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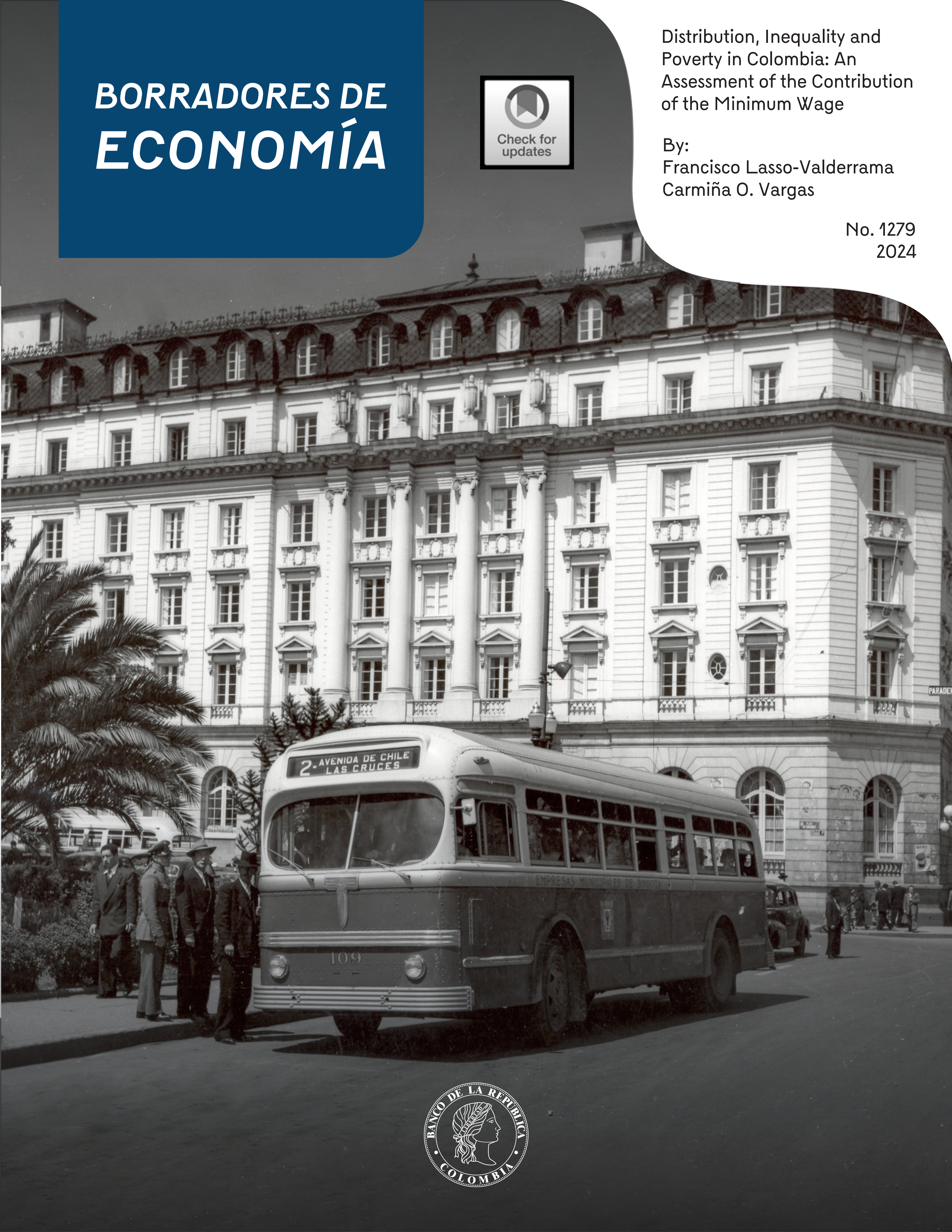

BANCO DE LA REPUBLICA
COLOMBIA

Distribution, Inequality and Poverty in Colombia: An Assessment of the Contribution of the Minimum Wage

Francisco Lasso-Valderrama ⓡ Carmiña O. Vargas[1]

Abstract

In Colombia, 50% of labor income is lower than the legal MW level. It is in this context that we analyze the effect of increasing MW on labor income distribution and its inequality, household income distribution and its inequality, and on monetary poverty prevalence. Specifically, we study the unconditional quantiles to establish whether there are differential effects for low quantiles, for those closer to MW, and for higher quantiles. We perform this analysis for different occupational groups. We also assess the effects of MW relative to median on labor income inequality, measured by its Gini coefficient, and on monetary poverty prevalence. We find that increases in MW raises quantile values of labor income for most occupational groups, except for the 10th quantile of those distributions. For this quantile, the effects are mostly not statistically significant. With respect to household income per-capita, we find that increasing MW raises all income quantiles, except for the lowest 10% of income. The effect for the 10th quantile is negative. Consistent with those results, we find that increasing MW when it is high relative to median income increases inequality measured by the Gini coefficient as well as monetary poverty prevalence. We use unconditional quantile regressions for our analysis. We use the microdata of a pooled sample of household surveys in Colombia from 2008 to 2019.

Keywords: minimum wage; wage inequality; income inequality; poverty.
JEL CODES: J39, J31, C31

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[1] ⓡ Random author order; confirmation code: 11Nl6CVf8kTO. https://www.aeaweb.org/journals/policies/random-author-order/search?RandomAuthorsSearch%5Bsearch%5D=11Nl6CVf8kTO. Francisco Lasso Valderrama, Banco de la República (flassova@banrep.gov.co); Carmiña Vargas Riaño, Banco de la República (cvargari@banrep.gov.co). The authors are thankful for the helpful comments and discussions provided by Luis Eduardo Arango, Juan Esteban Carranza, Margarita Gáfaro, and conference and seminar participants at Banco de la República (Bogotá), the RES & SES Annual Conference (Glasgow), the International Economic Association World Congress (Medellín) and the Annual Conference of the European Society for Population Economics (Rotterdam). We thank Diego Chiquillo Torres and Alejandra Díaz Londoño for excellent research assistance. All errors are our responsibility. The findings, views and interpretations expressed herein are those of the authors and should not be attributed to Banco de la República or its Board of Directors.

Distribución, desigualdad y pobreza en Colombia: una evaluación de la contribución del salario mínimo

Francisco Lasso-Valderrama ⓡ Carmiña O. Vargas

Resumen

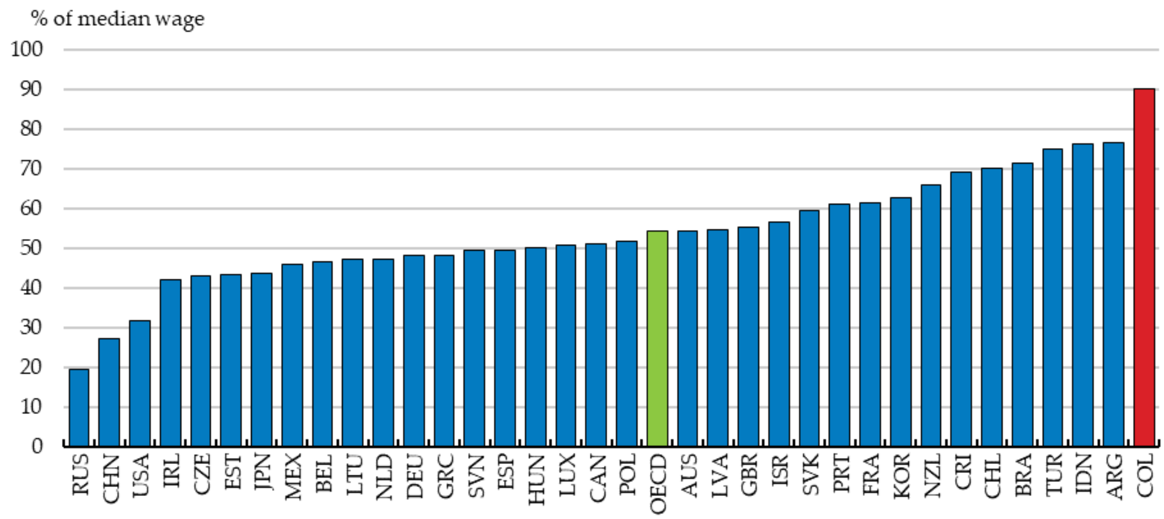
En Colombia, el 50% de los ingresos laborales son más bajos que el salario mínimo (SM). En este contexto, analizamos el efecto del aumento del SM relativo al ingreso mediano sobre la distribución del ingreso laboral y su desigualdad, la distribución del ingreso de los hogares y su desigualdad, y sobre la prevalencia de pobreza monetaria. Específicamente, estudiamos los cuantiles incondicionales para establecer si existen efectos diferenciales para los cuantiles bajos, para los más cercanos al SM y para los cuantiles superiores. Realizamos este análisis para diferentes grupos ocupacionales. También evaluamos los efectos de incrementos en el SM relativo al mediano sobre la desigualdad de ingresos, medida por su coeficiente de Gini, y sobre la prevalencia de pobreza monetaria. Encontramos que los aumentos en el SM relativo incrementan el valor de los cuantiles de la distribución de los ingresos laborales para la mayoría de los grupos ocupacionales, excepto para el cuantil 10 de esas distribuciones. Para este cuantil, los efectos son en su mayoría no estadísticamente significativos. Con respecto al ingreso per cápita de los hogares, encontramos que el aumento del SM relativo incrementa todos los cuantiles de la distribución de estos ingresos, excepto el 10% más bajo. El efecto para el cuantil 10 es negativo. En concordancia con estos resultados, encontramos que incrementos del SM cuando éste es alto relativo al ingreso mediano incrementa la desigualdad medida por el coeficiente de Gini, así como la prevalencia de pobreza monetaria. Para nuestro análisis, utilizamos regresiones cuantílicas incondicionales. Usamos los microdatos de una muestra agrupada de encuestas de hogares en Colombia de 2008 a 2019.

Palabras clave: salario mínimo, desigualdad salarial, desigualdad de ingresos, pobreza.
Códigos JEL: J39, J31, C31

1. Introduction

Colombian minimum wage (MW) is high relative to its median labor income[2]. On average for the period 2008 - 2019, half of employed individuals have a real labor income equal to or less than the real legal MW. Among full-time wage earners, OECD (2022) finds that the proportion MW relative to median salary for Colombia is the highest among all OECD countries, according to data from 2019. While in the United States MW is 30% of the median salary, and in Spain it is 50%, in Colombia its MW is 90% of median salary (Graph 1).

Graph 1. Colombian minimum wage as percentage of median wages of full-time workers is the highest in the OECD, 2019



Note: Exactly half of all workers have wages either below or above the median wage. Percentage of minimum to average wage 2017 for China, Indonesia and the Russian Federation.
Source: Taken from OECD (2022). OECD, OECD Employment Outlook Database; China Ministry of Human Resources and Social Security, National Bureau of Statistics; Instituto Brasileiro de Geografia e Estatística (Pesquisa Nacional por Amostra de Domicílios); International Labour Organisation (ILO) Database on Conditions of Work and Employment Laws; Ministry of Man Power and Transmigration of the Republic of Indonesia and Statistics Indonesia (BPS); Russia Federal State Statistics Service; National Institute of Statistics and Census of Argentina.

One of the considerations about MW is that it should constitute one element of policy to overcome poverty and reduce inequality.[3] When the MW is as high relative to other incomes as in Colombia, how do increases in MW affect labor income distribution and its inequality? Do increases in the MW raise low labor incomes? How are household income distribution and its inequality along with monetary poverty prevalence affected?

[2] The median labor income corresponds to that income level such that half of those employed obtain a labor income lower than that level and, consequently, the other half of those employed obtain a higher labor income. In Colombia, in the period 2008-2019, on average the median monthly real labor income (December 2018 prices) for total employed (wage earners and self-employed) workers is around COP 763,000.
[3] See ILO (definition) and ILO (1970).

In this document, we seek to provide an answer to those questions. To do so, we use quarterly data from 12 years of the Colombian Gran Encuesta Integrada de Hogares (GEIH), a large-scale, nationally representative household survey, to look at whether there is a systematic relationship between (i) the value of the quintiles and inequality of labor income distribution and how high the MW is relative to other labor incomes; and (ii) the value of the quintiles and inequality of household income distribution as well as monetary poverty prevalence and how high the MW is relative to household income.

We are interested on the unconditional distributions. Therefore, we employ the methodology introduced by Firpo, Fortin, and Lemieux (2009) for estimating unconditional quantile regressions, known as RIF regressions. We use individual-level data from each quarter as our primary units of observation to estimate those regressions. Because the GEIH is a repeated cross-section and not longitudinal, we include appropriate controls as well as geographical unit fixed effects and quarter fixed effects.

In Colombia, the legal nominal MW pertains to the entire national territory and all industries and jobs. Therefore, to identify the effects on income distribution, we take advantage of the variability in both the median real labor and household incomes that exists in Colombia. Those medians vary over cities at any point in time, as well as over time for each city. Our independent variables of interest are, therefore, appropriately chosen ratios of MW to median income. This is a measure of relative MW widely used in the literature and known as the Kaitz index. The convenience of this relative measure of MW impact is twofold. Firstly, it captures our concern about the MW being high relative to other wages and incomes. Secondly, it gives us ample variability in MW across time and among cities even though the legal MW in Colombia is uniquely set for all cities, industries and jobs.

Our work is most closely related to the extensive theoretical and empirical literature on MW and its distributional effects. Some theoretical models assume that MW changes only affects workers who earn income between the old and the new MW; others find that further labor income levels could be affected if, for example, wage differentials are important for encouraging workers' effort or if demand for workers who earn above the MW increases.[4] The effects on MW changes on household incomes would depend on the combination of the effects on labor income distribution, employment, and other sources of income. Most empirical studies for the US take advantage of the cross-state minimum wage variation (e.g. DiNardo, Fortin, and Lemieux, 1996; Lee, 1999; Autor, Manning and Smith, 2016, among many). Other set of studies exploit the introduction of a MW policy in different countries (e.g. Katzkowicz, et *al*., 2011, for Uruguay; Bossler and Schank, 2023, for Germany, among many). The studies that are closest in spirit to our work are Dube (2019) and Bossler and Schank (2023) which use unconditional quantile regressions (RIF regressions) to study

[4] Brown (1999) reviews the theory of MW and its distributional effects, Leonard (2000) presents a history of the MW in Economics, and the works of Welch (1976), Gramlich (1976), and Mincer (1976) include models with covered (by the MW legislation) and uncovered sectors.

the distributional effects of changes in the MW. Dube (2019) evaluates how the US MW policies shift the distribution of family incomes, estimating unconditional quintile partial effects of the policy. Dube finds positive effects of minimum wages on family incomes below the twentieth quantile. The largest impact occurs at the tenth and fifteenth quantiles. Furthermore, he finds a significant reduction in poverty levels. Bossler and Schank (2023) evaluate the distributional effects of the introduction in Germany in 2015 of a nation-wide hourly minimum wage. Their results show that monthly wages significantly increased from the bottom up to the median of the wage distribution. Consequently, there was a meaningful reduction of overall wage inequality measured by the variance of log wages.

For Colombia, Maloney and Núñez (2004) conclude that a 1% hike in the legal MW leads to increases between 0.16% and 1.74% in labor income, with the largest rises pertaining to the lowest incomes. The greatest impacts are found in wages close to the MW. Given the significant positive effects on wage levels lower than MW as well as on earnings of self-employed individuals (not covered by MW legislation), the authors indicate the presence of a "lighthouse effect"; that is, MW serves as a reference for the entire economy, including the informal sector. In turn, Arango and Pachón (2007) find significant positive effects on labor income distribution, the largest being between the 45th and 60th percentiles, with no significant effects on percentiles lower than the 30th[5]. However, Mondragón *et al*. (2011) maintain that MW effect on the formal sector is decreasing throughout the income distribution, being negative for the two thirds of workers with higher incomes; moreover, the most important negative effects are observed in the labor income of the informal sector. Also, Pérez (2020) finds that, following the unexpected increase in 1999´s real MW due to unexpectedly low inflation that year, wages close to the MW increased both in the formal and informal sectors, with higher increases in the formal sector.

This paper contributes to the literature by studying the effects of MW on distributional outcomes and poverty in the context of an economy in which the MW is relatively high and the labor market experiences high informality rates, hovering around 56% for the period 2008-2019. This in contrast to previous literature which mostly studies the effects on advanced economies where MW is relatively low compared to other wages and incomes; and where the informal labor market is not as prevalent. Furthermore, many works on developed economies focus their studies on the population mostly affected by the MW, like teenagers, cashiers, etc. In general, it is expected that the affected population would experience small effects on employment and even on wages when MW changes. Therefore, the expected effect on other population, those not directly affected by the MW, is even smaller. In Colombia, the population affected is so big, that the discussion focuses on the effects on all the labor market due to the changes in the MW. We consider the effects on different occupational groups as well as on household income distribution and poverty.

Our main results are:

[5] Arango and Pachón (2007), page 179, Table 6, second panel.

For the distributions of hourly labor income, increments in the mean value of the MW relative to the median (i) increases the value of most of the quantiles of the distribution of labor income of the occupational groups considered, moving the distributions to the right, (ii) wage earners exhibit the relatively largest effects, (iii) the quantiles of real labor earnings closest to the real MW generally experience the largest percentage increase in each group, (iv) labor income inequality increases for self-employed workers who do not contribute to social security, and decreases for wage earners. Even labor incomes much higher than the MW and those not compliant with the law (below the MW) are affected by changes in the MW relative to the median. In Colombia, spillover effects are relevant not only for those workers 'just above' the MW, but also for higher wages.

The impact on the lowest family incomes of changes in the real MW would depend on the combined effects on labor income distribution, employment, labor informality, labor participation, among other effects that the MW may have on labor markets. For the distribution of household income, we find that increments in the mean value of the MW relative to the median (i) reduces the value of its 10th quantile, (ii) increases the value of the remaining quantiles and the effects are increasing with the quantiles, (iii) increases household income inequality, consistent with the previous results.

Finally, our findings indicate that monetary poverty prevalence increases when the mean value of the MW relative to the median increases.

The remainder of this paper is organized as follows. Section 2 presents the data and discusses some summary statistics. In section 3, the empirical framework is presented. In section 4, the empirical results are presented and discussed. Section 5 concludes and provides suggestions for future research.

2. Data and Descriptive Statistics

We use data from the GEIH[6], a continuous household survey conducted by the Colombia´s Departamento Administrativo Nacional de Estadística (DANE). The GEIH sample is selected every year to be representative at the national level as well as for 23 main cities[7] plus the domain *other municipal capitals, populated centers, and scattered rural areas*. The GEIH provides information about the size and structure of the labor force in Colombia, as well as on their sociodemographic characteristics.

The data include individual-level sampling weights, which we use throughout our analysis. We use quarterly repeated cross sections from the first quarter of 2008 to the last quarter of 2019 inclusively.

[6] Gran Encuesta Integrada de Hogares.

