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Article

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Article

Portuguese Textiles and Apparel Industry: Assessing the Effect of International Trade on Employment and Green Employment

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Abstract: This study examines the impact of international trade activities on employment in the Portuguese textiles and apparel industry from 2010 to 2017. It finds evidence that imports and exports have a persistent, negative, and significant effect on overall job creation, with this impact intensifying over the long-run. Additionally, the increasing elasticity of substitution between imports and exports indicates that private companies of this industry have benefited from a win-win situation characterised by higher production volumes and lower marginal costs. By applying an unsupervised machine-learning method, followed by a discrete choice analysis to infer the firm-level propensity to possess green capital, we identify a phenomenon termed the *green international trade paradox*. This study also reveals that international trade activities positively influence green job creation in firms lacking green capital if and only if these players are engaged in international markets while negatively affecting firms already endowed with green technologies. As such, empirical results suggest that the export-oriented economic model followed over the last decade by the Portuguese textiles and apparel industry has not necessarily generated new domestic employment opportunities but has significantly altered the magnitude and profile of skill requirements that employers seek to identify in new workforce hires.

Keywords: circular economy; textiles and apparel industry; employment; green employment; international trade; panel data; unsupervised machine learning



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1. Introduction

The textiles and apparel industry (TAI) is a vital component of the European economy, playing a significant role in both employment and international trade. The European Commission (EC) reports that exports of textiles and apparel from the European Union (EU) account for more than 30% of the world's total market exports (EC 2015a). Although currently dealing with a negative trade balance, exports (imports) of the TAI in European member states are growing on average at a rate of 13% (4%), respectively (EC 2015a). In addition to the evidence of convergence in the trade balance, European TAIs are gaining international prominence due to their size, quality, design, flexibility, and innovation in new products. The EC has been responsible for this outstanding performance, as it guarantees a level playing field through the application of Free Trade Agreements (FTAs) and World Trade Organisation (WTO) rules, while simultaneously being actively engaged in third-party dialogues (e.g., Colombia, China) on sensitive topics such as industrial and regulatory policies (EC 2015b).

Within the European territory, emphasis is given to the Euro-Mediterranean Dialogue on the Textile and Clothing Industry (EUROMED), which was launched in 2014 (EUROMED 2014). This agreement is not only the unique industry-based dialogue celebrated between Mediterranean countries, but it is also extremely important as a driver of economic growth, social development and political stability for the Euro-Mediterranean region. Indeed, EC (2015b) reports that the trade value of TAIs in this European area amounts to €35 billion per year and 35% of EU products have this region as final destination. Unsurprisingly, the TAI is considered the second-most relevant industry after oil and gas in this transnational

jurisdiction from Europe. The Euro-Mediterranean region also has a strategic role by ensuring the possibility to maintain the entire production chain geographically located in the European territory, thereby enabling the persistence of onshoring practices and the promotion of cost savings. The European Skills Council (ESC) recognises that European TAIs are experiencing a renaissance era marked by innovation and technical developments, which are affecting several business organisations (ESC 2014).

This shift in paradigm has been particularly visible in Portugal. Since China's entry into the WTO in 2001, and by the end of the Multi-Fiber Agreement in 2005, the Portuguese textiles and apparel industry (PTAI) lost more than 100,000 jobs, which created a need to reinvent it. After a decade and a half, the PTAI seems to have recovered in fundamental indicators. As clarified in Figure 1, this industry has contributed nearly €7.2 billion in terms of production to the national gross domestic product (GDP) and generated a private spending on goods and services of approximately €7.3 billion by the end of 2016. It also employed more than 135,000 workers, which is almost 20% of the total manufacturing employment in Portugal. *Associação Têxtil e de Vestuário em Portugal* (ATP), which is the most relevant association of textiles and apparel in the country, confirms that the total number of employees increased almost 3% between 2015 and 2016 (ATP 2018).

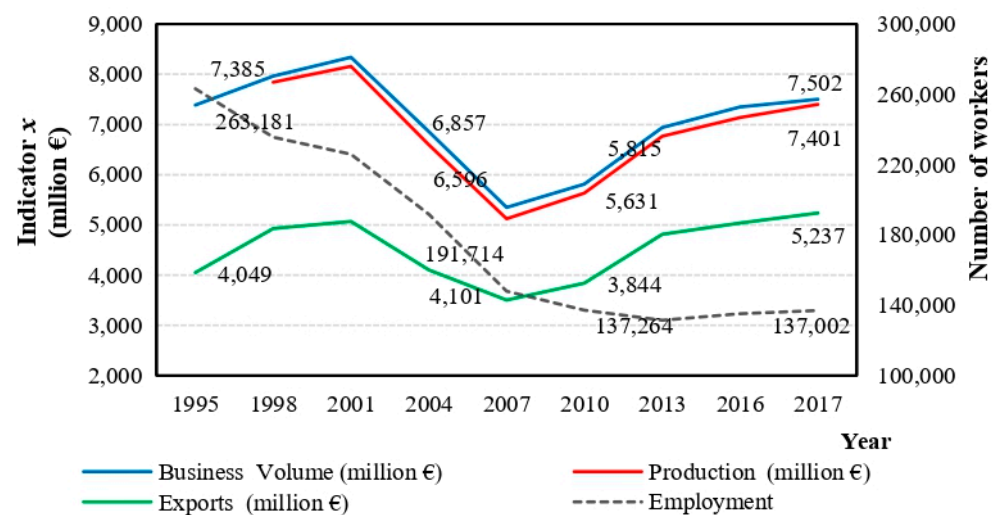


Figure 1. Evolution of key indicators in the PTAI (1995–2017). Source: own development based on data from ATP (2018).

Moreover, this evolution is not only felt in absolute value but also in relative terms. Figure 2 shows the evolution of PTAI's apparent labour productivity during the 2010–2017 period. This economic indicator has evolved positively, going from €12.8 thousand to €16.7 thousand between 2010 and 2016. Nevertheless, ATP (2018) reports that such a threshold remains below the national average, which was €23.1 thousand in 2016. This productivity gain has been complemented by the improvement in several domains of the economic activity, such as industrial know-how and technological innovations, upgrade of design and quality attributes, quicker time-to-market responses, higher degree of flexibility and reliability, creation of added value services, and development of structured and dynamic clusters backed up by competence centres (Hodges and Link 2019). Furthermore, despite the relevance of Europe as the main destination market for goods and services created by PTAI companies, ATP (2018) clarifies that the United States of America (USA) is becoming a relevant destination market for *Made in Portugal* products. As such, two stylised facts seem to characterize the evolution of PTAI since 2010:

- The recovery of this industry relied on a significant increase in exports; and
- There was a downward trend in the number of workers, which has been slightly reversed in recent years.

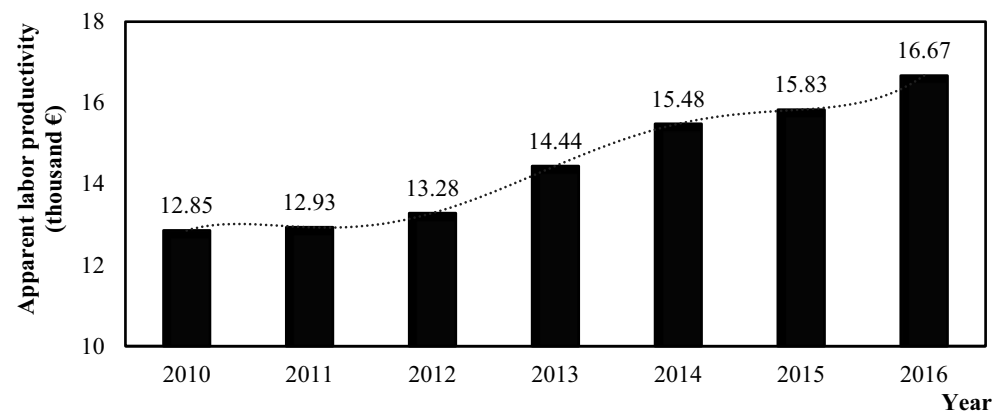


Figure 2. Evolution of the apparent labour productivity in the PTAI (2010–2016). Source: own development based on data from ATP (2018)¹.

Nevertheless, it is relevant to highlight that the literature focused on assessing the dynamics of TAIs has been silent about two aspects:

- Generically, on clarifying the association of the relation between international trade activities (i.e., imports and exports) and employment growth opportunities; and
- For the case of PTAI companies, on identifying explanatory variables with significant impact on employment or, equivalently, drivers behind the persistence (reversal) of job destruction between 2010 and 2014 (2015 and 2017), respectively.

Although several reasons may be pointed out from a theoretical point of view (e.g., efforts to enhance the product innovation through technological developments; greater agility and organisation, while maintaining the experience of old guard entrepreneurs combined with the technical knowledge of a new generation of managers), the unique conclusion expressed by specialists so far is that PTAI companies tend to operate sub-optimally, relative to firms from different manufacturing industries (Marques and Guedes 2016). Motivated by this fact, firm-level data were collected to satisfy the research gap of identifying whether international trade activities have a significant impact on employment in the PTAI during the period 2010–2017. In this body of literature, recent studies present differing views on the impact of international trade activities in the TAI. Some studies emphasize negative outcomes, such as layoffs and plant closures (Kabish 2023; Ruteri 2023; Majumder and De 2023), while others highlight opportunities for innovation and adaptation in response to the evolving global environment (Keough and Lu 2021; Khan et al. 2022; Lu 2022a, 2024a, 2024b; Laurits and Lu 2023; Botwinick and Lu 2023; Carswell and De Neve 2024).

Additionally, this study brings the novelty of analysing the impact of international trade on employment by differentiating between *employment defined in a broad sense* and *green employment*. Employment in the EU-28 environmental economy rose from 2.8 million full-time equivalents (FTEs) in 2000 to 4.5 million FTEs in 2016, generating €746 billion of output and €303 billion of value added in 2016 (Eurostat 2022). These trends in employment and value added indicate considerably faster growth than that observed in the GDP. Moreover, ILO (2018) claims that actions to limit global warming up to 2 degrees Celsius will create more than 6 million green jobs worldwide. Like other environmentally concerned industries, the PTAI helps manage pollution and natural resources, covering inter alia resource efficiency, waste management, air pollution, controlling and cleaning up soil, as well as recycling, renewable energy, low carbon footprint, and water supply. Green employment also accommodates economic activities such as the design of sustainable clothing, eco-production, and many other jobs, which are impacted indirectly. In this sense, the growth of green employment can be interpreted as a challenge for enabling PTAI's sustainable development.

Knowing that the promotion of this industry in international markets is currently viewed as a priority to consolidate the global relevance of Portugal, the main goal of this study is to understand the effect of international trade on employment in the PTAI by applying a panel data analysis and several extensions based on unsupervised machine learning, discrete choice, and limited dependent variable models. Since the final sample consists of 5557 registered firms, this research guarantees the extrapolation of richer information relative to past studies. In this body of literature, recent studies have focused on a variety of institutional elements as determinants of the green transition. These include the impact of renewable raw material sourcing, production re-evaluation, and recycling methods (Brydges 2021; Hartley et al. 2022); the mediating role of product innovation in the relationship between economic performance and green entrepreneurial orientation (GEO) and green transformational leadership (GTL) (Asad et al. 2024); the urgent need for updated infrastructure and cutting-edge vital inputs (Tumpa et al. 2019; Virtanen et al. 2019; Sandvik and Stubbs 2019; Todeschini et al. 2020); the impact of internal pressures, such as process innovation and digitalisation (Yang et al. 2023), and external pressures, such as environmental regulations and media (Kazancoglu et al. 2021; Andersén 2021; Bressanelli et al. 2022; Reike et al. 2023); and the impact of information sharing among employees (Cao et al. 2019). It is also remarkable that the recent penetration of gaming elements (e.g., avatars) into the TAI has prompted an empirical analysis of the mediating role of brand coolness on the equity maintained by TAI companies (Salem et al. 2023). Notably, none of these recent studies have addressed the impact of international trade on green capital endowment and green job creation, nor have they analysed whether green capital significantly mediates the relationship between green employment and international trade. Motivated by this gap and using data from the PTAI, this study aims to address three key research questions:

1. What is the relationship between green capital endowment and international trade? Is this relationship statistically significant? What is the impact of exports and imports on the proliferation of green capital in the PTAI?
2. What is the relationship between green job creation and international trade? Is this relationship statistically significant? What is the impact of exports and imports on the proliferation of green jobs in the PTAI?
3. Does green capital mediate the relationship between green employment and international trade in the PTAI?

The goal is to complement ongoing research on the TAI, which often concentrates on specific organisational aspects, by examining how international trade activities impact the effectiveness of the green transition in terms of both green employment and green capital.

Methodologically, this study has the concern to control for the presence of heteroscedasticity and endogeneity. Initially, it performs a panel data analysis to infer the impact of international trade activities on the proliferation of employment defined in a broad sense. Afterwards, it uses an unsupervised machine-learning method to capture a proxy of green capital and green employment and then executes statistical inference to understand the role of international trade activities on the penetration of green employment by considering a two-step approach that consists of adopting a discrete choice analysis to estimate the likelihood of firms' green capital adoption followed by the application of several limited dependent variable models, while controlling for the presence of self-selection bias, to infer the firm-level propensity to create green jobs. Finally, it performs a mediation analysis to identify statistically significant mediators of the relationship between green employment and international trade.

The main results can be summarised as follows. Firstly, the analysis demonstrates that international trade activities have a permanent, negative, and significant effect on job creation when this is defined in a broad sense. This is confirmed through the identification of the mechanism through which PTAI companies benefit from the appropriation of knowledge spillovers when they interact with international peers. Although globalisation ensures the absorption of technological progress, this is being used by PTAI companies to

satisfy alternative ends other than promoting new employment opportunities. Moreover, the negative impact of exports and imports is unambiguously stronger in the long-run, which implies that public policy measures conceived to support this industry should not be characterised by structural breaks after their initial uptake. Secondly, this study confirms that the imposition of geographical restrictions on international trade activities do not necessarily lead to a stronger negative effect on PTAI's job creation. In light of the recent pandemic that affected the world, this result suggests that employment opportunities in the PTAI tend to face less adverse effects compared to other manufacturing industries. Thirdly, we provide evidence that exports and imports have a stronger impact on employment in companies located in the north of Portugal and whose juridical form is representative of a greater realisation of own capital, which may legitimize the imposition of discriminatory clauses when deemed necessary, proportionate, and appropriate. Fourthly, results suggest that international trade activities do not necessarily create green jobs in companies endowed with green capital. However, differently from the case of employment defined in a broad sense, as companies without green capital have been able to participate in international trade, this stylised fact has allowed to maintain a stabilised level of employment from 2015 onwards. In this context, a discussion is presented to claim that better targeting and coordination of labour market measures and tools are essential to create the necessary conditions to support green employment in the PTAI, bridge skill gaps and labour shortages, and anticipate changes in human capital needs. Results also confirm that international trade activities have a positive (negative) and significant effect on the creation of green jobs in firms without (with) green capital, respectively. This is not only indicative of a short-run transition that may reflect a structural transformation of this industry due to marginal productivity gains caused by the penetration of green technologies, but also reflects that niche employment opportunities are being created, some traditional jobs are being replaced, and others are being relocated to firms without green capital if and only if these have the chance to participate in international markets. Overall, the results of this study suggest that the economic model oriented to exports followed the last decade by the PTAI does not necessarily promote new employment opportunities in the domestic market, but it has contributed to modifying the profile of skills required of the labour force.

The manuscript has the following organisation: Section 2 presents a literature review, clarifies research hypotheses, and provides a mathematical background to support the empirical approach. Section 3 displays econometric details. Results are clarified in Section 4. A discussion is presented in Section 5. Conclusions are presented in Section 6. Appendices A–C contain details not exposed in the main text for the sake of brevity.

2. Theory

2.1. Literature and Research Hypotheses

This study quantifies the impact of international trade activities on employment and green employment in the PTAI. Since this research goal necessarily requires the comprehension of several conceptual elements, an exhaustive literature review has been relegated to Appendix C for the sake of brevity. We divide it into smaller parts as follows:

1. General effects of the 2005 international trade's liberalisation on employment;
2. Role of the international trade on employment;
3. Role of firm-specific characteristics on employment;
4. Past contributions focused on evaluating determinants of employment in the TAI; and
5. Employment defined in a broad sense vs. the penetration of green employment.

2.1.1. Impact of the TAI's Internationalisation on Employment

The first point discusses that the TAI's internationalisation has had a profound impact on employment, particularly following trade liberalisation after 2005. The TAI is widely regarded as a key pillar of the global economy, significantly contributing to job creation and economic growth, especially in low- and middle-income countries (Eppinger 2022). Addi-

tionally, this industry plays a crucial role in increasing household income and providing access to affordable clothing for economically disadvantaged households (Xu et al. 2024).

However, the rapid expansion of the TAI has led to pressing sustainability challenges (Millward-Hopkins et al. 2023). The industry's product lifecycle tends to be short, while its global supply chain is highly fragmented, with competitive advantages often centred around product design and style differentiation (Tumpa et al. 2019). Textile production processes are also energy-intensive and rely on chemicals that present significant environmental concerns (Reike et al. 2023). Developed countries, particularly in Europe and the USA, have witnessed considerable declines in their manufacturing sectors, largely due to competition from low-cost producers in developing countries. A significant consequence has been the sharp drop in employment, particularly in low-skilled jobs. The lack of adequate training programs at the company level has also emerged as a barrier to the adoption of environmentally sustainable innovations within organisations. This, in turn, has resulted in a shortage of a skilled workforce capable of effectively implementing decarbonisation and circularity practices (Todeschini et al. 2020). Mishra et al. (2023), underscoring the critical need for training both managers and workers to ensure alignment with technological advancements and operational improvements.

It is not surprising, then, that researchers hold differing views on the impact of international trade activities in the TAI. Some researchers focus on the negative outcomes, such as layoffs and plant closures (Kabish 2023; Ruteri 2023; Majumder and De 2023), while others highlight the potential for innovation and adaptation to the evolving global environment (Keough and Lu 2021; Khan et al. 2022; Lu 2022a, 2024a, 2024b; Laurits and Lu 2023; Botwinick and Lu 2023; Carswell and De Neve 2024). In light of these findings, we adopt the optimistic perspective and propose the following hypothesis:

H1. *The elasticity of substitution of imports by exports has a positive effect on employment.*

This hypothesis aligns with the notion that the trade-off between imports and exports in the PTAI may positively impact employment, as companies adjust to international trade dynamics by adapting their workforce and production processes.

2.1.2. Role of Geographical Reach and Scope

The second point addresses the role of geographical reach and scope in shaping how international trade affects employment in the TAI. Past evaluations, using the Heckscher–Ohlin–Samuelson (HOS) framework, suggest that trade liberalisation typically leads to a redistribution of employment between import-substitute sectors and export-oriented sectors. In this framework, import growth often results in job losses in domestic industries, while export expansion boosts employment by creating new opportunities in global markets. However, the literature remains divided on whether the overall net effect of international trade on employment is positive or negative, particularly due to the shifting demands for different types of skills required for modern jobs. One of the key issues in this debate is the transformation of the labour market within the TAI, where globalisation has driven companies to adopt new technologies and business models that alter the traditional skills required for employment. As firms engage in international trade, they face pressures to adapt to global standards, often resulting in a demand for higher-skilled workers while reducing the reliance on lower-skilled labour (Xu et al. 2024). This shift in skill requirements complicates the assessment of trade's net impact on employment, as it may increase job opportunities for some while causing displacement for others.

Additionally, the sustainability agenda plays a significant role in shaping the geographical scope of TAI companies' operations (Eppinger 2022). It is widely accepted that the TAI must address environmental challenges comprehensively and transition towards sustainable practices. For instance, TAI companies have increasingly adopted decarbonisation strategies aimed at reducing carbon emissions throughout their supply chains (Guo et al. 2024). These efforts include shifting from a linear business model to a circular economy

model, which extends product lifecycles, enhances recycling of second-hand clothing, and fosters new employment opportunities by creating jobs in recycling and circular production processes (Hartley et al. 2022).

Moreover, the geographical reach of a firm's international trade activities is critical to its ability to absorb the positive spillover effects of international trade on employment (Krugman et al. 1995). Firms with a broad geographic presence can leverage international knowledge, innovations, and market access to enhance job creation. However, companies operating within more geographically restricted markets, such as those limited to EU territories, may find it easier to comply with region-specific regulations and standards, thereby benefiting more directly from the localised nature of trade relationships within the EU. This allows firms to better manage their labour needs and ensure compliance with sustainability goals, especially when it comes to eco-friendly practices. Given the importance of geographical considerations in determining the employment outcomes of international trade, the following hypothesis is formulated:

H2. *Exports and imports have a stronger impact on employment in PTAI companies when international trade activities are geographically restricted to regions inside the EU territory.*

This hypothesis posits that limiting trade activities to the EU can amplify the positive employment effects of exports and imports. This is likely due to the closer alignment of trade regulations, labour standards, and sustainability practices within the EU, which may better support employment growth in the PTAI.

2.1.3. Role of Juridical Form and Own-Capital Realisation

The third point explores how firm-specific factors—such as innovation, product differentiation, juridical form, and the skill level of employees—affect employment within the TAI. Research shows that firms adjust differently to global competition based on their size, age, efficiency, and governance structures (Hodges and Link 2019). Moreover, Nouinou et al. (2023) review decision-making processes in Industry 4.0 within the TAI, identifying trends like data-driven, real-time, decentralised, integrated, and sustainable decision-making. These factors, crucial to modern competitive strategies, influence how firms manage employment during transitions to digitalised and globalised production processes.

One of the most crucial factors determining how well firms can adapt to these challenges is their juridical form, which reflects how they are structured in terms of ownership and capital realisation (Ribeiro and Soares 2024). Firms with higher capital endowment are generally better equipped to invest in technological innovations and manage the high fixed costs associated with scaling up production and expanding globally. Smaller firms, or those without sufficient innovation capacity, may struggle to compete and might downsize as a result.² For instance, in a recent study focused on the PTAI, Santos and Castanho (2022) highlight that smaller firms in the PTAI performed better during periods of global economic crisis compared to larger firms. This was likely due to the higher fixed costs that larger firms face, which makes them more vulnerable to economic downturns when global orders decline. Their analysis also underscores the importance of factors such as management experience and organisational flexibility in determining a company's resilience during such periods. Moreover, Portugal is one of Europe's leading textile exporters, and the performance of PTAI firms has implications for the country's broader economic sustainability. However, Santos and Castanho (2022) overlook a key point: the fact that more than 98% of PTAI firms are small- and medium-sized enterprises (SMEs), which can introduce a self-selection bias in their empirical analysis. Larger firms, with their higher fixed costs, are more likely to perform worse in times of crisis, which skews the empirical results if self-selection is not properly accounted for. Given that juridical form and capital endowment play crucial roles in how firms respond to international trade dynamics and employment demands, the following hypothesis is proposed:

H3. *Exports and imports have a stronger effect on employment in PTAI companies whose juridical form is representative of a greater endowment of own capital realisation.*

This hypothesis suggests that firms with a juridical form reflecting a higher degree of capital investment are better positioned to leverage the benefits of international trade for employment growth. These firms are more likely to have the financial and technological resources necessary to capitalise on export opportunities and mitigate the negative effects of increased competition from imports.

2.1.4. Role of Clustering and Agglomeration Effects

The fourth point examines the role of agglomeration and clustering effects within the TAI, focusing on various factors influencing employment and the implications of regional concentration. Recently, X. [Chen et al. \(2024\)](#) conducted a systematic review of 68 papers on decarbonisation in textile supply chains. Their study led to the development of a comprehensive conceptual framework that integrates antecedents, decarbonisation practices, influential factors, and outcomes. This review also suggests that regional characteristics, including the countries in which firms operate, play a crucial role in shaping decarbonisation and employment patterns.

A notable aspect of the TAI is the geographical concentration of companies, particularly in Portugal, where firms are clustered into three main regions ([ATP 2018](#)). This spatial concentration suggests that the role of regional characteristics and clustering effects should be considered when assessing employment trends and industry dynamics. Moreover, [Han and Jeon \(2019\)](#) and [Jeong et al. \(2021\)](#) claim that understanding the concept of revitalisation and the impact of spatial characteristics is essential for analysing the TAI.

[Lu \(2022b\)](#) also clarifies that while the TAI is global, its trade patterns remain predominantly regional. Countries often engage in import and export activities with partners within the same region ([Dicken 2015](#)). Given the exacerbation of this regional concentration, it is crucial to explore how international trade affects employment in the TAI within specific clusters. Consequently, the following hypothesis is proposed:

H4. *Exports and imports have a stronger effect on employment in PTAI companies belonging to the North of Portugal.*

This hypothesis investigates the differential impact of international trade on employment within various regional clusters, contributing to better understanding the role of clustering and agglomeration effects in the PTAI.

2.1.5. Impact of the TAI's Internationalisation on Green Jobs

The focus on sustainable development within the TAI has increasingly shifted towards green practices. However, much of the existing research remains theoretical, concentrating on strategies such as renewable raw material sourcing, production re-evaluation, and recycling methods ([Brydges 2021](#)). These studies often lack practical applicability and fail to address emerging trends in green employment ([Xu et al. 2024](#)). Consequently, the fifth point explores the impact of internationalisation on green jobs, particularly as it pertains to the transition towards sustainable and eco-friendly production practices in the TAI.

