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Influence of the Sectoral Composition of Production on Occupational and Sectoral Wage Structures: Evidence from Multiple Economies

Nelson Marconi[*], Danilo Spinola[†], Tiago Porto[‡], Eliane Araújo[§]

Abstract

This paper explores the impact of the sectoral composition of production on the evolution of occupational structures and relative wage differentials. We employ a shift-share analysis over three periods to highlight the relevance of sectoral employment in explaining shifts in the occupational employment structure. We introduce the Weighted Occupational Unemployment by Sector (WOUS), to capture the influence of sectoral demand by occupation and the influence of labor supply on relative wage differentials. We also leverage the sectoral share on total value added (VA) as a proxy for the direct impact of sectoral production composition on relative wages. Finally, we explore the determinants of sectoral wage differentials through an econometric panel regression analysis. Our results suggest that the sectoral composition of output influences the labor demand for distinct skills, affecting the occupational composition of employment and, thus, relative wages.

JEL: J21, J31, L16, O14

Keywords: Occupational structure, Relative wages, Structural change, Sector-specific labor demand

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1. Introduction

The recent standard literature on labor markets (Katz and Murphy, 1992; Goldin & Katz, 2008; Acemoglu and Autor, 2011; Goos et al., 2014; Goos et al., 2022) suggests that significant changes over the past few decades, such as the polarization of occupational structure, have been driven by an increased supply and demand for more skilled workers and by skill-biased technological change. However, alternative explanations, such as those of Bárány and Siegel (2018), Buera et al. (2022), and Nömaler et al. (2021), among others, have focused on sectors to examine shifts in the labor market from a structural change standpoint.

In this article, we aim to reconcile these two streams of literature, highlighting the role of changes in the sectoral composition of production[1] in determining the occupational composition of employment and relative sectoral wages. We argue that the perspectives based on skills and on sectors are not mutually exclusive. Sectors undertake various activities and require diverse skills, technologies and capital-labor endowments (Tregenna, 2009). Consequently, the sectoral composition of output should influence the labor demand for distinct skills, affecting the occupational composition of employment and, thus, relative wages.

There is significant debate about the effects of structural change and, consequently, sectoral employment composition on wage inequality (Chongvilaivan and Hur, 2019; Compagnucci et al., 2021; Galbraith and Berner, 2001; Martorano and Sanfilippo, 2015; Mokre, 2023; Nömaler et al. (2021); Rada et al., 2022; Shim and Yang, 2018; Tyrowicz and Smyk, 2019; Xu, 2022). However, there is still a large gap in the research regarding the effect of structural change on sectoral relative wages, and that is the focus of the current study.

To present our argument, we first demonstrate the relevance of the sectoral composition of output in determining the occupational structure. We start by implementing Bárány and Siegel's (2018) shift-share method of decomposing the change in the employment share of occupations. We expand their contribution by decomposing job variations into within, static, and dynamic components.[2] Additionally, we develop a novel decomposition centered on variations in sectoral employment. This approach focuses on how changes in the productive structure impact the labor market.[3]

Second, we propose an empirical econometric model to explain the determinants of relative sectoral wage variations. We propose a novel index, the Weighted Occupational Unemployment by Sector (WOUS) index, to discuss how occupational composition by sector affects relative sectoral wages. This index corresponds to a sectoral average unemployment rate by former occupation, weighted by the participation of each occupational group in that sector. It captures the integrated influence of supply and demand (for a particular set of tasks, skills, and occupational groups) on the relative wage paid by the sector.

Finally, we examine the direct impact of changes in sectoral production composition on relative wages. We then employ the value-added (VA) share of each sector in total VA as one of the explanatory variables in our econometric estimations.

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[1] We use the term *changes in sectoral composition of production* instead of *structural change* because the latter refers to a longer-term perspective.
[2] Summing the *static* and *dynamic* components results in the *between* effect (de Vries et al., 2015; McMillan and Rodrik, 2011)
[3] The interpretation of the *within* component becomes connected to sectoral shifts on employment.

Our econometric estimations consist of a dynamic panel regression analysis that covers 2011-2020 for 31 countries, 20 industries and nine occupational groups (see the respective lists in Tables A1, A2 and A3 in the Appendix).[4] The size of our sample is large for studies on these issues. We use two databases: IPUMS[5] and ILOSTAT. IPUMS consists of microdata from census surveys. It offers flexible occupational and sectoral groupings, and we use data from the 1990s to 2010s census years.[6] ILOSTAT is composed of aggregated tabulated data. It facilitates the comparison of job market characteristics among a greater number of countries over a more recent period (2000 to 2020).

Our contribution to the literature resides in the following points:

(i) Provide an analysis of the joint effect of labor demand—which results from the sectoral composition of output—and labor supply—which is related to the availability of skills—on occupational structure and relative wages. This includes the development of a novel index to explain occupational unemployment by sector (WOUS).

(ii) Create a method for the shift-share decomposition of sectoral employment. This expands upon the standard method that decomposes only the shift in occupational share. Our results, which use an expanded dataset of developing countries, contrast with those of Acemoglu and Autor (2011) and Goos et al. (2014).

(iii) Observe the determinants of sectoral relative wage via a dynamic panel regression estimation analysis, given the sectoral heterogeneity and the endogeneity between technical progress, labor supply and demand. We employ the WOUS as an independent variable and introduce the sectoral value-added (VA) share of total VA as another explanatory variable.

(iv) Build a large three-dimensional dataset on labor market, exports and productivity indicators by sector, country and year, which allows us to perform the analyses and tests included in this article. The dataset can be used in future surveys.

While this study does not explicitly address labor market polarization as outlined by Autor (2019), Goos et al. (2014) and Heyman (2016), it is related to this discussion. We aim to show that shifts in the occupational structure across different economies cannot be attributed solely to skills and movements within occupational groups that are driven by technological advancements but, beyond that, by changes in the sectoral composition of production. Therefore, we also consider the significance of movements across sectors and their impact on occupational structure, which suggests a broader array of influences on the changing distribution of employment and wages.

Following this introduction, Section 2 presents the theoretical and empirical advances in the literature; in Section 3, we present stylized facts and the results of the shift-share decompositions. In Section 4, we discuss the behavior and determinants of relative wages and introduce the novel WOUS index; in Section 5, we describe the data adopted in the subsequent tests. Finally, in Section 6, we present the econometric model and results and then the conclusions.

[4] The sample for the econometric tests does not extend to more recent years because we opted to maintain consistency with the availability of data for the control variables used in those tests.

[5] Minnesota Population Center, (2023).

[6] For the set of countries whose source is the IPUMS database, we built an occupational classification that is similar to the one proposed by Dorn (2009) and adopted by Autor (2019).

2. Theoretical framework

Standard theory suggests that factor-augmenting technological change (Katz and Murphy, 1992) has been critical in explaining how the labor market has changed since the mid-20th century. Technological progress induces an increased availability of skills that enhance work efficiency, a phenomenon known as skill-biased technical change (Acemoglu and Autor, 2011). In this context, a mix of elements interact, such as technological advancements increasing efficiency, new machines taking over specific tasks, and fluctuating labor supply. As a result, these factor-augmenting technological developments influence the need for different tasks, skills, and jobs heterogeneously, thereby altering the wage structure (Nomaler et al., 2021).

Technological changes have significantly decreased demand for medium-skill occupations because of routinization and automation (Acemoglu and Autor, 2011; Goss et al., 2022; Kearney et al., 2015). This shift has led to a surplus of workers with medium skills being redirected to lower-skill (nonroutine) tasks. At the same time, there is an implied growing need for highly skilled workers and occupations for supervisory positions overseeing routine tasks. Outsourcing and offshoring can result in similar effects.

Although the importance of technological change and its impacts on the labor market is evident, we argue that the role of structural change in the occupational composition of employment and wages is central, in the same vein as Barani and Siegel (2018) and Nomaler et al. (2021).

Palma (2005), Rodrik (2016), Szirmai (2012), and Tregenna (2009) highlight the importance of changes in the composition of the productive structure, moving towards manufacturing, as a crucial element of the development process. Manufacturing is characterized by rising productivity, economies of scale, positive externalities, and the generation of technological advancements. The movement toward manufacturing also leads to spillover and linkage effects and creates jobs offering median wages, underpinning its critical role in economic development.

The decrease in the manufacturing share within Western economies, coupled with the globalization-driven relocation of the production of this sector to Southeast Asia and China, has likely contributed to the decline in the corresponding sectoral employment in the former regions (Breemersch et al., 2019; Felipe et al., 2019; Rowthorn and Wells, 1987). This shift, combined with the automation-induced changes in the capital–labor ratio within the sector, has decreased employment opportunities for middle-skilled workers (Breemersch et al., 2019) and exacerbated wage inequality (Chongvilaivan and Hur, 2019). Furthermore, relocating the workforce to other sectors can affect sectoral productivity and influence relative wages (Barani and Siegel, 2018).

Recognizing the significance of movements between sectors in shaping the occupational structure, we explore another critical topic, the effect of sectoral employment composition on sectoral relative wage. As sectors develop at varying paces and incorporate diverse tasks into their operations, they play a crucial role in determining the demand for specific skills and occupations and, subsequently, relative wages. Hence, shifts in the sectoral composition of production may alter the sectoral labor demand for specific skills and affect relative wages.

We adopt a demand-side perspective. Income shifts, as discussed by forerunners Baumol (1967) and Chenery et al. (1960), lead to changes in the composition of demand for specific and complementary goods and services, as in Engel's law. Such transformations affect the demand for labor across different sectors. This, in turn, puts pressure on sectoral relative wages and may contribute to a cumulative growth process (Zeli et al., 2022).

To avoid overlooking the effects of labor availability on wages and, consequently, to address the links between labor supply and demand at the sectoral level, we estimate sectoral unemployment, which ultimately influences sectoral wages. Galbraith and Cantú (1999) assert that the unemployment rate is essential for explaining the wage rate distribution.

This does not imply that we overlook the role of productivity in wage setting; rather, we emphasize the impact of demand, as they are complementary factors. Different capital endowments influence the capital–labor ratio, productivity, and structural change itself. The resulting increase in productive capacity and productivity, according to Kaldor-Verdoon (Kaldor, 1978[1966]; Verdoorn, 1949), can also boost the relative sectoral demand for labor, provided that the labor-displacing effects of capital intensification do not dominate. Variations in sectoral productivity and labor-replacing capital intensification influence shifts in labor supply and demand, thereby affecting relative wage levels (Barany and Siegel (2018); Baumol, 1967; Buera et al., 2022; Felipe et al., 2019; Lewis, 1954; Rada et al., 2022). Nomaler et al. (2021) also suggest that differences in technological advancement and productivity across various sectors will have long-term impacts on the demand and supply of certain skills. Therefore, productivity and labor demand are interconnected. Since our research focuses on the effects of labor demand on wages—triggered by shifts in the composition of an economy's productive structure—the impacts of productivity on workers' pay are indirectly considered.

Therefore, changes in the sectoral composition of production can influence the sectoral demand for labor and, consequently, relative sectoral wages. We measure this effect on wages using two variables: the sectoral composition of production and an estimated unemployment rate, which allows us to account for the relationship between the sectoral demand for specific skills and the corresponding supply of these skills. In the following sections, we present the facts and data that, along with these theoretical arguments, support the adoption of our model to explain the behavior of relative sectoral wages.

3. Stylized facts about changes in the employment structure

This section presents an analysis of employment shifts by occupational group and sector across various countries over the past three decades. We use two databases: IPUMS and ILOSTAT. IPUMS includes census microdata with a more detailed classification of occupations. However, owing to the differing occupational classifications used by various countries, our approach, which follows Dorn (2009), is compatible with only a limited sample of countries.

In contrast, the ILOSTAT database does not include microdata. Nevertheless, it has sectoral and occupational data on employment and wages, standardized for a larger sample of countries in a more recent period. We present the shift-share decomposition analysis for each dataset to compensate for their specific advantages and disadvantages.

Initially, we examine employment trends by identifying the contribution of shifts in sectoral composition to changes in occupational employment shares across a broad range of countries and periods.[7] We decompose changes in total occupation, adapting the model by Barany and

[7] Following Nomaler et al (2021), we adopt occupations instead of tasks. Occupation consists of a set of related tasks, and, because of data availability, it allows the use of a broader dataset, with a larger sample of countries.

