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

Manuela Cerimelo† Pablo de la Vega‡ Natalia Porto§

Last updated: August 31, 2023

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 and explore possible heterogeneities that may arise within countries in the same region. 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 Porto et al. (2022). Our results suggest that the wage greenium for the period 2012-2019 was, on average, 23% in Latin America, ranging from 15% to 30%. 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.

†Instituto de Investigaciones Económicas, Facultad de Ciencias Económicas, Universidad Nacional de La Plata, Argentina

‡Instituto de Investigaciones Económicas, Facultad de Ciencias Económicas, Universidad Nacional de La Plata, Argentina

§Instituto de Investigaciones Económicas, Facultad de Ciencias Económicas, Universidad Nacional de La Plata, Argentina.

1 Introduction

The green transition is one of the biggest 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 straightforward for those workers with higher skills, making it more difficult for those workers in occupations that require 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 environmental policies and instruments that countries are implementing may have heterogeneous implications for changes in the level and composition of labor demand OECD (2017). Such consequences are already becoming apparent. 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 the wage differentials between green and non-green industries (Jackman and Moore, 2021). However, few studies have analyzed if the jobs with a higher share of green tasks have a wage premium (Bluedorn et al., 2022; Vona et al., 2019), that is, if they are economically attractive; and there is even little evidence for Latin America.

The aim of this paper is to shed light on the potential 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 pathways with the aim of moving to greener forms of production, so investigating the potential wage greenium can help assess the labour market implications of the green transition. We contribute to 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 Porto et al. (2022). Our results suggest that the wage greenium for the period 2012-2019 was, on average, 23% in LA9, ranging from 15% to 30% 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 describes the literature review. 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 seeks to measure the wage premium in green jobs.

The study of wage gaps 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 wide, since many variables -such as the level of education, the industry affiliation, gender, amongst others- contribute to explain this phenomena. The typical analysis of the study of wage gaps uses Mincer-type equations (Mincer, 1958, 1974), which originally focused on the returns of human capital accumulation, particularly the returns of schooling[1]. The literature has subsequently been implementing this type of model, with its variations, to evaluate earnings differences due to other characteristics, such as the type of contract of the person, the type of occupation, the 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 being incorporated into 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. The evidence, so far, 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 occupations targeted as green 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 for defining green jobs, Bergant et al. (2022) find that, on average, high-skilled U.S. 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. For the U.S., 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) also 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, those jobs generally do not pay much more than other non-low-carbon jobs.

Outside advanced economies, Jackman and Moore (2021) study wage differences between green and non-green industries in Barbados during 2004-2014. They investigate if 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 controlling for time effects and determinants of wages such as age, gender, education and employment type and status, finding a wage premium for green industries until 2010, at which point it fell significantly and virtually vanished.

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 (LCSPP), that contains information on the household surveys of those countries. Table 2 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

[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.

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. By using the O*NET database, we adopt the occupational approach as in Porto et al. (2022)[4]. As explained in Vona (2021), the O*NET database is relevant because since 2011 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).[5] For (ii) and (iii), O*NET also identifies green tasks within each occupation, but not for (i) because they may benefit only indirectly from the greening of an economy. In consequence, 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.

In this paper, we estimate green jobs using the continuous definitions and we obtain two greenness indicators. 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.[6] As stated in Vona (2021), the greenness indicator can be considered as a proxy for the amount of time spent on green activities and technologies in the average job post within a certain occupation. Additionally, O*NET identifies core tasks within each occupation, thus we can also calculate a more restrictive score:

$$greenness\_core_j = \frac{\#\text{ green core tasks}}{\#\text{ total core tasks}} \tag{2}$$

Because O*NET updates the information on occupations and tasks frequently, the identification of green jobs and the analysis of their characteristics is carried out using the first available version (version 16.0, released July 2011), with the aim of capturing changes in results due to only changes in occupations and green tasks reported by O*NET. In other words, the greenness scores are fixed within the whole period, thus changes in the green potential of jobs must be understood as triggered by changes in the occupational structures of the country or region under analysis.

Occupations in O*NET are classified according to the U.S. Standard Occupational Classification (SOC) System. Once the greenness scores indicators are obtained at the 8-digit SOC level, the goal 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)[7].

The process of extrapolating the greenness scores to the Latin American occupational structures is as follows. First, we calculate the simple average of the greenness indicators at the 6-digit SOC.

[4]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).

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

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

[7]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.