[7] The 23 state capitals and metropolitan areas are: Barranquilla, Cartagena, Sincelejo, Valledupar, Santa Marta, Riohacha, Bogotá, Tunja, Villavicencio, Neiva, Florencia, Bucaramanga, Cúcuta, Cali, Pasto, Popayán, Manizales, Ibagué, Pereira, Armenia, Medellín, Montería and Quibdó.

We express all monetary values in real terms in December 2018 Colombian pesos (COP). We use the monthly CPI of the respective city. For the domain *other municipal capitals, populated centers, and scattered rural areas*, we use total (national) CPI for perishable food.

2.1. Outcomes of interest

We have four main outcomes of interest for the impact of changes in the MW: (i) the distribution of real labor earnings per hour, by occupational group; (ii) the distribution of real monthly household income; (iii) prevalence of monetary poverty; and (iv) inequality in labor and household income. In what follows, we explain the construction of each variable in turn and present and discuss descriptive statistics.

2.1.1. Labor earnings per hour by occupational group

To construct the distribution of labor income per hour, we use the information on labor income and hours of work reported by each individual in the survey. We use information on employed persons between the ages of 18 and 65 who normally work 40 or more hours a week.

As labor earnings, we use their base income from their first occupational activity[8]. Base income per person is their monetary income. For wage earners, the reported value of in-kind income (food, housing, transportation, appliances, clothing and others) is also included; the values reported for extra hours worked, food allowance, transportation, family and education premiums and bonuses are not included. For self-employed individuals, monetary income includes the values reported for fees and net profits.

In GEIH, people report the monthly income earned last month. Furthermore, the person reports the weekly hours usually worked in that activity last week. To obtain the monthly hours, we multiply those weekly hours by 30 and divide them by 7. Labor earning per hour for each employed individual is, therefore, calculated as her (real) monthly income divided by her so computed monthly working hours.

We analyze these four occupational groups: wage earners[9], self-employed individuals without higher education, self-employed individuals with higher education[10] and total employed (the sum of the three previous groups). We also consider a classification of occupational groups based on whether the individual contributes to social security[11]. With these criteria, the six occupational groups we analyze are: wage earners who contribute, wage earners who do not contribute, self-

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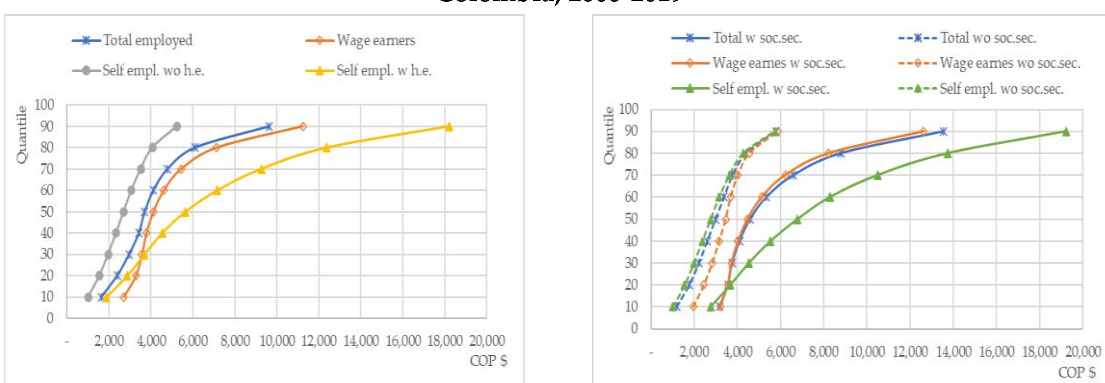
[8] In our sample, 6% of the employed individuals have a second job. On average, 2% of total labor income comes from the second job.
[9] In this article, wage earners are private and public workers and employees. We did not include domestic employees and day laborers in this analysis (occupational categories also included in the GEIH).
[10] A person is classified as “without higher education” if her educational level is complete high school or less; and as "with higher education" if she has at least one year of studies beyond complete high school.
[11] A person contributes to social security if she contributes to both health and pensions.

employed individuals who contribute, self-employed individuals who do not contribute, total employed (wage earners and self-employed) individuals who contribute and total employed individuals who do not contribute[12].

The hourly labor income distribution of each of these occupational groups differs from each other. In Graph 2, we report the cumulative distribution of the hourly labor income for each occupational group, average for the period 2008-2019.[13] It indicates that 40% of wage earners had hourly earnings of less than COP 3,782. On the other hand, 40% of self-employed individuals without higher education earned hourly labor income of less than COP 2,347. Furthermore, in the group of wage earners, one in five (20%) workers earned no more than COP 3,285 per hour; but in the total employed group, one in five earned no more than COP 2,397 per hour. The 50th quantile indicates the median labor income; it divides each occupational group into two large equal parts. It indicates that, for example, half of the total employed group had hourly earnings of less than COP 3,707. In contrast, 50% of the self-employed individuals who contribute to social security earned hourly earnings of less than COP 6,789.

Graph 2. Distribution of hourly labor income by occupational group
Colombia, 2008-2019



Notes: value of each quantile in the labor income distribution of each occupational group. Values in real COP, base 2018. For details on the calculation of hourly labor income, see Section 2.1.1 in this paper. Calculations use the information of all individuals belonging to each group in each city-quarter during the period 2008-I – 2019-IV. "Total employed" corresponds to the sum of wage earners and self-employed workers. "Wage earners" are private and public workers and employees. We did not include domestic employees and day laborers in this analysis (occupational categories also included in the GEIH). "wo h.e." stands for "without higher education". "w h.e." stands for "with higher education". A person is classified as "without higher education" if her educational level is complete high school or less. A person is classified as "with higher education" if she has at least one year of studies beyond complete high school. "w soc.sec." stands for "with social security". "wo soc.sec." stands for "without social security". A person contributes to social security if she contributes to both health and pensions. As a reference, the real hourly MW in 2018 is COP 3700. See Appendix E, Table E.2, for these values in table format.
Source: DANE-GEIH, authors calculations.

In the analysis, we use the logarithm of the real hourly labor income per individual residing in city c in quarter t (y_{1ict}). Section 3 provides details on the estimation.

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[12] Table E.1 in Appendix E provides data on the size of each occupational group.
[13] Appendix E, Table E.2, reports these values in table format. Also, Graph E.1. presents the evolution of the quantile values for the group of Total Employed during the period of analysis.

Not only do the distributions differ from each other, but also the institutional conditions for each occupational group are diverse. Notably, compliance with MW regulation varies among groups; so, it is likely that MW relative to the median has distinguishing effects on the distribution of labor income for each of these groups. We hypothesize that the effect of MW relative to the median on those distributions differs for each occupational group due to the heterogeneity of the parts that make up the labor market[14]; such heterogeneity is reflected in the observable and unobservable characteristics, which are not always clearly definable, of supply and demand.

2.1.2. Monthly household income per capita

Strictly, for this dimension of the analysis, we employ the concept of an "expenditure unit" used by Dane. However, in this article we refer to the "expenditure unit" as a "household".[15]

We are interested in the distribution of household income. Hourly income is not applicable in this context. Therefore, we use the real monthly total income per capita[16] of each household. We assign this income per capita to each household member. We use the official data DANE uses to calculate poverty rates between 2008 and 2019.

Table 1. Value of the quantiles of the distribution of real monthly total income per capita of households, Colombia 2008 - 2018

q10	q20	q30	q40	q50	q60	q70	q80	q90
144,351	211,082	276,509	341,124	420,837	519,177	653,436	873,270	1,342,441

Notes: value of each quantile in the household income distribution. Values in real COP, base 2018. For details on the calculation of total household income per capita, see Section 2.1.2 in this paper. Calculations use the information of all individuals in each city-quarter during the period 2008-I – 2018-IV. For reference, the legal monthly MW in 2018 was about COP 789,000.
Source: DANE-GEIH; authors calculations.

In Table 1 we report the quantiles of the distribution of real monthly total household income per capita using the average for the period 2008-2018 deflated at December 2018 prices. Using the average of real values between 2008 and 2018, 50% of households in Colombia received real income of less than COL$421,000 per household member per month[17].

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[14] A labor market refers to the activities associated with supply and demand of labor services to accomplish certain types of trades and tasks, as well as to the process of determining the salary to be paid for the execution of said tasks. The labor market concept typically incorporates the degree of wage flexibility to shocks, labor mobility, and related regulations and institutions.

[15] The annual average population for household income and poverty analyzes are reported in Appendix E, Table E.3.

[16] Monthly total household income per capita is the sum of the labor and non-labor income of all household income recipients divided by the total household members not counting tenants nor domestic employees living in the household. Labor income is the income from the first and second activities including salaries in-kind, subsidies, extra hours, premiums, bonuses, and travel expenses, plus the income of self-employed workers from fees and net profits. Non-labor income comes from pensioners, disability or pension substitution, capital income from interest, dividends from investments and leases, and aid from other homes or institutions including alimony due to paternity, divorce or separation.

[17] As a reference, the legal monthly MW in Colombia for 2018 was about COP 789,000. Then, 50% of households in Colombia received real total income of less than 53% of the legal monthly MW per household member per month. Graph E.2 in Appendix E presents the evolution of quintile values and monthly MW during the period of analysis.

For the analysis of the effects on quantiles, we use the logarithm of this real monthly total household income per capita. We assign this value to each member of the household (y_{2ict}). Section 3 provides details on the estimation.

2.1.3. Monetary poverty

The monetary poverty line (MPL) indicates the monthly monetary cost of a basket of basic food and non-food items needed for a person's subsistence. In Colombia, the MPL's value is determined by DANE for each geographic domain each month (MPL_{ct}). If the monthly income per capita of the person's household is less than or equal to its corresponding MPL_{ct}, that person is in a situation of monetary poverty.

We consider four poverty levels determined by the multiples 0.5, 1, 1.5 and 2 of MPL_{ct}.

Our dataset for this analysis on monetary poverty prevalence uses the information from GEIH for the period first quarter of 2008 to the fourth quarter of 2018[18].

Average real MPL for that period, at December 2018 prices, was COP 280,473, value located between the 30th and 40th quantiles of the distribution of real monthly total household income per capita (Table 1). The average value of 0.5 MPL would be in the 10th quantile and that of 2 MPL in the 50th quantile of that households' income distribution.

Colombia experienced an important decrease in monetary poverty prevalence during the period of analysis 2008-2018 (Table E.3). Prevalence of monetary poverty in the Colombia went from 42% of the population classified as being under monetary poverty in 2008, to 27% of the population being in that condition in 2018.

For analyzing the influence of the MW on monetary poverty prevalence in Colombia, our dependent variables are indicators for whether person *i*'s household monthly total income per capita is below each specific poverty level. These indicator variables are equal to 1 for person *i* if her household's real monthly total income per capita, in their city of residence *c,* in quarter *t* is less than or equal to each MPL_{ct}'s multiple considered; otherwise, the indicator variables are equal to 0.

$$I(y_{2ict}, \lambda MPL_{ct}) = \begin{cases} 1\ if\ e^{y_{2ict}} < \lambda MPL_{ct} \\ 0\ otherwise \end{cases}$$

Where λ = {0.5, 1, 1.5, 2} and $e^{y_{2ict}}$ is person *i*'s household real monthly total income per capita in their city of residence c in quarter t. Section 3 provides details on the estimation.

[18] In 2019, DANE adjusted its methodology for establishing poverty lines. Consequently, we use data from the 2008-2018 period so that all MPLs are determined by DANE using the same methodology.

2.1.4. Income inequality

Inequality is another important dimension of income distribution. There are various measures of inequality. In this article, we use the Gini coefficient.

We analyze the Gini coefficient of the labor income distribution of each one of the occupational groups considered. In every case, we calculate the Gini coefficient for the distribution of real hourly labor income (not on its logarithm) since the logarithm underestimates the Gini by minimizing the dispersion of the distribution of labor income per hour.

We observe important variations in labor income inequality across occupational groups. Self-employed individuals with higher education exhibit the highest inequality in their hourly labor income distribution, with a Gini coefficient of 0.48. In contrast, self-employed individuals without higher education have the lowest hourly labor income inequality, with a Gini coefficient of 0.35 (Table 2).

Table 2. Gini coefficient of labor earnings per hour for each occupational group, Colombia 2009 – 2019.

	Gini	Observations
Total employed	0.430	9,143,464
Wage earners	0.396	5,334,272
Self-employed, without higher education	0.350	3,193,249
Self-employed, with higher education	0.480	619,942
Total employed who contribute	0.392	4,179,347
Total employed who do not contribute	0.398	4,964,117
Wage earners who contribute	0.379	3,759,172
Wage earners who do not contribute	0.382	1,575,100
Self-employed, who contribute	0.435	420,175
Self-employed, who do not contribute	0.393	3,389,017

Notes: Gini calculations use the information of all individuals belonging to each group in each city-quarter during the period 2009-I – 2019-IV. "Total employed" corresponds to the sum of wage earners and self-employed workers. "Wage earners" are private and public workers and employees. We did not include domestic employees and day laborers in this analysis (occupational categories also included in the GEIH). A person is classified as "without higher education" if her educational level is complete high school or less. A person is classified as "with higher education" if she has at least one year of studies beyond complete high school. A person contributes to social security if she contributes to both health and pensions. Number of observations adjusted by sample weights; corresponds to the average number of observations per quarter for the period.
Source: DANE-GEIH; authors calculations.

Similarly, we perform inequality analysis for household's income distribution. We calculate the Gini coefficient for the Colombia's distribution of real monthly total household income per capita. This income distribution exhibits high inequality, with a Gini coefficient of 0.50 on average for the period of analysis.

See section 3 for details on the estimation.

2.2. Independent variable: MW to median income

In Colombia, the legal nominal MW pertains to the entire national territory and all industries and jobs. Therefore, to identify the effects on income distribution, we take advantage of the variability in both the median real labor and household incomes that exists in Colombia. Those medians vary over cities at any point in time, as well as over time for each city. Our independent variables of interest are, therefore, appropriately chosen ratios of MW to median income. This is a measure of relative MW widely used in the literature and known as the Kaitz index.[19] In this document, we use the terms *MW to median* and *Kaitz index* indistinctively. We proceed to describe and discuss them in this section.

2.2.1. MW relative to the median for labor income

For the analysis of effects on labor income distribution and its inequality, our independent variable of interest is the ratio between real hourly MW and median real hourly labor income (MW relative to the median). This ratio is calculated for each occupational group, for each city each quarter.

As all other monetary values, the legal monthly MW is expressed in real terms in December 2018 COP. Each city in each quarter would have its own real monthly MW, given that we use the monthly CPI of the respective city.

To calculate the real MW per hour for each city-month, we divide its real monthly MW by 30 to obtain the daily MW, then multiply it by 7/6 to obtain the daily MW including Sundays and, finally, divide it by 8 hours.

The MW to median for an occupational group for each city-quarter is calculated as the mean of the city's real hourly MW for the corresponding months of the quarter, divided by the median of the real hourly labor income of that group in that city during the quarter.

Current median labor income could be affected by the current legal MW. To avoid this endogeneity, we use the median real hourly labor income lagged by one year. Therefore, our independent variable, by occupational group, is the ratio of the mean real hourly MW in quarter t to the corresponding occupational group's median real hourly labor income lagged four quarters (quarter $t-4$). We calculate this variable for each city and each quarter. As a result, for each occupational group, we have both cross-sectional and time variability in the MW relative to the median. That is,

[19] Among others, see Lee (1999) and Autor, Manning, and Smith (2016) for the case of the United States, Engbom and Moser (2022) for Brazil, and Arango and Pachón (2007) and Pérez (2020) for Colombia.

$$(MW\ to\ median)_{1ct} \equiv Kaitz_{1ct} = \frac{mean(MW^h_{cm})}{median(e^{y_{1ict-4}})}$$

where MW^h_{cm} is the real hourly MW in city c in month m of the quarter t; y_{1ict} is the logarithm of the real hourly labor income of individual i that belongs to that occupational group residing in city c in quarter t (Section 3.1.1 provides details on its construction).[20]

Table 3. Characteristics of the MW relative to the median for each occupational group, Colombia 2009 - 2019

Occupational group	Average	Standard deviation	Minimum	Maximum
Total employed	1.02	0.14	0.80	1.50
Wage earners	0.90	0.08	0.66	1.15
Self-employed, without higher education	1.41	0.28	0.91	2.33
Self-employed, with higher education	0.67	0.16	0.35	1.35
Total employed who contribute	0.80	0.08	0.46	1.03
Total employed who do not contribute	1.28	0.21	0.86	1.97
Wage earners who contribute	0.82	0.08	0.47	1.04
Wage earners who do not contribute	1.08	0.10	0.79	1.82
Self-employed, who contribute	0.57	0.12	0.22	0.93
Self-employed, who do not contribute	1.39	0.30	0.88	2.35

Notes: The descriptive statistics of the Kaitz index of the corresponding occupational group are reported in each row; the data are all the averages of the city-quarter indices of the group in the period 2009-I – 2019-IV. "Total employed" corresponds to the sum of wage earners and self-employed workers. "Wage earners" are private and public workers and employees. We did not include domestic employees and day laborers in this analysis (occupational categories also included in the GEIH). A person is classified as "without higher education" if her educational level is complete high school or less. A person is classified as "with higher education" if she has at least one year of studies beyond complete high school. A person contributes to social security if she contributes to both health and pensions.
Source: DANE; authors calculations.

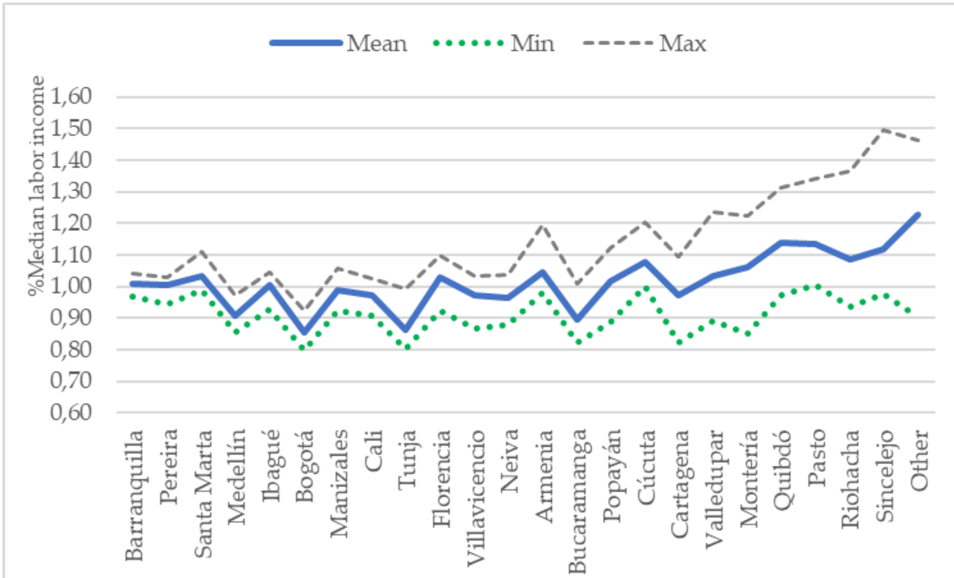
In addition to being high compared to other wages, another characteristic of the MW concerning labor income distribution in Colombia is that the proportion of workers whose labor income is less than the MW differs markedly between occupational groups. For example, while 40% of wage earners receive labor income below MW (Kaitz of 0.90), this proportion increases to around 75% for self-employed individuals without higher education (Kaitz of 1.41) (Graph 1 and Table 3).