Siegel (2018). We expand their model by incorporating a *dynamic* component[8], which provides a more accurate decomposition (de Vries et al., 2015), as it enables more accurate splitting of the *within* and *static* effects and estimation of the *joint* effect of variations in the sectoral and occupational composition of employment.

Starting from Barany and Siegel (2018) and de Vries et al. (2015), we develop the following shift-share equation to capture the contribution of sectoral employment shifts to changes in the share of occupational categories:

$$\frac{N_i^t}{N^t} - \frac{N_i^0}{N^0} = \sum_j \frac{N_j^0}{N^0}\left(\frac{N_{ij}^t}{N_j^t} - \frac{N_{ij}^0}{N_j^0}\right) + \sum_j \frac{N_{ij}^0}{N_j^0}\left(\frac{N_j^t}{N^t} - \frac{N_j^0}{N^0}\right) + \sum_j \left(\frac{N_{ij}^t}{N_j^t} - \frac{N_{ij}^0}{N_j^0}\right)\left(\frac{N_j^t}{N^t} - \frac{N_j^0}{N^0}\right) \quad (1)$$

where i refers to the occupation, j denotes the sector, and N represents the number of employees. The variables t and 0 indicate the final and initial periods, respectively.

The first term of the right-hand side of equation (1) corresponds to the *within* component. It measures the weighted average of the observed variations in an occupation across various productive sectors, holding a constant share of a sector on initial employment. The second term is the *static* component, which measures the change in employment across various sectors, holding constant the initial participation of the occupation under scrutiny in each sector. A positive value means that workers are moving toward sectors in which the participation of that occupation is greater. This component, as discussed in the literature, relates to the impact of structural change on employment when we analyze a longer period (McMillan & Rodrik, 2011; Barany and Siegel, op. cit., among others). The third term is related to the *dynamic* component. It corresponds to the joint sum of (i) variations in the share of occupation in each sector and (ii) the participation of that corresponding sector in total employment. A positive result implies that workers in a certain occupation shift toward sectors that increase their share of employment. The *between* component is the sum of *static* and *dynamic*, whereas *overall* is the sum of *between* and *within*.

We use the IPUMS database to structure the same occupational classification defined by Dorn (2009) and adopted by Autor (2019) for the USA. This definition includes 12 occupational groups; additionally, according to the ISIC classification, we combine sectoral information into 22 groups. These occupational and sectoral groups are included in Tables 1 and 3. Our analysis

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There is an extensive literature relating tasks to occupations. Acemoglu and Autor (2011) classify managerial, professional, and technical occupations into abstract, nonroutine cognitive tasks; clerical, administrative and sales occupations into routine cognitive tasks; production and operative occupations into routine manual tasks; and service occupations into nonroutine manual tasks. In ILOSTAT series, occupational groups are linked to skill levels.

[8] We split the *between* component in *static* and *dynamic*, as used by de Vries et al. (2015). However, we apply that decomposition for employment instead of productivity.

includes, beyond the USA, five other countries: Brazil, Greece, Ireland, Mexico, and Portugal. We use data from two census periods (the 1990s and 2010s).[9]

Table 1 shows the shift-share decomposition for changes in occupational employment. We present a simple average of results by country, in line with Breemersch et al. (2019).[10]

[9] We harmonize occupations within countries for three different periods: 1990s, 2000s and 2010s, to make the 1990s and 2010s classifications compatible, and then we group them according to the taxonomy created by Dorn (2009). We use the following supplementary tables to facilitate the correspondence among occupations: the International Standard Classification of Occupations (ISCO-68, 88 e 08); the 1960-2000 System of Census Occupations for the USA (Meyer and Osborne, 2005); and country-specific classifications of occupations. We group the productive sectors according to the International Standard Industrial Classification (ISIC) 3 and 4. The correspondence tables for occupational and industrial groups can be made available upon request.

[10] We adopt the simple average to avoid granting a higher weight to the size of a country's economy or labor market.

Table 1. Employment share decomposition by occupational categories (in p.p.). 6 countries. 1990-2010.

	within	*static*	*dynamic*	*between*	*overall*
High-skill occupations					
Managers and executives	1,13	0,88	-0,15	0,74	1,87
Professional and financial/advertising sales	0,68	4,31	-0,64	3,67	4,35
Technicians + fire and police	1,08	0,72	-0,15	0,57	1,65
Middle-skill occupations					
Sales minus financial/advertising sales	0,41	1,60	-0,04	1,55	1,96
Clerical and administrative support	-2,22	1,96	-0,53	1,44	-0,78
Production and operative	-1,91	-3,16	0,57	-2,59	-4,50
Low-skill occupations					
Transportation	1,04	-0,55	0,01	-0,54	0,50
Construction and mechanics	-0,82	-0,60	0,21	-0,39	-1,21
Services: Cleaning and protective	-0,74	1,43	0,28	1,71	0,97
Services: Personal	0,85	1,40	-0,02	1,38	2,23
Services: Health	0,89	0,36	0,30	0,66	1,55
Farm and mining	-0,39	-8,36	0,16	-8,20	-8,58

Prepared by the authors, on the basis of data from IPUMS

In Table 1, high-skill occupational groups (managers, professionals, and technicians) show positive relative growth in their share of total employment. Mid-skill occupations experience an average but not uniform decline. Low-skill occupations increase if farm and mining workers are excluded. These results match recent findings on job polarization (Acemoglu and Autor, 2011; Autor et al., 2006; Autor, 2019; Goos et al., 2022).[11] However, that literature attributes the shifts in the labor market to educational attainment and technological advancements. Those results downplay the effects of structural change on output composition, and the argument in such studies is compatible with a predominance of the *within* component over the *static* one.

In contrast to those results and in line with Barany and Siegel's (2018) findings, our shift-share decomposition shows that the *static* effect, in absolute terms, predominates in half of the occupational groups. We can argue from our dataset that the sectoral composition of jobs helps to determine the occupational shift. The sign of the *dynamic* component is negative for half of the occupations, indicating opposing effects for (a) shifts in the share of occupation in diverse sectors and (b) the sector shares on total employment.

[11] Conversely, Martins-Neto et al (2023) argue that developing countries do not face relevant polarization in the labor market due to limited technological content and the offshoring of routine tasks to those regions, and Hunt and Nunn (2019) advocate that polarization detected in the literature results from redefinitions of occupation codes.

We replicate the same exercise using ILOSTAT for a larger sample of countries. The periods analyzed depend on data availability and compatibility (2000-2007 and 2011-2020).[12] For each period, we include only countries with available data for all sectors and occupational groups in the comparable years. The definitions of occupational groups are somewhat similar to those of the Dorn (2009) and Autor (2019) classifications, except for service workers, who are grouped with commerce workers in the ILOSTAT classification. This approach results in nine occupational groups and 20 sectors.[13]

Table 2 displays the average results of the employment share decomposition by occupational group for the periods defined above.[14] Even considering groups of countries that are not similar in all decompositions, it is possible to highlight some common results in the observed data. We note an increase in the relative share of occupations requiring high-skill workers and a decrease in those associated with mid-skills workers for all periods and groups of countries. Elementary occupations show irregular behavior. With respect to the more disaggregated classification of occupations, we observe a reduction in the share of agricultural and craft workers and an increase in the share of professionals and technicians for all cases.

The magnitude of the *static* effect exceeds that of the *within* effect in 9 of 18 decomposition estimations. This underscores the significant role of worker movement between sectors in determining changes in job composition. In our estimations, the predominance of *static* effects over *within* effects is evident for skilled agricultural, plant and machine operators, as well as for service and sales workers. The static effect is also predominant for similar occupational groups in the decomposition based on IPUMS data (Table 1). The coincidence of results suggests that shifts in the share of these occupational groups are linked to changes in the sectoral share of employment. For other occupational groups, the predominance of *within* or *static* effects varies in our estimations.

[12] We are unable to merge the ILOSTAT databases for before and after 2010 because of changes in the classification of occupations and sectors., i.e., water supply, broadcast activities and repair of personal goods changed classification groups between ISIC-3 and ISIC-4.
[13] Additionally, "Skilled agricultural and fishery workers" are considered mid-skill occupations in the ILOSTAT, but not in Dorn's classification. For 2000-2007, occupations and sectors follow ISCO-88 and ISIC-3, respectively. However, for 2011-2020 they follow ISCO-08 and ISIC-4. The list of countries included in the decomposition estimates are in the Appendix (Table A1). We disregard (i) nonclassified occupations and sectors, (ii) activities of extraterritorial organizations and bodies, and, following Dorn (2009), (iii) armed forces occupations.
[14] We use W as *within*, S as *static*, D as *dynamic* and O as *overall*.

Table 2. Employment share decomposition by occupational categories (in p.p.) using distinct samples according to the period.

2000-2007 - 12 countries	W	S	D	O	2011-2020 - 23 countries	W	S	D	O
High skill occupations					High skill occupations				
Legislators, Senior Officials and Managers	0,41	0,07	-0,02	0,46	Managers	-0,34	0,07	0,01	-0,26
Professionals	0,45	0,69	-0,08	1,07	Professionals	2,29	1,33	0,09	3,70
Technicians and Associate Professionals	1,39	0,47	-0,07	1,80	Technicians and Associate Professionals	0,02	0,48	-0,07	0,44
Medium skill occupations					Medium skill occupations				
Clerks	-0,74	0,03	-0,02	-0,73	Clerical Support Workers	-0,57	0,28	-0,03	-0,32
Service Workers and Shop and Market Sales Workers	-0,29	0,60	0,01	0,33	Service and Sales Workers	-0,13	0,18	-0,06	-0,01
Skilled Agricultural and Fishery Workers	-0,64	-1,99	0,19	-2,44	Skilled Agricultural, Forestry and fishery Workers	-0,34	-1,50	0,14	-1,71
Craft and Related Trades Workers	-1,56	-0,08	0,07	-1,57	Craft and Related Trades Workers	-0,68	-0,19	-0,07	-0,95
Plant and Machine Operators and Assemblers	-0,19	-0,38	0,04	-0,53	Plant and Machine Operators, and Assemblers	-0,03	0,12	0,05	0,14
Elementary occupations	1,16	0,59	-0,12	1,63	Elementary occupations	-0,22	-0,77	-0,04	-1,03

Prepared by the authors, on the basis of data from ILOSTAT

To refine our findings, we examine variations in sectoral employment composition, to determine whether they are due to inherent changes within sectors or shifts in the distribution of occupations. In this shift-share analysis, we reverse the analytical logic of employment variation decomposition by analyzing changes in the sectoral employment share rather than changes in the occupational composition share, as in Eq. (1):

$$\frac{N_j^t}{N^t} - \frac{N_j^0}{N^0} = \sum_i \frac{N_i^0}{N^0}\left(\frac{N_{ij}^t}{N_i^t} - \frac{N_{ij}^0}{N_i^0}\right) + \sum_i \frac{N_{ij}^0}{N_i^0}\left(\frac{N_i^t}{N^t} - \frac{N_i^0}{N^0}\right) + \sum_i \left(\frac{N_{ij}^t}{N_i^t} - \frac{N_{ij}^0}{N_i^0}\right)\left(\frac{N_i^t}{N^t} - \frac{N_i^0}{N^0}\right) \quad (2)$$

In Eq. (2), the *within* effect (first term on the right-hand side of the equation) corresponds to the weighted average[15] of changes in the sectoral share of employment by occupation. A positive effect indicates that the average share of a specific sector in the distinct occupations increased. The *static* component measures the change in the share of different occupations on employment, holding constant the initial share of a specific sector by occupation. A positive sign indicates that workers are moving to occupations where the sector's employment share is larger. Finally, the *dynamic* component measures the joint effect of (i) changes in the sector's share in an occupation and (ii) the occupation's share of total employees. A positive result

[15] Weighted by the initial share of each occupation on employment.

means that an employment increase in the sector under consideration shifts toward occupations that increase their share of employment. The *within* component is the most important for our analysis because it measures the process of mobility of workers among sectors.

