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Beyond traditional wage premium. An analysis of wage greenium in Latin America *

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Abstract

This paper estimates wage differentials between green and non-green jobs (wage greenium) in nine major Latin American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Mexico, Peru and Uruguay), which account for 81% of the region's GDP. We contribute to the recent literature highlighting a positive wage gap for those working in green jobs in developed countries. A positive wage gap for green jobs may be a virtuous market feature, as it means that in the future workers might be encouraged to switch to greener occupations. To do so, we define green jobs as those occupations with high greenness scores using the occupational approach as in Vona et al. (2018), Vona (2021) and de la Vega et al. (2024). Our results suggest that the wage greenium for the period 2012-2019 in Latin America was between 18% to 22%. Moreover, this wage gap has remained relatively stable over the years.

Keywords: labor markets, green jobs, wage premium, wage differentials, Latin America.
JEL: E24, Q50, J31.

*The opinions expressed herein are solely those of the authors and do not necessarily represent the view(s) of affiliated institutions.

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1 Introduction

The green transition is one of the greatest challenges facing labor markets around the world today. While some types of jobs are disappearing, others are undergoing substantial changes in terms of skills and human capital requirements, and some are also emerging. Wallach (2022) predicts that the transition to cleaner forms of production, such as the implementation of greener forms of energy, will create more than 10 million new jobs worldwide by 2030, exceeding the number of jobs expected to be lost in most polluting sectors, such as fossil fuels. Furthermore, IMF (2022) highlights that this transition will be mostly easy for those workers with higher skills, being more difficult for those workers with lower skills. Thus, labor markets face risks and opportunities due to this transition, which is shaping a new scenario in the characteristics of the labor force.

Although this transition is thought to be a global trend, the policies countries are implementing may have heterogeneous implications for changes in the level and composition of labor demand (OECD, 2017). OECD regions, for example, are experiencing an increase in the demand for green-task jobs; i.e, occupations with at least 10% of their tasks considered green. In Latin America and the Caribbean, the demand for green skills, especially environmental services, indicates a clear growth of these trends, but at a slower pace than in OECD countries (Alfonso et al., 2022). In the region, this green transition is expected to add 10.5% more new jobs by 2030 (OECD et al., 2022). In addition to the increase in the demand for jobs with green tasks, green jobs appear to be more financially attractive than non-green jobs. Across the OECD countries, the wage premium of green-task jobs over non-green-task jobs is 20% (OECD, 2023).

In this context, a growing literature has been analyzing the current situation of countries regarding green jobs and how they manage this transition, and its effects. The focus has been mainly on the measurement of the green potential of jobs, particularly in developed countries (Bowen et al., 2018; Lobsiger and Rutzer, 2021), and on the differences between green and non-green jobs in terms of skills and human capital (Consoli et al., 2016; Rutzer and Niggli, 2020; Vona et al., 2018), and less on the quality and characteristics of green jobs (Valero et al., 2021), or on wage differentials between green and non-green industries (Jackman and Moore, 2021). However, few studies have analyzed if jobs with a higher share of green tasks have a wage premium (Bluedorn et al., 2022; Vona et al., 2019), i.e., whether they are economically attractive; and there is even little evidence for Latin America.

The objective of this paper is to shed light on the wage premium amongst workers in green and non-green occupations ("wage greenium") in nine major countries of Latin America (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Mexico, Peru and Uruguay; LA9 hereafter), which accounted for 81% of the region's GDP in 2021. The region is currently embarking on more sustainable development paths with the goal of shifting to greener forms of production, so investigating potential wage greenium can help assess the labour market implications of the green transition. We contribute to the recent literature highlighting a positive wage gap for those working in green jobs in developed countries and explore possible heterogeneities that may arise within countries in the same region. To this end, we define green jobs as those occupations with high greenness scores using the occupational approach as in Vona et al. (2018), Vona (2021) and de la Vega et al. (2024). Our results suggest that the wage greenium for the period 2012-2019 was, on average, 20% in LA9, ranging from 18% to 22% depending on the country. Moreover, this wage gap has remained relatively stable over the years.

The rest of this paper is organized as follows. Section 2 reviews the literature. Section 3 presents the sources of information used. Section 4 deals with the empirical strategy. Finally, Section 5 presents the results and Section 6 concludes.

2 Literature review

This section provides an overview of the relevant literature that attempts to measure the wage premium in green jobs. The study of wage differentials between different groups of workers has been an important topic of academic debate for a long time. The literature on the determinants of wage differentials is extensive, since many variables -such as educational level, industry affiliation, gender, among others- contribute to explain this phenomenon. The typical analysis uses Mincer-type equations (Mincer, 1958, 1974), which originally focused on the returns of human capital accumulation, n particular the returns of schooling[1]. Subsequently, the literature has been implementing this model and its variations, to assess differences in earnings due to other characteristics, such as type of contract, type of occupation, type of firm, age, etc.[2]

More recently, in line with the growing interest in sustainability and climate change, the study of wage differentials between green and non-green jobs is entering the literature on wage determinants. A positive wage gap for green jobs may be a virtuous market feature, as it means that in the future workers might be encouraged to switch to greener occupations. So far, the evidence is mostly for developed economies. Bluedorn et al. (2022) show that the implied wage premium of green-intensive jobs vis-à-vis pollution-intensive ones is 6.7 log points, using a sample of 34 countries (mainly the U.S. and advanced economies in Europe), covering the period 2005–2019. The authors define green jobs as a multidimensional concept, in which they examine three environmental properties of jobs: green-, pollution- and emissions-intensity of the job[3].

Specifically for the U.S., Vona et al. (2019) use the occupational approach to analyze the characteristics of green jobs between 2006 and 2014 and suggest that green occupations yield a 4% wage premium vis-a-vis non-green ones. This wage greenium is highly sensitive to the economic cycle and is larger for workers in lower-skill green jobs than for workers in higher-skill green ones. For a longer period, using the same approach to defining green jobs, Bergant et al. (2022) find that, on average, high-skilled workers have more green intensive jobs than low-skilled workers. Their results show that the wage premium of green jobs is nearly 2% and there is a wage penalty for those who held green jobs and then switched occupations to non-green jobs. There are also differences across types of green occupations. Bowen et al. (2018) identify wage premiums between "new and emerging green jobs" and other green jobs (like existing jobs expected to be in high demand due to greening, but do not require significant changes in tasks, skills) in 2014.

