | 0.0%|
|        | Tocantins      | 1,515,126  | 0.7%| 45,737                 | 0.4%| 26,046      | 0.5%| 3026    | 0.4%|
| Northeast | Maranhão     | 6,904,241  | 3.4%| 117,863                | 1.2%| 69,370      | 1.3%| 4920    | 0.6%|
|        | Piauí          | 3,204,028  | 1.6%| 56,770                 | 0.6%| 34,723      | 0.7%| 1566    | 0.2%|
|        | Ceará          | 8,904,459  | 4.4%| 197,634                | 1.9%| 114,157     | 2.2%| 4702    | 0.6%|
|        | Rio Grande do Norte | 3,442,175 | 1.7%| 86,808                 | 0.8%| 50,889      | 1.0%| 1323    | 0.2%|
|        | Paraíba        | 3,972,202  | 1.9%| 78,614                 | 0.8%| 49,610      | 1.0%| 591     | 0.1%|
|        | Pernambuco     | 9,345,173  | 4.6%| 254,178                | 2.5%| 134,105     | 2.6%| 4183    | 0.5%|
|        | Alagoas        | 3,340,932  | 1.6%| 66,093                 | 0.6%| 41,993      | 0.8%| 1863    | 0.2%|
|        | Sergipe        | 2,242,937  | 1.1%| 58,130                 | 0.6%| 34,415      | 0.7%| 486     | 0.1%|
|        | Bahia          | 15,203,334 | 7.4%| 451,016                | 4.4%| 215,660     | 4.2%| 24,598  | 3.2%|
| Southeast | Minas Gerais  | 20,869,101 | 10.2%| 914,121                | 8.9%| 457,284     | 8.9%| 80,273  | 10.5%|
|        | Espírito Santo | 3,929,911  | 1.9%| 198,155                | 1.9%| 100,343     | 1.9%| 23,734  | 3.1%|
|        | Rio de Janeiro | 16,550,024 | 8.1%| 1,075,206              | 10.5%| 556,164     | 10.8%| 81,734  | 10.7%|
|    | São Paulo | 44,396,484  | 21.7%| 3,333,909 | 32.6%| 1,633,314  | 31.7%| 269,021 | 35.1%|

(Continued)
Table 1. Continued.

| Region   | State              | Population | (%) | Gross Regional Product | (%) | Value-added | (%) | Exports | (%) |
|----------|--------------------|------------|-----|-------------------------|-----|-------------|-----|---------|-----|
| South    | Paraná             | 11,163,018 | 5.5%| 695,425                | 6.8%| 327,047     | 6.3%| 60,006  | 7.8%|
|          | Santa Catarina     | 6,819,190  | 3.3%| 419,358                | 4.1%| 209,667     | 4.1%| 34,692  | 4.5%|
|          | Rio Grande do Sul  | 11,247,972 | 5.5%| 699,511                | 6.8%| 334,842     | 6.5%| 66,034  | 8.6%|
| Midwest  | Mato Grosso do Sul | 2,651,235  | 1.3%| 149,485                | 1.5%| 74,086      | 1.4%| 13,633  | 1.8%|
|          | Mato Grosso        | 3,265,486  | 1.6%| 223,301                | 2.2%| 97,283      | 1.9%| 36,031  | 4.7%|
|          | Goiás              | 6,610,681  | 3.2%| 314,404                | 3.1%| 154,347     | 3.0%| 17,459  | 2.3%|
|          | Federal District   | 2,914,830  | 1.4%| 309,813                | 3.0%| 183,769     | 3.6%| 1088    | 0.1%|
| Brazil   |                    | 204,450,049| 100.0%| 10,226,869            | 100.0%| 5,155,601     | 100.0%| 767,032 | 100%|

Source: Authors’ own elaboration based on the Brazilian interregional input–output (IRIO) system.
gender, education, tenure, occupation code, wage) and information on the firms (industry, size, location).4

The individual skills of workers were aggregated to the region and industry levels. We measure the skill content of an industry or region according to the sophistication of its occupations. Employees work for a firm in a particular region \( r \), in a specific occupation,5 which requires a set of skills, as defined by the American Occupational Information Network (ONET)6 survey, adapted to the Brazilian labour market by Maciente (2013, 2016).7 Each occupation receives a number between 0 and 1, representing the intensity of the required skills, as estimated by das Neves Júnior (2018).8

By construction, the skill-intensity indicator reflects the demand for labour and can vary within the same industry \( i \) and region \( r \), depending on the characteristics of the regional production systems. It is used as a proxy for the degree of sophistication of productive activities. Three skill dimensions were considered: (1) cognitive, related to logical reasoning, learning ability, and the oral and verbal domain of the language; (2) social, considering interpersonal relationships, negotiation, etc.; and (3) motor, related to manual dexterity, strength and the ability to perform exhaustive work. The final indicator for each occupation, ranging from 0 to 1, is the average of these three indices, weighted by the associated wage returns (Neves et al., 2019). The total amount of skills requirements is computed by adding up the skill-intensity levels of all workers in an industry \( i \) in a region \( r \). It is possible that two states with the same number of workers in an industry could have different amounts of skills depending on their employees’ mix of occupations.

