

The Influence of Structural Change on Occupational and Sectoral Wage Structures: Evidence from Multiple Economies

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Preliminary Draft

Abstract

This paper discusses the intricate dynamics of the occupational structure of numerous economies, a phenomenon that has notably resulted in labour market polarisation. The canonical model and its subsequent elaborations emphasise skill supply, skill-biased technological advancements, and educational expansion as primary drivers. However, our research introduces a nuanced perspective by asserting the central role of structural change, or the long-term shifts in the composition of sectoral production, in shaping occupational compositions. We draw our theoretical framework from Keynesian and structuralist theories, which state that investments targeting sectors with different characteristics are instrumental in boosting economic growth, altering consumption patterns, and consequently driving changes in the labour market. The paper employs a refined shift-share method to dissect job market changes and consider the influence of sectoral production shifts on occupational composition. Contrary to past findings, our results highlight the significance of shifts in the sectoral composition of employment in explaining job composition variations. Additionally, we develop a model to explore the determinants of relative sectoral wages, integrating a unique index to comprehend the balance of job supply and demand, which we denominate Weighted Occupational Unemployment by Sector (WOUS). The results show that this unemployment index and the composition of sectoral production are central in explaining the dynamics of the relative sectoral wages.

JEL: J21, J31, O33, O14

Keywords: Labour market polarisation, Occupational structure, Relative wages, Structural change, Skill-biased technological advancement

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1. Introduction and Preliminary Literature Review

The labour market has undergone significant changes over the past few decades, with one of the most prominent being the polarisation of its occupational structure. That is evidenced by the relative decline in jobs demanding intermediate skills and the relative growth of roles requiring both high and low skills. Based on Katz and Murphy (1992), the canonical model states that the relative supply of skills (with recent decades witnessing an increased supply of more skilled workers) and skill-biased technological advancement led to this labour market polarisation in occupations and wages. This shift arose due to changes in demand and supply for workers with specific educational levels. Subsequently, Acemoglu and Autor (2011) argued that the structure or occupational composition (understood as the relative share of occupations in total jobs) is a pivotal variable, more so than the educational level itself. They suggested that occupations relate to a range of tasks demanding various skills; hence, there isn't a direct relationship between these tasks, intrinsic to a role, and a specific set of skills. This perspective has gained consensus in recent analyses of labour market polarisation. For instance, Autor (2019) extensively examined the polarisation process in the American labour market based on representative occupational groups, a categorisation crafted by Dorn & Autor (2009). An initial contribution of our article is to structure a classification similar to Dorn and Autor's for five countries beyond the USA. We aim to demonstrate that labour market polarisation also occurred in these economies, which possess different attributes and income levels than the USA.

Studies by Acemoglu and Autor (2011), as well as Goos et al. (2014) and others, mainly attribute the labour market changes to technological sophistication, which altered the demand for different occupations, and to the availability of more skilled workers due to the expansion of educational services. Technological advancements necessitate more skilled workers for emerging tasks and lead to the automation of repetitive production and administrative tasks. Moreover, an improved skill set among workers would have significantly influenced consumer preferences, driving demand for more sophisticated goods and services. More straightforward operational tasks, however, requiring non-routine decisions linked with various traditional services, saw their relative share in the labour market grow. According to these authors, structural change, understood as a shift in sectoral production composition, played a less pivotal role in this labour market transformation.

However, in this article, we contend and aim to illustrate that the long-term process of altering sectoral production composition, known as structural change, is also vital in determining employment's occupational composition. These perspectives aren't mutually exclusive; factors tied to skill development and technological progress are crucial. Still, different sectors undertake varied activities and need diverse skills and technologies, influencing employment's occupational composition. Other researchers, such as Barany and Siegel (2018), Buera et al. (2022), and Nomaler et al. (2021), have also examined this issue from a structural change standpoint and vouched for its relevance.

Our study stands out as our theoretical foundation is rooted in Keynesian and structuralist theories. By merging these theoretical models, we argue that investment is pivotal for economic growth. For sustained growth leading to an elevation in per capita income, investments should target sectors producing higher added value per capita. The investment would boost demand for goods and services, raising income and fostering employment and wage growth due to the

multiplier effect. This process would result in altered consumption patterns (Engel's law) and the sectoral production composition. The structuralist perspective holds that sectors possess unique technological traits and produce varied added values per capita due to factors related to technology, workforce, or the differentiation of goods and services in the consumer market. As income rises, the economy should produce more sophisticated products to meet evolving demands. Sectors manufacturing these advanced products should also provide better jobs with higher wages. Educational advancements, subsequent human capital accumulation, skill acquisition, and technological progress are essential conditions for economic growth. However, they aren't enough on their own. Without productive investment, consistent income growth, labour demand, job growth, aggregate demand, and the ensuing shift towards high-value-added sectors won't occur. Thus, another significant contribution of our work is introducing variables associated with demand behaviour from a Keynesian and structuralist viewpoint, which traditional studies overlook.

Considering that the features of sectoral production are distinct and result in the diversity of task compositions requiring varied skills, and given that there is a specific availability of workers to perform particular tasks (which changes over time), the average wages practised in various sectors will also differ. Indeed, more qualified skills are better paid, but there's also an intersection between supply and demand that influences the determination process of sectoral wages. In this paper, we seek to highlight the factors that might contribute to this process, emphasising the relationship between supply and demand in the job market and the role of investment as a representative variable of the role played by the sectoral composition of production in determining the occupational composition and relative sectoral wages in the various economies examined in this study.

To analyse the changes that have taken place in the job market and to demonstrate the relevance of the shift in the sectoral composition of production on educational composition, we opted for the shift-share method of decomposing observed variations in total jobs, initially adopted by Barany and Siegel (2018). However, unlike these authors, we introduced a rule for decomposing job variations comprised of three components – within, static, and dynamic, with the last two forming the between effect (as adopted by de Vries et al. (2015) from the model developed by McMillan and Rodrik (2011), which provides a more accurate decomposition, considering base periods to estimate the contribution of its components and including the dynamic component that estimates the joint effect of variations in the sectoral composition of production and jobs. Additionally, this paper makes an innovative contribution by developing a decomposition rule centred on sectoral job variations. We aim to analyse the variations resulting from job changes, the importance of sectoral employment changes on job behaviour, and to comprehend the constituents of sectoral job variations. This approach is rooted in our exploration of how shifts in the productive structure can impact the job market.

Decomposition estimates indicate that, besides a polarisation of jobs in the job market, changes in the sectoral composition of employment are crucial in explaining the variations in job composition, with its magnitude, in some cases, being more significant than the component related to intra-occupational change. This finding contrasts with Acemoglu and Autor (2011) and Breemersch et al. (2019) for different samples. Furthermore, we found that the intra-sectoral shift in jobs is also significant in explaining the variations in sectoral job composition, and not just the variations observed in various occupations, with its magnitude also larger in several cases, differing from the result of Goos et al. (2014). We were also able to identify

some trends in sectoral employment behaviour due to variations that occurred more frequently in specific directions: a decrease in the participation of manufacturing, agriculture, extraction sector and electricity, and a relative growth in the participation of service sectors, both knowledge-intensive and in support activities, as well as education, health, accommodation and food.

Since sectoral composition is crucial in determining job composition variations, we aim to show that sectors have different occupational structures. We then develop a model to explain variations in relative sectoral wages. We carried out an analysis of the determinants of such remunerations through econometric tests. To discuss the effects that job composition and its variations can have on relative sectoral wages, we designed a unique index, the Weighted Occupational Unemployment by Sector (WOUS), which corresponds to a sectoral average of unemployment rates by job, weighted by the participation of each job group in the sector under analysis. Estimating this index allows for an understanding of supply and demand for various jobs, represented by the unemployment rate calculated for each job, and, consequently, its effect on relative wages by considering, as a weighting factor, the participation of various jobs (or occupational groups) in each sector, we capture the influence of this differentiated supply and demand, which results in specific unemployment rates for jobs, on the relative wage paid in the sector under analysis. To incorporate the discussion on the influence of changes in sectoral production composition on relative wages, we added the investment rate to the econometric model, which also constitutes a novelty in our study.

Thus, our research also seeks to assess the influence that the sectoral composition of jobs, the supply and demand for such jobs, and the process of change in the sectoral composition of production have on the relative wage in a specific sector. The results of the econometric tests confirm that both variables are significant in determining relative sectoral wage variations, in a different approach from the traditionally adopted one that analyses variables that contribute to explaining individual wage levels or variations based on household survey microdata.

The article is structured as follows: besides this introduction, it includes Section 1, where we discuss the theoretical and empirical advances on the topic; in Section 2, we present stylised facts and the results of the shift-share decompositions conducted for job variations; Section 3 then includes the description of data adopted in the subsequent tests; Section 4 introduces the econometric model and show the test results that aim to prove the significance of the two variables mentioned above in the determination process of relative sectoral wages. Finally, we present the study's conclusions.

2. Stylised Facts and Shift Share Decompositions

To analyse the shifts in the job market over recent decades, we utilised a data series that enabled us to study the behaviour of employment and wages by occupational groups and sectors across various countries. We chose two distinct databases for our analyses. The first one is based on microdata from census surveys included in IPUMS (2023), which allows for analysis over two decades (1990 to 2010) and offers more flexible occupational and sectoral groupings. The second utilises data from ILOSTAT, presenting aggregated tabulated data but facilitating the comparison of job market behaviour for a more significant number of countries over a more recent period (1998 to 2021, defined by data availability).

The IPUMS database enabled us to structure the same occupational classification as used by Autor (2019) and expand the analysis to include five other countries beyond the USA, namely Brazil, Greece, Ireland, Mexico, and Portugal, using data from three census periods (the 1990s, 2000s, and 2010s).¹

We began our examination of employment trends by seeking to identify the contribution of sectoral composition shifts to changes in occupational employment composition and to confirm the job polarisation trend across a broader range of countries and periods than previously studied. We employed a decomposition methodology for the variations observed in total occupations, adapting the basic model to incorporate a dynamic component.

Contribution of sectoral employment shifts to changes in occupational categories share:

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

i = occupation

j = sector

N = number of employees

t and 0 = final and initial periods, respectively

The first term of equation (1) corresponds to the 'within' component, which measures the weighted average, based on each sector's share in initial employment, of the observed variations in an occupation across various productive sectors. A positive result indicates that the weighted average of such occupation's participation across different sectors has increased. The second term pertains to the 'static' component, quantifying the contribution of different sectors to the total variation of employees in a given occupation, considering the significance of the occupation's participation in each sector. Put another way, this component gauges the change that has occurred in employment across various sectors, holding constant the initial participation of the occupation under scrutiny in each sector. A positive outcome signifies that workers are moving towards sectors where the analysed occupation's participation is notable.

Consequently, the influence of the sectoral composition of the production process on such occupation's share in total jobs would be positive. The third term of the equation relates to the 'dynamic' component. It assesses the combined effect of variations in an occupation's participation in a sector and that sector in total employment on the change in that occupation's share in employment. A positive result would imply that workers in the occupation under review are shifting towards sectors increasing their share in employment (or vice-versa, with workers in such occupations decreasing their share in sectors that are lessening their

¹ The correspondence table for roles across the countries and periods included in the sample can be requested from the authors. It was also possible to harmonise the occupational classification for three additional countries (France, Hungary, and Spain), but only for the decades of 2000 and 2010.

participation in employment). The sum of the static and dynamic effects constitutes the 'between' effect.

The result of the shift-share decomposition, based on occupational employment variations, can be found in Table 1. We employed a simple average of the outcomes obtained per country, in line with Breemersch et al. (2019), as we did not wish to grant more significance to the result observed in a country due to the size of its economy or its labour market.