For the United Kingdom, Valero et al. (2021) find a positive wage premium in green jobs, which tends to be more pronounced among less skilled occupations. Additionally, Sato et al. (2023) investigate wage gaps in the UK (during the 2012-2021 period) and the U.S. (during the period 2010-2019) for workers in a subset of green occupations: those in low-carbon jobs. While they show that low-carbon jobs are concentrated in occupations that pay higher wages,

[1] See for example Heckman et al. (2003) and Lemieux (2006) for a discussion of the theoretical foundations of the Mincer model.

[2] Foster-McGregor et al. (2014), for example, provide an in-depth evaluation of the impact of individual, job and firm characteristics on earnings differences.

[3] The first two properties are based on workers' occupations and the third property is based on the sector in which they are employed.

those jobs generally do not pay much more than other non-low-carbon jobs.

Outside of advanced economies, Jackman and Moore (2021) study wage differences between green and non-green industries in Barbados during 2004-2014. They investigate whether industries that reduce the demand for resources or help to remediate the outputs of other industries pay higher wages. The authors estimate a traditional wage equation that controls for for time effects and wage determinants such as age, gender, education and employment type and status, and find a wage premium for green industries until 2010, at which point it was significantly reduced and virtually disappeared.

3 Data Sources

The analysis of wage premium in green jobs in Latin America involves two data sources. First, we rely on employment data from household surveys for LA9 countries for the period 2012-2019. We use the Socio-Economic Database for Latin America and the Caribbean (SEDLAC) database, which is a project jointly developed by CEDLAS at the Universidad Nacional de La Plata and the World Bank's LAC poverty group, containing information on household surveys of those countries. Table 3 in the Appendix lists the surveys considered as well as the years included for each country. The sample is restricted to salaried individuals between 15 and 65 years old to avoid the influence of educational and retirement decisions on labor market participation.

Second, we use the O*NET database that provides information on occupations and their task composition for the United States (U.S.) focusing on the tasks that each person performs in their occupation in order to identify green jobs.[4] By using the O*NET database, we adopt the occupational approach as in de la Vega et al. (2024)[5]. As explained in Vona (2021), the O*NET database is relevant because since 2011 it identifies groups of occupations that will be affected by the greening of an economy: (i) occupations that are expected to experience an increase in demand (Green Increased Demand); (ii) occupations that will see major changes to the tasks content of work (Green Enhanced Skills); and (iii) occupations that did not exist before and that will be created (Green New and Emerging).[6] For (ii) and (iii), O*NET also identifies green tasks within each occupation, but not for (i) because they may only indirectly benefit from the greening of an economy. Consequently, green jobs can be identified by using O*NET data in two ways: i) a binary definition where an occupation is considered either green or non-green depending on whether it falls under any of the three categories mentioned above; ii) a continuous definition of occupational greenness that exploits information on the greenness of the task content of occupations.

Following Vona (2021), we calculate the greenness of an occupation j as follows:

$$greenness_j = \frac{\#\text{ green tasks}}{\#\text{ total tasks}} \tag{1}$$

which takes values greater than zero only for Green Enhanced Skills and Green New and Emerging occupations.[7] As stated in Vona (2021), the greenness indicator can be considered

[4] We use the four versions corresponding to the year 2019 (23.2, 23.3, 24.0 and 24.1).

[5] There are other approaches, such as the industry-based, but those ignore the fact that there may be people doing green tasks in industries considered "brown", or vice versa (Rutzer and Niggli, 2020).

[6] It is worth remembering that non-green occupations are not necessarily 'dirty' or 'brown' but are not affected by the greening of an economy.

[7] Given that O*NET also provides data on the importance of each task within an occupation, a weighted version of this indicator can be calculated. However, according to Vona (2021), the correlation between

as a proxy for the amount of time spent on green activities and technologies in the average job post within a certain occupation. [8]

Thus, we have two greenness indicators: 1) a binary definition in which an occupation is considered green or non-green (*green_occ*); and 2) a task-based indicator that considers the proportion of green tasks on total tasks within an occupation (*greenness*).

O*NET Occupations are classified according to the U.S. Standard Occupational Classification (SOC) System. Once the greenness scores are obtained at the 8-digit SOC level, the objective is to extrapolate them to the 2-digit ISCO (International Standard Classification of Occupations) classification, which is the occupational classification used in the SEDLAC database. This procedure has already been applied in several papers (Rutzer and Niggli, 2020; Lobsiger and Rutzer, 2021; Elliott et al., 2021; Valero et al., 2021) and is common in the automation literature (Gasparini et al., 2020; Brambilla et al., 2021) and more recently in the teleworking literature (Albrieu et al., 2021; Bonavida Foschiatti and Gasparini, 2020; de la Vega, 2021; de la Vega and Gasparini, 2023; Porto and de la Vega, 2023)[9].

The process of extrapolating the greenness scores to the SEDLAC database is as follows. First, we calculate the simple average of the greenness indicators at the 6-digit SOC. The U.S. Bureau of Labor Statistics provides a correspondence between the 6-digit SOC and 4-digit ISCO classifications.[10] Following Elliott et al. (2021) and Rutzer and Niggli (2020), the second step is to average the indicators to 2 digits of ISCO. With the greenness scores at 2-digit ISCO, we impute them to each person employed in the SEDLAC database. In our analysis, the greenness scores are fixed over the entire period, thus changes in the green potential of jobs should be understood as caused by changes in the occupational structures of the country or region analyzed.

Finally, we follow previous literature and identify green jobs as occupations with high green potential. Elliott et al. (2021) consider an individual to be a green worker if his corresponding occupational greenness score is greater than the average greenness in their sample. Similarly, Lobsiger and Rutzer (2021) define high-green-potential occupations as those with green potential larger than or equal to 0.5[11].

