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Labor Income Effects of External Shock in Emerging Markets: Factors Explaining the Decline During the COVID-19 Pandemic in Ecuador

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Abstract

This study examines labour earnings dynamics across Ecuador's income distribution during the COVID-19 pandemic and the 2021 recovery, using recentered influence function regressions. Ecuador's high levels of informal employment, self-employment, and exposure to pandemic-related shocks make it a particularly informative case for Latin America and other economies characterised by widespread labour informality. The analysis applies Oaxaca–Blinder decompositions at the mean and across quantiles to disentangle the contributions associated with worker characteristics, or endowment effects, from those of wage premiums, or wage structure effects. The results show that earnings losses were most severe among lower-income groups and were driven primarily by changes in factor prices rather than by shifts in employment composition. The subsequent U-shaped recovery reflects the combined influence of price and composition effects. Informal self-employment played a central role in these dynamics, as mobility restrictions disrupted its usual countercyclical adjustment mechanism and altered the wage premiums associated with this form of work. Overall, the findings highlight the importance of self-employment wage premiums in explaining post-pandemic earnings trajectories.

Keywords: COVID-19, labor earnings, informal self-employment, Ecuador.
JEL codes: J31, R10, 017.

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1. Introduction

The COVID-19 pandemic triggered the most severe economic crisis in Latin America and the Caribbean since the early twentieth century (Beccaria et al., 2022). Regional GDP contracted by 7.5% (CEPAL, 2023), more than double the global decline of 3.12% (World Bank, 2023). Ecuador entered this crisis amid economic deceleration and persistent structural weaknesses, including high informality and self-employment (Table 1). After a period of strong growth between 2000 and 2014, the economy slowed down, recording negative growth in 2016 and stagnation by 2019 (BCE, 2023). The pandemic struck this fragile economy in March 2020, and prompted a State of Exception and restrictive measures that paralyzed economic activity (Registro Oficial, 2020) and led to an 8.1% contraction in real output (BCE, 2023), one of the most severe contractions in South America.

This paper examines the factors driving changes in labor income distribution in Ecuador during the pandemic and the subsequent recovery in 2021. Understanding the causes of these changes is critical, since labor income determines individuals' access to health, education, and overall living standards (Gachet et al., 2019; Lugo, 2007). In Ecuador, employment dynamics play a central role in shaping labor income outcomes. The economic shock from lockdowns and collapsing demand caused both massive job losses and a sharp contraction in average labor income. Between December 2019 and September 2020, Ecuador lost approximately 520,000 jobs (INEC, 2023).

One defining feature of labor markets in Latin America is the high incidence of informal labor and self-employment, which account for a significant share of total employment (Gasparini and Tornarolli, 2009; Maurizio, 2014). Ecuador's labor market reflects this structure, with pronounced informality and a substantial self-employed sector (Table 1). Historically self-employment in Ecuador has exhibited a countercyclical pattern (Goñi Pacchioni, 2013; Ontaneda Jiménez et al., 2022). However, the COVID-19 crisis was unprecedented: during the early months of the pandemic, strict restrictions prevented self-employment from fulfilling its traditional role as a buffer during economic downturns (Beccaria et al., 2022). By late 2020, the decline in formal employment was accompanied by a relative increase in self-employment, which reflected its countercyclical function in cushioning income shocks.

Nonetheless, these compositional shifts alone fail to fully account for the magnitude of income changes. Between Q4 2019 and May/June 2020, average hourly income fell only slightly for formal wage employees (-0.11 USD), while declines were significantly larger for informal wage workers (-0.62 USD) and the self-employed (-0.93 USD), with self-employment experiencing the most severe contraction among all employment types. By September 2020, formal wage employees showed signs of recovery, whereas average incomes in the informal and self-employment sectors remained below pre-pandemic levels. In fact, for both informal workers and the self-employed, hourly labor income had not returned to pre-pandemic levels even by Q4 2021 (Table 2). These patterns underscore that fully understanding the impact of the crisis requires the examination of price effects, that is, changes in the returns to worker characteristics.

In order to quantify these effects, the paper employs decomposition methods based on recentered influence function regressions (Firpo et al., 2009; Fortin et al., 2011) to estimate the relative importance of various factors in explaining changes in labor earnings across the income distribution. For each explanatory variable, it is determined what can be attributed to observable differences in worker characteristics (the endowment effect) and what is due to differences in premiums associated with those characteristics (the wage structure effect). To this end, the standard Oaxaca-Blinder decomposition is applied to the mean and to several percentiles across the income distribution. The main advantage of this method is that it enables the identification of the contribution of a covariate or groups of variables to income changes observed during the pandemic and post-pandemic years, both at the mean and across other distributional statistics, such as quantiles, thereby offering deeper insights into the underlying effects. This paper uses data from the National Employment and Unemployment Survey (ENEMDU), which is the principal instrument for monitoring labor market dynamics

in Ecuador. By examining differences across education, sector of activity and employment type, the analysis identifies how various groups were differentially affected across the income distribution.

As a contribution to the study of the impact of the crisis on labor markets in developing countries, five labor sectors are analyzed that reflect this key aspect of the developing labor market and the diversity within the informal sector: formal wage employees, upper-tier informal wage employees, lower-tier informal wage employees, formal self-employed, and informal self-employed.

Another key dimension addressed in this paper is that of the pronounced heterogeneity within Ecuador. Regional labor markets differ substantially in both employment levels and quality, reflecting variations in economic structures, educational attainment, and employment formality. These structural differences shape each city's capacity to withstand and recover from economic disruptions such as the COVID-19 pandemic. National averages, therefore, obscure significant disparities in the evolution of urban areas.

Evidence from five major Ecuadorian cities (Cuenca, Quito, Guayaquil, Ambato, and Machala) shows that both the magnitude and timing of income adjustments during the pandemic varied sharply. Formal wage employees experienced only temporary losses and recovered rapidly by 2021, whereas informal wage workers and the self-employed faced income contractions of a more persistent nature. The steepest declines were concentrated among lower-tier informal employees and workers with primary education or limited experience, while university-educated and formally self-employed individuals exhibited greater resilience. These findings underscore the uneven capacity of Ecuador's heterogeneous labor segments to absorb and recover from the pandemic-induced shock.

Regional disparities further influenced these dynamics. Cities with formal and diversified labor markets, such as Quito and Cuenca, were better positioned to absorb the economic shock, while those of higher informality (particularly Guayaquil and Machala) suffered greater income losses (Figueroa Campoverde et al., 2024). The intensity of the crisis also reflected local economic structures: Quito and Guayaquil endured the most severe contractions due to stricter containment measures and heavy dependence on the service sector, whereas Cuenca and Ambato maintained greater stability supported by manufacturing activity and formal wage employment. In contrast, Machala exhibited a delayed but vigorous recovery, largely driven by the expansion of self-employment.

These city-level disparities show that the COVID-19 shock was not a uniform national event, but a set of localized labor market responses shaped by structural and compositional factors. A disaggregated approach is therefore essential. This paper contributes towards understanding the impact of the pandemic on labor markets in developing countries through a detailed analysis of Ecuador's major cities.

The remainder of this article is organized as follows. Section 2 outlines the theoretical framework. Sections 3 and 4 describe the methodology and data. Section 5 presents descriptive trends in labor income, while Section 6 reports the empirical results, and Section 7 concludes.

2. Literature Review

This section briefly presents the most important contributions to the literature that form the foundation of the present study.

The distribution of human capital is considered one of the primary determinants of labor income distribution. The theory of human capital explains that labor incomes are directly influenced by productivity, education, and experience. Becker (1964) and Mincer (1974) established a connection between education and labor incomes by pointing out that individuals' inherent characteristics related to their skills, abilities, and knowledge are sources of income. Furthermore, the research by Mincer (1974) shows that labor income

increases with more years of schooling and work experience due to heightened productivity from investing in human capital. The human capital model therefore implies that the distribution of labor incomes is primarily determined by the level and distribution of education among the population.

Labor informality, where informal jobs typically represent a significant proportion of employment, forms a distinctive feature of labor markets in Latin American countries (Gasparini and Tornarolli, 2009; Maurizio, 2014). According to Maloney (2004) and Perry et al. (2007), there are primarily two perspectives aimed at explaining the existence of labor informality. The first perspective suggests that the informal sector emerges because of the limited capacity of the formal sector to absorb labor, causing individuals to prefer engaging in the informal sector rather than facing unemployment. From the traditional point of view, the existence of a large informal sector constitutes proof of labor market segmentation and is a reflection of the existence of entry barriers to the formal sector, which could be explained by salary rigidities and the presence of unions, among other factors (Bosch and Maloney, 2008, 2010). On the other hand, Perry et al. (2007) point out that certain workers, especially self-employed individuals and micro-entrepreneurs, may voluntarily choose to exit the formal sector based on the value they place on the benefits of formality and the enforcement capacity of the state. Informality is therefore the result of many businesses and individuals voluntarily choosing not to belong to formal institutions. The consensus in the literature suggests that the informal sector is a combination of segmented and self-selected workers (Perry et al., 2007), which implies that there is significant heterogeneity even within the informal sector.

It is worth mentioning that there is currently no consensus on the magnitude of wage gaps between formal and informal workers. The evidence has yielded mixed results. In a study for Mexico, Maloney (1999), when considering self-employed individuals as informal workers, finds that average labor incomes in the informal sector are higher than the wages of formal sector workers. On the other hand, Gasparini and Tornarolli (2009) and Maurizio (2013), when examining wage gaps associated with labor informality in a set of Latin American countries, determine that informal workers experience a significant reduction in their labor incomes compared to formal workers.

Most literature on labor informality examines its cyclical behavior to determine which view dominates. Bosch and Maloney (2008), Bosch and Maloney (2010) and Maloney (2004) find that pro-cyclical transitions from the formal to the informal sector suggest that much of the informal sector, particularly self-employment, is voluntary, while informal salaried work aligns with the traditional view. They argue that informality often arises from inefficiencies in social benefits and non-merit-based promotions, which render informality more attractive.

In Ecuador, Goñi Pacchioni (2013) finds that outflows from formal employment to self-employment are countercyclical, while transitions from self-employment to formal employment are procyclical, which suggests a segmented self-employment sector. Ontaneda Jiménez et al. (2022) later observe that formal employment is procyclical, informal employment is weakly countercyclical, and self-employment rates are countercyclical in response to the business cycle. The inference is that, in response to the negative impact of the pandemic, a decline in formal employment would be observed alongside an increase in self-employment and informal employment. Bosch and Esteban-Pretel (2009) propose a model to understand these results and suggest that, in markets with large informal sectors, economic expansions increase vacancies and company/-worker interactions (meeting effect), which leads to contracts of a more formal nature (offer effect) and boosts formal employment. However, the impact on informal job rates is ambiguous, and the effect on the share of formal employment depends on the strength of job creation in each sector.

2.1. The COVID-19 pandemic and its distributive effect on the labor market

In order to contain the spread of the virus, governments implemented lockdown policies of various degrees. Simultaneously, individuals took their own precautions to avoid contagion. As a result, demand for many goods and services fell drastically. Compounded by the decline in exports, tourism, and capital inflows triggered by the global economic meltdown, these disruptions in domestic demand and supply caused sharp reductions in output, employment, and income (Lustig et al., 2023). The findings suggest a significant decline in employment, working hours, and income due to the sharp economic downturn caused by the pandemic. Projections indicate a global increase in inequality, with the economic impact within a country closely tied to factors such as income, education, location, occupation, age, gender, and race. Workers unable to work remotely faced a greater economic impact, with remote work opportunities increasing at higher wage levels (Narayan et al., 2022).

The forecast suggests that, compared to their pre-shock income, households across the entire income distribution are worse off on average after the pandemic shock. However, simulations indicate that the losses tend to be higher for the middle deciles, which reflects that the poorest and richest households are somewhat more protected from this shock, albeit for different reasons (Lustig et al., 2023). The poorest households have a cushion provided by existing targeted social assistance programs, while households in the highest quintiles enjoy income not at risk: social security pensions, salaries earned in the public sector, and labor earnings of white-collar workers such as CEOs, managers, and researchers with internet access at home (Lustig et al., 2023).

There are striking differences regarding the impacts within countries depending on job and worker characteristics and hence an inequality in the impact of the coronavirus shock. Workers in non-essential sectors were hit harder due to lockdown policies (Clark et al., 2021). There were significant differences in job-loss probabilities between employed and self-employed workers, as well as between employees in different work arrangements. Workers who reported that they could do a large share of their tasks from home were substantially less prone to losing their jobs during the coronavirus outbreak. Employees in permanent contracts and salaried jobs were significantly less likely to lose their jobs compared to employees in other alternative work arrangements (Clark et al., 2021).

In contrast to previous crises, employment losses were largely driven by the pandemic's impact on informal employment and self-employment, which suffered a sharper contraction than formal employment. Nearly all the losses, including those amongst the highest earners, occurred in these sectors (Beccaria et al., 2022; Clark et al., 2021). Income losses disproportionately affected casual workers and self-employed individuals in the non-farm sector, whose livelihoods depend on dense traffic and face-to-face interactions: the factors most impinged upon by mobility restrictions (Narayan et al., 2022). Since formal wage employment, especially in the public sector, tends to provide greater protection against layoffs and wage cuts in developing countries (Narayan et al., 2022), formal employment therefore experienced moderate contraction with smaller losses probably due to expectations of it being a short crisis and to effective corporate strategies. This situation differs from other crises, since pandemic-related restrictions disrupted the traditional adjustment mechanism of informal employment (Beccaria et al., 2022). Furthermore, the employment impacts of the pandemic in countries of upper-middle and high income appear to be associated with the gender, education level, and age of the workers. Previous studies indicate that women and low-skilled workers were significantly more likely to stop working compared to men and to those with a college education. In line with this, Narayan et al. (2022) found that the rate of job loss was higher for the youngest and oldest workers with a college education. Workers in manufacturing, commerce, and other services before the pandemic were also significantly more likely to have stopped working than those in agriculture (Narayan et al., 2022).

As for economic recovery, growth in total employment at the end of 2020 almost exclusively reflected the trends in self-employment and informal wage employment. This indicates that the self-employed and

employees of small businesses were able to resume activities. Part of this job growth may also be explained by the traditional adjustment role that informal employment plays in troubled labor markets (Beccaria et al., 2022). On the other hand, studies such as that by Campos-Vazquez et al. (2021) do not find evidence of a permanent or significant change in the structure of work during this period in Mexico. The results of Campos-Vazquez et al. (2021) indicate that there is a decline in the number of job advertisements, but there is no structural change in labor demand. Although one might have expected that companies would maintain or increase labor demand for telecommuting, the possibilities offered for telecommuting underwent no increase in this period.

In conclusion, the previous literature indicates that the COVID-19 pandemic led to a significant global economic downturn, with governments implementing various degrees of lockdown policies to curb the spread of the virus. This resulted in sharp reductions in output, employment, and income and especially triggered an impact on self-employment and non-wage employment. Notably, formal wage employment saw relatively smaller losses compared to these affected sectors, and recovery trends in total employment were largely influenced by the resilience of self-employment and informal wage employment. Based on this review, the following research questions arise:

RQ1. What were the main factors that contributed to the variations in labor income during the COVID-19 pandemic?

RQ2. What role did different types of employment play in changes to labor income during the pandemic, and is their contribution uniform across the income distribution?

3. Methodology

Due to the COVID-19 pandemic, the distribution and attributes of the labor market workforce, together with their returns, have undergone significant changes. These modifications are expected to influence the distribution of workers' income. In this paper, the approach based on recentered influence function (RIF) regressions is employed as proposed by Firpo et al. (2009) and Fortin et al. (2011) to identify which part of the observed changes in labor income can be attributed to shifts in workforce characteristics and which part corresponds to changes in the wage structure for those characteristics. Moreover, our aim is to determine which specific variables contribute towards explaining the changes observed across the income distribution.

Several methodologies exist for the analysis of wage differences across the distribution. For example, Machado and Mata (2005) extend the Oaxaca-Blinder decomposition to quantile regressions, while DiNardo et al. (1996) use a reweighting procedure to calculate the composition effect of a binary variable. However, these methods either do not decompose wage differences by individual covariate contributions or they depend on the order of covariate inclusion. Our study employs a decomposition method that overcomes these limitations. The main advantage of the RIF-based approach over others is that it provides a detailed decomposition of each covariate's contribution in explaining both the composition effect and the price effect at the mean and at other points in the distribution. This approach also enables us to consider that factors important at the mean of the distribution may not have the same relevance at the lower or upper ends of the distribution, which calls for a detailed analysis of the causes of wage disparities, with an emphasis on specific factors and income ranges.

Following Firpo et al. (2018), the analysis starts with a labor income equation of the following structure:

$$Y_{ti} = X_i'\beta_t + u_{ti}, \quad t = 0, 1 \tag{1}$$

where Y represents the logarithm of labor income per hour and the subscript t refers to the time period. X denotes a vector of covariates of dimension H that determine the labor income of individuals, including: i)

human capital; ii) demographic characteristics; iii) working conditions; and iv) sector of economic activity. β is the parameter price vector of dimension H that measures the relationship between the covariates and the dependent variable. The subscript t refers to time. $\mathbb{E}(u_{ti} \mid X_i, T = t) = 0$.

Following the Oaxaca-Blinder decomposition (OB), the labor income gap between the two periods is defined (Firpo et al., 2018) as:

$$\hat{\Delta}_O^u = \mathbb{E}[Y \mid T = 1] - \mathbb{E}[Y \mid T = 0] \tag{2}$$

This can be reduced to:

$$\hat{\Delta}_O^u = \mathbb{E}[X \mid T = 1]'\beta_1 - \mathbb{E}[X \mid T = 0]'\beta_0$$

Adding and subtracting the term $\mathbb{E}[X \mid T = 1]'\beta_0$ from the previous equation, and replacing expected values with sample averages and parameters with estimators, results in:

$$\hat{\Delta}_O^u = \bar{X}_1'(\hat{\beta}_1 - \hat{\beta}_0) + (\bar{X}_1 - \bar{X}_0)'\hat{\beta}_0 \tag{3}$$

$$\hat{\Delta}_O^u = \hat{\Delta}_P^u + \hat{\Delta}_C^u \tag{4}$$

The term on the left ($\hat{\Delta}_O^u$) indicates the difference between average labor incomes between periods 0 and 1. The first term on the right-hand side ($\hat{\Delta}_P^u$) reflects the portion of this difference due to the different remunerations of the characteristics (wage structure), while the second term ($\hat{\Delta}_C^u$) indicates the portion of the difference due to the dissimilar characteristics of the workers between the periods (composition effect). The detailed decomposition of wage structure and composition can be calculated in terms of the explanatory variables:

$$\hat{\Delta}_P^u = \sum_{h=1}^{H} \bar{X}_{1,h}(\hat{\beta}_{1,h} - \hat{\beta}_{0,h}) \tag{5}$$

$$\hat{\Delta}_C^u = \sum_{h=1}^{H} (\bar{X}_{1,h} - \bar{X}_{0,h})\hat{\beta}_{0,h} \tag{6}$$

where $\bar{X}_{1,h}(\hat{\beta}_{1,h} - \hat{\beta}_{0,h})$ represents the contribution of the h^{th} variable to the wage structure and composition effect, respectively. However, the above decomposition can only be utilized to analyze differences in labor income in the mean income and not across the entire income distribution. The approach used herein is that proposed by Firpo et al. (2009), Firpo et al. (2018), and Fortin et al. (2011) based on the Recentered Influence Function (RIF) to extend the method by Oaxaca and Blinder to distributional statistics, such as inequality measures.

The approach begins with the estimation of a RIF-regression, which is a regression in which the dependent variable is the RIF of the distributional statistic of interest. Consider F_y as the distribution function of y, and $\nu(F_y)$ as the distributional statistic of F_y. The influence function $IF(y; \nu(F_y))$ measures the change in the distributional statistic ν caused by a small change in the distribution F_y (Rios-Avila, 2020). The RIF is defined

as $RIF(y;\nu) = \nu(F_y) + IF(y;\nu)$, and it is understood as the relative contribution that the observation y makes to the construction of ν. $RIF(y;\nu)$ can be modeled as a linear function of explanatory variables X:

$$RIF(y;\nu) = X'\gamma \tag{7}$$

Taking the conditional expectation yields the distributional statistic, since the expectation of the influence function is zero (Fortin et al., 2011):

$$\mathbb{E}[RIF(y;\nu) \mid X] = \nu(F_y) = \mathbb{E}(X')\gamma \tag{8}$$

where γ is a parameter which represents the effect that a unit change in the average value of X ($\mathbb{E}(X')$) exerts on the statistic ν, ceteris paribus. In equivalence with equation (4), $\hat{\Delta}_O^\nu$ can be written as:

$$\hat{\Delta}_O^\nu = \hat{\Delta}_P^\nu + \hat{\Delta}_C^\nu \tag{9}$$

The elements of the detailed decomposition can be calculated equivalently as:

$$\hat{\Delta}_P^\nu = \sum_{h=1}^{H} \bar{X}_{1,h}(\hat{\gamma}_{1h,\nu} - \hat{\gamma}_{0h,\nu}) \tag{10}$$

$$\hat{\Delta}_C^\nu = \sum_{h=1}^{H} (\bar{X}_{1h} - \bar{X}_{0h})\hat{\gamma}_{0h,\nu} \tag{11}$$

This study uses decomposition methods to measure how various factors explain income changes during the pandemic and post-pandemic periods. The advantage of this methodology is that it allows for a detailed decomposition of the factors that explain income changes. What is novel about this approach is that it decomposes observed changes not only at the mean but across the entire income distribution, and hence enables a detailed analysis of the factors that explain income changes at different points in the distribution.

4. Data

The information comes from the ENEMDU, which is the main database for the measurement, monitoring and characterization of the labor market, carried out by the National Institute of Statistics and Censuses (*Instituto Nacional de Estadísticas y Censos* (INEC)). The sample includes public sector employees, private wage earners, domestic workers, the self-employed, and patrons. The sample weights provided by the survey are used in all the analyses. Individuals aged between 15-70 years old are considered.

Data from different rounds of the ENEMDU survey is used. To provide timely information on the labor market during the COVID-19 pandemic, INEC conducted a series of telephone-based surveys beginning in the second quarter of 2020. The main objective of these surveys was to capture the immediate effects of the pandemic on labor market dynamics. Given the constraints of telephone interviews, the questionnaire was shortened to 81 questions, compared to 227 questions in the traditional face-to-face ENEMDU, in order to maintain response rates and minimize respondent fatigue. The May/June 2020 ENEMDU survey is nationally representative and includes data from 37,406 individuals, approximately one-third interviewed in May and two-thirds in June, thereby providing the earliest and most reliable snapshot of labor market conditions at the onset of the pandemic.

Although the May/June 2020 ENEMDU was conducted by telephone due to mobility restrictions, its methodological design ensures the representativeness and comparability of labor market indicators relative to the conventional in-person rounds. The sampling frame and probabilistic design of the ENEMDU were fully preserved from pre-pandemic surveys. Specifically, the telephone sample was drawn from effective households previously interviewed in the December 2019 round, thereby ensuring full continuity with the established sampling structure. These rounds were based on a nationally representative, stratified, two-stage probabilistic sampling design. By relying on this pre-existing and rigorously designed sample, the telephone ENEMDU preserved the same population coverage, representativeness across domains, and sampling weights as the traditional survey. In accordance with CEPAL and ILO recommendations, INEC applied rigorous non-response adjustments, calibration, and balancing procedures to the expansion factors to correct possible coverage and response biases. Furthermore, a comprehensive matching process between the original ENEMDU databases and the telephone survey ensured the traceability and consistency of households and individuals across waves. Collectively, these methodological safeguards confirm that the 2020Q2 ENEMDU data remains statistically representative and comparable with previous face-to-face rounds, regardless of the data collection mode.