Recent literature suggest that GEO has gained prominence over traditional entrepreneurial orientation as a critical factor in enhancing the performance of entrepreneurial firms while mitigating ecological impacts ([Muangmee et al. 2021](#); [Asad et al. 2024](#)). GEO focuses on integrating environmental considerations into business practices, which aligns with the broader goals of sustainable development and can influence the creation of green jobs.

Dynamic capability theory (DCT) further supports this notion by explaining how enterprises can adopt, adapt, and innovate in ways that align with consumer preferences and competitive pressures ([Hasegan et al. 2018](#); [Zahid et al. 2022](#); [Asad et al. 2024](#)). Ac-

cordingly, firms that leverage their dynamic capabilities effectively can enhance their green innovation efforts. This view posits that the ability to develop and share knowledge among employees contributes significantly to green innovation, which is increasingly demanded in the current information era (Cao et al. 2019).

From a resource-based view (RBV), GLT is identified as a vital resource that significantly impacts the performance of entrepreneurial firms (Barney 1991). Effective use of organisational resources can lead to superior performance, especially in green product innovation, which necessitates a focus on environmental preservation (Andersén 2021). Past literature has examined green entrepreneurial orientation and GTL independently, as well as dynamic capabilities and RBV approaches as separate constructs (Hamdoun 2020).

The growing emphasis on green employment is evident from international initiatives such as the Green Jobs Initiative (UNEP 2008). These initiatives highlight the role of green jobs in reducing energy consumption, minimising pollution, and supporting sustainable development. The ongoing debate revolves around defining green jobs, measuring their impact, and understanding their contribution to the broader transition towards a circular economy (Vona et al. 2019). In light of the above theoretical frameworks and practical considerations, the following hypothesis is articulated:

H5. *International trade activities have a positive impact on the creation of green jobs.*

This hypothesis evaluates how internationalisation drives the growth of green jobs, contributing to sustainable development and supporting the transition towards more eco-friendly industry practices.

While H1 and H2 correspond to direct effects due to their focus on the immediate impact of international trade characteristics (i.e., elasticity of substitution and contingency measures) on employment, H3 and H4 correspond to indirect effects since their concern relies on the influence of firm-specific characteristics (i.e., juridical form and location) on international trade activities (i.e., exports and imports), which, in turn, affect the employment dynamics of PTAI. Finally, H5 identifies whether international trade activities foster a differentiated impact between employment defined in a broad sense vis-à-vis the availability of green jobs.

2.2. Mathematical Formalisation: Transitioning from the Theory into the Empirical Analysis

While most academic studies only select the set of inputs to be used in the empirical analysis by relying on postulates from existing studies, this research complements such a view by providing a mathematical foundation to justify the deterministic component of the multiple linear regression model to be employed. A Cobb–Douglas production function is assumed to represent characteristics of the supply side, which implies that the real output of firm i in period t is given by

$$Q_{it} = A_{it}^{\gamma} K_{it}^{\alpha} L_{it}^{\beta} \quad (1)$$

where Q stands for the real output, K represents the capital stock, L represents labour units, α is the elasticity of output with respect to capital, β is the elasticity of output with respect to labour, and A^{γ} represents the technological progress or the improvement in total factor productivity, which occurs at the rate γ representative of Newton's *giant shoulders effect*. Economically speaking, this effect suggests that the more past inventions help to boost the rate of current inventions, the faster the growth rate will be. From a theoretical point of view, profit maximisation requires labour (capital) being set at the level where marginal revenue is equal to wage w (marginal cost c), respectively. Knowing that, each firm yields

$$\varepsilon_i^K = \frac{\partial \ln Q_i}{\partial \ln K_i} = \alpha$$

$$\varepsilon_i^L = \frac{\partial \ln Q_i}{\partial \ln L_i} = \beta$$

the marginal revenue of capital and labour, respectively, corresponds to

$$MPK_i = \frac{Q_i}{K_i} \varepsilon_i^K = \frac{Q_i}{K_i} \alpha$$

$$MPL_i = \frac{Q_i}{L_i} \varepsilon_i^L = \frac{Q_i}{L_i} \beta$$

Given the concern related to the effects on the labour factor, K_i can be re-expressed as a function of L_i , w and c

$$MPK_i = c_i \Leftrightarrow K_i = \frac{Q_i}{c} \alpha$$

$$MPL_i = w_i \Leftrightarrow Q_i = \frac{L_i}{\beta} w$$

such that

$$K_i = \frac{\alpha}{\beta} \frac{w_i}{c_i} L_i$$

Substituting the previous expression in Equation (1) yields

$$Q_{it} = A_{it}^{\gamma} \left(\frac{\alpha}{\beta} \right)^{\alpha} \left(\frac{w_{it}}{c_{it}} \right)^{\alpha} L_{it}^{\alpha+\beta} \Leftrightarrow L_{it} = A_{it}^{-\frac{\gamma}{\alpha+\beta}} \left(\frac{\beta}{\alpha} \right)^{\frac{\alpha}{\alpha+\beta}} \left(\frac{w_{it}}{c_{it}} \right)^{-\frac{\alpha}{\alpha+\beta}} Q_{it}^{\frac{1}{\alpha+\beta}}$$

Taking the natural logarithm of this expression, one obtains

$$\ln(L_{it}) = c_0 + \phi_1 \ln\left(\frac{w_{it}}{c_{it}}\right) + \phi_2 \ln(Q_{it}) + a \ln(A_{it}) \quad (2)$$

where $c_0 = \alpha[\ln(\beta) - \ln(\alpha)]/(\alpha + \beta)$, and with $\phi_1 = -\alpha/(\alpha + \beta)$, $\phi_2 = 1/(\alpha + \beta)$, and $a = -\gamma/(\alpha + \beta)$. Similar to [Greenaway et al. \(1999\)](#), the technical efficiency of production processes is assumed to increase over time. Additionally, the rate of technology adoption and increases in x -efficiency are assumed to be correlated with changes in international trade. However, while [Greenaway et al. \(1999\)](#) assume a Cobb–Douglas production function to represent the variation of parameter A for a given exogenous change in the magnitude of imports and exports, this study extends their framework by considering that parameter A also varies based on substitutability patterns between imports and exports. This refinement, which requires one to rely on a variable elasticity of substitution (VES) production function, ensures the necessary flexibility to clarify how the evolution of PTAI based on international trade affects its technological progress because the representative parameter of the elasticity of substitution between imports and exports turns out to be affected by the size of both inputs. Historically, the VES production function was firstly introduced in [Hicks \(1932\)](#). Thenceforth, [Vinod \(1972, 1976\)](#) adopted it to analyse the telecommunications industry, and, more recently, [Ramcharran \(2001\)](#) and [Kouliavtsev et al. \(2007\)](#) have used it to formalise the textile industry's strategic behaviour. Formally, one hypothesises that the technological progress varies in the following manner

$$A_{it} = e^{\delta_0 T_i} M_{it}^{m+\delta_1 \ln(X_{it})} X_{it}^x$$

where T_i captures the firm-specific time trend, M corresponds to imports, X corresponds to exports, δ_0 captures the sensitivity of technological progress with respect to the time trend, m is the elasticity of technological progress with respect to imports, x is the elasticity of technological progress with respect to exports and δ_1 captures the sensitivity of technological progress with respect to the interaction term that represents the international trade dynamics. This specification assumes constant technology across firms and over time, despite the fact that the elasticity of substitution is allowed to vary in both dimensions. Although this assumption may not be completely innocuous because the universe of PTAI companies is expected to be heterogeneous, the time period under analysis is relatively

short. As such, the key property that the previous function brings seems to constitute a sufficient condition to allow the capture of international trade patterns on the formation of technological progress at the firm level. The marginal rate of technical substitution (MRTS) measures the rate at which both factors can be interchanged, while holding parameter A constant. For each firm, MRTS is formally equal to the ratio of marginal revenue products

$$MRTS_{(M,X)_i} = \frac{MPM_i}{MPX_i} = \frac{X_i \varepsilon_i^M}{M_i \varepsilon_i^X} = \frac{X_i [m + \delta_1 \ln(X_i)]}{M_i [x + \delta_1 \ln(M_i)]}$$

Based on Vinod (1972), the scale elasticity corresponds to the sum of all input elasticities

$$SE_i = m + x + \delta_1 \ln(M_i X_i)$$

The elasticity of substitution between M and X at the technological progress level faced by firm i is given by

$$s_i = \frac{\varepsilon_i^M + \varepsilon_i^X}{\varepsilon_i^M + \varepsilon_i^X + 2\delta_1} = \frac{m + x + \delta_1 [\ln(X_i) + \ln(M_i)]}{m + x + \delta_1 [2 + \ln(X_i) + \ln(M_i)]}$$

which depends on both M and X levels. Since the expression of parameter A in natural log form is given by

$$\ln(A_{it}) = \delta_0 T_i + m \ln(M_{it}) + x \ln(X_{it}) + \delta_1 \ln(M_{it}) \ln(X_{it})$$

the substitution of the previous expression in Equation (2) allows one to obtain the estimable static panel data model

$$\ln(L_{it}) = \phi_0 + \phi_1 \ln\left(\frac{w_{it}}{c_{it}}\right) + \phi_2 \ln(Q_{it}) + \phi_3 \ln(M_{it}) + \phi_4 \ln(X_{it}) + \phi_5 \ln(M_{it}) \ln(X_{it})$$

with $\phi_0 = c_0 + a\delta_0 T_i$, $c_0 = \alpha \frac{[\ln(\beta) - \ln(\alpha)]}{\alpha + \beta}$, and $a = -\gamma / (\alpha + \beta)$. The remaining parameters are given as follows: $\phi_1 = -\alpha / (\alpha + \beta)$, $\phi_2 = 1 / (\alpha + \beta)$, $\phi_3 = am$, $\phi_4 = ax$, and $\phi_5 = a\delta_1$. In terms of a panel regression model equation, the previous expression becomes

$$\ln(L_{it}) = \phi_i + \eta_t + \phi_1 \ln(w_{it}) + \phi_2 \ln(Q_{it}) + \phi_3 \ln(M_{it}) + \phi_4 \ln(X_{it}) + \phi_5 \ln(M_{it}) \ln(X_{it}) \quad (3)$$

where:

- L_{it} is the total employment of firm i in period t ;
- ϕ_i is a firm-specific intercept term;
- η_t is a period-specific trend factor;
- w_{it} is the average real wage of firm i in period t , with marginal cost c normalised to 1;
- Q_{it} is a measure of real output (e.g., gross value added (GVA), business volume, sales) representative of firm i in period t ;
- M_{it} is the import volume of firm i in period t ;
- X_{it} is the export volume of firm i in period t ;
- v_{it} is the disturbance term, which may include a random component in addition to a white noise.

Two caveats are worth detailing. First, Equation (3) can be used to accommodate different regression models by applying appropriate restrictions. For instance, introducing the constraint $\beta_i = \beta_0 \forall i$, $\eta_t = 0 \forall t$, and assuming that v_{it} is white noise implies the definition of a pooled regression, which can be estimated by ordinary least squares (OLS). Similar reasoning is applied to the inference of two-way fixed effects or random effects models. Second, Equation (3) can be extended to a log–log regression model grounded by a dynamic panel data approach aimed at quantifying the impact of time-lagged covariates on the target. The need of including a dynamic component (e.g., lagged dependent variable) into

the regression model is theoretically justified by the fact that adjustment costs in the level of employment frequently require short-term deviations from the steady-state equilibrium. Moreover, since the employment measure is the aggregation of workers potentially characterised by holding distinct adjustment costs, additional lags may be necessary to control for heterogeneity (i.e., unit-specific effects) (Nickell 1986). A longer lag structure may also be needed if serially correlated shocks are present in the data. Furthermore, lagged dependent variables may be introduced when bargaining considerations are internalised (e.g., expectations on future wages and output levels). Purely specifying dynamics in terms of lags applied to the dependent variable implicitly imposes a common evolution for employment. This restriction may be relaxed by introducing a lag structure in some regressors of interest (i.e., exports and imports).

3. Methods

3.1. Data

The dataset was downloaded from the Sistema de Análisis de Balancos Ibéricos (SABI). After pre-processing raw data, the final sample consists of 5557 registered companies, whose operational activity covers the 18 four-digit sectors of the PTAI over the period between 2010 and 2017. Firm-level data include observations on the following:

- The number of workers (L).
- Average wage (W).
- Import volume (M).
- Export volume (X).
- GVA (Q).

The development of several robustness checks required the collection of information on the following:

- Juridical form (JF).
- Own capital founded or not by family funds (Fam).
- Maturity (i.e., years since market entry) of firms (AGE).
- The segmentation of import and/or export volumes by origin and/or destination market (i.e., outside the EU territory vs. inside the EU territory).

Furthermore, using a dummy variable, PTAI companies were agglomerated based on the geographical place of the respective cluster in order to distinguish between clusters located in the north of the country and clusters located in any other region of the country. Additional controls were included in the deterministic component of the regression model when unsupervised machine learning is used to study the formation of green capital and green employment in the PTAI, whose details are clarified in Section 3.2.

3.1.1. Descriptive Statistics

Table 1 shows descriptive statistics for the period 2010–2017 after all the selected variables measured in nominal terms being deflated through the appropriate price index, but before introducing a logarithmic form.

Table 1. Summary statistics.

Acronym	Obs.	Mean	Std. Dev.	Min.	Max.	Description	Unit of Measure
L	36,449	23.820	47.720	0	891	Number of workers	#
W	35,545	325.740	784.370	0	17,646	Average net wage per worker	€1
M	44,428	678.180	3718.180	0	100,756	Total imports	€1000
X	44,421	221.230	1600.000	0	54,665	Total exports	€1000
Q	36,464	386.300	1226.790	−9543	59,538	Gross value added	€1000

Notes: period 2010–2017. Units of observation are PTAI companies, $n = 5557$. The panel is strongly balanced due to missing values. SABI does not distinguish between part-time and full-time jobs.

On average, a PTAI company has 24 workers and €326 corresponds to the average net wage paid to the representative worker. On average, the import (export) value of PTAI companies is equal to €678 (221) thousand, respectively. PTAI companies provide, on average, a contribution of €286 thousand to the domestic economic activity of Portugal. Overall, PTAI's business is characterised by a high degree of heterogeneity due to the considerably high standard deviation that transversely affects the selected explanatory variables.

3.1.2. Preliminary Statistical Tests to Evaluate the Satisfaction of Classical Hypotheses

Recall that deterministic component of the multiple linear regression model is based on our extension of the mathematical model seminally proposed by [Greenaway et al. \(1999\)](#). To reinforce this theoretical ground, we analyse beforehand:

- Multicollinearity through the correlation matrix and variance inflation factor (VIF) statistics and, as confirmed by the panoply of results exposed in Table 2, conclude that all explanatory variables should be used to explain the target.
- Specification through the Ramsey RESET test³ and, from the test statistic whose outcome is $F(3, 26, 695) = 3207.29$, conclude that a linear model cannot properly explain the target due to the rejection of the null hypothesis; as such, the introduction of logarithmic form in the target and explanatory variables, as specified in Equation (3), is the appropriate option for this case study.
- Homoscedasticity, whose Breusch–Pagan test detects the presence of heteroscedasticity ($\chi^2(1) = 3257.210$, p -value = 0.000), thus creating the need to apply the Huber–White procedure to restore the classical hypothesis of homoscedasticity.
- The absence of autocorrelation and the exogeneity of regressors were also inspected.

Table 2. Correlation matrix and VIF statistics.

	L	W	M	X	Q	VIF
L	1					
W	0.612 ***	1				2.200
M	0.588 ***	0.700 ***	1			3.560
X	0.515 ***	0.657 ***	0.837 ***	1		4.400
Q	0.789 ***	0.684 ***	0.772 ***	0.721 ***	1	2.850

Notes: *** represents 0.01 level of significance, respectively. Mean VIF equals 3.25.

In the literature focused on assessing employment dynamics and trends, studies can be observed that analyse either developed countries ([Bottazzi and Secchi 2006](#); [Bottazzi et al. 2011](#)) or developing countries ([Yu et al. 2015](#); [Mathew 2017](#)). Moreover, it is transversally accepted that the distribution of employment level and employment growth rate is heavy tailed. Figure 3 allows for inferring that both distributions exhibit this property in the PTAI. The level of employment is also right-skewed, thereby reflecting a positive skewness since more than 80% of PTAI companies have less than 10 workers. Similar to past studies, the majority (a small number) of PTAI companies contain a low (high) number of employees, which means that the business tissue is predominantly characterised by the presence of SMEs, respectively.

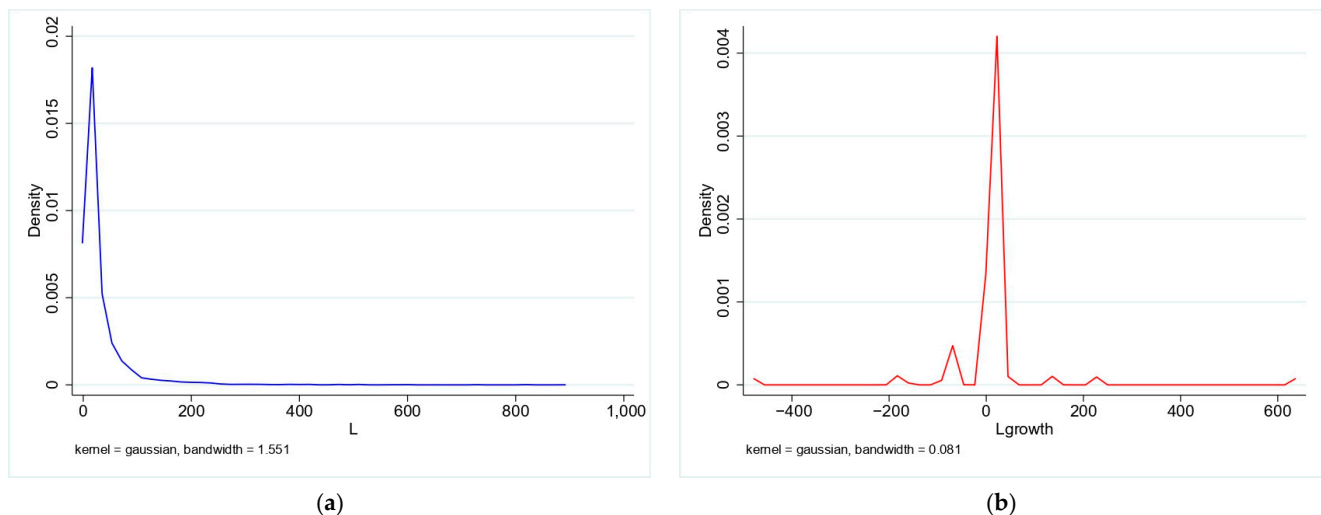


Figure 3. Kernel density estimation: (a) level of employment in the PTAI (2010–2016); (b) growth rate of employment in the PTAI (2010–2016).

3.2. Empirical Strategy to Analyse Employment Defined in a Broad Sense

The empirical assessment is focused on a panel data analysis, which follows five main steps summarised as follows:

We start by considering three static panel data models—pooled OLS (POLS), fixed effects, and random effects—to evaluate the behaviour of the dependent variable based on the deterministic component described by Equation (3). Under the POLS, explanatory variables are assumed to have a common impact across firms. This may be questionable because, for instance, each PTAI company may exhibit specific characteristics. Firm-specific fixed effects allow for unaccounted differences between firms, which are constant over time. Therefore, taking the first difference transformation of Equation (3) may be necessary in order to transform firm-specific fixed effects and accommodate time-specific fixed effects. However, Baltagi (2008) warns that the lagged dependent variable can be serially correlated with unobserved fixed effects in the residuals, which causes bias and inconsistency in the estimated coefficient of the lagged target. To overcome this debility, Anderson and Hsiao (1981) suggest complementing the first difference transformation of Equation (3) with the use of a lagged dependent variable as instrument to ensure consistent estimates of parameters.

The second task consists of applying two different types of dynamic panel data models aimed at incorporating dynamic adjustments of the dependent variable over time. On this domain, the generalised method of moments (GMM) technique of Arellano and Bond (1991) and Blundell and Bond (1998) was adopted in this study. Exploiting it allows for controlling for the endogeneity of the lagged dependent variable in cases where there is correlation between explanatory variables and disturbance terms. Surpassing the endogeneity problem is particularly relevant because, for instance, exports and imports are likely to influence GVA which, in turn, is likely to have a significant effect on employment, thereby reflecting that reverse causality can exist, at least from a theoretical perspective. To mitigate this source of concern, Arellano and Bond (1991) and Blundell and Bond (1998) propose the use of instrumental variables to infer moment conditions by means of applying a difference GMM model. The basic idea is to eliminate individual fixed effects by proceeding with the first difference in the regression equation in first place. Then, the lagged dependent variable is regarded as the corresponding instrumental variable of endogenous variables in the difference equation, which allows for exploiting the orthogonality conditions between the dependent variable and the disturbance term. Bond et al. (2001) confirm that the difference GMM model may suffer from the weak instruments problem in finite samples, being thus characterised by a poor estimation precision since the endogeneity problem can still persist.

A solution to this concern is proposed by [Arellano and Bover \(1995\)](#), which consists of including additional moment restrictions through a system GMM model where a system of two equations is defined: an equation in differences instrumented by lagged levels and an equation in levels instrumented by lagged differences. This method not only introduces more moment conditions to increase the efficiency of instruments, but it also transforms existing instruments to make them uncorrelated with fixed effects. In addition to reducing the imprecision and potential bias related to the difference GMM estimator, the system GMM estimator is able to correct the unobserved heterogeneity problem, omitted variable bias and measurement errors ([Blundell and Bond 1998](#)). Additionally, [Roodman \(2009\)](#) clarifies that a system GMM estimator is efficient in the sense that it expands the instrument set as the panel progresses and the number of potential lags increases. When resorting to dynamic panel data models, the lagged dependent variable is used as the internal or endogenous instrument, while dummy variables representing years 2010 and 2013 are used as external or exogenous instruments to dissuade concerns related to endogeneity.⁴ Furthermore, it is important to highlight that the number of instruments must be lower than the number of units or groups of the panel in GMM. Otherwise, estimates are considered invalid ([Roodman 2009](#)).

The third step consists of following the rule-of-thumb proposed in [Bond et al. \(2001\)](#) to choose between the difference GMM model and the system GMM model. Initially, the dynamic model is estimated through POLS and fixed effects. The coefficient associated with the lagged dependent variable under the POLS (fixed effects) serves as the upper (lower) bound of reference, respectively. Thenceforth, the dynamic model is estimated through difference GMM. If the coefficient associated with the lagged dependent variable is close or below the fixed effects estimate, then the GMM estimate is downward-biased because of weak instrumentation, so that the system GMM estimator should be adopted.

The fourth action consists of executing a test to check for the presence of autocorrelation and a test to check the validity of external instruments. On the one hand, the system GMM estimator is said to be robust to heteroscedasticity and autocorrelation as long as the differenced equation is free of second- or higher-order serial correlation. The respective validity is based on the calculation of test statistics, which are normally distributed under the null hypothesis of no serial correlation. The key idea is that the number of instrumental variables must not exceed the number of endogenous variables to ensure that moment conditions are not overly constrained. Thereafter, for lagged endogenous variables and weak exogenous variables to be valid as instruments, it is necessary that the transient disturbances in the base model are free of autocorrelation ([Blundell and Bond 1998](#)). To satisfy this purpose, we consider the Arellano–Bond test for first-order (i.e., AR(1)) and second-order (i.e., AR(2)) serial correlation in first-differenced residuals ([Arellano and Bond 1991](#)). Because first differences in independently and identically distributed (iid), idiosyncratic errors will be serially correlated, rejecting the null hypothesis of no serial correlation in the first differenced error at order one does not imply that the model is incorrectly specified. However, rejecting the null hypothesis that the differenced error term is not second- or higher-order serially correlated implies that the moment conditions are not valid. Contrarily, failure to reject the null hypothesis of no second-order serial correlation implies that the original error term is serially uncorrelated, and the moment conditions are correctly specified. As a result, we restrict the focus on analysing the observed *p*-value associated with the AR(2) statistic. If the AR(2) statistic test is not significant, such that the observed *p*-value is above the critical *p*-value of 0.05, then the null hypothesis cannot be rejected, and, consequently, the absence of second-order serial correlation cannot be rejected.

On the other hand, the validity of moment conditions can be tested by Sargan and Hansen—in case of heteroscedasticity—tests, whose null hypothesis is that instruments are overall exogenous and, thus, valid. The Sargan test statistic has a good behaviour only when disturbances are homoscedastic ([Iqbal and Daly 2014](#)). Additionally, the Sargan test may have a low power to reject the null hypothesis; instruments may be only valid when the

sample size is small and tend to over-reject the null hypothesis of serial uncorrelated errors in case of one-step GMM estimations (Bowsher 2002). Based on the debilities associated with the Sargan test and knowing that the Hansen test is the most widely adopted statistical test in econometrics practical work (Chen and Sun 2014), this is the one considered to assess the validity of instruments. If the Hansen test is not significant such that the observed p -value is above the critical p -value of 0.05, then the null hypothesis cannot be rejected, and thus, the exogeneity of instruments cannot be rejected.

Recent studies focused on econometric aspects recognise that combining lagged instrumental variables with the GMM technique may not be adequate, given that, under this circumstance, researchers are simultaneously trying to control for unobserved heterogeneity, while, at the same time, lagged and endogenous regressors are included, which can cause estimation problems (e.g., lack of significance and loss of statistical validity for inference), particularly when the panel is either weakly or strongly balanced due to missing data. Moreover, criticism can emerge with respect to the presence of omitted variable bias. To dissuade these sources of concern, Moral-Benito et al. (2019) propose an alternative method that consists of estimating coefficients through a linear dynamic panel data model that resorts to a quasi-maximum likelihood (QML) estimator under a structural-equation-modelling (SEM) approach. As detailed in Appendix A, the choice of random effects for the linear dynamic QML–SEM model is justified by the set of arguments exposed in Bell and Jones (2015). Consequently, the fifth step introduces this improvement based on the rationale that it is substantially more efficient than the GMM technique when the normality assumption is satisfied, mitigates selectivity problems, and suffers less from finite sample biases (Williams et al. 2018).