We follow a similar approach and define high green potential occupations as those with greenness scores greater than the LA9 75th percentile. Thus, the thresholds are set within the sample and, in our case, are slightly more conservative. The resulting greenness scores at the 2-digit ISCO level along with the thresholds separating green and non-green jobs are shown in Figure 1. The results are very similar to previous literature (Vona et al., 2018; Elliott et al., 2021; Rutzer and Niggli, 2020; Lobsiger and Rutzer, 2021). Table 1 lists the occupations that are classified as green jobs based on each green measure. It is valid to note that it is possible for an occupation to be classified as a green job when one green score is

the unweighted and the weighted version is extremely high, thus the use of such weights is unnecessary.

[8] Additionally, O*NET identifies core tasks within each occupation, thus we can also calculate a more restrictive score using only the core tasks. However, the results are very similar to the greenness score and are available upon request.

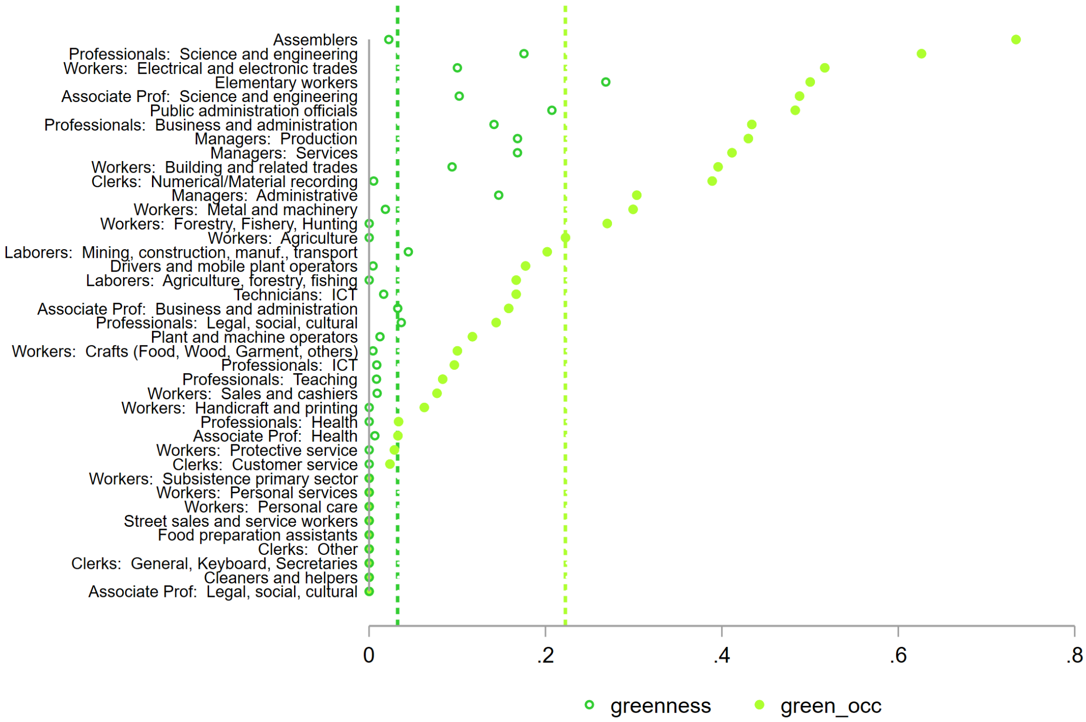
[9] These studies have been criticized because the task content varies depending on the level of development and, therefore, it would not be advisable to extrapolate estimates based on the United States to other countries, particularly emerging ones (Dicarlo et al., 2016; LoBello et al., 2019). However, we lack alternatives based on data availability on occupational information for Latin American countries.

[10] This step is very common in the literature (see, for example, OECD (2017), Goos et al. (2014), Consoli et al. (2016), Vona et al. (2018), Elliott et al. (2021), Rutzer and Niggli (2020)).

[11] This threshold was adopted because they find a significant positive association between an increase in the implicit emission tax and demand only for occupations with a green potential equal to or above 0.5. Moreover, the median green potential is 0.27 in their sample, thus high-green-potential occupations include occupations that have more than one and a half times the median green potential.

used, but as a non-green job when the other score is used.

Figure 1: Greenness over ISCO 2-digit occupations



Own elaboration based on SEDLAC. The figure shows the estimated greenness scores at the 2-digit ISCO level. *green_occ* refers to a binary definition where an occupation is considered either green or non-green; and *greenness* is a task-based indicator that accounts for the proportion of green tasks on total tasks within an occupation. The thresholds for identifying green jobs correspond to the 75th percentile of each score. Occupations are listed at the ISCO 2-digit level. Survey weights were used.

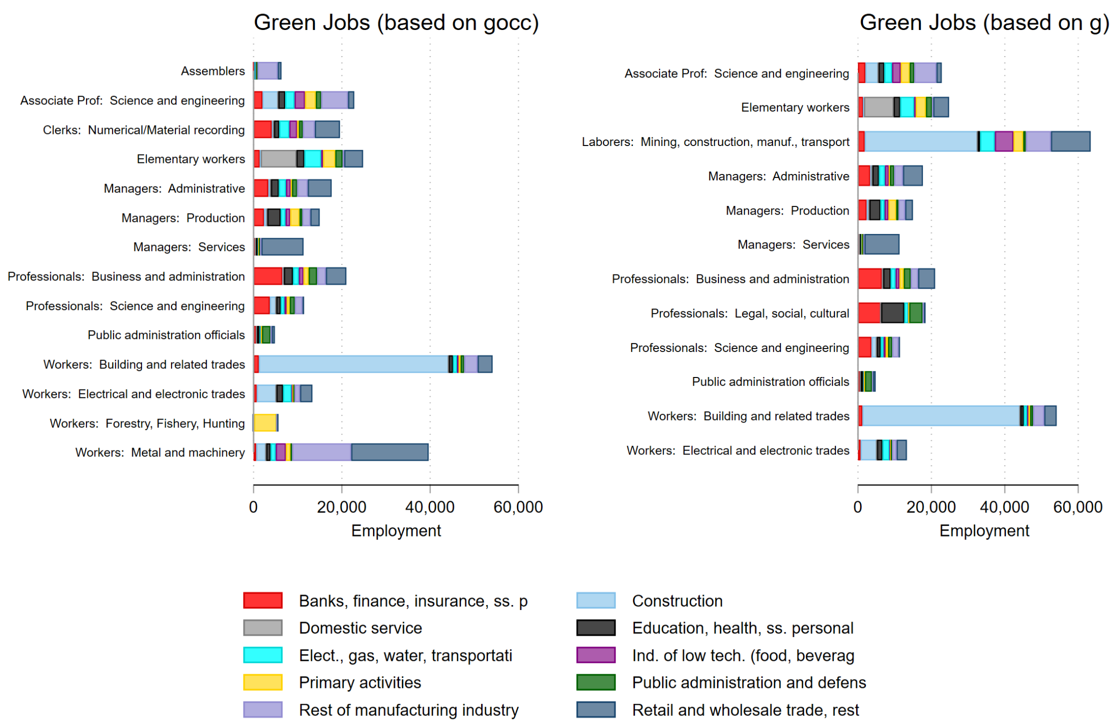
Table 1: Green Jobs (ISCO Classification)

