



Agglomeration and skills: explaining regional wage disparities in Colombia

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ABSTRACT

Regional wage gaps persist, and understanding them is crucial for policy design and for comprehending phenomena such that agglomeration. This article analyzes regional wage differences in Colombia by incorporating the composition of skills and specialization patterns into the analysis. To do this, wage equations are estimated, and decomposition techniques are implemented to assess the importance of these factors. The results suggest that both skills and specialization patterns are relevant to the magnitude of the regional wage gap, though in different ways. For skills, the key factor is the differences in composition between cities, while in the case of specialization, the critical element is the return it generates on wages. This analysis serves as a crucial input for public policy formulation aimed at reducing adjustments and structural skill gaps among different cities in Colombia.

1. Introduction

The relationship between city size and labor productivity is a topic that has been extensively studied in the literature (Marshall, 1890; Jacobs, 1969; Glaeser, 2008). The presence of agglomeration economies has been identified as one of the factors shaping this relationship. In this regard, Duranton and Puga (2004) describe three channels that explain this relationship: exchanging, matching, and learning. These channels refer to the fact that the agglomeration or concentration of firms and workers in a given area leads to cost-sharing and the generation of knowledge externalities. Labor markets benefit from agglomerations through enhanced job opportunities, improved quality of matches between labor supply and demand, and the promotion of economies of scale and specialization.

The benefits of agglomeration are influenced by labor market characteristics, such as worker attributes and patterns of specialization. For instance, workers in more agglomerated cities tend to accumulate human capital more rapidly (Rauch, 1993; Glaeser, 1999; Glaeser and Henderson, 2017). Additionally, there are occupations with higher levels of interpersonal and cognitive skills due to interactions within a more specialized market environment (Baum-Snow and Pavan, 2012; Andersson et al., 2013). Therefore, the interplay between agglomeration economies and the skill composition of the labor force is a crucial factor

in explaining regional wage disparities.

Existing literature provides evidence of the positive effect of agglomeration on wages and its dependence on the level of specialization (Wheeler, 2001; Glaeser and Mare, 2001; Wheaton and Lewis, 2002; Combes et al., 2008; Matano and Naticchioni, 2011; Baum-Snow and Pavan, 2012). However, the impact of agglomeration on wages is heterogeneous among workers and depends on their individual characteristics. Specifically, workers with higher levels of qualifications or skills benefit the most from agglomeration¹ (Combes et al., 2008; Matano and Naticchioni, 2011).

In this regard, Matano and Naticchioni (2011), using an employer-employee database for Italy, find a complementary effect between agglomeration and skill composition on wages, as well as significant role of specialization, indicating that workers in more specialized cities (with a higher concentration of workers in specific sectors) receive higher wages (see also Wheaton and Lewis, 2002). The authors attribute these results to the fact that non-routine skills (e.g., analytical, social, and cognitive skills) tend to exhibit higher wage premia² (Glaeser & Maré, 2001; Wheeler, 2006; Yankow, 2006; Gould, 2007; Melo et al., 2009; Bacolod et al., 2009; Puga, 2010; Florida et al., 2012; Andersson et al., 2013; Neves et al., 2017).

Similarly, a body of empirical literature examines agglomeration and worker skills as determinants of regional wage disparities.³ For instance,

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¹ There is also evidence of opposite results, as described in Graham and Melo (2009), Rinz (2018).

² Wheeler (2001), (2004), (2007) provides evidence that agglomeration also affects wage inequality.

³ Some seminal works have explored the relationship between the regional wage differential and different factors such as migration, living costs, and the labor force composition (Krumm, 1983; Newman, 1982).

Combes et al. (2008) analyze spatial disparities in France and quantify the impact of worker skill composition, local endowments (such as geography and local institutions), and the interaction between workers and firms. Their findings indicate that the skill composition significantly accounts for regional wage differences, providing evidence of sorting.⁴ Evidence for developing countries presents some nuances. For example, Pan et al. (2016) and Chauvin et al. (2017) find mixed evidence regarding the relationship between agglomeration and wages when comparing developed and developing countries, while Neves et al. (2017) find a significant and positive correlation between the premium of cognitive and social skills and the size of cities.

Recent research has emphasized how agglomeration, labor policies, and institutional settings shape regional wage dynamics, particularly in segmented labor markets (see Oyarzo and Ferrada, 2024; Barufi et al., 2023; Capello et al., 2023). This paper contributes to that literature by providing a deeper understanding of the drivers of spatial wage differences in a developing economy context. In addition, we build on Latin American studies that analyze regional specialization and skill measurement in labor markets with structural heterogeneity. For example, Galetti et al. (2024) explore occupational relatedness and branching across Brazilian regions, offering valuable insight into how specialization patterns evolve. Likewise, Azzoni and Tessarin (2024) and Maciente (2013) discuss the challenges of adapting U.S.-based frameworks such as O*NET to the Latin American context. By combining a task-based approach to skills with measures of urban specialization, we provide insights into how labor market segmentation and city structure jointly influence wage inequality across Colombian regions. In particular, this paper examines how agglomeration forces and skill composition shape regional wage disparities.

Previous evidence highlights the relevance of these factors in explaining wages in Colombia. For instance, Duranton (2016) estimated that the wage elasticity with respect to agglomeration was 5 % in Colombia, in line with what was postulated by Baum-Snow and Pavan (2012). Additionally, this study also shows that the regional distribution of wages is shaped by the growth of cities and industrial shocks. Other studies such as Nupia (1997), Galvis (2002), and Mesa et al., (2008) study regional wage differentials from a segmented markets perspective. This paper aims to contribute to this literature by incorporating factors such as the composition of skills and sectoral specialization into the analysis. The goal is to understand the role of these factors in the wage structure at the regional level.

Our empirical exercises use information from the Great Integrated Household Survey (GEIH, for its Spanish acronym) for 2019. GEIH collects monthly data across the Colombian territory on workforce characteristics. Our analysis focuses on the 13 largest cities, which host 70 % of the urban population. This approach is taken because the labor market in Colombia is highly segmented, with the rural and urban labor markets exhibiting structural differences in their performance and levels of specialization.

Due to the limited availability of standardized skill information in Colombia, this study proposes a methodology for measuring occupational skills based on the Occupational Information Network (O*NET), building on the prior work of Autor et al. (2006), Autor and Dorn (2013), and Autor (2013). One of the primary challenges in this task is adapting the O*NET skill measures to the Colombian context and integrating them with the GEIH data. Following the occupation categories used by Autor and Dorn (2013), we built a bridge between the National Classification of Occupations (CNO) in GEIH and the O*NET. This enables the assignment of levels for three types of skills to each worker: routine, manual, and cognitive.

In turn, to capture sectoral specialization, we compute a location

⁴ This is the result of different circumstances, such as the fact that large cities offer a wide range of services that attract workers and promote the accumulation of human capital.

quotient which is measured by comparing the relative share of each sector to the total employment in a specific city with respect to the same ratio computed at the national level. This approach follows the methodologies proposed by Combes (2000), Mion and Naticchioni (2009), Matano and Naticchioni (2012), and Glaeser and Henderson (2017). We use this information to implement the Oaxaca-Blinder decomposition in order to understand the role of each factor in the regional wage differentials.

Our results provide evidence that sectoral specialization and skills are relevant determinants of regional wage disparities. Both differences in skills composition among local labor markets and the wage returns from specialization emerge as relevant factors. Additionally, the skills premium shows that non-routine skills consistently tend to increase wages.

The rest of the paper is organized as follows. The second section presents the methodology and explains the adaptation of the occupational classification used to measure skill composition in Colombia. The third section describes the relationship between skill composition and agglomeration patterns. The fourth section contains the results of the wage differential decomposition. Finally, the fifth section presents the conclusions drawn from these findings.

2. Measurement of skills content for occupations in Colombia

Measuring skills is a complex task. Early studies have measured skills using educational levels; however, this approach fails to account for key dimensions of workers' capabilities. An accurate measure of skills requires identifying critical dimensions such as cognitive, social, and motor skills, rather than relying solely on educational attainment.⁵ The pioneering work of Autor et al. (2006) introduces an occupational classification based on the composition of required skills according to O*NET. This approach identifies job task content across various categories, including analytical, manual, and cognitive skills.⁶

Occupations are heterogeneous in their skill composition. In this context, a skill is understood as the application of knowledge about a subject to perform a task. Tasks vary in nature; for example, some are repetitive or routine, while others involve analytical knowledge and reasoning, such as reading or calculating equations. Consequently, some occupations are intensive in analytical skills, while others have a higher concentration of routine skills. For instance, driving requires skills such as quick reaction times and good memory.

The GEIH provides an occupational analysis framework adapted to the conditions of the labor market, known as the National Occupational Classification of Colombia (CNO, for its Spanish acronym). This classification does not contain detailed information about the specific tasks associated with occupations. Therefore, it is necessary to link the CNO with the International Standard Classification (ISCO), which allows the imputation of measurements of skill intensity from Autor et al. (2006) and Autor and Dorn (2013). These papers provide a methodology to measure five skill categories in the U.S.: non-routine analytical, non-routine interactive, non-routine manual, routine cognitive and routine manual. See Table 2 in the Appendix for a description including definitions and examples of each skill category.