3.3. Empirical Strategy and Measurement Tools to Analyse the Penetration of Green Employment

Regarding the extension that allows for distinguishing between employment defined in a broad sense and green employment, one should start by emphasising that the empirical identification of the penetration of green employment in any industry is challenging because of five main reasons, which are summarised as follows:

1. It is not easy to define what a green job is because of the ample spectrum of actions devoted to environmental concerns and sustainability.
2. Empirical evidence on green employment is still limited in terms of timespan and scope due to data constraints.
3. Addressing environmental challenges entails adapting the skill base and, thus, the composition of the labour force, which suggests that the definition of green employment is expected to be mutable due to its dynamic nature.
4. Uncoordinated data collection by national statistical offices frequently fosters different statistical accounts even within a given national jurisdiction.
5. The literature presents different methods to define green employment, namely:
 - A strand of studies measures green jobs through the definition of a dichotomous variable, thus disregarding the continuous nature of green activities.
 - Some studies approximate the share of green employment with the share of green capital over total production, thus inferring green jobs indirectly from industry and/or product characteristics; therefore, this approach does not capture the effective engagement of workers with activities that use green technologies and environmentally efficient production processes.
 - Other studies quantify workers' dedication to green activities by computing the ratio between green occupational tasks and the total number of occupational tasks, thus disregarding that green occupational tasks exist because firms previously adopt technologies that require different skills (also known as green skills), regardless of whether the type of occupation is permanent or not.

Given these sources of ambiguity, a robust ensemble approach is used to identify and measure the penetration of green employment in the PTAI, which is summarised as follows:

1. In a first stage, an unsupervised machine-learning model—principal component analysis (PCA)—is applied to endogenously determine latent dimensions capable of representing green capital and green employment; and
2. In a second stage, a two-step procedure is considered to distinguish between the following:
 3. The first step—capital-based—discrete choice (i.e., yes or no probabilistic decision with respect to the endowment of green technologies and environmentally efficient production processes by PTAI companies); and
 4. The second step—labour-based—continuous choice (i.e., knowing that PTAI companies have previously implemented green technologies and environmentally efficient production processes, it consists of assessing determinants of green employment by applying three distinct estimation methods: OLS estimation, Cragg’s model, and Heckman’s selection model).

This robust ensemble approach reduces the estimation bias and reinforces the notion that all occupations are potentially interconnected with green activities, at least up to a certain extent, since these are contingent on the ex-ante adoption of green technologies and environmentally efficient production processes at the firm level. Furthermore, aligning with contemporary conceptual frameworks (Salem et al. 2023; Asad et al. 2024), an SEM approach is employed to analyse the role of two mediators in the relationship between international trade and green employment:

- The accommodation of green technologies and environmentally friendly processes by PTAI companies; and
- The maturity of PTAI companies.

In doing so, a novel contribution is provided to the literature, which consists of giving a dynamic, though realistic, notion of the penetration of green jobs in PTAI companies.

4. Results

4.1. Benchmark Analysis: Impact of International Trade on Employment Defined in a Broad Sense

4.1.1. Coefficients

Table 3 presents benchmark outcomes, which are subject to interpretation and discussion. Two different models are empirically tested:

- Model (A) disregards the interaction term between imports and exports.
- Model (B) incorporates the strategic interaction between exports and imports.

As described in Equation (3), this means that model (B) captures the endogenous mechanism whereby PTAI companies initially benefit from the appropriation of knowledge spillovers given their engagement in international trade activities. Thenceforth, the appropriated know-how affects the internal technological progress of PTAI companies, which turns out to influence the employment dynamics. As such, international trade activities can be interpreted as having a purely direct and isolated effect on the dependent variable only in the case of model (A).

Let us start by focusing on the results of model (A). In terms of statistical significance, all estimated coefficients are significant at the 1% level. In terms of sign, wages, exports, and imports affect employment negatively. While the wage effect is expected, a similar effect is not applied to international trade activities, where the results indicate that a higher degree of openness to international markets has a permanent, negative, and significant effect on employment in the PTAI. Although several reasons justify the efficiency gain caused by the combination of increasing exports with decreasing employment, it should be emphasised the gradual replacement of labour-intensive goods by capital goods, which are characterised by technological refinements (e.g., at the level of machinery and equipment) throughout the entire value chain.

The reduction in employment for increasing import volumes can be justified by the increase in outsourcing practices in traditional activities of the upstream market (e.g., input purchases), which promotes external dependence from developing countries at the

wholesale market level. Although increasing the dependence on foreign suppliers implies that PTAI companies are more likely to face input price volatility, it also exacerbates a reduction in domestic labour needs.

Table 3. Estimated coefficients of the QML–SEM regression model with random effects.

	(A)		(B)	
	Short-Run	Long-Run	Short-Run	Long-Run
L_{t-1}	0.307 *** (0.025)		0.309 *** (0.025)	
W	−0.042 *** (0.010)	−0.060 *** (0.015)	−0.038 *** (0.011)	−0.055 *** (0.002)
X	−0.024 *** (0.006)	−0.035 *** (0.008)	0.008 (0.009)	0.011 *** (0.0004)
M	−0.030 *** (0.006)	−0.043 *** (0.008)	0.014 (0.012)	0.021 *** (0.001)
Q	0.661 *** (0.027)	0.954 *** (0.019)	0.663 *** (0.027)	0.960 *** (0.035)
$X \times M$			−0.007 *** (0.002)	−0.010 *** (0.003)
Independent term	−1.151 *** (0.071)	−1.661 *** (0.079)	−1.391 *** (0.098)	−2.014 *** (0.073)
Input elasticities				
Capital (α)		0.063		0.057
Labour (β)	1.450	0.985	1.450	0.984
Exports (x)	−0.028	0.019	−0.005	−0.006
Imports (m)	−0.034	0.024	−0.010	−0.011
Interaction term (δ_1)			0.004	0.005

Notes: Robust standard errors in parentheses. Symbols *** represent 0.01 level of significance, respectively. QML–SEM stands for unconditional quasi-maximum likelihood estimator in the sense of Hsiao et al. (2002) under a SEM approach, whose mathematical details can be consulted in Kripfganz (2016). Model (A) disregards the interaction term between exports and imports, thus being representative of a regression model without elasticity of substitution. Convergence was achieved in the fifth iteration with $f(p) = -2794.355$, $n = 5125$ observations, and 940 groups. Model (B) includes the interaction term between exports and imports, thus being representative of a regression model with elasticity of substitution. Convergence was achieved in the fifth iteration with $f(p) = -2784.334$, $n = 5125$ observations, and 940 groups. No trend was included since 2010–2017 is a short time span, so that time-fixed effects $\delta_0 T_i$ were normalised to 1. All the covariates are in logarithmic form.

The previous outcomes are counterbalanced by the permanent, positive, and significant effect of GVA on employment. This result suggests that the willingness to hire remains high when PTAI companies deal with favourable economic contexts (e.g., increasing consumer purchasing power). Moreover, the lagged dependent variable affects employment positively, which suggests the persistence of a positive autocorrelation. In terms of the magnitude of effects, all covariates have an inelastic relation with the dependent variable because estimated coefficients are below the unit value. In fact, most estimates are close to zero, which reflects the high degree of rigidity that characterises the PTAI's labour market. The strongest elasticity is observed in GVA, where a 1% increase implies a 0.66% employment growth in the short-run, *ceteris paribus*. Although the value increases to 0.954, it remains inelastic in the long-run. We also emphasize that the sensitivity of employment in relation to exports is weaker than its sensitivity in relation to imports ($\phi_4 = -0.030 > \phi_3 = -0.024$). Lastly, results demonstrate that all impacts on the dependent variable are unambiguously stronger in the long-run.

Let us now reflect on the results of model (B). One can observe that the estimated coefficient associated with the covariate XM is permanently negative and significantly affects the dependent variable, which implies that the enhancement of the internal technological progress boosted by the intensification of export and import volumes does not contribute to increase the level of domestic employment. Results also reveal that the sign of X coefficient is positive, which validates the argument that exports promote domestic

employment presented in [Greenaway et al. \(1999\)](#). However, the estimated coefficient does not exhibit statistical significance, as does the estimated coefficient associated with imports. In fact, both elasticities are negative, meaning that they affect firms' output negatively, which discourages job creation. Both have an inelastic nature and a redundant increase of 1 percentage point (p.p.) in terms of magnitude once adjusting for the long-run equilibrium. Despite the negative impact of international trade activities on employment, benefits from the absorptive capacity of external knowledge can be particularly relevant for the economic growth of a small open economy like Portugal. Knowing that model (B) captures the effectiveness of the absorptive capacity of PTAI companies, it brings the technical advantage of avoiding the overestimation of the capital elasticity (i.e., $\alpha = 0.063$ in model A vs. $\alpha = 0.057$ in model B). As expected, similar is not applied to the labour factor due to the long-term adjustment mechanism previously detailed.

4.1.2. Scale and Substitution Elasticities

To obtain estimates on the theoretical constructs clarified in Section 2.1, we combine the estimated coefficients of model (B) with the time series of M_{it} , X_{it} , and L_{it} . Regarding the marginal productivity on imports (MPM) and the marginal productivity on exports (MPX), we briefly report that PTAI companies tend to exhibit a positive and increasing value over time in the 2010–2017 period, which is consistent with reports from other manufacturing industries ([ATP 2018](#)).

While a few firms experience adverse productivity shocks on exports between 2010 and 2011, a steady growth is observed in the MPX for most firms from 2012 to 2014. In general, the 2015–2017 period is characterised by the same upward trend, but with the provision that some major jumps are identified. Therefore, the best performance of PTAI companies in terms of exports has been achieved in recent years. PTAI companies are also characterised by upward adjustments in imports. Once confronting marginal productivities, results show that the MPM surpasses the MPX in most PTAI companies during 2010–2017.

Short-run- and long-run-scale elasticities are constructed as the sum of marginal elasticities of both international trade activities plus the adjustment caused by the interaction term between imports and exports. The scale elasticity measures the percentage variation between imports and exports caused by the distortion in transacted volumes in favour (disfavour) of exports (imports), which means that a higher (lower)-scale elasticity indicates a stronger substitutability pattern of imports by exports caused by the increasing (decreasing) variation in exports relatively to imports, respectively. In other words, a stronger (weaker) relative importance of exports is not verified due to additional firms changing their behavioural nature from being import-dependent to become export promoter but merely due to the higher (lower) transacted volume of exports relative to imports, respectively. Overall, scale elasticities are relatively stable across PTAI companies. Average values are bounded between -0.015 and 0.099 in the 2010–2017 period, which reflects the accommodation of all types of possibilities: decreasing, constant, and increasing returns. At the individual level, a considerable number of PTAI companies faced substantial positive changes in the scale elasticity over time, thereby reflecting that PTAI companies may actually export more, but their trading profile has not changed significantly. Increases in the scale elasticity were identified in almost 40% of observations, despite some being relatively modest. A few firms felt a modest decline in the scale elasticity from 2010 to 2011, which turned out to be readjusted in subsequent years, particularly in the biennium 2015–2016.

In terms of the elasticity of substitution of imports by exports, Table 4 shows that the global mean value for the PTAI is equal to 0.605, and annual mean values are between 0.5 and 0.7. Therefore, results are consistent with the theoretical expectation of negatively sloped isoquants ($\bar{\sigma} < 1$) as well as with the empirical regularity of finding substitution elasticities within the unit interval. The interpretation of the global mean value reveals that a 1% increase in imports implies a 0.6% increase in exports, so that we cannot corroborate that the good performance of PTAI companies is attributed to business models oriented to exports. Instead, the inelastic nature suggests that the good performance of PTAI

companies is predominantly caused by the reformulation of their cost structure, mainly in the wholesale market, which is currently more flexible than in any other historical period. Nevertheless, pronounced differences are found in the variation and magnitude of the elasticity of substitution between imports and exports across PTAI companies: approximately 55% exhibit a rise in s , while near 48% define a modest increase (i.e., $s < 1$). The complementary fraction suggests that fewer firms are characterised by a decline in the elasticity of substitution of imports by exports, with only 8% of the sample corresponding to a strong drop. The analysis of the magnitude of effects indicates that, on average, declines were smaller than increments, which is consistent with the effort to promote a substitutability.

Table 4. Estimated scale and substitution elasticities of imports by exports in the PTAI.

Scale Elasticity	2010		2012		2014		2016		2010–2017	
	SR	LR	SR	LR	SR	LR	SR	LR	SR	LR
$\overline{SE}_i = \sum_{i=1}^n SE_i/n$	0.032	0.039	0.032	0.038	0.033	0.039	0.032	0.039	0.032	0.039
σ_{SE_i}	0.018	0.021	0.018	0.022	0.019	0.022	0.019	0.022	0.018	0.022
Max SE_i	0.079	0.095	0.081	0.097	0.082	0.098	0.081	0.097	0.082	0.099
Min SE_i	−0.010	−0.012	−0.015	−0.014	−0.015	−0.018	−0.015	−0.018	−0.015	−0.018
Kurtosis	−0.500	−0.500	−0.470	−0.482	−0.364	−0.374	−0.426	−0.437	−0.429	−0.437
Elasticity of Substitution of Imports by Exports	2010	2011	2012	2013	2014	2015	2016	2017	2010–2017	
$\bar{s}_i = \sum_{i=1}^n S_i/n$	0.596	0.662	0.646	0.661	0.608	0.496	0.562	0.614	0.605	
σ_{s_i}	2.739	1.962	1.981	1.938	2.682	3.675	3.160	2.581	2.668	
Max s_i	8.821	8.821	8.821	8.821	8.821	8.821	8.821	8.821	8.821	
Min s_i	−61.598	−61.598	−61.598	−61.598	−61.598	−61.598	−61.598	−61.598	−61.598	
Kurtosis	494.002	920.263	908.600	929.933	507.532	274.018	374.759	560.404	515.062	

Notes: The elasticity of substitution of imports by exports is unchanged with respect to the time horizon, while similar is not applied to the scale elasticity. SR (LR) stands for short- (long)-run in the case of scale elasticities, respectively.

Table 4 also shows that the annual mean value of the elasticity of substitution between imports and exports follows a non-monotone configuration since it increased between 2010 and 2014, decreased from 2014 to 2015, but increased again from 2015 to 2017. The positive trend reflects the reduction in external dependence and enhancement of the external penetration, which suggests that PTAI companies are moving to a business logic characterised by increasing exports. As such, empirical results demonstrate that H1 is rejected in the PTAI's context: the elasticity of substitution of imports by exports has a negative effect on employment.

In what follows, four robustness checks are applied to model (A). We disregard the interaction term between exports and imports since this refinement is only mandatory to find evidence about H1. Moreover, the qualitative nature of results remains unchanged regardless of whether the covariate XM is included or not.

4.1.3. Geographical Restrictions on International Trade

At first glance, it may seem paradoxical to analyse this particularity in the context of a globalised world. However, recent experiences have demonstrated that geographical restrictions on international trade can be imposed due to some exogenous shock (e.g., COVID-19, Brexit, Russia–Ukraine conflict). Two cases are covered by this refinement:

1. The circumstance where the Portuguese international trade is restricted to regions belonging to the European territory (i.e., the analogous situation to that observed under the COVID-19 pandemic).

2. The circumstance where the Portuguese international trade is restricted to regions outside the European territory (i.e., the analogous situation to that observed under the Brexit).

Estimated coefficients are presented in Table 5. Model (A) covers the first case, while model (B) covers the second case. Results in model (A) indicate that all explanatory variables are statistically significant. Moreover, all covariates remain with the same sign, relative to the benchmark analysis, thereby reflecting that the EU territory is the main destination market of PTAI companies. If the Portuguese international trade is restricted to regions inside the EU territory, then a negative impact on employment is expected to persist. Differently, results in model (B) indicate that all explanatory variables are statistically significant with the exception of exports to countries outside the EU. Although the positive sign of the estimate suggests that it is not necessarily true that the domestic employment is reduced, the absence of significance on the dependent variable undermines its statistical validity. The lack of significance suggests that additional efforts are needed to increase the reputation of PTAI companies in destination markets outside the EU.

Table 5. Impact of international trade's geographical restrictions on PTAI's employment.

	(A)		(B)	
	Short-Run	Long-Run	Short-Run	Long-Run
L_{t-1}	0.317 *** (0.029)		0.363 *** (0.042)	
W	−0.065 *** (0.012)	−0.095 *** (0.017)	−0.075 *** (0.021)	−0.118 *** (0.032)
X	−0.014 ** (0.007)	−0.021 ** (0.010)	0.001 (0.009)	0.001 (0.014)
M	−0.025 *** (0.006)	−0.036 *** (0.009)	−0.019 ** (0.008)	−0.030 ** (0.012)
Q	0.664 *** (0.031)	0.971 *** (0.021)	0.624 *** (0.052)	0.981 *** (0.037)
Independent term	−1.192 *** (0.084)	−1.743 *** (0.090)	−1.206 *** (0.154)	−1.894 *** (0.192)

Notes: Robust standard errors in parentheses. Symbols (**) [***] represent (0.05) [0.01] level of significance, respectively. In model (A), convergence was achieved in the fifth iteration with $f(p) = -2814.883$, $n = 5045$ observations, and 856 groups. In model (B), convergence was achieved in the fifth iteration with $f(p) = -959.101$, $n = 1783$ observations, and 322 groups. All the covariates are in logarithmic form.

The validation of H2 requires to restrict the attention to model (A) and compare the estimated coefficients of X and M with those obtained in the benchmark analysis. If both coefficients have a stronger magnitude under this extension, then H2 is not rejected. However, results indicate failure to provide evidence in favour of a stronger negative impact of exports and imports on employment when the international trade is restricted to regions inside the EU territory. The estimated short-run coefficient of exports (−0.024, p -value < 0.01), the estimated long-run coefficient of exports (−0.035, p -value < 0.01), the estimated short-run coefficient of imports (−0.030, p -value < 0.01), and the estimated long-run coefficient of imports (−0.043, p -value < 0.01) under the benchmark analysis are all higher than the respective value obtained under this extension.

From an economic point of view, the rejection of H2 is justified by the diversification of supply sources and new destination markets of PTAI companies, which reduces their dependence on the EU market, particularly with respect to exports. As such, the effort of PTAI companies to conquer new destination markets implicitly has a detrimental impact on domestic employment.

4.1.4. Alternative Dependent Variable Measured in Relative Terms

Table 6 provides outcomes considering the employment growth rate (i.e., Lgrowth) as the dependent variable. Results show that covariates have a qualitatively similar influence on employment growth and employment level.

Table 6. Robustness check: changing the type of dependent variable to a relative measure.

	Short-Run	Long-Run
Lgrowth _{t-1}	−0.110 * (0.066)	
W	−0.763 (0.608)	−0.687 (0.544)
X	−1.312 *** (0.304)	−1.182 *** (0.270)
M	−1.147 *** (0.313)	−1.033 *** (0.282)
Q	6.311 *** (0.616)	−5.686 *** (0.517)
Independent term	−18.863 *** (3.284)	−16.993 *** (2.989)

Notes: Robust standard errors in parentheses. Symbols * [***] represent 0.1 [0.01] level of significance, respectively. Convergence was achieved in the fifth iteration with $f(p) = -22,831.949$, $n = 4814$ observations, and 943 groups. All the covariates are in logarithmic form.

The main difference is that wage is no longer statistically significant and, thus, one cannot corroborate that wages and employment growth have a negative relation. Moreover, the magnitude of effects is unambiguously stronger when employment growth is the dependent variable since this is elastic to changes in exports, imports, and GVA. Finally, there is evidence of convergence in employment growth since the lagged dependent variable presents a negative and significant coefficient, whose magnitude is below the unit value.

4.1.5. Firm-Specific Control Variable: Own-Capital Realisation

While past contributions normally include age and size as firm-specific characteristics, our database allows for considering two original features: magnitude and source of own-capital realisation.

In model (A), we consider a dummy variable ‘JF’ that takes the value 1 if a *Sociedade Anónima* is established, which is a type of firm with limited responsibility that requires a minimum amount of €50,000 for constitution. Otherwise, the dummy variable takes value 0, which captures cases where either *Sociedade por Quotas* or *Sociedade Unipessoal por Quotas* is established.

In turn, model (B) follows [Hodges and Link \(2017\)](#) by considering a dummy variable ‘Fam’ that takes the value 1 if 100% of the own capital comes from family funds, while taking the value 0 otherwise.

Results in Table 7 confirm that the magnitude and source of own-capital realisation do not significantly affect the dependent variable, which suggests that employment fluctuations can occur regardless of the type of juridical form and funding source of PTAI companies. Thereafter, the database is segmented by the criterion used to define the dummy variable JF. This allows for isolating the effect of covariates strictly representative of *Sociedades Anónimas* on the dependent variable to confirm the validity of H3. Results in column C correspond to the case where only the covariates representing *Sociedades Anónimas* affect the dependent variable, while estimated coefficients of the alternative possibility (i.e., *Sociedades por Quotas* and *Sociedades Unipessoais por Quotas*) are presented in column D. The comparison between estimated coefficients of covariates X and M reveals that exports and imports of *Sociedades Anónimas* have the strongest impact on employment both in the short- and long-run horizon, which implies that H3 cannot be rejected. Another

interesting finding is that wages only have a negative and significant effect on employment in the set of *Sociedades por Quotas* and *Sociedades Unipessoais por Quotas*. We also conclude that the positive impact of GVA on employment is stronger for *Sociedades Anónimas*, thereby meaning that these exhibit a higher propensity to hire.

Table 7. Impact of the magnitude and source of own capital realisation on PTAI's employment.

	(A)		(B)		(C)		(D)	
	Short-Run	Long-Run	Short-Run	Long-Run	Short-Run	Long-Run	Short-Run	Long-Run
L_{t-1}	0.307 *** (0.025)		0.307 *** (0.025)		0.309 *** (0.049)		0.285 *** (0.027)	
W	−0.041 *** (0.011)	−0.059 *** (0.016)	−0.042 *** (0.010)	−0.061 *** (0.015)	0.001 (0.038)	0.001 (0.054)	−0.049 *** (0.011)	−0.068 *** (0.015)
X	−0.024 *** (0.006)	−0.035 *** (0.010)	−0.024 *** (0.006)	−0.035 *** (0.008)	−0.036 ** (0.016)	−0.053 ** (0.023)	−0.020 *** (0.006)	−0.027 *** (0.009)
M	−0.030 *** (0.006)	−0.043 *** (0.008)	−0.030 *** (0.006)	−0.043 *** (0.008)	−0.044 ** (0.018)	−0.064 ** (0.027)	−0.026 *** (0.006)	−0.037 *** (0.027)
Q	0.661 *** (0.028)	0.954 *** (0.019)	0.661 *** (0.027)	0.954 *** (0.019)	0.690 *** (0.062)	0.998 *** (0.055)	0.671 *** (0.029)	0.939 *** (0.204)
JF	−0.012 (0.032)	−0.017 (0.046)						
Fam			−0.010 (0.025)	−0.015 (0.036)				
Independent term	−1.158 *** (0.079)	−1.672 *** (0.092)	−1.144 *** (0.073)	−1.652 *** (0.084)	−1.497 *** (0.292)	−2.165 *** (0.383)	−1.146 *** (0.086)	−1.601 *** (0.097)

Notes: Robust standard errors in parentheses. Symbols (**) [***] represent (0.05) [0.01] significance level, respectively. In model (A), convergence was achieved in the fifth iteration with $f(p) = -2793.328$, $n = 5125$ observations, and 940 groups. In model (B), convergence was achieved in the fifth iteration with $f(p) = -2794.246$, $n = 5125$ observations, and 940 groups. In model (C), convergence was achieved in the sixth iteration with $f(p) = -710.351$, $n = 1179$ observations, and 188 groups. In model (D), convergence was achieved in fifth iteration with $f(p) = -2072.119$, $n = 3862$ observations, and 754 groups. All the covariates are in logarithmic form.

4.1.6. Geographical Control Variable: Location of PTAI Companies

Data reveal that the majority of PTAI companies is located in the north of Portugal. This is not surprising since two important clusters are located in this region, which has a strong tradition of developing textiles and apparel (ATP 2018). Bearing in mind the objective of validating H4, we construct a dummy variable 'Cluster' that takes value 1 if the firm is located in the north of Portugal, while taking value 0 otherwise. The empirical strategy consists of understanding whether the additive effect has a significant impact on employment and analyse whether the effect of covariates X and M on employment is stronger for the cluster of firms from the north of Portugal compared to clusters from other parts of the country.

Results in column A of Table 8 confirm that the physical location of PTAI companies does not have a significant effect on the dependent variable, which means that employment is transversely affected by international trade activities, wages, and GVA. Column B shows outcomes related to PTAI companies located in the north of Portugal, while estimated coefficients of the alternative case are presented in column C. The comparison between estimated coefficients of covariates X and M reveals that that exports and imports of PTAI companies located in the north of Portugal have the strongest impact on employment both in the short- and long-run horizon, thereby meaning that H4 cannot be rejected. Indeed, exports of firms from other parts of the country lack statistical significance on employment, and imports of firms are merely weakly significant.

