Understanding Food Value Chain Labor Dynamics During Structural Transformation

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Abstract

This paper analyzes how labor markets within global food value chains (FVCs) evolve during structural transformation. We combine supply chain analysis with a novel structural decomposition framework to study annual FVC employment and worker compensation across 189 countries from 1993–2021. The findings suggest that primary production's employment share declines sharply with rising GNI per capita, while downstream FVC segments—processing, transportation, wholesale, retail, and hospitality—expand their labor shares in the broader economy. Despite the falling overall FVC employment share, payroll gaps between FVC and non FVC sectors narrow as workers move into better compensated downstream FVC roles and agricultural wages rise. While labor productivity gains and increased import penetration associated with structural transformation are negatively associated with FVC payroll, those effects are more than offset by the payroll and employment gains associated with rising food expenditures, including those related to the higher incomes arising from rising worker productivity and gains from international trade. Expenditure scale is the dominant factor explaining FVC labor expansion. Estimated payroll and employment elasticities are generally higher in upstream FVC sectors like primary production and processing in lower-income countries but higher in downstream, consumer-facing sectors like hospitality and retail in higher-income countries.

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1. Introduction

The structural transformation of food value chains (FVCs) arises through a combination of technological and institutional changes as well as growth and shifts in consumer demand that occur as incomes grow, populations urbanize, and domestic and global markets integrate. At early stages of development, FVCs are the dominant locus of employment and income generation in predominantly rural economies (Timmer, 2009; Mellor, 2017; Barrett et al., 2010, 2022). But FVC employment shares decline as growing incomes boost demand for non-food goods and services, rising productivity within food systems lowers labor intensity, and expanding non-food manufacturing and services absorb labor released from FVCs. This structural transformation has considerable FVC labor market implications (Barrett 2021; Barrett et al. 2022; Yi et al. 2025). Old jobs disappear while new ones get created at different FVC industry stages, and relative labor compensation adjusts as labor productivity and market integration evolve. Yet relatively little is understood about the within-FVC dynamics of this process, especially over extended periods nor on a global scale. This background paper builds on Yi et al.'s (2025) descriptive study of FVC labor dynamics over the course of structural transformation to further unpack the aggregate patterns and to explore heterogeneity across stages of development.

Yi et al. (2025) applies supply chain analysis (SCA) to decompose final consumer expenditures on food and agriculture into both FVC labor value-added and employment across six industries: primary production in agriculture, forestry and fisheries (AFF), food and beverage manufacturing and processing, transportation, wholesale trade, retail trade, and food service. SCA (Leontief, 1967; Canning, 2011) allows us to study the sequence of activities from primary production through various points of purchase to analyze factor market – including labor market – dynamics, covering direct employment and subcontracting activities (e.g., Cerilli, et.al., 2024; Yi, et.al., 2025). This study builds on that work by combining structural decomposition analysis (SDA) methods with SCA to study the dynamics of FVC labor market transformation. SDA (Rose and Casler, 1996; De Boer and Rodrigues, 2020) decomposes observed year-on-year changes in FVC employment and labor compensation into the share associated with each underlying driver – such as labor productivity, domestic self-reliance, and final consumer demand – by attributing the observed change to one factor at a time while holding the other factors fixed (Yang and Lahr, 2010; Roncolato and Kucera, 2014).

We use the global data framework described in Yi et al. (2025), which characterizes labor compensation, employment, and average worker compensation within FVCs by country, year, and final consumer sub-market—domestic retail (food at home, FAH), domestic food service (food and accommodations away from home, FAAFH[1]), and international exports (retail plus food service across all foreign markets)—for the six distinct FVC industries. This method works from final food demand upstream through the economy. This approach captures agricultural output that supports non-food intermediate demand within the FVC (e.g., ethanol used in FVC transportation and fiber used in FVC worker uniforms), but it omits agricultural output that supports non-food final consumer demand. This method also permits incorporation of indirect employment and associated compensation arising from subcontracting by FVC industries of service providers in other sectors (e.g., accountants or construction).

[1] Conceptually, we would prefer to focus strictly on food away from home (FAFH). We include accommodation services due to the nature of aggregation in the underlying national accounts data. As Yi et al. (2021) note, however, food represents the vast majority of FAAFH, even in high-income countries such as the United States, and the FAFH share of FAAFH varies relatively little over time.

We extend Yi et al. (2025) with a novel adaptation of SDA that decomposes observed year-on-year changes in FVC employment and total worker compensation (henceforth 'payroll'[2]) – measured for each country across consecutive years (e.g., Afghanistan from 2020 to 2021) - into six components: changes in (i) direct and (ii) subcontracting labor intensity (i.e., labor per unit output, the inverse of labor productivity) within a given FVC industry, changes in each sector's (iii) domestic self-reliance (i.e., the share of its product sourced from domestic production), and changes in final consumer food expenditures in each marketing channel: (iv) food at home, (v) food away from home, and (vi) exports to foreign markets. The former three largely reflect technological and institutional changes that affect labor dynamics within the FVC. For example, reduced self-reliance can reflect lowering of trade barriers, global supply chain restructuring, or differential productivity growth between domestic and foreign suppliers. Changes in labor intensity can similarly arise from technological change (e.g., new equipment that boosts labor productivity), from evolving management practices, even from shifts in commodity composition caused by shifting consumer demand where labor intensity varies by products. The latter three components reflect the composition and absolute level of (global) consumer food demand. This decomposition yields natural, testable hypotheses as one might reasonably expect different factors to be more or less important at different levels of gross national income per capita (GNIpc) and across different FVC industries.[3] We can test, for example, whether labor productivity gains have similar employment and compensation effects throughout the FVC and across income levels.

The combination of SCA with SDA unlocks the possibility of exploring these more nuanced questions about how FVC labor evolves over the arc of economies' structural transformation. By applying both SDA and SCA to globally comparable labor and input–output data spanning essentially the whole global economy over 29 years, our approach enables systematic empirical examination of how FVC labor markets evolve within and across countries and different FVC segments over an extended period. These methodological advances yield new empirical insights on the evolution of employment and compensation in FVCs as economies undergo structural transformation. These empirical analyses are necessarily purely descriptive, not causal. Phenomena such as shifts in labor productivity and in expenditure levels are fundamentally linked, with complex, potentially multidirectional causality among different factors associated with changes in FVC employment and compensation. These descriptive findings, however, shed new light on FVC labor dynamics under structural transformation and lay the foundation for future research designs to causally identify the mechanisms underpinning the patterns we report.

Nuanced descriptive analysis is crucial because many things change simultaneously over the course of structural transformation. Technological and institutional changes boost factor productivity, reducing labor intensity (i.e., increasing labor productivity) throughout the FVC. Labor productivity growth also translates into rising compensation per FVC worker but could also reduce the number of workers needed. The product of those two effects is total payroll expenditures, which could rise or fall, depending on which effect dominates. Rising incomes – partly arising from FVC labor productivity growth or supply chain restructuring associated with changing industry-level self-reliance, for example – boost total consumer food expenditures, but disproportionately in favor of FAAFH and imports, reflecting the relatively high expenditure elasticity of demand for convenience, quality, safety and variety attributes and the relatively low expenditure elasticity of demand for calories, at least beyond a low level of GNIpc (Barrett et al. 2022). Meanwhile, steady globalization over most of our study period – at least until the

[2] "Payroll" represents total worker compensation (the wage bill component of value added), not the labor share of sector value added.

[3] "Per capita income   proxies for stages of economic development. Geographic variation could be studied analogously but is not our focus.

tariff and trade wars that began in 2019 – increased the reliance of domestic FVCs on imports, both for intermediate inputs and in final markets. How those various, countervailing factors net out, and which ones matter most, is a key empirical question not well answered to date in the literature.

Our findings confirm the well-known empirical regularity that primary production's share of employment and of total FVC payroll costs decline sharply with economic development, as proxied by increasing GNIpc.[4] We likewise show, echoing Yi et al. (2025), that the share of payroll costs and employment in the five post-farmgate FVC industries grow as GNIpc rises through the upper-middle-income country (UMIC) range. Indeed, the economywide share of employment in post-farmgate value-adding sectors – processing, wholesale, transportation, retail and hospitality, inclusive of subcontracting – rises steadily over the low- and middle-income range before declining somewhat over the HIC range, reflecting an inverted-U shape. This appears a new stylized fact in the literature.

We then turn to three interrelated findings. First, although overall FVC employment falls as a share of economywide jobs, the gap between FVC and non-FVC payrolls does not expand. Even in low-income countries in which agriculture accounts for the largest sectoral employment share, total payroll expenditures outside FVCs exceed those within FVCs, reflecting the stark intersectoral gaps in average compensation per worker. But as workers switch from poorly compensated primary production work on farms, fisheries and forests to better-compensated jobs in post-farmgate FVC industries, and as AFF compensation rates converge on those of other sectors (Yi et al. 2025), the total payroll gap between FVC and non-FVC actually shrinks as GNIpc rises. The more than 2.2-fold gap in LLMICs between average worker compensation in non-FVC versus FVC jobs shrinks to less than a 40 percent premium in high-income countries even as the FVC's overall share of employment declines. Decomposing FVC payroll into its two underlying margins — the number of workers and compensation per worker — reveals two simultaneous shifts as countries develop: the workforce reallocates from low-paying AFF toward better-paying post-farmgate FVC industries, while per-worker compensation rises across all six FVC sectors. Jointly, these two shifts close much of the the FVC/non-FVC payroll gap.

Second, SDA decomposition reveals that growth in food expenditures outweighs productivity gains and globalization in accounting for FVC payroll and employment dynamics. Changes in FVC labor productivity and globalization (i.e., self-reliance) are both consistently, negatively associated with FVC payroll costs, although the productivity effects are far larger in magnitude than those arising from globalization, and labor productivity growth among a sector's subcontractors tends to boost employment in that sector. The main story, however, is that increased food expenditures associated with rising GNIpc have, by far, the strongest association with payroll and employment growth that, on average, more than offsets the declines directly associated with productivity growth and increased import dependence. Sectorally, the share of jobs in primary production (farming and fishing) declines, especially as labor productivity in AFF rises. But payroll declines much less rapidly as per worker compensation in primary production rises in response to labor productivity improvements. Meanwhile, employment grows in the better compensated downstream FVC industries, consistent with the expectation that expanding consumer demand for convenience, quality, safety, and variety drives growth in those FVC industries. These two shifts — reallocation toward FVC downstream sectors and rising compensation per worker through the FVC, especially in AFF — jointly account for the FVC/non-FVC payroll-gap convergence reported above.

Finally, the factors associated with FVC payroll and employment growth adjust systematically with structural transformation. Over lower income ranges, upstream FVC labor markets – in AFF and processing – respond most elastically to changes in factors strongly associated with labor market

[4] We emphasize that the central findings relate to shares; absolute, real payroll expenditure and even employment levels may rise as incomes and total food demand grow.

dynamics (i.e., productivity, globalization, market scale), as per capita incomes rise. By contrast, in higher-income countries, the downstream sectors – hospitality and retail, in particular – become most responsive, presumably reflecting the relative income elasticities of demand for convenience, quality, safety and variety attributes in food. The overall picture is that FVC labor responsiveness – both negative in response to, for example, productivity gains, and positive in response to growth in downstream market scale – moves downstream along with FVC workforce as incomes rise.

2. Data

The primary data source for payroll expenditures, used to estimate labor value added, is the Eora global Multi-Regional Input-Output (MRIO) data.[5] The Eora dataset offers a comprehensive, annually updated compilation of economic activity data at the country and industry levels, including trade flows with other countries. More specifically, we use the Eora26, Eora full tables, and the Eora transportation margin tables. These cover 189 countries—listed in Appendix Table A1—annually from 1993-2021. These data cover 99% of the global economy in 2021. Eora26 is a harmonized classification with 26 sectors —listed in Appendix Table A2— derived from the more detailed sectors present in the Eora full tables which we refer to as 'Eora sectors' hereafter. The aggregation of these sectors from the detailed sectors available in the Eora full tables is documented in a concordance table provided by Eora. In this paper, we combine the agriculture and fishing sectors into a single primary production sector, reducing our economywide accounts to 25 industry aggregates. The quality and reliability of the Eora dataset have been thoroughly examined and discussed in Moran and Wood (2014). The processed data are described in Yi et al. (2025), which also makes available the underlying, processed expenditures data set described below.

As an MRIO account, exports from all countries directly enter the domestic supply chains of all countries to which commodities are exported. Trade enters every calculation across all three marketing channels—food at home (FAH)—i.e., the food retail sector— food and accommodations away from home (FAAFH) – i.e., the hospitality sector—and Exports. For FAH and FAAFH, all domestic production includes imported inputs which enter the domestic supply chains across all commodity categories through all domestic industries. The exports marketing channel measures all domestic farm and food production that is directly marketed to other countries' FAH or FAAFH food consumers. For each year, global FVC value added is the sum of Exports, FAH and FAAFH.[6] This yields a balanced panel of 5,481 total country-year pairs covering 189 countries' payroll expenditures – i.e., the share of industry value added that accrues to labor – for each of the 29 years from 1993 to 2021. Note that the MRIO accounts may underestimate labor value added – especially in LLMICs – insofar as the share of value added counted as mixed income—that is, non-wage compensation earned by households or profits earned by household enterprises—falls steadily as income per capita rises (Yi et al. 2025). This can result in slight upward bias in the estimated relationship between the labor share of total AVC value addition and GNIpc.

We match the money metric payroll expenditures data with headcount employment data sourced from the International Labor Organization (ILO).[7] The ILO obtains national-level employment data from nationally reported sources and modeled estimates, primarily collected from Labor Force Surveys and Population Censuses, supplemented by data gathered from household surveys. ILO employment data include both paid and self-employed working age people, defined as age 15 and above, both formal and

[5] The data are available from https://worldmrio.com/. We use them under a data use agreement with the provider.
[6] Our analysis does not quantify jobs and pay linked to sector outputs exported and used as intermediate inputs to non-domestic food and hospitality production.
[7] Specifically, we use data downloaded from ILOSTAT Data Explorer: Employment by economic activity – ISIC level 2 (thousand) – Annual, accessed on 1 March 2024 (https://ilostat.ilo.org/data/).

informal laborers. The ILO data do not account, however, for either variation in hours worked nor for anything other than primary jobs. Insofar as workers' likelihood of having secondary, tertiary or seasonal jobs or underemployment may be associated with GNIpc, variation in these headcount primary employment numbers may either over- or under-estimate variation in total hours worked across all jobs and in the association of employment with income levels.[8] The ILO data cover 154 countries annually from 1993-2021, as identified by an asterisk in Appendix Table A1. The Eora26 data are mapped to the ILO employment data using the codes from ILO - ISIC revision 3.1 (see Yi et al. 2025 for details on the merger of Eora26 data with ILO data). This matching yields an unbalanced panel of 2,884 total country-year pairs covering 114 countries' employment from 1993 to 2021.

We use GDP deflator data sourced from the World Bank to generate constant price series and GNI per capita (GNIpc) data from the sources to classify countries by income group.[9] We use World Bank income group classifications of each country-year observation, allowing countries to shift groups over time (unless indicated otherwise for a specific analysis). In employment analyses, we group low- and lower-middle income countries (LLMICs) together because of sparse employment data availability for many years for the low-income group.

3. Input-Output Decomposition Methods

In this section, we first explain the input-output multiplier approach employed to analyze FVC labor markets. Next, we describe how we adapt this input-output application to FVC supply chain analysis. Subsequently, we explain the application of the SDA method to study the dynamics of year-on-year changes in FVC employment and worker compensation (i.e., payroll expenditures).

3.1 Input-Output Multiplier Analysis of FVC Labor Markets

To apply multiplier analysis of global FVCs, the Eora26 (E26) MRIO data are consolidated to 25 industry aggregates (agriculture and fishing are aggregated into a single industry sector) and reorganized into industry-by-industry input-output (IO) accounts for each country-year pair in the Eora source data:

$$\mathbf{E25}^{c\times t} = \begin{bmatrix} \mathbf{Z}^{c\times t} & \mathbf{Y}^{c\times t} \\ \mathbf{Vm}^{c\times t} & \end{bmatrix}, \forall\, c \times t \in C \times T \quad (1)$$

We redefine the $\mathbf{E26}^{c\times t}$ of Yi, et.al (2025) to represent a single country annual IO account aggregated from the source Eora26 MRIO annual data. Submatrix **Z** reports all inter-industry transactions among the S industry aggregates (see Appendix Table A2 for a list of the 25 sector classification of the Eora26 database) for country $c \in C$ in year $t \in T$ (see Appendix, Table A1 for lists of countries). Submatrix **Y** represents all final demand in the domestic economy enumerated into products of S industry aggregates (rows) and partitioned across J institutional spending categories (columns) such as household, government, and global (non-domestic) institutions. This study focuses on total food and beverage final market spending, **Yf**, which is further partitioned into three non-overlapping marketing channels; **yfah** (domestic FAH, or retail food sales), **yfaafh** (domestic FAAFH or domestic hospitality sales), and **yexp** (food retail and hospitality export sales). Submatrix **Vm** represents all gross domestic income (**V**) in the

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[8] Davis et al. (2023, 2026) carefully document the extent of such differences by comparing household survey data from a number of countries with the ILO data. They find considerable cross-country variation in the difference between ILO employment data and their estimates of 'engagement' (i.e., employment adjusted for hours worked and non-primary employment), with engagement exceeding employment and by more in LLMICs than in HICs, on average. Note that engagement only captures direct employment, not indirect employment arising due to subcontracting which rises sharply with GNIpc with FVCs (Yi et al. 2025).

[9] Accessed from the World Bank Open Data repository (https://data.worldbank.org/indicator) on 8 March 2024.

economy plus total international imports into the economy (**m**), each enumerated across the 25 industry aggregates (columns). Gross domestic income (GDI) is partitioned into income categories (rows) including labor income (row 1 of **Vm** matrix) and all remaining gross factor incomes denoted as gross operating surplus (row 2 of **Vm** matrix). Imports from non-domestic sources are grouped by the same 25 global industry aggregates and are reported across row 3 of the **Vm** matrix.

Accounting identities of a balanced IO account as specified in equation 1 are well established (see Chapters 2 and 6 in Miller and Blair, 2022). These include the identities for measuring total payroll (**w**) and jobs (**e**) linked to total final demand, and by application of the linear homogeneity property, linked to all final market food and beverage sales (suppressing *c×t* superscripts for clarity)[10]:

$$\mathbf{w\_yf} = \boldsymbol{\omega}'' \times \mathbf{d}'' \times \mathbf{L} \times \mathbf{Yfs} \times \mathbf{yfb} \tag{2}$$

$$\mathbf{e\_yf} = \boldsymbol{\varphi}'' \times \mathbf{d}'' \times \mathbf{L} \times \mathbf{Yfs} \times \mathbf{yfb} \tag{3}$$

To the right of equalities in equations 2 and 3, **L** is the total requirement multiplier matrix that converts total final demand (**Y**) or any subset such as **Yf** into the gross availability (domestic production plus import) requirements, denoted **xf**, to accommodate final demand. **Yf** is as defined above and comprises column vectors for **yfah**, **yfaafh**, and **yexp**. In equations 2 and 3 **Yf** is restated as the matrix product of **yfb** (total food budgets) by marketing channel and **Yfs (**budget shares) among the 25 industry aggregates (rows) by marketing channel (columns). The **d** multiplier converts gross availability (**x**) into measures of domestic production across the 25 industry outputs. Payroll and employment multipliers measure salaries and jobs per unit of availability (**ν** and **ϵ**) or per unit of domestic production (**ω** and **φ**). These multipliers are compiled as follows:

$$\mathbf{d}^{c\times t} = \{(\mathbf{x}^{c\times t})''\}^{-\mathbf{1}} \times (\mathbf{x}^{c\times t} - (\mathbf{m}^{c\times t})') \tag{4}$$

$$\boldsymbol{\nu}^{c\times t} = \{(\mathbf{x}^{c\times t})''\}^{-\mathbf{1}} \times \mathbf{V}^{c\times t}[1,*]' \tag{5}$$

$$\boldsymbol{\omega}^{c\times t} = \{(\mathbf{d}^{c\times t})''\}^{-\mathbf{1}} \times \boldsymbol{\nu}^{c\times t} \tag{6}$$

$$\boldsymbol{\epsilon}^{c\times t} = \{(\mathbf{x}^{c\times t})''\}^{-\mathbf{1}} \times \mathbf{e}^{c\times t} \tag{7}$$

$$\boldsymbol{\varphi}^{c\times t} = \{(\mathbf{d}^{c\times t})''\}^{-\mathbf{1}} \times \boldsymbol{\epsilon}^{c\times t} \tag{8}$$

$$\mathbf{yfb}^{c\times t} = (\mathbf{i}_{25}' \times \mathbf{Yf}^{c\times t})' \tag{9}$$

$$\mathbf{Yfs}^{c\times t} = \mathbf{Yf}^{c\times t} \times \{(\mathbf{yfb}^{c\times t})''\}^{-1} \tag{10}$$

$$\mathbf{L}^{c\times t} = \{\mathbf{i}_{25}'' - \mathbf{Z}^{c\times t} \times \{(\mathbf{x}^{c\times t})''\}^{-1}\}^{-1} \tag{11}$$

$$\mathbf{x}^{c\times t} = \mathbf{Z}^{c\times t} \times \mathbf{i}_{25} + \mathbf{Y}^{c\times t} \times \mathbf{i}_J \tag{12}$$

Multiplier vectors in equations 4 to 8 are of dimension 25×1 corresponding to the Eora26 industry groups after we combine agriculture and fishing. The food budget vector in equation 9 is of dimension 3×1 corresponding to the three marketing channels (two domestic and one export), and the budget shares matrix in equation 10 is of dimension 25×3 corresponding to the 25 industry aggregates and 3 marketing channels. The technology (also called the total requirement and Leontief) matrix in equation 11 is of dimension 25×25 representing total inter-industry transactions per unit of final demand ($\mathbf{Y}_{s,j}$ ϵ

[10] We use ′ to denote a transposed vector or matrix, ′′ to denote a diagonalized vector, $\{\}^{-1}$ to denote a matrix inversion, $\mathbf{i}_{\#}$ to denote a unit vector of dimension # which when transposed and pre multiplied produces matrix column sums and when post multiplied produces matrix row sums. Vectors are represented by bold lower-case letters, matrices by bold upper-case letters. Sets are denoted with italicized upper-case letters and set elements by italicized lower-case letters. Letters are from the Roman or Greek alphabet.