Table 1. Decomposition of share by occupational categories – 6 countries - 1990-2010

in p.p	within	static	dynamic	between	overall
High-skill occupations					
Managers and executives	1,1306	0,8829	-0,1467	0,7361	1,8667
Professional and financial/advertising sales	0,6762	4,3072	-0,6369	3,6703	4,3466
Technicians + fire and police	1,0784	0,7192	-0,1477	0,5715	1,6499
Middle-skill occupations					
Sales minus financial/advertising sales	0,4101	1,5965	-0,0432	1,5533	1,9634
Clerical and administrative support	-2,2201	1,9619	-0,5258	1,4361	-0,7840
Production and operative	-1,9108	-3,1600	0,5731	-2,5869	-4,4977
Low-skill occupations					
Transportation	1,0407	-0,5516	0,0080	-0,5436	0,4972
Construction and mechanics	-0,8165	-0,5997	0,2102	-0,3895	-1,2059
Services: Cleaning and protective	-0,7369	1,4330	0,2761	1,7091	0,9723
Services: Personal	0,8452	1,4045	-0,0235	1,3811	2,2263
Services: Health	0,8919	0,3559	0,3022	0,6581	1,5500
Farm and mining	-0,3889	-8,3577	0,1619	-8,1958	-8,5847

Source: IPUMS database

The results first show that the broad occupational group defined as high-skill categories by Autor (2019) – managers, professionals, and technicals – saw a relative growth in their share of total employment. The group of occupations classified as mid-skill experienced a decline; however, its behaviour isn't uniform. While production and administrative workers saw a decrease in representation, those linked to sales increased. There was a rise for occupations classified as low-skill if we excluded workers in agriculture and mineral extraction, whose decline is quite significant (in other words, in occupations demanding low skills and predominantly located in urban areas, there was relative growth).

A portion of this research attributes the shift in the job market to factors mainly linked to technological advancements, which would have altered the demand for various occupations. However, we find that the within effect is significant when we examine the shift-share decomposition outcomes for this set of countries and periods under consideration. Still, the static effect is even more pronounced for six occupational groups. Indeed, the magnitude of the within effect is substantial for mid-skill occupations – administrative and production-related. Still, the static effect's magnitude is also significant in both instances and for the professional group, whose job share growth has always been more tied to an increased demand for higher skills due to technological shifts. The static effect is non-negligible for all occupational groups in the analysis, albeit to varying degrees (the extreme case being agriculture, one of the leading sectors in the structural production change, where the sector-related jobs have dramatically

reduced). Thus, we believe that the sectoral composition of jobs was also pivotal in determining the occupational shift in the economies analysed. The dynamic component is harmful for half of the occupations examined, indicating in these scenarios that the influence of shifts in job and sector shares on job composition had opposing effects.

The exercise was replicated using the ILOSTAT database, which covers non-census (already consolidated) employment data by occupation and sector but a larger sample of countries. We analysed all countries with the necessary information to conduct the decomposition and subsequently performed the econometric tests included in this study. The occupational groups are similar to those defined by Autor (2019), except for service workers, who we group with commerce workers. The analysis was carried out for two distinct periods without merging the databases, as there was a change in the classification of occupations and sectors over the period, and the list of countries included in the sample was more comprehensive in the latter period. Therefore, Table 2 displays the average results of employment variation decomposition by occupational group for the period between 1998 and 2007 (years with higher data availability before the change in job and sector classification) across 22 countries, while Table 3 shows the decomposition outcomes for the period between 2011 and 2021 (also determined based on data availability for the latest classifications of occupations and sectors) across 36 countries. We also present the findings for the period 2011-2019, enabling analysis of the outcomes without the pandemic's influence, in Table 4.²

Table 2. Decomposition of share by occupational categories – 22 countries – 1998-2007

in p.p	within	static	dynamic	between	overall
Armed Forces Occupations	-0,0366	-0,0050	0,0022	-0,0029	-0,0395
Legislators, Senior Officials and Managers	0,0080	0,0058	0,1334	0,1392	0,1472
Professionals	1,0505	0,8073	0,1324	0,9397	1,9902
Technicians and Associate Professionals	0,5578	0,1458	0,3429	0,4887	1,0465
Clerks	-0,7870	0,0934	-0,1845	-0,0911	-0,8780
Craft and Related Trades Workers	-1,4716	-0,4017	0,1294	-0,2722	-1,7439
Plant and Machine Operators and Assemblers	0,2053	-0,9937	-0,3175	-1,3112	-1,1060
Service Workers and Shop and Market Sales Workers	0,5474	0,7107	-0,0802	0,6305	1,1779
Elementary Occupations	1,0602	-0,2512	-0,2076	-0,4589	0,6014
Skilled Agricultural and Fishery Workers	-1,1373	-2,0073	0,0497	-1,9576	-3,0949

Source: ILOSTAT database

The results reported in Table 2 also suggest an increase in the relative share of occupations requiring high skills and a decrease in those associated with mid-skills. Although occupations more oriented towards personal services are grouped with those in commerce, thereby preventing a clear distinction within this occupational category between mid and low-skill jobs, the upward trend of elementary occupations is evident (albeit proportionally smaller), contributing to the polarisation in the urban labour market (assuming that jobs linked to

² Whilst the groupings of occupations and sectors follow the ISCO-88 and ISIC-3 classifications in the first period, in the second period they are defined by the ISCO-08 and ISIC-4 classifications. The list of countries included in the decomposition estimates can be found in the appendix (Tables A2, A3 e A4 respectively). The analysis for the period 2011-2019 includes the same 36 countries covered in the estimates for the period 2011-2021.

agriculture and fishing are more associated with rural environments, which seems reasonable). The magnitude of the static effect exceeds the within effect in three occupational groups and accounts for more than 50% of the magnitude of the within effect in another two groups, underscoring the significant role of worker movement between sectors in determining changes in job composition.

Tables 3 and 4 present the results of a similar decomposition of employment variations by occupational group for more recent periods. Again, we observe a greater magnitude of the static effect in three occupational groups in each analysed period and two and four situations, respectively, for the periods 2011-2019 and 2011-2021, where the magnitude of the static component exceeds 50% of the magnitude of the within effect. Hence, the contribution of the static effect remains significant in the decomposition analysis in more recent years.

Table 3. Decomposition of share by occupational categories – 36 countries – 2011-2019

in p.p.	within	static	dynamic	between	overall
Armed forces occupations	0,0283	-0,0197	0,0041	-0,0156	0,0127
Managers	-0,3342	0,1180	-0,0353	0,0827	-0,2515
Professionals	1,6076	0,9200	-0,0060	0,9140	2,5215
Technicians and associate professionals	0,0861	0,3732	-0,0629	0,3103	0,3964
Clerical support workers	-0,5135	0,2097	-0,0318	0,1779	-0,3356
Craft and related trades workers	-0,4603	-0,1945	-0,0178	-0,2124	-0,6727
Plant and machine operators, and assemblers	0,0673	-0,0149	0,0166	0,0017	0,0690
Service and sales workers	0,1969	0,4941	0,0220	0,5161	0,7131
Elementary occupations	-0,6067	-0,4427	0,0222	-0,4205	-1,0272
Skilled agricultural, forestry and fishery workers	-0,0668	-1,5081	0,0896	-1,4185	-1,4853

Source: ILOSTAT database

Table 4. Decomposition of share by occupational categories – 36 countries – 2011-2021

in p.p.	within	static	dynamic	between	overall
Armed forces occupations	0,0233	0,0112	0,0030	0,0142	0,0375
Managers	-0,3082	0,1131	-0,0658	0,0473	-0,2609
Professionals	2,3588	1,5268	0,0804	1,6072	3,9660
Technicians and associate professionals	0,2730	0,6090	-0,1139	0,4951	0,7680
Clerical support workers	-0,4030	0,2730	-0,0605	0,2126	-0,1904
Craft and related trades workers	-0,6351	-0,0621	-0,0642	-0,1263	-0,7613
Plant and machine operators, and assemblers	-0,0953	-0,0529	0,0107	-0,0422	-0,1375
Service and sales workers	-0,4502	0,2633	-0,0273	0,2360	-0,2142
Elementary occupations	-0,4824	-0,8113	0,0850	-0,7263	-1,2087
Skilled agricultural, forestry and fishery workers	-0,2771	-1,8849	0,1530	-1,7319	-2,0090

Source: ILOSTAT database

Additionally, we can observe a clear trend of a more significant share of high-skill demanding occupations for the countries and periods analysed in Tables 3 and 4 and a reduced share of mid-skill associated occupations. As for the low-skill demanding jobs, the trend isn't consistent, indicating a decline in their share in the most recent period.

We conducted decomposition exercises to analyse variations in job composition across different periods, countries, and sample types. They help confirm the polarisation between occupations in the labour market, especially in the periods preceding the 2010s. The presented results also showcase the significance of the within and static effects in explaining the noted variations. Their magnitude varies based on the occupational group and the period analysed, and we don't see an overarching predominance of the contribution derived from the within effect. There are situations where the magnitude of the static effect is greater than that of the within, and others where, even if it's lesser, it accounts for a substantial portion of the total observed employment variation across various occupational groups. Therefore, we must acknowledge the importance of variations in the sectoral composition of employment in influencing the changes seen in the labour market's occupational makeup for the analysed periods and countries.

To improve our findings, we then examine the variations in the sectoral composition of employment and try to discern whether we can attribute them to inherent changes within the sectors or shifts in the distribution of occupations amongst sectors. In this exercise, we invert the analytical logic of employment variation decomposition, adopting an innovative shift-share decomposition model that prioritises investigating sectoral behaviour.

Contribution of occupational categories shifts to changes in sectoral employment share:

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

In Equation 2, the result of the within effect corresponds to the weighted average, by the initial share of each occupation in employment, of the observed change in the sector under consideration's share of total employees in each occupation. If the sign is positive, the weighted average of the sector's share across various occupations will have increased. If the magnitude of this indicator is significant, it will be relevant in explaining the variations in sectoral employment, which, in turn, assist in clarifying fluctuations in total employment. The result of the static component measures the change in the share of various occupations in employment, considering the significance of the initial share of the sector under study in each occupation. A positive sign indicates that workers are moving into occupations where the sector's share under analysis is significant. Meanwhile, the dynamic component gauges the combined effect of changes in the sector's share in an occupation and such occupation's share of total employees. A positive result means that employment in the sector under consideration is shifting towards occupations that are increasing their share in employment (or the opposite, that employment in the sector is decreasing its share in occupations that are also reducing their share in employment).

Table 5 presents the decomposition results from 1990 to 2010, based on data compiled from IPUMS between 1990 and 2010. Tables 6, 7, and 8 include the results based on data compilation from ILOSTAT for the periods between 1997 and 2008, 2011 and 2019, and 2011 and 2021, respectively. We performed the calculations for the same group of countries included in the decomposition estimated for variations in occupational groups.