Skill measures (scores) are calculated by integrating the occupational classification system from the American Community Survey

⁵ The challenges in measuring job task content stem from the fact that occupational characteristics evolve over time, often leading to the creation of new labor categories. Additionally, these patterns can vary across different countries (Autor and Handel, 2013; Spitz-Oener, 2006; Arntz et al., 2016).

⁶ Based on this skill measurement, significant contributions such as Autor and Dorn (2009) and Handel and Autor (2013) have explored the connections between human capital endowment, occupations, skills, polarization and wages (see also Bachmann, 2018; Cortes, 2018; Danieli, 2017; Goos et al., 2011; Goos and Manning, 2007; Bhalotra and Fernández, 2018; Bizopoulou, 2017).

(COC) with the Dictionary of Occupational Titles (DOT). Specifically, the DOT enables the assessment of the intensity of tasks such as performing calculations, repetitive movements, or interacting with customers relative to the total number of tasks in a particular occupation. Scores are coded on a 1–10 scale, where higher values indicate a more intensive use of the task. These skill measures are estimated as an index that aggregates task intensity through principal components analysis.

The main challenge in establishing a bridge between the DOT-COC and the CNO is that the matching between occupations is not perfect. In some cases, multiple occupations in DOT-COC correspond to a single category in the CNO. This occupational analysis is conducted using the Colombian adaptations of the International Standard Classification of Occupations⁷ (ISCO) and the Standard Occupational Classification System (SOC) for the U.S. This process matches the DOT-COC occupations (485 occupations) with the SOC, which maps directly to the international ISCO (436 occupations). Additionally, the ISCO has corresponding versions adapted for Colombia (449 occupations) that serve as a reference for the CNO (285 occupations). When a crosswalk merges various occupations from one classification to another, the measures are aggregated using the average score. The final number of occupation categories in the CNO correspond to 83 occupations.

The resulting scores are integrated into the GEIH data for the 13 main urban areas⁸ for 2019. Table 1 and Table 2 Table 3 present the average score at different levels of aggregation. Table 1 shows that, at the level of occupational groups, there is consistency in the relative intensity of skills. For instance, in the case of directors and managers, there is a higher skill intensity index for non-routine analytical skills (5.27) and non-routine interactive (interpersonal) skills (7.70), as expected. These skills are related to leadership, management, control, planning, and responsibility, among others. In contrast, the index is lower for routine manual skills (2.80), which are associated with strength, endurance, flexibility, balance, and coordination.

In turn, officials, operatives, craftworkers, and related trades exhibit higher routine cognitive skills (7.67) and routine manual skills (4.48) compared with non-routine interactive skills (0.90). These workers typically demonstrate greater abilities associated with adaptability to situations requiring precise achievement of established limits, tolerances, or standards and motor skills to manipulate small objects with their fingers.

To provide a broader overview of the five skills across occupations and establish potential correlations, Fig. 1 displays the scores, ordering occupations by their routine cognitive index. Notably, a correlation is observed between non-routine analytical and non-routine interactive skills. Similar patterns are also noted between non-routine and routine manual skills. Regarding the ordering of occupations, directors and managers exhibit a higher index for non-routine cognitive and interactive skills, while domestic workers show higher routine manual skills. Non-routine cognitive skills are more prevalent in STEM or science and engineering occupations.

⁷ This adapted ISCO classification, adopted by DANE, consists in a hierarchical structure based on four categories: large group, principal subgroups, subgroups, and primary groups. In addition to the structure, the classification is built under two relevant criteria: the level of skills and the specialization of skills.

⁸ The DANE defines an Urban Area (Metropolitan Area, AM, for its Spanish acronym) as an area of influence that includes surrounding municipalities, which with the city make up a single non-discontinuous urban fabric and have been legally recognized. The urban areas are: Medellín AM-MED-, Barranquilla AM-BAR-, Bogotá AM-BOG-, Manizales AM-MAN-, Ibagué AM-IBA-, Montería AM-MON-, Cartagena AM-CAR-, Villavicencio AM-VIL-, Pasto AM-PAS-, Cúcuta AM-CUC-, Pereira AM-PER-, Bucaramanga AM-BUC-, Cali AM-CAL-.

3. Empirical strategy

This section outlines the econometric strategy employed to analyze how variations in skill distribution impact wage levels and regional wage differences. The Colombian labor market exhibits significant regional heterogeneity. Differences in labor market performance and sector specialization among cities, particularly the major ones, are associated with regional wage differences. Our analysis uses data from the 2019 GEIH for both salaried workers and self-employed individuals. We do not impose any exclusion criteria for workers, which means our sample includes public and government employees as well as private sector workers, encompassing both part-time and full-time employees. The total sample consists of 137,281 observations, representing 8809,852 workers in the urban labor force when applying survey weights.

We implement Oaxaca-Blinder decomposition (Blinder, 1973; Oaxaca, 1973) techniques to conduct an accounting exercise that capture the portion of wage disparities attributable to specific factors. Specifically, this procedure splits the wage differential between two groups into two components: one that is "explained" by differences in productivity-related characteristics, such as education, specialization, or skills. And another that remains "unexplained" by these factors. The "unexplained" component is often interpreted as differences in characteristic premiums. Additionally, this method enables further disaggregation of these components, allowing for an assessment of the contribution of each covariate. The Oaxaca-Blinder decomposition has been used in similar context by a large amount of literature, e.g., Firpo et al. (2011), (2018), Bhalotra and Fernández (2018), Matano and Naticchioni (2012), and Bacolod (2017), among many others.

Compared to other decomposition techniques, the Oaxaca-Blinder decomposition has several advantages due to its simplicity (Firpo et al., 2007). It imposes fewer assumptions on the data and provides more informative results since it does not impose a functional form on the earnings equation and can be adapted for assessing differences beyond the mean. This decomposition is conducted in two stages. In the first stage, a wage equation is estimated separately for each city, including the usual socioeconomic characteristics as well as the specialization index and skill scores. Specifically, for worker i in city j , the following specification is estimated:

$$\ln W_{ij} = \beta_j X_{ij} + \lambda_j S_{ij} + \alpha_j Z_{ij} + \varepsilon_{ij} \quad (1)$$

Where $\ln W_{ijt}$ represents the natural logarithm of hourly wages, X_{ij} is a set of socioeconomic characteristics such as age, gender, years of schooling, type of worker (wage employee or self-employed), and type of employment (formal or informal), S_{ij} refers to the skills associated with the worker's occupation, and Z_{ij} is an index of geographic specialization, a proxy of industry concentration. The local sector specialization index is calculated following the methods of Mion and Naticchioni (2009) and Matano and Naticchioni (2012), who determine the ratio of sectoral employment to total employment within a city compared to the corresponding sectoral employment and total employment at the national level. Finally, ε_{ijt} represents unobserved factors. β , λ , and α are parameters to be estimated. The differences in coefficients at the city level are analyzed by comparing their magnitude with city size to highlight patterns between agglomeration and wage returns.

Using the estimates from the first stage, a decomposition is performed to quantify the contribution of each factor to the regional wage differences. Comparisons are made between each city and Bogotá (City 1), which is defined as the reference city. This decomposition can be written as follows:

Table 1
Skill intensity score by occupations group.

Group	Non-Routine Analytical Index	Non-Routine Interactive Index	Routine Cognitive Index	Routine Manual Index	Non-Routine Manual Index
Military forces	2.13	1.11	1.07	2.53	3.28
Directors and Managers	5.27	7.70	0.70	2.80	0.39
Professionals, Scientists, and Intellectuals	6.01	5.53	2.79	3.70	0.67
Intermediate Level Technicians and Professionals	4.46	3.09	4.08	3.77	1.05
Administrative Support Staff	3.04	1.19	5.00	3.95	0.21
Service Workers and Sellers of Shops Markets	2.79	1.48	1.33	3.21	1.44
Farmers and Skilled Agricultural, Forestry, and Fisheries Workers	2.57	3.52	1.56	2.90	2.40
Officials, Operatives, Craftworkers, and Related Trades	3.31	0.90	7.67	4.48	1.97
Plant and Machine Operators and Assemblers	1.73	1.20	3.60	3.06	3.16
Elementary Occupations	1.17	0.56	2.03	3.02	1.63

Source: Authors' calculations based on GEIH 2019.