$\mathbf{Y}^{cxt}$). The total domestic availability vector in equation 12 is of dimension 25×1 corresponding to the Eora26 industry groups with agriculture and fishing combined.

Equations 2 and 3 are a typical specification for IO labor market studies. For example, accounting for the fact that parameters **Yfs** and **yfb** in equations 2 and 3 have both domestic market and export market elements, each of the variables in Yang and Lahr (2010) for their SDA study of the China labor market has a similar expression in equation 2 above, with some minor caveats. For example, the parameter designation '**P**' in Yang and Lahr (2010) represents domestic production for the domestic market as a share of domestic availability by industry (see Section 2 in Yang and Lahr 2010). In this report we use '**d**' to denote domestic production as a share of domestic availability by industry.

3.2 Food Value Chain Analysis

We adapt this IO application to a FVC analysis using the method of double inversion (Leontief, 1967; Canning, 2011; Cerilli, et.al, 2024; Yi, et.al., 2025). Preserving the full **E25** account defined in equation 1, data are split into two parts. All FVC industries that produce outputs and final deliveries of goods and services for domestic and global consumer food markets are combined in group 1. These include agriculture and fishing, food manufacturing goods production, wholesale, retail, transportation, and hospitality (food and accommodation) services production. All remaining industries are combined in group 2, and we call these subcontracting (*sub*) industries. The inclusion of subcontracting is important because as economies grow, specialization becomes more commonplace. As a result, the share of total FVC employment subcontracted – rather than employed directly within FVC industries – rises rapidly as GNIpc grows (Yi et al. 2025).

This partitioning of the system of equations produces the following restatement of equations (2) and (3):

$$\begin{bmatrix}\mathbf{w\_yf}_{fvc}\\ \mathbf{w\_yf}_{sub}\end{bmatrix}=\begin{bmatrix}\boldsymbol{\omega}''_{fvc}\times\mathbf{d}''_{fvc}\times\mathbf{L}_{fvc,fvc} & \boldsymbol{\omega}''_{fvc}\times\mathbf{d}''_{fvc}\times\mathbf{L}_{fvc,sub}\\ \boldsymbol{\omega}''_{sub}\times\mathbf{d}''_{sub}\times\mathbf{L}_{sub,fvc} & \boldsymbol{\omega}''_{sub}\times\mathbf{d}''_{sub}\times\mathbf{L}_{sub,sub}\end{bmatrix}\times\begin{bmatrix}\mathbf{Yfs}_{fvc,J}\times\mathbf{yfb}_J\\ 0\end{bmatrix} \tag{13}$$

$$\begin{bmatrix}\mathbf{e\_yf}_{fvc}\\ \mathbf{e\_yf}_{sub}\end{bmatrix}=\begin{bmatrix}\boldsymbol{\varphi}''_{fvc}\times\mathbf{d}''_{fvc}\times\mathbf{L}_{fvc,fvc} & \boldsymbol{\varphi}''_{fvc}\times\mathbf{d}''_{fvc}\times\mathbf{L}_{fvc,sub}\\ \boldsymbol{\varphi}''_{sub}\times\mathbf{d}''_{sub}\times\mathbf{L}_{sub,fvc} & \boldsymbol{\varphi}''_{sub}\times\mathbf{d}''_{sub}\times\mathbf{L}_{sub,sub}\end{bmatrix}\times\begin{bmatrix}\mathbf{Yfs}_{fvc,J}\times\mathbf{yfb}_J\\ 0\end{bmatrix} \tag{14}$$

Because only FVC goods and services are among final market sales, only the left quadrants of the middle-bracketed expressions above are relevant, and only the lower left quadrant has any cross-partition flows. We know that all outputs of subcontracting industries linked to *FVC* final demand are indirect demand of *FVC* industry production and so can be traced back to an *FVC* industry output. This facilitates application of the double inversion method to measure the augmented labor value added and jobs of each *FVC* industry "imputed through all the goods and services which the particular *FVC* sector receives from (subcontracting industries)" (Leontief, 1967). When applied to the labor payment equation, the reduced dimension restatement of equation 2 becomes:

$$\mathbf{w\_yf}^*_{fvc}=\mathbf{d}''_{fvc}\times\begin{bmatrix}\boldsymbol{\omega}''_{fvc} & \boldsymbol{\Omega}^*_{fvc,sub}\end{bmatrix}\times\begin{bmatrix}\mathbf{Xfs}_{fvc,J}\\ \mathbf{Xfs}_{sub,J}\end{bmatrix}\times\mathbf{yfb}, \tag{15}$$

where:

$$\boldsymbol{\Omega}^*_{fvc,sub}=\left\{\left(\mathbf{d}^{c\times t}_{fvc}\right)''\right\}^{-1}\times\left\{\mathbf{L}'_{fvc,fvc}\right\}^{-1}\times\mathbf{L}'_{sub,fvc}\times\mathbf{v}''_{sub}, \tag{16}$$

$$\mathbf{Xfs}_{fvc,J} = \mathbf{L}_{fvc,fvc} \times \mathbf{Yfs}_{fvc,J}, \tag{17}$$

$$\mathbf{Xfs}_{sub,J} = \mathbf{L}_{sub,fvc} \times \mathbf{Yfs}_{fvc,J} \tag{18}$$

Equation 15 distills the technical change impacts on payroll reported in equation 2. The augmented payroll productivity expression defined in equation 16 employs Leontief's double inversion procedure.[11] The product of the last two matrices in equation 16 ($\mathbf{L}'\times\mathbf{v}''$) distributes the per unit payroll of all subcontracting industries ($\mathbf{v}_{sub}$) among the *FVC* industries in proportion to the per-unit availability requirements of subcontracting industries. In turn, these values are redistributed among *FVC* industries based on the immediate technical interdependence among these industries as measured by the double inverted expression, $\{\mathbf{L}'_{FVC,FVC}\}^{-1}$. This inversion of a partition of the previously inverted total requirement matrix does not recover the pre-inverted partition. Rather, it captures the augmented technical interdependencies among *FVC* industries which includes intermediate purchases for subcontractors. Equations 17 and 18 translate budget unit final demand shares by marketing channel into availability requirements of *FVC* (equation 17) and *sub* (equation 18) products per final demand unit by marketing channel.

Similarly, the reduced dimension statement of derived demand for employment of equation 3 and the augmented employment productivity expression are as follows:

$$\mathbf{e\_yf}^{*}_{fvc} = \mathbf{d}''_{fvc} \times \left[\boldsymbol{\varphi}''_{fvc} \,\vdots\, \boldsymbol{\Phi}^{*}_{fvc,sub}\right] \times \begin{bmatrix}\mathbf{Xfs}_{fvc,J}\\ \mathbf{Xfs}_{sub,J}\end{bmatrix} \times \mathbf{yfb} \quad , \tag{19}$$

$$\boldsymbol{\Phi}^{*}_{fvc,sub} = \left\{\left(\mathbf{d}^{c\times t}_{fvc}\right)''\right\}^{-\mathbf{1}} \times \left\{\mathbf{L}'_{fvc,fvc}\right\}^{-1} \times \mathbf{L}'_{sub,fvc} \times \boldsymbol{\epsilon}''_{sub} \tag{20}$$

By way of example, consider equation 19 applied to the primary production (*fvc* = *AFF*) for FAH expenditures (*j* = *FAH*) in some fictional 2012 economy. Assume 90-percent of all marketed *AFF* product in 2012 for this country originated from domestic production ($\mathbf{d}_{AFF}$=0.9). Of the \$100 billion spent on food and beverages marketed in 2012 (**yfb**), total availability of *AFF* product required to accommodate the domestic *FAH* share of that \$100 billion was valued at \$0.3 billion ($\mathbf{Xfs}_{AFF,FAH} \times \mathbf{yfb}$), with 90 percent of this availability coming from domestic production ($\mathbf{d}_{AFF} \times \mathbf{Xfs}_{AFF,FAH}$ = \$0.27 billion). On average, the domestic *AFF* industry employed 25 workers per \$1 million in gross domestic output ($\boldsymbol{\varphi}_{AFF}$ = 25), so total domestic *AFF* employment linked to domestic *FAH* spending was 6,750 (25×0.27×1,000). Next, to illustrate equation 20, consider one of the 19 potential subcontracting industries, construction (*sub* = *A14*).[12] Of all the construction output in the 2012 fictional economy, total availability of construction services required to accommodate the domestic FAH spending is valued at \$0.01 billion ($\mathbf{Xfs}_{A14,FAH} \times \mathbf{yfb}$). Among *fvc* sectors only 10 percent of services are provided to the domestic *AFF* sector at a rate of 15 workers per \$1 million of construction services, so this amounts to 150 (15x0.01x1,000) subcontracted construction workers supporting the *AFF* industry. Recall from equation 19 that all *sub* industries potentially provide subcontracting workers to the *AFF* industry and each of these up to 18 other calculations are included in the construction calculations. The same applies to the other five *fvc* industries.

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[11] See equations 12 to 15 in Leontief (1967) for the steps of transforming the price equation, $\mathbf{p} = \mathbf{L}'\times\mathbf{v}$ (here $\mathbf{v}$ is redefined as a total value-added multiplier) into the augmented value-added expression in equation 16.

[12] See appendix table A2 for list of the 25 model sectors and recall six of these are *FVC* sectors (*A01T02, A04, A16, A17, A18, A19*).

3.3 Structural Decomposition Analysis (SDA)

We apply the SDA method (Rose and Casler, 1996; Dietzenbacher and Los, 1998; Su and Ang, 2012; DeBoer and Rodrigues, 2020) to formulate and study the dynamics of year-on-year changes in FVC employment and worker compensation (i.e., total payroll expenditures). The direct results, combined with regression analysis, allow us to evaluate the role of structural transformation in global FVC labor market outcomes using the MRIO data.

Our SDA approach compiles jobs and payroll data by sector for a sequence of consecutive years. From country-and-year-specific system of national accounts data we compile the components of our labor market calculations in equations of the form $\mathbf{y}^t = f(\mathbf{X}^t)$, where $\mathbf{y}^t$ is a vector of year t sector employment or payroll statistics and $\mathbf{X}^t$ is a matrix of period t sector (rows) variable factors (columns) that collectively determine employment or payroll[13]. For each FVC sector in each country of our panel dataset, our data sources allow us to measure (i) total domestic and global personal consumption of domestically produced food and hospitality products, (ii) total availability requirements of sector products, on average, to accommodate a unit of final demand for food and hospitality products for each of three marketing channels, (iii) the share of total sector products availability in the period that are domestically sourced, and (iv) the number of domestic jobs and payroll required by FVC sectors and their subcontractors, on average, per unit of FVC sector domestic production.

Because we work with historical data, the equation $\mathbf{y}^t = f(\mathbf{X}^t)$ is an identity for each period. We also know that for an infinitesimal time interval, $d\mathbf{y} \equiv \sum_j f' d\mathbf{X}_j$. Intuitively, changes to each factor are measured in the context of all remaining factors being held at the base period levels. For example, suppose period 1 availability requirements in sector i coexist with all other factor measures from period 0, and similarly for all other factors $j \in J$. Alternatively, suppose period 0 availability requirements in sector i coexist with all other factor measures from period 1, and similarly for all other factors $j \in J$. The former case amounts to compiling Laspeyres indices to measure the cumulative change and the latter case compiles Paasche indices for the same measure. For an infinitesimal interval both indices produce the same result with each factor change precisely measured and the sum of the J changes exactly equal the change in $\mathbf{y}$.

In practice, however, we can only observe changes over discrete time intervals, such as annual year-on-year changes. Further, some dependent and independent variables are in monetary units and are only available in nominal values such that combining changes in these variables with base values of other variables produces observations in different base year prices. Our SDA analysis overcomes these two limitations by first only using consecutive year data intervals and by applying a hybrid indexing method (Hoekstra & Van Den Bergh, 2002) to approximate instantaneous changes in constant prices, as follows:

$$\Delta\mathbf{y} \approx \sum_{j\in J}\left(\mathbf{z}_j^{\mathbf{0}} + \alpha\Delta\mathbf{z}_j\right)\Delta\mathbf{X}_{\boldsymbol{j}}\,, where\ \mathbf{z}_j^{\mathbf{0}} = \prod_{(j'\neq j)\in J}\mathbf{X}_{j'}^{\mathbf{0}} \qquad (21)$$

The $\mathbf{z}_j$ parameters of this index are weights that determine impacts of the change parameters ($\Delta\mathbf{X}_j$). They represent base year values for all other change parameters. Three well-known index number methods are represented in this equation: the Laspeyres (α=0), the Paasche (α=1), and a hybrid Marshall-Edgeworth (M-E) index (α=0.5). There are no ideal indexes for measurement of discrete changes that produce an exact solution to the above equation; however, SDA applications using the M-E indexing approach consistently produce results that represent roughly the mean value of solutions across all iterations of sequential changes to all change factors, $j \in J$ (Dietzenbacher and Los, 1998). Table 1 illustrates the mechanics of this calculation for agriculture, forestry, and fishing (AFF) jobs in the 2012-13

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[13] We use a simplified notation in this section where **y** represents any dependent variable, **X** represents all indepent variables, and **z** (see below) are weight parameters. In the formal statement of SDA that follows we use the parameters assigned in earlier equations.

Vietnam FVC. In this example, the SDA forecast captures 99.99 percent of measured job growth over the period.

AFF (i=1)	Domestic share of availability (j=1)	Direct jobs per $1,000 output (j=2)	Sub-contracting jobs per $1,000 output (j=3)	Gross AFF availability for food at home (j=4)	Gross AFF availability for food away from home (j=5)	Gross AFF availability for exported food and hospitality (j=6)
$\mathbf{X}^0$	0.9841	0.9065	0.0127	17,689,096	183,575	2,554,762
$\mathbf{X}^1$	0.9843	0.8211	0.0110	19,946,528	207,068	2,672,699
d$\mathbf{X}$	0.0002	-0.0853	-0.0017	2,257,433	23,493	117,937
$\mathbf{z}^0$	18,776,311	20,103,314	20,103,314	0.90	0.90	0.90
$\mathbf{z}^1$	18,995,242	22,468,998	22,468,998	0.82	0.82	0.82
d$\mathbf{z}$	218,931	2,365,684	2,365,684	(0.09)	(0.09)	(0.09)
$d\mathbf{y}_i/d\mathbf{X}_j$	4,040	(1,816,383)	(35,651)	1,945,598	20,248	101,645

Table 1. SDA Calculation Using Marshall-Edgeworth Index of 2012-13 Vietnam AFF Labor Market

Note: Bottom row total indicates an SDA forecasted 218,498 in AFF job growth within the FVC, compared to an observed 219,521 increase using conventional 2012 and 2013 employment multiplier analysis.

More formally, in order to characterize how total FVC payroll and jobs evolve over time we totally differentiate equations 15 and 19 with respect to time (*t*). Empirically we can only observe changes in both left- and right-side variables from equations 15 and 19 over discrete time periods (e.g., annually). To empirically attribute the relative contribution of the different change factors over time on the right side of equations 15 and 19, SDA provides an approximate decomposition whose values are not unique but depend on the order of change considered, except in the trivial case of only 2 right side factors. Dietzenbacher and Los (1998) demonstrate how an approach of taking the average of polar decompositions (APD) proves effective at approximating the average from the multitude of SDA measures distinguished by the order of change considered. Hoekstra and Van Den Bergh (2002) show how the APD approach is equivalent to applying the Marshall-Edgeworth (M-E) index measure to approximate instantaneous change over a discrete time interval. We adopt the APD approach and given the highly aggregated industry accounts in the Eora26 data we collapse the product of the last two matrices in equations 15 and 19, which produces the vector **xf = Xfs×yfb** of dimension 25×1. We note **xf** is the sum of availability requirements over three marketing channels and we can partition these distinct requirements in our SDA application.

The discrete time analog of total differentiation for equations 15 and 19 over time is:

$$\begin{aligned}\Delta\mathbf{w\_yf} &= [\Delta\boldsymbol{\omega}'' \times \mathbf{d}'' \times \mathbf{xf}] + [\Delta\boldsymbol{\Omega}^* \times \mathbf{d}'' \times \mathbf{xf}] + [\Delta\mathbf{d}'' \times (\boldsymbol{\omega}'' + \boldsymbol{\Omega}^*) \times \mathbf{xf}] \\ &\quad + [\Delta\mathbf{xfah}'' \times (\boldsymbol{\omega}'' + \boldsymbol{\Omega}^*) \times \mathbf{d}] + [\Delta\mathbf{xfaafh}'' \times (\boldsymbol{\omega}'' + \boldsymbol{\Omega}^*) \times \mathbf{d}] \\ &\quad + [\Delta\mathbf{xexp}'' \times (\boldsymbol{\omega}'' + \boldsymbol{\Omega}^*) \times \mathbf{d}]\end{aligned} \tag{22}$$

$$\begin{aligned}\Delta\mathbf{e\_yf} &= [\Delta\boldsymbol{\varphi}'' \times \mathbf{d}'' \times \mathbf{xf}] + [\Delta\boldsymbol{\Phi}^* \times \mathbf{d}'' \times \mathbf{xf}] + [\Delta\mathbf{d}'' \times (\boldsymbol{\varphi}'' + \boldsymbol{\Phi}^*) \times \mathbf{xf}] \\ &\quad + [\Delta\mathbf{xfah}'' \times (\boldsymbol{\varphi}'' + \boldsymbol{\Phi}^*) \times \mathbf{d}] + [\Delta\mathbf{xfaafh}'' \times (\boldsymbol{\varphi}'' + \boldsymbol{\Phi}^*) \times \mathbf{d}] \\ &\quad + [\Delta\mathbf{xexp}'' \times (\boldsymbol{\varphi}'' + \boldsymbol{\Phi}^*) \times \mathbf{d}]\end{aligned} \tag{23}$$

In equations (22) and (23), Δw_yf denotes the year-on-year change in total FVC payroll, and Δe_yf the corresponding change in total FVC employment. A paucity of detailed sector and final market price indices over time for many of the countries in the Eora26 database precludes a price normalization of the panel IO database, as is typically done for application of the SDA model. For this reason, we restrict our study to analysis of consecutive years with the expectation that our APD/M-E approach will effectively approximate a constant price analysis when comparing consecutive years.[14] This approach imposes no restrictions on use of the full data set for payroll analysis since that is a balanced panel over the full 29 year study period.