Likewise, the relationship between MW and median labor income varies considerably between Colombian cities (Graph 3). For the total employed group, the MW is close to 90% of the respective median labor income in Medellín, Bogotá and Tunja; while in Cúcuta and Riohacha, the MW is

[20] In general terms, our variable Kaitz index (MW relative to the median) is given by: $Kaitz_{ct} = \frac{MW_{ct}/CPI_{ct}}{y_{ct-4}/CPI_{ct-4}}$, where MW is the nominal hourly MW, y is the nominal median hourly labor income, c indicates the city and t, the quarter. This expression could be rewritten as $Kaitz_{ct} = \frac{MW_{ct-4}(1+r_{ct})}{y_{ct-4}}$, where r is the real growth rate of the hourly MW between the quarters *t-4* and *t*.

110% of their respective median labor income. Additionally, there are differences among cities in the variability of this measure through time.

Graph 3. MW relative to the median labor income varies across time and cities. Total employed, Colombia, 2008-2019



Note: for each city, we present the simple mean, the minimum and the maximum of their quarterly Kaitz index during the period 2008.I – 2019-IV for the occupational group Total Employed. The cities are ordered from the lowest to the highest standard deviation during the period of their respective Kaitz indexes.
Source: Authors calculations. DANE – GEIH.

2.2.2. MW relative to the median for household income and poverty

For the analysis of effects on household income distribution, its inequality and poverty prevalence, our independent variable of interest is the ratio between real monthly MW and median real monthly total household income per capita (monthly MW relative to the median). This ratio is calculated for each city each quarter.

Similarly to the ratio for studying labor income, to avoid endogeneity, this monthly MW relative to the median is calculated as the mean of real monthly MW of quarter *t* divided by the median real monthly total household income per capita in quarter *t-4*, for each city each quarter. We use the official data DANE uses to calculate poverty rates between 2008 and 2019. That is,

$$(monthly\ MW\ to\ median)_{2ct} \equiv Kaitz_{2ct} = \frac{mean(MW_{cm})}{median(e^{y_{2ict-4}})}$$

where MW_{cm} is the real monthly MW in city c in month m of the quarter t; y_{2ict} is the logarithm of the real monthly total household income per capita of individual i residing in city c in quarter t (Section 2.1.2 provides details on its construction).

We present descriptive statistics of monthly MW relative to the median in Table 4. On average during the period 2008 - 2019, 50% of Colombian households perceived a real monthly total income per capita of less than half the real MW per household member.[21]

Table 4. Descriptive statistics of the monthly MW relative to the median real monthly total income per capita per household. 2009 - 2019

Average	Standard deviation	Minimum	Maximum
1.93	0.63	0.98	3.90

Notes: The descriptive statistics of the Kaitz index for monthly household income are presented. The data are all the city-quarter indices in the period 2009-I – 2018-IV.
Source: DANE; authors calculations.

3. Empirical Framework

As indicated, in this article we assess whether increases in the MW relative to the median affect the distribution of labor income, household income, their inequality, and the prevalence of monetary poverty. For income distribution, we study the effects on the unconditional quantiles from 10 to 90; for income inequality, we study the effects on the Gini coefficient of each income distribution; for monetary poverty, we study whether the individual's household income per capita is below the MPL.

Our estimation strategy consists of three approaches: one for the effects on income distribution, one for the effects on inequality, and a third one for the prevalence of monetary poverty.

3.1 Income distribution

To study the effects on income distribution, we use the methodology introduced by Firpo, Fortin, and Lemieux (2009) for estimating unconditional quantile regressions, known as RIF regressions. These regressions estimate the marginal effect on any of the unconditional quantiles of the income distribution under consideration of a change in an explanatory variable's distribution that increases its unconditional mean by one unit[22].

In the case of hourly labor income distribution, the empirical model we use to estimate the effect of MW relative to the median on each unconditional quantile for each occupational group is:

$$RIF(y_{1ict}, Q_\tau) = \alpha_{1,\tau} + \beta_{1,\tau} Kaitz_{1ct} + \beta_{2,\tau} Kaitz_{1ct-4} + \boldsymbol{X}_{1ict}\boldsymbol{\Gamma}_{1,\tau} + \boldsymbol{Z}_{ct}\boldsymbol{\Theta}_{1,\tau} + \sigma_{1c,\tau} + \rho_{1t,\tau} + \varepsilon_{1ict,\tau} \qquad (1)$$

[21] A graph qualitatively similar to Graph 3 could be presented for this indicator. For space's sake, we do not reproduce it here.

[22] See methodological details on RIF regression in Appendix A. We emphasize that, because the methodology estimates marginal effects, its results are valid for small changes in the explanatory variables (in our case, small changes in the MW relative to the median). This methodology does not allow us to evaluate the results of "excessive" changes in this explanatory variable.

where subscript i represents the person, c represents person's city of residence ($c = 1, \dots, 24$), t represents the quarter in which the person is observed ($t = 2008{:}I, \dots, 2019{:}IV$) and τ represents the quantile under consideration ($\tau = 10, 20, \dots, 90$). To avoid cluttering the notation, we do not include a subscript to identify the occupational group. It is important to keep in mind that a regression of this type is performed for each occupational group and that the information for individual i is included only for the group to which she belongs.

$RIF(y_{1ict}, Q_\tau)$ is the RIF transformation for the quantile (Q_τ) under consideration (Equation A1 in Appendix A) calculated for each observation of the logarithm of real hourly labor income (y_{1ict}) (See section 2.1.1 for its description). This transformation is the dependent variable of the unconditional quantile regressions.

$Kaitz_{1ct}$ refers to our independent variable of interest, the hourly MW relative to the median of each occupational group in city c and quarter t, as describe in Section 2.2.1. The four-quarter lag of the Kaitz index ($Kaitz_{1ct-4}$) is included to capture possible lagged responses of the labor income distribution to changes in the legal MW[23]. The contemporary Kaitz index coefficient ($\beta_{1,\tau}$) captures the short-term effect on quantile τ, and the sum of the contemporary and lagged indices coefficients ($\beta_{1,\tau}$+$\beta_{2,\tau}$) indicates the total effect[24] on quantile τ. One thing that should be noted for emphasis is that our independent variable of interest varies both within cities over time as well as between cities for a given quarter.

During the ten years studied, the labor income distribution could have shifted due to a variety of factors unrelated to changes in the MW relative to the median. Therefore, in the vector $\boldsymbol{X}_{1ict}$ we control for person's characteristics that could determine her labor income regardless of the MW.[25]

Additionally, we control in $\boldsymbol{Z}_{ct}$ for characteristics of the person's city of residence to capture the impact that the city's economic cycle may have on labor income.[26]

[23] For reference, Neumark, Schweitzer, and Wascher (2004) find that the lagged effects of the MW are important. In particular, they find that contemporaneous effects overstate wage increases and understate the decrease in hours experienced by low-wage workers when MW rise. See also Neumark and Wascher (2002) and Neumark, Schweitzer, and Wascher (2005). In these studies, the lagged effects are justified by the existence of long-term adjustments that happen through quantities by laying off workers, while short-term or contemporary adjustments occur through prices.
[24] The sum of coefficients assumes that the change in MW relative to the median is the same in both periods (in quarter *t* and in quarter *t-4*). If the changes are different, the corresponding weighted calculation must be performed.
[25] At the individual level, we control for age, age squared, indicator of whether she is a woman, number of years of education, indicators of whether she receives transfers, income or pensions, whether she is a worker or public employee, whether she is self-employed, occupational level and sector to which the first activity in which she is engaged belongs. We report descriptive statistics of these variables in Appendix E, Table E.4.
[26] To capture cities' business cycle, we include its unemployment rate, participation rate and percentage of the working-age population (WAP) with higher education. We include these variables as the average of the last six months, lagged one quarter. We report descriptive statistics of these variables in Appendix E, Table E.4.

Similarly, period fixed effects, ρ_{1t}, are included to control for factors common to all people in the country in a given quarter but that can differ between quarters[27], and city fixed effects, σ_{1c}, to control for those factors common to all residents of a city but that differ between cities. Finally, ε_{1ict} is an error term. Confidence intervals are computed using bootstrap method with 100 replications.

It is crucial to remember that the estimated results are population results. RIF regression results should be interpreted on the population to which the distribution under consideration corresponds; these are not results on an average or representative individual. Also, the estimated coefficients show how much the relevant statistic changes (in this case, the value of the quantile) given a marginal change in the population mean of the corresponding independent variable[28].

We also consider that the labor force characteristics have changed over the course of the ten-year period. For example, the average years of education and the average age of those employed have both increased. These changes in labor force composition are likely to have contributed to shifts in labor income distribution during the period. Ideally, to capture changes in distribution that are not due to changes in composition, we would want to keep the characteristics of the labor force constant over the period but paid according to each year's structure of wages and labor income. To get closer to that ideal scenario, we balance the characteristics of the observations over the period using *inverse probability weighting* (IPW) [29]. In this way, we keep labor force characteristics relatively constant over the years.

For the estimation of the unconditional quantile regressions with IPW, we use all data from the four quarters of each year, results that we interpret as the annual average effect on each quantile of variations in the MW relative to the median.

Similarly, for the analysis for household income we use RIF regressions on the unconditional quantiles of the distribution. Specifically, the empirical model used to estimate the effect of monthly MW relative to the median on each unconditional quantiles of household income distribution is:

$$RIF(y_{2ict}, Q_\tau) = \alpha_{2,\tau} + \beta_{3,\tau} Kaitz_{2ct} + \beta_{4,\tau} Kaitz_{2ct-4} + \boldsymbol{X}_{2ict}\boldsymbol{\Gamma}_{2,\tau} + \boldsymbol{Z}_{ct}\Theta_{2,\tau} + \sigma_{2c,\tau} + \rho_{2t,\tau} + \varepsilon_{2ict,\tau} \tag{2}$$

In this case, $RIF(y_{2ict}, Q_\tau)$ is the RIF transformation for the quantile (Q_τ) under consideration (Equation A1 in Appendix A) calculated for each observation i of the logarithm of real monthly total household income per capita (y_{2ict}) (See Section 2.1.2 for description of this variable).

[27] An example of this type of common factor is an inflationary shock that affects the entire country. By including the period fixed effect in each quantile, we incorporate the fact that this inflationary shock may have differential effects for each income quintile. For example, a shock in the price of food due to the El Niño phenomenon may affect the lower quintiles more than the higher ones. Another example of this type of common factor would be productivity shocks that impact the entire country.

[28] See Firpo, Fortin and Lemieux (2009), Rios-Ávila (2020) and Rios-Ávila and Maroto (2022). For more details on RIF methodology, see also Cowell and Flachaire (2015) and Essama-Nssah and Lambert (2012).

[29] IPW technical details are discussed in Appendix B.

$Kaitz_{2ct}$ refers to our independent variable of interest, the monthly MW relative to the median in city c and quarter t, as describe in Section 2.2.2.

In the individual control variables $\boldsymbol{X}_{2ict}$ we include individual characteristics as well as individual's household characteristics.[30] The variables $\boldsymbol{Z}_{ct}$ that control for characteristics of the person's city of residence are the same as in Equation (1) (Footnote 26).

3.2. Income inequality

To study the effects of MW on income inequality, we use RIF regressions for the Gini coefficient.

To find the impact on inequality of hourly labor income of each occupational group, we estimate:

$$RIF(y_{1ict}, Gini) = \alpha_3 + \beta_5 Kaitz_{1ct} + \beta_6 Kaitz_{1ct-4} + \boldsymbol{X}_{1ict}\boldsymbol{\Gamma}_3 + \boldsymbol{Z}_{ct}\boldsymbol{\Theta}_3 + \sigma_{3c} + \rho_{3t} + \varepsilon_{3ict} \quad (3)$$

$RIF(y_{1ict}, Gini)$ is the RIF transformation for the Gini coefficient (Equation A2 in Appendix A) calculated for each observation of the logarithm of real hourly labor income (y_{1ict}) of the occupational group under consideration. The independent variable of interest $Kaitz_{1ct}$ and the control variables $\boldsymbol{X}_{1ict}$ and $\boldsymbol{Z}_{ct}$ are as defined for Equation (1).

For inequality of household income, we estimate:

$$RIF(y_{2ict}, Gini) = \alpha_4 + \beta_7 Kaitz_{2ct} + \beta_8 Kaitz_{2ct-4} + \boldsymbol{X}_{2ict}\boldsymbol{\Gamma}_4 + \boldsymbol{Z}_{ct}\Theta_4 + \sigma_{4c} + \rho_{4t} + \varepsilon_{4ict} \quad (4)$$

$RIF(y_{2ict}, Gini)$ is the RIF transformation for the Gini coefficient calculated for each observation of the logarithm of real monthly total household income per capita (y_{2ict}). The independent variable of interest $Kaitz_{2ct}$ and the control variables $\boldsymbol{X}_{2ict}$ and $\boldsymbol{Z}_{ct}$ are as defined for Equation (2).

3.3. Monetary poverty prevalence

To assess the effect of MW on national monetary poverty prevalence, we consider four poverty levels determined by the multiples 0.5, 1, 1.5 and 2 of MPL_{ct}. The model we estimate is given by:

$$I(y_{2ict}, \lambda MPL_{ct}) = \alpha_5 + \beta_9 Kaitz_{2ct} + \beta_{10} Kaitz_{2ct-4} + \boldsymbol{X}_{2ict}\boldsymbol{\Gamma}_5 + \boldsymbol{Z}_{ct}\Theta_5 + \sigma_{5c} + \rho_{5t} + \varepsilon_{5ict} \quad (5)$$

[30] At the individual level, we control for age, age squared, an indicator of whether she is a woman, number of years of education, an indicator of whether she receives transfers, income and pensions, an indicator of whether the head of the household lives with her spouse, an indicator of whether the individual is separated or widowed or single (reference group is individuals who live as a couple (married or in a free union), indicator of whether the household resides in its own fully paid home, dependency ratio of the household (the sum of children under 15 years of age and adults over 65 years of age divided by the total number of people between 15 and 64 years of age in the household), and the natural logarithm of the number of people in the household (excluding pensioners and domestic employees and their children). We report descriptive statistics of these variables in Appendix E, Table E.5.

$I(y_{2ict}, \lambda MPL_{ct})$ is the indicator variable described in Section 2.1.3. The independent variable of interest $Kaitz_{2ct}$ and the control variables $\boldsymbol{X}_{2ict}$ and $\boldsymbol{Z}_{ct}$ are as defined for Equation (2). We estimate Equation (5) with least squares, with robust standard errors clustered at the city level.

4. Results and Discussion

4.1. Effects on the distribution of hourly labor income

In general, our estimation results indicate that increases in the mean of the real hourly MW (of quarter *t*) relative to the median of the real hourly labor income (of quarter *t-4*) shift the labor income distribution to the right and increase the value of most of the quantiles for all occupational groups analyzed; this both in the contemporary and in the lagged effects and, consequently, in the total effect. The largest impacts are estimated for the quantiles close to the real hourly MW. In any case, quantile values increase by less than the real MW relative to the median.

In addition, comparing between groups, the largest effects are found in the group of wage earners. While the other groups have (generally) positive effects, these are relatively small, especially for groups with lower average labor incomes, such as self-employed individuals without higher education.[31] Although, as we indicated, in general the estimated effects are positive, we obtain some negative effects and some not statistically different from zero for the 10th quantile (the lowest 10% of incomes) of some occupational groups.

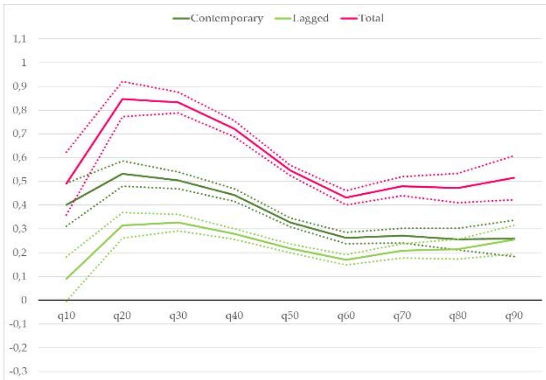
There are important differences in the size of the effects, both between groups as well as between the quantiles of the same group. One advantage of quantile analysis is the ability to determine responses beyond the mean and examine the heterogeneous effects that the MW relative to the median may have on labor income distribution.

In Graph 4, we report the estimated effects for each occupational group.[32] In Appendix C1, we report the results as tables.

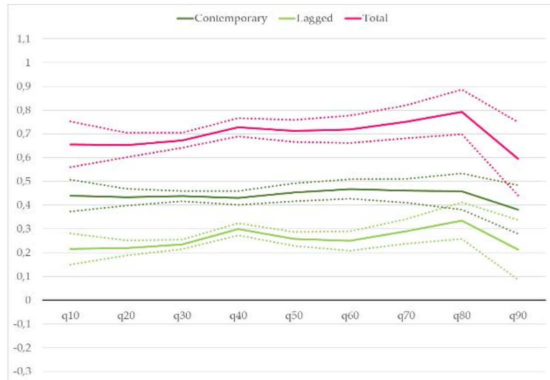
[31] Most self-employed individuals without higher education belong to the subsistence informality group, according to the classification by Fernández and Villar (2017).
[32] In this article, coefficients with a *p-value* greater than 0.05 are considered not statistically different from zero.

Graph 4. Effects of increases in the MW relative to the median on the distribution of labor income by occupational groups

A. Total employed



B. Wage earners



C. Self-employed, with higher education

D. Self-employed, without higher education

Notes: In each panel, the solid line plots the value of the estimated coefficient for the contemporary value of the MW relative to the median (dark green) in each quantile, the estimated coefficient for the lag of the MW relative to the median (light green), and the sum of these two coefficients (total effect, pink). These estimates are obtained from a series of RIF regressions of the logarithm of the hourly labor income of individual *i* residing in city *c* in quarter *t* using as an independent variable the MW relative to the median of each city-quarter, contemporaneous and lagged four quarters, as well as controls. All specifications include city and period fixed effects, individual-level controls, and city-level controls (see Section 3.1 and Eq. (1) for more details). The area between the dotted lines represents the 95% confidence interval computed using bootstrap method with 100 replications. We use information from employed people aged 18 to 65 who typically work 40 or more hours a week. "Total employed" corresponds to the sum of wage earners and self-employed individuals. "Wage earners" are private and public workers and employees. We did not include domestic employees and day laborers in this analysis (occupational categories also included in the GEIH). A person is classified as "without higher education" if her educational level is complete high school or less. A person is classified as "with higher education" if she has at least one year of studies beyond complete high school. For more details, see sections 2 and 3. In Appendix C1, we report the results as tables.
Source: DANE-GEIH; authors calculations.