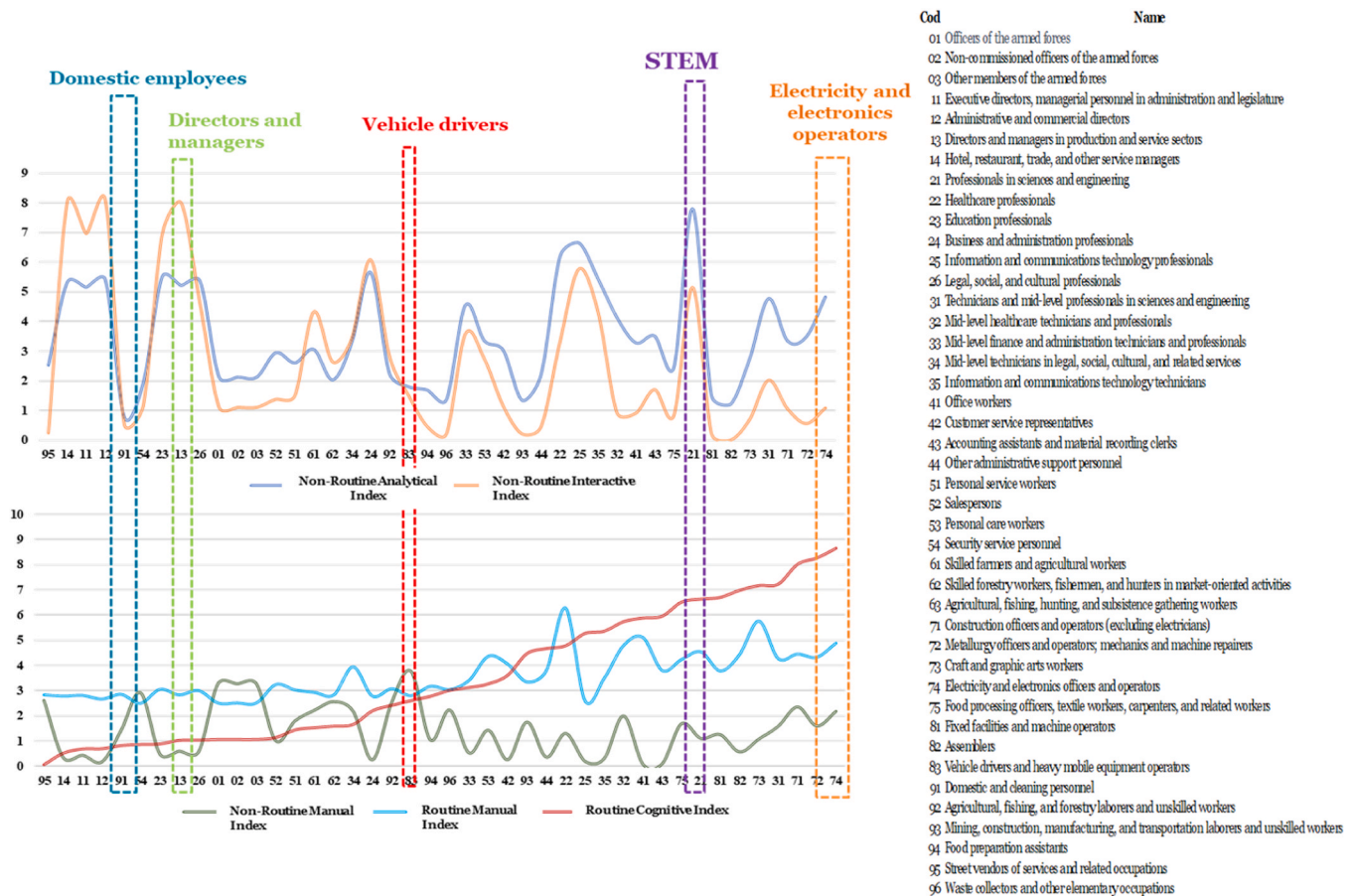


Fig. 1. Skill intensity score by occupations.
Source: Authors' calculations based on GEIH 2019.

$$\begin{aligned}
 E(\ln W|c=1) - E(\ln W|c=0) &= \beta_1 [E(X|c=1) - E(X|c=0)] + \lambda_1 [E(S|c=1) - E(S|c=0)] + \alpha_1 [E(Z|c=1) - E(Z|c=0)] + E(X|c=0)(\beta_1 - \beta_0) + E(S|c=0)(\lambda_1 - \lambda_0) + E(Z|c=0)(\alpha_1 - \alpha_0) \\
 &= A + B + C + D + E + F
 \end{aligned}
 \quad (2)$$

A + B + C capture the variation due to differences in characteristics, known as the composition effect (CE). Meanwhile, D + E + F represent the structure effect (SE), which accounts for the part of the wage

differential attributable to the prices of characteristics, skills, and geographic specialization. For instance, B + E measures the portion of the wage differential explained by skills, including both skill composition and skill premiums, respectively. C + F are the corresponding quantities for specialization.

The previous methodology studies differences in the mean. However, other statistics of the distribution such as the Gini coefficient and quartiles are also relevant to consider. Therefore, an additional decomposition exercise is conducted to study wage inequality differences. For this purpose, the methodology proposed by [Firpo et al. \(2011\)](#) is employed, which suggests the use of Recentered Influence Functions

(RIF). This function-based method has a similar logic to the Oaxaca-Blinder decomposition but considers a different dependent variable that is linked with the outcome of interest, in our case, the 25th percentile, 75th percentile, and Gini coefficient. The decomposition follows the same structure as in Eq. 2. The equation to be estimated is as follows:

$$RIF_{ij} = \beta_j X_{ij} + \lambda_j S_{ij} + \alpha_j Z_{ij} + \varepsilon_{ij} \quad (3)$$

4. Regional wage disparities, agglomeration, and skills

4.1. Regional disparities in regional labor markets

As an initial analysis, we examine wage differences and key labor market indicators at the regional level (see Fig. 2 and Table 4). There is limited evidence of convergence among cities. For example, there are differences in the informality rate⁹ of up to 30 percentage points and wage disparities exceeding 80 %. Bogotá is the city with the highest employment rate (61.5 %), the highest labor income per hour (7235), and the lowest informality rate (40.6 %). Average wage differences are significant and wage levels appear to be associated with higher employment rates and lower informality rates, although the latter relationship seems weaker. For instance, Manizales exhibits relatively low employment rates but high wages, while Cali shows a relatively high informality rate alongside a high average wage.

Source: Authors' calculations based on GEIH 2019.

The above suggests significant differences in average regional wages, which are related to the structural patterns of the local labor market. For instance, this aligns with the findings of Bacolod et al. (2021) who find that more talented and better-trained individuals concentrate in large cities due to educational choices. To explore this idea further, we analyze the distribution of hourly wages at the occupational level. If regional factors did not influence wages, it would be expected that the ranking of wages by occupation remains consistent across cities. Fig. 3 presents two heatmaps. Panel A shows the counterfactual of what would be observed if all cities maintained a constant average wage at the occupational level,¹⁰ i.e., there is no difference between cities in the hourly wage paid for the same occupation. In turn, panel B corresponds to the observed wage levels at the occupational level. The differences in vertical color intensity indicate variation in wages across occupations, while the horizontal differences represent regional disparities. Generally, professional occupations (ISCO code lower than 20) tend to have higher wages. However, there are notable exceptions in cities like Cúcuta or Montería, where wages are structurally lower. Additionally, clustering patterns of cities can be observed, with larger cities such as Bogotá, Medellín, and Cali displaying similar patterns across occupations.

Source: Authors' calculations based on GEIH 2019.

A factor that potentially explains these differences is the presence of agglomeration economies, with local sectoral specialization as a potential mechanism (Combes, 2000; Combes et al., 2008; Mion and Naticchioni, 2009; Glaeser and Henderson, 2017). Because agglomeration works as a major factor leading to regional disparities (Krugman, 1991; Fujita et al., 1999; Duranton, 2016), wages and employment opportunities depend on the regional concentration. Following Matano and Naticchioni (2012), we constructed a local-level specialization index for each sector, calculated by comparing the share of sectoral employment in a given city to the corresponding share of sectoral employment at the national level.

According to Fig. 4, cities in Colombia exhibit significant variation in

the specialization of economic activities. In the absence of specialization patterns, one would expect the color intensity to be uniformly distributed. While cities like Medellín and Cali are more concentrated in the industrial sector, Bogotá shows a relatively higher concentration of employment in the financial sector. All the evidence suggests that there are systematic regional differences in worker characteristics, skills, and specialization patterns. This makes it compelling to assess how regional wage disparities are shaped by this combination of factors.

4.2. The regional hourly wage premium

Based on the estimation of Eq. 1, we analyze the relevance of the variables of interest as determinants of wages (see Fig. 5 and Table 5). Worker characteristics such as educational attainment, age, gender, formality, and employment type exhibit the expected signs and are generally statistically significant. Age and education are positively associated with higher wages, while being self-employed or female is associated with lower wages. Lastly, employment in the formal sector is linked to significantly higher wages.

In contrast, there is greater heterogeneity in the coefficients for the skill scores and the specialization index. Specifically, it can be observed that non-routine analytical and interactive (interpersonal) skills positively affect wages for all cities. Consistent with Baum-Snow and Pavan (2012) and Florida et al. (2012), we find that differences in wage levels across city sizes are not solely due to specialization, but rather reflect underlying differences in returns to human capital and task-specific skills. In particular, analytical and cognitive tasks are more highly rewarded.

This result has also been documented in Glaeser & Maré (2001), Wheeler (2006) and Bacolod (2009). Our results mirror those of Bacolod et al. (2009), who find that urban wage premia in the U.S. are concentrated among cognitive and people-oriented skills. Similarly, in Colombia, wages for analytical and interactive tasks are higher in large cities, whereas routine task intensity is not significantly rewarded. In most cases, the magnitude of the coefficient associated with non-routine interactive skills is greater than that for non-routine analytical skills, and the variance appears to be higher for the latter. The highest returns for non-routine analytical skills are observed in Bogotá, Bucaramanga, and Pereira.