Table 3 presents the second shift-share decomposition results based on IPUMS between 1990 and 2010, whereas Table 4 uses the ILOSTAT database, with the same countries and periods included in Tables 1 and 2, respectively.

Table 3. Employment share decomposition by sectoral employment (in p.p.). 6 countries. 1990-2010.

	within	static	dynamic	between	overall
Farming	-1,11	-8,20	0,01	-8,20	-9,30
Mining, quarry, refined petroleum	-0,14	-0,10	0,02	-0,08	-0,22
Low and medium-low technology manufacturing	-3,12	-2,55	0,35	-2,21	-5,33
Medium-high and high-technology manufacturing	-0,21	-0,25	-0,11	-0,36	-0,57
Electricity, gas	-0,14	0,00	-0,03	-0,03	-0,16
Water, sewerage	0,22	0,01	-0,03	-0,02	0,20
Construction	0,06	-0,59	0,06	-0,53	-0,47
Sales	0,83	2,36	-0,52	1,84	2,67
Transport, warehousing, mail	-0,64	0,57	-0,31	0,26	-0,38
Accommodation and food	0,51	1,58	0,09	1,67	2,18
Information and communication	0,73	0,13	0,23	0,36	1,09
Financial services	-0,22	0,23	0,19	0,42	0,20
Real estate	0,10	0,07	0,00	0,07	0,17
Knowledge services	1,23	0,45	0,23	0,68	1,92
Admin and support services	2,17	0,18	0,11	0,29	2,45
Public administration	-0,48	0,99	-0,02	0,98	0,50
Education	0,50	1,73	-0,17	1,55	2,05
Health	0,52	2,30	-0,17	2,13	2,65
Culture, leisure, sports	0,17	0,24	0,00	0,24	0,41
Personal services and assoc. organizations	-0,65	0,45	0,01	0,46	-0,19
Household services	-0,33	0,40	0,08	0,48	0,15
Extraterritorial organizations	0,00	0,00	0,00	0,00	0,00

Prepared by the authors, on the basis of data from IPUMS

Table 4. Employment share decomposition by sectoral employment (in p.p.) using distinct samples according to the period.

2000-2007 - 12 countries					2011-2020 - 23 countries				
	W	S	D	O		W	S	D	O
Agriculture, hunting, forestry and fishing	0,02	-2,32	0,21	-2,09	Agriculture	-0,33	-2,00	0,04	-2,28
Mining and quarrying	-0,10	0,01	-0,01	-0,09	Mining and quarrying	-0,05	0,00	0,00	-0,05
Electricity, gas and water supply	-0,11	0,01	0,00	-0,10	Electricity	0,01	0,01	0,00	0,02
					Water supply	0,03	-0,01	0,00	0,02
Manufacturing	-1,49	-0,32	0,10	-1,71	Manufacturing	0,09	-0,06	0,06	0,10
Construction	1,16	-0,35	-0,03	0,78	Construction	-0,16	-0,36	-0,01	-0,54
Services					Services				
Wholesale & retail trade; repair vehicles/personal/house goods	-0,49	0,40	0,12	0,02	Wholesale and retail trade	-0,66	-0,02	-0,01	-0,69
Hotels and restaurants	0,14	0,15	0,01	0,31	Accommodation and food	0,11	-0,02	-0,01	0,09
Transport/storage/communic	-0,04	-0,05	0,01	-0,08	Transportation and storage	0,28	-0,02	-0,04	0,22
					Information / communication	0,21	0,23	0,07	0,51
Financial intermediation	-0,28	0,11	-0,01	-0,17	Financial/insurance activities	-0,29	0,14	0,02	-0,13
Real estate/business activities	1,28	0,45	0,01	1,74	Real estate activities	0,13	0,02	0,01	0,16
					Professional/scient/technical	0,43	0,49	0,04	0,97
					Administrative and support	0,54	-0,07	-0,03	0,44
Publ adm/defense/social secur	-0,41	0,35	-0,14	-0,20	Publ adm and defense	-0,12	0,23	-0,03	0,08
Education	-0,40	0,58	-0,07	0,11	Education	-0,46	1,08	-0,18	0,44
Health and social work	0,43	0,54	-0,09	0,88	Human health/social work	0,44	0,44	0,04	0,91
Other community, social and personal service activities	0,14	0,22	-0,07	0,29	Arts,entertainment,recreation	0,00	0,08	-0,01	0,07
					Other service activities	0,07	0,03	0,01	0,11
Activ priv hous as employers	0,15	0,21	-0,06	0,31	Activ households as employers	-0,28	-0,20	0,03	-0,45

Prepared by the authors, on the basis of data from ILOSTAT

The results from Tables 3 and 4 indicate a decrease in the share of agriculture, mining and quarrying, and manufacturing in total employment. This decline is more pronounced for low- and medium-technology industries when the manufacturing sector is analyzed between 1990 and 2010 for the six countries included in the IPUMS sample. Most of the service sectors show an increasing share in total employment.

It is also possible to emphasize the prevalence of the *within* over *static* effect on mining and quarrying, manufacturing (except for medium-high and high technology in the IPUMS decomposition) and administrative services. These findings confirm that the reduction in employment in manufacturing has been offset by increased jobs in administrative and support services.

The magnitude of the *within* component confirms its relevance in explaining changes in sectoral employment. For the 1990s-2010s period, the magnitude of the *within* effect (in absolute values) exceeds that of the *static* effect in 10 of the 20 sectors. For the ILOSTAT sample, *within* is more significant in 54% of the cases (19 out of 35 estimations).

The results reveal the importance of shifts in sectoral employment to explain changes in overall employment composition. The results are consistent across both decompositions, whether considering the share of occupational categories or the share of sectors in total employment. Given that movements among sectors appear to significantly explain employment composition, understanding the impact of sectoral production composition on relative wages is also important.

4. Determinants of sectoral relative wages

In this section, we explore stylized facts and propose a methodology to examine the impact of unemployment rates and sectoral value-added share on the evolution of sectoral relative wages. The data cover 31 countries from 2011 to 2020, the same sample used for the econometric tests (see the list of countries in the Appendix, Table A1).

The sectoral relative wage in sector j is defined as the average wage of employees in that sector divided by the aggregate average wage for employees in the entire economy:[16]

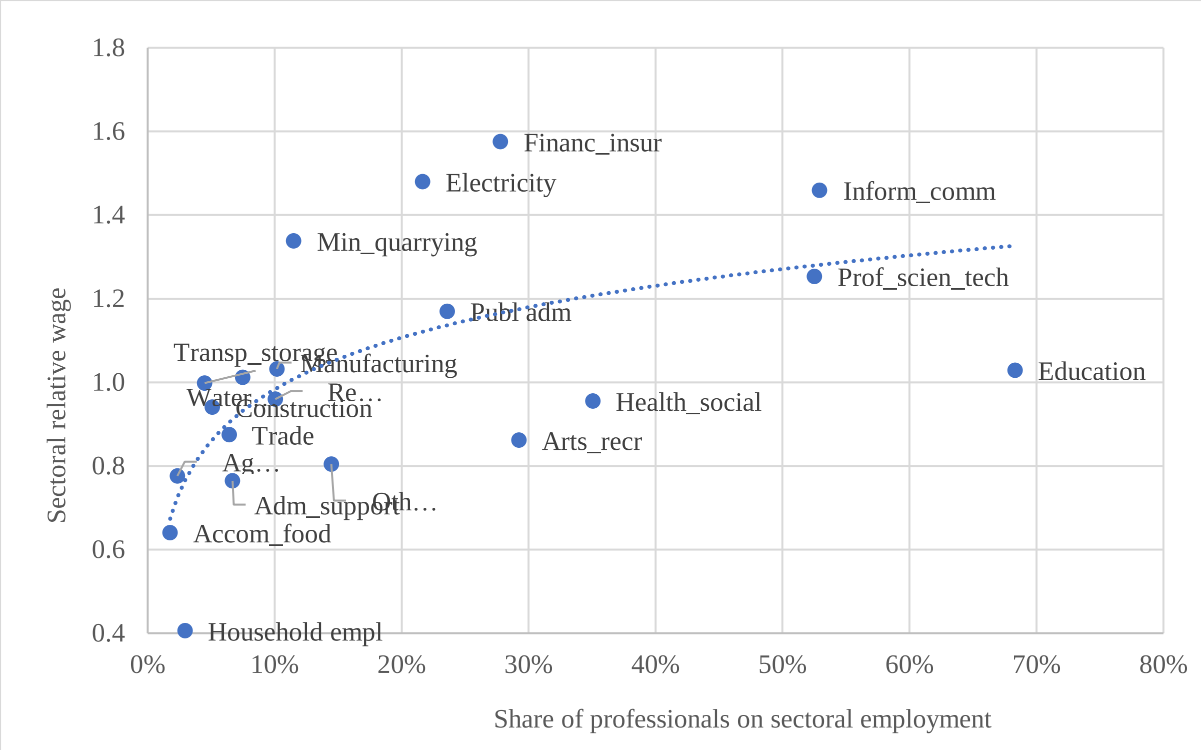
$$Relwage_j = \frac{Average\ Wage_j}{Aggregate\ Average\ Wage} \qquad (3)$$

Chart 1 plots (a) the relative sectoral average wage and (b) the share of professionals in sectoral employment (number of professionals in total employment divided by total employment), with a logarithmic trend line added. Chart 2 plots the relative average wage for the occupational groups considered in our tests.[17]

Chart 1 - Relative wage of employees and % share of professionals by sector – Average for 31 countries in the 2011-2020 period

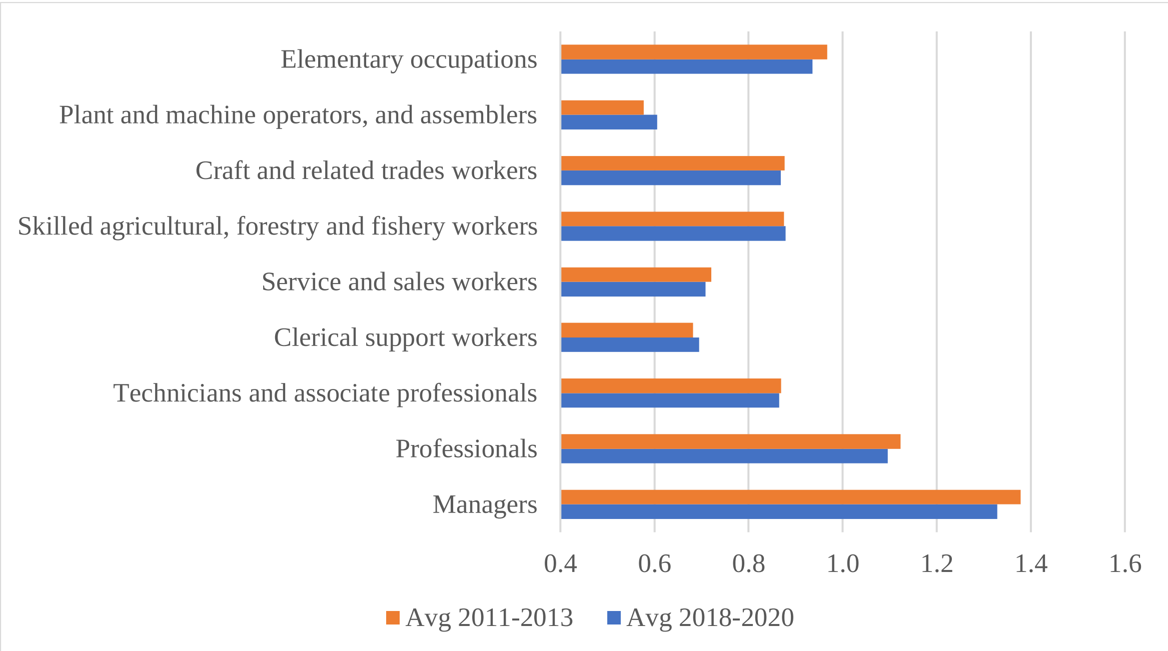
[16] We use employees instead of employment wage due to data availability. ILOSTAT does not provide wage information for employment, which includes informal workers, the self-employed, and employers. However, we observe a correlation of 0.96 between the number of employees and overall employment across sectors, occupations, years, and countries. Therefore, we can use either measure in our analysis.