Second, the analysis uses data from the September 2020 ENEMDU, a household survey conducted by Ecuador's National Institute of Statistics and Censuses (INEC), which includes 30,317 individual observations. A distinctive feature of Ecuador during this period is that pandemic containment measures remained in place almost continuously throughout 2020. Following the WHO's declaration of COVID-19 as a global pandemic, the government issued multiple states of emergency: first on March 16, 2020, and subsequently renewed on May 15, June 15, August 14, and again on December 21 in the wake of a resurgence of infections. This persistent policy environment makes September 2020 and the fourth quarter of 2020 particularly relevant for the assessment of the effects of the pandemic since they capture both the immediate shock of the initial lockdown and the cumulative impact of prolonged restrictions. The incorporation of this period into the analysis therefore provides a more comprehensive perspective on the magnitude and persistence of COVID-19's impact on Ecuador's labor market.

It should be borne in mind that, unfortunately, the May/June and September 2020 ENEMDU surveys do not provide sufficient information to disaggregate informal employment, self-employment, and city-level data. Therefore, all results from these rounds are presented at the national level and in aggregate form across three labor sectors: formal salaried, informal salaried, and self-employed.

Third, ENEMDU surveys are used for the fourth quarter of 2019, 2020, and 2021. These quarterly surveys provide data disaggregated at the national, urban, and rural levels, as well as for the five major cities: Quito, Guayaquil, Cuenca, Ambato, and Machala. The number of individuals surveyed was approximately 59,208 in 2019, 92,433 in 2020, and 91,169 in 2021.

The study defines informal workers as those who are not affiliated with social security (Hussmanns, 2004).[1] In Ecuador, formal employees must be affiliated with social security to receive legal benefits. This definition helps determine the proportion of salaried workers who comply with labor laws.[2] An innovation in this paper concerning the study of the Ecuadorian labor market involves the identification of five different work statuses among workers, as defined by Maurizio and Monsalvo (2021). The new feature lies in recognizing the heterogeneity within the informal sector of the Ecuadorian labor market and in using these five levels to analyze their contributions towards explaining changes in income: 1) Formal wage employees, defined as those who receive social insurance from their job; 2) Upper-tier informal wage employees, including informal

[1]This measure has been used in the literature, for example, by Maloney (2004) and Gasparini and Tornarolli (2009), and in the case of Ecuador by Canelas (2014).

[2]It should be noted that this definition of informal employment differs from the definition of employment in the informal sector. The definition of informal employment used in the study refers to employment that lacks social security coverage and can also be found in formal enterprises.

wage workers in firms with more than five employees; 3) Lower-tier informal wage employees, encompassing informal wage workers in firms with up to five employees; 4) Formal self-employed owners in enterprises with more than five employees, along with professional own-account workers; and 5) Informal self-employed owners in enterprises with up to five employees, non-professional own-account workers, and unpaid family workers.

A two-step research strategy is followed. First, in Section 5, the paper examines the evolution of the main determinants of labor income during the period 2019-2021, with an emphasis on employment composition. Subsequently, in Section 6, a decomposition analysis is carried out to identify the determining factors of the change in income.

5. Basic Trends in Labor Earnings Inequality in Ecuador During the Pandemic

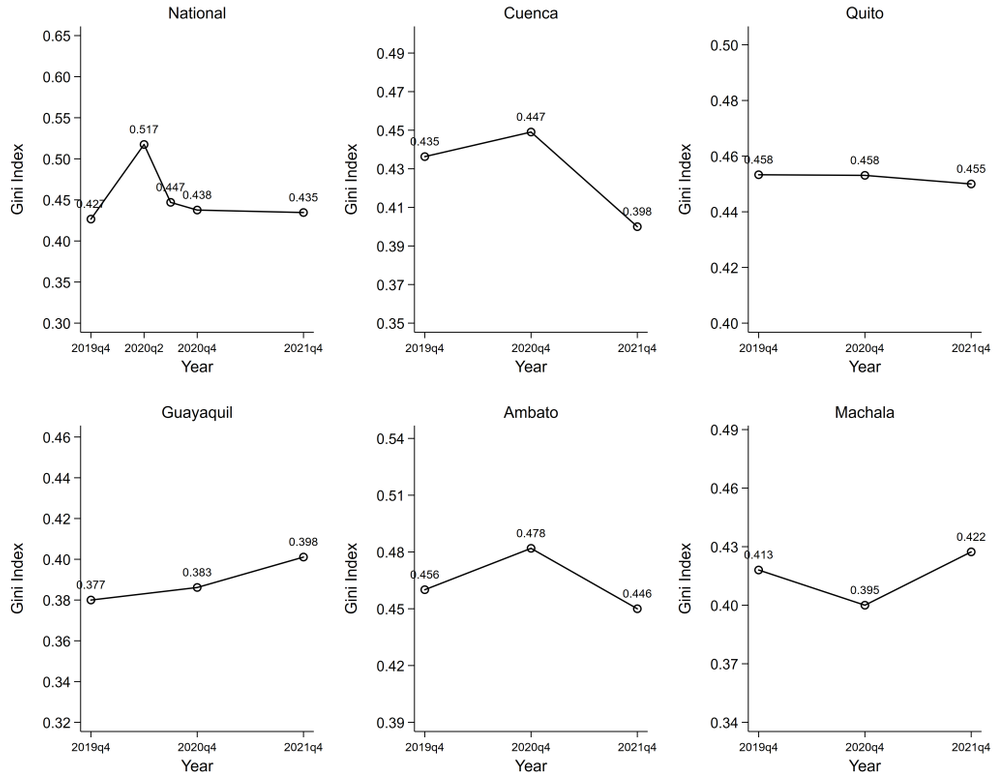
Annex 1 provides evidence of a significant decline in hourly labor earnings during the initial phases of the COVID-19 pandemic. Specifically, earnings fell by 0.37 between May and June 2020 and by 0.19 in September 2020, relative to the pre-pandemic benchmark of Q4 2019. Although a partial recovery is observed in the subsequent periods (particularly in the fourth quarter of 2020 and throughout 2021) the levels of earnings did not fully return to those registered prior to the health crisis. Figure 1 complements this evidence by examining the evolution of the Gini coefficient for labor earnings. The results reveal that inequality rose sharply by 9 percentage points in the second quarter of 2020 relative to the last quarter of 2019, before moderating to a 2-point increase in September 2020. This trajectory suggests that the peak of the distributional impact of the pandemic was concentrated in the second quarter of 2020. These findings align with the broader macroeconomic context: Ecuador's GDP contracted by 12.4% in the second quarter of 2020 (the steepest quarterly decline since 2000) before partially rebounding with a 4.5% quarter-on-quarter expansion in the third quarter. Taken together, the evidence underscores the severe but temporary nature of the initial economic shock, as well as the uneven pace of recovery across different segments of the population (BCE, 2020, 2021).

Considerable heterogeneity emerges across cities in Q4 2020: Machala, Ambato, and Quito experienced the sharpest contractions, whereas Guayaquil and Cuenca exhibited comparatively milder declines. For the last quarter of 2020, notably, in Guayaquil and Quito, no significant variation in labor income inequality was observed. However, other cities experienced a considerable increase in inequality. Specifically, Ambato and Cuenca recorded significant increases of 2.2 and 1.2 Gini points, respectively, which contrasted with the national trend. In the case of Machala, there was in fact a decrease of 1.8 points. This highlights notable regional differences and emphasizes the need for subnational analysis. In 2021, inequality declined moderately in most urban areas, which reflected the gradual national recovery. However, exceptions were observed in Guayaquil and Machala, where inequality levels did not follow the broader downward trend. These findings confirm the persistence of regional disparities and suggest that recovery dynamics were uneven.

The upper panel of Figure 2 displays the kernel density functions of labor income for the analysis of the factors behind the increase in income inequality in 2020 and its partial reversal in 2021, and offers a detailed view of income dispersion for each year. In the comparison of 2019 to the pandemic year, the May/June 2020 distribution reveals greater dispersion and increased negative skewness, which indicates a decline in average income and heightened inequality. The data shows a reduced proportion of workers in the middle of the distribution, accompanied by a rise in this proportion at the lower end, along with a slight decrease in the share of upper-tier workers. By September 2020, a partial recovery in the shape of the distribution is observed. Specifically, the dispersion of earnings narrows, yielding a more leptokurtic distribution, while the negative skewness diminishes. These changes are associated with a reduction in the share of workers located in the

lower tail of the distribution and a corresponding increase in the proportion of workers in the middle segment. Nevertheless, the levels of earnings in the middle of the distribution failed to reach their pre-pandemic values, which indicates an incomplete recovery. At the upper end of the distribution, the shape remains very similar to that observed in May/June 2020, suggesting that the pandemic did not produce significant additional changes among higher-income workers during this period. Overall, the evidence points to a relative downward shift in labor earnings, characterized by a concentration of workers in the lower and middle ranges of the distribution.

Figure 1: Trends in Inequality: Gini index. Ecuador 2019-2021



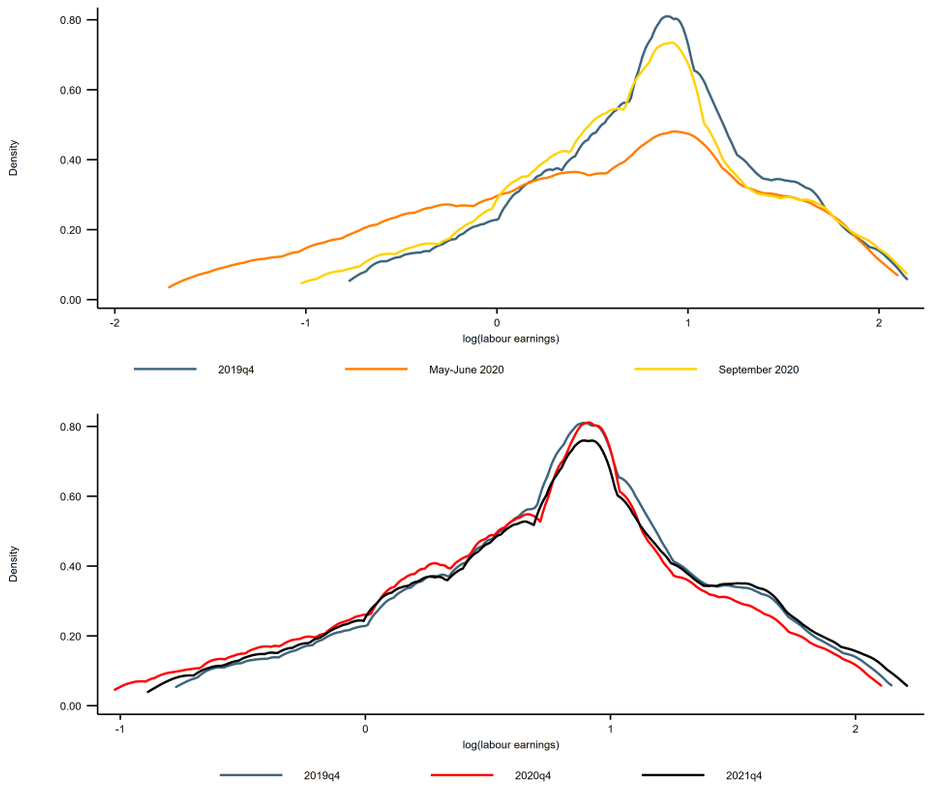
Source: Authors' own based on household surveys.
Note: Data refers to constant dollars of the year 2014.

The lower panel of Figure 2 reveals that the income decline observed in the fourth quarter of 2020 is associated with a leftward shift in the income distribution relative to 2019. In contrast, the 2021 data shows the opposite pattern: the share of workers earning below the mean decreases, resulting in a greater concentration of incomes around the median. This shift reduces income dispersion and reflects both an increase in average income and a decline in inequality.

It is interesting to contrast the effects observed in the different cities across the country (Figure 3). In Guayaquil, the rate of workers earning around the median income increased, while those in the upper-middle part of the distribution moved to the lower-middle part. This caused a drop in average income but did not significantly affect income distribution. In Quito, the situation differed, with workers earning around the median falling below the median income. In Cuenca, a considerable transition of workers from the upper-middle part to the lower-middle part of the distribution was observed. Meanwhile, Machala and Ambato exhibited a similar pattern to Quito, with a notable shift of workers from the middle to the lower-middle part of the distribution. This subnational effect highlights significant disparities across income levels, while

high-income groups were the least affected during the pandemic.

Figure 2: Kernel density functions of labor earnings

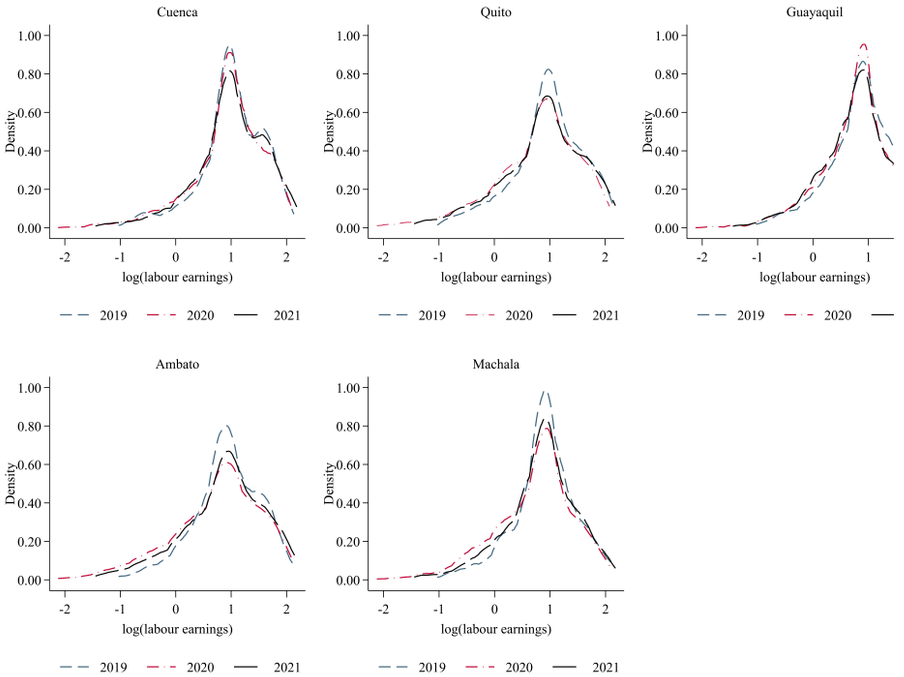


Source: Authors' own based on household surveys.
Notes: The density functions are based on a Gaussian kernel with an optimal bandwidth given by the rule suggested by Silverman (1998).

Annex 2 presents the evolution of the 10th, 30th, 70th, and 90th percentile ratios relative to the median. In May/June 2020, the distribution of income shifted notably. Ratios comparing the lower percentiles to the median declined, which reflects a contraction of incomes in the lower and middle segments of the distribution. In contrast, ratios for the upper percentiles increased, with the rise being substantially greater at the top of the distribution. This pattern indicates that while the lower and middle segments experienced a fall in income, the highest earners maintained or even expanded their relative position, leading to a pronounced increase in inequality. These changes highlight the pandemic's pronounced impact on the lower and middle segments of the income distribution.

By September 2020, the 10-50 and 30-50 ratios recovered, while the 70-50 and 90-50 ratios fell, although the latter remained above pre-pandemic levels. This pattern reflects an increase in inequality at the upper end of the income distribution. By the end of 2020, the 10-50 and 30-50 ratios experienced a smaller decline, while the 70-50 ratio increased, which indicates growing inequality in the lower and middle segments. Conversely, the 90-50 ratio decreased, thereby suggesting a reduction in dispersion at the top of the distribution.

Figure 3: Kernel density functions of labor earnings: 2019, 2020, and 2021.



Source: Authors' own based on household surveys.
Notes: The density functions are based on a Gaussian kernel with an optimal bandwidth given by the rule suggested by Silverman (1998).

In Q4 2021, the distribution of income exhibited a divergent pattern across its segments. On one hand, the 10-50 and 30-50 percentile ratios increased, thereby indicating a reduction in inequality in the lower and lower-middle parts of the distribution. On the other hand, the 70-50 and 90-50 percentile ratios also increased, which reflects a rise in inequality at the upper end of the distribution. This pattern explains the persistence of overall inequality in 2021: although inequality decreased among the lower and lower-middle income groups, the relative gains in the upper part of the distribution reinforced overall inequality. These results suggest that improvements in the lower segments are insufficient to offset the greater inequality of income at the top.

Annex 2 highlights the heterogeneous evolution of income distribution across cities during the pandemic. Despite several differences, all cities exhibit a broadly similar pattern: a sharp contraction in the lower part of the distribution, accompanied by a slight decrease or even improvement in the upper part. Among the cities analyzed, Ambato experienced the largest contraction in the 10-50 percentile, followed by Machala, with the 30-50 percentile showing a similar pattern. Guayaquil represents an exception, displaying a progressive contraction across all percentile ratios during the pandemic year, which explains why overall inequality did not increase in that city. Overall, the data indicates a widening of the income distribution, which reflects a significant increase in the gap between the poorest and the richest households. For 2021, city-level data reveals that earnings in the lower part of the distribution increased more than in the upper part in most cities. Quito and Guayaquil stand out as exceptions: in these cities, lower-income groups experienced declines while upper-income groups saw gains, which explains the sharper rise in inequality in 2021. In contrast, other cities either maintained or reduced inequality. The following section explores the factors driving these trends in labor earnings across cities.

5.1. Changes in the distribution of factors

This section first outlines the main trends in labor income distribution during the pandemic, then examines how the factors influencing labor income evolved over time. Table 1 reports key employment characteristics for Q4 2019, May/June 2020, September 2020, Q4 2020, and Q4 2021. Between Q4 2019 and September 2020, human capital experienced notable shifts in educational attainment. The share of workers with studies of a secondary education level increased sharply from 0.38 in May/June 2020 to 0.46 in September 2020, while the proportion of workers with only primary education declined from 0.40 to 0.37 over the same period. The number of university-educated workers remained relatively stable, fluctuating slightly around 0.18-0.22. The average years of schooling initially fell from 12.79 in Q4 2019 to 12.38 in September 2020, which reflects a temporary dip in educational composition, before rising again by 2021. In terms of experience, the overall distribution remained broadly stable, although the share of younger workers with less than 11 years of experience increased slightly by 2021, which suggests a modest rejuvenation of the workforce.

These trends in human capital complement the labor market dynamics observed over the same periods. Between Q4 2019, May/June 2020, and September 2020, formal wage employment rises from 0.33 to 0.41 but subsequently falls to 0.30, which reflects a net contraction in formal jobs. Informal wage employment starts at 0.24 in Q4 2019, increases to 0.34 in May/June 2020, and returns to 0.24 in September 2020, which shows a temporary recovery followed by stabilization at its initial level. Self-employment shifts from 0.43 in Q4 2019 to 0.42 in May/June 2020 and then rises to 0.46 in September 2020: this suggests a sustained expansion in own-account activities. Taken together, these dynamics highlight three key patterns: a decline in formal wage employment, a fluctuating adjustment in informal wage employment, and a gradual strengthening of self-employment as a buffer strategy during the COVID-19 crisis, in line with trends observed in other Latin American countries (Beccaria et al., 2022). By Q4 2020, employment rates returned to pre-pandemic levels, and by Q4 2021, the share of skilled workers had increased, thereby reducing the proportion with only primary education.

For 2020, the data indicates a slight decrease in the share of female workers, followed by an increase in 2021. This increase, although modest, may reflect an added worker effect as a response to the decline in income from the primary earner in the household (Cahuc et al., 2014; Gasparini and Marchionni, 2017). Between Q4 2019, May/June 2020, and September 2020, the sectoral composition of employment exhibits notable shifts. There was a marked increase in the share of workers employed in agriculture, rising from 0.23 in Q4 2019 to 0.34 in May/June 2020: this reflects a reallocation of labor from manufacturing, commerce and services, which were severely disrupted by pandemic containment measures. Employment in manufacturing fell from 0.19 to 0.13, commerce from 0.19 to 0.17, and services from 0.38 to 0.34, with decreases particularly among professionals, technicians, and operators. As restrictions were gradually relaxed, a partial recovery occurred by 2021: agriculture declined to 0.24, manufacturing and commerce returned to 0.20 and 0.19 respectively, and services rebounded to 0.37. These trends reflect a temporary rise in agricultural employment shares during the pandemic, since restrictions limited manufacturing, commerce, and services while agriculture remained exempt, followed by a recovery as activities normalized.

The data underscores a key feature of Latin American labor markets (Gasparini and Marchionni, 2017): the high prevalence of informal self-employment and lower-tier informal wage employment. Self-employment was dominant throughout the period analyzed, thereby confirming the central role of informality in the economy. As highlighted by Islas and Cortez (2019), different forms of informality respond asymmetrically to shocks: survival-driven self-employment rises during downturns, voluntary self-employment is procyclical, and informal wage employment may contract or expand depending on the adjustment strategies of firms. Results reveal that self-employment and informal wage employment initially declined during the pandemic due to lockdown restrictions, consistent with Beccaria et al. (2022) who emphasize the atypical nature of COVID-19 compared to previous crises. Once restrictions were lifted, informal employment resumed its

countercyclical role: self-employment rose as a survival strategy, and lower-tier informal jobs expanded as businesses adapted, while formal wage employment contracted. Although informal self-employment peaked in late 2020, it declined from 46% to 42% in 2021, which suggests a partial return to formality. In contrast, formal self-employment remained stable at around 1% throughout the period, unaffected by cyclical fluctuations.

Table 1: *Sample averages*

	2019	2020 May/June	2020 September	2020	2021
Human capital					
Years of education	12.79	12.48	12.38	12.83	13.16
Primary education	0.375	0.401	0.368	0.382	0.338
Secondary education	0.432	0.378	0.455	0.434	0.463
University education	0.193	0.221	0.177	0.184	0.199
Experience	24.6	23.74	22.81	24.14	23.66
Experience < 11	0.224	0.232	0.246	0.244	0.251
$11 \leq$ Experience ≤ 20	0.21	0.209	0.224	0.199	0.208
$21 \leq$ Experience ≤ 30	0.227	0.237	0.223	0.221	0.216
$31 \leq$ Experience ≤ 40	0.166	0.174	0.179	0.167	0.164
$41 \leq$ Experience ≤ 50	0.104	0.099	0.089	0.107	0.103
$51 \leq$ Experience	0.069	0.049	0.039	0.062	0.058
Worker characteristics					
Female	0.346	0.335	0.338	0.343	0.357
Minority group	0.21			0.192	0.177
Rural	0.281	0.359	0.288	0.278	0.28
Sector of employment					
Formal wage employees	0.327	0.407	0.305	0.285	0.294
Upper-tier informal wage employees	0.068	0.175	0.235	0.069	0.082
Lower-tier informal wage employees	0.169	0.175	0.235	0.18	0.191
Formal self-employed	0.012	0.418	0.460	0.01	0.009
Informal self-employed	0.424	0.418	0.460	0.456	0.424
Sector of activity					
Agriculture, livestock, hunting, and forestry	0.232	0.335	0.264	0.263	0.244
Manufacturing	0.194	0.132	0.199	0.183	0.198
Commerce	0.191	0.168	0.198	0.197	0.189
Services	0.383	0.365	0.339	0.357	0.369

Source: Authors' own based on household surveys.