For the measure of change between discrete periods t=0 to t=1, the APD/M-E index approximation of equations 21 and 22 are as follows:

$$\Delta \mathbf{w\_yf} = \left(\boldsymbol{\omega}^{1} - \boldsymbol{\omega}^{0}\right)'' \times \left[\mathbf{d}^{0''} \times \mathbf{xf}^{0} + \mathbf{d}^{1''} \times \mathbf{xf}^{1}\right] \times \mathbf{0.5} + \tag{24}$$

$$\left(\boldsymbol{\Omega}^{*1} - \boldsymbol{\Omega}^{*0}\right) \times \left[\mathbf{d}^{0''} \times \mathbf{xf}^{0} + \mathbf{d}^{1''} \times \mathbf{xf}^{1}\right] \times \mathbf{0.5} + \tag{25}$$

$$\left(\mathbf{d}^{1} - \mathbf{d}^{0}\right)'' \times \left[\left(\boldsymbol{\omega}^{0''} + \boldsymbol{\Omega}^{*0}\right) \times \mathbf{xf}^{0} + \left(\boldsymbol{\omega}^{1''} + \boldsymbol{\Omega}^{*1}\right) \times \mathbf{xf}^{1}\right] \times \mathbf{0.5} + \tag{26}$$

$$\left(\mathbf{xfah}^{1} - \mathbf{xfah}^{0}\right)'' \times \left[\left(\boldsymbol{\omega}^{0''} + \boldsymbol{\Omega}^{*0}\right) \times \mathbf{d}^{0} + \left(\boldsymbol{\omega}^{1''} + \boldsymbol{\Omega}^{*1}\right) \times \mathbf{d}^{1}\right] \times \mathbf{0.5} + \tag{27}$$

$$\left(\mathbf{xfaafh}^{1} - \mathbf{xfaafh}^{0}\right)'' \times \left[\left(\boldsymbol{\omega}^{0''} + \boldsymbol{\Omega}^{*0}\right) \times \mathbf{d}^{0} + \left(\boldsymbol{\omega}^{1''} + \boldsymbol{\Omega}^{*1}\right) \times \mathbf{d}^{1}\right] \times \mathbf{0.5} + \tag{28}$$

$$\left(\mathbf{xexp}^{1} - \mathbf{xexp}^{0}\right)'' \times \left[\left(\boldsymbol{\omega}^{0''} + \boldsymbol{\Omega}^{*0}\right) \times \mathbf{d}^{0} + \left(\boldsymbol{\omega}^{1''} + \boldsymbol{\Omega}^{*1}\right) \times \mathbf{d}^{1}\right] \times \mathbf{0.5} \tag{29}$$

$$\Delta \mathbf{e\_yf} = \left(\boldsymbol{\varphi}^{1} - \boldsymbol{\varphi}^{0}\right)'' \times \left[\mathbf{d}^{0''} \times \mathbf{xf}^{0} + \mathbf{d}^{1''} \times \mathbf{xf}^{1}\right] \times \mathbf{0.5} + \tag{30}$$

$$\left(\boldsymbol{\Phi}^{*1} - \boldsymbol{\Phi}^{*0}\right) \times \left[\mathbf{d}^{0''} \times \mathbf{xf}^{0} + \mathbf{d}^{1''} \times \mathbf{xf}^{1}\right] \times \mathbf{0.5} + \tag{31}$$

$$\left(\mathbf{d}^{1} - \mathbf{d}^{0}\right)'' \times \left[\left(\boldsymbol{\varphi}^{0''} + \boldsymbol{\Phi}^{*0}\right) \times \mathbf{xf}^{0} + \left(\boldsymbol{\varphi}^{1''} + \boldsymbol{\Phi}^{*1}\right) \times \mathbf{xf}^{1}\right] \times \mathbf{0.5} + \tag{32}$$

$$\left(\mathbf{xfah}^{1} - \mathbf{xfah}^{0}\right)'' \times \left[\left(\boldsymbol{\varphi}^{0''} + \boldsymbol{\Phi}^{*0}\right) \times \mathbf{d}^{0} + \left(\boldsymbol{\varphi}^{1''} + \boldsymbol{\Phi}^{*1}\right) \times \mathbf{d}^{1}\right] \times \mathbf{0.5} + \tag{33}$$

$$\left(\mathbf{xfaafh}^{1} - \mathbf{xfaafh}^{0}\right)'' \times \left[\left(\boldsymbol{\varphi}^{0''} + \boldsymbol{\Phi}^{*0}\right) \times \mathbf{d}^{0} + \left(\boldsymbol{\varphi}^{1''} + \boldsymbol{\Phi}^{*1}\right) \times \mathbf{d}^{1}\right] \times \mathbf{0.5} + \tag{34}$$

$$\left(\mathbf{xexp}^{1} - \mathbf{xexp}^{0}\right)'' \times \left[\left(\boldsymbol{\varphi}^{0''} + \boldsymbol{\Phi}^{*0}\right) \times \mathbf{d}^{0} + \left(\boldsymbol{\varphi}^{1''} + \boldsymbol{\Phi}^{*1}\right) \times \mathbf{d}^{1}\right] \times \mathbf{0.5} \tag{35}$$

The six factors of change are the first bracketed difference terms ($\mathbf{term}^{1}$-$\mathbf{term}^{0}$) in each line of equations 24-29 and 30-35 for payroll and jobs, respectively, measuring year-on-year changes to each factor of change. The first two lines of both equation groups are inverse productivity parameters, also called factor intensity parameters, and include direct *FVC* sector labor use intensity ($\Delta\boldsymbol{\omega}$ and $\Delta\boldsymbol{\phi}$), and subcontracting FVC sector labor use intensity ($\Delta\boldsymbol{\Omega}$ and $\Delta\boldsymbol{\Phi}$). We refer to these parameters as inverse productivity parameters since they measure factor inputs per unit of sector output. This is merely the reciprocal of labor productivity (units of output per unit labor employed), for those who prefer to think in terms of factor productivity rather than intensity.

Expressions 26 and 32 measure annual change to domestic sector market shares ($\Delta\mathbf{d}$). This parameter measures annual changes to the share of annual domestic availability (or self-reliance) for each sector's product sourced from domestic production. This would capture, for example, changes in domestic market share of feeds and forages used in domestic livestock production which translates to variation in domestic jobs and wages.

[14] The restriction to consecutive country–year observations reduces the employment sample from 2,884 country–year observations to 1,405 country–year pairs.

Finally, expressions 27-29 and 33-35 measure annual changes to total availability requirements (production plus imports) to accommodate all final market sales of FVC sector products, where factors of change parameters are measured separately for each FVC marketing channel (Δ**xfah**, Δ**xfaafh**, and Δ**xexp**). This captures the role that change in both the level and composition of final consumer food demand – due, for example, to income and population growth, to changes to trade policy, or to shifting tastes for eating at home or away from home.

The complete results from applying these calculations for both total employment and total payroll expenditures to all country/consecutive-year IO accounts are available online.[15] Calculations are made for overall annual change in employment and total worker compensation as well as for each of the six FVC industry stages: AFF, food and beverage manufacturing and processing, wholesale trade, transportation, retail trade, and hospitality services. Overall, our analysis produces over 200,000 observations related to payroll, and over 60,000 observations for total employment.

4. Descriptive Results

We first compare FVC to non-FVC employment and payroll shares so as to see what role the FVC plays in overall labor market development over the period 1993-2021 (Section 4.1). Then we examine the structural decomposition results, studying what portion of annual changes in payroll and employment are attributable to year-on-year changes in direct and indirect (i.e., subcontracting) labor intensity, self-reliance, and final consumer expenditures by market (FAH, FAAFH, or exports), both over time and by country income group (Section 4.2). We also examine these same relationships disaggregating for the different stages of FVCs (AFF, hospitality, retail, etc.).

4.1 FVC employment shares

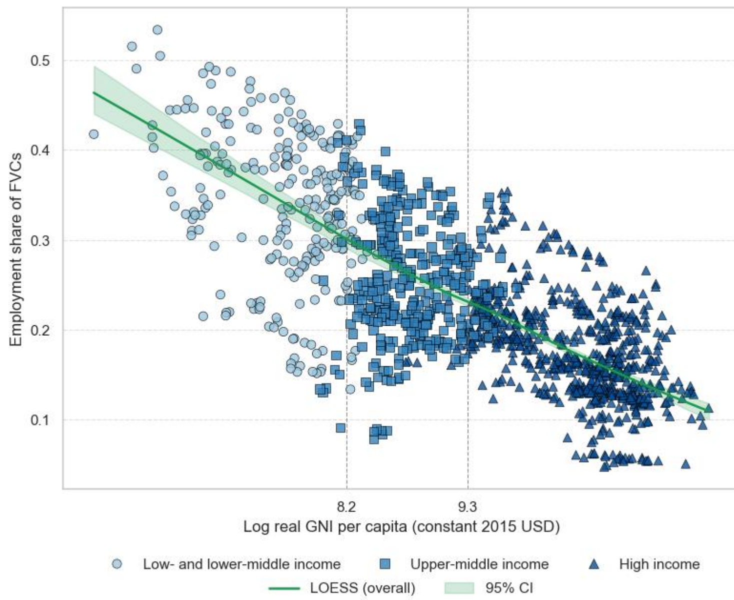
Figure 1 illustrates the relationship between economywide FVC employment share and log real GNIpc, always expressed in constant 2015 US dollars. As is well-known, in LLMIC economies most workers labor in FVCs (Davis et al., 2023; Thurlow et al., 2023; Yi et al., 2025; Davis et al., 2026), while FVCs employ a far lower share in HICs. Each point represents a country–year observation, with colors following a gradient from light (LLMIC countries) to dark (HIC countries) and distinct marker shapes.[16] Panel A shows a strong negative relationship between real income and the FVC share of employment (Spearman's rank correlation, $\rho = -0.726$, $p = 0.000$; Kendall's $\tau = -0.539$, $p = 0.000$). Figure 1 Panel A also overlays a nonparametric LOESS regression and its 95% confidence interval, clearly showing the negative relationship between income and FVC employment share. This nonparametric evidence strongly suggests a nearly log-linear functional form in FVC employment shares as incomes rise.

Figure 1 Panel B then decomposes the FVC into primary production (AFF, the left subpanel), which declines steeply as incomes rise, nearly log linearly until countries reach the HIC threshold, and at an asymptotically slowing rate thereafter. The five post-farmgate FVC industries combined (the right subpanel), exhibit the opposite pattern over the LLMIC and UMIC range, with significant log linear growth in economywide employment share. Post-farmgate FVC employment overtakes AFF employment, on average, within the UMIC income range. In UMICs, the post-farmgate share averages 0.14 (median = 0.15). The economywide share of post-farmgate FVC employment falls over the HIC range, however(HIC group mean = 0.14, median = 0.13). Theese overall employment shares exceed prior estimates of direct

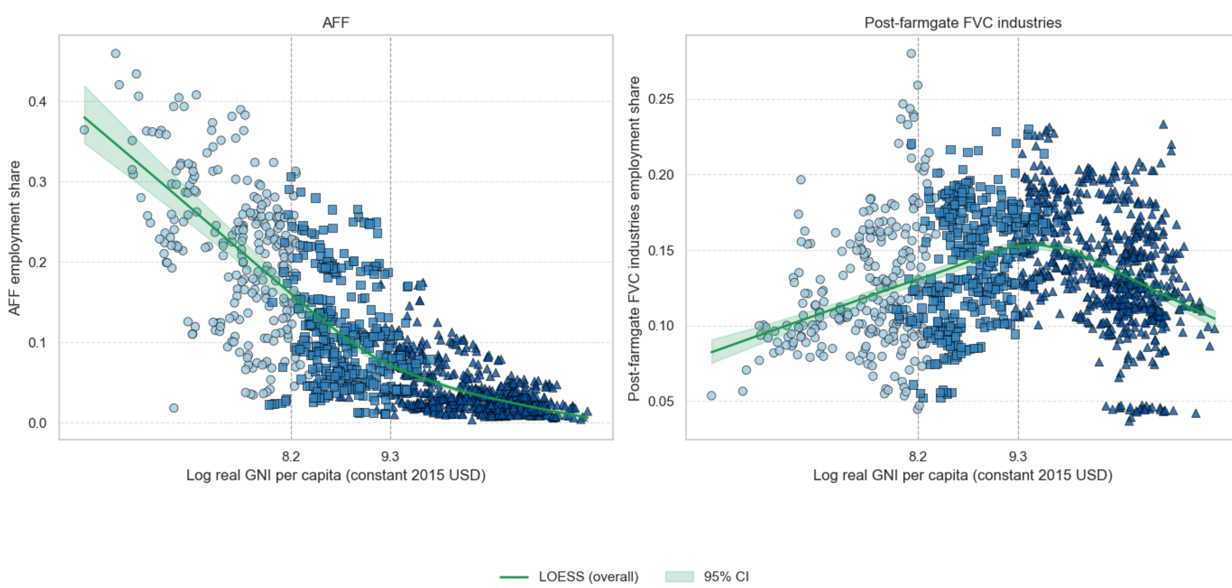
[15] We will add a link to the data set once the paper is accepted for publication.

[16] Outliers are identified separately within each income group using a standard deviation rule. Observations are omitted as outliers if the change in FVC employment share for any sector lies more than ±3 standard deviations from the income-group mean. The original sample contains 1,405 observations, of which 1,319 remain after outlier removal. Finally, observations missing GNI data are excluded, yielding a final sample of 1,315 observations.

employment within FVCs (e.g., Yi et al. 2025, Davis et al. 2026), especially in the UMIC and HIC range, because unlike prior studies we include jobs arising from subcontracting outside of the six FVC industries and the subcontracting share of total employment rises sharply as incomes grow (Yi et al. 2025).



Panel A. Economywide employment share in FVC by real GNI per capita



Panel B. Economywide employment shares in AFF (left) and post-farmgate (right) FVC industries

Figure 1: Employment share in FVC by real GNI per capita. Note: Scatter points represent country–year observations of the employment share of FVCs—calculated as FVC employment divided by total national employment. Observations are included only when employment data are available for consecutive years, thus these are the same observations used in the SDA reported below. These shares are plotted against log real GNIpc (constant 2015 USD). Marker colors follow a gradient from light (LLMIC) to dark (HIC). Distinct marker shapes further distinguish the income groups for visibility in grayscale. The green line shows the nonparametric LOESS regression with a 95% confidence interval. The dashed vertical lines depict the thresholds between lower-middle and upper-middle income countries (8.2) and between the latter and high-income countries (9.3).

Together, Panels A and B of Figure 1 demonstrate that structural transformation within food systems involves not only a contraction of farm-based employment, but also an expansion of post-farmgate FVC employment as countries approach and reach the high income threshold. Together, these patterns reflect a systematic reallocation of labor toward increasingly downstream, higher value-added FVC activities that deliver convenience, quality and variety as economies grow. Once countries reach high-income status and AFF's share of economywide employment has shrunk well below 10%, there is little room for further compression. Then the post-farmgate FVC share of economywide employment begins shrinking. This yields a steady log linear decrease in the overall FVC share of economywide employment throughout the observed income range.

Appendix Figure A1 further unpacks this dynamic across the six FVC industries by presenting the average composition of FVC employment across income groups during the period of analysis. This disaggregation shows a nuanced pattern of structural transformation in which labor shifts out of agriculture and related upstream activities and into downstream wholesale, retail and food service sectors. In LLMICs, FVC employment is heavily (~60%) concentrated in AFF. As economies transition to UMIC status, AFF employs only a minority (~40%) of FVC workers. In HICs, FVC employment becomes dominated by retail and hospitality services, and the AFF share declines sharply, to less than 20%, on average. Together, the two panels show a consistent structural pattern: as real incomes rise, employment shifts away from upstream AFF toward midstream and downstream service segments that add greater value within the food system.

Figure 2 illustrates how the FVC share of economywide employment has evolved over time, by income groups. Non-FVC employment exceeds FVC employment in every income group throughout the period, and the gap between the two widens as countries develop. In LLMICs (upper panel), non-FVC exceeds FVC by a moderate margin, with both series relatively stable across the period. In UMICs (middle panel), non-FVC remains substantially above FVC, and the gap widens slightly over time. In HICs (lower panel), non-FVC employment dominates decisively, with non-FVC rising and FVC declining gradually across the period. Together with Figure 1, these patterns offer a different perspective on the same core point reflected above; as economies grow and diversify, labor increasingly shifts towards non-food activities.

Now we introduce money metric estimates of total payroll expenditures. Figure 3 presents the analog plot for total payroll expenditure shares in FVC and non-FVC activities.[17] Because payroll expenditures come from the MRIO data, without requiring matching with the ILO employment data,[18] it is important to keep this compositional difference in mind when comparing Figures 2 and 3. The added observations enable separation of the low-income (LIC) from the lower-middle-income country (LMIC) groups in studying the evolution of payroll expenditures (Figure 3), which is infeasible in the more limited ILO employment data (Figure 2).[19]

[17] The qualitative results in Figure 2 for low- and lower-middle income countries are robust to dropping a small number of outlier observations (more details available from the authors upon request).
[18] For each income group, observations are omitted as outliers if the payroll share in either FVC or non-FVC activities lies outside ±3 standard deviations of the income group mean. Combined with 115 observations for which we lack an income group classification, this reduces the sample by 188, yielding 5,178 total observations.
[19] Appendix Figure A2 compares FVC and non-FVC employment growth rates by country group and by region over time, showing significant differences across regions.

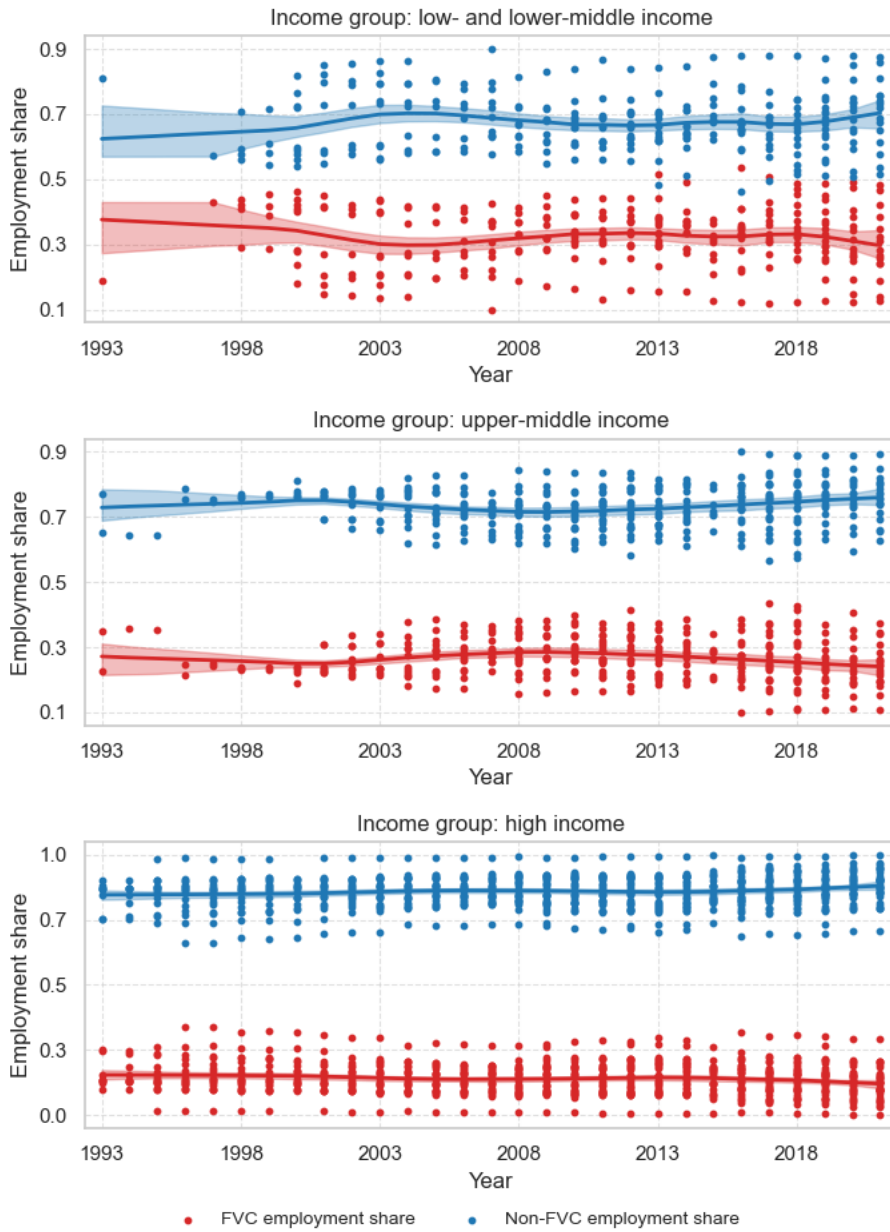


Figure 2: Employment shares by country income group, 1993-2021. Notes: Each panel plots country-year observations together with LOESS-smoothed trends and 95% confidence bands. The figure is generated based on 1,319 observations.

