Universidade do Minho
Escola de Economia e Gestão

Sergey Volozhenin

Greening the Employment: Empirical Evidence for Portugal

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Greening the Employment: Empirical Evidence for Portugal

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Work developed under the supervision of:
Professor Doutor João Carlos Cerejeira Silva
Professora Doutora Rita Mafalda Dionísio Sousa

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Empregos verdes: Evidência empírica para Portugal

Resumo

Esta tese é constituída por três estudos empíricos com foco no emprego verde em Portugal. O Capítulo 2 analisa os empregos verdes em Portugal através de três classificações: ocupações, tarefas e competências. Para tal, são utilizados os dados longitudinais (Quadros de Pessoal, 2010–2019) com o objetivo de quantificar o emprego verde e examinar os impactos das características dos trabalhadores e das empresas no prémio salarial verde. Os resultados revelam que os empregos verdes representam entre 2% e 14% do emprego total, dependendo do método de classificação utilizado. A decomposição de Blinder-Oaxaca demonstra disparidades salariais entre empregos verdes e não verdes, sendo que o modelo baseado em tarefas reporta prémios mais elevados para quem muda de emprego. Além disso, identificámos disparidades significativas de género e de educação, sendo os homens e os trabalhadores com educação superior mais propensos a ocupar empregos verdes. As correlações entre os diferentes métodos de classificação realçam a necessidade de uma estrutura multidimensional. O Capítulo 3 investiga o prémio salarial verde em Portugal. Quantificamos as diferenças salariais entre empregos verdes e não verdes e separamos o impacto das características observáveis e dos fatores não observáveis. Os resultados sugerem que os trabalhadores em empregos verdes ganham mais do que os de empregos não verdes. Através do modelo de efeitos fixos e decomposições estruturais dos salários, descobrimos que os empregos verdes oferecem retornos mais baixos para competências não observáveis, sugerindo que dependem mais de qualificações formais e de conteúdos estruturados das tarefas. Os padrões persistem no teste de robustez, onde utilizamos uma amostra de trabalhadores despedidos. O Capítulo 4 estima a elasticidade de substituição entre empregos verdes e não verdes e avalia o impacto das políticas fiscais no emprego verde com recurso a um modelo CGE (PEP-1-1), calibrado com microdados e contas nacionais de Portugal. Nesta etapa é considerada a abordagem das ocupações verdes. Os resultados indicam que os empregos verdes e não verdes são substitutos. No entanto, a ausência de compensação pelo corte das taxas de imposto afeta negativamente o rendimento disponível do governo. As simulações sugerem que a redução das taxas de imposto sobre a produção no sector da construção leva ao aumento mais significativo da procura de mão-de-obra verde em todos os sectores. Em conclusão, esta tese permite a melhor compreensão do mercado de trabalho verde ao considerar abordagens multidimensionais, as dinâmicas salariais e os impactos das políticas.

Palavras chave: Competências Verdes; Empregos Verdes; Modelo de Equilíbrio Geral; Prémio Salarial; Tarefas Verdes

Greening the Employment: Empirical Evidence for Portugal

Abstract

This thesis consists of three empirical studies focusing on green employment in Portugal. Chapter 2 analyses green jobs in Portugal using three classification approaches, occupations, tasks, and skills, to assess their prevalence, characteristics, and wage effects. By employing a matched employer-employee dataset (*Quadros de Pessoal*, 2010–2019), we quantify green employment, examine workers' and firms' attributes, and estimate a green wage premium. The results reveal that green jobs account for between 2% and 14% of total employment, depending on the classification method used. A Blinder–Oaxaca decomposition reveals wage gaps between green and non-green jobs, with the task-based model showing the highest premium for job changers. Additionally, we identify significant gender and educational disparities, with men and highly educated workers being more likely to hold green jobs. Weak correlations between the different classification methods highlight the need for a multidimensional framework. Chapter 3 investigates the green wage premium in Portugal using the same dataset as Chapter 2. We quantify the wage differentials between green and non-green jobs and disentangle the roles of both observable characteristics and unobservable factors. Our results show that workers in green jobs earn more than those in non-green jobs. Using fixed effects and structural wage decompositions, we find that green jobs offer lower returns to unobservable abilities, suggesting that they depend more on formal qualifications and structured task content. These patterns persist in robustness checks using a sample of displaced workers, addressing concerns about endogenous matching. Chapter 4 estimates the elasticity of substitution between green and non-green jobs and evaluates the impact of fiscal policies on green employment using a CGE model (PEP-1-1), calibrated with Portuguese microdata and national accounts, employing the occupation-based approach for this analysis. The results indicate that green and non-green jobs are substitutes. However, the absence of compensation for the tax cut negatively affected the government's disposable income. The simulations suggest that lowering production taxes in construction leads to the most significant increase in demand for green labour across all sectors. In conclusion, this thesis enhances the understanding of green labour markets by considering multidimensional approaches, wage dynamics, and policy impacts.

Keywords: Computable General Equilibrium Model; Green Jobs; Green Tasks; Green Skills; Wage Premium

Index

1 Introduction 1

2 Measuring Green Jobs: Evidence from task, skill, and occupational data. 5

2.1 Introduction 5

2.2 Defining and measuring green jobs 6

2.3 Data and methodology 9

2.3.1 Green jobs classification 9

2.3.2 Data and variables 11

2.3.3 Empirical strategy 13

2.4 Results 14

2.4.1 Green jobs distribution in Portugal 14

2.4.2 Characteristics of green jobs 16

2.4.3 Green skills, tasks and occupations: complementary or substitute? 21

2.5 Discussion: the implications of differing green job definitions 22

2.6 Conclusion 24

3 Unpacking the Green Wage Premium: The Role of Observable and Unobservable Characteristics in Green Job Wages 26

3.1 Introduction 26

3.2 Data and summary statistics 28

3.2.1 Data sources and sample selection 28

3.2.2 Measuring green jobs 29

3.2.3 Descriptive statistics 30

3.2.4 The wage gap between green and non-green jobs 37

3.3 Accounting for unobserved heterogeneity - An econometric framework 41

3.4 Results and robustness checks 44

3.4.1 Main findings 44
3.4.2 Unobservables and Greenness Interaction 49
3.4.3 Robustness checks – results from a displaced workers sample 54
3.5 Discussion and policy implications 57
4 Green Jobs and Fiscal Policy: Modelling Employment Dynamics in the Portuguese Transition 60
4.1 Introduction 60
4.2 Data and methodology 63
4.2.1 Data 63
4.2.2 Methodology 64
4.3 Results 74
4.3.1 Elasticity of substitution between green and non-green jobs 74
4.3.2 Simulations results 77
4.4 Conclusion 85
5 Conclusion 87
Bibliography 90
Appendix 95

List of figures

Figure 1 – Green and non-green jobs average nominal hourly income (€), by green tasks intensities. . 37
Figure 2 – Green and non-green jobs average real hourly income (€) (base year = 2016), by green tasks intensities..... 38
Figure 3 - Green and non-green jobs average nominal hourly income (€), by green occupations. 38
Figure 4 - Green and non-green jobs average real hourly income (€) (base year = 2016), by green occupations..... 39

List of tables

Table 1 - Summary statistics 12
Table 2 - Correlation coefficients between different green jobs classifications 13
Table 3 - Share of green employment in Portugal in 2019 14
Table 4 - Percentage of green jobs in different sectors, classified by skills, tasks, and occupations - percentage within sector, Portugal 15
Table 5 - Factors influencing employment in green jobs: average marginal effects of the Probit model 17
Table 6 - Wage differences in green jobs: high-dimensional fixed effect wage models 18
Table 7 - Decomposition of the green wage premium: three-fold Blinder-Oaxaca decomposition 19
Table 8 - Explaining the green wage gap: two-fold Blinder-Oaxaca decomposition 20
Table 9 - Cross-correlation table 21
Table 10 - Summary statistics 32
Table 11 - Summary statistics displaced workers 34
Table 12 - Means of green and non-green jobs 36
Table 13 - Two-fold Blinder-Oaxaca decomposition of green and non-green jobs 40
Table 14 - Green Wage Premium – Base Specification 45
Table 15 - Green Wage Premium – Base specification with observable skill intensities 47
Table 16 - Wage Returns by Green Task Intensities 50
Table 17 - Wage Returns by Green Occupation Intensities 52
Table 18 - Green Wage Premium - Displaced Workers Sample 54
Table 19 - Green Wage Premium (Interacted Models) - Displaced Workers Sample 56
Table 20 - Share distribution of production factors within each sector by capital, green and non-green labour 68
Table 21 - Distribution of production factors across agents (in millions of €) 68
Table 22 - Distribution of direct taxes by agents (in millions of €) 69
Table 23 - Distribution current transfers by agents (in millions of €) 70
Table 24 - Summary statistics of the sample for elasticity of substitution 74
Table 25 - POLS, HDFE and IV estimation of elasticity equation 75
Table 26 - Elasticity of substitution of composite labour per sector 77
Table 27 - Wages, Income and Transfers vs BAU 78
Table 28 - Labour Demand vs BAU 80
Table 29 - Consumption vs BAU 81

Table 30 - Production vs BAU 82
Table 31 - Government disposable income, real GDP at basic and market prices and CPI vs BAU 83

List of appendix tables

Table A 1 - Summary statistics of green occupations 95
Table A 2 - Summary statistics non-green occupations 95
Table A 3 - Summary statistics green tasks intensities 96
Table A 4 - Summary statistics non-green tasks intensities 97
Table A 5 - Full-length Results - Wage Returns by Green Task Intensities 98
Table A 6 - Full-length Results - Wage Returns by Green Occupation Intensities 102
Table A 7 - Full-length Green Wage Premium (Interacted Models) - Displaced Workers Sample 106
Table A 8 - Elasticities per sectors 110
Table A 9 - POLS, HDFE and IV. Agriculture, forestry and fishing. Estimation of elasticity equation 111
Table A 10 - POLS, HDFE and IV. Industry, energy, water supply and sewerage. Estimation of elasticity equation 112
Table A 11 - POLS, HDFE and IV. Construction. Estimation of elasticity equation 113
Table A 12 - POLS, HDFE and IV. Wholesale, retail trade, repair of motor vehicles and motorcycles; transportation and storage; accommodation and food service activities. Estimation of elasticity equation 114
Table A 13 - POLS, HDFE and IV. Information and communication. Estimation of elasticity equation 116
Table A 14 - POLS, HDFE and IV. Financial and insurance activities. Estimation of elasticity equation 117
Table A 15 - POLS, HDFE and IV. Real estate activities. Estimation of elasticity equation 118
Table A 16 - POLS, HDFE and IV. Professional, scientific, and technical activities; administrative and support service. Estimation of elasticity equation 119
Table A 17 - POLS, HDFE and IV. Public administration and defence; compulsory social security; education; human health and social work. Estimation of elasticity equation 120
Table A 18 - POLS, HDFE and IV. Arts; entertainment; repair of household goods and other services. Estimation of elasticity equation 122

List of Acronyms

BLS - Bureau of Labour Statistics

CES - Constant Elasticity of Substitution

CGE - Computable General Equilibrium

CPI - Consumer Price Index

DGO - Directly Green Occupations

ESCO - European Skills, Competences, Qualifications, and Occupations

EU - European Union

FE - Fixed Effects

GDP - Gross Domestic Product

GES - Green Enhanced Skills

GHG - Greenhouse Gas

GID - Green Increased Demand

GNE - Green New and Emerging

GO - Degree of Greenness of Occupations

GS - Green Skills Intensity

GT - Green Tasks Intensity

GTR - Green Tax Reform

HDFE - High-dimensional Fixed Effects

IGO - Indirectly Green Occupations

ISCO08 - International Standard Classification of Occupations 2008

IV - Instrumental Variables

O*NET - Occupational Information Network

OECD - Organization for Economic Co-operation and Development

OLS - Ordinary Least Square

POLS - Pooled Ordinary Least Square

PP - Percentage Points

QP - *Quadros de Pessoal*

RNC2050 - Roadmap to Carbon Neutrality 2050

SAM - Social Accounting Matrix

SCIE - *Sistema de Contas Integradas das Empresas*

SOC2010 - Standard Occupational Classification 2010

UN - United Nations

1 Introduction

The discussion surrounding sustainable transition has gained significant importance in recent decades. This concern has been present for over 50 years and typically encompasses a similar definition: the transformation of traditional economic, social, productive, and energy models into more balanced, inclusive, and environmentally sustainable systems. This involves reducing greenhouse gas (GHG) emissions, protecting ecosystems, using natural resources efficiently, adapting renewable energy sources, improving energy efficiency, implementing circular economy models, and creating green jobs while ensuring fair adaptation for workers.

The concept of a green transition lacks a unified definition. Instead of being based on a single foundation, it is shaped by a combination of objectives and commitments set by international, national, and local authorities, which together influence the path toward sustainable transformation. For example, at the international level, we have the Paris Agreement (2015)[1] and the European Green Deal[2], both of which focus on addressing global warming and achieving carbon neutrality. Additionally, the United Nations (UN) Agenda 2030[3] emphasizes human development, while reports from the Organization for Economic Co-operation and Development (OECD)[4] focus on economic policies, social inclusion, and technological innovation.

In accordance with international frameworks, Portugal, as a member of the European Union (EU) and the UN, has developed a series of commitments and goals. These include the National Strategy for Adaptation to Climate Change[5] and the Roadmap to Carbon Neutrality 2050 (RNC2050)[6], which focus on climate mitigation and the reduction of GHG emissions. Additionally, the Portugal 2030[7] initiative emphasizes circular economy, social and territorial inclusion, and technological innovation. Lastly, the National Roadmap for Sustainable Development 2030[8] aligns with the UN Agenda 2030.

One of the key national policy instruments guiding the sustainable transition is the Green Tax Reform (GTR), enacted in 2014. The primary objectives of this law are to promote eco-innovation, enhance energy efficiency, stimulate sustainable production and consumption, and encourage green employment.

[1] https://unfccc.int/process-and-meetings/the-paris-agreement.
[2] https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en.
[3] https://sdgs.un.org/2030agenda.
[4] https://www.oecd.org/en/about.html.
[5] https://apambiente.pt/clima/estrategia-nacional-de-adaptacao-alteracoes-climaticas.
[6] https://descarbonizar2050.apambiente.pt/.
[7] https://portugal2030.pt/.
[8] https://ptsustentavel.gov.pt/roteiro-nacional-para-o-desenvolvimento-sustentavel-2030/.

The implementation of the GTR has produced measurable results, as the percentage of terminated ecological contracts among national institutions increased from 0.01% to 4.77% between 2014 and 2023.[9] These contracts are classified as green public procurement that adheres to both national and EU guidelines for sustainable public procurement. Under this framework, a contracting authority designates a contract as green when the procurement process explicitly incorporates environmental criteria or resource efficiency requirements, as outlined in Portuguese legislation or EU directives.

While ecological contracts operate under clear regulatory frameworks and can be effectively monitored, the same cannot be said for green employment. The lack of a universally accepted definition at both international and national levels creates significant ambiguity, leading to various interpretations. As a result, the quantification of green employment can vary widely, with measurement outcomes depending on the scope of activities and professions included in the definition. In this context, two primary approaches to classifying green employment can be distinguished: top-down and bottom-up. The top-down perspective categorises green jobs through the macro-level aggregation of economic sectors or broad occupational groups (see, for example, Elliot and Lindley, 2017, or, for a more classical definition, OECD, 1999). In contrast, the bottom-up approach uses a more granular level of analysis, classifying employment based on specific professions (Consoli et al., 2016), the tasks associated with those professions (Vona et al., 2018), or even the skill sets required to perform them. Some authors have employed more detailed methods, employing vacancy-level data that capture labour market dynamics (Saussay et al., 2022) and product-level information that links employment to environmental content (Bontadini and Vona, 2023).

The second Chapter of this thesis addresses a gap in the literature by exploring three widely accepted classifications of the Portuguese labour market: occupation-based, task-based, and skill-based classifications. It also examines wage differentials and employment probabilities by analysing workers' attributes and labour market characteristics. The first contribution to existing literature is the implementation and application of a skill-based approach using linked employer-employee data from Portugal. Secondly, the study offers a comparative analysis of the three approaches. The findings indicate that these classifications are not interchangeable, rather, they are complementary, each rooted in distinct conceptual frameworks. The occupation-based approach emphasises professional outputs, the task-based approach focuses on job-related tasks, and the skill-based approach centres on the skills provided by workers. Lastly, this study quantifies green employment in Portugal. Estimates for green employment

[9] Public procurement data available at https://www.base.gov.pt/base4.

in 2019 range from 2.68% to 7.98%, depending on the classification method used, with the highest concentrations found in the electricity production and water and waste management sectors. The final contribution includes an empirical analysis of the characteristics of both workers and firms that influence the likelihood of being employed in green jobs. It also identifies a wage premium associated with the transition to these greener jobs. The findings indicate that men are more likely than women to hold green jobs. Additionally, green jobs tend to offer higher wages and a greater probability of fixed-term contracts. However, the impact of other worker attributes and firm characteristics yields more ambiguous results, which vary depending on the classification considered.

The Chapter 3 investigates the cause behind the wage gap between green and non-green jobs. Building on the findings from the second chapter, it analyses wage differentials between these two types of jobs. This chapter makes three main contributions. First, it examines the wage gap between green and non-green jobs by considering factors such as workers' and firms' characteristics, working conditions, skill intensity indicators, and unobservable worker abilities. The results reveal a significant wage gap according to both occupation-based and task-based approaches. Nearly 70% of this gap can be attributed to differences in workers' and firms' characteristics, as well as skill intensity indicators. Second, we estimate the impact of job changers on income returns in green positions. Our analysis indicates that workers who transition to greener jobs experience a positive effect on their income, on average. While this effect is smaller for those who change both occupation and employer, it remains positive and statistically significant. Robustness checks using an additional sample of displaced workers affected by firm closures support these findings, as the same positive effect is observed. Lastly, we assess the returns of unobservable worker characteristics across different job types. The results indicate that there is no evidence of compensation for unobservable abilities among workers in greener jobs when using the task-based approach. However, the occupation-based approach shows a negative effect, suggesting that as the greenness of a profession increases, green jobs tend to place greater emphasis on observable worker characteristics rather than unobservable abilities.

Beyond the importance of conceptualising green jobs and measuring green employment, it is also crucial to identify strategies that effectively promote green employment, as the discourse on sustainable transition inherently incorporates the promotion of green jobs. However, before formulating policy interventions, it is essential to determine whether green and non-green jobs are substitutes or complements. Therefore, the Chapter 5 of this thesis aims to estimate whether green and non-green jobs are substitutes and investigate different scenarios that promote green employment relying on a

Computable General Equilibrium (CGE) model. This chapter presents three main contributions to existing literature. First, we estimate the elasticity of substitution of composite labour between green and non-green jobs in Portugal across ten different sectors. Using an occupational-based approach, the results indicate that green and non-green jobs are substitutes for each other. Secondly, we constructed a Social Accounting Matrix (SAM) that incorporates both green and non-green composite labour, based on the baseline SAM for Portugal developed by Gião and Sousa (2023). Lastly, we employed a static single-period (PEP-1-1) CGE model to evaluate three fiscal policy scenarios involving income and production taxes designed to promote green employment. We analysed the effects of these scenarios on key macroeconomic variables. The findings suggest that production taxes are the most effective policy intervention, as this scenario leads to a higher demand for green jobs across all sectors while simultaneously reducing the Consumer Price Index (CPI). Furthermore, this policy option results in the smallest reduction in government disposable income, although the same cannot be said for consumption and production.

The final Chapter of this thesis summarises the key findings, discusses the limitations, and provides suggestions for future research.

2 Measuring Green Jobs: Evidence from task, skill, and occupational data.

2.1 Introduction

Since the middle of the last century, society has been undergoing a shift in values, with the transition to a more sustainable future requiring large investments across diverse sectors. Several countries and regions, particularly in the EU, have been implementing climate and energy transition strategies. These strategies aim to protect the environment, improve social and governance levels, and potentially boost economic growth, innovation, and employment (UNEP et al., 2008; Elliott and Lindley, 2017; Georgeson and Maslin, 2019). Valuing environmentally friendly solutions is therefore indispensable, with the demand for green activities and sustainability support services shaping the job market.

Adapting existing jobs and fostering new professions with green skills is essential for meeting national and international commitments to climate, energy, and the circular economy (OECD/Cedefop, 2014). This shift requires a precise understanding of how jobs contribute to environmental objectives and the broader green transition. Furthermore, the increasing importance of skills in green jobs, and the potential shift towards skill-based hiring, is highlighted by Bone et al. (2025), suggesting a re-evaluation of traditional degree-based hiring approaches. While various approaches exist to define and classify green jobs, they differ in scope and methodology. Some classifications focus on the economic sector in which jobs are embedded, while others consider the specific occupations, tasks, or skills involved. These distinctions are critical in assessing the evolving demand for green skills, the structural transformation of labour markets, and the effectiveness of policies aimed at fostering sustainable employment.

However, current metrics do not provide clear information on the relationship between green jobs, occupations, tasks, and skills, relevant for understanding labour market dynamics, assessing skill mismatches, designing targeted education and training programs, and formulating effective employment policies to support the green transition. This study addresses this gap by focusing on the Portuguese case, examining how different classification approaches (occupations, tasks, and skills) can be used to measure and characterize green jobs. This study investigates how different classification approaches, based on occupations, tasks, and skills, can be employed to measure and characterize green jobs, using Portugal as a case study. Additionally, it examines the implications of these classification frameworks for labor market outcomes, particularly wage differentials and employment probabilities.

To address this question, we use unique employer-employee data to compare different green job classifications based on O*NET (Occupational Information Network) and ESCO (European Skills, Competences, Qualifications, and Occupations) methodologies. We analyse the demographic and professional characteristics of workers in green jobs, identify firm-level factors associated with green job creation, and examine the presence of a green wage premium. Finally, we assess whether classifications based on occupations, tasks, and skills are complementary or substitutable.

To do so, we assess the extent, characteristics, and wage effects of green jobs in Portugal, comparing different classification systems to understand their implications for labour market policies during the transition to a sustainable economy. The remainder of this paper is structured as follows: Section 2 defines the different measurement, Section 3 describes the data, their features, and the models; Section 4 presents our main findings, Section 5 discuss implications of different green jobs definitions, and Section 6 concludes.

2.2 Defining and measuring green jobs

As societies transition toward sustainability, green jobs have become increasingly important, driving economic growth, innovation, and employment opportunities (UNEP et al., 2008; Elliot and Lindley, 2017; Georgeson and Maslin, 2019). However, measuring green jobs has been challenging due to the lack of a universally agreed-upon definition. Measurements have been made at the sector/industry level (Elliot and Lindley, 2017), the occupation level (Consoli et al., 2016; Bowen et al., 2018; Bowen and Hancké, 2019; Valero et al., 2021), the task level (Vona et al., 2018; Vona et al., 2019; Vona, 2021; Elliott et al., 2024), the vacancy level (Saussay et al., 2022; Curtis and Marinescu, 2023) and product level (Bontadini and Vona, 2023).

Broadly, approaches to defining green jobs can be categorized by their focus. Some approaches, like top-down measurements, start from an aggregate level (sectors), while bottom-up approaches build from granular sources like occupations, skills, and product-level data. As a result, we consider three classifications under the bottom-up approach: the O*NET Green Occupations, the O*NET Green Tasks and the ESCO Green Skills. In the first classification, green jobs are occupations that are likely to be affected by the transition to a low-carbon circular (greener) economy. The second classification looks at tasks, where a green task is a work activity that makes a positive contribution to the green economy. The last one defines green professions according to their green skills.

We define professions or occupations as a group of jobs with similar tasks that demand a similar set of skills. Tasks are a composite of duties and functions, and skills are a set of competences and knowledge that workers possess. There is a hierarchical structure between tasks and occupations, as professions consist of specific tasks. However, tasks are independent as they can be shared between different professions. This suggests that we might classify a set of tasks as green, but their share within professions might vary, leading to different quantifications of green professions. From a conceptual point of view, tasks and skills are allocated to different sides of the labour market. Tasks are located on the demand side, which are tech-driven due to changes due to technological processes and used to study job evolution. Skills, on the other hand, are located at the supply side as they are possessed by workers. In contrast to tasks, they are adaptable and transferable, for instance, through training.

Regardless of the fact that measures of occupations, tasks and skills are employed for different purposes (for example, job polarization and education policies), we use these metrics to construct green indexes as shown in the following section.

Sector-based approaches classify green jobs based on the environmental performance of the sector in which they operate. The OECD (1999) defined green jobs as those producing goods and services that mitigate environmental damage. This approach considers all workers in sectors directly involved in environmental protection and resource management as part of the green workforce *(OECD/Eurostat, 1999;* Eurostat, 2016). While useful for labour market policy analysis, it has limitations, such as assuming a direct correlation between green production and employment and lacking specificity in identifying workers and tasks contributing to green activities (Vona, 2021). Consequently, top-down classifications can misrepresent green employment by overestimating it in sectors where not all occupations involve green tasks and underestimating it in sectors where green tasks exist but are not dominant.

Occupation-based approaches focus on identifying specific occupations that contribute to environmental sustainability. In O*NET, Dierdorff et al. (2009) identify 204 green occupations, categorized as:

- Green Increased Demand (GID) Occupations – Existing jobs in greater demand.
- Green Enhanced Skills (GES) Occupations – Existing jobs with significantly changed tasks and skills.
- Green New and Emerging (GNE) Occupations – New jobs emerging due to green activities.

A limitation is that most systems are designed for particular geographies. For example, Dierdorff et al. (2009) designed their approach using the US reality and encoded at an 8-digit O*NET Standard Occupational Classification (SOC2010) code. Hence, some adjustments are necessary when considering other classifications such as the International Standard Classification of Occupations 2008 (ISCO08), as in Bowen and Hancké (2019). Another limitation is that O*NET is binary: ignoring the idea that all occupations potentially engage with green activities to a varying degree. A method used to solve this is by using weighted values for occupations (Lobsiger and Rutzer, 2021; Valero et al., 2021; Elliott et al., 2024).

Task-based approaches quantify greenness by assessing how much greenness the activities that occupations use is, instead of directly measuring the occupation. Vona et al. (2018) proposed an alternative to O*NET binary classification of green occupations by focusing on tasks. They developed a continuous measure called the Green Tasks Index, which is calculated as the share of green tasks performed per occupation, and can be interpreted as a proxy of the relative importance of a particular class of job tasks related, more or less directly, with environmental sustainability. To provide a more precise measure of green jobs, it is recommended to establish a top and bottom boundary for possible variations of the degree of greenness of each profession. This overcomes the binary limitation and provides a more accurate measure of green jobs (Vona et al., 2019; Vona, 2021). We also apply here a continuous measure, as we wish to assess to what extent can tasks vary between occupations.

Skills-based approaches assess green jobs based on skills, competences, qualifications and occupations relevant to the EU labour market and education and training. In 2022, ESCO published a list of green competences and knowledge (European Commission, 2022a). The ESCO classification is based on the ISCO08 system and follows a methodology based on a three-step process, which combines human labelling and validation, and the use of machine learning algorithms. The ESCO process to classify green competences and knowledge resulted in 381 competences, 185 knowledges and 5 transversal green skills out of 13,890 skills. The ESCO 2022 green skills classification brings new and valuable information to Europe's full ranking of green jobs.

Despite that those measures are interconnected, it is important to differentiate them as the effect of the measurement of green employment might vary according to the trends in the labour market. As tasks are tech-driven, they are susceptible to changes due to automatization, being one of the causes of job polarization (Goos et al., 2009), and more recently, due to alternative work arrangements (Katz and Krueger, 2019), which includes freelance (online) and on call workers. While the first might lead to an

extension of some professions (see, for example, Frey and Osborne (2017) probabilities), the second fragments the composition of jobs in a specific set of tasks. On the supply side, emerges the problem of skills mismatches, defined as vertical/horizontal mismatch and skills gaps, shortages and obsolescence (McGuinness et al., 2018). Shown as a difference between demanded and supplied skills, it is discussed as overqualification or underqualification, which might lead to potential hidden unemployment that either requires upskilling or reskilling.

2.3 Data and methodology

This study analyses green jobs using Portugal as a case study, drawing on the *Quadros de Pessoal* (QP), dataset provided by Statistics Portugal (INE). QP is a comprehensive, longitudinal employer-employee registry collected annually via mandatory questionnaires issued by the Ministry of Labour and Social Security. This registry covers private-sector employment from 2010-2019, providing detailed information on workers, establishments, and firms. To ensure data quality and address outliers, we exclude workers who: work less than 30 weekly hours, receive extreme wages (less than half or more than 25 times the national minimum wage), or are outside the economically active age range (younger than 17 or older than 67 years). By focusing on this dataset and applying data cleaning procedures, we aim to provide insights into the characteristics and dynamics of green jobs in the Portuguese labour market.

2.3.1 Green jobs classification

To systematically assess green jobs, we use three bottom-up classifications: O*NET Green Occupations, O*NET Green Tasks, and ESCO Green Skills. Our methodology adapts the degree of greenness to ISCO08.

Green Occupations (O*NET to ISCO08) - O*NET identifies green professions using an 8-digit O*NET SOC2010 code. Due to the lack of a direct crosswalk, we followed uniform weights distribution, dividing the number of 8-digit O*NET SOC2010 green occupations in each 6-digit occupation in SOC2010 by the total number of 8-digit occupations in each 6-digit occupation group to obtain the degree of greenness at the 6-digit SOC2010, as shown in Equation 1:

$$\text{Degree of greenness } \text{SOC}_{6d,i} = \frac{\text{Total number of green occupations in ONET SOC }_{8d,i}}{\text{Total number of occupations in ONET SOC}_{8d,i}} \quad \text{Eq. 1}$$

Then, we performed a connection between the 4-digit ISCO08 with the 6-digit SOC2010. In this step, we used the Bureau of Labor Statistics (BLS) crosswalk (ONS, 2020). An occupation in 4-digit ISCO08 can be directly linked to several professions in 6-digit SOC2010. Therefore, using uniform weights distribution we divided the sum of the degree of greenness of 6-digit SOC2010 occupations linked to a profession in 4-digit ISCO08 by the total number of occupations in 6-digit SOC2010 connected to the same profession in 4-digit ISCO08. The process is expressed below in Equation 2:

$$\text{Degree of greenness ISCO}_{4\text{d,i}} = \frac{\sum \text{Degree of greenness of linked SOC occupations}_{6\text{d,i}}}{\text{Total number of linked SOC occupations}_{6\text{d,i}}} \quad \text{Eq. 2}$$

We separated the O*NET approach into GNE, GES, and GID occupations, considering directly green (GNE and GES) and indirectly green (GID).

Green Tasks (O*NET Approach) - We employ Elliot et al.'s (2024) continuous task-based green measures, excluding GID occupations. These authors calculate occupations green tasks intensities by summing the product of normalised occupations tasks importance score with binary indicators of green or non-green tasks.

Green Skills (ESCO Approach) - The ESCO classification system uses ISCO08. Green skills intensity is defined as the share of green skills per profession, obtained by dividing the total number of green essentials and optional competences and knowledge by the total number of skills within each occupation, as expressed in Equation 3:

$$Green\ skills\ intensity\ ISCO_{5d,i} = \frac{\text{Total number of green skills (ESCO)in occupation ISCO}_{5\text{d,i}}}{\text{Total number of skills (ESCO)in occupations ISCO}_{5\text{d,i}}} \quad \text{Eq. 3}$$

Green skills intensity is then the share of green skills of an occupation *i* in ISCO08 at level 5 of aggregation. We divide the sum of green skills intensities per occupation, by the total number of occupations identified at 5-digits ISCO08 within each occupation group at the 4-digit level of aggregation, as presented in Equation 4:

$$Green\ skills\ intensity_{4d,i} = \frac{\sum \text{Green skills intensities ISCO}_{5d,i}}{\text{Total number of occupations in ISCO}_{5d,i}} \quad \text{Eq. 4}$$

2.3.2 Data and variables

The Portuguese QP dataset contains:

- **Greenness measures:** Continuous indices for skills (ESCO), tasks (O*NET), and occupations (O*NET).
- **Worker characteristics:** Age, education (bellow secondary, secondary and higher education), gender (female and male), and potential experience.
- **Job/firm features:** Wage, contract type (fixed-term/effective), firm size, capital, foreign investment share, and seniority.