[17] The complete dataset is unbalanced. Consequently, we include only registers (year/country/sector) where data on relative wages, the share of professionals, the estimated Weighted Occupational Unemployment by Sector and the sectoral share of total value added are simultaneously available. The same applies to Charts 3 and 4. Regarding Chart 2, the respective dataset is also unbalanced. Consequently, the estimation of averages includes only the registers (year/country/occupational group) with available data for all nine occupational groups considered (see Table A3 in the Appendix).



Prepared by the authors, on the basis of data from ILOSTAT

Chart 2 – Relative wage of employees by occupation – Average for 31 countries in the 2011-2013 and 2019-2020 periods



Prepared by the authors, on the basis of data from ILOSTAT

In Chart 1, the relative wage in manufacturing is close to one, highlighting its role in contributing to a more equitable wage structure. Additionally, Chart 1 shows a positive correlation between sectoral relative wages and the sectoral share of professionals. On the other hand, Chart 2 confirms that occupations requiring higher skills have higher relative salaries.

This suggests that the differentiation between sectoral relative wages may be partly due to distinct occupational structures within each sector.

To reinforce our arguments, we perform several correlation tests on the same sample of countries via the ILOSTAT database for occupations and sectors between 2011 and 2020. We employ the Spearman correlation method to estimate the correlation between the rankings of two variables, as this method is more suitable for comparing relative wages.[18]

Our first correlation analysis focuses on the sectoral composition of occupations. We test the correlation of occupational composition across various sectors to determine whether the participation of each occupational group within one sector correlates with their participation in other sectors. For the entire set of countries in our sample, the average correlation is 0.2425. Second, we examine whether a sector exhibits a similar occupational structure across different countries. Here, the average correlation is significantly greater, at 0.8106.

Hence, sectors have distinct occupational compositions, and countries have similar occupational compositions in the same specific sector. This strengthens our previous assertion that sectors have specific occupational traits in their employment structure.

We then conduct additional tests to estimate the correlation between the relative wages of occupations and sectors. Initially, we test whether the relative wage of each specific occupational group is similar across different countries, yielding a result of 0.8855. Next, we examine whether the relative wages for each specific sector correlate within the group of countries studied, resulting in a correlation of 0.7518. These findings indicate that occupations tend to be valued similarly, in relative terms, across countries during the analyzed period. Additionally, each sector presents similar relative wages across different countries.

When combining our correlation results, we observe that the primary factor differentiating relative wages across sectors is each sector's unique occupational composition. The distinct skills required for the specific goods and services produced in each sector lead to variations in occupational composition, which in turn influence the average wage.

Weighted Occupational Unemployment by Sector (WOUS)

Next, we discuss how the composition of occupations can affect relative sectoral wages. Initially, we have unemployment data from former occupations from ILOSTAT. Since each sector has a specific occupational composition, we are then able to compute a (weighted) average of unemployment rates by sector, which we call the Weighted Occupational Unemployment by Sector (WOUS).[19] This index accounts for the supply and demand for various occupations, as represented by the unemployment rate estimated for each occupation. This enables us to adopt an approach that connects occupations and industries to explain sectoral relative wages.

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[18] Tables A5-A8 in Appendix exhibit the detailed results for the Spearman correlation tests. The standard correlation tests, based on absolute values, produced similar results.

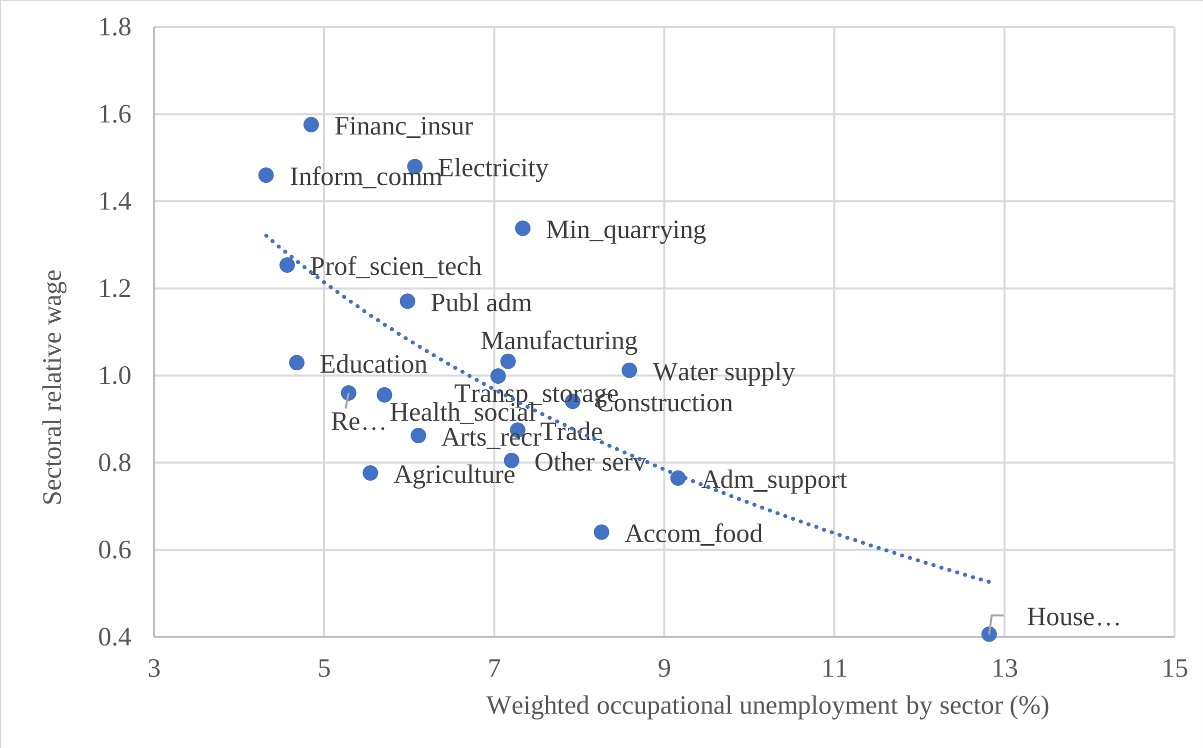
[19] The WOUS is not a sectoral unemployment rate but an average among unemployment rates for existing occupations within a sector. We could simply adopt the unemployment rate estimated by sector from the ILOSTAT database. However, we believe that the use of the unemployment rate by occupation is more accurate. In accordance with the findings about career mobility (Jacobs, 1983; Mayer and Carroll, 1987), we argue that an unemployed worker searches for a new job that is more closely aligned with their previous skills and tasks rather than within the same sector.

The formula for the WOUS can be conceptualized as follows:

$$WOUS_j = \sum_{i=1}^{n} (U_i W_{ij}) \qquad (4)$$

where $WOUS_j$ represents the weighted occupational unemployment for a specific sector j. U_i denotes the unemployment rate for occupation i, as sourced from ILOSTAT. W_{ij} signifies the weight of occupation i within sector j, indicating the share of occupation i in that sector. The variable n represents the count of distinct occupations within sector j. The index i refers to the occupations within the sector, whereas j identifies the specific sector under consideration.

Chart 3 - Relative wage of employees and Weighted Occupational Unemployment by Sector – Average for 31 countries from 2011 to 2020



Prepared by the authors, on the basis of data from ILOSTAT

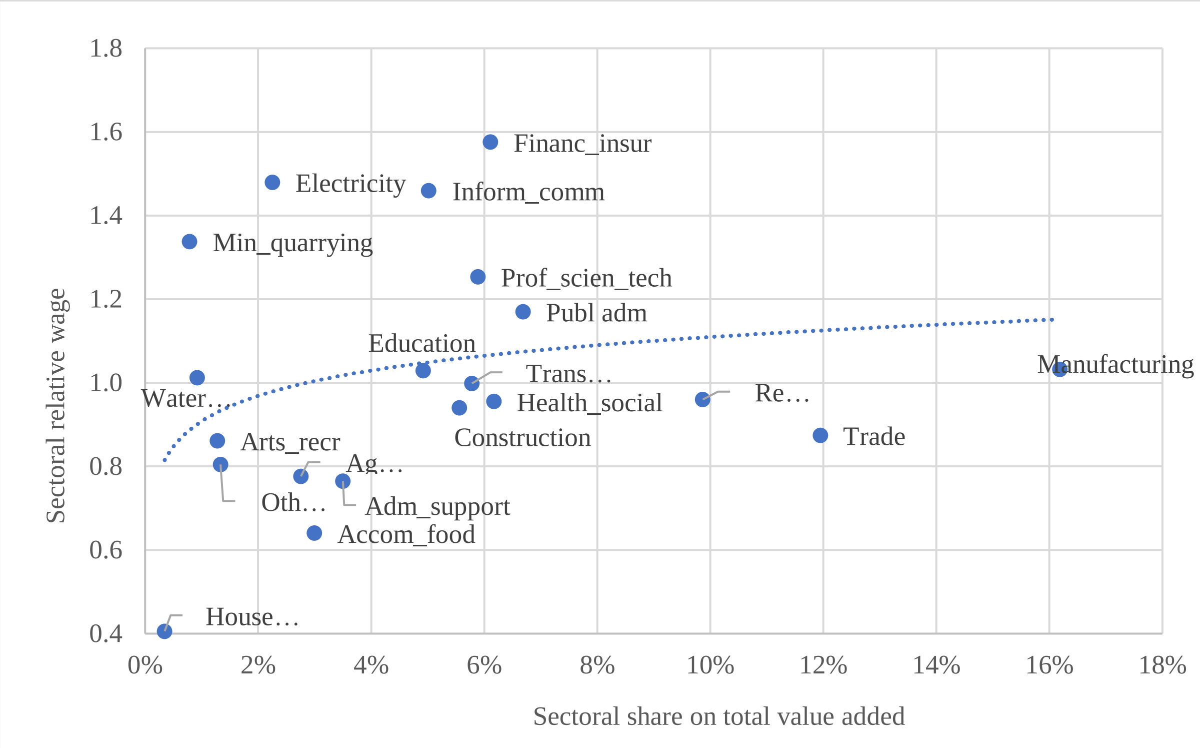
Chart 3 plots the average sectoral relative wages against the corresponding WOUS, revealing a negative correlation. This correlation may help explain the cases observed in Chart 1, where sectors with a similar share of professionals exhibit different relative wages. For example, wages in financial and insurance activities compared with those in arts, entertainment, and recreation. Manufacturing and transport/storage are positioned in the intermediate portion of the distribution, with both sectors showing similar relative wages and weighted unemployment rates. The unemployment rate is higher for traditional services.

Sectoral Value-Added Share

Furthermore, we argue that variations in sectoral demand for goods and services will alter the sectoral composition of production and, consequently, the demand for workers with specific skills. To capture the influence of these shifts on sectoral relative wages, we use the sectoral value-added share ($VAShare$):

$$VAShare_j = \frac{Sectoral\ Value\ Added_j}{Total\ Value\ Added} \qquad (5)$$

Chart 4 - Relative wage of employees and sectoral share on value added – Average for 31 countries in the 2011-2020 period



Prepared by the authors, on the basis of data from ILOSTAT and OECD

Chart 4 shows a positive, albeit small, correlation between the sectoral relative wage and the sectoral share of total value added.

In summary, our model captures the influence of labor supply (availability of skills) and sectoral demand (specific task requirements) on relative wages. We use our novel WOUS index as a proxy for this supply and demand interaction. Additionally, we measure the direct effect of shifts in the sectoral composition of production on relative wages. Next, we start our econometric analysis of the determinants of relative sectoral wages.

5. Data Description

The foundation of our dataset lies in three predominant sources: (I) the ILO's ILOSTAT, which provides data on wages and employment by occupation and sector for a large set of countries; (II) the OECD's Inter-Country Input–Output (ICIO) Tables, including the Trade in Value Added (TiVA) and Multi-Regional Input–Output (MRIO) tables, which showcase interindustrial economic transactions and offer a detailed understanding of global production dynamics, allowing us to build sectoral indicators related to trade, global value chains, value added, and productivity; and (III) the World Bank's World Development Indicators (WDI), which are used for macroeconomic and institutional variables.