The skill-intensity level of a worker \( l \), \( q_l \) \( \forall q_l = [0 \leq q_l \leq 1] \), is a continuous variable. To create skill-intensity levels, we breakdown \( q_l \) into five quintiles. In order to make the skill-intensity levels compatible with the regional VA at the industrial level, every worker \( l \) in each industry \( s \) and located in a region \( r \) is allocated to a quintile \( k = 1, \ldots, 5 \).9 To build a \((K \times NR)\) matrix \( F \), we use these five skill-intensive levels to disaggregate the regional VA according to the labour sophistication embedded in production (Timmer et al., 2019) and to the wage bill distribution for \( r \) and \( i \).10

In order to identify spatial heterogeneities, we grouped the firms into three size brackets (small, medium and large) in each industry, with one-third of the total employment each. To avoid the composition problem, we determined the three firm sizes at the five-digit level of the Brazilian National Classification of Economic Activities.11 We then aggregated the results for the 67 industries of the IRIO system. Table 2 displays the average wage level associated with the \( k\) skill-intensity levels and firm sizes by region. As expected, the wage level significantly increases with skills involved in the productive process, irrespective of firm size. The wage difference is wider in small firms and smaller in large firms, in general.

Figure 1 shows the regional distribution of high-skilled workers in Brazil. The left-hand map indicates that most of these employees are concentrated in the dense Southeastern labour markets; the right-hand map shows their share in total employment. Interestingly, high-skilled occupations make up more than 11% of São Paulo state’s employment, while some states have very small shares (the Federal District and the Northern states of Amapá, Acre and Roraima represents 0.74% of the national labour market).

Figure 2 shows the relationship between the skill level and share of VA by large industrial groups at the national level (for details, see the supplemental data online). The first graph shows the average of the top 20 skill levels by industry, and the second graph the bottom 20. There is concentration of VA in tertiary activities (such as S41, S53, S40 and S52). The level of sophistication is highest in education (S61), health (S63), scientific activities (S56) and financial intermediation (S52).

The next section shows the results of the breakdown of LTiVA into the five skill-intensive levels and presents a discussion of the functional specialization in trade at the subnational level.
This section presents the results for the interregional and international LTiVA for \( k \) levels of skill intensity and the functional specialization measures. Section 4.1 details the spatial structure of workflows in local VA trade for domestic value chains, identifying the main spatial patterns of the implicit content of local labour skills embedded in trade. Section 4.2 considers the labour factor content in the VA exports. Section 4.3 incorporates firm size differences to assess how regional business structures integrate domestic and international VA trade measures.

### 4.1. Skill-based LTiVA at the interregional and international levels

Table 3 shows the distribution of bilateral LTiVA for the regions by skill-intensity levels. The Southeastern states account for 56% of the regional origin of VA, followed by the South (17%), indicating a highly concentrated pattern. On average, 26% of aggregate outflows (sum of regional results) are associated with occupations with low and medium-low skill intensity. The share of domestic LTiVA is highest in the top skill-intensity brackets in all regions, but the distribution varies across states, indicating uneven territorial capabilities. In the rich Southeast region, 61% of LTiVA comes from mid-high and high-intensity levels, while it does not reach 50% in the other regions. As for the states, the positive highlights\(^{12}\) for the relative share of the sum of medium-high and the highest intensity levels are strongly concentrated in São Paulo (38.45%), Rio de Janeiro (12.13%) and Distrito Federal (8.01%), while the average of the rest of states stands at 4%. The main finding here reveals that sophisticated functions are associated with richer and more diversified Brazilian states. Generally, these regions have dense and specialized economic centres that occupy intensive-knowledge human capital and have the highest ratio of wage bill to VA. Hence, this pattern is consistent with the concentration of high-tech industries, innovative industries and educational poles in Southeastern Brazil. It is also associated with regional
Figure 1. Regional distribution of higher skill-intensity levels.  
Source: Authors based on Annual Social Information Relation (RAIS) raw data (2020).
Figure 2. Average value added at the state level and average skills by Brazilian National Accounts System (NAS) industry.