For most occupational groups, the quantiles of real labor earnings closest to the real MW generally experience the largest percentage increase when the MW relative to the median increases. For example, for the total employed group, an increase of 0.01 in the MW relative to the median[33] increases the value of the 20th and 30th quantiles by approximately 0.80% in the total effect[34], while this effect on quantiles above the 50th lies between 0.40% and 0.50% (Graph 4, Panel A). For self-employed individuals without higher education, the total effect of a 0.01 increase in the MW relative to the median is very similar in all quantiles of their labor income distribution, ranging from 0.20% to 0.30%, except for quantile 10 whose total effect is not significantly different from zero (Graph 4, Panel D)[35].

We find similar results when analyzing the occupational groups determined by contribution to social security (Graph 5 and Appendix C1). In general, for all these occupational groups we find positive effects for most quantiles of their respective income distribution. Nevertheless, for the self-employed individuals who contribute to social security, the effects are not significantly different from zero (Graph 5, panel E). Also, for self-employed individuals without higher education (Graph 4, panel D) and self-employed individuals not contributing to social security (Graph 5, panel F), their 10th quantile's total effect is not statistically significant.

In summary, in a context of high MW relative to other incomes, as in Colombia, spillover effects are relevant not only for those workers 'just above' the MW, but for the whole income distribution. In general, it is expected that spillovers are limited to a minority of workers above the MW and die out quickly as one moves up the labor income distribution. That is not the case for Colombia, where the MW is high relative to other incomes. Among the occupational groups, we find that the biggest effects are for wage workers, specially those that contribute to social security. Also, our results indicate that informal labor (those occupational groups that do not contribute to social security) have the smallest effects on their distribution (about half the size of those for formal labor).

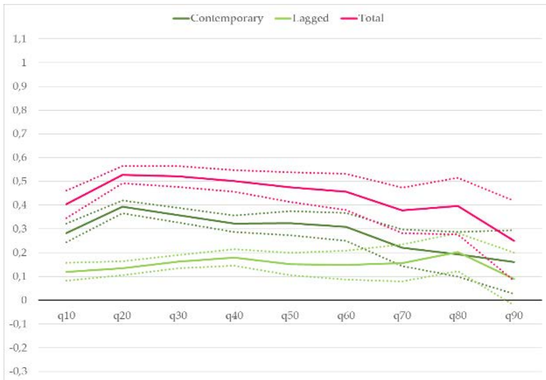
[33] We report the effect of a 0.01-unit increase in the Kaitz index, which is equivalent to a 0.01-unit increase in real hourly MW for the quarter relative to median labor income (from four quarters ago). The coefficient of these RIF regressions is interpreted on the quantile value of the logarithm of real labor income per hour (Section 3). Therefore, the estimated coefficients indicate the percentage increase in the value of the corresponding quantile of hourly labor earnings given an increase of 0.01 in the MW relative to the median.

[34] In line with what is indicated in footnote no. 24, the total effects reported assume that the real MW of four quarters ago has increased by 0.01 with respect to the (real) median of eight quarters ago, and that the current real MW increased by 0.01 with respect to the median of four quarters ago.

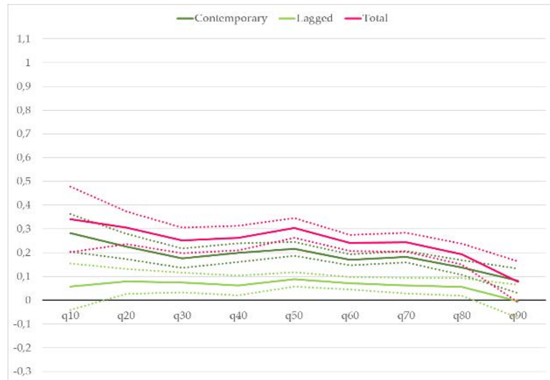
[35] As a reference, in Appendix D we show the increase in real pesos (at 2018 prices) in the value of the quantiles of hourly labor income distribution of each group. For example, for wage earners, the 0.01 increase in the MW relative to the median results in an increase in the value of the 30th quantile of COP 24.07 (Table D.1), changing from COP 3,576 (Table E.2) to COP 3,600.07.

Graph 5. Effects of increases in the MW relative to the median on the distribution of labor income of the occupational groups according to social security contribution

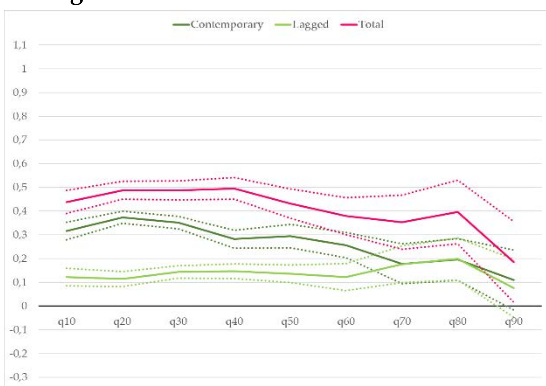
A. Total Employed who contribute to SS



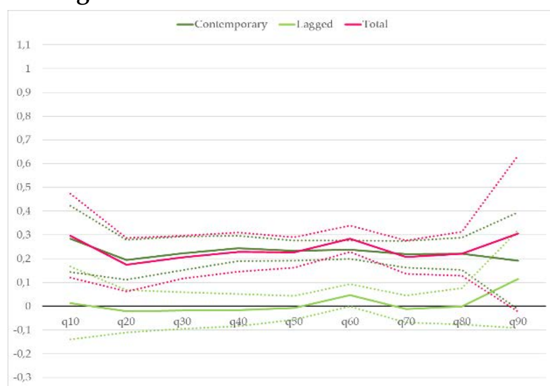
B. Total Employed who do not contribute to SS



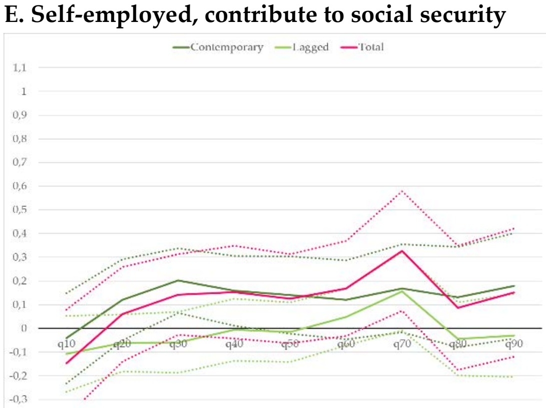
C. Wage earners who contribute to SS



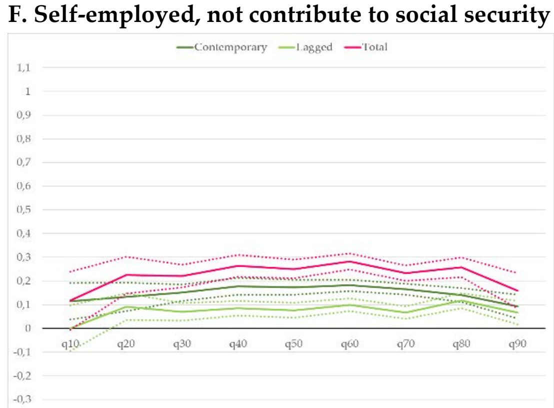
D. Wage earners who do not contribute to SS



E. Self-employed, contribute to social security



F. Self-employed, not contribute to social security



Notes: In each panel, the solid line plots the value of the estimated coefficient for the contemporary value of the MW relative to the median (dark green) in each quantile, the estimated coefficient for the lag of the MW relative to the median (light green), and the sum of these two coefficients (total effect, pink). These estimates are obtained from a series of RIF regressions of the logarithm of the hourly labor income of individual *i* residing in city *c* in quarter *t* using as an independent variable the MW relative to the median of each city-quarter, contemporaneous and lagged four quarters, as well as controls. All specifications include city and period fixed effects, individual-level controls, and city-level controls (see Section 3.1 and Eq. (1) for more details). The area between the dotted lines represents the 95% confidence interval computed using bootstrap method with 100 replications. We use information from employed people aged 18 to 65 who typically work 40 or more hours a week. "Total employed" corresponds to the sum of wage earners and self-employed individuals. "Wage earners" are private and public workers and employees. We did not include domestic employees and day laborers in this analysis (occupational categories also included in the GEIH). A person is classified as "without higher education" if her educational level is complete high school or less. "SS" stands for social security. A person contributes to social security if she contributes to both health and pensions. For more details, see sections 2 and 3. In Appendix C1, we report the results as tables.

Source: DANE; authors calculations.

The rise in labor incomes of wage earners already paid more than the MW is consistent with the presence of efficiency wages where wages are set according to a job ladder and where firms preserve their internal wage structure due to internal incentives issues.[36] That the labor income distributions for self-employed individuals do not shift similarly to those of wage earners would indicate that this efficiency wage mechanism does not play a similar role in setting the remuneration for those self-employed.

For its part, the informal sector in Colombia, defined as those employed individuals that do not contribute to social security, is big; it could absorb most of the workers displaced from the formal sector by a MW increase. We find a relatively small increase in the informal sector labor income distribution (about half of the effect in the formal sector) as a result of the increase in MW relative to the median, which suggest that demand in the informal sector is relatively elastic and/or some demand for labor also moves from the formal to the informal sector. Also, we cannot discard the presence of a lighthouse effect; that is, the MW may serve as reference for labor remuneration in the informal sector. Further research is needed in order to disentangle the mechanisms that lead to a shift (albeit comparatively small) to the left in the labor income distribution in the informal sector.

The effects on labor income distribution for those occupational groups that do not contribute to social security (either wage earners or self-employed individuals) are very similar among them (not significantly different from each other) and about half of the effects on the labor income distributions of those that contribute to social security.

In this article, we do not estimate effects on total employment nor on its formal and informal segments. Other works (e.g., Millea *et al.*, 2017 for South Africa) find that increases in labor income quantile values could be accompanied by increases in unemployment and reductions in labor participation. We cannot rule out that this happens in Colombia. The evaluation of whether these effects on prices and quantities concur in Colombia is left for future research. Additionally, increases in labor income quantile values could correlate with losses in social welfare if they are accompanied by important increases in unemployment and reductions in labor participation due to discouragement to look for work. We do not assess these welfare effects here.

4.2. Results on labor income inequality of occupational groups

In this section we are interested in two questions. First, does MW contribute to reducing labor income inequality? Secondly, does the answer differ by occupational group? Studies have shown that increase in inequality in the United States is connected to the decrease in the real MW (e.g., Lee, 1999; Autor, Manning and Smith, 2016); Brazil has also experienced a decrease in labor income inequality in part caused by increases in its real MW (Engborn and Moser, 2021). For its part,

[36] See Grossman (1983), Brink, Kuang and Majerczyk (2021), Brochu, Green, Lemieux and Townsend (2023), Stennek (2020), among others.

Germany's national MW stablished in 2015 led to a decrease in inequality (Bossler and Schank, 2023).

In this section, we estimate for Colombia the effect that increases in real MW relative to the median has on labor income inequality as measured by the Gini coefficient, as explained in Section 3.2. We estimate this effect for each occupational group considered above.

The heterogeneous effects estimated in the previous section on labor income quantiles for each occupational group do not allow us to easily infer whether increases in MW relative to the median increase or decrease labor income inequality of those groups. To determine the effect of increases in the unconditional mean of the MW relative to the median on labor income inequality for each group, we estimate Equation (3) (Section 3.2) where the dependent variable is the RIF transformation of the Gini coefficient of each group's hourly labor income distribution[37]. As we describe in Section 2.1.4, there are important variations in labor income inequality across occupational groups.

Our results for the total effect indicate that increases in MW relative to the median increase labor income inequality (measured by the Gini coefficient) for three of the groups considered: total employed, total employed who do not contribute to social security, and self-employed individuals who do not contribute. Further, we estimate a reduction in labor income inequality in three groups: wage earners, wage earners who contribute and wage earners who do not contribute. The estimated effects are not significantly different from zero for the groups of self-employed individuals with and without higher education, self-employed individuals who contribute to social security and total employed who contribute to social security (Graph 6 and tables in Appendix C1).

To have a better sense of how much income inequality changes when MW relative to the median changes, we calculate the percentual change in the Gini of each group when the MW relative to its median increases in 0.01 (Table 5). We find that the group of wage earners who do not contribute to social security has the biggest percentual total change on labor income inequality. Its total-effect coefficient of -0.20 indicates that an increase of 0.01 in the unconditional mean of the MW relative to its median reduces the Gini coefficient of this occupational group by 0.0020 units, that is, a decrease of 0.53% in the average value of its Gini coefficient[38]. The second-highest relative effect is on the inequality of wage earners, for which we estimate a reduction of 0.21% in their Gini coefficient. The estimated effect on total employed persons indicates that an increase of 0.01 in the unconditional mean of the MW relative to its median increases inequality in their distribution of real labor income, corresponding to an increase of 0.09% in their Gini coefficient (Table 5)[39].

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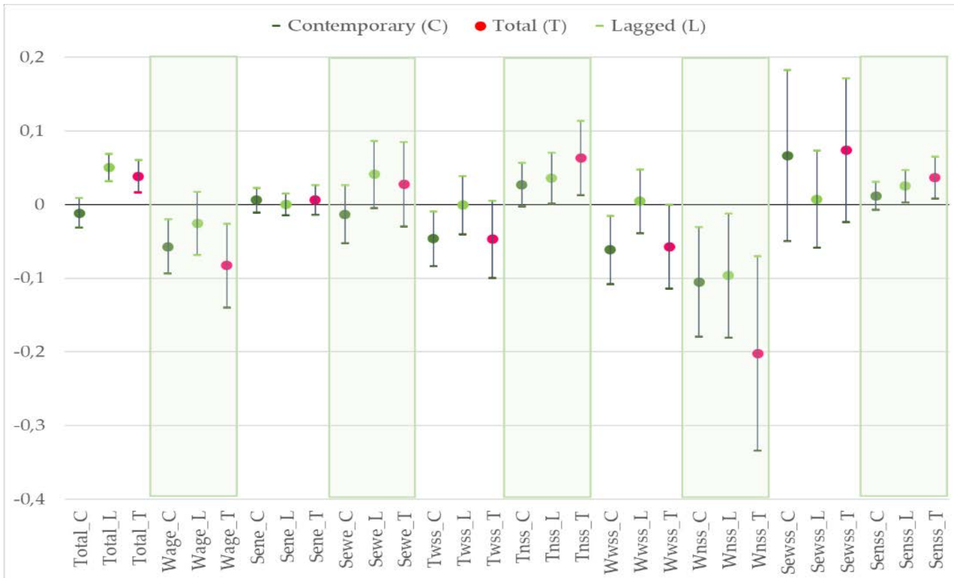
[37] We calculate the Gini coefficient for the distribution of real hourly labor income (not on its logarithm) since the logarithm underestimates the Gini by minimizing the dispersion of the distribution of labor income per hour.
[38] We calculate $\Delta\%Gini = [(\Delta Gini)/Gini] * 100$. For wage earners, the change is a reduction of 0.0020 points from a group's (average) Gini coefficient of 0.3820. Therefore, $\Delta\%Gini = [0{,}0020/0{,}3820] * 100$= 0.53%
[39] For comparison, Ocampo *et al*. (2004), based on microsimulations in a computable general equilibrium model, calculate the impact of different policies and external shocks on labor income inequality. Their baseline scenario uses data from 1997.

Graph 6. Estimated effects on labor income inequality for each occupational group (contemporary, lagged, and total effects)



Notes: the circle indicates the value of the estimated coefficient for the contemporary MW relative to the median (dark green, *C*), the estimated coefficient for the lag of the MW relative to the median (light green, *L*) and the sum of these two coefficients (total effect, pink, *T*). The bar in each circle indicates the 95% confidence interval computed using bootstrap method with 100 replications. Total: total employed; Wage: wage earners; Sene: self-employed, without higher education; Sewe: self-employed, with higher education; Twss: total employed who contribute to social security; Tnss: total employed who do not contribute to social security; Wwss: wage earners who contribute to social security; Wnss: wage earners who do not contribute to social security; Sewss: self-employed, who contribute to social security; Senss: self-employed, who do not contribute to social security. Results of RIF regressions for the Gini of the hourly labor income of each individual in each occupational group. All specifications include city and period fixed effects, individual-level controls, and city-level controls (see Section 3.2 and Eq. (3) for more details). We use information from employed people aged 18 to 65 who typically work 40 or more hours a week. "Total employed" corresponds to the sum of wage earners and self-employed individuals. "Wage earners" are private and public workers and employees. We did not include domestic employees and day laborers in this analysis (occupational categories also included in the GEIH). A person is classified as "without higher education" if her educational level is complete high school or less. "SS" stands for social security. A person contributes to social security if she contributes to both health and pensions. For more details, see sections 2 and 3. In Appendix C1, we report the results as tables.
Source: DANE; authors' calculations.

They find that a unilateral tariff reduction of 50% reduces the Gini coefficient of labor income from an initial value of 0.374 by -0.05 points (13% reduction). On the other hand, an increase in export prices of 10% or an increase in import prices of 10% reduces the Gini of labor income by 6%. In turn, a 10% increase in productivity does not affect the Gini. The authors indicate that the general equilibrium model used in their work does not capture effects of trade liberalization processes on wage inequality because it does not incorporate complementarity between technology and skilled labor.

Table 5. Relative total effects on labor income inequality by occupational group

Occupational Groups	Gini	Total Effect coefficient	Relative effect (%)
Total employed	0.430	0.038	0.089
Wage earners	0.396	-0.083	-0.209
Self-employed, without higher education†	0.350	0.000	0.000
Self-employed, with higher education†	0.480	0.000	0.000
Total workers who contribute†	0.392	0.000	0.000
Total workers who do not contribute	0.398	0.063	0.158
Wage earners who contribute	0.379	-0.057	-0.151
Wage earners who do not contribute	0.382	-0.202	-0.529
Self-employed, who contribute†	0.435	0.000	0.000
Self-employed, who do not contribute	0.393	0.037	0.093

Notes: † The total effects estimated for these groups are not significantly different from zero, so we record a coefficient equal to zero in this table. Column (1) reports the Gini coefficient of the distribution of hourly labor income of the corresponding group, based on the hourly labor income information of each person in each city and month for the period from 2008-I to 2019-IV. Column (2) reports the estimated total effect in the RIF regression (Graph 6 and Appendix C1). Column (3) indicates the percentage change in the Gini coefficient as a result of an increase of 0.01 in the real MW (of quarter t) relative to the median real labor income (of quarter t-4) of the occupational group (Footnote 37). We use information from employed people aged 18 to 65 who typically work 40 or more hours a week. "Total employed" corresponds to the sum of wage earners and self-employed individuals. "Wage earners" are private and public workers and employees. We did not include domestic employees and day laborers in this analysis (occupational categories also included in the GEIH). A person is classified as "without higher education" if her educational level is complete high school or less. "SS" stands for social security. A person contributes to social security if she contributes to both health and pensions. For additional details, see sections 2 and 3.
Source: DANE; authors calculations.