The U.S. Bureau of Labor Statistics provides a correspondence between the 6-digit SOC and 4-digit ISCO classifications.[8] The second step consists of adding the indicators to 2 digits of the ISCO, which is done by means of simple averages following Elliott et al. (2021) and Rutzer and Niggli (2020).

The resulting greenness scores at the 2-digit ISCO level 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). Occupations with the highest greennes score are science and engineering professionals, managers, assemblers, whereas among those with the lowest green potential we find health and personal services workers, and clerks.

Figure 1: Greenness over ISCO-2d occupations

Own elaboration.

Note: the gure shows the estimated greenness scores at the 2-digit ISCO level. *greenness* is a task-based indicator that accounts for the proportion of green tasks on total tasks within an occupation; and *greenness_core* is a task-based indicator that accounts for the proportion of green core tasks on total core tasks within an occupation.

Once we have the greenness scores at 2-digit ISCO, we impute them to each person employed in the SEDLAC database.[9] Finally, to identify green jobs we follow previous literature which defines those jobs as high green potential occupations. Elliott et al. (2021) consider an individual to be a green worker if their 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[10].

We follow a similar approach defining high green potential occupations as those with greenness scores greater than the LA9 average for the period 2012-2019. Therefore, salaried workers who have a

[8]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)).

[9]As already mentioned, it is worth noting that the greenness scores are fixed within the whole period, thus changes in the green potential of jobs must be understood as triggered by changes in the occupational structures.

[10]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.

greenness score higher than the average for LA9 are in green jobs[11].

4 Estimation approach

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

$$W_{i;j;c;t} = \beta_0 + \beta_1 \text{ Green }_{i;j;c;t} + \phi' X_{i;j;c;t} + \epsilon_{i;j;c;t} \tag{3}$$

where the dependent variable (W) is the log of hourly labor income of 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 average for LA9.

The estimation also includes individual-level characteristics summarized in the vector $X_{i;j;c;t}$ such as age group (from 15 to 25; from 25 to 40; and from 41 to 65), gender (female/male), educational attainment (low, from 0 to 8 years of education; medium, from 9 to 13 years of education; and high, with more than 13 years of education), location (rural/urban) and sector of activity of the main job. Standard errors are clustered at the 2-digit ISCO-08 occupation level, that is, 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 1 presents some descriptive statistics about workers in green and non-green jobs for the sample of wage earners in LA9 during the period 2012-2019. On average, workers in green jobs are mostly men, older than 25 years old, and 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, between 34 and 38% of workers have more than 14 years of education, while workers in non-green jobs have mostly medium and low educational levels (more than 80% of workers are in those educational groups), and only 21% have more than 14 years of education. On the other hand, the average hourly wage (measured in logarithm) of workers in green jobs is higher than that of those in non-green jobs.

[11] Table 3 in the Appendix shows the thresholds estimated for the two continuous definitions that will be used to define green jobs in all Latin American countries.

Table 1: Summary statistics for workers in Latin America in green and non-green jobs (2012-2019)

	Greenness		Greenness core	
	Non-green job	Green job	Non-green job	Green job
	Per cent (%)	Per cent (%)	Per cent (%)	Per cent (%)
Gender				
Women	47.20	29.44	46.52	27.84
Men	52.80	70.56	53.48	72.16
Groups of age				
$[15, 24]$	19.72	14.49	19.43	14.74
$[25, 40]$	43.93	47.89	44.34	46.31
$[41, 65]$	36.34	37.62	36.23	38.95
Educational level (in years)				
Low: $[0, 8]$ years	29.86	22.87	28.75	28.71
Medium: $[9, 13]$ years	49.54	39.18	49.21	37.73
High: $[14+]$ years	20.60	37.94	22.04	33.56
Area of residence				
Rural	11.35	8.16	10.97	9.84
Urban	88.65	91.84	89.03	90.16
Sector of activity				
Banks, finance, insurance, prof. ss.	9.32	12.96	9.62	12.00
Construction	4.74	17.92	4.62	23.85
Domestic service	9.08	5.81	8.63	8.02
Education, health, personal ss.	18.85	8.36	18.35	8.17
Elect., gas, water, transportation, communication	6.40	9.36	6.77	7.67
Ind. of low tech. (food, beverages and tobacco, textiles and clothing)	6.17	4.27	6.01	4.76
Primary activities	8.20	4.12	7.85	5.25
Public administration and defense	6.90	8.09	7.10	7.02
Rest of manufacturing industry	7.42	14.78	8.01	13.15
Retail and wholesale trade, restaurants, hotels, repairs	22.92	14.31	23.04	10.11
Continuous variable	Mean (std. dev.)	Mean (std. dev.)	Mean (std. dev.)	Mean (std. dev.)
Hourly wage (in logs)	0.74 (0.76)	1.12 (0.89)	0.77 (0.78)	1.02 (0.87)

Own elaboration.