Our econometric tests cover the period from 2011 to 2020. The data utilize the ISIC4 sectoral classification, encompassing 20 distinct sectors, and cover nine varied occupations following the ISCO-08 occupational classification. Detailed breakdowns of these sectors and occupations are provided in Tables A2 and A3 in the Appendix.[20]

The availability of data dictate our sampling approach, resulting in a dataset that represents 31 countries. This includes one nation from the Americas, two from Asia, and 28 from Europe (see Table A1 in the Appendix).

The custom variables include **Weighted Occupational Unemployment by Sector (WOUS), Relative wage (by sector),** and **Sectoral Share on Total Value Added**, as defined in Section 4. Additionally, we include **Relative Productivity** in our robustness tests, which, for each sector j, corresponds to the sectoral value added per sectoral employment divided by the total value added per total employment.

$$Relative\ productivity_j = \frac{Sector\ Value\ Added_j}{Sector\ Total\ Employment_j} \Big/ \frac{Total\ Value\ Added}{Total\ Employment} \quad (6)$$

Table 5. Table of Variables

Variable in tests	**Description**	**Level**	**Unit**	**Source**
relWage	Relative wage	Sector	Index	ILOSTAT
secUnemp	WOUS	Sector	%	ILOSTAT
VAShare	Sectoral value-added share	Sector	%	ICIO, OECD
part_prof	Sectoral share of professional occupations in total employment	Sector	%	ILOSTAT
expOrientOutput	Export-oriented output share	Sector	%	ICIO, OECD
fvax_x	Foreign value added embodied in exports as a share of total exports[21]	Sector	%	ICIO, OECD
femaleRatio	Female employment on total employment	Sector	%	ILOSTAT
GDPconst2017ppp_cap	GDP per capita, constant 2017 US$ ppp	Aggregate	Const USD	WDI
govExpendEduOfGDP	Government expenditure on education as a percentage of GDP	Aggregate	%	WDI
ageDependency	Age dependency ratio (% Working-age population)	Aggregate	%	WDI
prod_rel	Relative productivity	Sector	%	ICIO, OECD and ILOSTAT

[20] We exclude *armed force occupations*, adhering to the same criteria used for shift-share decompositions, and remove occupations and sectors *not elsewhere classified* and *activities of extraterritorial organizations and bodies*.

[21] Foreign Value-Added Content of Gross Exports was calculated following the Guide to OECD's TiVA indicators (Guilhoto et al., 2022). This metric quantifies the value of imported intermediate goods and services incorporated within the exports of a domestic industry. The process involves first diagonalizing a matrix representing the value added-to-output ratio, followed by multiplication with the Leontief Inverse. Subsequently, this product is postmultiplied by the gross exports vector. Within the Leontief Inverse, rows that correspond to inputs originating from domestic industries within the countries are assigned a value of zero, ensuring that the focus remains on foreign value-added content.

Table 6. Summary Statistics

	Obs	NAs	Mean	Std.Dev	Min	Q1	Median	Q3	Max
relWage	8580	1302	1.054	0.326	0.289	0.842	0.992	1.221	4.654
secUnemp	8580	525	0.060	0.045	0.000	0.030	0.048	0.077	0.348
part_prof	8580	1267	0.215	0.211	0.000	0.049	0.127	0.334	1.000
VAShare	8580	1780	0.050	0.047	0.000	0.015	0.041	0.065	0.374
expOrientOutput	8580	2428	0.130	0.162	0.000	0.007	0.057	0.205	0.908
fvax_x	8580	2773	0.188	0.114	0.018	0.110	0.163	0.234	0.731
femaleRatio	8580	409	0.439	0.218	0.008	0.260	0.445	0.578	1.000
GDPconst2017ppp_cap	8580	2136	38212	20057	6659	26224	34980	49830	116283
govExpendEduOfGDP	8580	1100	0.049	0.012	0.028	0.041	0.048	0.055	0.085
ageDependency	8580	0	0.514	0.061	0.365	0.479	0.519	0.552	0.744
prod_rel	8580	3960	2.454	8.934	0.024	0.663	0.922	1.586	230.63

6. An empirical analysis of the relationships among sectoral added value, employment and wages

We use the following model to investigate how changes in the composition of productive structure and sectoral occupation affect sectoral wages, which are represented by the sectoral value-added share and by the weighted occupational unemployment by sector (WOUS):

$$relWage_{s,i,t} = \delta_i + relWage_{s,i,t-1} + secUnemp_{s,i,t} + vaShare_{s,i,t} + Sec_{Controls_{s,i,t}} + Agg_{Controls_{i,t}} + \eta_{s,i,t} + \varepsilon_{s,i,t} \qquad (7)$$

where *relWage* is the relative sectoral wage; *secUnemp* is the WOUS variable; and *vaShare* is the share of sectoral VA in the total VA. Sector-level controls ($Sec_{Controls}$) and aggregate-level controls ($Agg_{controls}$) – estimated at the country level – are listed in Table 5; η represents the specific fixed effects not observed for each country, incorporating factors that influence the wage of each sector and are potentially correlated with the explanatory variables; and ε is the idiosyncratic error term. The subscripts s, i and t refer to the sector, country and period, respectively. Additionally, we incorporate time dummies into our analysis—although not explicitly shown in the equations—to account for changes in the global framework over time that impact sector performance across various countries in our sample. The inclusion of time dummies helps support the assumption that there is no correlation among individual units in the idiosyncratic errors, which is crucial for conducting autocorrelation tests and accurately estimating standard errors (Roodman, 2009).

We are particularly concerned with endogeneity among the variables included in our model. Relative wages may be contemporaneously correlated with weighted occupational unemployment by sector and the sectoral share of total value added. Additionally, there is potential endogeneity between technical progress (related to the sectoral composition of production), labor supply, and demand. Moreover, the variable concerned with relative wages may be quite persistent, meaning that the sector's relative wages today are influenced by its past values.

To address endogeneity and autocorrelation concerns, we use a dynamic panel data methodology. We adopt a generalized method of moments (GMM) dynamic panel data model developed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998).

We enhance our analysis by incorporating both sectoral and country-specific control variables, which are described in Table 5. They are included with the aim of underscoring the significance of our primary explanatory variables while mitigating the risk of biases due to omitted variables. Specifically, we integrate demand-related factors, with a particular focus on those associated with trade, given their importance in elucidating trends in relative wages. This approach aligns with the findings of Breemersch et al. (2019), Feenstra and Hanson (2001), Freeman (1995), Krugman (2008), and Pavcnik et al. (2004). The key variables in this category include export orientation ($expOrientOutput$) and the foreign value added embodied in exports ($fvax\_x$). Additionally, we consider per capita income ($GDPconst2017ppp\_cap$) and its squared term to control for the influence of income country level on the sectoral wage dynamics.

Afterward, we include a set of control variables associated with aggregate supply-side characteristics: (a) female employment share (*femaleRatio*), which helps estimate the effect of women entering the labor market on the sectoral wage premium (Cerina et al, 2021); (b) government expenditures on education as a share of GDP (*govExpendEduOfGDP*), which serves as a proxy to capture the impact of human capital accumulation, in line with most theories about wage differentials (Mincer, 1974; Goldin and Katz, 2008); and (c) the age dependency ratio (*ageDependency*) to capture effects of demographic characteristics on relative wages (Katz and Murphy, 1992; Mahlberg et al., 2013).

There are other relevant characteristics of labor markets that can be used to determine sectoral relative wages, such as the institutional framework, the prevailing workload and the share of informal employment, and other supply-side variables, such as the share of workers by level of education and sectoral expenditure and R&D or ICT capital services (as a proxy for automation). Unfortunately, this information is not available or is scarce and strongly unbalanced at the sectoral level and is restricted to a smaller set of countries. For that reason, we do not consider them in the tests; otherwise, they would be included. This does not invalidate our results because they are robust, as seen below.

Model 1 (Table 7) validates our hypothesis with two distinct observations. First, an increase in the WOUS index, which is a *proxy* for sectoral unemployment, decreases sectoral relative wages. This suggests that sectors experiencing higher unemployment levels directly suppress sectoral relative wages. Additionally, changes in labor supply and specific sectoral labor demand, which determine the WOUS index, also influence these wages. Second, there is a positive and significant impact of the sectoral share on total value added on relative wages. This effect underlines the significance of shifts in the productive structure's composition in shaping sectoral wage patterns and reinforces the role of sectoral labor demand in defining those wages. Notably, the primary variables of the model retain their significance across different specifications, reinforcing that lower unemployment or a higher value-added share boosts relative sectoral wage levels.

The results related to the control variables reveal some relevant patterns. The negative coefficient associated with the proportion of women in sectoral employment underscores the persistent gender wage gap. Additionally, a sector's export orientation has a positive effect on its relative wages in most specifications, suggesting that sectors more oriented toward exports tend to offer higher wages. However, the contribution of foreign value added to exports does not demonstrate a significant influence. This observation suggests that while exporting activities bolster relative wages, deeper integration into global value chains might not directly increase wage levels. However, this particular aspect warrants further exploration in subsequent research, as it extends beyond the scope of the current article.

The other control variables show positive but not significant coefficients, with a few exceptions for the square of per capita GDP, which presents the expected negative sign. One possible explanation for the nonsignificance of these aggregate control coefficients is the sectoral characteristic of the mean variables in our model.

In Model 2 (Table 8), we replace the Weighted Unemployment ($WOUS$) variable with the sectoral share of professional occupations in employment ($part\_prof$). This modification addresses a critical gap in our initial model—the absence of a variable directly linked to skill level or educational attainment. Including this dimension allows for more nuanced control over variations in relative wages and their absolute levels, enriching our analysis by integrating a key determinant of wage dynamics. Its inclusion also allows us to consider an important characteristic of skill-based technical change models—the increasing supply of more skilled workers—in our tests and to verify the remaining significance of the sectoral value added share in explaining shifts in sectoral relative wages.[22] The results of Model 2 are considerably similar to those of Model 1. However, it is notable that the variable *part_prof* is positive but not significant in some specifications.

The estimates' consistency depends on the instruments' validity and the error term's absence of second-order serial correlation. Thus, we use two specification tests recommended by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998), and they reveal that all the models presented are consistent.[23]

We also conduct multiple procedures to evaluate the robustness of our findings. As Tables 7 and 8 demonstrate, we apply the same models via diverse econometric methods (system GMM and difference GMM) and utilize several control variables previously described and commonly employed in the literature on wage determination.[24] The models control for the endogeneity between relative wages, unemployment (WOUS), and occupational structure by including the lagged dependent variable and the lags of sectoral unemployment (in Model 1) and professional participation (in Model 2) as instruments for the endogenous variables in both the system and difference GMM approaches. The variable related to global value chain integration (fva_x) is also included as endogenous, following the literature that analyses its relationship with wages (Frenkel and Ngo, 2024). Robust standard errors, clustered at the country level, are reported in parentheses. In all the models, the instruments are collapsed to limit their number (Roodman,

[22] As previously mentioned, sectoral information on educational attainment is scarce in the ILOSTAT database. Including it in the model would reduce the sample size and the consistency of the results. Therefore, we use the variable *part_prof* as a proxy. We test its relevance in an alternative model instead of Model 1, as the share of professionals is used to calculate our WOUS variable, and testing them together would cause multicollinearity.

[23] In these tests, we should not reject the null hypothesis. The first test is the Hansen test for overidentification restrictions, where the null hypothesis is that the model is correctly specified and the instruments are valid. The second is the Arellano–Bond AR(2) test, with the null hypothesis being the absence of second-order serial correlation in the error term, assuming first-order correlation in AR(1) but not in higher orders.

[24] We also conduct tests on a reduced dataset that excludes the first year of the COVID-19 pandemic (2020), which implies significant changes in the labor market. The coefficients and significance of the results remain similar.

2009). Time dummies and other control variables are also included in the model as instrumental variables (IVs).

In addition to the models presented in Tables 7 and 8, we also perform regressions by including the controls individually in the basic model and progressively adding them across the different methods adopted. The results and interpretations remained consistent.