Source: Authors based on Annual Social Information Relation (RAIS) raw data (2021).

(a) Top 20 skill-level by SCN industries

(b) Bottom 20 skill-level average by SCN industries
Table 3. Regional distribution of skill-intensity in Domestic Value Chains outflows (BRL millions).

| Macrozone | Federal Unity | Skill-intensity level | Total TiVA for DVC by origin |
|-----------|---------------|-----------------------|-------------------------------|
|           |               | Low (%)               | Medium-low (%)                | Medium (%)                   | Medium-high (%)              | High (%)                     | Total TiVA (%)   |
| North     | RO            | 533 13%               | 1100 26%                      | 957 23%                      | 810 19%                      | 830 20%                      | 4231 0%          |
|           | AC            | 124 11%               | 178 16%                       | 202 18%                      | 255 23%                      | 343 31%                      | 1103 0%          |
|           | AM            | 1689 12%              | 2404 17%                      | 2749 20%                     | 3093 22%                     | 4126 29%                     | 14,060 2%        |
|           | RR            | 73 10%                | 57 8%                         | 144 19%                      | 141 19%                      | 328 44%                      | 743 0%           |
|           | PA            | 1569 18%              | 1547 17%                      | 1612 18%                     | 2011 23%                     | 2127 24%                     | 8865 1%          |
|           | AP            | 93 10%                | 187 19%                       | 169 18%                      | 117 12%                      | 393 41%                      | 960 0%           |
|           | TO            | 451 13%               | 547 16%                       | 631 19%                      | 807 24%                      | 927 28%                      | 3364 0%          |
|           | Total         | 4532 14%              | 6020 18%                      | 6465 19%                     | 7233 22%                     | 9075 27%                     | 33,325 4%        |
| Northeast | MA            | 1084 12%              | 1193 13%                      | 2366 26%                     | 1843 20%                     | 2730 30%                     | 9216 1%          |
|           | PI            | 513 10%               | 657 13%                       | 843 17%                      | 1191 24%                     | 1851 37%                     | 5054 1%          |
|           | CE            | 2181 15%              | 1958 14%                      | 2117 15%                     | 4013 29%                     | 3809 27%                     | 14,077 2%        |
|           | RN            | 852 12%               | 823 12%                       | 1152 17%                     | 1768 26%                     | 2248 33%                     | 6842 1%          |
|           | PB            | 1051 14%              | 911 12%                       | 1199 16%                     | 2102 29%                     | 2094 28%                     | 7357 1%          |
|           | PE            | 3609 16%              | 3089 14%                      | 3460 16%                     | 4967 22%                     | 7143 32%                     | 22,269 2%        |
|           | AL            | 1540 24%              | 837 13%                       | 1166 18%                     | 1535 23%                     | 1471 22%                     | 6549 1%          |
|           | SE            | 632 13%               | 665 14%                       | 920 19%                      | 1349 28%                     | 1298 27%                     | 4865 1%          |
|           | BA            | 4993 17%              | 4510 15%                      | 5386 18%                     | 6583 22%                     | 8650 29%                     | 30,123 3%        |
|           | Total         | 16,454 15%            | 14,643 14%                    | 18,610 17%                   | 25,352 24%                   | 31,293 29%                   | 106,352 12%      |

(Continued)
Table 3. Continued.