Variables are defined as follows: potential experience = age - years of schooling – 6; education is categorical (1=less than secondary, 2=secondary, 3=higher); gender is binary (1=female, 0=male); contract type is binary (1=effective, 0=fixed-term); and firm seniority (<2 years, 2-5 years, >5 years). Gender and contract type are referred as woman and effective contract, respectively, to make tables reading easier.

We organized variables into four major groups: the greenness measures, the socio-economic characteristics, the working conditions variables, and the firms' indicators. Table 1 reports summary statistics. Where from now on GS stands for Green Skills intensity, GT for Green Tasks intensity and GO for Degree of Greenness of Occupations that includes GNE, GES and GID occupations. Furtherly, we consider GES and GNE as Directly Green Occupations (DGO) and GID as Indirectly Green Occupations (IGO), in accordance with Consoli et al. (2016) view.

Table 2 presents the correlation coefficients between different green job classifications. GT and DGO show the highest correlation of 0.782, suggesting that the distribution of green jobs across sectors follows a similar pattern. GS reveals the lowest correlation among all approaches, with the highest value of 0.349 with GT and the lowest value of 0.148 with DGO. These differences may reflect the unique aspects of green employment captured by each approach.

Table 1 - Summary statistics

	Mean	SD	Min	Max	N
Time spawn					
Year	2015	3	2010	2019	22240822
Greenness Measure					
GS	0.04	0.06	0.00	0.60	22187596
GT	0.03	0.09	0.00	1.00	22240829
GO	0.13	0.25	0.00	1.00	22240821
GNE	0.02	0.06	0.00	0.50	22240821
GES	0.05	0.17	0.00	1.00	22240821
GID	0.06	0.17	0.00	1.00	22240821
Socio-economics characteristics					
Age	40.19	10.76	17.00	67.00	22240822
Tenure	8.17	8.84	0.00	55.00	22238560
Potential Experience	24.29	12.52	0.00	57.00	22240822
Women	0.46	0.50	0.00	1.00	22240822
Lower Education	0.51	0.50	0.00	1.00	22240822
Secondary Education	0.29	0.45	0.00	1.00	22240822
Higher Education	0.20	0.40	0.00	1.00	22240822
Working conditions					
Wage (€)	1067.30	846.20	237.50	15000.00	22240822
Effective Contract	0.72	0.45	0.00	1.00	22240822
Firms indicators					
No. of workers	1049.44	3351.25	1.00	27340.00	22240822
Social capital (in millions of €)	77.69	526.06	0.00	7068.17	22240822
Share of foreign capital (%)	13.22	32.85	0.00	100.00	22240822
Firms seniority (below 2 years)	0.06	0.23	0	1	22240822
Firms seniority (between 2 and 5 years)	0.05	0.22	0	1	22240822
Firms seniority (more than 5 years)	0.89	0.31	0	1	22240822

Note: GS is Green Skills Intensity, GT is Green Tasks Intensity, GO is Degree of Greenness of Occupations, GNE is Green New and Emerging Occupations, GES is Green Enhanced Skills Occupations and GID is Green Increased Demand Occupations.
Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

Table 2 - Correlation coefficients between different green jobs classifications

	Green Skills	Green Tasks	Directly Green Occupations	Indirectly Green Occupations
Green Skills	1.000	0.349	0.148	0.183
Green Tasks		1.000	0.782	0.464
Directly Green Occupations			1.000	0.507
Indirectly Green Occupations				1.000

Note: Table report the correlation coefficients between different green jobs classifications. Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

2.3.3 Empirical strategy

In this study we apply a nonlinear probability model (Probit), testing the likelihood of being employed in a green job given by workers' and firms' characteristics and job conditions, providing a comparative analysis between the skill-based, task-based and occupation-based approaches. The model is specified in equations 6 and 7.

$$P(Y_{ift}|Z_{ift}) = \Phi(Z_{ift}) \quad \text{Eq. 6}$$

$$Z_{ift} = X_{ift}\beta + \gamma_f + \delta_t + \varepsilon_{ift} \quad \text{Eq. 7}$$

Y means being employed in a green job, defined as 1 when a worker *i* is working in a green job and 0 otherwise. *X* is the matrix of independent variables, such as age, education, gender, type of contract, wage, firms' capital, number of workers, firms' seniority and share of foreign capital.

Another goal is to study the wage premium associated with green job transition, testing if workers improve their income by changing to greener jobs or not. Thus, we have adapted an extension of the Mincer model, specified in equation 8 (Mincer, 1974).

$$Ln(\frac{W_{ift}}{H_{ift}}) = GM_{ift}\lambda + X_{ift}\beta + \alpha_i + \gamma_f + \delta_t + \varepsilon_{ift} \quad \text{Eq. 8}$$

To study the wage gap between green and non-green jobs we provide a Blinder-Oaxaca decomposition (Oaxaca and Ransom, 1994). For the Probit and Blinder-Oaxaca decomposition models, we employ a discrete measure. Since there is not a defined criterion, we consider a job as green if Green Skills and Tasks intensities are higher or equal to 0.1 and for occupations we consider a value of 0.5. We consider these criteria because we have more than twice green occupations than green skills and tasks

in terms of percentage. Thus, with these criteria, we end up with approximately the same number of green professions for all approaches, between 40 and 60 out of 427.

2.4 Results

This section presents our empirical findings on green jobs in Portugal, focusing on their prevalence, characteristics, and wage effects. We analyse the results from our three classification approaches: O*NET Green Occupations, O*NET Green Tasks, and ESCO Green Skills.

2.4.1 Green jobs distribution in Portugal

For 2019, according to our analysis, we found that 3.55% of jobs are related to green employment due to their green skills. Another 2.68% of jobs are related to green employment due to their green tasks, which is similar to the values observed by Vona et al. (2019). Additionally, 7.98% of jobs are directly related to green occupations, while 6.10% are indirectly related as showed in table 3.

Table 3 - Share of green employment in Portugal in 2019

Green Employment		
Approach	Category	Share
Degree of greenness of Occupations	*Directly green*	*7.98%*
	Indirectly green	*6.10%*
	Total	14.08%
Green Skills Intensity		3.55%
Green Tasks Intensity		2.68%

Note: This table presents the share of green employment in Portugal in 2019 following degree of greenness, green skills and tasks intensities approaches.
Source: *Quadros de Pessoal* 2019. Made by authors.

Table 4, below, displays the percentage of green jobs per sector in 2019, with darker shades indicating a higher proportion of green jobs. Note that these are rough estimates of the presence of green work.

Table 4 - Percentage of green jobs in different sectors, classified by skills, tasks, and occupations - percentage within sector, Portugal

Sector	Description	GS	GT	DGO	IGO
		%	%	%	%
A	Agriculture	21.46	1.50	2.93	5.03
B	Extracting Ind.	5.16	3.04	11.26	5.97
C	Manufacture	3.63	2.34	5.46	13.32
D	Electricity and gas	5.16	6.38	16.14	23.30
E	Water and waste	13.83	11.46	17.89	5.81
F	Construction	5.48	8.66	13.01	12.25
G	Trade	2.34	1.84	7.33	2.63
H	Transport	3.94	2.60	17.16	8.37
I	Accomodation	3.51	0.51	1.28	1.01
J	Communication	1.01	2.47	6.93	6.15
K	Financial Act.	1.53	4.03	12.06	0.28
L	Real estate	3.52	3.99	7.73	1.57
M	Consulting	3.58	4.27	12.20	3.05
N	Administrative	3.49	1.70	4.15	6.11
P	Education	1.58	0.82	2.04	0.58
Q	Health	1.41	0.47	1.01	0.46
R	Arts	2.95	1.88	3.92	2.36
S	Other serv.	2.67	1.64	3.10	1.53
U	International org.	1.18	1.12	7.37	0.00

Note: GS is Green Skills Intensity, GT is Green Tasks Intensity, DGO is Directly Green Occupations that include Green New and Emerging Occupations and Green Enhanced Skills Occupations and IGO is Indirectly Green Occupations that includes Green Increased Demand Occupations. Sectors defined accordingly with Portuguese CAE rev. 3.
Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

According to the GS, the agriculture sector presents the highest share of green employment, around 21.46%, highlighting the importance of green skills in this industry. Followed by Water and Waste Management and Construction with 13.83% and 5.48%, respectively. Regarding GT, statistics show that the Water and Waste Management, Construction and Electricity and Gas sectors have the highest share of green employment, between 6.38% and 11.46%. These sectors are also highlighted in the DGO, including Transport, Consulting, Financial Activity and Extracting sectors with share of green employment above 10%. Regarding IGO, we observe that sectors with the highest share of green jobs are Electricity and Gas, Manufacture and Construction with 23.30%, 13.32% and 12.25%, respectively. These facts suggest that the distribution of green jobs across sectors follows a similar pattern. The discussion regarding professions follows in subsection 2.5.

2.4.2 Characteristics of green jobs

One of the aims of this paper is to study green employment characteristics and analyse which type of firms are more likely to provide green job vacancies. For that, we tested the likelihood of being employed in a green job given by workers' and firms' characteristics and job conditions. Table 5 presents the marginal effects of factors influencing employment in green jobs, where we tested the likelihood of being employed in a green job given by workers' and firms' characteristics and job conditions.

As shown in Table 5, men are 2-5% more likely to work in green jobs than women. This trend may reflect existing gender imbalances in certain sectors or occupations, as shown by Goldin (2006) which may contribute to disparities in environmental awareness or preferences for green careers.

Additionally, and consistent with previous studies by Consoli et al. (2016), Bowen et al. (2018), Vona et al. (2018), Valero et al. (2021), and Bontadini and Vona (2023), green jobs demand more years of education and labour market experience, since workers in such jobs are more educated or experienced.

However, we found out that some indirect green jobs, which may involve manual work, require fewer years of education, where this relation becomes inverse. Furthermore, younger workers tend to dominate both indirect green jobs and green jobs identified by GT.

Working conditions are similar between approaches. In all models, green jobs pay higher wages and tend to offer fixed-term contracts, when compared with their non-green counterparts, as supported by previous studies (Saussay et al., 2022; Bluedorn et al., 2023; Curtis and Marinescu, 2023). These trends may reflect the higher value placed on green skills and knowledge in the labour market, as well as the temporary nature of some green projects or initiatives. The impact of industry affiliation on wages can differ based on the specific sector's commitment to sustainability. Moreover, regarding firms' characteristics, we found that older, smaller, and less capital-intensive firms with foreign investment are more likely to open green vacancies. Only in the GS, firms with a larger social capital have a higher probability of providing green jobs. Furthermore, GT jobs are more likely to be provided by younger firms.

Given these premises, previously reported Table 5 suggests that high-wage workers have a higher probability of being employed in a green job than low-wage workers, suggesting the existence of a green wage premium. The next step examines the disparities in pay, which are a good indicator of the overall quality of a job, using the wage regression model with fixed effects for workers. Within this model, the coefficients of the greenness measure indicate the increase or decrease in wages associated with changes in jobs. Results are reported in table 6.

Table 5 - Factors influencing employment in green jobs: average marginal effects of the Probit model

	GS	GT	DGO	IGO
Being employed in a Green Job				
Age (between 25 - 44)	0.016***	-0.016***	0.021***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Age (older than 44)	0.019***	-0.003***	0.033***	-0.012***
	(0.000)	(0.000)	(0.000)	(0.000)
Women	-0.023***	-0.042***	-0.048***	-0.041***
	(0.000)	(0.000)	(0.000)	(0.000)
Secondary	0.008***	0.008***	-0.006***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Higher Education	0.059***	0.060***	0.057***	-0.025***
	(0.000)	(0.000)	(0.000)	(0.000)
Effective Contract	-0.008***	-0.003***	-0.005***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
Wage (ln)	0.009***	0.050***	0.029***	0.020***
	(0.000)	(0.000)	(0.000)	(0.000)
Social Capital (ln)	0.001***	-0.004***	-0.002***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
No. Employees (1/1000)	-0.005***	-0.0004***	-0.003***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Share of Foreign Capital	0.028***	0.039***	0.004**	0.225***
(1/100)	(0.002)	(0.002)	(0.002)	(0.001)
Firm age (2-5 years)	-0.001**	-0.004***	0.000	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm age	0.001*	-0.007***	0.003***	0.003*
(more than 5 years)	(0.000)	(0.000)	(0.000)	(0.000)
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	19815435	19815435	19815435	19815426

Note: GS is Green Skills Intensity, GT is Green Tasks Intensity, DGO is Directly Green Occupations that include Green New and Emerging Occupations and Green Enhanced Skills Occupations and IGO is Indirectly Green Occupations that includes Green Increased Demand Occupations. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Source: *Quadros de Pessoal* from 2010 to 2019. Share of green tasks by occupation was collected from Elliott et al. (2024). Made by authors.

According to the GO, if a worker switches to a job with a higher level of greenness than their current job, they will receive a higher wage. This has been observed in previous studies (Sussay et al., 2022; Bluedorn et al., 2023; Curtis and Marinescu, 2023). The same effect is observed for GID, GES and

GNE occupations. However, the wage premium is higher when a worker switches to a greener GNE Occupation job within the same industry, revealing that greater training makes a greater return on wages. Additionally, the GS yielded similar results, but the wage premium was only half of what was previously observed.

On the other hand, the GT model showed the highest returns associated with a job transition. If a worker decides to switch to a greener position by 1 percentage point, they will receive a 0.063% increase in salary, while everything else remains constant. The higher returns to GT jobs suggest a labour shortage of workers with those specific green task skills. Overall, these results emphasize that the existence of a green wage premium can be used as a strong argument for education to train workers to adapt to new economic situations.

Table 6 - Wage differences in green jobs: high-dimensional fixed effect wage models

	Green Occupations				GS	GT
	GO	GID	GES	GNE		
Greenness	0.032***	0.024***	0.034***	0.066***	0.015***	0.063***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Secondary	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Higher Education	0.088***	0.088***	0.088***	0.088***	0.088***	0.088***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure	0.007***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure^2 (1/1000)	-0.201***	-0.202***	-0.201***	-0.202***	-0.202***	-0.202***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Potential experience	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Potential experience^2	-0.218***	-0.219***	-0.218***	-0.219***	-0.219***	-0.219***
(1/1000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.618***	1.621***	1.620***	1.621***	1.622***	1.620***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Worker fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22055844	22055844	22055844	22055844	22000572	22055845

Note: GS is Green Skills Intensity, GT is Green Tasks Intensity, GO is Degree Of Greenness of Occupations, GNE is Green New and Emerging Occupations, GES is Green Enhanced Skills Occupations and GID is Green Increased Demand Occupations. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Source: *Quadros de Pessoal* from 2010 to 2019. Share of green tasks by occupation was collected from Elliott et al. (2024). Made by authors.

All variables are statistically significant at 1% and are controlled for worker, industry, and year-fixed effects. The results remain robust even when firms' controls are included.

To further analyse, we present the three-fold Blinder-Oaxaca decomposition for the 2019 period in Table 7. This allows us to estimate to which extent the green wage premium is related with workers characteristics or jobs features.

From our point of view the results are aligned with the findings presented by Consoli et al. (2016), Bowen et al. (2018), Vona et al. (2018), Valero et al. (2021), and Bluedorn et al. (2023), since table 7 shows that the differences in employees' characteristics explain between around 35% and 80% of the salary gap between different approaches. Also, it has been shown that there is a considerable and unexplained difference in wages, that can be attributed to a premium over green collar workers[10] of approximately 24% and 58% of the wage gap. However, all the effects needed to be adjusted with the last row, which is the interaction that measures simultaneously the effect of endowments and coefficients.

Table 7 - Decomposition of the green wage premium: three-fold Blinder-Oaxaca decomposition

	GS	GT	DGO	IGO
Green Jobs	1.780***	1.914***	1.925***	1.770***
	(0.001)	(0.000)	(0.000)	(0.000)
Non-green Jobs	1.705***	1.689***	1.692***	1.706***
	(0.000)	(0.000)	(0.000)	(0.000)
Difference	0.075***	0.225***	0.233***	0.065***
	(0.001)	(0.001)	(0.000)	(0.000)
Endowments effect	0.060***	0.120***	0.135***	0.023***
	(0.000)	(0.000)	(0.000)	(0.000)
Coefficients effect	0.018***	0.087***	0.100***	0.038***
	(0.000)	(0.000)	(0.000)	(0.000)
Interaction	-0.004***	0.018***	-0.002***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	19813653	19813653	19813653	19813653

Note: GS is Green Skills Intensity, GT is Green Tasks Intensity, DGO is Directly Green Occupations that include Green New and Emerging Occupations and Green Enhanced Skills Occupations and IGO is Indirectly Green Occupations that includes Green Increased Demand Occupations. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Source: *Quadros de Pessoal* from 2010 to 2019. Share of green tasks by occupation was collected from Elliott et al. (2024). Made by authors.

[10] We define them as workers from green jobs.

To add to the insight, we follow to a two-fold Blinder-Oaxaca decomposition, presented in Table 8, below, which shows that the unexplained part of the wage gap is of 0.015, which means that around 20% of the wage gap can't be explained by endowments in the GS.

These findings highlight the complexity of the green wage premium, suggesting that it is influenced by a combination of factors, including worker characteristics, job attributes, and unobservable components. We conclude that green occupations pay better wages, regardless of workers' socio-demographics, productivity and firms' characteristics. For green jobs, by GT, we observe that around 46% of the wage gap remains unexplained. For DGO, adjusting employee socio-demographic, productivity and firms' characteristics to the same level as the green collar workers can explain around 58% of the wage gap. For IGO, the model is only capable of explaining around 35%.

Table 8 - Explaining the green wage gap: two-fold Blinder-Oaxaca decomposition

	GS	GT	DGO	IGO
Green Jobs	1.780***	1.914***	1.925***	1.770***
	(0.001)	(0.000)	(0.000)	(0.000)
Non-green Jobs	1.705***	1.689***	1.692***	1.706***
	(0.000)	(0.000)	(0.000)	(0.000)
Difference	0.075***	0.225***	0.233***	0.065***
	(0.001)	(0.001)	(0.000)	(0.000)
Explained	0.059***	0.123***	0.136***	0.023***
	(0.000)	(0.000)	(0.000)	(0.000)
Unexplained	0.015***	0.103***	0.097***	0.042***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	19813653	19813653	19813653	19813653

Note: GS is Green Skills Intensity, GT is Green Tasks Intensity, DGO is Directly Green Occupations that include Green New and Emerging Occupations and Green Enhanced Skills Occupations and IGO is Indirectly Green Occupations that includes Green Increased Demand Occupations. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.
Source: *Quadros de Pessoal* from 2010 to 2019. Share of green tasks by occupation was collected from Elliott et al. (2024). Made by authors.

The Blinder-Oaxaca decomposition showed that standard market factors are unable to totally explain the wage difference between two types of jobs. This indicates that we are either missing some crucial set of controls or that green jobs are indeed of better quality and, hence, offer higher wages. GS was shown to have the lowest wage gap and the percentage of unexplained difference, which makes sense, as skills are unobservable to the employer and, therefore, the compensation for possession of

green skills is lower. Because the absence of knowledge might be compensated with on-site training programs. On the other hand, GT was shown to have a higher share of unexplained gap which might be associated with the possibility to observe tasks and thus compensate them with higher prices. Thus, it leaves us with a question: what is hidden behind the unexplained part of the wage gap?

2.4.3 Green skills, tasks and occupations: complementary or substitute?

As described, green skills, tasks, and occupations capture different aspects of green employment. This subsection examines their correlations to determine whether they are complementary or distinct classifications. Table 9 presents the correlation coefficients.

Table 9 - Cross-correlation table

Variables	GS	GT	GO	GNE	GES	GID
GS	1.000					
GT	0.256	1.000				
GO	0.246	0.380	1.000			
GNE	0.217	0.695	0.327	1.000		
GES	0.192	0.280	0.651	0.040	1.000	
GID	0.098	0.051	0.702	0.106	-0.034	1.000

Note: This table presents the cross-correlation between all green jobs' approaches employed in this paper. GS is Green Skills Intensity, GT is Green Tasks Intensity, GO is Degree Of Greenness of Occupations, GNE is Green New and Emerging Occupations, GES is Green Enhanced Skills Occupations and GID is Green Increased Demand Occupations. Significance (p-value) of each correlation is 0.000.
Source: *Quadros de Pessoal* from 2010 to 2019. Share of green tasks by occupation was collected from Elliott et al. (2024). Made by authors.

The highest correlation between classifications is between GT and GNE occupations (0.695), while the lowest correlation is between GID and GES (-0.034).

If we adopt a threshold of 0.5 or higher to classify an occupation as green, only two occupations are simultaneously identified as green by both the GO and GS frameworks: Waste Collector (ISCO08 code 9611) and Waste Sorting (ISCO08 code 9612). This limited overlap reflects the fact that the two classifications are grounded in distinct conceptual foundations. The GO framework defines green jobs as those that, following the process of decarbonization, will contribute to the green economy through the development and deployment of environmentally sustainable technologies and activities. In contrast, the

GS framework identifies occupations as green based on the presence of specific competences and knowledge that facilitate the transition to a green economy.

As a result, the same occupation can be classified differently under the two approaches. For example, bus and tramway drivers are identified as green in the GO framework, as public transport use reduces car dependency and thereby mitigates emissions, which in turn increases demand for such occupations. However, in the GS framework, this occupation is associated with only one green competence, namely the promotion of sustainable transportation, and is therefore not categorized as green overall. This discrepancy illustrates that neither framework can be unambiguously regarded as superior, as each captures a distinct dimension of what constitutes a green job.

Although the correlation across approaches is weak, between 13 and 20 occupations are jointly classified as green depending on the methodology. Out of 427 occupations, 61 are identified as green under the GS approach, 43 under GT, and 60 under GO. The share of occupations jointly classified as green varies between 21.3% and 41.9%, depending on the pair of frameworks compared.

2.5 Discussion: the implications of differing green job definitions

The transition to a green economy demands precise tools to measure and analyse labour market shifts, yet our findings reveal that no single definition of green jobs suffices. By comparing three bottom-up classification systems, namely O*NET Green Occupations, O*NET Green Tasks, and ESCO Green Skills, this study shows how conceptual differences in measurement frameworks shape our understanding of green employment, labour market outcomes, and policy design. The Portuguese case demonstrates that green jobs account for 2-8% of employment depending on the methodology used, with significant variations in sectoral distribution, worker demographics, and wage premiums. These disparities underscore a critical result: green jobs are not a well-delimited category but a composition of roles shaped by varying economic, technological, and educational drivers.

The sectoral analysis highlights the practical challenges of relying on singular definitions. For instance, agriculture emerges as the greenest sector under the skill-based approach (21.46%), reflecting the need for environmentally conscious farming practices, while electricity and gas dominate occupation-based metrics (23.30%) due to renewable energy roles. Such divergence arises because skill-based and task-based approaches capture granular, often overlooked contributions to sustainability, such as a factory worker optimizing energy efficiency (tasks) or a technician trained in waste management (skills).

Conversely, occupation-based classifications prioritize roles directly tied to green technologies, like solar engineers, but risk overlooking partial greenness in hybrid jobs. This misalignment complicates sector-targeted policies. For example, a renewable energy push might boost occupation-based metrics but leave skill-driven sectors like agriculture underfunded.

Theoretical distinctions between classifications further shape their utility. Occupation-based metrics, rooted in industrial policy, assume green jobs cluster in specific sectors, making them ideal for macroeconomic planning. However, they oversimplify intra-sectoral diversity: a “brown" logistics firm employing electric vehicle technicians would be misclassified. Task-based approaches, aligned with technology-driven labour demand, better reflect incremental changes in roles shaped by automation and green innovation, such as retrofitting buildings for energy efficiency. These tasks are often transient, tied to evolving technologies, and susceptible to job polarization. Skill-based frameworks, emphasizing human capital adaptability, identify transferable competencies like environmental compliance, which span industries but lack sectoral specificity. While skills enable workforce resilience, their unobservability to employers (evidenced by lower wage premiums: 0.032% vs. 0.063% for tasks) suggests on-the-job training often substitutes formal education, masking inequities in access to green careers.

Empirically, the Blinder-Oaxaca decomposition reveals relevant inequities. While worker characteristics (education, experience) explain 35-80% of the green wage gap, a significant portion remains unexplained, notably 24-58% for tasks and occupations, 20% for skills. This residual premium signal structural biases, for green task-based roles, concentrated in tech-driven sectors like energy, disproportionately reward observable technical expertise (e.g., operating wind turbines), often excluding women and older workers. In contrast, the smaller unexplained gap in skill-based jobs suggests hidden disparities, such as unequal access to green training programs. Such findings challenge policymakers to look beyond aggregate employment figures and address systemic barriers in green transitions.

The weak correlation between classifications (e.g., 0.256 between Green Skills and Tasks) further underscores their complementary roles. For example, Waste Collectors (ISCO08 9611) are classified as green by all three systems, reflecting their direct environmental impact. However, most roles diverge: bus drivers are indirectly green under occupations (promoting public transport) but lack green skills beyond basic sustainability awareness. This misalignment has real-world consequences. A policymaker relying solely on occupation data might invest in renewable energy training, neglecting the need to upskill manufacturing workers in energy-efficient tasks. Conversely, a skill-focused strategy might prioritize generic sustainability competencies, overlooking sector-specific technical demands.

These insights require a detailed and thoughtful policy framework. For education and training, skill-based metrics should guide curricula to build adaptable competencies like circular economy principles, while task-based data can identify technical skills needed for emerging roles (e.g., carbon capture technicians). Industrial strategies should blend occupation and task metrics to target sectors with high green potential, such as retrofitting Portugal's aging construction sector. Considering that men dominate green roles across all metrics, equity initiatives must address demographic gaps by subsidizing STEM education for women and reskilling programs for older workers in declining industries.

However, the methodological approach shows limitations, namely, using uniform weights in crosswalking O*NET SOC2010 to ISCO08 introduced aggregation biases, potentially overestimating greenness in heterogeneous occupations. Future studies could weight occupations by employment shares or leverage real-time vacancy data to capture dynamic skill demands. Additionally, our pre-COVID data predate the EU's green stimulus, which may accelerate demand for roles in renewable energy and sustainable infrastructure.

In conclusion, the green transition is not a uniform process but an interaction of occupations, tasks, and skills. Policymakers must adopt hybrid strategies using occupation-based metrics for sectoral investments, task-based data for workforce adaptation, and skill-based frameworks for lifelong learning. For Portugal, this means pairing solar energy investments with vocational training in green construction tasks and competency certifications in sustainability. Our findings support multi-metric frameworks that balance precision with inclusivity, ensuring the green economy benefits all workers, and not just those in visibly green roles, for labour markets to fully harness the potential of the net-zero transition.

2.6 Conclusion

This study provides key insights into green employment, comparing classifications based on occupations (O*NET), tasks (O*NET), and skills (ESCO). Depending on the framework used, in our case study of Portugal, green jobs account for between 2% and 14% of total employment, with sectoral differences. Agriculture leads in skill-based roles (21.5%), while energy and construction dominate occupation-based classifications (23.3%). A clear green wage premium, particularly for task-based roles (0.063% per greenness unit), highlights the market's demand for sustainability-related skills, though gender and education gaps remain.

While our analysis enhances the understanding of green jobs, limitations remain. The mapping of O*NET to ISCO08 may introduce biases, and the pre-pandemic dataset may not fully reflect labour market shifts or recent EU green policies. Hence, future research should refine classification methods and incorporate real-time labour data to track evolving trends.

The findings emphasize the importance of adopting a balanced policy approach. A mix of occupation-based investments, task-driven vocational training, and skill-focused education programs can help align workforce development with sustainability goals. Recognizing the relationship between classifications will be essential in shaping a resilient labour market that supports both economic growth and environmental sustainability.

3 Unpacking the Green Wage Premium: The Role of Observable and Unobservable Characteristics in Green Job Wages

3.1 Introduction

There is no widely accepted definition of what constitutes green jobs. Early conceptual frameworks (e.g., OECD and Eurostat, 1999; European Commission, 2007; UNEP et al., 2008; Dierdorff et al., 2009; Ecorys, 2012), established the basis for future empirical applications (e.g., Becker and Shadbegian, 2009; Consoli et al., 2016; Bowen et al., 2018; Vona et al., 2018; Saussay et al., 2022). The literature is now rich in concepts and approaches to defining green jobs, allowing for flexibility and adaptability to the nature of the available data. Despite methodological diversity, most classifications fall into four categories: sector or industry-based (Becker and Shadbegian, 2009; Elliot and Lindley, 2017; Bontadini and Vona, 2023), occupation-based (Consoli et al., 2016; Bowen et al., 2018; Bowen and Hancké, 2019), task-based (Vona et al., 2018; Vona et al., 2019; Vona, 2021; Elliott et al., 2024), and job vacancy-based (Saussay et al., 2022; Curtis and Marinescu, 2023).

The conceptual and methodological diversity in measuring green employment leads to a wide range of estimated green job shares. Studies adopting industry-based or sector-based definitions (e.g., European Commission, 2007; Becker and Shadbegian, 2009; BLS, 2012, 2013; Elliot and Lindley, 2017; Eurostat, 2021; Saussay et al., 2022; Bontadini and Vona, 2023) or task-based classifications (Vona et al., 2019) typically report green employment shares of approximately 2%. In contrast, studies using binary occupational classifications (e.g., Consoli et al., 2016; Bowen et al., 2018) estimate green employment to exceed 10%.

A consistent empirical finding is that green jobs tend to offer higher wages (Consoli et al., 2016; Bowen et al., 2018; Saussay et al., 2022; Bluedorn et al., 2023). This wage premium is partly attributable to higher levels of observable human capital, such as formal education and work experience (Consoli et al., 2016; Bowen et al., 2018; Vona et al., 2018; Saussay et al., 2022; Bluedorn et al., 2023). However, unobserved skills, that are commonly referred to as ability, may also play a key role, particularly if such abilities are rewarded differently in green versus non-green occupations. For instance, worker productivity in green jobs may also benefit from the complementarity between human and physical capital, especially in more capital-intensive green jobs.

Several studies (Becker and Shadbegian, 2009; Elliot and Lindley, 2017; Saussay et al., 2022; Bluedorn et al., 2023) report increasing demand for skilled and middle-skilled workers, alongside declining demand for unskilled labour, within green sectors. This trend may amplify wage differentials between green and non-green employment. Nevertheless, this relationship is not necessarily linear. For example, Popp et al., (2021) show that skilled workers in renewables may earn less than those in fossil fuels, while unskilled workers tend to earn more, challenging the assumption that higher qualifications always translate into higher green wages.

To address these complexities, this paper employs a methodology that estimates not only individual fixed effects but also a rich set of interactions between unobserved heterogeneity and key explanatory variables. This approach allows us to control for variation in the returns to unobserved characteristics across job types, while simultaneously estimating returns to observable worker characteristics.

In this study, we use QP, a longitudinal linked employer-employee dataset from Portugal. Our approach follows the continuous measurement of green tasks and occupations proposed by Dierdorff et al. (2009), excluding occupations with increased demand due to the green transition, as suggested by Consoli et al. (2016), since these roles only indirectly benefit from sustainable development efforts. As the original classification of green occupations was based on the U.S. SOC2010, we adapt this to the ISCO08 by computing a simple weighted average to reflect the degree of greenness of each occupation. This adaptation follows a similar methodology to that used by Vona et al. (2018, 2019), Valero et al. (2021), Vona (2021) and Elliot et al. (2024). For task-level green intensity, we directly use the scores provided by Elliot et al. (2024). Additionally, we construct a binary green job indicator, as detailed in subsection 3, for decomposition analyses.

This paper offers two main contributions. First, it disentangles the green wage premium by controlling for observable worker characteristics (such as tenure, age, and education), firm-level variables (including size, ownership, and social capital), and unobserved heterogeneity at both the worker and firm level. Second, it estimates the returns to unobservable abilities associated with green occupations, replicating the analysis for a sample of displaced workers, a strategy that mitigates concerns regarding endogenous worker–firm matching.

The remainder of this paper is structured as follows: Subsection 2 presents the econometric framework, and subsection 3 describes the dataset. Subsection 4 discusses the results, and subsection 5 concludes.

