European Commission

Social Situation Monitor

Green specialization and labour market outcomes in EU manufacturing industries

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Directorate-General for Employment, Social Affairs & Inclusion

Directorate F— Employment and Social Governance, Analysis

Unit F4 — Analysis and Statistics

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Green specialization and labour market outcomes in EU manufacturing industries

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December 2022

Manuscript completed in December 2022.

Luxembourg: Publications Office of the European Union, 2022

PDF ISBN 978-92-76-60139-5 ISSN 2811-6798 doi:10.2767/93467 KE-CF-22-008-EN-N

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INTRODUCTION

Governments worldwide put a large bet on using the post-pandemic fiscal stimulus to tackle both the climate and the socio-economic crises. In both the EU and the US, an important goal of the so-called green fiscal push –a coherent set of subsidies and taxes aimed at accelerating the transition towards a low-carbon economy—is to create new employment opportunities for workers displaced by pandemic and by the induced substitution of brown productions with greener ones (Agrawala et al., 2020; Chen et al., 2020). The European Green Deal Plan (EGD) of the EU mobilizes an unprecedented funding, at least for the EU past budgets, to ease the transition towards a clean, sustainable and smart economy, focusing on renewable energy and storage technologies, new grid and transport infrastructures, material reuse and the circular economy. Besides job creation, reducing emissions (especially of Greenhouse Gases) and rebuilding the obsolete EU infrastructures, one of the main goals of the EGD is to ensure a "just" green transition across countries and workers. However, in so far as green productions are concentrated in rich and technological advanced countries, the benefits of a green transition may exacerbate existing inequalities across countries and regions.

It goes without saying that the size of the aggregate labour market impact of a green fiscal plan depends on several factors acting at various level of aggregation. At the macroeconomic level, the effectiveness of spending multipliers varies depending on phases of the business cycle, the elasticity of the labour supplies and the response of the monetary authority if inflation goes up (for a survey see, Chodorow-Reich, 2019). In an open economy, employment gains rest on the capacity of a country to be engaged in the production of green equipment, whose demand will grow fast in international markets. To understand this induced competitiveness effects, which is reminiscent of the so-called Porter hypothesis (a positive effect of environmental policies on competitiveness, Porter and van der Linde, 1995), and their consequences for job creation, it is necessary to conduct analysis at a finer, sectoral level of aggregation as the expansion of the green economy induced by a green push is unbalanced across sectors (Popp et al., 2021).

The goal of this paper is to shed some light on some structural characteristics that shape the employment effects of an expansion of the demand (either global or local) of green goods in the European manufacturing sectors over more than a decade. Since ex-post evaluations of the EU green stimulus could be conducted only in the future, we use data on green production to approximate a green demand push. In particular, green production is measured using the PRODCOM dataset, extended to incorporate a credible definition of green products for 4-digit manufacturing sectors (Bontadini and Vona, 2020). Our research thus complements ex-ante policy evaluation of the impact of European Green Deal plan by looking at specific part of the aggregated effect: that on tradable manufacturing productions. In other words, our analysis isolates the direct effect of a green demand push on manufacturing employment.

As discussed in details in Section 2, focusing on a push to green manufacturing is important to assess the differential effect of the EGD across countries and regions. To give an intuition, imagine that a country has to decide how to allocate the EGD funds. A part of such funds will go to non-tradable sectors, such as construction, grid infrastructure, waste management, etc. The employment impact of such spending will be similar across EU countries, conditional on the differences in the level of public sector efficiency of the country. Then, there will be another part of the green funding that is spent in tradable goods, such as wind turbines, electric vehicles and batteries. Such part is going to have different labour market effects across countries depending on the capacity of a country to absorb a demand shocks for green goods[1]. That is: depending on the country's level of technological expertise in green goods. Our analysis sheds light on this direct effect of increasing importance of green manufacturing on employment.

Note that this direct impact is particularly important for policymakers for three reasons. First, industrial policies such as green subsidies under the EGD seek to establish or reinforce a comparative advantage in sectors that are expected to grow fast in the future. Second and related to this, if the technological expertise needed to be engaged in green production is highly persistent (as shown in the literature on green innovation, Popp et al., 2010), a green demand push will create large cross-country and cross-regional distributional effects that will exacerbate existing inequalities. Third, a job created in a tradable sector has often a multiplier effect on the rest of the local economy, as shown in the literature on local multiplier (e.g., Moretti, 2010, Faggio and Overman, 2014). Green local multipliers appear large (Vona et al., 2019), at least relative to the multiplier associated with other types of spending. This implies that countries able to capture a larger fraction of the global demand for green goods will also create positive feedback on the local economy in terms of indirect job creation. Overall, this brief discussion motivates our focus on the employment effect of going green in tradable and high-tech industries.

Our main findings are the following. First, at the purely descriptive level, green production is highly concentrated in a few sectors that are also doing relatively better in terms of wages and employment. Green sectors are usually high-tech, so this is supporting the EU strategy of specializing in a knowledge-based economy. Second, when controlling for other drivers of labour market dynamics in our econometric analysis, we still find that employment grows faster in potentially green sectors, both at the extensive (i.e. between potentially green and non-green sectors) and the intensive margin (i.e., intensifying green production within potentially green sectors). Both margins are quantitatively important over the twelve years considered in our analysis: the employment gain is 13.2% at the extensive margin and between 2.1%-4.2% at the intensive margin in correspondence to a 10.2% long-term increase in the share of green production. These results contrast with the sharp decline of employment in polluting sectors over the same periods. Third, when controlling for other drivers of labour market dynamics in our econometric analysis, the green wage premium disappears. This evidence seems to suggest that, within the same 4-digit sector, green and non-green activities, require a similar set of skills so the average wages are also

[1] This capacity in turn depends on several factors related to the country's technological capabilities, skills, institutional features and trade openness.

similar. . However, we find a green wage premium that emerges for green exporters, but such premium remains smaller than the wage premium for non-green exporters within potentially green sectors. Finally, green exporting has an additional, although modest, effect on job creation on top of the effect of domestic green production. This implies that the labour market benefits of going green are not necessarily associated with international competitiveness and are still small in terms of wage gains.

This work is organized in seven sections. Section 2 briefly reviews the existing literature on the labour market adjustment to environmental policies and green technological change. Section 3 presents the data used to analyse the relationship between green production and labour market outcomes. Section 4 discusses descriptive evidence based on these data. Section 5 moves to present to econometric specification that is used to rigorously test the labour market adjustment of greening manufacturing. Section 6 contains the main results of the paper, while Section 7 briefly concludes.

RELATED LITERATURE

Our empirical analysis sheds light on the direct effect of a green demand push on labour demand and wages. A “green demand push” can have several, not mutually exclusive, sources: a regulatory push such as a green spending plan, an independent effort of the private sector or an increase in the global demand for green goods. To understand this direct effect, it is useful to take stock from the literature on the employment effect of environmental regulation (Berman and Bui, 2001; Morgenstern et al., 2002; Yamazaki, 2017; Hille and Mobius, 2019) and decompose the total effect of a push in the demand for green goods on employment into three components:

i. An effect through the induced change in total output;
ii. A technological effect lined to the labour intensity of green productions;
iii. A local multiplier effect to other sectors, including input-output linkages.

The first and the second effects are the direct, partial equilibrium effects of a green demand push on labour demand that are estimated in our reduced-form specification (Berman and Bui, 2001).[2] The effect through changes in the level of total output captures the extent to which the demand of green products expands relative to that of non-green products. Such difference may either reflect a faster growth of green demand in foreign country or a domestic push, often triggered by policy (Popp et al., 2021). Obviously, the first effect is expected to be positive if the green-related shock is positive, i.e. green demand grows faster than non-green demand or there is a green policy push, and negative if the green-

[2] The literature on the US Clean Air Act usually estimates employment effects at the level of local labour markets, thus it can capture both a direct effect and some general equilibrium effects. However, most of the focus has been on the direct employment effect on polluting industries (e.g., Greenstone, 2002; Walker, 2011; Kahn and Mansur, 2013).

related shock is negative, i.e. a more stringent environmental policy increases compliance cost. Because green products are newer and more innovative than non-green products, theory on the employment effect of product innovation predicts a positive differential effect of going green on total demand and thus labour demand (Harrison et al., 2014).

The second effect is purely technological: it compares the difference in labour intensity (and thus of production factor mix) between green and non-green productions. Identifying this effect is the core contribution of our paper, so it is worth pausing to discuss this contribution in relation to previous literature.

A first strand of literature on eco-innovation has investigated the employment effect of adopting a green innovation at the firm-level using the Community Innovation Survey (CIS) to build measures of green innovation (e.g., Pfeiffer and Rennings, 2001; Rennings et al., 2004; Horbach and Rennings, 2013; Gagliardi et al., 2016). This literature focuses on the job creation capacity of green gazelles and the effect of different types of eco-innovation,[3] but it is not directly answering the question of difference in labour intensity of green and non-green productions.[4] More closely related to our contribution, a few papers directly exploit information on green products and services for the US (Becker and Shadbegian, 2009; Elliott and Lindley, 2017) or for Europe (Cecere and Mazzanti, 2017). Similar to us, the two sector-level studies for the US exploit data of a special survey seeking to estimate the size of the sectoral environmental production. However, because these surveys were not repeated for several years, the authors can only estimate the labour intensity of green productions in a cross-section. The main finding of these two studies is that there are no notable differences between green and non-green plants (or industries) in terms of employment and wages. A positive expected effect of green production on green job creation is instead found by Cecere and Mazzanti (2017) for a cross-section of small and medium-sized enterprises. Differently from the US studies, the author uses a self-reported dummy to capture the firm's engagement in green good and service production. Our analysis complements and extends these studies by looking at a longer time period (12 years) and an objective (as based on official statistics)

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[3] End-of-pipe solutions tend to have a negative effect on employment, while cleaner production methods a positive one (Pfeiffer and Rennings, 2001; Rennings et al., 2004). Recently, Horbach and Remmer (2020) highlight the positive association between employment growth and innovation related to the circular economy, while Kunapatarawong and Martínez-Ros (2016) find a stronger positive association in pollution industries. Some studies find also that green innovation leads to additional jobs created relative to non-green innovation (e.g., Gagliardi et al., 2016), but other studies find no differential effects of green innovation (Licht and Peters, 2013, 2014). Recent firm-level evidence from the Netherlands shows that the association between green innovation and labour demand is concentrated among green jobs (Elliott et al., 2021) defined using the task-approach proposed by Vona et al. (2018, 2019).

[4] Two types of estimation issues typically emerge in using the Community Innovation Survey to retrieve an effect that is representative of the entire population. First, the association between employment and green innovation is conditional on survival, therefore it is not representative of the average firm in the sector as, for instance, it does not capture the job destruction effects on green innovators that do not succeed. Second, in the CIS survey, innovation is measured with a self-reported assessment of the internal innovation capacity that is likely to be overstated.

and time-varying measure of green production. In addition, the panel dimension of our data allows to study both short- and long-term effects, thus controlling for unobserved heterogeneity across country-sector pairs. Finally, the richness of our data allows to purge our estimate from other mega-trends affecting employment dynamics in manufacturing including automation (e.g., Acemoglu and Restrepo, 2018) and exposure to international trade (e.g., Autor et al., 2013).

A second strand of literature assesses the degree of substitutability between energy (a dirty input), on the one hand, and labour and capital, on the other (see, e.g., Koetse et al., 2008; Labandeira et al., 2017). The main conclusion of this literature is that capital is a better substitute for energy than labour, thus an increase in energy prices (a proxy of environmental policy stringency) reduces the demand of both energy and labour (Deschenes, 2011; Kahn and Mansur, 2013; Marin and Vona, 2020), especially in the long-run (Marin and Vona, 2020). In other words, going green –in the sense of reducing energy consumption—will induce changes in the input mix that eventually favours capital over labour. In line with this literature, we estimate a labour demand equation conditional on output. However, we focus on green enabling sectors, i.e. sectors producing goods and technologies that help reduce environmental impacts also in other sectors, while these papers concentrate on energy intensive sectors. Another important insight emerging from this literature is that the time horizon is critical to evaluate the effect of going green on job creation. A positive short-term effect can be more than offset in the long-run by a process of induced innovation that is ultimately labour saving. For this reason, we estimate the relationship between employment and the green product share using a relatively long panel and retrieving both the short and the long-run effects.

Finally, skill shortage can undermine the effort of a company to increase green productions, or force companies to choose a sub-optimal input mix. Horbach (2014) finds that firms in the German environmental sector are considerably more likely to experience difficulties in hiring new employees than the rest of the economy. These labour shortages are reported by both high-tech green sectors (environmental R&D) and by low-tech sector (waste disposal and recycling). Vona et al. (2018) show that engineering and technical skills, usually in short supply due to the fierce competition for these skills, are essential to operate and develop green technologies (see also Marin and Vona, 2019). Walker (2013) finds that the transitional costs of a job change induced by environmental regulation are significantly larger when workers change sector and, thus, arguably face more relevant skill mismatches. We conclude that the *observed* labour intensity of green production may differ from the *unobserved* optimal labour intensity due to skill shortages. Importantly, this is a possible source of endogeneity if the skill mismatches preventing an optimal adjustment are an omitted variable that is also correlated with the unobserved component of employment growth.

Going back to the decomposition of the aggregated employment effect, the third effect concerns localized general equilibrium effects associated with sectoral spillovers and input-output linkages induced by an expansion of green production. While identifying these effects require finer level of geographical aggregation in the data, it is important to discuss in which direction it may operate using insights from previous research. To illustrate the effect, recall that our paper estimates the impact of expanding the production of green tradable goods in manufacturing. This remark is important as tradable productions have a positive multiplier effect on non-tradable service productions and thus employment (Moretti, 2010). This positive effect, in turn, emerges from localized externalities; for instance, new workers in the tradable industries spend money in the local economy. Multiplier effects are usually magnified by input-output linkages both within the manufacturing sector (i.e. steel production needed for wind turbines) and outside it (i.e. consulting services). Vona et al. (2019) find that the multiplier effect of green employment is quite large relative to the multipliers generated by other activities including fossil fuel extraction (Marchand, 2012). Horbach and Janser (2016) find that, for German firms, industry agglomeration (i.e. the concentration of similar industrial activities in the same region) is more strongly associated with employment growth in the environmental sector than in other sectors.

Taking stock from these findings, we can conclude that the aggregated (general equilibrium) effect of moving to green production is probably larger than the direct (partial equilibrium) effect estimated through the econometric model presented in Section 4. In the current context of green fiscal push, this conclusion is likely to hold although, in a general setup, it may not.[5] An implication of this argument is that countries or regions with a comparative advantage in green production are likely to benefits disproportionally from a green fiscal stimulus compared to countries without such advantage. In the evaluation of green fiscal stimulus of the Obama administration, Popp et al. (2021) show indeed that regions with the appropriate green competences benefit disproportionately in terms of job creation relative to regions without such competences.

Finally, the wage rate is an important variable to assess the quality of jobs created in green production. Moretti (2010) notes that, because multiplier effects mostly operates through pecuniary externalities, larger multiplier are associated with the creation of high-skilled, high-paid jobs. Vona et al. (2019) ascribe the large multiplier of green employment to the higher skills and thus wages of green workers. In the empirical analysis, we tackle this issue by estimating the impact of going green also on wages. In doing so, we explore an issue where the literature is still scant and mostly descriptive. Antoni et al. (2015) find a statistically significant wage premium, conditional on workers' characteristics, for renewable energy workers in Germany, which is mostly concentrated in construction and engineering services. A positive wage premium for low-skilled green workers is also found by Vona et al. (2019) for the US, but again low-skilled green jobs are mainly in construction and thus it is difficult to compare these results with the green wage premium estimated here for manufacturing workers. In contrast with these findings, both Becker and Shadbegian (2009) and Elliott and Lindley (2017) find no statistically significant differences in wages between green and non-green producers. Note that the results of Becker and Shadbegian

[5] Indeed, this conclusion is misleading without a careful comparison of the opportunity cost of going green. Since green production is concentrated in high-tech sectors, job creation associated with going green may be associated with job destruction in other high-tech activities within the same sector, mitigating or even reversing the local multiplier effect.

(2009) pertain only within-manufacturing comparisons and thus are those more closely related to our work. Overall, we do not have clear guidance from previous literature regarding the wage rate paid in green productions relative to non-green productions in the same sector.

DATA

To carry out our analysis of the labour market impact of going green, we assemble a dataset with time-varying information on production, green production share, employment, annual wages, investment in capital equipment, exports and imports, across European countries and industries. While all the data sources used in this project are publicly available, they require some extensive harmonisation and we are not aware of other papers combining them to study labour market and industrial dynamics. In this section, we discuss each data source in turn, providing details on how we compute our key variables. In Table 1, we provide an overview of each variable and its source.

TABLE 1: VARIABLES CONSIDERED IN THE ANALYSIS

Variable	Description	Source
Total output	Total sold production across EU countries and 4-digit NACE industries.	PRODCOM – Eurostat. See Bontadini and Vona (2020) for further details on harmonisation of PRODCOM codes.
Green share of production	Sold production of green products as a share of total output across EU countries and 4-digit NACE industries.	PRODCOM – Eurostat. See Bontadini and Vona (2020) for further details on harmonisation of PRODCOM codes and the building of the list of green goods.
Employment	Number of employees in full time equivalent (FTE).	Structure of Business Survey (SB) – Eurostat.
Average wage	Total wage bill divided by employees in FTE.	Structure of Business Survey (SB) – Eurostat.
Investment intensity	Total investment as a share of value added.	Structure of Business Survey (SB) – Eurostat.
Green export and revealed comparative advantage (RCA).	Balassa index for revealed comparative advantage, using export, of green products and total.	UNCOMTRADE.
Green import penetration.	Import of green products as a share of total output.	UNCOMTRADE.
Low-wage import penetration	Import of all products from non-OECD countries.	UNCOMTRADE.