Table 5. Decomposition of share by sectoral employment – 6 countries – 1990-2010

em p.p	within	static	dynamic	between	overall
Farming	-1,1065	-8,2023	0,0071	-8,1952	-9,3017
Mining, quarr, refined petroleum	-0,1401	-0,1008	0,0168	-0,0840	-0,2242
Low and medium-low technology manufacturing	-3,1207	-2,5548	0,3486	-2,2063	-5,3270
Medium-high and high technology manufacturing	-0,2059	-0,2520	-0,1076	-0,3596	-0,5656
Electricity, gas	-0,1350	-0,0028	-0,0258	-0,0286	-0,1636
Water, sewerage	0,2218	0,0107	-0,0328	-0,0221	0,1997
Construction	0,0602	-0,5906	0,0560	-0,5346	-0,4745
Sales	0,8267	2,3598	-0,5212	1,8386	2,6653
Transport, warehousing, mail	-0,6360	0,5720	-0,3116	0,2603	-0,3757
Accomodation and food	0,5106	1,5793	0,0895	1,6688	2,1794
Information and communication	0,7268	0,1341	0,2295	0,3636	1,0904
Financial services	-0,2166	0,2317	0,1868	0,4185	0,2019
Real estate	0,0960	0,0677	0,0030	0,0707	0,1667
Knowledge services	1,2316	0,4502	0,2340	0,6842	1,9158
Admin and support services	2,1667	0,1780	0,1090	0,2870	2,4536
Public administration	-0,4793	0,9941	-0,0190	0,9751	0,4958
Education	0,4964	1,7287	-0,1747	1,5540	2,0504
Health	0,5177	2,3002	-0,1718	2,1284	2,6462
Culture, leisure, sports	0,1746	0,2391	-0,0009	0,2381	0,4127
Personal services and assoc. organizations	-0,6546	0,4520	0,0094	0,4614	-0,1932
Household services	-0,3312	0,4035	0,0769	0,4803	0,1491
Extraterritorial organizations	-0,0038	0,0027	-0,0013	0,0014	-0,0024

Source: IPUMS database

Table 6. Decomposition of share by sectoral employment – 22 countries – 1998-2007

em p.p.	within	static	dynamic	between	overall
Agriculture, hunting and forestry	-0,77285	-2,01179	-0,24200	-2,25379	-2,07576
Fishing	-0,00158	-0,12559	-0,02423	-0,14981	-0,13171
Mining and quarrying	-0,40749	0,26405	-0,27170	-0,00765	-0,29807
Manufacturing	-4,70458	-0,65855	0,12971	-0,52884	-3,45642
Electricity, gas and water supply	-0,33971	-0,00450	0,01667	0,01217	-0,20278
Construction	1,43961	-0,50482	0,00189	-0,50293	1,66321
Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	-1,23502	0,17990	0,45529	0,63519	0,66710
Hotels and restaurants	-0,07502	0,17015	0,04089	0,21103	0,54376
Transport, storage and communications	-1,17862	-0,52319	0,36413	-0,15906	-0,75538
Financial intermediation	-0,08829	0,06234	0,06785	0,13020	0,22368
Real estate, renting and business activities	1,49038	0,64285	-0,14869	0,49415	2,40590
Public administration and defence; compulsory social security	-0,40646	0,24814	0,04679	0,29492	0,38729
Education	-0,84312	0,98611	-0,23049	0,75562	0,42306
Health and social work	-0,12405	0,81349	-0,11791	0,69558	0,99373
Other community, social and personal service activities	-0,74282	0,26848	-0,07131	0,19717	-0,24477
Activities of private households as employers and undifferentiated production activities of private households	-0,51157	0,14752	0,00290	0,15042	-0,29385

Source: ILOSTAT database

Table 7. Decomposition of share by sectoral employment – 36 countries – 2011-2019

em p.p.	within	static	dynamic	between	overall
Agriculture	-0,5573	-1,8372	0,0930	-1,7442	-2,3015
Mining and quarrying	-0,1037	0,0058	-0,0022	0,0036	-0,1001
Manufacturing	-0,2799	-0,0595	0,0546	-0,0049	-0,2848
Electricity	-0,0247	0,0144	-0,0035	0,0109	-0,0138
Water supply	0,0143	-0,0061	-0,0047	-0,0109	0,0034
Construction	0,1382	-0,2913	-0,0399	-0,3312	-0,1930
Wholesale and retail trade	-0,7402	0,2555	-0,0193	0,2362	-0,5040
Transportation and storage	0,2684	-0,0092	-0,0339	-0,0430	0,2253
Accommodation and food service activities	0,6396	0,0684	0,0254	0,0938	0,7334
Information and communication	0,2015	0,1764	0,0455	0,2218	0,4234
Financial and insurance activities	-0,3312	0,0912	-0,0002	0,0910	-0,2402
Real estate activities	0,1378	0,0084	0,0039	0,0123	0,1501
Professional, scientific and technical activities	0,4074	0,3407	0,0230	0,3637	0,7711
Administrative and support service activities	0,5832	-0,0315	-0,0336	-0,0651	0,5181
Public administration and defence	-0,3475	0,2127	-0,0058	0,2069	-0,1406
Education	-0,3387	0,7065	-0,1293	0,5772	0,2385
Human health and social work activities	0,2734	0,3645	0,0335	0,3979	0,6714
Arts, entertainment and recreation	0,1479	0,0597	0,0063	0,0660	0,2138
Other service activities	-0,0150	0,0326	0,0148	0,0475	0,0325
Activities of households as employers	-0,0994	-0,1162	-0,0188	-0,1350	-0,2344

Source: ILOSTAT database

Table 8. Decomposition of share by sectoral employment – 36 countries – 2011-2021

em p.p.	within	static	dynamic	between	overall
Agriculture	-0,6290	-2,4152	0,1344	-2,2807	-2,9097
Mining and quarrying	-0,1398	0,0015	0,0010	0,0025	-0,1373
Manufacturing	-0,4151	-0,0253	0,0896	0,0643	-0,3508
Electricity	-0,0513	0,0261	0,0096	0,0356	-0,0157
Water supply	0,0595	-0,0091	-0,0008	-0,0099	0,0496
Construction	0,3317	-0,3121	-0,0564	-0,3685	-0,0368
Wholesale and retail trade	-0,4034	-0,0066	0,0432	0,0366	-0,3668
Transportation and storage	0,1963	-0,0508	-0,0383	-0,0891	0,1072
Accommodation and food service activities	0,0956	-0,0630	-0,0090	-0,0720	0,0236
Information and communication	0,3946	0,2981	0,1031	0,4013	0,7958
Financial and insurance activities	-0,3655	0,1886	0,0001	0,1887	-0,1768
Real estate activities	0,1387	0,0178	0,0063	0,0241	0,1628
Professional, scientific and technical activities	0,4075	0,5550	0,0452	0,6002	1,0077
Administrative and support service activities	0,4748	-0,0602	-0,0479	-0,1081	0,3667
Public administration and defence	-0,0306	0,3289	-0,0304	0,2985	0,2679
Education	-0,4174	1,0898	-0,2408	0,8490	0,4317
Human health and social work activities	0,4915	0,4764	-0,0094	0,4670	0,9585
Arts, entertainment and recreation	-0,0200	0,0974	-0,0110	0,0864	0,0664
Other service activities	0,0625	0,0160	-0,0037	0,0123	0,0749
Activities of households as employers	-0,2184	-0,1751	0,0213	-0,1538	-0,3723

Source: ILOSTAT database

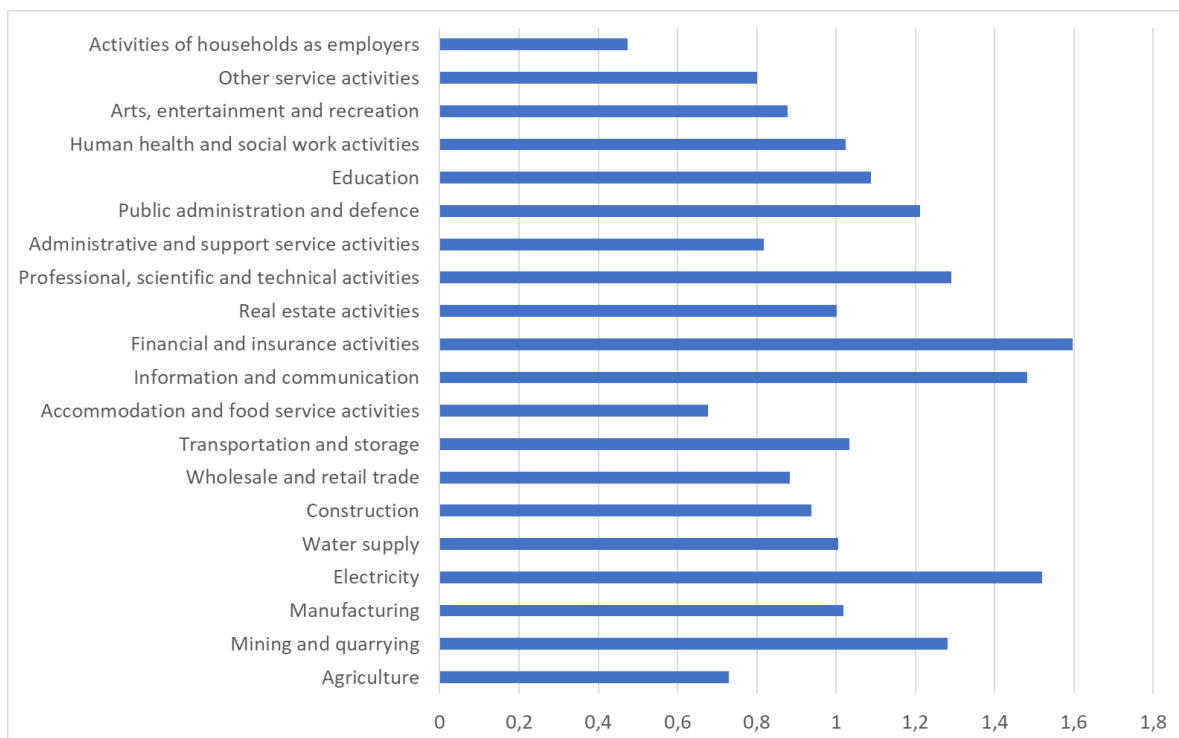
The magnitude of the within effect is greater than that of the static effect in various sectors across the periods considered. For the period between the 1990s and 2010s, the magnitude exceeds that of the static effect in 50% of the sectors analysed. In contrast, for the remaining periods, it is more significant in roughly 70% of the cases. That highlights that the intrasectoral job shift, on its own, is important in explaining variations in the sectoral composition of employment and, consequently, reinforces the argument advocating its importance in explaining overall employment fluctuations.

The results also consistently show a decrease in the share of manufacturing and agriculture in total employment. When we break down manufacturing between 1990 and 2010 for the six countries included in the IPUMS sample, it's evident that the decline is more pronounced in low and medium-technology manufacturing. The decline in the share of total employment is also consistently observed for the extractive sector, electricity, and gas. Service sectors, both knowledge-intensive and support activities, show growth in the analyses where they can be distinguished, as do education, health, accommodation, and food services. In the most recent period of analysis (2011-2019 or 2011-2021), all sectors offering personal services saw an increase in their share of employment.

Whether through the criteria of decomposing variations in the share of occupational categories or sectors in total employment, the results reveal that the observed shifts in sectoral employment are pivotal in explaining the changes seen in overall employment composition. Consequently, they will also play a role in explaining wage behaviour in the labour market. Different sectors offer different relative wages, and if the change in sectoral employment composition significantly impacts overall employment variations, it will also influence the

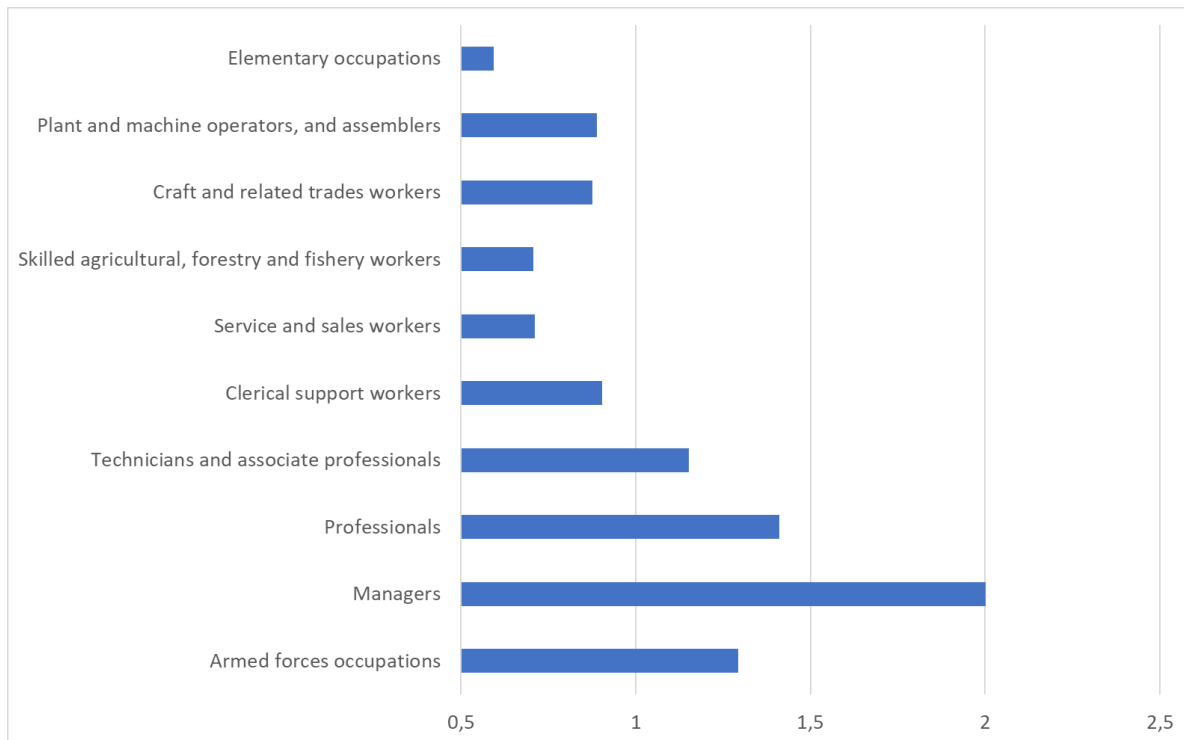
average wage in an economy (see Chart 1). We can observe that the relative wage in manufacturing is close to one, and this result highlights the role of manufacturing in contributing to a more equalised wage structure. Since the reduction of manufacturing share in employment was accompanied by the increase in the share of traditional services that practice lower relative wages in the 2011-2019/21 periods and of other knowledge-intensive service sectors that practice higher relative wages, the changes in the sectoral employment composition seem to play a role not only in the employment but also in the wage polarisation. Therefore, the determinants of the sectors' relative wages are crucial to investigate.'