3.2 Data and summary statistics

3.2.1 Data sources and sample selection

In this study, we use QP, a longitudinal linked employer-employee dataset that includes all paid private sector workers in Portugal. QP provides detailed socioeconomic and demographic information on workers, such as age, gender, tenure, occupation, salary, working hours, contract type and duration, as well as comprehensive firm-level data, including firm size, location, industry, and ownership type. Each worker and their corresponding firm are assigned a unique, anonymized identifier, allowing for longitudinal tracking while preserving confidentiality. QP dataset is based on a mandatory annual survey conducted by the Portuguese Ministry of Labour and Social Security, covering all firms with at least one dependent employee. The data is made available through Statistics Portugal.

To ensure data quality and consistency, we imposed several exclusion criteria. Specifically, we removed individuals who: worked fewer than 30 hours during the reference month; earned less than half or more than 25 times the national minimum wage; were self-employed; were younger than 17 or older than 67; were employed in firms with fewer than six employees; presented missing information in any of the relevant variables. Furthermore, we excluded all singleton observations to facilitate within-group variation analyses. The analysis focuses on the period between 2010, the year in which the current Portuguese classification system of occupations was last revised, and 2019, the final pre-pandemic year. The final analytical sample comprises 16,368,859 observations.

To reduce the endogeneity created by worker-firm mobility, such as the bargain effect on job change, we also consider a sample of displaced employees who lost their jobs due to the firm's closure between 2013 and 2015. After applying similar cleaning procedures, we also excluded all observations with at least one variable missing and that we weren't able to track in the period between 2010 and 2019. Reducing our sample to 174,652 observations.

We further incorporate information on observable skill intensities to characterise occupations, drawing from the European multilingual classification ESCO, developed by the European Commission. The ESCO framework identifies and hierarchically organises skills, competences, and occupations relevant to the EU labour market, education, and training systems, ranging from broad occupational groups to specific professions and skill sets. ESCO systematically maps the relationships between occupations and the underlying competences and knowledge requirements, enabling a structured analysis of skill intensity across occupations. For the purposes of this study, we utilise data on eight broad skill categories across 423 occupations, classified at the 4-digit level of the ISCO-08 taxonomy.

3.2.2 Measuring green jobs

The O*NET (developed under the sponsorship of the U.S. Department of Labor/Employment and Training Administration (USDOL/ETA), is one of the primary sources of occupational information in the United States. Its database includes hundreds of standardised and occupation-specific descriptors for nearly 1,000 occupations, covering a wide range of skills, tasks, and work activities. As part of the O*NET Green Economy initiative, Dierdorff et al. (2009) introduced a classification of occupations based on their anticipated evolution in response to the green transition. This classification distinguishes among: existing occupations for which demand is expected to increase without significant changes in task or skill composition (GID Occupations)*;* existing occupations that are likely to undergo substantial transformations in tasks and required skills (GES Occupations); and entirely new and emerging occupations driven by green technologies and activities (GNE Occupations).

In this Chapter, we employ O*NET version v24.1, considering only GES and GNE occupations, as proposed by Consoli et al. (2016). We exclude GID occupations due to weaker conceptual grounding and lack of input-output analysis validation to corroborate projected demand increases.

The O*NET classification of green occupations is based on the 8-digit SOC 2010 system, whereas the Portuguese Classification of Professions follows the 4-digit ISCO-08 taxonomy. To adapt the O*NET classification to our analytical framework, we proceeded in two steps. First, for each 6-digit SOC 2010 occupational group, we calculated the proportion of green occupations, defined as either green enhanced or green new and emerging, relative to the total number of 8-digit occupations within that group. This ratio was interpreted as the degree of greenness of the 6-digit SOC2010 occupation. Second, using the correspondence table provided by the U.S. BLS, which maps 4-digit ISCO08 occupations to 6-digit SOC2010 codes, we computed the degree of greenness for each ISCO08 occupation by averaging the greenness scores of all associated SOC2010 occupations. The process is summarised as follows:

$$Degree\ of\ greenness_{6d-SOC2010} = \frac{Number\ of green\ professions_{8d-SOC2010}}{Total\ number\ of\ professions_{8d-SOC2010}} \quad \text{Eq. 9}$$

$$Degree\ of\ greenness_{4d-ISCO08} = \frac{\sum Degree\ of\ greenness\ of\ linked\ SOCprofessions_{6d-SOC2010}}{Total\ number\ of\ linked\ SOCprofessions_{6d-SOC2010}} \quad \text{Eq. 10}$$

Moreover, the O*NET database includes over 19,000 occupation-specific task statements, from which a subset of 1,369 green tasks has been identified. These tasks reflect changes in work content and worker requirements driven by the adoption of green technologies and environmentally sustainable practices. Based on this information, it is possible to compute a green task intensity score for each occupation, representing the extent to which green tasks are embedded in the occupation's task profile, a continuous measure of job greenness (Vona et al., 2018). The mapping and calculation of green task intensities for the ISCO08 classification were previously carried out by Elliott et al. (2024). In this study, we draw on their estimates, using the available values for 83 out of the 436 ISCO08 occupations in our dataset.

3.2.3 Descriptive statistics

Tables 10 and 11 present summary statistics for the full sample and for the subsample of displaced workers. The statistics are organised into seven groups: time period; green job measures (continuous and binary); workers' socioeconomic characteristics; working conditions; firm-level indicators; and measures of occupational skill intensities. We employ two continuous measures of green jobs. The first captures the degree of greenness associated with each occupation, based on classifications of GES and GNE Occupations, hereafter referred to as green occupations. The second is a measure of the intensity of green tasks performed in each job, as reported by Elliott et al. (2024).

In addition, for statistical description and decomposition analysis, we include binary classifications. For green occupations, the binary variable equals 1 if the greenness score is greater than or equal to 0.5, and 0 otherwise. For green task intensity, the cut-off is set at 0.1.

The socioeconomic indicators include workers' age, tenure, potential experience, gender, and education level. Age, tenure, and potential experience are measured in years. Since direct data on potential experience were not available, we computed it as: Experience = Age – Years of Schooling – 6. This follows the assumption that formal schooling in Portugal typically begins at age six. Gender is captured by a binary variable that equals 1 for women and 0 for men. Education is treated as a categorical variable: 1 for below secondary education, 2 for secondary education, and 3 for tertiary education.

Regarding working conditions, we include total nominal wage income (expressed in euros), the number of regular and extra hours worked in the reference month, and the type of employment contract.

The latter is represented by a binary variable that equals 1 for open-ended (permanent) contracts and 0 for fixed-term contracts.

Firm-level controls include the number of employees, ownership structure (measured as the percentage of foreign investment), firm capital (social capital), and average labour productivity. As direct data on productivity were unavailable, we approximated it by dividing firms' total turnover by the number of employees.

Finally, we summarise the observable skill intensities of ESCO occupations. These are continuous variables ranging from 0 to 1 and serve primarily as controls for occupational characteristics. In practice, the specific combination of skill intensities defines a given occupation. While it would be possible to replace these controls with occupation fixed effects (i.e., profession dummies), doing so may create multicollinearity issues with the green job measures, since both are time-invariant and occupation-specific.

Table 1 provides summary statistics for the whole sample of over 16 million observations. The proportion of green jobs in the sample is relatively low, with only 7% of observations classified as green occupations and an average green task intensity of just 3%. This suggests that green employment continues to be a specialised area within the labour market.

The average worker in terms of socioeconomic indicators is approximately 40 years old, with nearly 9 years of tenure and 24 years of potential experience. The sample consists of 43% female workers, and half of the workers have an educational level of less than secondary education. Regarding working conditions, the average monthly income is approximately €1,150, with employees working an average of 167.5 normal hours per month and 1.75 extra hours, on average. The majority (74%) are employed on open-ended contracts.

Firm-level statistics reveal substantial variation: firms employ an average of 1,272 workers, but with a very high standard deviation, indicating significant heterogeneity in firm size. The average share of foreign ownership is about 17%, and firm productivity varies widely.

Finally, the occupational skill intensities show that tasks related to communication, information, and care are the most prominent, while technical and manual skills like constructing or operating machinery are less frequent, reflecting a service-oriented labour market.

Table 11 presents summary statistics for displaced workers, a subgroup of approximately 175,000 observations. Compared to the full sample in Table 10 (over 16 million observations), displaced

workers differ in several important dimensions from the overall workforce. On average, they are slightly older (41.2 vs. 40.1 years), possess higher educational attainment, reflected in a greater share holding tertiary education (26% vs. 20%), and show higher levels of potential experience. They earn higher wages on average (€1,340 vs. €1,150) and are more likely to hold open-ended contracts (84% vs. 74%), indicating that displacement is not confined to precarious or low-skilled employment.

In terms of job content, displaced workers are more concentrated in green occupations and exhibit higher intensities of green tasks, whether measured continuously or via binary classifications. They also show slightly higher values in skill dimensions such as communication, information processing, and management, suggesting greater engagement in cognitive, non-routine tasks. Conversely, they are less involved in manual or physically intensive occupations.

These patterns suggest that job displacement may increasingly affect mid-skilled to high-skilled workers, potentially linked to sectoral restructuring and environmental transitions. This underscores the importance of considering both skill composition and occupational greenness when analysing labour market disruptions.

Table 10 - Summary statistics

	Mean	SD	Min	Max	N
Time spawn					
Year	2015	3	2010	2019	16368859
Green Continuous Measures					
Green occupations	0.07	0.18	0.00	1.00	16368859
Green tasks intensities	0.03	0.09	0.00	1.00	16368859
Green Binary Measures					
Green occupations	0.07	0.26	0.00	1.00	16368859
Green tasks intensities	0.09	0.28	0.00	1.00	16368859
Socioeconomics indicators					
Age	40.14	10.62	17.00	67.00	16368859
Tenure	8.78	9.10	0.00	55.00	16368859
Potential experience	24.17	12.39	0.00	57.00	16368859
Woman	0.43	0.49	0.00	1.00	16368859

Bellow secondary education	0.50	0.50	0.00	1.00	16368859
Secondary education	0.29	0.46	0.00	1.00	16368859
Higher education	0.20	0.40	0.00	1.00	16368859
Working conditions					
Total income (€)	1149.70	906.82	237.50	15000.00	16368859
Normal worked hours	167.50	14.65	30.00	260.00	16368859
Extra worked hours	1.75	7.78	0.00	301.00	16368859
Open-ended contract	0.74	0.44	0.00	1.00	16368859
Firms indicators					
Number of employees	1272.24	3587.92	6.00	25612.00	16368859
Share of foreign ownership (%)	16.75	36.14	0.00	100.00	16368859
Social capital (in millions of €)	104.20	608.18	1.00e-06	7068.17	16368859
Productivity (in thousands of €)	163.38	850.38	0.00	206469.70	16368859
Observable skills intensities					
Communication, collaboration and creativity	0.22	0.13	0.00	0.90	16368859
Information skills	0.19	0.09	0.00	0.62	16368859
Assisting and caring	0.16	0.13	0.00	0.60	16368859
Management skills	0.14	0.11	0.00	0.51	16368859
Working with computers	0.04	0.06	0.00	0.69	16368859
Handling and moving	0.13	0.15	0.00	0.79	16368859
Constructing	0.02	0.06	0.00	0.37	16368859
Working with machinery and specialised equipment	0.09	0.11	0.00	0.59	16368859

Note: Summary statistics of the full sample.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

Table 11 - Summary statistics displaced workers

	Mean	SD	Min	Max	N
Time spawn					
Year	2015	3	2010	2019	174652
Green Continuous Measures					
Green occupations	0.08	0.18	0.00	1.00	174652
Green tasks intensities	0.04	0.11	0.00	1.00	174652
Green Binary Measures					
Green occupations	0.08	0.27	0.00	1.00	174652
Green tasks intensities	0.11	0.31	0.00	1.00	174652
Socioeconomics indicators					
Age	41.18	8.56	17.00	67.00	174652
Tenure	8.18	7.82	0.00	52.00	174652
Potential experience	24.72	10.25	0.00	57.00	174652
Woman	0.39	0.49	0.00	1.00	174652
Bellow secondary education	0.43	0.50	0.00	1.00	174652
Secondary education	0.30	0.46	0.00	1.00	174652
Higher education	0.26	0.44	0.00	1.00	174652
Working conditions					
Total income (€)	1340.57	966.75	237.50	14675.69	174652
Normal worked hours	167.83	12.46	30.00	217.00	174652
Extra worked hours	1.37	6.89	0.00	173.00	174652
Open-ended contract	0.84	0.37	0.00	1.00	174652
Firms indicators					
Number of employees	882.62	2223.69	6.00	25612.00	174652
Share of foreign ownership (%)	16.57	35.81	0.00	100.00	174652
Social capital (in millions €)	129.76	600.46	1.00e-06	7068.17	174652
Productivity (in thousands of €)	253.60	1443.94	0.00	1717.62	174652

Observable skills intensities					
Communication, collaboration and creativity	0.23	0.12	0.00	0.90	174652
Information skills	0.21	0.10	0.00	0.62	174652
Assisting and caring	0.13	0.11	0.00	0.60	174652
Management skills	0.15	0.11	0.00	0.51	174652
Working with computers	0.05	0.07	0.00	0.69	174652
Handling and moving	0.11	0.13	0.00	0.79	174652
Constructing	0.02	0.05	0.00	0.37	174652
Working with machinery and specialised equipment	0.09	0.11	0.00	0.59	174652

Note: Summary statistics of displaced workers between 2013 and 2015. The analysis is based on the original sample of 16,368,859 observations.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

Table 12 provides a comparison of means between green and non-green occupations based on a binary classification. Four categories of professions are considered: green occupations (in this Chapter referred as GO), defined as those with a degree of greenness that is equal to or above 0.5; non-green occupations (in this Chapter referred as NGO), with a degree of greenness below 0.5; green jobs (in this Chapter referred as GT), where green task intensity is higher than or equal to 0.1; and non-green jobs (in this Chapter referred as NGT) where green task intensity is lower than 0.1.

Workers from green and non-green jobs differ across several key dimensions. On average, workers in green jobs tend to be slightly older (42.0 and 40.9 years) than those in non-green jobs (40.0 and 40.1 years). They are also more likely to hold a higher education, as the share of holders of tertiary education is higher (31% vs 19%). Additionally, the representation of women in green jobs is significantly lower than that of men (19% and 26% vs 45% and 44%). On average, workers from green jobs earn more (€1561 and €1597 vs €1116 and €1107), are employed in more productive firms (195 and 207 vs 160 and 159, in thousands of €), in smaller firms (872 and 959 vs 1304 and 1301 workers) and in firms with higher social capital (167 and 165 vs 99 and 98, in millions of €).

The full-length summary statistics, including measures of central tendency and dispersion for different types of jobs, are provided in tables A1, A2, A3 and A4 in the appendix.

Table 12 - Means of green and non-green jobs

	GO	NGO	GT	NGT
Time span				
Year	2015	2015	2015	2015
Socioeconomics indicators				
Age	42.00	40.00	40.90	40.07
Tenure	8.64	8.79	9.16	8.74
Potential experience	25.52	24.06	24.25	24.16
Woman	0.19	0.45	0.26	0.44
Bellow secondary education	0.48	0.51	0.44	0.51
Secondary education	0.21	0.30	0.25	0.30
Higher education	0.31	0.19	0.31	0.19
Working conditions				
Total income (€)	1561.89	1116.76	1597.70	1107.45
Normal worked hours	168.28	167.44	167.75	167.48
Extra worked hours	2.08	1.73	1.87	1.74
Open-ended contract	0.74	0.74	0.75	0.74
Firms indicators				
Number of employees	872.16	1304.21	959.72	1301.71
Share of foreign ownership (%)	17.35	16.71	20.37	16.41
Social capital (in millions of €)	167.84	99.12	165.61	98.41
Productivity (in thousands of €)	195.36	160.82	207.52	159.22
Observable skills intensity				
Communication, collaboration and creativity	0.20	0.22	0.21	0.22
Information skills	0.22	0.19	0.21	0.19
Assisting and caring	0.14	0.16	0.14	0.16
Management skills	0.14	0.14	0.14	0.14
Working with computers	0.04	0.04	0.03	0.04
Handling and moving	0.11	0.14	0.14	0.13

Constructing	0.02	0.02	0.03	0.02
Working with machinery and specialized equipment	0.14	0.09	0.09	0.09

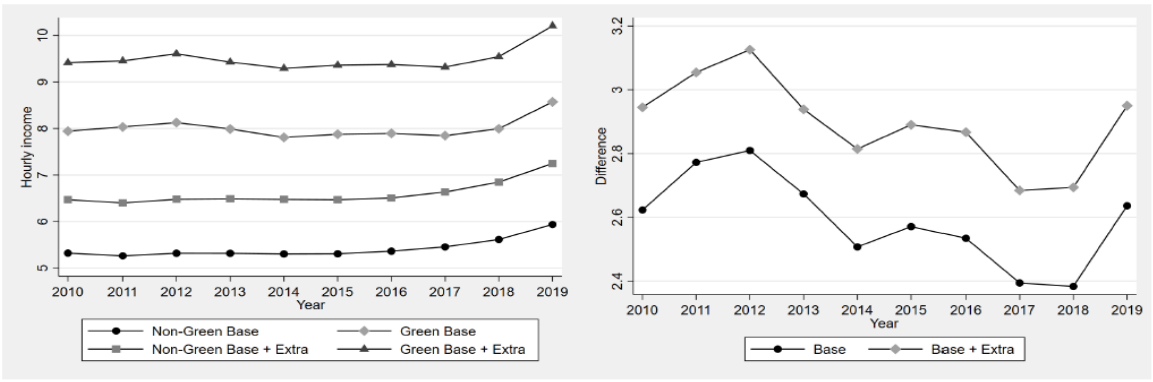
Note: All reported values correspond to sample means. The analysis is based on four distinct classifications, each derived from the original sample of 16,368,859 observations. GO are occupations with a greenness score greater than or equal to 0.5. NGO are non-green occupations with a greenness score lower than 0.5. GT are green occupations with green task intensity higher than or equal to 0.1. NGT are non-green occupations with green task intensity lower than 0.1.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

3.2.4 The wage gap between green and non-green jobs

Figures 1 and 2 present the average nominal hourly wages for green and non-green jobs using the binary classification based on green task intensity, where a job is considered green if its intensity is equal to or greater than 0.1. Figures 3 and 4 depict the same comparison, but using an alternative classification in which occupations are considered green if their degree of greenness is equal to or above 0.5.

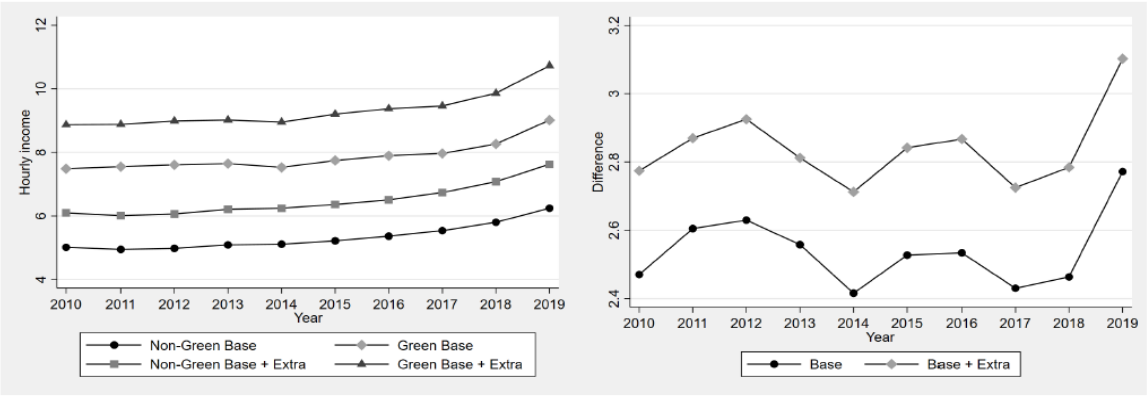
Figure 1 reveals that, when using the task-based classification, green jobs pay on average between €2.60 and €2.80 more per hour in base nominal wages compared to non-green jobs. As shown in Figure 2, the gap is even wider when considering total real wages, ranging between €2.70 and €3.10 per hour.



(a) Base and total income (b) Difference

Figure 1 – Green and non-green jobs average nominal hourly income (€), by green tasks intensities.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

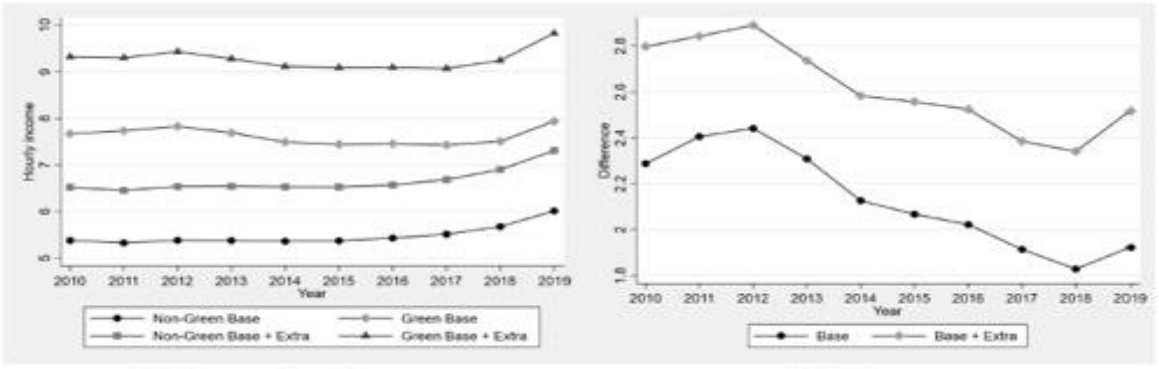


(a) Base and total income (b) Difference

Figure 2 – Green and non-green jobs average real hourly income (€) (base year = 2016), by green tasks intensities

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

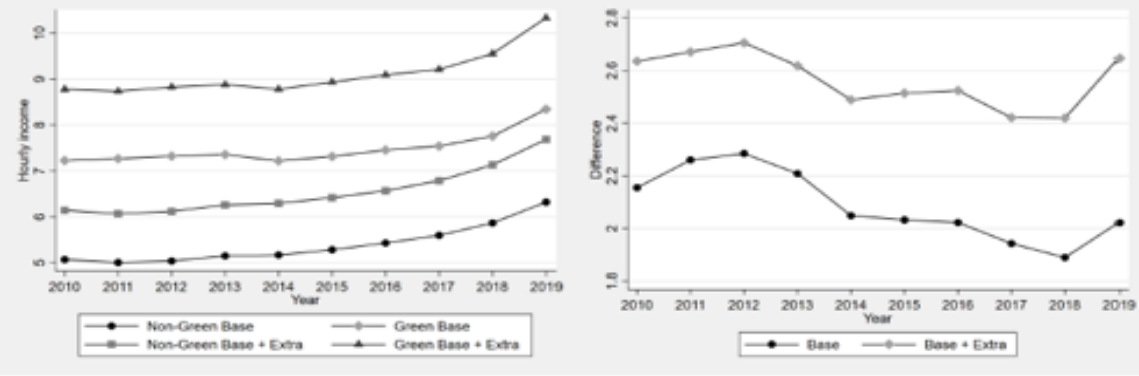
In relation to green occupations (see Figure 3), we notice a similar trend: green jobs pay, on average, between €1.80 and €2.40 more per hour than non-green jobs when considering base nominal hourly income. When examining total hourly income, the difference increases to around €2.40 to €3.00 (Figure 4 for real income).



(a) Base and total income (b) Difference

Figure 3 - Green and non-green jobs average nominal hourly income (€), by green occupations.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.



(a) Base and total income (b) Difference

Figure 4 - Green and non-green jobs average real hourly income (€) (base year = 2016), by green occupations.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

We then apply the two-fold Blinder-Oaxaca wage decomposition to examine wage differentials between green and non-green jobs. This technique decomposes the observed wage gap into two components: the explained component (endowment effect), which accounts for differences in observable characteristics between the two groups, such as education, experience, and tenure; and the unexplained component (coefficient effect), which reflects differences in the returns to those characteristics, as well as the influence of unobserved factors and potential labour market discrimination.

Table 13 presents the results of the Blinder-Oaxaca decomposition, where the dependent variable is the logarithm of nominal hourly wages for both groups. The overall wage differential between green and non-green jobs is positive and statistically significant at the 1% level. This finding remains robust across specifications with different sets of controls.

In Column 1, we find that approximately 59.70% of the wage gap can be explained by differences in workers' socioeconomic and demographic characteristics, productivity-related variables, and firm-level indicators. However, when occupational controls are included, the explained portion of the gap declines to 54.85%, suggesting that occupational sorting plays a role in the wage structure. For decompositions based on the alternative definition of green occupations, the explained share ranges from 66.02% to 67.57%, indicating slightly higher explanatory power under this classification.

The unexplained component, therefore, accounts for a substantial portion of the wage premium associated with green jobs. This may reflect higher returns to unobserved abilities or task-specific competencies that are more common in green occupations. It could also signal a labour market valuation

of green-related tasks or the presence of compensating wage differentials for engaging in environmentally sustainable activities. Alternatively, it may indicate structural differences in wage setting mechanisms between green and non-green segments of the labour market.

Table 13 - Two-fold Blinder-Oaxaca decomposition of green and non-green jobs

Type of occupation	GT	GT	GO	GO
Controls	Workers and firms	Workers, firms and skills	Workers and firms	Workers, firms and skills
Green jobs	1.993***	1.993***	1.988***	1.988***
	(0.001)	(0.001)	(0.001)	(0.001)
Non-green jobs	1.725***	1.725***	1.729***	1.729***
	(0.000)	(0.000)	(0.000)	(0.000)
Difference	0.268***	0.268***	0.259***	0.259***
	(0.001)	(0.001)	(0.001)	(0.001)
Explained	0.160***	0.147***	0.175***	0.171***
	(0.000)	(0.000)	(0.000)	(0.000)
Unexplained	0.108***	0.121***	0.084***	0.088***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	16249392	16249392	16249392	16249392

Note: GO is green occupations with a greenness score greater than or equal to 0.5. GT is green occupations with green task intensity higher than or equal to 0.1. Workers and firms include: gender, age, age^2, education, potential experience, potential experience^2, tenure, tenure^2, open-ended contract, productivity, firm's social capital, number of employees and share of foreign ownership. Skills control include: communication, collaboration and creativity, information skills, assisting and caring, management skills, working with computers, handling and moving, constructing, working with machinery and specialised equipment. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

The existence of a wage gap between the two groups is evident. While more than half of this gap, ranging from approximately 55% to 67% depending on the specification, is explained by observable characteristics, a meaningful share remains unexplained. What lies behind this residual component? If standard endowments fail to fully account for the differential, does it imply that firms value unobservable

worker traits more when hiring for green jobs? Is there a premium associated with the green label itself? Or are there other latent factors influencing wage formation?

These questions motivate the next stage of our analysis, where we move beyond standard decomposition techniques to estimate a structural model that explicitly controls for unobserved worker heterogeneity and differential returns across job types.

3.3 Accounting for unobserved heterogeneity - An econometric framework

To address our research questions, we estimate two empirical models. The first is an extension of the Mincerian wage equation (Mincer, 1974), augmented to account for both worker and firm heterogeneity. The model is specified as follows:

$$Ln\left(\frac{W_{ift}}{H_{ift}}\right) = \sigma G_{ift} + \sum_{k} \beta_k X_{ift}^{k} + \alpha_i + \gamma_f + \delta_t + \epsilon_{ift} \qquad \text{Eq. 11}$$

Where the dependent variable is a natural logarithm of nominal hourly wage of worker *i*, in firm *f*, at time *t*. The variable G_{ift} represents a continuous measure of greenness, either in terms of the green content of the occupation or the green task intensity. The vector X_{ift}^{k} includes a set of *k* control variables capturing worker-level socioeconomic characteristics, working conditions, firm-level attributes, and observable skill intensities. The terms α_i and γ_f denote worker and firm fixed effects, respectively, capturing time-invariant unobserved heterogeneity. δ_t represents a full set year dummies, and ϵ_{ift} is the idiosyncratic error term.

This framework is versatile as it captures different effects of wage differences between workers from green and non-green jobs. If the model is estimated by means of Ordinary Least Square (OLS), excluding all fixed effects, the coefficient σ captures the average wage difference associated with green versus non-green jobs. When worker fixed effects (α_i) are included, σ reflects the within-worker return to transitioning into a greener occupation, net of time-invariant individual characteristics. Further adding firm fixed effects (γ_f) enables the model to account for firm-specific wage premiums, allowing σ to isolate the wage return to greenness while controlling for changes in employer. Each specification has its strengths and limitations. The OLS model may be biased due to unobserved worker and firm heterogeneity. Including worker fixed effects controls for time-invariant individual traits, but may still miss time-varying

factors. Adding firm fixed effects accounts for employer-specific wage premiums, but restricts identification to mobile workers, potentially limiting the generalisability of the results.

The second empirical model builds on the framework proposed by Cerejeira and Guimarães (2012), which was originally developed to estimate the employer size wage premium while controlling for unobserved worker heterogeneity. This model assumes an exponential production function and perfect competition, under which output is equated to hourly wages. The log hourly wage equation for green and non-green jobs is specified as follows:

$$Ln\left(\frac{W_{ift}}{H_{ift}}\right)^{j} = \beta_0^j + \sum_k \beta_k^j X_{ift}^k + c^j\theta_i + \gamma_f + \delta_t + \epsilon_{it}, \qquad \text{Eq. 12}$$

where $j \in \{g, ng\}$ denotes whether the worker is in a green (g) or in a non-green occupation (ng). θ represents the worker's unobserved effective ability, which may be priced differently in green and non-green jobs (i.e., $c^j \in \{c^g, c^{ng}\}$). X_{ift}^k is a vector of observed human capital endowments and firm characteristics, whose returns are also occupation-specific ($\beta_k^j \in \{\beta_k^g, \beta_k^{ng}\}$). γ_f denotes firm fixed effects, δ_t captures time effects, and ϵ_{it} is the error term.

For each worker, the expected wage differential between a green and a non-green job is given by:

$$E(G_{ift}) = \beta_0 + \sum_k \beta_k X_{ift}^k + c\theta_i, \qquad \text{Eq. 13}$$

where $\beta_0 = \beta_0^g - \beta_0^{ng}$, $\beta_k = \beta_k^g - \beta_k^{ng}$ and $c = c^g - c^{ng}$. Thus, the wage differential between green and non-green jobs can be decomposed into three components: a pure green job wage premium, reflected in differences in the intercepts of the wage equations; the differences in the returns to observable characteristics (e.g., education, experience, firm size); and, the returns to unobservable abilities, which may be valued differently across occupations.

An estimable equation based on equation (12) can be written as:

$$Ln\left(\frac{W_{ift}}{H_{ift}}\right) = \beta_0^{ng} + \sum_k \beta_k^{ng} X_{ift}^k + c^{ng}\theta_i + G_{ift}[\beta_0 + \sum_k \beta_k X_{ift}^k + c\theta_i] + \gamma_f + \delta_t + \epsilon_{it}, \qquad \text{Eq. 14}$$

Which can be rearranged as:

$$Ln\left(\frac{W_{ift}}{H_{ift}}\right) = \beta_0^{ng} + G_{ift}\beta_0 + \sum_k \beta_k^{ng} X_{ift}^k + G_{ift} \sum_k \beta_k X_{ift}^k + c^{ng}\theta_i + G_{ift}c\theta_i + \gamma_f + \delta_t + \epsilon_{it} \quad \text{Eq. 15}$$

This specification allows the time-invariant unobserved heterogeneity θ_i to interact with the green job indicator G_{ift}, which equals 1 when the worker is employed in a green job and 0 otherwise. Although G_{ift} can also be modelled as a continuous measure of occupational greenness, we treat it as a binary variable here for simplicity. In the empirical estimation, however, we will employ the continuous measure to capture variation in greenness intensity more precisely.

Estimating the previous equation using OLS would yield inconsistent estimates of the average wage gap β_0 and the interaction coefficients β_k. This inconsistency arises because the error component, specifically, $[c^{ng} + G_{ift}c]\theta_i + \gamma_f + \delta_t + \epsilon_{it}$, is correlated with the green job indicator G_{ift} if θ_i (the unobserved ability) influences the worker's occupational choice. Moreover, θ_i cannot be eliminated by first-differencing since it interacts with G_{ift}, making the term $[c^{ng} + G_{ift}c]\theta_i$ time-varying and therefore not differenced out.