Notes: all data are available at the country-by-sector (4-digit NACE classification) level. The total number of manufacturing sectors included is 228. The countries included are 18.

Definition of what is green

A novel aspect to this study is the use of a measure of green production that varies by country, year and detailed (4-digit) manufacturing industries. This presents both conceptual and empirical issues. While we refer the interested reader to Bontadini and Vona (2020) for a detailed discussion, we tackle here the most salient aspects. Indeed, it is not obvious to define what is a green good. The literature has developed two approaches. On the one hand, a researcher can look at the pollution that results from production of a good (the process approach). On the other hand, a researcher can consider as green a good depending on the potential for beneficial effects on the environment (the output approach).[6]

While the first approach is intuitive and considers greenness as the inverse of the pollution embodied in the production of good, due to data limitation it is hard to obtain a measure of pollution content of production processes that varies across countries, years and sectors (Sato, 2014). The literature has made some progress by relying on input-output methodology, but the resulting data sets are only available for a limited number of countries and years with sectors identified at a high level of aggregation (Rodrigues et al., 2018). The output approach looks at products' potential for beneficial effects on the environment, both by reducing the harmful impacts of production processes and through environmental remediation activities. Empirically speaking, this approach presents the significant advantage of relying on information readily available in the descriptions of product classifications at a highly disaggregated level. As a result of this, the approach has been preferred to compile lists of green goods (Steenblik, 2005; Sauvage, 2014) and it is the one we also use in order to have a highly granular measure of green production. Obviously, the interpretation of our results depends on the particular definition of green production that we have chosen. The output-based definition is the preferred one to look at the creation of a comparative advantage in green production and at its consequences for competitiveness and labour market outcomes (Becker and Shadbegian, 2009).

Data on green production

The other main issue to conduct an analysis on green production issue is to identify the appropriate source of data providing time-varying information on green good production across industries and countries. Bontadini and Vona (2020) show that the PRODCOM dataset compiled by Eurostat can be a useful tool in devising such measures. The dataset contains information on sold production for manufactured goods identified with 8-digits codes, covering on average, 4,288 single products per year.[7] What makes the PRODCOM data particularly suited to compute industry-level measures of green production is that the very detailed product codes are nested within the NACE industrial classification, with the first 4 out of 8 digits of each PRODCOM code corresponding to a NACE code. This makes it possible to univocally allocate information from PRODCOM codes to a NACE industry.

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[6] To further illustrate this difference, we can think of batteries that can be an effective method to store energy and remedy the intermittent nature of many renewable sources and that would therefore qualify as a green good under the output approach. However, the production of batteries themselves involves high level of emissions, therefore under the process approach they would rank as quite polluting.

[7] It should be noted that PRODCOM codes are reviewed yearly and as such the number of products varies from year to year, for this reason we report here the average number of product 8-digit product codes contained between 1995-2015. In order to obtain a measure of green production that accounts for the annual reviews of PRODCOM codes we have followed Van Beveren, Bernard and Vandenbussche (2012), as detailed in Bontadini and Vona (2020).

Our approach relies on the classification developed in Bontadini and Vona (2020) to identify green products and compute green production as a share of total sold production across European countries and industries. In doing so, our analysis uses a measure of greenness that varies across countries, industries, and years and that is computed with the most fine-grained data available for European countries for the period 1995-2015.[8] We have deflated the data using the price indexes provided by the 2017 release of EUKLEMS, to ensure comparability of sold production values over time.

Second, PRODCOM data only include manufacturing goods, and we cannot therefore include service industries into our analysis, which means we cannot include into our analysis the effect of green production on green jobs in service industries such as construction and waste management activities (Popp et al. 2021).

Data on wages and employment

Our second source of data is the Structure of Business Survey (SBS) from Eurostat, which collects information on businesses' structural characteristics for non-financial firms in the market sector at 4 digit NACE industries, for the period 1998-2018. We use this dataset to compute our two key dependent variables in our analysis. Employment, which is computed as the number of full time equivalent (FTE henceforth) employees and average wages are computed by dividing the total wage bill by the number of employees in full time equivalent.

Wages play a two-fold role in our analysis; on the one hand they are a variable of interest, whose relationship with green production is at the core of our research. On the other hand, they are also an important control variable when we look at employment, as we discuss in detail in section 5. However, for wages to be used as control we need to obtain a proxy for labour cost that is less related to endogenous factors affecting both employment and wages, such as the skill composition.

Some limitations in our data should be borne in mind. First and foremost, our data only provides information on employment across industries and countries, with no breakdown across occupational categories. This is largely because publicly available data from Eurostat do not provide this information at the necessary level of disaggregation[9]; this has two implications. First, we cannot look at employment, or wage, outcomes within country-industries, even though there is likely a significant degree of heterogeneity of labour demand for different occupations. Second, we cannot use occupations to identify

[8] PRODCOM data are updated yearly by Eurostat, when we obtained access to the microdata these were available up until 2015.

[9] Eurostat does provide information on employment and wages across occupations, identified through ISCO codes, in the Labour Force Survey (LFS) and the Structure of Earning Survey (SES). However, industry breakdown for both these sources is only available at 1 or 2 digits of NACE, while our analysis looks at much more granular industries identified at 4 digits and only 1 or 2 ISCO codes that would make for a very coarse occupation classification. For these reasons we prefer to use SBS data which provides information on employment and wages across 4-digit NACE industries, while leaving the issue of occupational categories for further research.

green jobs, which would have complemented our measure of green share of production. This also applies to wages, because while our exogenous measure of wages does rely on occupation level information, the industrial component of this is derived from data on the US.

Data on capital equipment, import and export flows

The association between green production and employment (or wages) should be depurated from other mega-trends affecting labour market outcomes. Among these trends, as discussed in the introduction, automation and trade exposure from low-wage countries are the most important.

Concerning a proxy for automation investments, the SBS dataset does not contain direct information on investment in robots or ICT technologies. It does however provide information on gross investment in the broader asset "machinery and equipment" which includes transport equipment, other machinery equipment and, crucially, ICT equipment.[10] The SBS data also provides a broader measure of capital intensity, i.e. the investment rate which is captured as investment as a share of total value added. We resolve to use this measure as our main proxy of investment embodying new technologies because of its broader coverage, internal coherence with the SBS dataset and because it uses value added – which is not readily available to us – as a rescaling variable for investment, providing a more accurate picture of the rate of investment in each country-industry in our sample.[11]

Concerning exposure to international competition, we are also interested in import and export of green goods as well as in the impact of the raise of emerging economies on production and employment in Europe. The relationship between employment and green production can be affected by importing certain components for green goods from a foreign country. In general, import substitution should decrease total employment in the EU industry affected, but it is unclear if it is going to change the relationship between employment and green production. International competition can also be a source of job creation since green production may be associated with exporting (Becker and Shadbegian 2009). As the competitiveness of a given industry in the global market is likely to lead to increase productivity and operating margins, exporting firms are expected to pay higher wages (Bernard and Jensen, 1997; Schank et al., 2007 and Amiti and Davis, 2012), while the effect in terms of job creation is ambiguous.

[10] In more technical terms, the SBS data provides information on gross investment in machinery and equipment, corresponding to asset N11M in the ESA 2010, containing N113, N110 and N1132, which correspond to "Transport equipment", "Other machinery equipment and weapon" and "ICT equipment", respectively. Alternative source such as EUKLEMS offer finer asset breakdown, but a much coarser industry aggregation making these unsuitable for our study.

[11] We have also performed our analysis using investment in machinery and equipment as a share of total output in the industry as a reasonable proxy of investment embodying new technologies. The results remain unchanged and are available upon request.

We obtain information on import of green products, as well as import from low-wage countries[12], and exports from UNCOMTRADE data. This dataset is a repository of international trade statistics on a bilateral basis that is constantly updated, we have retrieved information on import and exports for pairs of countries for the years 1995-2015. Products are identified with 6-digit codes from the Harmonised System (HS), which we map into PRODCOM codes, making it possible to compute measures of import penetration – i.e. imports as a share of output – and exports of green products across countries and industries.

Proxy of competitiveness in green production

Using UNCOMTRADE data we are also able to compute measures that capture a country's competitiveness in green export in each industry. This is important because countries that have built a comparative advantage in the global market for green goods are likely to reap the bulk of the benefits from an expansion of green production induced by a policy push. Again, it is not clear whether these benefits will translate into gains for workers. To obtain our measure of competitiveness in green export we use a modified version of Balassa index, which is a well-established measure for revealed comparative advantage:

$$RCA^{g}{}_{ij} = \frac{y_{ij}^{g} \Big/ \sum_j y_{ij}}{\sum_i y_{ij}^{g} \Big/ \sum_j \sum_i y_{ij}}, \qquad (1)$$

where y_{ij}^{g} (resp. y_{ij}) is export of green goods (resp. all goods) from country i and industry j. Furthermore, the literature has pointed out that Balassa indexes can be hard to interpret because of the asymmetry of the index that is bound between 0 and infinity, which means that econometric analysis may give too much weight to values above one (Dalum et al., 1998; Cole et al., 2005; Yu et al., 2009). To deal with this issue we follow Laursen (1998) and make the Balassa indexes symmetrical around 0 and bounded between -1 and +1: $SRCA^{g}_{ij} = (RCA^{g}_{ij} - 1)/(RCA^{g}_{ij} + 1)$.

Finally, while the mapping between PRODCOM codes and HS codes is possible, it is not a one-to-one match and HS codes do not cover all manufacturing industries in the NACE classification, as a result the data on green production and green trade are not fully consistent and some minor discrepancies may persist.[13]

[12] We consider non-OECD countries to be low-wage.

[13] Notably, the repair and installation of equipment (NACE 33) that is, strictly speaking, a service activity and as such does not generate any physical cross-border flows.

The key issue here is that PRODCOM codes vary yearly and in order to make meaningful comparisons over time we followed Van Beveren, Bernard and Vandenbussche (2012) methodology, obtaining time-invariant PRODCOM codes.

The use of these time-invariant codes meant that the match with HS codes was not univocal. This was a challenge specifically when computing measures of green exports because some HS code may match with both green and non-green PRODCOM codes.[14] Considering an HS codes matching with both green and non-green PRODCOM as green because of the match with the green PRODCOM code may lead to seriously overestimating green export because we would have to consider the entirety of its export as green even though we know that it is likely to contain only some green products. We also know that green production is highly concentrated in few countries (Bontadini and Vona, 2020) and therefore this may lead to a geographically biased overestimation of green export and green competitiveness.
To resolve this, we have computed for all time-invariant PRODCOM codes matching with the same HS code the average share of green production across countries and years and applied this share to the export value corresponding to the HS code. In this way, we obtained a measure of green export consistent with the green shares of production of each country and year.

Our efforts in harmonising these several data have led to an integrated dataset on trade and production of green goods, employment, wages and investment in equipment across European countries and industries. Because of the challenges with each data source discussed above, in addition to some pre-existing gaps in the time series, our final data is an unbalanced panel. We have filled as many gaps as possible performing linear interpolation whenever possible and appropriate. Despite this, some missing values persist. These are due to the fact that PRODCOM data only includes most Eastern European countries from the early 2000's onwards, that there is a misalignment between the PRODCOM classification and the Harmonised System, as we've discussed above, and that the SBS data also has some missing values for certain countries and sectors. We report a full mapping of missing values across

[14] Many-to-many matches involved 13 out of the 123 HS codes that matched at least with one green time-invariant PRODCOM code. The discrepancies between HS and PRODCOM also lead to two additional issues:
First, the official crosswalk, provided by Eurostat's Reference and Management of Nomenclatures (RAMON) server, between PRODCOM and the Combined Nomenclature (Eurostat's 8-digit version of the HS), does not provide any match for certain industries, such as: finishing of textile (1330), printing of newspapers (1811), binding and related services (1814), reproduction of recorded media (1820), casting of light metals (2453), casting of other non-ferrous metals (2454), Forging, pressing, stamping and roll-forming of metal; powder metallurgy (2550), Treatment and coating of metals (2561), Machining (2562), Building of ships and floating structures (3011), repair and installation of machinery and equipment (2-digit NACE rev. 2 sector 33). This last sector is missing by default in export data because it is, strictly speaking, a service activity that does not generate any flow of physical goods that cross a border and it is therefore not recorded in trade statistics.
Second, because of the many to many matches that exist between the time invariant PRODCOM codes, the HS and the NACE classification sometimes products are not univocally allocated to the same NACE industry across production and export variables. We have strived to resolve as many of these discrepancies as possible, but some still persist in some rare cases where green production is zero, but export is not. We have replicated our results excluding these observations and they remain unchanged.

countries and years for our key variables in Table A1 in the Appendix. In order to maximise the number of complete country-industry time series, we have restricted our analysis to a sample of 18 countries over the period 2003-2015.[15]

DESCRIPTIVE EVIDENCE

We define green production by taking the "output approach" discussed above, identifying green products within industries following Bontadini and Vona (2020); it is therefore important to detail how these products are distributed across industries. Table 2 reports the average green production as a share total production, across countries for selected years for each 2-digit NACE industry. It complements this information with the pollution intensity, which we measure as greenhouse gas (GHG) intensity following Marin and Vona (2019), which allows comparing our "output approach" with the alternative "process approach".

Two key features emerge from Table 2. First and foremost, green production is extremely concentrated,[16] the four industries with the highest green share of production account for 85% of total green production. We know that this high degree of concentration is also present when we look at 4-digit industries (Bontadini and Vona, 2020).

Second, the greenest industries have very low GHG intensity, while conversely the most polluting industries have virtually no green production. This means that output and process approaches are complementary with each other and in no immediate contradiction. It also means that green industries are only marginally affected by environmental policies that aim at increasing the cost of polluting production processes that are one of the key channels through which environmental policies operate.

Once we have established some key facts at the aggregate level for green production, we turn to descriptive statistics on our 4-digit NACE data, in Table 3. The top panel looks at all industries in our data, while the bottom panel focuses on green industries, which we define as those industries that have positive green production in at least one country-year in our data.

[15] The countries we include in our analysis are: Austria, Belgium. Bulgaria, Germany, Denmark, Spain, Finland, France, UK, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Slovenia and Sweden.

[16] It is worth pointing out that we refer here to concentration in terms of distribution of green production across industries and, later on, across countries. We do not refer to concentration as the number of firms that operate in a given industry or the degree of competition within green industries.

TABLE 2 – GREEN AND POLLUTING SHARES BY 2-DIGIT NACE INDUSTRIES (SOURCE BONTADINI AND VONA, 2020)

NACE	Label	Mean green share 2005	Mean green share 2010	Mean green share 2015	Share of total green production	Absolute Change 2005-2015	Average GHG intensity
28	Manufacture of machinery and equipment n.e.c.	0.074 (0.068)	0.084 (0.083)	0.096 (0.098)	0.28	0.022	0.54
27	Manufacture of electrical equipment	0.108 (0.166)	0.103 (0.078)	0.162 (0.217)	0.22	0.054	0.30
26	Manufacture of computer, electronic and optical products	0.069 (0.06)	0.121 (0.131)	0.103 (0.076)	0.22	0.034	0.30
30	Manufacture of other transport equipment	0.281 (0.292)	0.346 (0.318)	0.38 (0.334)	0.13	0.098	0.61
33	Repair and installation of machinery and equipment	0.022 (0.031)	0.033 (0.024)	0.028 (0.026)	0.04	0.006	0.74
29	Manufacture of motor vehicles, trailers, and semi-trailers	0.002 (0.01)	0.007 (0.031)	0.003 (0.011)	0.01	0.001	0.61
31	Furniture	0 (0)	0 (0)	0 (0)	0	0	0.74
32	Other manufacturing	0 (0)	0 (0)	0 (0)	0	0	0.74
16	Products of wood, cork, straw, plaiting	0 (0)	0 (0)	0 (0)	0	0	0.88
22	Rubber and plastic products	0 (0)	0 (0)	0 (0)	0	0	0.94
13	Textiles	0 (0)	0 (0)	0 (0)	0	0	0.97
14	Wearing apparel	0 (0)	0 (0)	0 (0)	0	0	0.97
15	Leather and related products	0 (0)	0 (0)	0 (0)	0	0	0.97
17	Paper and paper products	0 (0)	0 (0)	0 (0)	0	0	1.18
18	Printing and reproduction of recorded media	0 (0)	0 (0)	0 (0)	0	0	1.18
10	Food products	0 (0)	0 (0)	0 (0)	0	0	1.45
11	Beverages	0 (0)	0 (0)	0 (0)	0	0	1.45
12	Tobacco products	0 (0)	0 (0)	0 (0)	0	0	1.45
	Polluting industries						
19	Coke and refined petroleum products	.	0 (0)	0 (0)	0	.	44.99
23	Other non-metallic mineral products	0.029 (0.029)	0.033 (0.022)	0.033 (0.026)	0.05	0.003	7.78
20	Chemicals and chemical products	0 (0)	0 (0)	0 (0)	0	0	5.11
21	Basic pharma. products, preparations	0 (0)	0 (0)	0 (0)	0	0	5.11
25	Fabricated metal products, exc. machinery	0.018 (0.018)	0.019 (0.016)	0.017 (0.014)	0.05	-0.001	4.23
24	Basic metals	0.006 (0.021)	0.007 (0.023)	0.008 (0.03)	0.01	0.002	4.23

TABLE 3 – DESCRIPTIVE STATISTICS

	Employees FTE units	Average wages (th-€)	Output (mln€)	Green share of production	Investment as a share of value added	Green import as a share of output	Low-wage import over output	Green RCA
All industries								
10th percentile	3,894	21.431	606.83	0	0.0580	0	0.003	-1
25th percentile	9,490	28.348	1,727.59	0	0.0850	0	0.014	-1
median	23,568	35.605	4,699.53	0	0.125	0	0.048	-1
75th percentile	57,437	43.552	10,891.42	0	0.185	0	0.140	-1
90th percentile	113,148	51.056	2,0641.50	0.022	0.266	0.260	0.338	0.48
Mean	53,884.78	35.692	11,380.01	0.023	0.159	0.122	0.459	-0.783
St. dev.	91,500.84	11.779	23,461.59	0.092	0.556	2.847	27.306	0.548
Obs.	38,044	37,540	43,083	43,083	40,929	43,083	39,698	43,083
Green industries								
10th percentile	10,087	26.796	1,290.66	0	0.053	0.002	0.015	-1
25th percentile	23,846	32.959	3,943.69	0	0.075	0.009	0.039	-1
median	60,680	41.333	12,085.79	0.010	0.134	0.184	0.084	0.376
75th percentile	124,463	48.902	27,727.79	0.142	0.207	0.513	0.172	0.698
90th percentile	464,929	57.108	129,282.32	0.369	0.299	1.552	0.303	0.779
Mean	122,173.37	40.775	29,204.51	0.103	0.163	0.554	0.549	-0.017
St. dev.	156,556.45	11.891	43,243.31	0.173	0.138	6.046	6.207	0.78
Obs.	3,881	3,777	4,335	4,335	4,219	4,335	4,335	4,335

Notes: Authors' elaboration on SBS, PRODCOM and UNCOMTRADE data Average wages are computed annually by dividing the country-industry wage bill by employment in full time equivalent, both measures are taken from the SBS database. Green share of production is the sold production of green goods – based on Bontadini and Vona (2020) – divided by total sold production within each country-industry, as reported in PRODCOM. RCAs are Balassa indexes, computed with UNCOMTRADE data, made symmetrical and bounded between -1 and +1, following Laursen (1998).