Chart 1 - Relative wage of employees by sector – Average for 39 countries in the 2011-2021 period



The differentiation between sectoral relative wages is, in part, due to their distinct occupational structures, since occupations are paid differently, as we can observe in Chart 2, due to the diverse tasks and skills they perform and require, respectively.'

Chart 2 – Relative wage of employees by occupation – Average for 39 countries in 2011-2021 period



Source: ILOSTAT database

We present the results of several correlation tests conducted for 39 countries to foster our arguments. We have detailed information from the ILOSTAT database concerning occupations and sectors between 2011 and 2021. We employed the Spearman method, which allows us to estimate the correlation between the rankings of two variables.³ This method seemed more suitable for our purposes than comparing absolute values. The first correlation test focused on the sectoral composition of occupations. We tested the correlation across various sectors in their occupational makeup, meaning we examined if the participation of each occupational group in a sector's employment correlates with such participation in other sectors. We conducted this test for all 39 countries in our sample. The overall average correlation result was 0.2602.⁴ We then estimated the correlation between occupational compositions observed in a specific sector across different countries, testing whether a sector displays a similar occupational makeup across various countries. The average correlation for this was considerably higher, at 0.7229. Hence, sectors appear to have distinct occupational compositions, but a particular sector's occupational composition pattern tends to be consistent across many countries. That strengthens our previous assertion – sectors have specific traits regarding each occupational group's participation in that sector's total employment.

We then perform subsequent tests to estimate the correlation between the relative wages of occupations and sectors. Firstly, we tested if the relative wages of various occupations are similar across different countries. The overall average correlation result reached 0.8893. We then examined if the relative wages across different sectors correlate within the group of countries studied, and the average result was 0.7264. Hence, occupations seem to be valued

³ The standard correlation test, based on absolute values, yielded quite similar results.

⁴ The detailed results of the correlation tests conducted can be found in the Appendix, Tables A4 to A7.

similarly, in relative terms, across the various countries and the period analysed. We also observed that each sector offers close relative wages for the same analysed sample. Combining the correlation results, the factor differentiating the relative wages across various sectors is the unique occupational composition (percentage participation of each occupational group) in each sector. Since the specificity of goods and services produced in each sector requires distinct activities and skills, the sectoral composition of occupations will vary across sectors, influencing the average wage offered in each. Thus, the characteristics of occupations certainly impact the wages offered, but sectors have a different composition of occupations.

To discuss the effects that occupational composition and its variations can have on relative sectoral wages, we have structured a novel index corresponding to a sectoral average of unemployment rates by occupation, weighted by the participation of each occupational group in the sector under scrutiny. The estimation of this index allows us to consider, first and foremost, the supply and demand for various occupations – represented by the unemployment rate estimated for each occupation – and, consequently, its effect on the relative wages of these occupations by taking into account the participation of a particular occupation (or occupational group) in the sector as a weighting factor, we capture the influence of this differentiated supply and demand by occupation, resulting in specific unemployment rates for occupations, on the relative wage paid in the sector. We are assuming that a high relative participation in a sector of occupations with a high unemployment rate may reduce the relative wage observed in that sector and vice versa. Adopting this approach also indirectly allows us to consider factors associated with the supply and demand for labour in wage determination, which is embodied in the estimate of this indicator related to the sectoral average of unemployment rates by occupation.⁵

Supplementing our arguments about the determinants of relative sectoral wages, and in line with our previous discussion, we also understand that variations in demand for goods and services produced in a sector, resulting in a shift in the sectoral composition of production (and if maintained in the long term, involves what's known as a structural change process), will also influence the relative wage of a sector by increasing demand for workers in it. A relevant variable to represent this shift in the sectoral composition of production, affecting both demand and supply, within the frameworks of Keynesian and structuralist theories, is the investment rate in various sectors.

Thus, our model will seek to capture the influence that the sectoral composition of occupations, through its sectoral supply and demand, represented by the sectoral averages of unemployment rates by occupation, and the sectoral composition of production, characterised by sectoral investment rates, have on the relative wage in a given sector. In the next section, we will present the data description and then conduct tests that will allow us to analyse the relevance of those variables in determining these wages.

⁵We could simply adopt the unemployment rate estimated by sector, which is calculated on the ILOSTAT database, but we prefer to use the unemployment rate by occupation because we are implicitly assuming that an unemployed worker looks for a new role more closely aligned with their previous skills and tasks rather than the sector they previously worked in. The estimated unemployment data by occupation also comes from the ILOSTAT database.

3. Data Description

Our primary data source has been secondary information garnered from various international institutions. The foundation of the dataset we use in our model lies in three predominant sources:

- a. **International Labour Organisation (ILO):** The initial segment of our data is extracted from the International Labour Organisation, which includes data on wages/employment by occupation/sector for a large set of countries.
- b. **Organisation for Economic Co-operation and Development (OECD):** We focus on the OECD's Inter-Country Input-Output (ICIO) tables. These tables offer an intricate matrix showcasing inter-industrial economic transactions. Of particular note within the ICIO are the Trade in Value Added (TiVA) and Multi-Regional Input-Output (MRIO) tables. These tools provide a detailed understanding of the global dynamics in production and the intricate interdependencies within the supply chain.
- c. **World Development Indicators (WDI):** These include variables related to macroeconomic and institutional issues.

Time Span & Specifics: The period under our analytical lens spans a decade, covering the years from 2011 to 2021. Central to our research and structured on the ISIC4 sectoral classification, our dataset encompasses 20 distinct sectors. Furthermore, our data covers nine varied occupations which follow the ISCO-08 occupational classification. We provide a detailed breakdown of these sectors and occupations in the appendix.

Sampling Methodology & Geographical Spread: The data availability dictated our sampling approach. Our dataset thus represents a total of 39 countries. That includes five nations from the Americas, three from the Asian continent, and 27 countries from Europe.

Custom Variables

In this paper, we build two novel variables.

- I. **Weighted Occupational Unemployment by Sector (WOUS):** First, we employ the unemployment rate by occupation obtained from ILOSTAT. This unemployment rate by occupation is estimated considering the former occupation of the interviewed person. Following that, we compute the sector-specific weighted average for occupational unemployment. The weights correspond to the share of each occupation in the employment of a specific sector.
- II. **Relative Salary by Sector:** We use the Average Monthly Earnings of Employees from ILOSTAT, estimated by sector.⁶ Then, we calculate the aggregate average earnings. Finally, we divide the sectoral average by the average for all sectors.

⁶ We estimate average salary for the economy disregarding non-classified sectors and “activities of extraterritorial organizations and bodies”

Table 9. Table of Variables

Variable	Description	Unit	Source
lnrelSal	Log of relative salary (sectoral)	Index (computed as Current LCU)	ILO
lnsecUnemp	Log of WOUS (sectoral)	Index	ILO
lninvShare	Log of sectoral investment Rate (to ValueAdded)	%. Current USD/Current USD	ICIO, OECD
IntradePercGDP	Log of trade as a percentage of GDP (trade openness) (aggregate)	%. Current USD/Current USD	WDI
lnRDofGDP	Log of R&D expenditure as a percentage of GDP (aggregate)	Unit: %. Current USD/Current USD	WDI
lnfemaleRatio	Log of female share on total employment (sectoral)	Index	ILO
lnInformalEmpRate	Log of informal employment rate (sectoral)	Index	ILO
lnexpOrientOutput	Log of export-oriented output (sectoral)	%. Current USD/Current USD	ICIO, OECD
lnfvax_x	Log of foreign value added embodied in exports as a share of total exports (sectoral).	%. Current USD/Current USD	ICIO, OECD
lnnatIncomeConst2015	Log of national income (aggregate)	Constant USD (2015 prices)	WDI
lngovExpendEduOfGDP	Log of government expenditure on education as a percentage of GDP (aggregate)	Unit: %. Current USD/Current USD	WDI
lnageDependency	Log of age dependency ratio (% of Working-age Population) (aggregate)	index	ILO
lnruleLaw	Log related to the rule of law metric (aggregate)	Index	WDI
lnregQuality	Log related to a measure of regulatory quality (Estimate) (aggregate)	Index	WDI
lngovEffect	Log related to a government effectiveness metric (aggregate).	Indicator. In units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5."	WDI
lnpatentAppRes	Log of patent applications by residents (aggregate)	Patents	WDI

Table 10. Summary Statistics

	Obs	NAs	Mean	Std.Dev	Min	Q1	Median	Q3	Max
lnrelSal	8580	1302	0.006	0.307	-1.241	-0.172	-0.008	0.199	1.538
lnsecUnemp	8580	525	-3.102	0.828	-11.625	-3.494	-3.045	-2.565	-1.057
lninvShare	8580	2770	-5.009	2.453	-19.517	-6.518	-5.084	-3.159	-0.217
IntradePercGDP	8580	80	4.604	0.48	3.152	4.308	4.605	4.981	5.961
lnRDofGDP	8580	1220	0.092	1.025	-3.767	-0.272	0.251	0.828	1.572
lnfemaleRatio	8580	409	-0.992	0.654	-4.846	-1.348	-0.81	-0.548	0
lnInformalEmpRate	8580	1780	12.481	1.623	9.49	11.006	12.378	13.508	16.84
lnexpOrientOutput	8580	2428	-3.442	2.475	-36.651	-4.953	-2.864	-1.583	-0.097
lnfvax_x	8580	2773	-1.849	0.619	-3.996	-2.211	-1.813	-1.452	-0.313
lnnatIncomeConst2015	8580	1360	25.821	1.708	23.064	24.408	25.788	26.897	30.468
lngovExpendEduOfGDP	8580	1100	1.556	0.239	1.036	1.401	1.56	1.698	2.139

InageDependency	8580	0	3.932	0.122	3.597	3.868	3.95	4.011	4.31
InruleLaw	8580	1540	-0.086	0.85	-4.17	-0.419	0.124	0.545	0.754
InregQuality	8580	880	-0.076	0.689	-3.858	-0.419	0.09	0.452	0.716
IngovEffect	8580	1080	-0.171	0.915	-5.889	-0.546	0.082	0.431	0.804
InpatentAppRes	8580	1300	6.5	2.619	0	4.762	6.691	7.736	12.596

4. Econometric Estimations and Analysis of Results

This empirical analysis aims to investigate the influence of changes in the composition of productive structure and sectoral occupation on sectoral wages observed. We base it on two hypotheses: different sectors have distinct task and occupational compositions, therefore asking for different skill profiles, and the sectoral composition of production influences the demand and supply of particular types of skills and occupations. These assumptions seek to integrate the approaches based on the occupational structure and the composition of productive structure to explain the difference in relative wages among sectors.