Letting $c^{ng}\theta_i = \alpha_i$ and $c\theta_i = \lambda_i$, the model can be expressed in the following matrix form:

$$\boldsymbol{Y} = \boldsymbol{XB} + \boldsymbol{D\alpha} + \boldsymbol{GD\lambda} + \boldsymbol{\epsilon} \quad \text{Eq. 16}$$

Where **Y** is the vector of log hourly wages, the matrix **X** includes all observed covariates X_{ift}^k and their interactions with the green job indicator, **D** of individual-specific dummy variables capturing unobserved heterogeneity and, finally, **GD** contains the interactions between these fixed effects and the green job indicator. Given the high dimensionality of the model, particularly due to the inclusion of numerous fixed effects, the standard Least Squares Dummy Variable (LSDV) approach becomes computationally infeasible. To address this, we follow the simplification proposed by Guimarães (2012), applying the Frisch-Waugh-Lovell (FWL) theorem to partial out fixed effects efficiently. For a detailed explanation of this procedure, see Cerejeira and Guimarães (2012) and Guimarães and Portugal (2010).

3.4 Results and robustness checks

3.4.1 Main findings

Table 14 presents the estimation results of Eq. 11, initially excluding observable occupations' skill intensities. The three specifications correspond to pooled ordinary least square (POLS), a fixed effects (FE) model with worker-level controls, and a high-dimensional fixed effects (HDFE) model, respectively, controlling for both worker and firm heterogeneity, as well as year effects. Across all models, the results are robust and statistically significant at the 1% level.

According to the green task intensity specification (first sub-column in each model), green jobs pay substantially more than their non-green counterparts. Specifically, a 1 percentage point increase in the green intensity of a job is associated with a 0.464% increase in wages in the POLS model. In practical terms, if an individual move from a job with a green task intensity of 0.50 to one with 0.51, they would receive, on average, a 0.464% wage premium, all else equal. When using green occupations as the measure, the premium is approximately 0.192% per percentage point, when everything else is kept constant.

The FE model allows for a dynamic interpretation. If a worker transitions to a greener job within the same firm, they can expect a modest wage gain (0.037%–0.070%). However, when this move involves switching employers, thus introducing firm fixed effects, the premium drops further by 0.003–0.005 percentage points (pp), implying that part of the green premium may be tied to firm-specific wage policies. These patterns suggest that part of the green wage premium is due to worker sorting and firm-specific effects, but a meaningful within-individual premium remains.

Beyond green intensities, the results confirm expected patterns. Regarding returns to schooling, transitions from below secondary to higher education yield wage increases of 7.8% for internal movers and 6.4% for those who change employers. Gains from secondary to higher education range from 5.8% to 6.9%. Additional years of experience and tenure also offer positive returns, albeit with diminishing marginal effects, and employees with permanent contracts earn significantly more. On the employer side, firms that double their productivity offer 2.4% wage increases to incumbent workers and about 0.9% for new hires. Social capital similarly yields a 0.6% increase for existing employees, and a marginal gain of 0.002% per pp difference for movers. Lastly, foreign owned firms consistently pay more. Interestingly, firm size shows a negative relationship with wages in POLS and FE models, but a positive coefficient in the HDFE models, suggesting that wages follow firms' growth.

Table 14 - Green Wage Premium – Base Specification

	POLS		FE		HDFE	
	Green Tasks	Green Occupations	Green Tasks	Green Occupations	Green Tasks	Green Occupations
Green measure	0.464***	0.192***	0.070***	0.037***	0.067***	0.032***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Woman	-0.183***	-0.182***	-	-	-	-
	(0.000)	(0.000)	-	-	-	-
Secondary education	0.261***	0.261***	0.003***	0.003***	0.002***	0.002***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Higher education	0.774***	0.774***	0.078***	0.078***	0.064***	0.064***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure	0.009***	0.009***	0.004***	0.004***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure^2 (1/1000)	0.033***	0.034***	-0.131***	-0.131***	-0.137***	-0.137***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Potential experience	0.026***	0.026***	0.010***	0.010***	0.011***	0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Potential experience^2 (1/1000)	-0.375***	-0.374***	-0.265***	-0.265***	-0.243***	-0.243***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Open-ended contract	0.070***	0.071***	0.033***	0.033***	0.032***	0.032***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Productivity (Ln)	0.074***	0.073***	0.024***	0.024***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Social capital (Ln)	0.024***	0.024***	0.006***	0.006***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of employees (1/1000)	-0.002***	-0.002***	-0.002***	-0.002***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ownership status (1/100)	1.347***	1.332***	0.507***	0.507***	0.037***	0.036***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Intercept	-0.075***	-0.059***	1.267***	1.267***	1.482***	1.481***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Firm Fixed Effect	No	No	No	No	Yes	Yes
Worker Fixed Effect	No	No	Yes	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes	Yes	Yes
Observations	16249392	16249392	16238966	16238966	16230175	16230175
R^2	0.554	0.551	0.935	0.935	0.945	0.945

Note: Green measure is a continuous green measure variable within 0 and 1. For Green Tasks column it stands for green tasks intensities. For Green Occupations column it stands for green occupations. Below secondary act as the omitted group for education. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Source: Quadros de Pessoal from 2010 to 2019. Made by authors.

Table 15 introduces observable skill intensities into the model, providing a more detailed analysis. The green premium remains positive and statistically significant across all models, indicating that even when accounting for skill composition, green jobs offer higher wages. Although the magnitude of the green premium decreases slightly, it still remains economically significant.

The wage differentials related to job and firm changes persist, reinforcing the robustness of previous findings. Notably, the relative importance of different skill types becomes apparent. Skills in management, construction, information technology, and computer related fields are the most highly

rewarded. Management skills, in particular, stand out as the most valued both within individual firms and across the industry, while skills related to handling and moving tasks receive the least compensation.

Overall, the evidence indicates that green jobs provide considerable wage premiums, even when accounting for worker characteristics, job skills, and unobserved differences at both the worker and firm levels.

Table 15 - Green Wage Premium – Base specification with observable skill intensities

	POLS		FE		HDFE	
	Green Tasks	Green Occupations	Green Tasks	Green Occupations	Green Tasks	Green Occupations
Green measure	0.452***	0.194***	0.070***	0.035***	0.069***	0.034***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Woman	-0.188***	-0.188***	-	-	-	-
	(0.000)	(0.000)	-	-	-	-
Secondary education	0.190***	0.190***	0.003***	0.003***	0.001***	0.001***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Higher education	0.641***	0.641***	0.077***	0.076***	0.062***	0.062***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure	0.008***	0.008***	0.004***	0.004***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure^2 (1/1000)	0.023***	0.025***	-0.131***	-0.135***	-0.137***	-0.137***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Potential experience	0.024***	0.024***	0.011***	0.011***	0.011***	0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Potential experience^2 (1/1000)	-0.344***	-0.342***	-0.264***	-0.264***	-0.242***	-0.242***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Open-ended contract	0.054***	0.055***	0.033***	0.033***	0.031***	0.031***

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Productivity (Ln)	0.062***	0.061***	0.024***	0.024***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Social capital (Ln)	0.025***	0.025***	0.006***	0.006***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of employees (1/1000)	-0.005***	-0.005***	-0.002***	-0.002***	0.006***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ownership status (1/100)	1.396***	1.393***	0.516***	0.515***	0.040***	0.039***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Communication and creativity	0.310***	0.297***	0.041***	0.037***	0.042***	0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Information skills	0.498***	0.477***	0.127***	0.114***	0.105***	0.091***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Assisting and caring	0.221***	0.208***	0.049***	0.046***	0.071***	0.067***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Management skills	0.706***	0.730***	0.172***	0.176***	0.201***	0.205***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Working with computers	0.425***	0.384***	0.045***	0.039***	0.062***	0.055***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Constructing	0.311***	0.329***	0.108***	0.094***	0.119***	0.101***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Working with machinery and specialised equipment	0.126***	0.112***	0.099***	0.098***	0.085***	0.084***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)

Intercept	-0.204***	-0.179***	1.192***	1.196***	1.398***	1.401***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Firm Fixed Effect	No	No	No	No	Yes	Yes
Worker Fixed Effect	No	No	Yes	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes	Yes	Yes
Observations	16249392	16249392	16238966	16238966	16230175	16230175
R^2	0.579	0.577	0.935	0.935	0.945	0.945

Note: Green measure is a continuous green measure variable within 0 and 1. For Green Tasks column it stands for green jobs measured by green tasks intensities. For the Green Occupations column, it stands for green jobs measured by the greenness score. Handling and moving, and Below secondary act as the omitted group for skills and education. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

3.4.2 Unobservables and Greenness Interaction

To assess the wage returns associated with workers' unobservable abilities and to isolate the specific income premium linked to green jobs, we estimated the model outlined in Equation 16. The results are presented in Tables 16 (for green task intensities) and 17 (for green occupations). For each specification, we provide two versions: one that includes occupation-related observable skills and another that excludes them. Each specification features two sub-columns: the first (FE) corresponds to the fixed-effects model, which applies when we cannot reject the null hypothesis that $\lambda = 0$ and the second (Interacted FE) shows the results of the model that relaxes the assumption that $\lambda = 0$. Due to the similarity in estimated coefficients between both interacted FE models, our discussion will primarily focus on the latter.

The coefficients for the interaction terms in the green task intensities model provide valuable insights into how green jobs influence income returns based on observable worker attributes. The results indicate that older workers benefit more from transitioning into greener occupations, as the income premium associated with age increases with the intensity of green tasks. This suggests that green jobs may disproportionately reward experience. Although the direct effect of tenure is statistically insignificant, the positive and significant marginal correction implies that companies tend to reward employee loyalty more in green jobs. Interestingly, the negative interaction effect associated with higher education indicates that lower educated workers experience a greater percentage gain when moving to greener positions compared to their more educated peers. For example, when comparing two workers with identical characteristics, one with a university degree and the other with only nine years of schooling, both would

experience wage increases upon transitioning to a greener job. However, the more educated worker would experience a smaller relative income increase, approximately 0.239% lower when transitioning to a job with one percentage point higher in green task intensity, compared to the less educated worker. No significant effects were observed for middle-skilled workers.

As reported earlier, moving to an open-ended contract or to a more productive firm is generally associated with higher wages. However, the interaction effects reveal that these income returns diminish in greener roles. This implies that green jobs tend to offer relatively better compensation when associated with fixed-term contracts and less productive firms. Moreover, workers in occupations requiring higher intensities of assisting and caring, management, or computer related skills enjoy higher wage returns in greener roles, compared to those in other skill intensive jobs. A further finding is that employment in firms with a higher share of green jobs is positively associated with wage compensation. However, taking on a greener role within such firms is linked to reduced income returns. This suggests that workers may fare better financially by occupying less green roles in firms already engaged heavily in green employment.

To evaluate the role of unobservable abilities, we regressed λ on α. The resulting coefficient is statistically insignificant (0.0001), and the correlation between λ and α is near zero. These results imply no evidence of compensation for unobservable abilities among workers in greener jobs under the green task intensities framework.

Table 16 - Wage Returns by Green Task Intensities

	Without skills		With skills	
	FE	Interacted FE	FE	Interacted FE
Endowments interacted with green professions				
Age	0.008***	0.016***	0.012***	0.016***
	(0.001)	(0.002)	(0.001)	(0.002)
Age^2(1/1000)	-0.092***	-0.183***	-0.157***	-0.181***
	(0.009)	(0.022)	(0.010)	(0.022)
Tenure	-0.000	0.001	-0.001***	0.001
	(0.000)	(0.001)	(0.000)	(0.001)
Tenure^2(1/1000)	0.047***	0.120***	0.083***	0.114***
	(0.015)	(0.022)	(0.015)	(0.022)
Secondary education	0.027***	-0.012	0.014***	-0.010
	(0.005)	(0.013)	(0.005)	(0.013)
Higher education	0.032***	-0.244***	-0.036***	-0.239***
	(0.005)	(0.026)	(0.007)	(0.026)
Open-ended contract	0.018***	-0.012***	0.001	-0.012***

	(0.003)	(0.004)	(0.003)	(0.004)
Productivity (Ln)	-0.006***	-0.005***	0.004***	-0.004**
	(0.001)	(0.002)	(0.001)	(0.002)
Skills intensity interacted with green professions				
Communication and creativity			-0.100***	-0.368***
			(0.035)	(0.140)
Information skills			-0.419***	0.171
			(0.031)	(0.153)
Assisting and caring			-0.389***	1.492***
			(0.044)	(0.247)
Management skills			0.439***	1.273***
			(0.031)	(0.143)
Working with computers			-0.216***	0.754***
			(0.081)	(0.289)
Constructing			-0.143***	-0.153
			(0.032)	(0.176)
Working with machinery and specialised equipment			-0.333***	0.172
			(0.027)	(0.147)
Share of green employment per firm	0.078***	0.070***	0.071***	0.065***
Share of green employment per firm interacted with green professions	-0.356***	-0.267***	-0.205***	-0.241***
	(0.012)	(0.022)	(0.012)	(0.022)
Non-Interacted Workers Endowments	Yes	Yes	Yes	Yes
Non-Interacted Professions Controls	No	No	Yes	Yes
Non-Interacted Firms Controls	Yes	Yes	Yes	Yes
Worker Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	16249392	16249392	16249392	16249392
R^2	0.255	0.952	0.257	0.952
$\rho_{\lambda,\alpha}$	-	-0.022***	-	-0.022***
λ regressed on α	-	$\hat{\lambda}_i = 0.0001\alpha_i$	-	$\hat{\lambda}_i = -0.0001\alpha_i$
p-value	-	0.973		0.971

Note: Controls interacted with green task intensities, a continuous green measure variable within 0 and 1. Workers' endowments and firms' controls include: age, age^2, education, tenure, tenure^2, potential experience, potential experience^2, open-ended contract, productivity, firm's social capital, number of employees, share of foreign ownership, set of industry dummies and set of locations dummies. Professions control include: communication, collaboration and creativity, information skills, assisting and caring, management skills, working with computers, handling and moving, constructing, working with machinery and specialised equipment. Handling and moving, and Below secondary act as the omitted group for skills and education. For industry dummies, the agriculture sector acts as the omitted group. 2010 and Lisbon act as the omitted group for the year and the firm's location. Robust standard

errors are clustered at the worker level. *p<0.10, **p<0.05, ***p<0.01. The full-length estimation table A5 is reported in the appendix.
Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

In relation to the green occupations measure (Table 17), the results follow a similar interpretative framework, but there are a few notable differences. Unlike the green task intensities approach, the signs of the interaction terms for contract type and productivity are reversed, indicating opposite effects. Furthermore, in the green occupations' specification, we find a statistically significant negative correlation between individual fixed effects and the level of occupational greenness. The regression analysis of λ on α yields a statistically significant coefficient of -0.598. This suggests that the returns on unobservable worker abilities decrease as the level of occupational greenness increases. Consequently, this implies that greener occupations tend to rely more on observable characteristics or structured task environments, which reduces the relative importance of unmeasured traits, such as motivation or informal skills.

Table 17 - Wage Returns by Green Occupation Intensities

	Without skills		With skills	
	FE	Interacted FE	FE	Interacted FE
Endowments interacted with green professions				
Age	0.002***	0.015***	0.004***	0.015***
	(0.000)	(0.001)	(0.000)	(0.001)
Age^2 (1/1000)	-0.028***	-0.133***	-0.049***	-0.132***
	(0.005)	(0.012)	(0.006)	(0.012)
Tenure	0.001***	0.001*	0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure^2 (1/1000)	-0.028***	-0.006	-0.016**	-0.009
	(0.007)	(0.012)	(0.008)	(0.012)
Secondary education	0.005**	-0.068***	0.002	-0.067***
	(0.002)	(0.007)	(0.003)	(0.007)
Higher education	0.012***	-0.162***	0.011***	-0.159***
	(0.003)	(0.012)	(0.003)	(0.012)
Open-ended contract	0.010***	0.004*	0.008***	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Productivity (Ln)	-0.000	0.005***	0.003***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Skills intensity interacted with green professions				
Communication and creativity			-0.023*	-0.076
			(0.014)	(0.060)
Information skills			-0.300***	-0.334***

			(0.015)	(0.077)
Assisting and caring			0.016	0.042
			(0.027)	(0.113)
Management skills			0.216***	0.452***
			(0.016)	(0.068)
Working with computers			-0.148***	-0.076
			(0.035)	(0.140)
Constructing			-0.074***	-0.379***
			(0.018)	(0.105)
Working with machinery and specialised equipment			-0.097***	-0.100
			(0.019)	(0.083)
Share of green employment per firm	0.040***	0.031***	0.036***	0.027***
	(0.002)	(0.003)	(0.002)	(0.003)
Share of green employment per firm interacted with green professions	-0.118***	-0.123***	-0.104***	-0.111***
	(0.004)	(0.009)	(0.005)	(0.009)
Non-Interacted Workers Endowments	Yes	Yes	Yes	Yes
Non-Interacted Professions Controls	No	No	Yes	Yes
Non-Interacted Firms Controls	Yes	Yes	Yes	Yes
Worker Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	16249392	16249392	16249392	16249392
R^2	0.255	0.954	0.257	0.954
$\rho_{\lambda,\alpha}$	-	-0.190***	-	-0.193***
λ regressed on α	-	$\hat{\lambda}_i = -0.528\alpha_i$	-	$\hat{\lambda}_i = -0.591\alpha_i$
p-value	-	0.000	-	0.000

Note: Controls interacted with greenness score, a continuous green measure variable within 0 and 1. Workers' endowments and firms' controls include: age, age^2, education, tenure, tenure^2, potential experience, potential experience^2, open-ended contract, productivity, firm's social capital, number of employees, share of foreign ownership, set of industry dummies and set of locations dummies. Professions control include: communication, collaboration and creativity, information skills, assisting and caring, management skills, working with computers, handling and moving, constructing, working with machinery and specialised equipment. Handling and moving, and Below secondary act as the omitted group for skills and education. For industry dummies, the agriculture sector acts as the omitted group. 2010 and Lisbon act as the omitted group for the year and the firm's location. Robust standard errors are clustered at the worker level. *p<0.10, **p<0.05, ***p<0.01. Full-length estimation table A6 is reported in the appendix.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

3.4.3 Robustness checks – results from a displaced workers sample

To address the endogeneity that arises from worker-firm mobility, particularly the bargaining effects linked to job changes, we repeat the analysis using a sample of displaced employees who lost their jobs due to firm closures between 2013 and 2015. The results based on the model presented in Equation 11 for this sample are shown in Table 18. Our findings remain robust, although the magnitude of the premium is smaller: the green wage gap continues to exist and is statistically significant at the 1% level. Additionally, income gains for those who change jobs or firms range from 0.022% to 0.053% for each 1-percentage-point increase in job greenness, which is measured either by green task intensity or by the greenness of occupation level.

Workers' socioeconomic characteristics and working conditions generally remain robust and significant at the 1% level, except for secondary education in the HDFE model, which loses statistical significance. Among firm-level variables, all remain robust except for ownership status, which changes sign in the HDFE model, and social capital, which also loses statistical significance. Among occupational skill intensities, assisting and caring, working with computers, and constructing and working with machinery lose statistical significance in both the FE and HDFE models.

Table 18 - Green Wage Premium - Displaced Workers Sample

	POLS		FE		HDFE	
	Green Tasks	Green Occupations	Green Tasks	Green Occupations	Green Tasks	Green Occupations
Green measure	0.356***	0.273***	0.053***	0.035***	0.032***	0.022***
	(0.009)	(0.006)	(0.009)	(0.007)	(0.009)	(0.006)
Woman	-0.206***	-0.200***	-	-	-	-
	(0.002)	(0.002)	-	-	-	-
Secondary education	0.213***	0.212***	0.020***	0.019***	-0.003	-0.002
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Higher education	0.653***	0.641***	0.057***	0.056***	0.030***	0.030***
	(0.003)	(0.003)	(0.007)	(0.007)	(0.006)	(0.006)
Tenure	-0.001***	-0.001*	0.002***	0.002***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure^2 (1/1000)	0.214***	0.208***	-0.098***	-0.098***	-0.113***	-0.113***
	(0.011)	(0.011)	(0.007)	(0.007)	(0.008)	(0.008)
Potential Experience	0.036***	0.035***	0.011***	0.011***	0.013***	0.013***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Potential experience^2 (1/1000)	-0.510***	-0.503***	-0.247***	-0.246***	-0.264***	-0.263***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)
Open-ended contract	0.076***	0.078***	0.030***	0.030***	0.026***	0.026***

	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Productivity (Ln)	0.062***	0.061***	0.021***	0.021***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Social capital (Ln)	0.021***	0.021***	0.003***	0.003***	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Number of employees (1/1000)	-0.009***	-0.008***	-0.007***	-0.007***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Ownership status (1/100)	1.543***	1.536***	0.511***	0.510***	-0.131***	-0.132***
	(0.026)	(0.026)	(0.025)	(0.025)	(0.042)	(0.042)
Communication and creativity	0.291***	0.242***	0.029***	0.025**	0.034***	0.032***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Information skills	0.680***	0.672***	0.084***	0.077***	0.025**	0.021*
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)
Assisting and caring	0.181***	0.185***	0.004	0.003	-0.011	-0.010
	(0.010)	(0.010)	(0.014)	(0.014)	(0.015)	(0.015)
Management skills	0.795***	0.846***	0.127***	0.132***	0.085***	0.089***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
Working with computers	0.243***	0.220***	0.025	0.022	0.004	0.002
	(0.014)	(0.014)	(0.016)	(0.016)	(0.014)	(0.014)
Constructing	0.302***	0.286***	-0.002	-0.022	0.004	-0.010
	(0.019)	(0.019)	(0.031)	(0.031)	(0.032)	(0.032)
Working with machinery and specialised equipment	0.001	-0.005	-0.019	-0.021	0.014	0.014
	(0.012)	(0.011)	(0.015)	(0.015)	(0.015)	(0.015)
Intercept	-0.271***	-0.252***	1.431***	1.434***	1.611***	1.610***
	(0.011)	(0.011)	(0.020)	(0.020)	(0.022)	(0.022)
Firm Fixed Effect	No	No	No	No	Yes	Yes
Worker Fixed Effect	No	No	Yes	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes	Yes	Yes
Observations	172156	172156	172156	172156	170692	170692
R^2	0.640	0.642	0.943	0.943	0.965	0.965

Note: Sample of displaced workers between 2013 and 2015. Green measure is a continuous green measure variable within 0 and 1. For Green Tasks column it stands for green jobs measured by green tasks intensities. For the Green Occupations column, it stands for green jobs measured by the greenness score. Handling and moving, and Below secondary act as the omitted group for skills and education. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

The interacted model discussed in Equation 16, applied to displaced workers, is presented in Table 19. In the interacted FE specification, considering green task intensity and green occupations along with observable skill intensities, most regressors lose statistical significance. However, the share of green employment per firm remains positive and statistically significant at the 1% level.

For the green task intensity approach, regressing λ on α yields a statistically significant coefficient of zero and a correlation of -0.025. This can be interpreted as a proxy for the return to unobservable abilities in green jobs, suggesting that such occupations offer no significant income returns to unobserved worker skills. Conversely, for green occupations, the analysis reveals a weak correlation of -0.140 and a statistically significant coefficient of -0.533. This implies a reduction in income returns associated with unobservable worker attributes in green occupations, in line with the main results presented before.

Table 19 - Green Wage Premium (Interacted Models) - Displaced Workers Sample

	Green Tasks		Green Occupations	
	FE	Interacted FE	FE	Interacted FE
Endowments interacted with green professions				
Age	0.014**	0.012	0.004	0.001
	(0.007)	(0.014)	(0.005)	(0.011)
Age^2(1/1000)	-0.205**	-0.217	-0.063	-0.009
	(0.088)	(0.162)	(0.061)	(0.123)
Tenure	0.001	-0.006	0.002	-0.000
	(0.004)	(0.004)	(0.002)	(0.003)
Tenure^2(1/1000)	-0.160	0.058	-0.092	-0.053
	(0.187)	(0.168)	(0.085)	(0.097)
Secondary education	-0.016	-0.060	0.017	0.008
	(0.056)	(0.136)	(0.032)	(0.091)
Higher education	-0.168***	-0.274	0.002	-0.204
	(0.065)	(0.178)	(0.033)	(0.126)
Open-ended contract	0.033	0.041	0.049***	0.030
	(0.031)	(0.040)	(0.018)	(0.024)
Productivity (Ln)	0.003	-0.015	0.001	-0.002
	(0.008)	(0.012)	(0.005)	(0.007)
Skills intensity interacted with green professions				
Communication and creativity	-0.099	1.466	0.008	0.427
	(0.317)	(1.116)	(0.128)	(0.551)
Information skills	-0.148	1.728	-0.219	1.415*
	(0.279)	(1.499)	(0.170)	(0.840)
Assisting and caring	-0.497	4.239*	-0.008	0.776

	(0.330)	(2.427)	(0.243)	(1.015)
Management skills	0.357	0.712	0.149	0.330
	(0.282)	(1.162)	(0.167)	(0.641)
Working with computers	0.628	-0.234	-0.098	0.354
	(0.530)	(1.812)	(0.281)	(1.100)
Constructing	-0.605*	-0.198	-0.372**	-0.113
	(0.335)	(1.639)	(0.179)	(0.824)
Working with machinery and specialised equipment	-0.410*	2.119	0.104	0.675
	(0.249)	(1.795)	(0.204)	(0.914)
Share of green employment per firm	0.222***	0.222***	0.101***	0.087***
	(0.040)	(0.045)	(0.025)	(0.029)
Share of green employment per firm interacted with green professions	-0.296***	-0.250	-0.126**	-0.039
	(0.111)	(0.179)	(0.050)	(0.086)
Non-Interacted Workers Endowments	Yes	Yes	Yes	Yes
Non-Interacted Professions Controls	Yes	Yes	Yes	Yes
Non-Interacted Firms Controls	Yes	Yes	Yes	Yes
Worker Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	172156	172156	172156	172156
R^2	0.229	0.957	0.229	0.957
$\rho_{\lambda,\alpha}$	-	-0.025***	-	-0.140***
λ regressed on α	-	$\hat{\lambda}_i = 0.00003\alpha_i$	-	$\hat{\lambda}_i = -0.683\alpha_i$
p-value	-	0.999	-	0.000

Note: Sample of displaced workers between 2013 and 2015. Controls interacted with green tasks intensities and greenness score for Green Tasks and Green Occupations columns. Both variables are continuous green measures ranging from 0 to 1. Workers' endowments and firms' controls include: age, age^2, education, tenure, tenure^2, potential experience, potential experience^2, open-ended contract, productivity, firm's social capital, number of employees, share of foreign ownership, set of industry dummies and set of locations dummies. Professions control include: communication, collaboration and creativity, information skills, assisting and caring, management skills, working with computers, handling and moving, constructing, working with machinery and specialised equipment. Handling and moving, and Below secondary act as the omitted group for skills and education. For industry dummies, the agriculture sector acts as the omitted group. 2010 and Lisbon act as the omitted group for the year and the firm's location. Robust standard errors are clustered at the worker level. *p<0.10, **p<0.05, ***p<0.01. Full-length estimation table A7 is reported in the appendix.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

3.5 Discussion and policy implications

This Chapter examined the impact of both observable and unobservable factors on the wage premium associated with green jobs. Our findings indicate that workers employed in green occupations earn, on

average, between 20% and 50% more than those in non-green roles. Additionally, transitions to greener positions either through job or firm changes are associated with positive income gains, even when controlling for worker and firm characteristics.

While our models explain up to 60% of the observed wage gap, the returns to unobservable worker attributes differ depending on the greenness measure. Specifically, we find no significant returns to unobservables under the green task intensity approach and negative returns under the green occupation approach. This suggests that as the degree of occupational greenness increases, the marginal return to unobserved skills diminishes, potentially indicating that non-green jobs rely more heavily on such unobserved attributes for wage determination. The analysis of displaced workers confirms the robustness of our main findings.

Our study faces two main limitations. First, green jobs and tasks are defined using the O*NET taxonomy at the 8-digit SOC2010 level, for which employment shares are not available. As a result, we were constrained to apply uniform weights. Second, our dataset classifies occupations using ISCO08, and the only available correspondence table is the 6-digit SOC2010 from the U.S. BLS. As an alternative, the ESCO framework has recently released a preliminary classification of green skills linked to ISCO08, which could be used to compute green skill intensities. However, ESCO's green skill taxonomy is still in its pilot phase and subject to future updates.

Future research could also explore the causal mechanisms behind these wage differentials, for example, by applying regression discontinuity designs or using instrumental variables, and test the generalizability of these findings in other countries or using task-level data more directly linked to green skills.

The empirical evidence presented in this study has direct implications for labour market policy design and green transition strategies. First, the observed and statistically significant wage premium associated with green occupations, even after controlling for observable and unobservable heterogeneity, suggests that green employment pathways can serve as effective instruments to both promote decarbonisation and improve labour income (Vona et al., 2018). Efforts to facilitate worker mobility into greener occupations through retraining or transition subsidies may yield not only environmental but also economic benefits.

Second, our findings indicate that green occupations exhibit lower returns to unobservable worker characteristics. This may imply a compression of income distribution or lower wage premia for informal,

non-certifiable skills. From a policy perspective, this underscores the importance of designing skill certification systems and green credentialing mechanisms to improve the signalling of informal capabilities in green labour markets (Bowen et al., 2018). Additionally, training programs should focus on transversal and digital skills, given their increasing demand in green intensive roles (ILO, 2019; European Commission, 2022b).

Third, results obtained from the displaced worker subsample reinforce the robustness of the green wage premium. This has important implications for active labour market policies. Specifically, displaced workers should be prioritised in green upskilling initiatives, given their relatively higher mobility and vulnerability in the labour market. Public employment services could integrate green career pathways into reskilling and job-matching services (Vona et al., 2019).

Fourth, the study's methodological limitations point to the necessity of improved green labour statistics. The reliance on U.S. O*NET data and crosswalks to European ISCO08 classifications reflects a broader gap in harmonised, high-resolution data on green skills in Europe. Policymakers and statistical institutions should prioritise the development of a European standard classification of green jobs and competences, such as through the further expansion and institutionalisation of the ESCO green skills framework. Such harmonisation would improve the accuracy of green labour market monitoring and the targeting of educational and industrial policy.

In sum, our findings highlight the strategic role of green jobs in the just transition framework. Policy interventions should be multidimensional, encompassing labour mobility support, skill certification, labour market policies reform, and statistical infrastructure upgrades to maximise the economic and equity benefits of the green transition.

4 Green Jobs and Fiscal Policy: Modelling Employment Dynamics in the Portuguese Transition

4.1 Introduction

The sustainable transition remains one of the central focuses of international and national policy agendas. This includes the Paris Agreement 2015, the European Green Deal, UN Agenda 2030 and the EU Emissions Trading System. Under these frameworks, the creation and transition to sustainable jobs represents one of the main subjects. Sustainable jobs, commonly referred to as green jobs, not only ensure the promotion of decent employment opportunities, but also highlight the environmental, economic and social benefits. These include the reduction of GHG emissions, the development and usage of clean technologies, the promotion of renewable energy sources, and enhancing well-being through improved public health outcomes.

The Portuguese government, through Resolution No. 28/2015 of the Council of Ministers[11], introduced the Green Growth Commitment, which establishes a connection between sustainable development, the reduction in the consumption of natural resources, the improvement of living conditions, and social as well as territorial inclusion. This initiative is consistent with multiple national frameworks, including the National Energy and Climate Plan 2030[12], and the RNC2050[13].

To put the Green Growth Commitment into practice, the Portuguese Parliament enacted Law No. 82-D/2014[14], which restructured environmental taxation across different sectors, particularly energy and emissions, transport, water, waste, land use, forests, and biodiversity. This reform became known as the GTR, with the main objectives of ensuring tax neutrality, safeguarding the environment, strengthening energy independence, fostering economic growth, creating sustainable employment, enhancing fiscal responsibility, and reducing external imbalances. In this context, sustainable employment refers to the creation of jobs that are environmentally responsible and contribute to the preservation and restoration of environmental quality. This broad understanding is in line with the general notion of green jobs, which, despite their importance, still lack a universally agreed-upon definition among institutions. An essential methodological challenge, addressed in detail in Chapter 2, concerned the definition and measurement

[11] https://diariodarepublica.pt/dr/detalhe/resolucao-conselho-ministros/28-2015-67120682.
[12] https://commission.europa.eu/publications/portugal-final-updated-necp-2021-2030-submitted-2024_en.
[13] https://descarbonizar2050.apambiente.pt/.
[14] https://www.pgdlisboa.pt/leis/lei_mostra_articulado.php?nid=2253&tabela=leis.

of green jobs. Establishing a consistent distinction between green and non-green employment was a prerequisite for analyzing the labor market impacts of the policy simulations presented in this chapter.