Table 2 presents the evolution of hourly labor income across different employment characteristics before, during, and after the main phases of the COVID-19 pandemic. The results show a sharp decline in hourly labor income during the second quarter of 2020 (May/June) and in September 2020, with the most pronounced contraction occurring in the second quarter of 2020. A partial recovery is observed in the last quarter of 2020; however, in most cases, income levels remain below those recorded in 2019. Even by 2021, hourly wages have not yet returned to pre-pandemic levels.

Distinct patterns can be identified across groups. For most categories, the steepest drop occurred in the second quarter of 2020. Nevertheless, for certain groups, such as those with university education, women, urban workers, employees in the services sector, and workers with 21-30 years of experience, the largest decline

is observed in September 2020. In the case of manufacturing, income fell almost as sharply in September 2020 as in May/June 2020. This suggests that the labor market adjustment was uneven across groups, since some workers faced immediate income losses, whereas others experienced delayed effects, probably driven by differences in exposure to containment measures and levels of employment protection.

Among formal wage employees, the sharpest decline occurred in the second quarter of 2020, followed by a quick recovery to pre-pandemic levels. In contrast, informal wage workers and the self-employed experienced persistent income losses throughout the period, with no full recovery by 2021. The largest drop for informal wage workers took place in May/June 2020, while the self-employed faced a similar but slightly more prolonged contraction extending into September. When comparing magnitudes, average hourly income fell only slightly among formal employees (-0.11 USD between 2019 and May/June 2020), but much more sharply among informal workers (-0.62 USD) and the self-employed (-0.93 USD). These results show that income losses in the informal and self-employment sectors were substantially greater than in the formal sector, with the self-employed experiencing the most severe contraction of all employment types.

Overall, these trends highlight the asymmetric changes in labor income during the COVID-19 pandemic across employment types and worker characteristics. Formal employees exhibited faster recovery dynamics, while informal and self-employed workers experienced income losses of a more prolonged nature, which reflected structural vulnerabilities in Ecuador's labor market.

Annex 4 highlights diverse city characteristics in education, economic structure, and employment, which reflect significant variations as noted in previous studies (Pontarollo et al., 2019). Quito stands out as having the highest education levels and formal employment (50.82%) and a dominant services sector (58.05%). Guayaquil has a diversified economy but lower educational levels (12.19 years) and higher labor informality (63.43%). Cuenca features strong education (12.86 years) and formal employment (44.83%) with a focus on the tertiary sector. Ambato, with the highest educational level (13.09 years), has a balanced economy led by commerce (27.84%) and services (46.35%). Machala, with the lowest education (12.07 years), emphasizes agriculture (13.34%) and manufacturing (16.02%), resulting in the highest labor informality (65.34%). Since the data focuses on cities, agriculture employment is low since it primarily occurs in rural areas. The city employment analysis shows varying trends: formal employees dominate in Cuenca and Quito, while informal self-employed workers prevail in Guayaquil, Ambato, and Machala.

The data reveals variations in labor force dynamics across cities, thereby suggesting diverse mechanisms of adjustment to the pandemic. As observed in the national data, formal employment and informal self-employment were the main forms of adjustment. All cities saw a decline in formal employment, with the largest drops in Quito and Guayaquil (5.4% and 3.69%, respectively), compared to Cuenca (2.07%). In Cuenca and Ambato, informal self-employment remained stable, unlike in Quito and Guayaquil, where it increased by 3.6% and 2.8%, respectively. Conversely, Cuenca and Ambato saw a rise in lower-tier informal wage employees of 3.09% and 1.37%. In Machala, the decline in formal employment led to increases in both informal self-employment and lower-tier informal wage employees. Notably, no city showed a significant increase in formal self-employment.

Annex 5 illustrates the evolution of hourly labor income across Ecuador's main cities, and highlights significant heterogeneity in both the magnitude and timing of income adjustments during the COVID-19 crisis. The data reveals a widespread decline in earnings across all employment types in 2020, with the sharpest contractions among informal and self-employed workers. While formal wage employees experienced only temporary losses and a relatively swift rebound by 2021, income levels among informal wage workers and informal self-employed individuals remained well below their 2019 levels. The most pronounced declines occurred among lower-tier informal employees and workers with primary education or limited experience, thereby underscoring the regressive nature of the pandemic's impact. In contrast, those with university education and formal self-employment exhibited greater resilience, and reflected differences in sectors, remote

work opportunities, and human capital endowments.

Table 2: *Hourly labor income. Q4 2019, May/June 2020, and September 2020*

	2019	2020 May/June	2020 September	2020	2021
Human capital					
Primary education	2.03	1.41	2	1.83	1.87
Secondary education	2.78	2.39	2.55	2.39	2.53
University education	5.26	5.03	4.92	5.13	5.05
Experience					
Experience < 11	2.92	2.84	2.75	2.56	2.69
$11 \leq$ Experience ≤ 20	3.26	2.88	3.04	3.05	3.12
$21 \leq$ Experience ≤ 30	3.21	2.85	2.74	2.86	3.08
$31 \leq$ Experience ≤ 40	3.13	2.43	2.76	2.88	2.89
$41 \leq$ Experience ≤ 50	2.55	2.14	3.11	2.21	2.34
$51 \leq$ Experience	1.69	1.17	1.53	1.81	1.74
Worker characteristics					
Female	2.98	3.01	2.76	2.68	2.81
Male	3.01	2.42	2.82	2.74	2.85
Minority group	2.29			2.04	2.05
Rural	2.2	1.69	2.1	2.11	2.12
Urban	3.32	3.14	3.08	2.96	3.12
Sector of employment					
Formal wage employees	4.3	4.19	4.33	4.25	4.33
Upper-tier informal wage employees	2.39			2.08	2.14
Lower-tier informal wage employees	2.03			1.82	1.81
Informal wage employees	2.13	1.51	1.95	1.89	1.91
Formal self-employed	4.61			4.55	5.08
Informal self-employed	2.42			2.13	2.32
Self-employed	2.49	1.56	2.22	2.19	2.39
Sector of activity					
Agriculture, livestock, hunting, and forestry	2.03	1.39	1.84	1.86	1.88
Manufacturing	2.85	2.53	2.56	2.46	2.67
Commerce	2.71	2.41	2.78	2.49	2.58
Services	3.83	3.86	3.69	3.62	3.71

Source: Authors' own based on household surveys.

City-level differences further emphasize the uneven trajectory of recovery. Quito and Guayaquil recorded the most severe income contractions in 2020, consistent with their stricter lockdowns and higher exposure to service-sector disruptions, whereas Cuenca and Ambato showed greater income stability thanks to stronger formal employment bases and manufacturing activity. By 2021, Cuenca and Machala displayed the fastest recovery, particularly in formal and self-employed sectors, while Guayaquil continued to experience depressed informal incomes. The persistence of income gaps between formal and informal workers, and between upper- and lower-tier informal employees, suggests that Ecuador's labor market recovery was highly asymmetric. These patterns suggest that informality, low education, and limited experience amplify exposure to economic shocks, by slowing down the post-pandemic convergence in labor incomes.

5.2. Changes in Labor Market Premiums

This section analyzes changes in the partial associations between the factors and earnings during the pandemic period. The analysis is based on estimating Mincerian wage equations[3] for each year using Ordinary Least Squares (OLS). The explanatory variables considered include: i) human capital; ii) demographic characteristics and geographic location; iii) sectorial employment; and iv) the economic sector.

Table 3 reports the estimated labor market returns for 2019, Q2 2020, and September 2020, which are later used in the decomposition. Labor sectorial data for 2019 is aggregated to ensure comparability with the May/June and September 2020 surveys.

Table 3: *Labor Market returns. Hourly labor income (logs). Q4 2019, May/June 2020, and September 2020*

	2019		2020 May/June		2020 September	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Secondary education	0.1102***	0.0136	0.1311***	0.0308	0.0851***	0.0225
University education	0.4235***	0.0181	0.6178***	0.0385	0.4161***	0.0316
11 $\leq$Experience$\leq$ 20	0.1079***	0.0137	0.1109***	0.0305	0.1133***	0.0243
21 $\leq$Experience$\leq$ 30	0.1369***	0.0147	0.0942***	0.0326	0.0897***	0.0254
31 $\leq$Experience$\leq$ 40	0.1452***	0.0175	0.1340***	0.0352	0.1442***	0.0278
41 $\leq$Experience$\leq$ 50	0.1272	0.0222	0.1794***	0.0489	0.1478***	0.0359
51 $\leq$Experience	0.0456***	0.0283	0.1266**	0.0641	0.0526	0.0565
Informal employees	-0.3950***	0.0129	-0.6130***	0.0329	-0.4194***	0.0205
Self-employed	-0.5233***	0.0120	-0.9105***	0.0342	-0.5997***	0.0205
Female	-0.1428***	0.0109	-0.0397*	0.0238	-0.0870***	0.0196
Agriculture	-0.076***	0.0181	-0.151***	0.0395	-0.1881***	0.0311
Manufacture	0.0603***	0.0166	-0.023	0.0411	-0.0014	0.0284
Services	0.1576***	0.0149	0.0768**	0.0347	0.0928***	0.0275
Rural	-0.052***	0.0125	-0.047*	0.0265	-0.0339	0.0212
Constant	0.8911***	0.0199	0.7022***	0.0457522	0.9382***	0.0363
N	19,944		7,616		9,104	
Adj. R-sq	0.3314		0.4256		0.3385	

Robust standard errors. * p<0.05, ** p<0.01, *** p<0.001.
Source: Authors' own based on household surveys.
Note: The base category includes male employee, urban, formal wage workers in the trade sector, with primary education or less, and up to 10 years of experience.

The results show notable changes between Q4 2019, May/June 2020, and September 2020. Workers with studies of a secondary education level experienced an initial increase in their wage premium from 0.1102 in 2019 to 0.1311 in May/June 2020, followed by a decline to 0.0851 in September, while university-educated workers saw a sharp rise in May/June 2020 (0.6178) relative to 2019 (0.4235), returning to near pre-pandemic levels by September (0.4161). Since these premiums are measured relative to primary-educated workers, the increases may partly reflect a decline in the earnings of the least educated. Experience-based premiums remained stable for mid-career workers (11-30 years) but fluctuated among senior groups, with the most experienced (51+) showing a May/June rise followed by a September decline.

[3]For a detailed description and analysis of Mincerian wage equations applied to regression-based decompositions. See Firpo et al. (2009) and Firpo et al. (2018).

Informal employees and the self-employed faced pronounced wage penalties, reaching -0.613 and -0.9105 respectively in May/June 2020, and although partially recovering by September 2020, these remained -2.44 and -7.64 logarithm points (l.p.) lower than in Q4 2019, which highlights that pre-pandemic wage levels had not yet been restored and emphasizes their sustained vulnerability.

Sectoral premiums fell in agriculture (from -0.076 to -0.1881) and manufacturing (from 0.0603 to near zero), while services experienced a partial recovery after an initial decline. Rural premiums remained negative and largely unchanged, which indicates stable urban/rural disparities. The wage penalty for women declined at the onset of the pandemic but partially rebounded by September 2020, remaining below pre-pandemic levels, possibly because men's earnings fell more sharply, thereby temporarily narrowing the gender gap.

Overall, the pandemic temporarily increased returns to formal education and senior experience while raising wage penalties for informal and self-employed workers and affecting key sectors. The most severe disruptions occurred in May/June 2020, with only partial recovery by September and continued disparities through the end of the year.

Table 4 presents labor market returns for 2019, Q4 2020, and Q4 2021, using survey data that allows employment to be disaggregated into the five labor sectors described in the data section. The results indicate that, for the last quarter of 2020, returns to university education increased relative to workers with only primary education, while returns to those with studies at a secondary education level remained relatively unchanged.

As found by Gasparini and Tornarolli (2009) and Maurizio (2013), formal employees receive a positive wage premium of 29.47% compared to lower-tier informal wage earners, while formal self-employed workers have an average income 5.31% below the baseline category. As expected, lower-tier informal wage employees face a -14.97% (2019) wage penalty compared to upper-tier informal workers, while informal self-employed individuals experience a 26.13% income penalty, which confirms the heterogeneity within Ecuador's informal sector. In line with Beccaria et al. (2022) and Clark et al. (2021), informal self-employed workers experienced the most significant declines during the pandemic, with income coefficients dropping by 13.98 l.p., while the wage premium for formal self-employed workers decreased by 3 l.p. in 2020. For professionals and scientists, the reduction is linked to self-employed individuals whose face-to-face interactions were significantly affected by mobility restrictions (Beccaria et al., 2022). Wage premiums decreased across all economic sectors, with the agricultural sector notably dropping by 5.52 l.p. relative to the baseline category.

For 2021, the data shows an increase in the wage premium for all types of workers, except for lower-tier informal wage employees. Specifically, the wage premium for formal employees increased by 7.57 l.p. and for informal self-employed workers it rose by 11.44 l.p., thereby suggesting a recovery as self-employed individuals and small businesses resumed activities (Beccaria et al., 2022).

Annex 6a shows labor market returns per city. As previously documented by Herrera-Idárraga et al. (2016), Ontaneda (2020), and Pereira and Galego (2014), the results reveal significant wage differences within the national territory, which highlights the importance of location in determining returns. The highest return to formal work was observed in Quito, Ambato, and Guayaquil, where the wage premium for formal employment reached 0.435, 0.393, and 0.356, respectively (2021). Across all cities, lower-tier informal workers and informal self-employed individuals earn a wage premium below that of upper-tier informal workers. The wage penalty for informal self-employed workers varied for each city, with Ambato showing the highest penalties, while Guayaquil revealed a positive wage premium for this type of employment. Significant differences can also be observed in the returns to other determinants of labor income, such as human capital, gender, and economic sector. The differences in labor income between regions can be explained by various theoretical factors. Spatial wage differences arise from the concentration of skilled individuals in larger, more qualified labor markets, together with geographical characteristics and local interactions that boost productivity (Combes et al., 2008). Knowledge spillovers in spatial agglomerations enhance innovation and productivity (Glaeser et al., 1992). Economic geography further explains regional income divergence through economies

of scale and transportation costs, with firms near large markets able to pay higher wages due to cost savings and increased returns to scale (Kosfeld and Eckey, 2010; Krugman, 1991).

Table 4: *Labor Market returns. Hourly labor income (logs). Fourth quarter of 2019, 2020, and 2021*

	2019		2020		2021	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Secondary education	0.0963***	0.0138	0.0965***	0.0965	0.0927***	0.0168
University education	0.3833***	0.0177	0.4108***	0.4108	0.3840***	0.0180
11 ≤Experience≤ 20	0.1116***	0.0144	0.1184***	0.1184	0.1315***	0.0155
21 ≤Experience≤ 30	0.1476***	0.0155	0.1536***	0.1536	0.1609***	0.0174
31 ≤Experience≤ 40	0.1689***	0.0181	0.1773***	0.1773	0.1999***	0.0189
41 ≤Experience≤ 50	0.1252***	0.0234	0.1723***	0.1723	0.1537***	0.0235
51 ≤Experience	0.0592**	0.0257	0.0486	0.0486	0.0715**	0.0313
Formal employees	0.2947***	0.0203	0.2744***	0.0189	0.3501***	0.0196
Lower-tier informal wage employees	-0.1497***	0.0220	-0.1895***	0.0256	-0.1831***	0.0213
Formal self-employed	-0.0531	0.0506	-0.0831	0.0531	0.0456	0.0449
Informal self-employed	-0.2613***	0.0220	-0.4011***	0.0218	-0.2867***	0.0220
Female	-0.1549***	0.0112	-0.1457***	0.0151	-0.1125***	0.0124
Agriculture	-0.0985***	-0.0985	-0.1537***	0.0248	-0.1411***	0.0218
Manufacture	0.0571***	0.0571	0.0318	0.0262	0.0396**	0.0168
Services	0.1526***	0.1526	0.1450***	0.0214	0.1418***	0.0155
Minority group	-0.0541***	-0.0541	-0.0306	0.0207	-0.0925***	0.0177
Rural	-0.0524***	-0.0524	-0.0414**	0.0164	-0.0097	0.0157
Constant	0.6179***	0.6179	0.5649***	0.0296	0.5304***	0.0263
N	20346		30615		31703	
Adj. R-sq	0.3368		0.3157		0.33	

Robust standard errors. * p<0.05, ** p<0.01, *** p<0.001.
Source: Authors' own based on household surveys.
Note: The base category includes male employee, urban, upper-tier informal wage employees in the trade sector, with primary education or less, and up to 10 years of experience.

There are notable differences in returns across cities, which indicates that labor markets responded unevenly to the pandemic. These disparities persisted into 2021, with significant variations in wage structure adjustments across locations. The following section examines how changes in composition and prices contributed to shifts in labor income across cities.

6. Explanatory factors for the change in income distribution during the pandemic

Labor income changes in May/June 2020 and September 2020

The analysis focuses on the decomposition of labor income changes, using May/June 2020 and September 2020 as reference points, since they provide the data closest to the onset of the pandemic. The analysis covers changes both in the mean and across different points of the distribution, as outlined in equations 10 and 11. Results for the mean are presented in Table 4, while graphical results for the quantiles are shown in Figures 4 and 5 due to space constraints.

Table 5 shows that the 34.59 l.p. decrease in mean income for Q2 2020 is mainly due to changes in factor prices (37 l.p.), while composition shifts contributed to an increase in income (2.42 l.p.), meaning income would have fallen further without these composition changes. The main factor contributing to the income decline in Q2 2020 is the decrease in returns to self-employment and informal work, which together account for 69% of the difference in mean income between Q4 2019 and Q2 2020. Additionally, the results indicate that an increase in workers with university education raised incomes, while a reduction in those with studies at a secondary education level had the opposite effect. At the same time, the decline in informal and self-employed workers, who generally earn less than formal workers, contributed to higher incomes. It is interesting to note that changes in employment composition per economic activity, rather than shifts in wage premiums, were the primary contributors to the decline in labor income at the onset of the pandemic. While changes in economic activity premiums had a negative contribution, they were not statistically significant.

Table 5: *Decomposition of Mean Labor Income Changes: Q4 2019 to May/June 2020 and Q4 2019 to September 2020*

Total labor income gap [coef. (s.d.)]	May/June 2020 -0.3459*** (0.0175)				September 2020 -0.0803*** (0.0080)			
	Composition effect		Structure effect		Composition effect		Structure effect	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Secondary education	-0.0058***	0.0009	0.004	0.0214	0.0024***	0.0006	-0.0099	0.0077
University education	0.0116***	0.0008	0.04**	0.0156	-0.0059***	0.0017	-0.0002	0.0041
Experience	0.0013***	0.0004	-0.0013	0.0380	0.0004	0.0006	-0.0069	0.0126
Informal employees	0.0239***	0.0011	-0.0421***	0.0106	-0.0033*	0.0017	-0.0062	0.0047
Self-employed	0.0124***	0.0010	-0.1702***	0.0216	-0.0103***	0.0026	-0.0363***	0.0076
Female	0.002***	0.0003	0.0292**	0.0146	0.0012*	0.0007	0.0207***	0.0050
Agriculture	-0.0083***	0.0025	-0.0302	0.0243	-0.0026***	0.0006	-0.0289***	0.0062
Manufacture	-0.0037***	0.0013	-0.0122	0.0099	0.0003	0.0002	-0.0109**	0.0043
Services	-0.0036***	0.0005	-0.0363	0.0232	-0.0071***	0.0009	-0.0207***	0.0065
Rural	-0.0041***	0.0012	0.0073	0.0175	-0.0005*	0.0003	0.0064	0.0052
Constant			-0.1567*	0.0839			0.0386	0.0288
Total	0.02416***	0.0036	-0.3700***	0.0221	-0.0253***	0.0062	-0.0550***	0.0080

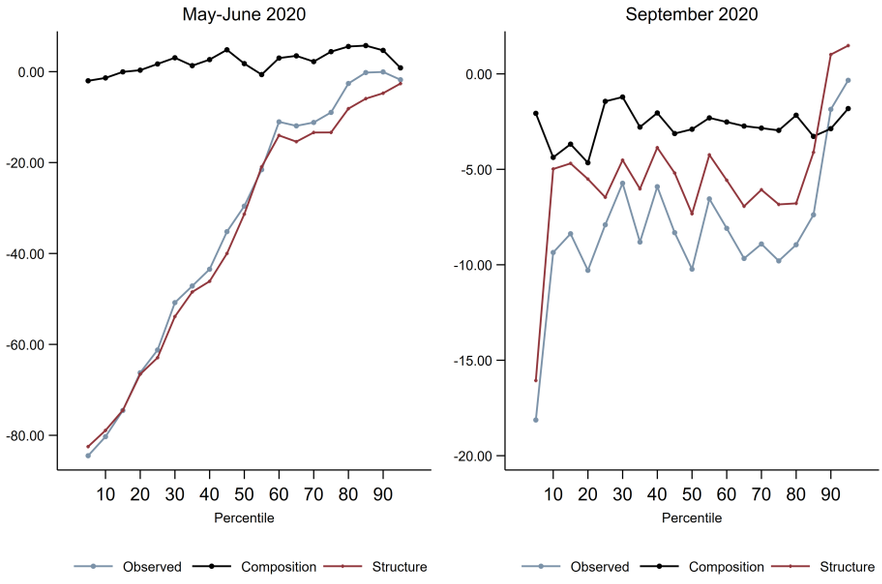
Bootstrap standard errors in parentheses (500 replications). * p<0.05, ** p<0.01, *** p<0.001.
Source: Authors' own based on household surveys.

In September 2020, average labor income declined by 8.03 l.p. Unlike the previous period, changes in workforce composition accounted for a larger share of the variation. Specifically, 31% of the decline in mean income can be attributed to shifts in composition, while the remaining 69% is explained by changes in prices. The composition effect is mainly associated with variations in the share of self-employed workers, the proportion of workers with university education, the increase in agricultural employment, and the reduction in employment in services. These structural shifts reshaped the labor force and contributed to the observed income decline. Regarding price effects, the evidence is consistent with findings from the second quarter of 2020: the sharp decline in wage premiums for self-employment explains 45% of the total changes in income observed between 2019 and September 2020. This was followed by the deterioration of wage premiums in agriculture (36%), services (26%), and manufacturing (14%). These results highlight that, beyond compositional changes, the erosion of sectoral and occupational wage premiums became a decisive factor in the income contraction during this period.

Figure 4 illustrates changes in labor income across percentiles, decomposing the total income change into composition effects and price effects. According to the data, during May/June 2025, wage declines were predominantly concentrated in the lower segment of the distribution, up to approximately the 60th percentile. The price effect accounts for nearly 95% of the total change, which highlights its dominant role in driving overall income reductions. In contrast, the composition effect, although smaller in magnitude, exhibits a

distinct pattern: it operates as a compensatory mechanism, with an increasingly larger contribution at the upper percentiles, thereby exacerbating inequality. For September 2020, the evidence points to smaller income declines compared to those of 2025. In this period, compositional changes played a more significant role in explaining the observed variation. Income reductions are observed across the distribution, with a particularly sharp decline in the lower percentiles. Notably, from the 90th percentile onwards, income levels remain largely unaffected.

Figure 4: Decomposition of the labor income difference, Q4 2019 to Q2 2020. Log difference (100).