The empirical analysis does not intend to disregard the role played by advances in skill acquisition or other factors associated with the economy's labour supply in job polarisation. However, in addition to the variables traditionally related to supply, we will investigate whether factors associated with demand and which influence the sectoral composition of production and occupations are also important in determining the average wages practised by sector, which contribute to the changes observed in the labour market in recent decades.

The estimated theoretical model is as follows:

$$relSal_{s,i,t} = \delta_i + relSal_{s,i,t-1} + secUnemp_{s,i,t} + prodStruct_{i,t} + \eta_{sit} + \varepsilon_{s,i,t} \quad (3)$$

Where *relSal* is the sectoral relative average wage in each sector; *secUnemp* is the Weighted Occupational Unemployment by Sector (WIOS); *prodStruct* is the variable representing the productive structure of each country, the term η represents the specific fixed effects not observed for each country, which incorporates factors that influence the salary of each sector and are potentially correlated with the explanatory variables, ε is the error term and the subscripts *s*, *i* and *t* refer to the sector, countries and the period, respectively. Temporal dummies are also included in this work — for simplicity, not presented in the equations — to control for international conditions that vary over time and affect the performance of sectors in the different countries in the sample.

It's worth noting that relative wages indicate the repercussions of shifts occurring within the sectoral composition of occupations. Additionally, the WIOS represents an average of unemployment rates within occupation groups, with weighting based on the participation of the various occupation groups in the employment composition within each sector, and the structural change variables seek to represent the impacts of the composition of sectoral production on occupational composition and relative wages. Following the discussion in the previous sections, we decided to adopt the sectoral investment rate (as a share of value added)

as a representative variable of the structure of production composition since the inversion increases may contribute to amplifying a sector share in the aggregated value added.

The research adopts as an econometric methodology a dynamic panel data model using the Generalized Method of Moments (GMM), developed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998). The motivation for using panel data methodology, which combines cross-section data and time series, lies in the relative advantages brought by this approach. First, panel data allow exploring the temporal relationship and adjustment dynamics between the explanatory variables and the dependent variable, in addition to other effects not detectable in purely cross-section or time series data. Second, they allow controlling for unobservable specific individual effects that affect the dependent variable and that are potentially correlated with the explanatory variables, which could generate biased estimates. Furthermore, by including more information, panel data guarantee a greater number of degrees of freedom, greater variability and less collinearity between variables, thus improving the quality of parameter estimation. Finally, dynamic panel models allow series to be related to each other by controlling the potential endogeneity of all variables in the model, in addition to taking into account the persistence of the dependent variable over time (Baltagi, 2008).

Tables 11 and 12 summarise the results of the estimated models. The tests reported in Table 11 include, besides our main explanatory variables, control variables essentially associated with demand or Keynesian factors that can exert influence on relative wages, primarily those related to trade - openness, export orientation, and foreign value added embodied in exports - and per capita income. They include the research and development expenditure share in GDP as a measure of innovation and automation. The only available supply-side variable for sectoral values in the test countries is the female employment share. This variable helps estimate the gender wage differential. Estimating the sectoral informal employment share was also viable as an additional control to labour market features⁷. Conversely, the tests reported in Table 12 include a set of control variables associated with aggregate supply-side characteristics, like government expenditures on education as a share of GDP, the age dependency rate and the number of patent applications by residents, along with institutional indicators design by the World Bank such as the rule of law, regulatory quality and government effectiveness, to contemplate not only controls related to demand effects on relative wages but also to evaluate the significance of the explanatory variables of our model even on tests which take in account traditional variables adopted in models of wage setting. We used a sectoral classification similar to that adopted in the shift-share decomposition for the periods 2011-2019/21.

Table 11 – Determinants of sectoral relative wages – Model 1

⁷ Unfortunately, most of the variables associated with supply side effects which are available in the ILOSTAT and includes sectoral and occupational data are restricted to a smaller (only 20) set of countries, so we have chosen to disregard them in the tests. The same applies to sectoral expenditure on R&D or ICT capital services.

VARIABLES	-1	-2	-3	-4	-5	-6	-7	-8
	InrelSal	InrelSal	InrelSal	InrelSal	InrelSal	InrelSal	InrelSal	InrelSal
LInrelSal	0.116	0.177	0.115	0.179	0.174	0.147	0.127	0.18
	-0.17	-0.139	-0.142	-0.129	-0.13	-0.125	-0.086	-0.113
L2.InrelSal	0.190**	0.191**	0.226***	0.219***	0.229***	0.215***	0.175***	0.245***
	-0.09	-0.076	-0.074	-0.079	-0.069	-0.076	-0.065	-0.073
InsecUnemp	-0.102*	-0.092	-0.089**	-0.069*	-0.071*	-0.079**	-0.038**	-0.054*
	-0.057	-0.059	-0.04	-0.035	-0.041	-0.038	-0.018	-0.029
LIninvShare	0.010**	0.010**	0.010**	0.008*	0.007*	0.006*	0.010**	0.009**
	-0.004	-0.004	-0.004	-0.004	-0.004	-0.003	-0.005	-0.004
LIntradePercGDP		-0.02	-0.033	-0.021	-0.059			-0.047*
		-0.03	-0.026	-0.022	-0.039			-0.025
L2.InRDofGDP			-0.024	-0.015	-0.006	-0.009	-0.020**	-0.002
			-0.024	-0.02	-0.023	-0.02	-0.01	-0.015
LInfemaleRatio				-0.030**	-0.031**	-0.039***	-0.046***	-0.027**
				-0.013	-0.014	-0.015	-0.013	-0.011
L2.InInformalEmpRate					-0.016			
					-0.012			
LInexpOrientOutput						0.009**		
						-0.005		
LInfvax_x							-0.015*	
							-0.008	
LInnatIncomeConst2015								-0.014*
								-0.008
Constant	0.000	-0.120	0.000	0.000	0.245	0.000	0.000	0.000
	0.000	-0.165	0.000	0.000	-0.245	0.000	0.000	0.000
Observations	4,154	4,154	4,031	4,006	4,006	3,947	3,824	3,820
Number of panelid	549	549	549	543	543	537	507	516
AR(1)	0.0005	1.70E-05	0.000454	9.27E-06	4.11E-05	2.35E-05	1.80E-06	8.58E-06
AR(2)	0.966	0.621	0.244	0.539	0.38	0.358	0.444	0.506
Hansen	0.117	0.319	0.138	0.626	0.403	0.309	0.769	0.589
Number of Instruments	34	35	36	37	38	37	37	38

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 12. Determinants of sectoral relative wages – Model 2

VARIABLES	-1 lnrelSal	-2 lnrelSal	-3 lnrelSal	-4 lnrelSal	-5 lnrelSal	-6 lnrelSal
L.lnrelSal	0.112 -0.18	0.085 -0.167	0.104 -0.188	0.114 -0.183	0.097 -0.194	-0.011 -0.161
L2.lnrelSal	0.195** -0.084	0.181** -0.079	0.189** -0.089	0.196** -0.085	0.191** -0.09	0.183** -0.086
InsecUnemp	-0.101* -0.061	-0.087* -0.053	-0.100* -0.059	-0.100* -0.059	-0.097* -0.059	-0.098* -0.052
L.lninvShare	0.009* -0.005	0.009* -0.005	0.010* -0.005	0.009* -0.005	0.009* -0.006	0.013** -0.005
L.lnGovExpendEduOfGDP	0.015 -0.052	-0.006 -0.056	0.037 -0.053	0.018 -0.054	0.031 -0.055	0.027 -0.058
lnageDependency		0.142 -0.096				
lnruleLaw			-0.033 -0.053			
L.lnregQuality				-0.012 -0.074		
lnGovEffect					-0.031 -0.059	
L.lnpatentAppRes						-0.004 -0.005
Constant	0.000 0.000	-0.739* -0.423	0.000 0.000	0.000 0.000	-0.298* -0.180	-0.282 -0.193
Observations	4,106	4,106	4,106	4,106	4,106	3,914
Number of panelid	549	549	549	549	549	549
AR(1)	0.00107	0.00117	0.00183	0.00116	0.00295	0.0086
AR(2)	0.946	0.928	0.946	0.936	0.869	0.288
Hansen	0.138	0.148	0.14	0.119	0.127	0.115
Number of Instruments	35	36	36	36	36	36

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The results in Tables 11 and 12 corroborate the main theses of the research. The first is a correlation between the WIOS rate and the observed relative wages in different sectors. Furthermore, we observe the relevance of the variable representing the productive structure (invShare), which is the sectoral share of investment in value-added, to explain relative sectoral wages, reinforcing our argument about the relevance of the composition of the productive structure to explain the pattern of those wages.

Other sectoral and country-level variables were added as controls in the models to reinforce the role of our explanatory variables in the model. We incorporate sectoral (to the extent that they are available by sector and/or occupation for most countries and years included in the sample) and aggregated variables related to demand and supply side effects.¹ The inclusion of these variables aimed to consider several variables that are relevant to explain relative wages and avoid the problem of bias caused by relevant omitted variables. After considering those controls, results show that the model's main variables remain significant (with only one exception for the variable related to investment in the specified models).

Additionally, the signs of coefficients of explanatory variables are as expected. The Weighted Occupational Unemployment by Sector (WIOS) coefficient is negative; therefore, a larger

sectoral share of occupations that exhibit higher unemployment implies a reduction of its relative wage. This result confirms the relevance of sectoral occupational structure, aggregate supply, and sectoral demand for labour to set the sectoral relative wage. The coefficient of the sectoral investment share in value-added, defined as the representative variable of the pattern of the sectoral composition of production (and the structural change in the long term), is positive, which confirms that the relative sectoral growth is accompanied by greater demand for correlative occupations and a subsequent increase in the sectoral relative wages.

The signs and relevance of the interest variables in the performed tests reinforce our previous argument about the importance of interaction between occupational structure and the composition of sectoral production to set those wages: Organisations in a particular sector demand workers for specific occupations based on sectoral task compositions. These compositions influence the relative wages, considering the supply of workers with the necessary skills to perform those tasks. The larger the sector growth, and therefore its share of value-added, the greater the demand for workers that perform the tasks linked to specific occupations, pressuring to increase the relative wages of sectors for whom those jobs are included in their task composition. It means that both occupational and sectoral composition of production, which we call structural change in the long term (and therefore sectoral employment), are relevant in setting relative sectoral wages.

Regarding the control variables in Model 1, we found a negative sign for the female share in sectoral employment, confirming the undesirable and well-known gender effect on wage differentials. We also found a positive effect for sectoral export orientation on relative wages but a negative effect on sectoral trade openness and the foreign value added embodied in exports. This result suggests a negative impact on imports when they do not significantly impact the value added of exports, negatively affecting employment and relative wages. Still, it is just a hypothesis for future studies since this issue is not the focus of this article. Conversely, control variables related to the supply side and institutional effects included in Model 2 exhibit no significance. That may mean broad institutional and supply-side variables would not impact sectoral relative wages. Still, again, it is just a prediction for future research.

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). In those tests, we should not reject the null hypothesis. The first test is the Hansen test for overidentification restrictions, and the null hypothesis is that the model is correctly specified and the instruments together are valid. The second is the Arellano-Bond AR (2) test, whose null hypothesis is the absence of second-order serial correlation of the error term since it assumes a first-order correlation in AR (1) but not in higher order. Tests for all models presented reveal that they are consistent.

5. Conclusion

Following theoretical foundations, job polarisation is the concurrent increase in highly-skilled, well-remunerated positions, low-skilled, poorly-paid roles, and a simultaneous decrease in mid-level employment. This trend is progressively discernible in the labour markets of developed economies and propelled by factors such as shifts in workforce composition,

heightened levels of education, and technological advancements that automate routine tasks. Eminent scholars such as Acemoglu and Autor (2011) and Goos et al. (2014) have drawn attention to this phenomenon.