Note: The Table summarizes the average of the variables for the period 2012-2019 in Latin America. *greenness* is a task-based indicator that accounts for the proportion of green tasks on total tasks within an occupation; and *greenness_core* is a task-based indicator that accounts for the proportion of green core tasks on total core tasks within an occupation.

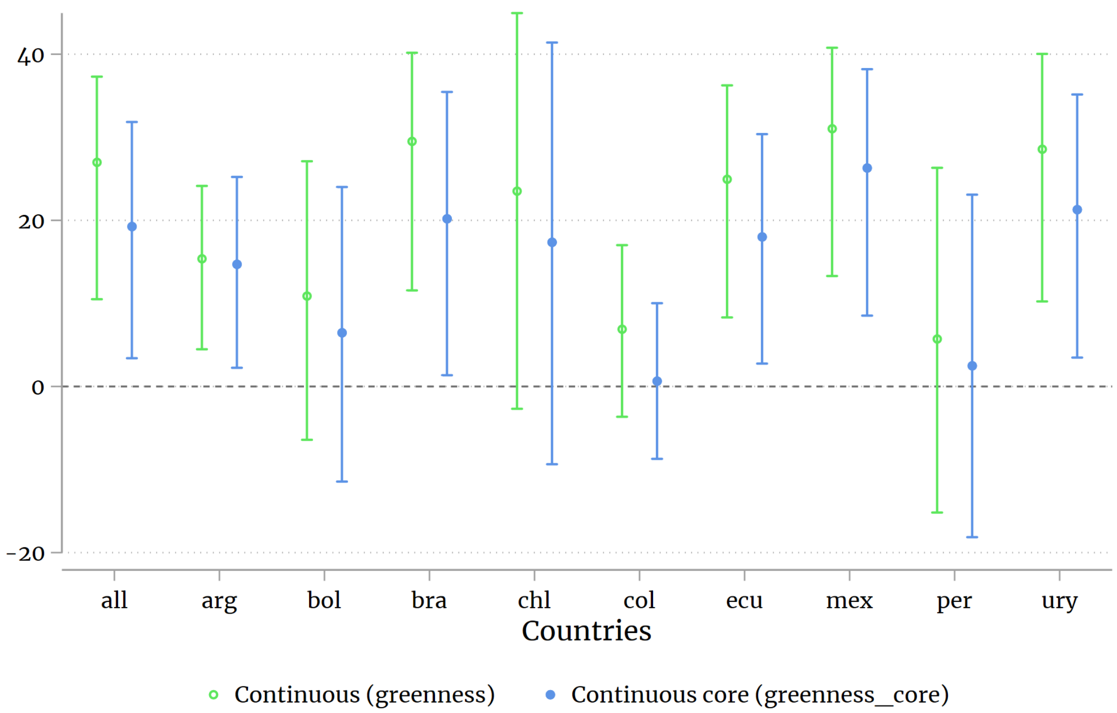
Tables 4 and 5 in the Appendix present the regression results all LA9 countries (column 1) and for each country separately (columns 2-10), for both the continuous the continuous (*greenness*) and continuous core (*greenness_core*) definitions, respectively, during the period 2012-2019. The results are summarized in Figure 2. In LA9, according to the continuous definition, the implied wage gap between those in green jobs and those in non-green jobs is approximately 26%[12]. This means that salaried workers in green jobs earn, on average, 26% more than those in non-green jobs. Nonetheless, the wage gap falls to 19% when green jobs are defined using the restrictive continuous definition.

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

There are also differences across countries. For example, in Bolivia, Chile, Colombia and Peru, the earnings premium for being in a green job is not statistically significant with any of the two definitions considered. On the other hand, in Brazil, Ecuador, Mexico and Uruguay, salaried workers in green jobs earn, on average, 28% more than those in non-green occupations using the broader definition of green jobs (and 21% more by the continuous core definition). The wage gap narrows for salaried workers in Argentina to nearly 15% in both definitions.

