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Keywords: Green transition, Employment, Manufacturing, Shift-share

JEL classification: J21, J31, L6, O14

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Does Green Re-industrialization Pay off? Impacts on Employment, Wages and Productivity*

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August 5, 2024

Abstract

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1 Introduction

The recent approval of the US Inflation Reduction Act (IRA), which combines subsidies to green technologies and stringent local content requirements, revamped the attention to the role of industrial policies to win the race for green technologies (Rodrik, 2014). While the US and China are emerging as leaders in key green technologies, such as electric vehicles and PV panels, EU countries lag behind in this race and often remain reliant on traditional manufacturing industries. The EU response to the IRA, the Net Zero Industry Act (NZIA), aims at improving competitiveness in key sectors for the energy transition, reducing economic dependency from both oil exporting countries and green tech leaders (Kleimann et al., 2023). In the political discourse, capturing a larger share of the global demand for green technologies helps create well-paid green jobs, thus alleviating the concerns on the social and distributional effects of the energy transition (Bergquist et al., 2020; Vona, 2023).

Although decarbonizing manufacturing is inevitable, it remains unclear whether and to what extent investing in green technologies and production processes pays off in terms of job creation, higher wages and enhanced competitiveness. This issue is impossible to answer empirically before the policy effects of, e.g., IRA materialize. In one of the few papers assessing the effect of a green fiscal stimulus, Popp et al. (2021) show that the employment effect of green part of stimulus American Recovery and Reinvestment Act (ARRA) was highly heterogeneous across regions and heavily dependent on the skill level of the workforce. The alternative of ex-ante model-based evaluations relies on specific assumptions on the elasticity of the labour supply, the incidence of market imperfections and the monetary policy response, which cannot be corroborated against the data (Chodorow-Reich, 2019).

To assess the effect of a green demand push, with this paper we circumvents some of these methodological hurdles by using fine-grained production data for 21 EU countries and almost 200 4-digit industries over the period 2003-2017. Green production is constructed aggregating data on the sales of green products at 8-digit level available in the Eurostat PRODCOM database. We follow Bontadini and Vona (2023) who identify a "conservative" list of green products, starting from various lists that were proposed in negotiations at the World Trade Organization to reduce excessive trade barriers on key products for the energy transition (Shapiro, 2021). Production data are combined with Eurostat Structural Business Statistics to retrieve information on our dependent variables: Full-Time Equivalent (FTE) employment, average wages, value added, and value added per worker. Notably, we study the effect of expanding green productions both on sectors that develop green technologies and on those adopting such technologies through input output linkages (Acemoglu & Restrepo, 2020; Acemoglu et al., 2016, 2022) as well as the heterogeneous effects depending on pre-existing capabilities (Popp et al., 2021).

For identification, we rely on a shift-share instrumental variable design (Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020) that leverages exogenous improvements in green technologies for non-

European countries. The intuition is simple: a new green patent – the conventional proxy of green technological change (Aghion et al., 2016; Popp, 2002) – by a non-EU country creates economic opportunities *primarily* in EU countries with pre-existing capabilities in such technologies.[1] The exclusion restriction rests on the assumption that a new green patent impacts our dependent variables only through an expansion in green production. While violations of the exclusion restriction are untestable, we lend support to the credibility of our research design by conducting an extensive analysis of pre-trends and covariates' balancing (Goldsmith-Pinkham et al., 2020), testing the robustness of the results for plausible violations of the exclusion restriction (Conley et al., 2012) and considering different sources of residual data variation to identify the effect of interest (i.e., including different sets of fixed effects).

Our approach is agnostic on the origins of the green demand push, but we argue that expanding production is the primary channel through which green industrial policy, either in the form of subsidies (e.g., grants, tax credits) or regulation (e.g., local-content requirement), impacts the economy. To shed some light on these channels, we construct an alternative leave-one-out shift-share instrument leveraging shocks at the product level in other EU countries (Carluccio et al., 2015). Compared to the patent instrument, such instrument is more likely driven by current EU policies rather than by long-term R&D policies, which stimulate inventive activities over a longer time horizon (Popp, 2016). In light of previous assessments of job creation effects of green policies (Popp et al., 2021; Vona et al., 2019), we expect that effects driven by a technology push, i.e. patents, are larger than effects driven by current policies, i.e. EU green production.

Because green production is highly concentrated in just 22 (out of 199) 4-digit NACE industries, our main contribution rests on the estimation of the causal effect of expanding green production within these few industries, which incidentally are high-tech producers of capital equipment. Thus, we capture an intensive margin effect on the innovators that is *a priori* ambiguous on employment. On the one hand, green productions can crowd out inputs from non-green productions, thus workers simply shift from one line of production to another. On the other hand, new products are expected to be more labour intensive than old ones as the new tasks associated with new products are difficult to automate (Acemoglu & Restrepo, 2019; Harrison et al., 2014). Importantly, intensive-margin effects on wages and productivity depend on changes in the input mix (notably the skill mix) associated with an expansion of green productions. However, these compositional changes cannot be detected with our data, thus our estimates of the wage and productivity effects allow us to assess only the average quality of new jobs and productions.

The intensive margin effect captures one part of the economy-wide impact of green re-industrialization, which may involve a substantial labour reallocation across sectors. Our second contribution explores two additional channels through which green re-industrialization reshapes the manufacturing sector. First,

[1] Alternatively, one can think about it using a distance to the frontier argument (Acemoglu et al., 2006; Vandenbussche et al., 2006): only country-sector close to the frontier are engaged in neck-to-neck competition.

we compare the evolution of wages, employment and productivity in potentially green sectors with that of other manufacturing sectors, including highly polluting ones, conditional on other drivers such as capital deepening, globalization and the incidence of energy costs. Second, we use OECD input-output tables to assess the indirect effects on the adopters of green products and on the upstream suppliers of intermediate goods required for green production (Acemoglu et al., 2016). Because these two analyses are not part of a fully-fledged structural model, it is impossible to quantify precisely quantify the role of these additional effects. However, our analysis provides insights on the direction and size of these additional channels, which allow to assess the economy-wide impacts of green re-industrialization.

We find that €10 million increases in green production, induced by a technology push, leads to a statistically significant increase of 0.31% in employment and of 0.36% in value added in the industries with a potential to active green productions. This number corresponds to a short-term cost per job of €29.1 thousands and to a long-term cost per job just above €38.2 thousands. Importantly, we do not find that job creation translates into higher productivity or wages. However, positive, but small, wage effects emerge in some specifications, notably by replacing country-sector fixed effects with country-year and sector-year fixed effects. This indicates that sector-country pairs where green production is concentrated offer higher wages, but not a more sustained wage growth.

The intensive margin effect on employment is a lower bound of the total effect of green re-industrialization. Our data highlights that the 22 industries with a potential to activate green production exhibit faster annual growth in terms of employment (+0.88%), wages (+0.55%) and value added (+1.1%) than non-green industries, conditional on other intervening factors. We also find that job creation effects in potentially green industries double when accounting for input output linkages. This implies that adopting green products is relatively labour-intensive, although the lack of granularity of input-output data makes us cautious in interpreting this result.

The job creation effect is much smaller and statistically insignificant effects when using the green production instrument, which more closely mimics a demand-pull and thus to a green industrial policy. However, demand-pull and technology-push effects are highly heterogeneous across countries. Early EU members drive them for the green technology-push instrument, while a green demand-pull instrument boosts employment and wages only in late member states. This is consistent with the fact that early EU member countries are technologically advanced and benefit more from catching up with innovation at the frontier (Acemoglu et al., 2006). To corroborate this interpretation, we also find larger employment effects in countries with an initial specialization in potentially green industries, which are translated into modest wage gains. In contrast, a demand-pull for green products possibly driven by policies is beneficial to the less technologically advanced late EU member countries. Taken together, these results can provide insights on the potential effects of a green industrial policy, which can be beneficial especially for laggard countries.

Related literature. Our paper is the first to explore the implications of green re-industrialization on labour market outcomes and competitiveness, thus it covers an uncharted territory. In doing so, it indirectly contributes to three strands of literature.

First, we contribute to the literature on technological change and labour markets (Acemoglu & Restrepo, 2020; Acemoglu et al., 2022; Autor et al., 2003; Goos et al., 2014; Graetz & Michaels, 2018) by looking at one aspect of green innovation: the development and the adoption of green products. Research identifies the labour market impacts of new products using self-reported assessments of product and process innovation. A consistent finding in this literature is that product innovation is associated with job creation, while process innovation is associated with job destruction (e.g. Harrison et al., 2014).[2]

Second, we complement the firm-level literature on the effects of eco-innovation that often uses self-reported measures of innovation, especially from the Community Innovation Survey (Elliott et al., 2021; Gagliardi et al., 2016; Horbach & Rennings, 2013; Pfeiffer & Rennings, 2001; Rennings et al., 2004). This literature focuses on the association between employment and different types of eco-innovation: particularly end-of-pipe solutions vs. cleaner production (Pfeiffer & Rennings, 2001).[3] Gagliardi et al. (2016), who use a measure of innovation based on patents, find also that green innovation leads to additional jobs created relative to non-green innovation, but other studies find no differential effects of green innovation (e.g. Licht and Peters, 2013). Elliott et al., 2021 show that the association between green innovation and labour demand is concentrated among green jobs. While the focus of this literature has been mostly on employment, a few studies also explore the relationship between labour productivity or wages, on the one hand, and eco-innovation, on the other, finding mixed results.[4] Overall, due to data limitations, the eco-innovation literature primarily exploits cross-sectional variation in the data, often uses self-reported measures of innovation and thus struggles to solve endogeneity concerns. We complement this literature by using a new measure of green production, providing more convincing causal evidence and covering several countries over a long time period.

Finally, we contribute to the burgeoning literature on the labour market implications of the green transition. An established strand of literature focuses on policies imposing a cost on polluting firms and sectors, generally finding a modest (Greenstone, 2002; Kahn & Mansur, 2013; Marin & Vona, 2021) or muted (Martin et al., 2014; Yamazaki, 2017) job losses and quite substantial life-long wage losses (Walker, 2013; Yip, 2018), mostly depending on the policy design. Recent literature seeks to identify the winners of the green transition, the so-called green jobs, using the task-approach (Vona et al., 2018, 2019), job vacancy data (Curtis & Marinescu, 2022; Saussay et al., 2022), focusing on the direct observation

[2] This finding resonates with those of the recent paper of Autor et al. (2022) that convincingly identify the long-term effects of labour-replacing vs. labour-augmenting innovations, combining data on patents, tasks and new occupational titles to identify the two margins of innovation. A key feature of labour-augmenting innovations is that they are usually associated with the emergence of new occupations and products (see also Lin, 2011).