For the other three skills, the sign and magnitude of the coefficients vary significantly across cities. The premium for routine manual skills is positive in most cities, with the exception of Bogotá, among others. Meanwhile, the coefficients for routine cognitive skills exhibit less variability in magnitude. Overall, the evidence suggests that skill composition significantly influences wage levels, with non-routine skills generally leading to higher wages. Similar to Elvery (2010), our results remark that differences in skill returns may be a significant factor in explaining regional wage disparities. The specialization index also provides insights into the sign and magnitude of the coefficients. This closely aligns with Ridhwan (2021), who shows that urban density and industrial specialization contribute significantly to spatial wage differentials.

Source: Authors' calculations based on GEIH 2019.

Understanding both the direction and magnitude of skill premiums is crucial for grasping labor market equilibrium. To explore this issue, Fig. 7 in the Appendix illustrates the relationship between the coefficients of variables of interest and population density. Although weak, the relationship between returns to non-routine analytical skills and population density is positive, indicating that agglomeration is associated with higher returns for these skills. Similar findings are also reported by Neves et al. (2017). This may be explained by the higher sophistication of local economies, which generate stronger complementarities between labor and capital. Conversely, higher levels of agglomeration are associated with lower returns to non-routine interpersonal skills. These skills are often more prevalent in service-oriented occupations, which tend to be linked to higher levels of informality. A

⁹ Following official definition in Colombia, informal workers are those in firm up to five workers.

¹⁰ The data associated in the illustration corresponds to the average salary of the occupation at the national level.

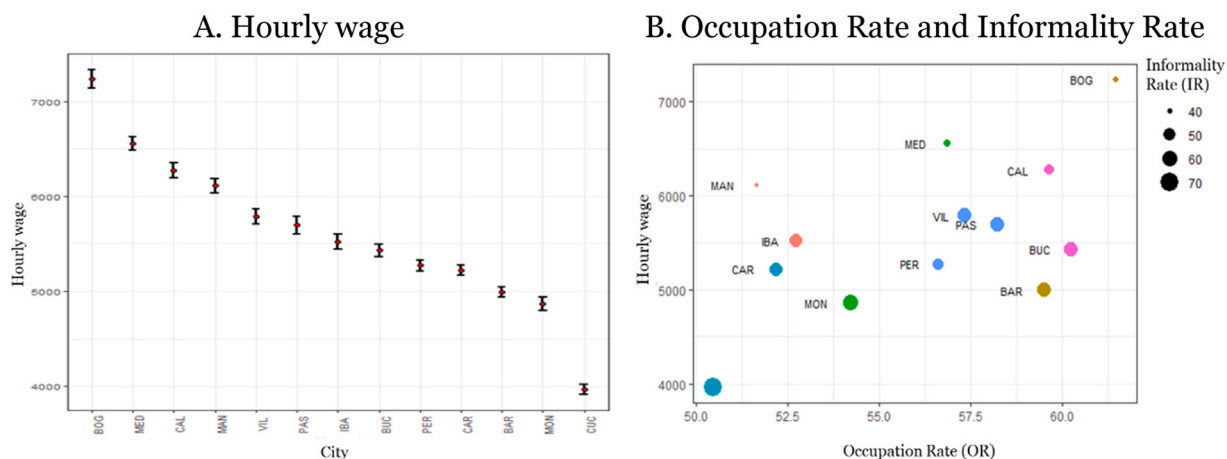


Fig. 2. Wages and labor market indicators by cities. Note: BAR: Barranquilla AM, BOG: Bogotá D.C., BUC: Bucaramanga AM, CAL: Cali AM, CAR: Cartagena, CUC: Cúcuta AM, IBA: Ibagué, MAN: Manizales AM, MED: Medellín AM, MON: Montería, PAS: Pasto, PER: Pereira AM, VIL: Villavicencio.

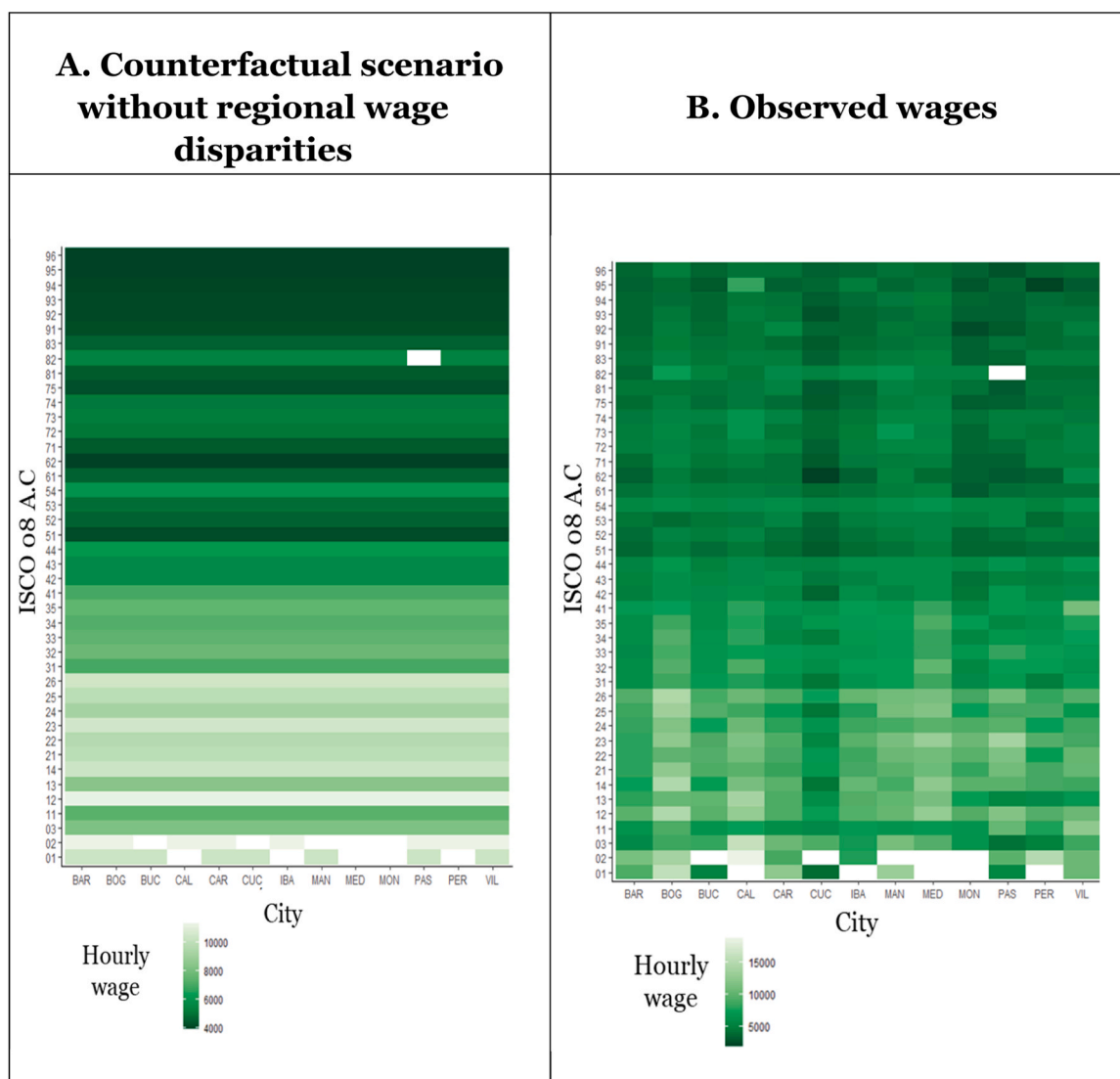


Fig. 3. Hourly wage by occupation and city. Note: the 2-digit ISCO 08 codes used are presented in Fig. 1. The blank entry boxes associated with occupations in the illustration indicate that salary information for those occupations is not available in certain cities. BAR: Barranquilla AM, BOG: Bogotá D.C., BUC: Bucaramanga AM, CAL: Cali AM, CAR: Cartagena, CUC: Cúcuta AM, IBA: Ibagué, MAN: Manizales AM, MED: Medellín AM, MON: Montería, PAS: Pasto, PER: Pereira AM, VIL: Villavicencio.