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 19-26% compared to non-green jobs (an implied wage premium of 23%, 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 2: Wage premium between green and non-green workers

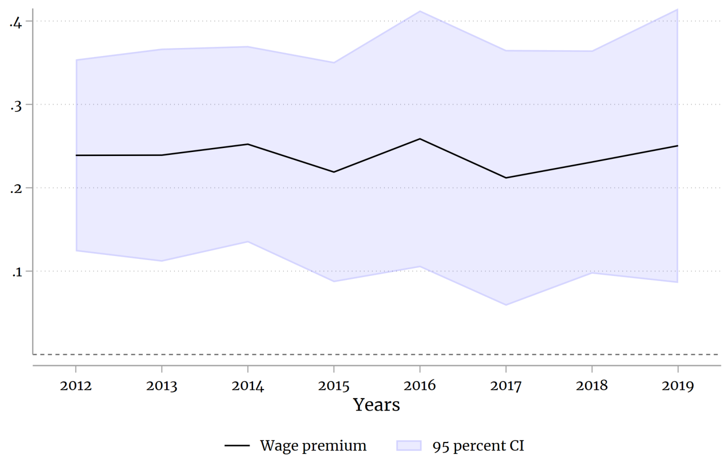


Own elaboration.
Note: the wage gap is calculated from the estimated coe cients of the green job variable (Tables 4 and 5). The column \all" refers to all Latin American countries (LA9).

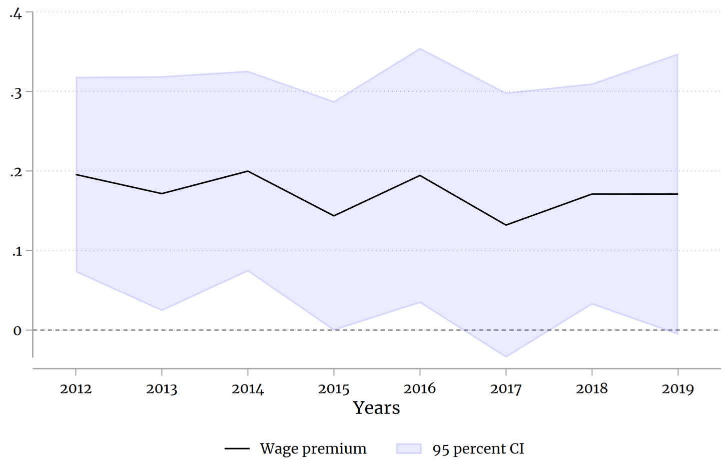
Another aspect of the analysis of the wage premium in green jobs concerns the evolution of this wage gap over the period 2012-2019. In Figure 3, we study the trend in wage premiums over the years for LA9 re-estimating the model (3) for each year with country-fixed effects included. In both Figures the wage gap is statistically significant in all years. That is, workers in Latin America who are 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 3: Evolution of wage premium

(a) Greenness



(b) Greenness_core



Own elaboration.
Note: the Figures show the estimated coe cients from model (3) for each year with country- xed e ects.

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 contribute to the understanding of the current situation 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 find that the wage greenium is, on average, 23% in Latin America, and has remained stable across the period 2012-2019. There are also differences across countries. For example, in Bolivia, Chile, Colombia and Peru, salaried workers in green jobs do not earn more; that is, the earnings premium is not statistically significant. On the contrary, in Brazil, Ecuador, Mexico and Uruguay, the implied wage gap is, on average, 28%, which suggests green occupations pay more than non-green ones. The wage gap narrows for salaried workers in Argentina to nearly 15% in both definitions.

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. The accumulation of human capital (educational level, work training and experience) and worker productivity (associated with the skills required for a job) are among the mechanisms that help explain these differences. A plausible interpretation of the results is that the skills and educational level needed 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. As a result, education and training programs must take into account the changing global production paradigm, which involves greener labor markets with technological changes of activities and skills adaptation of human resources.

The limitations of our study are crystal clear since our measurements of occupational greenness are calculated with data from the United States, given that Latin American countries do not have descriptions of work content and skills at the occupational level. Further investigation will be necessary when data availability ceases to be a constraint.