| Regions | Skill-intensity level | Total TiVA for DVC by origin |
|---------|-----------------------|-----------------------------|
|         | Low (TiVA) (%) | Medium-low (TiVA) (%) | Medium (TiVA) (%) | Medium-high (TiVA) (%) | High (TiVA) (%) | Total TiVA (%) |
| Macrozone | Federal Unity | | | | | |
| Southeast | MG | 10,087 15% | 10,556 16% | 11,438 17% | 15,516 23% | 20,235 30% | 67,831 7% |
| | ES | 2082 14% | 2214 14% | 2603 17% | 3670 24% | 4772 31% | 15,342 2% |
| | RJ | 9000 10% | 10,103 11% | 11,761 12% | 25,639 27% | 38,187 40% | 94,690 10% |
| | SP | 38,125 12% | 39,327 12% | 48,711 15% | 67,405 21% | 134,844 41% | 328,412 36% |
| Total | Southeast | 59,294 12% | 62,200 12% | 74,512 15% | 112,230 22% | 198,038 39% | 506,275 56% |
| South | PR | 10,892 18% | 8661 14% | 11,305 18% | 12,472 20% | 18,849 30% | 62,179 7% |
| | SC | 7772 20% | 5757 14% | 7381 19% | 8275 21% | 10,673 27% | 39,858 4% |
| | RS | 8689 17% | 7369 14% | 8971 17% | 9912 19% | 16,739 32% | 51,681 6% |
| Total | South | 27,353 18% | 21,787 14% | 27,657 18% | 30,660 20% | 46,261 30% | 153,718 17% |
| Midwest | MS | 2077 17% | 1652 14% | 2264 19% | 2969 25% | 2931 25% | 11,893 1% |
| | MT | 2717 19% | 1923 14% | 3420 24% | 3098 22% | 2991 21% | 14,148 2% |
| | GO | 4213 17% | 4216 17% | 4970 20% | 5312 21% | 6476 26% | 25,187 3% |
| | DF | 2487 4% | 3844 7% | 9464 16% | 14,263 25% | 27,853 48% | 57,911 6% |
| Total | Midwest | 11,494 11% | 11,634 11% | 20,119 18% | 25,641 23% | 40,251 37% | 109,139 12% |
| Brazilian TiVA | 119,128 13% | 116,284 13% | 147,362 16% | 201,116 22% | 324,919 36% | 908,809 100% |

Note: The content of the labour factor embedded in DVC is computed. The lines show the total labour-based value-added embedded in interregional trade by each source state. For each skill-intensity level, the values along the columns show the relative share of each state in the total.

TiVA, trade in value-added.

Source: Authors, 2021.
Figure 3. Bilateral interregional trade in value-added (TiVA) flows (by Brazilian macro-regions).
Note: Bilateral flows of labour content in value added (VA) are shown broken down into three skill intensities levels: (a) low, (b) medium and (c) high. By deduction of the hypothetical extraction method (HEM) technique, intra-state flows are excluded, computing only bilateral flows (origin–destination, and vice versa). On the right side of each bar is the acronym of the Brazilian macro-regions. Source: Authors, 2021.
Table 4. Skill-intensity in value-added exports.

| Regions | Macrozone | Federal Unity | Skill-intensity level | Value-added exports Distribution |
|---------|-----------|---------------|-----------------------|---------------------------------|
|         |           |               | Low (TiVA (%)) | Medium-low (TiVA (%)) | Medium (TiVA (%)) | Medium-high (TiVA (%)) | High (TiVA (%)) | Total TiVA (%) |
| North   | RO        | 205           | 17%              | 145                   | 10%              | 173                   | 16%              | 130               | 7%              | 94               | 5%              | 746               | 10%               |
|         | AC        | 3              | 0%               | 3                     | 0%               | 4                     | 0%               | 3                 | 0%              | 2                | 0%              | 15               | 0%                |
|         | AM        | 151            | 12%              | 168                   | 12%              | 128                   | 12%              | 185               | 9%              | 216              | 11%             | 848              | 11%               |
|         | RR        | 2              | 0%               | 1                     | 0%               | 1                     | 0%               | 1                 | 0%              | 1                | 0%              | 6                | 0%                |
|         | PA        | 750            | 62%              | 1040                  | 72%              | 672                   | 64%              | 1545              | 79%             | 1585             | 81%             | 5592             | 73%               |
|         | AP        | 14             | 1%               | 16                    | 1%               | 7                     | 1%               | 13                | 1%              | 9                | 0%              | 59               | 1%                |
|         | TO        | 92             | 8%               | 67                    | 5%               | 66                    | 6%               | 72                | 4%              | 50               | 3%              | 348              | 5%                |
| Total   |           | 1218           | 14%              | 1440                  | 18%              | 1051                  | 19%              | 1948              | 22%             | 1958             | 27%             | 7615             | 4%                |
| Northeast | MA        | 185            | 12%              | 148                   | 13%              | 152                   | 25%              | 177               | 20%             | 163              | 30%             | 825              | 9%                |
|         | PI        | 41             | 10%              | 32                    | 13%              | 33                    | 17%              | 36                | 24%             | 25               | 37%             | 167              | 2%                |
|         | CE        | 488            | 15%              | 196                   | 14%              | 169                   | 15%              | 252               | 29%             | 262              | 27%             | 1368             | 15%               |
|         | RN        | 59             | 12%              | 45                    | 12%              | 41                    | 17%              | 56                | 26%             | 41               | 33%             | 242              | 3%                |
|         | PB        | 91             | 14%              | 20                    | 12%              | 16                    | 16%              | 27                | 29%             | 27               | 28%             | 182              | 2%                |
|         | PE        | 216            | 16%              | 132                   | 14%              | 130                   | 16%              | 209               | 22%             | 224              | 32%             | 910              | 10%               |
|         | AL        | 358            | 24%              | 70                    | 13%              | 91                    | 18%              | 93                | 23%             | 86               | 22%             | 698              | 8%                |
|         | SE        | 43             | 13%              | 22                    | 14%              | 22                    | 19%              | 25                | 28%             | 22               | 27%             | 133              | 1%                |
|         | BA        | 970            | 17%              | 683                   | 15%              | 628                   | 18%              | 1045              | 22%             | 1074             | 29%             | 4400             | 49%               |
| Total   |           | 2451           | 15%              | 1348                  | 14%              | 1282                  | 17%              | 1920              | 24%             | 1924             | 29%             | 8926             | 4%                |
|                | MG    | 15% | 2804 | 16% | 2839 | 17% | 3961 | 23% | 4854 | 30% | 17,256 | 13% |
|----------------|-------|-----|------|-----|------|-----|------|-----|------|-----|--------|-----|
| SE             | 566   | 14% | 672  | 14% | 642  | 17% | 1165 | 24% | 1249 | 31% | 4294   | 3%  |
| RJ             | 2827  | 10% | 2780 | 11% | 3558 | 12% | 7707 | 27% | 9386 | 40% | 26,259 | 19% |
| SP             | 13,236| 12% | 11,756| 12% | 13,644| 15% | 18,020| 21% | 31,587| 41% | 88,243 | 65% |
| Total          | 19,428| 12% | 18,012| 12% | 20,682| 15% | 30,853| 22% | 47,077| 39% | 136,052| 68% |