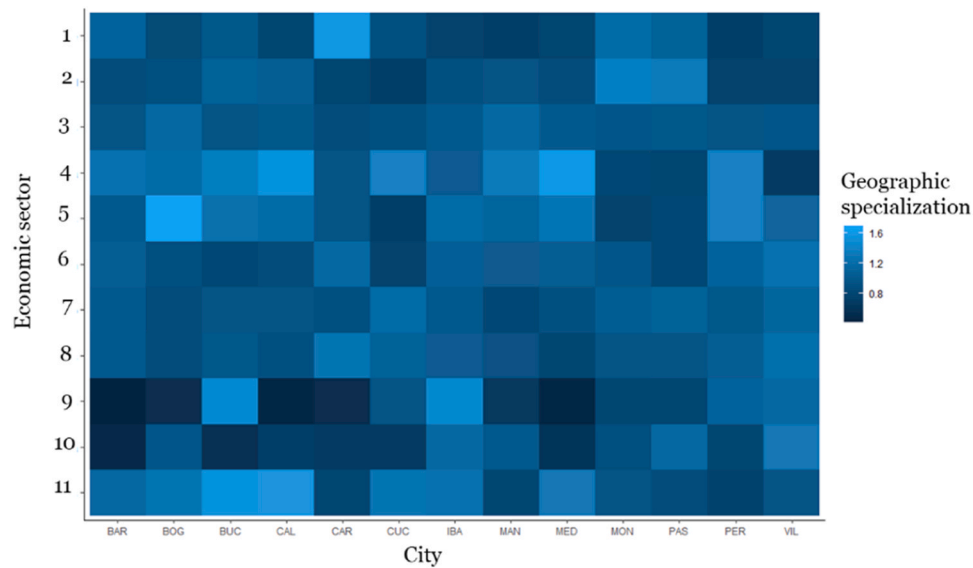


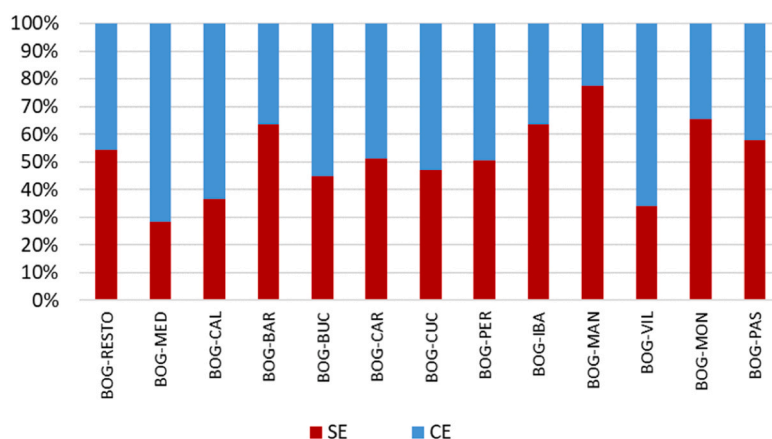
Fig. 4. Specialization index by city. Note: The economic sector: 1. Transport, 2. Health, 3. Other services, 4. Industry, 5. Financial, 6. Construction, 7. Trade, 8. Accommodation and meals, 9. Agriculture and mine, 10. Public administration, 11. Activities Households. BAR: Barranquilla AM, BOG: Bogotá D.C., BUC: Bucaramanga AM, CAL: Cali AM, CAR: Cartagena, CUC: Cúcuta AM, IBA: Ibagué, MAN: Manizales AM, MED: Medellín AM, MON: Montería, PAS: Pasto, PER: Pereira AM, VIL: Villavicencio.

Source: Authors' calculations based on GEIH 2019.

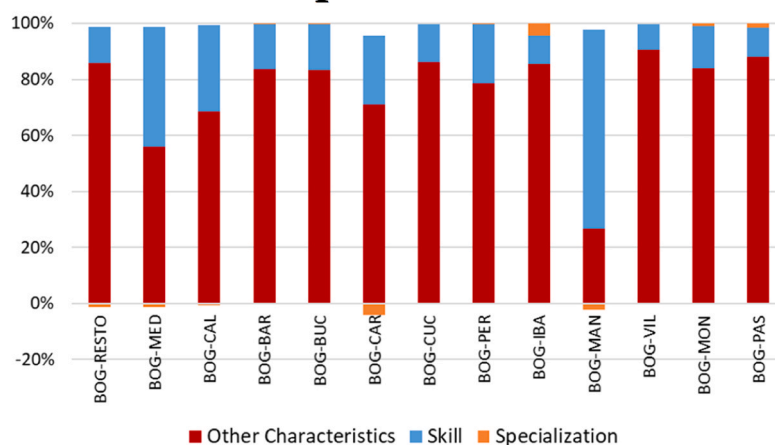


Fig. 5. Estimates coefficients for skills and specialization. Note: BAR: Barranquilla AM, BOG: Bogotá D.C., BUC: Bucaramanga AM, CAL: Cali AM, CAR: Cartagena, CUC: Cúcuta AM, IBA: Ibagué, MAN: Manizales AM, MED: Medellín AM, MON: Montería, PAS: Pasto, PER: Pereira AM, VIL: Villavicencio.

A. Aggregate decomposition



B. Composition effect



C. Structure effect

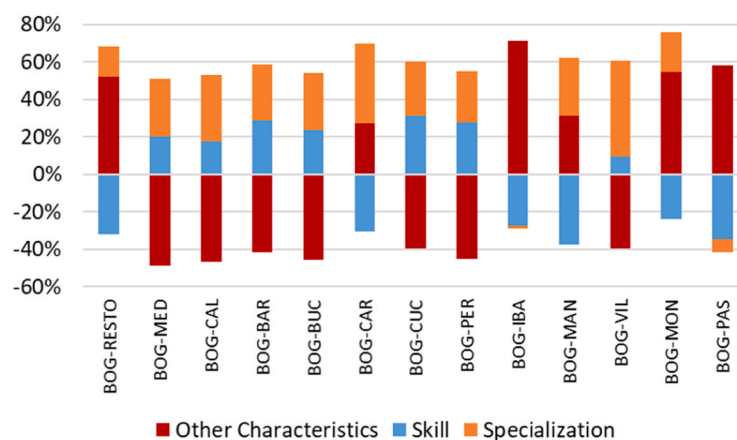


Fig. 6. Results of the Oaxaca-Blinder Decomposition. Note: CE is the Composition Effect and SE refers to Structure Effect. Barranquilla AM, BOG: Bogotá D.C., BUC: Bucaramanga AM, CAL: Cali AM, CAR: Cartagena, CUC: Cúcuta AM, IBA: Ibagué, MAN: Manizales AM, MED: Medellín AM, MON: Montería, PAS: Pasto, PER: Pereira AM, VIL: Villavicencio.

Source: authors' work using GEIH 2019.

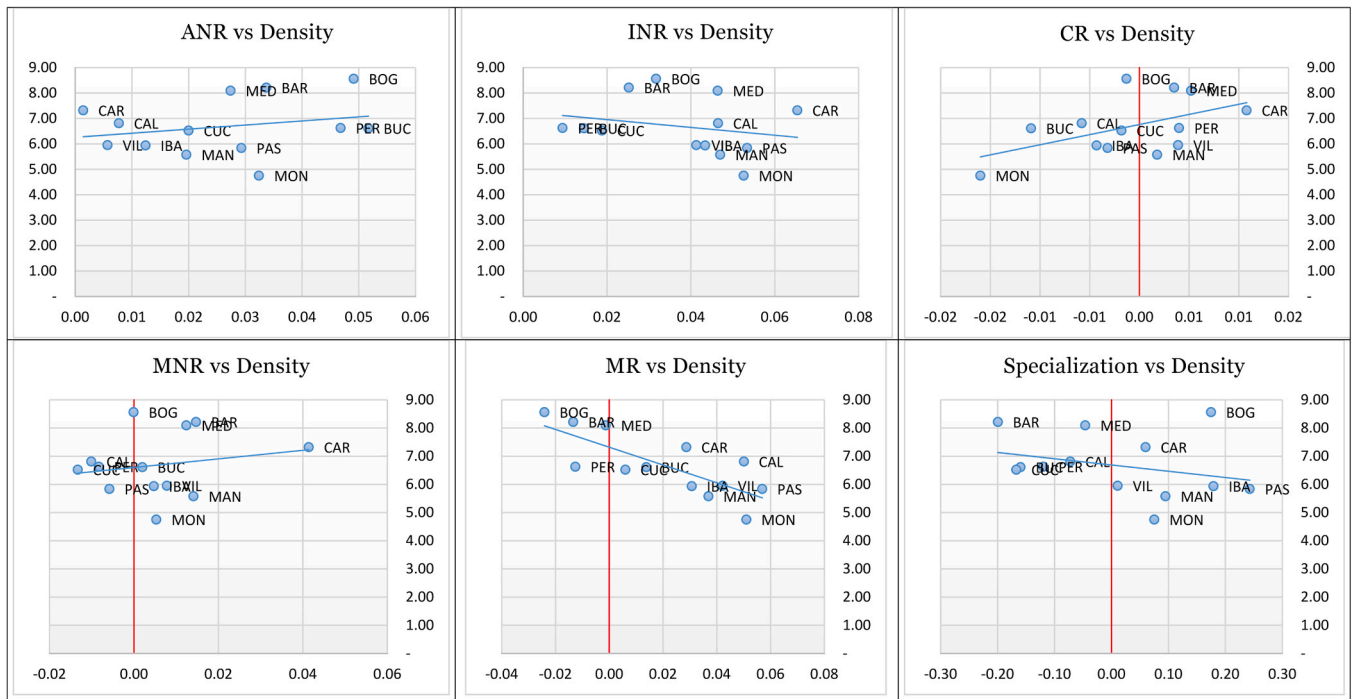


Fig. 7. Wage premium and population density. Note: Population density is calculated as the total population of an area divided by its surface area in square kilometers (km²). ANR= Non-Routine Analytical, INR= Non-Routine Interactive, CR= Routine Cognitive, MR= Routine Manual, MNR= Non-Routine Manual, Geographic specialization index.

Source: Authors' calculations based on GEIH 2019.