Source: Authors' own based on household surveys.

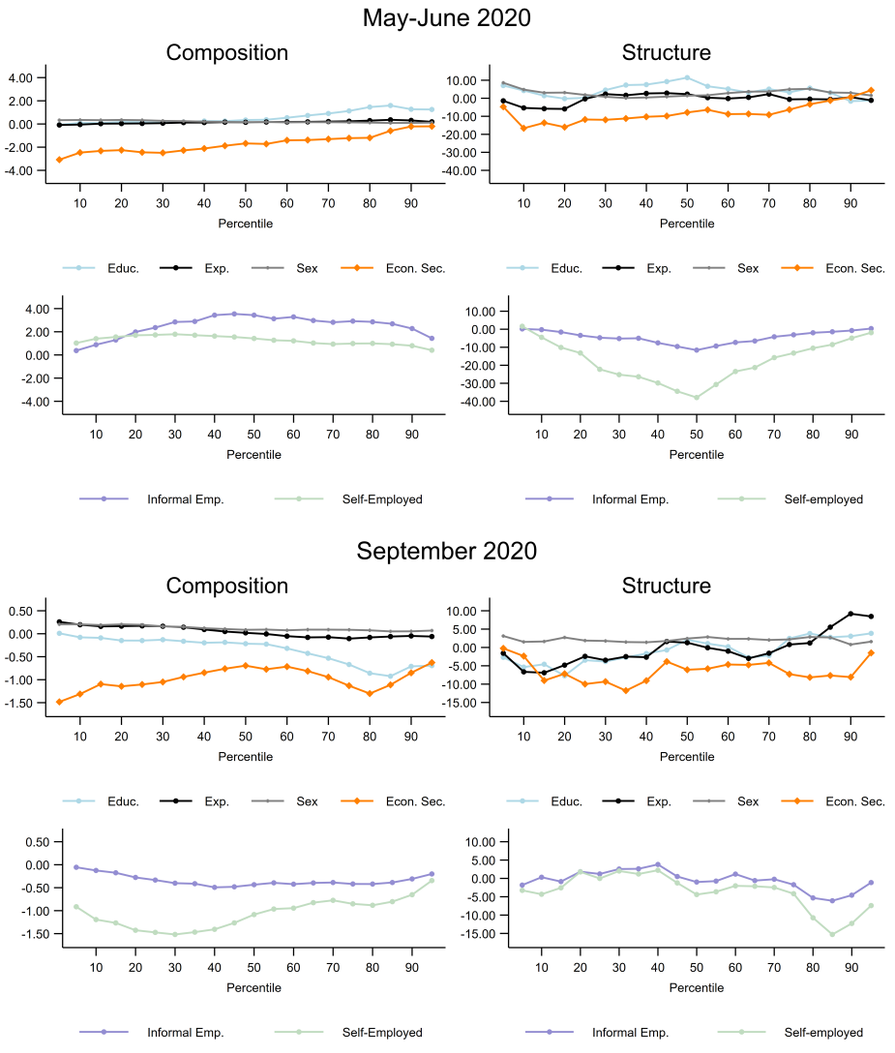
The results for Q2 2020, which were obtained using linear RIF regressions, reveal how individual covariates contributed to changes in the income distribution (Figure 5). Shifts in educational composition, particularly the increased share of workers with primary and university education, contributed to income growth at the top of the distribution. By contrast, higher employment in low-paying sectors, such as agriculture, reduced incomes at the lower and middle percentiles, with compositional effects declining along the distribution. No significant impact was observed from changes in age composition. The decomposition further indicates that variations in returns played a critical role. In particular, changes in returns to education offset income losses, especially in the middle of the distribution. Conversely, returns to experience followed an inverted U-shaped pattern, whereby incomes were depressed at both the lowest and highest percentiles. Lastly, the reduction in sectoral premiums (most notably in agriculture and services) disproportionately affected lower percentiles, thereby underscoring how the crisis eroded wage premiums across virtually all economic sectors.

The role of self-employment and informal work highlights the interplay between price and composition effects. Results for Q2 2020 shows that the contraction of self-employment during the pandemic reduced the proportion of low-income workers, slightly mitigating income declines in the lower percentiles. However, the negative price effect of self-employment reduced incomes by 22, 38, and 13 l.p. in the first, second, and third quartiles respectively, which made it a key driver of income losses. Declining returns from informal salaried work further reduced incomes, especially in the middle of the distribution.

In summary, during Q2 2020, price effects were the primary driver of rising inequality, while composition

effects played a secondary role. Although compositional changes slightly mitigated losses among the lower percentiles, these gains were overshadowed by substantial income declines resulting from reduced returns across various sectors, self-employment, and informal work.

Figure 5: Decomposition of the labor income difference. Log difference (100).



Source: Authors' own based on household surveys.

For September 2020, the decomposition analysis reveals distinct patterns when comparing composition and structure effects across the income distribution. From the perspective of composition changes, variations in the distribution of workers across economic sectors contributed significantly to income declines in the lower percentiles. Similarly, the rising share of self-employment exerted downward pressure on earnings at the bottom of the distribution. These compositional dynamics suggest that shifts in the structure of employment, particularly the concentration of workers in lower-paying sectors and in self-employment, were key drivers of income drops at the lower end of the distribution. Turning to structure (price) effects, the results indicate that wage penalties associated with the economic sector contributed to income declines in the middle and upper parts of the distribution. Moreover, deteriorating wage premia in informal employment and self-employment account for the contraction of incomes not only at the bottom but, more importantly, also across the middle

and upper percentiles of the distribution. The negative price effect of self-employment reduced incomes by 4.4 l.p. and 4 l.p. in the second and third quartiles, respectively.

Taken together, these findings underscore that in September 2020 the decline in labor income was shaped both by composition and by price effects and adverse price dynamics playing a stronger role in the middle and upper parts of the distribution. In Q2 2020, declining wage premiums in informal employment and self-employment became the main drivers of income losses, particularly in the lower and middle parts of the distribution. By September 2020, however, the impact of these premiums had shifted upwards: while they continued to depress earnings at the bottom, their deteriorating returns became more influential in the middle and upper percentiles. This transition indicates that what initially represented a shock concentrated among low-income workers evolved into a broader erosion of labor market returns, thereby extending the effects of the crisis across the entire income distribution.

Labor income changes in Q4 2020 and Q4 2021

This section analyzes labor income dynamics across two periods: Q4 2019–Q4 2020 and Q4 2020–Q4 2021.According to Table 6, the wage gap is statistically significant for both periods. Most earnings losses during the first period are due to changes in the returns to the characteristics analyzed, not changes in labor force composition. Of the -16.84 l.p. reduction in mean earnings between 2019 and 2020, -12.95 l.p. (77%) is due to changes in factor prices, and -3.89 l.p. (23%) is due to changes in employment composition. Fifty-one percent of the price effect is due to the increased wage penalty for informal self-employment (-6.60 l.p.): a major factor contributing to the decline in mean income during the pandemic year. A considerable part of the structural effect during the pandemic is due to the constant term, which indicates a broad-based wage decline across all worker subgroups that is consistent with an economy in crisis. Changes in job composition are primarily explained by a decrease in formal workers contributing -0.0133 (34%), an increase in informal self-employment contributing -0.0106 (27%), a reduction in workers with university education contributing -0.0047 (9%), an increase in agricultural sector workers contributing -0.0036 (9%), and a decline in the services sector contributing -0.0043 (11%).

A combination of differences in characteristics and wage structure explains the 0.0825 recovery in earnings for 2021. Among the changes in employment composition that contributed to the shift in average earnings is an increase in workers with a university education (13% of the total income change), a decrease in informal self-employed workers (17%), and a decrease in the percentage of workers in agriculture (4%). At the same time, the increase in lower-tier informal workers and the rise in the female workforce mitigated income growth. In terms of factor price changes, incomes primarily benefited from a reduction in the wage penalty associated with informal self-employment and from the recovery of the wage premium for formal workers. Together, these factors contributed 55% and 20%, respectively, to the total increase in mean income during the period.

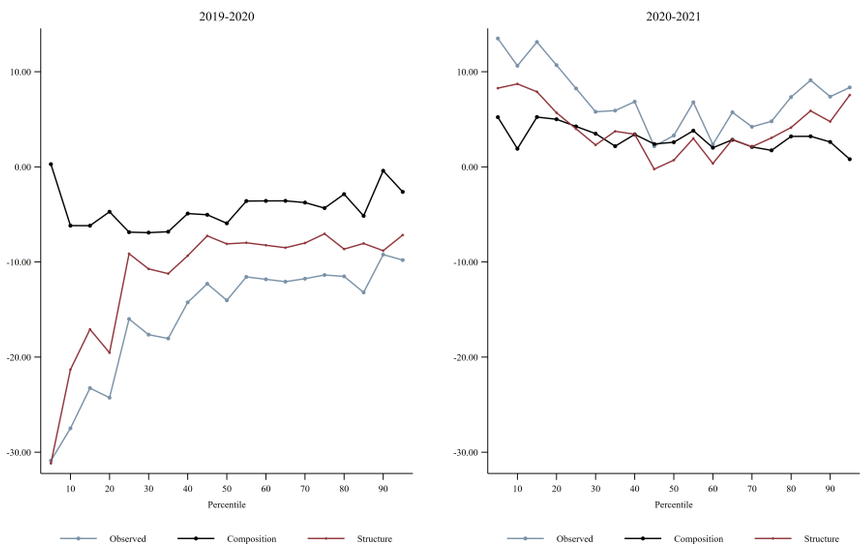
Table 6: *Decomposition of the labor income difference in the mean*

Total labor income gap [coef. (s.d.)]	2019/2020 -0.1684*** (0.0103)				2020/2021 0.0825*** (0.009)			
	Composition effect		Structure effect		Composition effect		Structure effect	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Secondary education	0.0008	0.0008	0.0016	0.0080	0.0017*	0.0009	-0.0003	0.0078
University education	-0.0047**	0.0018	0.0065	0.0061	0.0108***	0.0022	-0.0041	0.0064
Experience	-0.0013	0.0041	0.0079	0.0214	0.00	0.0054	0.01	0.0242
Formal employees	-0.0133***	0.0022	-0.0065	0.0100	0.0025	0.0022	0.0163**	0.0083
Lower-tier informal wage employees	-0.0014	0.0012	-0.0063	0.0062	-0.0024*	0.0014	-0.0004	0.0059
Formal self-employed	0.0001	0.0001	-0.0004	0.0007	0.0000	0.0001	0.0011	0.0007
Informal self-employed	-0.0106***	0.0027	-0.0660***	0.0190	0.0141***	0.0001	0.0454***	0.0160
Female	-0.0005	0.0014	0.0064	0.0061	-0.0017	0.0012	0.0108	0.0071
Agriculture	-0.0036***	0.0011	-0.0157*	0.0095	0.0032***	0.0012	0.0030	0.0068
Manufacture	-0.0008	0.0005	-0.0038	0.0053	0.0005	0.0005	0.0019	0.0055
Services	-0.0043***	0.0012	-0.0016	0.0093	0.0021	0.0013	-0.0002	0.0086
Minority group	0.0009*	0.0005	0.0052	0.0054	0.0005	0.0003	-0.0107**	0.0045
Rural	-0.0002	0.0004	0.0042	0.0057	0.0000	0.0003	0.0074	0.0071
Constant			-0.0606	0.0400			-0.0275	0.0354
Total	-0.0389***	0.0052	-0.1295***	0.01	0.0302***	0.0063	0.0523***	0.0064

Bootstrap standard errors in parentheses (500 replications). * p<0.05, ** p<0.01, *** p<0.001.
Source: Authors' own based on household surveys.

Figure 6 decomposes the change in labor income differences into price and composition effects across the income distribution. It confirms that pandemic decline in labor incomes is mainly due to changes in factor prices rather than shifts in employment composition, although these effects vary across the distribution. The greatest income contraction occurs in the lower part of the distribution, which indicates a larger drop for lower-income workers. In 2021, earnings recovery follows a U-shaped pattern, with increases attributed to both price improvements and composition changes. The detailed decomposition below provides a clearer understanding of this result.

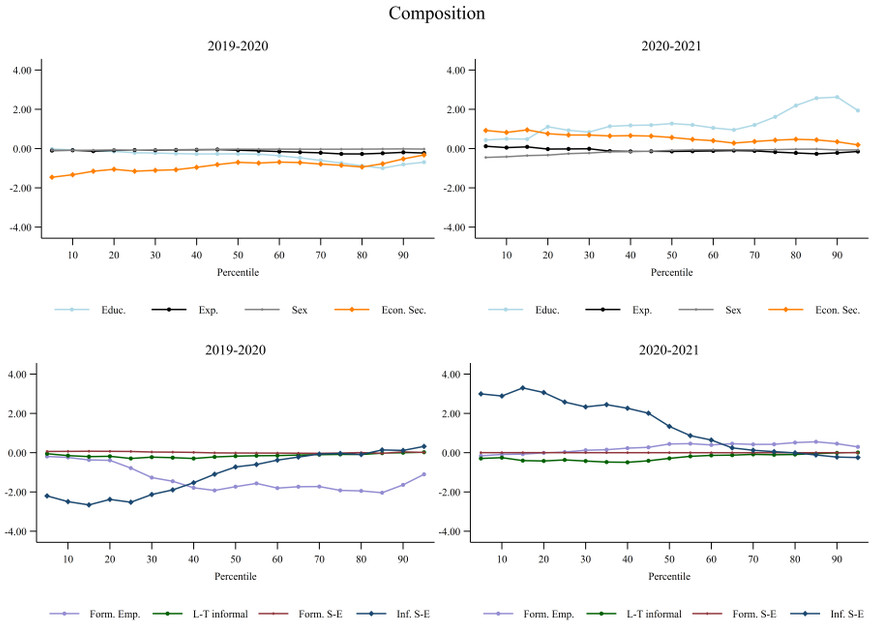
Figure 6: Decomposition of the labor income difference. Log difference (100).



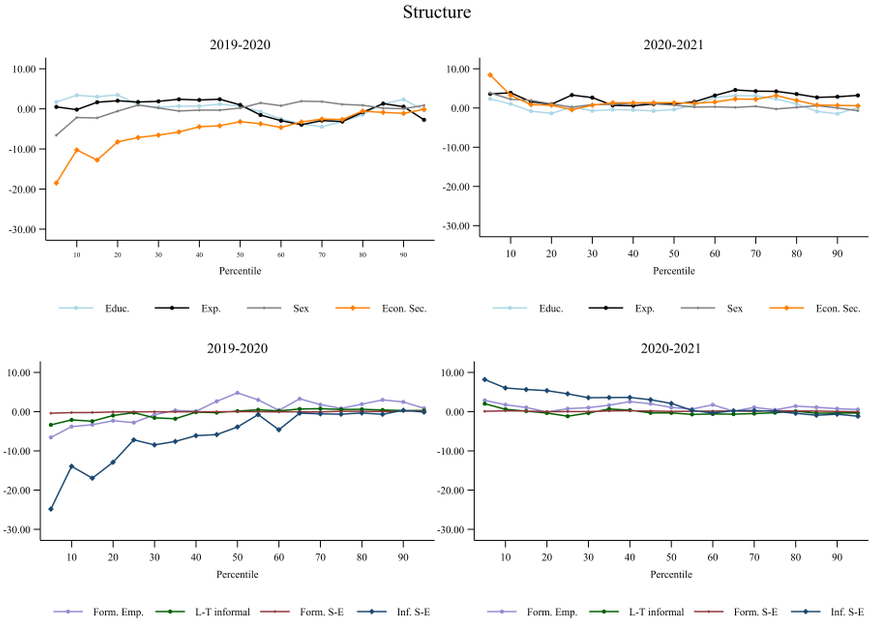
Source: Authors' own based on household surveys.

Figure 7 presents a detailed decomposition per percentile. The results support the premise that the factors explaining changes in labor income during the pandemic and post-pandemic periods vary across the income distribution.

(7a) Decomposition of the labor income difference regarding Composition. Log difference (100)



(7b) Decomposition of the labor income difference regarding Structure. Log difference (100)



Source: Authors' own based on household surveys.

The analysis highlights the most significant factors that contribute to both the composition effect and the price effect. First, the increase in informal self-employment is the main compositional factor explaining the income decline for lower-income workers. The rise in the informal self-employment rate accounts for a reduction of -2.52 l.p. in the gap in the first quartile, -0.73 l.p. in the second, and -0.04 l.p. in the third quartile. The opposite applies to formal employment, where the decline in this category helps explain the drop in middle-to-high incomes: -0.78 l.p. of the income drop in the first quartile, -1.73 l.p. in the second, and -1.92 l.p. in the third quartile. Second, shifts in industry composition, such as the rise in agricultural workers, explain the income decline at the lower end of the distribution, while the decline in service workers primarily affected the upper end of the distribution. Third, changes in employment composition by education level had effects on both the lower and upper parts of the income distribution. The decrease in workers with higher education contributed to the income drop at the upper end of the distribution (-0.27 l.p., -0.35 l.p., and -0.86 l.p. in the first, second, and third quartiles, respectively). Simultaneously, the increase in workers with studies at a secondary education level helped mitigate the income decline. However, changes in the wage structure during the pandemic year overshadowed the effects of job composition.

Regarding the contribution of changes in the wage structure, the following effects stand out. First, results confirm that shifts in the wage structure of informal self-employed workers accounted for a significant portion of the income decline at the lower end of the distribution, with diminishing effects at the upper end: -7.19 l.p. in the first quartile, -3.90 l.p. in the second, and -0.64 l.p. in the third. This aligns with Herrera-Idárraga et al. (2016), who found that informality significantly contributes towards the income gap at the lower end. Second, during the pandemic, the wage structure of formal employment sustained income in the middle and upper parts of the distribution, by contributing 4.80 l.p. and 0.84 l.p. in the second and third quartiles, respectively. Lower-tier informal work primarily exerted downward pressure on incomes at the lower end, with negligible effects at the top, while formal self-employment had little impact. Third, changes in sectoral wage premiums also explain the income decline, especially at the lower end. Price changes in the agricultural sector accounted for decreases of -3.41, -2.37, and -0.42 log points in the first, second, and third quartiles, respectively. Meanwhile, changes in wage premiums in the services sector contributed -2.20, -0.93, and -2.14 log points in the first, second, and third quartiles, respectively. Other variables contributed minimally compared to the impact of the labor sector. Overall, the decomposition highlights the significant role of price effects from informal self-employment in influencing incomes at the lower end of the distribution, accounting for 63.02% of the total changes in income in the first quartile, 39.96% at the median, and 9.38% in the third quartile.

In 2021, the decline in informal self-employment improved incomes at the lower end of the distribution, by contributing 2.6 l.p. in the first quartile and 1.30 in the second, with no effect in the third. The recovery of formal employment boosted upper-end incomes by 0.44 l.p. at the median and 0.43 l.p. in the third quartile. Simultaneously, the rise in lower-tier informal workers dampened recovery at the lower end, by contributing -0.37 and -0.29 log points in the first and second quartiles, respectively, while other compositional changes also explained income shifts across the distribution. Higher educational attainment, particularly the increase in workers with higher education, raised upper-end incomes by 1.03 l.p. at the median and 1.44 l.p. in the third quartile. The decline in agricultural workers and rise in service workers contributed to income growth at both ends, which reflects a shift from agricultural to professional roles.

On the other hand, the analysis of changes in the wage structure in 2021 highlights the significant role of price effects among informal self-employed workers. These effects contributed to income improvements at the bottom of the distribution: 3.81 l.p. in the first quartile, 0.74 l.p. in the second, and 0.97 l.p. in the third quartile. This contribution represents 78%, 7%, and 11% of the total observed changes at these points in the distribution, respectively. The price effect of formal employment also contributed towards increasing incomes at both the lower and upper ends of the distribution. Once again, lower-tier informal and formal self-employed workers made only a minimal contribution to income recovery. The contribution of other factors is summarized below. Changes in the price structure for education and experience levels exerted a positive

impact on the top end of the distribution. At the same time, the wage premium in the agricultural sector contributed towards raising incomes at the lower end of the distribution, while the wage premium in services contributed towards higher incomes at the upper end of the distribution. Detailed decomposition therefore highlights the significant role of price effects from informal self-employment in improving incomes at the bottom of the distribution: an effect influenced by changes in other factors.

6.1. Subnational evolution of labor income during the pandemic

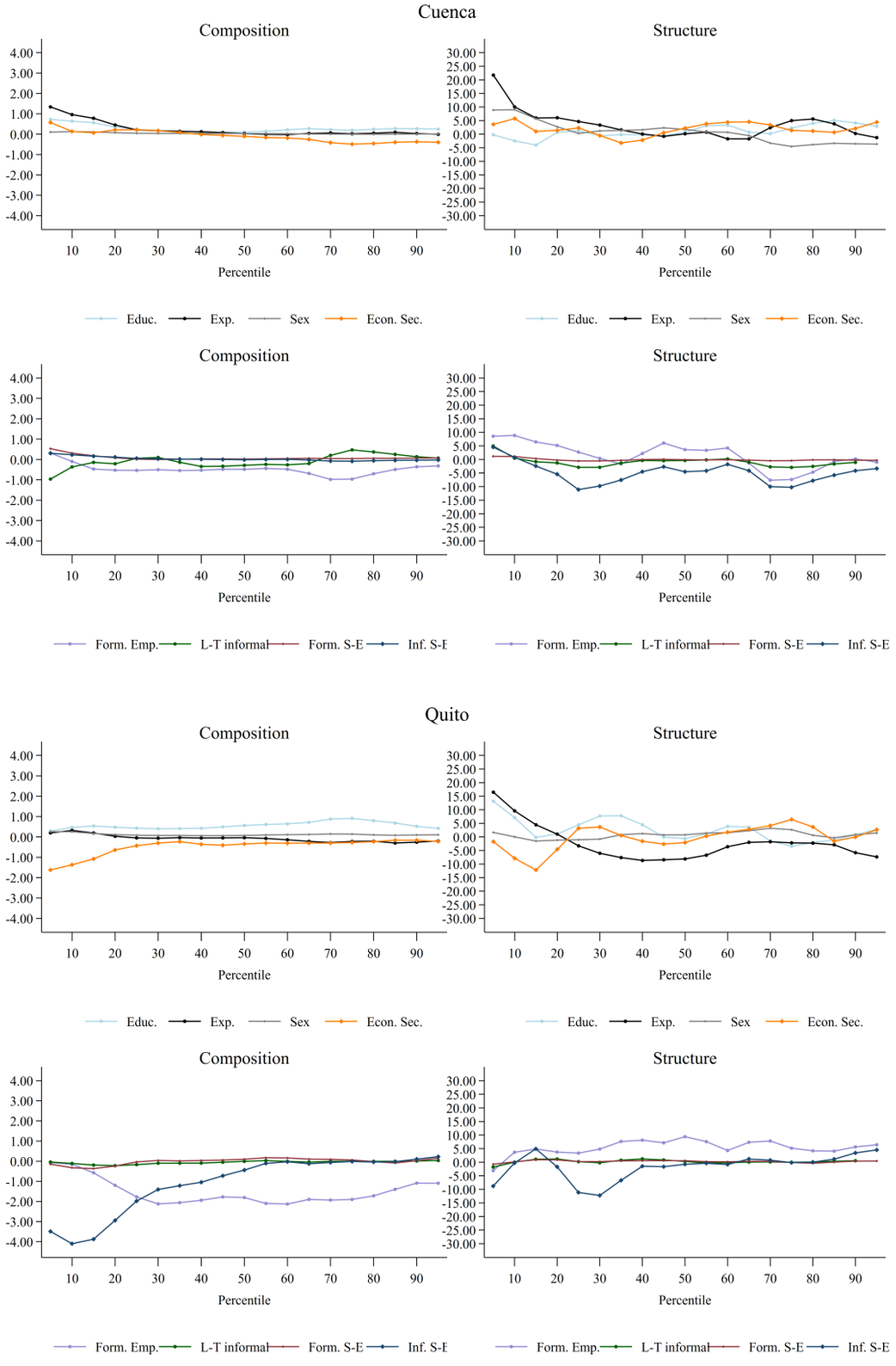
The analysis of income distribution across major cities reveals consistent patterns that align closely with national trends. However, unique variations in each city are also highlighted. Nationally, shifts in income distribution are driven predominantly by price changes rather than compositional adjustments. This pattern is observed across cities, where declines in formal employment and the rise in informal self-employment significantly contribute towards income reductions, particularly in lower income brackets. National patterns indicate that formal employment changes explain much of the income decrease in the middle-income range, while growth in informal self-employment correlates with declines at the lower end of the distribution.