[3] End-of-pipe solutions tend to have a negative effect on employment, while cleaner production methods a positive one (Pfeiffer & Rennings, 2001; Rennings et al., 2004). Horbach and Rammer (2020) highlight the positive association between employment growth and innovation related to the circular economy

[4] For excellent surveys, see Ambec et al. (2013), Dechezleprêtre and Sato (2017), and Ghisetti (2018).

of investments in the energy sector, that can easily classified as green or not (Chan & Zhou, 2024; Fabra et al., 2023), or on green subsidies (Popp et al., 2021). We complement this literature by using a production-based measure of greenness[5] and by looking at green manufacturing rather than at the whole economy or at the power generation sector. This is particularly important because manufacturing is a strategic sector, paying higher than average wages, and usually has larger local job multipliers than other sectors (Moretti, 2010).

The reminder of this paper has a standard structure. Section 2 presents the data. Section 3 a few interesting facts on the dynamics of green production and of the outcomes of interest. Section 4 illustrates the identification strategy. Sections 5 and 6 cover the main results and the extensions, respectively. Section 7 concludes.

2 Data

To analyse the labour market impacts of green re-industrialization, we assemble a new dataset containing information on production, green production, stock of green patents, employment, annual average wages, value added, labour productivity, investment in machinery equipment, total imports and energy purchases across European countries, years (2003-2017) and 199 4-digit industries.

2.1 Measure of green production

One key novel contribution of this study is the use of a measure of green production that varies by country, year, and detailed (4-digit) manufacturing industries. The creation of this measure presents both conceptual and empirical issues.

To begin with, it is not obvious what a green good is. The literature has proposed two main approaches: the *process approach* and the *output approach* (Bontadini & Vona, 2023; Elliott & Lindley, 2017; Rodrigues et al., 2018; Sato, 2014; Sinclair-Desgagné, 2017). According to the *process approach*, green production is the inverse of the pollution content of production. According to the *output approach*, a good's greenness depends on its potential beneficial effects on the environment in its usage. To further illustrate this difference, we can think of wind turbines, which allow the production of carbon-free electricity and, therefore, are green goods under the *output approach*. However, the production of wind turbines themselves involves high levels of emissions, mainly due to the processing of iron, and, therefore, under the *process approach*, they would rank as quite polluting.[6] We follow the *output approach* to define a green good. Indeed, it is green production, intended as *output*, that will benefit from generous

[5] Two early papers use the so-called US Green Goods and Services survey that also allow to build a production-based measure similar to ours (Becker & Shadbegian, 2009; Elliott & Lindley, 2017). However, due to data limitations, such papers can only exploit cross-sectional variation of the data and thus offer a descriptive analysis of the relationship between green production and employment.

[6] For wind turbines and the vast majority of green goods defined using the output approach, the emissions saved in the usage largely offset the emissions needed in the production stage.

subsidies and that is expected to contribute to employment and productivity growth in manufacturing. Another key conceptual challenge lies in identifying the set of functions that benefit the environment. For example, there are products with different usages, and depending on the usage, they can be classified as green or not (e.g. pipes). By exploiting highly disaggregated product level data, we follow Bontadini and Vona (2023) and define a list of green goods that excludes goods with double usage.

Production data. The PRODCOM dataset compiled by EUROSTAT contains information on the sold production of manufactured goods identified with 8-digit codes. The dataset covers, on average, 4,288 single products per year, from 1995 to 2017. The PRODCOM dataset is particularly suited to compute industry-level measures of production because the 8-digit product codes are nested within the NACE industrial classification, with the first 4 out of 8 digits of each product code corresponding to a NACE code. This makes it possible to allocate PRODCOM codes univocally to a NACE industry. However, the usage of PRODCOM dataset poses practical challenges. Product codes are reviewed yearly, and, as such, the number of products covered varies yearly, making it difficult to have a balanced panel of products. To obtain a measure of production that accounts for the annual updates of PRODCOM codes, we have followed and refined Bontadini and Vona (2023). Concisely, we identify chains of product codes that change over time due to classification updates, and attribute a "synthetic code" to each chain that does not change over time. We then obtain a consistent measure of production over time by product and sector. Because of this aggregation, we cannot differentiate between new and old products, which are stacked within "synthetic code".[7] However, it is worth noting that most green goods are relatively recent and hence "new". This implies that our measure of green production can be seen as a proxy for product innovation.

Green goods. We use the list of green goods proposed by Bontadini and Vona (2023), which we briefly describe here. They start from the intersection of two existing lists: the Combined List of Environmental Goods (CLEG) of the OECD, and the list of green goods compiled by the German Statistical Office, which is based on the EUROSTAT criteria to define environmental goods (Eurostat, 2016).[8] After joining the two lists, Bontadini and Vona (2023) manually inspect the product descriptions of the PRODCOM dataset to exclude goods with double usage, so that to identify green goods with an unambiguous beneficial effect to the environment. This procedure leads to the identification of 221 green products.[9]

Aggregation from products to industries. Since the data on labour market outcomes are only available at 4-digit NACE codes, we sum the green production of each "synthetic product" at this

[7] Additional details on the Bontadini and Vona (2023) procedure of PRODCOM codes harmonization, which is based on Van Beveren et al. (2012), can be found in Appendix A.

[8] Note that the CLEG list is using the Harmonized System (HS) that can be linked to PRODCOM codes using crosswalks provided by Eurostat. In turn, the list of the German Statistical Office is built on PRODCOM codes.

[9] Additional details on the management of the green goods list can be found in Appendix A.

level of aggregation.[10] The resulting measure of green production is the first that, to the best of our knowledge, varies by industry-country-year. We deflate green and non-green production using the price indexes provided by the 2019 release of EUKLEMS to ensure comparability over time.[11] Compared to measures adopted in the literature that use either trade (Cantore & Cheng, 2018; He et al., 2015; Mealy & Teytelboym, 2022), patents (Calel & Dechezleprêtre, 2016; Nesta et al., 2014; Perruchas et al., 2020; Popp, 2002), or both (Fankhauser et al., 2013), this production dataset can: i. depict a more precise assessment of where green production is distributed; ii. capture technology adoption rather than invention; iii. extend over a long horizon, and cover an extensive set of country-industry pairs.

2.2 Other data sources

Data on patents. For identification purposes, we exploit green invention as an instrument for green production, consistently with a production function augmented for knowledge or ideas widely used in endogenous growth models (Aghion et al., 2014). We measure green invention activities using patents (see Popp, 2019 for a recent review). We retrieve information on patent applications at the European Patent Office (EPO) from PATSTAT, select green patents using the widely used Y02 tag that allows us to identify green technological classes, and compute stocks with the perpetual inventory method following Verdolini and Galeotti (2011). To account for the existing know-how available to firms, we focus on stocks to fully exploit the cumulative knowledge produced and to not put an implicit constraint on the timing of the relationship between invention and production (Brunel, 2019). Moreover, created knowledge is adopted with a lag and, in this sense, stocks, i.e. technological knowledge produced up until a specific period, are likely to matter more for production processes than counts, i.e. technological knowledge produced in a given period (Wang & Hagedoorn, 2014). We attribute green patents' technological classes from the Cooperative Patent Classification (CPC) to 4-digit NACE rev.2 industries, relying on the methodology developed by Lybbert and Zolas (2014).[12] This procedure allows us to measure the stock of green patents in a country-industry in a given year of our sample.

Data on employment, value added and wages. We gather data on the outcomes investigated in this paper from the Structure of Business Survey (SBS) from EUROSTAT. The dataset contains information on structural characteristics of non-financial firms in the market sector at 4-digit NACE industries from 1998 onward. Employment is computed as the number of full-time equivalent (FTE henceforth) employees. Value added is computed at factor costs. Average wages are computed by dividing the total wage bill by the number of employees in FTE. Labour productivity is computed by dividing value added by the number of employees in FTE. We deflate value added using value added

[10] Virtually no product within each synthetic code changes between NACE 4-digit sectors.
[11] EUKLEMS stands for EU level analysis of capital (K), labour (L), energy (E), materials (M) and service (S) inputs.
[12] We provide additional details on this methodology in Appendix A.

price indexes from EUKLEMS, while we use harmonised index of consumer prices to deflate wages.

Data on other covariates. Our econometric analysis seeks to purge the effect of green re-industrialization from other trends potentially correlated with labour market and competitiveness outcomes. Among these trends, automation, shocks in energy costs and trade exposure are the most important.

The SBS dataset does not contain direct information on automation investment or ICT technologies. These assets are included in the broader category "machinery and equipment", which includes transport equipment, other machinery equipment and, crucially, ICT equipment. We use this category, scale it by value added, and employ it as a proxy for investments in automation and robots. The SBS contains information on energy purchases, which we scale by turnover. This is our proxy of energy intensity and exposure to energy cost shocks. Lastly, we obtain aggregate information on total imports and exports from BACI trade data. This dataset is a repository of harmonised international trade statistics at the product level sourced from UNCOMTRADE on a bilateral basis that is constantly updated. Products are identified with 6-digit codes from the Harmonised System (HS). Using the HS-PRODCOM crosswalk, we compute the total import of a country-industry pair and use it as a proxy of trade exposure.[13]

Final dataset We combine these different data sources using the above-mentioned crosswalks between product, patent, tradable goods and industry classifications. Because of pre-existing gaps in some time series, our final data is a country-industry panel over the period 2003-2017. We begin the analysis in 2003 as Eastern European countries are not included in PRODCOM before that year. The SBS data has some missing values for certain countries and sectors, filled by performing interpolation whenever possible and appropriate. Overall, to maximise the number of complete country-industry time series, we have restricted our analysis to a sample of 21 countries over the period 2003-2017.[14]

3 Descriptive Evidence

In this Section, we uncover six stylized facts that, on the one hand, describe the dynamics of green production in Europe and, on the other hand, the relationship between green production and the outcomes inspected. The first two facts update and confirm the descriptive analysis of Bontadini and Vona (2023), while the subsequent four provide new evidence on the economic performance of potentially green industries compared to other industries.