We finalise this subsection by emphasising that the significant and negative sign of X and M estimated coefficients is resilient to the inclusion of several control variables. This suggests that the participation of PTAI companies in international markets has reduced employment opportunities defined in a broad sense. Given the strategic relevance of the Euro-Mediterranean region as the main wholesale supplier of the EU, these results reflect that the persistence of onshoring practices in Europe will be a challenging task in the future. Considering that these ensure positive returns to EU Member States, a

transnational coordination seems mandatory to ensure the sustainability of TAI jobs in Europe (Clarke-Sather and Cobb 2019).

Table 8. Impact of the location of firms on PTAI's employment.

	(A)		(B)		(C)	
	Short-Run	Long-Run	Short-Run	Long-Run	Short-Run	Long-Run
L_{t-1}	0.307 *** (0.025)		0.306 *** (0.026)		0.315 *** (0.069)	
W	−0.042 *** (0.010)	−0.060 *** (0.015)	−0.042 *** (0.011)	−0.060 *** (0.016)	−0.034 (0.029)	−0.049 (0.039)
X	−0.024 *** (0.006)	−0.035 *** (0.008)	−0.027 *** (0.006)	−0.039 *** (0.009)	0.008 (0.017)	0.011 (0.025)
M	−0.030 *** (0.006)	−0.043 *** (0.008)	−0.029 *** (0.006)	−0.041 *** (0.009)	−0.035 * (0.020)	−0.051 * (0.027)
Q	0.661 *** (0.027)	0.954 *** (0.019)	0.663 *** (0.029)	0.955 *** (0.019)	0.643 *** (0.103)	0.939 *** (0.080)
Cluster	−0.037 (0.033)	−0.053 (0.048)				
Constant	−1.118 *** (0.076)	−1.614 *** (0.090)	−1.146 *** (0.074)	−1.651 *** (0.082)	−1.261 *** (0.260)	−1.840 *** (0.293)

Notes: Robust standard errors in parentheses. Symbols * [***] represent 0.1 [0.01] significance level, respectively. In model (A), convergence was achieved in the fifth iteration with $f(p) = -2792.889$, $n = 5125$ observations, and 940 groups. In model (B), convergence was achieved in the fifth iteration with $f(p) = -2638.140$, $n = 4367$ observations, and 870 groups. In model (C), convergence was achieved in the fifth iteration with $f(p) = -141.834$, $n = 362$ observations, and 70 groups. All the covariates are in logarithmic form.

4.2. Extension: Analysing the Penetration of Green Employment in the PTAI

4.2.1. First Stage of the Ensemble Approach: Determination of Green Capital and Green Jobs

Following Bai and Ng (2003), we start by identifying relevant dimensions of the PTAI through a PCA. Because of using this unsupervised machine-learning method, covariates no longer have to take a logarithmic form. In addition to L , W , X , M , and Q , and knowing that the available data to perform this kind of analysis are scarce and limited, this extension considers the following:

- Labor factor lagged in time up to 5 periods (L_{t-1} , L_{t-2} , L_{t-3} , L_{t-4} , L_{t-5}).
- Maturity of firms (AGE).
- GVA of high and medium-high technologies (HMH).

This means that a total number of 12 input variables is used to assess the optimal number of principal components, latent variables, or dimensions representative of the PTAI. We consider the Kaiser's rule to identify the optimal number of principal components, which states that the last integer whose eigenvalue is above one corresponds to the optimal number of dimensions to explain the target. Figure 4 allows for concluding that two dimensions define the characterising elements of this industry. While the first dimension is influenced by the labour factor, the second dimension is influenced by the remaining input variables with the exception of firms' age. After providing an economic interpretation to each principal component—principal component 1 was labelled as green labour, while principal component 2 was labelled as green capital—validation results are clarified in Table 9. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy is above 0.70, thereby legitimising the approach taken in this extension. Afterwards, we moved to the second stage of the ensemble approach, which consists of a two-step procedure.

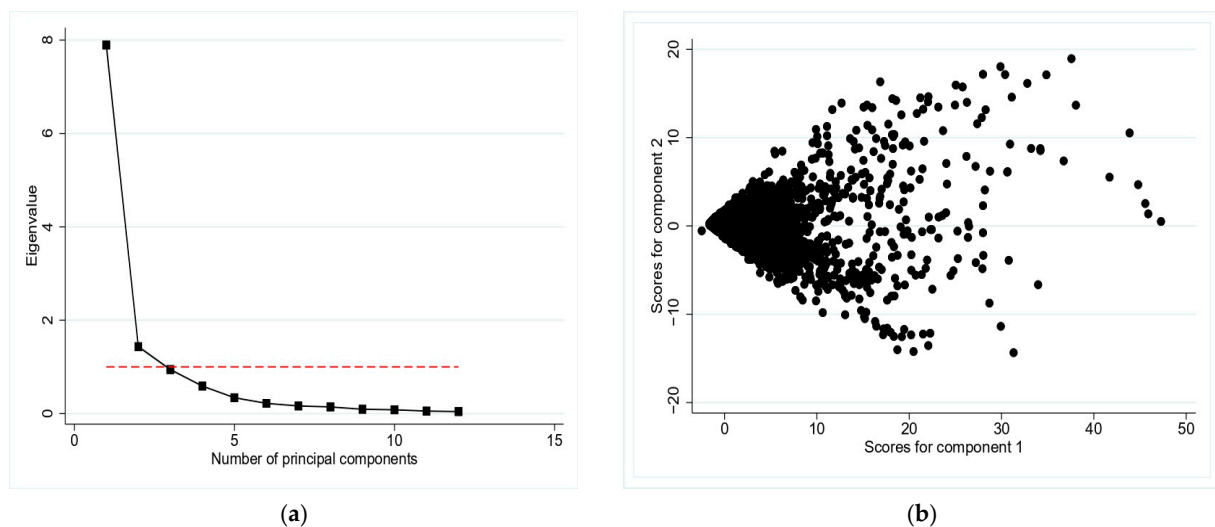


Figure 4. PCA outcomes: (a) optimal number of components; (b) scatterplot of final scores.

Table 9. Dimensionality reduction with PCA: component matrix results with rotation and sampling adequacy.

Principal Component	Variance	Difference	Fraction of Variance Explained		Cumulative
PC1—Green labour	5.208	1.089	0.434		0.434
PC2—Green capital	4.119		0.343		0.777
Input variable	PC1	PC2	Median test	UV (%)	KMO
L_t	0.327			0.225	0.904
L_{t-1}	0.384			0.146	0.893
L_{t-2}	0.424			0.089	0.913
L_{t-3}	0.443			0.081	0.909
L_{t-4}	0.435			0.127	0.874
L_{t-5}	0.400			0.225	0.905
W		0.414		0.259	0.918
X		0.477	$\chi^2(1) = 1.1 \times 10^3$ *** $\chi^2(1) = 1.3 \times 10^3$ ***	0.147	0.913
M		0.494		0.193	0.936
Q		0.335		0.210	0.957
AGE				0.873	0.904
HMH		0.445		0.099	0.903
Validation metrics					
Overall KMO measure of sampling adequacy					0.910
Average interitem covariance					792,557.900
Number of items in the scale					12
Scale reliability coefficient (Cronbach's α)					0.770

Notes: symbols *** represent 0.01 significance level, respectively. Method of extraction is PCA. Method of rotation is orthogonal varimax (Kaiser's option off). Rotation has converged with $n = 22,062$, trace = 12, and $\rho \approx 0.777$ with 2 components being the optimal outcome. Blank spaces correspond to the absolute value of loadings below 0.3. Given the definition of the first stage's target green capital expressed in Equation (4), median tests applied to the set of explanatory variables considered in the first stage to explain the target (i.e., X and M) allow to identify the presence or not of equal medians between both categories under $H_0: X_{|Green\ Capital = 0} = X_{|Green\ Capital = 1}$ and $H_0: M_{|Green\ Capital = 0} = M_{|Green\ Capital = 1}$.

4.2.2. First Step of the Second Stage of the Ensemble Approach: Role of International Trade on the Creation of Green Capital

In the first step of the second stage of the ensemble approach, the maximum likelihood estimation method is applied to explain determinants of green capital in the PTAI. Before detailing the results, it is important to briefly summarize the ongoing structural change that is affecting this productive factor in recent years. On 2 December 2015, the EC adopted the legislative package for the transition to a circular economy in the EU. In addition to the legislative proposals on waste and targets aimed at encouraging the diversion of disposal

options and reinforcing reuse and recycling, an Action Plan for the Circular Economy (APCE) was established, which supports this approach throughout the value chain—from production to consumption, repair, manufacturing, waste management, and secondary raw materials. The ambition of APCE has a pragmatic basis: Today, we consume around 62 billion tons of resources per year, of which we only recycle 7%. In 2050, we will consume between 85 and 186 billion tons to feed a global economy of 9 billion people, but the EU is only able to supply 9% of the 54 critical raw materials for its domestic economy (EC 2022). Additionally, more than half of greenhouse gas emissions globally are related to the management of materials and resources. Therefore, guaranteeing the objectives of the Paris Agreement is inseparable from a substantial improvement in the efficiency and productivity associated with the transformation process of raw materials that we have available today in the economy and, specially, in European TAIs. On a planet with finite resources and environmental services at the limit of their capacity (e.g., sand for construction, arable soil, CO₂ concentration in the atmosphere, high concentration of NO₂, and PM_x in cities), persisting with a linear economic model of *take–consume–dispose* will not be viable, so that it is necessary to change the strategic approach. The circular economy is a model that meets human needs and fairly distributes mobilised resources without harming the functioning of the biosphere or crossing any physical boundaries of the planet. This model depends on the development of strategies—technological, product, service, use or consumption—that induce the continuous reuse of materials and resources at their maximum productive potential (i.e., maximum financial value and utility, for as long as possible), in cycles properly energised by renewable sources. Not only are resources preserved, but it is possible to regenerate natural capital extracted from the biosphere, such as water and nutrients. As a result, the so-called *new avenue of green capital* is expected to allow for a reduction in the dependence on the extraction and/or import of raw materials and minimize emissions and waste in industries such as the PTAI.

Results of probit and logit models are both presented in Table 10, but, for the purpose of interpreting coefficients and average marginal effects, we only focus on the binary discrete choice model that has the lowest information criteria (e.g., AIC, BIC) and the highest log pseudolikelihood value, which is the one whose disturbance terms are represented by a reduced standard normal distribution. To execute the first step properly, we take advantage from PC2 previously computed, which acts as a latent variable to define the following dichotomous target

$$\text{Green Capital}_i = \begin{cases} 1, & \text{PC2}_i^* > 0 \\ 0, & \text{PC2}_i^* \leq 0 \end{cases} \quad (4)$$

Essentially, we take as a given that positive (negative) scores of the second principal component reflect the existence (inexistence) of green technology at the firm level, respectively. Several nonparametric tests justify the choice of the cut-off point set at zero. For the sake of brevity, we only present the median test in Table 9, whose results support the rejection of the null hypothesis of equal medians between the two categories formed in the set of explanatory variables that materialise international trade activities (i.e., X and M) due to the dichotomous formulation of green capital expressed in Equation (4). In terms of interpretation of the estimated coefficients, results in Table 10 indicate that:

- One unit increase in exports decreases the probability of owing green capital, *ceteris paribus*; and
- One unit increase in imports increases the probability of owing green capital, *ceteris paribus*.

In turn, average marginal effects reveal that:

- It is estimated that, for an additional €1,000,000 in exports, the probability of PTAI companies adopting green technology decreases, on average, 0.859 p.p., *ceteris paribus*; and
- It is estimated that, for an additional €1,000,000 in imports, the probability of PTAI companies adopting green technology increases, on average, 1.300 p.p., *ceteris paribus*.

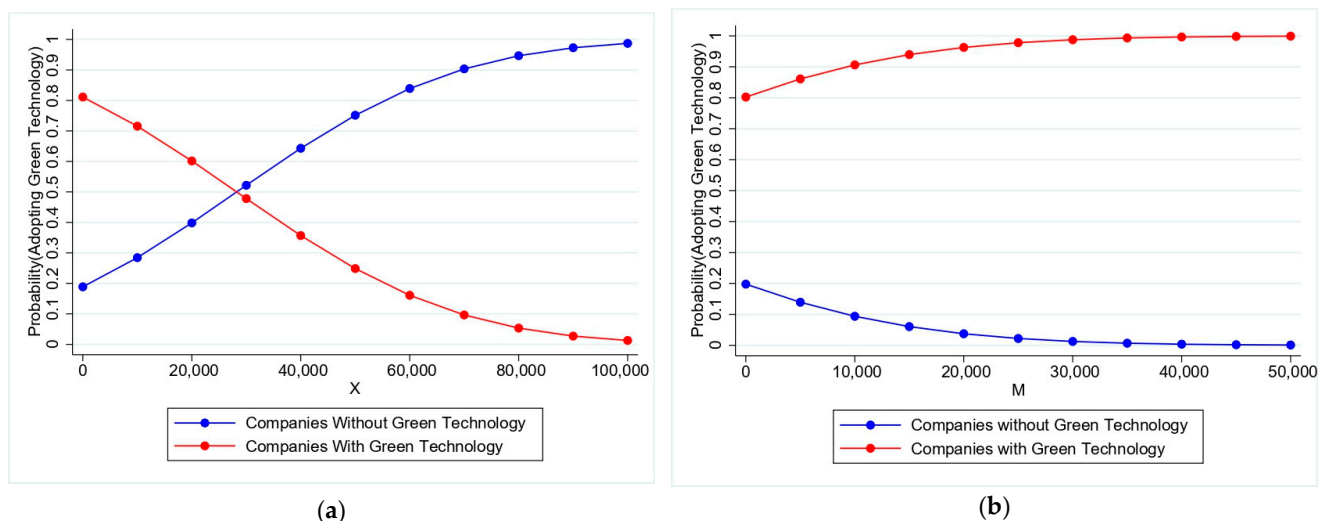
Table 10. First-step results of the second stage of the ensemble approach: propensity to adopt green capital in PTAI (2010–2017).

	Coefficient		Average Marginal Effects	
	Logit	Probit	Logit	Probit
X	$-5.44 \times 10^{-5} ***$ (0.000)	$-3.13 \times 10^{-5} ***$ (0.000)	$-8.50 \times 10^{-6} ***$ (0.000)	$-8.59 \times 10^{-6} ***$ (0.000)
M	$8.82 \times 10^{-5} ***$ (0.000)	$4.72 \times 10^{-5} ***$ (0.000)	$1.38 \times 10^{-5} ***$ (0.000)	$1.30 \times 10^{-5} ***$ (0.000)
Independent term	1.442 *** (0.012)	0.874 *** (0.007)		
Log pseudolikelihood	−21,826.305	−21,824.169		
AIC	43,658.610	43,654.340		
BIC	43,684.710	43,680.440		
Observations	44,421	44,421		

Notes: the dependent variable is *green capital* defined in Equation (4). Symbols *** represent 0.01 significance level, respectively. Huber–White robust standard errors were considered based on the Breusch–Pagan test's result $\chi^2(1) = 54,149.640$, p -value = 0.000, which indicates the presence of heteroscedasticity in the within-variation component of the panel.

Intuitively, these results suggest that PTAI companies have a strong incentive to adopt green technologies when they are excessively dependent on external markets. Differently, PTAI companies have a redundant incentive to adopt green technologies when the national economy is predominantly an exporter of goods and services. To fully clarify this conclusion, which may be interpreted as a *green international trade paradox*,⁵ we provide a graphical representation of the average marginal effect of adopting green technologies as a function of the range of values taken by exports and imports for the segmentation imposed by Equation (4). Figure 5 allows for the conclusion that:

- As the volume of exports increases, the probability of adopting green technologies decreases (increases) for companies equipped with (without any kind of) green technologies, respectively.
- As the volume of imports increases, the probability of adopting green technologies decreases (increases) for companies without any kind of (endowed with) green technologies, respectively.

**Figure 5.** Evolution of predicted probabilities of being endowed with green capital $Pr(\text{Green Capital} = 1)$ for holders and non-holders of green capital as a function of international trade activities: (a) exports; (b) imports.

4.2.3. Second Step of the Second Stage of the Ensemble Approach: Role of International Trade on the Proliferation of Green Jobs

In turn, the second step of the second stage of the ensemble approach consists of estimating the effect of international trade activities on the creation of green jobs conditional on the presence of green capital in PTAI companies through the application of four estimation methods:

- OLS regression model with and without additive and multiplicative effects.
- Type I Tobit model (also known as. standard censored regression model) with and without additive and multiplicative effects due to [Tobin \(1958\)](#).
- The truncated regression which, once combined with the first step of the second stage of the ensemble approach, materialises the Hurdle model seminally developed in [Cragg \(1971\)](#).
- Heckman's selection procedure based on the economic rationale that incidental truncation in the sense of [Heckman \(1979\)](#) may be observed in this case study.

In a nutshell, main conceptual differences between these four estimation methods are summarised as follows: OLS results related to the second step of the second stage of the ensemble approach presented in Table 11 do not allow for distinguishing between providers and non-providers of green employment. Estimated coefficients of the Tobit model allow for capturing the effects on green employment by considering only PTAI firms that provide a positive number of green jobs. Estimated coefficients of Cragg's model show the effects on green employment considering only PTAI companies that are endowed with green capital (i.e., holders of a positive latent variable), and Heckman's selection model assumes the presence of incidental truncation due to the fact that it may not be possible to extract with precise the subsample of PTAI firms that have green capital, which requires to introduce a selection equation. Knowing that PC1 is a proxy for green employment at the firm level in the PTAI, the OLS results reflect determinants of green employment regardless of whether PTAI companies offer green jobs or not. Formally, these emerge from the following regression model

$$\text{Green Employment}_i = \begin{cases} \beta_1 + \beta_2 X_i + \beta_3 M_i + u_i, & \text{without additive and multiplicative effects;} \\ \beta_1 + \beta_2 X_i + \beta_3 M_i + \beta_4 \text{Green Capital}_i + u_i, & \text{with an additive effect on the ex-ante endowment of green capital;} \\ \beta_1 + \beta_2 X_i + \beta_3 M_i + \beta_4 \text{Green Capital}_i + \beta_5 \text{Green Capital}_i X_i + \beta_6 \text{Green Capital}_i M_i + u_i, & \text{with additive and multiplicative effects,} \end{cases} \quad (5)$$

and can be summarised as follows: When considering the universe of PTAI firms indistinctively, as recognised in Equation (5), it is estimated that:

- A €10,000,000 increase in exports leads to the creation, on average, of 3.34 additional green jobs, *ceteris paribus*; and
- A €10,000,000 increase in imports leads to the creation, on average, of 2.96 additional green jobs, *ceteris paribus*.

In turn, the additive effect introduced in model (2) confirms that, on average, PTAI companies with green technologies provide 1.335 less green jobs compared to PTAI companies without green technologies, *ceteris paribus*. Furthermore, when differentiating between holders and non-holders of green technology by introducing both additive and multiplicative effects, it is estimated that:

- A €10,000,000 increase in exports leads to the creation, on average, of 3.76 additional green jobs in PTAI companies without green technologies, *ceteris paribus*.
- A €10,000,000 increase in imports leads to the creation, on average, of 9.49 additional green jobs in PTAI companies without green technologies, *ceteris paribus*.
- On average, PTAI companies with green technologies have 1.097 less green jobs compared to PTAI companies without green technologies, *ceteris paribus*.
- A €10,000,000 increase in exports leads to the destruction, on average, of 0.14 green jobs in PTAI companies with green technologies, *ceteris paribus*.
- A €10,000,000 increase in imports leads to the destruction, on average, of 5.56 green jobs in PTAI companies with green technologies, *ceteris paribus*.

Table 11. Second-step results of the second stage of the ensemble approach with the OLS regression and Tobit model: role of international trade activities on green job creation in the PTAI (2010–2017).

	OLS			Tobit—Truncated Sample (Average Marginal Effects)		
	(1)	(2)	(3)	(4)	(5)	(6)
X	$3.34 \times 10^{-4} ***$ (0.000)	$3.34 \times 10^{-4} ***$ (0.000)	$3.76 \times 10^{-4} ***$ (0.000)	$1.07 \times 10^{-4} ***$ (0.000)	$1.07 \times 10^{-4} ***$ (0.000)	$1.20 \times 10^{-4} ***$ (0.000)
M	$2.96 \times 10^{-4} ***$ (0.000)	$3.11 \times 10^{-4} ***$ (0.000)	$9.49 \times 10^{-4} ***$ (0.000)	$6.47 \times 10^{-5} ***$ (0.000)	$7.27 \times 10^{-5} ***$ (0.000)	$2.13 \times 10^{-4} ***$ (0.000)
Green capital dummy		−1.335 *** (0.024)	−1.097 *** (0.021)		−0.847 *** (0.021)	−0.714 *** (0.017)
X × Green capital dummy			−1.43 × 10 ^{−5} *** (0.000)			−5.58 × 10 ^{−6} *** (0.000)
M × Green capital dummy			−5.56 × 10 ^{−4} *** (0.000)			−9.53 × 10 ^{−5} *** (0.000)
Constant	−0.539 *** (0.011)	0.267 *** (0.022)	0.018 (0.018)			
Log pseudolikelihood				−20,623.549	−18,818.992	−17,749.702
Total observations	22,062	22,062	22,062	22,062	22,062	22,062
Uncensored				5502	5502	5502
Left-censored				16,560	16,560	16,560
R ² [Pseudo R ²]	0.659	0.713	0.779	[0.169]	[0.242]	[0.285]

Notes: dependent variable is green employment measured by PC1. *** $p < 0.01$. Robust standard errors in parentheses. Reported log pseudolikelihood and pseudo-R² values are associated with the latent variable model, from which one can obtain marginal effects associated with the latent variable, the censored sample, and the truncated sample. Models (1) and (4) are absent of additive and multiplicative effects, models (2) and (5) only include additive effects, and models (3) and (6) include both additive and multiplicative effects. Model (1)–(3) are estimated by OLS. The Tobit model is considered in (4)–(6).

These results are not paradoxical, as they materialise that the need for qualified labour with a specialisation in green activities is less necessary when the company is highly intensive in green capital. Hence, outcomes reflect efficiency gains (i.e., increasing marginal productivity or positive returns to scale) at the firm level as the ratio of green capital per worker increases. Thenceforth, we extend the initial assessment to analyse three different estimation methods: Tobit, Hurdle, and Heckman. This is because, as proven in McDonald and Moffitt (1980), applying OLS to a corner solution model—either to the entire sample or to a subsample with strictly positive values taken by the dependent variable—implies generally inconsistent estimators of parameters. A flexible alternative is the Tobit regression model, where, under the typical maximum likelihood assumptions, the maximum likelihood estimator is consistent and asymptotically normally distributed. Conceptually, knowing that

$$y = \max(0, \mathbf{x}\beta + u) \quad (6)$$

where u is unobservable, the Tobit regression model assumes $u|\mathbf{x} \sim N(0, \sigma^2)$, meaning that the disturbance term is independent from the set of regressors. Equation (6) has the benefit of directly relating the variable of interest, y , to the observed explanatory variables and disturbance terms. Nevertheless, it may be useful to write Equation (6) as a latent variable model, such that

$$y^* = \mathbf{x}\beta + u, \quad u|\mathbf{x} \sim N(0, \sigma^2)$$

and

$$y = \max(0, y^*)$$

define the type I Tobit model (Tobin 1958). In corner solution models, the interest relies on probabilities or expectations involving the dependent variable. Frequently, the focus relies on expected values $E(y|\mathbf{x}, y > 0)$ and $E(y|\mathbf{x})$. If u is independent of \mathbf{x} and follows a normal distribution, then an explicit expression for $E(y|\mathbf{x})$ can be found. First, we derive $Pr(y > 0|\mathbf{x})$ and $E(y|\mathbf{x}, y > 0)$. Thereafter, the law of iterated expectations can be used to obtain $E(y|\mathbf{x})$. Knowing that

$$E(y|\mathbf{x}) = Pr(y = 0|\mathbf{x})0 + Pr(y > 0|\mathbf{x})E(y|\mathbf{x}, y > 0) = Pr(y > 0|\mathbf{x})E(y|\mathbf{x}, y > 0)$$

we can derive $Pr(y > 0|\mathbf{x})$, on the one hand, by defining $w = 1$ if $y > 0$ and $w = 0$ if $y = 0$ and, on the other hand, considering that w follows a probit model, which implies

$$Pr(w = 1|\mathbf{x}) = Pr(y^* > 0|\mathbf{x}) = Pr(u > -\mathbf{x}\beta|\mathbf{x}) = Pr(u/\sigma > -\mathbf{x}\beta/\sigma|\mathbf{x}) = \Phi(\mathbf{x}\beta/\sigma) \quad (7)$$

The main implication of Equation (7) is that $\gamma \equiv \beta/\sigma$, rather than β and σ separately, can be consistently estimated from a probit model of w on \mathbf{x} . In turn, to derive $E(y|\mathbf{x}, y > 0)$, we need to internalise the following stylised fact about the normal distribution: if $z \sim N(0, 1)$, then for any constant c

$$E(z|z > c) = \frac{\phi(c)}{1 - \Phi(c)}$$

and

$$E(z|z < c) = -\frac{\phi(c)}{\Phi(c)}$$

where $\phi(\cdot)$ is the standard normal density function. Consequently, since $u|\mathbf{x} \sim N(0, \sigma^2)$, then it follows that

$$E(u|u > c) = \sigma E\left(\frac{u}{\sigma} \middle| \frac{u}{\sigma} > \frac{c}{\sigma}\right) = \sigma \left[\frac{\phi(c/\sigma)}{1 - \Phi(c/\sigma)} \right]$$

We can use this Equation to find $E(y|\mathbf{x}, y > 0)$ when y follows a Tobit model:

$$E(y|\mathbf{x}, y > 0) = \mathbf{x}\beta + E(u|u > -\mathbf{x}\beta) = \mathbf{x}\beta + \sigma \left[\frac{\phi(-\mathbf{x}\beta/\sigma)}{1 - \Phi(-\mathbf{x}\beta/\sigma)} \right] = \mathbf{x}\beta + \sigma \left[\frac{\phi\left(\frac{\mathbf{x}\beta}{\sigma}\right)}{\Phi\left(\frac{\mathbf{x}\beta}{\sigma}\right)} \right] \quad (8)$$

Although it may not be obvious at first glance, Equation (8) implies that the right-hand-side of this Equation is positive for any values of \mathbf{x} and β . Technically, for any generic value c , the quantity

$$\lambda(c) = \frac{\phi(c)}{\Phi(c)} \quad (9)$$

is the inverse Mills ratio. Mathematically, it corresponds to the ratio between the density function and the distribution function of the argument c . Economically, it reflects the propensity to move from being a corner solution from below (e.g., zero) to become a positive. Hence, in light of Equation (8), $E(y|\mathbf{x}, y > 0)$ is the sum of $\mathbf{x}\beta$ and σ times the inverse Mills ratio evaluated at $\mathbf{x}\beta/\sigma$.