ISCO 1-digit	ISCO 2-digit	gocc	g
Managers	Public administration officials	Green	Green
Managers	Managers: Administrative	Green	Green
Managers	Managers: Production	Green	Green
Managers	Managers: Services	Green	Green
Professional	Professionals: Science and engineering	Green	Green
Professional	Professionals: Business and administration	Green	Green
Professional	Professionals: Legal, social, cultural	Non-Green	Green
Technicians and associate professionals	Associate Prof: Science and engineering	Green	Green
Clerical support workers	Clerks: Numerical/Material recording	Green	Non-Green
Skilled agricultural, forestry and fishery workers	Workers: Forestry, Fishery, Hunting	Green	Non-Green
Craft and related trades workers	Workers: Building and related trades	Green	Green
Craft and related trades workers	Workers: Metal and machinery	Green	Non-Green
Craft and related trades workers	Workers: Electrical and electronic trades	Green	Green
Plant and machine operators, and assemblers	Assemblers	Green	Non-Green
Elementary occupationss	Laborers: Mining, construction, manuf., transport	Non-Green	Green
Elementary occupationss	Elementary workers	Green	Green

Own elaboration. *gocc* refers to the binary definition where an occupation is considered either green or non-green; and *g* is a task-based indicator that accounts for the proportion of green tasks on total tasks within an occupation.

Figure 2 shows the sectoral distribution of employment in occupations that were identified as green jobs. The results are very similar for both measurements. The green jobs with the highest level of employment are building workers, machinery operators, refuse workers, science and engineering associate professionals, among others.

Figure 2: Sectoral distribution of Green Jobs



Own elaboration based on SEDLAC. The figure shows the sectoral distribution of employment for green jobs according to *green_occ* (left) and *greenness* (right). *green_occ* refers to a binary definition where an occupation is considered either green or non-green; and *greenness* is a task-based indicator that accounts for the proportion of green tasks on total tasks within an occupation. Occupations are listed at the ISCO 2-digit level. Survey weights were used.

4 Estimation approach

To empirically analyze whether there is a wage premium for working in green occupations, we estimate the following model:

$$W_{i,j,c,t} = \beta_0 + \beta_1 \text{ Green }_{i,j,c,t} + \phi' X_{i,j,c,t} + \epsilon_{i,j,c,t} \tag{2}$$

where the dependent variable (W) is the log of hourly labor income from the main job (in U.S. 2011 dollars) for each individual i, in the occupation j, in the country c and year t. The main independent variable is Green $_{i,j,c,t}$, which is a dummy variable that equals 1 if the occupation j of individual i in country c in period t is a green job and 0 otherwise. As explained in Section 3, we consider a person to be in a green job if their corresponding greenness score is above the LA9 75th percentile.

We control for individual-level characteristics summarized in the vector $X_{i,j,c,t}$ such as age group (15 to 25; 25 to 40; and 41 to 65), gender (female/male), educational attainment (low, 0 to 8 years of education; medium, 9 to 13 years of education; and high, with more than 13 years of education), location (rural/urban) and sector of activity. Standard errors are clustered at the 2-digit ISCO-08 occupation level, i.e., at the same level as the green potential variables, to consider the possible correlation between unobservable characteristics of individuals employed in the same occupation. As stated before, the sample is restricted to salaried individuals between 15 and 65 years old to avoid the influence of educational and retirement decisions on labor market participation.

We investigate the potential wage gap both for all LA9 countries and for each of them separately. In the regressions for LA9 we control for level differences across countries and sectors and include country-year fixed effects. For the regressions for each country, we include fixed effects by year and by region.

5 Results

Table 2 presents some descriptive statistics on workers in green and non-green jobs for the sample of wage earners in LA9 over the period 2012-2019. On average, workers in green jobs are mostly men, over 25 years old, living in urban areas. Although workers in non-green jobs also share the last two characterizations, the distribution between men and women is more balanced. In addition, the proportion of green workers in higher educational levels is greater than the observed for workers in non-green jobs. In fact, almost 30% of workers have more than 14 years of education, while workers in non-green jobs have mostly medium and low educational levels (around 80% of workers are in those educational groups), and only 21% have more than 14 years of education. Furthermore, the average hourly wage (measured in logarithm) of workers in green jobs is higher than that of those in non-green jobs. There are no major differences in the characterization of green and non-green jobs between the two definitions considered. However, it should be noted that, according to the binary definition, the proportion of workers in green jobs in the construction sector is 15%, while it is about 25% with the continuous definition. Similarly for workers in the rest of the manufacturing industry, 18% of them have a green job according to the binary definition, but around 12% if the continuous definition is considered.