Fact 1. *The share of green production is (and remains) highly concentrated in a few industries that have a low GHG intensity.*

[13] We deflate total import by NBER PISHIP shipment deflator. We did not rescale import to avoid rescaling multiple times with turnover or value added. However, all the results hold by using a standard measure of import penetration.

[14] The countries we include in our analysis are Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Spain, Sweden, United Kingdom.

We begin by exploring how green production (output approach) and emissions (process approach) are distributed across industries. Table B1 in Appendix B reports the mean value (in millions of €) and the mean share of green production across 2-digit NACE industries, comparing it with information on average direct and indirect greenhouse gasses (GHG) emissions.[15] We find that out of 24 2-digit industries, only 9 have any green production over our observed period, and 85% of green production occurs in the four greener industries. Interestingly, greener industries have a GHG intensity well below that of the main polluting industries, while polluting industries account for a very small fraction of total green production. Moreover, green industries are also high-to-medium tech. This suggests that the two groups of industries may follow very different dynamics even in the absence of ambitious green policies.

In Table B2 in Appendix B, we exploit the granularity of production data within 4-digit NACE rev.2 green industries. We find similar evidence, that is: 94.79% of green production is concentrated in 13 industries that we name "high-green potential" industries, while only 22 industries have positive green production in at least one country-year. We name them "green potential" industries. Further, Figure B1 in Appendix B shows that the ranking of 4-digit industries in terms of green production is remarkably stable over time.[16]

Fact 2. *Across countries, the share of green production is mildly increasing, with Denmark being the main EU leader.*

To complement the industry-level evidence, we examine country-level dynamics. Figure B2 in Appendix B shows that the share of green production across countries, weighted by total production to account for size, increased from 0.017 in 2003 to 0.022 in 2017, especially between 2003 and 2009. The green share is also highly heterogeneous and persistent across countries. Denmark is the country with the largest green production share (0.103 in 2017), followed by Austria (0.049 in 2017), Germany (0.034 in 2017), Sweden (0.027 in 2017) and the Czech Republic (0.026 in 2017). The rest of the countries rank at or below the European average for the period (0.021). In particular, France (0.018), Spain (0.016), and Italy (0.014) are consistently below it; Poland (0.021), Hungary and the Netherlands (0.020) hover around it; Bulgaria (0.024) shows a mild positive trend, overtaking the EU average at the end of the sample.

Fact 3. *Employment, value added, average wages and labour productivity grow faster in green potential industries.*

In light of the persistence of green production across both countries and industries, it is important to understand if potentially green industries differ significantly from non-green ones in terms of economic

[15] We use World Input-Output Tables to compute total GHG emissions. The green share of production is defined as: $Gsh_{cj,t} = \frac{Gp_{cj,t}}{Tp_{cj,t}}$, that is the ratio between green production and the total production in country-sector cj at time t.

[16] The only exception is the manufacture of electronic components (2611), which includes photovoltaic panels. The production of this green good has undergone a very rapid growth in the first half of our observed period, only to plummet from 2009 onwards as China has emerged as a new key competitor for European firms.

performance. Figure 1 depicts the dynamic of our outcome variables across three groups of industries: i. potentially green industries, defined as above; ii. polluting industries (see Table B1 in Appendix B); iii. other industries that are neither green nor polluting.

We find that green industries outperform both other industries and polluting ones in terms of all four outcome variables. Looking at employment dynamics (panel a), green industries appear more resilient to the great financial crisis and faster to recover. This contrasts with the pattern of polluting industries that are the worst performing group. Note that, in European countries, polluting sectors experienced a long-term historical decline, which is unrelated to increasing environmental policy stringency (Rosés & Wolf, 2018). Similar patterns are observed in terms of value added (panel b) and wage (panel c) growth. Labour productivity is the only variable in which green industries surpass the rest of manufacturing only in the latest years (panel d). Quantifying these differential patterns in the 15 years covered in our analysis, we find that: employment growth has been 13.70% higher in green industries than polluting ones, and 7.80% higher than in others; value added has been 38.04% higher in green than in polluting, and 40.73% higher than in others; wage growth has been 15.92% higher in green than in polluting, and 20.52% than in others; labour productivity has been 15.92% higher in green than in polluting, and 27.91% than in others.

[Figure 1 about here]

Fact 4. *Potentially green industries do not differ from others in terms of incidence of energy costs and automation, while they are less exposed to foreign competition than polluting industries.*

Before inspecting more formally the performance of green potential industries, it is important to investigate the relationship that these industries have with aggregate trends that influence the outcomes of interest. Previously, we alluded to the role of automation, shocks in energy costs and trade exposure, measured as in Section 2. We also consider non-green production since it captures a scale effect and will be a key control in the econometric analysis.

Figure 2 shows the dynamic of these control variables across the three groups of industries. If for energy purchases over turnover and for machinery investment over value added green, polluting and other industries exhibit quite similar trends, this is not the case for total import. In fact, green and other industries exhibit quite stable levels of total import, while polluting industries show a markedly increasing trend. This, jointly with Figure 1, aligns with the evidence studying the high exposure of polluting manufacturing to import shocks and the potentially negative effect on employment, both in the US and in Europe (Marin & Vona, 2019; Weber, 2020).

[Figure 2 about here]

Lastly, non-green production exhibits a higher growth rate in polluting and other industries than in green industries. Importantly, this does not imply that green production replaced non-green production in green potential industries. On the contrary, Figure B3 in Appendix B shows a positive correlation between the (IHS-transformed) long-term change in the two types of production in green potential industries. This implies that, on average, expanding green production does not come at the cost of reducing non-green production.

Fact 5. *The superior performance of potentially green industries holds conditionally on intervening factors correlated with the outcome variables.*

Fact 3 begs the question of whether the superior performance of green industries may be due to observable and unobservable factors correlated with both the outcomes and the industry's propensity to be green. To shed light on the role of these confounders, we use OLS to estimate conditional correlations between the outcome variables (transformed using the inverse hyperbolic sine, IHS) and a dummy variable equal to one for green potential industries interacted with a time trend, conditional on country-year fixed effects and controls presented in Fact 4.[17] Table 1 provides details on these results. In Panel A, being a potentially green industry is associated with a higher and statistically significant annual growth of employment (0.88%), value added (1.95%), average wages (0.55%) and labour productivity (1.1%). Cumulatively, comparing conditional and unconditional differences between green and other industries yields the following. Employment grew more by 13.2%, which is 5.4 p.p. higher than the unconditional difference, implying a widening of the gap due to the inclusion of the covariates.[18] The opposite pattern is observed for value added, wages and productivity where the addition of the covariates reduce the advantage of green potential industries.[19] In contrast, the polluting sectors exhibit, on average, a lower and statistically significant annual growth rate for all the variables of interest except wages: 0.91% for employment, 1.44% for value added and 0.69% for labour productivity. Combining these results, the cumulative conditional differences between potentially green and polluting industries are exacerbated by including the confounders. The cumulative differences are all substantially higher than their unconditional counterparts.

[Table 1 about here]

Fact 6. *High green potential industries drive the better performance of green potential industries.*

In panel B of Table 1, we differentiate green potential industries between highly green potential and the rest, i.e. marginally green industries. Remarkably, we observe that the superior performance of green potential industries is entirely driven by high-green potential ones, except for labour productivity. Still, the analysis of this section just allows us to obtain generic insights on the performance of potentially green industries without any claim of causality. The next section will make causal claims on the impact

[17] See Appendix B for the details on the estimating equation.

[18] We compute cumulative growth conditional on covariates for employment as $0.0088 \times 100 \times 15$. The same applies to the other outcomes.

[19] Value added grew more by 29.25%, which is 11.48 p.p. lower. Average wages grew more by 8.25%, which is 12.27 p.p. lower. Lastly, labour productivity grew more by 16.60%, which is 11.41 p.p. lower.

of expanding green production on the labour market by exploiting the observed variation in measured green production within green potential industries.

4 Empirical Framework

We investigate the impact of an expansion in green production on labour market outcomes within the 22 potentially green industries. In doing so, we focus on an *intensive margin effect* that is basically equivalent to the partial equilibrium effect of green industrialization on a subset of potentially affected industries. Especially because green industries are high-to-medium tech, this choice allows us to tighten the comparison group by excluding other industries that are more likely to be exposed to a different set of unobserved shocks. This rules out the role of input-output linkages and extensive margin effects associated to labour reallocation towards green potential industries. While input-output linkages will be investigated in Section 6, the previous section shows that green potential industries outperform other industries. In light of this evidence, labour reallocation in favour of green industries is likely to amplify a positive intensive-margin effect of green re-industrialization on employment.

To be concrete, we estimate the intensive margin effect using the following equation:

$$IHS(y_{cj,t}) = \alpha + \beta Gp_{cj,t} + \delta \boldsymbol{X'_{cj,t}} + \tau_t + \sigma_{cj} + \epsilon_{cj,t}. \tag{1}$$

$IHS(y_{cj,t})$ is the inverse hyperbolic sine of one of the four dependent variables (FTE employment, average wages, value-added or labour productivity).[20] $Gp_{cj,t}$ is the main variable of interest: the level of green production in a country-4digit industry pair cj in year t.[21] We include year, τ_t, and country-sector, σ_{cj}, fixed effects to account for common EU-level shocks and time-invariant unobserved heterogeneity, respectively. This implies that we only use the within country-industry pair variation to estimate the effects of green production.

We include the set of control variables, $\boldsymbol{X'_{cj,t}}$, discussed in Section 2 and 3 to purge the estimate of β from the influence of confounding factors. To carefully assess the role played by confounders, we also compare three specifications: i. without any additional controls; ii. controlling for non-green production of country-industry cj in the initial period (average 2000-2003) interacted with time fixed effects; iii. further adding time-varying controls (all IHS-transformed) for machinery investment over value added, total imports and energy purchase over turnover.[22] We chose the third specification as our favourite one as green production shocks are small compared to other structural transformations in the time period

[20] The IHS transformation allows us to deal with the zeros in the dependent variable while keeping the interpretation of the estimated coefficient as semi-elasticities. However, given the IHS sensitivity to the unit of measurement (Aihounton & Henningsen, 2021), we also report results with a $log + \epsilon$ as a transformation.

[21] Green production is deflated as discussed in Section 2 and scaled by €10 millions to enhance the readability of the coefficient.

[22] Non-green production is a proxy of size. We include it in the initial period to mitigate endogeneity concerns for this variable and focus only on fixing endogeneity concerns for green production.

covered in our analysis, thus controlling for them is essential.