In the context of this study, the Tobit regression model corresponds to the case where the dependent variable is censored from below as follows:

$$\text{Green Employment}_i = \begin{cases} \text{PC1}_i^* & \text{if } \text{PC1}_i^* > 0 \\ 0 & \text{if } \text{PC1}_i^* \leq 0 \end{cases} \iff \text{Green Employment}_i = \max(0, \text{PC1}_i^*) \quad (10)$$

The formalisation expressed in Equation (10) allows for restricting the focus on the effect of international trade activities on green employment by considering only the subsample of PTAI companies that provide a positive number of green jobs. If no observations are censored, then the Tobit model coincides with the OLS regression model. Formally, the Tobit regression model is a combination of two decisions:

1. In a first step, the probit model is used to estimate the discrete decision, that is, the likelihood of moving from the base category that represents the absence of green

employment to the alternative category that represents the presence of a positive amount of green employment (Y/N):

$$Pr(\text{Green Employment}_i > 0) = \begin{cases} \Phi(\beta_1 + \beta_2 X_i + \beta_3 M_i), & \text{without additive effects;} \\ \Phi(\beta_1 + \beta_2 X_i + \beta_3 M_i + \beta_4 \text{Green Capital}_i), & \text{with an additive effect on the ex-ante endowment of green capital.} \end{cases}$$

2. In a second step, considering only the universe of positives, a truncated-regression model is used to estimate the continuous decision (i.e., determinants of the amount of green employment created conditional on the presence of a positive number of green jobs):

$$E(\text{Green Employment}_i | \text{Green Employment}_i > 0) = \begin{cases} \beta_1 + \beta_2 X_i + \beta_3 M_i + \sigma \lambda \left(\frac{\beta_1 + \beta_2 X_i + \beta_3 M_i}{\sigma} \right) + u_i, & \text{without additive effects;} \\ \beta_1 + \beta_2 X_i + \beta_3 M_i + \beta_4 \text{Green Capital}_i + \sigma \lambda \left(\frac{\beta_1 + \beta_2 X_i + \beta_3 M_i + \beta_4 \text{Green Capital}_i}{\sigma} \right) + u_i, & \text{with additive effect on green capital.} \end{cases}$$

Such a consideration is of utmost importance in the context of this study due to the need to distinguish between censoring and truncation regarding the creation of green employment in PTAI companies. Since the goal of this research is to analyse determinants of green employment, we may have the incentive to restrict the analysis to the subsample of PTAI companies that have green vacancies and, thus, that necessarily provide a positive number of green jobs through the observation of outcomes from the second step of the Tobit regression model.⁶

A few remarks on the Tobit model regarding the computation of average marginal effects are mandatory. First, average marginal effects coincide with estimated coefficients for the latent variable $PC1_i^*$ and correspond to marginal effects on the desired number of green jobs created (e.g., $dE(PC1_i^*)/dX_i = n^{-1} \sum_{i=1}^n \beta_2$ for the case of exports and with n representing the number of observations of the sample) due to the satisfaction of some exogenous reason (e.g., firms are endowed with green capital; firms are committed to corporate social responsibility practices). Second, the Tobit model allows for obtaining average marginal effects for both the censored sample and the truncated sample. For the censored sample—which includes both zeros and positive amounts of green employment—average marginal effects are the coefficients multiplied by a positive scale factor (e.g., $dE(\text{Green Employment}_i)/dX_i = n^{-1} \sum_{i=1}^n \beta_2 \Phi(\beta_1 + \beta_2 X_i + \beta_3 M_i)$ for the case of exports without additive effects) and correspond to marginal effects on the actual number of green jobs created in the entire universe of PTAI companies (i.e., both those with and without provision of green jobs). Differently, average marginal effects of the truncated sample—which only includes positive amounts of green employment—are the main point of interest of this extension and correspond to marginal effects on the actual number of green jobs created by PTAI companies that effectively provide green employment, thus being the ones reported in Table 11. To formally understand how the computation of average marginal effects is performed in the truncated sample of the Type I Tobit model, we need to consider Equation (8) and the generalisation of Equation (9), such that, if x_j is a continuous explanatory variable, then

$$\frac{\partial(y|x, y > 0)}{\partial x_j} = \beta_j + \beta_j \left[\frac{d\lambda}{dc}(c) \right]$$

assuming that x_j is not functionally related to other regressors. By differentiating Equation (9), it can be shown that

$$\frac{d\lambda}{dc}(c) = -\lambda(c)[c + \lambda(c)]$$

thus yielding

$$\frac{\partial E(y|x, y > 0)}{\partial x_j} = \beta_j \left\{ 1 - \lambda \left(\frac{\mathbf{x}\beta}{\sigma} \right) \left[\frac{\mathbf{x}\beta}{\sigma} + \lambda \left(\frac{\mathbf{x}\beta}{\sigma} \right) \right] \right\}$$

Consequently, for the particular example of exports without additive effects in this case study, we obtain

$$\frac{\partial E(y|x, y > 0)}{\partial X_i} = \beta_2 \left\{ 1 - \lambda \left(\frac{\beta_1 + \beta_2 X_i + \beta_3 M_i}{\sigma} \right) \left[\frac{\beta_1 + \beta_2 X_i + \beta_3 M_i}{\sigma} + \lambda \left(\frac{x\beta_1 + \beta_2 X_i + \beta_3 M_i}{\sigma} \right) \right] \right\}$$

These equations confirm that the average partial effect of x_j on $E(y|x, y > 0)$ is not entirely determined by β_j . Indeed, there is an adjustment factor that stems from multiplying β_j by the term in $\{\cdot\}$, which depends on x through the point $x\beta/\sigma$. A simple arithmetic sum of individual marginal effects divided by the sample size allows for obtaining average marginal effects. Results of the estimated average marginal effects related to the truncated sample confirm that, for the universe of PTAI firms that create a positive number of green jobs, it is estimated that:

- A €10,000,000 increase in exports leads to the creation, on average, of 1.07 additional green jobs, *ceteris paribus*; and
- A €10,000,000 increase in imports leads to the creation, on average, of 0.65 additional green jobs, *ceteris paribus*.

In turn, the additive effect introduced in model (5) confirms that, on average, PTAI holders of green capital that provide green jobs create, on average, 0.847 fewer green jobs compared to PTAI companies that create a positive number of green jobs without holding green capital, *ceteris paribus*. When differentiating between holders and non-holders of green technologies by introducing both additive and multiplicative effects, it is estimated for the subsample of PTAI firms providing a positive number of green jobs that:

- A €10,000,000 increase in exports leads to the creation, on average, of 1.20 additional green jobs in PTAI companies without green technologies, *ceteris paribus*.
- A €10,000,000 increase in imports leads to the creation, on average, of 2.13 additional green jobs in PTAI companies without green technologies, *ceteris paribus*.
- On average, PTAI companies with green technologies have 0.714 fewer green jobs compared to PTAI companies without green technologies, *ceteris paribus*.
- A €10,000,000 increase in exports leads to the destruction, on average, of 0.06 green jobs in PTAI companies with green technologies, *ceteris paribus*.
- A €10,000,000 increase in imports leads to the destruction, on average, of 0.95 green jobs in PTAI companies with green technologies, *ceteris paribus*.

Once confronting OLS and Tobit results, it can be concluded that:

- Exports have a weaker magnitude of impact considering only the subsample of companies that provide a positive number of green jobs.
- Imports have a stronger magnitude of impact considering only the subsample of companies that provides a positive number of green jobs, except in the case of introducing additive and multiplicative effects, where it is shown that imports have a softer magnitude of effect both in the subsample of companies endowed with green capital as in the subsample of companies lacking green capital.
- Therefore, PTAI companies that provide a positive number of green jobs are more (less) strongly influenced by imports (exports) compared to the entire universe of PTAI companies, respectively.

Afterwards, we present results of the Cragg's model, which brings the advantage of relaxing the restrictive assumption of the Tobit regression model that discrete and continuous decisions are similar or, equivalently, that both decisions result from the same data generation process.⁷ Knowing that the determinant to be scrutinised is PTAI firms' international trade volume, this extension is justified by three reasons:

1. First, since firms' characteristics may differently affect:
 - The discrete decision to create or not green jobs (Y/N); and
 - The continuous decision of how many green jobs will be created.
2. Second, by a principle of rationality, it is plausible to bear the conviction that firms endowed with green capital can create green vacancies and search for workers with a specialisation in green jobs, while the opposite holds in firms lacking green capital,

which may imply different data generation processes between the discrete decision and the continuous decision on green employment.

3. Third, based on the argument that firms having businesses with foreign parties (considered purely domestic) are less (more) likely to be labour-intensive, thus claiming less (more) creation of green jobs, respectively. Given the conclusions resulting from the confrontation between the OLS and Tobit results, this would imply that purely domestic firms that provide a positive number of green jobs are subject to a weaker (stronger) influence by exports (imports) compared to the entire universe of PTAI companies (i.e., those that provide green jobs plus those that do not provide green jobs), respectively. However, in actual practice, green jobs created by purely domestic firms may be smaller than the ones theoretically predicted because these companies:⁸

- May be resilient to the incorporation of green technologies; and
- May exhibit some inertia on implementing environmentally friendly processes.

Generically, let s be a binary variable that determines whether y is zero or strictly positive and introduce a continuously distributed, nonnegative latent variable labelled as w^* . Then, we assume that y is generated as

$$y = s \cdot w^*$$

Other than s being binary and w^* being continuous, there is another important difference between both variables: we effectively observe s because it is observationally equivalent to the indicator $1[y > 0]$. However, w^* is only observed when $s = 1$, in which case $w^* = y$. To proceed in a parametric setting, we assume that s and w^* are specific functions of observable covariates and unobservable disturbance terms, and we will impose distributional assumptions to the unobservable disturbance terms. A useful assumption is that s and w^* are independent, conditional on the matrix of explanatory variables \mathbf{x} . When this assumption holds, the resulting model has typically been called a two-part model or hurdle model. The assumption is that conditional on a set of observed covariates \mathbf{x} , mechanisms determining s and w^* must be independent. Therefore,

$$E(y|\mathbf{x}, s) = sE(w^*|\mathbf{x}, s) = sE(w^*|\mathbf{x}) \quad (11)$$

When $s = 1$, Equation (11) becomes

$$E(y|\mathbf{x}, y > 0) = E(w^*|\mathbf{x})$$

such that the conditional expectation of y is simply the expected value of w^* conditional on \mathbf{x} . Furthermore, the unconditional expectation is

$$E(y|\mathbf{x}) = E(s|\mathbf{x})E(w^*|\mathbf{x}) = Pr(s = 1|\mathbf{x})E(w^*|\mathbf{x})$$

In general, a two-part model for a corner solution response is then given by

$$f(y|\mathbf{x}) = \begin{cases} Pr(s = 0|\mathbf{x}) & \text{if } y = 0 \\ Pr(s = 1|\mathbf{x})f(y|s = 1, \mathbf{x}) & \text{if } y > 0 \end{cases} \quad (12)$$

Although the same regressors often appear in both parts of the model, this can and should be relaxed if there are flagrant exclusion restrictions.⁹ In Cragg (1971), a natural two-part extension of the type I Tobit model is proposed. The conditional independence assumption exposed in Equation (11) is assumed to hold, and the binary variable s is assumed to follow a probit model, such that

$$P(s = 1|\mathbf{x}) = \Phi(\mathbf{x}\gamma) \quad (13)$$

The unique feature of Cragg's model is that the latent variable w^* is assumed to have a truncated normal distribution with parameters that can vary freely from those in Equation (13). Define

$$w^* = \mathbf{x}\beta + u$$

where u given \mathbf{x} has a truncated normal distribution with lower truncation point $-\mathbf{x}\beta$. Because $y = w^*$, when $y > 0$, we can write the truncated normal assumption in terms of the density of y given $y > 0$ and \mathbf{x} as follows:

$$f(y|\mathbf{x}, y > 0) = \left[\Phi\left(\frac{\mathbf{x}\beta}{\sigma}\right) \right]^{-1} \left\{ \phi\left[\frac{(y - \mathbf{x}\beta)/\sigma}{\sigma}\right] \right\}$$

The density of y given \mathbf{x} becomes

$$f(y|\mathbf{x}, \gamma) = 1[y = 0][1 - \Phi(\mathbf{x}\gamma)] + 1[y > 0] \left\{ \Phi(\mathbf{x}\gamma) \left[\Phi\left(\frac{\mathbf{x}\beta}{\sigma}\right) \right]^{-1} \left\{ \phi\left[\frac{(y - \mathbf{x}\beta)/\sigma}{\sigma}\right] \right\} \right\}$$

This equation yields the standard censored Tobit density when one observes $\gamma = \beta/\sigma$. A note of mention goes to the derivation of the Lagrange multiplier test of this restriction by [Schmidt and Lin \(1984\)](#), which allows the Tobit model to be tested against Cragg's model.

In the context of this study, let $w_i^* := \text{PC1}_i^*$ be a latent variable representing whether the desired number of green jobs provided by firm i has been achieved based on the satisfaction of exogenous reasons (e.g., own green capital, engagement in corporate social responsibility activities), let s_i be a binary variable revealing whether firm i creates green jobs or not, and consider that $y_i := \text{Green Employment}_i$ captures the positive number of green jobs effectively created by firm i . Knowing that this conceptualisation collapses with the formal definition of green employment presented in Equation (10), Cragg's model consists of a two-step estimation procedure where:

1. In the first step, the probit model is used to estimate the discrete decision, that is, the likelihood of moving from the base category characterised by the absence of green employment to the alternative category that captures the presence of a positive number of green jobs:

$$\begin{aligned} &Pr(\text{PC1}_i^* > 0) \\ &= \begin{cases} \Phi(\beta_1 + \beta_2 X_i + \beta_3 M_i), & \text{without additive effects;} \\ \Phi(\beta_1 + \beta_2 X_i + \beta_3 M_i + \beta_4 \text{Green Capital}_i), & \text{with an additive effect on the ex-ante endowment of green capital.} \end{cases} \end{aligned}$$

2. In the second step, the truncated-regression model is used to estimate the continuous decision of how many green jobs are effectively created considering the universe of uncensored observations defined in Equation (10):

$$\begin{aligned} &E(\text{Green Employment}_i | \text{PC1}_i^* > 0) = \\ &\begin{cases} \beta_1 + \beta_2 X_i + \beta_3 M_i + \sigma \lambda\left(\frac{\beta_1 + \beta_2 X_i + \beta_3 M_i}{\sigma}\right) + u_i, & \text{without additive effects;} \\ \beta_1 + \beta_2 X_i + \beta_3 M_i + \beta_4 \text{Green Capital}_i + \sigma \lambda\left(\frac{\beta_1 + \beta_2 X_i + \beta_3 M_i + \beta_4 \text{Green Capital}_i}{\sigma}\right) + u_i, & \text{with additive effect on green capital.} \end{cases} \end{aligned}$$

Two notes are in order. First, estimated coefficients of the first step may not correlate with the ones of the second step. Second, different explanatory variables can be incorporated in both steps of the Cragg's model. In this study, we pretend to analyse average marginal effects associated with the second-step procedure of the Cragg's model, which are related to the subsample of positives, that is, PTAI companies with available green vacancies and, thus, that necessarily provide green jobs. Moreover, it is convenient to observe that expected values for the truncated normal hurdle (TNH) model are straightforward extensions of the standard Tobit model, but with the difference that $Pr(y > 0|\mathbf{x})$ is allowed to follow an unrestricted probit model

$$E(y|\mathbf{x}, y > 0) = \mathbf{x}\beta + \sigma\lambda(\mathbf{x}\beta)$$

Therefore, for the TNH model, it follows that

$$E(y|\mathbf{x}) = \Phi(\mathbf{x}\gamma)[\mathbf{x}\beta + \sigma\lambda(\mathbf{x}\beta/\sigma)]$$

such that marginal effects

$$\frac{\partial E(y|\mathbf{x})}{\partial x_j} = \gamma_j \Phi(\mathbf{x}\gamma)[\mathbf{x}\beta + \sigma\lambda(\mathbf{x}\beta/\sigma)] + \Phi(\mathbf{x}\gamma)\beta_j \theta(\mathbf{x}\beta/\sigma)$$

where $\theta(z) = 1 - \lambda(z)[z - \lambda(z)]$. Since we can estimate $E(y|x)$, we can compute the squared correlation between y_i and $\hat{E}(y_i|x_i)$ across all i as a R^2 measure, which implies that goodness-of-fit statistics can be compared to the type I Tobit model.

Average marginal effects in Table 12 quantitatively confirm, for firms that effectively have green employment, that:

- A €10,000,000 increase in exports leads to the creation of 0.91 additional green jobs, *ceteris paribus*; and
- A €10,000,000 increase in imports leads to the creation of 0.54 additional green jobs, *ceteris paribus*.

Table 12. Second-step results of the second stage of the ensemble approach with the Cragg's model: role of international trade activities on green job creation in the PTAI (2010–2017).

	Hurdle-Truncated Sample		
	Average Marginal Effect		
	(1)	(2)	(3)
X	$9.07 \times 10^{-5} ***$ (0.000)	$1.09 \times 10^{-4} ***$ (0.000)	$1.46 \times 10^{-4} ***$ (0.000)
M	$5.37 \times 10^{-5} ***$ (0.000)	$7.20 \times 10^{-5} ***$ (0.000)	$2.58 \times 10^{-4} ***$ (0.000)
Green capital dummy		−1.175 *** (0.100)	−0.886 *** (0.086)
X × Green capital dummy			−6.75 × 10 ^{−6} *** (0.000)
M × Green capital dummy			−1.19 × 10 ^{−4} *** (0.000)
σ	5.600 *** (0.264)	4.860 *** (0.228)	3.840 *** (0.138)
Log pseudolikelihood	−9970.272	−9840.086	−9224.743
Observations	5502	5502	5502

Notes: dependent variable is green employment measured by PC1. *** $p < 0.01$. Robust standard errors in parentheses. Reported log pseudolikelihood and σ values are associated with the truncated-regression model. Model (1) is absent of additive and multiplicative effects, model (2) only includes additive effects and model (3) includes additive and multiplicative effects.

In turn, the additive effect introduced in model (2) confirms that, on average, holders of green capital that provide green jobs create, on average, 1.175 less green jobs compared to PTAI companies that create a positive number of green jobs without holding green capital, *ceteris paribus*. For firms that effectively have green employment and differentiating between holders and non-holders of green capital by introducing both additive and multiplicative effects, it is estimated that:

- A €10,000,000 increase in exports leads to the creation, on average, of 1.46 additional green jobs in PTAI companies without green technologies, *ceteris paribus*.
- A €10,000,000 increase in imports leads to the creation, on average, of 2.58 additional green jobs in PTAI companies without green technologies, *ceteris paribus*.
- On average, PTAI companies with green technologies have 0.886 less green jobs compared to PTAI companies without green technologies, *ceteris paribus*.
- A €10,000,000 increase in exports leads to the destruction, on average, of 0.07 green jobs in PTAI companies with green technologies, *ceteris paribus*.

- A €10,000,000 increase in imports leads to the destruction, on average, of 1.19 green jobs in PTAI companies with green technologies, *ceteris paribus*.

Although these results are qualitatively similar to the ones obtained with the Tobit model, it should be emphasised that the likelihood ratio test confronting Tobit vs. Cragg's model reveals that the Tobit model is rejected for a critical p -value of 1% because, from the comparison of both models in the absence of additive and multiplicative effects, we obtain $\chi^2(2) = 17,315.301$, p -value = 0.000. Hence, the TNH model is preferred to explain the impact of international trade activities on green employment and clearly confirms the presence of a gap in the proliferation of green employment between holders and non-holders of green capital in the PTAI. It is equally important to observe that parameter σ is statistically significant in the Cragg's model, which is indicative of pronounced differences between the latent variable in the total sample—which accommodates green employment in the entire universe of PTAI companies—and the truncated sample—which only considers PTAI firms that provide a positive number of green jobs.

Lastly, outcomes from the Heckman's model need to be presented. From a theoretical point of view, this option is justified by the potential persistence of sample selection bias and incidental truncation. Theoretically, sample selection bias occurs when units select themselves into a group. In the context of this study, where we want to study international trade factors affecting the provision of green jobs by PTAI companies, we have the following:

- The selection decision (i.e., whether companies choose to provide green jobs or not); and
- The selected sample (i.e., a set of explanatory variables for PTAI companies that effectively provide green jobs).

Under this circumstance, it should be clear that:

- Different factors can affect both decisions.
- A given factor may have influential power only in one decision (e.g., whether firms provide green jobs or not may be influenced by green incentives, but the number of green jobs effectively created should not be influenced by green incentives).
- It may occur the case where the dependent variable is not observed if the observation does not belong to the sample (e.g., the identification of jobs directly affected by the circular economy is a feasible action, but the identification of jobs indirectly affected by the circular economy may not be possible even though this number is not zero).

Additionally, incidental truncation and truncation are different concepts. When studying drivers of green employment, truncation exists if the sample is based on the number of green jobs effectively created. Differently, incidental truncation exists, for instance, if the sample is based on whether firms have corporate social responsibility values. Although a high correlation between corporate social responsibility and green employment is expected, both concepts are not exactly the same. The Heckman's model surpasses this source of concern by assuming that the discrete decision s_i and the continuous decision Green Employment $_i$ have a bivariate distribution with correlation ρ .¹⁰ Moreover, it can accommodate a maximum likelihood estimation or a two-step estimation procedure. The second option is then summarised as follows:

1. In the first step, the probit model is used to estimate the selection mechanism

$$Pr(s_i = 1) = \begin{cases} \Phi(\beta_1 + \beta_2 X_i + \beta_3 M_i), & \text{without additive effects;} \\ \Phi(\beta_1 + \beta_2 X_i + \beta_3 M_i + \beta_4 \text{Green Capital}_i), & \text{with an additive effect on the ex-ante endowment of green capital} \end{cases}$$

which requires computing the inverse Mills ratio generically presented in Equation (9) and is given by

$$\lambda(.) = \frac{\phi(\beta_1 + \beta_2 X_i + \beta_3 M_i)}{\Phi(\beta_1 + \beta_2 X_i + \beta_3 M_i)}$$

in order to have a notion about the propensity to transit to the selected sample.

2. In a second step, OLS regression model is estimated for the selected sample

$$E(\text{Green Employment}_i | s_i = 1) = \begin{cases} \beta_1 + \beta_2 X_i + \beta_3 M_i + \sigma \lambda \left(\frac{\beta_1 + \beta_2 X_i + \beta_3 M_i}{\sigma} \right) + u_i, & \text{without additive effects;} \\ \beta_1 + \beta_2 X_i + \beta_3 M_i + \beta_4 \text{Green Capital}_i + \sigma \lambda \left(\frac{\beta_1 + \beta_2 X_i + \beta_3 M_i + \beta_4 \text{Green Capital}_i}{\sigma} \right) + u_i, & \text{with additive effect on green capital.} \end{cases}$$

The Heckman's model may or may not have similar regressors for the selection equation and the second-step regression. Moreover, estimates of ancillary parameters ρ , λ , and σ should be reported. Results exposed in Table 13 confirm that all regressors are significant and qualitatively similar between the entire sample and the selected sample. Estimates of ρ confirm evidence of a significant and negative correlation between the discrete decision and the continuous decision. This conclusion is reinforced by the result of the chi-squared statistics testing the null hypothesis of absence of correlation, which clearly justifies the inclusion of the Heckman's selection equation regardless of whether additive effects are introduced or not.

Results of the inverse Mills ratio λ suggest evidence of significant selectivity effects. Average marginal effects quantitatively confirm that:

- For PTAI companies that effectively create green jobs, a €10,000,000 increase in exports creates between 1.25 and 1.36 additional green jobs depending on whether the two-step procedure or the maximum likelihood estimation method is adopted, *ceteris paribus*; and
- For PTAI companies that effectively create green jobs, a €10,000,000 increase in imports creates between 1.72 and 2.32 additional green jobs depending on whether the two-step procedure or the maximum likelihood estimation method is adopted.