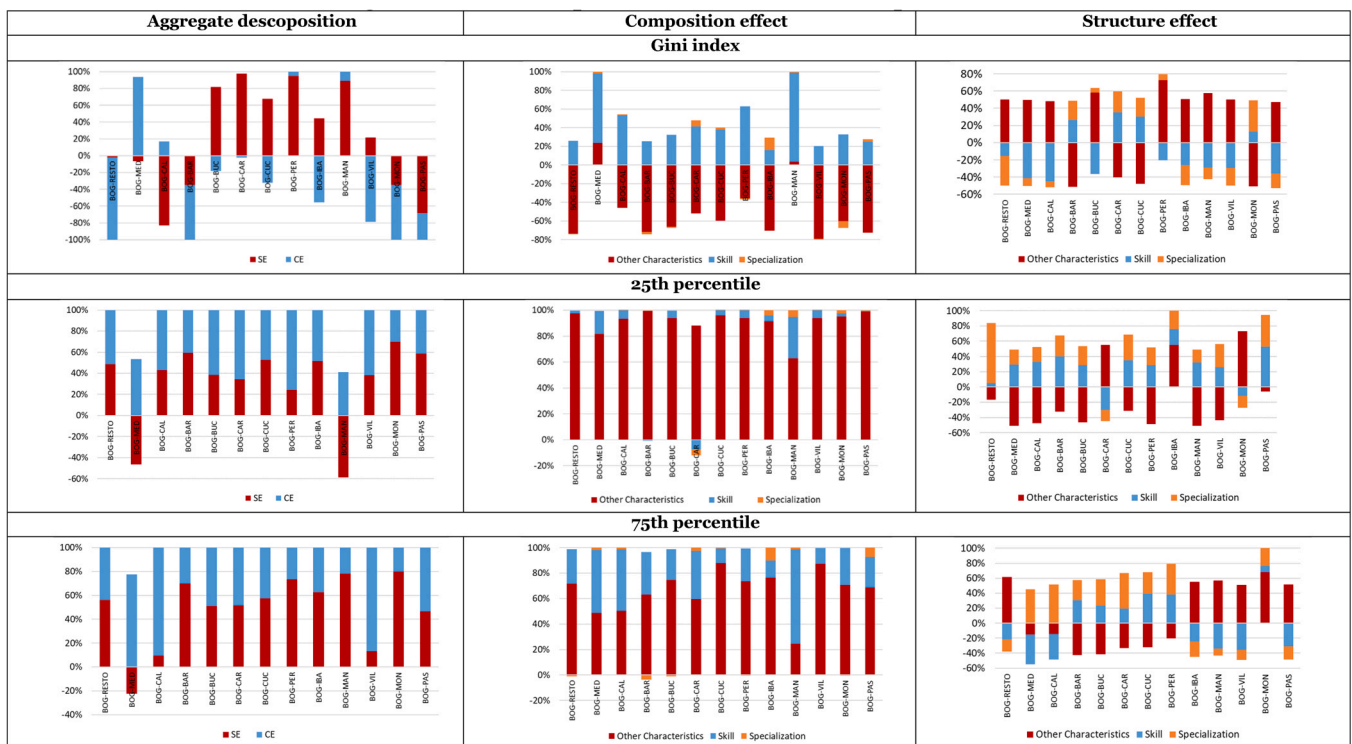


Fig. 8. RIF decomposition for Gini index and quartiles. Note: CE is the Composition Effect and SE refers to Structure Effect. Barranquilla AM, BOG: Bogotá D.C., BUC: Bucaramanga AM, CAL: Cali AM, CAR: Cartagena, CUC: Cúcuta AM, IBA: Ibagué, MAN: Manizales AM, MED: Medellín AM, MON: Montería, PAS: Pasto, PER: Pereira AM, VIL: Villavicencio.

Source: authors' work using GEIH 2019.

similar pattern is observed with routine manual skills. Finally, returns to specialization appear to be unrelated to agglomeration levels. These results suggest that high population density often enhances productivity through agglomeration economies, but this effect is not solely explained by specialization patterns.

5. Decomposition of regional wage disparities

Using Oaxaca-Blinder decomposition techniques, we analyze the factors influencing regional wage disparities by comparing each city to Bogotá. The aggregated decomposition reveals that both the structure effect and the composition effect are significant for all comparisons (see Fig. 6 and Table 6 in the Appendix). Notably, for all cities, both components are relevant. This implies that even if the populations between cities were identical (i.e., the composition effect were zero), persistent wage differences would still exist due to variations in returns. Combes et al. (2008) also document the role of skills in explaining wage disparities. Importantly, the structure effect is less pronounced in labor markets that are more similar, such as Bogotá, Medellín, and Cali, which means that returns to workers characteristics are more similar among these cities.

Each of these components is further broken down to assess the relevance of the variables of interest, allowing for a comparison of the significance of skills and sectoral specialization to determine regional wage gaps. In general, the specialization index appears less relevant in terms of the composition effect, though it does play a role in terms of structure effect. This suggests that differences in specialization patterns contribute relatively little to explaining the regional wage gap compared to differences in returns, which show magnitudes similar to the relative importance of skills returns. Specifically, differences in specialization returns tend to increase wage disparities relative to Bogotá. In contrast, skill premiums are more heterogeneous. In other words, the returns on skills widen the regional wage gap in cities such as Medellín, Cali, and Barranquilla, but reduce the gap in others like Cartagena, Manizales, or Pasto.

Although the differences in average wages help to understand the role of skills and city specialization, these results may vary across the wage distribution. For example, skills may play a more significant role at the upper end of the wage scale, and wage inequality might depend more on skills than on specialization patterns. To address these questions, the Oaxaca-Blinder decomposition is applied using RIF function regressions, which allows for the decomposition of the Gini index and the quartiles of the wage distribution. Fig. 7

Regarding the Gini index (see Fig. 8), the disparities compared to Bogotá are varied. Specifically, Bogotá exhibits higher inequality than cities like Medellín, Bucaramanga, Cartagena, but lower inequality than Cali, Barranquilla, Montería, or Pasto. Interestingly, it is observed that the structure effect accounts for the higher inequality in Bogotá compared to other cities. In contrast, for cities with higher inequality than Bogotá, the demographic composition of workers plays a more substantial role. In fact, differences in skills composition tend to increase the Gini index disparities relative to Bogotá.

As expected, the wage quartiles in Bogotá tend to be higher than in other cities. In this case, the result remains consistent, indicating that specialization emerges as an important factor in the structure effect, meaning that differences in the returns to specialization matter. Regarding skills, their role primarily influences the structure effect, which generally depends on the other characteristics of the worker. As Zapata-Román (2021) and Ballon and Dávalos (2020) highlight in the case of Chile and Peru, understanding wage dispersion requires attention to the specific skills and tasks embedded in occupations.

6. Concluding remarks

This paper aims to examine regional wage disparities in Colombia, focusing on the roles of worker skills and specialization patterns as key drivers. Our findings support the idea that wage differences between regions are not only persistent at the aggregate level, but also exhibit notable variations across occupation. Considering that wages are determined by skill returns and demand-side factors such as specialization, we investigated the relevance of these factors in regional disparities. In particular, skills can yield varying returns in the labor market depending on the demand for specific capabilities and their contribution to worker productivity. These conditions can differ between local markets due to the influence of agglomeration economies and regional specialization levels. Therefore, a relevant question is to quantify the returns on skills and how their differences explain regional disparities.

To this end, we applied Oaxaca-Blinder decompositions. This technique allows us to analyze wage disparities by separating the portion attributed to differences in labor force characteristics, tasks and skills, and specialization from the portion attributed to differences in the returns to these characteristics. The results reveal that while worker characteristics contribute substantially to regional wage gaps, both skills and specialization are also important factors. Specifically, returns to specialization and differences in skill composition are found to be significant.

The results suggest that to design more effective public policies aimed at reducing salary disparities between cities, it is insufficient to simply increase the number of years of education for workers. It is essential to also assess the type of skills being developed and to promote local sectoral specialization. Public policy can address various interrelated factors to mitigate the negative effects of skill mismatch and leverage potential opportunities. For instance, individuals often make educational and occupational choices with incomplete information about the economic returns, which contributes to a skills mismatch. Additionally, wages may not fully reflect the market value of skills, and adjusting the supply of skills is both time-consuming and costly. Therefore, enhancing higher education, strengthening job training programs, and improving labor market flexibility, along with ensuring the sustainability of the social security system, are crucial institutional pillars for addressing these issues.

Finally, in developing countries, the challenge is exacerbated by the persistence of informal employment relationships, which are characterized by low productivity and serve as an alternative for vulnerable groups facing unemployment. In this context, skills gaps can significantly contribute to higher informality and affect the quality of employment. This is further evidenced by ongoing discussions about labor relations within collaborative economy platforms.