We find, in alignment with Table 2, a high level of skewness in the green share of production. When looking at all industries, we see that three quarters do not have any green production at all, while the 90th percentile has 0.022 as green share of production, slightly below the average share of green production (0.023). This suggests that there are very few country-industries that exhibit very high green shares of production.

When we look at only green industries the distribution is less skewed, but we still find that half of our observations have less than 0.01 as a green share of production and the average value (0.103) is well above the median.

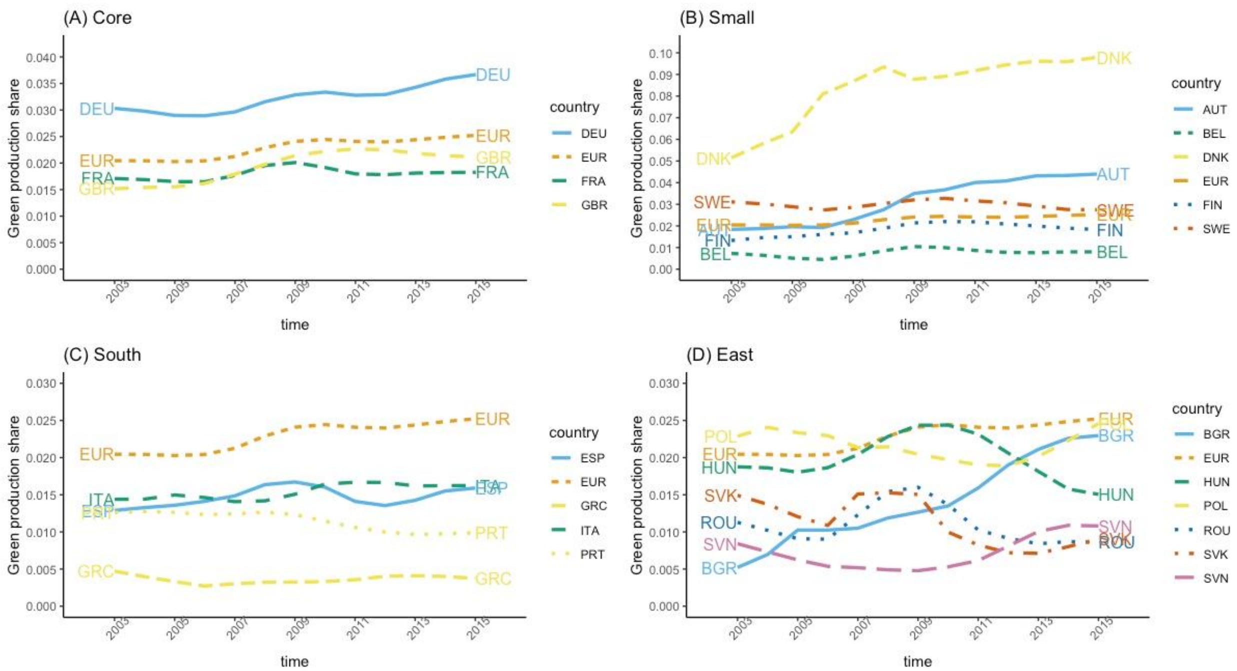
It is interesting to compare these measures of green share of production with the green RCA (revealed comparative advantage), capturing country-industries competitiveness in green export. When we look at all industries, we find a distribution similar to that of the green share production: three quarters of our observation do not export any green product, with a green RCA equal to -1. The average value of green RCA is -0.783; recall that with the symmetric Balassa index, zero is the threshold above which a country-industry is deemed to have an RCA. This means that on average industries do not have a green RCA, and in contrast only the 90th percentile have an RCA above zero (0.48). These results overall confirm the idea that green export, like green production more in general, is rather concentrated within very few country-industries.

When we turn to green industries however, we see that green RCAs are distributed in a rather different way than green production. The median value is above zero (0.376) – the same measure for green share of production is 0.01 – indicating that while half of the green country-industries in our sample have quite a small share of green production, this is enough for them to develop a green RCA. In contrast, we find that on average green country-industries do not have a green RCA (the mean value is -0.017). It therefore appears that while at least 25% of green country-industries does not export any green product at all, those that do so can achieve a green RCA even with little amounts of export.

The evidence discussed so far suggests, albeit at a rather aggregate level, that green production is quite concentrated in few industries. It is of course important to assess whether this is true also across countries and over time. We plot therefore the evolution of green shares of production across selected European countries, which we group in four broad regions, in Figure 1. The European average, weighted on production, which we include in all panel as a benchmark, fluctuates between 2% and 2.5% with all countries, with the salient exception of Denmark, remaining below 4%. These estimates are, broadly speaking, in line with previous evidence for the US economy (Elliot and Lindley, 2017 and Vona et al. 2019).

Beyond Denmark, we also detect few other countries that are consistently above the European average, i.e. Germany, Sweden and Austria. Southern European countries all rank well below the European average, with Italy and Spain showing green shares of production on a par with other large European countries such as the UK and France. Eastern European countries are also, broadly speaking, below the European average, showing however significant variation both within and across countries. Notably, Bulgaria has increased its green share of production quite rapidly, Poland remains among the greenest countries in the region[17], while Hungary appears to have reduced its share of green production quite sharply over our observed period.

FIGURE 1 – TRENDS IN GREEN SHARE OF PRODUCTION BY COUNTRY (SOURCE BONTADINI AND VONA, 2020)



Notes: Authors' elaboration on PRODCOM data. Green production share corresponds to green production divided by total output, measured in PRODCOM, i.e. sold production. EUR is the European average, weighted on production.

Overall, these findings resonate with the fact that green production is concentrated in few high-tech sectors producing mostly capital goods in which only few countries that are close to the technological frontier have successfully specialised.

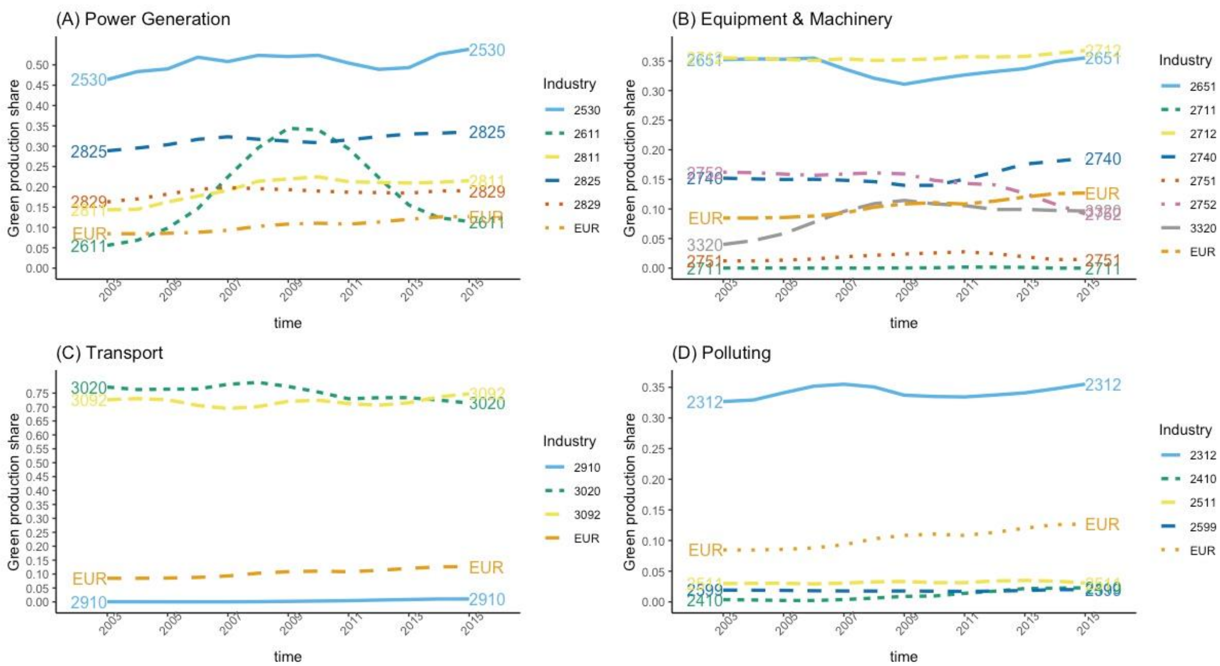
These features also help explain the quite stable patterns we find when looking at the evolution of green shares across industries in Figure 2. Green shares of production across industries are driven by the kinds of products that any given industry produces and how many of those are green. It is therefore to be expected that no huge changes in green production shares take place within the same industry. It follows

[17] This means that manufacturing production in Poland has a higher share of green products, in line with the EU average and above other Eastern European economies. It should however be borne in mind that while our methodology is not in direct contradiction with the process approach discussed above, it does not capture embodied emissions, which are likely to be significant for countries with high reliance on coal.

that the changes in green shares of production we observe at the country level, in Figure 1, are likely to be the outcome of reallocation of production across industries, rather than changes within the same industry.

The only industry that does not display a stable pattern is the manufacture of electronic components (NACE 2611). This is a particularly relevant industry in terms of green production because it includes LED lights and photovoltaic panels. The significant fluctuations in the share of green production in this industry reflects the rise and fall of Germany in the production of photovoltaic panels and the emergence of non-EU producers, notably China (Algieri, Aquino and Succurro, 2011; Sawhney and Kahn, 2012; Liu and Goldstein, 2013).

FIGURE 2 – TRENDS IN GREEN SHARE OF PRODUCTION BY INDUSTRY

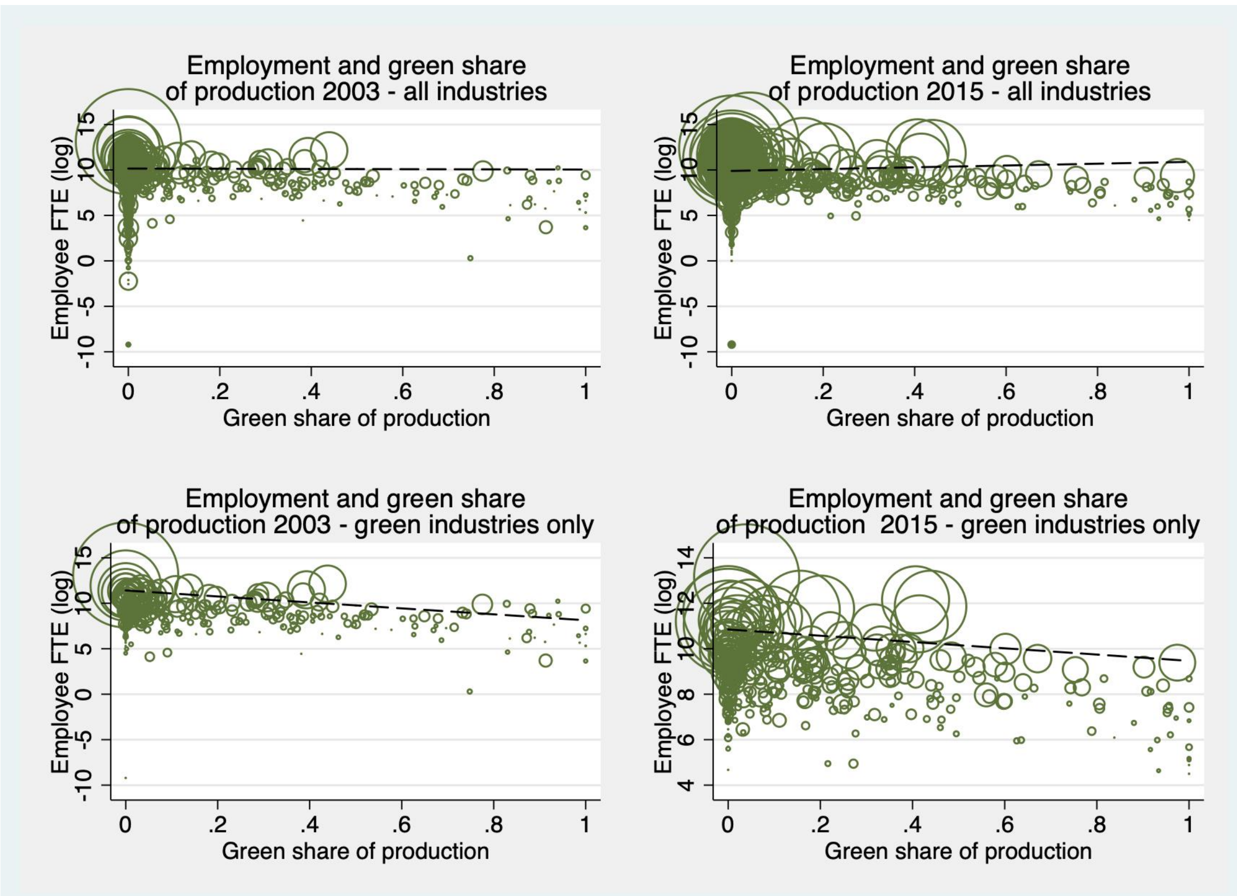


Notes: Authors' elaboration on PRODCOM data. Green production share corresponds to green production divided by total output, measured in PRODCOM, i.e. sold production. EUR is the European average, weighted on production. The industry codes correspond to Power Generation; steam generators (2530), electronic components (2611), engines and turbines (2811) other general purpose machinery (2829) – Equipment and Machinery: instruments and appliances for measuring (2651), electric motors, generators and transformers (2711), electricity distribution and control apparatus (2712), electric lighting equipment (2740), electric domestic appliances (2751), non-electric domestic appliances (2752), industrial machinery and equipment (3320). – Transport: motor vehicles (2910), railway locomotives and rolling stock (3020), bicycles (3092) – Brown industries: shaping and processing of flat glass (2312), basic iron and steel (2410), metal structures (2511) and fabricated metal products (2599).

The descriptive evidence put forward thus far focuses on the dynamic of the green share of production. Our analysis however concerns itself with the relationship between green production and labour market outcomes, specifically employment and wages.

We therefore provide some prima facie evidence on these two relationships. In Figure 3 we plot the share of green production and employment levels, weighting these on country-industries' total production, to prevent our results to be driven by small country-industries. We look both at all industries and green industries alone. Overall, we find no strong correlation between the green share of production and levels of employment, with a slightly negative slope when we look at green industries. In Figure 4, we replicate our correlation analysis looking at average wages, finding again no statistically significant correlation with the share of green production.