The first striking feature of Figure 3 is that average non-FVC payroll expenditures exceed FVC payroll expenditures in all country income groups in all years, even in LICs with greater FVC employment shares (Figure 2). This reflects how considerably non-FVC worker compensation exceeds that of FVC workers, on average, especially in LLMICs. The second big takeaway from Figure 3 is that the average gap between the non-FVC and FVC payroll expenditures shrinks as countries move from low- to high-income groups.[20]

Table 2 explores this new finding further, reporting the coefficient estimates on the regression:

[20] These patterns do not arise because of changing income group composition, as shown in Figure A3.

$$\log\left(\frac{\overline{w}_{\text{xFVC}}^{c\times t}}{\overline{w}_{\text{FVC}}^{c\times t}}\right) = \beta \log\left(\text{GNIpc}_{ct}\right) + \gamma_t + \mu_c + \varepsilon_{ct} \tag{36}$$

where $\overline{w}_{\text{xFVC}}^{c\times t}$ and $\overline{w}_{\text{FVC}}^{c\times t}$ represent the average compensation per worker in non-FVC and FVC activities, respectively, defined as payroll expenditures divided by headcount employment, and $\log\left(\text{GNIpc}_{ct}\right)$. We include year and country fixed effects in the regression specification. As the statistically significant -0.18 β coefficient estimate indicates, the relative average compensation gap between the non-FVC and FVC workforces narrows substantially as incomes rise. This presumably reflects, in part, intersectoral labor market integration that moves wages closer across sectors, plus rapid exit of workers from the poorest compensated FVC sub-sector, primary production (Yi et al. 2025), and entry into better compensated, post-farmgate FVC industries, perhaps also reduced underemployment within FVCs. As Table A3 shows, the dependent variable in equation (36) falls from an average of 0.80 – implying average non-FVC compensation is more than 2.2 times that within FVCs – in LLMICs included in the data to just 0.32 in HICs, implying an average non-FVC premium of just under 40 percent. These results provide novel evidence that as employment shifts away from poorly compensated AFF activities toward higher-paying, post-farmgate FVC and non-FVC industries, the non-FVC–FVC compensation and payroll gaps narrow. As AFF's employment share shrinks, growing economies get more and better compensated post-farmgate FVC jobs.

Dependent variable = Relative compensation gap	
Log real GNI per capita	-0.175***
	(0.054)
Country fixed effects	Yes
Year fixed effects	Yes
Observations	1,315
R^2	0.871

Table 2. Trends in relative non-FVC/FVC real compensation per worker

The descriptive results so far have characterized FVC labor markets either through FVC-versus-non-FVC aggregates or through a single AFF-versus-post-farmgate split. Figure 4 separates all six FVC industries — primary production (AFF), food processing, wholesale trade, transportation, retail trade, and hospitality — and decomposes total FVC payroll within each industry into its two underlying components: the number of workers (rectangle width) and the compensation paid per worker (rectangle height). The figure does this for the median country in each income group, with rectangle area representing the median sector payroll.[21]

[21] The decomposition pools 1,305 country-year observations spanning 1993–2021 from our matched Eora–ILO data and uses medians rather than means because, in this disaggregated cross-section, unweighted country-year means are heavily influenced by the largest economies in each income group, obscuring the pattern of a typical country.

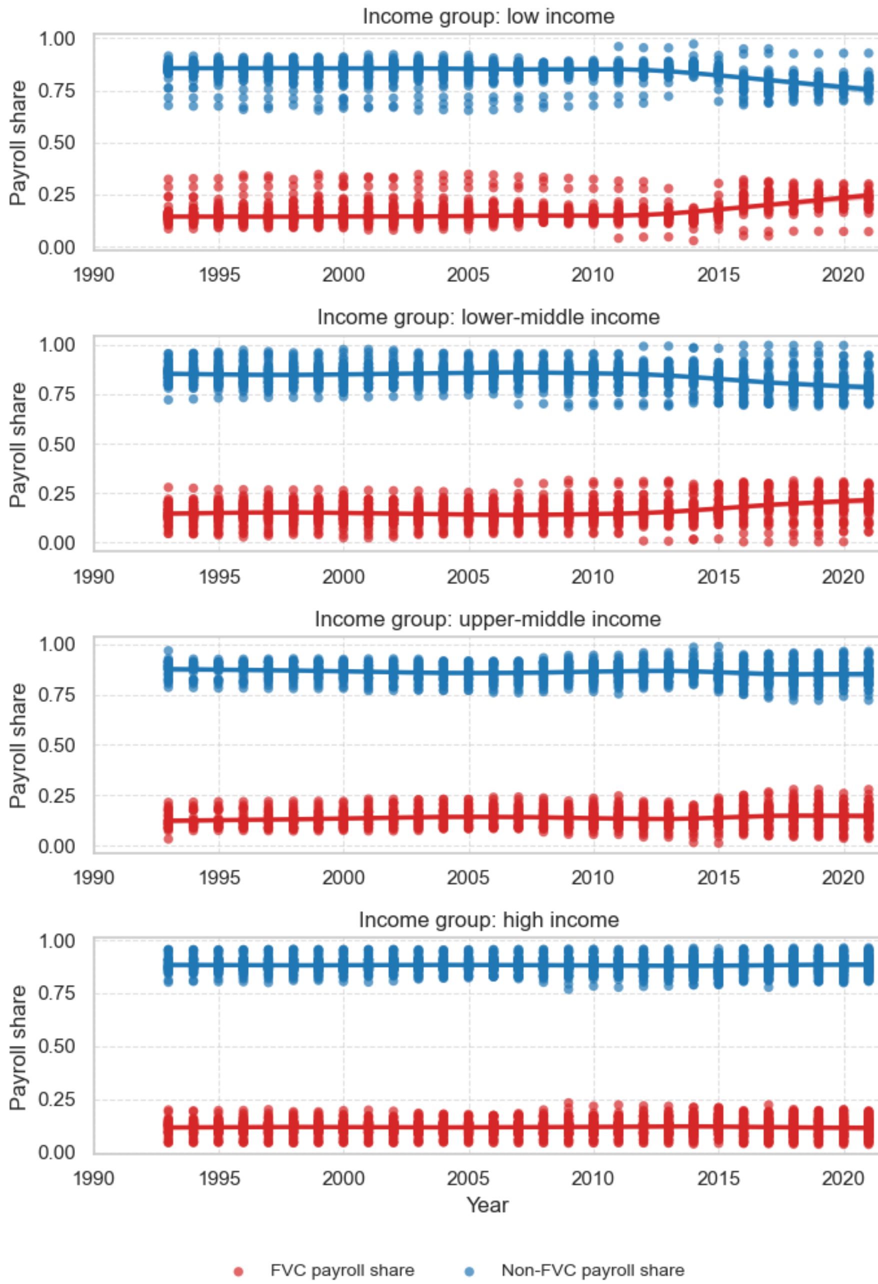


Figure 3: Payroll expenditures shares by country income group, 1993-2021

Note: This plots country-year observations of payroll shares in FVC and non-FVC activities, shown separately by income group. Red points and curves represent the payroll share in FVC, while blue points and curves represent the payroll share outside FVC. Solid lines are LOWESS smoothers with shaded areas indicating 95% bootstrap confidence intervals.

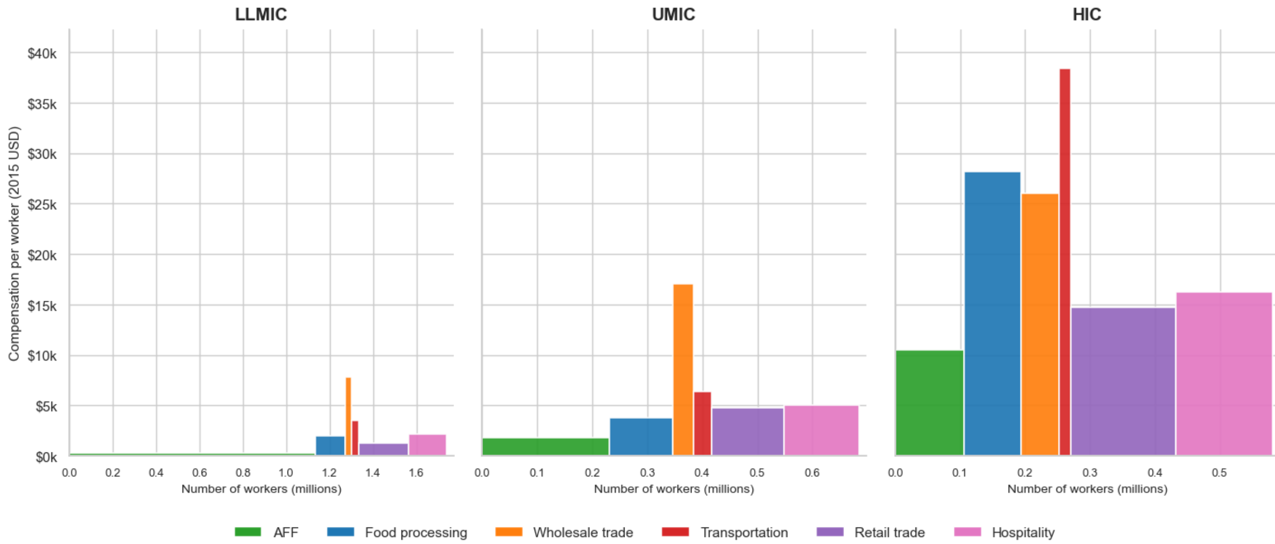


Figure 4. Decomposition of FVC payroll into employment scale and compensation per worker

Note: FVC payroll decomposed into employment and compensation per worker, by income group for 1993–2021 (median per country-year). In each panel, rectangle width is the median number of workers in a sector (millions), height is the median compensation per worker (constant 2015 USD), and area is the implied median sector payroll. Sectors are tiled left-to-right as AFF → Food processing → Wholesale trade → Transportation → Retail trade → Hospitality. Medians are taken across 1,305 country-year observations spanning 1993–2021, distributed across LLMIC (n = 262), UMIC (n = 351), and HIC (n = 692). Horizontal axes are panel-specific to maximize within-panel composition legibility; the vertical axis is shared to enable cross-panel median compensation comparisons.

Figure 4 reveals three key findings. First, AFF dominates FVC employment in LLMICs — the green AFF rectangle is by far the widest in the LLMIC panel — yet contributes a comparatively small share of FVC payroll because AFF compensation per worker is substantially lower than in any post-farmgate FVC industry (Yi et al., 2025). Second, compensation per worker varies considerably across the post-farmgate FVC industries. Workers in the transportation and wholesale sectors are among the best compensated in FVCs, and AFF workers the worst compensated, at all stages of development. Compensation per worker grows more rapidly with GNIpc in food processing and transportation than in other sectors, both overtaking wholesale as the best compensated sector(s) in the HIC range. Third, as countries develop the AFF rectangle width contracts sharply while median compensation per worker rises across all six FVC industries; AFF's median share of total FVC payroll falls correspondingly from roughly 20 percent in LLMICs (24 percent under mean aggregation) to 16 percent (18 percent) in UMICs and just 9 percent in HICs, and within-FVC composition shifts from upstream-dominated in LLMICs to post-farmgate-dominated in HICs (Yi et al., 2025).

The cross-sectional decomposition in Figure 4 also raises a question as to how much of the observed cross-country differences arises from changes in technology and labor productivity, how much from changes in domestic versus imported supply, and how much from the level and composition of consumer food demand. Section 4.2 turns to that question by extending our lens from cross-sectional snapshots to structural decomposition of year-on-year observed changes in FVC employment and labor compensation.

4.2 Structural decomposition

We next perform a structural decomposition analysis (SDA) to attribute observed year-on-year changes in FVC employment and payroll to t changes in each underlying supply- and demand-side factors.[22] We emphasize that these are correlational, not causal, estimates.

Using a balanced panel of the 176 countries for which payroll data are available for the full period, Figure 5 shows that over this period of increasing globalization[23], modest average decreases in domestic self-reliance within FVC industries led to only very slight decreases in FVC payroll. Changes in FVC labor intensity/productivity – reflecting technological and institutional innovations – are negatively related to FVC payroll costs by a far larger amount than did globalization. The central finding, however, is that increased food sales – domestically and abroad, via exports – generate payroll increases that more than offset the declines arising from productivity growth and globalization. Since productivity growth and globalization both tend to increased GNIpc we can identify the effects of demand growth that arise from productivity gains inside[24] and outside the FVC separately from the effects of changes in globalization and labor productivity within the AVC, but not vice versa. The key takeaway is that payroll losses associated with labor productivity growth in FVC and globalization are more than compensated for by the associated expansion in final consumer demand that boosts overall FVC payroll expenditures. The contribution of FAH sales to FVC payroll costs far exceeds the contribution of FAAFH sales, while export sales exhibit the smallest contribution to payroll. The implication is that growth in domestic food demand is most strongly associated with increases in FVC payroll. Per Yi et al. (2025), per capita income growth is strongly, positively associated with changes in both post-farmgate FVC employment shares and average worker compensation, with domestic food demand (the sum of FAH and FAAFH) seemingly the main driving force behind FVC labor transitions over the course of economies' structural transformation.

Figure 6 disaggregates the SDA of Figure 5 into country income groups, classifying countries according to their group membership in the base year for each sub-period.[25] Mechanically, this leads to steady decline in the number of countries in the LIC group, which explains the shrinking magnitudes of the changes across sub-periods. Conversely, the number of UMICs and HICs increased 1993-2012 (Appendix

[22] Because SDA requires using consecutive years and ILO employment data are spotty over the period, selection effects become pronounced for SDA of employment. Only six high-income European countries (Belgium, Denmark, Ireland, Luxembourg, Netherlands and Portugal) have continuous employment data over the period. Thus we focus here on FVC payroll expenditures, for which we have far broader coverage.

[23] It might be helpful to clarify how the SDA partitions the labor and employment consequences of international trade across countries. When country A reduces its domestic share of intermediate inputs, the labor market loss associated with that substitution enters A's $\omega \cdot \Delta d \cdot xf$ term, while the corresponding production gain in country B enters B's $\omega \cdot d \cdot \Delta xf$ term as expanded export demand. By construction, trade flows therefore appear in different decomposition components for different countries. Because the loss in Country A appears in the Δd component while the gain in Country B appears in the Δxf component, the two do not cancel within the same decomposition term when averaged across countries. It is likewise worth noting that because the SDA is country-specific, the payroll impact of a given dollar of production differs across countries due to different labor coefficients (ω).

[24] Although sector-specific productivity growth within the FVC may drive down compensation to labor in the FVC, income to capital within the FVC is likely to increase other than in the unlikely event that imports replace all reduced labor services, since the market value of final sales equals sum total of value added and imported inputs throughout the FVC.

[25] For 1995–2000, the sample includes 60 LICs, 55 LMICs, 23 UMICs, and 38 HICs. For 2000–2005, these counts shift to 60 LICs, 47 LMICs, 27 UMICs, and 42 HICs. During 2005–2010, the sample comprises 50 LICs, 53 LMICs, 29 UMICs, and 44 HICs. For 2010–2015, the corresponding counts are 33 LICs, 48 LMICs, 43 UMICs, and 52 HICs. For 2016–2021, the counts are 28 LICs, 48 LMICs, 43 UMICs, and 57 HICs.

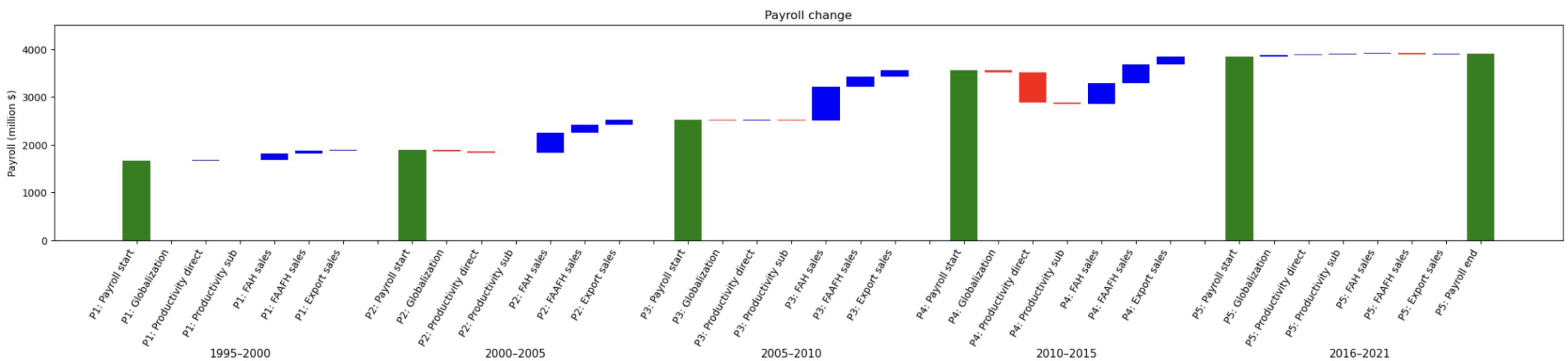


Figure 5: Net change in payroll aggregated across 5-year periods for the 176 countries in the balanced panel, decomposed into self-reliance, direct labor intensity, subcontracted lab intensity, and total sales in each of the three final markets: FAH, FAAFH, and exports. The green bars show the beginning year (in parentheses) total. Red bars indicated declines over the subsequent seven years. Blue bars reflect increases over the subsequent seven years.

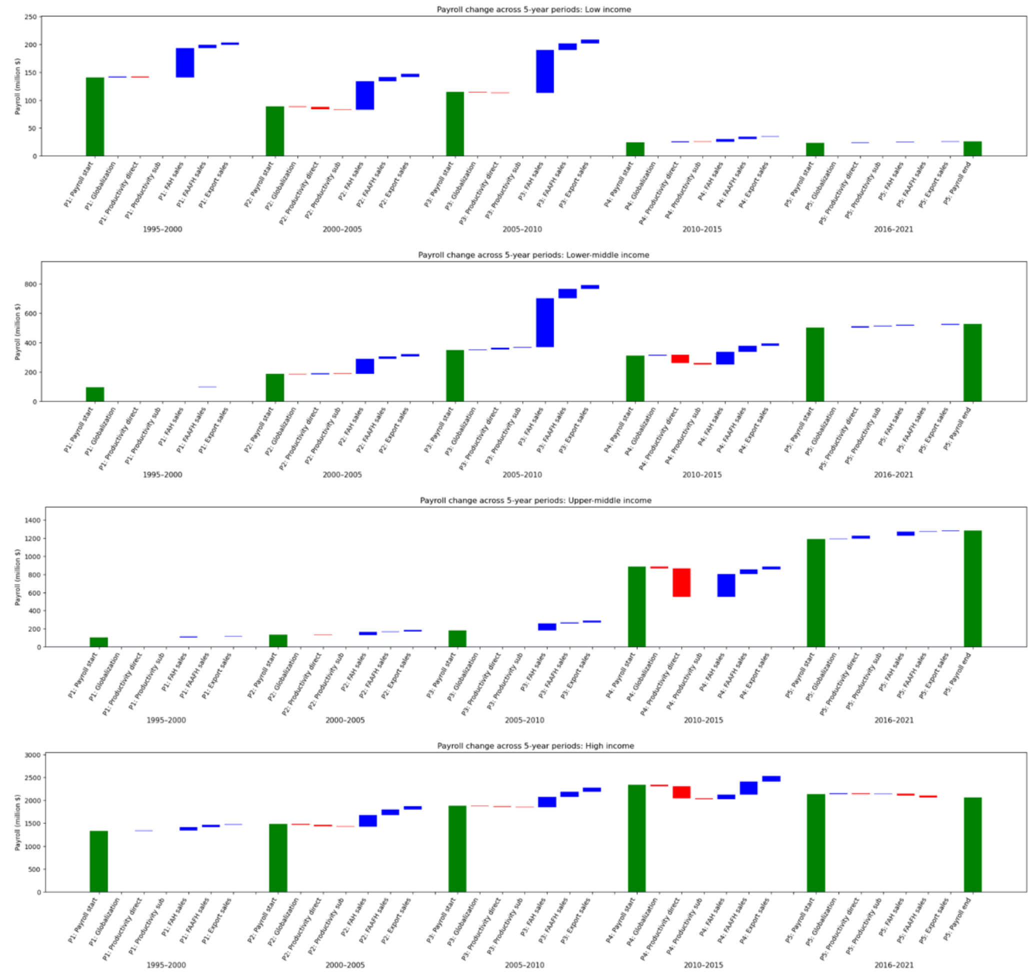


Figure 6: Net change in payroll aggregated across 5-year periods by income group.