Intuitively, these outcomes reflect that the creation of green jobs is more reactive to changes in imports than exports. The inclusion of additive effects capturing the endowment of green capital at the firm level in the deterministic component of the selected regression model confirms that, for PTAI companies that effectively create green jobs, holders of green technologies provide, on average, less green jobs compared non-holders of green technologies in a magnitude ranging between 0.796 and 0.830, *ceteris paribus*.

Finally, Table 14 shows the results of Heckman's two-step procedure estimation model with the inclusion of additive and multiplicative effects. These are qualitatively similar to the results of Tobit and Hurdle models, as they confirm that the additional volume of exports and imports increases green job creation in firms without green technologies, while the opposite is verified in PTAI companies holding green capital. Intuitively, this conclusion suggests the presence of strategic substitutability between green capital and green labour in the PTAI. Therefore, the implementation of green technologies reduces the need to hire new human resources at the firm level. Ultimately, this conclusion raises a reasonable doubt regarding the creation of new employment opportunities in the context of this new Industry 4.0 and its circular economy. In the case of PTAI, this study makes it clear that the drop in employment since 2005 has been attenuated from 2015 onwards based on net job creation in companies not endowed with green technology. In other words:

- Companies endowed with green capital created new qualified jobs in a magnitude that does not surpass the number of unskilled jobs destroyed; although this fact leads to an increase in marginal productivity, it also originates an effective net loss of employment; and
- In opposition, companies not endowed with green capital absorb unskilled employment from companies endowed with green capital in a magnitude that allowed for stabilising the level of employment since 2015.

Table 13. Second-step results of the second stage of the ensemble approach with the Heckman’s model: role of international trade activities on green job creation in the PTAI (2010–2017).

	(A)						(B)					
	Two-Step Estimates			Maximum Likelihood			Two-Step Estimates			Maximum Likelihood		
	Coefficient		AME	Coefficient		AME	Coefficient		AME	Coefficient		AME
	(1)	(2)		(1)	(2)		(1)	(2)		(1)	(2)	
X	$2.48 \times 10^{-4} ***$	$3.93 \times 10^{-4} ***$	$1.36 \times 10^{-4} ***$	$1.79 \times 10^{-4} ***$	$3.28 \times 10^{-4} ***$	$1.25 \times 10^{-4} ***$	$2.84 \times 10^{-4} ***$	$4.53 \times 10^{-4} ***$	$1.36 \times 10^{-4} ***$	$2.52 \times 10^{-4} ***$	$4.25 \times 10^{-4} ***$	$1.38 \times 10^{-4} ***$
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
M	$3.14 \times 10^{-4} ***$	$6.89 \times 10^{-4} ***$	$1.72 \times 10^{-4} ***$	$3.31 \times 10^{-4} ***$	$7.07 \times 10^{-4} ***$	$2.32 \times 10^{-4} ***$	$3.24 \times 10^{-4} ***$	$8.57 \times 10^{-4} ***$	$1.72 \times 10^{-4} ***$	$3.28 \times 10^{-4} ***$	$8.60 \times 10^{-4} ***$	$1.79 \times 10^{-4} ***$
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Green capital dummy							$-1.770 ***$	$-1.391 ***$	$-0.830 ***$	$-1.458 ***$	$-1.314 ***$	$-0.796 ***$
							(0.0812)	(0.025)	(0.034)	(0.142)	(0.033)	(0.047)
Independent term	$1.598 ***$	$-1.090 ***$		$3.317 ***$	$-1.046 ***$		$1.763 ***$	$-0.493 ***$		$2.395 ***$	$-0.510 ***$	
	(0.084)	(0.012)		(0.244)	(0.014)		(0.068)	(0.015)		(0.216)	(0.015)	
σ		2.663			2.841			2.539			2.573	
$\ln(\sigma)$					1.044 ***						0.945 ***	
					(0.034)						(0.030)	
ρ		-0.128			-0.644			-0.051			-0.357	
$\operatorname{atanh} \rho$					$-0.765 ***$						$-0.373 ***$	
					(0.088)						(0.102)	
λ		$-0.340 ***$			-1.829			$-0.130 ***$			-0.918	
		(0.067)						(0.066)				
$\chi^2(1) _{\rho=0}$					75.890 ***						13.510 ***	
Log p-likelihood					$-22,295.080$						$-20,315.740$	
Total observations		22,062			22,062			22,062			22,062	
Selected obs.		5502			5502			5502			5502	
Non-selected obs.		16,560			16,560			16,560			16,560	

Notes: column (A) presents estimates without additive component, while column (B) presents estimates with additive component. Under Heckman’s two-step estimate procedure, model (1) shows estimated coefficients for the entire sample (PC1), while model (2) shows estimated coefficients for the selected sample of firms that provide green jobs (PC1 > 0), and conventional standard errors are used. AME stands for average marginal effects of the selected sample. Under maximum likelihood, robust standard errors are used. $\operatorname{Atanh} \rho$ is the inverse hyperbolic tangent of ρ , and given by $(1/2)\ln[(1 + \rho)/(1 - \rho)]$. The standard error of the residual σ in the PC1 equation is not directly estimated under maximum likelihood; instead, for numerical stability, $\ln(\sigma)$ is estimated. Evidence of a selectivity effect is summarised by the inverse Mills ratio $\lambda = \rho\sigma$. *** $p < 0.01$.

Table 14. Second-step results of the second stage of the ensemble approach with Heckman’s model: additive and multiplicative effects of international trade activities on green job creation in the PTAI (2010–2017).

	Two-Step Estimates		
	Coefficient		AME
	(1)	(2)	
X	$3.62 \times 10^{-4} ***$ (0.000)	$4.69 \times 10^{-4} ***$ (0.000)	$1.40 \times 10^{-4} ***$ (0.000)
M	$8.75 \times 10^{-4} ***$ (0.000)	$1.26 \times 10^{-3} ***$ (0.000)	$3.40 \times 10^{-4} ***$ (0.000)
Green capital dummy	$-1.595 ***$ (0.078)	$-1.333 ***$ (0.026)	$-0.620 ***$ (0.027)
X × Green capital dummy	$-1.35 \times 10^{-5} ***$ (0.000)	$-3.90 \times 10^{-5} ***$ (0.000)	$-5.23 \times 10^{-6} ***$ (0.000)
M × Green capital dummy	$-4.85 \times 10^{-4} ***$ (0.000)	$-4.83 \times 10^{-4} ***$ (0.000)	$-1.89 \times 10^{-4} ***$ (0.000)
Independent term	0.638 *** (0.067)	$-0.529 ***$ (0.016)	
σ		2.285	
ρ		0.285	
λ		0.651 *** (0.062)	
Total observations		22,602	
Selected (non-selected) observations		5502 (16,560)	

Notes: model (1) shows estimated coefficients for the entire sample (PC1), while model (2) shows estimated coefficients for the selected sample of firms that provide green jobs (PC1 > 0), and conventional standard errors are used. AME stands for average marginal effects in the selected sample. *** $p < 0.01$. Evidence of a selectivity effect is summarised by the inverse Mills ratio $\lambda = \rho\sigma$.

Consequently, the evolution of PTAI can be explained by a mechanism of allocative efficiency between holders and non-holders of green capital: companies endowed with green capital are not necessarily interested in creating new employment opportunities because, in fact, green technology requires successively fewer needs for qualified labour due to economies of scale. Instead, holders of green capital try to reduce their job vacancies, which have been accommodated by companies without endowment of green technology because these are engaged either directly or indirectly in international trade activities.

As such, these results imply that H5 cannot be completely corroborated. Although the economic model oriented to exports followed by stakeholders of the PTAI in recent years does not necessarily promote new employment opportunities in firms endowed with green capital, it has certainly contributed to modifying the profile of skills required to new workers. Notwithstanding, the contribution of international trade activities to firms without green capital is a significant factor to explain the persistence of employment levels since 2015.

4.2.4. Mediation Analysis: Role of Green Capital and Maturity on the Relationship between International Trade Activities and Green Employment

We also study how green employment is influenced by the mediation of green capital and firms’ maturity. The estimates are obtained from a mediation analysis that decomposes the total effect of the volume of exports and imports into the following:

- Direct effects not explained by changes in green capital and firms’ maturity; and
- Indirect effects promoted by the green capital and firms’ maturity.

Tables 15–18 summarize the results. In addition to the delta method, we consider bootstrapping with 100 replications to construct confidence intervals. The mediation analysis combines two regression models into a structural equation and shows direct and

indirect significant effects for both mediators of the relationship between international trade activities and green employment.

Table 15. Green capital mediation between international trade and green employment.

	Estimate	CI (95%)	β	t	p -Value
Total effect					
X	3.34×10^{-4} *** (0.000)	$[3.27 \times 10^{-4}, 3.42 \times 10^{-4}]$	0.607	84.200	<0.001
M	2.96×10^{-4} *** (0.000)	$[2.78 \times 10^{-4}, 3.14 \times 10^{-4}]$	0.233	32.300	<0.001
Component effect					
X \Rightarrow Green capital	2.63×10^{-5} *** (0.000)	$[2.14 \times 10^{-5}, 3.12 \times 10^{-5}]$	0.119	10.500	<0.001
M \Rightarrow Green capital	2.24×10^{-4} *** (0.000)	$[2.12 \times 10^{-4}, 2.35 \times 10^{-4}]$	0.413	38.900	<0.001
Direct effect					
Green capital \Rightarrow Green employment	-1.260 *** (0.007)	$[-1.270, -1.240]$	-0.536	-191.200	<0.001
X \Rightarrow Green employment	3.68×10^{-4} *** (0.000)	$[3.63 \times 10^{-4}, 3.72 \times 10^{-4}]$	0.667	150.400	<0.001
M \Rightarrow Green employment	5.77×10^{-4} *** (0.000)	$[5.66 \times 10^{-4}, 5.89 \times 10^{-4}]$	0.455	99.500	<0.001
Indirect effect					
X \Rightarrow Green capital \Rightarrow Green employment	-3.30×10^{-5} *** (0.000)	$[-3.92 \times 10^{-5}, -2.69 \times 10^{-5}]$	-0.060	-10.500	<0.001
M \Rightarrow Green capital \Rightarrow Green employment	-2.81×10^{-4} *** (0.000)	$[-2.96 \times 10^{-4}, -2.67 \times 10^{-4}]$	-0.222	-38.200	<0.001

Notes: delta method used. β contains completely standardised effect sizes. *** $p < 0.01$.

Table 16. Green capital mediation between international trade and green employment.

	Estimate	CI (95%)	β	t	p -Value
Total effect					
X	3.34×10^{-4} *** (0.000)	$[3.27 \times 10^{-4}, 3.42 \times 10^{-4}]$	0.607	84.190	<0.001
M	2.96×10^{-4} *** (0.000)	$[2.78 \times 10^{-4}, 3.14 \times 10^{-4}]$	0.233	32.330	<0.001
Component effect					
X \Rightarrow Green capital	2.63×10^{-5} *** (0.000)	$[6.00 \times 10^{-6}, 4.62 \times 10^{-5}]$	0.119	2.560	0.010
M \Rightarrow Green capital	2.24×10^{-4} *** (0.000)	$[1.83 \times 10^{-4}, 2.69 \times 10^{-4}]$	0.413	10.190	<0.001
Direct effect					
Green capital \Rightarrow Green employment	-1.260 *** (0.018)	$[-1.290, -1.230]$	-0.536	-71.350	<0.001
X \Rightarrow Green employment	3.68×10^{-4} *** (0.000)	$[3.50 \times 10^{-4}, 3.85 \times 10^{-4}]$	0.667	40.420	<0.001
M \Rightarrow Green employment	5.77×10^{-4} *** (0.000)	$[5.25 \times 10^{-4}, 6.23 \times 10^{-4}]$	0.455	23.100	<0.001
Indirect effect					
X \Rightarrow Green capital \Rightarrow Green employment	-3.30×10^{-5} ** (0.000)	$[-5.82 \times 10^{-5}, -7.56 \times 10^{-6}]$	-0.060	-2.560	0.011
M \Rightarrow Green capital \Rightarrow Green employment	-2.81×10^{-4} *** (0.000)	$[-3.39 \times 10^{-4}, -2.30 \times 10^{-4}]$	-0.222	-38.200	<0.001

Notes: 100 bootstrapping replications. β contains standardised effect sizes. ** $p < 0.05$, *** $p < 0.01$.

Table 17. Maturity mediation between international trade and green employment.

	Estimate	CI (95%)	β	<i>t</i>	<i>p</i> -Value
Total effect					
X	3.34×10^{-4} *** (0.000)	$[3.27 \times 10^{-4}, 3.42 \times 10^{-4}]$	0.607	84.190	<0.001
M	2.96×10^{-4} *** (0.000)	$[2.78 \times 10^{-4}, 3.14 \times 10^{-4}]$	0.233	32.330	<0.001
Component effect					
X \Rightarrow maturity	4.72×10^{-4} *** (0.000)	$[4.09 \times 10^{-4}, 5.36 \times 10^{-4}]$	0.175	14.520	<0.001
M \Rightarrow maturity	2.41×10^{-4} *** (0.000)	$[9.42 \times 10^{-5}, 3.88 \times 10^{-4}]$	0.039	3.220	0.001
Direct effect					
maturity \Rightarrow Green employment	0.030 *** (0.000)	[0.028, 0.032]	0.146	37.560	<0.001
X \Rightarrow Green employment	3.20×10^{-4} *** (0.000)	$[3.13 \times 10^{-4}, 3.28 \times 10^{-4}]$	0.581	82.780	<0.001
M \Rightarrow Green employment	2.89×10^{-4} *** (0.000)	$[2.71 \times 10^{-4}, 3.06 \times 10^{-4}]$	0.227	32.530	<0.001
Indirect effect					
X \Rightarrow maturity \Rightarrow Green employment	1.41×10^{-5} *** (0.000)	$[1.21 \times 10^{-5}, 1.62 \times 10^{-5}]$	0.026	13.540	<0.001
M \Rightarrow maturity \Rightarrow Green employment	7.22×10^{-6} *** (0.000)	$[2.81 \times 10^{-6}, 1.16 \times 10^{-5}]$	0.006	3.210	0.001

Notes: delta method used. β contains completely standardised effect sizes. *** $p < 0.01$.

Table 18. Maturity mediation between international trade and green employment.

	Estimate	CI (95%)	β	<i>t</i>	<i>p</i> -Value
Total effect					
X	3.34×10^{-4} *** (0.000)	$[3.27 \times 10^{-4}, 3.42 \times 10^{-4}]$	0.607	84.190	<0.001
M	2.96×10^{-4} *** (0.000)	$[2.78 \times 10^{-4}, 3.14 \times 10^{-4}]$	0.233	32.330	<0.001
Component effect					
X \Rightarrow maturity	4.72×10^{-4} *** (0.000)	$[3.77 \times 10^{-4}, 5.77 \times 10^{-4}]$	0.175	9.250	<0.001
M \Rightarrow maturity	2.41×10^{-4} ** (0.000)	$[3.53 \times 10^{-5}, 4.34 \times 10^{-4}]$	0.039	2.370	0.018
Direct effect					
maturity \Rightarrow Green employment	0.030 *** (0.000)	[0.028, 0.032]	0.146	27.990	<0.001
X \Rightarrow Green employment	3.20×10^{-4} *** (0.000)	$[2.96 \times 10^{-4}, 3.46 \times 10^{-4}]$	0.581	25.270	<0.001
M \Rightarrow Green employment	2.89×10^{-4} *** (0.000)	$[2.24 \times 10^{-4}, 3.52 \times 10^{-4}]$	0.227	8.820	<0.001
Indirect effect					
X \Rightarrow maturity \Rightarrow Green employment	1.41×10^{-5} *** (0.000)	$[1.11 \times 10^{-5}, 1.75 \times 10^{-5}]$	0.026	8.770	<0.001
M \Rightarrow maturity \Rightarrow Green employment	7.22×10^{-6} ** (0.000)	$[1.08 \times 10^{-6}, 1.30 \times 10^{-5}]$	0.006	2.370	0.018

Notes: 100 bootstrapping replications. β contains standardised effect sizes. ** $p < 0.05$, *** $p < 0.01$.

Empirical results confirm that not only does international trade directly affect the existence of green jobs, but also the mediating role of green capital and firms' maturity indirectly influences this relationship by allowing it to remain globally significant. Therefore, this extension identifies two statistically significant mediators, which means that effective policy measures for promoting green employment opportunities in the PTAI should be put in place.

- Reduce the dependence of green capital, despite the fact that this leads to a loss of productivity gains, which can harm production surplus; and

- Foster the survival of firms at an early stage of maturity by ensuring that these stakeholders actively participate in international markets.

Recent research has underscored the significant impact of product innovation as a mediator in the relationship between GEO, GTL, and the economic performance of firms (Asad et al. 2024). Building on this context, our study adds a new predictive dimension—international trade—to address three critical research questions within the TAI: the relationship between green capital endowment and international trade, the connection between green job creation and international trade, and whether green capital mediates the relationship between green employment and international trade.

Our assessment of the green transition in the PTAI reveals several key insights. First, we identify a *green international trade paradox*, where the propensity to adopt green capital is positively associated with external dependence. Specifically, green capital adoption increases with higher imports and decreases with higher exports. This suggests that firms are more willing to invest in green capital when they depend more on imported inputs and less on exporting. This finding complements the analysis by Ribeiro and Soares (2024), which introduces a novel method for calculating firms' willingness to pay (WTP) from a supply-side perspective. Their study demonstrates that PTAI companies are willing to offer retail price discounts to sustain the distribution of low-quality products, which result from importing low-quality inputs.

Second, we find that green job creation in firms without green technologies is positively influenced by international trade activities. Conversely, in firms equipped with green technologies, green job creation is negatively affected by both imports and exports. This result, rather than being paradoxical, indicates that firms heavily invested in green technologies require less specialised labour for green activities, as their advanced technology reduces the need for such roles.

Finally, the mediation analysis reveals that green capital significantly and negatively mediates the relationship between international trade and green employment. This indicates that higher levels of green capital tend to reduce the positive impact of international trade on green job creation. Consequently, our analysis supports the outcome identified by Asad et al. (2024) in the sense that firms with substantial investments in green technologies require less specialised labour for green activities which, in turn, allows them to enhance their economic performance. In contrast, the maturity of firms plays a positive and significant mediating role, suggesting that more mature firms experience a stronger positive effect of international trade on green employment.

5. Discussion

In general, creating green jobs allows for mitigating two sources of concern: economic downturns and environmental damage. Although the EU Green Employment Initiative (GEI) acts as a remedy to solve both problems, the Keynesian school has been warning since 1936 that job creation is the key driver for economic growth and sustainable development. However, questions like how many and which type of green jobs are necessary to achieve this ultimate end are neither overexploited nor consensual among academics and practitioners. It is widely recognised that a successful transition to a green economy can reshape labour markets. Since many EU Member States have shortages in the set of skills required to join the green paradigm towards decarbonisation, there is significant potential for creating new jobs in the production of RES, energy efficiency, waste and water management, air quality, restoring and preserving biodiversity, climate change, and green network infrastructures. Workers are needed for new roles and updated traditional jobs, so that specialised training policies can promote these skills to maximize opportunities in industries such as the PTAI. Bearing these stylised facts in mind, a discussion is now presented to identify pros and cons of PTAI's current business model and suggest prospective policy recommendations to ensure that ongoing transformations promote social welfare gains in the future.

5.1. Benefits and Challenges with the Renewal of PTAI through the Creation of Green Jobs

The shift to a green economy is a valuable opportunity to increase PTAI's global competitiveness, ensure the wellbeing of future generations, and support sustainable employment while contributing to the recovery from exogenous shocks such as economic, pandemic, and war crises. The EU GEI presents an integrated framework to ensure that labour market policies play an active role on supporting the transition to a low-carbon and resource-efficient economy by

- Anticipating new skills and their alignment with the ongoing structural change.
- Strengthening governance and partnership initiatives.
- Putting the promotion of green jobs at the core of the public policy debate.

Specifically, the EU GEI defines actions to be taken at European and national levels, including the following:

- Bridging skill gaps by fostering their development and forecasting primary needs across sectors and industries.
- Supporting adequate labour market legislation and facilitating occupational mobility to meet demand and supply needs in the green economy era.
- Boosting job creation and making efficient use of EU funding by shifting taxes to pollution, while promoting public procurement and green entrepreneurship.
- Increasing data quality and monitoring market developments by providing financial support and training to national statistical offices.
- Promoting a social dialogue and support workers' involvement in matters related to environmental management, risks at the workplace, access to credible information and the development of efficiency roadmaps.

EU's cooperation experience confirms the potential contribution of green sectors for job creation, which requires the internalisation of the social dimension of climate change and its interconnection with the 2015 United Nations sustainable development goals (SDGs). In this sense, several challenges should not be neglected, namely:

- Ensuring that green jobs are decent, which requires labour inspection, occupational safety, and minimum quality of service (QoS) standards in health and related areas.
- Dissuading the informal economy and adopt training policies to meet new skills required by the green economy.
- Celebrating more resilient multilateral dialogues to guarantee that green jobs are boosted globally.

5.2. Scholarly Implications

This study deepens the understanding of how knowledge spillovers from international trade impact employment dynamics. The finding that PTAI companies use knowledge absorption for purposes beyond job creation suggests a theoretical shift from the traditional view that technological progress and globalisation inherently lead to job growth. This contrasts with the conventional wisdom that knowledge spillovers naturally stimulate labour demand and aligns more closely with a RBV perspective, where firms leverage external knowledge primarily to enhance internal efficiencies rather than to expand their workforce (Cohen and Levinthal 1990), thus limiting opportunities for unexpected job creation, which can be considered a form of serendipity (Busch 2024).

The significant long-term negative impact of exports and imports on employment shifts the academic debate around trade liberalisation and labour markets. Theoretical models that emphasize the benefits of international trade, such as neoclassical models, may need revision, particularly in industries like PTAI, where automation and capital-intensive practices driven by international knowledge spillovers may supplant jobs. This also supports more heterodox economic theories, which posit that the global integration of markets might not be universally beneficial for job creation (Mireles-Flores 2022; Spash 2024).

The findings about the stronger impact of trade on firms located in the north of Portugal and those with specific legal forms point to the importance of regional and firm-level heterogeneity in trade theories. This suggests that location-specific factors and organisational forms may modulate the effects of internationalisation, adding to the body of literature on spatial economics, international business, and firm governance (Goerzen et al. 2024; Francioni and Martín 2024). These results imply that international trade theories should incorporate more granular, regional considerations to predict employment outcomes more accurately.

Our results also suggest the presence of a *green international trade paradox* in the sense that green capital acquisition increases with a higher degree of external dependence, acting as an announced expropriation for the domestic country, inducing it to accelerate imports to increase its green capital endowment. Conversely, green capital acquisition decreases with increasing exports, as green capital firms already hold the ability to drain their products to international markets without the need to incur additional productive investment in green technologies.

The mixed effects of international trade on the creation of green jobs challenge traditional ecological economics frameworks, which assume a direct relationship between trade liberalisation and economic growth—proxy for green job creation—when preferences are homothetic (Lopez 1994). The distinction between firms with and without green capital highlights the importance of firm-level sustainability readiness in adapting to international trade dynamics. This contributes to the emerging green growth theory and suggests that green jobs may emerge not necessarily from green capital investment but rather from market-driven competitive advantages (Altenburg and Rodrik 2017; Jiang et al. 2024), namely the access to international markets by companies lacking green capital.

Moreover, the study supports the notion of skill-biased technological change within the PTAI, emphasising that international trade may not directly increase the quantity of jobs but significantly alters the profile of skills required. In particular, companies with green capital seek a specialised workforce, while companies without green capital accommodate both high- and low-quality workers provided that they operate internationally. This underlines the relevance of human capital theory and adds preponderance to the idea that labour market policies need to evolve alongside international trade policies to support changing workforce needs (Bamber and Lansbury 2024; Groenewald et al. 2024; Ross et al. 2024).

Additionally, our mediation analysis offers several important scholarly implications that advance the understanding of the green transition within the TAI. First, the discovery that green capital negatively mediates the relationship between international trade and green employment challenges contemporary perspectives, such as those presented by Tekala et al. (2024). Our result suggests that the interaction between international trade and green job creation is more complex than previously thought, particularly in firms with significant investments in green technologies. This requires a re-evaluation of existing theories to incorporate the effect green capital has on trade-related green employment outcomes. Second, results underscore the need to integrate technological sophistication into studies of the green transition. In line with insights from Zhou et al. (2024), the significant role of green capital in mediating the relationship between trade and employment underscores how technological investment affects labour market dynamics. As such, future research may develop more refined theoretical frameworks that account for the interplay between advanced green technologies and employment, enhancing the understanding of how technology adoption affects green transition outcomes. Third, our findings support the work of Asad et al. (2024) by affirming the role of green capital as a mediator between international trade and green employment in similar vein that product innovation significantly mediates the relationship between economic performance vis-à-vis GEO and GTL. This suggests that international trade not only drives green jobs but also interacts with green capital to influence green employment dynamics. Fourth, the evidence that international trade's impact on green employment varies depending on the level of green capital implies that policymakers need to consider firms' technological maturity when de-

signing trade policies aimed at promoting green jobs. Tailoring policies to the technological capabilities of firms could enhance the effectiveness of trade interventions in fostering green employment (Kim et al. 2024). Lastly, the negative mediating effect of green capital on the relationship between international trade and green employment suggests that increasing green capital alone may not be sufficient to achieve socially desired outcomes (Bracarense and Costa 2024). As such, further investigation is needed into alternative mediators and moderators with influential power this relationship, potentially revealing additional factors that contribute to the success of green transitions.