Figure 8 shows that despite these shared trends, each city exhibits specific dynamics that shape local earnings outcomes. In Cuenca, the overall income decline in the lower part of the distribution is significantly influenced by a decrease in formal salaried workers, which explains the reductions of -0.54 l.p. in the first quartile, -0.53 l.p. in the second, and -1.10 l.p. in the third. Price changes, especially the decline in informal self-employment wages, play a decisive role in Cuenca, with contributions of -9.61 l.p. in the first quartile, -4.55 l.p. in the second, and -11.49 l.p. in the third quartile. These pronounced price effects render Cuenca's pattern unique among cities where price shifts primarily drive income variations, far exceeding compositional impacts.

In Quito, the increase in informal self-employment is a notable driver of income decline in the lower distribution, since it contributes -2.34 l.p. in the first quartile, -0.60 l.p. in the second, and contributes a slightly positive 0.02 l.p. in the third. Further amplifying this trend, a reduction in informal self-employment premiums adds additional downward pressure, with the same figures observed across quartiles. The decline in formal employment also causes a significant impact on income, particularly as we move up the distribution, with contributions of -1.45 l.p. in the first quartile, -1.65 l.p. in the second, and -2.08 l.p. in the third quartile. This indicates a marked sensitivity to changes in formal salaried employment in Quito, which differs from other cities where formal employment plays a smaller role. In contrast, Quito's formal wage premiums positively influence income, by adding 2.44 l.p. in the first quartile, 7.92 l.p. in the second, and 5.25 l.p. in the third, thereby counterbalancing several of the declines in other segments.

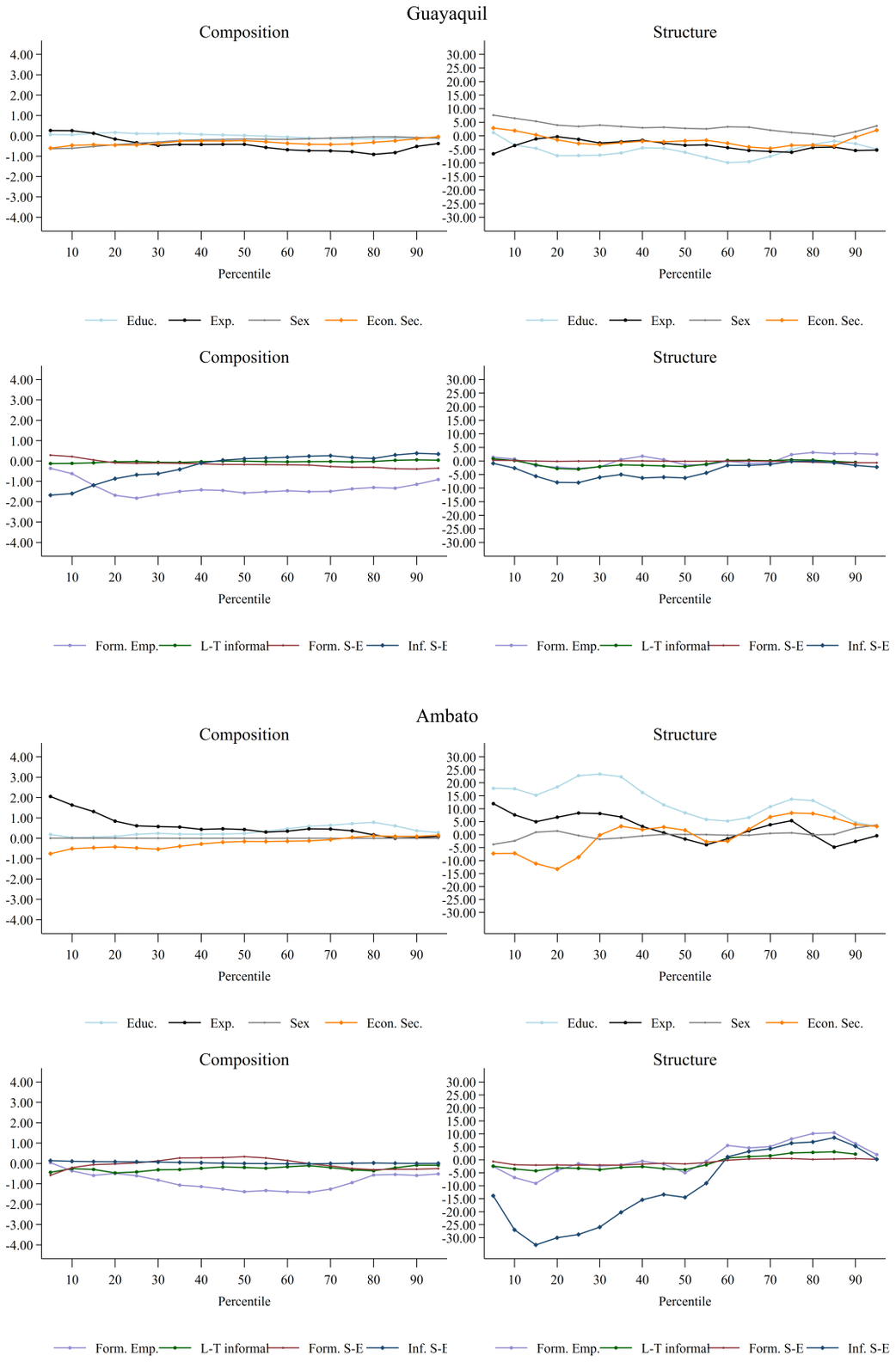
Guayaquil presents a distinct pattern, where the most significant contribution to changes in income stems from adjustments in formal salaried employment, sector composition, and experience. While informal self-employment increases are notable in the lower distribution, like other cities the primary effect on income stems from changes in informal self-employment premiums and returns to education, and especially exerts an impact on lower and middle segments. A unique factor in Guayaquil is the reduction in the gender wage penalty, which helps mitigate income declines across distribution levels, by contributing 2.85 l.p. in the first quartile, 3.47 l.p. in the second, and 1.37 l.p. in the third quartile. This trend differentiates Guayaquil from other cities where gender-based wage adjustments are less pronounced.

Figure 8a. Decomposition of the labor income difference. Cuenca and Quito, 2019-2020. Log difference (100)



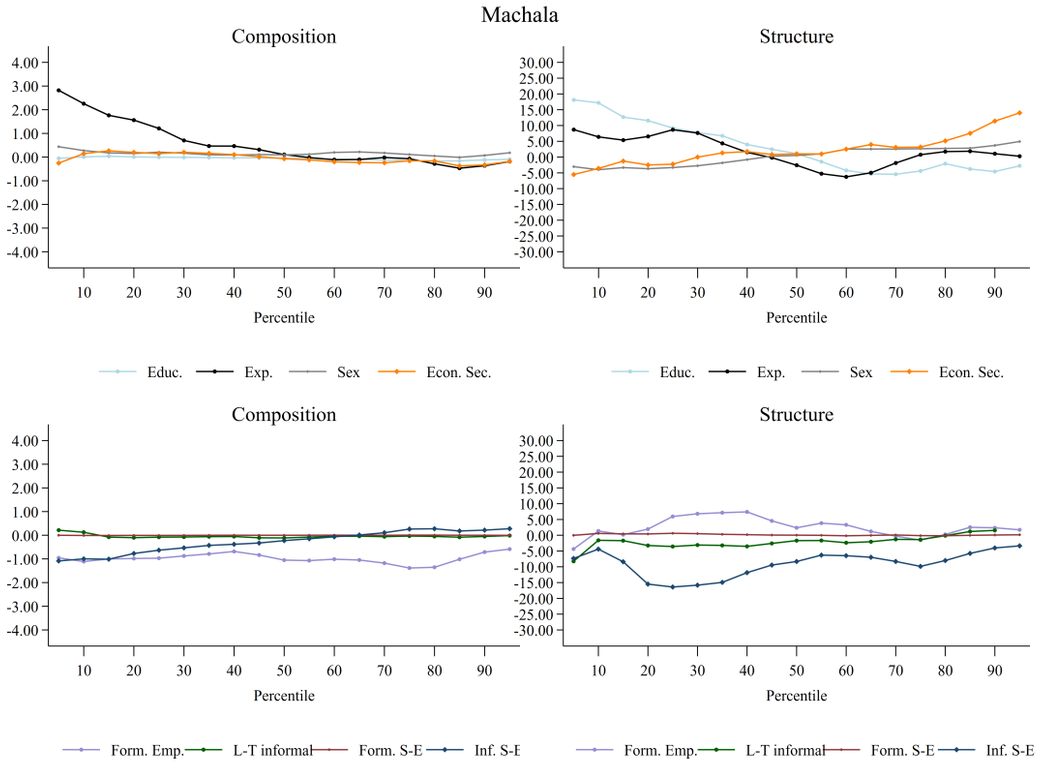
Source: Authors' own based on household surveys.

Figure 8b. Decomposition of the labor income difference. Guayaquil and Ambato, 2019-2020. Log difference (100)



Source: Authors' own based on household surveys.

Figure 8c. Decomposition of the labor income difference. Machala, 2019-2020. Log difference (100)



Source: Authors' own based on household surveys.

In Ambato, income declines are driven primarily by a decrease in formal salaried workers (-0.53 l.p. in the first quartile, -1.42 l.p. in the second, and -1.17 l.p. in the third), compounded by shifts in informal self-employment premiums (-29.51 l.p. in the first quartile, -12.51 l.p. in the second, and 5.93 l.p. in the third). Distinctively, increases in the rate of lower-tier informal workers had a negative impact on incomes in the lower part of the distribution. This is contrary to other cities, where informal self-employment rates are the primary drivers of income declines in the lower brackets. Furthermore, the change in workforce experience, particularly among those with 21 to 30 years of experience, has a positive effect on lower incomes, which mitigates declines in this segment. However, price effects, particularly those related to informal self-employment premiums and the economic sector, remain the predominant factor behind income declines.

In Machala, the decline in informal self-employment contributes towards explaining income reductions at the lower end of the distribution (-0.67 log points in the first quartile, -0.27 log points in the second, and a slight increase of 0.18 log points in the third). Moreover, reduced rates of formal salaried employment contribute towards declines across all distribution levels, with impacts of -1.07 l.p. in the first quartile, -0.99 l.p. in the second, and -1.25 l.p. in the third. An observed shift in the age composition of workers, including a decrease in the rate of workers over 50 and an increase in those aged 21 to 30, slightly counters the income declines, which contributes 1.50 l.p. in the first quartile, 0.15 l.p. in the second, and 0.04 l.p. in the third quartile. However, as in other cities, price effects outpace composition, with informal self-employment premiums and lower-tier informal wages driving income reductions across the distribution. Improved education and experience premiums also help mitigate these declines, particularly at the lower end of the income spectrum.

In Ecuador's 2021 economic recovery, shifts in wage premiums and employment composition primarily drove income changes, with notable variations across cities and income levels. Nationwide increases in in-

formal self-employment premiums were key, especially regarding recovering incomes for the lower-income distribution where informal employment remained common. However, specific factors contributing to income growth varied per city.

Figure 9 shows that, in Cuenca, a rise in workers with university education had a positive impact on income across the distribution, with effects increasing from lower to upper quartiles: 0.96 l.p. in the first quartile, 0.98 l.p. in the second, and 2.27 l.p. in the third. Wage premiums for both formal salaried and informal self-employed work contributed significantly, especially for informal self-employed workers, where contributions rose from 5.54 l.p. in the first quartile to 8.48 l.p. in the third. Higher returns in the manufacturing and service sectors also helped boost incomes, particularly in the lower quartiles, by adding 9.05 l.p. in the first quartile. Cuenca's pattern aligns with national trends, with both wage structure shifts and changes in educational composition explaining income gains.

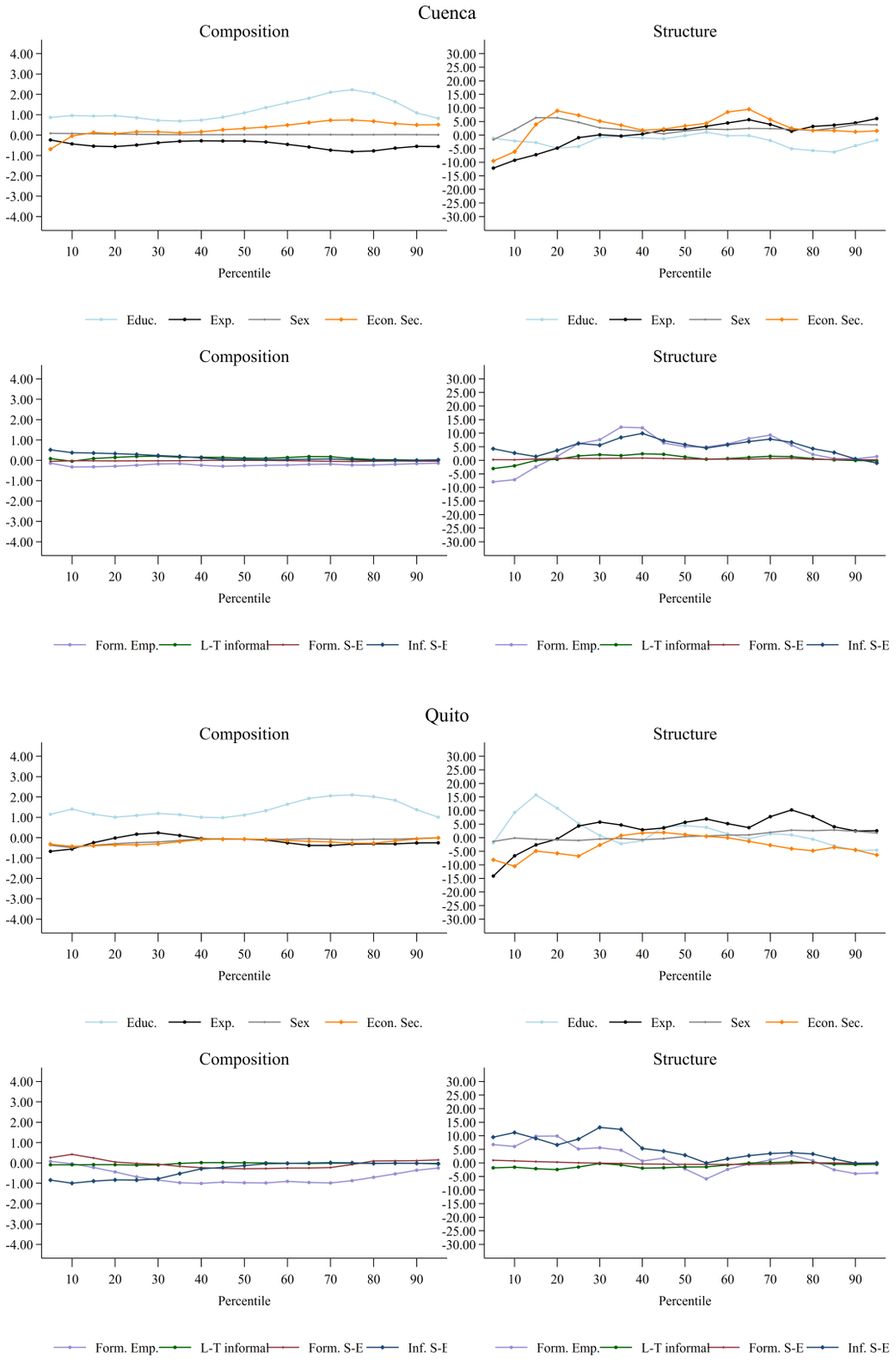
Quito also experienced income growth driven by changes in wage premiums, particularly at the lower end of the distribution. Informal self-employment premiums contributed 7.82 l.p. in the first quartile, 6.36 l.p. in the second, and 4.02 l.p. in the third. Premiums based on experience, especially for those with 21-40 years thereof, boosted incomes primarily in the upper distribution, with effects increasing from 2.44 l.p. in the first quartile to 10.59 l.p. in the third. Shifts in employment composition reveal two contrasting effects: increased rates of university-educated workers supported incomes in the upper distribution, while a drop in formal salaried employment negatively influenced mid-level incomes. This effect sets Quito apart from other cities.

In Guayaquil, wage premiums, rather than composition shifts, primarily drove income changes. Here, informal self-employment premiums contributed across the distribution, albeit less strongly than in other cities, with gains of 2.10 l.p. in the first quartile, 0.99 l.p. in the second, and 1.81 l.p. in the third. Experience premiums also played a role in income gains, particularly in the third quartile (5.41 l.p.). Guayaquil's lack of significant composition effect differentiates it from other cities.

In Ambato, informal self-employment premiums contributed heavily, especially to incomes in the lower distribution, by adding 18.21 l.p. in the first quartile and 15.82 l.p. in the second, despite turning negative in the third (-3.83 l.p.). Formal salaried work premiums also contributed notably to the lower distribution, starting at 8.01 l.p. in the first quartile and declining to a negative effect in the third (-4.75 l.p.). Unlike Cuenca and Quito, Ambato's rise in informal self-employment partially offset income gains, thereby marking a distinct trend.

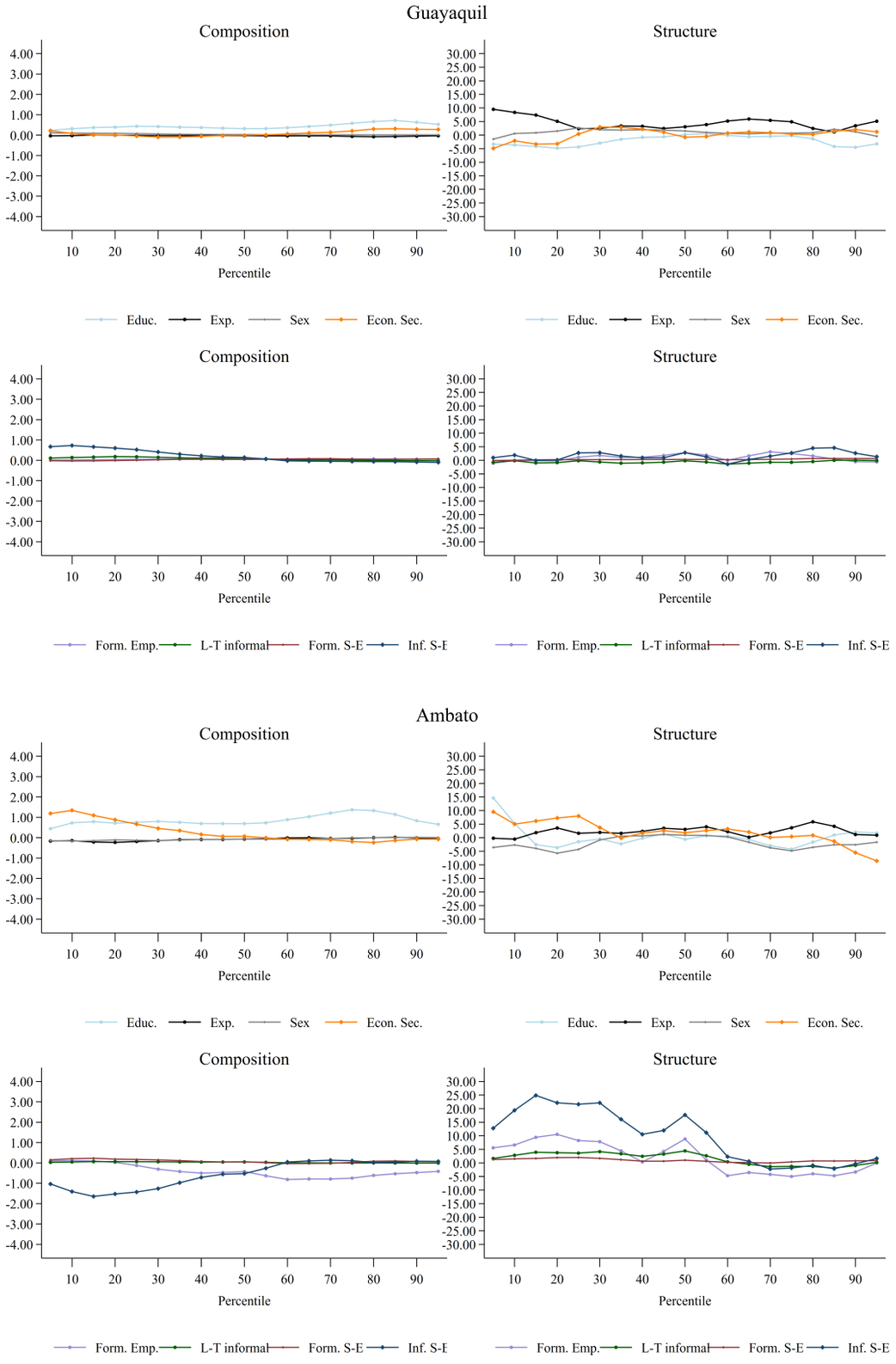
In Machala, shifts in wage premiums within informal self-employment were the primary drivers of income changes, with the most significant contributions at the lower end of the distribution (12.54 l.p. in the first quartile), decreasing to negative in the third quartile (-0.53 l.p.). In contrast to other cities where educational factors supported income growth, returns on those with studies at secondary and higher education levels negatively impacted Machala's lower-income groups. In summary, Ecuador's income recovery in 2021 was primarily driven by shifts in wage premiums and, to a lesser extent, by changes in composition, with the most significant gains occurring at the lower end of the income distribution. Cuenca and Quito closely mirrored national trends, where shifts in wage structure and composition supported income growth. In contrast, Guayaquil, Ambato, and Machala exhibited distinct recovery patterns, which underscores the variety of ways local labor markets adjusted to the 2021 recovery. This classification highlights that Cuenca, Ambato, and Machala primarily experience price effects in income reductions, while Quito is more affected by changes in employment composition. In contrast, Guayaquil exhibits a totally distinct dynamic, where composition effects are minimal in 2021. This suggests that economic policies should be tailored to the specific circumstances of each city to effectively address income inequalities.