Notes: The waterfall plots are constructed separately for each income group. For each 5-year period, countries are assigned to income groups based on their income classification at the beginning of that period; they can only switch groups at the beginning of multi-year periods. Payroll at the start of each period is aggregated across countries within the same base-year income group. Factor contributions are then summed within each period and income group using the SDA decomposition. The ending payroll shown for the final period reflects the aggregated observed payroll for countries belonging to that income group at the beginning of the period. Green bars indicate observed FVC payroll levels, blue bars represent positive factor contributions, and red bars represent negative contributions.

Figure A3). The overall pattern is consistent across income groups. Modest declines associated with reduced self-reliance and labor intensity are more than offset by increases in final food sales to consumers, particularly domestic consumers in non-HICs. The relative importance of sales growth becomes more pronounced as countries move up the income distribution classification, reflecting rising demand for food consumed at home, away from home, and increased participation in international markets. Jobs in the hospitality sector are especially responsive to growth in FAAFH spending in HICs (elasticity = 0.56, vs. 0.44 in UMICs, and 0.19 in LLMICs; Table A5).

4.3 Structural factor elasticities

Jobs, payroll, production, personal consumption expenditures, and trade statistics are among the most widely measured national statistics and most United Nations (UN) member countries maintain official statistical programs in adherence with UN official guidelines for maintenance of a system of national accounts (SNA, United Nations, 2010). The two equations described in expressions 24-29 and 30-35 link various national statistics for the six structural components to changes in jobs and payroll. We use multiple regression analysis to test the sensitivity of job and payroll growth to the structural relationships derived in the SDA framework. We hypothesize that the relationship between annual changes to FVC jobs and worker compensation and the six change factors is structural and systematic, both overall and for each FVC supply chain stage. To test this hypothesis, we pool all consecutive annual employment or payroll observations by country and conduct multiple regression analysis.

For employment and pay, recall from equations 15 and 19 that for each FVC sector s, total employment and payroll are calculated as the product of variables measuring globalization ($\mathbf{d}_s$), productivity ($\boldsymbol{\omega}_s$ & $\boldsymbol{\Omega}_s$ for pay and $\boldsymbol{\varphi}_s$ & $\boldsymbol{\Phi}_s$ for jobs), and final demand ($\mathbf{Xf}_{s,j,}$, $j \in \{fah, faafh, exp\}$). This can be simplified to $\mathbf{Y}^t = \prod_k(\mathbf{X}_k^t)$ for $t \in \{1993\ (0),\dots,2021\ (28)\}$ and $k \in \{1,2,3\}$ (k represents globalization, productivity, and final demand factors, respectively), with no intercept term because the dependent variable ($\mathbf{Y}$) passes through the origin when any independent variable equals zero. Recall that values for $\mathbf{X}_2$ are determined by two factors ($\boldsymbol{\omega}$ & $\boldsymbol{\Omega}$ for pay and $\boldsymbol{\varphi}$ & $\boldsymbol{\Phi}$ for jobs) and $\mathbf{X}_3$ by three factors ($\mathbf{Xf}_j$). Consider this expression for the first two consecutive periods ($t \in \{0,1\}$). If we take the natural log of both periods and restate as an expression of first differences for consecutive years, we have $\mathrm{Ln}(\mathbf{Y}^1/\mathbf{Y}^0) = \sum_k Ln(\mathbf{X}_k^1/\mathbf{X}_k^0)$. If we pool our panel data for all countries $c \in C$, control for country and year fixed effects, and introduce binary variables to isolate a small pool of highly irregular expenditure data to control for interactions with our independent expenditure variables, we estimate regressions of the form:

$$\mathbf{ln}\left(\frac{\mathbf{Y}_s^{c,t+1}}{\mathbf{Y}_s^{c,t}}\right) = \sum_k \theta_{s,k}\, \mathbf{ln}\left(\frac{\mathbf{X}_{s,k}^{c,t+1}}{\mathbf{X}_{s,k}^{c,t}}\right) + \sum_l \sum_{k2(k)} \left(\mathbf{b}_{s,k2,l}^{c,t}\left(\rho_{s,k2,l} + \pi_{s,k2,l}\mathbf{X}_{s,k2}^{c,t}\right)\right) + \gamma_t + \mu_c + \epsilon_{c,t} \tag{37}$$

The dependent variable (Y) is the year-on-year growth rate in total employment or total payroll (in 2015 US dollar prices) for income group $c \in \{0,\dots,4\}$, which indexes the four World Bank country income levels plus all countries (c=0), year t, and FVC industry groups s, or the full value chain if s=0.[26] k indexes the six independent variables ($\boldsymbol{x}$),[27] and $k2(k)$ denotes the subset of the independent variables measuring consumer expenditures by marketing channel. Because $\mathbf{Y}_s$ and $\mathbf{X}_{s,k}$ are natural log transformed, the $\theta_{s,k}$ coefficients represent annual employment (or payroll) growth rate elasticities with respect to each independent variable ($\mathbf{X}_{s,k}$). For example, for the s-k pair representing "AFF-productivity" the $\theta_{s,k}$ coefficient represents the percentage change in the annual AFF employment (or payroll) growth rate from a 1-percent change in the AFF productivity growth rate. The variables γ_t and μ_c represent year and country fixed effects, respectively, while $\varepsilon_{c,t}$ is an iid error term. All input data are compiled from the SDA analysis described above.

A small number of Eora observations have implausibly large changes that seem to arise from unspecified adjustments made in Eora's margins estimation.[28] The binary variables, $\boldsymbol{b}_{s,k2,l}$ identify expenditure

[26] We focus on growth rates because economies vary so dramatically in scale across countries and years.

[27] Our globalization variable ($\mathbf{X}_1$) equals 1-$\mathbf{d}$ and measures imports as a share of domestic availability in 2015 prices by sector-country-year; our productivity variables ($\mathbf{X}_2$,$\mathbf{X}_3$) are measured as the sum of direct and subcontracting productivities (1/$\boldsymbol{\omega}$ & 1/$\boldsymbol{\Omega}$ for pay and 1/$\boldsymbol{\phi}$ & 1/$\boldsymbol{\Phi}$ for jobs) measuring output per worker or real (constant price) unit-pay by sector-country-year; our expenditure variables ($\mathbf{X}_4$,$\mathbf{X}_5$,$\mathbf{X}_6$) measure total fah, faafh, and export expenditures in 2015 prices by sector-country-year.

[28] Queries to Eora to try to unpack this more went unanswered.

observations that indicate an annual increase of ≥100 percent ($l=1$) or a decrease of ≤ -50 percent ($l=2$), in that specific supply-chain/marketing-channel pair (s,$k2$). These six binary variables per supply chain stage identify about 1 percent of observations for payroll and about 2 percent for jobs. We also specify the interactions of each binary variable with its corresponding expenditure variable. We include these as controls in case something opaque in construction of a few Eora data points generates outliers that might distort the estimates.[29] The parameter estimates $\rho_{s,k2,l}$ and $\pi_{s,k2,l}$ account for the impact of these outlier observations on the of employment (or payroll) year-on-year growth rate (ρ) and the impacts of interactions of these outliners with independent variables they measure (π).

Appendix Table A4 reports the $\theta_{s,k}$ coefficient estimates from equation (37) for all countries pooled together and by country income group, respectively. Figure 7 summarizes Table A4's results for the 'All countries' column visually, as payroll elasticity estimates. Overall, direct labor productivity gains within each industry are associated with reduced payroll, ceteris paribus, with the estimated effects largest in hospitality and retail. In all sectors other than food manufacturing and processing, however, increased subcontractor labor productivity increases payroll among firms in that sector. Having subcontractors with greater labor productivity leads to greater employment, higher compensation, or both, within those five sectors. These results suggest that rising labor productivity among service providers generates labor market spillover gains within the FVC.

Figure 8 shows analogous elasticity estimates disaggregated by country income group, each estimated and displayed in a separate panel. Labor productivity growth's payroll reducing effect in AFF is far higher in LICs than in HICs. This underscores the AFF sector's foundational influence and the relatively greater scope for improvements in labor productivity in lower-income countries. Conversely, payroll in the hospitality sector responds far more elastically in UMICs and HICs to labor productivity gains than in LICs or LMICs. In general, low- and lower-middle income countries exhibit high absolute payroll growth elasticities across the board in upstream FVC sectors, while high-income countries show relatively greater absolute payroll growth elasticities in downstream FVC sectors, suggesting greater labor market responsiveness in consumer-facing segments of the food system as incomes rise.

The downstream-upstream differences appear elsewhere, too. For example, food at home expenditure growth generates the biggest payroll response in the upstream FVC sectors – AFF, manufacturing, wholesale, and transport – while payroll in the downstream sectors – retail and hospitality – responds more robustly to expanded FAFH expenditures. Payroll in primary production (AFF) is the most responsive among the sectors to export market growth, especially in LICs. Greater industry self-reliance (i.e., more domestic provisioning of inputs) is associated with statistically significantly positive employment effects in all FVC industries except hospitality. The self-reliance payroll growth elasticities are quite small in magnitude, however. Clearly, income growth and productivity gains arising from technological and institutional innovation play a larger role in shaping the evolution of FVC value chains than globalization does.

[29] Qualitatively similar estimates without those controls are available by request. The fit on the regressions without those outliers controls is poorer, consistent with the hypothesis of noise in the underlying data series.

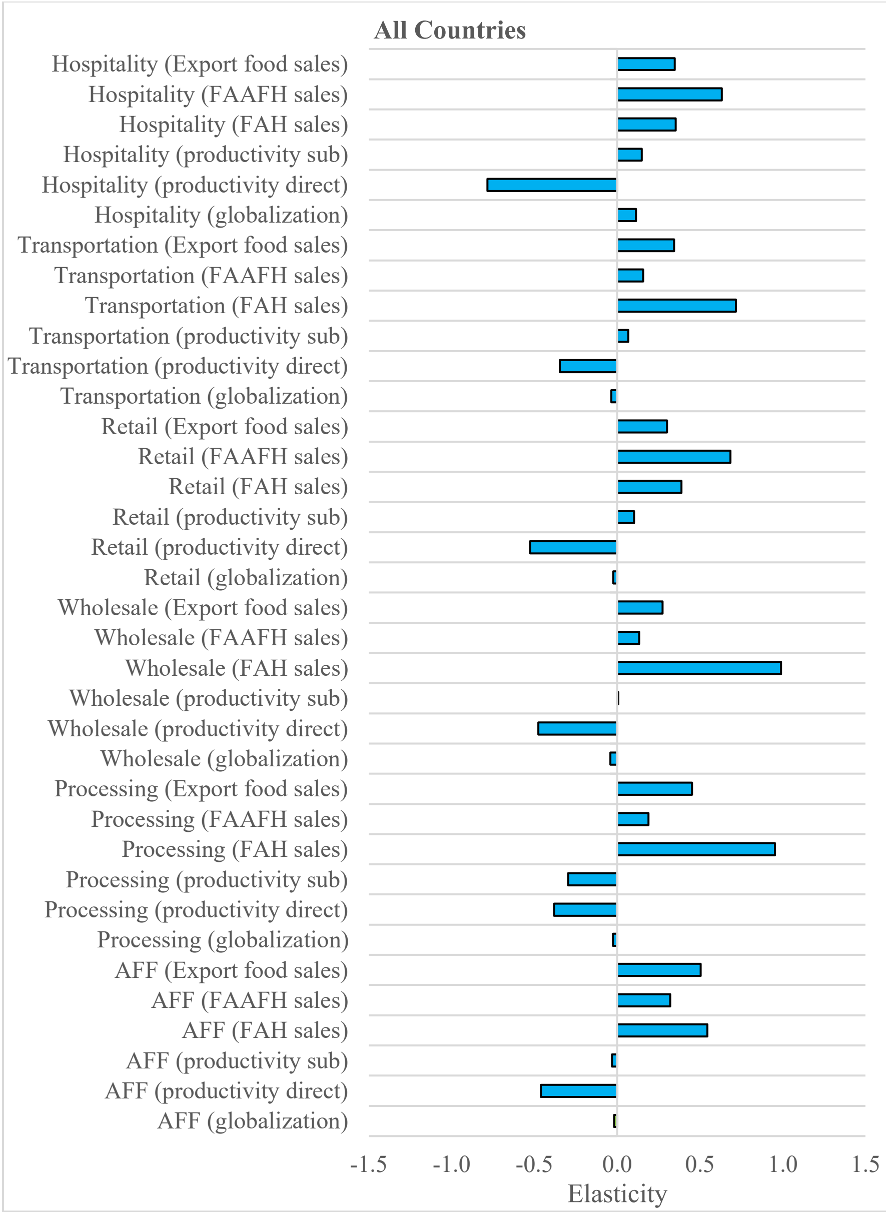


Figure 7. Estimated elasticities of FVC payroll (in 2015 U.S. Dollars)

Note: blue bar indicates $p < 0.001$; green bar $p < 0.01$; yellow bar $p < 0.05$; red bar p-value < 0.1; white bar $p \geqslant 0.1$.

Appendix Table A4 provides the regression estimates behind figures 7 and 8. Appendix Table A6 and Figures A4 and A5 present analogous estimates and figures for employment. Since the employment data set is far smaller – and especially thin for LICs – and loses many observations for want of consecutive annual observations, we emphasize the payroll estimates instead. But the broad patterns are the same in the employment headcount series as in the money-metric payroll series. These findings can therefore be understood as broadly reflective of labor dynamics within FVCs over the course of structural transformation more broadly.

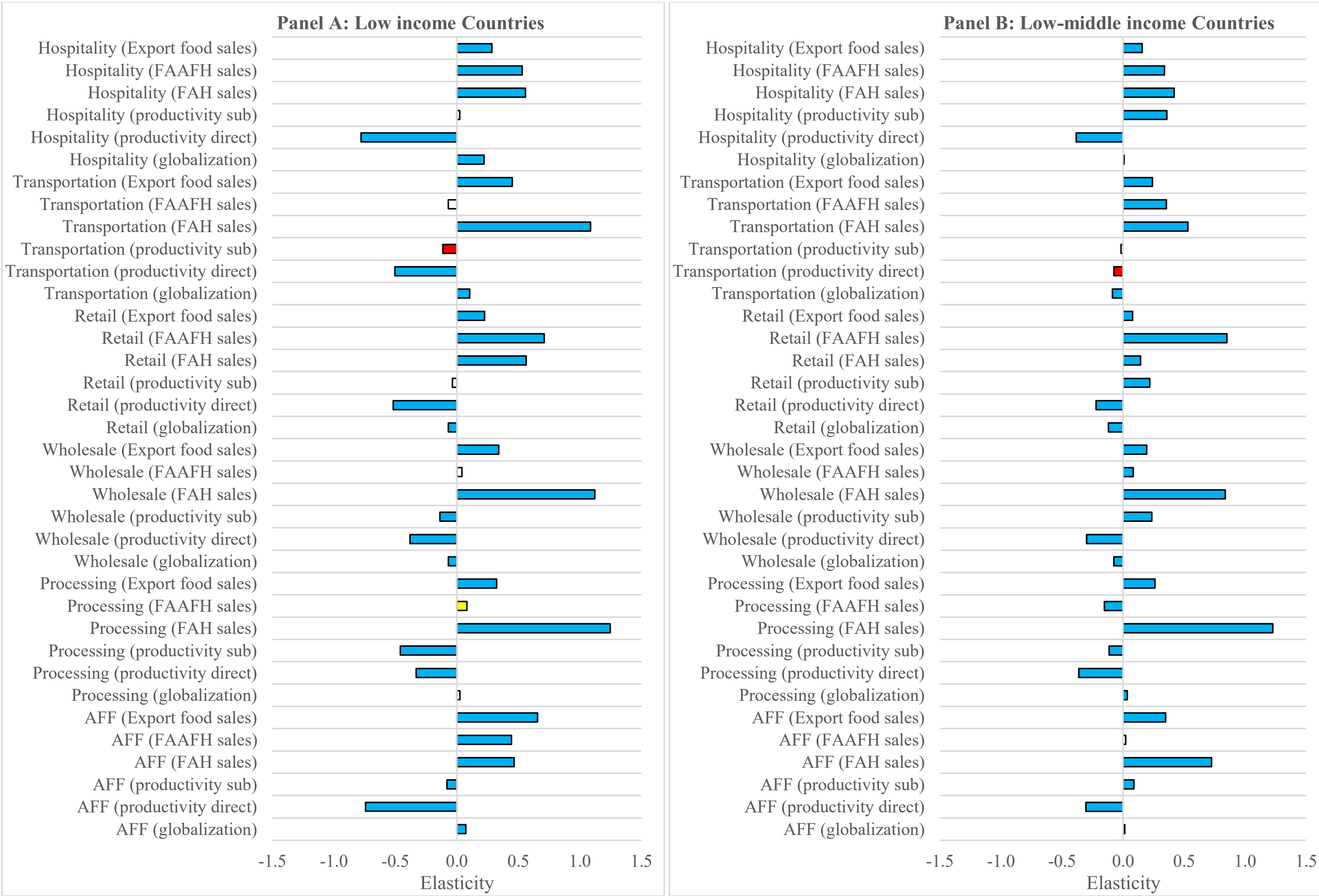


Figure 8: Estimated elasticities of FVC payroll by country income group (in 2015 U.S. Dollars)

Note: blue bar indicates p < 0.001; green bar indicates p < 0.01; yellow bar indicates p < 0.05; red bar indicates p-value < 0.1; white bar indicates p ≥ 0.1

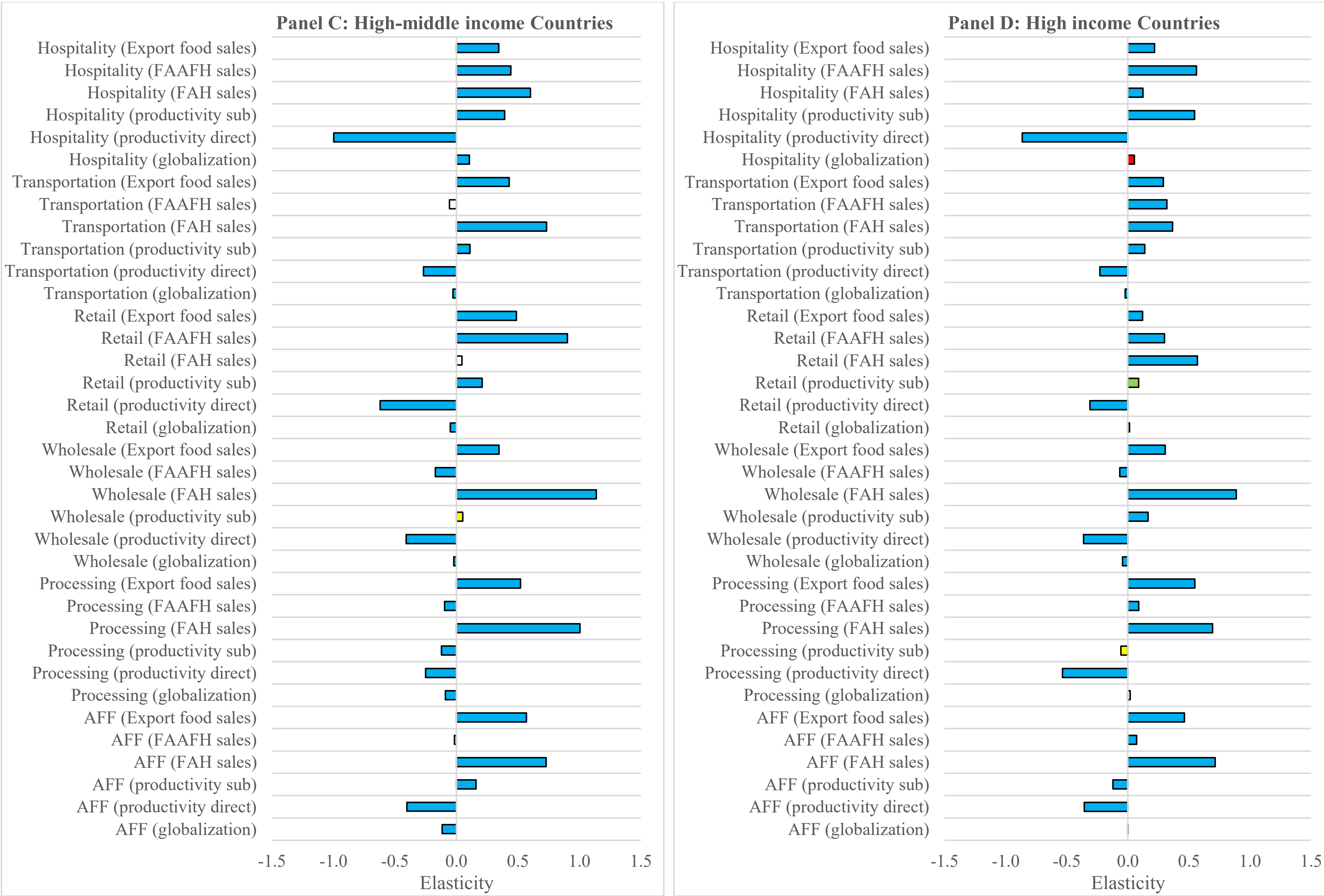


Figure 7 (cont): Estimated elasticities of FVC payroll by country income group (in 2015 U.S. Dollars)

Note: blue bar indicates $p < 0.001$; green bar indicates $p < 0.01$; yellow bar indicates $p < 0.05$; red bar indicates p-value < 0.1; white bar indicates $p \geq 0.1$

5. Conclusions

This paper has laid out a novel method of structural decomposition of FVC labor dynamics – as reflected in payroll expenditures and employment headcount – within six industry sectors that comprise the FVC and applied that method to 29 years of data from 189 different countries, 1993-2021. The empirical results replicate several well-known empirical regularities – such as the sharp fall in the economywide employment share of agriculture as incomes rise – while uncovering at least four new important insights about FVC labor dynamics under structural transformation.