FIGURE 3 – CORRELATION BETWEEN GREEN SHARE OF PRODUCTION AND EMPLOYMENT



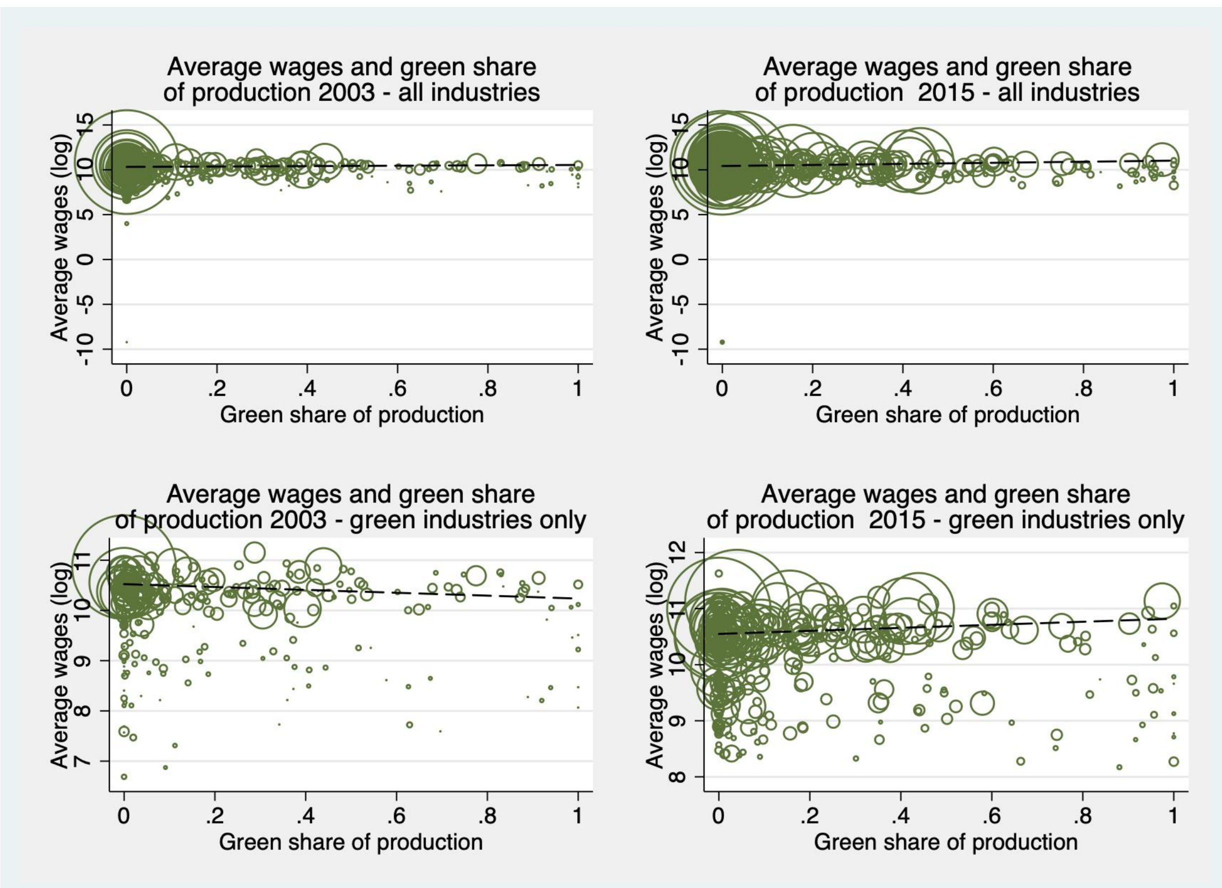
Notes: Authors' elaboration on SBS and PRODCOM data. Employment is measured as number of persons employed in full time equivalent and reported in logs. The correlations are weighted on country-industries' total output, measured in PRODCOM, i.e. sold production – depicted as the size of the circles in the figure.

This is in line with evidence put forward in the literature. Becker and Shadbegian (2009) use the 1995 Survey of Environmental Products and Services that find that on average green and non-green plants are not different from each other in terms of employment or wage and when controlling for plant-level characteristics, they find that manufacturers of green products employ fewer workers, specifically fewer production workers.

More recently, Elliot and Lindley (2017), use the US Bureau of Labor Statistics' Green Goods and Services survey to explore how production of green goods and provision of green services affects the US economy, finding no evidence that greener industries experience higher levels of employment growth, compared to non-green industries.

Our results add to this body of evidence in a twofold way. First, they rely on panel data and show that the absence of correlation between greenness and employment levels is persistent over time. Second, we provide new evidence on European countries and industries, for which data on green production and employment is harder to come by than the United States.

FIGURE 4 – CORRELATION BETWEEN GREEN SHARE OF PRODUCTION AND AVERAGE WAGES



Notes: Authors' elaboration on SBS and PRODCOM data. Average wages are computed annually by dividing the country-industry wage bill by employment in full time equivalent and reported in logs. The correlations are weighted on country-industries' total output, measured in PRODCOM, i.e. sold production.

While we find little evidence that green industries are significantly different, at least in terms of some labour market outcomes, from non-green ones, we are also interested in exploring whether they have different dynamics over time. To make a meaningful comparison it is necessary to bear in mind that green production is highly concentrated in few high-tech, capital intensity industries. As a result, it is important to have a benchmark to compare green industries against that shares some of the key characteristics of green industries. We therefore compare green and non-green industries – which we identify at 4 digits of the NACE classification – within the same 2-digit broader industrial category.

We carry this out in Figures 5 and 6, looking at the dynamics of employment and average wages, respectively. In both figures, the first panel reports the evolution of employment (wages in Figure 6) for polluting industries (as identified in Table 2), non-polluting industries and the subset of such industries that are also green[18]. Panel B looks at all 2-digit industries that contain at least one green industry and compares employment (wages in Figure 6) between 4-digit green and non-green industries.

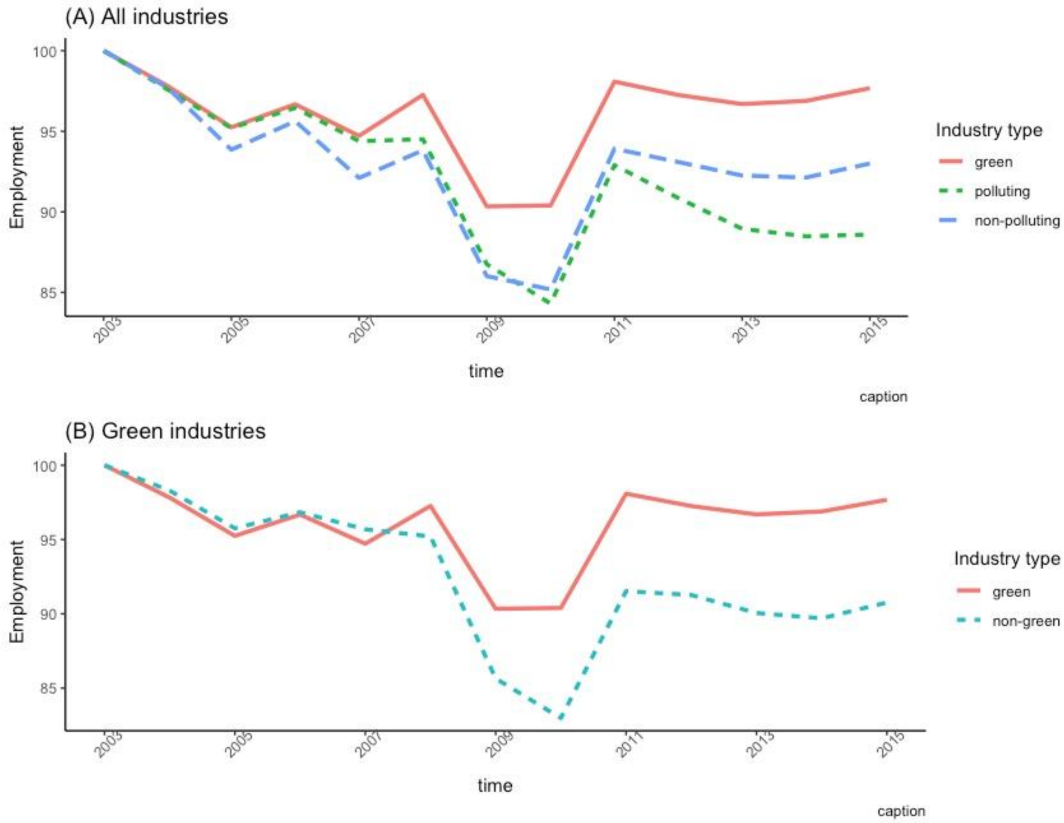
In Figure 5, we observe rather stark differences in employment dynamics that set green industries apart from others. We see across all industry groups a decline in employment during the financial crisis and a rebound from 2011 onwards. However, it is only green industries that regain pre-crisis levels of employment in Europe, while employment in non-green industries, and polluting ones in particular, starts declining again after 2011.

In Figure 6, we find again that green industries experience a stronger growth in average wages, relative to both the non-green and polluting benchmark. Overall, Figure 6 shows that wages have experienced a sharp decrease during the financial crisis, with a quicker rebound than employment; however, it is only green industries that bounce back to average wage levels higher compared to the pre-crisis period.

The evidence discussed in this section suggests that while green industries do not set themselves apart from non-green industries in terms of levels of either employment or wages, they do show a higher resilience to crisis periods and a more positive dynamics in both measures. This makes such industries particularly important in the current context of recovery from the global crisis caused by the pandemics.

[18] It is worth noting that non-polluting industries do include green ones. While it is possible that such green industries are also driving the trend in non-polluting industries, this is unlikely since green industries are only a small subset of non-polluting industries. Furthermore, our main focus here lies with the different dynamics of both polluting and green industries that exhibit quite different trends.

FIGURE 5 – TREND IN EMPLOYMENT IN POLLUTING VS. NON-POLLUTING AND GREEN VS. NON-GREEN INDUSTRIES

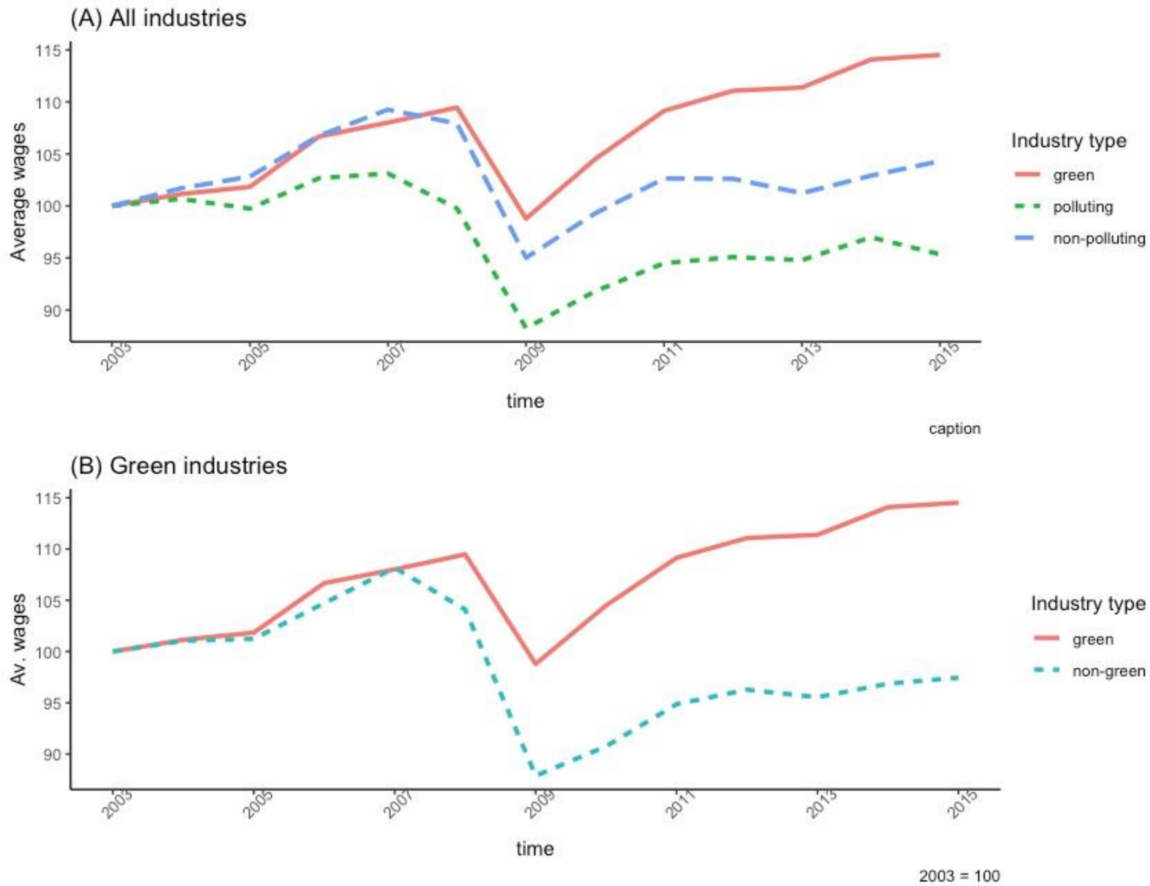


Notes: Authors' elaboration on SBS data. Panel A compares the dynamic – i.e. setting taking 2003 as base year = 100 – in employment between polluting and non-polluting industries as well as those that are not only non-polluting but also green. We define an industry as green if it contains at least one green product. Panel B compares employment dynamics of green and non-green industries among 2-digit industries that contain at least one green product.

Moreover, exploiting the *within* component of variation also appears as an interesting avenue to perform more robust empirical analysis that can properly take into account country-industries idiosyncratic characteristics in order to isolate, as much as possible, the link between the green share of production and labour market outcomes. However, we also know that most variation in terms of green shares comes from differences across industries and countries.

Two key findings emerge from the descriptive evidence presented in this section. First, green production is heavily concentrated in few industries, and countries, while the majority of economic activity has no to little potential for developing green production. Second, both employment and wages appear to follow a distinctly different trend in green industries compared to non-green industries; in contrast increases in green shares of production within the same industry show weak relationship with either higher employment or wages.

FIGURE 6 – TRENDS IN AVERAGE WAGE IN POLLUTING VS. NON-POLLUTING AND GREEN VS. NON-GREEN INDUSTRIES



Notes: Authors' elaboration on SBS data. Panel A compares the dynamic in average wages between polluting and non-polluting industries as well as those that are not only non-polluting but also green. We define an industry as green if it contains at least one green product. Panel B compares average wage dynamics of green and non-green industries among 2-digit industries that contain at least one green product. Panel C and D do the same isolating 2-digit industries that contain at least one high-green potential and marginally green product, respectively.

This has significant policy implications in terms of what strategy for increasing green production is likely to yield the most benefits in terms of employment outcomes. It means that the extensive margin, i.e. shifting countries' productive structure from non-green towards green industries, is more likely to be a successful strategy for greening European economies, while ensuring improvements in labour market outcomes, than relying on the intensive margin, i.e. increasing the share of green production of each sector without changing the overall productive structure of an economy. In light of this preliminary finding, we further investigate both the extensive and the intensive margin in our econometric analysis, to which we turn in the following sections.

EMPIRICAL FRAMEWORK

Our starting point to estimate the association between green production and employment is a classical labour demand framework (Hamermesh, 1996). In particular, we consider labour demand equations conditional on output that can be derived in a straightforward manner from a standard firm's profit maximization problem (e.g., Hijzen and Swaim, 2010). One equation refers to labour demand in green production Y^G and another of labour demand in non-green production Y^{NG}. These two equations read, respectively, as:

$$\ln\left(L_{ijt}^{G}\right) = \beta_G \ln\left(Y_{ijt}^{G}\right) + \boldsymbol{\theta_G} \boldsymbol{p}_{ijt}^{G} + \boldsymbol{\tau_G} \boldsymbol{Z}_{ijt}^{G} + \varepsilon_{ijt}^{G}, \qquad (2)$$

$$\ln\left(L_{ijt}^{NG}\right) = \beta_{NG} \ln\left(Y_{ijt}^{NG}\right) + \boldsymbol{\theta_{NG}} \boldsymbol{p}_{ijt}^{NG} + \boldsymbol{\tau_{NG}} \boldsymbol{Z}_{ijt}^{NG} + \varepsilon_{ijt}^{NG}, \qquad (3)$$

where, to be consistent with the level of aggregation of our data, indexes stay for country (*i*), the 4-digit manufacturing sector (*j*) and time (*t*). L is green (*G*) and non-green (*NG*) labour demand. That is: workers employed in green or non-green productions. **p** and $\boldsymbol{Z}$ are two vectors for, respectively, the prices and quantities of other inputs (e.g., capital, materials, etc.) in green and non-green productions. ε^G and ε^{NG} are error terms. The log-transformation allows to interpret the coefficients as elasticities or semi-elasticities.

We are interested to assess the difference in labour intensity between green and non-green productions, within the same sector. Observing all the elements of equations (2) and (3), we could construct to a statistical test of the difference between the estimated $\hat{\beta}_G$ and $\hat{\beta}_{NG}$. Unfortunately, our data do not contain detailed information on the inputs (including labour) and factor prices employed in green and non-green productions within the same sector. In other words, rather than observing $\boldsymbol{p}^k, \boldsymbol{Z}^k$ and L^k (where $k = G, NG$), we only observe $\boldsymbol{p}, \boldsymbol{Z}$ and L.

To circumvent this data constraint in the empirical estimation, we have to make two assumptions: i. the marginal effects of factor prices and other inputs' quantity on labour demand are the same in both green and non-green production within the same sector; ii. green and non-green production use the same set of (broadly defined) inputs. Under these assumptions, we model the possible differences in the labour intensity of green and non-green production by adding the share of green production over total production to a single labour demand equation, conditioning on total production. In formula, this boils down to estimating the following equation:

$$\ln\left(L_{ijt}\right) = \beta_1 \ln\left(Y_{ijt}\right) + \beta_2 s_{ijt}^{G} + \boldsymbol{\vartheta} \boldsymbol{X}_{ijt} + \nu_{ijt}, \qquad (4)$$

where ν is an error term, L_{ijt} is the 4-digit sectoral employment in full-time equivalent (FTE), Y is total production and $\boldsymbol{X}$ is a vector of controls including prices and quantities of other inputs, which is discussed below.

The key variable of interest, added to the conditional labour demand equation for the entire sectoral production, is the share of green production on total production measured using the PRODCOM dataset (Bontadini and Vona, 2020):

$$s_{ijt}^{G} = \frac{Y_{ijt}^{G}}{Y_{ijt}^{NG} + Y_{ijt}^{G}}. \qquad (5)$$

This share captures the greenness of the sector in a particular country. Recalling that we use an output based proxy of what is green, this share captures the extent to which a sector is developing and producing products that potentially reduces the harmful environmental and climate effects of production. Note that, because we cannot distinguish input quantities and prices used in green vs. non-green production, we use a single demand equation where the variable s_{ijt}^{G} captures the difference in labour intensity of green and non-green production.