CGE models serve as a robust and widely used analytical framework for evaluating the impacts of macroeconomic shocks and policy interventions on various aspects of national economic performance. In particular, they have been extensively applied to evaluate the impacts of labour market policies (Dewatripont et al., 1991; Gelauff et al., 1991; Hutton & Ruocco, 1999; Bovenberg et al., 2000; Bajo-Rubio & Gómez-Plana, 2004; Aaberge et al., 2007; Arntz et al., 2008; Fæhn et al., 2009; Boeters, 2013; Severini et al., 2019), ranging from analyses addressing aggregate unemployment reduction (Dewatripont et al., 1991; Bovenberg et al., 2000) to more disaggregated research that decompose labour market responses into more detailed characteristics such as education, age, and gender (Aaberge et al., 2007; Arntz et al., 2008; Fæhn et al., 2009; Severini et al., 2019).

Building on the contextual discussion above, this study employs a CGE model to assess the relative effectiveness of environmentally sustainable policies, under GTR framework, in promoting sustainable employment and analysing their impact over agents' income and consumption, sectorial production, and government indicators. Following previous studies, "sustainable employment" is here operationalized in accordance with the definition of "green jobs" provided by Dierdorff et al. (2009). The authors define them as: "GES occupations", the occupations that are expected to undergo significant skill transformation due to the impact of economic activities and technologies; "GNE occupations", the creation of new and unique jobs; and "GID occupations", which are referred to professions for which employment demand is projected to grow, without substantial changes in the nature of the work or the workers requirements.

Within the broader policy debate on the transition towards a low-carbon economy, particular attention has been devoted to how fiscal measures can reconcile environmental objectives with employment creation and fiscal sustainability (Popp et al., 2021; Caselli et al., 2024). In this context, key economic dimensions such as income distribution, production structure, and sectoral competitiveness become central to assessing how policy interventions can promote greener forms of employment acknowledging their macroeconomic effects. These considerations are particularly relevant for Portugal, where the main challenge lies in aligning fiscal incentives for households and firms while preserving a stable tax base and supporting productive investment.

One of the key objectives of these policies is to foster sustainable employment, support environmentally responsible firms, and stimulate innovation and reskilling within traditional economic

sectors. Building on this rationale, three indicative policy scenarios were designed to introduce tax incentives for green agents and environmental taxation for non-green agents, each addressing a distinct channel through which fiscal policy can influence employment dynamics and production outcomes.

Scenario A addresses the role of income taxation in promoting sustainable employment. It simulates a reduction in income taxes applied to green agents, namely, households and firms engaged in environmentally sustainable activities. This mechanism reflects the policy idea that fiscal incentives directed at green labour and production can increase their competitiveness and foster a gradual reallocation of employment toward low-carbon sectors. The scenario isolates the income channel of the reform, allowing the analysis to assess how changes in disposable income and labour costs translate into employment and output responses.

Scenario B extends this framework by introducing a compensatory element on the production side. Alongside the income tax reduction for green agents, it assumes an increase in production taxes within the energy sector. This adjustment serves two purposes: it preserves fiscal neutrality and reinforces the environmental signal of the reform. By taxing energy production, typically associated with high emissions intensity, the scenario captures the corrective dimension of a Pigouvian tax, while the continued income relief for green agents maintains incentives for behavioural change. It thus examines whether a balanced combination of income and production instruments can generate both economic and environmental dividends.

Scenario C focuses exclusively on production-side incentives, targeting the construction sector. The reduction in production taxes for this sector aims to test how alleviating fiscal pressure on a key industry for energy efficiency and material innovation can stimulate output and employment. The construction sector plays a highly relevant role in the green transition due to its capacity to diffuse cleaner technologies across the economy. This scenario, therefore, evaluates whether targeted production stimulus can drive sustainable employment through investment led expansion rather than through income-based incentives.

Translating the policy rationale outlined above into a CGE analytical framework requires addressing several technical aspects that allow for a consistent evaluation of the employment and distributional effects of a GTR. In particular, the analysis demands a representation of the labour market capable of distinguishing between green and non-green employment, together with a data structure reflecting this differentiation across agents and sectors. It also requires empirically grounded measures of substitution between these two types of labour to parameterise behavioural responses in production

and income generation. These methodological components that aim to define, quantify, and integrate green labour into an economy-wide framework, form the technical foundation that supports the assessment of the indicative policy scenarios presented earlier.

Building on this framework, this Chapter makes three main methodological and analytical contributions to the literature. First, it estimates the elasticities of substitution of composite labour between green and non-green jobs, both at the national level and across various economic sectors. Second, it builds a green SAM that distinguishes between green and non-green labour and divides agents into green and non-green households and firms. Third, it evaluates alternative fiscal policy instruments under the GTR framework, identifying the configuration that most effectively promotes green employment while assessing its broader effects on consumption, production, and government indicators.

The structure of the Chapter follows with section 2 that presents the data, methodology, analytical framework, key modelling features and the elasticity of substitution of composite labour. Section 3 outlines the estimation and simulation results, their implications and discussion. Finally, Section 4 concludes the study.

4.2 Data and methodology

4.2.1 Data

The empirical analysis requires data that consistently link macroeconomic accounts with firm-level and worker-level information to calibrate and parameterise the CGE model. In particular, the construction of the SAM and the estimation of the elasticity of substitution between green and non-green labour both depend on combining national aggregates with detailed microdata on firms and employment. This study draws on three primary data sources. The first is the Portuguese National Accounts for 2017, which consolidate key macroeconomic indicators and serve as the core basis for constructing the SAM.

The second source is QP, a longitudinal linked employer–employee dataset that provides detailed information on the Portuguese labour market. Collected annually through a mandatory survey by the Ministry of Labour and Social Security, QP includes individual-level data on demographic and job characteristics of private-sector employees, excluding public servants and the self-employed. Each worker is anonymised with a unique fictitious identifier, which enables longitudinal tracking while safeguarding confidentiality. Firms are also assigned unique identifiers, making it possible to analyse employment relationships over time. To improve the reliability of the data, several filters were applied to the QP dataset.

Observations were excluded if workers reported fewer than 30 hours in the reference month, earned less than half or more than 25 times the national minimum wage, or were aged below 17 or above 67.

The third source is the *Sistema de Contas Integradas das Empresas* (SCIE), a longitudinal database that contains statistical, financial, and accounting information on Portuguese firms, apart from those in the financial and insurance sectors. SCIE is compiled from firms' administrative and annual accounting data reported to the Ministry of Finance and complemented by information from Statistics Portugal.

4.2.2 Methodology

The distinction between green and non-green employment constitutes a key starting point for this work, as it directly shapes the structure of the green SAM developed for the analysis. This distinction relies on the greenness index established in the previous Chapter 2 of this thesis. This index provides a consistent measure of the environmental content of occupations, ensuring the coherence of the labour market representation adopted in the CGE model. In brief, the classification follows the O*NET-based framework adapted to the Portuguese context through SOC2010–ISCO08 correspondences, generating a continuous greenness index for each occupation, later operationalised as a binary measure of green employment.

Analytical framework

This analysis relies on a CGE approach. As previously mentioned, CGE models are particularly suited to examining the economy-wide implications of fiscal and environmental policies. They provide a coherent framework to capture interactions among production, income, and expenditure while ensuring consistency between macroeconomic balances and microeconomic behaviours. This methodological choice is especially appropriate for assessing the distributional and employment impacts of green fiscal reforms, since it allows tracing indirect effects across sectors and institutional agents that partial-equilibrium approaches cannot capture.

CGE models are numerically implemented using a SAM, which serves as the core database of the economy. The SAM records all monetary transactions among production activities, institutional agents, and factors of production in a square, balanced matrix. It represents the circular flow of income in an economy, linking production, factor remuneration, institutional income, and expenditure, while ensuring accounting consistency across all agents. In equilibrium models, the SAM provides both the

benchmark data for calibration and the structure through which policy shocks, such as fiscal or environmental measures, propagate through the system.

Building on this rationale, the study employs the PEP-1-1 CGE model developed by Decaluwé et al. (2009), which is a static, single-country framework designed for transparent and adaptable national-level analysis. Its structure balances analytical rigour with computational simplicity, making it well-suited to analysis where the objective is to evaluate domestic policy scenarios rather than long-term or cross-country dynamics. The model builds on the EXTER framework (Decaluwé et al., 2001) and is implemented in GAMS with the CONOPT3 solver for nonlinear optimisation. It follows neoclassical microeconomic foundations, assuming profit and utility maximisation under perfect competition. It encompasses production, income generation and distribution, consumption, savings, trade, and market equilibrium conditions. A defining feature of the PEP architecture is its modular organisation, which enables the adaptation of model components, such as production structures, tax instruments, and institutional sectors, without compromising internal consistency. Full details on the PEP 1-1 model may be found at Decaluwé et al. (2009)[15].

Regarding model specification and extensions, for this study, the standard PEP-1-1 model is augmented in two main ways. First, it incorporates a wage-curve specification, following Escalante et al. (2025), introducing a negative relationship between wages and unemployment (Blanchflower and Oswald, 1995). This modification allows the model to capture labour market rigidities relevant to employment transitions. Second, the model explicitly distinguishes between green and non-green components across both factors and institutions, which is crucial for analysing the fiscal and employment effects of green transition policies. These conceptual modifications form the analytical foundation of the model, while their empirical implementation and calibration are described in the following section on Key Modelling Features.

Key modelling features

Beyond the standard structure of the PEP-1-1 model, several elements are specified in greater detail to reflect the objectives of this analysis and the characteristics of the Portuguese economy. These include the treatment of production factors, taxation, consumption and savings behaviour, and current transfers.

[15] https://www.pep-net.org/research-resources/cge-models.

Each is briefly described below, highlighting assumptions and extensions that differ from the baseline PEP-1-1 configuration.

Data source and SAM

The empirical implementation uses a SAM for Portugal (2017), originally developed by Gião and Sousa (2023) within the CLICTOUR project. This SAM captures the circular flow of income, production, and expenditure across institutional sectors and was extended to include green and non-green agents, enabling the explicit examination of interactions between fiscal instruments, employment composition, and sustainability outcomes. These extensions required restructuring the original SAM and adapting the PEP-1-1 model accordingly.

Elasticity parameters are drawn primarily from Decaluwé et al. (2009), except where country-specific evidence is available. Armington and income elasticities follow Blake (2000) for Spain, due to its similarity with Portugal. The elasticity of substitution between green and non-green labour derives from the estimations presented in Elasticity of substitution between green and non-green jobs section, and the wage-curve elasticity is set at -0.10 (Blanchflower and Oswald, 1995; Card, 1995). The unemployment rate is fixed at 0.092 (Statistics Portugal). All prices are normalised to one, and intercepts are set to zero. The complete set of not default parameters values employed in the model per sector is presented in tables A8 in appendix.

Model calibration combines endogenous SAM data with standard exogenous parameters, including substitution elasticities between capital and labour, Armington elasticities (substitution between imports and domestic goods), export transformation elasticities, world demand elasticity, the Frisch parameter, and income elasticities of consumption. Based on this calibrated SAM, the next subsection describes the overall economic and institutional structure underpinning the model.

Structure of factors, agents and sectors

The model represents the Portuguese economy through ten economic sectors and corresponding products, namely: agriculture, forestry, and fishing; Industry, energy, water supply, and sewerage; construction; wholesale and retail trade, repair of motor vehicles and motorcycles; transportation and storage; accommodation and food service activities; information and communication; financial and

insurance activities; real estate activities; professional, scientific, and technical activities; administrative and support services; public administration, defence, compulsory social security, education, human health and social work; arts, entertainment, repair of household goods and other services. This sectoral disaggregation maintains consistency with the Portuguese National Accounts and ensures the comparability of model results with official statistics.

Production relies on three factors of production, namely capital, green labour, and non-green labour, and four institutional agents, including green households, non-green households, green firms, and non-green firms, in addition to the government and the Rest of the World. Tax instruments include direct, indirect, and import taxes. This structure enables the explicit assessment of how fiscal and labour-market measures influence the distribution of income between green and non-green components of the economy.

Building on this structure, the following subsections detail how production factors, consumption, taxation, and current transfers are represented and parameterised within the model.

Production factors

The distribution of production factors across sectors was estimated for 2017 using data from the QP and Portuguese National Accounts. The share of green labour income was computed as the ratio of total nominal wages of green job holders to total wages in each sector, and these shares were used to adjust labour income in the SAM. Table 20 presents the resulting distribution of the three production factors, capital, green labour, and non-green labour, across ten economic sectors.

To allocate factor income across institutional agents, linked QP-SCIE data were used to identify the number of green jobs per firm. The corresponding shares of gross operating surplus were then applied to the National Accounts, assigning 10.2% of capital income to green firms[16] and 89.8% to non-green firms. The final allocation of production factors among agents is shown in Table 21.

The calibrated factor distribution provides the basis for estimating the consumption and savings patterns of institutional agents.

[16] We consider a firm as green if the share of within green jobs is higher or equal to 50%.

Table 20 - Share distribution of production factors within each sector by capital, green and non-green labour

Sectors	Green labour	Non-green labour	Capital
Agriculture, forestry, and fishing	0.026	0.224	0.751
Industry, energy, water supply and sewerage	0.095	0.377	0.528
Construction	0.152	0.491	0.357
Wholesale and retail trade	0.077	0.433	0.490
Information and communication	0.085	0.437	0.479
Financial and insurance activities	0.050	0.424	0.525
Real estate activities	0.005	0.028	0.968
Professional, scientific and technical activities	0.088	0.569	0.344
Public administration, education and human health	0.021	0.755	0.223
Arts and entertainment	0.021	0.755	0.352

Note: The table represents the distributions of the shares of production factors. Calculated as a factor divided by the sum of all production factors, namely, green labour, non-green labour and capital. The sum of all factors per line is equal to 1.

Source: Nominal values for labour and capital factors from Portuguese National Accounts for 2017. Data for green and non-green labour from *Quadros de Pessoal* for 2017. Made by authors.

Table 21 - Distribution of production factors across agents (in millions of €)

Agents	Green labour	Non-green labour	Capital
Green Households and Firms	10,162.86	0.00	7,942.84
Non-green Households and Firms	0.00	76,178.14	69,594.16
Government	0.00	0.00	278.00
Rest of the World	-28.70	-215.15	4,843.52

Note: The table represents the distributions of production factors among four economic agents: green and non-green households and firms, the government and the Rest of the World.

Source: Nominal values for labour and capital factors from Portuguese National Accounts for 2017. Data for green and non-green labour from *Quadros de Pessoal* for 2017. Data for the operation surplus from the linked *Quadros de Pessoal – Sistema de Contas Integradas das Empresas* for 2017. Made by authors.

Consumption and savings

The consumption and savings of green and non-green agents were estimated by distinguishing four groups: green households, non-green households, green firms, and non-green firms. For households, consumption and savings levels were derived using the previously calculated distribution shares of the labour production factor. For firms, the corresponding shares of gross operating surplus were considered to estimate their contributions. Finally, the results for households and firms were aggregated to obtain the total consumption and savings attributable to green and non-green agents.

In parallel, the fiscal structure of the model requires a consistent disaggregation of direct taxes by agent type, described next.

Direct taxes

According to the National Accounts, direct taxes comprise income taxes and other current taxes on capital, including levies on capital ownership as well as on land and buildings. In our model, these components are treated equivalently.

To estimate the share of income tax attributable to green workers, we used the official monthly retention rate tables published by the Government of Portugal for the mainland and the autonomous regions for 2017. These rates were applied to the regular income of each worker using data from QP. The average tax withheld from green job workers was then calculated and divided by the total tax withheld, yielding a green income tax share of 17.5%. This proportion was subsequently applied to the total income tax reported in the SAM.

Corporate income tax for 2017 was estimated using data from the SCIE. The proportion of total corporate income tax paid by environmentally friendly firms amounted to 14.6% of the total and was used to adjust the corresponding entries in the SAM.

Table 22 reports the resulting allocation of direct taxes across institutional agents, with €3,268.85 million attributed to green households and firms and €15,933.15 million to non-green agents. This disaggregation ensures consistency between the fiscal structure of the SAM and the policy simulations explored in the following section.

Table 22 - Distribution of direct taxes by agents (in millions of €)

Direct Taxes	Households	Firms
Green Income Taxes	2,255.354	919,411
Non-green Income Taxes + Others	10,652.646	5.373,589

Note: The tables present the distribution of direct taxes by green and non-green per household and firms.

Source: Nominal values from Portuguese National Accounts 2017. Data regarding green income tax of households from *Quadros de Pessoal* 2017 and of firms from *Sistema de Contas Integradas das Empresas* 2017. Made by authors.

Current transfers

Data on current transfers between the government and the Rest of the World was obtained from the Portuguese National Accounts. However, detailed data on transfers between green and non-green households and firms was not available. To address this gap, the Row–Adjustment–Column method was applied, adjusting the relevant submatrix so that all row and column totals matched the observed aggregates. Given the absence of microdata, a simplifying assumption was introduced: transfers from green households and firms to non-green agents were set to zero, allocating the total available amount to green agents. Using this assumption, and the known row and column totals, the two remaining cells of the 2×2 matrix representing transfers from non-green to green agents and from non-green households and firms were derived accordingly.

The same approach was applied to estimate other current transfers related to consumption and savings. Transfers from households and firms to the government were calculated using the average income tax rate for green workers (17.47%) and the average corporate tax rate for green firms (14.61%). Transfers involving the Rest of the World and the government were distributed according to the income share of green households (11.77%) and the gross operating surplus share of green firms (10.24%). Finally, all transfers were consolidated into two categories: green and non-green households and firms. The resulting distribution is presented in Table 23, maintains the standard input–output reporting allocations from columns to rows.

Table 23 - Distribution current transfers by agents (in millions of €)

Current Transfers	Green households and firms	Non-green Households and firms	Government	Rest of the World
Green households and firms	148.27	2,777.37	4,012.47	875.49
Non-green Households and firms	0.00	12,658.36	30,768.53	6,782.51
Government	4,439.61	20,274.39	0.00	876.93
Rest of the World	219.82	1,938.18	1,792.02	0.00

Note: The tables present distribution of current transfers per green households and firms, non-green households and firms, government and Rest of the World.

Source: Nominal values from Portuguese National Accounts 2017. Share of income tax, income and operation surplus distribution between green and non-green households and firms estimated from *Quadros de Pessoal* and *Sistema de Contas Integradas das Empresas* for 2017. Made by authors.

Together, these components define a consistent and disaggregated framework, which allows simulating fiscal and labour policy shocks across green and non-green segments of the economy. The following section introduces the estimation of the substitution elasticity between green and non-green labour, which constitutes a key behavioural parameter in this framework.

Elasticity of substitution between green jobs and non-green jobs

The elasticity of substitution between green and non-green labour is empirically estimated in this study to assess the responsiveness of labour demand to changes in the composition of the workforce. Although estimated econometrically, the resulting parameter is subsequently used as a structural input for calibrating the CGE model. The methodological framework for this estimation is presented below, while the empirical results are discussed in the following section. To formalise the estimation framework, it is assumed that sectoral value-added results from the combination of labour and capital inputs, following a Constant Elasticity of Substitution (CES) production function consistent with the standard specification adopted in CGE models. This can be expressed mathematically as:

$$VA_j = B_j^{VA}\left[\beta_j^{VA} \cdot L_j^{-\rho_j^{VA}} + \left(1-\beta_j^{VA}\right) \cdot K_j^{-\rho_j^{VA}}\right]^{-1/\rho_j^{VA}} \quad \text{Eq. 17}$$

Where *VA* denotes the value added in sector *j*. *B* is the scale parameter for value added in sector *j*. β is the share parameter associated with the labour factor in sector *j*. ρ is the elasticity parameter of value added. *L* and *K* represent labour and capital inputs, respectively. Considering two types of labour, green and non-green, the composite labour factor can be expressed using a CES function to capture the imperfect substitutability between these labour types:

$$L_j = B_j^L * \left[\beta_j^L * G_j^{-\rho_j^L} + \left(1-\beta_j^L\right) * NG_j^{-\rho_j^L}\right]^{-1/\rho_j^L} \quad \text{Eq. 18}$$

Where *G* and *NG* denote green and non-green labour, respectively. The parameter *B* represents the labour specific scale parameter in sector *j*. The β is the share parameter that determines the contribution of green labour to the production process. The elasticity of substitution between green and non-green labour is denoted by ρ.

Under the assumption of perfect competition, the production factors are paid according to their marginal products. As a result, the relative wage between green and non-green labour must equal the ratio of their marginal products.

$$\frac{w_{G_j}}{w_{NG_j}} = \frac{\beta_j^L}{1-\beta_j^L}\frac{G_j^{-\rho_j^L-1}}{NG_j^{-\rho_j^L-1}} \quad \text{Eq. 19}$$

Where *W* denotes the wage paid to green jobs and non-green jobs in sector *j*. Furthermore, by decomposing the elasticity parameter is obtained the expression for the elasticity of substitution between green and non-green labour factors:

$$\rho_j^L = \frac{1-\sigma_j^L}{\sigma_j^L} \quad \text{Eq. 20}$$

Where σ is the elasticity of substitution of labour in sector *j*. Substituting equation 20 into equation 19 and taking logarithms yields:

$$\frac{w_{G_j}}{w_{NG_j}} = \frac{\beta_j^L}{1-\beta_j^L}\frac{G_j^{-\frac{1}{\sigma_j^L}}}{NG_j^{-\frac{1}{\sigma_j^L}}} \quad \text{Eq. 21}$$

$$\frac{w_{G_j}}{w_{NG_j}} = \frac{\beta_j^L}{1-\beta_j^L}\left(\frac{NG_j}{G_j}\right)^{\frac{1}{\sigma_j^L}} \quad \text{Eq. 22}$$

$$ln\left(\frac{w_{G_j}}{w_{NG_j}}\right) = ln\left(\frac{\beta_j^L}{1-\beta_j^L}\right) + \frac{1}{\sigma_j^L} ln\left(\frac{NG_j}{G_j}\right) \quad \text{Eq. 23}$$

$$ln\left(\frac{NG_j}{G_j}\right) = -\sigma_j^L ln\left(\frac{\beta_j^L}{1-\beta_j^L}\right) + \sigma_j^L ln\left(\frac{w_{G_j}}{w_{NG_j}}\right) \quad \text{Eq. 24}$$

This straightforward exemplification is widely employed in the literature (see, for example, Katz and Murphy, 1992; Borjas, 2003; Cerejeira, 2008; Card, 2009). For alternative frameworks see Havranek et al. (2020). The labour scale parameter β only varies across sectors *j*. Although, in dynamic perspective, it also changes over time. This implies that within any sector *j* at a given moment of time, the labour scale parameter β and the elasticity of substitution of composite labour σ remains constant. As a result, the term involving -σ_j^L multiplied by the natural logarithm of the ratio between β_j^L over 1 minus β_j^L can be

removed by including time dummies and sector fixed effects. Following Ciccone et al. (2005), the labour-biased technology parameters can be expressed as a sets of market time invariant fixed effects, denoted by π in the following final model specification:

$$ln\left(\frac{NG_j}{G_j}\right) = \pi_j + \sigma_j^L * ln\left(\frac{w_{G_j}}{w_{NG_j}}\right) \quad \text{Eq. 25}$$

To identify the sign and magnitude of σ_j^L, following econometric model was specified:

$$ln\left(\frac{NG_{ft}}{G_{ft}}\right) = X\beta + \sigma * ln\left(\frac{w_{G_{ft}}}{w_{NG_{ft}}}\right) + \gamma_f + \delta_t + \varepsilon_{ft} \quad \text{Eq. 26}$$

The dependent variable is the natural logarithm of the ratio between green and non-green labour within firm *f* in year *t* measured in worked hours. The key independent variable is the logarithm of the wage ratio between workers from green and non-green jobs in the firm *f* and year *t*. The corresponding coefficient σ represents the constant elasticity of substitution between green and non-green labour factors. The matrix *X* includes a set of control variables. γ denotes time-invariant firm fixed effects. δ represents year-specific effects. ε is the error term.

Since the wage ratio is likely to be correlated with the error term due to unobserved shocks in labour demand (Cerejeira, 2008), the coefficient σ cannot be consistently estimated using OLS. To address this endogeneity problem, it was considered an instrumental approach, where the instruments for the wage ratio are its first and second-order lags.

The lags of dependent variables are commonly used as instruments to address endogeneity problems. Additionally, they are frequently considered for robustness checks (see, for example, David Card, 2009 analysis). However, it is well recognized that lagged instrumental variables can increase bias relative to classical linear regression methods. Therefore, this paper employs three different estimation strategies: standard POLS, HDFE, and instrumental variables (IV) models.

The estimation uses a merged firm-level dataset from QP and SCIE for 2010–2019, including only firms employing at least one green and one non-green worker. Variables are grouped into three sets, including main indicators, such as number of green and non-green workers, total hours, and average hourly income; workers' socio-economic characteristics, such as average potential experience (age minus six minus and minus years of schooling), share of women, and share of tertiary-educated workers; and

firm-level controls, such as total assets, sales, and employees (or business volume and employment for financial firms). Summary statistics are reported in Table 24.

Table 24 - Summary statistics of the sample for elasticity of substitution

	Mean	SD	Min	Max	N
Year	2015	3	2010	2019	420195
Main Indicators					
Number of green workers	5.60	32.39	1.00	4954.00	420195
Number of non-green workers	25.04	176.70	1.00	18471.00	420195
Total worked hours by green	954.14	5492.45	30.00	860635.00	420195
Total worked hours by non-green	4236.50	29399.34	32.00	3115078.00	420195
Total green workers income	7589.66	56801.15	237.50	8055030.97	420195
Total non-green workers income	28730.62	244341.17	237.50	21148863.59	420195
Workers Socioeconomics Controls					
Average workers potential experience	25.43	7.44	0.50	57.00	420195
Share of women	0.33	0.29	0.00	1.00	420195
Share of graduated workers	0.18	0.26	0.00	1.00	420195
Firms Controls (Non-Financial Firms)					
Total actives (1/1000)	7061.49	113712.81	0.00	24144756.00	404030
Total sells (1/1000)	4025.80	58233.27	0.00	9559035.00	404030
Number of paid workers	37.50	253.95	0.00	26857.00	404030
Firms Controls (Financial Firms)					
Volume of business (1/1000)	62128.79	401044.13	0.00	11319688.00	4454
Total number of workers	139.83	736.80	2.00	11103.00	4469

Note: Summary statistics are based on the merged *Quadros de Pessoal* and *Sistema de Contas Integradas das Empresas* datasets for 2010–2019. The sample includes only firms employing both green and non-green workers. Potential experience is calculated as age minus six minus years of schooling.

Source: Authors' calculations based on *Quadros de Pessoal – Sistema de Contas Integradas das Empesas* linked data.

4.3 Results

4.3.1 Elasticity of substitution between green and non-green jobs

Table 25 presents the estimated coefficients of the equation 26 for Portugal. In columns 1, 3 and 5, the dependent variable is the natural logarithm of the ratio of green to non-green workers. In the remaining columns (2, 4 and 6), the dependent variable is the natural logarithm of the ratio of hours worked by green to non-green workers. The first two columns present estimates based on POLS. The second set

employs a HDFE model. The last was estimated employing an IV approach. All models were estimated with White's robust standard errors to correct for heteroskedasticity and autocorrelation.

The estimated coefficients are robust, showing a maximum variation of approximately 0.1 pp between models, except for the coefficient of the share of graduated workers. Evidence of endogeneity is detected through the C test (ρ -value < 0.1). The selected instruments satisfy validity, as indicated by Hansen's J-test (ρ -value > 0.1), and they are strong (first-stage F-statistic > 20)[17].

The σ varies between -0.85 and -0.97 across models. This suggests that relative wages are a strong driver of green job promotion. When green jobs pay higher wages, the labour market shifts in their favour, with a nearly one-to-one response in the ratio of green against non-green jobs. In terms of interpretation, a 10% increase in the wage ratio of green to non-green jobs, caused by an increase in wages of green or decrease in non-green jobs, leads to an approximate 8.5–9.7% reduction in the relative employment of non-green jobs to green jobs. The negative elasticity estimates indicate that green and non-green jobs act as substitutes, as higher green wages become more financially attractive for workers, which move away from non-green jobs. While the CES production framework typically assumes a positive elasticity of substitution, these negative estimates suggest that the empirical relationship is dominated by labour supply dynamics rather than firm-level substitution. Therefore, to ensure that the CGE model reflects the high degree of responsiveness between green and non-green labour while maintaining the mathematical consistency required for general equilibrium analysis, we set the negative sign of the elasticity of substitution to its absolute value.

In the appendix, tables A9 through A18 present sector-specific estimates of the elasticity of substitution for ten distinct industries within Portugal. The sector that showed the highest elasticity variation across models was real estate activities at around 0.17 pp, while the financial and insurance sectors showed the lowest variation of around 0.08 pp. This implies that these sectors are the most and least responsive to relative wages.

Table 25 - POLS, HDFE and IV estimation of elasticity equation

	POLS		HDFE		IV	
	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)
Ln(WageG/WageNG)	-0.966***	-0.969***	-0.859***	-0.883***	-0.917***	-0.904***

[17] In column 5, the ρ -value of Hansen's test is approximately 0.1. Given the proximity to the decision threshold and potential approximation error, we consider the instruments valid.

	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)	(0.005)
Share of women	0.238***	0.221***	0.146***	0.128***	0.133***	0.128***
	(0.003)	(0.003)	(0.007)	(0.007)	(0.011)	(0.010)
Share of graduated workers	0.057***	0.093***	-0.164***	-0.124***	-0.123***	-0.109***
	(0.004)	(0.004)	(0.010)	(0.009)	(0.014)	(0.013)
Average workers potential experience	-0.000**	0.000	-0.003***	-0.002***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Total sales)	0.012***	0.013***	0.004***	0.001**	0.002**	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Total actives)	0.052***	0.035***	0.035***	0.015***	0.026***	0.016***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Ln(Number of paid workers)		0.030***		0.056***		0.036***
		(0.001)		(0.003)		(0.004)
Constant	-0.719***	-0.568***	-0.143***	-0.021		
	(0.007)	(0.008)	(0.025)	(0.023)		
Firms Fixed Effect	No	No	Yes	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes	Yes	Yes
Hansen P-value	-	-	-	-	0.099	0.893
C Statistitcs P-value	-	-	-	-	0.000	0.003
1st Stage F	-	-	-	-	7950.701	7545.621
Observations	282558	282368	265294	265108	153053	152958
R^2	0.906	0.912	0.980	0.983	0.815	0.845

Note: In this table are presented the estimation results of equation 26. In columns 1, 3 and 5, the dependent variable is the natural log of the ratio of the number of non-greens by green workers (WorkersNG/WorkersG). In columns 2, 4 and 6, the dependent variable is the natural log of the ratio of the total number of hours worked by workers from green to non-green jobs (HoursNG/HoursG). G stands for green and NG for non-green. For financial firms, the total sales, total activities and number of paid workers were not included, due to lack of information. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Source: Linked *Quadros de Pessoal - Sistema das Contas Integradas das Empresas* from 2010 to 2019. Made by authors.

Table 26 summarises the final values used for model calibration. Preferred estimates were selected through a two-stage procedure: first, choosing the HDFE specification with the highest explanatory power, and second, adopting IV estimators when endogeneity was detected. These elasticities were then incorporated into the PEP-1-1 CGE framework to reflect differences in labour substitutability across sectors. Full econometric results are available in Appendix Tables A9–A18.