Figure 9a. Decomposition of the labor income difference. Mayor cities, 2020-2021. Log difference (100)



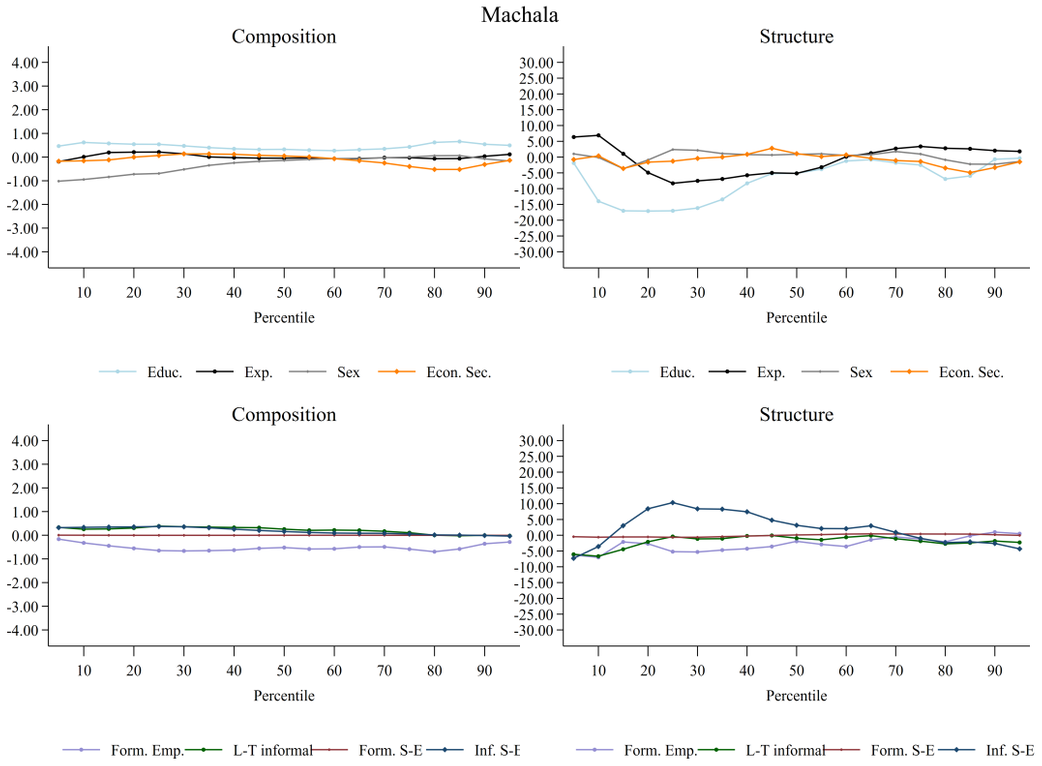
Source: Authors' own based on household surveys.

Figure 9b. Decomposition of the labor income difference. Mayor cities, 2020-2021. Log difference (100)



Source: Authors' own based on household surveys.

Figure 9c. Decomposition of the labor income difference. Mayor cities, 2020-2021. Log difference (100)



Source: Authors' own based on household surveys.

6.2. Mortality, Robustness of the Distributional Results

This section addresses concerns regarding potential sample selection effects induced by excess mortality during the COVID-19 pandemic and their implications for the interpretation of the distributional income changes documented in the paper. In particular, the spatially heterogeneous increase in mortality in 2020 raises the possibility that observed changes in the income distribution may partly reflect non-random selection of individuals into the post-pandemic sample, rather than genuine changes in labour market returns or workforce composition.

In the RIF-based decomposition, changes in composition are interpreted as changes in the distribution of observable worker characteristics—such as education, experience, sector of activity, and employment form—between the pre-pandemic workforce in 2019 and the population of workers observed in subsequent years. In the context of the COVID-19 pandemic, this comparison necessarily refers to the set of surviving and economically active individuals in 2020 and 2021, and therefore captures not only standard labour market adjustments but also any changes in observable characteristics arising from differential survival and continued labour force participation. As the RIF framework conditions on the observed sample in each period and does not explicitly model selection into survival or labour force participation, any mortality-related selection operating through changes in observable worker characteristics is absorbed into the composition component, while selection affecting the estimated returns to those characteristics is reflected in the price component of the decomposition. More broadly, the pandemic is a multifaceted shock that may affect employment through multiple channels, ranging from conventional changes in the structure of the labour force to adjustments related to survival; the composition effect therefore captures the net outcome of these mechanisms, even though

it is not possible to separately identify the contribution of each underlying process.

Our empirical strategy treats mortality not as a direct determinant of individual earnings, but as an exogenous shifter of the observed sample that may affect both the composition of workers and the estimated returns to observable characteristics. The objective is therefore not to attribute income changes to mortality per se, but to evaluate whether the main distributional results are robust to plausible selection mechanisms associated with the pandemic.

To this end, we extend the baseline Recentered Influence Function (RIF) regression framework by allowing local mortality intensity to interact with individual labour market characteristics. This approach makes it possible to test whether the returns to education, experience, sector of activity, and employment form vary systematically across areas with different levels of pandemic-related mortality. Within the RIF-based decomposition, these interactions enter through the price effect, capturing changes in the returns to observable labour market characteristics associated with differences in local COVID-19 mortality.

Crucially, the interpretation of these augmented specifications is deliberately conservative. Significant interaction effects would indicate that mortality-related selection alters the estimated returns to labour market characteristics, thereby contaminating the price component of the decomposition. Conversely, the absence of such effects lends support to the interpretation that the observed distributional changes reflect genuine labour market adjustments during the pandemic.

The section proceeds by progressively depurating the baseline results through a series of robustness exercises. These robustness checks include interacting mortality with labour market indicators, considering alternative cumulative mortality measures, allowing for non-linear effects through mortality quartiles, and assessing sensitivity to specifications that focus on high-mortality locations. These exercises implicitly account for interactions with vulnerability-related factors by interacting local COVID-19 mortality rates with the full set of worker characteristics. These characteristics already embed key dimensions of labour market vulnerability, including female gender, minority status, informal salaried employment, self-employment, and employment in rural areas. Taken together, these exercises aim to isolate the component of changes in labour market returns that can plausibly be attributed to mortality-induced selection, while ensuring that the core findings of the paper are not driven by a limited number of severely affected areas or specific population subgroups.

Information on mortality is obtained from the General Deaths Database (INEC, 2025). This source contains records of deaths that occurred and were registered nationwide in 2020 and 2021. The mortality variable is constructed by identifying deaths associated with COVID-19 and closely related respiratory conditions, including confirmed and suspected COVID-19 cases, as well as diagnoses of viral pneumonia, respiratory failure, acute respiratory distress syndrome, and influenza. We use a per-capita measure of mortality, defined as the number of COVID-19-related deaths in a city divided by its population, in order to distinguish true pandemic severity from differences in city size. For the robustness exercises, the periods 2019, 2020, and 2021 are taken as reference points, as these are the only survey waves that retain an adequate level of representativeness for consistent matching with cantonal-level mortality data aggregated and linked to the ENEMDU survey.

Robustness results are presented in two tables. The first baseline robustness exercise relies on the following specification:[4]

[4]The functional form of the COVID-19 mortality rate variable is selected using a five-fold cross-validation procedure based on out-of-sample predictive performance. The sample is randomly partitioned into five folds, and the model is iteratively estimated on four folds while predictions are generated for the remaining fold. This procedure is implemented for alternative specifications of $covidpc$—linear, quadratic, and logarithmic—where the variable enters both directly and through interactions with the full set of covariates. Model comparison is based on the root mean squared prediction error (RMSE) averaged across folds. The resulting RMSEs are 0.6064 for the linear specification, 0.6073 for the quadratic specification, and 0.6065 for the logarithmic specification. Given the negligible differences in out-of-sample performance, the linear specification is retained as the preferred functional form,

$$Y_{ti} = X_i'\beta_t + (X_i \times M_{c(i),t})'\gamma + u_{ti}, t = 0, 1 \tag{12}$$

$M_{c(i),t}$: COVID mortality in city c for individual i in time t.[5]
γ: Mortality-related changes in returns

Table 7 presents the decomposition of changes in mean labour income incorporating interactions between individual characteristics and the city-level COVID-19 mortality rate. At the aggregate level, the results for both the composition and structure (price) effects remain very similar to those obtained in specifications that do not account for mortality, thereby reinforcing the robustness of the main findings for both the 2019–2020 and 2020–2021 periods. In particular, neither the magnitude nor the sign of the total change in labour income is materially affected by the inclusion of these interaction terms.

At a more disaggregated level, several interactions between COVID-19 mortality and labour market characteristics make statistically significant contributions to the structure effect, indicating that pandemic intensity is associated with changes in the estimated returns to specific characteristics in more severely affected cities. However, these contributions are generally moderate in size and, in many cases, operate in offsetting directions, so that their net impact on the aggregate structural component remains limited.

For instance, during the 2019–2020 period, the interaction terms between mortality and secondary and tertiary education contribute negatively to the change in mean labour income (0.0233 and 0.0171 l.p., respectively), suggesting that returns to education declined more sharply in cities experiencing higher mortality rates. Similarly, the interaction between experience and mortality contributes 0.0392 l.p., indicating an additional reduction in returns to experience in areas most severely affected by the pandemic.

In contrast, positive contributions from interaction terms are observed for certain employment categories. In particular, changes in wage premia associated with formal employment, formal self-employment, and informal self-employment in high-mortality cities partially mitigated the decline in mean labour income. By contrast, no statistically significant contributions are identified for interactions involving lower-tier informal wage earners.

Taken together, these findings suggest that while COVID-19 mortality is associated with heterogeneous adjustments in returns to different labour market characteristics, such adjustments do not materially alter the aggregate decomposition of labour income changes. This supports the interpretation of the main results as reflecting structural changes in the labour market during the pandemic, rather than mortality-induced selection effects.

For the 2020–2021 period, no substantial differences emerge relative to the previously reported results. Consistent with earlier findings, changes in prices remain the dominant factor explaining variations in mean labour income. The composition effects associated with the interaction terms capture shifts in the distribution of worker characteristics across areas with differing levels of pandemic mortality among the post-pandemic workforce. Although some interaction terms are statistically significant, their magnitudes are small and do not meaningfully affect the aggregate composition effect, suggesting limited worker reallocation across high-mortality locations during the recovery phase. For instance, the negative composition effects for the interactions between COVID-19 mortality and secondary and university education indicate a modest decline in the relative presence of more educated workers in high-mortality cities between 2020 and 2021. Similarly, the negative coefficient for informal self-employed workers interacted with mortality suggests a small reduction

providing no empirical evidence of economically meaningful non-linearities in the relationship between COVID-19 mortality and labor income.

[5]In the 2019–2020 comparison, mortality interactions are identified only in 2020, as the pre-pandemic period precedes the emergence of COVID-19 mortality; by contrast, in the 2020–2021 comparison they enter symmetrically in both periods.

in the concentration of this group in areas that experienced higher pandemic severity during the recovery period. By contrast, the positive composition effect associated with the manufacturing sector interaction points to a slight relative increase in manufacturing employment in high-mortality locations, although the magnitude of this effect remains economically negligible. Overall, these patterns are consistent with mild post-pandemic recomposition across locations rather than with large-scale mobility or selection mechanisms driven by differential mortality.

For the 2020–2021 period, the price effects associated with the interaction terms indicate heterogeneous adjustments in labour market returns across cities with different levels of pandemic mortality during the recovery phase. Positive and statistically significant contributions for the interactions between COVID-19 mortality and secondary education, university education, and experience suggest that returns to human capital increased relatively more in high-mortality cities. By contrast, the negative and statistically significant price effects for the manufacturing sector and minority group interactions point to a relative deterioration in returns for these groups in more severely affected areas. In the case of interactions between mortality and types of employment, these do not show statistically significant contributions. Overall, although several interaction terms are statistically significant, their aggregate contribution to the structure component remains moderate, indicating that mortality-related heterogeneity in returns does not drive the overall income recovery between 2020 and 2021.

The Table 7 also reports decomposition results for the 2020–2021 period using the cumulative COVID-19 mortality rate, defined as the accumulation of COVID-19 deaths up to each point in time at the city level. The results are qualitatively unchanged relative to those obtained using the contemporaneous COVID-19 mortality rate.

To allow for non-linear effects, mortality is discretised into mutually exclusive quartiles based on the city-level distribution of COVID-19 mortality rates. Let $Q_{kc(i),t}$, $k = 2, \ldots, 4$, be indicator variables equal to one if city c belongs to mortality quartile k in period t (with the first quartile—lowest mortality—as the omitted category). The estimating equation becomes:

$$Y_{ti} = X_i'\beta_t + \sum_{k=2}^{4}(X_i \times Q_{kc(i),t})'\gamma_k + u_{ti},\ t = 0, 1 \tag{13}$$

This specification allows the returns to worker characteristics to vary flexibly across mortality exposure groups, without imposing linearity in the intensity of the pandemic shock.

Table 8 presents two complementary robustness analyses. In the first part, the decomposition is re-estimated excluding high-mortality locations, defined as cities with COVID-19 mortality rates above the 95th percentile of the distribution. In the second part, the table reports RIF–Oaxaca decompositions augmented with interactions between each explanatory variables and dummy indicators for quartiles of the COVID-19 mortality rate. Empty cells reflect the use of the lowest mortality quartile as the reference category and the exclusion of some interactions due to collinearity or lack of identifying variation, so only differential effects relative to low-mortality cities are reported.

Table 7: *Robustness checks: Decomposition with interactions by COVID-19 mortality rates (current and cumulative)*

	Current COVID-19 mortality rate				Current COVID-19 mortality rate				Cumulative COVID-19 mortality rate			
	2019/2020				2020/2021				2020/2021			
Total labor income gap [coef. (sd)]	-0.1658*** (0.0060)				0.0761*** (0.0056)				0.0777*** (0.0056)			
	Composition effect		Structure effect		Composition effect		Structure effect		Composition effect		Structure effect	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Secondary education	0.0000.	0.0005	0.0310***	0.0077	0.0050***	0.0008	-0.0300***	0.0094	0.0050***	0.0008	-0.0316***	0.0096
University education	-0.0032**	0.0015	0.0256***	0.0050	0.0089***	0.0017	-0.0357***	0.0063	0.0093***	0.0017	-0.0339***	0.0065
Experience	-0.0014.	0.0009	0.0552***	0.0088	-0.0019.	0.0013	-0.0219**	0.0102	-0.0020.	0.0013	-0.0252**	0.0105
Formal employees	-0.0139***	0.0015	-0.0184**	0.0084	0.0017*	0.0009	0.0289***	0.0094	0.0018**	0.0009	0.0319***	0.0097
Lower-tier informal wage employees	-0.0007.	0.0006	-0.0083.	0.0053	-0.0031***	0.0007	-0.0057.	0.0060	-0.0031***	0.0007	-0.0015.	0.0061
Formal self-employed	0.0001.	0.0001	-0.0034***	0.0011	0.0000.	0.0003	0.0029**	0.0013	0.0000.	0.0003	0.0023*	0.0013
Informal self-employed	-0.0116***	0.0014	-0.0978***	0.0122	0.0163***	0.0020	0.0504***	0.0122	0.0167***	0.0020	0.0518***	0.0125
Female	0.0013*	0.0007	0.0055.	0.0059	-0.0022***	0.0006	0.0072.	0.0072	-0.0022***	0.0006	0.0048.	0.0074
Agriculture	-0.0040***	0.0007	-0.0205***	0.0061	0.0037***	0.0007	0.0017.	0.0063	0.0042***	0.0008	0.0052.	0.0064
Manufacture	-0.0006**	0.0002	-0.0196***	0.0046	-0.0009**	0.0004	0.0166***	0.0057	-0.0010**	0.0004	0.0199***	0.0059
Services	-0.0052***	0.0008	0.0002.	0.0082	0.0022***	0.0006	-0.0139.	0.0102	0.0024***	0.0006	-0.0106.	0.0106
Minority group	0.0008***	0.0003	-0.0031.	0.0035	0.0010***	0.0003	-0.0002.	0.0038	0.0011***	0.0003	-0.0028.	0.0039
Rural	-0.0002.	0.0002	0.0023.	0.0052	0.0000.	0.0001	0.0162***	0.0058	0.0001.	0.0001	0.0155***	0.0059
Secondary education X Covid mortality			-0.0233***	0.0057	-0.0015***	0.0005	0.0167**	0.0074	-0.0016***	0.0005	0.0455***	0.0125
University education X Covid mortality			-0.0171***	0.0041	-0.0015***	0.0005	0.0246***	0.0054	-0.0016***	0.0005	0.0420***	0.0090
Experience X Covid mortality			-0.0392***	0.0063	0.0004.	0.0005	0.0159**	0.0076	0.0004.	0.0005	0.0591***	0.0127
Formal employees X Covid mortality			0.0104*	0.0061	0.0003.	0.0002	-0.0068.	0.0073	0.0003.	0.0002	-0.0204*	0.0123
Lower-tier informal wage employees X Covid mortality			0.0020.	0.0032	0.0002.	0.0003	0.0056.	0.0040	0.0002.	0.0003	-0.0004.	0.0067
Formal self-employed X Covid mortality			0.0030***	0.0010	-0.0000.	0.0003	-0.0014.	0.0011	-0.0000.	0.0003	-0.0037*	0.0019
Informal self-employed X Covid mortality			0.0302***	0.0075	-0.0020***	0.0006	-0.0044.	0.0087	-0.0020***	0.0006	-0.0363**	0.0144
Female X Covid mortality			0.0021.	0.0045	0.0001.	0.0002	0.0022.	0.0057	0.0001.	0.0002	0.0022.	0.0096
Agriculture X Covid mortality			0.0042.	0.0029	-0.0004.	0.0003	-0.0013.	0.0032	-0.0004.	0.0003	-0.0085.	0.0053
Manufacture X Covid mortality			0.0153***	0.0035	0.0012***	0.0004	-0.0120***	0.0043	0.0013***	0.0004	-0.0318***	0.0074
Services X Covid mortality			-0.0018.	0.0062	-0.0001.	0.0003	0.0115.	0.0080	-0.0001.	0.0003	0.0081.	0.0135
Minority group X Covid mortality			0.0090***	0.0021	-0.0006**	0.0002	-0.0080***	0.0025	-0.0006**	0.0002	-0.0137***	0.0042
Rural X Covid mortality			0.0024.	0.0027	0.0000.	0.0001	-0.0068*	0.0035	-0.0000.	0.0000	-0.0088.	0.0058
Constant			-0.0726***	0.0263			-0.0037	0.0234			-0.0043	0.0235
Total	-0.0380***	0.0062	-0.1278***	0.0060	0.0268***	0.0058	0.0494***	0.0055	0.02796***	0.0058	0.0497***	0.0056

Bootstrap standard errors in parentheses (500 replications). * p<0.05, ** p<0.01, *** p<0.001.
Source: Authors' elaboration base on household surveys.

Table 8: *Robustness checks: Decomposition excluding high-mortality locations and allowing for non-linear mortality effects*

	2019/2020				2020/2021				2019/2020				2020/2021			
Total labor income gap [coef. (sd)]	-0.2090*** (0.0070)				0.1114*** (0.0070)				-0.1658*** (0.0060)				0.0761*** (0.0056)			
	Composition effect		Structure effect		Composition effect		Structure effect		Composition effect		Structure effect		Composition effect		Structure effect	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Secondary education	-0.0028***	0.0005	0.0115*	0.0061	0.0073***	0.0009	-0.0158**	0.0069		0.0005	0.0355**	0.0141	0.0053***	0.0012	-0.0655.	0.0525
University education	-0.0117***	0.0015	0.0125***	0.0033	0.0154***	0.0019	-0.0157***	0.0038	-0.0032**	0.0015	0.0314***	0.0066	0.0094***	0.0019	-0.0208.	0.0376
Experience	-0.0006.	0.0010	0.0153**	0.0072	-0.0017.	0.0012	0.0081.	0.0068	-0.0014.	0.0009	0.0720***	0.0138	-0.0024.	0.0015	-0.0330.	0.0539
Formal employees	-0.0184***	0.0016	-0.0116.	0.0071	0.0050***	0.0012	0.0240***	0.0071	-0.0139***	0.0015	-0.0197.	0.0160	0.0017*	0.0009	0.0154.	0.0520
Lower-tier informal wage employees	-0.0025***	0.0006	-0.0086*	0.0052	-0.0012.	0.0008	-0.0013.	0.0049	-0.0007.	0.0006	-0.0046.	0.0065	-0.0027***	0.0007	-0.0151.	0.0345
Formal self-employed	0.0002.	0.0001	-0.0009.	0.0006	-0.0000.	0.0002	0.0014**	0.0006	0.0001.	0.0001	-0.0054***	0.0018	0.0001.	0.0005	-0.0062.	0.0050
Informal self-employed	-0.0123***	0.0014	-0.0875***	0.0115	0.0153***	0.0024	0.0547***	0.0100	-0.0116***	0.0014	-0.0357**	0.0150	0.0115***	0.0017	-0.0324.	0.0717
Female	0.0022***	0.0007	0.0068.	0.0045	-0.0028***	0.0008	0.0093**	0.0046	0.0013*	0.0007	-0.0101.	0.0077	-0.0028***	0.0008	0.0405.	0.0365
Agriculture	-0.0115***	0.0015	-0.0189***	0.0067	0.0132***	0.0014	-0.0035.	0.0050	-0.0042***	0.0007	-0.0550***	0.0115	0.0067***	0.0014	0.0006.	0.0335
Manufacture	-0.0012***	0.0004	-0.0078**	0.0033	-0.0002.	0.0004	0.0052.	0.0036	-0.0006**	0.0002	-0.0281***	0.0064	-0.0015***	0.0006	0.0228.	0.0352
Services	-0.0093***	0.0009	0.0009.	0.0059	0.0057***	0.0009	-0.0058.	0.0062	-0.0052***	0.0008	-0.0039.	0.0195	0.0021**	0.0010	-0.0191.	0.0562
Minority group	-0.0010***	0.0003	0.0043.	0.0034	0.0016***	0.0005	-0.0103***	0.0029	0.0008***	0.0003	-0.0083*	0.0046	0.0014***	0.0004	0.0425**	0.0166
Rural	-0.0044***	0.0010	0.0147***	0.0057	0.0003.	0.0010	0.0037.	0.0043	-0.0002.	0.0002	0.0085.	0.0101	0.0000	0.0000	0.0179.	0.0305
Secondary education X Q3											0.0012.	0.0020	0.0001.	0.0002	0.0058.	0.0072
Secondary education X Q4											-0.0246**	0.0115	-0.0017**	0.0008	0.0461.	0.0398
University education X Q2											-0.0004.	0.0004	-0.0001.	0.0001	-0.0016.	0.0025
University education X Q4											-0.0207***	0.0058	-0.0019***	0.0007	0.0143.	0.0320
Experience X Q2											0.0065***	0.0012	-0.0004.	0.0003	-0.0159**	0.0062
Experience X Q3											-0.0060***	0.0015	0.0002.	0.0003	0.0134.	0.0089
Experience X Q4											-0.0519***	0.0110	0.0010.	0.0008	0.0261.	0.0389
Formal employees X Q3											0.0032*	0.0018	0.0000	0.0001	-0.0052.	0.0066
Formal employees X Q4											0.0049.	0.0134	0.0001.	0.0004	0.0104.	0.0408
Lower-tier informal wage employees X Q2											-0.0001.	0.0007			0.0016.	0.0044
Lower-tier informal wage employees X Q4											-0.0030.	0.0048	-0.0003.	0.0004	0.0134.	0.0227
Formal self-employed X Q2											0.0001.	0.0000	0.0000	0.0001	0.0000	0.0000
Formal self-employed X Q3															0.0011**	0.0005
Formal self-employed X Q4											0.0047***	0.0017	0.0000	0.0004	0.0066.	0.0045
Informal self-employed X Q2											-0.0063***	0.0019	0.0006*	0.0003	0.0152*	0.0089
Informal self-employed X Q4											-0.0295***	0.0109	0.0022**	0.0009	0.0614.	0.0523
Agriculture X Q3											0.0076**	0.0030	-0.0005*	0.0003	0.0059.	0.0105
Agriculture X Q4											0.0275***	0.0068	-0.0024***	0.0008	-0.0063.	0.0164
Manufacture X Q2											0.0245***	0.0056	0.0018***	0.0006	-0.0208.	0.0270
Services X Q3											-0.0038*	0.0021	-0.0003.	0.0002	0.0052.	0.0060
Minority group X Q3															-0.0092**	0.0042
Minority group X Q4											0.0146***	0.0032	-0.0011***	0.0004	-0.0353***	0.0096
Rural X Q3											-0.0020.	0.0028	0.0000	0.0001	0.0002.	0.0094
Constant			-0.0670**	0.0309			-0.0003.	0.0292			-0.0717***	0.0264			-0.0107.	0.0235
Total	-0.0724***	0.0062	-0.1366***	0.0071	0.0569***	0.0077	0.0545***	0.0069	-0.0385***	0.0062	-0.1273***	0.0060	0.0270***	0.0058	0.0491***	0.0056

Bootstrap standard errors in parentheses (500 replications). * p<0.05, ** p<0.01, *** p<0.001.