In our favourite specification, we account for unobserved time-invariant characteristics of each country-sector pair (τ_{ij}) and for time shocks (μ_t) common to all country-sector by further decomposing the error term as follow: $\nu_{ijt} = \mu_t + \tau_{ij} + \gamma_{ijt}$. As a result, we estimate the following fixed effect version of equation (6):

$$\ln(L_{ijt}) = \beta_1 \ln(Y_{ijt}) + \beta_2 s_{ijt}^{G} + \boldsymbol{\vartheta X}_{ijt} + \mu_t + \tau_{ij} + \gamma_{ijt}. \qquad (6)$$

Equation (4) exploits only the within country-sector variation to estimate the relationship between labour demand and sectoral greenness.[19] Clearly, this specification mitigates but not fully solves endogeneity concerns. While we anticipate that there is no ideal solution for these concerns, we discuss and present some extensions intended to further mitigate such concerns in Section 6.2. These extensions show that endogeneity is not a big concern in our case. Conceptually, this is not surprising for two reasons. First, it is not clear to what extent, within the same 4-digit sector, the unobserved variables (i.e. quantities and prices of other inputs, skill composition) should be extremely different between green and non-green productions to create a severe estimation bias (Altonji et al., 2005). And even if such differences exist, it is not clear which is the direction of the estimation bias for $\hat{\beta}_2$. Second, it could be plausible that, within the same 4-digit sector, countries going green were doing better than other countries. Indeed, one can

[19] For the sake of comparison, we also estimate equation (6) using OLS by just including country and 2-digit sector dummies that absorb, respectively, country and sector characteristics (such as institutions and the global technological level) affecting labour market outcomes.

imagine that such countries had more resources to invest in green productions where demand is expecting to grow in the future but it is also highly uncertain. As we will see in the extensions, our long panel allows us to directly control for pre-trends in employment and wages, thus testing the extent to which pre-existing trends affect our estimation of β_2.

We are also interested in assessing the quality of the job created by moving to green products. Wage rates are the principal and most easily available proxy of job quality. Therefore, we estimate the association between the average wage w_{ijt} and the green production share at the sectoral level using equation (7):

$$\ln(w_{ijt}) = \beta_1 \ln(Y_{ijt}) + \beta_2 s_{ijt}^G + \boldsymbol{\vartheta X}_{ijt} + \mu_t + \tau_{ij} + \gamma_{ijt}, \qquad (7)$$

where we replace employment in FTE with the average wage at the sectoral level. In both equations (6) and (7) our coefficient of interest is β_2, which captures the short-term association between green production and employment (or average wage, respectively). For employment, it can be interpreted as a difference in labour intensity of green and non-green productions.[20] For wages, it can be interpreted as a green wage premium.[21] It is also worth mentioning that, in order to get a representative effect for the entire European manufacturing sector, we estimate equations (6) and (7) weighting each observations by total production.[22]

Because green production is highly concentrated in a few sectors (Bontadini and Vona, 2020), we estimate these two equations either for all manufacturing sectors or for the subset of sectors where at least one country produces green goods. In the first case, we replace the green share with a dummy equal to one for green sectors (defined as above) interacted with a time trend.[23] This modification allows us to appreciate the difference between the extensive and the intensive margin adjustment to greening production. The extensive margin captures the differential trend of sectors that are potentially green, thus highlighting the future benefits of reallocating labour from other manufacturing to green manufacturing sectors. The intensive margin captures the payoff of going green within potentially green sectors. The descriptive evidence of Section 3 suggests that the extensive margin is far more important than the intensive margin.

[20] This interpretation is in the same vein of that of Berman and Bui (2001) for the impact of environmental policies on labour demand. Indeed, such impact can be decomposed into an output effect, i.e. environmental policies can either reduce (taxes) or increase (subsidies) output, and a technological effect, i.e. green activities are more or less labour intensive than non-green activities. The coefficient β_2 (on the green share) captures the second effect, while the coefficient β_1 (on total output) partly captures the first effect.
[21] The association between the green share of production and wages also depends on the skill and demographic composition of the workforce as well as on observed institutional factors that we cannot observe in our data. We discuss these issues in details in the next section.
[22] In addition, we cluster standard errors at the country-by-sector level to account for a general form of auto-correlation of the residuals.
[23] Thus, for all sectors, the fixed-effect specification becomes: $\ln(o_{ijt}) = \beta_1 \ln(Y_{ijt}) + \beta_2 1_{j\in green} \times time + \boldsymbol{\vartheta X}_{ijt} + \mu_t + \tau_{ij} + \gamma_{ijt}$, where o_{ijt} is either wages or employment.

Concerning the controls, previous discussion highlights the importance of controlling for the sectoral output Y_{ijt}, which takes into consideration the influence of expanding size on employment growth. In labour demand theory (Hamermesh, 1996), labour demand depends on the price and the quantity of other inputs used in production. However, such prices are often unobservable (e.g. price of capital) or measured with an error (e.g., wages are an imperfect proxy of real labour cost). Consequently, we consider a vector of controls $\boldsymbol{X}_{ijt}$ that reflect the exposure to other structural shocks that affect the prices and the demand of all inputs, including labour. Such controls are chosen taking inspiration from the voluminous literature on structural transformations and labour market outcomes. As capital is the main substitute of labour, we include the investment intensity (defined as a total investment in machinery and equipment as a share of total turnover, see the data source description in Section 3) to capture capital deepening in each specific sector-country pair. Note that capital deepening does not necessarily reduce labour demand. Contrary to common sense, capital can either complement or substitute labour depending on the skills possessed by workers and the technology embodied in the machines. We also include imports of green products (defined as total import of green goods as a share of total output, see data source description in Section 3) that captures the offshoring of green production. The literature assessing the effect of offshoring on employment has found mixed results, with some studies detecting a positive effect (Hijzen and Swaim, 2007), while others find a negative impact (OECD 2007) or no effect at all (Amiti and Wei, 2005, 2009). Controlling for import penetration of green products is also important because green production takes place in high-tech sectors in which competition from foreign technology can have negative effects on employment (Gagliardi, 2019).

Finally, we also include in our favourite specification a dummy for polluting sectors (which we define following Vona and Marin (2019, see Section 3) interacted with a time trends. Polluting sectors are more exposed to environmental and climate policies, which are partly determined at the EU level. In European countries, polluting sectors also experienced a long-term historical decline that is unrelated to increasing policy stringency (Rosés and Wolf, 2018; Marin and Vona, 2019). Thus, the differential trend for polluting sector captures both these aspects.

Note that green sectors are not energy and pollution intensive (Bontadini and Vona, 2020), hence marginally affected by higher energy prices or other pollution taxes. While it is difficult to control for energy prices or other environmental policies at such level of sectoral details, we augment the vector of controls adding proxies of input costs, including energy. In such augmented specification, we include the purchase of energy input over value added as a proxy of the incidence of energy costs, which we both retrieve from SBS data. Furthermore, we include import competition from low-wage countries that reduces the bargaining power and thus the wages of low-skilled workers (e.g., Autor et al., 2014; Matano et al., 2019). We also test the robustness of our results by modifying our favourite specification by adding country-by-year dummies (a proxy of time-varying country characteristics, including country-level environmental policies) and estimating dynamic versions of the main specification. While these and other extensions are discussed in detail in Section 6.2, the beginning of the next Section presents the main results of the paper.

ECONOMETRIC RESULTS

This section contains the econometric results of empirical specifications discussed in previous section. We begin by showing the results of our favourite specification. Then, we move to the main extensions where we include proxies of labour costs to our model, and we examine the labour market effects with respect of international competitiveness in green productions.

GREEN PRODUCTION AND LABOUR MARKET OUTCOMES

Table 4 represents the benchmark of all subsequent analyses as it presents the main results of the paper. The Table is organized in two panels. In the first panel, the dependent variable is the number of full-time equivalent employees (in log). In the second panel, the dependent variable is the average wage (in log). Column 1 presents the OLS results for all sectors. This specification exploits both the data variation within a particular country-sector pair (e.g., Manufacture of computer, electronic and optical products in Germany) and that between different country-sector pairs.[24] We find that the employment level is significantly higher in sectors that are potentially green (i.e., 4-digit industries where at least one country is producing green goods). In other words, the dummy green is positive and statistically significant at conventional level, consistently with the descriptive evidence of Figure 5.

Column 2 presents the OLS results for green sector only. Again, consistently with the descriptive evidence of Figure 3, the coefficient of the green production share is far from being statistically significant at conventional level. Increasing green production within a sector that is potentially green does not add any gains in terms of employment, even conditioning on a set of intervening factors and to non-green production. Note, however, the OLS estimator used in both columns 1 and 2 conflates the within and between sector variation, hence it is difficult to understand which source of data variation drives these results.

[24] Recall that we add 2-digit sector dummies, so identification exploits variation within a 2-digit sector that includes both a green and non-green sector. In results available upon request, we show that removing these dummies does not alter our conclusions.

TABLE 4 – GREEN SHARES OF PRODUCTION, EMPLOYMENT AND WAGES, OLS AND FE RESULTS

	(1)	(2)	(3)	(4)
		Employees FTE (log)		
Green dummy * year			0.0103**	
			(0.00499)	
Green dummy	0.329***			
	(0.0902)			
Green share of production		0.0676		0.411**
		(0.267)		(0.190)
Investment rate (log)	0.137***	0.0503	0.193***	0.150
	(0.0385)	(0.0654)	(0.0510)	(0.0909)
Output (log)	0.770***	0.709***	0.164***	0.156***
	(0.0170)	(0.0662)	(0.0265)	(0.0461)
Green import penetration (log)	-0.0341**	0.0479*	0.0358	0.0343*
	(0.0163)	(0.0247)	(0.0229)	(0.0206)
Polluting dummy * year	-0.0132**	-0.0218**	-0.00786	-0.0188***
	(0.00608)	(0.00865)	(0.00506)	(0.00655)
Constant	-8.169***	37.97**	5.636*	14.63***
	(0.340)	(17.69)	(3.327)	(2.713)
Observations	38,641	3,902	38,641	3,902
R-squared	0.813	0.916	0.109	0.109
		Mean wages (log)		
Green dummy * year			0.00278	
			(0.00348)	
Green dummy	-0.0568			
	(0.0348)			
Green share of production		0.0626		-0.133
		(0.0890)		(0.127)
Investment rate (log)	0.0474***	0.0251	0.0435**	0.0413**
	(0.0122)	(0.0158)	(0.0198)	(0.0191)
Output (log)	0.0117	0.0580***	-0.0555***	-0.00899
	(0.00722)	(0.0176)	(0.0158)	(0.0214)
Green import penetration (log)	0.0205***	0.0188	0.0170	0.0317**
	(0.00609)	(0.0115)	(0.0141)	(0.0159)
Polluting dummy * year	-0.00220	-0.00825	-0.00421	-0.00663
	(0.00478)	(0.00591)	(0.00432)	(0.00613)
Constant	10.12***	25.70**	12.45***	13.33***
	(0.137)	(11.84)	(2.275)	(2.341)
Observations	38,577	3,898	38,577	3,898
R-squared	0.706	0.810	0.078	0.197
Country FE	Yes	Yes		
2-digit industry FE	Yes	Yes		
Year FE	Yes	Yes	Yes	Yes
Industries	All	Green	All	Green
Country-industry FE			Yes	Yes

*Note: Authors' elaboration on PRODCOM, SBS and UNCOMTRADE data. Panel 1 reports results for the employment in FTE, while panel 2 reports results for average wages. All results are weighted on total output. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Our favourite specifications are presented in columns 3 and 4 of panel 1. In these specifications, we add sector-country fixed effects (FE). In doing so, we use the within sector-country variation in the green production share to identify the association with employment growth. The FE estimator is also a first step to identify a causal effect because it accounts for sources of endogeneity related to time-invariant unobservable characteristics. While we still find that potentially green sectors are associated with stronger employment growth (column 3), we find that intensifying green production within potentially green sectors also pays in terms of employment gains (column 4). The latter result suggests that the insignificant effect in the OLS estimator of column 2 was driven by cross-sectional differences, not reflecting the dynamics of green production and employment that prevails within the average country-sector pair.

In both models of columns 3 and 4, the estimated associations can be interpreted as a semi-elasticity. The "extensive margin" gain of potentially green sector is 1.1% per year relative to other sectors,[25] or 13.2% over the twelve years considered in our analysis. To quantify the gain of intensifying green production (the "intensive margin"), note that the annual change in the green production share is 0.85% in the estimation sample of potentially green sector. Thus, the annual average increase in the green share adds a 0.34% annual increase of employment. If the estimated coefficient on the green share were to be interpreted as a long-term effect, the 12-years increase in the green share could account for 4.2% increase of employment. Because employment in manufacturing experienced a decline of 13.3% between 2015 and 2003 in green sectors (see also Figure 5), going green was able to offset almost 1/3 of such decline. Recall that green sectors are usually high-tech sectors that produce equipment, including energy-efficient and low-carbon ones, for other sectors. A laggard country that is not specialized in such sectors will receive a pay-off both in moving to these sectors and to green production within these sectors. Next section will show that, due to endogeneity issues, the quantification presented here is likely to be an upper bound of the true "intensive margin" effect.

Compared to previous literature, our main finding resonates with those of the firm-level literature on eco-innovation (e.g., Pfeiffer and Rennings, 2001; Rennings et al., 2004; Horbach and Rennings, 2013; Gagliardi et al., 2016). However, the reasons for such positive association between green production and employment are different given the different level of aggregation. In the firm-level literature, we do not know if such association is explained by the fact that green innovators capture the market shares of non-green innovators or by the higher probability of survival of green innovators. In our sector-level analysis, we estimate the effect net of entry, exit and within-sector reallocation. Furthermore, we carefully control for time varying characteristics such as the total production of the sector. By conditioning on total production, the estimated coefficient of the green share reflects a higher labour intensity of green productions with respect to non-green productions, within the same sector.[26]

[25] This number is derived as: $100 \times (e^{\beta_2} - 1) = 100 \times (e^{0.0102} - 1) = 1.1\%$.

[26] To lend further support to this interpretation, our data reveal a negative correlation between capital intensity and the share of green production. The correlation between capital intensity and the share of green production is -0.13 within green industries, while it is only of -0.03 (but still statistically significant) for all industries.

Still, it would be misleading to interpret the higher labour intensity of green production as a static technological parameter of a production function. On the one hand, greener sectors may be correlated with demand shocks associated with the global increase in the demand of green equipment, such as wind turbines and electric engines. The green production share is likely to be correlated with these demand shocks that are partly unobserved to the econometrician (see next section for a discussion). On the other hand, the higher labour intensity may depend upon the degree of maturity of green productions. Because green products are relatively new and innovative compared to non-green products, they are likely to be less routinized than non-green productions (Vona and Consoli, 2015; Acemoglu and Restrepo, 2018). Capital-labour complementarity thus prevails in less mature and more high-tech sectors in so far as humans retain a comparative advantage in performing new tasks.

When moving to panel 2 and consider the wage results, we do not observe any statistically significant green wage premium. The lack of association between wages and industrial greenness holds both for green sectors and for all manufacturing sectors and is consistent with the cross-sectional evidence presented for the US by Becker and Shadbegian (2009). Two, not mutually exclusive, explanations account for this finding. First, the skill composition of green and non-green productions may be quite similar within 4-digit (thus very narrow) manufacturing sector. Because the average wage within a 4-digit industry is the weighted average of the wages of different skill groups, one should expect that such average wage will be similar in green and non-green production. However, this argument does not suffice in explaining the lack of a green wage premium in the larger sample of all manufacturing sectors. Table 3 shows that, on average, green sectors pay a higher wage than non-green sector, so the lack of a green wage premium for the regression with all industries deserve further research. Second, green businesses are not more profitable than non-green businesses and, consequently, do not offer larger-than-average rents to share with workers. The latter explanation seems consistent with our data. Indeed, the correlation between the share of green production and productivity (i.e., value added per capita) is zero in our estimation samples, i.e. for both all industries and for green industries only.

It is important to briefly comment the effects of the other covariates that are relevant to contextualize our results. Recall that the log-log specification allows to interpret most of the coefficients as elasticities. First and foremost, the positive association between employment and green production (or green sector) is in contrast with the significant employment decline experienced by polluting industries. The relative employment decline of polluting industries is between 1.2% (column 3) and 2% (column 4) per year. Combining the long-term results for green potential sectors and polluting sectors (column 3), the differential employment growth is just below 30%. Second, we find that investment intensity is positively correlated with both higher wages and employment levels in all specifications. Because investments increase productivity, the positive association with wages is somehow expected. In turn, the positive association with employment lends further support to the complementarity between investments in physical and human capital in high-tech sectors, including green ones. Finally, we observe that importing green products not only does not harm European workers, but it leads to significant benefits in terms of employment and wages in most specifications. While this result may appear somewhat surprising, it is worth noting that the association between import penetration and increased competitiveness is well established in the literature (Goldberg et al., 2010; Bas and Strauss-Kahn, 2015). Intra-industry trade has recently attracted attention especially in terms of vertical integration, where most competitive firms and sectors rely heavily on global value chains for higher quality imported inputs (Fieler et al., 2018). However, it has been long known that horizontal intra-industry trade takes place among countries and industries with similar levels of income, demand and technology (Balassa, 1986; Clark and Stanley, 1999). More recently, Roy (2017), has explored the role of intra-industry trade on the environment as potential driver of both technological diffusion and economic growth that could have positive effects on both employment and the emergence of green production.

Before moving to the next section, where we investigate the results for employment in greater details, we present in Table 5 a distributed lag model that gives insights on the long-term association between the green production share and labour market outcomes within green sectors. For all variables, we add lags up to *t-2*. The sum of the estimated coefficient for the green production share captures the cumulative association with employment growth. The main takeaway of this extension is that the short- and the long-term coefficient of the green share are of similar size. For employment (column 1), the long-term association between the green share and employment is approximately 20% larger than the short-term association estimated in Table 4. For wages (column 2), we again do not find any significant effect.[27] Taking stock from these findings, we concentrate in what follows on the simpler model without lags.