Finally, the result that firms' maturity significantly and positively mediates the relationship between international trade and green employment also offers several important scholarly implications. First, it highlights the critical role of organisational maturity in shaping how international trade affects green job creation. This suggests that more mature firms, with established processes and a greater degree of stability, are better positioned to leverage international trade opportunities to enhance green employment (Zhang et al. 2024). Second, this result implies that the benefits of international trade in promoting green employment are not uniformly distributed across firms. Instead, mature firms, which likely have more sophisticated management practices and better resource allocation, are more capable of capitalising on international trade opportunities to boost green job creation. In this sense, our empirical assessment validates contemporaneous research confirming that firm-level characteristics influence the effectiveness of international trade policies (Chen et al. 2024). Lastly, the positive mediating effect of firms' maturity suggests that policymakers and industry stakeholders should focus on supporting the growth and development of firms to maximize the impact of international trade on green job creation. Initiatives that foster firm maturity and organisational learning—such as providing resources for capacity building, improving management practices, and encouraging long-term strategic planning—could enhance the ability of firms to translate international trade opportunities into green employment benefits (Ademi et al. 2024).

5.3. Managerial Implications

For practitioners within the PTAI, this study indicates that relying on international trade alone may not be a viable strategy for expanding employment. Firms should focus on value-creation strategies that go beyond simple participation in global trade, such as investing in innovation and technology-driven efficiency improvements, without expecting these activities to automatically generate new jobs. Managers should realign expectations and business models to focus on productivity gains rather than employment growth when engaging in internationalisation strategies.

Our findings suggest that policymakers need to design targeted labour market interventions that align with industry needs in the PTAI. These policies could focus on bridging skill gaps and fostering green employment opportunities by supporting upskilling and reskilling programs tailored to the shifting demands of the labour force. For managers, this implies a need to collaborate with local governments and higher education institutions (HEIs) to ensure their workforce is equipped with the required skills for future growth areas, particularly in green technologies and sustainable production.

The stronger impact of international trade on firms located in the north of Portugal and those with certain legal structures suggests that regional inequalities in trade outcomes may require managers to adopt differentiated strategies based on geographical location. Regional managers may need to advocate for policies that address these disparities and work with local governments to attract investments that counterbalance the negative employment effects of trade, such as regional development initiatives or infrastructure improvements. This also opens the scope to moving forward in highly controversial debates, such as the need to impose decentralisation and regionalisation.

This study also reveals that firms without green capital tend to create more green jobs when participating in international trade, which implies a strategic opportunity for companies to capitalise on emerging green markets even without substantial prior investment in

green technologies. Managers of these firms can leverage international market access to create niche employment in green sectors, focusing on gradual transitions rather than large-scale green investments. This also suggests that firms should explore partnerships with sustainability-focused organisations to benefit from knowledge transfers and potentially access new market segments.

Given that geographical trade restrictions do not necessarily worsen employment outcomes for PTAI, managers should focus on maintaining trade relationships and diversified supply chains rather than fearing the effects of trade limitations.

This study also suggests that PTAI companies have shown relative employment stability during the last decade, highlighting the resilience of PTAI employment to external trade shocks (e.g., Troika's intervention). Managers can use this insight to reassure stakeholders that international trade restrictions may not have as severe an impact on job creation as feared and focus more on building resilient operational structures.

The result suggesting a stronger employment impact in firms with certain legal structures may legitimize discriminatory trade clauses. On limitations, this presents a reasonable doubt for advocacy efforts by PTAI firms to ensure that trade agreements and public policies are designed to protect firms with more capital realisation and that public policy considers firm-level differences in exposure to global competition when crafting national and supranational regulations on international trade.

5.4. Public Policy Recommendations

The results of this study indicate that international trade activities do not create positive net employment in PTAI companies endowed with green capital. However, since PTAI companies without green capital have been participating, either directly or indirectly, in international markets, this industry has maintained a stabilised level of employment from 2015 onwards. Hence, the recent revival of employment in the PTAI has been characterised by three stylised facts:

1. A structural change in the profile of employees required for the execution of economic activities, at least in companies endowed with green capital.
2. Redundant creation of green jobs in companies endowed with green capital due to economies of scale and relocation of the overstaff to companies without green capital.
3. Absorption of the overstaff identified in the previous point by companies without green capital, if these actively participate in international markets.

Although it may be politically legitimised to claim that public policy decisions on employment need to support the proliferation of green jobs while better matching the primary needs demanded by stakeholders with soft and hard skills offered by workers, it can also be considered demagogic because the abovementioned stylised facts necessarily require understanding that:

1. A considerable reduction in employment in the PTAI in the next and subsequent decades due to the strategic substitutability between green capital and the labour factor is likely to exist.
2. Only supporting the transition to the green economy and unilaterally disregarding inefficient forms of employment by subsidising the proliferation of green technologies can give rise to serious problems of social stratification, shrinking of the middle class, and social dissidence due to the reduction in total net employment.
3. Measures to effectively guarantee the sustainability of employment opportunities in the PTAI are all those that encourage the participation of companies lacking green capital in international markets.

In this sense, the following priorities should be pursued:

- Improving the integration and coordination between supranational and national policies and initiatives in the PTAI.

- Developing governance structures to facilitate the transition towards a green economy by establishing a closer relation between HEIs, private partners, government, civil society, and the natural environment (i.e., strengthening the Quintuple Helix model).
- Leveraging the role of international trade activities on green employment by ensuring that only firms truly committed to create positive net employment in Portugal have access to funding programs, either through the provision of warranties or celebrating self-enforcement contracts.
- Monitoring the progress related to green employment and building a strategy for new jobs, skills, and education in the PTAI.
- Sharpening a logic of *flexi-security* in the PTAIS's labour market.¹¹
- Enforcing the principle of active responsibility through the creation of heavy fines, levied both on corporate assets and on individual assets belonging to the personal domain of managers and shareholders, in cases of non-compliance with the creation of green jobs.
- Imposing the principle of active incentives through the provision of additional fiscal benefits, levied both on corporate assets and on individual assets belonging to the personal domain of managers and shareholders, in cases of compliance with ex-ante targets defined for the creation of green jobs.

5.5. Limitations and Future Research Directions

Despite the effort to provide a valid contribution, this study is not exempted from limitations. Advanced age and small size of firms, scarce and unskilled human resources, financial fragility, cultural characteristics, and the availability of distribution networks can be other determinants of employment in the PTAI, which nevertheless can be evaluated in future research. New challenges emerging from the digital economy, the expected technological diversification of the industry (e.g., technical and functional textiles, new raw materials and markets, use of artificial intelligence to reduce defection rates) and the prospect of *Portuguese-owned brands* may constitute other domains of actuation to consolidate the position of PTAI in international markets, which may have a positive effect on employment. Incentive programs, which have been properly used to increase the international recognition of PTAI companies, can also play a key role on fostering employment growth. The internationalisation strategy defined for the PTAI in line with public policies aimed at stimulating new employment gates can facilitate the consolidation of this industry and reinforce it as the most successful case study in the Portuguese economy. Moreover, the lack of real data covering green employment is also a debility that should be disclosed. We also warn that the results of this study should be viewed with caution given that we were unable to segment employment by the type of skills, and, consequently, positive effects of exports and imports may prevail only in specific workforce niches. Artificial intelligence is another domain that can be used to perform similar assessments. Furthermore, knowing that there is a considerable number of PTAI companies that neither provide specialised training to their employees nor have internal ongoing restructuring processes, we can take advantage of available data on the 2017 Environmental Fund stimulus, which acts as a policy shock, to assess whether the provision of subsidies to support the circular economy is beneficial to the proliferation of green jobs, and apply a difference-in-differences analysis to evaluate its effectiveness in 2018 and subsequent years. Finally, our findings associated with the mediation analysis encourage future research to explore how different dimensions of green capital and firm maturity, such as financial stability, managerial experience, and strategic planning capabilities, influence the relationship between international trade and green employment. Understanding these dynamics could provide deeper insights into how various green organisational elements contribute to achieving sustainable employment outcomes.

6. Conclusions

The PTAI is an extremely important component of the Portuguese economy due to its role in wealth and job creation. After a period of decline, the PTAI has found new avenues for renewal in several domains (e.g., fashion design, technological innovation, intensification of value-added services, and internationalisation). The good performance of the PTAI has been achieved not by means of a price war against developing countries, but through the development of vertical differentiation strategies. The investment in external promotional campaigns helps to highlight one of the most dynamic and exporting industries in Portugal, which is characterised by technologically advanced firms with renowned know-how, creativity, flexibility, and a strong orientation to international markets. The deep knowledge on production technologies has allowed for increasing the industry's added value and the speed of responses, which, combined with structured and organised clusters, define key pillars for the sustainability of this industry. However, doubts prevail on whether the good performance observed in the last few years will be accompanied by new employment opportunities.

This study provides a comprehensive assessment of the impact of international trade activities—specifically imports and exports—on employment trends within the PTAI during the period from 2010 to 2017. The findings reveal that both imports and exports exert a permanent, negative, and significant effect on job creation when employment is considered in a broad sense. Notably, this effect intensifies in the long-run, highlighting the importance of consistent public policy support for the industry. This evidence holds because PTAI companies benefit from the appropriation of knowledge spillovers when strategically interacting with international peers, which ensures the creation of internal technological progress that is used to promote cost-savings—including labour costs—and economies of scale. Furthermore, this study uncovers an increased elasticity of substitution between imports and exports over time, suggesting that private companies are capitalising on a win-win scenario marked by higher production volumes and reduced marginal costs. Another interesting conclusion is that geographical restrictions on international trade do not necessarily imply a stronger negative effect on the level of employment, which suggests that employment in the PTAI is expected to face less adverse effects compared to other manufacturing industries. It is also confirmed that exports and imports have a stronger effect on employment in PTAI companies either located in the north of Portugal or whose juridical form is representative of a higher level of own-capital realisation.

A particularly significant contribution of this research is its examination of the role of international trade in shaping the profile of green jobs within the PTAI. The results indicate a dual effect: while trade activities positively influence green job creation in firms without green capital, they have a negative impact on firms already equipped with such capital. This nuanced finding contributes to the ongoing discourse on sustainable business practices and their implications for employment. Since PTAI companies without green capital have been participating, either directly or indirectly, in international markets, this industry has maintained a stable level of employment from 2015 onwards.

Consequently, the recent revival of PTAI's employment has been characterised by three stylised facts: a structural change in the profile of workers required for the execution of economic activities, at least in companies endowed with green capital; redundant creation of green jobs in companies endowed with green capital due to economies of scale and relocation of the overstaff to companies without green capital; and absorption of the overstaff identified in the previous point by companies without green capital, as long as these actively participate in international markets. Whether this will bring good or bad consequences in the near future is beyond the scope of this study. Considering the forecast shortage of skilled and unskilled labour across Europe in the future ([Euroactiv 2022](#)), given the current strong marginal rate of substitution of work by leisure, several recommendations aimed at maximising economic objectives that do not necessarily coincide with those of minimising social inefficiency are provided.

This study's findings have both theoretical and practical implications. It challenges existing trade theories about job creation, underscores the role of regional heterogeneity, and highlights the complex relationship between international trade and green job creation. Moreover, it provides guidance on strategies for mitigating the negative employment impacts of international trade and emphasises the need for more targeted labour market policies that align with the evolving skill demands of the industry under scrutiny.

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Appendix A. Additional Econometric Details

The complete procedure in order to reach benchmark outcomes exposed in the main text is compiled and explained here. Table A1 presents estimated coefficients of static panel data models: POLS, fixed effects, and random effects. Following Wooldridge (2003), the generalised least squares (GLS) estimation method is used with fixed effects and random effects models due to debilities associated with OLS (e.g., asymptotically less efficient when time-constant attributes are present). The Hausman test is performed to choose between both models. The respective result demonstrates that fixed effects is the static panel data model that should be adopted. Thereafter, the Breusch–Pagan test is applied to evaluate the presence of heteroscedasticity in the within-variation component of the panel. Since the result indicates that the null hypothesis of homoscedasticity is rejected, the panel exhibits a heteroscedasticity that needs to be corrected for by applying the Huber–White procedure.

Meanwhile, dynamic panel data GMM models are considered to ensure the exogeneity of regressors. Indeed, it can be observed that the sign of estimated coefficients under the optimal static panel data model may not be adequate (e.g., sign of estimated coefficient related to imports (M) is positive), which suggests that the static panel data model may suffer from endogeneity, thus reinforcing the need to consider dynamic panel data models. Thereafter, we estimate the POLS and the fixed-effects model with lagged dependent variable (LDV) and analyse the rule-of-thumb proposed by Bond et al. (2001).

Table A1. Estimated coefficient results of static panel data models.

Covariate	POLS	Fixed Effects	Random Effects
W	−0.027 *** (0.006)	−0.012 (0.019)	−0.002 (0.011)
X	−0.016 ** (0.004)	−0.018 * (0.010)	−0.014 *** (0.005)
M	−0.030 *** (0.004)	0.009 (0.008)	−0.010 * (0.005)
Q	0.869 *** (0.006)	0.765 *** (0.023)	0.808 *** (0.016)
Constant	−1.564 *** (0.032)	−1.344 *** (0.179)	−1.451 *** (0.062)
Hausman		94.450 *** [4]	
Breusch Pagan		3257.210 *** [1]	

Note: Robust standard errors in parentheses. Degrees of freedom in brackets. Symbols * (**) [***] represent 0.1 (0.05) [0.01] of significance level, respectively.

This approach informs which option to choose between the difference and system GMM models. Based on this rule-of-thumb, the estimated coefficient of the POLS model

with lagged dependent variable acts as a ceiling, while the estimated coefficient of the fixed-effects model with lagged dependent variable acts as a floor. If the estimated coefficient of the lagged dependent variable under any of the two difference GMM models—i.e., regardless of whether the researcher follows either one-step or two-step procedure—is strictly below the floor (i.e., the estimated coefficient of the lagged dependent variable under the fixed-effects model with lagged dependent variable), then the system GMM should be adopted. Otherwise, the optimal dynamic panel data model that must be chosen is the difference GMM. The results exposed in Table A2 demonstrate that the estimated coefficient associated with the lagged dependent variable under both difference GMM models is strictly below the estimated coefficient associated with the fixed-effects model with lagged dependent variable (i.e., either -0.056 or -0.056 are lower than 0.264), which implies that the dynamic panel data model that should be adopted is the system GMM model.

Table A2. Decision on which dynamic panel data model to adopt based on Bond et al. (2001)'s rule.

Covariate	POLS with LDV	FE with LDV	One-Step Difference GMM		Two-Step Difference GMM	
L_{t-1}	0.457 *** (0.007)	0.264 *** (0.020)	-0.056 (0.347)		-0.040 (0.353)	
W	-0.004 *** (0.005)	-0.095 *** (0.017)	-0.119 (0.232)		-0.103 (0.229)	
X	-0.017 ** (0.003)	-0.021 ** (0.010)	-0.448 (0.450)		-0.490 (0.422)	
M	-0.028 *** (0.003)	-0.036 *** (0.009)	0.480 (0.478)		0.526 (0.460)	
Q	0.532 *** (0.008)	0.971 *** (0.021)	0.880 *** (0.279)		0.913 *** (0.281)	
Constant	-0.962 *** (0.029)	-1.743 *** (0.090)				
AR (1) AR (2)			-1.310 -0.780		-1.520 -0.830	
Sargan Hansen			[p -value = 0.189] [p -value = 0.436]		[p -value = 0.128] [p -value = 0.407]	
[3] [3]			0.990 0.940		0.990 0.940	
Nr. of instruments			[p -value = 0.804] [p -value = 0.815]		[p -value = 0.804] [p -value = 0.815]	
Nr. groups			8		8	
			1162		1162	

Note: Robust standard errors in parentheses. Degrees of freedom in brackets. Symbols (**) [***] represent (0.05) [0.01] of significance level, respectively. Instruments for first difference equation clarified in footnote 4 of the main text. Accordingly, the present analysis considers five external instruments. On the one hand, 2013- and 2016-year dummies correspond to external instruments based on the justification that ATP released market guidelines precisely in these years aimed at improving the performance of PTAI companies. On the other hand, the other three external instruments correspond to dummy variables representative of own-capital realisation, education degree of the founder(s) and/or administrator(s) of the firm and geographical location of the firm (i.e., JC, Educ, and Cluster).

Table A3 clarifies estimated coefficients under the one-step and two-step system GMM models. One should emphasize that the empirical performance of both system GMM models is satisfactory and robust. The test of second-order serial correlation AR(2) shows the absence of a second-order serial correlation problem since the AR(2) test statistic is unable to reject the null hypothesis of no second-order serial correlation, given the p -value is equal to 0.958 under the one-step system GMM model and the p -value is equal to 0.916 under the two-step system GMM model. The Hansen test applied to over-identification indicates that the null hypothesis of exogenous instruments is not rejected, given the p -value is equal to 0.459 under both one-step and two-step system GMM models. Moreover, the total number of instruments (i.e., 33) is strictly below the total number of panel groups (i.e., 1561), which means that the estimated coefficients resulting from system GMM models are valid. Nevertheless, recent studies focused on technical aspects recognize that combining an instrumental variables approach (e.g., covariates lagged in time) with the GMM method may not be adequate in some circumstances (e.g., weakly and strongly balanced panels due to missing data), which can imply serious estimation problems (Moral-Benito et al. 2019).

Common problems include the lack of significance and differences in the significance of covariates between one-step and two-step system GMM models.

Table A3. Estimated coefficient results under the optimal dynamic panel data model.

Covariate	One-Step System GMM		Two-Step SYSTEM GMM	
	Short-Run	Long-Run	Short-Run	Long-Run
L_{t-1}	0.392 *** (0.066)		0.403 *** (0.574)	
W	0.072 (0.064)	0.119 (0.101)	0.046 (0.052)	0.077 (0.086)
X	−0.026 (0.076)	−0.043 (0.123)	−0.063 (0.058)	−0.105 (0.095)
M	−0.123 * (0.074)	−0.203 * (0.117)	−0.062 (0.054)	−0.104 (0.090)
Q	0.608 *** (0.088)	1.001 *** (0.057)	0.590 *** (0.073)	0.989 *** (0.051)
Constant	−1.315 *** (0.290)		−1.155 *** (0.213)	
AR (1) AR (2)	−7.380 −0.050 [p-value = 0.000] [p-value = 0.958]		−7.500 0.100 [p-value = 0.000] [p-value = 0.916]	
Sargan Hansen [27] [27]	30.930 27.090 [p-value = 0.274] [p-value = 0.459]		30.930 27.090 [p-value = 0.274] [p-value = 0.459]	
Number of instruments	33		33	
Number of groups	1561		1561	

Note: Robust standard errors in parentheses. Degrees of freedom in brackets. Symbols * [***] represent 0.1 [0.01] of significance level, respectively. Instruments for first difference equation clarified in footnote 4 of the main text. Accordingly, the present analysis considers five external instruments. On the one hand, 2013- and 2016-year dummies correspond to external instruments based on the justification that ATP released market guidelines precisely in these years aimed at improving the performance of PTAI companies. On the other hand, the other three external instruments correspond to dummy variables representative of own capital realisation, education degree of the founder(s) and/or administrator(s) of the firm and geographical location of the firm. From a statistical point of view, all external instruments influence the vector X of covariates but are uncorrelated with the disturbance terms.

Since these sources of concern are identified in Table A3, one should move to a QML–SEM approach. The respective coefficients, which can be estimated either by maximum likelihood or QML, are presented in Table 3 of the main text. Finally, Bell and Jones (2015) justify the choice of a random effects estimator in a dynamic QML–SEM model. The authors consider that “(…) random effects can provide everything that fixed effects promises and more, as confirmed by Monte-Carlo simulations, which additionally show problems with Pluempfer and Troeger’s fixed effects Vector Decomposition method when data are unbalanced. As well as incorporating time-invariant variables, random effects models are readily extendable, with random coefficients, cross-level interactions and complex variance functions (…).” and that “(…) disregarding these extensions can produce misleading results. We argue not simply for technical solutions to endogeneity, but for the substantive importance of context/heterogeneity, modelled using random effects”.

Appendix B. Portuguese Classification of Economic Activities (CAE Rev. 3) (In Portuguese Language)

13. Fabricação de têxteis (i.e., textiles)

131. Preparação e fiação de fibras têxteis

1310. Preparação e fiação de fibras têxteis

13101. Preparação e fiação de fibras do tipo algodão

13102. Preparação e fiação de fibras do tipo lã

13103. Preparação e fiação da seda e preparação e texturização de filamentos sintéticos e artificiais

13104. Fabricação de linhas de costura

- 13105. Preparação e fiação de linho e de outras fibras têxteis'
 - 132. Tecelagem de têxteis
 - 1320. Tecelagem de têxteis
 - 13201. Tecelagem de fio do tipo algodão
 - 13202. Tecelagem de fio do tipo lã
 - 13203. Tecelagem de fio do tipo seda e de outros têxteis
 - 133. Acabamento de têxteis
 - 1330. Acabamento de têxteis
 - 13301. Branqueamento e tingimento
 - 13302. Estampagem
 - 13303. Acabamento de fios, tecidos e artigos têxteis, n.e
 - 139. Fabricação de outros têxteis
 - 1391. Fabricação de tecidos de malha
 - 13910. Fabricação de tecidos de malha
 - 1392. Fabricação de artigos têxteis confeccionados, excepto vestuário
 - 13920. Fabricação de artigos têxteis confeccionados, excepto vestuário
 - 1393. Fabricação de tapetes e carpetes
 - 13930. Fabricação de tapetes e carpetes
 - 1394. Fabricação de cordoaria e redes
 - 13941. Fabricação de cordoaria
 - 13942. Fabricação de redes
 - 1395. Fabricação de não tecidos e respectivos artigos, excepto vestuário
 - 13950. Fabricação de não tecidos e respectivos artigos, excepto vestuário
 - 1396. Fabricação de têxteis para uso técnico e industrial
 - 13961. Fabricação de passamanarias e sirgarias
 - 13962. Fabricação de têxteis para uso técnico e industrial, n.e.
 - 1399. Fabricação de outros têxteis, n.e.
 - 13991. Fabricação de bordados
 - 13992. Fabricação de rendas
 - 13993. Fabricação de outros têxteis diversos, n.e.
- 14. Indústria do vestuário (i.e., apparel)**
- 141. Confecção de artigos de vestuário, excepto artigos de peles com pêlo
 - 1411. Confecção de vestuário em couro
 - 14110. Confecção de vestuário em couro
 - 1412. Confecção de vestuário de trabalho
 - 14120. Confecção de vestuário de trabalho
 - 1413. Confecção de outro vestuário exterior
 - 14131. Confecção de outro vestuário exterior em série
 - 14132. Confecção de outro vestuário exterior por medida
 - 14133. Actividades de acabamento de artigos de vestuário
 - 1414. Confecção de vestuário interior
 - 14140. Confecção de vestuário interior
 - 1419. Confecção de outros artigos e acessórios de vestuário
 - 14190. Confecção de outros artigos e acessórios de vestuário
 - 142. Fabricação de artigos de peles com pêlo
 - 1420. Fabricação de artigos de peles com pêlo
 - 14200. Fabricação de artigos de peles com pêlo
 - 143. Fabricação de artigos de malha
 - 1431. Fabricação de meias e similares de malha
 - 14310. Fabricação de meias e similares de malha
 - 1439. Fabricação de outro vestuário de malha
 - 14390. Fabricação de outro vestuário de malha

Appendix C. Extensive Literature Review

Appendix C.1. General Effects of the 2005 International Trade's Liberalisation on Employment

Both the USA and European manufacturing industries have experienced a decline in operational activities since the late 1990s. After the finalisation of the international trade liberalisation process in 2005, TAIs from developed countries have been suffering profound reforms throughout the entire value chain (Dziuba and Jabłońska 2017). These readjustments were predominantly caused by pressures from intense global competition, low-cost manufacturing in developing countries and retail restructuring (Nelson Hodges and Karpova 2006). The main impact was felt by the labour factor due to the sharp decline of employment in activities related to textiles and apparel (Oh and Suh 2003). To reflect on this point, researchers either analyse the industry as a whole (Franklin 1995; Mittelhauser 1997; Taplin 1999; Gereffi 2000) or present case studies to emphasize specific events (Rocha 2001; Norris 2003).

Overall, effects on employment have a twofold interpretation. On the one hand, specialists tend to assess negative consequences by highlighting that a considerable number of production facilities may be closed, and a wave of layoffs and dismissals may be identified in an attempt to ensure the industry's consolidation (Zingraff 1991). These events frequently promote negative externalities over the region where foreclosure occurs (Hodges and Lentz 2010; Hodges 2013; Hodges and Frank 2013, 2014). A negative impact may also prevail on the reputation of the industry, especially in cases holding “(. . .) a degree of resentment, though not necessarily directed at their former employer, about losing jobs to overseas companies and even supplying these companies with the plant's own equipment (. . .)” (Hodges and Lentz 2010, p. 36). On the other hand, experts emphasize that restructuring TAIs constitutes the opportunity to change the nature of this industry and respective economic and social impacts on local communities (Tyler 2003).

Within the macroeconomics spectrum, Oh and Suh (2003) propose concrete strategic actions to ensure that TAI in the USA recovers its preponderance in international markets. Considering that the globalised nature of TAI requires to be capable of dealing with cultural differences and diverse perspectives on a multinational scale, Hodges et al. (2011) develop a project aimed at creating learning modules based on real-world industry issues to boost competences among TAI professionals. Despite improving the global competence of participants, the authors emphasize that further testing is mandatory.