Finally, we weigh the estimates by the total level of production and cluster standard errors at the country-sector level. The former choice ensures that our estimates represent the average of the 22 potentially green industries in Europe. The latter choice is consistent with the fact that green production varies by country-sector (Abadie et al., 2023).

The effect of green re-industrialization on employment is usually depicted as positive and large in the policy literature, while evidence is scant in the academic literature. Popp et al. (2021) find that the effect of the green part of the US American recovery and Reinvestment Act is highly uncertain because regions receiving more subsidies were already growing faster. However, their study does not focus on green industrialization. Few other studies find a positive correlation between measures of green innovation and employment at the firm-level (Elliott et al., 2021; Gagliardi et al., 2016), but without any strong causal claim. Since green products are generally new and new products (and tasks) are associated with job creation (Acemoglu & Restrepo, 2019; Autor et al., 2022; Harrison et al., 2014), this evidence reinforces the expectation that green re-industrialization will have a positive effect on job creation. On wages, there is mixed evidence. Previous studies estimate a positive but declining green wage premium using job vacancy data (Saussay et al., 2022), but also find no evidence of a positive effect of green subsidies on wages (Popp et al., 2021). Similar mixed findings are obtained in the literature estimating the effect of green policies or green innovation on productivity, again without any causal claim (see, e.g.,Ghisetti, 2018). Aggregated data are not ideal to understand what is behind wage and productivity effects. On the former, the adoption of new technologies affect both the price of skills and the composition of the workforce. On the latter, assessing the role of compositional effects is exceedingly complex due to entry and exist dynamics. Overall, we are able to estimate the net effect of green re-industrialization on wages and productivity, but a correct interpretation would require more disaggregated data at the worker and firm level.

4.1 Shift-share instrumental variable design

In Equation 1, including country-sector fixed effects and controlling for observable drivers of labour market outcomes help mitigate endogeneity concerns. However, this is not sufficient for two main reasons.

First, green production is measured with errors arising from the over-time harmonization of product codes in PRODCOM, which creates aggregation biases. Typically, measurement error leads to an attenuation bias in the OLS estimates. Second, the usual omitted variable bias characterizes all setups where labour market outcomes are regressed on indicators of structural transformations (Acemoglu & Restrepo, 2020; Autor et al., 2013). To illustrate, technological choices are hard to observe, but also correlated with green production and the inspected outcomes. On the one hand, previous research shows that greener regions or industries are high-tech, better endowed with skills and capabilities required to operate green technologies, and already positioned on a better economic trajectory (Bontadini & Vona, 2023; Popp et al., 2021; Vona et al., 2019). On the other hand, investments in green production are jointly made with investments in automation, which are labour-saving (Acemoglu & Restrepo, 2022). Overall, the direction of the omitted variable bias is unclear in this context.

Following a standard approach to solve the endogeneity problem in similar contexts (Acemoglu & Linn, 2004; Acemoglu & Restrepo, 2020; Autor et al., 2013; Bartik, 1993; Jaravel, 2019; Marin & Vona, 2019), we propose a shift-share instrument that isolates changes in green re-industrialization driven by a green technology push. We use patent applications to measure green technological change as described in Section 2.

Specifically, we construct the instrument in the following way:

$$IVGpat_{cj,t} = \sum_{i(j)} \left(\frac{Gpat_{ci(j),t_0}}{\sum_c Gpat_{ci(j),t_0}} \cdot \sum_{k \neq EU} Gpat_{ki(j),t} \right), \tag{2}$$

where the shares, $\frac{Gpat_{ci(j),t_0}}{\sum_c Gpat_{ci(j),t_0}}$, are the shares of green EPO (European Patent Office) patents stocks for country c, patent i assigned to sector j, over all green EPO patent stocks in the EU at time t_0 (average 1991-1998). We take the pre-sample average of patents to mitigate endogeneity concerns on the share component of the instrument (Goldsmith-Pinkham et al., 2020). The shift, $\sum_{k \neq EU} Gpat_{ki(j),t}$ is the aggregate level of green patent i filed in the EPO by non-EU countries, at time t.

The intuition is that a country-sector's with better initial green capabilities can benefit more from current and future worldwide improvements in green technologies, and hence take advantage of a technology push. This instrument is similar in spirit to shift-shares that exploit technological shocks to investigate labour market dynamics (Acemoglu & Restrepo, 2020; Acemoglu et al., 2022). Moreover, it is theoretically consistent with a production function augmented for knowledge or ideas (Aghion et al., 2014) or path-dependency in knowledge and production specializations (Acemoglu et al., 2012).

We also use an alternative shift-share IV design based on green production and reflecting more a green demand pull:

$$IVGp_{cj,t} = \sum_{p(j)} \left(\frac{Gp_{cp(s),t_0}}{\sum_c Gp_{cp(j),t_0}} \cdot \sum_{k \neq c} Gp_{kp(j),t} \right), \tag{3}$$

where the shares, $\frac{Gp_{cp(s),t_0}}{\sum_c Gp_{cp(j),t_0}}$, are the share of the sold production of the green product p in industry j and country c at t_0 (average 2000-2003), over the sold production of the green good p in industry j in all countries at t_0. The shifts $\sum_{k \neq c} Gp_{kp(j),t}$ have the leave-one-out structure, being the sold production of green good p in industry j at time t in all EU countries except c. [23]

The intuition is to isolate an EU-wide source of exogenous variation in green production, netting out the idiosyncratic and country-specific sources of endogeneity. This instrument is thus more similar

[23] Note that, similar to Carluccio et al. (2015), we instrument green production at the 4-digit industry level starting from the 8-digit product dimension, thus exploiting a higher degree of data variation.

in its spirit to the shift-share instruments used to estimate local job multipliers (Blanchard & Katz, 1992; Chodorow-Reich, 2019; Moretti, 2010). Being driven by demand rather than supply factors, this instrument is more likely to replicate how labour markets would adjust in response to a policy-driven increase in green production.

Together with the main results of the paper, the next section presents an extensive validation of the credibility of our IV design following the approach of Goldsmith-Pinkham et al. (2020). In particular, we will test for the presence of pre-existing trends in the sectors accounting for the larger exposure to green shocks and for the plausibility of the exclusion restriction (Conley et al., 2012).

5 Results

This section presents the main results of the paper on the intensive margin effects of green re-industrialization. Table 2 shows the results of both OLS and 2SLS specifications. Specifically, Panel A presents the coefficients of green production on FTE employment and value added, while Panel B presents the ones on average wages and labour productivity.

[Table 2 about here]

Starting from Panel A, we find a positive and significant effect of expanding green production on employment and value added, both in the OLS (col. 1 and 3) and the 2SLS specifications (col. 2 and 4). Consistently with the expectation that technological and production capacities are aligned, the patent instrument is strong with a Cragg-Donald (CD) F-statistic for weak identification of 588.5.[24]. The 2SLS also deliver larger coefficients than the OLS ones for employment and value added. This can be the effect of a classical measurement error in green production, but it also highlights the fact that compliers, i.e. countries with strong technological and production capacities, can create more jobs and value out of green re-industrialization. This gap between IV and OLS results resonates with the concern that green re-industrialization may exacerbate regional and cross-country inequalities (Bontadini & Vona, 2023; Popp et al., 2021).

The coefficients can be interpreted as semi-elasticities. Thus an increase in green production of €10 millions implies an increase in FTE employment of 0.31% and an increase in value added of 0.36%. To give a sense of the size of the effect, the mean value of green production in 2003 in €10 million is 1.29, implying that the just commented increase is close to an average one. While the effect on value added is not politically contentious, the job creation effect is crucial to justify large spending plans for the green economy. To quantify precisely the cost per job associated with an increase of €10 millions in sold green production, we compute the job created by multiplying the estimated coefficient for the average initial

[24] This implies that the instrument is highly relevant in explaining the endogenous variable, in line with the fact that the first-stage coefficient of green patent on green production is highly statistically significant. The Cragg-Donald (CD) F-statistic is well above the threshold of 16.38 to have 10% the bias of the OLS (Stock & Yogo, 2002).

number of jobs that are likely associated with green production. This calculation implies a cost per job of €29,102, which is larger than the estimate obtained by (Popp et al., 2021) for green spending or on the upper end of the estimates of the fiscal multipliers (Chodorow-Reich, 2019).[25] Recall that our estimates are not job multipliers on the entire economy, but only partial equilibrium effects within a subset of high-to-medium tech manufacturing sectors.

Panel B reports the results for average wages and labour productivity. We find muted effects of green re-industrialization on these two variables, both in OLS and 2SLS specifications. This is consistent with the null wage premia of green spending found by Popp et al. (2021), but for the whole economy. On the productivity effects, results of previous studies were also mixed depending, e.g., on the environmental policy, the level of analysis and the measure of productivity used (Dechezleprêtre & Sato, 2017; Ghisetti, 2018), but no study is comparable to ours in terms of the level of analysis and green measure. It is important to emphasize that there are no effects on wages and productivity within narrowly defined high-to-medium tech sectors. The descriptive result of Section 3 suggests that the reallocation of labour towards green sectors will increase the average wages as such sectors, on average, pay higher wages. This is in line with mixed results on the wage premium for green occupations, which is larger if a researcher compares very different occupational groups (Draca et al., 2021) and much smaller if the comparison groups are narrower (Saussay et al., 2022; Vona et al., 2019). Finally, a muted effect on wages also implies that, at least in manufacturing, the tangible and intangible capital (including human capital) required to produce non-green goods can be easily reused to produce green goods. Otherwise, green re-industrialization would have caused a detectable increase in the average price of green skills.