[27] These results are confirmed in an alternative auto-regressive model (Table A.3 of the Appendix), where we replace the country fixed effect with the pre-sample mean of the dependent variable to mitigate the inconsistency of the FE model when the lagged dependent variable is added to the set of controls (i.e., the so-called Nickell bias, (Nickell, 1981).

TABLE 5 – GREEN SHARES OF PRODUCTION, EMPLOYMENT AND WAGES, DISTRIBUTED LAG MODEL FOR LONG TERM EFFECTS

VARIABLES	(1) Employees FTE (log)	(2) Mean wages (log)
Green share of production	0.323*	-0.128
	(0.174)	(0.0823)
Green share of production (t-1)	-0.0180	-0.0200
	(0.127)	(0.0880)
Green share of production (t-2)	0.273	-0.0463
	(0.172)	(0.182)
Investment rate (log)	0.129*	0.0199
	(0.0761)	(0.0145)
Investment rate (log) (t-1)	0.0369	0.0463***
	(0.0344)	(0.0139)
Investment rate (log) (t-2)	0.0366**	0.0153
	(0.0173)	(0.0134)
Output (log)	0.123***	-0.0265
	(0.0415)	(0.0195)
Output (log) (t-1)	0.0113	-0.00211
	(0.0240)	(0.0115)
Output (log) (t-2)	0.0430**	0.0227
	(0.0205)	(0.0161)
Green import penetration (log)	0.0253**	0.00703
	(0.0110)	(0.00919)
Green import penetration (log) (t-1)	0.00917	0.00736
	(0.0143)	(0.00803)
Green import penetration (log) (t-2)	-0.0106	0.0227**
	(0.01000)	(0.0108)
Constant	6.337***	10.48***
	(1.554)	(0.585)
Cumulative effect of green share of production	0.578	-0.1943
Observations	3,750	3,748
R-squared	0.122	0.220
Number of geosector	329	329
Country-industry FE	Yes	Yes
Year FE	Yes	Yes
Industries	Green	Green

*Note: Authors' elaboration on PRODCOM, SBS and UNCOMTRADE data. The one-year lag and current level of the green share of production are included in the specification but omitted for space's sake, the cumulative effect is the sum of the three coefficients. All results are weighted on total output. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

ROBUSTNESS ANALYSIS OF EMPLOYMENT RESULTS

This section analyses the employment results in greater details. We concentrate on employment because job creation is an important goal of the EU green deal and of green recovery packages around the world. Moreover, wage effects are not only statistically insignificant, but also are more difficult to interpret without matched employer-employee data allowing to control for firm and worker unobserved characteristics. However, the results for wages are unchanged in the extensions presented in this section and remain available upon request by the authors.

One concern for the policy relevance of our results is that the share of green production may be endogenous as correlated with unobserved components of the error terms. Endogeneity can emerge for two main reasons. First, politicians are more willing to subsidize the green economy in sectors where the employment payoff is more likely to emerge, hence helping them to be re-elected. Unfortunately, we cannot observe the size of the green subsidies for each sector and country in our sample. We only have information on subsidies at the country level, but these are of little help as they are slow moving and largely absorbed by country-sector fixed effects.[28] More in general, if the green share grows more in sectors that were already growing faster, this source of endogeneity (called reverse causality) creates a positive bias in the FE estimates of the green share. This "picking the winners" bias emerges as the main source of endogeneity also in Popp et al. (2021), who evaluate the effect of green subsidies on employment in US regions.

Second, several omitted variables can be correlated with both the error term and the green share. For instance, labour costs can be larger or smaller in greener sector depending on the skill composition of such sectors or to unobserved skill mismatches. As we discussed above, unobserved demand shocks can be positively correlated with the green share. To illustrate, sectors identified as green are capable to attract environmentally conscious customers. It is, however, unclear the direction of the estimation bias associated with these sources of endogeneity. Note that the green share exhibits no correlation with turnover, so there is no red flag for the relevance of unobserved demand shocks.

To fix multiple endogeneity issues, shift-share instruments are usually the main solution (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2021). In our setting, a researcher would need to construct global demand shocks in green production mapping them to each country-sector in the EU through the initial shares of green production. However, as it will be clear in the next section on green competitiveness and employment, exports of green products (the "shift" of such shift-share instrument) does not satisfy the exclusion restrictions, being significantly correlated with labour market outcomes conditional on the controls. In Table 6, we tackle endogeneity issues exploring the robustness of our results to the addition of controls that are correlated with the sources of endogeneity discussed above.

In the first two columns of Table 6, we add country-by-year dummies that fully absorb observable and unobservable country-level environmental policies as well as other country-level confounders, such as

[28] The common practice of interacting country-level policy with the green share is not of help in our case. Recall that the distribution of the green share is already very skewed, thus any attempt to enrich the model with interaction terms which capture heterogeneity along one specific dimension (i.e. capital intensity of the sector) or used to identify a variable that varies at the country-level (i.e. environmental policies) is deemed to fail in our setting.

changes in the ruling coalitions. As it would be expected, we observe smaller effects both at the extensive margin (column 1) and the intensive margin (column 2). The coefficient associated to the green dummy declines by about 20% (from 0.012 to 0.009), while the green share exhibits a smaller decrease of 17% (from 0.415 to 0.345).

TABLE 6 – GREEN SHARES OF PRODUCTION AND EMPLOYMENT, WITH ROBUSTNESS CHECKS

VARIABLES	(1)	(2)	(3)	(4)	(5) Employees FTE (log)	(6)	(7)	(8)	(9)
Green dummy * year	0.00947**		0.0246***			0.0121**		0.0121**	
	(0.00382)		(0.00632)			(0.00484)		(0.00480)	
Share green production		0.345**		0.198			0.374*		0.399**
		(0.156)		(0.137)			(0.195)		(0.183)
Investment rate (log)	0.169***	0.123*	0.151***	0.126*	0.156	0.207***	0.163	0.181***	0.147
	(0.0390)	(0.0712)	(0.0307)	(0.0709)	(0.101)	(0.0484)	(0.103)	(0.0449)	(0.0923)
Output (log)	0.135***	0.155***	0.113***	0.116***	0.170***	0.180***	0.138***	0.146***	0.151***
	(0.0182)	(0.0369)	(0.0197)	(0.0349)	(0.0544)	(0.0233)	(0.0481)	(0.0212)	(0.0458)
Green import pen. (log)	0.0312*	0.0300*	0.0343*	0.0251	0.0350*	0.0293	0.0423**	0.0367*	0.0382*
	(0.0176)	(0.0159)	(0.0193)	(0.0165)	(0.0210)	(0.0229)	(0.0213)	(0.0214)	(0.0198)
Polluting dummy * year	-0.011***	-0.0177***	-0.0142***	-0.0189***	-0.0230***	-0.0134***	-0.0185***	-0.0125***	-0.0206***
	(0.00310)	(0.00600)	(0.00392)	(0.00659)	(0.00796)	(0.00379)	(0.00672)	(0.00342)	(0.00648)
Emp. FTE-PSM (log) * 2003			0.189***	0.0733*					
			(0.0655)	(0.0410)					
Emp. FTE - PSM (log) * 2004			0.182***	0.0791*					
			(0.0666)	(0.0435)					
Emp. FTE - PSM (log) * 2005			0.171**	0.0828**					
			(0.0668)	(0.0354)					
Emp. FTE - PSM (log) * 2006			0.0914***	0.0874*					
			(0.0231)	(0.0477)					
Emp. FTE - PSM (log) * 2007			0.104***	0.0818**					
			(0.0275)	(0.0394)					
Share green prod. (t+1)					0.105				
					(0.164)				
Share green prod. (t+2)					0.0450				
					(0.152)				
Energy cost						0.0408	-0.0458		
						(0.0550)	(0.0367)		
Low-wage import pen.						0.0199**	-0.0188		
						(0.00980)	(0.0449)		
Average wages (log)								-0.120**	-0.118
								(0.0546)	(0.0730)
Constant	8.317***	14.26***	1.649	14.73***	16.01***	6.405**	14.62***	8.816***	16.74***
	(2.428)	(2.243)	(3.000)	(2.526)	(2.789)	(2.738)	(2.811)	(2.658)	(2.813)
Observations	38,255	3,864	36,932	3,762	3,123	33,605	3,698	38,255	3,864
R-squared	0.199	0.274	0.250	0.315	0.128	0.149	0.134	0.130	0.125
Number of geosector	3,467	333	3,203	312	327	3,149	331	3,467	333
Country-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industries	All	Green	All	Green	Green	All	Green	All	Green

*Note: Authors' elaboration on PRODCOM, SBS and UNCOMTRADE data. All results include country-industry fixed effects. Columns 3 and 4 also include pre-trends by interacting pre-sample means (PSM) computed over 2003-2005 interacted with year dummies. For space's sake, we only report the interactions until year 2007 after which the interaction loses significance for the sample with all industries, while all interactions remain significant for the subsample of only green industries. Columns 6 and 7 include two additional controls. Energy cost is computed combining energy cost as reported in the SBS data as a share of value added also reported in the SBS. The penetration of low-wage import is imports from non-OECD countries from UNCOMTRADE as a share of total output computed with PRODCOM data. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

With the similar goal of controlling for unobserved time-varying factors, in the next two columns we consider a very rich specification augmented by the pre-sample mean of employment (in log) interacted with time dummies. The associated coefficients captures pre-existing employment dynamics that are influenced by private and public investment in the green economy. In the sample of all manufacturing sectors (column 3), we observe a large increase in the estimated coefficient of the green sector dummy, which doubles in size. In the sample of green industries only (column 4), the coefficient becomes insignificant at conventional level, but not far from it (p-value=0.15). The semi-elasticity is still modestly large in this case, being equal to 0.2. In column 5, we test for the presence strong anticipation effects by replacing the contemporaneous green share with the future green shares (at time t+1 and t+2). Both coefficients are insignificant (and jointly insignificant) at conventional level, thus we safely exclude a strong reverse causality bias. Overall, we consider the semi-elasticity of 0.2 for the green as a plausible lower bound: intensifying green production allows to offset between 1/6 and 1/3 of the historical employment decline in industries that are potentially green.

The next robustness checks consider additional proxy of production costs, enriching the set of controls included in the main specification. We consider an indirect proxy of wage costs, the import penetration from low-wage countries, and a proxy of energy costs, energy purchase over value added. We observe no difference in the coefficients of interest with respect to the main specification of Table 4. Interestingly, the incidence of energy costs has no effect on employment which is consistent with analysis of Marin and Vona (2019) on the employment effect of energy prices. This result also indicates that the time trend specific to polluting sectors successfully control for changes in environmental policies that mostly affect those sectors. Last, we explicitly control for the average wage in the sector. Again, results on the green share remains unchanged, with wages showing a negative and statistically significant association. Overall, while we do not have a first-best solution to fix endogeneity issues related to omitted variable, these results suggest that these issues are not particularly relevant in our case.

The Table A.4 in the Appendix reports other robustness checks that are not directly tackling endogeneity concerns but are relevant for other aspects of the estimation strategy. Results are generally robust when we consider only a subset of sectors where the share of green production is even more concentrated[29] (column 1 and 2), when we exclude outliers[30] (columns 3 and 4) and when we consider total person employed (column 5 and 6). In particular, the fact that outliers or extremely green sectors do not drive the results, gives credibility to our findings.

This being said, it is worth noticing that other robustness checks reveal new interesting features of our results, which we report in the Appendix in Table A.5. In particular, the positive association between the green share and employment becomes quantitatively smaller when we log-transform also the green production share (column 1). The elasticity of employment to the green share is 0.015 for the sample of green industries, suggesting the presence of a group of countries and sectors that are not "extreme" outliers but drives the results.[31] Next, not weighting the estimates does not alter the results at the extensive margin (column 2), but kill the statistical significant association between employment and the green share (columns 3). Overall, this result suggests that the job creation effect of going green is concentrated in large countries and sectors, which is somehow consistent with previous findings of the job creation effects of green subsidies in the US (Popp et al., 2021). To illustrate, when removing Germany—the largest European manufacturing sector—from the estimation sample (columns 4 and 5),

[29] We identify these industries as high-green potential, based on previous work in Bontadini and Vona (2020).
[30] We identify outliers with a rather conservative approach, as observations for which either employment, wage, green import penetration or investment are in either top or bottom 5%.
[31] However, the long-term elasticity as estimated by adding lagged terms of the green share almost doubles in this log-log specification: 0.31. Results are available upon request by the authors.

the green effect disappears at the extensive margin and remain only nearly significant at the intensive margin (p-value=0.11).[32]

INTERNATIONAL COMPETITIVENESS IN GREEN PRODUCTION AND LABOUR MARKET OUTCOMES

In this final Section, we briefly investigate how the relationship between employment and green production changes depending on the level of international competitiveness. We expect that countries exporting green products or with a green comparative advantage in such products may be able to create additional jobs in the domestic economy, conditional on the share of green production. Likewise, as green exporters are likely to be more productive than green producers that do not export (Bernard et al., 2012), we expect to observe a green exporter wage premium. We test these conjectures by augmenting our main specification with proxies of green and non-green international competitiveness.

In choosing the appropriate specification, note that only 6.2% of observations in our estimation sample of all manufacturing sectors are green exporters. This figure increases to 66% for the subsample of green sectors. In turn, 90% of all manufacturing sectors do export at least one non-green product. Taking stock from this descriptive evidence, we augment our main specifications of equations (6) and (7) by adding the level of non-green and green export (in log).[33]

Table 7 presents the results of this important extension using the FE specification for both employment (columns 1 and 2) and wages (columns 5 and 6). First, we find that green and non-green exporting are associated with more sustained employment growth, but the estimated coefficients are small especially for green exporting. Notably, the coefficients associated with the green sector dummy, or the share of green production remain unchanged with respect to the main Table 4. This implies that green exporting has an additional, although modest, effect on job creation, but does not capture the bulk of the positive association between green production and employment.

Second, we find that workers reap wage benefits of exporting in both green and non-green productions. The wage premium of exporting is statistically significant for all sectors (column 5) and green sectors (column 6). The estimated wage elasticities are much larger for exporting of non-green products than

[32] Interestingly, excluding eastern European countries does not alter the results on wages and employment. However, if we consider only eastern countries, the green wage premium becomes negative and significant. Considering only Nordic countries also does not alter the main results of the paper. This set of results by groups of countries remain available upon request by the authors.

[33] While this allows us to compare the elasticities of non-green and green exporting, in the Table A.6 of the Appendix we replace the level of green exporting with a dummy equal to one for green exporters. This modification is especially relevant for the case of all industries where there is only 6% of green exporters. Results are qualitatively consistent with those presented in the main text.

for exporting green products. Note, however, in the 12-year period of our analysis non-green export decreases (-19.3% in potentially green sectors and -14.6% in all sectors), while green exports increase substantially (50% in potentially green sectors and 20.9% in all sectors). Overall, going green leads to wage gains, and thus increases job quality, only for those countries that are engaged in growing international markets for green products.

We directly explore in columns 3, 4, 7 and 8 the role of the green comparative advantage in international markets. Because starting to export green products is more likely in large and more diversified sectors, this is not equivalent to have comparative advantage in international markets for green products. We use Balassa indexes (normalized to vary between -1 and 1) to capture the comparative advantage in green and non-green products. The main takeaway of this result is that both employment and wages exhibit a positive, though statistically insignificant, association with green production. In turn, a non-green comparative advantage ensures significant wage gains. Taken together, the evidence of Table 7 indicates that, as expected, labour market outcomes are positively associated with country-industries' engagement in international markets for green products. However, the effects are quantitatively small or estimated imprecisely.

TABLE 7 – GREEN SHARES OF PRODUCTION, EMPLOYMENT, WAGES, AND INTERNATIONAL COMPETITIVENESS

VARIABLES	(1)	(2) Employees FTE (log)	(3)	(4)	(5)	(6) Mean wages (log)	(7)	(8)
Green dummy * year	0.0104**		0.00947*		0.00322		0.00245	
	(0.00499)		(0.00491)		(0.00353)		(0.00367)	
Green share of production		0.426**		0.401**		-0.0810		-0.120
		(0.190)		(0.193)		(0.107)		(0.123)
Non-green export (log)	0.0786***	0.0768*			0.0809***	0.211***		
	(0.0219)	(0.0429)			(0.0220)	(0.0409)		
Green export (log)	0.00275	0.00264			0.00198	0.00618***		
	(0.00187)	(0.00200)			(0.00137)	(0.00164)		
Investment rate (log)	0.192***	0.145	0.193***	0.149	0.0439**	0.0381**	0.0440**	0.0425**
	(0.0512)	(0.0932)	(0.0509)	(0.0917)	(0.0201)	(0.0163)	(0.0197)	(0.0189)
Output (log)	0.157***	0.145***	0.163***	0.160***	-0.0634***	-0.0469***	-0.0574***	-0.00743
	(0.0274)	(0.0438)	(0.0265)	(0.0416)	(0.0163)	(0.0179)	(0.0159)	(0.0207)
Green import penetration (log)	0.0273	0.0245	0.0377*	0.0356*	0.00899	0.00515	0.0190	0.0356**
	(0.0242)	(0.0219)	(0.0225)	(0.0204)	(0.0130)	(0.0125)	(0.0140)	(0.0163)
Polluting dummy * year	-0.00826	-0.0212***	-0.00779	-0.0187***	-0.00454	-0.0110*	-0.00416	-0.00664
	(0.00509)	(0.00671)	(0.00504)	(0.00637)	(0.00430)	(0.00628)	(0.00434)	(0.00610)
Green RCA			0.0204	0.00932			0.00893	0.0208
			(0.0218)	(0.0240)			(0.0166)	(0.0169)
Non-green RCA			0.0959	-0.0160			0.153**	0.201**
			(0.0777)	(0.149)			(0.0760)	(0.0848)
Constant	4.501	14.39***	5.982*	14.53***	11.01***	11.48***	12.58***	13.24***
	(3.375)	(2.675)	(3.315)	(2.577)	(2.368)	(2.375)	(2.324)	(2.348)
Observations	38,524	3,785	38,641	3,902	38,460	3,781	38,577	3,898
R-squared	0.112	0.112	0.109	0.109	0.087	0.285	0.080	0.205
Country-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industries	All	Green	All	Green	All	Green	All	Green

*Note: Authors' elaboration on PRODCOM, SBS and UNCOMTRADE data. Columns 1 to 4 report results for the employment in FTE, while columns 5 to 8 report results for average wages. Export and non-green exports are computed with UNCOMTRADE data, the RCAs are computed as symmetrical Balassa indexes. All results are weighted on total output. Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

CONCLUSIONS

Greening the manufacturing sector is challenging as several technological solutions to reduce emissions have yet to be discovered. However, as markets for green goods and services are likely to grow rapidly in the future, such challenge may also create opportunities for workers and companies in certain, mostly high- and medium-tech, sectors. Reaping these benefits is an essential goal of the green fiscal stimuli that are discussed in both Europe and the US.