In the microeconomics field, Hodges and Karpova (2008), as well as Hodges and Link (2017), emphasize that the continuity of outsourcing practices may require some degree of impression management (e.g., invest in the local community through actions of corporate social responsibility). Wyatt (2019) considers that onshoring is a key step to revolutionize TAI in the USA. This approach contrasts with the offshoring logic of developing countries, which is predominantly based on low wages and reduced quality in a context of mass production. Clarke-Sather and Cobb (2019) reveal that the TAI's onshoring is possible and it can be profitable due to the use of endogenous resources at the local level, namely the ability of human resources on absorbing technical capabilities and know-how to ensure the development of value-added products, which can boost new employment opportunities in developed countries.

Appendix C.2. Role of the International Trade on Employment

While it is clear that past contributions provide information on expected impacts and future opportunities, little is known about the identification of factors affecting the trajectory of employment in TAIs in the context of globalisation. Although widely accepted the decline of less qualified employment in developed countries in the post-liberalisation era, hiring new and highly qualified human resources has also been verified. Consequently, doubts can prevail on whether the net effect on employment is positive, and which determinants have a significant effect on the final outcome. Unsurprisingly, experts explicitly recognize that “much more research is needed in order to understand what twenty-first century industry

dynamics mean not just for the macro-level picture (. . .), but for the micro-level picture of everyday life in former mill towns” (Hodges and Lentz 2010, p. 36).

By restricting the focus on the PTAI, the primary goal of this study is to evaluate the effect of international trade activities on employment devoted to textiles and apparel. From a theoretical point of view, the HOS framework holds a valuable insight on this domain of knowledge. When trade barriers are alleviated, the import substitute (export) sector contracts (expands) such that employment in the former (later) sector declines (increases), respectively. Hence, changes in international trade imply a redistribution of employment between import substitute and export sectors, which suggests that changes in international trade can promote allocative efficiency in the labour factor (Mussa 1978). Several attempts have been developed in the academic mainstream to evaluate the impact of international trade on employment. From a historical point of view, two predominant methodologies have been used: factor content and growth accounting (Greenaway et al. 1999). Under the former, experts estimate the level of employment considered mandatory to produce a given number of exports or, alternatively, that must be displaced due to the increase in a given number of imports (Wood 1991; Baldwin 1995; Krugman et al. 1995). Alternatively, changes in employment are decomposed into domestic demand, trade and productivity elements. These are assumed to have independent nature, which is a consideration subject to criticism (Caves et al. 1993; Messerlin 1995; Feenstra and Hanson 1996). Furthermore, the literature focused on linking employment and export orientation frequently relies on the *learning by exporting* hypothesis, which refers to the mechanism whereby employment level may either increase or decrease after the entry in foreign markets (Wadho et al. 2019). In general, studies use data from innovation surveys to show the impact of exports on the level of human resources devoted to innovative activities (Löf and Heshmati 2002; Löf et al. 2004).

Lastly, environmental factors related to international trade (e.g., imposition of geographical restrictions, strategic location of firms) and the degree of exposure to international markets could also affect employment. Accordingly, the sensitivity of employment to exports and imports is expected to be low (high) if adjustments to the trade expansion occur gradually (abruptly), respectively. In fact, Greenaway et al. (1999) clarify that the main message of this strand of research is that increased imports (exports) are associated with employment reductions (increases), respectively.

Appendix C.3. Role of Firm-Specific Characteristics on Employment

The impact of international trade dynamics on employment may be more difficult to assess once considering firm-specific factors such as the type of innovative products (Antonucci and Pianta 2002; Bogliacino and Pianta 2010), vertical and horizontal differentiation measures applied to innovation processes (Roper 1997; Yasuda 2005) and the qualification of human resources (Ciccone and Papaioannou 2009). Moreover, a strand of literature also identifies reverse causation between firm growth and exports when focusing on capital factor attributes of innovation (e.g., product innovation) based on self-selection arguments (i.e., most innovative products are the ones exported by firms) given that successful innovations improve firm productivity, which turns out to hold the ability to self-select the foreign markets with a higher WTP for improved products (Lachenmaier and Wößmann 2006). Consequently, it can be hypothesised that firm-specific characteristics affect employment dynamics (Wadho and Chaudhry 2018).

From a historical point of view, the attention dedicated by experts to firm-specific characteristics emerges from the seminal contribution of Gibrat (1931), where the author claims that firm employment growth is unpredictable and, ultimately, constitutes a random phenomenon. Differently, Lucas (1978) and Jovanovic (1982) show that firm employment growth results from a non-arbitrary learning process. Their assumption is that prospective entrepreneurs do not have perfect information on their own efficiency level after market entry occur. However, the process of discovery becomes a common knowledge once firms start competing against rivals. Accordingly, the more (less) efficient a firm is, the more

(less) likely are adjustments in the scale of operations, thus, increasing (decreasing) its size, which can ultimately lead to a scenario of market dominance (exit), respectively.

Indeed, [Audretsch \(1995\)](#) and [Teruel-Carrizosa \(2010\)](#) clarify that the firm size may be a relevant factor on explaining employment trends, particularly in industries characterised by increasing economies of scale given that small firms bear multiple cost disadvantages compared to larger competitors and due to their need to grow more rapidly to reach the minimum efficient scale.

Mutatis mutandis, similar reasoning is applied to the firm age. [Evans \(1987\)](#) demonstrates that the learning process is inversely related to the maturity of firms: young firms exhibit higher growth rates than older firms, which justifies higher workforce needs. Unsurprisingly, negative size-growth and age-growth relationships are currently viewed as stylised facts ([Coad 2009](#)).

Appendix C.4. Past Contributions Focused on Evaluating Determinants of Employment in the TAI

To the best of our knowledge, [Hodges and Link \(2017\)](#) is the study closest to ours. In their empirical analysis applied to 84 TAI companies operating across different EU countries, the authors try to find determinants of employment by considering the following covariates: a dummy variable capturing whether the firm is founded or not in 100% by family own resources, a dummy variable materialising gender ownership (i.e., female vs. male), a representative variable of the number of education years of the primary founder, and country-specific binary variables applied to Portugal, France and Greece. Interestingly, all covariates exhibit a significant and negative effect on the dependent variable with the exception of the representative dummy variables of Portugal and Greece, which reinforces the importance of the present study. Besides revealing that businesses with imminently family nature and characterised by female leadership where the founder is highly educated are likely to reduce employment, the authors also suggest that more research is needed as well as improvements such as the inclusion of covariates capable of representing additional characteristics of founders and the social network established with peers ([Leyden and Link 2015](#)).

Appendix C.5. Employment Defined in a Broad Sense vs. the Penetration of Green Employment

More than in any other historical period, recent literature emphasises the necessity to identify trending niches rather than focusing on employment defined in a broad sense. Currently, specialists warn for the importance of moving forward with the Green Jobs Initiative, which emerged from a partnership between the United Nations Environment Program (UNEP), the International Trade Union Confederation (ITUC), the International Organisation of Employers (IOE) and the International Labor Organisation (ILO) in 2008. The first report on Green Jobs Initiative defines *green jobs* as any decent labour activity that contributes to maintain and restore the quality of the environment by reducing energy consumption and raw materials, minimising pollution and waste, protecting ecosystems and enabling companies and communities to adapt to climate changes ([UNEP 2008](#)). Since then, several studies have tried to assess the ability of green jobs to reduce negative effects on these domains. As claimed in [EC \(2022\)](#), green labour activities should decrease the consumption of energy, raw materials and water by implementing efficient strategies aimed at:

- Decarbonising the economy and decreasing greenhouse gas emissions;
- Minimising waste and pollution; and
- Protecting ecosystems and biodiversity.

Historically, scholars disagree on the existence of a singular way to define green ([Bowen et al. 2018](#)). Since different jobs can have differentiated impacts on the environment, and decarbonisation is a process that occurs gradually, the concept is neither viewed as a finalised construct nor interpreted with a precise meaning ([Staneff-Puica et al. 2022](#)). Moreover, despite the green idiosyncrasy has gained preponderance in recent years, approaches to define green jobs differ among published studies and regions analysed ([Sulich](#)

and Rutkowska 2020). Unsurprisingly, the lack of a widely accepted definition for green employment raises several issues, such as the need to create guidelines to define it properly.

Van der Ree (2019) considers that, from a classification standpoint, some studies, such as Darmandieu et al. (2022), view green jobs as a process, moderator, mediator or input variable (i.e., jobs that generate environmentally concerned goods and services such as clean transport and solar water heating systems). Other studies, like Sulich and Sołoducho-Pelc (2022), extrapolate green jobs as the target or final output that national economies pretend to reach.

Stanef-Puica et al. (2022) claims that, from a substantive or normative point of view, some studies, such as Arnedo et al. (2021), follow a top-down approach to define green jobs (i.e., they depart from centralised governmental policies to consider industries, sectors or economic activities directly relevant to influence decarbonisation patterns). Other studies, such as Unay-Gailhard and Bojnec (2019), accommodate a bottom-up principle to define green jobs (i.e., they depart from local community contexts to consider industries, sectors or economic activities that indirectly influence the effectiveness of decarbonisation).

In turn, from a formal or methodological point of view, some studies, such as Bassi and Guidolin (2021), introduce a dichotomous variable to determine whether a given unit of observation is green or not. Other studies, such as Vona et al. (2019), introduce relative measures (e.g., ratio between hours dedicated to green activities and total working hours) to determine whether a given unit of observation is green or not.

Given the lack of consensus in the mainstream, recent reviews developed by Yong et al. (2019), Sołoducho-Pelc and Sulich (2022) and Stanef-Puica et al. (2022) are important to systematize key ideas, identify points of harmony among specialists, and classify the existing literature focused on green jobs. A first point of agreement is observable in Rutkowska and Sulich (2020), which consider that green collar workers include individuals who practice a profession encompassing sustainable development principles. Studies falling into this category can be either quantitative or qualitative: while the quantitative approach requires to conceive econometric models, the qualitative approach describes green jobs in terms of mandatory skills to execute specific tasks (Sulich and Sołoducho-Pelc 2022). It is also accepted among the scientific community that green jobs boost the creation of a new management framework, which relies on the need to be interconnected with eco-efficient technologies of the future and requires to use resources more efficiently to reduce the environmental footprint (Rutkowska and Sulich 2020). Moreover, Sulich and Zema (2018) propose a measurable definition of green jobs based on balanced, durable and sustainable development to show that the green jobs concept can be much wider than just a qualitative description of an organisation's strategy. In this sense, EC (2022) defines green jobs as those that directly deal with information, technologies and materials to preserve and restore the environmental quality, which demands specialised skills, knowledge, training and experience. A final point of unanimity stems from the compilation of findings in recent applied empirical studies, whose main idea being disseminated is that green jobs are here to stay and tend to become a common knowledge.

Using data on 13,117 SMEs from the Flash Eurobarometer 2017, Darmandieu et al. (2022) analyse whether circularity in production processes generates a reduction in firms' production costs and expose conditions that determine the intensity of such a reduction, while considering eco-innovativeness (i.e., investments dedicated to the adequate implementation of circular practices in current production processes) and green jobs (i.e., human resources dedicated to circular practices) as moderators. Results of ordered probit models confirm that a higher level of circularity in processes achieved by European SMEs is related to a reduction in their production costs. While eco-innovativeness positively influences this relation, the relative share of green jobs decreases the impact of circularity on production costs. Intuitively, this study shows that green jobs are characterised by a skill premium. Focusing on the creation of green jobs in the circular economy, Sulich and Sołoducho-Pelc (2022) analyse the environmental goods and services sector (EGSS) among 28 EU countries between 2009 and 2019 by considering a multiple linear regression model.

They conclude that the satisfaction of United Nation's SDGs supports the circular economy and increases the proliferation of green jobs. Additionally, [Arnedo et al. \(2021\)](#) provide a normative reflection that nests the European Green Deal framework and the Spanish recovery plan, with a special attention given to actual opportunities for green jobs in the Spanish tourism market. In a nutshell, this study provides valuable information to improve Spain's economic recovery in the post-pandemic period through a coordination between elements of the quadruple helix model (i.e., universities, policymakers, business managers, entrepreneurs and civil society).

The penetration of green employment in EU SMEs is analysed in [Bassi and Guidolin \(2021\)](#), as well as the role of green jobs and skills for the implementation of circular economy practices based on data from the Eurobarometer survey. Determinants of green behaviour was completed by the analysis of heterogeneity across firms and within countries with a multilevel latent class model. Their main finding is that the absence of green jobs is strongly correlated to the probability of adopting resource-efficiency practices. Notwithstanding, perceiving the need of environmental skills has a positive effect on the intention to implement actions in the future. In [Song et al. \(2021\)](#), the authors match green job supply and demand using a big data analysis of online job market recruiting services in South Korea between 2009 and 2020. The authors conclude that green job creation should reflect timing, regional and sectoral needs. Moreover, their study demonstrates that matching green jobs is likely to reduce environmental harm and unemployment, thereby fostering social welfare gains. [García Vaquero et al. \(2021\)](#) estimate the number of new green jobs expected to be created as a consequence from the implementation of the Recovery Plan in Spain, assess which skills are needed to develop such new green jobs and provide a valuable source of information to coordinate sectoral plans by policymakers responsible for the economy, green activities and education.

Furthermore, [Iddagoda et al. \(2021\)](#) examine logical reasons that govern *greenwashing* work–life balance based on a cross-sectional study in the banking industry with a sample of 170 managerial employees. Results support evidence that employee engagement significantly mediates the relation between work–life balance and job performance. [Moreno-Mondejar et al. \(2021\)](#) focus on the association between the probability and the number of green jobs at the firm level, and circular economy strategies related to the 4R (i.e., reduce, reuse, recycle and redesign) approach implemented by companies located in the EU. Considering a zero-inflated negative binomial model, results confirm that firms involved in the circular economy have a higher probability to generate green jobs. When each action is considered in isolation, results indicate that energy efficiency and waste minimisation have a positive impact on the number of green jobs, while recycling practices are insignificant. Reusing materials and redesign influence positively the probability of proliferating green employment. Regarding firm resources and capabilities, larger firms are more likely to belong to the group of firms that dispose green vacancies. Firms' technological capabilities, openness to external sources of knowledge and green specialisation are crucial not only for the probability, but also for ensuring a higher number of green jobs.

In [Vesere et al. \(2021\)](#), it is highlighted the importance of green enterprises, green jobs and civil society to ensure separate collection and waste recycling. [Sulich and Rutkowska \(2020\)](#) confirm that approximately 15% of young people find their first employment in the green jobs sector in Poland and Belgium. Similar outcome is observed in [Ismail et al. \(2019\)](#). The main message emerging from both studies is that giving additional emphasis to build a green-based economy provides new employment opportunities for young workers.

[Lee and van der Heijden \(2019\)](#) examine the impact of HEIs on the growth of green jobs in the 100 largest USA metropolitan regions. Their results suggest that enhanced HEIs and sustainability-oriented research centres have a positive impact on green job development in urban regions. With data extracted from Eurobarometer Flash 456–SMEs, resource efficiency and green markets, representative for the 28 EU Member States that comprise interviews held between 11–26 September 2017. Moreover, [Luca et al. \(2019\)](#) apply a multilevel logistic regression to show a higher likelihood that manufacturing companies

with over 50 employees use staff for green jobs. The authors also confirm the statistical significance of an index that represents the efficient use of resources to implement several green measures on the creation of new green jobs. In turn, [Unay-Gailhard and Bojnec \(2019\)](#) combine top-down and bottom-up principles to analyse the green economy experience of Slovenia, where agri-environmental measures (AEM) play a key role in the country's rural development. Results show that AEM adoption of green policy measures by very large dairy and field crop farms significantly increases total labour use. The authors also present mandatory steps to ensure the creation of green jobs for rural youth in the primary sector.

In a qualitative analysis (i.e., semi-structured interviews with local representatives) focused on two Italian regions, [Battaglia et al. \(2018\)](#) reflect on the link between new green jobs and new green business models based on their industrial reconversion through the implementation of environmental agreements. The study reveals positive factors (i.e., stakeholder cooperation and industry-university interaction) and barriers (i.e., bureaucracy and lack of infrastructural investment). Similar work is observed in [Otieno and Ochieng \(2018\)](#) focusing on northern provinces of South Africa after collecting data on 24 wastewater treatment plants in 11 municipalities. Their results show that most respondents disseminate non-green jobs given that only 13.5% of employees report to be involved in the provision of green jobs. [Otieno and Ochieng \(2018\)](#) consider that this structural barrier stems from the shortage and lack of training in green skills. Nevertheless, they warn that several opportunities for the creation of green jobs exist, including the implementation of renewable energy sources (RES), reuse of treated effluent, and processing of waste sludge into compost.

In the political spectrum, [Hess et al. \(2018\)](#) analyse the USA during the Obama administration years of 2007–2013, where energy transition policies were framed as green jobs and green economic development to overcome opposing views from alternative stakeholders and conservative politicians. The study demonstrates that media reports at national and global levels are less positive than those at local and state-government levels. At the global level, the study reports stronger negative impacts in countries where conservative parties that control the national government are opposed to sustainability development practices.

In [Vona et al. \(2019\)](#), the authors consider the task approach of [Acemoglu and Autor \(2011\)](#) to approximate the time a worker spends in green activities, so as to provide how green employment has evolved between 2006 and 2014 in the USA. Their research reveals that green employment is pro-cyclical, highly skilled, leads to a 4% wage premium and is geographically concentrated. Green employment is positively correlated with local green subsidies within the American Recovery and Reinvestment Act, local green knowledge, and resilience to the great recession. Additionally, they find evidence that one additional green job is associated with 4.2 new local jobs in non-tradable non-green activities, while being related to 2.2 new local jobs in the 2008–2009 crisis period.

Regarding the supply of electricity based on RES, [Dell'Anna \(2021\)](#) inspects the potential for investment realisation in Italy through the application of input-output analysis. Results confirm that RES investments can have a positive impact occupational performance. [Martínez-Cruz and Núñez \(2021\)](#) apply a discrete choice experiment to a sample of urban residents in Aguascalientes, Mexico to identify determinants of household electricity expenditures. By choosing between four types of electricity contracts (i.e., a status quo option confronted against three alternatives described in terms of the type of RES, namely percentage of RES in the current electricity mix, new jobs in the RES sector and percentage increase in self-reported bimonthly electricity bill), respondents report a positive WTP for RES in the current electricity mix, and a higher WTP for solar energy compared to biomass energy.

Notes

- ¹ Apparent labour productivity is defined as the industry's gross value added divided by the total number of workers (INE 2019).
- ² Prior research on employment determinants in the TAI has highlighted other critical factors implicit to ownership structure and capital realisation, in particular by providing evidence that family-owned businesses, female leadership, and highly educated founders are associated with reduced employment levels. Technological innovation is also recognised as a key driver for sustainable transitions in the TAI. However, developing countries face significant barriers due to outdated facilities and insufficient advanced production technologies. Virtanen et al. (2019) emphasises the urgent need for updated infrastructure and cutting-edge technologies to facilitate waste recycling. Sandvik and Stubbs (2019) note that limited technological capabilities create challenges in material separation, hindering sustainable transitions. Additionally, innovation appears as a key determinant of a company's ability to sustain and grow employment. Firms with greater innovation capabilities and a more qualified workforce are better positioned to thrive in an increasingly competitive global market. They are often able to upgrade both production and distribution processes through the adoption of new production technologies and information communication technologies (Yang et al. 2023). This transition toward innovation is driven not only by internal stakeholders within the organisation but also by external pressures such as environmental regulations (Bressanelli et al. 2022). For these firms, collaboration among stakeholders is critical for implementing innovative solutions that enhance efficiency and reduce costs (Li et al. 2020). However, this shift is not without challenges. The sustainable transition in the TAI faces several entry barriers, including financial limitations, organisational constraints, and technological issues (Kazancoglu et al. 2021). Overcoming these concerns requires a coordinated effort to integrate new technologies and align them with both environmental and economic goals, which implicitly suggests that own capital realisation—the ground for such investment efforts—is likely to affect employment dynamics.
- ³ A note should be given to the fact that Ramsey RESET is not really a test for omitted variables that are missing from the deterministic component of the regression model, but rather a test for evaluating the functional form. If any polynomial term (e.g., an explanatory variable raised to the square) is statistically significant, the test essentially confirms that a linear specification is rejected such that $y = f(x)$ must not take a linear form. Moreover, failure to reject the null hypothesis does not necessarily mean that there is no omitted variable bias. Indeed, this last point constitutes the reason for having a theoretical model—Equation (3)—as the background for supporting the specification adopted in the multiple linear regression model.
- ⁴ The analysis uses five external instruments, which should be correlated with the vector of initial covariates, but uncorrelated with the disturbance terms of the original model. On the one hand, dummy variables covering years 2013 and 2016 are introduced as external instruments based on the justification that ATP released market guidelines precisely in these years to improve the performance of PTAI companies. On the other hand, the other three external instruments correspond to dummy variables representative of yes-or-no own capital realisation, education degree of founder(s) and/or administrator(s) and geographical location of the firm.
- ⁵ Focusing on the universe of firms endowed with green technologies, the *green international trade paradox* describes the empirical observation that green capital acquisition increases with a higher degree of external dependence, acting as an announced expropriation for the domestic country, inducing it to accelerate imports—instead of exports—to increase its green capital endowment. Conversely, green capital acquisition decreases with increasing exports, as firms already hold the ability to drain their products to international markets without the need to incur additional productive investment in green technologies.
- ⁶ By definition, the initial sample may be segmented to obtain a second sample, which consists of a subsample of the initial one. Censoring occurs when limit observations belong to the final sample such that only the value of the dependent variable is censored, while truncation holds when some observations do not belong to the final sample. The censored sample is representative of the entire population because all observations of the initial sample are included in the final sample, while the truncated sample is representative of a subsample of the population because some observations of the initial sample are not included in the final sample. Therefore, truncation has greater loss of information than censoring (e.g., due to missing observations). In the context of this study, a censored sample is the case where it is observed PTAI firms that do not provide green employment such that their jobs are recorded as zero. A truncated sample corresponds to the case where nothing is observed about the subsample of PTAI firms that do not provide green employment. Hence, this case study is representative of censoring from below, which implies that the truncated sample has fewer observations and higher mean than the censored sample. In the Tobit model, which assumes a normal distribution for disturbance terms just like the probit model, estimated coefficients associated with the set of explanatory variables are restricted to be the same in both steps.
- ⁷ From a theoretical point of view, in corner solution applications, an important limitation of the standard Tobit model is that a single mechanism determines the choice between $y = 0$ vs. $y > 0$ and the amount of y given $y > 0$. In particular, one has that $\partial P(y > 0|x)/\partial x_j$ and $\partial E(y|x, y > 0)/\partial x_j$ have the same sign. Alternatives to the censored Tobit regression model have been suggested to allow the initial decision of $y > 0$ vs. $y = 0$ to be separate from the decision of how much y given that $y > 0$. These are often called hurdle models or two-tiered models, where the hurdle or first tier is whether or not to choose positive y .
- ⁸ Based on Tobit outcomes, effects of exports and imports on the creation of green employment are unlikely to be equal between the subsample of firms that provide green jobs and the entire universe of PTAI companies. If that is the case, then any ongoing research becomes less interested in evaluating the discrete choice on whether PTAI companies create green employment or not (i.e., there is a redundant need to focus on the discrete choice associated with the second step of the second stage of the ensemble approach). Instead, any ongoing research becomes predominantly interested in capturing the initial effect of PTAI firms'

international trade volume on the probability of adopting green capital (i.e., the discrete choice associated with the first-step of the second stage of the ensemble approach) to then immediately analyse the continuous decision regarding the effect of PTAI firms' international trade volume on the amount of green employment effectively created (i.e., the focus is expected to rely only on the continuous choice associated with the second-step of the second stage of the ensemble approach), thereby justifying the transition from the Tobit model to Cragg's model.

- 9 In this sense, asymmetric impacts of exports and imports on green employment between the subsample of firms that provide green jobs and the entire universe of PTAI companies identified after confronting OLS and Tobit results reinforce the need to relax the restrictive assumption of the Tobit regression model that discrete and continuous decisions must be the same because one may be interested in assessing either only one specific impact (e.g., imports) or both international trade effects on the creation of green jobs.
- 10 Intuitively, Cragg's model assumes that disturbance terms of the regression model that represents the discrete decision are independent from disturbance terms of the regression model that represents the continuous decision conditional on observed covariates x , either in the full distributional sense or in the conditional mean sense. The class of models from which Heckman's selection model is an integrant part (also known as. type II Tobit models) explicitly allows for a correlation between the willingness to provide green jobs and the number of green jobs after conditioning on covariates. Generally, we might expect some common unobserved factors to affect both the participation decision (i.e., whether s_i is 0 or 1) and the degree of participation (i.e., how large Green Employment _{i} is). In the context of this study, unobserved factors that affect the decision to provide or not green jobs might be correlated with factors that affect the number of green jobs effectively provided.
- 11 This requires, on the one hand, increase the dynamism in the perspective of the worker or, equivalently, the flexibility in the perspective of the firm by allowing an increase in the time available for dismissal with just cause based on the lack of QoS provided by the employee in the performance of technical duties and introducing a variable component in the remuneration of green workers based on their productivity. And, on the other hand, increase the security in the perspective of the worker or, equivalently, the rigidity in the perspective of the firm through the imposition of a maximum time from the moment of receipt of a green subsidy until the creation of a green job and by establishing a minimum period of maintenance of a green job in the company after a green subsidy being received.

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