We conduct extensive tests of the robustness of our main results, which we collectively report in Appendix C. Table C1 reports the main estimates, progressively adding controls up to our favourite specification. It shows that the coefficients of interest remain remarkably stable. Table C2 exploits a different set of fixed effects. While using country-sector and year fixed effects mitigates omitted variable biases, it also limits the sources of data variation used for the estimation. We thus change the set of fixed effects used by including country-year and industry-year fixed effects. In the favourite 2SLS specification, we find much larger semi-elasticity for employment (+0.56%) and value added (+0.63%) and no detectable changes for productivity. Remarkably, here wages positively respond to a green re-industrialization shock, but the semi-elasticity remains small (+0.08%). The bottom line is again that unobserved and persistent country-sector characteristics play an important role in explaining the gains, especially the wage gains, of an expansion in green production. Inspired by the descriptive results of Section 3, Table C3 shows the effects of green production for the restricted sample of high-green potential

[25] The jobs created are computed with respect to the initial share of employment involved in green production, which is assumed to be proportional to the share of green production in the initial period. That is: initial share green = $\overline{Emp(FTE)_{cj,0}} \times \overline{GpSh_{cj,0}}$, where $\overline{Emp(FTE)_{cj,0}}$ is the average level of FTE employment and $\overline{GpSh_{cj,0}}$ is the average weighted share of green production, both taken in the initial period. Then, we compute the job created as: job created = $\hat{\beta} \times 100 \times \overline{Emp(FTE)_{cj,0}} \times \overline{GpSh_{cj,0}} = 0.0031276 \times 100 \times 12801.57 \times 0.0858208$. Finally, cost per job = 10^7/(job created), as green production is expressed in €10 millions in our regressions for the readability of the coefficients.

industries. The estimates are in line with those of Table 2, with the exception of labour productivity for which we detect a positive and statistically significant effect. Specifically, a €10 millions increase in sold green production implies a 0.13% increase in labour productivity. Table C4 changes the clustering of standard errors to two-way clustering (Cameron & Miller, 2015); that is, country-sector and year: the standard errors remain in line with those presented in the main table. Table C5 shows that results are robust by changing the IHS transformation to $ln + \epsilon$, with $\epsilon = 0.0001$ (Aihounton & Henningsen, 2021). Lastly, Table C6 does not restrict the estimation sample to the 22 potentially green industries but just adds a green dummy interacted with a time trend and considers all manufacturing industries. Again, the coefficients of the favourite specification are in line with the main results.

5.1 Validation of the shift-share design

Parallel trends assumption. Recent developments in the literature on shift-share designs propose a formal elaboration of the underlined identifying assumptions and insights for testing the instrument's credibility (Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020). The approach of Goldsmith-Pinkham et al. (2020), which assumes the exogeneity of the initial shares in the shift-share formulas, is particularly suitable to our case as green production is highly concentrated in a few industries. To lend credibility to a shift-share design assuming the exogeneity of the initial shares, Goldsmith-Pinkham et al. (2020) suggests testing for violations of the parallel trend assumptions for both the entire instrument and every single component, i.e. the initial shares. This implies regressing pre-sample observations of the dependent variables for a subset of countries for which they are available before 2003 on the instrument or on the initial share in one of the most important sectors, e.g. the industries with a high green production level, conditional on the usual set of controls.[26] The idea is that the industries with a high level of green production will drive the results, and thus, it is important to discharge systematic violations of the parallel trend assumption for key industries.[27] Practically, we test the presence of pre-trends by regressing the pre-sample average value of the whole instrument (or the share of a key green industry) with year dummies on the outcome variables in the favourite specification of Equation 1.

[Figure 3 about here]

Across the board, none of the dependent variables in Figure 3 shows signs of pre-trends associated with the initial value of the whole instrument. In Figure D1 in Appendix D, we repeat this analysis for each of the top-5 4-digit industries where green production is concentrated. The Figure is made of four

[26] The countries not present in this exercise due to data availability are Greece and Poland.

[27] The five most important green industries in terms of volume of green goods sold are: 2651 - Manufacture of instruments and appliances for measuring, testing, etc; 2712 - Manufacture of electricity distribution and control apparatus; 2825 - Manufacture of non-domestic cooling and ventilation equipment; 3020 - Manufacture of railway locomotives and rolling stock; 2811 - Manufacture of engines and turbines, except aircraft, vehicle and cycle engines. In a more general context where the most important industries are not so clear as in our case, Goldsmith-Pinkham et al. (2020) propose an instrument decomposition to identify the industries weighing more in the instrument, the so-called Rotemberg weights (Rotemberg, 1983).

columns (for the outcomes investigated) and five rows (for the five green-intensive industries). Almost all sub-figures do not highlight persistent pre-trends that could significantly bias our result. On value added, there are pre-trends but negative, meaning that expanding green production reverses rather than reinforces the previous trend. On employment, we find some evidence of slightly positive pre-trend only for sector 2712 (Manufacture of electricity distribution and control apparatus) and of slightly negative pre-trend for sector 2651 (Manufacture of instruments and appliances for measuring, testing). To be sure that these modest violations do not affect our results, Table D1 in Appendix D presents the results by excluding industry 2712 (columns 1 and 3) or industry 2651 (columns 2 and 4). Results on employment remain always statistically significant. Overall, these tests show that the parallel trend assumption is plausibly valid in our research design.

Balancing of covariates. Also following Goldsmith-Pinkham et al. (2020), we evaluate, within the green potential industries, any unbalance in the covariates' distribution between "treated observations" (with a green production level above the median) and "untreated observations" (with a green production level below the median). Checking for unbalances in the observable covariates indirectly highlights the presence of an unbalance in the unobservables entering the error term (Altonji et al., 2005). Table 3 reports the means (weighted by total production) of the two groups defined above and their difference, net of country-sector and year fixed effects. None of the critical covariates exhibits statistically significant differences between the two groups of "treated" and "untreated". This conclusion is further corroborated by Figure D2 in Appendix D, which shows a series of k-density plots for each covariate divided by the two groups.

[Table 3 about here]

Plausible exclusion restriction. The key identifying assumption of any IV design is that the instrument only affects the outcome variable through the endogenous variable (so-called exclusion restriction). We argued that, theoretically, the primary channel through which green technological development affects labour market outcomes is that of green goods' production. However, one may also counter-argue that, for example, a green technological changes is associated with other technological changes like automation, impacting employment levels via a channel parallel to that of green production. Having this in mind, we employ the methodology developed by Conley et al. (2012), which allows us to test the sensitivity of the main coefficients of interest to controlled violations of the exclusion restriction. In a nutshell, referring to Table 2 coefficients on FTE employment and value added in the favourite 2SLS specification, we allow for a direct effect of the instrument on the outcome, bound by the coefficients of the instrumented green production.[28] Figure 4 displays the outcome of this methodology: the blue horizontal line corresponds

[28] Appendix D provides additional details on the methodology and its application.

to the estimated coefficient of the instrumented green production. The widening confidence intervals vary depending on a value δ, which scales the size of the assumed exclusion restriction violation.

[Figure 4 about here]

Notably, sub-figures (a) and (c) show that, for our estimated coefficient to become statistically insignificant, the green patents instrument's direct effect should be about the same size as the indirect one via green production, which however is more theoretically plausible. Alternatively, in sub-figures (b) and (d), we also try to rescale the max of the violation of the exclusion restriction using the ratio between the interquartile range of green production and that of green patents. We show that in this case, the green patents instrument should be about one-half of the size of the green production coefficient to make the effect of interest insignificant. Both specifications indicate that violations of the exclusion should be quite sizeable and, hence, likely implausible to make the causal effect of interest statistically insignificant.

6 Extensions

We expand the main analysis along four directions: i) we look directly at the long-term effect of green re-industrialization; ii) we use the alternative shift-share instrument based on green production described in Equation 3; iii) we explore the heterogeneity of the effects depending on the industrial capabilities; iv) we study multiplier effects within manufacturing using input-output tables.

Long-term specification. Equation 1 only retrieves the short-term, annualized effect of green re-industrialization. The estimated coefficient of green production is an average of the effects for each year. This coefficient is a good proxy of the long-term effect only if the positive effect of green re-industrialization, e.g., on employment is quite homogeneous across years. On the contrary, if such a positive effect is concentrated in the first years of our sample, the long-term effects are smaller than the short-term ones. We assess the extent to which the short-term effect is an accurate proxy of the long-term one by estimating a long-difference model by taking the first(long)-difference of Equation 1. We also take the first difference of the instrument, thus the "shifts" in Equation 2 are replaced by the long-difference in green patents' applications of non-EU countries. To reduce potential missing data and to smooth yearly fluctuations in industrial production, we average the first and last three years (2003-2005 and 2015-2017, respectively). Controls as well as estimation weights take all the value of the first period.

[Table 4 about here]

Table 4 reports the results of the long-term specification. Across the board, results are qualitatively similar, thus the short-term effects persist in the long term. However, we observe a smaller effect on FTE employment. This is somehow expected as green industries mature and thus start entering a new phase of replacing labour with capital in most automatable tasks (Acemoglu & Restrepo, 2018; Vona & Consoli, 2015). The long-term cost per job increases accordingly from to €29'102 to €38'227. That is: it increases by almost one-third. The other small difference is that long-term productivity effects are positive and bigger, although not statistically significant at conventional level. This is again consistent with the capital deepening story, although further research is required to examine the long-term impact of greening manufacturing on productivity. The takeaway is that green productions are entering in a more mature stage in which future job creation effects will be smaller.

Comparison with a green production shift-share. We use the shift-share instrument presented in Equation 3, which combines the pre-sample shares of green products and the (leave-one-out) aggregate EU level of production in that product. Recall that this is instrument is more likely to approximate the effect of a policy/demand-pull effect than the patent instrument.

[Table 5 about here]

Table 5 shows the new estimation results, while Figures D3, D4 and D5 in Appendix D provide detailed diagnostics on the validity of the green production instrument. The notable change in the result is that effects become smaller on value added and employment. The effect on FTE employment become also statistically insignificant.[29]. Another notable difference with respect to the main results is the presence of pre-trends. Indeed, Figure D3 shows a quite pronounced positive (and often statistically significant) correlation between the instrument and all the investigated outcomes. These positive pre-trends are likely to create a downward bias in the estimated coefficients, thus contributing to explain the insignificant effect on employment.

To shed some light on different results for the two IVs, we allow the effects to vary across countries depending on the level of technological development. The intuition is that most developed EU countries are more technologically advanced and thus benefit more from a technology push. In turn, emerging EU countries are still catching up with frontier technology and thus benefit more from a demand push that stimulates technology diffusion. In practice, we test this hypothesis by splitting the sample into early members of the EU, "the most developed group" of core EU countries, and late members of the EU, "the emerging group" of Eastern European countries. We refer to the former group as EU15 and to the latter one as EU12.[30] We then apply both the shift-share IVs separately to each group.

[Table 6 about here]

[Table 7 about here]

[29] This is not due to a weak instrument problem. Indeed, the CD F-statistic is consistently high across specifications, and the first stage coefficient is positive and similar to that of the green patents instrument.