In summary, we find increased inequality, measured by the Gini coefficient, for total employed, total employed who do not contribute to social security and self-employed individuals who do not contribute to social security. For its part, labor income inequality, measured by the Gini coefficient, decreases for wage earners, either those that contribute or do not contribute to social security.

4.3. Results on households' income distribution

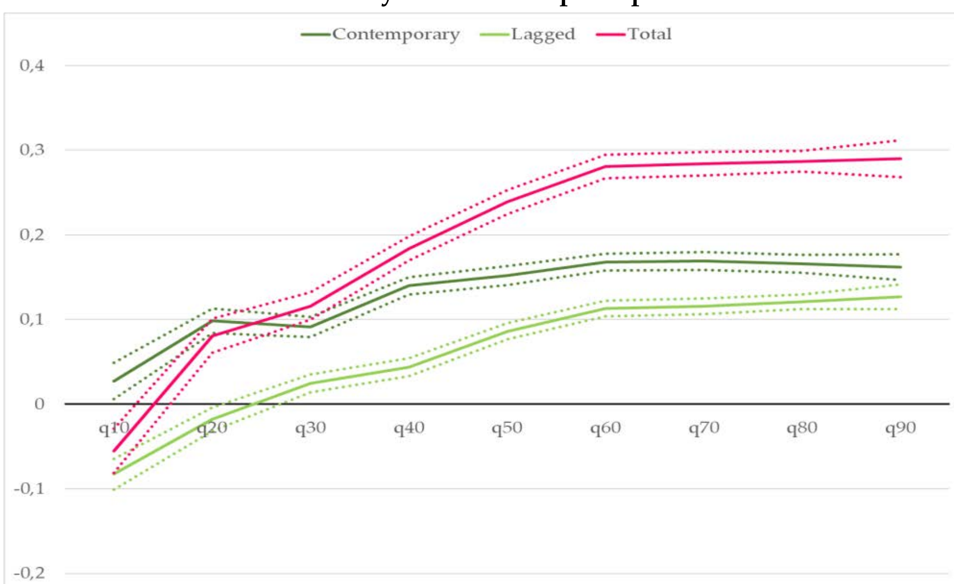
The heterogeneous effects of MW relative to the median in different occupational groups lead us to query about the implications for household's total income. Firstly, does the MW affect family income distribution? Specifically, do increases in real MW increase the lowest family incomes and those belonging to its lowest quantiles? Secondly, does MW aid in lowering Colombia's household-income inequality?

Real MW impact on the lowest family incomes would depend on its combined effects on labor income distribution, employment, labor informality, labor participation, among other effects that the MW may have on labor markets. For the United States between 1984 and 2013, Dube (2019) finds positive total effects for the 10th and 15th quantiles of the unconditional distribution of family income, with elasticities between 0.15 and 0.44. For Colombia between 1984 and 2001, Arango and Pachón (2007) estimate positive effects for the quantiles higher than 20 (coefficients between 0.30 and 0.50) and not statistically different from zero for the lower quantiles[40].

In this section, we evaluate how increases in the monthly MW relative to the median affect the distribution of real monthly total household income per capita; specifically, the effects on its quantiles, reported in Table 1, Section 2.1.2. We estimate Equation (2) in Section 3.1, where the dependent variable is the RIF transformation of the logarithm of real monthly total income per capita of households. We assign this income per capita to each household member. The explanatory variable of interest is the monthly MW relative to the median for each city each quarter, as describe in section 2.2.2.

As in the case of labor income, for analyzing household income per capita we use information for all quarters of the year[41].

Graph 7. Effects of monthly MW relative to the median on households' distribution of real monthly total income per capita



Notes: The solid line plots the value of the estimated coefficient for the contemporary value of the monthly MW relative to the median (dark green) in each quantile, the estimated coefficient for the lag of the monthly MW relative to the median (light green), and the sum of these two coefficients (total effect, pink). The area between the dotted lines represents the 95% confidence interval computed using bootstrap method with 100 replications. These estimates are obtained from a series of RIF regressions of the logarithm of the household's real monthly total income per capita of individual *i* residing in city *c* in quarter *t* using as an independent variable the monthly MW relative to the median of each city-quarter, contemporaneous and lagged four quarters, as well as controls. All specifications include city and period fixed effects, individual-level controls, and city-level controls (see Section 3.1 and Eq. (2) for more details). Also, see sections 2 and 3. In Appendix C2, Table C2.1, we report table with results.
Source: DANE-GEIH; authors calculations.

[40] See Arango and Pachón (2007), page 185, Graph 7, panel A.
[41] Similarly, as a robustness check, we replicate all exercises using data only for the first quarter of each year. This reduces the number of observations to about 25% of what we have when using all quarters. The results are quantitatively and qualitatively similar. They can be obtained from the authors upon request.

Our results indicate that increases in monthly MW relative to the median have positive, statistically significant, and increasing effects on all quantiles of family income, except in quantile 10 (Graph 7 and Table C2.1). For the lowest household incomes (those in quantile 10), we estimate a statistically significant total effect equal to -0.06%, determined mainly by the lagged effect of monthly MW relative to the median equal to -0.08%.

These results indicate that increases in monthly real MW relative to the median households' income per-capita do not increase income at the bottom 10% of the distribution but it could decrease it.

4.4. Effects on the prevalence of monetary poverty at the national level

From the point of view of economic policy and social welfare, we are interested in evaluating whether, in a context of a relatively high MW (like the case of Colombia), increases in MW contribute to decreasing its monetary poverty levels.

In this section, we assess whether increases in monthly real MW relative to the median of households' income per-capita modifies national monetary poverty prevalence. We consider four poverty levels determined by the multiples 0.5, 1, 1.5 and 2 of MPL_{ct}. We estimate Equation (5) in Section 3.3, where the dependent variables are indicators for whether person i belongs to each specific poverty level, as describe in Section 2.1.3.

Our results indicate that an increment of 0.01 in monthly real MW relative to the median increases the probability that individual i's household real monthly total income per capita be less than their corresponding MPL_{ct}. That is, it raises monetary poverty prevalence. This probability increases for the MPL's multiples 0.5, 1, and 1.5 (Graph 8 and Table C3.1)[42].

Nonetheless, the probability of being below the MPL increases relatively slightly. Using our results, the total effect of a 0.01 increase in monthly real MW relative to the median is an increase of 0.05 percentage points (pp) in the probability of being below 0.5 MPL and 1 MPL; and of 0.02 pp in that of being below 1.5 MPL [43].

The above results on monetary poverty prevalence are consistent with the negative effects found in Section 4.3 on households income distribution's lowest quantiles.

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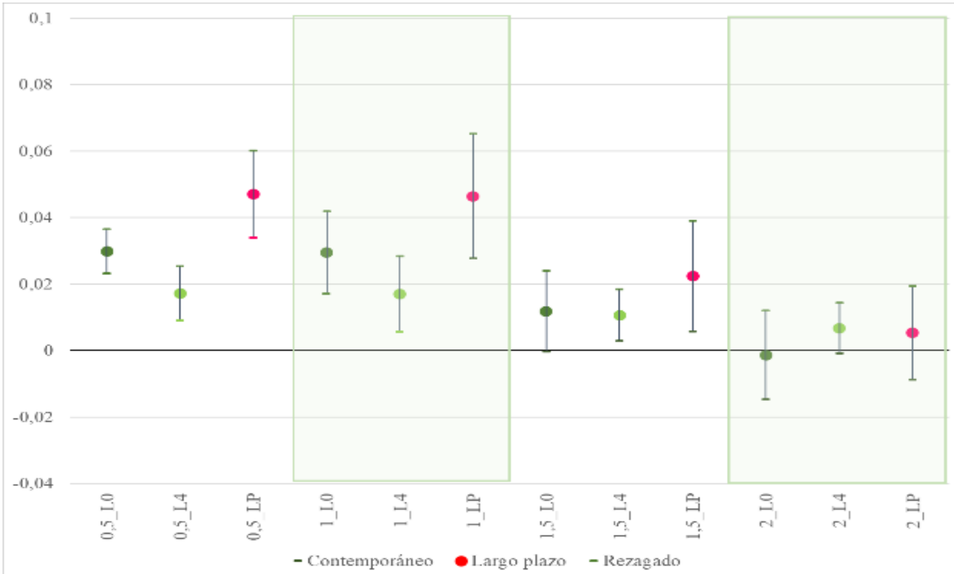
[42] When only first-quarters data is used, we find that the probability of being below half and one MPL increases, but the results are not statistically significant for 1.5 and 2 MPL.

[43] The 0.05 pp increase in the probability of being below the MPL implies that, for example, national monetary poverty prevalence would go from 40.8% to 40.85%, which corresponds to an increase of 0.12% in that prevalence. Likewise, a prevalence of 35.7% would increase to 35.75%, which corresponds to 0.14% increase in monetary poverty prevalence.

Graph 8. Effects of increases in monthly real MW relative to the median on the probability of being in a condition of monetary poverty



Notes: 0.5, 1, 1.5 and 2 indicate the MPL multiples that correspond to the illustrated effects. L0: contemporary effect; L4: lagged effect; LP: total effect. The circle indicates the value of the estimated coefficient for the contemporary monthly MW relative to the median (dark green, *L0*), the estimated coefficient for the lag of the monthly MW relative to the median (light green, *L4*) and the sum of these two coefficients (total effect, pink, *LP*). The bar in each circle indicates the 95% confidence interval, with robust standard errors clustered at the city level. These estimates are obtained from a series of OLS regressions of appropriate indicator variables for individual *i* residing in city *c* in quarter *t* using as an independent variable the monthly MW relative to the median of each city-quarter, contemporaneous and lagged four quarters, as well as controls. All specifications include city and period fixed effects, individual-level controls, and city-level controls (see Section 3.3 and Eq. (5) for more details). For more details, see sections 2 and 3. We report results in Table C3.1.
Source: DANE; authors calculations.

Also, these results for Colombia are opposite to those in Dube (2019) for the United States, where elasticities are negative and relatively high. Dube (2019) finds that increases in MW decrease the proportion of individuals whose family income is below the US MPL's multiples (varying between 0.5 and 1.25). With data for the period 1984-2013, Dube estimates total elasticities between -0.29 and -0.46 which are statistically significant for the mentioned MPL multiples. [44]

4.5. Effects on inequality in monthly household income per capita

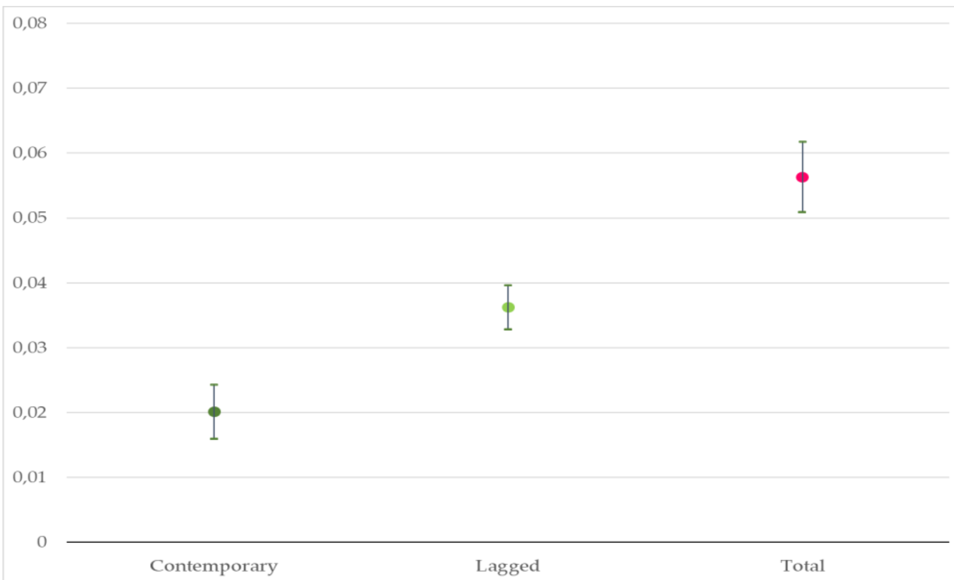
Inequality is another important dimension of household income distribution. Colombia's distribution of real monthly total household income per capita exhibits high inequality, with a Gini coefficient of 0.50. In this section, we ask whether increases in relative monthly real MW modify this inequality measured by its Gini coefficient, as explained in Section 3.2.

[44] It is important to keep in mind that the value of the US' MW relative to median family income is much lower than the equivalent ratio in Colombia.

The estimated total effect on this inequality measure indicates that an increase of 0.01 in monthly real MW relative to the median increases inequality (measured by the Gini coefficient) by 0.06 points (Graph 9 and Table C2.1). This represents an increase of 0.11% in the Gini coefficient of this distribution (Table 6).[45]

These results on inequality are consistent with the increasing positive effects on the quantiles (except for the 10th) of the total household income distribution of increments in MW relative to the median, found previously in Section 4.3.

Graph 9. Effects on the inequality of the distribution of monthly household income per capita (contemporary, lagged and total effects)



Note: The dark-green circle indicates the value of the estimated coefficient for the contemporary monthly MW relative to the median; the light-green circle, the estimated coefficient for the lag of the monthly MW relative to the median; and the pink circle, the sum of these two coefficients (total effect). The bar in each circle indicates the 95% confidence interval computed using bootstrap method with 100 replications. These estimates are obtained from a series of RIF regressions of the household's real monthly total income per capita of individual *i* residing in city *c* in quarter *t* using as an independent variable the monthly MW relative to the median of each city-quarter, contemporaneous and lagged four quarters, as well as controls. All specifications include city and period fixed effects, individual-level controls, and city-level controls (see Section 3.2 and Eq. (4) for more details). For additional details, see sections 2 and 3. We report results in Table C2.1.
Source: DANE; authors' calculations.

[45] For comparison, Ocampo *et al*. (2004) calculate effects of the evaluated policies on the Gini coefficient of income per capita. They find that none of those policies (footnote 38) affect this coefficient. Also, Kart (2004) builds a computable general equilibrium model for the Colombian economy to assess the effect of four simulations on inequality and poverty. His results for the Gini coefficient are: i) a unilateral reduction of tariff rates increases the Gini coefficient by 0.10%, ii) changing the VAT tax from 15% for some goods to 10% for all goods increases the Gini by 0.50%; iii) a 50% decrease in external flows to the country increases the Gini coefficient by 0.30% with respect to the base; and iv) a 22% increase in the government's external obligations together with an increase in VAT to keep the level of government consumption constant increases the Gini by 0.30%.

Table 6. Total effects on the inequality of monthly household income per capita

Gini coefficient	Total Effect coefficient	Relative effect (%)
0.50	0.06	0.11

Notes: Column (1) reports the Gini coefficient of the households' distribution of real monthly total income per capita, based on the information of each person in each city and month for the period from 2008-I to 2019-IV. Column (2) reports the estimated total effect in the RIF regression (Graph 9 and Table C2.1). Column (3) indicates the percentage change in the Gini coefficient as a result of an increase of 0.01 in the real monthly MW (of quarter t) relative to the median real household income (of quarter t-4) (see footnote 37 as a reference).
Source: DANE; authors' calculations.

As a robustness check, we replicate all our estimations using data for only the first quarter of each year. This reduces the number of observations to about 25% of what we have when using all quarters. The results are quantitatively and qualitatively similar. They can be obtained from the authors upon request. Also, we estimate the regressions dropping al control variables at the individual, household and city level (the Xs and Zs), leaving only the fixed effects. The results are presented in the tables in Appendix C. They are quantitatively and qualitatively similar to those obtained when including all controls in each specification.

5. Summary and Concluding Remarks

Colombian MW is high relative to other incomes in the economy. In this context, we explore the effects of increasing the MW relative to the median income on labor income distribution of different occupational groups and their income inequality, as well as on household income distribution, its inequality and on monetary poverty prevalence.

The results indicate that increases in MW relative to the median labor income translate into increases in the quantile values of hourly labor income distribution for most occupational groups. The largest effects are for wage earners and for those contributing to social security. Moreover, effects are not statistically significant for the 10th quantile of most groups, that is, the lowest hourly earnings are not affected by the increase in MW relative to the median.

For the distribution of real monthly total household income per capita, results indicate that an increase of 0.01 in real monthly MW relative to the median household income per capita decreases the 10th quantile of this distribution, that is, the lowest 10% of monthly household income per capita. The effects on other quantiles are positive and increase with the quantile. Consequently, these effects of increases in monthly MW relative to the median on the distribution of monthly household income per capita translate into increases in its inequality, measured by its Gini coefficient.

Furthermore, evidence presented in this article indicates that increases in monthly MW relative to the median increase the probability that person's household monthly income per capita would be below the MPL.

In this context, it does not seem that increases in real MW during the period of analysis have contributed to raise the lowest incomes in Colombia.

Whether the increase in low labor incomes for wage earners is due to a boost in the remuneration of those with low wages, or due to a substitution for better-paid workers and, therefore, a loss of employment for those with lower incomes, merits further research. The effects found on the lowest decile of the household income distribution would suggest the presence of losses to low-wage workers, both in employment and in labor income, suggesting that the gainers and loser are very different in their skills and other attributes. To reiterate, more research is needed to disentangle these effects.

In Colombia, where the MW is high relative to other labor incomes, it affects the labor income distribution up and below the MW level. It could result in distortions on the labor market, with implications on labor market formalization and on labor productivity growth. For example, when the MW is higher than the equilibrium wage for low productivity workers, it could lead to a rise in the proportion of informal workers, making it much harder to formalize low productivity workers. On the other hand, when the MW increases faster than the average or the median wage, it may have implications for the firms' internal incentives structure as well as on the effort and productivity of workers far above the MW. While firms will increase wage offers, wage premiums would decline, and thus employees would not increase their effort (See Brink *et al.*, 2021), negatively affecting labor productivity growth. This in an interesting avenue for further research in the context of a relatively high minimum wage.

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Appendices

Appendix A. Regression of the recentered influence function (RIF)

The influence function (IF) of a distribution's statistic (e.g., mean, variance, quantile, poverty rates, etc.) measures the influence that an observation has on that statistic. This function is used, for example, to measure the robustness of statistics to extreme data (*outliers*). The RIF is obtained by adding the respective distribution's statistic to its IF.

Recentering has the advantage that, by doing so, the RIF's expected value is the distribution statistic itself. That is, if $v(F_Y)$ is the distribution statistic of a variable Y with cumulative distribution function F_Y, and $RIF(Y; v, F_Y)$ is the corresponding RIF, then $\int RIF(Y; v, F_Y)dF_Y = v(F_Y)$. For example, the expected value of the quantile q's RIF is the quantile q.