Table 2: Summary statistics for workers in Latin America in green and non-green jobs (2012-2019)

	Green occ		Greenness	
	Non-green job	Green job	Non-green job	Green job
	Percent (%)	Percent (%)	Percent (%)	Percent (%)
Gender				
Women	49.28	26.22	49.72	25.75
Men	50.72	73.78	50.28	74.25
Groups of age				
$[15, 24]$	19.45	16.83	18.94	18.72
$[25, 40]$	43.88	47.09	44.15	46.00
$[41, 65]$	36.67	36.09	36.91	35.28
Educational level (in years)				
Low: $[0, 8]$ years	29.79	24.89	28.56	29.37
Medium: $[9, 13]$ years	48.49	45.64	49.96	40.66
High: [14+] years	21.72	29.47	21.48	29.97
Area of residence				
Rural	11.61	7.97	11.04	10.13
Urban	88.39	92.03	88.96	89.87
Sector of activity				
Banks, finance, insurance, prof. ss.	9.62	10.94	9.83	10.13
Construction	4.45	15.72	1.39	25.81
Domestic service	9.69	4.38	9.83	4.16
Education, health, personal ss.	19.99	6.77	19.85	7.85
Elect., gas, water, transportation, communication	6.60	7.87	6.65	7.63
Ind. of low tech. (food, beverages and tobacco, textiles and clothing)	6.09	5.04	5.94	5.61
Primary activities	8.31	4.71	8.63	3.79
Public administration and defense	7.31	6.30	6.96	7.56
Rest of manufacturing industry	5.91	18.55	7.67	11.82
Retail and wholesale trade, restaurants, hotels, repairs	22.04	19.71	23.25	15.64
Continuous variable	Mean (std. dev.)	Mean (std. dev.)	Mean (std. dev.)	Mean (std. dev.)
Hourly wage (in logs)	0.74 (0.77)	1.01 (0.83)	0.76 (0.76)	0.94 (0.90)

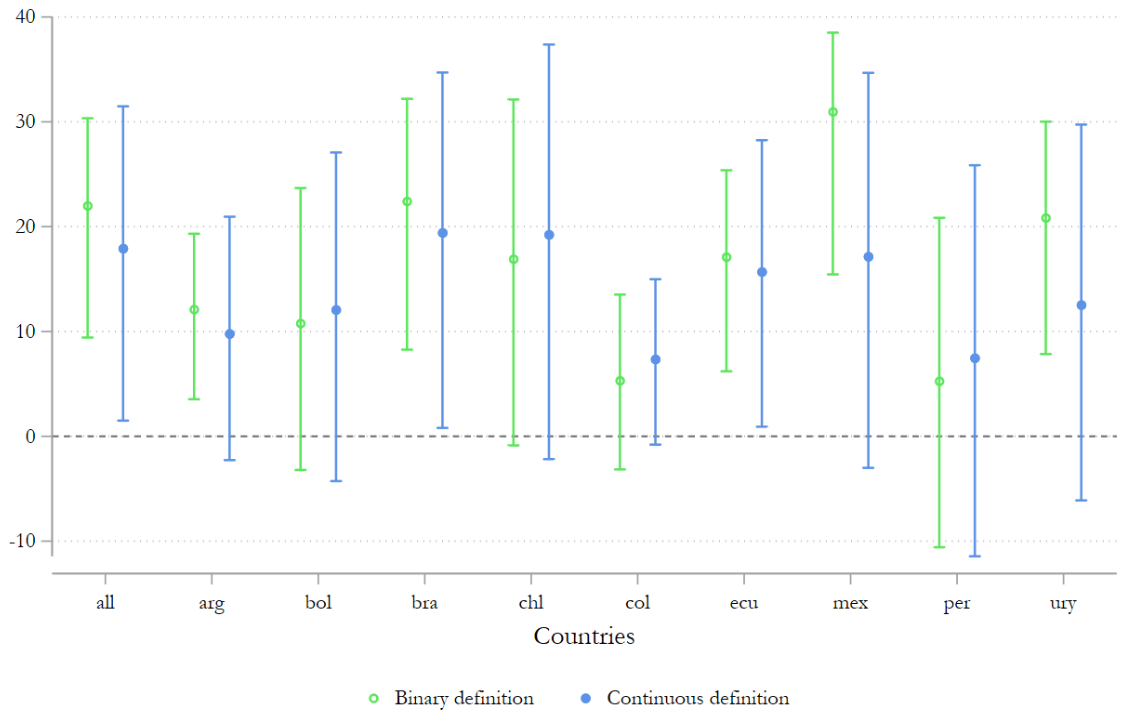
Own elaboration.

Note: The Table summarizes the average of the variables for the period 2012-2019 in Latin America. *green_occ* refers to the binary definition where an occupation is considered either green or non-green; and *greenness* is a task-based indicator that accounts for the proportion of green tasks on total tasks within an occupation.

Tables 4 and 5 in the Appendix present the regression results all LA9 countries (column 1) and for each country separately (columns 2-10), for both the binary (*gocc*) and continuous (*greenness*) definitions, respectively, over the period 2012-2019. The results are summarized in Figure 3. In LA9, according to the binary definition, the implied wage gap between those in green jobs and those in non-green jobs is about 22%[12]. This means that salaried workers in green jobs earn, on average, 22% more than those in non-green jobs. However, the wage gap narrows to 18% when green jobs are defined using the continuous definition. There are also differences across definitions and countries. For example, in Bolivia and Peru, the wage premium for being in a green job is not statistically significant under any of the definitions considered. In Argentina, Colombia and Uruguay, the wage gap is statistically significant using only one of the definitions. On the other hand, in Brazil and Mexico the wage premium is the highest of all countries: salaried workers in green jobs earn, on average, 22 (Brazil) and 30% (Mexico) more than those in non-green occupations using the binary definition of green jobs (and 19 (Brazil) and 17% (Mexico) more by the continuous definition). In Chile and Ecuador, workers in green jobs earn, on average, 16% more than those in non-green jobs. The wage gap narrows for salaried workers in Argentina to almost 12% for the binary definition.

These results show that green jobs are accompanied by a wage premium, which seems to make them more attractive than non-green ones, as suggested by the OECD (2023). In our sample, the wage premium for green jobs in Latin America is 18-22% compared to non-green jobs (an implied wage premium of 20%, on average), and in the OECD countries this gap is 20% compared to non-green jobs. In the U.S., for example, the wage premium between green and non-green jobs reaches 25% (OECD, 2023).