In this paper, we concentrate on the association between labour market outcomes and green production to shed light on the magnitude of these potential benefits. Because job creation is an important policy goal, the attractiveness of green deal plans (or of any push in green demand) rests also on their capacity to improve labour market outcomes. To this aim, we use very detailed production data (PRODCOM) where we can precisely identify a subset of green products and map them into standard industry classification. In the set of green products, we include goods, mostly high- and medium-tech, that allow reducing the harmful environmental impacts of economic activities, i.e. wind turbines or electric engines. The product-level data are aggregated at 4-digit industry level where we can obtain reliable measures of employment, wages and other factors affecting labour market dynamics, such as trade and automation. Having data at 4-digit sectoral level is important as green production is extremely concentrated in a few sectors. To the best of our knowledge, we are the first to analyse labour market outcomes of going green at a very granular level that includes detailed sectors, almost all EU countries and over a long panel spanning more than a decade (2003-2015). Overall, our analysis is able to shed light on the labour market adjustment to a green demand shock and thus indirectly inform the current debate on the green fiscal stimulus.

Our main findings are the following. First, regardless of the level of green production, the sectors where green production is usually concentrated are also doing relatively better in terms of wages and employment. Because green sectors are usually high- and medium-tech, this finding is in line with the EU strategy of reinforcing the specialisation in knowledge-intensive sectors. Second, when controlling for other drivers of labour market dynamics in our econometric analysis, we still find that employment grows faster in potentially green sectors, both at the extensive (i.e. between potentially green and non-green sectors) and at the intensive margin (i.e., intensifying green production within potentially green sectors). Both margins are quantitatively important over the twelve years considered in our analysis: the employment gain is 13.2% at the extensive margin and between 2.1%-4.2% at the intensive margin in correspondence to a 10.2% long-term increase in the share of green production. These results contrast with the sharp decline of employment in polluting sectors. Third, when controlling for other drivers of labour market dynamics in our econometric analysis, the green wage premium disappears, indicating that in the same sector, green and non-green activities require a similar set of skill levels and that the average wages are also similar. However, we find a green wage premium that emerges for green exporters, but such premium remains smaller than the wage premium for non-green exporters within potentially green sectors. Finally, green exporting has an additional, although modest, effect on job creation on top of the effect of domestic green production. This implies that the labour market benefits of going green are not necessarily associated with international competitiveness and are still small in terms of wage gains.

Further research using individual-level data is needed to understand the distribution of wage gains and losses across workers, controlling for unobserved heterogeneity and workers' sorting. However, worker-level or matched employer-employee dataset are only available for single EU countries. More important, our analysis suggests that a green push may exacerbate regional inequalities, by favouring greener countries that are already wealthier. However, a country-level analysis is not suited to identify the potential winners that emerge also in laggard countries. Moreover, our analysis is unable to identify local multiplier effect of going green in terms of employment in non-tradable service sectors. While the lack of a green wage premium suggests that such local multipliers are small, more research is needed to understand how regional labour markets adjust to the green transition.

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ANNEX

TABLE A1 – MISSING VALUES IN OUR DATASET

Variable	Country	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Employees FTE units	AUT	0.08	0.06	0.06	0.05	0.04	0.04	0.04	0.03	0.03	0.04	0.06	0.06	0.06	0.08	0.08	0.09	0.11	0.12
	BEL	1.00	1.00	1.00	0.12	0.12	0.08	0.08	0.07	0.07	0.06	0.05	0.06	0.06	0.05	0.05	0.08	0.09	0.10
	BGR	1.00	1.00	1.00	0.64	0.64	0.64	0.64	0.08	0.05	0.05	0.04	0.05	0.04	0.05	0.07	0.07	0.08	0.12
	DEU	1.00	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.04
	DNK	0.16	0.15	0.13	0.13	0.12	0.12	0.12	0.12	0.13	0.14	0.22	0.22	0.22	0.22	0.22	0.24	0.25	0.28
	ESP	1.00	0.03	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01
	EST	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	FIN	1.00	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.06	0.07	0.07
	FRA	1.00	0.03	0.03	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.02	0.03
	GBR	0.02	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.08	0.10	0.10	0.10	0.10	0.12	0.13
	GRC	1.00	1.00	1.00	1.00	1.00	0.06	0.05	0.05	0.03	0.03	0.01	0.01	0.01	0.02	0.02	0.02	0.03	0.03
	HRV	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	HUN	1.00	1.00	1.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.02	0.03	0.04	0.04	0.04	0.06
	IRL	0.31	0.27	0.26	0.24	0.24	0.19	0.19	0.19	0.19	0.19	0.25	0.26	0.29	0.30	0.33	0.38	0.39	0.60
	ITA	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.02	0.02
	LTU	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	LVA	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

	POL	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.07	0.05	0.05	0.04	0.04
	PRT	1.00	0.07	0.06	0.06	0.04	0.03	0.03	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.03
	ROU	1.00	1.00	0.69	0.69	0.15	0.15	0.12	0.11	0.10	0.11	0.13	0.15	0.15	0.16	0.17	0.19	0.21	0.21
	SVK	0.15	0.13	0.13	0.08	0.07	0.07	0.07	0.07	0.07	0.05	0.08	0.08	0.09	0.10	0.12	0.13	0.13	0.13
	SVN	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	SWE	0.20	0.16	0.15	0.12	0.13	0.09	0.09	0.09	0.08	0.08	0.12	0.12	0.12	0.12	0.12	0.13	0.14	0.17
	AUT	0.11	0.09	0.08	0.08	0.05	0.05	0.05	0.04	0.04	0.04	0.08	0.08	0.08	0.10	0.10	0.11	0.13	0.14
	BEL	1.00	1.00	1.00	0.12	0.12	0.09	0.08	0.08	0.08	0.07	0.05	0.07	0.07	0.06	0.06	0.09	0.10	0.11
	BGR	1.00	1.00	1.00	0.64	0.64	0.64	0.64	0.12	0.08	0.08	0.08	0.09	0.09	0.10	0.11	0.11	0.12	0.16
	DEU	1.00	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.04
	DNK	0.19	0.19	0.17	0.17	0.16	0.15	0.15	0.15	0.15	0.16	0.24	0.25	0.24	0.24	0.24	0.28	0.28	0.31
	ESP	1.00	0.03	0.02	0.02	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.03	0.03	0.01
	EST	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Average	FIN	1.00	0.07	0.07	0.07	0.07	0.05	0.06	0.05	0.04	0.04	0.07	0.07	0.06	0.07	0.06	0.08	0.10	0.11
wages	FRA	1.00	0.03	0.03	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.02	0.03	0.04
	GBR	0.03	0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.10	0.11	0.11	0.11	0.12	0.15	0.16
	GRC	1.00	1.00	1.00	1.00	1.00	0.06	0.06	0.05	0.04	0.03	0.04	0.02	0.04	0.03	0.03	0.03	0.04	0.05
	HRV	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	HUN	1.00	1.00	1.00	0.02	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.02	0.03	0.03	0.04	0.04	0.04	0.06
	IRL	0.41	0.39	0.38	0.35	0.37	0.31	0.33	0.32	0.31	0.31	0.35	0.37	0.40	0.40	0.42	0.46	0.47	0.64
	ITA	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02
	LTU	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

	LVA	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	POL	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.07	0.05	0.05	0.04	0.04
	PRT	1.00	0.09	0.07	0.07	0.06	0.05	0.04	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
	ROU	1.00	1.00	0.69	0.69	0.16	0.15	0.13	0.12	0.11	0.12	0.14	0.17	0.16	0.17	0.18	0.19	0.21	0.21
	SVK	0.25	0.23	0.18	0.13	0.13	0.12	0.11	0.12	0.10	0.09	0.12	0.11	0.11	0.12	0.14	0.15	0.15	0.15
	SVN	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	SWE	0.24	0.21	0.21	0.19	0.19	0.16	0.16	0.16	0.15	0.15	0.19	0.19	0.19	0.19	0.19	0.19	0.20	0.23
	AUT	0.10	0.09	0.08	0.09	0.09	0.08	0.08	0.08	0.04	0.04	0.05	0.04	0.04	0.05	0.05	0.06	0.06	0.07
	BEL	0.10	0.10	0.11	0.11	0.12	0.10	0.12	0.14	0.08	0.08	0.08	0.08	0.06	0.06	0.07	0.07	0.07	0.07
	BGR	1.00	1.00	1.00	0.05	0.05	0.05	0.07	0.07	0.03	0.03	0.03	0.01	0.02	0.02	0.02	0.02	0.02	0.02
	DEU	0.07	0.07	0.07	0.07	0.07	0.06	0.07	0.07	0.02	0.03	0.03	0.02	0.02	0.03	0.03	0.03	0.03	0.03
	DNK	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	ESP	0.07	0.07	0.06	0.06	0.06	0.06	0.07	0.07	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01
	EST	1.00	1.00	1.00	0.09	0.09	0.06	0.06	0.06	0.02	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Output	FIN	0.08	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	FRA	0.10	0.09	0.08	0.08	0.08	0.07	0.06	0.06	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01
	GBR	0.05	0.06	0.06	0.06	0.05	0.05	0.06	0.06	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.02	0.03
	GRC	0.08	0.08	0.07	0.06	0.06	0.07	0.08	0.08	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02
	HRV	1.00	1.00	1.00	0.08	0.07	0.05	0.05	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	HUN	1.00	1.00	1.00	0.14	0.06	0.06	0.07	0.06	0.01	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
	IRL	0.10	0.10	0.10	0.10	0.10	0.09	0.09	0.10	0.06	0.05	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.04
	ITA	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	LTU	1.00	1.00	1.00	0.07	0.06	0.07	0.06	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	LVA	1.00	1.00	1.00	0.08	0.08	0.08	0.07	0.08	0.03	0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.05	0.05
	POL	1.00	1.00	1.00	1.00	1.00	0.07	0.07	0.08	0.03	0.02	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.05
	PRT	0.06	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.02	0.02	0.03
	ROU	1.00	1.00	1.00	0.06	0.10	0.10	0.06	0.06	0.01	0.01	0.03	0.01	0.01	0.00	0.01	0.01	0.01	0.01
	SVK	1.00	1.00	1.00	0.24	0.07	0.06	0.07	0.08	0.03	0.02	0.03	0.02	0.02	0.03	0.03	0.03	0.03	0.03
	SVN	1.00	1.00	1.00	0.10	0.11	0.11	0.11	0.12	0.08	0.07	0.07	0.07	0.07	0.07	0.06	0.06	0.05	0.07
	SWE	0.10	0.10	0.10	0.10	0.10	0.12	0.13	0.13	0.10	0.11	0.10	0.09	0.10	0.11	0.11	0.11	0.11	0.11
Green share of production	AUT	0.20	0.20	0.20	0.15	0.20	0.20	0.25	0.25	0.25	0.10	0.10	0.15	0.15	0.15	0.10	0.15	0.15	0.15
	BEL	0.15	0.10	0.10	0.15	0.15	0.15	0.30	0.50	0.65	0.65	0.30	0.40	0.05	0.10	0.10	0.05	0.15	0.20
	BGR	1.00	1.00	1.00	0.90	0.90	0.85	0.05	0.05	0.05	0.05	0.10	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	DEU	0.05	0.05	0.05	0.05	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	DNK	0.00	0.00	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	ESP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	EST	1.00	1.00	1.00	0.35	0.30	0.20	0.20	0.20	0.20	0.05	0.10	0.15	0.05	0.05	0.05	0.00	0.00	0.05
	FIN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	FRA	0.05	0.05	0.05	0.05	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	GBR	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.05	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	GRC	0.20	0.20	0.20	0.20	0.20	0.10	0.10	0.05	0.00	0.05	0.05	0.10	0.15	0.20	0.25	0.20	0.20	0.25
	HRV	1.00	1.00	1.00	0.20	0.15	0.00	0.00	0.00	0.00	0.00	0.05	0.05	0.05	0.05	0.05	0.00	0.00	0.00
	HUN	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	IRL	0.25	0.25	0.25	0.25	0.25	0.20	0.20	0.20	0.25	0.30	0.40	0.35	0.35	0.35	0.40	0.40	0.35	0.40

	ITA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	LTU	1.00	1.00	1.00	0.30	0.15	0.10	0.10	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00
	LVA	1.00	1.00	1.00	0.60	0.55	0.50	0.45	0.45	0.70	0.70	0.65	0.60	0.60	0.60	0.50	0.50	0.55	0.60
	POL	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	PRT	0.10	0.10	0.05	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.05	0.05
	ROU	1.00	1.00	1.00	0.05	0.05	0.05	0.05	0.15	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.05
	SVK	1.00	1.00	1.00	0.05	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.10	0.10	0.10	0.10	0.05	0.05
	SVN	1.00	1.00	1.00	0.40	0.50	0.40	0.35	0.40	0.40	0.45	0.30	0.20	0.20	0.20	0.30	0.25	0.20	0.20
	SWE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.10	0.10
	AUT	0.16	0.15	0.14	0.14	0.13	0.12	0.12	0.12	0.08	0.08	0.12	0.11	0.12	0.14	0.14	0.15	0.18	0.18
	BEL	1.00	0.23	0.19	0.17	0.18	0.16	0.18	0.20	0.15	0.14	0.12	0.15	0.14	0.12	0.14	0.16	0.17	0.17
	BGR	1.00	1.00	1.00	0.67	0.66	0.66	0.65	0.25	0.14	0.13	0.14	0.13	0.14	0.15	0.15	0.16	0.17	0.20
	DEU	1.00	0.11	0.09	0.08	0.08	0.07	0.07	0.07	0.02	0.03	0.04	0.02	0.02	0.03	0.04	0.05	0.07	0.08
Investment	DNK	0.19	0.19	0.18	0.17	0.16	0.16	0.16	0.17	0.14	0.14	0.23	0.23	0.23	0.24	0.23	0.26	0.27	0.30
in	ESP	0.09	0.08	0.07	0.07	0.07	0.07	0.07	0.08	0.03	0.03	0.03	0.03	0.03	0.04	0.03	0.04	0.03	0.02
equipment	EST	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
as a share	FIN	0.14	0.08	0.08	0.08	0.09	0.07	0.07	0.07	0.03	0.03	0.05	0.05	0.05	0.05	0.05	0.07	0.09	0.10
of output	FRA	1.00	0.11	0.13	0.11	0.11	0.09	0.08	0.08	0.03	0.03	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	GBR	0.07	0.08	0.08	0.08	0.07	0.07	0.07	0.07	0.03	0.04	0.04	0.04	0.05	0.05	0.06	0.07	0.07	0.07
	GRC	1.00	1.00	1.00	1.00	1.00	0.14	0.13	0.13	0.06	0.06	0.11	0.06	0.07	0.08	0.10	0.09	0.13	0.14
	HRV	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	HUN	1.00	1.00	1.00	0.15	0.08	0.07	0.08	0.08	0.04	0.04	0.08	0.07	0.07	0.05	0.07	0.07	0.06	0.07

	IRL	0.40	0.38	0.38	0.37	0.39	0.34	0.36	0.35	0.35	0.35	0.41	0.43	0.45	0.47	0.50	0.47	0.48	0.64
	ITA	0.07	0.07	0.06	0.07	0.07	0.06	0.07	0.06	0.01	0.06	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02
	LTU	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	LVA	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	POL	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.11	0.07	0.06	0.05	0.06	0.07	0.06	0.06	0.06	0.06	0.07
	PRT	1.00	0.13	0.11	0.10	0.09	0.10	0.09	0.08	0.04	0.05	0.04	0.05	0.05	0.04	0.05	0.07	0.07	0.07
	ROU	1.00	1.00	1.00	0.19	0.20	0.20	0.16	0.15	0.12	0.13	0.15	0.17	0.19	0.19	0.19	0.21	0.22	0.23
	SVK	1.00	1.00	1.00	0.26	0.16	0.16	0.16	0.17	0.17	0.15	0.17	0.17	0.20	0.21	0.24	0.23	0.25	0.24
	SVN	1.00	1.00	1.00	0.33	0.25	0.27	0.31	0.23	0.21	0.24	0.25	0.26	0.26	0.28	0.29	0.32	0.34	0.48
	SWE	0.25	0.22	0.22	0.20	0.20	0.20	0.20	0.20	0.18	0.20	0.24	0.22	0.22	0.23	0.23	0.23	0.25	0.27
	AUT	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	BEL	0.05	0.05	0.10	0.10	0.10	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	BGR	1.00	1.00	1.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	DEU	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Green import as a share of output	DNK	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	ESP	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	EST	1.00	1.00	1.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	FIN	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	FRA	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	GBR	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	GRC	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	HRV	1.00	1.00	1.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