Our empirical study confirms this job polarisation process for many countries and periods. We showed that, aside from elements such as skill acquisition and technology improvements, the sectoral composition of employment also plays a relevant role in the observed occupational employment changes. Consequently, we developed a novel model to estimate the shift-share decomposition of changes in sectoral employment, which confirms our previous findings about the relevance of this variable. In light of these findings, we briefly demonstrated that sectoral relative wages are relevant to determining wage polarisation, and the distinction between wages practiced in different sectors, as well as in distinct occupations, even though both structures are similar among the large sample of countries.

Distinct sectoral task compositions would explain the difference among relative sectoral wages, and the diversity in sectoral occupational compositions, whilst the specific sectoral composition of production (which means structural change in the long term) accounts for the task composition and, consequently, the demand for specific skills and occupations. We structured a novel indicator to deal with labour force supply and demand and the influence of occupational composition on the sectoral relative wages, which we denominated Weighted Occupational Unemployment by Sector (WOUS) and corresponds to a sectoral average of unemployment rates by occupation, weighted by the participation of each occupational group in the sector under scrutiny. We also embraced the share of sectoral investment in value-added as a variable that induces changes in the sectoral composition of production and, therefore, in sectoral relative wages.

Subsequently, we performed econometric tests focusing on how changes in occupational composition and productive structure can elucidate variations in relative wages across sectors. While our primary examination centred on the impact of shifts in the productive structure and occupational categories on sectoral wages, we also acknowledged the role of improved skill acquisition and other factors on labour supply within the broader context of understanding the process of relative wage setting. The research posits that both alterations in productive and occupational compositions converge to determine sectoral average wages, thereby shaping the labour market landscape observed over the past few decades and offering a novel approach to deal with employment changes by reconciling demand and supply-related factors and two distinct approaches usually treated as concurrent and not complementary in the analysis of labour market-related issues.

Complementarily, the relevance of the productive structure confirmed by this empirical analysis highlights the concern with the deindustrialisation process observed in developed and developing countries. That is because deindustrialisation may have generated, on the one hand, a relatively more significant loss of occupations that require mid skills, implying a greater supply of workers with such skills for other sectors. At the same time, the process of structural change may have differentiated the sectoral demand for labour, helping to distinguish the levels and variations in sectoral relative wages.

Acknowledgements: We would like to acknowledge the financial support of CNPq - National Council for Scientific and Technological Development, via Productivity Grant, and CAPES - Brazilian Federal Foundation for Support and Evaluation of Graduate Education, via PRINT Program and Finance Code 001. We also acknowledge the statistical agencies that originally produced the data included in IPUMS and ILOSTAT.

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Appendix

Table A1: Countries in our complete dataset

Code	Country	Code	Country	Code	Country
AUT	Austria	CHE	Switzerland	IRL	Ireland
BEL	Belgium	CYP	Cyprus	ISL	Iceland
BGR	Bulgaria	CZE	Czech Republic	ITA	Italy
BIH	Bosnia and Herzegovina	DEU	Germany	KOR	South Korea
DNK	Denmark	ESP	Spain	LTU	Lithuania
EST	Estonia	FIN	Finland	LUX	Luxembourg
FRA	France	GBR	United Kingdom	LVA	Latvia
GRC	Greece	GTM	Guatemala	NLD	Netherlands
HRV	Croatia	HUN	Hungary	PAN	Panama
SLV	El Salvador	SVK	Slovakia	POL	Poland
SVN	Slovenia	SWE	Sweden	PRT	Portugal
THA	Thailand	TUR	Turkey	ROU	Romania
URY	Uruguay	VNM	Vietnam	USA	United States of America

Table A2: Countries in estimations of shift-share decomposition for the period 1998-2007

Code	Country	Code	Country
AUT	Austria	LTU	Lithuania
BEL	Belgium	LUX	Luxembourg
DNK	Denmark	LVA	Latvia
EST	Estonia	NLD	Netherlands
FRA	France	PRT	Portugal
FIN	Finland	ROU	Romania
DEU	Germany	SVN	Slovenia
HUN	Hungary	ESP	Spain
IRL	Ireland	SWE	Sweden
ISL	Iceland	GBR	United Kingdom
ITA	Italy	URY	Uruguay

Table A3: Countries in estimations of shift-share decomposition for the periods 2011-2019 and 2011-2021

Code	Country	Code	Country	Code	Country
AUT	Austria	CHE	Switzerland	IRL	Ireland
BEL	Belgium	CYP	Cyprus	ISL	Iceland
BGR	Bulgaria	DEU	Germany	ITA	Italy
BIH	Bosnia and Herzegovina	ESP	Spain	KOR	South Korea
DNK	Denmark	FIN	Finland	LUX	Luxembourg
EST	Estonia	GBR	United Kingdom	LVA	Latvia
FRA	France	GTM	Guatemala	NLD	Netherlands
GRC	Greece	HUN	Hungary	PAN	Panama
HRV	Croatia	SVK	Slovakia	POL	Poland
SLV	El Salvador	SWE	Sweden	PRT	Portugal
SVN	Slovenia	TUR	Turkey	ROU	Romania
URY	Uruguay	VNM	Vietnam	USA	United States of America

Table A4 - Spearman correlation among occupational compositions in different sectors, for 39 countries

	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_A	1,0000																			
ISIC4_B	0,2189	1,0000																		
ISIC4_C	-0,0105	0,5915	1,0000																	
ISIC4_D	-0,0053	0,3466	0,5574	1,0000																
ISIC4_E	0,3617	0,5167	0,5784	0,2715	1,0000															
ISIC4_F	0,1334	0,4630	0,8197	0,5205	0,5732	1,0000														
ISIC4_G	-0,1476	-0,0706	0,3475	0,2536	0,0712	0,3056	1,0000													
ISIC4_H	0,1374	0,4152	0,5110	0,1186	0,5216	0,3041	0,2560	1,0000												
ISIC4_I	0,0408	-0,2537	-0,0921	-0,1920	0,0865	-0,0177	0,6339	0,1873	1,0000											
ISIC4_J	-0,1676	-0,0561	0,1127	0,5827	-0,1023	0,0863	0,2175	-0,0096	-0,0304	1,0000										
ISIC4_K	-0,1131	-0,0313	0,0481	0,5032	-0,0034	0,0314	0,1908	0,1940	0,0035	0,8284	1,0000									
ISIC4_L	0,0151	0,0583	0,1380	0,4041	0,2015	0,1712	0,4528	0,2716	0,3482	0,4714	0,5561	1,0000								
ISIC4_M	-0,2225	-0,0487	0,1898	0,5597	-0,0156	0,1716	0,2716	0,1050	0,0355	0,8938	0,8495	0,5119	1,0000							
ISIC4_N	0,1237	-0,1374	0,0464	-0,0479	0,2212	0,0385	0,5718	0,2803	0,7282	0,0721	0,1530	0,3790	0,1598	1,0000						
ISIC4_O	-0,2410	-0,1535	0,0585	0,3592	-0,0222	-0,0213	0,5027	0,1826	0,3866	0,6912	0,7107	0,5775	0,6942	0,4750	1,0000					
ISIC4_P	-0,0932	-0,2048	-0,0093	0,1843	0,0061	-0,0163	0,4023	0,0549	0,4435	0,5561	0,4874	0,4301	0,6108	0,5193	0,7231	1,0000				
ISIC4_Q	-0,1159	-0,1301	0,0065	0,2892	0,0175	-0,0595	0,4428	0,1408	0,3874	0,6058	0,5568	0,5330	0,6289	0,4896	0,8004	0,8298	1,0000			
ISIC4_R	-0,1245	-0,1307	0,0684	0,3761	-0,0032	0,0142	0,4673	0,1535	0,3531	0,7164	0,6869	0,6137	0,7249	0,4568	0,7914	0,7350	0,7947	1,0000		
ISIC4_S	-0,0937	-0,0284	0,2019	0,2881	0,0398	0,1410	0,6998	0,0788	0,5069	0,3385	0,2032	0,4097	0,3387	0,5020	0,5933	0,5885	0,6162	0,5991	1,0000	
ISIC4_T	0,2421	-0,1173	-0,1371	-0,2701	0,1663	-0,0212	0,3886	0,0780	0,5845	-0,2230	-0,1542	0,1409	-0,1654	0,6220	0,1750	0,2736	0,2286	0,1773	0,3896	1,0000

ECO_ISIC4_A	Economic activity (ISIC-Rev.4): A. Agriculture
ECO_ISIC4_B	Economic activity (ISIC-Rev.4): B. Mining and quarrying
ECO_ISIC4_C	Economic activity (ISIC-Rev.4): C. Manufacturing
ECO_ISIC4_D	Economic activity (ISIC-Rev.4): D. Electricity
ECO_ISIC4_E	Economic activity (ISIC-Rev.4): E. Water supply
ECO_ISIC4_F	Economic activity (ISIC-Rev.4): F. Construction
ECO_ISIC4_G	Economic activity (ISIC-Rev.4): G. Wholesale and retail trade
ECO_ISIC4_H	Economic activity (ISIC-Rev.4): H. Transportation and storage
ECO_ISIC4_I	Economic activity (ISIC-Rev.4): I. Accommodation and food service activities
ECO_ISIC4_J	Economic activity (ISIC-Rev.4): J. Information and communication
ECO_ISIC4_K	Economic activity (ISIC-Rev.4): K. Financial and insurance activities
ECO_ISIC4_L	Economic activity (ISIC-Rev.4): L. Real estate activities
ECO_ISIC4_M	Economic activity (ISIC-Rev.4): M. Professional, scientific and technical activities
ECO_ISIC4_N	Economic activity (ISIC-Rev.4): N. Administrative and support service activities
ECO_ISIC4_O	Economic activity (ISIC-Rev.4): O. Public administration and defence
ECO_ISIC4_P	Economic activity (ISIC-Rev.4): P. Education
ECO_ISIC4_Q	Economic activity (ISIC-Rev.4): Q. Human health and social work activities
ECO_ISIC4_R	Economic activity (ISIC-Rev.4): R. Arts, entertainment and recreation
ECO_ISIC4_S	Economic activity (ISIC-Rev.4): S. Other service activities
ECO_ISIC4_T	Economic activity (ISIC-Rev.4): T. Activities of households as employers

Table A5 - Spearman correlation among sectoral occupational compositions by sector, for 39 countries