[30] The exact division of the countries is the following. EU15: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, United Kingdom. EU12: Bulgaria, Hungary, Poland, Romania, Slovakia. We keep the United Kingdom in the EU15 estimating sample despite its exit from the EU. We exclude the Czech Republic from the EU12 sample given its different trajectory outlined in Figure B2.

Table 6 shows that the main results on the patent instrument are driven by the EU15 sample of countries and the estimates for this sub-sample are quantitatively similar to the main ones of Table 2. In contrast, for the sample of EU12 countries, the 2SLS results are out of range reflecting an weak first-stage relationship. The instrument is weak because the green patent shares of EU12 countries are negligible and thus EU12 countries benefit much less from an exogenous technology push.

The opposite occurs when we exploit the demand-pull shock. Table 7 shows a positive effect of green production on FTE employment and average wages for EU12 countries.[31] The estimates imply a cost per job of €33'850 and that a green production increase of €10 millions would result in a 0.32% increase in average wages. Conversely, effects on value added remain positive and significant only for EU15 countries.

This result suggests that countries at different stages of development exhibit heterogeneous responses to different policies, i.e. technology-push vs. demand-pull, and it is reminiscent of classical distance-to-the-frontier theorizing (Acemoglu et al., 2006). In such theory, imitation strategies pay off for countries distant to the frontier, while innovation strategies pay off closer to the frontier. This result also has an important policy implication hinting at a potential inequality-reducing effect of green industrial policies.

Countries capabilities. To explain heterogeneous effects, here we investigate the role of country-industry capabilities in specific manufacturing production. This is inspired by Popp et al. (2021), who shows that employment impacts of green subsidies are crucially mediated by the availability of green skills.

Absent reliable green skills data for Europe, we construct a measure based on non-green production in the initial period, which arguably approximates the country's capacity in "green-related products".[32] This measure is a classical Relative Comparative Advantage (RCA) Balassa index using export data from BACI.[33] That is:

$$RNGA_{cj,t_0} = \frac{NGexp_{cj,t_0}/Totexp_{cj,t_0}}{\sum_c NGexp_{cj,t_0}/\sum_c Totexp_{cj,t_0}}, \tag{4}$$

where $NGexp_{cj,t_0}/Totexp_{cj,t_0}$ is the ratio of non-green export over the total exports of a country-industry pair cj at baseline t_0, and $\sum_c NGexp_{cj,t_0}/\sum_c Totexp_{cj,t_0}$ is the same ratio summed over all EU countries c. In line with the usual interpretation of Balassa indexes, we transform $RNGA_{cj,t_0}$ into a dummy: for values of $RNGA_{cj,t_0}$ greater than 0, the country is indeed a global leader in that sector (dummy=1); for values of $RNGA_{cj,t_0}$ smaller or equal 0, it is not (dummy=0). Subsequently, we augment our specification of Equation 1 adding the interaction between this dummy and green production.

[31] Note that now the IV is strong for both groups of countries. This aligns with the fact that industrial production was already relocated to Eastern countries at the beginning of our sample period.

[32] Bontadini and Vona (2023) show that specialization in green productions is driven by previous specialization in non-green productions for a similar set of countries and years.

[33] Note that, as only highly productive firms are engaged in international competition, we take export data to provide a higher filter of quality for our capability measure.

[Table 8 about here]

Table 8 corroborates our expectation that country-industry pairs already specialized in green-related products, i.e. products in the same 4digit industry, reap larger benefits from green industrialization. More in details, they drive the positive effects for both FTE employment and value added. For value added, only the interaction term is positive and statistically significant at conventional level. For employment, both the interaction (row 2) and the linear (row 1) terms are positive, but not statistically significant. However, the linear combination of the two coefficients turns out positive and significant for the countries with the appropriate industrial capabilities (as shown in row 3). Quantitatively, the effects are sizeable: a €10 million increase in green production leads to a 0.14% (resp. 0.31%) increase in employment (resp. value added) in countries with specific capabilities.

Next, we find that countries with related capabilities obtain larger dividends (a positive interaction term) in terms of wages and productivity (columns 3 and 4). While the interaction terms is statistically significant only for wages (row 2), the combined effect is significant only for productivity (row 3). These results are expected in light of the higher competitiveness of exporters, which is reflected in the so-called exporter wage premium (Bernard et al., 1995; Schank et al., 2007). However, the additional effect on wages is small[34], possibly reflecting the fact that we do not exploit the granularity of firm-level data.

Input-output linkages. To broaden the interpretation of our partial equilibrium estimates, we exploit input-output linkages to assess the propagation of green production shocks outside the treated sectors, i.e. in non-green potential sectors. In doing so, we assess the indirect labour market effect within manufacturing, both for green potential industries and other industries. We expect that a positive green demand shock increases the demand for labour not only in "treated" industries but also in industries sourcing and buying from those industries.[35]

In practice, we do so by closely following the approach proposed by Acemoglu et al. (2016) to study the propagation of the China shock within manufacturing. The first step is to build two measures of upstream and downstream linkages using Inter-Country Input-Output (ICIO) Tables released in 2023 by the OECD. Specifically, the measure of upstream linkages reads as follows:

$$Up\,Gp_{cj,t} = \sum_{g \neq j} w_{cj,g} Gp_{c,g}, \tag{5}$$

using weights $w_{cj,g}$ that are equal to $w_{cj,g} = \frac{\mu_{j,g}}{\sum_{g \neq j} \mu_{j,g}}$, where $\mu_{j,g}$ is the domestic intermediate consumption within each country c, of industry j of inputs supplied by green industry g, averaged over the period 2000-03, i.e. at baseline.[36] Therefore, weight $w_{cj,g}$ can be understood as the share of domestic

[34] a €10 millions increase in green production implies an increase in wages of just 0.09% on average

[35] For instance, an increase in the demand for wind turbines would increase the upstream supply of steel.

[36] We already discuss the definition of green industries, here it is worth bearing in mind that we aggregate our data up to approximately 2-digits ISCI rev. 4 to match with the ICIO data.

intermediate consumption of each sector g in country-industry cj's total intermediate consumption, and $Up\,Gp_{cj,t}$ corresponds to the average green production of country-sector cj's suppliers, weighted on the input-output linkages connecting each supplier to cj.[37] We exclude, of course, the intermediate linkages emanating from g to the industry itself, since the goal of this exercise is to capture *inter*-sectoral linkages. We follow here Acemoglu et al. (2016)'s main application and only rely on direct input-output linkages as captured by the sourcing matrix from ICIO.[38] Taking the example of wind turbines, this means that we only consider the indirect demand shock that spills over to first-tier suppliers and buyers of the industry producing wind turbines: e.g. the supply of steel but not of energy needed to produce the steel itself. While looking at higher-order inter-sectoral linkages would possible, it is worth bearing in mind that first-order linkages have considerably larger magnitudes in the ICIO tables and are likely to account for the majority of the effect we aim to capture here.[39] Downstream green production is computed in a specular way.[40] Lastly, we include in our estimates either the downstream or the upstream measure of linkages in the intensive margin equation 1. Both measures are instrumented using the counterpart of the green patent shift-share instrument.

[Table 9 about here]

Table 9 presents the coefficients related to both the direct and indirect effects of an expansion of green production on the manufacturing sector. Closely following Acemoglu et al. (2016), Table 9 exploits domestic input-output linkages, while Table C7 in Appendix C exploits EU ones.[41] Starting from FTE employment, within green potential industries, accounting for sectoral linkages halves the cost per job of a €10 millions increase in green production. The cost ranges between €13'977 and €18'852, depending on whether one accounts for downstream or upstream green production. Outside of potentially green industries, neither upstream nor downstream green production affects FTE employment meaningfully. This therefore suggests that employment spillovers take place both up- and downstream, but only among green industries. It is worth bearing in mind here that green industries within the ICIO tables are identified at 2-digits NACE. Green production is therefore clustered essentially in few very closely related industries – namely the manufacture of computer, electronic equipment; machinery; electrical equipment

[37] In the application discussed here, we only focus on domestic inter-sectoral linkages, in line with Acemoglu et al., 2016; ICIO data allow, however, to also capture inter-country input-output linkages. We test our results using also intermediate linkages among EU countries and find similar results. Testing this model with the full range of inter-country results, and not only EU countries, is omitted here because (i) these linkages are significantly smaller than domestic ones and are unlikely to change our results significantly, and (ii) they might lead to correlation with our instruments affecting the reliability of our IV approach.

[38] To illustrate, the standard input-output model depicts total output $X = XA + F$, where F is final demand and AX is intermediate demand, with A being a square matrix of technical coefficients capturing the amount of intermediate production necessary to the production of one unit of output. Each element of the matrix A corresponds to $\mu_{j,g}$.

[39] Additional results on this are available upon request.

[40] Therefore we invert the indexes of our weight w and the previous equation becomes:

$$Down\,Gp_{cj,t} = \sum_{g \neq j} w_{g,cj} Gp_{c,g},$$

[41] Despite small differences in statistical significance, the coefficients of Table 9 are in line with the ones in Table C7. The fact that domestic IO linkages have higher predictive power than EU linkages is somewhat expected, as domestic industries are more connected that non-dometic ones, carrying this strength into the weight component w.

and transport equipment – sharing strong input-output linkages.[42] In light of this it is reasonable to understand increases in green production in a given industry as a proxy of broader technical change and the emergence of new productive activity, which triggers changes in input mix both up- and downstream the value chain. This also explains why, in contrast, such spillovers do not appear to be at play when considering linkages between green and non-green industries (col. 3 and 4 of panel A) that have significantly weaker input-output linkages.

Value added is not affected by upstream or downstream production, both outside and within green potential industries. Consistent with this and the positive effect on employment, we find a negative effect on average wages and labour productivity. If, therefore, green production can be understood as signalling technical change, requiring production adjustments and creating additional employment along the value chain, it appears that, in contrast, value added remains concentrated in the innovating country-sector, leading to a decrease in both wages and labour productivity in up- and downstream industries. An alternative, less mechanical, explanation may have to do with the fact that as industries introduce new green products, they also attract higher-wage and higher-productivity competing on these measures with suppliers and customers. This is in line with the evidence on nuanced effects of innovation along value chains (Bontadini et al., 2024; Costantini et al., 2017; Simonazzi et al., 2013).

7 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, especially in terms of job creation, is an essential goal of the green industrial policies that are discussed in both Europe and the US.