Figure 3: Wage premium between green and non-green workers



Own elaboration.
Note: the wage gap is calculated from the estimated coefficients of the green job variable (Tables 4 and 5). The column "all" refers to all Latin American countries (LA9).

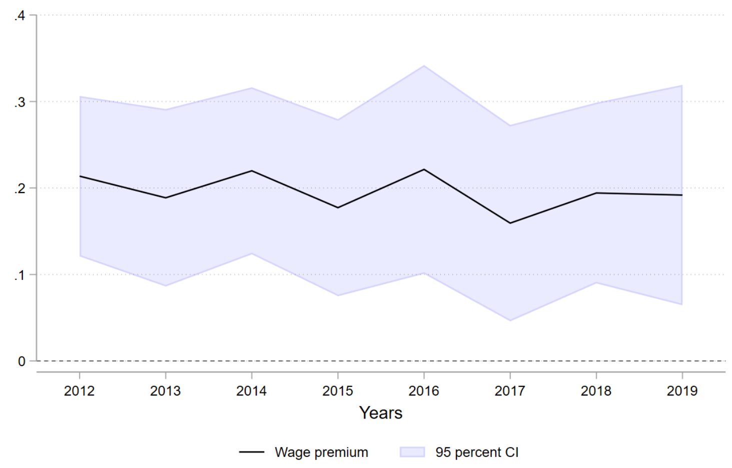
Another aspect of the analysis of the wage premium in green jobs concerns the evolution of this wage gap over the period 2012-2019. In Figure 4, we study the evolution of the wage

[12]The implied wage gap is obtained as follows: $\left(e^{\beta}-1\right)\cdot 100$.

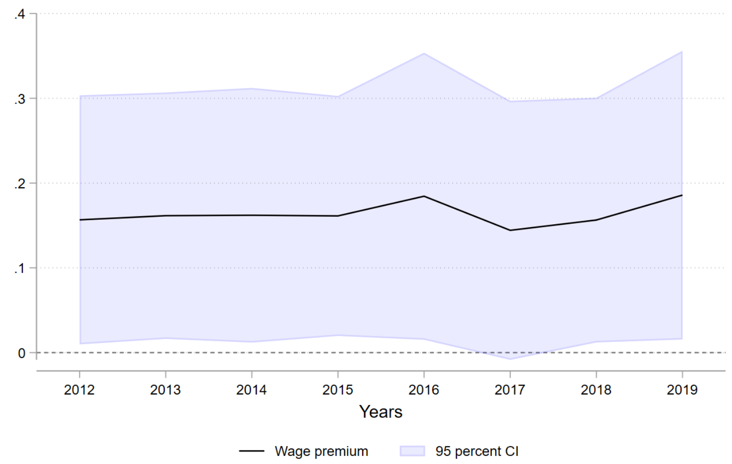
premiums over the years for LA9 re-estimating the model (2) for each year with country-fixed effects included. In both Figures the wage gap is statistically significant in all years. That is, Latin American workers in occupations considered green have been earning more than those in non-green jobs, on average. There is also evidence that the wage gap has remained relatively stable over the years, with an increase in 2014 and 2016.

Figure 4: Evolution of wage premium

(a) Green_occ



(b) Greenness



Own elaboration. Note: the Figures show the estimated coefficients from model (2) for each year with country-fixed effects.

6 Conclusion

Several countries recognize the importance of greening the economy and have been developing strategies to foster the implementation of green technologies, the creation of sustainable industries, the reduction in current pollution, among other goals. The Latin American region is not the exception. In recent years, many countries have made efforts to adapt their economies towards more sustainable forms of production, which has triggered changes in the prevailing conditions of the labor markets. In this context, it is relevant to understand some of the ramifications of the transition.

We contributed to the understanding of the current state of the transition to greener forms of production by analyzing wage differentials between green and non-green jobs (i.e., the wage greenium) in nine major countries of Latin America. We found that the wage greenium is, on average, between 18 and 22% in Latin America, and has remained stable across the period 2012-2019. There are also differences across countries and definitions. For example, in Bolivia and Peru, salaried workers in green jobs do not earn more; that is, the earnings premium is not statistically significant. According to the binary definition, salaried workers in green jobs in Brazil and Mexico earn, on average, 22 (Brazil) and 30% (Mexico) more than those in non-green occupations (and 19 (Brazil) and 17% (Mexico) more using the continuous definition). In Chile and Ecuador, workers in green jobs earn, on average, 16% more than those in non-green jobs. The wage gap narrows for salaried workers in Argentina to almost 12% for the binary definition.

According to previous literature and in line with our results, there are important differences between green and non-green jobs, particularly, in terms of wage returns. Human capital accumulation (educational level, work training and experience) and worker productivity (associated with the skills required for a job) are some of the mechanisms that help explain these differences. One plausible interpretation of the results is that the skills and educational level required for green jobs differ from those relevant for non-green jobs. In particular, some studies suggest that green jobs demand high-skilled workers with a high level of human capital accumulation (Consoli et al., 2016; Jackman and Moore, 2021) and require more non-routine tasks (Bowen et al., 2018). Others even find that green jobs appear to be associated with a wage premium at lower skills levels (Valero et al., 2021; Vona et al., 2019). Due to lack of data availability in Latin America about a person's skills, we cannot evaluate differences in skills between workers in green and non-green jobs. The information in our database reflects the fact that the proportion of workers with a high educational level is higher in the group of workers in green jobs. Consequently, education and training programs must take into account the changing global production paradigm, which involves greener labor markets with major technological changes.

The limitations of our study are crystal clear since our measurements of occupational greenness are calculated with data from the United States, given that in Latin American there is no information about the identification of the green content of tasks. Further investigation will be necessary when data availability ceases to be a constraint.

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Appendix

Table 3: Household surveys in Latin America. Characteristics.