	AUT	BEL	BGR	BIH	CHE	CYP	CZE	DEU	DNK	ESP	EST	FIN	FRA	GBR	GRC	GTM	HRV	HUN	IRL	ISL	ITA	KOR	LTU	LUX	LVA	NLD	PAN	POL	PRT	ROU	SLV	SVK	SVN	SWE	THA	TUR	URY	USA	VNM					
AUT	1,00																																											
BEL	0,88	1,00																																										
BGR	0,74	0,74	1,00																																									
BIH	0,77	0,74	0,77	1,00																																								
CHE	0,87	0,88	0,72	0,70	1,00																																							
CYP	0,80	0,82	0,75	0,74	0,75	1,00																																						
CZE	0,82	0,79	0,79	0,73	0,81	0,70	1,00																																					
DEU	0,91	0,88	0,73	0,75	0,89	0,80	0,83	1,00																																				
DNK	0,83	0,80	0,71	0,69	0,81	0,77	0,74	0,83	1,00																																			
ESP	0,89	0,90	0,80	0,79	0,83	0,84	0,85	0,90	0,79	1,00																																		
EST	0,71	0,78	0,77	0,67	0,73	0,65	0,80	0,73	0,69	0,76	1,00																																	
FIN	0,76	0,74	0,72	0,61	0,78	0,68	0,75	0,77	0,84	0,74	0,72	1,00																																
FRA	0,90	0,88	0,71	0,70	0,85	0,75	0,81	0,88	0,83	0,86	0,78	0,78	1,00																															
GBR	0,81	0,87	0,70	0,67	0,83	0,70	0,79	0,87	0,79	0,87	0,81	0,73	0,87	1,00																														
GRC	0,85	0,82	0,77	0,81	0,77	0,81	0,75	0,81	0,70	0,87	0,64	0,65	0,76	0,72	1,00																													
GTM	0,63	0,55	0,56	0,63	0,55	0,63	0,50	0,60	0,60	0,62	0,44	0,50	0,55	0,52	0,67	1,00																												
HRV	0,80	0,82	0,80	0,79	0,77	0,77	0,80	0,82	0,76	0,82	0,71	0,72	0,77	0,77	0,77	0,54	1,00																											
HUN	0,87	0,84	0,79	0,79	0,81	0,77	0,87	0,87	0,78	0,88	0,78	0,72	0,84	0,83	0,81	0,60	0,81	1,00																										
IRL	0,77	0,80	0,78	0,66	0,81	0,73	0,73	0,77	0,82	0,79	0,74	0,84	0,79	0,80	0,72	0,59	0,77	0,73	1,00																									
ISL	0,74	0,74	0,77	0,63	0,76	0,66	0,73	0,69	0,73	0,70	0,79	0,77	0,77	0,79	0,65	0,48	0,72	0,71	0,77	1,00																								
ITA	0,87	0,87	0,76	0,79	0,81	0,82	0,82	0,89	0,79	0,93	0,73	0,71	0,84	0,82	0,87	0,62	0,82	0,86	0,75	0,67	1,00																							
KOR	0,62	0,56	0,53	0,60	0,51	0,54	0,52	0,59	0,61	0,59	0,53	0,53	0,64	0,54	0,60	0,45	0,51	0,62	0,50	0,46	0,62	1,00																						
LTU	0,67	0,73	0,73	0,65	0,70	0,62	0,72	0,66	0,68	0,67	0,82	0,73	0,71	0,75	0,61	0,43	0,70	0,73	0,74	0,78	0,65	0,50	1,00																					
LUX	0,81	0,77	0,73	0,67	0,78	0,73	0,68	0,77	0,79	0,76	0,68	0,76	0,79	0,70	0,73	0,55	0,76	0,77	0,70	0,70	0,72	0,55	0,67	1,00																				
LVA	0,66	0,69	0,77	0,66	0,67	0,64	0,72	0,67	0,69	0,70	0,82	0,69	0,70	0,74	0,61	0,50	0,70	0,73	0,73	0,78	0,70	0,47	0,81	0,68	1,00																			
NLD	0,82	0,89	0,68	0,66	0,83	0,71	0,78	0,88	0,84	0,82	0,72	0,77	0,83	0,87	0,71	0,51	0,78	0,81	0,77	0,78	0,79	0,52	0,70	0,77	0,69	1,00																		
PAN	0,74	0,75	0,71	0,72	0,71	0,72	0,66	0,70	0,69	0,77	0,67	0,62	0,73	0,71	0,74	0,69	0,66	0,70	0,73	0,67	0,74	0,55	0,63	0,62	0,68	0,63	1,00																	
POL	0,84	0,85	0,78	0,75	0,83	0,73	0,85	0,85	0,78	0,84	0,84	0,76	0,86	0,86	0,78	0,51	0,82	0,86	0,77	0,80	0,83	0,62	0,79	0,73	0,78	0,83	0,70	1,00																
PRT	0,78	0,83	0,77	0,70	0,76	0,78	0,71	0,76	0,80	0,81	0,72	0,76	0,81	0,72	0,75	0,59	0,76	0,77	0,81	0,75	0,80	0,56	0,71	0,79	0,73	0,72	0,72	0,77	1,00															
ROU	0,73	0,75	0,83	0,78	0,69	0,76	0,71	0,74	0,72	0,78	0,71	0,69	0,69	0,70	0,77	0,61	0,79	0,79	0,72	0,69	0,75	0,57	0,73	0,77	0,73	0,69	0,68	0,77	0,76	1,00														
SLV	0,62	0,62	0,60	0,67	0,54	0,65	0,50	0,59	0,62	0,64	0,47	0,50	0,57	0,55	0,65	0,75	0,55	0,60	0,60	0,54	0,63	0,49	0,48	0,56	0,56	0,55	0,73	0,53	0,63	0,61	1,00													
SVK	0,76	0,71	0,73	0,73	0,58	0,67	0,84	0,62	0,62	0,78	0,68	0,61	0,64	0,62	0,69	0,49	0,73	0,81	0,63	0,64	0,74	0,46	0,65	0,58	0,64	0,57	0,60	0,67	0,66	0,66	0,53	1,00												
SVN	0,82	0,89	0,77	0,78	0,84	0,75	0,84	0,85	0,77	0,86	0,81	0,78	0,84	0,86	0,77	0,52	0,83	0,83	0,80	0,79	0,81	0,57	0,79	0,75	0,75	0,84	0,73	0,89	0,75	0,78	0,54	0,64	1,00											
SWE	0,82	0,83	0,72	0,65	0,85	0,69	0,84	0,85	0,84	0,78	0,80	0,84	0,86	0,84	0,68	0,46	0,76	0,80	0,78	0,79	0,76	0,56	0,76	0,76	0,72	0,85	0,66	0,84	0,76	0,71	0,46	0,64	0,83	1,00										
THA	0,79	0,74	0,67	0,77	0,71	0,70	0,71	0,75	0,69	0,78	0,67	0,61	0,77	0,75	0,76	0,66	0,68	0,76	0,69	0,64	0,77	0,59	0,62	0,60	0,67	0,69	0,78	0,78	0,68	0,67	0,72	0,56	0,75	0,68	1,00									
TUR	0,81	0,76	0,76	0,79	0,73	0,75	0,72	0,75	0,71	0,81	0,64	0,64	0,76	0,72	0,83	0,73	0,72	0,76	0,75	0,67	0,79	0,59	0,60	0,63	0,66	0,66	0,82	0,74	0,72	0,71	0,75	0,70	0,75	0,65	0,86	1,00								
URY	0,80	0,75	0,73	0,79	0,74	0,78	0,73	0,80	0,74	0,84	0,61	0,65	0,75	0,70	0,83	0,74	0,71	0,79	0,70	0,56	0,84	0,57	0,54	0,63	0,61	0,67	0,79	0,71	0,73	0,71	0,76	0,63	0,70	0,63	0,81	0,86	1,00							
USA	0,84	0,81	0,76	0,68	0,79	0,73	0,79	0,81	0,76	0,85	0,80	0,72	0,81	0,87	0,74	0,56	0,75	0,81	0,77	0,77	0,81	0,58	0,72	0,70	0,73	0,79	0,73	0,80	0,72	0,69	0,58	0,72	0,81	0,80	0,71	0,75	0,71	1,00						
VNM	0,72	0,67	0,62	0,76	0,66	0,65	0,61	0,72	0,69	0,71	0,60	0,62	0,71	0,71	0,71	0,66	0,62	0,73	0,64	0,59	0,70	0,65	0,59	0,58	0,60	0,67	0,71	0,71	0,62	0,68	0,71	0,54	0,69	0,62	0,84	0,78	0,78	0,67	1,00					

Table A6 – Spearman correlation among occupational relative wages by occupational group, for 39 countries

	AUT	BEL	BGR	BIH	CHE	CYP	CZE	DEU	DNK	ESP	EST	FIN	FRA	GBR	GRC	GTM	HRV	HUN	IRL	ISL	ITA	KOR	LTU	LUX	LVA	NLD	PAN	POL	PRT	ROU	SLV	SVK	SVN	SWE	THA	TUR	URY	USA	VNM						
AUT	1,00																																												
BEL	0,89	1,00																																											
BGR	0,92	0,90	1,00																																										
BIH	0,89	0,90	0,91	1,00																																									
CHE	0,91	0,89	0,92	0,91	1,00																																								
CYP	0,88	0,89	0,88	0,85	0,90	1,00																																							
CZE	0,93	0,90	0,94	0,94	0,91	0,88	1,00																																						
DEU	0,91	0,89	0,92	0,92	0,92	0,88	0,96	1,00																																					
DNK	0,91	0,92	0,92	0,90	0,90	0,88	0,93	0,91	1,00																																				
ESP	0,92	0,89	0,93	0,95	0,92	0,90	0,96	0,94	0,93	1,00																																			
EST	0,94	0,88	0,92	0,89	0,91	0,90	0,93	0,94	0,92	0,93	1,00																																		
FIN	0,94	0,88	0,92	0,88	0,94	0,91	0,93	0,92	0,93	0,93	0,94	1,00																																	
FRA	0,96	0,87	0,92	0,90	0,92	0,91	0,93	0,91	0,93	0,95	0,94	0,96	1,00																																
GBR	0,91	0,87	0,88	0,82	0,88	0,90	0,91	0,90	0,88	0,88	0,93	0,92	0,90	1,00																															
GRC	0,89	0,89	0,92	0,92	0,93	0,86	0,93	0,90	0,92	0,95	0,90	0,93	0,94	0,82	1,00																														
GTM	0,85	0,86	0,86	0,88	0,87	0,81	0,86	0,84	0,88	0,91	0,85	0,86	0,90	0,69	0,93	1,00																													
HRV	0,93	0,90	0,94	0,93	0,91	0,88	0,95	0,92	0,92	0,94	0,91	0,92	0,95	0,84	0,94	0,91	1,00																												
HUN	0,92	0,88	0,92	0,95	0,91	0,84	0,94	0,91	0,89	0,92	0,91	0,92	0,92	0,82	0,92	0,90	0,94	1,00																											
IRL	0,87	0,78	0,85	0,82	0,85	0,83	0,87	0,83	0,88	0,86	0,87	0,88	0,89	0,83	0,86	0,81	0,88	0,86	1,00																										
ISL	0,78	0,90	0,81	0,73	0,80	0,92	0,82	0,83	0,82	0,80	0,83	0,82	0,80	0,88	0,75	0,70	0,76	0,72	0,70	1,00																									
ITA	0,91	0,87	0,92	0,93	0,93	0,86	0,92	0,91	0,90	0,94	0,89	0,93	0,94	0,79	0,95	0,94	0,94	0,96	0,86	0,71	1,00																								
KOR	0,86	0,84	0,89	0,93	0,89	0,78	0,92	0,91	0,87	0,95	0,90	0,86	0,89	0,77	0,93	0,90	0,92	0,91	0,76	0,69	0,94	1,00																							
LTU	0,91	0,90	0,90	0,92	0,91	0,86	0,91	0,90	0,93	0,93	0,90	0,93	0,93	0,83	0,93	0,92	0,92	0,91	0,86	0,80	0,93	0,90	1,00																						
LUX	0,86	0,90	0,86	0,90	0,87	0,80	0,92	0,92	0,90	0,92	0,85	0,87	0,89	0,81	0,93	0,90	0,89	0,88	0,86	0,76	0,90	0,91	0,92	1,00																					
LVA	0,92	0,85	0,90	0,91	0,93	0,85	0,91	0,91	0,91	0,93	0,90	0,93	0,94	0,80	0,96	0,91	0,93	0,91	0,89	0,71	0,96	0,90	0,93	0,89	1,00																				
NLD	0,94	0,88	0,93	0,90	0,92	0,92	0,94	0,93	0,93	0,94	0,95	0,97	0,96	0,93	0,91	0,84	0,92	0,92	0,88	0,84	0,92	0,88	0,91	0,87	0,91	1,00																			
PAN	0,93	0,85	0,89	0,86	0,91	0,87	0,90	0,88	0,91	0,94	0,93	0,94	0,96	0,85	0,94	0,91	0,91	0,89	0,88	0,82	0,93	0,88	0,93	0,92	0,94	0,93	1,00																		
POL	0,93	0,92	0,94	0,92	0,95	0,91	0,92	0,90	0,91	0,91	0,92	0,95	0,93	0,89	0,93	0,86	0,94	0,93	0,85	0,82	0,93	0,86	0,92	0,87	0,91	0,94	0,90	1,00																	
PRT	0,90	0,86	0,91	0,92	0,90	0,87	0,93	0,93	0,91	0,95	0,90	0,91	0,96	0,81	0,93	0,93	0,95	0,93	0,87	0,74	0,95	0,92	0,92	0,92	0,95	0,91	0,92	0,90	1,00																
ROU	0,78	0,93	0,87	0,88	0,93	0,89	0,89	0,89	0,83	0,87	0,82	0,87	0,85	0,81	0,92	0,85	0,90	0,90	0,77	0,90	0,92	0,85	0,85	0,86	0,85	0,84	0,82	0,94	0,89	1,00															
SLV	0,84	0,94	0,91	0,88	0,85	0,82	0,88	0,91	0,89	0,92	0,82	0,82	0,87	0,79	0,95	0,91	0,92	0,87	0,80	0,83	0,89	0,93	0,90	0,95	0,88	0,83	0,90	0,86	0,93	0,86	1,00														
SVK	0,95	0,91	0,93	0,91	0,89	0,85	0,93	0,92	0,92	0,91	0,93	0,94	0,94	0,89	0,88	0,86	0,93	0,94	0,86	0,81	0,92	0,85	0,93	0,87	0,90	0,94	0,89	0,94	0,92	0,90	0,85	1,00													
SVN	0,88	0,90	0,93	0,94	0,89	0,87	0,94	0,93	0,91	0,93	0,88	0,89	0,90	0,81	0,92	0,90	0,94	0,91	0,82	0,82	0,93	0,91	0,92	0,90	0,90	0,89	0,88	0,90	0,93	0,87	0,92	0,90	1,00												
SWE	0,95	0,86	0,92	0,88	0,93	0,88	0,94	0,92	0,91	0,93	0,94	0,96	0,96	0,92	0,92	0,83	0,92	0,91	0,86	0,79	0,92	0,86	0,91	0,87	0,92	0,96	0,95	0,92	0,90	0,83	0,88	0,93	0,87	1,00											
THA	0,84	0,79	0,84	0,87	0,84	0,74	0,84	0,82	0,82	0,88	0,80	0,83	0,87	0,66	0,91	0,96	0,90	0,91	0,80	0,62	0,94	0,86	0,89	0,87	0,90	0,81	0,89	0,83	0,92	0,82	0,91	0,83	0,89	0,83	1,00										
TUR	0,87	0,83	0,89	0,90	0,87	0,78	0,90	0,87	0,85	0,92	0,84	0,87	0,89	0,75	0,94	0,93	0,94	0,95	0,83	0,69	0,96	0,90	0,90	0,93	0,86	0,90	0,87	0,94	0,88	0,95	0,88	0,90	0,86	0,95	1,00										
URY	0,85	0,89	0,90	0,90	0,87	0,84	0,90	0,92	0,90	0,94	0,86	0,82	0,88	0,84	0,96	0,87	0,90	0,83	0,84	0,78	0,85	0,94	0,88	0,91	0,88	0,85	0,93	0,85	0,90	0,77	0,95	0,80	0,89	0,92	0,88	0,91	1,00								
USA	0,96	0,88	0,92	0,88	0,91	0,88	0,95	0,92	0,91	0,91	0,95	0,93	0,92	0,92	0,90	0,79	0,91	0,90	0,83	0,83	0,89	0,83	0,88	0,87	0,88	0,95	0,90	0,94	0,87	0,86	0,86	0,93	0,86	0,95	0,78	0,85	0,90	1,00							
VNM	0,86	0,87	0,87	0,87	0,92	0,91	0,86	0,86	0,88	0,90	0,88	0,93	0,91	0,85	0,93	0,87	0,88	0,89	0,83	0,84	0,91	0,88	0,90	0,83	0,90	0,91	0,90	0,92	0,89	0,91	0,82	0,86	0,87	0,87	0,85	0,89	0,79	0,86	1,00						