CRedit authorship contribution statement

Andres García-Suaza: Writing – review & editing, Writing – original draft. **Diana Londoño Ms:** Writing – review & editing, Writing – original draft.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Andres Garcia-Suaza reports financial support was provided by Colombian Ministry of Science through the Alianza EFI Research Program (Project Code 60185, Contract #FP44842-220-2018), funded by The World Bank. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table 2

Description of task Categories

Source: Autor et al. (2006)

Types of Tasks	Measured by ...	Examples skills/activities
Non-routine analytical tasks	General educational development, mathematics.	Lowest level: adds and subtracts 2-digit numbers; performs operations with units such as cup, pint, and quart. Medium level: calculates discount, interest, profit, and loss; Inspects flat glass and compiles sample-based defect data to determine variances from acceptable quality limits. Highest Level: Performs and supervises aerodynamic and thermodynamic systems analyses to determine design adequacy for aircraft and missiles, etc.
Non-routine interactive (interpersonal) tasks	Adaptability to accept responsibility for directing, controlling, or planning an activity.	Plans and designs private residences, office buildings, factories, and other structures; Applies accounting principles to install and maintain the operation of the general accounting system; Carries out legal actions in court proceedings; Collects and analyzes evidence, reviews relevant decisions; etc.
Routine cognitive tasks	Adaptability to situations that require the precise achievement of established limits, tolerances, or standards	Operates a billing machine to transcribe data from office records; Calculates degrees, minutes, and seconds of latitude and longitude using standard navigation aids; Measures bottle dimensions using gauges and micrometers to verify bottle manufacturing setup meets manufacturing specifications; Prepares and verifies voter lists from official registration records; etc.
Routine manual tasks	Ability to move the fingers and manipulate small objects with the fingers, quickly or precisely. Skills that influence strength, endurance, flexibility, balance, and coordination.	Mixes and bakes ingredients according to recipes; Hangs fasteners and decorative trim for items; Operates the tabulation machine that processes the data from the tabulation cards into printed records; Packs produce such as bulbs, fruits, nuts, eggs, and vegetables for storage or shipping; etc.
Non-routine manual tasks	Ability to move the hand and foot in coordination with each other according to visual stimuli.	Lowest level: Has machine that crimps eyelets; Medium level: Takes care of the beef cattle on the ranch; Drives the bus to transport passengers; Pick plums from ornamental and shade trees. Highest Level: Performs gymnastic feats of skill and balance.

Table 3

Skill intensity index for occupations classified under ISCO 08 A.C

Code	Principal Subgroup	Non-Routine Analytical Index	Non-Routine Interactive Index	Routine Cognitive Index	Routine Manual Index	Non-Routine Manual Index
01	Military Forces Officers	2.13	1.11	1.07	2.53	3.28
02	Military Forces Sub-Officers	2.13	1.11	1.07	2.53	3.28
03	Other members of the military	2.13	1.11	1.07	2.53	3.28
11	Executive directors, senior administrative staff, and legislators	5.16	6.97	0.69	2.83	0.44
12	Administrative and commercial directors	5.42	8.11	0.70	2.68	0.18
13	Directors and managers in the production and service sectors	5.22	8.01	1.03	2.85	0.60
14	Managers of hotels, restaurants, shops, and other services	5.33	8.06	0.52	2.80	0.35
21	Science and engineering professionals	7.80	5.15	6.62	4.55	1.11
22	Healthcare professionals	6.21	3.33	4.78	6.27	1.31
23	Education professionals	5.51	6.94	0.89	3.07	0.49
24	Business and management professionals	5.66	6.09	2.20	2.80	0.26
25	Information and communications technology professionals	6.65	5.78	5.26	2.62	0.21
26	Professionals in law, social, and cultural sciences	5.36	4.60	1.04	3.02	0.57
31	Technicians and professionals at the middle level of science and engineering	4.77	2.02	7.21	4.28	1.59
32	Mid-level health technicians and professionals	4.14	0.93	5.73	4.80	2.01
33	Mid-level technicians and professionals in finance and administration	4.55	3.58	3.12	3.42	0.53
34	Mid-level technicians and professionals in legal, social, cultural, and related services	3.28	3.42	1.66	3.95	2.20
35	Technicians in information and communications technology	5.45	4.34	5.36	3.51	0.32
41	Office workers	3.28	0.91	5.87	5.11	0.08
42	Employees dealing directly with the public	3.03	1.15	3.61	4.06	0.26
43	Accounting assistants and those in charge of registering materials	3.51	1.71	5.95	3.81	0.11
44	Other administrative support staff	2.22	0.46	4.67	3.81	0.37
51	Personal service workers	2.61	1.50	1.45	3.04	1.81

(continued on next page)

Table 3 (continued)

Code	Principal Subgroup	Non-Routine Analytical Index	Non-Routine Interactive Index	Routine Cognitive Index	Routine Manual Index	Non-Routine Manual Index
52	Sellers	2.95	1.39	1.14	3.26	1.02
53	Personal care workers	3.35	2.75	3.27	4.37	1.44
54	Protection services staff	1.93	1.15	0.87	2.52	2.93
61	Farmers and skilled farm workers	3.06	4.33	1.54	2.95	2.23
62	Skilled forest workers, fishers, and hunters in market-oriented activities	2.04	2.64	1.60	2.84	2.58
71	Construction officials and workers (excluding electricians)	3.35	1.06	8.00	4.46	2.37
72	Officials and operators of the metallurgy; mechanics and repairers of machines and related	3.49	0.57	8.25	4.33	1.61
73	Artisans and operators of the graphic arts and related	2.74	0.70	7.16	5.75	1.09
74	Officials and operators of electricity and electronics	4.83	1.09	8.64	4.89	2.19
75	Officials and operators of food processing, clothing, cabinetmakers, and related	2.45	0.83	6.51	4.24	1.70
81	Operators of fixed installations and machines	1.49	0.20	6.69	3.79	1.27
82	Assemblers	1.21	0.01	6.97	4.43	0.57
83	Vehicle drivers and mobile heavy equipment operators	1.81	1.52	2.61	2.82	3.78
91	Domestic and cleaning staff	0.79	0.55	0.83	2.87	1.44
92	Agricultural, fishing, and forestry workers and laborers	2.24	2.82	2.42	3.09	2.56
93	Workers and laborers in mining, construction, manufacturing, and transportation	1.35	0.21	4.47	3.36	1.77
94	Food preparation helpers	1.69	0.46	2.78	3.19	1.05
95	Street vendors of services and related	2.53	0.25	0.07	2.85	2.63
96	Garbage collectors and other elementary occupations	1.36	0.22	3.01	3.06	2.25

Source: Authors' calculations based on GEIH 2019.

Table 4

Labor market indicators for the 13 urban areas

City	Total Population	Working age population	Labor force	Employed	Formal workers	Informal workers	OR	UR	IR	Hourly Wage
BOG	8264,020	6810,542	4698,377	4186,301	2485,410	1700,892	61.47	10.90	40.63	7235
MED	3773,109	3193,306	2067,926	1815,349	1060,022	755,327	56.85	12.21	41.61	6555
MAN	424,653	359,525	210,891	185,671	111,902	73,770	51.64	11.96	39.73	6111
CAL	2547,162	2105,008	1434,013	1255,227	682,108	573,119	59.63	12.47	45.66	6273
VIL	503,406	401,300	264,466	230,094	101,877	128,217	57.34	13.00	55.72	5788
BUC	1095,988	915,856	614,192	551,611	246,628	304,983	60.23	10.19	55.29	5431
PER	636,463	528,784	328,148	299,289	157,358	141,931	56.60	8.79	47.42	5274
CAR	1005,959	816,273	457,133	425,816	200,531	225,285	52.17	6.85	52.91	5222
IBA	543,555	443,218	279,232	233,666	111,412	122,254	52.72	16.32	52.32	5525
PAS	386,455	323,386	210,644	188,328	82,892	105,436	58.24	10.59	55.99	5696
MON	362,747	290,592	180,760	157,527	65,413	92,114	54.21	12.85	58.47	4867
BAR	1914,925	1545,359	997,803	919,522	403,911	515,611	59.50	7.85	56.07	4995
CUC	847,608	678,735	406,773	342,524	98,766	243,758	50.47	15.79	71.17	3964

Hourly Wage in Colombian pesos. BAR: Barranquilla AM, BOG: Bogotá D.C., BUC: Bucaramanga AM, CAL: Cali AM, CAR: Cartagena, CUC: Cúcuta AM, IBA: Ibagué, MAN: Manizales AM, MED: Medellín AM, MON: Montería, PAS: Pasto, PER: Pereira AM, VIL: Villavicencio. OR: Occupation rate, UR: unemployment rate, IR: Informality rate

Source: Authors' calculations based on GEIH 2019.