References

Albrieu, R., Allerand, M., and de la Vega, P. (2021). El teletrabajo en Argentina. Pandemia y después. Documento de trabajo 203, CIPPEC, Buenos Aires. 4

Alfonso, M., Herrera, O. A., and Mondragón, M. (2022). Green jobs and skills in Latin America: A look at the LinkedIn data. IDB Technical note 2551, International Development Bank. 2

Bergant, K., Mano, R., and Shibata, M. I. (2022). From polluting to green jobs: A seamless transition in the us? Technical Report 2022/129, International Monetary Fund. 3

Bluedorn, J., Hansen, N., Noureldin, D., Shibata, I., and Tavares, M. M. (2022). Transitioning to a Greener Labor Market Cross-Country Evidence from Microdata. *Energy Economics*, page 106836. 2, 3

Bonavida Foschiatti, C. and Gasparini, L. (2020). Asimetrías en la viabilidad del trabajo remoto. *Economica*, 66:015. 4

Bowen, A., Kuralbayeva, K., and Tipoe, E. L. (2018). Characterising green employment: The impacts of 'greening' on workforce composition. *Energy Economics*, 72:263–275. 2, 3, 10

Brambilla, I., César, A., Falcone, G., Gasparini, L., and Lombardo, C. (2021). The Risk of Automation in Latin America. Documentos de Trabajo del CEDLAS 281, CEDLAS-Universidad Nacional de La Plata. 4

Consoli, D., Marin, G., Marzucchi, A., and Vona, F. (2016). Do green jobs differ from non-green jobs in terms of skills and human capital? *Research Policy*, 45(5):1046–1060. 2, 5, 10

de la Vega, P. (2021). El Teletrabajo como Mitigador de los Impactos Económicos de la Pandemia de COVID-19 en Argentina. Documentos de Trabajo del CEDLAS 282, CEDLAS-Universidad Nacional de La Plata. 4

de la Vega, P. and Gasparini, L. (2023). Teleworking as a mitigator of the economic impacts of the COVID-19 pandemic. The case of Argentina. *Ecos De Econom a: A Latin American Journal of Applied Economics*, 25(53):88–131. 4

Dicarlo, E., L.Bello, S., Monroy-Taborda, S., Oviedo, A. M., Sanchez-Puerta, M. L., and Santos, I. (2016). The Skill Content of Occupations Across Low and Middle Income Countries: Evidence from Harmonized Data. IZA Discussion paper 10224. 4

Elliott, R., Kuai, W., Maddison, D., and Ozgen, C. (2021). Eco-Innovation and Employment: A Task-Based Analysis. IZA Discussion paper 14028. 4, 5

Foster-McGregor, N., Leitner, S., Leitner, S. M., Pöschl, J., and Stehrer, R. (2014). Earnings distributions and dimensions of inequality. Working Paper 399, The Vienna Institute for International Economic Studies. 3

Gasparini, L., Brambilla, I., César, A., Falcone, G., and Lombardo, C. (2020). The Risk of Automation in Argentina. Documentos de Trabajo del CEDLAS 260, CEDLAS-Universidad Nacional de La Plata. 4

Goos, M., Manning, A., and Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, 104 (8):2509–26. 5

Heckman, J., Lochner, L. J., and Todd, P. E. (2003). Fifty years of mincer earnings regressions. Working Paper 9732, National Bureau of Economic Research. 3

IMF (2022). World Economic Outlook: War Sets Back the Global Recovery. Technical report, International Monetary Fund, Washington, DC, April. 2

Jackman, M. and Moore, W. (2021). Does it pay to be green? An exploratory analysis of wage differentials between green and non-green industries. *Journal of Economics and Development*, 23(3):284–298. 2, 3, 10

Lemieux, T. (2006). The "Mincer equation" thirty years after schooling, experience, and earnings. In Grossbard, S., editor, *Jacob Mincer a pioneer of modern labor economics*, pages 127–145. Springer US., Boston, MA. 3

LoBello, S., Puerta, M. L. S., and Winkler, H. (2019). From Ghana to America: The Skill Content of Jobs and Economic Development. Mimeo, World Bank. 4

Lobsiger, M. and Rutzer, C. (2021). The green potential of occupations in Switzerland. *Swiss J Economics Statistics*, 157:8. 2, 4, 5

Mincer, J. (1958). Investment in Human Capital and Personal Income Distribution. *Journal of Political Economy*, 66:281–302. 3

Mincer, J. (1974). Schooling, Experience, and Earnings. *Human Behavior & Social Institutions*, 2. 3

OECD (2017). *Getting Skills Right: Skills for Jobs Indicators*. OECD Publishing, Paris. 2, 5

OECD (2023). *Job Creation and Local Economic Development 2023: Bridging the Great Green Divide*. OECD Publishing, Paris. 2, 8