Firpo, Fortin and Lemieux (2009) propose using RIF to estimate the impact of changes in the distribution of explanatory variables X on the distribution's statistic $v(F_Y)$ of the outcome variable Y. In the case of quantiles, this would be an unconditional quantile regression. The authors show that, for linear regressions, the estimated coefficient indicates the marginal effect on the distribution statistic $v(F_Y)$ of a change in the expected value of the corresponding explanatory variable.

Each distribution statistic has a specific RIF. For quantiles, the RIF of each observation is calculated as:

$$RIF\left(y_i, Q_\tau(.), F_y\right) = Q_\tau(y) + \frac{\tau - \mathbf{1}(y_i \leq Q_\tau(y))}{f_y(Q_\tau(y))} \qquad \text{(A1)}$$

where $Q_\tau(y)$ is the (value of) the unconditional quantile, τ is the quantile of interest, $\mathbf{1}$ is an indicator function that takes the value 1 if observation y_i is less than $Q_\tau(y)$ or 0 otherwise, and $f_y(Q_\tau(y))$ is the density function of y evaluated at $Q_\tau(y)$ (See Firpo, Fortin and Lemieux, 2018).

The RIF for the Gini coefficient can be written as (taken from Firpo, Fortin and Lemieux, 2018):

$$RIF(y; v^G, F_Y) = 2\frac{y}{\mu}\left[F_Y(y) - \frac{(1+v^G)}{2}\right] + 2\left[\frac{(1-v^G)}{2} + GL(p; F_Y)\right] + v^G, \qquad \text{(A2)}$$

where $(1 + v^G)/2$ and $(1 - v^G)/2$ correspond, respectively, to the areas above and below the Lorenz Curve. Recall that the Gini coefficient is defined as $v^G(F_Y) = 1 - 2\mu^{-1}R(F_Y)$, where $R(F_Y) = \int_0^1 GL(p; F_Y)dp$ with $p(y) = F_Y(y)$ and where $GL(p; F_Y)$ is the generalized Lorenz ordinate of F_Y given by $GL(p; F_Y) = \int_{-\infty}^{F^{-1}(p)} z dF_Y(z)$. The generalized Lorenz curve tracks the cumulative total of y divided by total population size against the cumulative distribution function. The generalized Lorenz ordinate can be interpreted as the proportion of earnings going to the $100p\%$ lowest earners.

Appendix B. Inverse Probability Weighting (IPW)

In a first stage of the RIF regression, we estimate, for each year, the probability that the combination of observed characteristics of individual i in year t shows up in the sample of year t. The combination of observed characteristics that we use in the logistic model are the vector variables $\boldsymbol{X}_{ict}$ and $\boldsymbol{Z}_{ct}$. We estimate, then, $\Pr(T = t| \boldsymbol{X}_{ict}, \boldsymbol{Z}_{ct})$ for each t =2008, …,2019. We generate the weights corresponding to each observation as:

$$IPW_{ict} = \sum_{t=2008}^{2019} \frac{T = t}{\Pr(T = t| \boldsymbol{X}_{ict}, \boldsymbol{Z}_{ct}, \sigma_c)}$$

Then we remove observations with IPW_{ict} values greater than 0.90 and lower than 0.10, so that we exclude from the sample individuals with a combination of characteristics that may not be found in every of the years studied. Subsequently, we multiply each IPW_{ict} by the individual's original sample weight to obtain a new adjusted sample weight, which we normalize so that these adjusted sample weights add up to one.

IPW is a way to correct a possible under- or over-representation in the sample of certain combinations of individual characteristics; where one or the other eventuality is reflected in the probability of that combination of characteristics be included in the sample. IPW weights the impact of each combination by the inverse of the probability that this combination appears in the sample[46]. We use this procedure to balance the characteristics of the samples over the years.

[46] As indicated by Wooldridge (2010), IPW is an alternative to correcting for non-random sampling when the selection is made according to observable variables. The key is that there are observable variables that are good predictors of the observation being selected in the sample. This is different from Heckman's (1979) selection correction, which refers to selection on unobservable variables. In this article we do not correct for selection bias for unobservable variables. The reason is that the two-stage process proposed by Heckman (1979) or the FIML estimation (*full information maximum likelihood estimator*) generate greater biases than OLS if appropriate exclusion restrictions are not applied. That is, if there are no variables that (for our case) are correlated with labor market participation and employment but are not correlated with labor income. In practice, these variables are difficult to find. Puhani (2000) summarizes evidence from Monte Carlo exercises on parametric methods to correct for this type of selection bias. It concludes that, if the exclusion restriction and the normality assumption required by these methods cannot be satisfied, it is advisable to use OLS.

Appendix C. Tables with results from the change in the MW relative to the median

C1. Results for quintile values, mean and Gini coefficient of real hourly labor income distribution from a change in (the respective) MW to median.

Table C1.1 Total employed

	Quantiles									Mean	Gini	Quantiles									Mean	Gini
	10	20	30	40	50	60	70	80	90			10	20	30	40	50	60	70	80	90		
MW to median	0.250***	0.411***	0.415***	0.391***	0.268***	0.201***	0.218***	0.201***	0.230***	0.270***	0.012	0.402***	0.533***	0.505***	0.443***	0.327***	0.262***	0.272***	0.257***	0.260***	0.343***	-0.012
	(0.048)	(0.030)	(0.021)	(0.014)	(0.009)	(0.013)	(0.018)	(0.026)	(0.037)	(0.016)	(0.012)	(0.045)	(0.027)	(0.018)	(0.013)	(0.009)	(0.012)	(0.016)	(0.023)	(0.038)	(0.013)	(0.010)
MW to median; lagged	0.034	0.264***	0.286***	0.254***	0.185***	0.128***	0.162***	0.151***	0.182***	0.163***	0.047***	0.090*	0.315***	0.327***	0.279***	0.218***	0.170***	0.208***	0.215***	0.255***	0.210***	0.050***
	(0.048)	(0.027)	(0.020)	(0.013)	(0.010)	(0.011)	(0.015)	(0.024)	(0.034)	(0.015)	(0.011)	(0.047)	(0.027)	(0.017)	(0.011)	(0.009)	(0.011)	(0.015)	(0.021)	(0.030)	(0.013)	(0.009)
MW to median; total	0.283***	0.674***	0.701***	0.645***	0.452***	0.329***	0.380***	0.352***	0.413***	0.434***	0.0597***	0.491***	0.847***	0.832***	0.722***	0.546***	0.432***	0.480***	0.472***	0.515***	0.553***	0.038***
	(0.071)	(0.036)	(0.026)	(0.018)	(0.012)	(0.016)	(0.020)	(0.034)	(0.041)	(0.019)	(0.016)	(0.066)	(0.037)	(0.022)	(0.017)	(0.011)	(0.015)	(0.020)	(0.031)	(0.046)	(0.014)	(0.011)
Observations	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162	2,104,162
Include controls	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include area f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include period f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors, computed using bootstrap method with 100 replications, are shown in parenthesis. Results from RIF regressions of the logarithm of the real hourly labor income per individual residing in city *c* in quarter *t*; except for Gini, in which case we use the real hourly labor income per individual. The independent variable "MW to median" correspond to hourly MW to hourly median. Where specified, we include controls for individual and for city of residence. "Total employed" corresponds to the sum of wage earners and self-employed individuals. For more details, see sections 2 and 3. Number of observations without sample weights; see Table E.1 for number of total employed using observations with sample weights.

Table C1.2. Wage earners

	Quantiles									Mean	Gini	Quantiles									Mean	Gini
	10	20	30	40	50	60	70	80	90			10	20	30	40	50	60	70	80	90		
MW to median	0.445***	0.434***	0.439***	0.423***	0.435***	0.450***	0.443***	0.451***	0.378***	0.430***	-0.053**	0.440***	0.433***	0.438***	0.430***	0.454***	0.468***	0.461***	0.458***	0.382***	0.435***	-0.057***
	(0.039)	(0.018)	(0.013)	(0.017)	(0.019)	(0.023)	(0.031)	(0.044)	(0.066)	(0.020)	(0.023)	(0.034)	(0.018)	(0.011)	(0.015)	(0.019)	(0.021)	(0.025)	(0.038)	(0.052)	(0.015)	(0.019)
MW to median; lagged	0.226***	0.226***	0.239***	0.304***	0.256***	0.240***	0.262***	0.294***	0.158**	0.253***	-0.050**	0.216***	0.220***	0.235***	0.299***	0.258***	0.250***	0.290***	0.335***	0.213***	0.269***	-0.026
	(0.039)	(0.020)	(0.012)	(0.013)	(0.020)	(0.025)	(0.032)	(0.052)	(0.068)	(0.023)	(0.022)	(0.033)	(0.016)	(0.010)	(0.013)	(0.015)	(0.021)	(0.026)	(0.038)	(0.063)	(0.015)	(0.022)
MW to median; total	0.670***	0.660***	0.678***	0.727***	0.691***	0.690***	0.705***	0.744***	0.536***	0.683***	-0.103***	0.656***	0.653***	0.673***	0.728***	0.712***	0.719***	0.751***	0.793***	0.595***	0.703***	-0.083***
	(0.061)	(0.029)	(0.017)	(0.022)	(0.024)	(0.035)	(0.041)	(0.062)	(0.084)	(0.029)	(0.031)	(0.048)	(0.026)	(0.016)	(0.019)	(0.023)	(0.029)	(0.035)	(0.047)	(0.077)	(0.020)	(0.029)
Observations	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593	1,177,593
Include controls	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include area f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include period f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors, computed using bootstrap method with 100 replications, are shown in parenthesis. Results from RIF regressions of the logarithm of the real hourly labor income per individual residing in city *c* in quarter *t*; except for Gini, in which case we use the real hourly labor income per individual. The independent variable "MW to median" in the regressions correspond to hourly MW to hourly median labor income. Where specified, we include controls for individual and for city of residence. "Wage earners" are private and public workers and employees. We did not include domestic employees and day laborers in this analysis (occupational categories also included in the GEIH). For more details, see sections 2 and 3. Number of observations without sample weights; see Table E.1 for number of wage earners using observations with sample weights.

Table C1.3. Self-employed individuals without higher education

	Quantiles									Mean	Gini	Quantiles									Mean	Gini
	10	20	30	40	50	60	70	80	90			10	20	30	40	50	60	70	80	90		
MW to median	0.037	0.059*	0.081***	0.093***	0.120***	0.135***	0.084***	0.100***	0.080***	0.075***	0.013	0.102**	0.124***	0.146***	0.154***	0.175***	0.191***	0.133***	0.144***	0.120***	0.128***	0.006
	(0.045)	(0.031)	(0.021)	(0.018)	(0.015)	(0.014)	(0.014)	(0.017)	(0.021)	(0.015)	(0.008)	(0.049)	(0.030)	(0.021)	(0.016)	(0.016)	(0.014)	(0.012)	(0.015)	(0.022)	(0.014)	(0.008)
MW to median; lagged	-0.036	0.058**	0.025	0.064***	0.025*	0.050***	0.051***	0.058***	0.037	0.024	-0.003	-0.026	0.075***	0.052***	0.091***	0.059***	0.087***	0.087***	0.097***	0.082***	0.053***	7.25e-05
	(0.047)	(0.029)	(0.020)	(0.021)	(0.013)	(0.014)	(0.014)	(0.016)	(0.024)	(0.015)	(0.009)	(0.049)	(0.027)	(0.020)	(0.023)	(0.015)	(0.015)	(0.014)	(0.015)	(0.022)	(0.014)	(0.007)
MW to median; total	0.001	0.118***	0.106***	0.156***	0.145***	0.185***	0.135***	0.158***	0.116***	0.098***	0.010	0.077	0.199***	0.198***	0.245***	0.234***	0.278***	0.220***	0.240***	0.202***	0.181***	0.006
	(0.068)	(0.037)	(0.026)	(0.024)	(0.018)	(0.018)	(0.019)	(0.023)	(0.031)	(0.017)	(0.011)	(0.069)	(0.037)	(0.029)	(0.025)	(0.022)	(0.019)	(0.017)	(0.019)	(0.032)	(0.018)	(0.010)
Observations	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760	743,760
Include controls	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include area f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include period f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors, computed using bootstrap method with 100 replications, are shown in parenthesis. Results from RIF regressions of the logarithm of the real hourly labor income per individual residing in city *c* in quarter *t*; except for Gini, in which case we use the real hourly labor income per individual. The independent variable "MW to median" in the regressions correspond to hourly MW to hourly median labor income. Where specified, we include controls for individual and for city of residence. A person is classified as "without higher education" if her educational level is complete high school or less. For more details, see sections 2 and 3. Number of observations without sample weights; see Table E.1 for number of self-employed individuals without higher education using observations with sample weights.

Table C1.4. Self-employed individuals with higher education

	Quantiles									Mean	Gini	Quantiles									Mean	Gini
	10	20	30	40	50	60	70	80	90			10	20	30	40	50	60	70	80	90		
MW to median	0.345***	0.113*	0.092	0.053	0.057	0.052	-0.090	-0.026	-0.050	0.090*	-0.012	0.336***	0.109*	0.092*	0.059	0.067	0.060	-0.085	-0.023	-0.051	0.091**	-0.013
	(0.099)	(0.068)	(0.060)	(0.055)	(0.061)	(0.061)	(0.060)	(0.062)	(0.063)	(0.048)	(0.022)	(0.083)	(0.057)	(0.049)	(0.050)	(0.054)	(0.052)	(0.055)	(0.058)	(0.064)	(0.039)	(0.020)
MW to median; lagged	0.083	0.021	0.025	0.047	0.083	0.003	0.022	-0.072	-0.049	0.056	0.038	0.087	0.006	0.001	0.025	0.060	-0.018	0.003	-0.085	-0.054	0.043	0.041*
	(0.104)	(0.061)	(0.049)	(0.050)	(0.057)	(0.060)	(0.059)	(0.060)	(0.066)	(0.043)	(0.025)	(0.097)	(0.059)	(0.052)	(0.054)	(0.048)	(0.051)	(0.062)	(0.061)	(0.066)	(0.043)	(0.023)
MW to median; total	0.428***	0.134	0.117*	0.100	0.139*	0.0548	-0.068	-0.098	-0.099	0.145**	0.026	0.422***	0.115	0.093	0.083	0.127*	0.042	-0.083	-0.108	-0.105	0.135**	0.028
	(0.141)	(0.082)	(0.065)	(0.070)	(0.077)	(0.081)	(0.073)	(0.085)	(0.088)	(0.061)	(0.031)	(0.122)	(0.075)	(0.062)	(0.066)	(0.067)	(0.063)	(0.078)	(0.084)	(0.086)	(0.053)	(0.029)
Observations	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809	182,809
Include controls	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include area f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include period f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors, computed using bootstrap method with 100 replications, are shown in parenthesis. Results from RIF regressions of the logarithm of the real hourly labor income per individual residing in city *c* in quarter *t*; except for Gini, in which case we use the real hourly labor income per individual. The independent variable "MW to median" in the regressions correspond to hourly MW to hourly median labor income. Where specified, we include controls for individual and for city of residence. A person is classified as "with higher education" if she has at least one year of studies beyond complete high school. For more details, see sections 2 and 3. Number of observations without sample weights; see Table E.1 for number of self-employed individuals with higher education using observations with sample weights.

Table C1.5. Total employed who contribute to social security

	Quantiles									Mean	Gini	Quantiles									Mean	Gini
	10	20	30	40	50	60	70	80	90			10	20	30	40	50	60	70	80	90		
MW to median	0.289***	0.402***	0.355***	0.308***	0.310***	0.293***	0.206***	0.196***	0.170**	0.272***	-0.038**	0.283***	0.393***	0.358***	0.322***	0.324***	0.309***	0.221***	0.193***	0.161**	0.271***	-0.046**
	(0.023)	(0.015)	(0.016)	(0.019)	(0.026)	(0.035)	(0.046)	(0.057)	(0.071)	(0.024)	(0.019)	(0.020)	(0.013)	(0.015)	(0.017)	(0.025)	(0.029)	(0.039)	(0.047)	(0.067)	(0.018)	(0.019)
MW to median; lagged	0.119***	0.130***	0.165***	0.171***	0.126***	0.102***	0.090***	0.116***	-0.013	0.129***	-0.030*	0.120***	0.135***	0.163***	0.180***	0.152***	0.148***	0.157***	0.202***	0.089	0.171***	-0.001
	(0.019)	(0.017)	(0.015)	(0.021)	(0.028)	(0.039)	(0.049)	(0.056)	(0.068)	(0.026)	(0.017)	(0.019)	(0.015)	(0.014)	(0.017)	(0.024)	(0.031)	(0.039)	(0.040)	(0.056)	(0.017)	(0.020)
MW to median; total	0.407***	0.532***	0.520***	0.478***	0.435***	0.395***	0.297***	0.312***	0.156*	0.400***	-0.068***	0.404***	0.528***	0.521***	0.502***	0.476***	0.456***	0.378***	0.396***	0.251***	0.441***	-0.047*
	(0.031)	(0.018)	(0.021)	(0.028)	(0.036)	(0.050)	(0.065)	(0.072)	(0.089)	(0.032)	(0.026)	(0.029)	(0.018)	(0.022)	(0.023)	(0.031)	(0.038)	(0.048)	(0.060)	(0.084)	(0.023)	(0.026)
Observations	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628	972,628
Include controls	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include area f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include period f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors, computed using bootstrap method with 100 replications, are shown in parenthesis. Results from RIF regressions of the logarithm of the real hourly labor income per individual residing in city *c* in quarter *t*; except for Gini, in which case we use the real hourly labor income per individual. The independent variable "MW to median" in the regressions correspond to hourly MW to hourly median labor income. Where specified, we include controls for individual and for city of residence. "Total employed" corresponds to the sum of wage earners and self-employed individuals. A person contributes to social security if she contributes to both health and pensions. For more details, see sections 2 and 3. Number of observations without sample weights; see Table E.1 for number of total employed who contribute to social security using observations with sample weights.