In this paper, we study the relationship between labour market outcomes and green production to shed light on the magnitude of these potential benefits. 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, value added, average wages and productivity, and of other factors affecting labour market and industry dynamics, such as trade and automation. Having data at a granular 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 such granular level

[42] These can be found in Table B1 in Appendix B

foralmost all EU countries and over a long panel spanning more than a decade (2003-2017). 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 industrial policies.

Our main findings are the following. First, regardless of the level of green production, the sectors where green production is concentrated are also doing relatively better in terms of employment, value added, average wages and productivity. 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, after controlling for other drivers of labour marker outcomes and taking care of the endogeneity of green production, we find that employment and value added grow faster in potentially green sectors at the intensive margin. Third, we observe a green wage and productivity premium when comparing green potential and other industries, but not at the intensive margin. This indicates that in the same sector, green and non-green activities require a similar set of skill levels and that the average wages and productivity are also similar. Fourth, our analysis also highlights that the most developed countries will reap most of the benefit of a green technology-push, while a green policy/demand-pull less developed ones. Finally, the short-term job creation effects are sizeable with a cost per job of €29.1 thousands and get even bigger when we account for input-output linkages within manufacturing. However, the long-term effect is smaller (€38.2 thousands per job) indicating that maturing green tasks will be easier to automate.

Further research is required to understand the distributional effects across regions, estimating local job mutipliers, and workers, using matched employer-employee datasets. On inequalities across workers, the average wage effects estimated here can be ascribed to both compositional and price effects that are impossible to observe with our data. On regional inequalities, it is important to assess the extent to which green industrial policies reinforce existing inequalities by also looking at region that are specialized in highly polluting industries.

References

Abadie, A., Athey, S., Imbens, G. W., & Wooldridge, J. M. (2023). When should you adjust standard errors for clustering? *The Quarterly Journal of Economics*, *138*(1), 1–35.

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. *American Economic Review*, *102*, 131–66.

Acemoglu, D., Aghion, P., & Zilibotti, F. (2006). Distance to frontier, selection, and economic growth. *Journal of the European Economic association*, *4*(1), 37–74.

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., & Price, B. (2016). Import competition and the great us employment sag of the 2000s. *Journal of Labor Economics*, *34*(S1), S141–S198.

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, *40*(S1), S293–S340.

Acemoglu, D., & Linn, J. (2004). Market size in innovation: Theory and evidence from the pharmaceutical industry. *The Quarterly journal of economics*, *119*(3), 1049–1090.

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American economic review*, *108*(6), 1488–1542.

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, *33*(2), 3–30.

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets. *Journal of political economy*, *128*(6), 2188–2244.

Acemoglu, D., & Restrepo, P. (2022). Demographics and automation. *The Review of Economic Studies*, *89*(1), 1–44.

Aghion, P., Akcigit, U., & Howitt, P. (2014). What do we learn from schumpeterian growth theory? In *Handbook of economic growth* (pp. 515–563, Vol. 2). Elsevier.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., & Reenen, J. V. (2016). Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry. *Journal of Political Economy*, *124*(1), 1–51.

Aihounton, G. B., & Henningsen, A. (2021). Units of measurement and the inverse hyperbolic sine transformation. *The Econometrics Journal*, *24*(2), 334–351.

Altonji, J. G., Elder, T. E., & Taber, C. R. (2005). Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. *Journal of political economy*, *113*(1), 151–184.

Ambec, S., Cohen, M. A., Elgie, S., & Lanoie, P. (2013). The porter hypothesis at 20: Can environmental regulation enhance innovation and competitiveness? *Review of environmental economics and policy*.

Autor, D., Chin, C., Salomons, A. M., & Seegmiller, B. (2022). *New frontiers: The origins and content of new work, 1940–2018* [National Bureau of Economic Research].

Autor, D., Dorn, D., & Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *American economic review*, *103*(6), 2121–68.

Autor, D., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, *118*(4), 1279–1333.

Bartik, T. J. (1993). Who benefits from local job growth: Migrants or the original residents? *Regional studies*, *27*(4), 297–311.

Becker, R. A., & Shadbegian, R. J. (2009). Environmental products manufacturing: A look inside the green industry. *The BE Journal of Economic Analysis & Policy*, *9*(1).

Belderbos, R., Park, J., & Carree, M. (2021). Do r&d investments in weak ipr countries destroy market value? the role of internal linkages. *Strategic Management Journal*, *42*(8), 1401–1431.

Bergquist, P., Mildenberger, M., & Stokes, L. C. (2020). Combining climate, economic, and social policy builds public support for climate action in the us. *Environmental Research Letters*, *15*(5), 054019.

Bernard, A. B., Jensen, J. B., & Lawrence, R. Z. (1995). Exporters, jobs, and wages in us manufacturing: 1976-1987. *Brookings papers on economic activity. Microeconomics*, *1995*, 67–119.

Blanchard, O. J., & Katz, L. F. (1992). Regional Evolutions. *Brookings Papers on Economic Activity*, *23*(1), 1–76. https://ideas.repec.org/a/bin/bpeajo/v23y1992i1992-1p1-76.html

Bontadini, F., Evangelista, R., Meliciani, V., & Savona, M. (2024). Technology, global value chains and functional specialisation in europe. *Research Policy*, *53*(2), 104908.

Bontadini, F., & Vona, F. (2023). Anatomy of green specialisation: Evidence from eu production data, 1995–2015. *Environmental and Resource Economics*, 1–34.

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies*, *89*(1), 181–213.

Brunel, C. (2019). Green innovation and green imports: Links between environmental policies, innovation, and production. *Journal of environmental management*, *248*, 109290.

Calel, R., & Dechezleprêtre, A. (2016). Environmental policy and directed technological change: Evidence from the european carbon market. *Review of economics and statistics*, *98*(1), 173–191.

Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of human resources*, *50*(2), 317–372.

Cantore, N., & Cheng, C. F. C. (2018). International trade of environmental goods in gravity models. *Journal of environmental management*, *223*, 1047–1060.

Carluccio, J., Fougère, D., & Gautier, E. (2015). Trade, wages and collective bargaining: Evidence from france. *The Economic Journal*, *125*(584), 803–837.

Castellani, D., Marin, G., Montresor, S., & Zanfei, A. (2022). Greenfield foreign direct investments and regional environmental technologies. *Research Policy*, *51*(1), 104405.

Chan, H. R., & Zhou, Y. C. (2024). *Charged up: Impacts of green energy transition on local labor markets.*

Chodorow-Reich, G. (2019). Geographic cross-sectional fiscal spending multipliers: What have we learned? *American Economic Journal: Economic Policy*, *11*(2), 1–34.

Conley, T. G., Hansen, C. B., & Rossi, P. E. (2012). Plausibly exogenous. *Review of Economics and Statistics*, *94*(1), 260–272.

Costantini, V., Crespi, F., Marin, G., & Paglialunga, E. (2017). Eco-innovation, sustainable supply chains and environmental performance in european industries. *Journal of cleaner production*, *155*, 141–154.

Curtis, E. M., & Marinescu, I. (2022). *Green energy jobs in the us: What are they, and where are they?* [National Bureau of Economic Research].

Dechezleprêtre, A., & Sato, M. (2017). The impacts of environmental regulations on competitiveness. *Review of environmental economics and policy.*

Domini, G., Grazzi, M., Moschella, D., & Treibich, T. (2022). For whom the bell tolls: The firm-level effects of automation on wage and gender inequality. *Research Policy*, *51*(7), 104533.

Draca, M., Li, J., Muller, S., Nguyen-Tien, V., Riom, C., & Valero, A. (2021). *Are'green'jobs good jobs?* [Centre for Economic Performance, LSE].

Elliott, R. J., Kuai, W., Maddison, D., & Ozgen, C. (2021). *Eco-innovation and employment: A task-based analysis* [IZA Discussion Paper].

Elliott, R. J., & Lindley, J. K. (2017). Environmental jobs and growth in the united states. *Ecological Economics*, *132*, 232–244.

Eurostat. (2016). *Environmental goods and services sector accounts manual: 2016 edition.* Luxemburg.

Fabra, N., Gutiérrez Chacón, E., Lacuesta, A., & Ramos, R. (2023). *Do renewables create local jobs?* [Banco de Espana Working Paper].

Fankhauser, S., Bowen, A., Calel, R., Dechezleprêtre, A., Grover, D., Rydge, J., & Sato, M. (2013). Who will win the green race? in search of environmental competitiveness and innovation. *Global Environmental Change*, *23*(5), 902–913.

Franco, C., & Marin, G. (2017). The effect of within-sector, upstream and downstream environmental taxes on innovation and productivity. *Environmental and resource economics*, *66*(2), 261–291.

Fusillo, F. (2023). Green technologies and diversity in the knowledge search and output phases: Evidence from european patents. *Research Policy*, *52*(4), 104727.

Gagliardi, L., Marin, G., & Miriello, C. (2016). The greener the better? job creation effects of environmentally-friendly technological change. *Industrial and Corporate Change*, *25*(5), 779–807.

Ghisetti, C. (2018). On the economic returns of eco-innovation: Where do we stand? *New developments in eco-innovation research*, 55–79.

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, *110*(8), 2586–2624.

Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American economic review*, *104*(8), 2509–2526.

Graetz, G., & Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, *100*(5), 753–768.

Greenstone, M. (2002). The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 clean air act amendments and the census of manufactures. *Journal of political economy*, *110*(6), 1175–1219.

Harrison, R., Jaumandreu, J., Mairesse, J., & Peters, B. (2014). Does innovation stimulate employment? a firm-level analysis using comparable micro-data from four european countries. *International Journal of Industrial Organization*, *35*, 29–43.

He, Q., Fang, H., Wang, M., & Peng, B. (2015). Trade liberalization and trade performance of environmental goods: Evidence from asia-pacific economic cooperation members. *Applied Economics*, *47*(29), 3021–3039.

Horbach, J., & Rammer, C. (2020). Circular economy innovations, growth and employment at the firm level: Empirical evidence from germany. *Journal of industrial ecology*, *24*(3), 615–625.

Horbach, J., & Rennings, K. (2013). Environmental innovation and employment dynamics in different technology fields–an analysis based on the german community innovation survey 2009. *Journal of Cleaner Production*, *57*, 158–165.

Jaravel, X. (2019). The unequal gains from product innovations: Evidence from the us retail sector. *The Quarterly Journal of Economics*, *134*(2), 715–783.

Kahn, M. E., & Mansur, E. T. (2013). Do local energy prices and regulation affect the geographic concentration of employment? *Journal of Public Economics*, *101*, 105–114.