Table 7. Determinants of sectoral relative wages (Model 1)

	(1)	(2)	(3)	(4)
VARIABLES	**Sys-GMM**	**Sys-GMM**	**Dif-GMM**	**Dif-GMM**
L.lnrelWage	0.153	0.150	0.159	0.300***
	(0.124)	(0.145)	(0.108)	(0.074)
L2.lnrelWage	0.212*	0.259**	0.268***	0.349***
	(0.109)	(0.102)	(0.077)	(0.076)
lnsecUnemp	-0.030**	-0.032*	-0.034**	-0.034**
	(0.014)	(0.018)	(0.017)	(0.017)
lnvaShare	0.014*	0.013**	0.014**	0.007*
	(0.008)	(0.007)	(0.006)	(0.004)
L.lnfvax_x	0.009	-0.024	-0.007	-0.030
	(0.048)	(0.035)	(0.048)	(0.034)
lnfemaleRatio	-0.039*	-0.048***	-0.040**	-0.035***
	(0.021)	(0.015)	(0.020)	(0.013)
L.lnageDependency	0.051	0.058	0.070	0.030
	(0.075)	(0.063)	(0.060)	(0.041)
L.lngovExpendEduOfGDP	-0.030	0.027	-0.003	0.004
	(0.048)	(0.032)	(0.016)	(0.014)
L.lnexpOrientOutput	0.011*	0.016***	0.013*	0.010**
	(0.007)	(0.006)	(0.007)	(0.004)
L2.lnGDPconst2017PPP_cap		0.000		0.000
		(0.000)		(0.000)
L2.lnGDP_cap_Sqr		-0.025		-0.013*
		(0.021)		(0.007)
Observations	3,680	3,680	3,680	3,680
Number of countries	31	31	31	31
Number of units of individuals (countryXsector)	524	524	524	524
AR(1)	9.91e-05	0.000448	1.65e-06	3.42e-10
AR(2)	0.713	0.331	0.158	0.121
Hansen	0.339	0.721	0.339	0.721
Number of instruments	36	40	36	40

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8: Determinants of sectoral relative wages (Model 2)

	(6)	(7)	(6)	(7)
VARIABLES	**Sys-GMM**	**Sys-GMM**	**Dif-GMM**	**Dif-GMM**
L.lnrelWage	0.108	0.135	0.071	0.132
	(0.162)	(0.110)	(0.126)	(0.091)
L2.lnrelWage	0.092	0.146	0.118*	0.147**
	(0.100)	(0.105)	(0.065)	(0.063)
lnpart_prof	0.076	0.050	0.111*	0.119**
	(0.064)	(0.055)	(0.062)	(0.058)
lnvaShare	0.017*	0.018**	0.024***	0.021***
	(0.009)	(0.009)	(0.008)	(0.006)
L.lnfvax_x	-0.008	-0.021	-0.052	-0.076
	(0.117)	(0.106)	(0.086)	(0.071)
lnfemaleRatio	-0.100	-0.088**	-0.139**	-0.147**
	(0.065)	(0.037)	(0.067)	(0.060)
L.lnageDependency	0.004	0.055	-0.030	-0.060
	(0.126)	(0.098)	(0.115)	(0.094)
L.lngovExpendEduOfGDP	-0.038	0.018	-0.026	0.001
	(0.075)	(0.065)	(0.035)	(0.026)
L.lnexpOrientOutput	0.015	0.016	0.023*	0.024**
	(0.018)	(0.013)	(0.012)	(0.010)
L2.lnGDPconst2017PPP_cap		0.000		0.000
		(0.000)		(0.000)
L2.lnGDP_cap_Sqr		-0.032		-0.035***
		(0.044)		(0.013)
Observations	3,524	3,524	3,524	3,524
Number of countries	31	31	31	31
Number of units of individuals (countryXsector)	509	509	509	509
AR(1)	0.000496	3.20e-08	1.89e-05	2.11e-10
AR(2)	0.746	0.892	0.636	0.650
Hansen	0.442	0.701	0.442	0.701
Number of instruments	36	40	36	40

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

We carry out other regression tests excluding the variable fva_x and including an explanatory variable for sectoral productivity (*prod_rel*, as defined in Section 5), and the results remain consistent. This robustness check is important because one could argue that the effect of the sectoral composition of production on relative wages is due primarily to differences in productivity among sectors. Despite the coefficient of the included variable is significant, the coefficients for the sectoral share of total value added, although reduced, remains significant in most specifications, as do the coefficients for the WOUS ($secUnemp$) variable. Detailed findings from this analysis can be found in the Appendix, specifically in Table A4 (Model 3).

Consequently, we argue that other sector-specific characteristics, beyond productivity, influence the behavior of sectoral relative wages. The significance and direction of our key variables support our predictions about the impact of occupational structure and sectoral production composition on sectoral wage determination. The interplay between a sector's task composition and the pool of workers skilled in performing these tasks shapes relative wage levels. As a sector's value- added share increases, the demand for workers skilled in sector-specific tasks also increases, driving up relative wages in sectors where these tasks are prevalent. Thus, the intersection between occupational and sectoral output composition plays a crucial role in defining relative sectoral wages.

7. Conclusion

In this article, we bridge the gap between the literature on skills and structural change to explore how shifts in sectoral production composition influence the occupational structure of employment and relative sectoral wages. First, we extend the shift-share analysis to include a novel decomposition focused on sectoral employment variations, highlighting the impact of productive structure shifts on the labor market. This approach reveals that significant shifts in sectoral employment are crucial for understanding changes in the composition of occupations, particularly with the observed decline in manufacturing and agriculture and the concurrent rise of diverse service sectors.

Second, our empirical econometric model introduces the Weighted Occupational Unemployment by Sector (WOUS) index to capture the effects of supply and demand on sectoral wage levels, acknowledging the diversity of skills within sectors. Finally, we examine the direct influence of sectoral value added on wage structures, thereby providing a comprehensive understanding of how sector-specific dynamics shape occupational composition and relative wages within sectors.

Our econometric analysis, which controls for traditional demand and supply factors, confirms the significance of our explanatory variables. The WOUS variable allows us to argue that, given the labor supply, the sectoral demand for labor differs, which influences relative wages. The relevance of the variable that represents the sectoral share of professionals in some tests reinforces this argument. The WOUS index and the share of professionals in sectors show how skills and sector-specific labor demands affect relative wages, highlighting a shift from traditional, individual-focused wage analysis to a sectoral perspective on what determines wages. In this sense, increasing the availability of information on the labor market at the industry level could contribute to future research on the determinants of sectoral relative wages.

Our study also distinguishes itself from previous research by exploring the interplay between sectoral relative wages and shifts in the sectoral share of total value added. Shifts in production between sectors increase demand for specific skills and influence relative wages. While variation in relative wages is often attributed to productivity differences across sectors, our analysis demonstrates that even after controlling for productivity, shifts in value-added shares still influence relative wages. This impact is likely due to the distinctive demand for skills and occupations in various sectors, as indicated by the significance of the weighted unemployment rate in our results.

Prolonged shifts in the sectoral composition of production lead to structural changes. If this relationship persists over the long term, it could establish a significant link between relative wages and the economic structure. Unfortunately, our time series data are not extensive enough to conclusively support long-term trends.

Finally, this study reinforces the importance of examining productive structural transformations, such as deindustrialization, and their broader economic implications. Policy makers should be concerned with the effects of structural change on relative wages and the need to design strategies to strengthen sectors with median and higher relative wages and a considerable share of employment. Future research should aim to deepen our understanding of how deindustrialization and the rise of the service sector alter wage structures, thereby informing strategies to address emerging challenges related to employment and wage disparities.

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Appendix

Table A1: List of countries included in the tests

Country	Econometric Dataset (ILOSTAT)	1990s-2010s Shift Share (IPUMS)	2000-2007 Shift-Share (ILOSTAT, ISIC3 & ISCO88)	2011-2020 Shift-Share (ILOSTAT, ISIC4 & ISCO08)
Austria	X		X	X
Belgium	X			
Brazil		X		
Bulgaria	X			X
Croatia	X			
Cyprus	X		X	X
Czech Republic	X			X
Denmark	X			
El Salvador				X
Estonia	X			
Finland	X			X
France	X		X	X
Germany	X		X	
Greece	X	X		X
Hungary	X		X	X
Iceland	X			
Ireland	X	X		
Italy	X		X	X
Latvia	X			
Lithuania	X			
Luxembourg	X			
Mexico		X		
Netherlands	X		X	X
Panama				X
Poland	X			
Portugal	X	X		X
Romania			X	
Slovakia	X			X
Slovenia	X			
South Korea	X			X
Spain	X		X	X
Sweden	X			
Switzerland	X			X
Thailand			X	X
Turkey	X			X
United Kingdom	X		X	X
United States of America	X	X		X
Uruguay			X	X
Vietnam				X

Table A2: Sectors included in the sample for the econometric tests (ISIC-Rev.4)

A	Agriculture	K	Financial and insurance activities
B	Mining and quarrying	L	Real estate activities
C	Manufacturing	M	Professional, scientific and technical activities
D	Electricity	N	Administrative and support service activities
E	Water supply	O	Public administration and defense
F	Construction	P	Education
G	Wholesale and retail trade	Q	Human health and social work activities
H	Transportation and storage	R	Arts, entertainment and recreation
I	Accommodation and food service activities	S	Other service activities
J	Information and communication	T	Activities of households as employers

Table A3: Occupation groups considered in the estimation of the WOUS (ISCO-08)

1	Managers	5	Service and sales workers
2	Professionals	6	Skilled agricultural, forestry and fishery workers
3	Technicians and associate professionals	7	Craft and related trades workers
4	Clerical support workers	8	Plant and machine operators, and assemblers
		9	Elementary occupations

Table A4: Determinants of sectoral relative wages (Model 3)

Model Sys_GMM
Database 2011-2020 Database

	(1)	(2)	(3)	(4)	(5)
VARIABLES	lnrelSal	lnrelSal	lnrelSal	lnrelSal	lnrelSal
L.lnrelWage	0.218	0.233	0.262*	0.239	0.201
	(0.158)	(0.160)	(0.156)	(0.174)	(0.185)
L2.lnrelWage	0.200**	0.228**	0.220**	0.268***	0.184
	(0.089)	(0.093)	(0.108)	(0.102)	(0.148)
lnsecUnemp	-0.055*	-0.045	-0.044*	-0.048*	-0.045**
	(0.030)	(0.037)	(0.024)	(0.027)	(0.023)
lnvaShare	0.018*	0.018*	0.017*	0.000	0.022*
	(0.009)	(0.010)	(0.010)	(0.008)	(0.013)
lnprod_rel	0.070**	0.059**	0.061**	0.054**	0.066*
	(0.027)	(0.028)	(0.026)	(0.027)	(0.036)
lnfemaleRatio	-0.056***	-0.054**	-0.050**	-0.039***	-0.059**
	(0.020)	(0.024)	(0.020)	(0.015)	(0.028)
L.lnageDependency		0.068			
		(0.077)			
L.lngovExpendEduOfGDP			0.020		
			(0.034)		
L2.lnexpOrientOutput				0.007	
				(0.005)	
L.lnGDPconst2017PPP_cap					0.037
					(0.341)
lnGDP_cap_sqr					-0.020
					(0.165)
Constant	0.000	0.000	-0.071	0.000	0.000
	(0.000)	(0.000)	(0.112)	(0.000)	(0.000)
Observations	2,961	2,961	2,943	2,813	2,961
Number of panelid	489	489	489	461	489
Number of countries	27	27	27	27	27
AR(1)	0.00159	0.00255	0.00223	0.00551	0.00120
AR(2)	0.588	0.731	0.633	0.917	0.596
Hansen	0.124	0.196	0.336	0.260	0.444
Number of instruments	29	28	31	30	32

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5

Correlation of occupational composition across different sectors

The database includes the same sample of countries and years of the econometric dataset