OECD, CAF, and European Comission (2022). *Latin American Economic Outlook 2022: Towards a Green and Just Transition*. OECD Publishing. 2

Porto, N., de la Vega, P., and Cerimelo, M. (2022). Going Green: Estimating the Potential of Green Jobs in Argentina. Documentos de Trabajo del CEDLAS 301, CEDLAS-Universidad Nacional de La Plata. 1, 2, 4

Rutzer, C. and Niggli, M. (2020). Environmental Policy and Heterogeneous Labor Market Effects: Evidence from Europe. Mimeo. 2, 4, 5

Sato, M., Cass, L., Saussay, A., Vona, F., and Mercer, L. (2023). Skills and wage gaps in the lowcarbon transition: comparing job vacancy data from the US and UK. Policy report, Grantham Research Institute on Climate Change and the Environment and Centre for Climate Change Economics and Policy, London School of Economics and Political Science., London. 3

Valero, A., Li, J., Muller, S., Riom, C., Nguyen-Tien, V., and Draca, M. (2021). Are 'green' jobs good jobs? How lessons from the experience to-date can inform labour market transitions of the future. *London: Grantham Research Institute on Climate Change and the Environment and Centre for Economic Performance, London School of Economics and Political Science.* 2, 3, 4, 10

Vona, F. (2021). Labour Markets and the Green Transition: a practitioner's guide to the task-based approach. In Biagi, F. and Bitat, A., editors, *Labour Markets and the Green Transition: a practitioner's guide to the task-based approach*. Publications Office of the European Union, Luxembourg. 1, 2, 4

Vona, F., Marin, G., and Consoli, D. (2019). Measures, drivers and effects of green employment: evidence from US local labor markets, 2006–2014. *Journal of Economic Geography*, 19(5):1021–1048. 2, 3, 10

Vona, F., Marin, G., Consoli, D., and Popp, D. (2018). Environmental Regulation and Green Skills: an empirical exploration. *Journal of the Association of Environmental and Resource Economists*, 5(4):713–753. 1, 2, 5

Wallach, O. (2022). How many jobs could the clean energy transition create? *World Economic Forum*. 2

Appendix

Table 2: 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 3: Thresholds for identifying green jobs with each definition

O*NET Definition	Threshold
Greenness	0.019
Greenness core	0.010

Note: the threshold for each definition corresponds to the average of each greenness score for all Latin American countries during the period 2012-2019.

Table 4: Wage premium (continuous definition, *greenness*)