Table C1.6. Total employed who do not contribute to social security

	Quantiles									Mean	Gini	Quantiles									Mean	Gini
	10	20	30	40	50	60	70	80	90			10	20	30	40	50	60	70	80	90		
MW to median	0.176***	0.123***	0.091***	0.115***	0.144***	0.109***	0.123***	0.080***	0.027	0.106***	0.052***	0.283***	0.226***	0.177***	0.200***	0.216***	0.170***	0.183***	0.138***	0.082***	0.178***	0.027*
	(0.036)	(0.027)	(0.019)	(0.018)	(0.016)	(0.014)	(0.013)	(0.015)	(0.028)	(0.014)	(0.017)	(0.040)	(0.027)	(0.020)	(0.020)	(0.015)	(0.012)	(0.012)	(0.016)	(0.026)	(0.012)	(0.015)
MW to median; lagged	0.016	0.038	0.037	0.022	0.053***	0.042***	0.033	0.026	-0.030	0.040**	0.048***	0.057	0.080***	0.075***	0.062***	0.088***	0.071***	0.062***	0.056***	-0.004	0.071***	0.036**
	(0.048)	(0.029)	(0.023)	(0.021)	(0.015)	(0.015)	(0.016)	(0.019)	(0.039)	(0.019)	(0.017)	(0.049)	(0.026)	(0.021)	(0.021)	(0.015)	(0.013)	(0.017)	(0.018)	(0.035)	(0.016)	(0.017)
MW to median; total	0.192***	0.160***	0.127***	0.137***	0.197***	0.151***	0.156***	0.105***	-0.004	0.146***	0.100***	0.341***	0.305***	0.252***	0.262***	0.304***	0.241***	0.244***	0.194***	0.078*	0.249***	0.063**
	(0.065)	(0.037)	(0.027)	(0.025)	(0.021)	(0.019)	(0.018)	(0.022)	(0.050)	(0.022)	(0.027)	(0.069)	(0.034)	(0.027)	(0.026)	(0.021)	(0.017)	(0.020)	(0.022)	(0.043)	(0.020)	(0.025)
Observations	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534	1,131,534
Include controls	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include area f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include period f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors, computed using bootstrap method with 100 replications, are shown in parenthesis. Results from RIF regressions of the logarithm of the real hourly labor income per individual residing in city *c* in quarter *t*; except for Gini, in which case we use the real hourly labor income per individual. The independent variable "MW to median" in the regressions correspond to hourly MW to hourly median labor income. Where specified, we include controls for individual and for city of residence. "Total employed" corresponds to the sum of wage earners and self-employed individuals. A person contributes to social security if she contributes to both health and pensions. For more details, see sections 2 and 3. Number of observations without sample weights; see Table E.1 for number of total employed who do not contribute to social security using observations with sample weights.

Table C1.7 Wage earners who contribute to social security

	Quantiles									Mean	Gini	Quantiles									Mean	Gini
	10	20	30	40	50	60	70	80	90			10	20	30	40	50	60	70	80	90		
MW to median	0.318***	0.384***	0.345***	0.266***	0.278***	0.235***	0.153***	0.180***	0.098	0.237***	-0.056***	0.317***	0.374***	0.352***	0.282***	0.295***	0.257***	0.178***	0.197***	0.110*	0.244***	-0.061***
	(0.019)	(0.013)	(0.015)	(0.021)	(0.028)	(0.036)	(0.051)	(0.054)	(0.077)	(0.024)	(0.022)	(0.018)	(0.013)	(0.013)	(0.019)	(0.025)	(0.027)	(0.042)	(0.044)	(0.063)	(0.019)	(0.023)
MW to median; lagged	0.117***	0.105***	0.147***	0.140***	0.108***	0.072*	0.095*	0.090	-0.070	0.086***	-0.037	0.122***	0.114***	0.144***	0.147***	0.137***	0.122***	0.176***	0.199***	0.076	0.142***	0.004
	(0.018)	(0.017)	(0.016)	(0.022)	(0.029)	(0.038)	(0.052)	(0.055)	(0.075)	(0.026)	(0.024)	(0.018)	(0.016)	(0.013)	(0.015)	(0.019)	(0.028)	(0.039)	(0.044)	(0.061)	(0.018)	(0.022)
MW to median; total	0.435***	0.488***	0.488***	0.492***	0.386***	0.307***	0.248***	0.270***	0.028	0.323***	-0.094***	0.439***	0.488***	0.488***	0.496***	0.432***	0.379***	0.354***	0.396***	0.186**	0.386***	-0.057**
	(0.029)	(0.021)	(0.022)	(0.027)	(0.037)	(0.045)	(0.073)	(0.073)	(0.092)	(0.033)	(0.030)	(0.024)	(0.019)	(0.020)	(0.023)	(0.031)	(0.039)	(0.057)	(0.067)	(0.085)	(0.024)	(0.028)
Observations	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479	861,479
Include controls	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include area f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include period f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors, computed using bootstrap method with 100 replications, are shown in parenthesis. Results from RIF regressions of the logarithm of the real hourly labor income per individual residing in city *c* in quarter *t*; except for Gini, in which case we use the real hourly labor income per individual. The independent variable "MW to median" in the regressions correspond to hourly MW to hourly median labor income. Where specified, we include controls for individual and for city of residence. "Wage earners" are private and public workers and employees. We did not include domestic employees and day laborers in this analysis (occupational categories also included in the GEIH). A person contributes to social security if she contributes to both health and pensions. For more details, see sections 2 and 3. Number of observations without sample weights; see Table E.1 for number of wage earners who contribute to social security using observations with sample weights.

Table C1.8. Wage earners who do not contribute to social security

	Quantiles									Mean	Gini	Quantiles									Mean	Gini
	10	20	30	40	50	60	70	80	90			10	20	30	40	50	60	70	80	90		
MW to median	0.252***	0.159***	0.183***	0.213***	0.205***	0.202***	0.175***	0.160***	0.0109	0.161***	-0.118**	0.284***	0.195***	0.223***	0.244***	0.234***	0.238***	0.219***	0.221***	0.191*	0.216***	-0.105***
	(0.074)	(0.044)	(0.033)	(0.027)	(0.024)	(0.024)	(0.028)	(0.04)	(0.105)	(0.036)	(0.049)	(0.070)	(0.042)	(0.036)	(0.027)	(0.022)	(0.020)	(0.028)	(0.034)	(0.102)	(0.030)	(0.037)
MW to median; lagged	0.050	0.009	0.008	0.005	0.015	0.068***	0.013	0.029	0.202	0.016	-0.081*	0.013	-0.020	-0.018	-0.016	-0.007	0.047***	-0.012	0,000	0.114	-0.023	-0.096**
	(0.073)	(0.049)	(0.045)	(0.040)	(0.028)	(0.027)	(0.031)	(0.048)	(0.132)	(0.040)	(0.045)	(0.077)	(0.045)	(0.038)	(0.034)	(0.025)	(0.024)	(0.029)	(0.038)	(0.103)	(0.030)	(0.042)
MW to median; total	0.302***	0.168**	0.191***	0.217***	0.219***	0.270***	0.187***	0.189***	0.213	0.177***	-0.199**	0.297***	0.175***	0.206***	0.228***	0.227***	0.284**	0.207***	0.221***	0.306*	0.194***	-0.202***
	(0.102)	(0.069)	(0.052)	(0.048)	(0.032)	(0.035)	(0.040)	(0.057)	(0.188)	(0.053)	(0.078)	(0.088)	(0.056)	(0.045)	(0.041)	(0.032)	(0.028)	(0.035)	(0.046)	(0.164)	(0.041)	(0.066)
Observations	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114	316,114
Include controls	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include area f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include period f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors, computed using bootstrap method with 100 replications, are shown in parenthesis. Results from RIF regressions of the logarithm of the real hourly labor income per individual residing in city *c* in quarter *t*; except for Gini, in which case we use the real hourly labor income per individual. The independent variable "MW to median" in the regressions correspond to hourly MW to hourly median labor income. Where specified, we include controls for individual and for city of residence. "Wage earners" are private and public workers and employees. We did not include domestic employees and day laborers in this analysis (occupational categories also included in the GEIH). A person contributes to social security if she contributes to both health and pensions. For more details, see sections 2 and 3. Number of observations without sample weights; see Table E.1 for number of wage earners who do not contribute to social security using observations with sample weights.

Table C1.9. Self-employed individuals who contribute to social security

	Quantiles									Mean	Gini	Quantiles									Mean	Gini
	10	20	30	40	50	60	70	80	90			10	20	30	40	50	60	70	80	90		
MW to median	-0.123	0.028	0.097	0.051	0.041	0.037	0.099	0.072	0.150	0.074	0.079	-0.042	0.121	0.202***	0.159**	0.141*	0.121	0.169*	0.132	0.180	0.151***	0.066
	(0.113)	(0.088)	(0.094)	(0.090)	(0.088)	(0.086)	(0.095)	(0.098)	(0.101)	(0.067)	(0.057)	(0.095)	(0.086)	(0.068)	(0.073)	(0.082)	(0.083)	(0.093)	(0.106)	(0.111)	(0.054)	(0.058)
MW to median; lagged	-0.227***	-0.181**	-0.177**	-0.130	-0.141*	-0.075	0.044	-0.159	-0.117	-0.154**	0.016	-0.107	-0.061	-0.059	-0.005	-0.015	0.048	0.157*	-0.044	-0.029	-0.043	0.007
	(0.081)	(0.075)	(0.078)	(0.082)	(0.083)	(0.089)	(0.109)	(0.101)	(0.108)	(0.063)	(0.036)	(0.080)	(0.060)	(0.064)	(0.066)	(0.063)	(0.060)	(0.083)	(0.077)	(0.088)	(0.050)	(0.033)
MW to median; total	-0.350***	-0.153	-0.080	-0.079	-0.100	-0.038	0.143	-0.087	0.033	-0.080	0.095*	-0.148	0.060	0.143	0.153	0.125	0.169*	0.327***	0.087	0.151	0.107	0.074
	(0.128)	(0.100)	(0.120)	(0.114)	(0.120)	(0.118)	(0.136)	(0.137)	(0.133)	(0.082)	(0.050)	(0.114)	(0.100)	(0.085)	(0.098)	(0.094)	(0.100)	(0.126)	(0.131)	(0.135)	(0.068)	(0.049)
Observations	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149	111,149
Include controls	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include area f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include period f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors, computed using bootstrap method with 100 replications, are shown in parenthesis. Results from RIF regressions of the logarithm of the real hourly labor income per individual residing in city *c* in quarter *t*; except for Gini, in which case we use the real hourly labor income per individual. The independent variable "MW to median" in the regressions correspond to hourly MW to hourly median labor income. Where specified, we include controls for individual and for city of residence. A person contributes to social security if she contributes to both health and pensions. For more details, see sections 2 and 3. Number of observations without sample weights; see Table E.1 for number of self-employed individuals who contribute to social security using observations with sample weights.

Table C1.10 Self-employed individuals who do not contribute to social security

	Quantiles									Mean	Gini	Quantiles									Mean	Gini
	10	20	30	40	50	60	70	80	90			10	20	30	40	50	60	70	80	90		
MW to median	0.054	0.070***	0.089***	0.120***	0.122***	0.127***	0.121***	0.095***	0.054**	0.083***	0.020**	0.115***	0.133***	0.151***	0.178***	0.174***	0.182***	0.166***	0.141***	0.092***	0.134***	0.012
	(0.040)	(0.026)	(0.018)	(0.015)	(0.013)	(0.011)	(0.013)	(0.016)	(0.023)	(0.013)	(0.009)	(0.039)	(0.030)	(0.017)	(0.018)	(0.016)	(0.012)	(0.012)	(0.015)	(0.025)	(0.012)	(0.009)
MW to median; lagged	-0.0307	0.0608**	0.0359	0.0521***	0.0429**	0.0617***	0.0336**	0.0751***	0.0262	0.0320*	0.022*	0.00121	0.0922***	0.0701***	0.0857***	0.0767***	0.100***	0.0668***	0.117***	0.0669***	0.0684***	0.025**
	(0.038)	(0.029)	(0.022)	(0.019)	(0.017)	(0.014)	(0.014)	(0.018)	(0.027)	(0.017)	(0.012)	(0.048)	(0.028)	(0.019)	(0.016)	(0.016)	(0.014)	(0.013)	(0.016)	(0.025)	(0.013)	(0.011)
MW to median; total	0.023	0.131***	0.125***	0.173***	0.165***	0.188***	0.154***	0.170***	0.080**	0.115***	0.042***	0.117*	0.225***	0.221***	0.264***	0.251***	0.282***	0.233***	0.258***	0.159***	0.203***	0.037**
	0.049	0.033	0.027	0.021	0.020	0.017	0.015	0.024	0.033	0.018	(0.014)	0.061	0.039	0.024	0.023	0.020	0.017	0.016	0.021	0.037	0.016	(0.014)
Observations	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420	815,420
Include controls	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include area f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include period f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors, computed using bootstrap method with 100 replications, are shown in parenthesis. Results from RIF regressions of the logarithm of the real hourly labor income per individual residing in city *c* in quarter *t*; except for Gini, in which case we use the real hourly labor income per individual. The independent variable "MW to median" in the regressions correspond to hourly MW to hourly median labor income. Where specified, we include controls for individual and for city of residence. A person contributes to social security if she contributes to both health and pensions. For more details, see sections 2 and 3. Number of observations without sample weights; see Table E.1 for number of self-employed individuals who do not contribute to social security using observations with sample weights.

C2. Results for quintile values, mean and Gini coefficient of real monthly household income per capita distribution from a change in (the respective) MW to median.

Table C2.1. Real monthly household income per capita

	Quantiles									Mean	Gini	Quantiles									Mean	Gini
	10	20	30	40	50	60	70	80	90			10	20	30	40	50	60	70	80	90		
MW to median	-0.007	0.057***	0.051***	0.097***	0.112***	0.127***	0.130***	0.127***	0.129***	0.083***	0.023***	0.027**	0.098***	0.091***	0.140***	0.152***	0.168***	0.169***	0.166***	0.162***	0.119***	0.020***
	(0.010)	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.004)	(0.002)	(0.011)	(0.007)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.008)	(0.003)	(0.002)
MW to median; lagged	-0.105***	-0.047***	-0.004	0.012**	0.056***	0.083***	0.087***	0.093***	0.101***	0.034***	0.038***	-0.083***	-0.018***	0.025***	0.044***	0.086***	0.113***	0.116***	0.121***	0.127***	0.060***	0.036***
	(0.011)	(0.007)	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.007)	(0.004)	(0.002)	(0.009)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.007)	(0.002)	(0.002)
MW to median; total	-0.112***	0.010	0.047***	0.109***	0.169***	0.210***	0.217***	0.220***	0.230***	0.117***	0.061***	-0.055***	0.081***	0.116***	0.184***	0.239***	0.281***	0.284***	0.287***	0.290***	0.180***	0.056***
	(0.012)	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.010)	(0.004)	(0.002)	(0.013)	(0.010)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.011)	(0.003)	(0.003)
Observations	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650	7,691,650
Include controls	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include area f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include period f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Standard errors, computed using bootstrap method with 100 replications, are shown in parenthesis. Results from RIF regressions of the logarithm of real monthly total household income per capita per individual residing in city *c* in quarter *t*; except for Gini, in which case we use the real monthly total household income per capita per individual. The independent variable "MW to median" corresponds to monthly MW to monthly median labor income. Where specified, we include controls for individual and for city of residence. For more details, see sections 2 and 3. Number of observations without sample weights; see Table E.3 for number of observations using sample weights.

C3. Results for multiples of the monetary poverty line from a change in the monthly MW to median

Table C3.1 Poverty prevalence at different multiples of monetary poverty line

	Multiple of monetary poverty line			
	0,5	1	1,5	2
MW to median	0.030***	0.029***	0.012*	-0.001
	(0.003)	(0.006)	(0.006)	(0.007)
MW to median; lagged	0.017***	0.017***	0.011***	0.007*
	(0.004)	(0.006)	(0.004)	(0.004)
MW to median; total	0.047***	0.046***	0.022***	0.005
	(0.007)	(0.009)	(0.008)	(0.007)
Observations	6,961,988	6,961,988	6,961,988	6,961,988
Include controls	Yes	Yes	Yes	Yes
Include area f.e.	Yes	Yes	Yes	Yes
Include period f.e.	Yes	Yes	Yes	Yes

Notes: ***, **, * denote statistical significance at the 1, 5 and 10 percent levels, respectively. Robust standard errors clustered at the city level are shown in parenthesis. Results from OLS regressions of indicator variables per individual residing in city *c* in quarter *t*. The independent variable "MW to median" corresponds to monthly MW to monthly median household income per capita. We include controls for individual and for city of residence (see Section 3.3 and Eq. (5) for more details) For additional details, see sections 2 and 3. Number of observations without sample weights; see Table E.3 for number of observations using sample weights.

Appendix D. Monetary change in the value of the hourly labor income quantiles of each occupational group

Table D.1 reports the amount of increase in the value of the quantiles of hourly labor earnings distribution when real MW relative to the median increases by 0.01, using the results of the unconditional quantile regressions estimated with all-quarters data (Graphs 4 and 5; tables in Appendix C1). For the initial values of the quantiles of each occupational group, we use those reported in Table E.2.

Table D.1. Change (in COP) in the value of the labor income quantiles by occupational group

	Quantiles								
	10	20	30	40	50	60	70	80	90
Total employed	8.03	20.30	24.65	24.76	20.24	17.81	23.01	28.79	49.61
Wage earners	17.77	21.45	24.07	27.53	29.32	33.18	40.87	56.59	66.86
Self employed, without higher education	-	3.08	3.89	5.75	6.32	8.55	7.73	9.78	10.58
Self employed, with higher education	7.97	-	-	-	-	-	-	-	-
Total employed who contribute to social security	12.84	18.79	19.59	20.59	21.86	24.38	24.93	34.83	34.04
Total employed who do not contribute to social security	4.03	5.39	5.59	6.83	9.08	8.15	9.21	8.53	4.51
Wage earners who contribute to social security	14.11	17.36	18.52	17.34	19.33	19.45	22.01	32.57	23.50
Wage earnes who do not contribute to social security	5.79	4.29	5.85	7.20	7.85	10.48	8.34	10.08	-
Self employed, who contribute to social security	-	-	-	-	-	-	34.30	-	-
Self employed, who do not contribute to social security	-	3.49	4.38	6.28	6.93	8.89	8.46	11.03	9.12

Notes: Not significant coefficients are replaced by zero.