	ISIC4_A	ISIC4_B	ISIC4_C	ISIC4_D	ISIC4_E	ISIC4_F	ISIC4_G	ISIC4_H	ISIC4_I	ISIC4_J	ISIC4_K	ISIC4_L	ISIC4_M	ISIC4_N	ISIC4_O	ISIC4_P	ISIC4_Q	ISIC4_R	ISIC4_S	ISIC4_T	ISIC4_X
ISIC4_A	1,0000																				
ISIC4_B	0,2147	1,0000																			
ISIC4_C	-0,0094	0,5919	1,0000																		
ISIC4_D	-0,0072	0,3458	0,5577	1,0000																	
ISIC4_E	0,3622	0,5157	0,5776	0,2713	1,0000																
ISIC4_F	0,1340	0,4631	0,8198	0,5216	0,5750	1,0000															
ISIC4_G	-0,1445	-0,0704	0,3494	0,2514	0,0730	0,3055	1,0000														
ISIC4_H	0,1399	0,4151	0,5124	0,1183	0,5218	0,3061	0,2578	1,0000													
ISIC4_I	0,0410	-0,2533	-0,0901	-0,1920	0,0863	-0,0173	0,6336	0,1871	1,0000												
ISIC4_J	-0,1676	-0,0564	0,1161	0,5821	-0,1005	0,0882	0,2188	-0,0076	-0,0301	1,0000											
ISIC4_K	-0,1135	-0,0341	0,0474	0,5001	-0,0051	0,0303	0,1922	0,1935	0,0064	0,8281	1,0000										
ISIC4_L	0,0122	0,0549	0,1377	0,4047	0,2001	0,1718	0,4506	0,2716	0,3473	0,4725	0,5558	1,0000									
ISIC4_M	-0,2220	-0,0491	0,1902	0,5608	-0,0142	0,1723	0,2693	0,1040	0,0346	0,8933	0,8484	0,5128	1,0000								
ISIC4_N	0,1238	-0,1380	0,0474	-0,0473	0,2230	0,0401	0,5703	0,2813	0,7270	0,0746	0,1559	0,3786	0,1601	1,0000							
ISIC4_O	-0,2390	-0,1562	0,0590	0,3577	-0,0211	-0,0219	0,5013	0,1825	0,3869	0,6909	0,7102	0,5757	0,6924	0,4764	1,0000						
ISIC4_P	-0,0910	-0,2070	-0,0075	0,1869	0,0072	-0,0161	0,4018	0,0553	0,4415	0,5579	0,4897	0,4302	0,6119	0,5175	0,7238	1,0000					
ISIC4_Q	-0,1145	-0,1328	0,0084	0,2884	0,0188	-0,0583	0,4407	0,1410	0,3873	0,6075	0,5578	0,5334	0,6294	0,4902	0,8004	0,8298	1,0000				
ISIC4_R	-0,1212	-0,1330	0,0690	0,3735	0,0000	0,0151	0,4683	0,1531	0,3550	0,7138	0,6834	0,6103	0,7202	0,4581	0,7885	0,7345	0,7938	1,0000			
ISIC4_S	-0,0924	-0,0291	0,2050	0,2855	0,0407	0,1436	0,6977	0,0805	0,5054	0,3395	0,2025	0,4078	0,3365	0,5018	0,5912	0,5854	0,6149	0,5991	1,0000		
ISIC4_T	0,2456	-0,1219	-0,1330	-0,2674	0,1677	-0,0179	0,3896	0,0793	0,5798	-0,2220	-0,1540	0,1401	-0,1654	0,6207	0,1725	0,2707	0,2260	0,1818	0,3896	1,0000	
ISIC4_X	-0,0649	0,0369	-0,0564	0,0982	0,0077	-0,0991	0,0665	-0,0607	-0,0025	0,1116	0,1129	0,1796	0,1558	0,0736	0,1474	0,1695	0,1927	0,1848	0,1467	0,0911	1,0000

Aggregate average	0,2425

Table A6

Correlation of occupational structure for each sector across different countries

The database includes the same sample of countries and years of the econometric dataset

	AUT	BEL	BGR	CHE	CYP	CZE	DEU	DNK	ESP	EST	FIN	FRA	GBR	GRC	HRV	HUN	IRL	ISL	ITA	KOR	LTU	LUX	LVA	NLD	POL	PRT	SVK	SVN	SWE	TUR	USA
AUT	1,0000																														
BEL	0,9280	1,0000																													
BGR	0,8171	0,8107	1,0000																												
CHE	0,9184	0,8930	0,7551	1,0000																											
CYP	0,8754	0,8384	0,8102	0,8210	1,0000																										
CZE	0,8689	0,8581	0,8834	0,8335	0,7879	1,0000																									
DEU	0,9521	0,9325	0,8128	0,9210	0,8492	0,8622	1,0000																								
DNK	0,9029	0,8821	0,8032	0,8713	0,8218	0,8274	0,8935	1,0000																							
ESP	0,9045	0,9017	0,8459	0,8830	0,9041	0,8779	0,9206	0,8641	1,0000																						
EST	0,8074	0,8196	0,8477	0,7972	0,7326	0,8626	0,8022	0,8122	0,8147	1,0000																					
FIN	0,8823	0,8648	0,8010	0,8793	0,7731	0,8554	0,8852	0,9194	0,8536	0,8495	1,0000																				
FRA	0,9244	0,9300	0,7776	0,8946	0,8482	0,8359	0,9219	0,8746	0,9043	0,8174	0,8637	1,0000																			
GBR	0,8953	0,9224	0,7854	0,8799	0,8023	0,8373	0,9197	0,8784	0,8786	0,8478	0,8761	0,9023	1,0000																		
GRC	0,8664	0,8382	0,8345	0,8099	0,8808	0,8047	0,8422	0,7836	0,8980	0,7215	0,7450	0,8042	0,7785	1,0000																	
HRV	0,8412	0,8246	0,8899	0,7895	0,8155	0,8814	0,8347	0,8242	0,8479	0,8051	0,8051	0,7918	0,8029	0,8205	1,0000																
HUN	0,8893	0,8830	0,8899	0,8256	0,8192	0,9137	0,8874	0,8546	0,8906	0,8393	0,8351	0,8584	0,8518	0,8410	0,8821	1,0000															
IRL	0,8762	0,8870	0,8081	0,8808	0,8122	0,8112	0,8680	0,8803	0,8744	0,8204	0,8748	0,8499	0,9140	0,8026	0,8155	0,8178	1,0000														
ISL	0,7861	0,7798	0,7502	0,7908	0,6946	0,7656	0,7528	0,7811	0,7500	0,8049	0,7958	0,7888	0,7960	0,6968	0,7396	0,7558	0,8177	1,0000													
ITA	0,8815	0,8728	0,8135	0,8652	0,8647	0,8643	0,9136	0,8616	0,9452	0,7937	0,8363	0,8804	0,8491	0,8789	0,8453	0,8644	0,8330	0,7175	1,0000												
KOR	0,6957	0,6464	0,5809	0,6489	0,6400	0,5790	0,6888	0,6958	0,6741	0,6045	0,6664	0,7120	0,6551	0,6562	0,5589	0,6512	0,6252	0,5427	0,7016	1,0000											
LTU	0,7754	0,8104	0,8438	0,7537	0,7081	0,8147	0,7743	0,7964	0,7667	0,8840	0,8154	0,7811	0,8055	0,7157	0,8083	0,8456	0,7811	0,7861	0,7410	0,5847	1,0000										
LUX	0,8112	0,8141	0,7112	0,7081	0,7911	0,6839	0,7987	0,7368	0,8116	0,6486	0,7142	0,7897	0,6814	0,7509	0,6851	0,7595	0,7027	0,6451	0,7526	0,5522	0,6742	1,0000									
LVA	0,7591	0,7736	0,8471	0,7459	0,7064	0,8118	0,7458	0,7970	0,7598	0,9070	0,8038	0,7591	0,7886	0,6940	0,8132	0,8208	0,7886	0,7941	0,7393	0,5531	0,8784	0,6500	1,0000								
NLD	0,9136	0,9173	0,7852	0,7741	0,8032	0,7849	0,9007	0,8177	0,8696	0,7698	0,8110	0,8406	0,8387	0,7721	0,7454	0,8659	0,8136	0,7531	0,8349	0,6538	0,8091	0,7737	0,7241	1,0000							
POL	0,8462	0,8678	0,8965	0,8180	0,7867	0,9099	0,8569	0,8562	0,8393	0,8943	0,8553	0,8371	0,8777	0,7943	0,8777	0,8918	0,8354	0,7880	0,8313	0,6244	0,8686	0,6807	0,8576	0,7436	1,0000						
PRT	0,8892	0,9028	0,8615	0,8524	0,8794	0,8492	0,8919	0,8726	0,9287	0,8302	0,8429	0,8993	0,8632	0,8733	0,8439	0,8796	0,8702	0,7867	0,8958	0,6716	0,8026	0,8182	0,8038	0,8546	0,8666	1,0000					
SVK	0,8253	0,8032	0,8644	0,6520	0,7715	0,8772	0,6965	0,7323	0,8224	0,7783	0,7194	0,7190	0,6914	0,7622	0,8330	0,8723	0,7254	0,6990	0,7781	0,5325	0,7727	0,6417	0,7606	0,6712	0,7923	0,8165	1,0000				
SVN	0,8645	0,8841	0,8793	0,8320	0,8205	0,8684	0,8622	0,8518	0,8559	0,8618	0,8512	0,8233	0,8647	0,8165	0,8922	0,8843	0,8585	0,8057	0,8324	0,6063	0,8518	0,6763	0,8333	0,7774	0,9032	0,8535	0,7463	1,0000			
SWE	0,8837	0,8789	0,7780	0,8682	0,7562	0,8399	0,8730	0,8940	0,8268	0,8512	0,9105	0,8830	0,8968	0,7253	0,7823	0,8252	0,8494	0,8100	0,8116	0,6436	0,8183	0,6928	0,8037	0,8349	0,8368	0,8379	0,6950	0,8449	1,0000		
TUR	0,8674	0,8221	0,8250	0,8217	0,8245	0,8096	0,8600	0,7917	0,8667	0,7512	0,7682	0,8304	0,8107	0,8612	0,7736	0,8298	0,8013	0,6824	0,8494	0,6676	0,7354	0,6654	0,7100	0,7964	0,8021	0,8588	0,7883	0,7991	0,7624	1,0000	
USA	0,8859	0,8854	0,7795	0,8865	0,7956	0,8311	0,8792	0,8582	0,8681	0,8490	0,8641	0,8716	0,9260	0,7820	0,7582	0,8354	0,8881	0,7871	0,8410	0,6769	0,7976	0,7254	0,7917	0,8802	0,8338	0,8360	0,7686	0,8384	0,8652	0,8034	1,0000

Aggregate average	0,8106

Table A7

Correlation of relative wages for each occupational group across different countries

The database includes the same sample of countries and years of the econometric dataset