Table 26 - Elasticity of substitution of composite labour per sector

Sectors	HDFE	IV
Agriculture, forestry, and fishing	-	-0.849
Industry, energy, water supply and sewerage	-0.909	-
Construction	-	-0.955
Wholesale and retail trade*	-0.848	-
Information and communication	-0.916	
Financial and insurance activities	-0.810	-
Real estate activities	-0.797	-
Professional, scientific, and technical activities; administrative and support service	-	-0.952
Public administration and defence; compulsory social security; education; human health and social work	-0.779	-
Arts; entertainment; repair of household goods and other services	-	-0.898

Note: This table reports the estimated elasticities of substitution between green and non-green jobs across sectors employed in the CGE model. Estimates are calculated using the High-Dimensional Fixed Effects (HDFE) model and the Instrumental Variables (IV) approach. The selection between HDFE and IV estimates was guided by econometric considerations. The IV estimates were preferred in scenarios where endogeneity was suspected. Otherwise, the HDFE estimates were chosen. * also include: repair of motor vehicles and motorcycles; transportation and storage; accommodation and food service activities. Full tables are reported in appendix tables A9 through A18.
Source: Linked *Quadros de Pessoal - Sistema das Contas Integradas das Empresas* from 2010 to 2019. Made by authors.

4.3.2 Simulations results

Policy scenarios

Building on previous steps of the CGE model, this section defines the fiscal policy scenarios designed to evaluate the macroeconomic and distributional effects of green transition measures. Three indicative policy scenarios were simulated under the GTR framework. Each represents a distinct fiscal adjustment targeting either income or production taxes while maintaining comparability across institutional agents.

Scenario A models a 1 pp reduction in income taxes for green households and firms (from benchmark 12.6 % to 11.6 %), isolating the direct effect of lower taxation on green agents, financed

through increased public debt. This scenario aims to incentivize workers to look for green jobs by lowering the fiscal burden on agents and offering higher income returns.

Scenario B combines the same income tax reduction with a compensatory 100% increase in the production tax applied to the energy sector (corresponding to a marginal 0.0035 pp increase), ensuring overall fiscal neutrality. The measure acts as a Pigouvian instrument designed to internalise pollution externalities, particularly CO_2 emissions, while promoting green employment and penalizing carbon-intensive production. According to Statistics Portugal, the energy sector has consistently accounted for approximately 75% of total national CO_2 emissions in recent years.

Scenario C focuses on the production side, introducing a 10% reduction (equivalent to 0.0004 pp) in the production tax applied to the construction sector. This sector was selected due to its relatively high concentration of green labour and income, making it a strategic target for stimulating employment through cost-reducing incentives. The measure aims to enhance the competitiveness of green labour-intensive activities and reinforce the employment effects of fiscal support within the transition framework.

Together, these simulations capture the fiscal mechanisms through which green-oriented taxation can influence sectoral performance, income distribution, and the transition toward sustainable employment. The following subsection presents the simulation outcomes, highlighting the macroeconomic adjustments and distributional implications across agents and sectors.

Wages, income and labour demand

Table 27 presents the percentage variations in wages and income for green and non-green households and firms across the three simulated policy scenarios, relative to the benchmark (Business-as-Usual, BAU) equilibrium, which represents the calibrated base-year economy prior to any policy intervention.

Table 27 - Wages, Income and Transfers vs BAU

	Wages		Disposable Income		Transfer income	
Scenarios	HFIRMG	HFIRMNG	HFIRMG	HFIRMNG	HFIRMG	HFIRMNG
Scenario A	-0.015	0.014	1.423	0.015	0.047	0.021
Scenario B	-0.227	-0.135	1.151	-0.205	-0.068	-0.072
Scenario C	0.002	0.001	0.002	0.001	0.0001	0.000

Note: This table presents simulated results for wages, disposable income and transfer income in percentage variation of business-as-usual scenario for scenarios A, B and C. HFIRMG and HFIRMNG stands for green and non-green households and firms, respectively.
Source: Results from green CGE model. Made by authors.

In Scenario A, the reduction in income taxes for green households and firms resulted in a 0.015% decline in their wage rate, consistent with the model's wage-curve specification linking real wages inversely to employment expansion. Nevertheless, disposable and transfer incomes, increasing by approximately 1.423% and 0.047%, respectively, reflecting the net positive effect of lower taxation. This policy also improves the income conditions of non-green households and firms, as wages and incomes rise slightly, suggesting limited cross-group income diffusion through general equilibrium feedbacks.

In Scenario B, the compensatory tax on the energy sector intensifies downward wage pressures, with wage rates falling for both green and non-green agents, by 0.227% and 0.135%, respectively. Transfer incomes also marginally decline. However, disposable income of green households and firms increases by 1.151%, while that of non-green agents declines by 0.205% evidencing the redistributive character of this policy.

Scenario C, yields nearly neutral outcomes. Wages and disposable income for green households and firms increased modestly by 0.002%, as for non-green agents (0.001%).

Table 28 presents percentage variations in labour demand across sectors for Scenarios A, B, and C, relative to the benchmark (Business-as-Usual, BAU) equilibrium.

In Scenario A, the reduction of income taxes for green households and firms leads to a general contraction in labour demand for green agents across four sectors, with the largest decline observed in construction (–0.659%) and largest increase in arts and entertainment (0.178%) The effect on non-green agents follow same pattern. In wholesale and retail trade, finance and insurance, real estate, public services, and arts, there was a slight increase in employment.

In Scenario B, the additional energy tax amplifies these contractionary effects. Labour demand decreases sharply for green agents in industry and energy (–1.168%) and agriculture (-0.331%), while remaining sectors showed a positive labour demand variation (between 0.016% to 0.251%). For non-green labour the negative effect is observed in the energy production, agriculture and construction sectors, -1.251%, -0.409% and -0.072%, respectively. While in the remaining sectors was observed a positive labour demand variation.

Scenario C produces the smallest variations. The production tax cut in the construction sector raises labour demand slightly only in construction sector for green agents (0.048%). For non-green agents, 8 out of 10 sectors exhibited negative variations, although these changes are near-zero.

Table 28 - Labour Demand vs BAU

	Scenario A			Scenario B			Scenario C		
Sectors	HFIRMG	HFIRMNG	Total	HFIRMG	HFIRMNG	Total	HFIRMG	HFIRMNG	Total
Agriculture, forestry and fishing	-0.041	-0.066	-0.063	-0.331	-0.409	-0.401	-0.003	-0.002	-0.002
Industry, energy, water supply and sewerage	0.000	-0.026	-0.021	-1.168	-1.251	-1.235	-0.002	-0.001	-0.001
Construction	-0.659	-0.686	-0.680	0.016	-0.072	-0.051	0.048	0.050	0.049
Wholesale and retail trade*	0.090	0.066	0.069	0.251	0.173	0.185	-0.002	-0.001	-0.001
Information and communication	-0.095	-0.122	-0.117	0.154	0.069	0.083	-0.006	-0.005	-0.005
Financial and insurance activities	0.136	0.112	0.115	0.096	0.021	0.029	0.000	-0.001	0.001
Real estate activities	0.131	0.108	0.111	0.162	0.088	0.099	-0.008	-0.007	-0.007
Professional, scientific and technical activities	-0.084	-0.112	-0.108	0.207	0.112	0.130	-0.005	-0.004	-0.004
Public administration, education and human health	0.061	0.038	0.039	0.156	0.084	0.086	-0.001	-0.0003	-0.0004
Arts and entertainment	0.178	0.152	0.154	0.157	0.076	0.081	-0.001	0.001	0.0004

Note: This table presents simulated results for labour demand in percentage variation of business-as-usual scenario for all sectors. HFIRMG and HFIRMNG stands for green and non-green households and firms, respectively. * also include: repair of motor vehicles and motorcycles; transportation and storage; accommodation and food service activities.

Source: Results from green CGE model. Made by authors.

Consumption and production

Table 29 presents the percentage variation in consumption by green and non-green households and firms across sectors, relative to the benchmark equilibrium.

Table 29 - Consumption vs BAU

	Scenario A		Scenario B		Scenario C	
Sectors	HFIRMG	HFIRMNG	HFIRMG	HFIRMNG	HFIRMG	HFIRMNG
Agriculture, forestry and fishing	0.465	0.004	0.408	-0.036	0.001	0.0004
Industry, energy, water supply and sewerage	1.390	0.008	1.081	-0.248	0.002	0.001
Construction	1.430	0.060	1.163	-0.154	0.027	0.026
Wholesale and retail trade*	1.512	-0.037	1.412	-0.082	0.001	0.0001
Information and communication	1.586	0.022	1.352	-0.154	0.003	0.002
Financial and insurance activities	1.545	-0.018	1.376	-0.131	0.002	0.001
Real estate activities	1.354	-0.042	1.203	-0.142	0.004	0.003
Professional, scientific and technical activities	1.568	0.018	1.345	-0.148	0.003	0.001
Public administration, education and human health	1.560	-0.003	1.359	-0.147	0.003	0.001
Arts and entertainment	1.542	-0.021	1.361	-0.146	0.002	0.001

Note: This table presents simulated results for consumption in percentage variation of business-as-usual scenario for all sectors. HFIRMG and HFIRMNG stands for green and non-green households and firms, respectively. * also include: repair of motor vehicles and motorcycles; transportation and storage; accommodation and food service activities.
Source: Results from green CGE model. Made by authors.

In Scenario A, the income tax reduction for green agents stimulates consumption across all sectors, with the strongest increases in information and communication, and professional, scientific and technical activities, in both cases more than 1.5%. Non-green agents also register moderate gains in five sectors. In Scenario B, green agents maintain positive consumption growth, though at lower magnitudes, while non-green agents experience broad declines in all sectors. The contraction is sharper in industry and energy, where the compensatory tax increases production costs and reduces real purchasing power. Scenario C produces marginal effects overall. Consumption by green agents rises slightly, up to 0.027% in construction and between 0.001% and 0.004% in all remaining sectors. The non-green agent's consumption remains also almost unchanged, with the biggest variation in construction (0.026%). These results confirm that income-side tax incentives (Scenarios A and B) have stronger transmission to household demand than production-side measures (Scenario C).

Table 30 reports the percentage change in sectoral output relative to the benchmark equilibrium.

Table 30 - Production vs BAU

Sectors	Scenario A	Scenario B	Scenario C
Agriculture, forestry and fishing	-0.016	-0.100	-0.0004
Industry, energy, water supply and sewerage	-0.010	-0.584	-0.0003
Construction	-0.437	-0.033	0.032
Wholesale and retail trade*	0.035	0.094	-0.001
Information and communication	-0.061	0.043	-0.003
Financial and insurance activities	0.054	0.014	0.0004
Real estate activities	0.004	0.003	-0.0002
Professional, scientific and technical activities	-0.071	0.086	-0.003
Public administration, education and human health	0.030	0.067	-0.0003
Arts and entertainment	0.100	0.053	0.0003

Note: This table presents simulated results for production in percentage variation of business-as-usual scenario for all sectors. HFIRMG and HFIRMNG stands for green and non-green households and firms, respectively. * also include: repair of motor vehicles and motorcycles; transportation and storage; accommodation and food service activities.
Source: Results from green CGE model. Made by authors.

In Scenario A, the reduction in income taxes for green agents produces a mixed output response. With the sharpest decline in construction by 0.437% and highest gains in arts and entertainment by 0.100%. 5 out of 10 sectors showed a positive variation and the remaining a negative effect, which might suggest a short-term reallocation of resources rather than broad stimulus. In Scenario B, most sectors experience slight output growth, reflecting the balanced nature of the fiscal shift. However, the energy and industry sectors still contract by 0.584%, driven by the compensatory tax burden on energy production, which dampens activity in carbon-intensive areas. Scenario C yields minimal changes overall. The construction sector shows a highest increase in production (0.032%), while other sectors remain almost unchanged.

Government and market

Table 31 presents the percentage variation of key macroeconomic indicators relative to the benchmark equilibrium, including government disposable income, real Gross Domestic Product (GDP) at basic and market prices, and the CPI.

Table 31 - Government disposable income, real GDP at basic and market prices and CPI vs BAU

Government and market indicators	Scenario A	Scenario B	Scenario C
Government disposable income	-0.352	-0.023	-0.008
Real GDP at basic prices	-0.007	-0.063	0.001
Real GDP at market prices	-0.015	-0.027	-0.002
Consumer Price Index	0.023	-0.027	-0.0004

Note: This table presents simulated results for government disposable income, real gross domestic product at basic and market prices, and consumer price index in percentage variation of business-as-usual scenario for all sectors. GDP stands for Gross Domestic Product.
Source: Results from green CGE model. Made by authors.

In Scenario A, government disposable income falls (0.352%) due to lower tax revenues, real GDP at basic and market prices also decrease slightly (by 0.007% and 0.015%, respectively). The CPI rises (0.023%), reflecting higher domestic demand pressures. In Scenario B, the introduction of the compensatory energy tax narrows fiscal losses (0.023%) but reduces GDP at both basic and market prices by 0.062% and 0.025%, respectively. The CPI also declines by 0.027%, indicating that the contractionary effect of the energy tax outweighs income-side stimulus. Scenario C yields negligible changes across all indicators. GDP variations are near zero, while the CPI and government income remain effectively unchanged, confirming the limited macroeconomic effect of targeted production-side incentives. Together, these results provide a comprehensive view of how alternative fiscal configurations influence green employment and income distribution within the Portuguese economy.

Discussion

The analysis reveals how fiscal policy design can shape the pace and inclusiveness of the green transition, influencing labour markets, income distribution, and macroeconomic equilibrium. By simulating three scenarios, the model highlights the trade-offs between green employment promotion, fiscal sustainability, and overall economic performance. The evidence suggests that while targeted fiscal reforms can promote greener forms of employment and production, their aggregate impact depends strongly on the balance between income incentives, production-side adjustments, and fiscal sustainability.

Scenario A, which simulates a reduction in income taxes for green households and firms without compensatory measures, shows that income-based incentives can effectively raise disposable income and stimulate short-term consumption. However, these benefits come at a fiscal cost and generate only modest gains in production and even negative effect on green employment in some sectors. The higher

consumption of green agents spills over to non-green sectors, but the absence of compensatory taxation leads to a reduction in government disposable income and in increase in prices. This result illustrates the classical trade-off between distributive gains and macroeconomic balance when fiscal expansion is not offset by revenue sources.

Scenario B introduces a compensatory environmental dimension by combining the same income tax reduction with a Pigouvian production tax on the energy sector. This adjustment partially restores fiscal balance and strengthens the "polluter pays" principle, promoting redistribution from carbon-intensive to greener activities. However, the reallocation of resources produces a contractionary effect on aggregate demand, as non-green agents experience declines in income and consumption. Although the overall effect on prices is deflationary, reflecting lower energy demand, the economy experiences a slight contraction in real output. Scenario B thus illustrates the needed balance between environmental goals and short-term macroeconomic stability.

Scenario C, centred on a 10% production tax reduction for the construction sector, produces smaller but more internally coherent results, with modest positive effects across wages, consumption, alongside minimal fiscal and price distortions. The sectoral targeting of this measure supports green employment in a green labour-intensive industry, without destabilising public finances or aggregate prices. Yet, by design, its scope is limited, for the positive effects are confined mainly to the targeted sector and its upstream linkages. Scenario C, therefore, emerges as a low-impact but low-risk instrument, highlighting the potential of selective production incentives to complement broader transition policies.

Taken together, these results indicate that each fiscal configuration advances one aspect of the green transition. Scenario A prioritises distributive fairness and short-run welfare through disposable income gains; Scenario B aligns taxation with environmental objectives but produces short-term adjustment costs; and Scenario C delivers stability and targeted employment benefits with limited macroeconomic reach.

Naturally, when comparing the three scenarios, no single configuration emerges as unequivocally superior. Each policy reveals specific advantages and trade-offs depending on the policy dimension considered. Scenario A demonstrates that income tax relief for green agents can effectively raise disposable income and stimulate short-term consumption, but at a notable fiscal cost and with only moderate effects on employment and production. Scenario B achieves an improved fiscal discipline by partially offsetting the tax reduction through environmental taxation, thereby advancing the "polluter pays" principle. However, the redistribution from non-green to green agents produces an uneven income pattern

and a contractionary effect on aggregate demand in high-emission sectors. Scenario C, in turn, shows that production-side incentives targeted at green labour-intensive sector can modestly enhance employment and output with minimal fiscal or price distortion, though their narrow focus limits the overall macroeconomic reach.

Taken together, the results show that the effectiveness of fiscal measures promoting green employment depends on their structural design and interaction across sectors. Income-based incentives can enhance short-term welfare but risk undermining fiscal sustainability, while Pigouvian taxation effectively redirects resources toward low-carbon production, though at the cost of temporary contraction in high-emission sectors. Targeted production incentives, by contrast, produce limited aggregate effects but help consolidate employment in green-intensive activities. These findings suggest that fiscal strategies aimed at supporting green jobs should prioritise sectoral calibration and ensure that incentives are aligned with labour reallocation capacities and the absorptive potential of green sectors.

4.4 Conclusion

This paper estimates the elasticity of substitution between green and non-green jobs and examined the effects of various fiscal policies under GTR aimed at promoting sustainable employment.

The results indicate that the elasticity of substitution for composite labour ranges between -0.85 and -0.97, suggesting that green and non-green jobs act as imperfect substitutes. In practical terms, a 1% increase in the wage ratio of green to non-green jobs leads to a 0.85–0.97% decline in the relative employment of non-green labour compared to green labour.

Policy scenarios A, B, and C revealed different outcomes in terms of income distribution, labour demand, consumption, production, and macroeconomic performance. Among them, Scenario C yielded the most coherent increases in green employment in targeted sector. Nevertheless, the limited magnitude of these impacts indicates that such an isolated policy is insufficient to drive a structural transformation toward a green economy.

Two primary limitations should be acknowledged. First, green jobs are identified using the O*NET taxonomy at the 8-digit SOC level, for which disaggregated employment shares are unavailable, requiring the application of uniform weighting. Second, the occupational data used follow the 4-digit ISCO08 classification, while the crosswalk provided by the BLS connects it to the 6-digit SOC2010, which may introduce minor inconsistencies in mapping between systems.

Future research should explore a composite fiscal framework that combine targeted tax benefits with environmental levies, potentially reconciling economic efficiency, fiscal sustainability, and labour market inclusiveness.

Ultimately, understanding how fiscal design shapes the dynamics of green employment is essential for ensuring that the green transition advances not only environmental objectives but also a fair and inclusive transformation of the economy.

5 Conclusion

This thesis contributes to the understanding of green employment by offering a multidimensional and empirically grounded analysis of the Portuguese labour market. Through three complementary studies, it integrates micro-level evidence from employer–employee data with macroeconomic modelling, addressing three major dimensions of the green transition: how green jobs are defined and measured; how wage structures differ between green and non-green employment; and, lastly, how fiscal policies can shape green job creation. By combining occupation-based (O*NET), task-based (O*NET), and skill-based (ESCO) frameworks, the research builds one of the most comprehensive assessments to date of the greening of employment in Portugal.

The first empirical study reveals that green jobs remain a relatively small but significant and growing component of total employment in Portugal, representing between 2% and 14% of all jobs depending on the classification method. This range highlights a key conceptual challenge: the classification framework strongly influences not only the quantification of green jobs but also their sectoral and occupational distribution. Occupation-based measures capture the visible dimension of the green transition, identifying roles directly engaged in environmental protection or resource efficiency, whereas task-based and skill-based approaches uncover more subtle greening processes within traditionally "brown" sectors. For instance, while the energy and waste management sectors emerge as the most intensive in green employment, task-based metrics reveal that green activities are increasingly embedded across manufacturing and construction, reflecting the diffusion of environmentally oriented tasks and technologies throughout the economy.

The second study deepens this understanding by analysing wage structures. The findings confirm the presence of a green wage premium: workers in green jobs earn higher wages, on average, than those in non-green roles. However, the size of this premium depends on the measurement framework. The task-based measure shows the highest wage returns, suggesting that the ability to perform specific green-related tasks, such as improving energy efficiency or controlling pollution, directly leads to higher pay. In contrast, the skill-based measure indicates a smaller premium, implying that green skills, while valuable, may still be under-recognised or under-compensated in the Portuguese labour market. The Blinder–Oaxaca decomposition further reveals that 55–66% of the wage gap can be attributed to observable factors like education, experience, and firms' attributes, although a significant portion remains unexplained. This unexplained part likely reflects unobserved differences in individual ability, motivation, or job quality, as well as institutional and structural labour market factors. The continued existence of

gender and educational disparities highlights the importance of inclusive upskilling policies to promote fair access to green employment opportunities.

The third study broadens the analysis to the macroeconomic level by employing a CGE model to examine how fiscal policy measures can promote green employment. The findings show that green and non-green jobs are interchangeable, meaning that policies promoting one type may partially crowd out the other if not well designed. Among the simulated fiscal scenarios, reductions in production taxes, especially in green labour-intensive sectors such as construction, lead to the most significant increase in demand for green labour, while income tax cuts have smaller effects. However, these policies come with a cost: without compensatory measures, they decrease government disposable income, which could limit the fiscal capacity for environmental and social initiatives. These results underline that fiscal policy can be an effective instrument for advancing the green transition but should be part of a broader, coherent strategy that balances economic, environmental, and social goals.

Across chapters, the thesis demonstrates that the Portuguese green labour market is shaped by structural inequalities. Green employment is disproportionately concentrated among men, highly educated workers, and firms with greater capital intensity or foreign ownership. Moreover, green occupations rely heavily on formal qualifications and structured task content, implying that educational institutions and training systems must adapt to supply the specialised competences demanded by green sectors. The findings reinforce the centrality of human capital development, lifelong learning, and targeted vocational training as prerequisites for an equitable and effective green transition.

From a methodological perspective, this thesis enhances the literature by including both microeconometric models and a macroeconomic simulation framework, linking individual-level labour concepts and dynamics to system-level policy effects, highlighting the significance of employing multidimensional measurement frameworks. The weak correlations between task-based, skill-based, and occupation-based measures confirm that no single classification can fully encompass the complexity of green work. Each approach offers unique insights: occupations reflect the industrial structure behind greening; tasks reveal the technological and organisational changes within jobs; and skills indicate the workforce's adaptive capacities. Collectively, these dimensions create a comprehensive understanding of how the labour market adapts to environmental policies and technological advancements.

This study, however, faces two methodological constraints. First, the O*NET taxonomy of green occupations and tasks operates at the 8-digit SOC2010 level, for which detailed Portuguese data are unavailable. As a result, uniform weighting schemes were used to estimate greenness shares. Second,

the crosswalk between SOC2010 and ISCO08 lacks a one-to-one correspondence, linking 6-digit SOC codes to 4-digit ISCO categories. Future research should explore alternative frameworks, particularly the ESCO system, which, though still evolving, is tailored to the European labour market and aligned with EU occupational classifications.

Building on these findings, future work should refine the measurement of green employment by incorporating real-time labour market data, vacancy-level dynamics, and employment-weighted approaches to capture ongoing structural changes. Understanding the causal mechanisms behind the green wage premium will require more advanced econometric techniques, such as regression discontinuity or instrumental variable methods. Comparative and post-pandemic analyses could further illuminate the impact of EU-level green stimulus initiatives on national labour markets.

From a policy perspective, several implications emerge. First, reliance on a single definition of green jobs can distort policy design and hinder accurate monitoring of the transition. A hybrid classification system combining occupations, tasks, and skills is essential to identify both visible and latent forms of green employment. Second, since green jobs offer higher wages but remain demographically concentrated, active labour market policies must close gender and educational gaps through targeted reskilling, particularly in carbon-intensive sectors at risk of contraction. Third, education and training systems should integrate sustainability competencies across all stages of formal and vocational education to enhance adaptability and resilience. Finally, fiscal and industrial policies must work together to encourage private investment in green technologies while ensuring social equity and employment stability.

To conclude, the findings of this thesis confirm that the green transition is multidimensional and complex, involving changes not only in technology but also in employment and skills. Building a sustainable and inclusive transition requires clear definitions of green jobs, fair labour markets, and policies that connect environmental ambition with economic opportunity. The Portuguese case illustrates both the challenges and potential of this transformation. Although green employment remains limited, its steady growth provides a solid basis for future progress toward a low-carbon, resilient, and fair economy.

Bibliography

Aaberge, R., Colombino, U., Strom, B., & Wennemo, T. (2007). *Population ageing and fiscal sustainability: An integrated micro-macro analysis of required tax changes.* In *Population Ageing, Social Security and Taxation: Modelling our Future* (Vol. 15, pp. 259–290). Elsevier.

Arntz, M., Boeters, S., Gürtzgen, N., & Schubert, S. (2008). Analysing welfare reform in a microsimulation-AGE model: The value of disaggregation. *Economic Modelling, 25*(3), 422–439. https://doi.org/10.1016/j.econmod.2007.07.001

Bajo-Rubio, O., & Gómez-Plana, A. G. (2004). Reducing Social Contributions for Unskilled Labor as a Way of Fighting Unemployment: An Empirical Evaluation for the Case of Spain. FinanzArchiv / Public Finance Analysis, 60(2), 160–185. http://www.jstor.org/stable/40913035

Becker, R. A., & Shadbegian, R. J. (2009). Environmental products manufacturing: A look inside the green industry. *The BE Journal of Economic Analysis & Policy, 9*(1). https://doi.org/10.2202/1935-1682.2117

Blake, A. (2000). *The economic effects of tourism in Spain.* Christel DeHaan Tourism and Travel Research Institute, Nottingham, UK.

Blanchflower, D. G., & Oswald, A. J. (1995). An introduction to the wage curve. *Journal of Economic Perspectives, 9*(3), 153–167. https://doi.org/10.1257/jep.9.3.153

Bluedorn, J., Hansen, N. J., Noureldin, D., Shibata, I., & Tavares, M. M. (2023). Transitioning to a greener labor market: Cross-country evidence from microdata. *Energy Economics, 126*, 106836. https://doi.org/10.1016/j.eneco.2023.106836

Boeters, S. Optimal Tax Progressivity in Unionised Labour Markets: Simulation Results for Germany. *Computational Economics* 41, 447–474 (2013). https://doi.org/10.1007/s10614-012-9330-2

Bone, M., González Ehlinger, E., & Stephany, F. (2025). Skills or degree? The rise of skill-based hiring for AI and green jobs. *Technological Forecasting and Social Change, 214*, 124042. https://doi.org/10.1016/j.techfore.2025.124042

Bontadini, F., Vona, F. Anatomy of Green Specialisation: Evidence from EU Production Data, 1995–2015. *Environmental and Resource Economics* 85, 707–740 (2023). https://doi.org/10.1007/s10640-023-00781-7

Borjas, G. J. (2003). The labour demand curve is downward sloping: Reexamining the impact of immigration on the labour market. *The Quarterly Journal of Economics, 118*(4), 1335–1374. https://doi.org/10.1162/003355303322552810

Bovenberg, A. L., Graafland, J. J., & De Mooij, R. A. (2000). Tax reform and the Dutch labour market: An applied general equilibrium approach. *Journal of Public Economics, 78*(1–2), 193–214. https://doi.org/10.1016/S0047-2727(99)00116-4

Bowen, A., & Hancké, B. (2019). The social dimensions of greening the economy: Developing a taxonomy of labour market effects related to the shift toward environmentally sustainable economic activities. *Publications Office of the European Union*.

Bowen, A., Kuralbayeva, K., & Tipoe, E. L. (2018). Characterising green employment: The impacts of 'greening' on workforce composition. *Energy Economics, 72*, 263–275. https://doi.org/10.1016/j.eneco.2018.03.015

Bureau of Labor Statistics. (2012). *Employment in green goods and services 2010*. U.S. Department of Labor. https://www.bls.gov/news.release/archives/ggqcew_03222012.pdf

Bureau of Labor Statistics. (2013). *Employment in green goods and services 2011*. U.S. Department of Labor. https://www.bls.gov/news.release/pdf/ggqcew.pdf

Card, D. (1995). The wage curve: A review. *Journal of Economic Literature, 33*(2), 285–299. https://www.jstor.org/stable/pdf/2729028.pdf

Card, D. (2009). Immigration and inequality. *American Economic Review, 99*(2), 1–21. https://doi.org/10.1257/aer.99.2.1

Caselli, F., & Medas, P. A. (2024). *Green fiscal rules? Challenges and policy alternatives* (IMF Working Paper No. 2024/125). International Monetary Fund. https://doi.org/10.5089/9798400280726.001

Cerejeira, J. (2008). *Young employment, job-skill composition and minimum wages: Evidence from a "natural experiment"* (NIPE Working Paper No. 04/2008). Universidade do Minho. https://hdl.handle.net/1822/7720

Cerejeira, J., & Guimarães, P. (2012). The price of unobservables and the employer-size wage premium. *Economics Letters, 117*(3), 878–880. https://doi.org/10.1016/j.econlet.2012.06.042

Ciccone, A., & Peri, G. (2005). Long-run substitutability between more and less educated workers: Evidence from U.S. states, 1950–1990. *Review of Economics and Statistics, 87*(4), 652–663. https://doi.org/10.1162/003465305775098233

Consoli, D., Marin, G., Marzucchi, A., & Vona, F. (2016). Do green jobs differ from non-green jobs in terms of skills and human capital? *Research Policy, 45*(5), 1046–1060. https://doi.org/10.1016/j.respol.2016.02.007

Curtis, E. M., & Marinescu, I. (2023). Green energy jobs in the United States: What are they, and where are they? *Environmental and Energy Policy and the Economy, 4*(1), 202–237. https://doi.org/10.1086/722677

Decaluwé, B., Lemelin, A., Maisonnave, H., & Robichaud, V. (2009). *PEP-1-1: The PEP standard computable general equilibrium model, single-country, static version.* PEP.

Decaluwé, B., Martens, A., & Savard, L. (2001). *La politique économique du développement et les modèles d'équilibre général calculable: Une introduction à l'application de l'analyse mésoéconomique aux pays en développement.* Presses de l'Université de Montréal.