Source: Authors' elaboration base on household surveys. For reasons of space, the table does not report coefficients that are numerically small and statistically insignificant. The complete set of results is available from the authors upon request.

Consistent with the baseline results, the decomposition confirms that changes in returns (price effects) remain the dominant channel explaining variations in labour income, both during the crisis (2019–2020) and the recovery phase (2020–2021). In particular, the structure effect associated with informal self-employment continues to account for a substantial share of the overall income changes, reinforcing the conclusion that adjustments in remuneration patterns, rather than shifts in worker characteristics, drive most of the observed income dynamics during the pandemic period.

With respect to the first robustness analysis, the results are qualitatively similar to those obtained in the baseline specification. Excluding high-mortality locations leads to an even larger decline in average labour income during the 2019–2020 period, indicating that the observed income losses are not solely driven by cities experiencing the most severe health shocks. Consistent with the main results, changes in prices remain the primary channel underlying both the contraction and the recovery of labour incomes, with adjustments in the returns to informal self-employment accounting for the largest contributions in both periods.

In the second robustness exercise, which allows for non-linear effects through mortality quartiles, the results shed light on the heterogeneity of price adjustments across locations with different levels of pandemic severity. For the 2019–2020 period, the interaction terms indicate that the largest negative price effects are concentrated in high-mortality cities (Q4). In particular, the interaction between informal self-employment and the highest mortality quartile is large and statistically significant, suggesting that informal self-employed workers in severely affected cities experienced an additional decline in returns relative to their counterparts in low-mortality locations.

Similar non-linear patterns emerge for human capital variables. The interactions of secondary and university education with the highest mortality quartile display negative and statistically significant structure effects in 2019–2020, indicating that the decline in returns to education was more pronounced in cities facing the most severe health shock. Likewise, the interaction between experience and the upper mortality quartiles reveals sizeable negative contributions to the price effect, pointing to steeper reductions in experience premia in high-mortality areas.

In contrast, the composition effects associated with the interaction terms are generally small, even when statistically significant, and do not materially alter the aggregate composition effect. This suggests that, although there is some reallocation of workers across mortality quartiles—for example, modest shifts in the distribution of informal self-employed or agricultural workers—these changes play a secondary role in explaining overall income dynamics.

For the 2020–2021 period, most interaction terms lose statistical significance in the price component, and their magnitudes decline substantially, although some residual price changes persist for specific groups, such as minority workers or informal self-employed individuals. Overall, the quartile-based specification corroborates the main finding that pandemic-induced income losses were driven primarily by changes in returns during the peak of the crisis, rather than by compositional shifts in the workforce.

7. Conclusions

This paper analyzes the changes in labor income observed in Ecuador during the 2020 pandemic period. The results consistently show that, regardless of the period, changes in self-employment, price, and composition constitute the key drivers of income evolution. The data shows that the adjustment in hourly labor income was non-linear: average earnings fell from 2.99 in late 2019 to 2.62 in Q2 2020, partially recovered to 2.80 in Q3 (September), dropped again to 2.71 in Q4, and finally rose to 2.82 by the end of 2021. This pattern underscores that the recovery was unstable and marked by short-term rebounds rather than a smooth trajectory.

Unlike previous crises, lockdown measures disrupted the traditional countercyclical role of self-employment as a refuge for displaced workers and led to significant initial declines in informal work. However, as restrictions eased, informal employment rebounded, with self-employment and lower-tier informal jobs expanding as key survival strategies for workers and businesses. By 2021, a partial increase in formal employment was evident, although formal self-employment remained consistently low, which highlighted its limited role within the labor market.

The data indicates that the contribution of various factors was not uniform across the income distribution. By Q2 2020, income declines were concentrated in the lower percentiles, primarily driven by price effects. The composition effect, although smaller, contributed to increased inequality by favoring higher percentiles. Changes in the composition of education, particularly regarding the larger share of workers with primary and university education, boosted incomes at the top, while increased employment in low-paying sectors such as agriculture reduced incomes in the lower percentiles. Sectoral premiums, especially in agriculture and services, had a disproportionate impact on the lower percentiles.

By September 2020, average labor income also showed a decline relative to 2019, although the composition of the workforce began to exert a stronger influence. About one-third of this reduction was explained by structural shifts (an increased share of self-employment, greater agricultural employment, a reduced presence in services, and a higher proportion of university-educated workers), while the remaining reduction stemmed from worsening price effects. The sharp fall in wage premiums for self-employment and agriculture dominated this period. Income losses remained concentrated at the lower percentiles, but the deterioration of returns extended to middle- and upper-income groups, thereby showing that the crisis evolved from a shock concentrated among low-income workers into a broader erosion of labor market returns.

By Q4 2020, income changes continued to vary across the income distribution. Key factors included the rise in informal self-employment, which reduced income at lower percentiles, and the decline in formal employment, which affected middle-to-high incomes. Shifts in sector composition, such as increases in agricultural workers and declines in service workers, also influenced income. Changes in education composition contributed to income shifts at both ends of the distribution, with a decrease in higher-education workers that reduced upper-end income. Price effects from informal self-employment played a significant role in income declines, particularly for lower-income workers, while formal employment helped sustain income at the middle and upper percentiles. In 2021, declines in informal self-employment and the recovery of formal employment improved incomes, although the rise in lower-tier informal workers dampened recovery at the lower end. Overall, price effects, sectoral shifts, and changes in the wage structure were crucial in shaping income dynamics.

The changes observed during the pandemic year varied across different cities. In Cuenca, the income decline at the lower end of the distribution was driven by a decrease in formal salaried workers, complemented by significant reductions in informal employment wages. Quito experienced an increase in informality that negatively affected lower incomes, while the decline in formal employment exerted an impact on the upper half of the distribution. Guayaquil presented a distinct pattern, where changes in formal employment were the primary factors influencing income changes, and the reduction in the gender wage penalty helped mitigate losses. In Ambato, income declines were primarily driven by a decrease in formal salaried workers and a negative impact from informal employment wages. In Machala, the decline in informal and formal employment also contributed to income reductions, although demographic changes offered slight counterbalancing effects.

In the post-pandemic period, recovery was evidenced differently in each city. In Cuenca, the rise in university-educated workers positively impacted income across the distribution, and highlighted informal employment wages. Quito showed income growth driven by informal employment premiums and an increase in educated workers, although the decline in formal employment negatively affected mid-level incomes. In Guayaquil, changes in wage premiums were the main driving force behind income increases in contrast to

other cities where changes in labor composition carried more weight. Ambato benefited from informal employment premiums, especially those in lower incomes, although with a negative effect at higher levels. Lastly, in Machala, shifts in informal employment premiums were the primary drivers of income changes, although returns on education and experience did not favor lower-income groups.

These findings underscore the complex impact of the pandemic on labor earnings in Ecuador, with significant variations across regions, sectors, and worker characteristics. The data shows that the way the COVID-19 pandemic influenced workers' labor income was through its effect on self-employment wage premiums. Notably, even within the informal sector, self-employed formal workers and lower informal employees contributed little to the observed changes during both the pandemic and post-pandemic periods. This supports the observation made by Maloney (2004): the informal sector is made up of various types of workers, each requiring specific attention. The results contradict the suggestion by Lustig et al. (2023) that the greatest income contraction occurred in the middle of the distribution, since the largest decline, at the onset of pandemic, was observed at the lower end. However, they do align with the view that the highest quintiles were less affected by the crisis. This analysis provides new evidence that shows that most income changes during the pandemic were driven by shifts in the price structure rather than changes in composition, with varying levels of impact across different income percentiles.

These results align with those of Beccaria et al. (2022) and Narayan et al. (2022), who found that employment losses during the crisis were mainly driven by a sharper contraction in informal employment compared to formal employment, due to pandemic restrictions disrupting the usual adjustment mechanisms in informal jobs. The findings highlight the atypical impact of COVID-19 on labor markets, particularly in informal employment. Unlike previous crises, lockdowns disrupted the countercyclical role of self-employment as a refuge for displaced workers and led to significant initial declines in informal work. However, as restrictions eased, informal employment rebounded, with self-employment and lower-tier informal jobs expanding as key survival strategies. By 2021, there was a partial transition back to formal employment, with a slight decline in informal self-employment. Formal self-employment, however, remained low throughout the period under study, which emphasized its limited role. These results underscore the resilience of the informal sector during economic stress while also highlighting the unique challenges posed by the pandemic.

Overall, the full set of robustness exercises confirms that the main distributional results are highly robust to the inclusion of COVID-19 mortality intensity. Allowing mortality to interact with individual labour market characteristics, do not materially alter the magnitude, sign, or interpretation of the aggregate decomposition results. Across all specifications, changes in returns (price effects) remain the dominant channel driving labour income dynamics during both the crisis and recovery phases, while mortality-related heterogeneity in returns and composition effects is quantitatively limited.

A key limitation of this analysis, however, is that the results should be interpreted as comparisons within a population of survivors and economically active individuals. Given that the empirical framework conditions on observed workers in each period and does not explicitly model survival or labour force participation, the estimated distributional changes reflect labour market adjustments among those who remained alive and active after the pandemic shock, rather than the full pre-pandemic population. This survivor-based perspective should be borne in mind when interpreting the findings, particularly in contexts characterised by large and spatially heterogeneous excess mortality.

References

BCE (2020), "La economía ecuatoriana decreció 12,4% en el segundo trimestre de 2020." https://www.bce.fin.ec. Banco Central del Ecuador.

BCE (2021), "La economía ecuatoriana creció 4,5% en el tercer trimestre, al comparar con el segundo trimestre de 2020." https://www.bce.fin.ec. Banco Central del Ecuador.

BCE (2023), "Boletín de Cuentas Nacionales Trimestrales." https://bit.ly/3ZZafIo. Dataset; Banco Central del Ecuador.

Beccaria, Luis, Fabio Bertranou, and Roxana Maurizio (2022), "COVID-19 in Latin America: The Effects of an Unprecedented Crisis on Employment and Income." *International Labour Review*, 161, 83–105.

Becker, Gary (1964), *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Schooling*. National Bureau of Economic Research, New York.

Bosch, Mariano and Julen Esteban-Pretel (2009), "Cyclical Informality and Unemployment." Manuscript, London School of Economics.

Bosch, Mariano and William F. Maloney (2008), "Cyclical Movements in Unemployment and Informality in Developing Countries." Technical Report 4648, The World Bank, URL http://elibrary.worldbank.org/doi/book/10.1596/1813-9450-4648.

Bosch, Mariano and William F. Maloney (2010), "Comparative Analysis of Labor Market Dynamics Using Markov Processes: An Application to Informality." *Labour Economics*, 17, 621–631.

Cahuc, Pierre, Stéphane Carcillo, and André Zylberberg (2014), *Labor Economics*. MIT Press.

Campos-Vazquez, Raymundo M., Gerardo Esquivel, and Rosario Y. Badillo (2021), "How Has Labor Demand Been Affected by the COVID-19 Pandemic? Evidence from Job Ads in Mexico." *Latin American Economic Review*, 30, 1–42.

Canelas, Carla (2014), "Minimum Wage and Informality in Ecuador." Technical Report 2014/006, UNU-WIDER. WIDER Working Paper.

CEPAL (2023), "Cepalstat: Producto interno bruto (PIB) total anual a precios constantes en dólares." https://bit.ly/3S31Kdq. Dataset.

Clark, Andrew E., Conchita D'Ambrosio, and Anthony Lepinteur (2021), "The Fall in Income Inequality during COVID-19 in Four European Countries." *The Journal of Economic Inequality*, 19, 489–507.

Combes, Pierre-Philippe, Gilles Duranton, and Laurent Gobillon (2008), "Spatial Wage Disparities: Sorting Matters." *Journal of Urban Economics*, 63, 723–742.

DiNardo, John, Nicole M. Fortin, and Thomas Lemieux (1996), "Labor Market Institutions and the Distribution of Wages, 1973–1992: A Semiparametric Approach." *Econometrica*, 64, 1001–1044.

Figueroa Campoverde, D. S., P. G. Ávila Villacís, and C. A. Mendoza Valencia (2024), "Vulnerabilidad e informalidad: ¿Los trabajadores vulnerables son más propensos a la informalidad? Evidencia empírica para el Ecuador." *Revista Desarrollo y Sociedad*, 33–58.

Firpo, Sergio, Nicole M. Fortin, and Thomas Lemieux (2009), "Unconditional Quantile Regressions." *Econometrica*, 77, 953–973.

Firpo, Sergio P., Nicole M. Fortin, and Thomas Lemieux (2018), "Decomposing Wage Distributions Using Recentered Influence Function Regressions." *Econometrics*, 6, 28.

Fortin, Nicole, Thomas Lemieux, and Sergio Firpo (2011), "Decomposition Methods in Economics." In *Handbook of Labor Economics*, volume 4A, chapter 1, 1–102, Elsevier, URL https://www.sciencedirect.com/science/article/pii/S0169721811004072.

Gachet, Iván, Diego F. Grijalva, Patricio A. Ponce, and Daniel Rodríguez (2019), "Vertical and Horizontal Inequality in Ecuador: The Lack of Sustainability." *Social Indicators Research*, 145, 861–900.

Gasparini, Leonardo and Mariana Marchionni (2017), "Deceleration in Female Labor Force Participation in Latin America." *Economía*, 18, 197–224.

Gasparini, Leonardo and Leopoldo Tornarolli (2009), "Labor Informality in Latin America and the Caribbean: Patterns and Trends from Household Survey Microdata." *Revista Desarrollo y Sociedad*, 13–80.

Glaeser, Edward L., Hedi D. Kallal, José A. Scheinkman, and Andrei Shleifer (1992), "Growth in Cities." *Journal of Political Economy*, 100, 1126–1152.

Goñi Pacchioni, Edwin A. (2013), "Andemic Informality: Assessing Labor Informality, Employment and Income Risk in the Andes." Inter-American Development Bank.

Herrera-Idárraga, P., E. López-Bazo, and E. Motellón (2016), "Regional Wage Gaps, Education and Informality in an Emerging Country: The Case of Colombia." *Spatial Economic Analysis*, 11, 432–456.

Hussmanns, Ralf (2004), "Defining and Measuring Informal Employment." Technical report, International Labour Office, Geneva.

INEC (2023), "ENEMDU, 2020." https://bit.ly/3ReBj2i. Dataset.

INEC (2025), "Defunciones Generales." https://www.ecuadorencifras.gob.ec/defunciones-generales/.

Islas, A. and Willy W. Cortez (2019), "¿Puede el sector informal afectar a la relación entre desempleo y producción? Un análisis del caso de México." *Revista de la CEPAL*, 2018, 151–169.

Kosfeld, Reinhold and Hans-Friedrich Eckey (2010), "Market Access, Regional Price Level and Wage Disparities: The German Case." *Jahrbuch für Regionalwissenschaft*, 30, 105–128.

Krugman, Paul (1991), "Increasing Returns and Economic Geography." *Journal of Political Economy*, 99, 483–499.

Lugo, María Ana (2007), "Employment: A Proposal for Internationally Comparable Indicators." *Oxford Development Studies*, 35, 361–378.

Lustig, Nora, Valentina Martinez Pabon, Guido Neidhöfer, and Mariano Tommasi (2023), "Short and long-run distributional impacts of COVID-19 in Latin America." *Journal of the Latin American and Caribbean Economic Association*, 22, 96–116.

Machado, José A. F. and José Mata (2005), "Counterfactual Decomposition of Changes in Wage Distributions Using Quantile Regression." *Journal of Applied Econometrics*, 20, 445–465.

Maloney, William F. (1999), "Does Informality Imply Segmentation in Urban Labor Markets? Evidence from Sectoral Transitions in Mexico." *The World Bank Economic Review*, 13, 275–302.

Maloney, William F. (2004), "Informality Revisited." *World Development*, 32, 1159–1178.

Maurizio, Roxana (2013), "Informalidad laboral y brechas salariales en América Latina." In *Población y trabajo en América Latina: Abordajes teórico-metodológicos y tendencias empíricas recientes*, 197–222.

Maurizio, Roxana (2014), "Labour Formalization and Declining Inequality in Argentina and Brazil in 2000s: A Dynamic Approach." Technical Report 9, International Labour Office, URL http://dx.doi.org/10.2139/ssrn.2530022.

Maurizio, Roxana and Ana P. Monsalvo (2021), "Informality, Labour Transitions, and the Livelihoods of Workers in Latin America." Technical Report 2021/19, United Nations University World Institute for Development Economics Research (UNU-WIDER).

Mincer, Jacob (1974), *Schooling, Experience, and Earnings*. National Bureau of Economic Research.

Narayan, Ambar, Alexandru Cojocaru, Shipra Agrawal, Tom Bundervoet, Maria E. Davalos, Natalia Garcia, Christoph Lakner, Daniel G. Mahler, V. S. Montalva Talledo, and A. Ten (2022), "COVID-19 and Economic Inequality: Short-Term Impacts with Long-Term Consequences." Technical Report 9902, The World Bank, URL https://ideas.repec.org/p/wbk/wbrwps/9902.html.

Ontaneda, Diego (2020), "Diferencias regionales en el ingreso laboral y el papel de la educación, informalidad laboral y el sector público: El caso de Ecuador." *Paradigma Económico*, 12, 59–107.

Ontaneda Jiménez, Diego Danny, Wilson Alejandro Guzmán Espinoza, Luis Rodrigo Mendieta Muñoz, and Monica Răileanu Szeles (2022), "Cohort Analysis of Labor Participation and Sectoral Composition of Employment in Ecuador." *Romanian Journal of Economic Forecasting*, 25, 67–87.

Pereira, João and Aurora Galego (2014), "Inter-Regional Wage Differentials in Portugal: An Analysis across the Wage Distribution." *Regional Studies*, 48, 1529–1546.

Perry, Guillermo E., William F. Maloney, Omar Arias, Pablo Fajnzylber, Jaime Saavedra-Chanduvi, Andrew Mason, and Jaime Saavedra-Chanduvi (2007), *Informalidad: Escape y Exclusión*. The World Bank.

Pontarollo, Nicola, Rodrigo Mendieta, and Diego Ontaneda (2019), "El crecimiento cantonal en el Ecuador y el papel de la heterogeneidad espacial." *Revista CEPAL*.

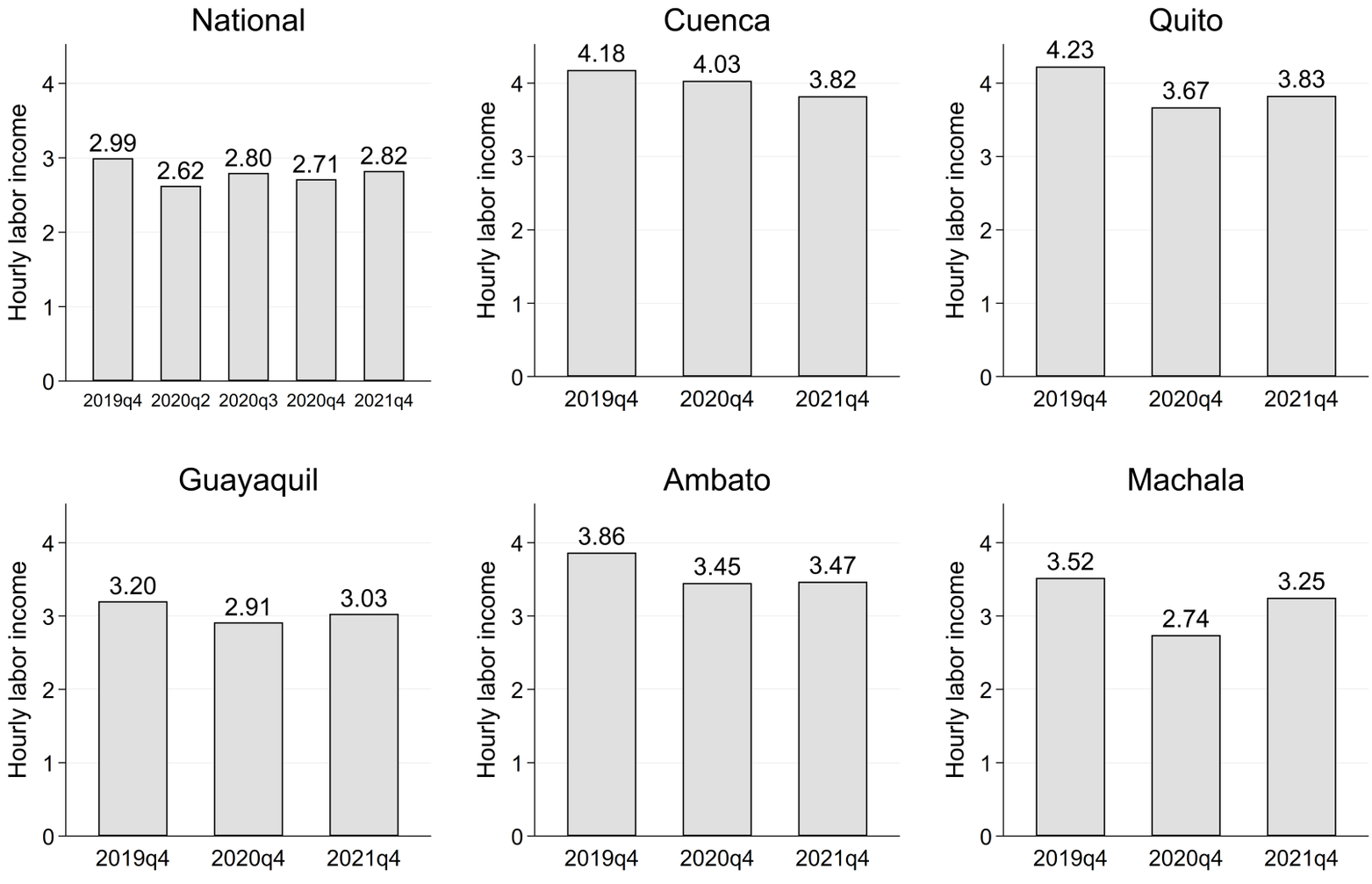
Registro Oficial (2020), "Decreto presidencial No. 1017." Suplemento Registro Oficial No. 163. Presidencia de la República del Ecuador.