	AUT	BEL	BGR	CHE	CYP	CZE	DEU	DNK	ESP	EST	FIN	FRA	GBR	GRC	HRV	HUN	IRL	ISL	ITA	KOR	LTU	LUX	LVA	NLD	POL	PRT	SVK	SVN	SWE	TUR	USA
AUT	1,0000																														
BEL	0,8875	1,0000																													
BGR	0,9112	0,8899	1,0000																												
CHE	0,9077	0,8636	0,9224	1,0000																											
CYP	0,8794	0,8884	0,8910	0,8934	1,0000																										
CZE	0,9311	0,8950	0,9398	0,9140	0,8806	1,0000																									
DEU	0,9101	0,8952	0,9093	0,8978	0,8766	0,9620	1,0000																								
DNK	0,8824	0,8993	0,9199	0,8479	0,8850	0,9250	0,8767	1,0000																							
ESP	0,9155	0,8868	0,9095	0,8875	0,8983	0,9585	0,9380	0,8971	1,0000																						
EST	0,9181	0,8527	0,9161	0,9059	0,9057	0,9259	0,9197	0,8555	0,9005	1,0000																					
FIN	0,9439	0,8804	0,9159	0,9169	0,9078	0,9286	0,9161	0,8947	0,9262	0,9198	1,0000																				
FRA	0,9489	0,8579	0,9219	0,9274	0,9080	0,9324	0,9147	0,8322	0,9168	0,9227	0,9497	1,0000																			
GBR	0,9076	0,8703	0,8772	0,8766	0,9037	0,9128	0,8972	0,8819	0,8752	0,9287	0,9109	0,9026	1,0000																		
GRC	0,8772	0,8687	0,9242	0,9108	0,8752	0,9299	0,8968	0,7233	0,9315	0,8698	0,8856	0,9318	0,8175	1,0000																	
HRV	0,9260	0,8947	0,9284	0,9002	0,8757	0,9489	0,9218	0,8454	0,9283	0,8746	0,9151	0,9405	0,8351	0,8875	1,0000																
HUN	0,9100	0,8832	0,9089	0,8913	0,8434	0,9369	0,9133	0,8086	0,9102	0,8959	0,9086	0,9217	0,8169	0,9121	0,9409	1,0000															
IRL	0,8599	0,7533	0,8519	0,8555	0,8323	0,8662	0,8097	0,7793	0,8377	0,8330	0,8574	0,8761	0,8250	0,8733	0,8265	0,8349	1,0000														
ISL	0,7811	0,8791	0,8113	0,8012	0,9222	0,8215	0,8185	0,8217	0,8005	0,8291	0,8207	0,7985	0,8804	0,7425	0,7525	0,7166	0,7032	1,0000													
ITA	0,9161	0,8737	0,9244	0,9373	0,8583	0,9234	0,9099	0,8931	0,9391	0,8864	0,9336	0,9434	0,7939	0,9464	0,9458	0,9570	0,8605	0,7050	1,0000												
KOR	0,8610	0,8130	0,8882	0,8720	0,7846	0,9242	0,9047	0,8603	0,9486	0,8917	0,8556	0,8990	0,7724	0,9232	0,9208	0,9085	0,7642	0,6999	0,9384	1,0000											
LTU	0,8885	0,8918	0,8996	0,9110	0,8576	0,9143	0,9011	0,8944	0,9084	0,8963	0,9046	0,9099	0,8069	0,8915	0,8958	0,9070	0,8585	0,7935	0,9321	0,8989	1,0000										
LUX	0,8641	0,9028	0,8574	0,8636	0,8032	0,9157	0,9240	0,8541	0,9166	0,8473	0,8616	0,8775	0,8072	0,9103	0,8934	0,8849	0,8486	0,7551	0,9002	0,9092	0,8901	1,0000									
LVA	0,9170	0,8544	0,8997	0,9268	0,8524	0,9052	0,9148	0,9044	0,9281	0,8881	0,9318	0,9390	0,7979	0,9345	0,9308	0,9120	0,8694	0,7131	0,9549	0,9059	0,9262	0,8953	1,0000								
NLD	0,9361	0,8726	0,9172	0,9052	0,9178	0,9398	0,9348	0,8135	0,9292	0,9252	0,9408	0,9447	0,9338	0,9219	0,9005	0,9154	0,8696	0,8379	0,9164	0,8855	0,8992	0,8761	0,9003	1,0000							
POL	0,9188	0,9200	0,9198	0,8944	0,9043	0,9241	0,8748	0,8685	0,9096	0,8575	0,9285	0,8941	0,8925	0,8564	0,9162	0,9118	0,8218	0,8011	0,9278	0,8318	0,8588	0,8616	0,9083	0,8960	1,0000						
PRT	0,9012	0,8568	0,9039	0,9020	0,8698	0,9318	0,9173	0,8889	0,9412	0,8812	0,9004	0,9498	0,8133	0,9220	0,9532	0,9282	0,8518	0,7294	0,9492	0,9126	0,9211	0,9023	0,9338	0,8952	0,8822	1,0000					
SVK	0,9192	0,9096	0,9199	0,8350	0,8605	0,9338	0,8895	0,8584	0,9068	0,8513	0,8959	0,9043	0,8425	0,7452	0,8720	0,9407	0,7713	0,7464	0,9248	0,7461	0,8756	0,8543	0,8764	0,8568	0,9060	0,8769	1,0000				
SVN	0,8783	0,9021	0,9246	0,8781	0,8743	0,9385	0,9303	0,8769	0,9327	0,8600	0,8852	0,8971	0,8093	0,8978	0,9417	0,9204	0,7997	0,8044	0,9304	0,8991	0,9026	0,9004	0,9010	0,8920	0,8863	0,9162	0,8995	1,0000			
SWE	0,9353	0,8336	0,8987	0,9025	0,8843	0,9386	0,9089	0,7892	0,9226	0,9062	0,9482	0,9387	0,9162	0,9161	0,8938	0,9115	0,8382	0,7802	0,9182	0,8697	0,8696	0,8674	0,9198	0,9495	0,8672	0,8854	0,7979	0,8492	1,0000		
TUR	0,8656	0,8332	0,8947	0,8723	0,7773	0,8971	0,8662	0,8487	0,9170	0,8402	0,8691	0,8880	0,7450	0,9387	0,9363	0,9488	0,8322	0,6907	0,9616	0,8995	0,9027	0,8993	0,9287	0,8583	0,8744	0,9380	0,8849	0,9000	0,8604	1,0000	
USA	0,9458	0,8835	0,9221	0,9082	0,8895	0,9472	0,9192	0,9112	0,9132	0,9427	0,9297	0,9207	0,9188	0,9057	0,9029	0,8957	0,8372	0,8303	0,8829	0,8233	0,8809	0,8660	0,8796	0,9453	0,9403	0,8647	0,9234	0,8645	0,9444	0,8528	1,0000

Aggregate average	0,8855

Table A8

Correlation of relative wages for each sector across different countries

The database includes the same sample of countries and years of the econometric dataset

	AUT	BEL	BGR	CHE	CYP	CZE	DEU	DNK	ESP	EST	FIN	FRA	GBR	GRC	HRV	HUN	IRL	ISL	ITA	KOR	LTU	LUX	LVA	NLD	POL	PRT	SVK	SVN	SWE	TUR	USA
AUT	1,0000																														
BEL	0,8072	1,0000																													
BGR	0,7991	0,6702	1,0000																												
CHE	0,8543	0,7545	0,7739	1,0000																											
CYP	0,8025	0,5717	0,8016	0,7943	1,0000																										
CZE	0,8600	0,7391	0,8852	0,8377	0,7827	1,0000																									
DEU	0,9165	0,8344	0,7462	0,8947	0,7926	0,8489	1,0000																								
DNK	0,8817	0,8084	0,6711	0,7699	0,7181	0,7306	0,8781	1,0000																							
ESP	0,8856	0,7590	0,8463	0,8501	0,8290	0,9158	0,8967	0,7991	1,0000																						
EST	0,8215	0,6885	0,8019	0,7878	0,7475	0,8848	0,7412	0,6634	0,8510	1,0000																					
FIN	0,9043	0,8813	0,7976	0,8755	0,7597	0,8795	0,9419	0,8602	0,8950	0,8055	1,0000																				
FRA	0,8489	0,8436	0,7209	0,7828	0,7197	0,7694	0,8683	0,8309	0,7517	0,6696	0,8592	1,0000																			
GBR	0,9138	0,7819	0,7444	0,8303	0,7701	0,8378	0,8577	0,8310	0,8576	0,8517	0,8823	0,7935	1,0000																		
GRC	0,8424	0,6190	0,7998	0,7906	0,8487	0,8212	0,7779	0,7177	0,8805	0,7925	0,7432	0,6456	0,7936	1,0000																	
HRV	0,7130	0,5847	0,8155	0,7379	0,8091	0,7533	0,7187	0,7020	0,7757	0,7289	0,6971	0,6066	0,6941	0,8144	1,0000																
HUN	0,8186	0,7332	0,7261	0,7555	0,7166	0,7822	0,7991	0,7620	0,7299	0,6713	0,7680	0,8280	0,7457	0,6982	0,6140	1,0000															
IRL	0,9035	0,8107	0,8310	0,8741	0,8091	0,9086	0,9432	0,8376	0,9555	0,8672	0,9345	0,7865	0,8974	0,8275	0,7469	0,7414	1,0000														
ISL	0,6718	0,5844	0,5503	0,5359	0,5591	0,6236	0,4354	0,5098	0,5756	0,7784	0,5579	0,4590	0,6508	0,5449	0,4847	0,3648	0,4659	1,0000													
ITA	0,8659	0,6587	0,7912	0,8043	0,8212	0,8259	0,8408	0,7386	0,8802	0,8221	0,8050	0,7042	0,8461	0,8680	0,7662	0,7062	0,8629	0,6129	1,0000												
KOR	0,7634	0,7754	0,6835	0,8147	0,6793	0,8065	0,7755	0,6917	0,7807	0,7866	0,8169	0,8156	0,7635	0,6754	0,5451	0,7394	0,8835	0,5236	0,7004	1,0000											
LTU	0,8416	0,7686	0,8358	0,8131	0,7373	0,9109	0,8284	0,7646	0,9108	0,8925	0,8662	0,7322	0,8368	0,7745	0,7420	0,6990	0,9029	0,6304	0,8131	0,7521	1,0000										
LUX	0,7352	0,7361	0,7787	0,7941	0,8113	0,7582	0,8114	0,7490	0,8033	0,6169	0,7834	0,7438	0,6816	0,7905	0,7732	0,7305	0,7209	0,3872	0,7581	0,5873	0,7404	1,0000									
LVA	0,7844	0,6919	0,7261	0,7440	0,7043	0,7707	0,6864	0,6823	0,7408	0,8885	0,7594	0,6799	0,7969	0,7040	0,7294	0,6433	0,8050	0,7261	0,7137	0,7214	0,7972	0,5740	1,0000								
NLD	0,8888	0,8531	0,6494	0,7838	0,7102	0,7245	0,8910	0,8880	0,8008	0,6908	0,8914	0,8064	0,8776	0,6934	0,6296	0,6846	0,8518	0,6097	0,7636	0,7242	0,7628	0,6889	0,6925	1,0000							
POL	0,7287	0,7578	0,8125	0,7485	0,7110	0,8131	0,7305	0,6625	0,7942	0,7489	0,8446	0,8090	0,7401	0,6920	0,6931	0,6730	0,8888	0,4790	0,6887	0,7475	0,8058	0,6903	0,7153	0,6981	1,0000						
PRT	0,6047	0,4958	0,6912	0,6729	0,6859	0,6991	0,5746	0,4732	0,7573	0,6177	0,6657	0,5383	0,5982	0,6903	0,5970	0,5094	0,6223	0,5270	0,6478	0,5589	0,6493	0,7387	0,4636	0,5039	0,6084	1,0000					
SVK	0,8664	0,7937	0,8598	0,7684	0,6612	0,8816	0,8136	0,7556	0,8188	0,8309	0,8777	0,8114	0,8003	0,6909	0,6530	0,7700	0,8478	0,7178	0,7345	0,7301	0,8558	0,6608	0,7795	0,7425	0,7870	0,5613	1,0000				
SVN	0,7445	0,7326	0,8676	0,7468	0,7992	0,8445	0,7638	0,6972	0,8512	0,7220	0,7955	0,7540	0,6807	0,7924	0,7735	0,6989	0,7827	0,5562	0,7945	0,6511	0,8262	0,8505	0,6354	0,6704	0,8486	0,7298	0,7749	1,0000			
SWE	0,8754	0,8255	0,6980	0,7791	0,6276	0,7685	0,7977	0,7964	0,7353	0,7507	0,8737	0,8423	0,8423	0,6153	0,5362	0,7345	0,7899	0,7171	0,7311	0,7259	0,7956	0,6390	0,7206	0,8422	0,7363	0,4825	0,8708	0,6929	1,0000		
TUR	0,6916	0,6670	0,7636	0,7612	0,7693	0,7827	0,7170	0,6075	0,8115	0,7116	0,6901	0,5699	0,6846	0,8032	0,7630	0,6101	0,7315	0,4103	0,7763	0,6600	0,7605	0,7974	0,6232	0,5988	0,6679	0,7518	0,6002	0,8153	0,5026	1,0000	
USA	0,9272	0,8040	0,8153	0,8376	0,7446	0,8619	0,9204	0,8800	0,8744	0,8233	0,9417	0,8195	0,9376	0,7849	0,7237	0,7636	0,9128	0,6845	0,8017	0,7383	0,8699	0,7252	0,7782	0,9133	0,8023	0,6215	0,8797	0,7451	0,8946	0,6660	1,0000

Aggregate average	0,7518

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