First, although the employment share in primary production – agriculture and fisheries – declines sharply as countries' incomes grow, the economywide share of employment in post-farmgate value-adding sectors – processing, wholesale, transportation, retail and hospitality – increases significantly as countries move from low- to high-income, before declining somewhat as incomes grow further within the HIC range. The post-farmgate industries account for a majority of FVC employment, on average, by the time countries reach the upper middle-income range, and the post-farmgate FVC workforce is more than five times the scale of that in primary food production in HICs. These patterns also speak to a question of considerable policy interest: whether the off-farm food system can generate additional jobs as primary agriculture's share of the workforce contracts. The cross-country pattern is consistent with off-farm AFS generating substantial employment opportunities as countries develop, responding to the relatively high income elasticity of demand for non-nutritive food attributes such as convenience, quality and safety — supporting the case for post-farm agrifood business as a focal point for jobs-oriented development policy.

Second, as agriculture sheds workers, better-paying downstream FVC segments employ more labor, and structural transformation increasingly integrates labor markets intersectorally and spatially, intersectoral compensation differentials shrink rapidly. The more than 2.2-fold gap in average worker compensation that exists between non-FVC and FVC sectors in LLMICs shrinks to just under a 40 percent premium in HICs even as the FVC's overall share of employment declines.

Third, the empirical results corroborate several longstanding assumptions of the structural transformation literature (Lewis 1954; Johnston and Mellor 1961; Timmer 2009; Mellor 2017; Duernecker and Herrendorf 2022). Labor productivity growth within each of the FVC sectors leads to employment and payroll reduction, especially in the AFF sector in low-income countries. But the income growth effects associated with the technological and institutional changes that improve labor productivity – within and outside of the FVC – dominate the labor-saving effects, resulting in increased employment and compensation in FVCs, albeit in different, downstream jobs than those predominant in low-income country food systems. Indeed, labor productivity growth among a sector's subcontractors tends to boost employment in the sector. As economies grow and open more to foreign trade, reduced self-reliance on domestic suppliers leads to some job loss. But, again, the increased access to export markets and the rising domestic food expenditures that result from gains from trade lead to FVC employment gains that more than offset the *ceteris paribus* job losses due to globalization. Income growth seems the most prominent factor associated with changes in FVC employment (Yi et al. 2025).

Fourth, over lower income ranges, upstream FVC labor markets – in AFF and manufacturing – respond most elastically to changes in any of the factors significantly associated with labor market dynamics (i.e., productivity, globalization, market scale). By contrast, as per capita incomes rise, the downstream sectors – hospitality and retail trade, in particular – become most responsive, presumably reflecting relatively high income elasticities of demand for convenience, quality, safety and variety attributes in food.

The use of structural decomposition methods of the sort introduced in this paper opens up a new line of inquiry into the dynamics of FVC labor markets. Fruitful extensions of this work might explore, for example, how the introduction and diffusion of specific new agricultural or food manufacturing technologies impact FVC labor markets, the distribution of gains from expanding food markets among workers and business owners, including farmers, how accommodating variation in hours worked across all jobs affects inferences, and more granular explorations of specific countries or food groups. As governments around the world increasingly focus on expanding access to quality employment opportuntiies, and in much of the world look to the FVC to do much of that work, the returns to more rigorous and nuanced study of FVC labor dynamics and what truly causes job and compensation growth only grow.

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APPENDIX

Table A1: Countries Included in Eora Data (Note: * indicates the country is also included in ILO data)

Country Code	Country	Country Code	Country
AFG*	Afghanistan*	ALB*	Albania*
DZA	Algeria	AND	Andorra
AGO*	Angola*	ATG	Antigua
ARG*	Argentina*	ARM*	Armenia*
ABW	Aruba	AUS*	Australia*
AUT*	Austria*	AZE	Azerbaijan
BHS	Bahamas	BHR	Bahrain
BGD*	Bangladesh*	BRB*	Barbados*
BLR*	Belarus*	BEL*	Belgium*
BLZ	Belize	BEN	Benin
BMU	Bermuda	BTN*	Bhutan*
BOL*	Bolivia*	BIH*	Bosnia and Herzegovina*
BWA*	Botswana*	BRA*	Brazil*
VGB	British Virgin Islands	BRN*	Brunei*
BGR*	Bulgaria*	BFA*	Burkina Faso*
BDI*	Burundi*	KHM*	Cambodia*
CMR	Cameroon	CAN	Canada
CPV*	Cape Verde*	CYM	Cayman Islands
CAF	Central African Republic	TCD*	Chad*
CHL*	Chile*	CHN	China
COL*	Colombia*	COG	Congo

Country Code	Country	Country Code	Country
COD*	Congo, Democratic Republic of the*	CRI*	Costa Rica*
CIV*	Cote d'Ivoire*	HRV*	Croatia*
CUB	Cuba	CYP*	Cyprus*
CZE*	Czech Republic*	DNK*	Denmark*
DJI	Djibouti	DOM*	Dominican Republic*
ECU*	Ecuador*	EGY*	Egypt*
SLV*	El Salvador*	ERI	Eritrea
EST*	Estonia*	ETH*	Ethiopia*
SWZ*	Eswatini*	FJI*	Fiji*
FIN*	Finland*	FRA*	France*
PYF	French Polynesia	GAB	Gabon
GMB	Gambia	GEO*	Georgia*
DEU*	Germany*	GHA*	Ghana*
GRC*	Greece*	GRL	Greenland
GTM*	Guatemala*	GIN	Guinea
GUY*	Guyana*	HTI	Haiti
HND*	Honduras*	HKG	Hong Kong
HUN*	Hungary*	ISL*	Iceland*
IND*	India*	IDN*	Indonesia*
IRN*	Iran*	IRQ*	Iraq*
IRL*	Ireland*	ISR*	Israel*
ITA*	Italy*	JAM*	Jamaica*

Country Code	Country	Country Code	Country
JPN*	Japan*	JOR*	Jordan*
KAZ	Kazakhstan	KEN*	Kenya*
KOR*	Korea, Republic of*	PRK	North Korea
KWT	Kuwait	KGZ*	Kyrgyzstan*
LAO*	Laos*	LVA*	Latvia*
LBN*	Lebanon*	LSO*	Lesotho*
LBR*	Liberia*	LBY	Libya
LIE	Liechtenstein	LTU*	Lithuania*
LUX*	Luxembourg*	MAC	Macao SAR
MDG*	Madagascar*	MWI	Malawi
MYS	Malaysia	MDV*	Maldives*
MLI*	Mali*	MLT*	Malta*
MRT*	Mauritania*	MUS*	Mauritius*
MEX*	Mexico*	MCO	Monaco
MDA	Moldova	MNG*	Mongolia*
MNE	Montenegro	MAR	Morocco
MOZ*	Mozambique*	MMR*	Myanmar*
NAM*	Namibia*	NPL*	Nepal*
NLD*	Netherlands*	NCL*	New Caledonia*
NZL	New Zealand	NIC*	Nicaragua*
NER*	Niger*	NGA*	Nigeria*
MKD*	North Macedonia*	NOR*	Norway*
OMN	Oman	PAK*	Pakistan*

Country Code	Country	Country Code	Country
PAN*	Panama*	PNG*	Papua New Guinea*
PRY	Paraguay	PER*	Peru*
PHL*	Philippines*	POL*	Poland*
PRT*	Portugal*	QAT	Qatar
ROU*	Romania*	RUS	Russia
RWA*	Rwanda*	WSM*	Samoa*
SMR	San Marino	SAU	Saudi Arabia
SEN*	Senegal*	SRB*	Serbia*
SYC*	Seychelles*	SLE*	Sierra Leone*
SGP*	Singapore*	SVK*	Slovakia*
SVN*	Slovenia*	SOM*	Somalia*
ZAF*	South Africa*	SDS	South Sudan
ESP*	Spain*	LKA*	Sri Lanka*
SUD	Sudan	SUR*	Suriname*
SWE*	Sweden*	CHE*	Switzerland*
SYR	Syria	TJK	Tajikistan
TWN	Taiwan	TZA*	Tanzania*
THA*	Thailand*	TGO*	Togo*
TTO	Trinidad and Tobago	TUN*	Tunisia*
TUR*	Turkey*	TKM	Turkmenistan
UGA*	Uganda*	UKR*	Ukraine*
ARE*	UAE*	GBR*	UK*
USA*	USA*	URY*	Uruguay*

Country Code	Country	Country Code	Country
UZB	Uzbekistan	VUT*	Vanuatu*
VEN*	Venezuela*	VNM*	Viet Nam*
YEM*	Yemen*	ZMB*	Zambia*
ZWE*	Zimbabwe*		

Table A2: 26 Sectors in the Eora26 Tables and our 25 Sector Variant

Index	Sectors
A01T02	Agriculture and Fishing
A03	Mining and Quarrying
A04	Food & Beverages
A05	Textiles and Wearing Apparel
A06	Wood and Paper
A07	Petroleum, Chemical and Non-Metallic Mineral Products
A08	Metal Products
A09	Electrical and Machinery
A10	Transport Equipment
A11	Other Manufacturing
A12	Recycling
A13	Electricity, Gas and Water
A14	Construction
A15	Maintenance and Repair
A16	Wholesale Trade
A17	Retail Trade
A18	Hotels and Restaurants
A19	Transport
A20	Post and Telecommunications
A21	Financial Intermediation and Business Activities
A22	Public Administration
A23	Education, Health and Other Services
A24	Private Households
A25	Others
A26	Re-export & Re-import

Table A3: Log compensation gap between non-FVC and FVC employment, by income group.

Income Group	Count	Mean	std	min	25%	50%	75%	max
LLMIC	263	0.802	0.393	-0.345	0.577	0.854	1.069	1.928
UMIC	354	0.636	0.357	-0.294	0.344	0.641	0.908	1.665
HIC	698	0.320	0.221	-0.281	0.174	0.288	0.423	0.957

Note: The table reports descriptive statistics for the log compensation gap between non-FVC and FVC employment, defined in equation (36).
Positive values indicate that average real compensation per worker is higher outside the FVC, while smaller values indicate a narrower compensation gap. Using log differences allows comparison across income groups by abstracting from scale differences in compensation levels.

Table A4. First difference of log regressions for total payroll by FVC stage and income group

	All countries	Low income	Low-middle income	High-middle income	High income
Sector: Agriculture					
X1 (globalization)	0.0361****	0.0860****	0.0212**	0.0625****	0.0005
	(0.0068)	(0.0196)	(0.0091)	(0.0111)	(0.0145)
X2 (productivity direct)	-0.5107****	-0.7284****	-0.2746****	-0.6900****	-0.3563****
	(0.0096)	(0.0437)	(0.0183)	(0.0198)	(0.0124)
X3 (productivity sub)	-0.0353****	-0.0769***	0.0835****	0.2145****	-0.1210****
	(0.0088)	(0.0279)	(0.0166)	(0.0177)	(0.0178)
X4 (FAH sales)	0.6903****	0.5302****	0.7324****	0.6220****	0.7153****
	(0.0168)	(0.0577)	(0.0261)	(0.0421)	(0.0241)
X5 (FAAFH sales)	0.1593****	0.4455****	0.0023	0.0653*	0.0724****
	(0.0099)	(0.0394)	(0.0116)	(0.0368)	(0.0241)
X6 (Export food sales)	0.5551****	0.6602****	0.3743****	0.6435****	0.4636****
	(0.0135)	(0.0434)	(0.0187)	(0.0259)	(0.0163)
BI5U (Upper bound FAAFH)	0.4203****	0.0226	0.2730****	-0.1877**	-0.8043****
	(0.0371)	(0.0967)	(0.0830)	(0.0900)	(0.2075)
BI6U (Upper bound Export)	0.0737***	0.1675*	0.0728*	0.1363***	0.3208****
	(0.0301)	(0.0952)	(0.0382)	(0.0555)	(0.0845)
BI4L (Lower bound FAH)	0.1806****	-0.1696	-0.0375	0.6830****	-0.0775
	(0.0418)	(0.1687)	(0.0648)	(0.0868)	(0.1191)
BI5L Lower bound FAAFH)	-0.0611*	0.1149	-0.9589****	-0.6403****	-0.2413
	(0.0360)	(0.1082)	(0.0674)	(0.0893)	(0.1591)
BI6L (Lower bound Export)	-0.0751***	-0.9867****	0.5214****	-0.3164****	-0.4053****
	(0.0301)	(0.1537)	(0.0413)	(0.0601)	(0.0376)
Country fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Model degrees of freedom	4669	545	1176	1164	1651
Adjusted r-squared	0.911	0.973	0.948	0.915	0.828
Sector: Food and Beverage					
X1 (globalization)	0.0237****	0.0192	0.0280**	0.0452****	0.0194
	(0.0082)	(0.0160)	(0.0133)	(0.0140)	(0.0179)
X2 (productivity direct)	-0.4234****	-0.3259****	-0.2975****	-0.2857****	-0.5341****
	(0.0118)	(0.0294)	(0.0219)	(0.0231)	(0.0207)
X3 (productivity sub)	-0.2621****	-0.4569****	-0.1652****	-0.1752****	-0.0563**
	(0.0121)	(0.0328)	(0.0197)	(0.0298)	(0.0279)
X4 (FAH sales)	1.1326****	1.2801****	1.2889****	0.9776****	0.6945****
	(0.0168)	(0.0407)	(0.0249)	(0.0349)	(0.0242)
X5 (FAAFH sales)	-0.0458****	0.0847**	-0.1907****	-0.0956****	0.0895****
	(0.0121)	(0.0395)	(0.0169)	(0.0331)	(0.0214)
X6 (Export food sales)	0.4930****	0.3248****	0.2716****	0.5028****	0.5481****
	(0.0118)	(0.0250)	(0.0161)	(0.0233)	(0.0150)

Table A4. First difference of log regressions for total payroll by FVC stage and income group

	All countries	Low income	Low-middle income	High-middle income	High income
BI4U (Upper bound FAH)	-0.3799****	-0.4650**	0.1063	0.7471****	0.6689****
	(0.0460)	(0.1937)	(0.2122)	(0.0874)	(0.0916)
BI6U (Upper bound Export)	-0.0641**	-0.4026**	-0.0684*	-0.0264	0.7435****
	(0.0283)	(0.1915)	(0.0370)	(0.0548)	(0.0940)
BI4L (Lower bound FAH)	0.3187****	0.1411	-0.0949	0.6919****	0.4440****
	(0.0431)	(0.1695)	(0.1241)	(0.0859)	(0.0926)
BI5L Lower bound FAAFH)	0.1746****	0.3118****	0.0820	-0.4740****	-0.5401***
	(0.0335)	(0.0631)	(0.1963)	(0.0737)	(0.2171)
BI6L (Lower bound Export)	-0.3016****	-0.1132**	0.1450****	-0.7137****	-0.5054****
	(0.0266)	(0.0494)	(0.0426)	(0.0749)	(0.0423)
Country fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Model degrees of freedom	4672	545	1176	1164	1655
Adjusted r-squared	0.925	0.990	0.932	0.918	0.867
Sector: Wholesale					
X1 (globalization)	-0.0378****	-0.0624****	-0.0726****	-0.0206****	-0.0425****
	(0.0041)	(0.0131)	(0.0067)	(0.0059)	(0.0061)
X2 (productivity direct)	-0.4705****	-0.3779****	-0.2872****	-0.4158****	-0.3619****
	(0.0138)	(0.0377)	(0.0226)	(0.0261)	(0.0231)
X3 (productivity sub)	0.0664****	-0.1307****	0.2428****	0.0545**	0.1660****
	(0.0108)	(0.0327)	(0.0166)	(0.0250)	(0.0217)
X4 (FAH sales)	1.0410****	1.1336****	0.8364****	1.1291****	0.8884****
	(0.0152)	(0.0389)	(0.0222)	(0.0313)	(0.0229)
X5 (FAAFH sales)	0.1010****	0.0515	0.0803****	-0.1669****	-0.0659****
	(0.0117)	(0.0331)	(0.0194)	(0.0252)	(0.0209)
X6 (Export food sales)	0.1949****	0.3369****	0.1922****	0.3328****	0.3062****
	(0.0085)	(0.0228)	(0.0126)	(0.0223)	(0.0182)
BI4U (Upper bound FAH)	-0.2828****	0.0616	0.2686***	0.3600****	0.4512****
	(0.0289)	(0.0593)	(0.1043)	(0.0550)	(0.0928)
BI5U (Upper bound FAAFH)	-0.1849****	-0.0950	0.1258**	-0.1401****	-0.6334****
	(0.0285)	(0.1183)	(0.0529)	(0.0422)	(0.0646)
BI6U (Upper bound Export)	0.1787****	-0.2178***	0.4457****	0.1997****	0.2264****
	(0.0292)	(0.0801)	(0.0439)	(0.0475)	(0.0483)
BI4L (Lower bound FAH)	-0.4226****	-3.5242****	-0.3302****	-0.1038	-0.5905****
	(0.0412)	(0.8265)	(0.0863)	(0.0987)	(0.0734)
BI5L Lower bound FAAFH)	0.4142****	2.5114****	0.1839	0.0468	1.4178****
	(0.0435)	(0.4601)	(0.1183)	(0.0812)	(0.2282)
BI6L (Lower bound Export)	-0.1768****	-1.0024****	-0.2245	0.0398	-0.2154*
	(0.0435)	(0.0963)	(0.1617)	(0.0930)	(0.1151)
Country fixed effect	Yes	Yes	Yes	Yes	Yes

Table A4. First difference of log regressions for total payroll by FVC stage and income group