Appendix E. Data description

Table E.1 Employed by occupational group and its size relative to the total employed individuals.
Colombia 2008-2019

year	Total employed		Wage earners		Self-employed without higher education		Self-employed with higher education		Employed who contribute		Employed who do not contribute		Wage earners who contribute		Wage earners who do not contribute		Self-employed who contribute		Self-employed who do not contribute	
	Number	%	Number	%	Number	%	Number	%	Number	%	Number	%	Number	%	Number	%	Number	%	Number	%
2008	7,855,759	100.0%	4,492,349	57.2%	2,915,312	37.1%	448,098	5.7%	3,231,516	41.1%	4,624,243	58.9%	2,968,141	37.8%	1,524,208	19.4%	263,375	3.4%	3,100,035	39.5%
2009	8,116,088	100.0%	4,506,904	55.5%	3,148,146	38.8%	461,038	5.7%	3,356,639	41.4%	4,759,449	58.6%	3,047,602	37.6%	1,459,302	18.0%	309,037	3.8%	3,300,147	40.7%
2010	8,359,872	100.0%	4,646,508	55.6%	3,192,413	38.2%	520,951	6.2%	3,491,676	41.8%	4,868,196	58.2%	3,147,703	37.7%	1,498,805	17.9%	343,973	4.1%	3,369,391	40.3%
2011	8,631,979	100.0%	4,805,226	55.7%	3,258,174	37.7%	568,579	6.6%	3,640,799	42.2%	4,991,180	57.8%	3,262,883	37.8%	1,542,343	17.9%	377,916	4.4%	3,448,837	40.0%
2012	8,754,251	100.0%	5,037,477	57.5%	3,144,951	35.9%	571,823	6.5%	3,819,992	43.6%	4,934,259	56.4%	3,444,497	39.3%	1,592,980	18.2%	375,495	4.3%	3,341,279	38.2%
2013	9,004,756	100.0%	5,256,934	58.4%	3,112,105	34.6%	635,717	7.1%	4,068,685	45.2%	4,936,071	54.8%	3,652,425	40.6%	1,604,509	17.8%	416,260	4.6%	3,331,562	37.0%
2014	9,379,334	100.0%	5,567,485	59.4%	3,155,101	33.6%	656,748	7.0%	4,386,795	46.8%	4,992,539	53.2%	3,932,966	41.9%	1,634,519	17.4%	453,829	4.8%	3,358,020	35.8%
2015	9,689,090	100.0%	5,800,448	59.9%	3,234,158	33.4%	654,484	6.8%	4,597,187	47.4%	5,091,903	52.6%	4,143,287	42.8%	1,657,161	17.1%	453,900	4.7%	3,434,742	35.4%
2016	9,833,785	100.0%	5,887,397	59.9%	3,275,614	33.3%	670,774	6.8%	4,750,937	48.3%	5,082,848	51.7%	4,266,113	43.4%	1,621,284	16.5%	484,824	4.9%	3,461,564	35.2%
2017	9,831,373	100.0%	5,867,497	59.7%	3,277,635	33.3%	686,241	7.0%	4,829,273	49.1%	5,002,100	50.9%	4,338,150	44.1%	1,529,347	15.6%	491,123	5.0%	3,472,753	35.3%
2018	9,986,075	100.0%	5,896,322	59.0%	3,358,131	33.6%	731,622	7.3%	4,876,699	48.8%	5,109,376	51.2%	4,358,068	43.6%	1,538,254	15.4%	518,631	5.2%	3,571,122	35.8%
2019	10,279,202	100.0%	6,246,719	60.8%	3,247,249	31.6%	785,234	7.6%	5,101,963	49.6%	5,177,239	50.4%	4,548,232	44.2%	1,698,487	16.5%	553,731	5.4%	3,478,752	33.8%

Note: Value each year for each group corresponds to the average number of individuals classified into that group each quarter. Sample weights are used in the calculation. The column with percentages indicates the participation of each group in the total employed individuals. “Total employed” corresponds to the sum of wage earners and self-employed workers. “Wage earners” are private and public workers and employees. We did not include domestic employees and day laborers in this analysis (occupational categories also included in the GEIH). A person is classified as “without higher education” if her educational level is complete high school or less. A person is classified as “with higher education” if she has at least one year of studies beyond complete high school. A person contributes to social security if she contributes to both health and pensions.

Table E.2. Distribution of hourly labor income by occupational group
Colombia, 2008-2019

Occupational group	Quantiles								
	10	20	30	40	50	60	70	80	90
Total employed	1.636	2.397	2.963	3.429	3.707	4.122	4.793	6.100	9.633
Wage earners	2.708	3.285	3.576	3.782	4.117	4.615	5.443	7.137	11.237
Self employed, without higher education	1.010	1.547	1.966	2.347	2.703	3.075	3.516	4.077	5.240
Self employed, with higher education	1.887	2.878	3.696	4.541	5.648	7.165	9.256	12.382	18.215
Total employed who contribute to social security	3.178	3.558	3.759	4.101	4.592	5.345	6.595	8.796	13.562
Total employed who do not contribute to social security	1.181	1.769	2.219	2.607	2.987	3.381	3.774	4.398	5.791
Wage earners who contribute to social security	3.213	3.558	3.733	4.032	4.474	5.131	6.217	8.226	12.632
Wage earnes who do not contribute to social security	1.951	2.453	2.838	3.156	3.460	3.689	4.028	4.560	5.872
Self employed, who contribute to social security	2.755	3.674	4.532	5.541	6.789	8.283	10.488	13.739	19.226
Self employed, who do not contribute to social security	1.008	1.553	1.982	2.378	2.760	3.153	3.630	4.277	5.739

Notes: value of each quantile in the labor income distribution of each occupational group. Values in real COP, base 2018. For details on the calculation of hourly labor income, see Section 2.1.1 in this paper. Calculations use the information of all individuals belonging to each group in each city-quarter during the period 2008-I – 2019-IV. “Total employed” corresponds to the sum of wage earners and self-employed workers. “Wage earners” are private and public workers and employees. We did not include domestic employees and day laborers in this analysis (occupational categories also included in the GEIH). A person is classified as “without higher education” if her educational level is complete high school or less. A person is classified as “with higher education” if she has at least one year of studies beyond complete high school. A person contributes to social security if she contributes to both health and pensions. As a reference, the real hourly MW in 2018 is COP 3700.

Table E.3. Population for household income and poverty analysis.
Colombia 2008-2019

	Population	Population in monetary poverty	%
2008	32,232,201	13,462,723	41.77
2009	32,666,821	13,103,505	40.11
2010	33,072,740	12,260,754	37.07
2011	33,480,549	11,366,937	33.95
2012	33,851,929	11,029,574	32.58
2013	34,241,741	10,415,412	30.42
2014	34,618,111	9,811,078	28.34
2015	35,013,369	9,689,809	27.67
2016	35,406,606	9,857,285	27.84
2017	35,792,448	9,558,626	26.71
2018	36,185,154	9,699,654	26.81
2019	36,565,139	n.d.	n.d.

Note: Value in each year corresponds to the average number of individuals. Population in monetary poverty corresponds to the number of individuals whose monthly household income per capita falls below the monetary poverty line (MPL). Sample weights are used in the calculation. The column with percentages indicates the proportion of population whose income falls below the monetary poverty line. In 2019, DANE adjusted its methodology for establishing poverty lines. Consequently, we use data from the 2008-2018 period so that all MPLs are determined by DANE using the same methodology.

Table E.4. Descriptive statistics of control variables used in regressions by occupational group
Colombia, 2008-2019

Variable	Total employed		Wage earners		Self-employed, without higher education		Self-employed, with higher education		Total workers who contribute		Total workers who do not contribute		Wage earners who contribute		Wage earners who do not contribute		Self-employed, who contribute		Self-employed, who do not contribute	
	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
Age	37.520	25.971	35.292	24.782	41.134	26.704	37.763	21.786	36.202	23.532	38.613	27.569	35.873	23.510	33.915	27.538	39.126	22.791	40.767	26.329
Age squared	1.546.857	2.074.678	1.366.364	1.907.289	1.843.383	2.220.321	1.547.899	1.767.098	1.423.593	1.832.235	1.649.179	2.228.002	1.398.285	1.820.675	1.290.622	2.104.328	1.647.911	1.855.665	1.813.582	2.186.061
Years of education	9.688	10.176	10.979	9.416	6.544	7.834	14.973	4.211	11.904	8.700	7.849	9.508	11.800	8.632	9.029	9.801	12.820	8.994	7.308	9.163
Woman	0.347	1.048	0.391	1.100	0.258	0.950	0.430	0.977	0.402	1.085	0.301	1.005	0.403	1.092	0.363	1.117	0.397	1.031	0.272	0.952
Receive income from transfers	0.080	0.596	0.068	0.569	0.096	0.639	0.092	0.571	0.059	0.523	0.097	0.648	0.058	0.519	0.094	0.678	0.074	0.551	0.098	0.635
Receive income from property rentals	0.040	0.433	0.043	0.458	0.031	0.379	0.063	0.480	0.051	0.488	0.031	0.381	0.050	0.484	0.027	0.379	0.065	0.521	0.033	0.382
Receive pensions income	0.010	0.220	0.008	0.202	0.011	0.225	0.022	0.290	0.003	0.123	0.016	0.273	0.003	0.125	0.020	0.325	0.003	0.109	0.014	0.251
Private wage earner	0.530	1.099	0.915	0.628	0.000	0.000	0.000	0.000	0.798	0.889	0.308	1.012	0.888	0.702	0.980	0.327	0.000	0.000	0.000	0.000
Public wage earner	0.049	0.476	0.085	0.628	0.000	0.000	0.000	0.000	0.101	0.666	0.006	0.174	0.112	0.702	0.020	0.327	0.000	0.000	0.000	0.000
Self-employed	0.421	1.087	0.000	0.000	1.000	0.000	1.000	0.000	0.101	0.668	0.686	1.018	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000
Professional or technician	0.112	0.693	0.140	0.783	0.012	0.240	0.382	0.959	0.191	0.870	0.046	0.460	0.174	0.844	0.061	0.556	0.340	0.998	0.039	0.416
Public director or administrator	0.025	0.342	0.033	0.403	0.007	0.183	0.045	0.410	0.036	0.413	0.015	0.270	0.036	0.415	0.026	0.371	0.036	0.392	0.011	0.219
Administrative staff	0.117	0.708	0.174	0.856	0.026	0.345	0.101	0.595	0.198	0.882	0.050	0.477	0.205	0.900	0.101	0.699	0.132	0.712	0.027	0.345
Merchant or seller	0.161	0.808	0.126	0.749	0.212	0.887	0.186	0.768	0.107	0.684	0.205	0.885	0.108	0.691	0.171	0.874	0.098	0.625	0.221	0.888
Service sector worker	0.157	0.802	0.189	0.883	0.115	0.694	0.106	0.607	0.183	0.856	0.136	0.752	0.189	0.873	0.189	0.909	0.126	0.699	0.112	0.675
Agricultural sector worker	0.113	0.697	0.051	0.495	0.233	0.917	0.020	0.273	0.035	0.408	0.177	0.837	0.037	0.421	0.084	0.643	0.018	0.280	0.220	0.886
Other non-agricultural sector worker	0.315	1.023	0.286	1.019	0.394	1.061	0.161	0.725	0.250	0.959	0.369	1.058	0.250	0.965	0.369	1.122	0.251	0.913	0.369	1.032
Agricultural sector	0.116	0.706	0.056	0.518	0.234	0.919	0.021	0.282	0.040	0.433	0.180	0.842	0.043	0.449	0.088	0.658	0.016	0.262	0.222	0.888
Mining sector	0.014	0.254	0.016	0.279	0.012	0.240	0.002	0.091	0.015	0.272	0.012	0.239	0.017	0.285	0.013	0.262	0.004	0.129	0.012	0.229
Manufacturing sector	0.141	0.767	0.178	0.863	0.094	0.634	0.072	0.510	0.170	0.832	0.117	0.705	0.184	0.863	0.164	0.862	0.050	0.460	0.096	0.629
Electricity, gas and water sector	0.008	0.196	0.013	0.252	0.001	0.068	0.004	0.127	0.016	0.274	0.002	0.088	0.016	0.282	0.004	0.145	0.009	0.199	0.001	0.051
Construction sector	0.078	0.589	0.077	0.600	0.087	0.611	0.037	0.374	0.051	0.485	0.100	0.658	0.052	0.494	0.136	0.796	0.039	0.408	0.084	0.592
Commerce, restaurants and hotels sector	0.257	0.962	0.242	0.965	0.290	0.984	0.218	0.815	0.181	0.853	0.320	1.022	0.189	0.871	0.368	1.121	0.118	0.678	0.298	0.978
Transportation and communications sector	0.107	0.680	0.075	0.595	0.161	0.798	0.095	0.579	0.089	0.631	0.122	0.716	0.081	0.608	0.061	0.557	0.159	0.771	0.149	0.762
Financial sector	0.019	0.300	0.030	0.387	0.002	0.087	0.012	0.213	0.034	0.403	0.006	0.173	0.037	0.421	0.015	0.279	0.010	0.207	0.002	0.106
Real estate sector	0.080	0.599	0.095	0.660	0.039	0.419	0.175	0.751	0.115	0.706	0.052	0.486	0.115	0.709	0.048	0.496	0.119	0.683	0.054	0.482
Service sector	0.180	0.845	0.219	0.932	0.081	0.591	0.363	0.949	0.288	1.003	0.090	0.626	0.267	0.986	0.103	0.707	0.476	1.052	0.083	0.591
Unemployment rate (1)	9.690	4.538	9.782	4.588	9.516	4.505	9.797	4.236	9.840	4.539	9.564	4.519	9.846	4.548	9.632	4.671	9.794	4.464	9.533	4.456
Employment rate (1)	57.863	9.755	58.459	10.079	56.761	9.002	58.488	8.718	58.725	9.769	57.148	9.461	58.732	9.855	57.811	10.482	58.655	9.059	56.843	8.959
% of the working-age population (WAP) with higher education (1)	20.666	21.357	22.433	21.476	17.309	19.883	22.992	18.203	23.470	20.370	18.337	20.789	23.545	20.433	19.795	22.822	22.811	19.815	17.669	19.781

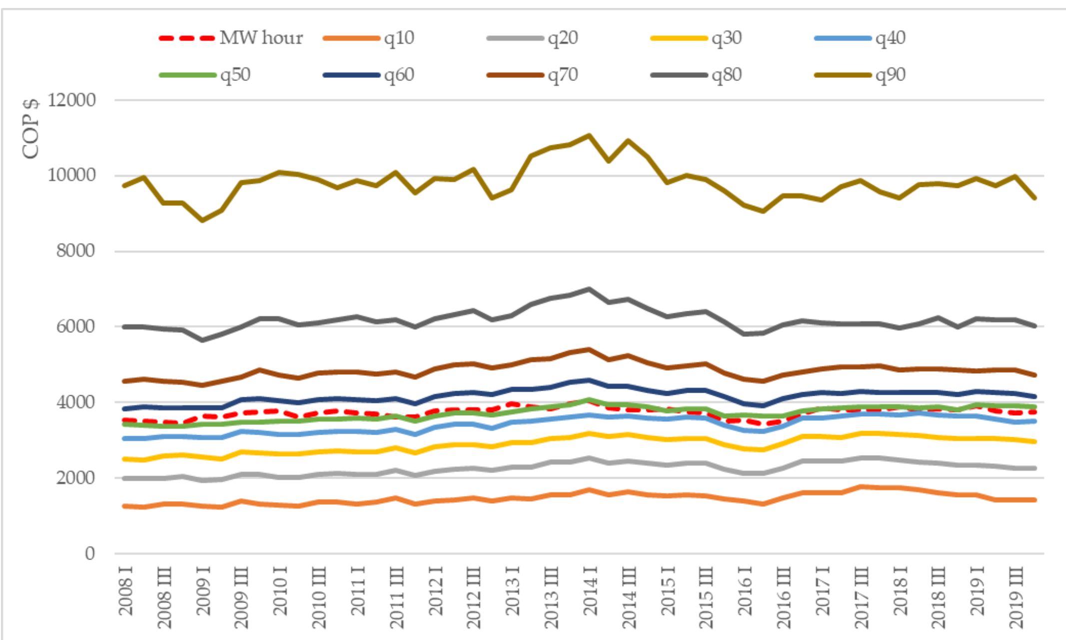
Note: (1) These are control at the city level. These variables are calculated as the average of the last six months, lagged one quarter, using information of the individual's city of residence.

Table E.5. Descriptive statistics of control variables used in regressions for household income Colombia, 2008 – 2019

Variable	Mean	STD
Age	30.809	46.164
Age squared	1,390.788	3,530.199
Years of education	6.817	11.222
Woman	0.507	1.098
Receive income from transfers	0.121	0.716
Receive income from property rentals	0.034	0.400
Receive pensions income	0.035	0.405
Head of the household lives with her spouse	0.681	1.024
Individual lives as a couple (married or in a free union)	0.387	1.070
Individual is separated or widowed	0.121	0.716
Individual is single	0.492	1.098
Household resides in its own fully paid home	0.416	1.083
Dependency ratio of the household (1)	0.708	1.552
Number of people in the household (2)	4.404	4.551

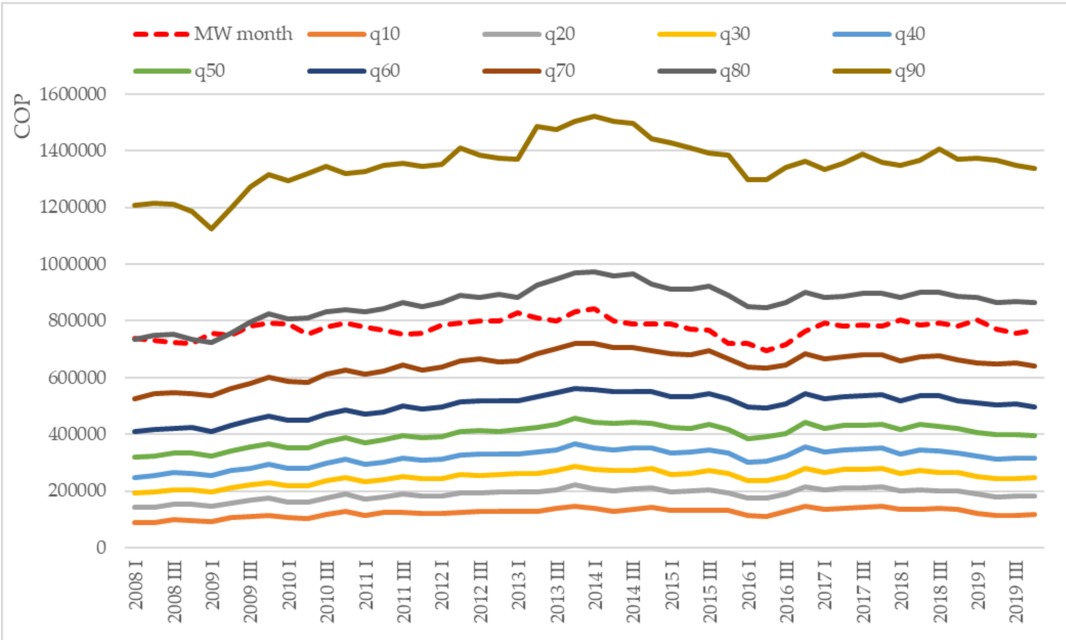
Notes: (1) The sum of children under 15 years of age and adults over 65 years of age divided by the total number of people between 15 and 64 years of age in the household. (2) Excluding pensioners and domestic employees and their children.

Graph E.1. Quintile values of the hourly labor income distribution for the occupational group of Total Employed. Colombia, 2008 – 2019



Notes: value of each quantile in the hourly labor income distribution of the occupational group Total Employed and of the average hourly real minimum wage (MW) for each quarter. Values in real COP, base 2018. For details on the calculation of hourly labor income, see Section 2.1.1 in this paper. Calculations use the information of all individuals reporting that they are employed in each city-quarter during the period 2008-I – 2019-IV. "Total employed" corresponds to the sum of wage earners and self-employed workers. "Wage earners" are private and public workers and employees. We did not include domestic employees and day laborers in this analysis (occupational categories also included in the GEIH).

Graph E.2. Quintile values of the distribution of monthly household income per capita. Colombia, 2008-2019



Notes: value of each quantile in the monthly household income distribution for each quarter. Values in real COP, base 2018. For details on the calculation of total household income per capita, see Section 2.1.2 in this paper. Calculations use the information of all individuals in each city-quarter during the period 2008-I – 2018-IV.