Rios-Avila, Fernando (2020), "Recentered Influence Functions (RIFs) in Stata: RIF Regression and RIF Decomposition." *The Stata Journal*, 20, 51–94.

Silverman, B. W. (1998), *Density Estimation for Statistics and Data Analysis*, 1 edition. Chapman & Hall/CRC. CRC reprint.

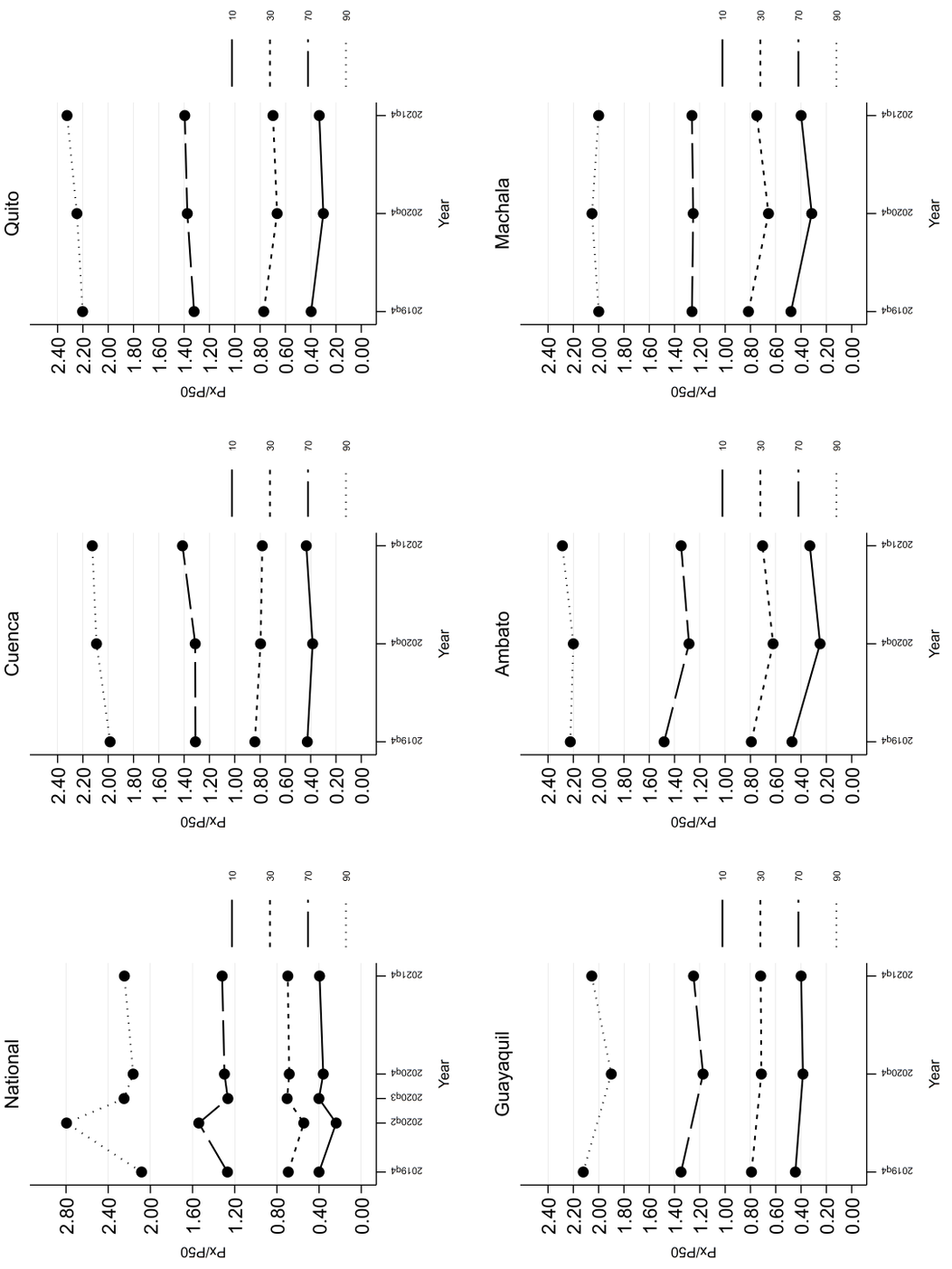
World Bank (2023), "Crecimiento del PIB." https://datos.bancomundial.org/indicador/NY.GDP.MKTP.KD.ZG.

Annex 1: Average labor earnings in Ecuador, 2019-2021.



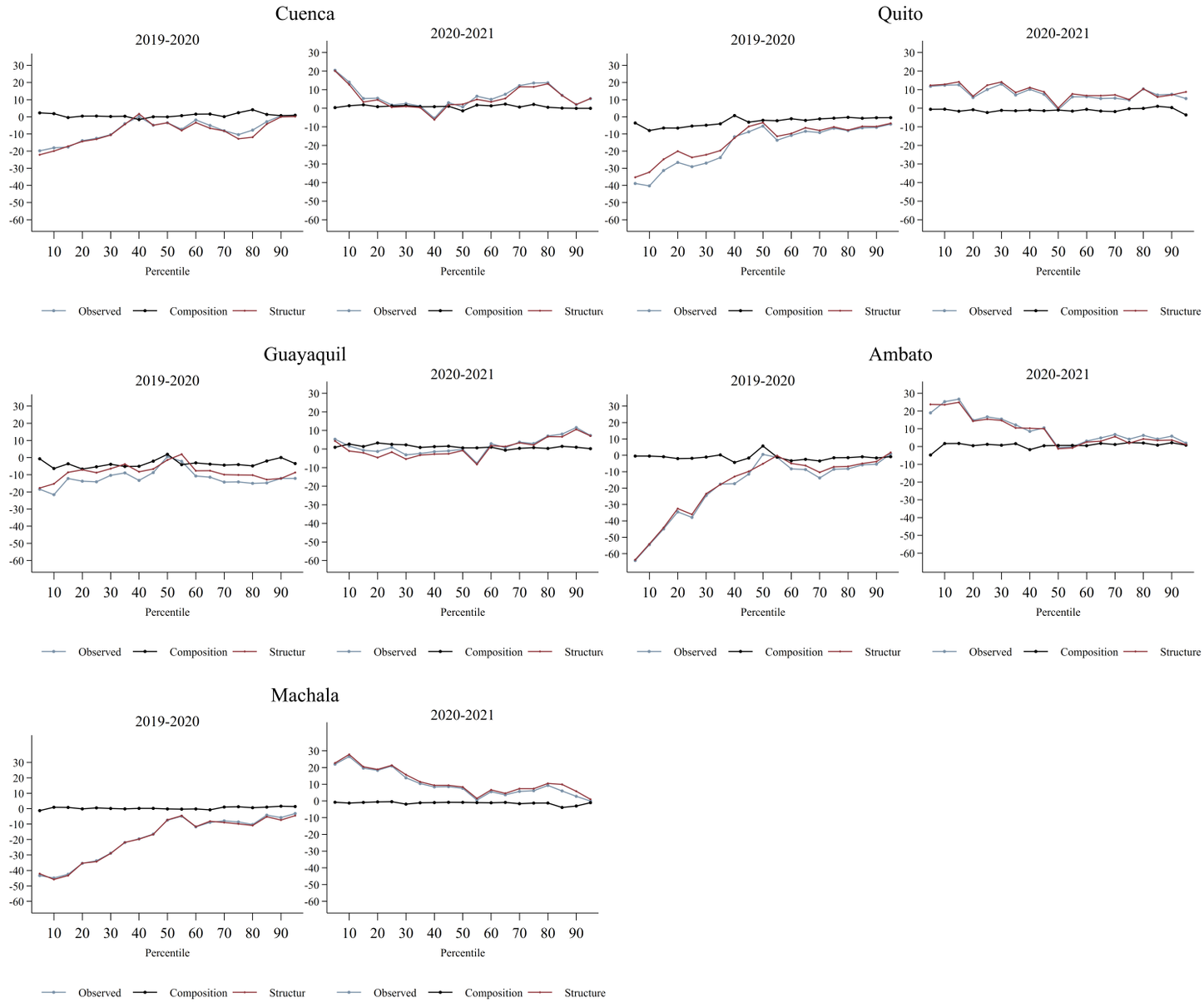
Source: Authors' own based on household surveys.
Note: The data refers to constant dollars of the year 2014.

Annex 2: Trends in Inequality: Ecuador 2020-2021.



Source: Authors' own based on household surveys.

Annex 3: Decomposition of the labor income difference: Main cities. Log difference (100).



Source: Authors' own based on household surveys.

Annex 4: *Sample averages. Main cities*

Variable	**Cuenca**			**Quito**			**Guayaquil**			**Ambato**			**Machala**		
	2019	2020	2021	2019	2020	2021	2019	2020	2021	2019	2020	2021	2019	2020	2021
Years of education	12.86	13.08	13.14	12.93	13.07	13.35	12.19	12.22	12.40	13.09	13.11	13.17	12.07	12.15	12.17
Primary education	0.29	0.27	0.26	0.26	0.24	0.22	0.32	0.31	0.28	0.27	0.28	0.27	0.33	0.34	0.32
Secondary education	0.33	0.35	0.33	0.37	0.38	0.36	0.40	0.42	0.44	0.34	0.32	0.31	0.38	0.38	0.39
University education	0.38	0.37	0.41	0.38	0.38	0.42	0.28	0.27	0.28	0.38	0.40	0.41	0.29	0.28	0.29
Experience	21.77	21.34	21.08	22.16	21.94	21.22	23.85	22.32	22.33	23.38	22.80	22.79	23.35	22.64	22.77
$11 \leq$Experience≤ 20	25.37	26.20	23.43	24.56	23.41	23.23	19.85	21.56	20.76	26.45	22.28	22.47	22.93	21.40	22.68
$21 \leq$Experience≤ 30	20.22	20.37	20.19	21.77	23.00	22.05	22.81	20.46	21.01	19.47	22.24	21.66	20.69	22.73	21.69
$31 \leq$Experience≤ 40	14.60	15.20	15.63	17.43	16.63	16.58	15.82	16.52	16.44	17.32	17.15	16.35	16.86	16.71	17.56
$41 \leq$Experience≤ 50	7.96	7.96	7.24	6.86	8.49	7.11	10.46	9.65	9.26	7.98	7.80	9.06	8.06	9.04	7.37
$51 \leq$Experience	4.73	3.57	4.04	4.09	2.63	2.90	6.12	3.98	4.30	5.87	4.82	4.93	6.89	4.22	5.19
Female	0.45	0.44	0.44	0.43	0.41	0.43	0.35	0.37	0.36	0.44	0.44	0.45	0.38	0.35	0.38
Minority group	0.02	0.01	0.03	0.09	0.09	0.08	0.12	0.09	0.10	0.04	0.05	0.06	0.09	0.06	0.05
Formal wage employees	0.45	0.43	0.42	0.51	0.45	0.44	0.37	0.33	0.33	0.37	0.35	0.34	0.35	0.31	0.30
Upper-tier informal wage employees	0.03	0.03	0.05	0.04	0.04	0.05	0.05	0.06	0.07	0.04	0.04	0.04	0.08	0.08	0.12
Lower-tier informal wage employees	0.11	0.14	0.13	0.09	0.10	0.11	0.13	0.13	0.13	0.11	0.13	0.13	0.18	0.19	0.18
Formal self-employed	0.03	0.02	0.03	0.02	0.03	0.02	0.02	0.01	0.02	0.02	0.03	0.03	0.02	0.02	0.02
Informal self-employed	0.38	0.38	0.37	0.34	0.38	0.38	0.44	0.46	0.45	0.45	0.45	0.47	0.38	0.40	0.39
Agriculture, livestock, hunting, and forestry	0.03	0.03	0.03	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.03	0.02	0.13	0.16	0.18
Manufacturing	0.24	0.26	0.24	0.21	0.20	0.20	0.26	0.24	0.24	0.24	0.22	0.24	0.16	0.16	0.17
Commerce	0.25	0.27	0.26	0.20	0.23	0.25	0.27	0.29	0.28	0.28	0.29	0.28	0.28	0.28	0.28
Services	0.47	0.45	0.48	0.58	0.55	0.54	0.46	0.45	0.47	0.46	0.46	0.46	0.43	0.41	0.38
Rural	0.02	0.00	0.02	0.00	0.00	0.01	0.00	0.01	0.00	0.09	0.02	0.03	0.04	0.01	0.08

Source: Authors' own based on household surveys.

Annex 5: *Average hourly labor income*

	Cuenca			Quito			Guayaquil			Ambato			Machala		
	2019	2020	2021	2019	2020	2021	2019	2020	2021	2019	2020	2021	2019	2020	2021
Human capital															
Primary education	2.54	2.23	2.31	2.12	1.79	1.80	2.08	2.07	2.02	2.08	1.80	1.81	2.76	1.90	2.13
Secondary education	3.14	2.88	3.06	3.15	2.61	2.93	2.83	2.43	2.55	3.83	2.49	2.73	2.76	2.45	2.93
University education	6.17	6.23	5.39	6.50	5.72	5.71	4.77	4.49	4.72	4.91	5.30	5.11	5.41	4.02	4.72
Experience															
Experience <11	4.84	3.58	3.58	4.03	3.52	3.73	3.02	2.83	2.80	3.53	3.61	3.10	3.76	2.64	2.91
$11 \leq$Experience≤ 20	3.95	5.39	4.18	4.90	4.39	4.20	3.50	3.17	3.16	3.50	4.01	4.41	3.27	3.00	3.12
$21 \leq$Experience≤ 30	4.03	3.95	4.16	4.58	3.63	4.07	3.39	3.03	3.58	3.96	3.51	3.65	3.35	2.98	3.33
$31 \leq$Experience≤ 40	4.40	3.63	3.88	4.18	3.58	3.88	3.47	2.88	3.02	3.63	3.23	3.31	3.79	2.54	4.47
$41 \leq$Experience≤ 50	3.50	2.91	3.37	2.79	2.60	2.75	2.96	2.59	2.48	7.72	2.42	2.58	4.47	2.54	2.43
$51 \leq$Experience	2.51	1.89	2.35	1.83	1.65	1.90	1.90	2.37	2.41	1.80	1.83	2.19	2.08	1.90	1.89
Worker characteristics															
Female	4.26	3.47	3.74	4.13	3.63	3.81	3.01	2.82	2.98	4.34	3.34	3.36	3.16	2.75	2.88
Male	4.10	4.47	3.88	4.29	3.66	3.82	3.31	2.97	3.06	3.50	3.52	3.54	3.74	2.73	3.46
Minority group	3.85	2.27	2.73	3.19	2.22	2.66	2.87	2.64	2.41	2.61	1.80	1.92	2.50	2.15	2.44
Sector of employment															
Formal wage employees	5.23	5.71	4.98	5.08	4.89	5.06	4.13	3.98	4.16	4.77	5.19	5.04	5.07	3.89	4.22
Upper-tier informal wage employees	2.81	3.06	2.48	3.26	2.28	2.48	2.46	2.19	2.15	2.42	2.33	2.50	2.38	2.27	2.38
Lower-tier informal wage employees	2.60	2.15	2.25	2.40	1.99	1.95	2.31	1.94	1.84	2.05	1.92	2.03	2.42	2.04	2.04
Formal self-employed	4.45	3.80	4.81	6.17	5.30	6.18	4.65	4.78	5.09	3.23	3.67	3.59	3.08	3.47	4.28
Informal self-employed	3.42	2.74	3.08	3.32	2.43	2.88	2.68	2.44	2.57	3.70	2.46	2.69	2.81	2.21	3.21
Sector of activity															
Agriculture, livestock, hunting, and forestry	2.44	1.72	1.70	8.66	2.96	2.55	3.99	2.69	3.01	2.62	1.46	2.37	3.36	2.79	3.09
Manufacturing	3.22	2.88	3.17	3.74	2.73	3.16	3.05	2.56	2.73	4.98	3.00	2.91	2.87	2.38	2.83
Commerce	3.95	3.09	3.11	3.40	2.79	2.99	2.58	2.53	2.50	2.93	2.93	3.02	3.94	2.26	2.53
Services	4.87	5.28	4.64	4.63	4.31	4.45	3.61	3.35	3.49	3.90	4.08	4.06	3.52	3.17	3.99

Source: Authors' own based on household surveys.

Annex 6a: *Labor Market returns. Hourly labor income (logs)*

	Cuenca						Quito						Guayaquil					
	2019		2020		2021		2019		2020		2021		2019		2020		2021	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Secondary education	0.10**	0.04	0.12***	0.03	0.09**	0.04	0.11***	0.04	0.15***	0.04	0.13***	0.04	0.16***	0.03	0.09***	0.02	0.06**	0.03
University education	0.39***	0.05	0.40***	0.04	0.36***	0.04	0.40***	0.04	0.43***	0.05	0.47***	0.04	0.40***	0.04	0.32***	0.02	0.30***	0.03
11 ≤Experience≤ 20	0.05	0.04	0.13***	0.03	0.14***	0.03	0.07**	0.03	0.05	0.04	0.04	0.03	0.12***	0.03	0.07***	0.02	0.14***	0.02
21 ≤Experience≤ 30	0.14***	0.04	0.17***	0.03	0.16***	0.04	0.11***	0.04	0.06	0.04	0.12***	0.03	0.14***	0.03	0.10***	0.02	0.20***	0.03
31 ≤Experience≤ 40	0.15***	0.05	0.16***	0.03	0.15***	0.05	0.10**	0.04	0.05	0.05	0.14***	0.03	0.16***	0.04	0.12***	0.02	0.18***	0.03
41 ≤Experience≤ 50	0.04	0.08	0.16***	0.06	0.14**	0.06	0.01	0.07	0.07	0.07	0.05	0.05	0.20***	0.04	0.12***	0.03	0.18***	0.04
51 ≤Experience	-0.03	0.12	-0.04	0.07	0.05	0.12	-0.01	0.09	0.08	0.10	-0.07	0.08	0.15**	0.06	0.06	0.04	-0.04	0.06
Female	-0.14***	0.03	-0.13***	0.02	-0.07***	0.03	-0.08***	0.03	-0.07**	0.03	-0.05**	0.02	-0.17***	0.02	-0.08***	0.01	-0.05***	0.02
Formal employees	0.23***	0.06	0.28***	0.06	0.35***	0.04	0.25***	0.05	0.38***	0.06	0.43***	0.04	0.33***	0.04	0.33***	0.02	0.36***	0.03
Lower-tier informal wage employees	-0.04	0.06	-0.10*	0.06	-0.07	0.05	-0.07	0.06	-0.05	0.07	-0.13***	0.05	-0.05	0.05	-0.11***	0.03	-0.15***	0.03
Formal self-employed	-0.15	0.12	-0.13	0.08	0.05	0.09	-0.04	0.12	0.05	0.12	0.03	0.08	0.15	0.10	0.07	0.06	0.28***	0.07
Informal self-employed	-0.08	0.06	-0.19***	0.06	-0.08	0.05	-0.31***	0.06	-0.35***	0.06	-0.18***	0.05	-0.10**	0.04	-0.17***	0.03	-0.14***	0.03
Agriculture	-0.16	0.12	-0.07	0.10	-0.16	0.11	0.17	0.18	0.12	0.14	0.04	0.10	0.15*	0.08	0.18***	0.05	-0.02	0.07
Manufacture	0.07	0.04	0.03	0.03	0.13***	0.04	0.13***	0.04	0.07	0.04	0.10***	0.03	0.11***	0.03	0.07***	0.02	0.06**	0.02
Services	0.11***	0.04	0.18***	0.03	0.20***	0.03	0.16***	0.04	0.16***	0.04	0.10***	0.03	0.13***	0.03	0.10***	0.01	0.10***	0.02
Minority group	0.08	0.06	-0.12*	0.07	-0.09	0.06	0.01	0.04	-0.13**	0.05	-0.08*	0.05	-0.09**	0.04	0.02	0.03	0.00	0.03
Constant	0.70***	0.07	0.58***	0.06	0.52***	0.06	0.61***	0.07	0.42***	0.08	0.41***	0.06	0.50***	0.05	0.52***	0.03	0.48***	0.04
N	1122		2833		2229		1424		1672		2921		1903		5378		3406	
Adj. R-sq	0.27		0.35		0.35		0.38		0.39		0.37		0.31		0.28		0.28	

Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Source: Authors´ own based on household surveys.

Note: The base category involves workers with primary education, with a maximum of 10 years of education, male employee, urban area, services and merchant workers in the trade sector, and lower-tier informal wage employees.

Annex 6b: *Labor Market returns. Hourly labor income (logs)*

	Ambato						**Machala**					
	2019		2020		2021		2019		2020		2021	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Secondary education	-0.02	0.05	0.14***	0.04	0.17***	0.05	0.10**	0.04	0.14***	0.03	0.02	0.04
University education	0.28***	0.05	0.43***	0.04	0.44***	0.05	0.26***	0.04	0.33***	0.04	0.24***	0.04
11 ≤Experience≤ 20	0.02	0.04	0.08**	0.0356	0.16***	0.04	0.13***	0.04	0.09***	0.03	0.05	0.04
21 ≤Experience≤ 30	0.15***	0.05	0.13***	0.04	0.12***	0.04	0.11**	0.04	0.15***	0.04	0.12***	0.04
31 ≤Experience≤ 40	0.11**	0.05	0.13***	0.04	0.14***	0.05	0.13***	0.05	0.10**	0.04	0.17***	0.04
41 ≤Experience≤ 50	0.01	0.07	0.09	0.07	0.04	0.07	0.07	0.07	0.10**	0.05	0.07	0.05
51 ≤Experience	-0.15*	0.08	-0.11	0.09	0.13	0.09	-0.17*	0.09	0.09	0.08	0.04	0.08
Female	-0.08***	0.03	-0.09***	0.03	-0.14***	0.03	-0.06*	0.03	-0.07**	0.08	-0.07**	0.03
Formal employees	0.34***	0.09	0.34***	0.05	0.39***	0.06	0.27***	0.05	0.33***	0.05	0.25***	0.06
Lower-tier informal wage employees	-0.11	0.09	-0.20***	0.06	-0.10	0.07	-0.03	0.05	-0.14**	0.05	-0.22***	0.05
Formal self-employed	-0.04	0.14	-0.29***	0.10	0.03	0.10	-0.01	0.15	0.09	0.09	0.04	0.09
Informal self-employed	-0.16*	0.09	-0.39***	0.05	-0.19***	0.06	-0.14**	0.06	-0.33***	0.05	-0.27***	0.06
Agriculture	-0.15	0.10	-0.27**	0.12	-0.03	0.14	0.04	0.06	0.07	0.04	-0.01	0.05
Manufacture	0.00	0.04	0.02	0.04	0.06	0.04	0.08*	0.05	0.11***	0.04	0.06*	0.03
Services	0.08*	0.04	0.06*	0.03	0.10***	0.04	0.08*	0.04	0.11***	0.03	0.13***	0.03
Minority group	-0.08	0.07	-0.07	0.06	-0.08	0.07	-0.05	0.06	-0.06	0.05	-0.08	0.06
Constant	0.73***	0.11	0.54***	0.06	0.47***	0.07	0.65***	0.07	0.49***	0.06	0.71***	0.05
N	1260		2473		1913		1024		2442		2576	
Adj. R-sq	0.36		0.38		0.35		0.26		0.31		0.26	

Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Source: Authors´ own based on household surveys.

Note: The base category involves workers with primary education, with a maximum of 10 years of education, male employee, urban area, services and merchant workers in the trade sector, and lower-tier informal wage employees.