|                | PR    | 18% | 2125 | 14% | 2468 | 18% | 2575 | 20% | 3182 | 30% | 13,501 | 36% |
| South          | SC    | 20% | 1557 | 14% | 1872 | 19% | 1905 | 21% | 1921 | 27% | 9613   | 26% |
|                | RS    | 17% | 2371 | 14% | 2459 | 17% | 2784 | 19% | 3490 | 32% | 14,418 | 38% |
| Total          | 8823  | 18% | 6053 | 14% | 6799 | 18% | 7263 | 20% | 8593 | 30% | 37,532 | 19% |

|                | MS    | 17% | 326  | 14% | 393  | 19% | 393  | 25% | 357  | 25% | 2105   | 22% |
| Midwest        | MT    | 19% | 578  | 14% | 892  | 24% | 892  | 22% | 708  | 21% | 4259   | 45% |
|                | GO    | 17% | 490  | 17% | 560  | 20% | 560  | 21% | 543  | 26% | 2848   | 30% |
|                | DF    | 4%  | 46   | 7%  | 50   | 16% | 50   | 25% | 61   | 48% | 285    | 3%  |
| Total          | 2596  | 11% | 1440 | 11% | 1895 | 18% | 1895 | 23% | 1669 | 37% | 9496   | 5%  |

| Total labour-based TiVA | 34,517 | 13% | 28,293 | 13% | 31,709 | 16% | 43,880 | 22% | 61,221 | 36% | 199,620 | 100% |

Note: The content of the labour factor embedded in value-added exports is considered. The lines show the total labour-based value-added embedded in exports traded by each Brazilian state of origin. For each skill-intensity level, the values along the columns show the relative share of each Brazilian state in the national total. TiVA, trade in value-added. Source: Authors, 2021.
technological progress and workforce quality, which could reinforce the strength of the local VA embedded in production and trade (Boschma et al., 2014).

The states in the Northern region have intense LTiVA outflows in activities with less skill intensity. This is related to the industrial composition of the region, which is characterized by low-skill activities (agriculture, livestock, mining) and poor integration with the rest of the

**Figure 4.** Skill-based specialization at the region aggregation for domestic and foreign destinations. Source: Authors, 2021.
country (long distances, lack of roads). Some Northern states are more integrated into global markets, as we will see in the next section. In the Northeast, approximately 29% of LTiVA outflows are based on low and medium-low levels of labour sophistication. The positive highlights in

Figure 5. Specialization index for Domestic Value Chains at different firm sizes and skill-intensity levels.
Source: Authors, 2021.
the region are the states of Alagoas (36%, exports of sugar) and Bahia (32%, with a more diversified economy). The states in the Midwest concentrate on the production of agricultural commodities and livestock and also show large shares of low and medium-low skills embedded in the Domestic Value Chains (DVC).