	All countries	Low income	Low-middle income	High-middle income	High income
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Model degrees of freedom	4672	546	1176	1164	1653
Adjusted r-squared	0.933	0.992	0.965	0.919	0.817
Sector: Retail					
X1 (globalization)	0.0358****	-0.0737****	-0.1156****	0.0369***	0.0140
	(0.0079)	(0.0229)	(0.0117)	(0.0133)	(0.0158)
X2 (productivity direct)	-0.6797****	-0.5096****	-0.2281****	-0.6551****	-0.3089****
	(0.0159)	(0.0410)	(0.0259)	(0.0371)	(0.0333)
X3 (productivity sub)	0.1526****	-0.0315	0.2246****	0.1680****	0.0889***
	(0.0122)	(0.0364)	(0.0127)	(0.0402)	(0.0339)
X4 (FAH sales)	0.3779****	0.5809****	0.1414****	-0.0039	0.5707****
	(0.0177)	(0.0515)	(0.0224)	(0.0437)	(0.0311)
X5 (FAAFH sales)	0.6973****	0.7299****	0.8597****	0.9291****	0.3007****
	(0.0211)	(0.0550)	(0.0256)	(0.0460)	(0.0342)
X6 (Export food sales)	0.3429****	0.2166****	0.0839****	0.5231****	0.1211****
	(0.0189)	(0.0361)	(0.0227)	(0.0392)	(0.0320)
BI4U (Upper bound FAH)	0.0924**	1.8293****	0.3716***	0.2496****	-0.8167****
	(0.0456)	(0.3366)	(0.1370)	(0.0791)	(0.1391)
BI5U (Upper bound FAAFH)	-0.2826****	-0.3613**	2.3100****	-0.3576****	2.0579****
	(0.0534)	(0.1702)	(0.1972)	(0.1099)	(0.1699)
BI6U (Upper bound Export)	0.4378****	-0.1685	-0.1179*	0.3546****	0.1113
	(0.0544)	(0.1467)	(0.0687)	(0.1103)	(0.1144)
BI4L (Lower bound FAH)	0.2848****	-6.6823****	3.7203****	0.0684	-0.7077****
	(0.0576)	(1.1832)	(0.3453)	(0.1556)	(0.1542)
BI5L Lower bound FAAFH)	-0.4822****	10.0100****	0.7186****	-0.1426	-0.1127
	(0.0560)	(1.5998)	(0.1627)	(0.1682)	(0.1327)
BI6L (Lower bound Export)	-0.0285	0.0065	-0.2097*	0.4063****	-0.4046****
	(0.0397)	(0.1117)	(0.1200)	(0.0914)	(0.0817)
Country fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Model degrees of freedom	4672	545	1176	1164	1653
Adjusted r-squared	0.890	0.987	0.935	0.854	0.675
Sector: Transportation					
X1 (globalization)	0.0031	0.0931****	-0.0826****	0.0044	-0.0208****
	(0.0052)	(0.0229)	(0.0159)	(0.0075)	(0.0066)
X2 (productivity direct)	-0.5071****	-0.4930****	-0.0499	-0.3152****	-0.2287****
	(0.0156)	(0.0647)	(0.0451)	(0.0341)	(0.0221)
X3 (productivity sub)	0.0619****	-0.1026*	0.0825**	0.0007	0.1390****
	(0.0157)	(0.0595)	(0.0355)	(0.0322)	(0.0249)
X4 (FAH sales)	0.7890****	1.0980****	0.6623****	0.9016****	0.3661****

Table A4. First difference of log regressions for total payroll by FVC stage and income group

	All countries	Low income	Low-middle income	High-middle income	High income
	(0.0228)	(0.0663)	(0.0491)	(0.0536)	(0.0326)
X5 (FAAFH sales)	0.1655****	-0.0602	0.1567****	-0.1666****	0.3205****
	(0.0146)	(0.0535)	(0.0388)	(0.0393)	(0.0274)
X6 (Export food sales)	0.3982****	0.4529****	0.2101****	0.4656****	0.2911****
	(0.0169)	(0.0438)	(0.0263)	(0.0339)	(0.0225)
BI4U (Upper bound FAH)	-0.6767****	-0.9785****	-0.9354****	-0.2564****	-0.6656****
	(0.0397)	(0.0883)	(0.1806)	(0.0761)	(0.1047)
BI5U (Upper bound FAAFH)	-0.2503****	0.1327	-0.3149****	-0.0823	-0.4281
	(0.0445)	(0.1396)	(0.1080)	(0.0588)	(0.4666)
BI6U (Upper bound Export)	0.4851****	0.7850****	0.2828****	0.4188****	0.7067****
	(0.0409)	(0.1244)	(0.0774)	(0.0824)	(0.1172)
BI4L (Lower bound FAH)	0.2418****	5.9497****	-0.6783****	0.5694****	0.4659****
	(0.0526)	(1.1680)	(0.1720)	(0.0984)	(0.1059)
BI5L Lower bound FAAFH)	0.2157****	-2.3029****	0.3714****	-0.4267****	0.0098
	(0.0437)	(0.6592)	(0.0912)	(0.0958)	(0.2419)
BI6L (Lower bound Export)	-0.0390	-0.3109**	0.2841****	-0.2432***	-0.5272****
	(0.0338)	(0.1572)	(0.0633)	(0.0878)	(0.0528)
Country fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Model degrees of freedom	4672	545	1176	1164	1653
Adjusted r-squared	0.860	0.975	0.860	0.835	0.655
Sector: Hospitality					
X1 (globalization)	0.1275****	0.1974****	0.0256	0.1451****	0.0540*
	(0.0131)	(0.0318)	(0.0240)	(0.0213)	(0.0299)
X2 (productivity direct)	-0.8855****	-0.7752****	-0.3382****	-0.9482****	-0.8634****
	(0.0191)	(0.0504)	(0.0346)	(0.0343)	(0.0372)
X3 (productivity sub)	0.2710****	0.0507	0.3343****	0.2976****	0.5469****
	(0.0163)	(0.0531)	(0.0270)	(0.0343)	(0.0412)
X4 (FAH sales)	0.4983****	0.5991****	0.4324****	0.5465****	0.1248****
	(0.0241)	(0.0753)	(0.0378)	(0.0482)	(0.0438)
X5 (FAAFH sales)	0.4446****	0.5454****	0.3668****	0.4549****	0.5620****
	(0.0174)	(0.0645)	(0.0261)	(0.0432)	(0.0408)
X6 (Export food sales)	0.3893****	0.2821****	0.1084****	0.3878****	0.2191****
	(0.0178)	(0.0457)	(0.0251)	(0.0339)	(0.0286)
BI5U (Upper bound FAAFH)	-0.1820****	0.6822****	-0.5597**	-1.1388****	-2.0052****
	(0.0609)	(0.2428)	(0.2737)	(0.0947)	(0.2927)
BI6U (Upper bound Export)	-0.2221****	-0.2649**	-0.1441	-0.2598****	0.3358**
	(0.0448)	(0.1277)	(0.1004)	(0.0835)	(0.1408)
BI4L (Lower bound FAH)	0.3891****	-1.3023****	0.7904****	-0.1908	-0.3541****
	(0.0650)	(0.3064)	(0.1985)	(0.1318)	(0.1125)

Table A4. First difference of log regressions for total payroll by FVC stage and income group

	All countries	Low income	Low-middle income	High-middle income	High income
BI5L Lower bound FAAFH)	0.4296****	0.4012****	0.4158**	0.6984****	-1.3339****
	(0.0463)	(0.1144)	(0.1767)	(0.1205)	(0.1283)
BI6L (Lower bound Export)	0.0717*	0.5421****	0.4721****	0.0000	0.1028**
	(0.0381)	(0.1481)	(0.0794)	(0.0735)	(0.0490)
Country fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Model degrees of freedom	4672	546	1176	1164	1654
Adjusted r-squared	0.827	0.965	0.855	0.849	0.615

Standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$. All regressions include observations across 178 Countries, annually 1993-2021. Countries that change income groups over the time series drop out of the income group regressions.

Table A5. First difference of log regressions for total jobs by FVC stage and income group

	All countries	Low & low-middle income	High-middle income	High income
Sector: Agriculture				
X1 (globalization)	-0.1477****	-0.1295****	-0.1394****	-0.1994****
	(0.0105)	(0.0108)	(0.0107)	(0.0227)
X2 (productivity direct)	-0.8717****	-0.9205****	-0.9405****	-0.7414****
	(0.0071)	(0.0116)	(0.0100)	(0.0092)
X3 (productivity sub)	-0.0573****	0.0306****	0.0056	-0.2474****
	(0.0073)	(0.0087)	(0.0116)	(0.0101)
X4 (FAH sales)	0.4979****	0.6153****	0.7572****	0.4041****
	(0.0219)	(0.0416)	(0.0333)	(0.0264)
X5 (FAAFH sales)	0.0814****	-0.0274	0.0004	0.0681***
	(0.0201)	(0.0344)	(0.0254)	(0.0248)
X6 (Export food sales)	0.3157****	0.3077****	0.1688****	0.3358****
	(0.0200)	(0.0346)	(0.0198)	(0.0248)
BI5U (Upper bound FAAFH)	0.3017****	0.5525****	-0.0035	-28.4614****
	(0.0935)	(0.1023)	(0.0974)	(6.8906)
BI6U (Upper bound Export)	0.1622****	0.0634	-0.1839****	5.8573****
	(0.0472)	(0.0476)	(0.0596)	(0.8429)
BI5L Lower bound FAAFH)	-0.2389****	3.8456****	-1.5715****	4.0152***
	(0.0656)	(0.8149)	(0.1327)	(1.5323)
BI6L (Lower bound Export)	-0.1708**	-0.2024	0.7097****	0.5081****
	(0.0850)	(0.1358)	(0.2405)	(0.1384)
Country fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Model degrees of freedom	1270	236	281	633
Adjusted r-squared	0.929	0.983	0.979	0.949
Sector: Food and Beverage				
X1 (globalization)	-0.1739****	-0.1188****	-0.1573****	-0.2406****
	(0.0243)	(0.0410)	(0.0132)	(0.0418)
X2 (productivity direct)	-0.6164****	-0.7679****	-0.8085****	-0.5229****
	(0.0089)	(0.0135)	(0.0108)	(0.0108)
X3 (productivity sub)	-0.3210****	-0.2766****	-0.1529****	-0.4790****
	(0.0089)	(0.0130)	(0.0117)	(0.0118)
X4 (FAH sales)	0.4751****	0.7914****	0.7688****	0.4282****
	(0.0301)	(0.0760)	(0.0249)	(0.0359)
X5 (FAAFH sales)	0.1467****	0.0170	-0.0129	0.1037****

Table A5. First difference of log regressions for total jobs by FVC stage and income group

	All countries	Low & low-middle income	High-middle income	High income
	(0.0261)	(0.0695)	(0.0227)	(0.0305)
X6 (Export food sales)	0.2723****	0.2412****	0.2053****	0.3719****
	(0.0248)	(0.0501)	(0.0171)	(0.0333)
BI4U (Upper bound FAH)	0.4108****	-3.3523****	0.5775****	0.8040****
	(0.1233)	(0.5217)	(0.0684)	(0.1786)
BI6U (Upper bound Export)	0.7886****	1.0142****	0.0410	4.1620****
	(0.1285)	(0.3577)	(0.0441)	(0.4087)
BI5L Lower bound FAAFH)	-0.1500**	2.8493****	0.3382****	1.0939**
	(0.0738)	(0.4208)	(0.0439)	(0.4904)
BI6L (Lower bound Export)	-0.1965****	0.1106	0.3924****	0.1621
	(0.0642)	(0.1725)	(0.0475)	(0.1613)
Country fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Model degrees of freedom	1271	236	283	634
Adjusted r-squared	0.861	0.935	0.978	0.896
Sector: Wholesale				
X1 (globalization)	-0.0117	0.0200	-0.0352*	0.0041
	(0.0137)	(0.0529)	(0.0194)	(0.0125)
X2 (productivity direct)	-0.1603****	0.1594*	-0.2290****	-0.2456****
	(0.0280)	(0.0872)	(0.0746)	(0.0234)
X3 (productivity sub)	-0.4711****	-0.3570****	-0.4539****	-0.6166****
	(0.0276)	(0.0781)	(0.0622)	(0.0272)
X4 (FAH sales)	0.5932****	0.4666	0.8454****	0.5279****
	(0.0660)	(0.2998)	(0.1466)	(0.0595)
X5 (FAAFH sales)	-0.0437	-0.2949	-0.0342	-0.0727
	(0.0616)	(0.3016)	(0.1379)	(0.0479)
X6 (Export food sales)	0.1894****	0.2304	0.0795	0.1965****
	(0.0586)	(0.2564)	(0.1066)	(0.0458)
BI4U (Upper bound FAH)	-0.5916	-0.6848	-0.3967	0.0039
	(0.3912)	(1.4619)	(0.3389)	(0.1400)
BI5U (Upper bound FAAFH)	-0.0099	0.4678	-0.3313	-0.8311****
	(0.1149)	(1.5059)	(0.2052)	(0.2714)
BI6U (Upper bound Export)	0.0506	0.2033	0.0635	0.0584
	(0.1237)	(0.5363)	(0.1676)	(0.1363)
BI4L (Lower bound FAH)	-0.4138	-10.7506*	0.2135	-0.1392

Table A5. First difference of log regressions for total jobs by FVC stage and income group

	All countries	Low & low-middle income	High-middle income	High income
	(0.3424)	(6.2655)	(1.3402)	(0.3329)
BI5L Lower bound FAAFH)	1.6529****	-14.2811*	1.3422*	0.6814****
	(0.5110)	(7.9245)	(0.7570)	(0.1416)
Country fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Model degrees of freedom	1272	237	282	634
Adjusted r-squared	0.292	0.038	0.373	0.695
Sector: Retail				
X1 (globalization)	-0.0266	-0.0433	-0.0074	-0.0408
	(0.0234)	(0.1133)	(0.0268)	(0.0269)
X2 (productivity direct)	-0.4479****	-0.2769****	-0.2466****	-0.6145****
	(0.0201)	(0.0464)	(0.0507)	(0.0237)
X3 (productivity sub)	-0.2145****	-0.1140**	-0.4135****	-0.3222****
	(0.0220)	(0.0482)	(0.0545)	(0.0268)
X4 (FAH sales)	0.3426****	0.4943****	0.2226***	0.3877****
	(0.0501)	(0.1592)	(0.0830)	(0.0478)
X5 (FAAFH sales)	0.4340****	0.1785	0.4623****	0.3709****
	(0.0534)	(0.1622)	(0.0899)	(0.0591)
X6 (Export food sales)	0.1813****	0.0288	0.0956	0.2467****
	(0.0540)	(0.1660)	(0.0904)	(0.0506)
BI4U (Upper bound FAH)	0.0544	-0.0881	-3.5959***	-1.3456****
	(0.1145)	(0.8518)	(1.3026)	(0.3677)
BI5U (Upper bound FAAFH)	-2.9671****	-0.2878	-38.1662****	-6.1784****
	(0.5544)	(0.2925)	(12.1859)	(1.5010)
BI6U (Upper bound Export)	0.4081**	0.0096	-0.1327	-2.8562**
	(0.2071)	(1.5219)	(0.2125)	(1.2947)
Country fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Model degrees of freedom	1270	239	284	631
Adjusted r-squared	0.462	0.110	0.468	0.805
Sector: Transportation				
X1 (globalization)	-0.0367****	-0.0040	-0.0572****	-0.0084
	(0.0092)	(0.0271)	(0.0126)	(0.0109)
X2 (productivity direct)	-0.0923****	-0.0071	-0.0940***	-0.2089****
	(0.0121)	(0.0177)	(0.0339)	(0.0214)
X3 (productivity sub)	-0.4750****	-0.3302****	-0.5011****	-0.6768****

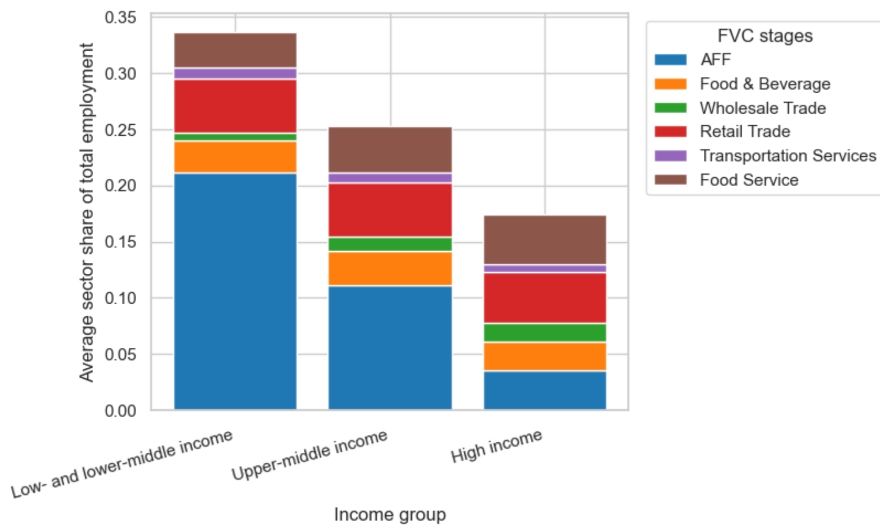
Table A5. First difference of log regressions for total jobs by FVC stage and income group

	All countries	Low & low-middle income	High-middle income	High income
	(0.0180)	(0.0354)	(0.0447)	(0.0245)
X4 (FAH sales)	0.4933****	0.9273****	0.3312**	0.3950****
	(0.0551)	(0.1740)	(0.1539)	(0.0617)
X5 (FAAFH sales)	0.0252	-0.4954****	0.1958*	0.2345****
	(0.0468)	(0.1468)	(0.1165)	(0.0530)
X6 (Export food sales)	0.0102	0.2025	-0.0896	0.0119
	(0.0543)	(0.1433)	(0.1087)	(0.0592)
BI5U (Upper bound FAAFH)	-0.6908****	-0.3936*	-0.5760	-0.4440**
	(0.1992)	(0.2354)	(0.5071)	(0.2221)
BI6U (Upper bound Export)	0.5716****	0.4631**	0.3292**	-28.0466****
	(0.1271)	(0.2241)	(0.1455)	(7.3748)
BI4L (Lower bound FAH)	1.9510****	-1.8582***	-16.3574****	3.5640****
	(0.5372)	(0.6633)	(2.6689)	(0.6059)
BI5L Lower bound FAAFH)	0.1007	-3.7836****	1.8702****	-26.9104****
	(0.1822)	(1.1779)	(0.3313)	(7.8866)
BI6L (Lower bound Export)	-0.0999	-0.3518	0.3392	-0.0609
	(0.1123)	(0.3792)	(0.4099)	(0.1149)
Country fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Model degrees of freedom	1270	236	281	633
Adjusted r-squared	0.414	0.240	0.471	0.722
Sector: Hospitality				
X1 (globalization)	-0.1318***	0.0228	0.0811	-0.2421****
	(0.0518)	(0.1813)	(0.0789)	(0.0546)
X2 (productivity direct)	-0.6513****	-0.3995****	-0.4801****	-0.8048****
	(0.0271)	(0.1056)	(0.0709)	(0.0218)
X3 (productivity sub)	-0.0853****	-0.2004****	-0.2078****	-0.0218
	(0.0200)	(0.0461)	(0.0663)	(0.0212)
X4 (FAH sales)	-0.0080	0.1356	0.2955**	0.0069
	(0.0673)	(0.2530)	(0.1368)	(0.0621)
X5 (FAAFH sales)	0.3182****	0.1227	0.3950****	0.2141****
	(0.0658)	(0.2319)	(0.1280)	(0.0645)
X6 (Export food sales)	0.0114	0.1314	-0.1752	0.0697
	(0.0548)	(0.1784)	(0.1082)	(0.0523)
BI5U (Upper bound FAAFH)	-0.0061	0.6401*	-0.8568****	9.5112**

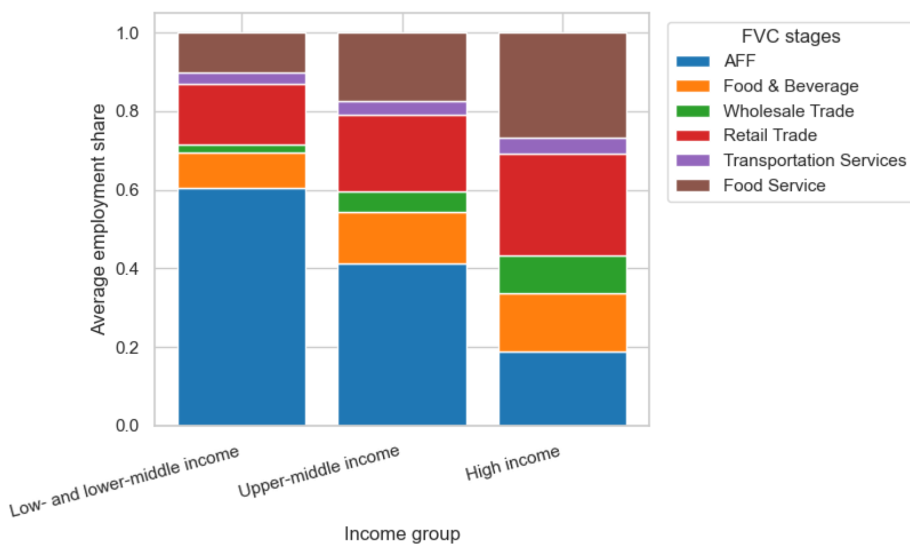
Table A5. First difference of log regressions for total jobs by FVC stage and income group

	All countries	Low & low-middle income	High-middle income	High income
	(0.3246)	(0.3502)	(0.2615)	(4.1693)
BI6U (Upper bound Export)	-0.0758	-1.5040*	0.1781	-0.2613
	(0.2097)	(0.8745)	(0.2025)	(0.3150)
BI5L Lower bound FAAFH)	0.1807	1.5844	-0.2658	-0.3165*
	(0.1400)	(1.4894)	(0.2242)	(0.1662)
BI6L (Lower bound Export)	-0.4892***	-0.7136	-0.0068	-0.5814***
	(0.1837)	(0.6155)	(0.4644)	(0.2132)
Country fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Model degrees of freedom	1270	237	284	632
Adjusted r-squared	0.357	0.037	0.372	0.734

Standard errors are shown in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01, **** p < 0.001. All regressions include observations across 112 Countries, annually 1993-2021. Countries that change income groups over the time series drop out of the income group regressions.