Dewatripont, C., Ehrlich, S., Ginsburgh, V., et al. (1991). The effects on unemployment of reducing social security contributions: A general equilibrium analysis for Belgium. *De Economist, 139*(3), 272–290. https://doi.org/10.1007/BF01460315

Dierdorff, E. C., Norton, J. J., Drewes, D. W., Kroustalis, C. M., Rivkin, D., & Lewis, P. (2009). *Greening of the world of work: Implications for O*NET®-SOC and new and emerging occupations*. National Center for O*NET Development. https://www.onetcenter.org/reports/Green.html

Ecorys. (2012). *The number of jobs dependent on the environment and resource efficiency improvements*. European Commission. https://ec.europa.eu/environment/enveco/jobs/pdf/jobs.pdf

Elliott, R. J., & Lindley, J. K. (2017). Environmental jobs and growth in the United States. *Ecological Economics, 132*, 232–244. https://doi.org/10.1016/j.ecolecon.2016.09.030

Elliott, R. J., Kuai, W., Maddison, D., & Ozgen, C. (2024). Eco-innovation and (green) employment: A task-based approach to measuring the composition of work in firms. *Journal of Environmental Economics and Management*, 103015. https://doi.org/10.1016/j.jeem.2024.103015

Escalante, L., Mamboundou, P., Meyimdjui, C., & Omoju, O. E. (2025). Economic and food security impacts of climate disasters and mitigation policies: Insights from Nigeria. *Environmental and Resource Economics, 88*, 1657–1677. https://doi.org/10.1007/s10640-025-00981-3

European Commission. (2007). *Facts and figures: The links between EU's economy and environment*. Office for Official Publications of the European Communities. https://ec.europa.eu/environment/enveco/pdf/facts.pdf

European Commission. (2022a). *Green skills and knowledge concepts: Labelling the ESCO classification*. https://esco.ec.europa.eu/en/publication/green-skills-and-knowledge-concepts-labelling-esco-classification

European Commission. (2022b). *GreenComp, the European sustainability competence framework*. Publications Office of the European Union. https://data.europa.eu/doi/10.2760/13286

Eurostat. (2016). *Environmental goods and services sector accounts: Practical guide*. Publications Office of the European Union. https://ec.europa.eu/eurostat/documents/3859598/7741794/KS-GQ-16-011-EN-N.pdf/3196a7bc-c269-40ab-b48a-73465e3edd89?t=1479717329000

Eurostat. (2021). *Environmental economy – Statistics on employment and growth*. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Environmental_economy_%E2%80%93_statistics_on_employment_and_growth

Fæhn, T., Gómez-Plana, A. G., & Kverndokk, S. (2009). Can a carbon permit system reduce Spanish unemployment? *Energy Economics, 31*(4), 595–604. https://doi.org/10.1016/j.eneco.2009.01.003

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Gelauff, G. M., Van Erp, F. A., Graafland, J. J., van Hien, A. E., & Nibbelink, A. G. (1991). Towards an analysis of tax effects on labour market and allocation: A micro/macro approach. *De Economist, 139*(2), 243–271. https://doi.org/10.1007/BF01460314

Georgeson, L., & Maslin, M. (2019). Estimating the scale of the US green economy within the global context. *Palgrave Communications, 5*(1), 1–12. https://doi.org/10.1057/s41599-019-0329-3

Gião, C. G., & Sousa, R. (2023). *Desenvolvimento de uma matriz de contabilidade social para a análise do efeito das alterações climáticas no turismo* (NIPE Working Paper No. 4/2023). Universidade do Minho. https://repositorium.sdum.uminho.pt/bitstream/1822/84119/1/WP-04.2023.pdf

Goldin, C. (2006). The quiet revolution that transformed women's employment, education, and family. *American Economic Review, 96*(2), 1–21. https://doi.org/10.1257/000282806777212350

Goos, M., Manning, A., & Salomons, A. (2009). Job polarization in Europe. *American Economic Review, 99*(2), 58–63. https://doi.org/10.1257/aer.99.2.58

Guimarães, P. (2012). *REGINTFE: Stata module to estimate a linear regression model with one interacted high-dimensional fixed effect* (Statistical Software Components S457517). Boston College Department of Economics. https://ideas.repec.org/c/boc/bocode/s457517.html

Guimarães, P., & Portugal, P. (2010). A simple feasible alternative procedure to estimate models with high-dimensional fixed effects. *Stata Journal, 10*(4), 628–649. https://doi.org/10.1177/1536867X1101000406

Havránek, T., Irsová, Z., Lašlopová, L., & Zeynalova, O. (2020). *The elasticity of substitution between skilled and unskilled labor: A meta-analysis* (MPRA Paper No. 102598). University Library of Munich, Germany. https://mpra.ub.uni-muenchen.de/102598/

Hutton, J. P., & Ruocco, A. (1999). Tax reform and employment in Europe. *International Tax and Public Finance, 6*(3), 263–287. https://doi.org/10.1023/A:1008730928998

ILO. (2019). *Skills for a greener future: A global view*. International Labour Organization. https://www.ilo.org/publications/skills-greener-future-global-view

Katz, L. F., & Krueger, A. B. (2019). The rise and nature of alternative work arrangements in the United States, 1995–2015. *ILR Review, 72*(2), 382–416. https://doi.org/10.1177/0019793918820008

Katz, L. F., & Murphy, K. M. (1992). Changes in relative wages, 1963–1987: Supply and demand factors. *The Quarterly Journal of Economics, 107*(1), 35–78. https://doi.org/10.2307/2118323

Lobsiger, M., & Rutzer, C. (2021). The green potential of occupations in Switzerland. *Swiss Journal of Economics and Statistics, 157*(1), 1–21. https://doi.org/10.1186/s41937-021-00076-y

McGuinness, S., Pouliakas, K., & Redmond, P. (2018). Skills mismatch: Concepts, measurement and policy approaches. *Journal of Economic Surveys, 32*(4), 985–1015. https://doi.org/10.1111/joes.12254

Mincer, J. (1974). *Schooling, experience, and earnings*. Human Behavior & Social Institutions, No. 2.

Oaxaca, R. L., & Ransom, M. R. (1994). On discrimination and the decomposition of wage differentials. *Journal of Econometrics, 61*(1), 5–21. https://doi.org/10.1016/0304-4076(94)90074-4

OECD/Cedefop. (2014). *Greener skills and jobs.* OECD Green Growth Studies, OECD Publishing. https://doi.org/10.1787/9789264208704-en

OECD/Eurostat. (1999). *The environmental goods and services industry: Manual for data collection and analysis*. OECD Publishing. https://doi.org/10.1787/9789264173651-en

ONS. (2020). *Classifying the Standard Occupational Classification 2020 (SOC 2020) to the International Standard Classification of Occupations (ISCO-08)*. Office for National Statistics. https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2020/classifyingthestandardoccupationalclassification2020soc2020totheinternationalstandardclassificationofoccupationsisco08

Popp, D., Vona, F., Marin, G., & Chen, Z. (2021). The employment impact of a green fiscal push: Evidence from the American Recovery and Reinvestment Act. *Brookings Papers on Economic Activity.* https://www.jstor.org/stable/27133172

Saussay, A., Sato, M., Vona, F., & O'Kane, L. (2022). *Who's fit for the low-carbon transition? Emerging skills and wage gaps in job ad data* (FEEM Working Paper No. 31). SSRN. https://doi.org/10.2139/ssrn.4260227

Severini, F., Felici, F., Ferracuti, N., Pretaroli, R., & Socci, C. (2018). Gender policy and female employment: A CGE model for Italy. *Economic Systems Research, 31*(1), 92–113. https://doi.org/10.1080/09535314.2018.1431612

UNEP, ILO, IOE, & ITUC. (2008). *Green jobs: Towards decent work in a sustainable, low-carbon world*. Worldwatch Institute. https://wedocs.unep.org/bitstream/handle/20.500.11822/8825/UNEPGreenJobs_report08.pdf?sequence=3

Valero, A., Li, J., Muller, S., Riom, C., & Nguyen-Tien, V. (2021). *Policy brief: Are "green" jobs good jobs?* Grantham Research Institute on Climate Change and the Environment & Centre for Economic Performance, London School of Economics and Political Science. https://www.lse.ac.uk/granthaminstitute/wp-content/uploads/2021/10/Are-Green-Jobs-Good-Jobs_Full-report-4.pdf

Vona, F. (2021). *Labour markets and the green transition: A practitioner's guide to the task-based approach* (JRC Research Report No. JRC126681). Joint Research Centre.

Vona, F., Marin, G., & 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. https://doi.org/10.1093/jeg/lby038

Vona, F., Marin, G., Consoli, D., & Popp, D. (2018). Environmental regulation and green skills: An empirical exploration. *Journal of the Association of Environmental and Resource Economists, 5*(4), 713–753. https://doi.org/10.1086/698859

Appendix

Table A 1 - Summary statistics of green occupations

	Mean	SD	Min	Max	N
Time span					
Year	2015	3	2010	2019	1211169
Socioeconomics indicators					
Age	42.00	10.05	17.00	67.00	1211169
Tenure	8.64	8.59	0.00	54.00	1211169
Potential experience	25.52	11.94	0.00	57.00	1211169
Woman	0.19	0.39	0.00	1.00	1211169
Bellow secondary education	0.48	0.50	0.00	1.00	1211169
Secondary education	0.21	0.41	0.00	1.00	1211169
Higher education	0.31	0.46	0.00	1.00	1211169
Working conditions					
Total income (€)	1561.89	1384.22	237.50	15000.00	1211169
Normal worked hours	168.28	13.87	30.00	217.00	1211169
Extra worked hours	2.08	8.92	0.00	173.00	1211169
Open-ended contract	0.74	0.44	0.00	1.00	1211169
Firms indicators					
Number of employees	872.16	2486.55	6.00	25612.00	1211169
Share of foreign ownership (%)	17.35	36.79	0.00	100.00	1211169
Social capital (in millions of €)	167.84	815.73	1.00e-06	7068.17	1211169
Productivity (in thousands of €)	195.36	1093.48	0.00	206469.70	1211169
Observable skills intensity					
Communication, collaboration and creativity	0.20	0.12	0.06	0.58	1211169
Information skills	0.22	0.07	0.09	0.49	1211169
Assisting and caring	0.14	0.06	0.00	0.28	1211169
Management skills	0.14	0.11	0.00	0.41	1211169
Working with computers	0.04	0.03	0.00	0.15	1211169
Handling and moving	0.11	0.10	0.00	0.48	1211169
Constructing	0.02	0.04	0.00	0.36	1211169
Working with machinery and specialised equipment	0.14	0.11	0.00	0.31	1211169

Note: Summary statistics for occupations with a greenness score greater than or equal to 0.5. The analysis is based on the original sample of 16,368,859 observations.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

Table A 2 - Summary statistics non-green occupations

	Mean	SD	Min	Max	N
Time span					

Year	2015	3	2010	2019	15157690
Socioeconomics indicators					
Age	40.00	10.65	17.00	67.00	15157690
Tenure	8.79	9.14	0.00	55.00	15157690
Potential experience	24.06	12.42	0.00	57.00	15157690
Woman	0.45	0.50	0.00	1.00	15157690
Bellow secondary education	0.51	0.50	0.00	1.00	15157690
Secondary education	0.30	0.46	0.00	1.00	15157690
Higher education	0.19	0.40	0.00	1.00	15157690
Working conditions					
Total income (€)	1116.76	848.68	237.50	14989.28	15157690
Normal worked hours	167.44	14.71	30.00	260.00	15157690
Extra worked hours	1.73	7.68	0.00	301.00	15157690
Open-ended contract	0.74	0.44	0.00	1.00	15157690
Firms indicators					
Number of employees	1304.21	3659.77	6.00	25612.00	15157690
Share of foreign ownership (%)	16.71	36.09	0.00	100.00	15157690
Social capital (in millions of €)	99.12	588.15	1.00e-06	7068.16	15157690
Productivity (in thousands of €)	160.82	827.82	0.00	206469.70	15157690
Observable skills intensity					
Communication, collaboration and creativity	0.22	0.13	0.00	0.90	15157690
Information skills	0.19	0.09	0.00	0.62	15157690
Assisting and caring	0.16	0.13	0.00	0.60	15157690
Management skills	0.14	0.11	0.00	0.51	15157690
Working with computers	0.04	0.06	0.00	0.69	15157690
Handling and moving	0.14	0.15	0.00	0.79	15157690
Constructing	0.02	0.06	0.00	0.37	15157690
Working with machinery and specialized equipment	0.09	0.11	0.00	0.59	15157690

Note: Summary statistics for occupations with the greenness score below 0.5. The analysis is based on the original sample of 16,368,859 observations.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

Table A 3 - Summary statistics green tasks intensities

	Mean	SD	Min	Max	N
Time span					
Year	2015	3	2010	2019	1410564
Socioeconomics indicators					
Age	40.90	10.70	17.00	67.00	1410564
Tenure	9.16	9.25	0.00	55.00	1410564

Potential experience	24.25	12.26	0.00	57.00	1410564
Woman	0.26	0.44	0.00	1.00	1410564
Bellow secondary education	0.44	0.50	0.00	1.00	1410564
Secondary education	0.25	0.43	0.00	1.00	1410564
Higher education	0.31	0.46	0.00	1.00	1410564
Working conditions					
Total income (€)	1597.70	1423.48	237.50	15000.00	1410564
Normal worked hours	167.75	14.39	30.00	217.00	1410564
Extra worked hours	1.87	8.02	0.00	180.00	1410564
Open-ended contract	0.75	0.43	0.00	1.00	1410564
Firms indicators					
Number of employees	959.72	2788.87	6.00	25612.00	1410564
Share of foreign ownership (%)	20.37	39.09	0.00	100.00	1410564
Social capital (in millions of €)	165.61	829.77	1.00e-06	7068.17	1410564
Productivity (in thousands of €)	207.52	1408.18	0.00	206469.70	1410564
Observable skills intensity					
Communication, collaboration and creativity	0.21	0.12	0.05	0.58	1410564
Information skills	0.21	0.10	0.08	0.51	1410564
Assisting and caring	0.14	0.06	0.01	0.25	1410564
Management skills	0.14	0.12	0.00	0.51	1410564
Working with computers	0.03	0.03	0.00	0.14	1410564
Handling and moving	0.14	0.18	0.00	0.48	1410564
Constructing	0.03	0.05	0.00	0.36	1410564
Working with machinery and specialised equipment	0.09	0.10	0.00	0.31	1410564

Note: Summary statistics for occupations with the green task intensity higher than or equal to 0.1. The analysis is based on the original sample of 16,368,859 observations.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

Table A 4 - Summary statistics non-green tasks intensities

	Mean	SD	Min	Max	N
Time span					
Year	2015	3	2010	2019	14958295
Socioeconomics indicators					
Age	40.07	10.61	17.00	67.00	14958295
Tenure	8.74	9.09	0.00	55.00	14958295
Potential experience	24.16	12.40	0.00	57.00	14958295
Woman	0.44	0.50	0.00	1.00	14958295
Bellow secondary education	0.51	0.50	0.00	1.00	14958295
Secondary education	0.30	0.46	0.00	1.00	14958295
Higher education	0.19	0.40	0.00	1.00	14958295

Working conditions					
Total income (€)	1107.45	829.50	237.50	14989.28	14958295
Normal worked hours	167.48	14.67	30.00	260.00	14958295
Extra worked hours	1.74	7.76	0.00	301.00	14958295
Open-ended contract	0.74	0.44	0.00	1.00	14958295
Firms indicators					
Number of employees	1301.71	3652.88	6.00	25612.00	14958295
Share of foreign ownership (%)	16.41	35.84	0.00	100.00	14958295
Social capital (in millions of €)	98.41	582.62	1.00e-06	7068.17	14958295
Productivity (in thousands of €)	159.22	777.26	0.00	206469.70	14958295
Observable skills intensity					
Communication, collaboration and creativity	0.22	0.13	0.00	0.90	14958295
Information skills	0.19	0.09	0.00	0.62	14958295
Assisting and caring	0.16	0.13	0.00	0.60	14958295
Management skills	0.14	0.11	0.00	0.48	14958295
Working with computers	0.04	0.06	0.00	0.69	14958295
Handling and moving	0.13	0.14	0.00	0.79	14958295
Constructing	0.02	0.06	0.00	0.37	14958295
Working with machinery and specialised equipment	0.09	0.11	0.00	0.59	14958295

Note: Summary statistics for occupations with the green task intensity below 0.1. The analysis is based on the original sample of 16,368,859 observations.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors.

Table A 5 - Full-length Results - Wage Returns by Green Task Intensities

	Without Skills		With skills	
	FE	Interacted FE	FE	Interacted FE
Share of green employment per firm	0.078***	0.070***	0.071***	0.065***
	(0.004)	(0.006)	(0.004)	(0.006)
Share of green employment per firm interacted with green professions	-0.356***	-0.267***	-0.205***	-0.241***
	(0.012)	(0.022)	(0.012)	(0.022)
Age	0.037***	0.034***	0.036***	0.034***
	(0.000)	(0.001)	(0.000)	(0.001)
Age^2 (1/1000)	-0.424***	-0.397***	-0.418***	-0.394***
	(0.003)	(0.004)	(0.003)	(0.004)
Tenure	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
$Tenure^2$ (1/1000)	-0.094***	-0.108***	-0.095***	-0.107***
	(0.002)	(0.002)	(0.002)	(0.002)
Potential Experience	-0.005***	-0.005***	-0.005***	-0.005***

	(0.000)	(0.000)	(0.000)	(0.000)
Potential Experience² (1/1000)	0.043***	0.050***	0.043***	0.049***
	(0.003)	(0.003)	(0.003)	(0.003)
Secondary education	-0.010***	-0.008***	-0.010***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Higher education	0.051***	0.054***	0.052***	0.053***
	(0.002)	(0.002)	(0.002)	(0.002)
Green measure × Age	0.008***	0.016***	0.012***	0.016***
	(0.001)	(0.002)	(0.001)	(0.002)
Green measure × Age² (1/1000)	-0.092***	-0.183***	-0.157***	-0.181***
	(0.009)	(0.022)	(0.010)	(0.022)
Green measure × Tenure	-0.000	0.001	-0.001***	0.001
	(0.000)	(0.001)	(0.000)	(0.001)
Green measure × Tenure² (1/1000)	0.047***	0.120***	0.083***	0.114***
	(0.015)	(0.022)	(0.015)	(0.022)
Green measure × Secondary education	0.027***	-0.012	0.014***	-0.010
	(0.005)	(0.013)	(0.005)	(0.013)
Green measure × Higher education	0.032***	-0.244***	-0.036***	-0.239***
	(0.005)	(0.026)	(0.007)	(0.026)
Green measure × Open-ended contract	0.018***	-0.012***	0.001	-0.012***
	(0.003)	(0.004)	(0.003)	(0.004)
Green measure × Productivity (Ln)	-0.006***	-0.005***	0.004***	-0.004**
	(0.001)	(0.002)	(0.001)	(0.002)
Open-ended contract	0.033***	0.031***	0.032***	0.031***
	(0.000)	(0.000)	(0.000)	(0.000)
Productivity (Ln)	0.024***	0.022***	0.023***	0.022***
	(0.000)	(0.000)	(0.000)	(0.000)
Social capital (Ln)	0.005***	0.004***	0.005***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of employees (1/1000)	-0.002***	-0.001***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Ownership status (1/100)	0.504***	0.444***	0.512***	0.451***
	(0.005)	(0.006)	(0.005)	(0.006)
North	-0.002**	-0.001	-0.002**	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Algarve	0.011***	0.012***	0.012***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)
Center	-0.019***	-0.017***	-0.019***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
Alentejo	-0.030***	-0.029***	-0.030***	-0.029***
	(0.001)	(0.002)	(0.001)	(0.002)
Azores	0.009***	0.012***	0.010***	0.012***

	(0.003)	(0.004)	(0.003)	(0.004)
Madeira	0.062***	0.058***	0.062***	0.059***
	(0.003)	(0.003)	(0.003)	(0.003)
Foreign	-0.073	-0.126	-0.100	-0.131*
	(0.102)	(0.081)	(0.106)	(0.078)
Mining and quarrying	0.074***	0.062***	0.064***	0.052***
	(0.005)	(0.006)	(0.005)	(0.006)
Manufacture	0.016***	0.017***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
Electricity, gas, steam and air-conditioning supply	0.081***	0.067***	0.069***	0.058***
	(0.005)	(0.006)	(0.005)	(0.006)
Water supply, sewerage, waste management and remediation	-0.004	-0.005	-0.009***	-0.009**
	(0.003)	(0.003)	(0.003)	(0.003)
Construction	0.003	0.007***	-0.007***	-0.006**
	(0.002)	(0.002)	(0.002)	(0.002)
Wholesale and retail trade, repair of motor vehicles and motorcycles	0.005**	0.006***	-0.004**	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Transportation and storage	0.039***	0.035***	0.030***	0.026***
	(0.002)	(0.003)	(0.002)	(0.003)
Accommodation and food service activities	-0.021***	-0.019***	-0.026***	-0.024***
	(0.002)	(0.002)	(0.002)	(0.002)
Information and communication activities	0.025***	0.031***	0.016***	0.021***
	(0.002)	(0.003)	(0.002)	(0.003)
Financial and insurance activities	0.148***	0.141***	0.137***	0.129***
	(0.003)	(0.004)	(0.003)	(0.004)
Real estate activities	0.010***	0.008**	0.002	0.001
	(0.003)	(0.004)	(0.003)	(0.004)
Consulting, scientific, technical and similar activities	0.015***	0.017***	0.006***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Administrative and support service activities	0.008***	0.005**	0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Public administration and defence, compulsory social security	0.034***	0.031***	0.024***	0.022***
	(0.005)	(0.006)	(0.005)	(0.006)
Education	0.023***	0.023***	0.017***	0.018***
	(0.003)	(0.004)	(0.003)	(0.004)

Human health and social support activities	0.001	0.002	-0.003	-0.001
	(0.002)	(0.003)	(0.002)	(0.003)
Arts, entertainment and recreation	0.038***	0.038***	0.032***	0.032***
	(0.004)	(0.004)	(0.004)	(0.004)
Other services	0.005**	0.005*	-0.002	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
2011	0.012***	0.012***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)
2012	0.019***	0.020***	0.019***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)
2013	0.026***	0.027***	0.026***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)
2014	0.045***	0.046***	0.045***	0.046***
	(0.001)	(0.002)	(0.001)	(0.002)
2015	0.062***	0.062***	0.062***	0.063***
	(0.002)	(0.002)	(0.002)	(0.002)
2016	0.089***	0.089***	0.089***	0.089***
	(0.002)	(0.002)	(0.002)	(0.002)
2017	0.130***	0.129***	0.130***	0.130***
	(0.003)	(0.003)	(0.003)	(0.003)
2018	0.179***	0.178***	0.179***	0.178***
	(0.003)	(0.003)	(0.003)	(0.003)
2018	0.227***	0.225***	0.227***	0.225***
	(0.003)	(0.004)	(0.003)	(0.004)
Communication, collaboration and creativity			0.045***	0.046***
			(0.002)	(0.002)
Information skills			0.134***	0.139***
			(0.003)	(0.003)
Assisting and caring			0.061***	0.051***
			(0.002)	(0.003)
Management skills			0.157***	0.142***
			(0.002)	(0.003)
Working with computers			0.049***	0.056***
			(0.004)	(0.005)
Constructing			0.119***	0.159***
			(0.005)	(0.007)
Working with machinery and specialised equipment			0.101***	0.092***
			(0.003)	(0.003)
Green measure × Communication, collaboration and creativity			-0.100***	-0.368***
			(0.035)	(0.140)

Green measure × Information skills			-0.419***	0.171
			(0.031)	(0.153)
Green measure × Assisting and caring			-0.389***	1.492***
			(0.044)	(0.247)
Green measure × Management skills			0.439***	1.273***
			(0.031)	(0.143)
Green measure × Working with computers			-0.216***	0.754***
			(0.081)	(0.289)
Green measure × Constructing			-0.143***	-0.153
			(0.032)	(0.176)
Green measure × Working with machinery and specialised equipment			-0.333***	0.172
			(0.027)	(0.147)
Constant	0.603***		0.545***	
	(0.014)		(0.014)	
Observations	16249392	16249392	16249392	16249392
R^2	0.255	0.952	0.257	0.952
$\rho_{\lambda,\alpha}$	-	-0.022***	-	-0.022***
λ regressed on α	-	$\hat{\lambda}_i = 0.0001\alpha_i$	-	$\hat{\lambda}_i = -0.0001\alpha_i$
p-value	-	0.973		0.971

Note: Controls interacted with the green tasks' intensities, a continuous green measure variable within 0 and 1. Handling and moving, and Below secondary act as the omitted group for skills and education, respectively. For industry dummies, the agriculture sector acts as the omitted group. Lisbon and 2010 acts as an omitted group for firms' location and year, respectively. Robust standard errors are clustered at worker level. *p<0.10, **p<0.05, ***p<0.01.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors

Table A 6 - Full-length Results - Wage Returns by Green Occupation Intensities

	Without Skills		With Skills	
	FE	Interacted FE	FE	Interacted FE
Share of green employment per firm	0.040***	0.031***	0.036***	0.027***
	(0.002)	(0.003)	(0.002)	(0.003)
Share of green employment per firm interacted with green professions	-0.118***	-0.123***	-0.104***	-0.111***
	(0.004)	(0.009)	(0.005)	(0.009)
Age	0.037***	0.034***	0.036***	0.033***

	(0.000)	(0.001)	(0.000)	(0.001)
Age² (1/1000)	-0.422***	-0.391***	-0.417***	-0.388***
	(0.003)	(0.004)	(0.003)	(0.004)
Tenure	0.004***	0.004***	0.004***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure² (1/1000)	-0.090***	-0.104***	-0.091***	-0.104***
	(0.002)	(0.002)	(0.002)	(0.002)
Potential Experience	-0.005***	-0.005***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Potential Experience² (1/1000)	0.041***	0.052***	0.041***	0.050***
	(0.003)	(0.003)	(0.003)	(0.003)
Secondary education	-0.010***	-0.004***	-0.010***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Higher education	0.051***	0.056***	0.050***	0.055***
	(0.002)	(0.002)	(0.002)	(0.002)
Green measure × Age	0.002***	0.015***	0.004***	0.015***
	(0.000)	(0.001)	(0.000)	(0.001)
Green measure × Age² (1/1000)	-0.028***	-0.133***	-0.049***	-0.132***
	(0.005)	(0.012)	(0.006)	(0.012)
Green measure × Tenure	0.001***	0.001*	0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Green measure × Tenure² (1/1000)	-0.028***	-0.006	-0.016**	-0.009
	(0.007)	(0.012)	(0.008)	(0.012)
Green measure × Secondary education	0.005**	-0.068***	0.002	-0.067***
	(0.002)	(0.007)	(0.003)	(0.007)
Green measure × Higher education	0.012***	-0.162***	0.011***	-0.159***
	(0.003)	(0.012)	(0.003)	(0.012)
Green measure × Open-ended contract	0.010***	0.004*	0.008***	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Green measure × Productivity (Ln)	-0.000	0.005***	0.003***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Open-ended contract	0.032***	0.030***	0.032***	0.029***
	(0.000)	(0.000)	(0.000)	(0.000)
Productivity (Ln)	0.024***	0.021***	0.023***	0.021***
	(0.000)	(0.000)	(0.000)	(0.000)
Social capital (Ln)	0.005***	0.004***	0.005***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of employees (1/1000)	-0.002***	-0.001***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Ownership status (1/100)	0.503***	0.429***	0.512***	0.436***
	(0.005)	(0.006)	(0.005)	(0.006)
North	-0.002***	0.001	-0.002***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Algarve	0.010***	0.012***	0.012***	0.013***

	(0.002)	(0.002)	(0.002)	(0.002)
Center	-0.019***	-0.015***	-0.019***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
Alentejo	-0.030***	-0.028***	-0.030***	-0.027***
	(0.001)	(0.002)	(0.001)	(0.002)
Azores	0.008**	0.013***	0.009***	0.014***
	(0.003)	(0.004)	(0.003)	(0.004)
Madeira	0.061***	0.059***	0.062***	0.059***
	(0.003)	(0.003)	(0.003)	(0.003)
Foreign	-0.055	-0.120	-0.068	-0.117
	(0.097)	(0.096)	(0.100)	(0.092)
Mining and quarrying	0.072***	0.059***	0.063***	0.050***
	(0.005)	(0.006)	(0.005)	(0.006)
Manufacture	0.017***	0.018***	0.010***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Electricity, gas, steam and air-conditioning supply	0.079***	0.062***	0.067***	0.054***
	(0.005)	(0.006)	(0.005)	(0.006)
Water supply, sewerage, waste management and remediation	-0.004	-0.003	-0.008***	-0.006*
	(0.003)	(0.003)	(0.003)	(0.003)
Construction	0.004*	0.006**	-0.006***	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Wholesale and retail trade, repair of motor vehicles and motorcycles	0.004**	0.007***	-0.005**	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Transportation and storage	0.037***	0.034***	0.029***	0.026***
	(0.002)	(0.003)	(0.002)	(0.003)
Accommodation and food service activities	-0.021***	-0.018***	-0.026***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)
Information and communication activities	0.025***	0.032***	0.017***	0.023***
	(0.002)	(0.003)	(0.002)	(0.003)
Financial and insurance activities	0.147***	0.140***	0.137***	0.130***
	(0.003)	(0.004)	(0.003)	(0.004)
Real estate activities	0.010***	0.009**	0.002	0.002
	(0.003)	(0.004)	(0.003)	(0.004)
Consulting, scientific, technical and similar activities	0.015***	0.017***	0.007***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
Administrative and support service activities	0.008***	0.006**	0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Public administration and defence, compulsory social security	0.032***	0.031***	0.022***	0.023***
	(0.005)	(0.006)	(0.005)	(0.006)

Education	0.023***	0.022***	0.017***	0.017***
	(0.003)	(0.004)	(0.003)	(0.004)
Human health and social support activities	0.001	0.003	-0.003	0.001
	(0.002)	(0.003)	(0.002)	(0.003)
Arts, entertainment and recreation	0.037***	0.036***	0.031***	0.031***
	(0.004)	(0.004)	(0.004)	(0.004)
Other services	0.005**	0.006**	-0.001	0.000
	(0.003)	(0.003)	(0.003)	(0.003)
2011	0.012***	0.012***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)
2012	0.019***	0.019***	0.019***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)
2013	0.026***	0.027***	0.026***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)
2014	0.045***	0.045***	0.045***	0.045***
	(0.001)	(0.002)	(0.001)	(0.002)
2015	0.062***	0.062***	0.062***	0.062***
	(0.002)	(0.002)	(0.002)	(0.002)
2016	0.089***	0.089***	0.089***	0.089***
	(0.002)	(0.002)	(0.002)	(0.002)
2017	0.130***	0.129***	0.130***	0.129***
	(0.003)	(0.003)	(0.003)	(0.003)
2018	0.179***	0.177***	0.179***	0.177***
	(0.003)	(0.003)	(0.003)	(0.003)
2019	0.227***	0.224***	0.227***	0.224***
	(0.003)	(0.004)	(0.003)	(0.004)
Communication, collaboration and creativity			0.041***	0.035***
			(0.002)	(0.002)
Information skills			0.132***	0.132***
			(0.003)	(0.003)
Assisting and caring			0.059***	0.052***
			(0.002)	(0.003)
Management skills			0.167***	0.152***
			(0.002)	(0.003)
Working with computers			0.038***	0.069***
			(0.004)	(0.005)
Constructing			0.117***	0.176***
			(0.005)	(0.008)
Working with machinery and specialised equipment			0.097***	0.090***
			(0.003)	(0.004)
Green measure × Communication, collaboration and creativity			-0.023*	-0.076
			(0.014)	(0.060)

Green measure × Information skills			-0.300***	-0.334***
			(0.015)	(0.077)
Green measure × Assisting and caring			0.016	0.042
			(0.027)	(0.113)
Green measure × Management skills			0.216***	0.452***
			(0.016)	(0.068)
Green measure × Working with computers			-0.148***	-0.076
			(0.035)	(0.140)
Green measure × Constructing			-0.074***	-0.379***
			(0.018)	(0.105)
Green measure × Working with machinery and specialised equipment			-0.097***	-0.100
			(0.019)	(0.083)
Constant	0.608***		0.549***	
	(0.014)		(0.014)	
Observations	16249392	16249392	16249392	16249392
R^2	0.255	0.954	0.257	0.954
$\rho_{\lambda,\alpha}$	-	-0.190***	-	-0.193***
λ regressed on α	-	$\hat{\lambda}_i = -0.528\alpha_i$	-	$\hat{\lambda}_i = -0.591\alpha_i$
p-value	-	0.000	-	0.000

Note: Controls interacted with the greenness score, a continuous green measure variable within 0 and 1. Handling and moving, and Below secondary act as the omitted group for skills and education, respectively. For industry dummies, the agriculture sector acts as the omitted group. Lisbon and 2010 acts as an omitted group for firms' location and year, respectively. Robust standard errors are clustered at worker level. *p<0.10, **p<0.05, ***p<0.01.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors

Table A 7 - Full-length Green Wage Premium (Interacted Models) - Displaced Workers Sample

	GT		GO	
	FE	Interacted FE	FE	Interacted FE
Share of green employment per firm	0.222***	0.222***	0.101***	0.087***
	(0.040)	(0.045)	(0.025)	(0.029)
Share of green employment per firm interacted with green professions	-0.296***	-0.250	-0.126**	-0.039
	(0.111)	(0.179)	(0.050)	(0.086)
Age	0.064***	0.062***	0.064***	0.064***
	(0.004)	(0.004)	(0.003)	(0.004)
Age^2 (1/1000)	-0.664***	-0.641***	-0.665***	-0.665***
	(0.031)	(0.033)	(0.031)	(0.033)
Tenure	0.002***	0.002***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$Tenure^2$ (1/1000)	-0.067***	-0.076***	-0.063***	-0.069***