The South region shows 32% of low and medium-low skills and 50% of medium-high and high skills. Even though the region exports resource-oriented goods, its industrial mix is diversified enough to transform the raw material produced regionally into intermediate goods of higher labour payments in terms of VA. This complementarity is markedly different from the North and Midwest, which also display a favourable geography for exploiting natural resources. Their states have not reached sufficient capacity to promote a level of vertical integration that could upgrade their participation in subnational production chains.

At country internal level, the geography of VA trade essentially involves national suppliers that meet interregional demand, indicating different competitiveness situations, potentially blocking the functional upgrading of other areas. The limitation of linkages implies skill-intensity levels dispersed at the national level and concentrated at the regional perspective. Figure 3 shows the bilateral flows of three skill-intensity levels and illustrate how the interregional flows are concentrated spatially. Figure 3a indicates that bilateral flows of low-skill content are more dispersed than the other two skill levels. These are more concentrated in mid-skill activities (Figure 3b) and even more in high-skill activities (Figure 3c). The bilateral flows reveal the relative importance of the flows involving the Southeast and South regions, particularly the state of São Paulo, which clearly dominates in the mid- and high-skill levels. For the high-skill level, the Federal District can be considered a relevant source of labour sophistication transferred within Brazilian regions.

Table 4 shows the composition of LTiVA exports of states disaggregated by skill-intensity levels (the sum in each state in rows equals 1). For each macrozone, the share is computed in relation to the national total of labour content in VA exports. Despite the concentration of the volume of LTiVA in the Southeastern states (68% of the national), the differences in composition between skill levels demonstrate a productive profile with severe regional differences. In the Northeastern states, on average, 32% is related to low skills in VA exports, followed by the Northern states with 27% and the South with 24%. Interestingly, in the Southeastern states, this average drops to 14%. However, the inverse pattern is observed for high skills, where the average of the Southeastern states rises to 32%, while the North and Northeast both have 18%.

The connectivity patterns of regions with global markets provide useful elements for understanding their regional development pattern. Thus, when analysing skills as a source of regional specialization, a relevant differentiation is incorporated in the composition of VA exports, which goes beyond the economic activity perspective of companies. The main results point out that the states of São Paulo and Rio de Janeiro have more than 70% of the VA embedded in exports in the high-skill group, against the national average of 31%. This pattern is consistent with evidence on the spatial division of labour in the United States, Canada and Europe (Bade & Nerlinger, 2000; Brühlhart & Koenig, 2006; Desmet & Fafchamps, 2005; Duranton & Puga, 2005; Polèse & Shearmur, 2006) In an opposite pattern, poorer peripheral regions exhibit a higher share of less skill-intensive activities and, consequently, lower wages. In contrast, high VA activities require locations with more variety and complexity of activities, allowing them to engage in activities with medium-high and high skill-level requirements (Iammarino & McCann, 2013; McCann & Mudambi, 2005; McCann & Ortega-Argilés, 2015).

A set of industrial activities requiring sophisticated skills concentrate in large economic spaces—in this case, the Southeast region. Smaller regions concentrating on the export of primary goods present another pattern. Their economies depend on activities processing natural resources, while the provision of the complementary services they demand is usually concentrated in large regional
centres or even in distant regions. As a result, the poor and peripheral states have higher shares of LTiVA for exports at lower skill levels. Comparing the composition of all LTiVA along the five skills levels, some states have higher shares for exports at lower skills, such as Alagoas, 51%, Paraíba, 50%, and Ceará, 36%, against a national average of 24%. The lower degree of labour sophistication potentially restricts their potential development opportunities related to the global level trade integration.

4.2. Regional functional specialization by skill intensity and firm size

This section presents the results for both domestic and international final-demand uses and disaggregated by firm size across regions. First, we have computed the skill-based specialization for LTiVA for domestic and international destinations, according to equation (10), in Figure 4. To avoid the problem of aggregation, we use the sum of regional results (Miller & Blair, 2009). Values > 1 indicate specialization and can be taken as a vertical integration measured at the sub-national level (the horizontal line is set at the unity). In the upper panel of Figure 4, we show the specialization indices for interregional trade, while in the lower part of Figure 4, the results for labour content in the exported VA. The regional results reveal a clear spatial divide: the North, South and Northeast regions specialize in the low and medium-low skill-intensity levels for both domestic and VA exports levels, while the Southeast and Midwest regions present functional specialization at the medium-high and the highest level of labour sophistication in both scales of VA trade flows. In relation to the VA exported, only the Southeastern region specializes in a high level of labour sophistication, while the North presents specialization in medium-high intensity level.