Panel A. Average stage composition of total employment



Panel B. Average stage composition of FVC employment

Figure A1: Average stage composition of FVC employment by income group. Note: Stacked bars show the average composition of employment across income groups. Panel A presents the average composition of total national employment, with stacked bars representing the mean employment shares of six FVC-related industries—AFF; food and beverage manufacturing; wholesale trade; retail trade; transportation services; and hospitality services. Panel B reports the analogous composition within FVC employment, where each bar shows the average share of these six stages in total FVC employment. Only country–year observations with employment data available in consecutive years are included.

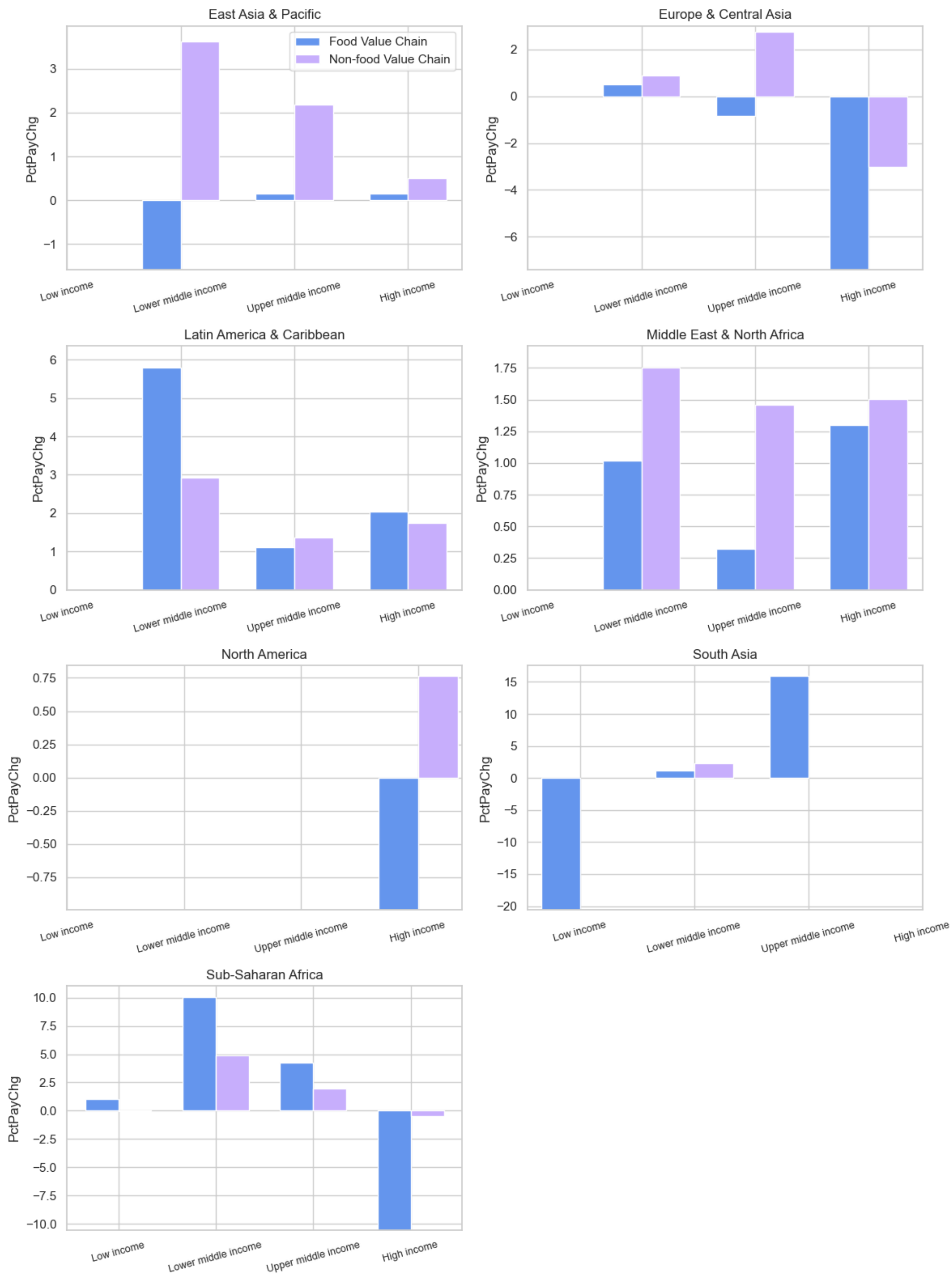


Figure A2: FVCs and Non-FVCs: Employment growth by income group and region

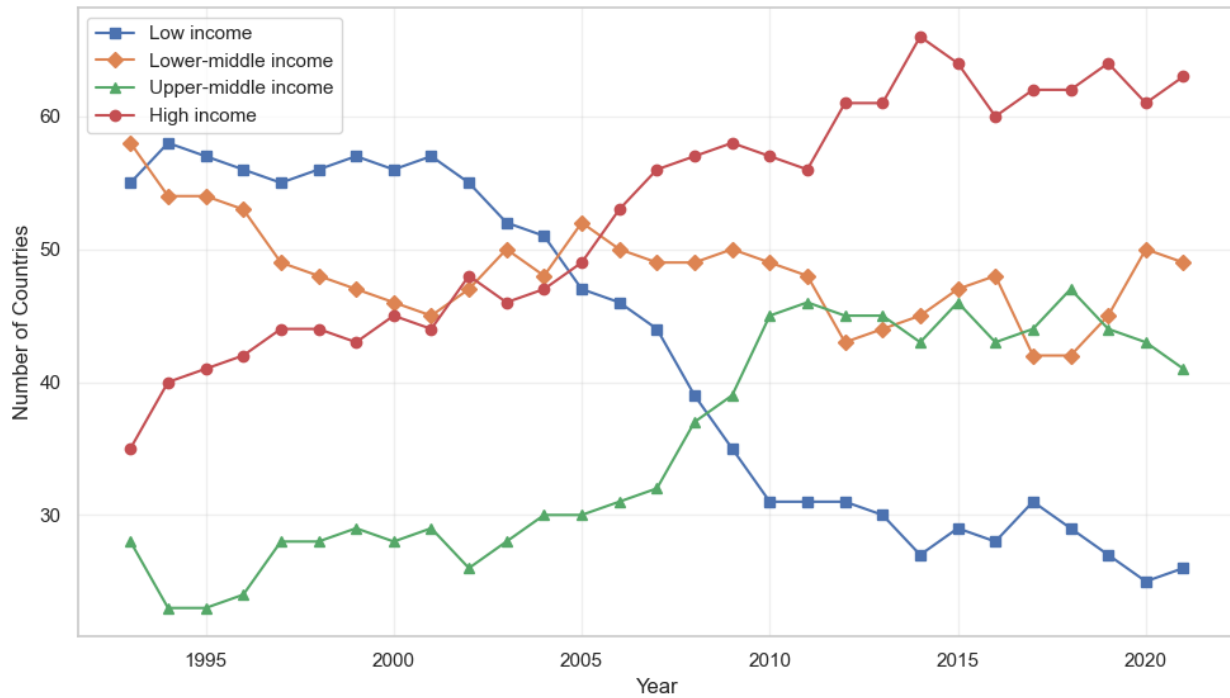


Figure A3. Number of countries in the total payroll data by income group by year, 1993-2021.

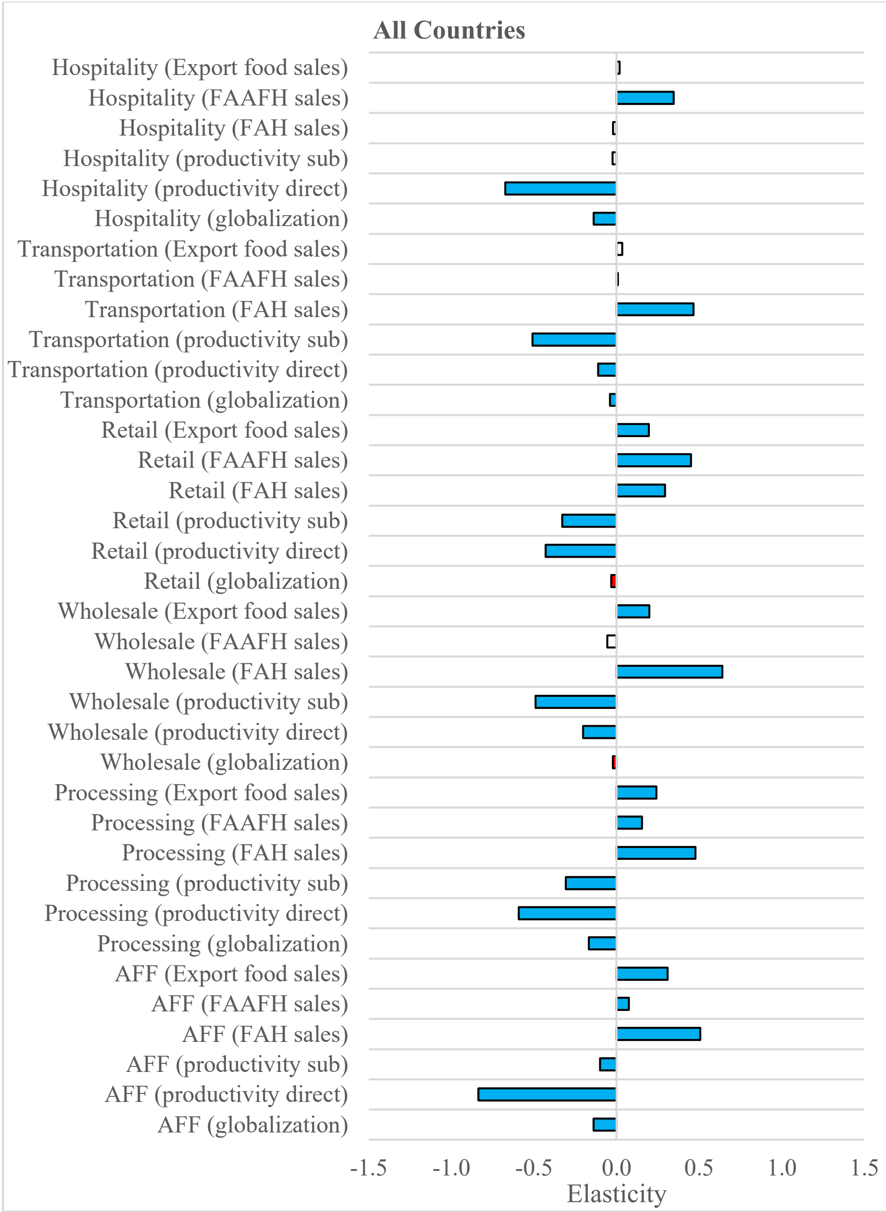


Figure A4: Estimated elasticities of FVC employment (in 2015 U.S. Dollars)

Note: blue bar indicates p < 0.001; green bar p < 0.01; yellow bar p < 0.05; red bar p-value < 0.1; white bar p ⩾ 0.1.

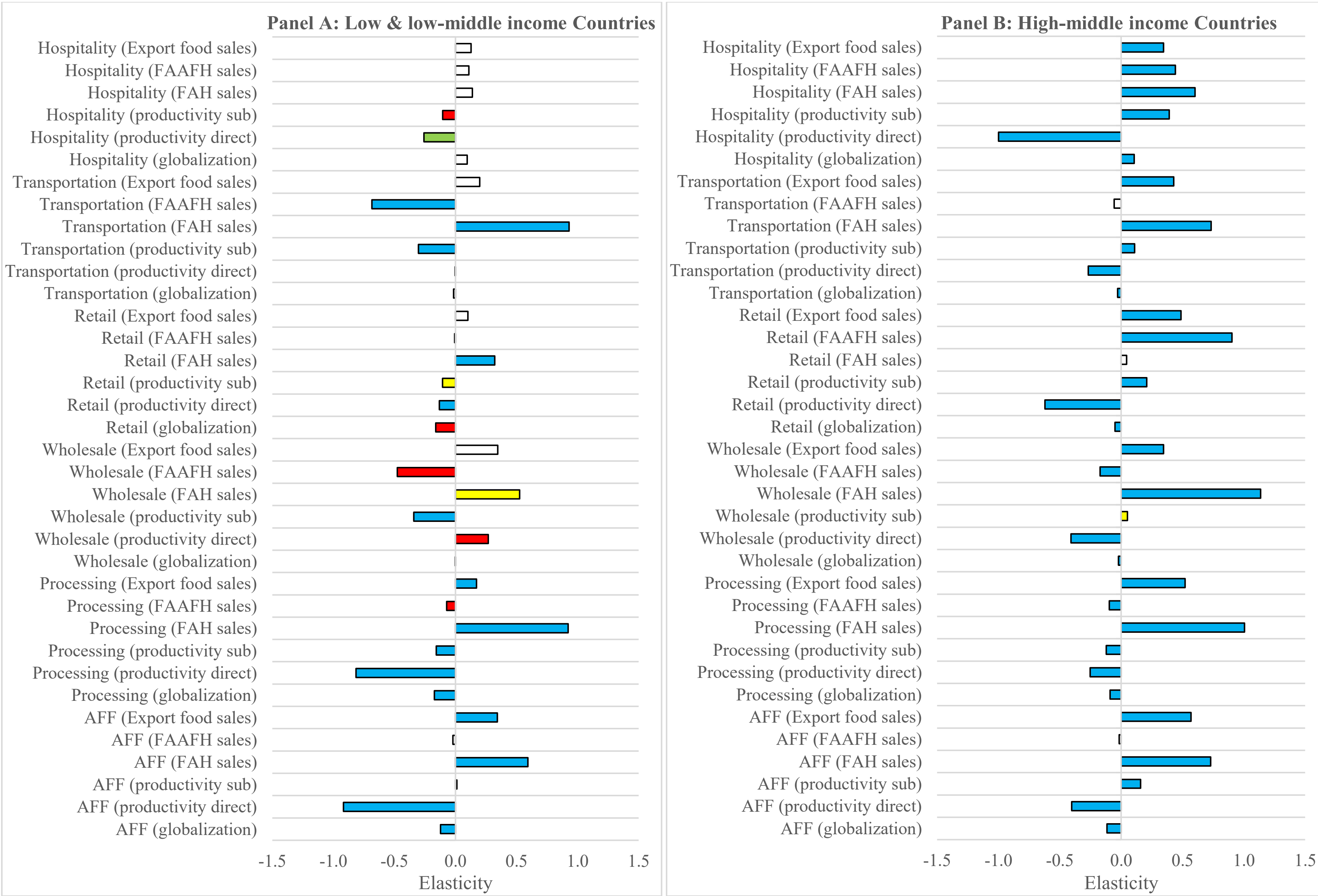


Figure A5: Estimated elasticities of FVC employment by country income group (in 2015 U.S. Dollars)

Note: blue bar indicates p < 0.001; green bar indicates p < 0.01; yellow bar indicates p < 0.05; red bar indicates p-value < 0.1; white bar indicates p ≥ 0.1

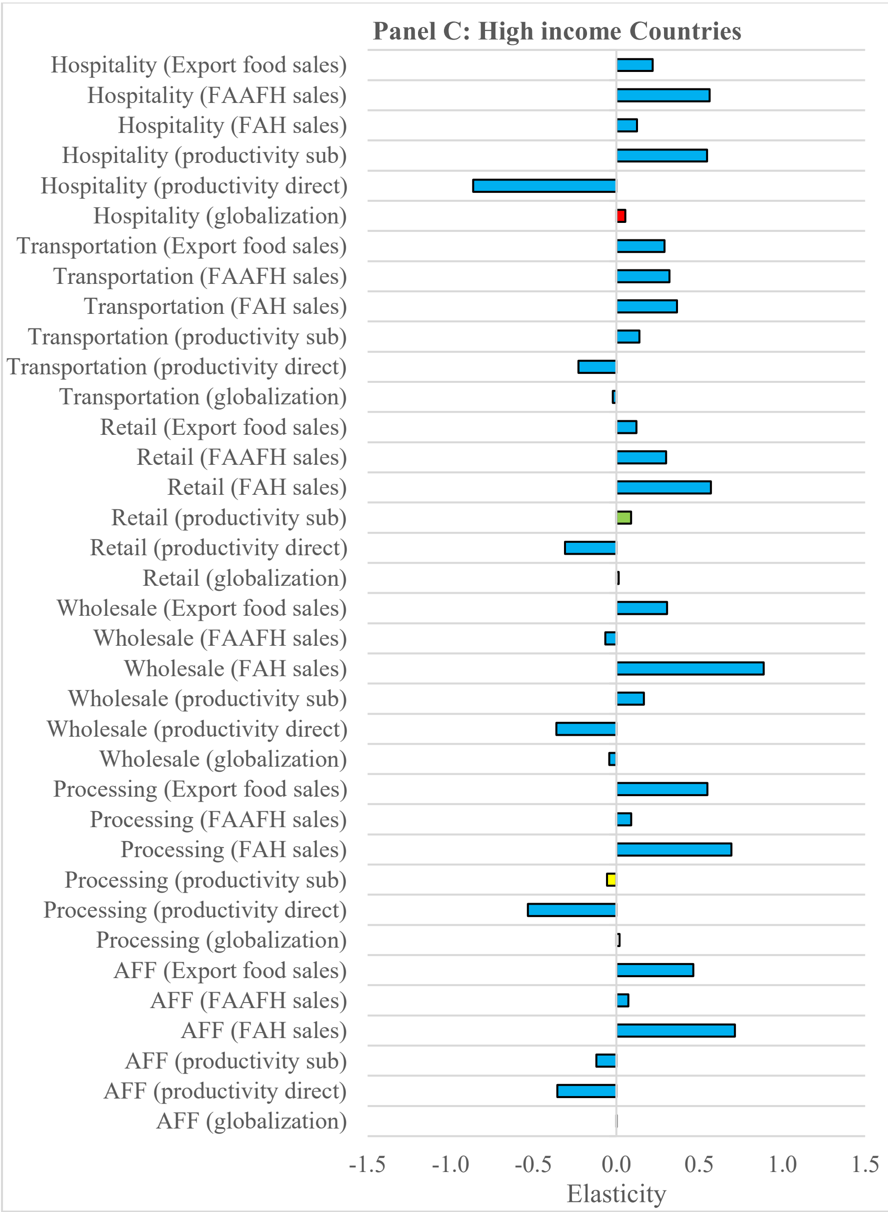


Figure A5 (continued): Estimated elasticities of FVC employment by country income group (in 2015 U.S. Dollars)

Note: blue bar indicates p < 0.001; green bar indicates p < 0.01; yellow bar indicates p < 0.05; red bar indicates p-value < 0.1; white bar indicates p ≥ 0.1