	(1) Latin America	(2) Argentina	(3) Bolivia	(4) Brazil	(5) Chile	(6) Colombia	(7) Ecuador	(8) Mexico	(9) Peru	(10) Uruguay
Green Job	0.239***	0.143***	0.103	0.259***	0.211*	0.067	0.223***	0.270***	0.056	0.251***
	(0.066)	(0.049)	(0.083)	(0.071)	(0.118)	(0.051)	(0.069)	(0.068)	(0.102)	(0.074)
Age groups (ref: [15-24] years)										
Age group: [25,40]	0.263***	0.243***	0.207***	0.277***	0.204***	0.257***	0.169***	0.266***	0.204***	0.297***
	(0.016)	(0.010)	(0.019)	(0.021)	(0.024)	(0.009)	(0.015)	(0.018)	(0.019)	(0.018)
Age groups: [41,65]	0.423***	0.383***	0.398***	0.451***	0.286***	0.406***	0.223***	0.376***	0.279***	0.483***
	(0.030)	(0.022)	(0.042)	(0.038)	(0.035)	(0.034)	(0.027)	(0.040)	(0.033)	(0.037)
Gender (ref: woman)										
Men	0.150***	0.100***	0.170***	0.170***	0.146***	0.130***	0.108***	0.153***	0.164***	0.146***
	(0.014)	(0.022)	(0.030)	(0.012)	(0.019)	(0.018)	(0.013)	(0.031)	(0.017)	(0.027)
Educational level (ref: low)										
Medium	0.259***	0.192***	0.190***	0.266***	0.213***	0.280***	0.145***	0.229***	0.170***	0.244***
	(0.024)	(0.022)	(0.035)	(0.030)	(0.028)	(0.028)	(0.024)	(0.027)	(0.030)	(0.027)
High	0.878***	0.552***	0.647***	0.939***	0.785***	0.996***	0.574***	0.827***	0.597***	0.681***
	(0.054)	(0.030)	(0.067)	(0.063)	(0.074)	(0.053)	(0.046)	(0.057)	(0.058)	(0.055)
Area of residence (ref: rural)										
Urban	0.059***	-	-0.071**	0.006	-0.059***	0.012	-0.049***	0.017	-	-0.133***
	(0.014)	-	(0.033)	(0.013)	(0.014)	(0.019)	(0.010)	(0.017)	-	(0.017)
Sector of activity (ref: banking, nance, etc.)										
Construction	-0.133**	-0.254***	0.046	-0.123*	-0.161*	-0.111***	-0.154***	-0.139*	0.161***	0.007
	(0.056)	(0.046)	(0.085)	(0.062)	(0.093)	(0.038)	(0.052)	(0.082)	(0.057)	(0.061)
Domestic service	-0.260***	-0.203**	-0.284***	-0.204**	-0.247***	-0.559***	-0.152***	-0.307***	-0.310***	-0.258**
	(0.071)	(0.092)	(0.065)	(0.086)	(0.088)	(0.033)	(0.043)	(0.086)	(0.042)	(0.119)
Education, health, ss. personal	0.089	0.129*	0.338***	0.082	-0.026	0.079	0.104*	0.253***	0.163**	0.088
	(0.059)	(0.067)	(0.120)	(0.057)	(0.067)	(0.076)	(0.059)	(0.084)	(0.068)	(0.056)
Elect., gas, water, transportation, comm.	-0.009	-0.054	-0.011	0.028	-0.095**	-0.110**	-0.009	-0.089	-0.020	0.041
	(0.033)	(0.077)	(0.069)	(0.033)	(0.047)	(0.043)	(0.039)	(0.098)	(0.042)	(0.037)
Ind. of low tech. (food, beverages and tobacco, textiles and clothing)	-0.113***	-0.127**	-0.030	-0.093***	-0.176***	-0.132***	-0.080*	-0.190**	-0.108**	-0.115***
	(0.036)	(0.052)	(0.068)	(0.033)	(0.054)	(0.036)	(0.042)	(0.075)	(0.048)	(0.039)
Primary activities	-0.200**	-0.042	0.078	-0.205**	-0.110	-0.187***	-0.178***	-0.236**	-0.041	-0.202***
	(0.075)	(0.087)	(0.132)	(0.084)	(0.073)	(0.049)	(0.047)	(0.091)	(0.069)	(0.061)
Public administration and defense	0.202***	0.162***	0.103***	0.255***	0.071*	0.250***	0.294***	0.242***	0.215***	0.160***
	(0.035)	(0.027)	(0.037)	(0.045)	(0.038)	(0.046)	(0.068)	(0.044)	(0.047)	(0.026)
Rest of manufacturing industry	0.023	0.013	-0.183***	0.031	-0.104*	-0.034	-0.049	-0.040	-0.021	-0.033
	(0.038)	(0.047)	(0.058)	(0.033)	(0.055)	(0.038)	(0.037)	(0.078)	(0.046)	(0.039)
Retail and wholesale trade, restaurants, hotels, repairs	-0.183***	-0.127**		-0.161***	-0.177***	-0.238***	-0.150***	-0.186**	-0.191***	-0.173***
	(0.032)	(0.047)		(0.027)	(0.053)	(0.039)	(0.032)	(0.070)	(0.038)	(0.032)
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	0.453	0.331	0.377	0.462	0.312	0.463	0.340	0.371	0.317	0.389
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 core definition, *greenness_core*)