Table 5
Estimation of the wage equation

Variables	POOL	BOG	MED	CAL	BAR	BUC	CAR	CUC	PER	IBA	MAN	VIL	PAS	MON
	Log Wage hour	Log Wage hour	Log Wage hour	Log Wage hour	Log Wage hour	Log Wage hour	Log Wage hour	Log Wage hour	Log Wage hour	Log Wage hour	Log Wage hour	Log Wage hour	Log Wage hour	Log Wage hour
Age	0.031*** (0.001)	0.0305*** (0.002)	0.0298*** (0.002)	0.0316*** (0.003)	0.0291*** (0.002)	0.0346*** (0.002)	0.0256*** (0.002)	0.0321*** (0.002)	0.0307*** (0.002)	0.0321*** (0.003)	0.0265*** (0.002)	0.0342*** (0.003)	0.0343*** (0.003)	0.0331*** (0.002)
Age ²	−0.000*** (0.000)	−0.0003*** (0.000)	−0.0003*** (0.000)	−0.0003*** (0.000)	−0.0003*** (0.000)	−0.0004*** (0.000)	−0.0002*** (0.000)	−0.0003*** (0.000)	−0.0003*** (0.000)	−0.0003*** (0.000)	−0.0003*** (0.000)	−0.0004*** (0.000)	−0.0003*** (0.000)	−0.0003*** (0.000)
Self employmente	−0.101*** (0.003)	−0.0913*** (0.014)	−0.0652*** (0.014)	−0.0504*** (0.015)	−0.0503*** (0.014)	−0.0946*** (0.014)	−0.1553*** (0.013)	−0.2051*** (0.017)	−0.1104*** (0.014)	−0.0983*** (0.017)	−0.0211 (0.014)	−0.0164 (0.015)	−0.1204*** (0.014)	−0.1306*** (0.016)
Women	−0.133*** (0.003)	−0.0835*** (0.011)	−0.0899*** (0.010)	−0.1003*** (0.012)	−0.1685*** (0.012)	−0.1345*** (0.011)	−0.1701*** (0.010)	−0.1421*** (0.012)	−0.1059*** (0.011)	−0.1210*** (0.014)	−0.0949*** (0.011)	−0.1127*** (0.014)	−0.1405*** (0.012)	−0.1836*** (0.013)
Year of Education	0.050*** (0.000)	0.0593*** (0.002)	0.0551*** (0.002)	0.0573*** (0.002)	0.0465*** (0.002)	0.0377*** (0.002)	0.0380*** (0.002)	0.0312*** (0.002)	0.0450*** (0.002)	0.0473*** (0.002)	0.0483*** (0.002)	0.0522*** (0.002)	0.0536*** (0.002)	0.0465*** (0.002)
Formal	0.357*** (0.003)	0.2880*** (0.013)	0.3328*** (0.012)	0.3493*** (0.015)	0.3799*** (0.014)	0.3482*** (0.013)	0.3410*** (0.014)	0.3918*** (0.018)	0.2366*** (0.012)	0.3644*** (0.015)	0.2497*** (0.013)	0.3774*** (0.014)	0.3981*** (0.014)	0.4133*** (0.016)
Non-Routine Analytical	0.025*** (0.002)	0.0491*** (0.008)	0.0274*** (0.007)	0.0077 (0.010)	0.0337*** (0.008)	0.0517*** (0.009)	0.0014 (0.008)	0.0200** (0.010)	0.0468*** (0.008)	0.0124 (0.010)	0.0196** (0.008)	0.0057 (0.010)	0.0293*** (0.010)	0.0324*** (0.010)
Non-Routine Interactive	0.044*** (0.001)	0.0317*** (0.006)	0.0464*** (0.006)	0.0465*** (0.007)	0.0252*** (0.007)	0.0145** (0.007)	0.0654*** (0.006)	0.0188** (0.008)	0.0094 (0.006)	0.0434*** (0.007)	0.0470*** (0.006)	0.0413*** (0.008)	0.0534*** (0.008)	0.0526*** (0.008)
Routine Cognitive	−0.004*** (0.001)	−0.0013 (0.003)	0.0052* (0.003)	−0.0058 (0.004)	0.0035 (0.003)	−0.0109*** (0.003)	0.0108*** (0.003)	−0.0018 (0.004)	0.0040 (0.003)	−0.0043 (0.004)	0.0018 (0.003)	0.0039 (0.004)	−0.0032 (0.004)	−0.0160*** (0.004)
Routine Manual	0.027*** (0.003)	−0.0241** (0.011)	−0.0013 (0.011)	0.0501*** (0.014)	−0.0134 (0.012)	0.0138 (0.012)	0.0287** (0.011)	0.0060 (0.015)	−0.0126 (0.011)	0.0307** (0.015)	0.0369*** (0.012)	0.0422*** (0.015)	0.0569*** (0.013)	0.0510*** (0.014)
Non-Routine Manual	0.004*** (0.001)	−0.0001 (0.005)	0.0124** (0.005)	−0.0101 (0.006)	0.0147*** (0.005)	0.0020 (0.006)	0.0414*** (0.005)	−0.0133** (0.007)	−0.0083 (0.006)	0.0047 (0.007)	0.0141** (0.005)	0.0078 (0.007)	−0.0058 (0.007)	0.0053 (0.006)
Geographic Specialization Index	0.115*** (0.005)	0.1750*** (0.026)	−0.0460*** (0.015)	−0.0722*** (0.022)	−0.1994*** (0.037)	−0.1595*** (0.028)	0.0601*** (0.018)	−0.1670*** (0.028)	−0.1195*** (0.026)	0.1793*** (0.056)	0.0950*** (0.025)	0.0110 (0.033)	0.2430*** (0.042)	0.0754** (0.037)
Constant	6.848*** (0.014)	6.7924*** (0.060)	6.9853*** (0.054)	6.8757*** (0.067)	7.1290*** (0.071)	7.1824*** (0.064)	7.0021*** (0.058)	7.2914*** (0.075)	7.2458*** (0.062)	6.7008*** (0.092)	6.8916*** (0.059)	6.7789*** (0.078)	6.2998*** (0.067)	6.5288*** (0.062)
Area Fixed Effects	YES	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Observations	205,964	11,961	14,771	10,056	14,192	9514	9414	7646	8757	7886	8852	8129	8285	8049
R-squared	0.420	0.418	0.375	0.341	0.298	0.357	0.454	0.378	0.339	0.380	0.392	0.354	0.514	0.472

Note: Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. First column refers to pool regression including all cities.

Source: Authors' calculations based on GEIH 2019.

Table 6
Estimation of the Oaxaca- Blinder decomposition

Área Urbana	BOG- RESTO	BOG- MED	BOG- CAL	BOG- BAR	BOG- BUC	BOG- CAR	BOG- CUC	BOG- PER	BOG- IBA	BOG- MAN	BOG- VIL	BOG- MON	BOG- PAS
Total Difference	0.258	0.066	0.129	0.346	0.217	0.222	0.532	0.221	0.238	0.085	0.205	0.378	0.270
Total Explained	0.118	0.047	0.082	0.127	0.120	0.109	0.282	0.110	0.087	0.019	0.135	0.131	0.114
Total Unexplained	0.141	0.019	0.047	0.220	0.097	0.113	0.250	0.111	0.151	0.066	0.070	0.247	0.157
Total Explained skills	0.016	0.021	0.026	0.020	0.020	0.030	0.038	0.023	0.009	0.014	0.012	0.020	0.012
Non-Routine Analytical	0.0046	0.0074	0.0097	0.0090	0.0126	0.0113	0.0154	0.0123	0.0038	0.0057	0.0038	0.0091	0.0046
Non-Routine Interactive	0.0113	0.0139	0.0154	0.0123	0.0073	0.0220	0.0228	0.0104	0.0054	0.0092	0.0081	0.0115	0.0072
Routine Cognitive	-0.0002	-0.0004	-0.0001	0.0000	-0.0001	0.0006	0.0000	0.0000	-0.0003	-0.0001	0.0008	-0.0012	-0.0003
Routine Manual	0.0004	0.0002	0.0001	0.0000	-0.0002	0.0000	-0.0003	0.0005	-0.0001	0.0001	-0.0001	0.0000	-0.0001
Non-Routine Manual	-0.0005	-0.0004	0.0005	-0.0009	-0.0001	-0.0043	0.0002	-0.0001	-0.0002	-0.0005	-0.0006	0.0003	0.0006
Total Explained Geographic Specialization	-0.0014	-0.0006	-0.0005	0.0003	0.0003	-0.0051	-0.0006	0.0004	0.0039	-0.0005	-0.0006	0.0011	0.0017
Total Explained Other Characteristics	0.104	0.027	0.057	0.106	0.100	0.084	0.245	0.086	0.075	0.005	0.124	0.110	0.100
Total Unexplained skills	-0.122	0.150	0.126	0.372	0.267	-0.087	0.380	0.308	-0.098	-0.100	0.032	-0.114	-0.323
Non-Routine Analytical	0.0878	0.0716	0.1327	0.0507	-0.0092	0.1509	0.0918	0.0070	0.1217	0.0972	0.1438	0.0548	0.0660
Non-Routine Interactive	-0.0276	-0.0319	-0.0310	0.0120	0.0364	-0.0697	0.0179	0.0445	-0.0256	-0.0329	-0.0214	-0.0443	-0.0475
Routine Cognitive	0.0047	-0.0221	0.0151	-0.0161	0.0323	-0.0398	0.0016	-0.0180	0.0100	-0.0104	-0.0171	0.0473	0.0065
Routine Manual	-0.1818	-0.0805	-0.2607	-0.0376	-0.1336	-0.1840	-0.1057	-0.0406	-0.1926	-0.2165	-0.2318	-0.2647	-0.2862
Non-Routine Manual	-0.0053	-0.0172	0.0139	-0.0212	-0.0029	-0.0656	0.0193	0.0120	-0.0066	-0.0197	-0.0109	-0.0085	0.0081
Total Unexplained Geographic Specialization	0.0617	0.2296	0.2562	0.3846	0.3437	0.1217	0.3551	0.3027	-0.0046	0.0826	0.1696	0.1020	-0.0695
Total Unexplained Other Characteristics	0.201	-0.360	-0.335	-0.537	-0.513	0.078	-0.485	-0.499	0.254	0.083	-0.132	0.258	0.549

Source: Authors' calculations based on GEIH 2019.

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