Country	Name of household survey	Acronym	Years	Coverage
Argentina	Encuesta Permanente de Hogares-Continua	EPH-C	2012-2019	Urban
Bolivia	Encuesta de Hogares	EH	2012-2019	National
Brasil	Pesquisa Nacional por Amostra de Domicilios Continua	PNADC	2012-2019	National
Chile	Encuesta de Caracterización Socioeconómica Nacional	CASEN	2013, 2015 and 2017	National
Colombia	Gran Encuesta Integrada de Hogares	GEIH	2012-2019	National
Ecuador	Encuesta de Empleo, Desempleo y Subempleo	ENEMDU	2014-2019	National
Mexico	Encuesta Nacional de Ingresos y Gastos de los Hogares	ENIGH	2012, 2014, 2016 and 2018	National
Peru	Encuesta Nacional de Hogares	ENAHO	2016-2019	Urban
Uruguay	Encuesta Continua de Hogares	ECH	2012-2019	National

Source: SEDLAC (CEDLAS and The World Bank).
Note: the available years correspond to the years in which it was possible to match the occupational classification used in each household survey with the 2-digit ISCO classification.

Table 4: Wage premium (binary definition, *grenn_occ*)

	(1) Latin America	(2) Argentina	(3) Bolivia	(4) Brazil	(5) Chile	(6) Colombia	(7) Ecuador	(8) Mexico	(9) Peru	(10) Uruguay
Green Job	0.199***	0.114***	0.102	0.202***	0.156*	0.052	0.158***	0.270***	0.051	0.189***
	(0.052)	(0.039)	(0.066)	(0.059)	(0.082)	(0.041)	(0.047)	(0.057)	(0.078)	(0.055)
Age groups (ref: [15-24] years)										
Age group: [25,40]	0.263***	0.243***	0.206***	0.280***	0.207***	0.259***	0.169***	0.261***	0.204***	0.296***
	(0.016)	(0.010)	(0.018)	(0.021)	(0.025)	(0.009)	(0.015)	(0.017)	(0.019)	(0.018)
Age groups: [41,65]	0.424***	0.384***	0.396***	0.454***	0.290***	0.407***	0.227***	0.369***	0.279***	0.481***
	(0.031)	(0.022)	(0.042)	(0.038)	(0.036)	(0.034)	(0.027)	(0.040)	(0.033)	(0.038)
Gender (ref: woman)										
Men	0.144***	0.104***	0.161***	0.164***	0.144***	0.132***	0.102***	0.139***	0.162***	0.152***
	(0.014)	(0.022)	(0.031)	(0.013)	(0.020)	(0.018)	(0.013)	(0.031)	(0.018)	(0.026)
Educational level (ref: low)										
Medium	0.258***	0.192***	0.188***	0.268***	0.205***	0.280***	0.140***	0.223***	0.168***	0.237***
	(0.025)	(0.022)	(0.034)	(0.031)	(0.027)	(0.028)	(0.024)	(0.027)	(0.030)	(0.027)
High	0.894***	0.559***	0.647***	0.965***	0.799***	0.996***	0.588***	0.833***	0.595***	0.688***
	(0.054)	(0.031)	(0.066)	(0.062)	(0.075)	(0.054)	(0.048)	(0.057)	(0.059)	(0.057)
Area of residence (ref: rural)										
Urban	0.055***	-	-0.071**	0.004	-0.062***	0.012	-0.052***	0.012	-	-0.138***
	(0.014)	-	(0.033)	(0.013)	(0.013)	(0.019)	(0.011)	(0.016)	-	(0.018)
Sector of activity (ref: banking, finance, etc.)										
Construction	-0.128**	-0.244***	0.050	-0.114*	-0.169*	-0.111***	-0.131**	-0.156*	0.165***	0.026
	(0.051)	(0.048)	(0.075)	(0.059)	(0.079)	(0.034)	(0.049)	(0.077)	(0.053)	(0.056)
Domestic service	-0.257***	-0.205**	-0.286***	-0.205**	-0.262***	-0.554***	-0.161***	-0.322***	-0.307***	-0.251**
	(0.069)	(0.092)	(0.065)	(0.086)	(0.090)	(0.029)	(0.043)	(0.081)	(0.041)	(0.119)
Education, health, ss. personal	0.084	0.123*	0.337***	0.073	-0.047	0.084	0.090	0.237***	0.168**	0.090
	(0.058)	(0.067)	(0.121)	(0.056)	(0.070)	(0.073)	(0.060)	(0.084)	(0.068)	(0.057)
Elect., gas, water, transportation, comm.	-0.005	-0.061	-0.000	0.043	-0.118**	-0.112**	-0.017	-0.105	-0.018	0.031
	(0.033)	(0.077)	(0.064)	(0.032)	(0.051)	(0.037)	(0.039)	(0.092)	(0.041)	(0.034)
Ind. of low tech. (food, beverages and tobacco, textiles and clothing)	-0.122***	-0.136**	-0.042	-0.102***	-0.198***	-0.129***	-0.092**	-0.208**	-0.106**	-0.121***
	(0.034)	(0.051)	(0.066)	(0.030)	(0.058)	(0.033)	(0.042)	(0.074)	(0.046)	(0.040)
Primary activities	-0.204**	-0.049	0.077	-0.208**	-0.136*	-0.181***	-0.191***	-0.254***	-0.039	-0.212***
	(0.074)	(0.087)	(0.132)	(0.082)	(0.073)	(0.049)	(0.046)	(0.086)	(0.067)	(0.059)
Public administration and defense	0.203***	0.159***	0.103***	0.255***	0.059	0.255***	0.298***	0.230***	0.219***	0.160***
	(0.034)	(0.028)	(0.037)	(0.045)	(0.041)	(0.042)	(0.066)	(0.045)	(0.047)	(0.027)
Rest of manufacturing industry	-0.003	-0.014	-0.198***	0.003	-0.154**	-0.035	-0.083*	-0.074	-0.029	-0.061
	(0.036)	(0.046)	(0.057)	(0.030)	(0.061)	(0.035)	(0.042)	(0.074)	(0.049)	(0.040)
Retail and wholesale trade, restaurants, hotels, repairs	-0.197***	-0.142**		-0.171***	-0.203***	-0.242***	-0.169***	-0.212**	-0.191***	-0.184***
	(0.031)	(0.044)		(0.027)	(0.057)	(0.036)	(0.033)	(0.067)	(0.037)	(0.033)
Observations	3,325,621	252,934	52,737	980,288	200,012	1,119,955	121,584	202,558	102,085	293,468
R-squared	0.451	0.330	0.377	0.459	0.309	0.463	0.336	0.373	0.317	0.388
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	-	-	-	-	-	-	-	-	-
Country x Year FE	Yes	-	-	-	-	-	-	-	-	-
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Wage premium (continuous, *greenness*)