Second, we have computed the specialization index disaggregating by three firm sizes, as the structure of companies could play an important role in the functional specialization levels of regions. In particular, firm size might matter for the regional position in both domestic and international VA trade scales, as large companies tend to have stronger linkages in production networks and are more likely to adopt strategies that improve job quality (Baffour et al., 2020).

Furthermore, as firm size is essential in determining the potential to increase demand and supply linkages, firms were allocated to three size brackets with an equal number of employees. To avoid composition problems, the allocation was defined at a fine sectoral level (subclass). Figure 5 displays the results for interregional VA trade and VA exports. Given the previous results on the importance of the Southeast, we show its results separately in the top panel and for the rest of Brazil in the bottom panel. For subnational level, the specialization index increases with firm size for all skill levels in the Southeastern region and decreases considerably in the rest of the country. Specialization levels in the Southeast are higher for large firms for high skills but also for small and medium sizes for medium-high labour sophistication levels. The opposite happens in the aggregated results for the rest of the country, in which we have identified specialization for all firm sizes related to low, medium-low, medium and medium-high levels of labour sophistication. The rest of the country does not have specialization founded in high skills, independent of the firm size.

Regarding the VA exports (Figure 5b), as in the case of domestic VA trade, the specialization levels in the Southeast have been identified for all firm sizes for the medium-high and high skill-intensity levels. The results for the rest of the country present a similar profile of DVCs; however, it is possible to note that all firm sizes have specialization in lower skills levels groups.

5. CONCLUSIONS

This article presented new perspectives to understand the interdependence between the domestic and international VA trade levels in Brazil from a skill-based functional perspective. We provide empirical novelty by adding the analysis of TiVA at the subnational level, combining IO methods
with occupational data. The analysis of the labour factor content embedded in TiVA disaggregated by skill levels and firm size allowed a more detailed view of the connection of multiscalar linkages along with production value chain from a subnational point of view. When analysing skills as a source of regional specialization, a relevant differentiation is incorporated in the composition of VA, which goes beyond the economic activity perspective of companies. Moreover, the extension of the VA in trade approach applied to the subnational level allowed a deeper understanding of the effect of trade on development. We applied the methodological structure of the GVC framework, concerning the vertical integration analysis, industrial clusters and trade linkages, extending it for the interregional level. The results indicate that vertical integration depends on regional structures, including regional skill-based assets.

The paper contributes to the literature by pointing to the need to consider the subnational dimension to evaluate regional assets created and transferred through production value chains. Three main results are revealed. First, peripheral commodity exploiting economies, which generally have sparse industrial and business services infrastructure, are less intense in intersectoral and interregional linkages of more incredible domestic skills. In contrast, they have a more significant connection with international markets at lower skill-intensity levels, such as the mining-based states in Northern Brazil. Consequently, these regions, which are disconnected from sophisticated labour flows, become simple resource providers with a solid external orientation, as industrial capacities are less demanding of local skills in production and trade. Second, a dense economic space is concentrated in prosperous and more diversified areas, which are more articulated with functions based on medium and higher skills that further contribute to increasing the regional VA. These regions include globalized centres in the subnational economic structure, such as the great state of São Paulo and Rio de Janeiro in Southeastern Brazil. These economic spaces are more integrated with the world economy, in which the specialization indices reveal the efficiency of the use of sophisticated labour. In particular, the Southeastern states transferred more VA towards foreign markets and exhibited complex network profiles for trade multiscalar levels of trade integration. Third, there is an economic space for production structures based on intermediate and medium-high skills. They represent essential labour inputs for regions articulated with both subnational and global markets. These regions can increase the quality linkages and induce direct and indirect effects on the origin and throughout value chains, as is the case of Southern Brazil, some Northeastern states and Amazonas (North).

Although location and agglomeration economies explain the functional geographical patterns, our results point out there is space for design public policies that could favour the upgrading of industries, capital and labour requirements, mainly in the exporting peripheries. In this regard, while the geography of natural resources can act as a driver to reduce regional inequality, interregional and intersectoral linkages are likely to promote the opposite direction. Further, regional upgrading can be related to the increase in the skill intensity in the industries for production and trade, including exports. Performing more sophisticated business functions requires more skills, which is reflected in an increase in the quality (and value) transferred across networks. The appreciation of intersectoral linkages is related to the change in the production mix to goods and services with a higher VA. Therefore, the policy could improve the shifts for more VA sectors, such as agriculture and natural resource extraction to manufacturing and, subsequently, more modern manufacturing and business services sectors (Haddad & Araújo, 2021). Conversely, this upgrade will require demands on the sophistication of the factors of production that make up the local VA. Thus, for the resource peripheries, increasing the position in terms of VA requires coordination to increase the sophistication requirements of the inputs used in production and exports.