	HUN	1.00	1.00	1.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	IRL	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.35
	ITA	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	LTU	1.00	1.00	1.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	LVA	1.00	1.00	1.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	POL	1.00	1.00	1.00	1.00	1.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	PRT	0.10	0.10	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	ROU	1.00	1.00	1.00	0.05	0.10	0.10	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	SVK	1.00	1.00	1.00	0.10	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	SVN	1.00	1.00	1.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	SWE	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	AUT	0.05	0.05	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	BEL	0.05	0.05	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	BGR	1.00	1.00	1.00	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	DEU	0.05	0.05	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	DNK	0.05	0.05	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
Green RCA	ESP	0.05	0.05	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	EST	1.00	1.00	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	FIN	0.05	0.05	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	FRA	0.05	0.05	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	GBR	0.05	0.05	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	GRC	0.05	0.05	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05

	HRV	1.00	1.00	1.00	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	HUN	1.00	1.00	1.00	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	IRL	0.05	0.05	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	ITA	0.05	0.05	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	LTU	1.00	1.00	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	LVA	1.00	1.00	1.00	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	POL	1.00	1.00	1.00	1.00	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	PRT	0.05	0.05	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	ROU	1.00	1.00	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	SVK	0.05	0.05	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	SVN	1.00	1.00	1.00	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	SWE	0.05	0.05	0.05	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.05	0.05	0.05	0.05
	AUT	0.16	0.16	0.16	0.16	0.16	0.15	0.15	0.15	0.11	0.11	0.12	0.12	0.12	0.12	0.12	0.12	0.13	0.13
	BEL	0.17	0.91	0.92	0.92	0.92	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91
	BGR	1.00	1.00	1.00	0.16	0.15	0.15	0.14	0.14	0.10	0.11	0.10	0.08	0.09	0.09	0.09	0.09	0.09	0.09
Low-wage	DEU	0.15	0.15	0.15	0.14	0.14	0.14	0.14	0.14	0.09	0.10	0.10	0.09	0.09	0.10	0.10	0.10	0.10	0.10
import	DNK	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
over	ESP	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.15	0.10	0.09	0.10	0.10	0.09	0.10	0.10	0.09	0.09	0.09
output	EST	1.00	1.00	1.00	0.16	0.16	0.13	0.14	0.14	0.08	0.09	0.09	0.09	0.09	0.08	0.08	0.07	0.08	0.08
	FIN	0.15	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.08	0.07	0.07	0.08	0.08	0.08	0.07	0.07	0.08	0.08
	FRA	0.15	0.15	0.15	0.15	0.15	0.13	0.13	0.13	0.08	0.08	0.07	0.08	0.08	0.08	0.08	0.08	0.08	0.09
	GBR	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.14	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.09	0.09	0.10

GRC	0.15	0.16	0.15	0.15	0.14	0.15	0.15	0.15	0.10	0.08	0.09	0.09	0.09	0.09	0.09	0.08	0.09	0.09
HRV	1.00	1.00	1.00	0.15	0.14	0.13	0.12	0.12	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
HUN	1.00	1.00	1.00	0.21	0.14	0.14	0.14	0.14	0.09	0.10	0.10	0.10	0.09	0.08	0.08	0.08	0.08	0.08
IRL	0.22	0.22	0.22	0.23	0.23	0.21	0.21	0.21	0.19	0.19	0.20	0.19	0.19	0.19	0.20	0.19	0.18	0.39
ITA	0.14	0.14	0.13	0.13	0.13	0.13	0.13	0.12	0.08	0.09	0.08	0.08	0.08	0.08	0.08	0.08	0.07	0.07
LTU	1.00	1.00	1.00	0.15	0.14	0.14	0.13	0.12	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
LVA	1.00	1.00	1.00	0.15	0.14	0.15	0.14	0.16	0.11	0.12	0.11	0.12	0.12	0.11	0.13	0.12	0.15	0.14
POL	1.00	1.00	1.00	1.00	1.00	0.14	0.15	0.16	0.10	0.10	0.11	0.11	0.12	0.12	0.12	0.11	0.11	0.12
PRT	0.14	0.14	0.13	0.13	0.13	0.13	0.13	0.13	0.10	0.08	0.09	0.10	0.09	0.09	0.09	0.10	0.09	0.11
ROU	1.00	1.00	1.00	0.14	0.18	0.18	0.13	0.14	0.08	0.09	0.10	0.09	0.08	0.08	0.09	0.09	0.09	0.09
SVK	1.00	1.00	1.00	0.29	0.15	0.14	0.14	0.15	0.09	0.09	0.10	0.09	0.09	0.10	0.10	0.10	0.10	0.10
SVN	1.00	1.00	1.00	0.17	0.17	0.16	0.17	0.18	0.13	0.13	0.13	0.12	0.13	0.12	0.12	0.12	0.11	0.12
SWE	0.18	0.18	0.18	0.18	0.19	0.21	0.22	0.22	0.20	0.21	0.19	0.19	0.19	0.20	0.19	0.20	0.19	0.19

Note: the table reports, for each key variable the share of sectors that have missing values in each country-year combination. For variables that are only available for green industries, such as green share of production, green RCA and import penetration of green goods, this is computed only on the total number of green industries. It should also be borne in mind that the manufacturing industries include also the repair and installation of machinery that has no physical goods crossing borders and as such is always missing for all trade related variables. Based on the distribution of missing values across countries and years we have limited our analysis to the 2003-2015 period, and to the countries in bold.

TABLE A.2 – GREEN INDUSTRIES

NACE rev.2 code	description
2312	Shaping and processing of flat glass
2410	Manufacture of basic iron and steel and of ferro-alloys
2511	Manufacture of metal structures and parts of structures
2530	Manufacture of steam generators, except central heating hot water boilers
2599	Manufacture of other fabricated metal products n.e.c.
2611	Manufacture of electronic components
2651	Manufacture of instruments and appliances for measuring, testing and navigation
2711	Manufacture of electric motors, generators and transformers
2712	Manufacture of electricity distribution and control apparatus
2740	Manufacture of electric lighting equipment
2751	Manufacture of electric domestic appliances
2752	Manufacture of non-electric domestic appliances
2811	Manufacture of engines and turbines, except aircraft, vehicle and cycle engines
2825	Manufacture of non-domestic cooling and ventilation equipment
2829	Manufacture of other general-purpose machinery n.e.c.
2899	Manufacture of other special-purpose machinery n.e.c.
2910	Manufacture of motor vehicles
3020	Manufacture of railway locomotives and rolling stock
3092	Manufacture of bicycles and invalid carriages
3320	Installation of industrial machinery and equipment

TABLE A.3 – GREEN SHARES OF PRODUCTION, EMPLOYMENT AND WAGES, DISTRIBUTED LAG MODEL FOR LONG TERM EFFECTS

VARIABLES	(1) Employees FTE (log)	(2) Mean wages (log)
Employees FTE - PSM (log)	0.0818**	
	(0.0380)	
Employees FTE (log) (t-1)	0.787***	
	(0.0473)	
Green share of production	0.135*	0.0268
	(0.0798)	(0.0274)
Investment rate (log)	0.0432*	0.0205***
	(0.0260)	(0.00699)
Output (log)	0.120***	0.0233***
	(0.0259)	(0.00689)
Green import penetration (log)	0.00382	0.00497
	(0.00478)	(0.00426)
Polluting dummy * year	-0.00634***	-0.0000588
	(0.00196)	(0.00256)
Mean wages - PSM (log)		0.104***
		(0.0263)
Mean wages (log) (t-1)		0.625***
		(0.0544)
Constant	11.31***	2.434
	(3.988)	(5.216)
Observations	3,775	3,759
R-squared	0.982	0.886
Country-industry FE	Yes	Yes
Year FE	Yes	Yes
Industries	Green	Green

*Note: Authors' elaboration on PRODCOM, SBS and UNCOMTRADE data, pre-sample means (PSM) are computed over the period 2003-2005. All results are weighted on total output. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

TABLE A.4 – GREEN SHARES OF PRODUCTION, EMPLOYMENT, ROBUSTNESS CHECKS

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		Employees FTE (log)			Employed persons FTE (log)	
High-green potential dummy * year	0.0170**					
	(0.00820)					
Green dummy * year			0.0113**		0.0103**	
			(0.00460)		(0.00476)	
Green share of production		0.344*		0.388**		0.374**
		(0.205)		(0.170)		(0.184)
Investment rate (log)	0.192***	0.186	0.0569***	0.0899	0.201***	0.140
	(0.0510)	(0.135)	(0.0161)	(0.0566)	(0.0576)	(0.0908)
Output (log)	0.158***	0.201***	0.137***	0.146***	0.151***	0.149***
	(0.0268)	(0.0733)	(0.0188)	(0.0416)	(0.0227)	(0.0430)
Green import penetration (log)	0.0339	-0.0870	0.0368*	0.0379*	0.0297	0.0306
	(0.0269)	(0.0880)	(0.0216)	(0.0210)	(0.0210)	(0.0198)
Polluting dummy * year	-0.00673	-0.0427**	-0.00883**	-0.0199***	-0.0104**	-0.0167***
	(0.00517)	(0.0191)	(0.00398)	(0.00638)	(0.00437)	(0.00637)
Constant	6.906**	9.190***	6.629**	15.46***	7.254**	14.19***
	(3.377)	(2.362)	(2.625)	(2.680)	(3.171)	(2.622)
Observations	38,641	2,524	37,702	3,868	41,696	4,234
R-squared	0.109	0.177	0.077	0.099	0.129	0.103
Number of geosector	3,469	217	3,429	333	3,626	351
Country-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industries	All	High green potential	All	Green	All	Green

*Note: Authors' elaboration on PRODCOM, SBS and UNCOMTRADE data. All results include country-industry fixed effects. High-green potential dummy is based on the classification developed in Bontadini and Vona (2020). Columns 3 and 4 replicate the main module, excluding outliers, i.e. observations for which employment, wage, green share of production, investment rate or green import penetrations lie beyond either the top or bottom 5%. Columns 5 and 6 use employed persons FTE, rather than employees FTS as outcome variable. All results are weighted on total output. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

TABLE A.5 – GREEN SHARES OF PRODUCTION, EMPLOYMENT, ADDITIONAL ROBUSTNESS CHECKS

	(1)	(2)	(3)	(4)	(5)
VARIABLES			Employees FTE (log)		
Green dummy * year		0.0185**		0.00134	
		(0.00770)		(0.00537)	
Green share of production (log)	0.0148*				
	(0.00844)				
Green share of production			-0.210		0.365
			(0.187)		(0.230)
Investment rate (lot)	0.150	0.164***	0.179***	0.199***	0.168
	(0.0918)	(0.0154)	(0.0531)	(0.0543)	(0.104)
Output (log)	0.169***	0.134***	0.133***	0.172***	0.198***
	(0.0390)	(0.0137)	(0.0513)	(0.0324)	(0.0496)
Green import penetration (log)	0.0403**	0.0277*	0.0262	0.0414**	0.0503***
	(0.0196)	(0.0149)	(0.0166)	(0.0203)	(0.0163)
Polluting dummy * year	-0.0183***	0.000293	0.0125	-0.00866	-0.0117
	(0.00610)	(0.00450)	(0.0252)	(0.00674)	(0.00721)
Constant	14.27***	1.203	-0.687	9.668**	11.01***
	(2.375)	(3.713)	(13.35)	(3.975)	(3.166)
Observations	3,902	38,641	3,902	35,868	3,642
R-squared	0.109	0.070	0.064	0.117	0.139
Number of geosector	333	3,469	333	3,247	313
Country-industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industries	Green	All	Green	All	Green

*Note: Authors' elaboration on PRODCOM, SBS and UNCOMTRADE data. All results include country-industry fixed effects. Column 1 replace the share of green production with its logarith. Column 2 and 3 does not weight our results on total output. Columns 3 and 4 exclude Germany from the estimation sample. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

TABLE A.6 – GREEN SHARES OF PRODUCTION, EMPLOYMENT, WAGES WITH EXPORT AND RCA AS DUMMY VARIABLES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Employees FTE (log)				Mean wages (log)			
Green dummy * year	0.0107**		0.00990**		0.00340		0.00265	
	(0.00508)		(0.00496)		(0.00351)		(0.00360)	
Green share of production		0.425**		0.404**	0.0797***	0.196***		
		(0.189)		(0.191)	(0.0217)	(0.0400)		
Non-green export (log)	0.0764***	0.0641			0.0409	0.124***		
	(0.0217)	(0.0416)			(0.0308)	(0.0381)		
Green export (log)	0.0529	0.0427			0.0440**	0.0394**	0.0441**	0.0428**
	(0.0438)	(0.0438)			(0.0201)	(0.0166)	(0.0197)	(0.0190)
Investment rate (log)	0.192***	0.146	0.193***	0.149	-0.0634***	-0.0453**	-0.0576***	-0.0104
	(0.0512)	(0.0930)	(0.0509)	(0.0915)	(0.0163)	(0.0180)	(0.0159)	(0.0206)
Output (log)	0.157***	0.145***	0.163***	0.158***	0.00999	0.00971	0.0186	0.0337**
	(0.0274)	(0.0437)	(0.0266)	(0.0429)	(0.0131)	(0.0126)	(0.0138)	(0.0161)
Green import penetration (log)	0.0286	0.0265	0.0369	0.0342*	-0.00459	-0.0115*	-0.00417	-0.00670
	(0.0249)	(0.0222)	(0.0227)	(0.0206)	(0.00430)	(0.00646)	(0.00433)	(0.00603)
Polluting dummy * year	-0.00832	-0.0212***	-0.00782	-0.0188***		-0.0838		-0.117
	(0.00509)	(0.00678)	(0.00505)	(0.00645)		(0.108)		(0.123)
Green RCA			0.0191	0.000524			0.00753	0.0178
			(0.0325)	(0.0339)			(0.0241)	(0.0230)
Non-green RCA			0.0847	-0.0467			0.148**	0.164**
			(0.0775)	(0.140)			(0.0743)	(0.0766)
Constant	4.442	14.67***	5.792*	14.60***	10.99***	11.97***	12.49***	13.33***
	(3.389)	(2.751)	(3.324)	(2.629)	(2.373)	(2.416)	(2.303)	(2.328)
Observations	38,524	3,785	38,641	3,902	38,460	3,781	38,577	3,898
R-squared	0.112	0.111	0.109	0.109	0.087	0.279	0.080	0.203
Country-industry FE	3,462	326	3,469	333	3,462	326	3,469	333
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industries	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Note: Authors' elaboration on PRODCOM, SBS and UNCOMTRADE data. Columns 1 to 4 report results for the employment in FTE, while columns 5 to 8 report results for average wages. Export and non-green exports are computed with UNCOMTRADE data and constructed as dummies taking value 1 if export is above zero, the RCAs are computed as symmetrical Balassa indexes to construct a dummy taking value 1 if the symmetrical RCA is above 0. All results are weighted on total output. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

TABLE A.7 – LONG TERM GROWTH RATES AND INITIAL VALUES OF KEY VARIABLES

	Employment FTE units – growth rate	Employment FTE units - initial	Average wages (th.€) – growth rate	Average wages (th.€) - initial	Green share of production – growth rate	Green share of production - initial	Green RCA – growth rate	Green RCA - initial	Non green RCA – growth rate	Non green RCA - initial
					All industries					
10th percentile	-0.490	3875.000	-0.090	20584.061	0.000	0.000	0.000	-1.000	-0.132	-0.004
25th percentile	-0.308	9793.000	0.041	25575.477	0.000	0.000	0.000	-1.000	0.021	0.304
Median	-0.120	25577.334	0.229	31364.451	0.000	0.000	0.000	-1.000	0.171	0.456
75th percentile	0.076	61200.641	0.370	40499.664	0.000	0.000	0.000	-1.000	0.336	0.579
90th percentile	0.391	110998.438	0.608	49488.453	0.000	0.014	0.140	0.479	0.759	0.708
Mean	87.571	55010.381	0.304	33165.172	0.134	0.021	-0.047	-0.708	0.166	0.361
Standard deviation	2651.976	92791.413	0.922	11584.355	1.827	0.090	1.783	0.588	17.592	0.403
Obs.	2857	3060	2847	3045	3702	3159	3699	3699	3699	3699
					Green industries					
10th percentile	-0.365	10041.028	-0.059	24061.162	-1.000	0.000	-0.840	-0.152	-0.132	0.264
25th percentile	-0.253	29023.018	0.038	29970.064	-0.137	0.000	-0.196	0.307	0.098	0.357
Median	-0.040	61200.641	0.242	36573.113	0.000	0.008	0.132	0.474	0.175	0.488
75th percentile	0.084	113079.797	0.342	47816.527	0.289	0.109	0.243	0.606	0.312	0.586
90th percentile	0.447	497637.438	0.843	52197.016	0.894	0.385	0.499	0.659	0.759	0.649
Mean	1.082	124496.278	0.333	37655.517	0.503	0.093	-0.216	0.342	0.302	0.452
Standard deviation	17.543	160438.848	0.650	11664.659	3.576	0.171	3.821	0.423	2.427	0.237
Obs	293.	304	293	303	354	323	354	354	354	354

Notes: Authors' elaboration on SBS, PRODCOM and UNCOMTRADE data. Growth rate are between 2003 and 2015 (divided by the initial level in 2003). Average wages are computed annually by dividing the country-industry wage bill by employment in full time equivalent, both measures are taken from the SBS database. Green share of production is the sold production of green goods divided by total sold production within each country-industry, as reported in PRODCOM. RCAs are Balassa indexes, computed with UNCOMTRADE data, made symmetrical and bounded between -1 and +1, following Laursen (1998).