	(1) Latin America	(2) Argentina	(3) Bolivia	(4) Brazil	(5) Chile	(6) Colombia	(7) Ecuador	(8) Mexico	(9) Peru	(10) Uruguay
Green Job	0.165**	0.093	0.144	0.178**	0.176*	0.171*	0.146*	0.158**	0.072	0.118
	(0.074)	(0.057)	(0.077)	(0.084)	(0.098)	(0.039)	(0.068)	(0.093)	(0.092)	(0.089)
Age groups (ref: [15-24] years)										
Age group: [25,40]	0.270***	0.251***	0.209***	0.285***	0.212***	0.257***	0.181***	0.279***	0.204***	0.310***
	(0.015)	(0.011)	(0.017)	(0.020)	(0.024)	(0.009)	(0.016)	(0.018)	(0.019)	(0.019)
Age groups: [41,65]	0.434***	0.393***	0.400***	0.461***	0.299***	0.406***	0.239***	0.393***	0.279***	0.500***
	(0.030)	(0.023)	(0.041)	(0.037)	(0.037)	(0.034)	(0.028)	(0.040)	(0.033)	(0.039)
Gender (ref: woman)										
Men	0.151***	0.104***	0.169***	0.174***	0.150***	0.128***	0.110***	0.143***	0.161***	0.155***
	(0.014)	(0.022)	(0.030)	(0.011)	(0.020)	(0.018)	(0.013)	(0.031)	(0.018)	(0.027)
Educational level (ref: low)										
Medium	0.268***	0.195***	0.192***	0.278***	0.215***	0.281***	0.146***	0.238***	0.172***	0.251***
	(0.025)	(0.022)	(0.035)	(0.032)	(0.029)	(0.028)	(0.025)	(0.029)	(0.029)	(0.028)
High	0.902***	0.563***	0.650***	0.967***	0.797***	0.997***	0.594***	0.863***	0.602***	0.708***
	(0.055)	(0.030)	(0.065)	(0.065)	(0.074)	(0.053)	(0.046)	(0.061)	(0.053)	(0.057)
Area of residence (ref: rural)										
Urban	0.062***	-	-0.069**	0.009	-0.061***	0.012	-0.050***	0.023	-	-0.134***
	(0.013)	-	(0.033)	(0.013)	(0.014)	(0.019)	(0.010)	(0.016)	-	(0.017)
Sector of activity (ref: banking, finance, etc.)										
Construction	-0.177***	-0.266***	0.029	-0.153**	-0.194**	-0.157***	-0.180***	-0.190**	0.121	0.008
	(0.064)	(0.053)	(0.084)	(0.067)	(0.091)	(0.042)	(0.066)	(0.085)	(0.095)	(0.055)
Domestic service	-0.256***	-0.213**	-0.276***	-0.204**	-0.257***	-0.553***	-0.160***	-0.236***	-0.305***	-0.280**
	(0.067)	(0.092)	(0.066)	(0.086)	(0.089)	(0.033)	(0.044)	(0.097)	(0.042)	(0.118)
Education, health, ss. personal	0.075	0.115*	0.342***	0.069	-0.047	0.084	0.084	0.221**	0.164**	0.057
	(0.057)	(0.066)	(0.120)	(0.056)	(0.071)	(0.076)	(0.060)	(0.082)	(0.068)	(0.054)
Elect., gas, water, transportation, comm.	-0.008	-0.064	0.001	0.038	-0.116**	-0.113***	-0.023	-0.102	-0.020	0.014
	(0.035)	(0.080)	(0.064)	(0.032)	(0.050)	(0.037)	(0.042)	(0.100)	(0.041)	(0.038)
Ind. of low tech. (food, beverages and tobacco, textiles and clothing)	-0.127***	-0.145***	-0.034	-0.101***	-0.198***	-0.126***	-0.099**	-0.225***	-0.111**	-0.149***
	(0.038)	(0.051)	(0.067)	(0.033)	(0.058)	(0.035)	(0.046)	(0.080)	(0.047)	(0.041)
Primary activities	-0.199**	-0.046	0.082	-0.203**	-0.125*	-0.183***	-0.187***	-0.242**	-0.036	-0.227***
	(0.076)	(0.089)	(0.131)	(0.084)	(0.074)	(0.050)	(0.048)	(0.092)	(0.067)	(0.061)
Public administration and defense	0.191***	0.152***	0.098***	0.245***	0.047	0.255***	0.285***	0.222***	0.208***	0.132***
	(0.033)	(0.027)	(0.036)	(0.044)	(0.039)	(0.046)	(0.068)	(0.043)	(0.042)	(0.025)
Rest of manufacturing industry	0.029	0.010	-0.180***	0.041	-0.122**	-0.035	-0.057	-0.030	-0.023	-0.057
	(0.037)	(0.048)	(0.058)	(0.031)	(0.057)	(0.037)	(0.040)	(0.077)	(0.046)	(0.040)
Retail and wholesale trade, restaurants, hotels, repairs	-0.191***	-0.141***	-	-0.167***	-0.194***	-0.236***	-0.161***	-0.204***	-0.189***	-0.205***
	(0.034)	(0.047)	-	(0.029)	(0.056)	(0.038)	(0.035)	(0.071)	(0.037)	(0.034)
Observations	3,325,621	252,934	52,737	980,288	200,012	1,119,955	121,584	202,558	102,085	293,468
R-squared	0.448	0.328	0.378	0.456	0.310	0.463	0.333	0.362	0.318	0.381
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	-	-	-	-	-	-	-	-	-
Country x Year FE	Yes	-	-	-	-	-	-	-	-	-
Region FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1