	(0.012)	(0.013)	(0.012)	(0.013)
Potential Experience	-0.016***	-0.016***	-0.016***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)
Potential Experience^2 (1/1000)	0.229***	0.239***	0.227***	0.256***
	(0.025)	(0.027)	(0.025)	(0.027)
Secondary education	-0.001	0.002	-0.002	-0.000
	(0.007)	(0.008)	(0.007)	(0.008)
Higher education	0.022*	0.025*	0.016	0.022
	(0.012)	(0.013)	(0.012)	(0.014)
Green measure × Age	0.014**	0.012	0.004	0.001
	(0.007)	(0.014)	(0.005)	(0.011)
Green measure × Age^2 (1/1000)	-0.205**	-0.217	-0.063	-0.009
	(0.088)	(0.162)	(0.061)	(0.123)
Green measure × Tenure	0.001	-0.006	0.002	-0.000
	(0.004)	(0.004)	(0.002)	(0.003)
Green measure × Tenure^2 (1/1000)	-0.160	0.058	-0.092	-0.053
	(0.187)	(0.168)	(0.085)	(0.097)
Green measure × Secondary education	-0.016	-0.060	0.017	0.008
	(0.056)	(0.136)	(0.032)	(0.091)
Green measure × Higher education	-0.168***	-0.274	0.002	-0.204
	(0.065)	(0.178)	(0.033)	(0.126)
Green measure × Open-ended contract	0.033	0.041	0.049***	0.030
	(0.031)	(0.040)	(0.018)	(0.024)
Green measure × Productivity (Ln)	0.003	-0.015	0.001	-0.002
	(0.008)	(0.012)	(0.005)	(0.007)
Open-ended contract	0.029***	0.028***	0.026***	0.025***
	(0.003)	(0.003)	(0.003)	(0.003)
Productivity (Ln)	0.020***	0.019***	0.020***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)
Social capital (Ln)	0.002***	0.001***	0.002***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Number of employees (1/1000)	-0.005***	-0.005***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Ownership status (1/100)	0.587***	0.503***	0.584***	0.432***
	(0.042)	(0.043)	(0.042)	(0.044)
North	-0.001	-0.000	-0.001	0.002
	(0.005)	(0.005)	(0.005)	(0.005)
Algarve	-0.013	-0.003	-0.012	0.001
	(0.016)	(0.017)	(0.016)	(0.016)
Center	0.003	0.013**	0.005	0.012*
	(0.006)	(0.007)	(0.006)	(0.007)
Alentejo	0.010	0.006	0.016	0.018

	(0.013)	(0.014)	(0.012)	(0.014)
Azore	0.013	0.001	0.011	-0.007
	(0.030)	(0.034)	(0.031)	(0.031)
Madeira	0.050***	0.039***	0.046***	0.033***
	(0.005)	(0.005)	(0.005)	(0.005)
Foreign	0.303***	-0.033**	0.334***	0.002
	(0.023)	(0.015)	(0.023)	(0.014)
Mining and quarrying	-0.036	-0.046*	-0.042	-0.038
	(0.028)	(0.027)	(0.028)	(0.032)
Manufacture	-0.039**	-0.035*	-0.041**	-0.033*
	(0.018)	(0.019)	(0.018)	(0.019)
Electricity, gas, steam and air-conditioning supply	-0.014	0.001	-0.019	-0.008
	(0.023)	(0.026)	(0.023)	(0.027)
Water supply, sewerage, waste management and remediation	-0.082***	-0.079***	-0.080***	-0.065***
	(0.021)	(0.023)	(0.021)	(0.022)
Construction	-0.056***	-0.056***	-0.054***	-0.055***
	(0.018)	(0.020)	(0.018)	(0.020)
Wholesale and retail trade, repair of motor vehicles and motorcycles	-0.038**	-0.029	-0.041**	-0.027
	(0.018)	(0.019)	(0.018)	(0.019)
Transportation and storage	-0.024	-0.039*	-0.034	-0.034
	(0.022)	(0.023)	(0.022)	(0.024)
Accommodation and food service activities	-0.037*	-0.029	-0.038*	-0.030
	(0.021)	(0.022)	(0.021)	(0.022)
Information and communication activities	-0.072***	-0.071***	-0.072***	-0.065***
	(0.019)	(0.020)	(0.019)	(0.020)
Financial and insurance activities	0.044*	0.050**	0.043*	0.048*
	(0.023)	(0.025)	(0.023)	(0.026)
Real estate activities	-0.012	-0.020	-0.016	-0.018
	(0.025)	(0.023)	(0.025)	(0.025)
Consulting, scientific, technical and similar activities	-0.050***	-0.050**	-0.051***	-0.047**
	(0.018)	(0.020)	(0.019)	(0.020)
Administrative and support service activities	-0.052***	-0.050***	-0.054***	-0.049**
	(0.018)	(0.019)	(0.018)	(0.019)
Public administration and defence, compulsory social security	-0.037*	-0.043*	-0.056**	-0.050**
	(0.022)	(0.024)	(0.022)	(0.024)
Education	-0.033	-0.035	-0.038	-0.061

	(0.037)	(0.041)	(0.037)	(0.043)
Human health and social support activities	-0.043*	-0.050*	-0.045*	-0.052*
	(0.025)	(0.026)	(0.025)	(0.027)
Arts, entertainment and recreation	0.017	0.028	0.017	0.024
	(0.026)	(0.027)	(0.026)	(0.026)
Other services	-0.041	-0.011	-0.044	-0.023
	(0.030)	(0.030)	(0.030)	(0.030)
2011	0.008***	0.010***	0.008***	0.009***
	(0.002)	(0.003)	(0.002)	(0.003)
2012	0.014***	0.016***	0.014***	0.015***
	(0.004)	(0.005)	(0.004)	(0.005)
2013	0.018***	0.019**	0.018***	0.019**
	(0.006)	(0.008)	(0.006)	(0.008)
2014	0.028***	0.029***	0.028***	0.029***
	(0.008)	(0.010)	(0.008)	(0.010)
2015	0.039***	0.039***	0.038***	0.039***
	(0.011)	(0.013)	(0.010)	(0.012)
2016	0.058***	0.058***	0.057***	0.058***
	(0.013)	(0.015)	(0.013)	(0.015)
2017	0.082***	0.082***	0.081***	0.081***
	(0.015)	(0.018)	(0.015)	(0.017)
2018	0.117***	0.116***	0.116***	0.116***
	(0.017)	(0.021)	(0.017)	(0.020)
2019	0.156***	0.154***	0.155***	0.154***
	(0.019)	(0.023)	(0.019)	(0.022)
Communication, collaboration and creativity	0.019	0.034	0.022	0.021
	(0.018)	(0.021)	(0.018)	(0.022)
Information skills	0.089***	0.107***	0.104***	0.116***
	(0.022)	(0.028)	(0.023)	(0.030)
Assisting and caring	0.018	-0.002	0.024	0.009
	(0.023)	(0.027)	(0.023)	(0.028)
Management skills	0.124***	0.104***	0.140***	0.121***
	(0.022)	(0.027)	(0.022)	(0.028)
Working with computers	0.035	0.089**	0.042	0.096**
	(0.031)	(0.045)	(0.031)	(0.047)
Constructing	0.054	0.075	0.080	0.135*
	(0.049)	(0.063)	(0.050)	(0.071)
Working with machinery and specialised equipment	-0.018	-0.042	-0.019	-0.042
	(0.026)	(0.032)	(0.026)	(0.034)
Green measure × Communication, collaboration and creativity	-0.099	1.466	0.008	0.427

	(0.317)	(1.116)	(0.128)	(0.551)
Green measure × Information skills	-0.148	1.728	-0.219	1.415*
	(0.279)	(1.499)	(0.170)	(0.840)
Green measure × Assisting and caring	-0.497	4.239*	-0.008	0.776
	(0.330)	(2.427)	(0.243)	(1.015)
Green measure × Management skills	0.357	0.712	0.149	0.330
	(0.282)	(1.162)	(0.167)	(0.641)
Green measure × Working with computers	0.628	-0.234	-0.098	0.354
	(0.530)	(1.812)	(0.281)	(1.100)
Green measure × Constructing	-0.605*	-0.198	-0.372**	-0.113
	(0.335)	(1.639)	(0.179)	(0.824)
Green measure × Working with machinery and specialised equipment	-0.410*	2.119	0.104	0.675
	(0.249)	(1.795)	(0.204)	(0.914)
Constant	0.320***		0.307***	
	(0.091)		(0.091)	
Observations	172156	172156	172156	172156
R^2	0.229	0.957	0.229	0.957
$\rho_{\lambda,\alpha}$	-	-0.025***	-	-0.140***
λ regressed on α	-	$\hat{\lambda}_i = 0.00003\alpha_i$	-	$\hat{\lambda}_i = -0.683\alpha_i$
p-value	-	0.999	-	0.000

Note: Sample of displaced workers between 2013 and 2015. Controls interacted with green tasks intensities and greenness score for the Green Tasks and Green Occupations columns. Both variables are continuous green measure ranging from 0 to 1. Handling and moving, and Below secondary act as the omitted group for skills and education, respectively. For industry dummies, the agriculture sector acts as the omitted group. Lisbon and 2010 acts as an omitted group for firms' location and year, respectively. Robust standard errors are clustered at worker level. *p<0.10, **p<0.05, ***p<0.01.

Source: *Quadros de Pessoal* from 2010 to 2019. Made by authors

Table A 8 - Elasticities per sectors

Sectors	σ^L (Own calculus)	σ^M (Blake, 2000)	σ^I (Blake, 2000)
Agriculture, forestry, and fishing	-0.849	2.31	0.33
Industry, energy, water supply and sewerage	-0.909	2.8	0.99
Construction	-0.955	1.9	0.98
Wholesale and retail trade*	-0.848	1.9	1.11
Information and communication	-0.916	1.92	1.12
Financial and insurance activities	-0.810	1.92	1.12
Real estate activities	-0.797	1.9	1

Professional, scientific, and technical activities; administrative and support service	-0.952	1.91	1.11
Public administration and defence; compulsory social security; education; human health and social work	-0.779	1.92	1.12
Arts; entertainment; repair of household goods and other services	-0.898	1.92	1.12

Note: This table presents the labour, armington and income elasticity across sectors. The σ^{L} stands for elasticity of substitution of composite labour between green and non-green jobs. σ^{M} stands for armington elasticity. The σ^{I} stands for income elasticity. *Also include: repair of motor vehicles and motorcycles; transportation and storage; accommodation and food service activities.

Source: Combined *Quadros de Pessoal* with *Sistema das Contas Integradas das Empresas* from 2010 to 2019. Armington and income elasticity adapted from Blake (2000). Made by authors.

Table A 9 - POLS, HDFE and IV. Agriculture, forestry and fishing. Estimation of elasticity equation

	POLS		HDFE		IV	
	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)
Ln(WageG/WageNG)	-0.932***	-0.914***	-0.866***	-0.887***	-0.897***	-0.849***
	(0.005)	(0.006)	(0.009)	(0.009)	(0.032)	(0.032)
Share of women	0.288***	0.231***	0.040	0.020	0.079	0.097**
	(0.019)	(0.018)	(0.035)	(0.030)	(0.054)	(0.046)
Share of graduated workers	0.166***	0.277***	-0.304***	-0.208***	-0.293***	-0.285***
	(0.029)	(0.028)	(0.061)	(0.058)	(0.102)	(0.097)
Average workers potential experience	0.001*	0.002***	0.000	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Total sales)	0.002	-0.008***	0.001	-0.000	-0.009	-0.007
	(0.003)	(0.003)	(0.005)	(0.005)	(0.007)	(0.006)
Ln(Total actives)	0.089***	0.059***	0.033***	0.019**	0.062***	0.045***
	(0.004)	(0.005)	(0.011)	(0.010)	(0.017)	(0.016)
Ln(Number of paid workers)		0.107***		0.062***		0.073***
		(0.008)		(0.013)		(0.019)
Constant	-1.107***	-0.797***	-0.073	-0.026		
	(0.053)	(0.055)	(0.151)	(0.132)		

Firms Fixed Effect	No	No	Yes	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes	Yes	Yes
Hansen P-value	-	-	-	-	0.024	0.454
C Statistitcs P-value	-	-	-	-	0.867	0.033
1st Stage F	-	-	-	-	166.902	148.223
Observations	7864	7864	7295	7295	3940	3940
R^2	0.884	0.898	0.976	0.981	0.849	0.874

Note: In this table are presented the estimation results of equation 26 for agriculture, forestry and fishing sectors. In columns 1, 3 and 5, the dependent variable is the natural log of the ratio of the number of non-greens by green workers (WorkersNG/WorkersG). In columns 2, 4 and 6, the dependent variable is the natural log of the ratio of the total number of hours worked by workers from green to non-green jobs (HoursNG/HoursG). G stands for green and NG for non-green. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Source: Combined *Quadros de Pessoal* with *Sistema das Contas Integradas das Empresas* from 2010 to 2019. Made by authors.

Table A 10 - POLS, HDFE and IV. Industry, energy, water supply and sewerage. Estimation of elasticity equation

	POLS		HDFE		IV	
	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)
Ln(WageG/WageNG)	-1.010***	-1.016***	-0.885***	-0.909***	-0.924***	-0.916***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.008)	(0.008)
Share of women	0.253***	0.234***	0.176***	0.152***	0.147***	0.137***
	(0.005)	(0.005)	(0.016)	(0.015)	(0.021)	(0.020)
Share of graduated workers	-0.014	0.021*	-0.138***	-0.095***	-0.094***	-0.067**
	(0.012)	(0.012)	(0.022)	(0.020)	(0.030)	(0.028)
Average workers potential experience	0.000*	0.000*	-0.002***	-0.001**	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Ln(Total sales)	0.002***	0.001	0.004***	0.001	0.003**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)

Ln(Total actives)	0.035***	0.025***	0.020***	0.003	0.015***	0.004
	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Ln(Number of paid workers)		0.015***		0.042***		0.039***
		(0.002)		(0.005)		(0.007)
Constant	-0.435***	-0.331***	-0.009	0.101**		
	(0.012)	(0.015)	(0.046)	(0.043)		
Firms Fixed Effect	No	No	Yes	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes	Yes	Yes
Hansen P-value	-	-	-	-	0.629	0.619
C Statistitcs P-value	-	-	-	-	0.000	0.585
1st Stage F	-	-	-	-	3338.739	3283.910
Observations	91985	91980	88578	88574	55759	55758
R^2	0.925	0.929	0.983	0.985	0.828	0.856

Note: In this table are presented the estimation results of equation 26 for industry, energy, water supply and sewerage sectors. In columns 1, 3 and 5, the dependent variable is the natural log of the ratio of the number of non-greens by green workers (WorkersNG/WorkersG). In columns 2, 4 and 6, the dependent variable is the natural log of the ratio of the total number of hours worked by workers from green to non-green jobs (HoursNG/HoursG). G stands for green and NG for non-green. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Source: Combined *Quadros de Pessoal* with *Sistema das Contas Integradas das Empresas* from 2010 to 2019. Made by authors.

Table A 11 - POLS, HDFE and IV. Construction. Estimation of elasticity equation

	POLS		HDFE		IV	
	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)
Ln(WageG/WageNG)	-0.971***	-0.989***	-0.881***	-0.921***	-0.947***	-0.955***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.016)	(0.015)
Share of women	0.069***	0.075***	0.137***	0.134***	0.110***	0.097***
	(0.014)	(0.013)	(0.026)	(0.022)	(0.041)	(0.037)
Share of graduated workers	0.138***	0.222***	-0.282***	-0.148***	-0.202***	-0.124**
	(0.015)	(0.014)	(0.031)	(0.029)	(0.054)	(0.048)

Average workers potential experience	0.003***	0.003***	0.001	0.001	0.002**	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Total sales)	-0.003***	-0.002**	0.001	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Total actives)	0.051***	0.042***	0.034***	0.017***	0.030***	0.026***
	(0.001)	(0.002)	(0.005)	(0.005)	(0.007)	(0.007)
Ln(Number of paid workers)		0.010***		0.036***		0.011
		(0.003)		(0.006)		(0.009)
Constant	-0.631***	-0.565***	-0.262***	-0.154**		
	(0.018)	(0.021)	(0.069)	(0.063)		
Firms Fixed Effect	No	No	Yes	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes	Yes	Yes
Hansen P-value	-	-	-	-	0.093	0.145
C Statistitcs P-value	-	-	-	-	0.000	0.012
1st Stage F	-	-	-	-	547.659	521.788
Observations	30821	30814	27768	27762	15746	15744
R^2	0.927	0.940	0.981	0.986	0.853	0.893

Note: In this table are presented the estimation results of equation 26 for construction sector. In columns 1, 3 and 5, the dependent variable is the natural log of the ratio of the number of non-greens by green workers (WorkersNG/WorkersG). In columns 2, 4 and 6, the dependent variable is the natural log of the ratio of the total number of hours worked by workers from green to non-green jobs (HoursNG/HoursG). G stands for green and NG for non-green. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Source: Combined *Quadros de Pessoal* with *Sistema das Contas Integradas das Empresas* from 2010 to 2019. Made by authors.

Table A 12 - POLS, HDFE and IV. Wholesale, retail trade, repair of motor vehicles and motorcycles; transportation and storage; accommodation and food service activities. Estimation of elasticity equation

	POLS		HDFE		IV	
	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)

Ln(WageG/ WageNG)	-0.916***	-0.904***	-0.826***	-0.848***	-0.884***	-0.862***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.010)	(0.010)
Share of women	0.208***	0.193***	0.152***	0.131***	0.156***	0.154***
	(0.004)	(0.004)	(0.010)	(0.009)	(0.015)	(0.014)
Share of graduated workers	0.072***	0.136***	-0.118***	-0.100***	-0.095***	-0.097***
	(0.007)	(0.006)	(0.014)	(0.013)	(0.020)	(0.019)
Average workers potential experience	-0.003***	-0.002***	-0.005***	-0.004***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Total sales)	0.029***	0.030***	0.010***	0.004***	0.005***	0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Ln(Total actives)	0.073***	0.030***	0.047***	0.024***	0.036***	0.023***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)
Ln(Number of paid workers)		0.084***		0.079***		0.054***
		(0.002)		(0.004)		(0.006)
Constant	-1.085***	-0.725***	-0.293***	-0.132***		
	(0.011)	(0.013)	(0.038)	(0.035)		
Firms Fixed Effect	No	No	Yes	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes	Yes	Yes
Hansen P-value	-	-	-	-	0.862	0.552
C Statistitcs P-value	-	-	-	-	0.000	0.406
1st Stage F	-	-	-	-	3113.302	2839.694
Observations	128234	128198	120317	120281	66310	66303
R^2	0.891	0.898	0.978	0.980	0.790	0.820

Note: In this table are presented the estimation results of equation 26 for wholesale, retail trade, repair of motor vehicles and motorcycles; transportation and storage; accommodation and food service activities. In columns 1, 3 and 5, the dependent variable is the natural log of the ratio of the number of non-greens by green workers (WorkersNG/WorkersG). In columns 2, 4 and 6, the dependent variable is the natural log of the ratio of the total number of hours worked by workers from green to non-green jobs (HoursNG/HoursG). G stands for green and NG for non-green. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Source: Combined *Quadros de Pessoal* with *Sistema das Contas Integradas das Empresas* from 2010 to 2019. Made by authors.

Table A 13 - POLS, HDFE and IV. Information and communication. Estimation of elasticity equation

	POLS		HDFE		IV	
	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)
Ln(WageG/WageNG)	-0.957***	-0.958***	-0.906***	-0.916***	-1.038***	-1.034***
	(0.005)	(0.005)	(0.011)	(0.011)	(0.030)	(0.031)
Share of women	0.092***	0.089***	0.120**	0.115**	-0.003	-0.021
	(0.020)	(0.020)	(0.049)	(0.048)	(0.070)	(0.067)
Share of graduated workers	-0.166***	-0.161***	-0.241***	-0.222***	-0.172***	-0.187***
	(0.021)	(0.021)	(0.048)	(0.047)	(0.066)	(0.064)
Average workers potential experience	-0.001	-0.000	-0.007***	-0.005**	-0.009***	-0.009***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Ln(Total sales)	0.005**	0.005**	-0.006	-0.008	-0.014**	-0.014**
	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.006)
Ln(Total actives)	0.063***	0.050***	0.005	-0.019	-0.015	-0.009
	(0.004)	(0.006)	(0.012)	(0.013)	(0.015)	(0.015)
Ln(Number of paid workers)		0.023**		0.054***		-0.023
		(0.009)		(0.018)		(0.028)
Constant	-0.623***	-0.517***	0.500***	0.638***		
	(0.043)	(0.058)	(0.179)	(0.175)		
Firms Fixed Effect	No	No	Yes	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes	Yes	Yes
Hansen P-value	-	-	-	-	0.005	0.007
C Statistitcs P-value	-	-	-	-	0.000	0.000
1st Stage F	-	-	-	-	236.313	221.519

Observations	5640	5638	5214	5211	2964	2964
R^2	0.915	0.919	0.977	0.978	0.855	0.866

Note: In this table are presented the estimation results of equation 26 for information and communication sectors. In columns 1, 3 and 5, the dependent variable is the natural log of the ratio of the number of non-greens by green workers (WorkersNG/WorkersG). In columns 2, 4 and 6, the dependent variable is the natural log of the ratio of the total number of hours worked by workers from green to non-green jobs (HoursNG/HoursG). G stands for green and NG for non-green. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Source: Combined *Quadros de Pessoal* with *Sistema das Contas Integradas das Empresas* from 2010 to 2019. Made by authors.

Table A 14 - POLS, HDFE and IV. Financial and insurance activities. Estimation of elasticity equation

	POLS		HDFE		IV	
	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)
Ln(WageG/WageNG)	-0.859***	-0.863***	-0.801***	-0.810***	-0.881***	-0.861***
	(0.010)	(0.011)	(0.022)	(0.021)	(0.053)	(0.053)
Share of women	0.095*	0.095*	0.153	0.123	0.320**	0.260**
	(0.050)	(0.050)	(0.104)	(0.099)	(0.131)	(0.128)
Share of graduated workers	-0.121***	-0.114***	-0.364***	-0.290***	-0.289*	-0.212
	(0.036)	(0.036)	(0.112)	(0.100)	(0.174)	(0.162)
Average workers potential experience	-0.008***	-0.007***	-0.013***	-0.011**	-0.009	-0.004
	(0.002)	(0.002)	(0.005)	(0.004)	(0.007)	(0.007)
Ln(Volume of business)	0.063***	0.058***	0.007	-0.018	-0.018	-0.036**
	(0.005)	(0.008)	(0.011)	(0.012)	(0.016)	(0.016)
Ln(Number of employees)		0.004		0.101***		0.119***
		(0.015)		(0.028)		(0.043)
Constant	-0.128	-0.089	1.031***	0.986***		
	(0.082)	(0.095)	(0.227)	(0.222)		
Firms Fixed Effect	No	No	Yes	Yes	Yes	Yes

Year Fixed Effect	No	No	Yes	Yes	Yes	Yes
Hansen P-value	-	-	-	-	0.337	0.638
C Statistitcs P-value	-	-	-	-	0.104	0.319
1st Stage F	-	-	-	-	108.700	107.809
Observations	2987	2987	2775	2775	1560	1560
R^2	0.869	0.871	0.976	0.977	0.793	0.810

Note: In this table are presented the estimation results of equation 26 for financial and insurance activities. In columns 1, 3 and 5, the dependent variable is the natural log of the ratio of the number of non-greens by green workers (WorkersNG/WorkersG). In columns 2, 4 and 6, the dependent variable is the natural log of the ratio of the total number of hours worked by workers from green to non-green jobs (HoursNG/HoursG). G stands for green and NG for non-green. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Source: Combined *Quadros de Pessoal* with *Sistema das Contas Integradas das Empresas* from 2010 to 2019. Made by authors.

Table A 15 - POLS, HDFE and IV. Real estate activities. Estimation of elasticity equation

	POLS		HDFE		IV	
	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)
Ln(WageG/WageNG)	-0.843***	-0.762***	-0.776***	-0.797***	-0.932***	-0.913***
	(0.011)	(0.016)	(0.026)	(0.027)	(0.093)	(0.095)
Share of women	0.077*	0.059	0.086	0.094	0.062	0.032
	(0.043)	(0.040)	(0.111)	(0.111)	(0.139)	(0.135)
Share of graduated workers	-0.214***	-0.083**	-0.558***	-0.518***	-0.353*	-0.392**
	(0.045)	(0.041)	(0.123)	(0.121)	(0.183)	(0.173)
Average workers potential experience	-0.008***	-0.005***	-0.004	-0.004	0.011*	0.009
	(0.002)	(0.002)	(0.004)	(0.004)	(0.006)	(0.006)
Ln(Total sales)	-0.007	-0.006	0.001	-0.002	0.007	0.004
	(0.005)	(0.004)	(0.005)	(0.005)	(0.007)	(0.006)
Ln(Total actives)	0.089***	0.049***	0.060***	0.061***	0.052	0.055
	(0.006)	(0.007)	(0.022)	(0.022)	(0.037)	(0.035)

Ln(Number of paid workers)		0.189***		0.009		-0.032
		(0.017)		(0.028)		(0.052)
Constant	-0.627***	-0.483***	-0.224	-0.238		
	(0.084)	(0.080)	(0.347)	(0.337)		
Firms Fixed Effect	No	No	Yes	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes	Yes	Yes
Hansen P-value	-	-	-	-	0.271	0.510
C Statistitcs P-value	-	-	-	-	0.215	0.464
1st Stage F	-	-	-	-	20.299	18.301
Observations	1947	1946	1564	1564	683	683
R^2	0.809	0.834	0.965	0.967	0.768	0.796

Note: In this table are presented the estimation results of equation 26 for real estate activities. In columns 1, 3 and 5, the dependent variable is the natural log of the ratio of the number of non-greens by green workers (WorkersNG/WorkersG). In columns 2, 4 and 6, the dependent variable is the natural log of the ratio of the total number of hours worked by workers from green to non-green jobs (HoursNG/HoursG). G stands for green and NG for non-green. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Source: Combined *Quadros de Pessoal* with *Sistema das Contas Integradas das Empresas* from 2010 to 2019. Made by authors.

Table A 16 - POLS, HDFE and IV. Professional, scientific, and technical activities; administrative and support service. Estimation of elasticity equation

	POLS		HDFE		IV	
	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)
Ln(WageG/WageNG)	-0.960***	-0.939***	-0.877***	-0.896***	-0.977***	-0.952***
	(0.004)	(0.004)	(0.008)	(0.008)	(0.030)	(0.031)
Share of women	0.243***	0.226***	0.141***	0.122***	0.142***	0.115**
	(0.017)	(0.016)	(0.034)	(0.032)	(0.053)	(0.049)
Share of graduated workers	-0.072***	-0.015	-0.182***	-0.158***	-0.109*	-0.116**
	(0.015)	(0.015)	(0.038)	(0.037)	(0.062)	(0.059)
Average workers	0.001**	0.002***	-0.002	-0.001	-0.001	-0.001

potential experience						
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Ln(Total sales)	0.002	0.005***	0.004	0.002	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Ln(Total actives)	0.065***	0.017***	0.021**	0.001	0.018	0.000
	(0.003)	(0.004)	(0.009)	(0.010)	(0.014)	(0.014)
Ln(Number of paid workers)		0.092***		0.053***		0.032
		(0.006)		(0.013)		(0.023)
Constant	-0.770***	-0.406***	0.030	0.158		
	(0.042)	(0.047)	(0.132)	(0.127)		
Firms Fixed Effect	No	No	Yes	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes	Yes	Yes
Hansen P-value	-	-	-	-	0.278	0.214
C Statistitcs P-value	-	-	-	-	0.001	0.097
1st Stage F	-	-	-	-	203.869	191.706
Observations	10057	10050	8726	8719	4514	4512
R^2	0.903	0.912	0.980	0.982	0.832	0.857

Note: In this table are presented the estimation results of equation 26 for professional, scientific, and technical activities; administrative and support service sectors. In columns 1, 3 and 5, the dependent variable is the natural log of the ratio of the number of non-greens by green workers (WorkersNG/WorkersG). In columns 2, 4 and 6, the dependent variable is the natural log of the ratio of the total number of hours worked by workers from green to non-green jobs (HoursNG/HoursG). G stands for green and NG for non-green. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.
Source: Combined *Quadros de Pessoal* with *Sistema das Contas Integradas das Empresas* from 2010 to 2019. Made by authors.

Table A 17 - POLS, HDFE and IV. Public administration and defence; compulsory social security; education; human health and social work. Estimation of elasticity equation

	POLS		HDFE		IV	
	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)
Ln(WageG/WageNG)	-0.881***	-0.830***	-0.759***	-0.779***	-0.778***	-0.758***
	(0.010)	(0.014)	(0.025)	(0.025)	(0.101)	(0.108)

Share of women	0.403***	0.338***	0.152	0.189*	-0.105	-0.087
	(0.040)	(0.040)	(0.109)	(0.097)	(0.127)	(0.129)
Share of graduated workers	-0.010	-0.104**	-0.133	-0.188**	-0.074	-0.108
	(0.045)	(0.045)	(0.097)	(0.089)	(0.135)	(0.133)
Average workers potential experience	0.010***	0.006***	-0.006	-0.006*	-0.011**	-0.009*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.005)
Ln(Total sales)	0.018***	0.013***	0.004	0.002	0.008	0.004
	(0.005)	(0.005)	(0.006)	(0.006)	(0.009)	(0.009)
Ln(Total actives)	0.106***	0.054***	0.041***	0.026*	0.007	0.004
	(0.007)	(0.009)	(0.014)	(0.014)	(0.021)	(0.020)
Ln(Number of paid workers)		0.132***		0.064**		0.062
		(0.019)		(0.025)		(0.046)
Constant	-1.599***	-0.992***	0.241	0.231		
	(0.112)	(0.121)	(0.239)	(0.232)		
Firms Fixed Effect	No	No	Yes	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes	Yes	Yes
Hansen P-value	-	-	-	-	0.489	0.542
C Statistitcs P-value	-	-	-	-	0.571	0.852
1st Stage F	-	-	-	-	40.658	37.827
Observations	2120	2115	1871	1866	1030	1025
R^2	0.893	0.897	0.977	0.978	0.692	0.709

Note: In this table are presented the estimation results of equation 26 for public administration and defence; compulsory social security; education; human health and social work sectors. In columns 1, 3 and 5, the dependent variable is the natural log of the ratio of the number of non-greens by green workers (WorkersNG/WorkersG). In columns 2, 4 and 6, the dependent variable is the natural log of the ratio of the total number of hours worked by workers from green to non-green jobs (HoursNG/HoursG). G stands for green and NG for non-green. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Source: Combined *Quadros de Pessoal* with *Sistema das Contas Integradas das Empresas* from 2010 to 2019. Made by authors.

Table A 18 - POLS, HDFE and IV. Arts; entertainment; repair of household goods and other services. Estimation of elasticity equation

	POLS		HDFE		IV	
	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)	Ln(WorkersNG/WorkersG)	Ln(HoursNG/HoursG)
Ln(WageG/WageNG)	-0.909***	-0.862***	-0.806***	-0.844***	-0.935***	-0.898***
	(0.008)	(0.009)	(0.017)	(0.016)	(0.069)	(0.067)
Share of women	0.050*	0.048*	0.033	0.029	0.125	0.195**
	(0.026)	(0.025)	(0.053)	(0.052)	(0.091)	(0.089)
Share of graduated workers	-0.016	-0.018	-0.312***	-0.279***	-0.448***	-0.478***
	(0.030)	(0.030)	(0.061)	(0.056)	(0.127)	(0.122)
Average workers potential experience	0.002**	0.002**	-0.006***	-0.004**	0.002	-0.003
	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.004)
Ln(Total sales)	0.006*	0.008**	-0.001	-0.003	-0.002	-0.003
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Ln(Total actives)	0.073***	0.026***	0.031***	0.022**	0.018	0.015
	(0.005)	(0.006)	(0.011)	(0.011)	(0.014)	(0.013)
Ln(Number of paid workers)		0.133***		0.055***		0.014
		(0.011)		(0.019)		(0.032)
Constant	-0.723***	-0.393***	0.315**	0.237		
	(0.063)	(0.068)	(0.152)	(0.154)		
Firms Fixed Effect	No	No	Yes	Yes	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes	Yes	Yes
Hansen P-value	-	-	-	-	0.979	0.703
C Statistitcs P-value	-	-	-	-	0.002	0.088
1st Stage F	-	-	-	-	48.505	39.389
Observations	3890	3763	3525	3401	1865	1789
R^2	0.882	0.891	0.981	0.983	0.741	0.788

Note: In this table are presented the estimation results of equation 26 for arts; entertainment; repair of household goods and other services sectors. In columns 1, 3 and 5, the dependent variable is the natural log of the ratio of the number of non-greens by green workers (WorkersNG/WorkersG). In columns 2, 4 and 6, the dependent variable is the natural log of the ratio of the total number of hours worked by workers from green to non-green jobs (HoursNG/HoursG). G stands for green and NG for non-green. Robust standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Source: Combined *Quadros de Pessoal* with *Sistema das Contas Integradas das Empresas* from 2010 to 2019. Made by authors.