Regarding these functional upgrading strategies, it is essential to point out a limitation of the data used in this study. Our empirical exercise disregarded the informal labour market, which despite a lower level of direct involvement with value chains, can show relevant
information about the status of local skills. The labour component of the VA was disaggregated into skill levels based solely on the occupational composition of the formal market. Despite this restricting the analytical scope of functional specialization, it was possible to identify heterogeneities in the different subnational economic spaces and highlight the role of skills in the composition of regional labour markets. In this sense, it is relevant for public policy to increase workers’ skills as a mechanism for productive inclusion in the formal sectors, which can take into account the disparities in skills endowments at the subnational level in Brazil. This need is most evident in strongly resource-based regions engaged in international markets that do not perform equally in the domestic production chain. Furthermore, the integration in international markets is characterized by the predominance of medium to low skills, while core regions are suppliers of more skilled labour to these global networks. Finally, more studies are needed to identify the dynamic perspective of how to translate skills on regional competitiveness in multiscalar geographical scale of value chains (Pahl & Timmer, 2020; Tian et al., 2019).

ACKNOWLEDGEMENTS

We are very grateful to Dr Edivaldo Neves Júnior for kindly sharing with us his estimates of the skill-content levels for each code of the Brazilian Classification of Occupations (CBO). We greatly appreciate the collaboration of the Regional and Urban Economics Lab at the University of São Paulo (NEREUS-USP) for sharing the updated database of the IRIO table for the Brazilian economy. The corresponding author extends his thanks to professors Marcelo Lufin and Eduardo Haddad, who wisely showed the broad possibilities of input–output models for the regional science field, and to professors Augusto Alvim and Miguel Atienza for support during the research.

DISCLOSURE STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

FUNDING

This work was supported by the Fundação de Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) from the Brazilian Ministry of Education [grant number 001]; and by the Dirección General de Postgrado (Universidad Católica del Norte, Antofagasta, Chile).

NOTES

1 In this sense, analyses by Markusen (2007) in the United States show how the complementarity and differences between both industrial and occupational approaches allow one to understand regional inequality and economic development opportunities.

2 The authors proposed an interregional extension of the HEM method to measure embedded water content in interregional and international flows of the Moroccan economy.

3 Appendix I in the supplemental data online details the regional and sectoral structure.

4 In order to identify the occupation of each individual, we use a detailed database that covers the formal labour market. In this sense, informal professionals are excluded because they are not counted in the Ministry of Economy’s database that we adopted here. Likewise, the IRIO used seeks to represent the structure of the productive economy.
As defined by the Brazilian Classification of Occupations (CBO), which follows the International Classification of Occupation.

ONET is part of the US Department of Labor, Employment & Training Administration and it developed the standardization of related occupations in the labour market.

Maciente (2013) made a set of variables from the ONET compatible with 2702 occupations of the CBO, thereby obtaining a measure of the general level of skills required in the national formal labour market. Neves et al. (2019) derived a vector of intensity of skills required for each of the CBO codes.

The existence of matching in the labour market is assumed.

In general, the literature adopts the classic approach of the functional specialization of workers (Massey, 1984; Brunèse, 2008; Timmer et al., 2014, 2019). Our approach provides a more refined perspective when considering the type of worker’s occupation and the measurement of the degree of labour sophistication. In order to promote the discussion about different methodological perspectives to consider work in the VA, we show results in the supplemental data online that consider the standpoint of occupational groups according to the CBO classification itself.

For a complete list with the codes of occupations (CBO), the skill-intensity level and the respective quintiles, see the supplemental data online.

The IRIO data are aggregated in [AQ33] SCN, representing two and three digits of [AQ34] CNAE, whereas we classify companies and workers based on Annual Social Information Relation (RAIS) data, which detail the main activity of each company at the five-digit subclass CNAE.

The Distrito Federal (Brasília) shows a higher share. It hosts the federal government, and its economy gravitates around government-related activities. Its productive structure is atypical compared with the other states, as it shows the highest share of high-skill workers and wage levels in the country.

The state of Amazonas is an exception because it hosts a highly subsidized tax-free import zone located in a small area in the state capital city, Manaus. International manufacturing firms assemble imported parts into products delivered to the rest of the country.

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