Table A7 - Spearman correlation among sectoral relative wages by sector, for 39 countries

	AUT	BEL	BGR	BIH	CHE	CYP	CZE	DEU	DNK	ESP	EST	FIN	FRA	GBR	GRC	GTM	HRV	HUN	IRL	ISL	ITA	KOR	LTU	LUX	LVA	NLD	PAN	POL	PRT	ROU	SLV	SVK	SVN	SWE	THA	TUR	URY	USA	VNM							
AUT	1,00																																													
BEL	0,81	1,00																																												
BGR	0,79	0,67	1,00																																											
BIH	0,66	0,51	0,77	1,00																																										
CHE	0,85	0,77	0,77	0,71	1,00																																									
CYP	0,80	0,57	0,81	0,74	0,79	1,00																																								
CZE	0,85	0,73	0,88	0,76	0,83	0,79	1,00																																							
DEU	0,91	0,84	0,75	0,65	0,89	0,78	0,84	1,00																																						
DNK	0,87	0,82	0,68	0,58	0,78	0,72	0,72	0,88	1,00																																					
ESP	0,88	0,76	0,85	0,76	0,85	0,84	0,91	0,89	0,79	1,00																																				
EST	0,82	0,69	0,80	0,79	0,78	0,76	0,89	0,74	0,66	0,85	1,00																																			
FIN	0,90	0,88	0,80	0,69	0,88	0,76	0,87	0,94	0,85	0,89	0,81	1,00																																		
FRA	0,84	0,84	0,72	0,57	0,79	0,71	0,76	0,86	0,83	0,74	0,67	0,85	1,00																																	
GBR	0,91	0,78	0,74	0,72	0,83	0,77	0,84	0,86	0,83	0,86	0,85	0,88	0,79	1,00																																
GRC	0,83	0,63	0,80	0,75	0,80	0,85	0,82	0,77	0,73	0,88	0,79	0,74	0,65	0,79	1,00																															
GTM	0,58	0,50	0,76	0,72	0,57	0,62	0,64	0,60	0,51	0,71	0,54	0,61	0,48	0,55	0,62	1,00																														
HRV	0,71	0,59	0,82	0,74	0,75	0,81	0,76	0,72	0,71	0,79	0,74	0,70	0,62	0,69	0,83	0,63	1,00																													
HUN	0,82	0,72	0,73	0,50	0,75	0,72	0,78	0,79	0,76	0,72	0,67	0,76	0,83	0,75	0,70	0,47	0,62	1,00																												
IRL	0,90	0,82	0,83	0,73	0,88	0,81	0,89	0,94	0,84	0,95	0,86	0,93	0,79	0,90	0,83	0,60	0,75	0,73	1,00																											
ISL	0,67	0,58	0,55	0,71	0,54	0,56	0,62	0,44	0,51	0,58	0,78	0,56	0,46	0,65	0,54	0,45	0,48	0,36	0,47	1,00																										
ITA	0,85	0,68	0,79	0,71	0,81	0,82	0,82	0,84	0,75	0,88	0,83	0,81	0,71	0,85	0,87	0,58	0,78	0,70	0,87	0,61	1,00																									
KOR	0,76	0,78	0,67	0,63	0,82	0,67	0,79	0,77	0,69	0,77	0,77	0,81	0,80	0,76	0,67	0,38	0,54	0,73	0,87	0,52	0,69	1,00																								
LTU	0,83	0,75	0,84	0,79	0,81	0,76	0,91	0,82	0,76	0,91	0,90	0,86	0,73	0,84	0,78	0,64	0,76	0,70	0,89	0,63	0,82	0,73	1,00																							
LUX	0,73	0,74	0,78	0,65	0,79	0,80	0,75	0,81	0,75	0,79	0,62	0,77	0,73	0,68	0,78	0,76	0,76	0,72	0,73	0,39	0,75	0,58	0,73	1,00																						
LVA	0,78	0,69	0,73	0,73	0,75	0,71	0,77	0,69	0,70	0,75	0,89	0,76	0,70	0,80	0,72	0,47	0,75	0,65	0,80	0,73	0,73	0,70	0,80	0,58	1,00																					
NLD	0,88	0,86	0,66	0,65	0,80	0,71	0,73	0,89	0,89	0,80	0,70	0,90	0,81	0,88	0,70	0,48	0,65	0,68	0,85	0,61	0,77	0,73	0,76	0,69	0,70	1,00																				
PAN	0,69	0,53	0,81	0,74	0,68	0,76	0,78	0,64	0,60	0,79	0,75	0,66	0,56	0,71	0,81	0,72	0,77	0,64	0,71	0,48	0,74	0,53	0,77	0,77	0,64	0,53	1,00																			
POL	0,73	0,75	0,81	0,72	0,75	0,72	0,81	0,73	0,66	0,79	0,75	0,84	0,80	0,74	0,70	0,62	0,71	0,68	0,88	0,48	0,69	0,74	0,81	0,68	0,72	0,70	0,60	1,00																		
PRT	0,61	0,51	0,71	0,65	0,68	0,71	0,70	0,59	0,51	0,77	0,63	0,67	0,55	0,60	0,70	0,71	0,63	0,52	0,64	0,53	0,67	0,55	0,67	0,74	0,50	0,52	0,67	0,62	1,00																	
ROU	0,78	0,64	0,85	0,76	0,74	0,79	0,88	0,76	0,67	0,84	0,82	0,79	0,67	0,76	0,81	0,69	0,78	0,73	0,83	0,58	0,78	0,68	0,83	0,75	0,73	0,66	0,78	0,81	0,68	1,00																
SLV	0,50	0,53	0,66	0,63	0,60	0,61	0,58	0,55	0,41	0,68	0,48	0,50	0,28	0,47	0,67	0,69	0,67	0,40	0,44	0,23	0,54	0,34	0,56	0,81	0,41	0,39	0,72	0,42	0,65	0,58	1,00															
SVK	0,87	0,79	0,86	0,65	0,77	0,66	0,88	0,81	0,76	0,82	0,83	0,88	0,81	0,80	0,69	0,64	0,65	0,77	0,85	0,72	0,73	0,73	0,86	0,66	0,78	0,74	0,70	0,79	0,56	0,80	0,45	1,00														
SVN	0,74	0,73	0,87	0,70	0,75	0,80	0,84	0,77	0,70	0,85	0,73	0,79	0,74	0,68	0,79	0,75	0,78	0,69	0,79	0,56	0,80	0,64	0,83	0,84	0,65	0,67	0,75	0,84	0,75	0,81	0,64	0,77	1,00													
SWE	0,86	0,82	0,70	0,57	0,79	0,63	0,76	0,80	0,80	0,73	0,75	0,88	0,85	0,84	0,62	0,48	0,55	0,73	0,79	0,72	0,74	0,72	0,79	0,64	0,73	0,85	0,54	0,73	0,50	0,66	0,27	0,87	0,69	1,00												
THA	0,71	0,59	0,85	0,70	0,75	0,77	0,79	0,71	0,64	0,83	0,72	0,74	0,66	0,70	0,79	0,78	0,78	0,71	0,76	0,33	0,73	0,60	0,79	0,83	0,62	0,56	0,86	0,71	0,75	0,83	0,77	0,71	0,80	0,55	1,00											
TUR	0,69	0,67	0,77	0,71	0,77	0,77	0,78	0,72	0,62	0,82	0,72	0,69	0,57	0,68	0,81	0,65	0,77	0,60	0,74	0,41	0,79	0,66	0,76	0,79	0,63	0,61	0,75	0,67	0,76	0,72	0,75	0,60	0,82	0,51	0,76	1,00										
URY	0,87	0,68	0,81	0,84	0,82	0,84	0,86	0,82	0,75	0,91	0,90	0,82	0,68	0,88	0,91	0,64	0,81	0,69	0,89	0,67	0,89	0,72	0,85	0,78	0,81	0,77	0,81	0,71	0,70	0,83	0,67	0,75	0,77	0,72	0,78	0,79	1,00									
USA	0,93	0,81	0,82	0,74	0,84	0,75	0,86	0,92	0,88	0,87	0,83	0,94	0,82	0,94	0,78	0,64	0,73	0,76	0,91	0,68	0,80	0,74	0,87	0,73	0,78	0,91	0,72	0,80	0,63	0,81	0,50	0,88	0,75	0,89	0,75	0,89	0,75	0,67	0,85	1,00						
VNM	0,68	0,57	0,80	0,72	0,67	0,71	0,70	0,69	0,67	0,71	0,64	0,69	0,70	0,71	0,69	0,78	0,75	0,69	0,66	0,41	0,65	0,50	0,72	0,76	0,61	0,58	0,82	0,65	0,61	0,71	0,63															