	(1) Latin America	(2) Argentina	(3) Bolivia	(4) Brazil	(5) Chile	(6) Colombia	(7) Ecuador	(8) Mexico	(9) Peru	(10) Uruguay
Green Job	0.176**	0.137**	0.063	0.184**	0.160	0.007	0.166**	0.234***	0.025	0.193**
	(0.070)	(0.057)	(0.088)	(0.084)	(0.125)	(0.046)	(0.068)	(0.073)	(0.102)	(0.078)
Age groups (ref: [15-24] years)										
Age group: [25,40]	0.267***	0.244***	0.208***	0.283***	0.207***	0.258***	0.172***	0.270***	0.204***	0.301***
	(0.016)	(0.010)	(0.018)	(0.021)	(0.024)	(0.009)	(0.015)	(0.018)	(0.019)	(0.018)
Age groups: [41,65]	0.429***	0.384***	0.401***	0.458***	0.289***	0.407***	0.229***	0.381***	0.279***	0.488***
	(0.032)	(0.022)	(0.042)	(0.040)	(0.035)	(0.034)	(0.027)	(0.041)	(0.033)	(0.038)
Gender (ref: woman)										
Men	0.157***	0.105***	0.174***	0.181***	0.157***	0.134***	0.114***	0.153***	0.167***	0.158***
	(0.015)	(0.022)	(0.031)	(0.012)	(0.020)	(0.018)	(0.013)	(0.030)	(0.018)	(0.028)
Educational level (ref: low)										
Medium	0.266***	0.193***	0.191***	0.276***	0.213***	0.282***	0.146***	0.234***	0.169***	0.248***
	(0.025)	(0.022)	(0.035)	(0.031)	(0.028)	(0.028)	(0.025)	(0.028)	(0.030)	(0.027)
High	0.908***	0.558***	0.657***	0.979***	0.802***	1.004***	0.596***	0.855***	0.600***	0.702***
	(0.057)	(0.030)	(0.064)	(0.068)	(0.074)	(0.052)	(0.048)	(0.063)	(0.055)	(0.056)
Area of residence (ref: rural)										
Urban	0.061***	-	-0.069**	0.009	-0.058***	0.011	-0.048***	0.018	-	-0.133***
	(0.014)	-	(0.033)	(0.013)	(0.014)	(0.019)	(0.010)	(0.017)	-	(0.017)
Sector of activity (ref: banking, nance, etc.)										
Construction	-0.124*	-0.261***	0.067	-0.104	-0.163*	-0.117***	-0.136**	-0.149*	0.161**	0.007
	(0.062)	(0.049)	(0.086)	(0.069)	(0.091)	(0.038)	(0.057)	(0.088)	(0.060)	(0.065)
Domestic service	-0.264***	-0.210**	-0.289***	-0.211**	-0.266***	-0.564***	-0.160***	-0.301***	-0.316***	-0.277**
	(0.070)	(0.092)	(0.065)	(0.088)	(0.091)	(0.032)	(0.045)	(0.094)	(0.042)	(0.119)
Education, health, ss. personal	0.070	0.119*	0.330***	0.062	-0.051	0.074	0.086	0.225***	0.159**	0.063
	(0.057)	(0.067)	(0.118)	(0.056)	(0.068)	(0.074)	(0.061)	(0.083)	(0.066)	(0.054)
Elect., gas, water, transportation, comm.	-0.003	-0.061	0.002	0.046	-0.112**	-0.109**	-0.010	-0.107	-0.024	0.023
	(0.039)	(0.079)	(0.067)	(0.031)	(0.049)	(0.043)	(0.042)	(0.103)	(0.041)	(0.040)
Ind. of low tech. (food, beverages and tobacco, textiles and clothing)	-0.120***	-0.137**	-0.034	-0.096**	-0.197***	-0.131***	-0.085*	-0.208**	-0.111**	-0.136***
	(0.039)	(0.053)	(0.069)	(0.036)	(0.057)	(0.037)	(0.046)	(0.078)	(0.050)	(0.039)
Primary activities	-0.210**	-0.050	0.074	-0.213**	-0.130*	-0.181***	-0.186***	-0.257***	-0.046	-0.226***
	(0.079)	(0.088)	(0.133)	(0.087)	(0.076)	(0.050)	(0.050)	(0.093)	(0.071)	(0.062)
Public administration and defense	0.197***	0.156***	0.107***	0.252***	0.056	0.246***	0.297***	0.235***	0.214***	0.142***
	(0.037)	(0.027)	(0.038)	(0.049)	(0.040)	(0.045)	(0.067)	(0.043)	(0.046)	(0.027)
Rest of manufacturing industry	0.035	0.014	-0.186***	0.045	-0.122**	-0.032	-0.048	-0.020	-0.025	-0.048
	(0.038)	(0.049)	(0.060)	(0.033)	(0.057)	(0.038)	(0.040)	(0.076)	(0.048)	(0.040)
Retail and wholesale trade, restaurants, hotels, repairs	-0.187***	-0.136***	-	-0.158***	-0.195***	-0.240***	-0.154***	-0.199***	-0.196***	-0.192***
	(0.037)	(0.047)	-	(0.032)	(0.056)	(0.039)	(0.036)	(0.073)	(0.040)	(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	0.446	0.330	0.375	0.454	0.307	0.462	0.333	0.365	0.316	0.383
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