Kleimann, D., Poitiers, N., Sapir, A., Tagliapietra, S., Véron, N., Veugelers, R., & Zettelmeyer, J. (2023). Green tech race? the us inflation reduction act and the eu net zero industry act. *The World Economy*, *46*(12), 3420–3434.

Licht, G., & Peters, B. (2013). *The impact of green innovation on employment growth in europe* [WWW-forEurope Working Paper].

Lin, J. (2011). Technological adaptation, cities, and new work. *Review of Economics and Statistics*, *93*(2), 554–574.

Lybbert, T. J., & Zolas, N. J. (2014). Getting patents and economic data to speak to each other: An 'algorithmic links with probabilities' approach for joint analyses of patenting and economic activity. *Research Policy*, *43*(3), 530–542.

Marin, G., & Vona, F. (2019). Climate policies and skill-biased employment dynamics: Evidence from eu countries. *Journal of Environmental Economics and Management*, *98*, 102253.

Marin, G., & Vona, F. (2021). The impact of energy prices on socioeconomic and environmental performance: Evidence from french manufacturing establishments, 1997–2015. *European Economic Review*, *135*, 103739.

Martin, R., De Preux, L. B., & Wagner, U. J. (2014). The impact of a carbon tax on manufacturing: Evidence from microdata. *Journal of Public Economics*, *117*, 1–14.

Mealy, P., & Teytelboym, A. (2022). Economic complexity and the green economy. *Research Policy*, *51*(8), 103948.

Moretti, E. (2010). Local multipliers. *American Economic Review*, *100*(2), 373–377.

Nesta, L., Vona, F., & Nicolli, F. (2014). Environmental policies, competition and innovation in renewable energy. *Journal of Environmental Economics and Management*, *67*(3), 396–411.

Perruchas, F., Consoli, D., & Barbieri, N. (2020). Specialisation, diversification and the ladder of green technology development. *Research Policy*, *49*(3), 103922.

Pfeiffer, F., & Rennings, K. (2001). Employment impacts of cleaner production–evidence from a german study using case studies and surveys. *Business strategy and the environment*, *10*(3), 161–175.

Popp, D. (2002). Induced innovation and energy prices. *American Economic Review*, *92*(1), 160–180.

Popp, D. (2016). Economic analysis of scientific publications and implications for energy research and development. *Nature Energy*, *1*(16020).

Popp, D. (2019). *Environmental policy and innovation: A decade of research* (Working Paper No. 25631) [National Bureau of Economic Research].

Popp, D., Vona, F., Marin, G., & Chen, Z. (2021). The employment impact of a green fiscal push: Evidence from the american recovery and reinvestment act. *Brookings Papers on Economic Activity.*

Rennings, K., Ziegler, A., & Zwick, T. (2004). The effect of environmental innovations on employment changes: An econometric analysis. *Business strategy and the environment*, *13*(6), 374–387.

Rodrigues, J. F., Moran, D., Wood, R., & Behrens, P. (2018). Uncertainty of consumption-based carbon accounts. *Environmental science & technology*, *52*(13), 7577–7586.

Rodrik, D. (2014). Green industrial policy. *Oxford review of economic policy*, *30*(3), 469–491.

Rosés, J. R., & Wolf, N. (2018). Regional economic development in europe, 1900–2010: A description of the patterns. In *The economic development of europe's regions* (pp. 3–41). Routledge.

Rotemberg, J. (1983). *Instrument variable estimation of misspecified models* [Cambridge, Mass.: Massachusetts Institute of Technology].

Sato, M. (2014). Product level embodied carbon flows in bilateral trade. *Ecological economics*, *105*, 106–117.

Saussay, A., Sato, M., Vona, F., & O'Kane, L. (2022). *Who's fit for the low-carbon transition? emerging skills and wage gaps in job ad data* [Centre for Climate Change Economics and Policy].

Schank, T., Schnabel, C., & Wagner, J. (2007). Do exporters really pay higher wages? first evidence from german linked employer–employee data. *Journal of international Economics*, *72*(1), 52–74.

Shapiro, J. S. (2021). The environmental bias of trade policy. *The Quarterly Journal of Economics*, *136*(2), 831–886.

Simonazzi, A., Ginzburg, A., & Nocella, G. (2013). Economic relations between germany and southern europe. *Cambridge Journal of Economics*, *37*(3), 653–675.

Sinclair-Desgagné, B. (2017). Innovation and the global eco-industry. In *The elgar companion to innovation and knowledge creation* (pp. 771–786). Edward Elgar Publishing.

Stock, J. H., & Yogo, M. (2002). Testing for weak instruments in linear iv regression.

Van Beveren, I., Bernard, A. B., & Vandenbussche, H. (2012). *Concording eu trade and production data over time* (tech. rep.). National Bureau of Economic Research.

Vandenbussche, J., Aghion, P., & Meghir, C. (2006). Growth, distance to frontier and composition of human capital. *Journal of economic growth*, *11*, 97–127.

Verdolini, E., & Galeotti, M. (2011). At home and abroad: An empirical analysis of innovation and diffusion in energy technologies. *Journal of environmental economics and management*, *61*(2), 119–134.

Vona, F. (2023). Managing the distributional effects of climate policies: A narrow path to a just transition. *Ecological Economics*, *205*, 107689.

Vona, F., & Consoli, D. (2015). Innovation and skill dynamics: A life-cycle approach. *Industrial and Corporate Change*, *24*(6), 1393–1415.

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

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

Walker, W. R. (2013). The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce. *The Quarterly journal of economics*, *128*(4), 1787–1835.

Wang, N., & Hagedoorn, J. (2014). The lag structure of the relationship between patenting and internal r&d revisited. *Research Policy*, *43*(8), 1275–1285.

Weber, J. G. (2020). How should we think about environmental policy and jobs? an analogy with trade policy and an illustration from us coal mining. *Review of Environmental Economics and Policy*.

Wurlod, J.-D., & Noailly, J. (2018). The impact of green innovation on energy intensity: An empirical analysis for 14 industrial sectors in oecd countries. *Energy Economics*, *71*, 47–61.

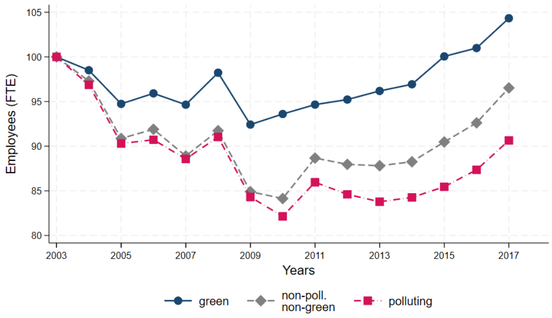
Yamazaki, A. (2017). Jobs and climate policy: Evidence from british columbia's revenue-neutral carbon tax. *Journal of Environmental Economics and Management*, *83*, 197–216.

Yip, C. M. (2018). On the labor market consequences of environmental taxes. *Journal of Environmental Economics and Management*, *89*, 136–152.

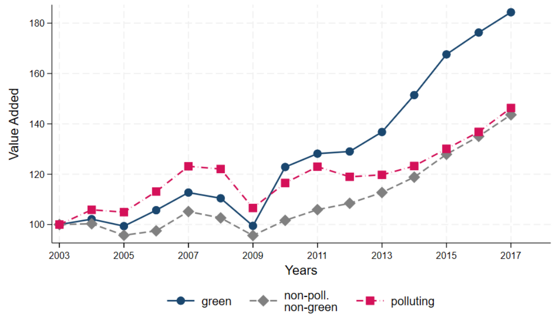
Figures and Tables

Figures

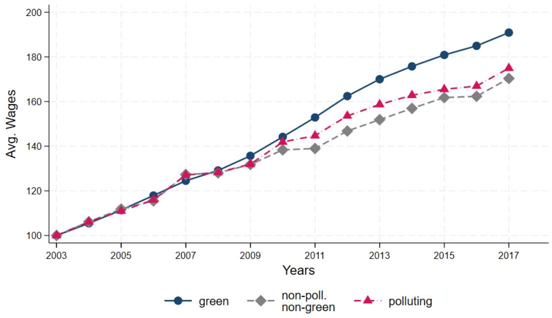
Figure 1: Trends in inspected outcomes by industry type



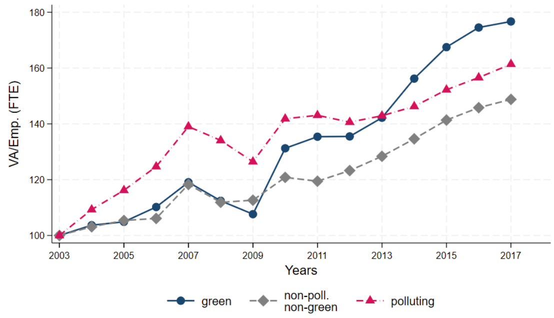
(a) Employment



(b) Value Added



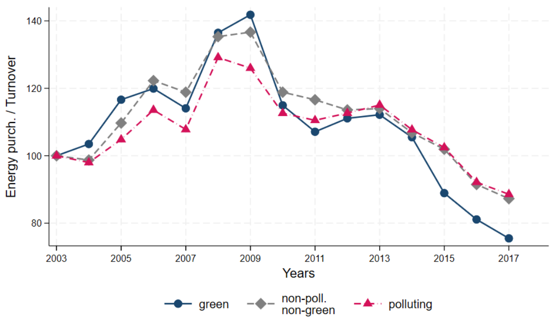
(c) Avg. Wages



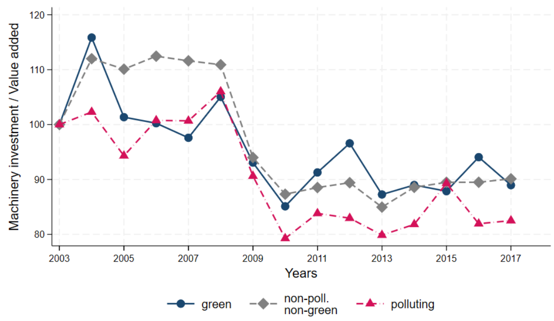
(d) Lab. Productivity

Notes. Authors' elaboration on SBS data. Panel A compares the dynamic – i.e. setting taking 2003 as base year = 100 – in employment between green, polluting and non-polluting-non-green industries. Panel B does so for value added. Panel C does so for average wages. Panel D does so for labour productivity.

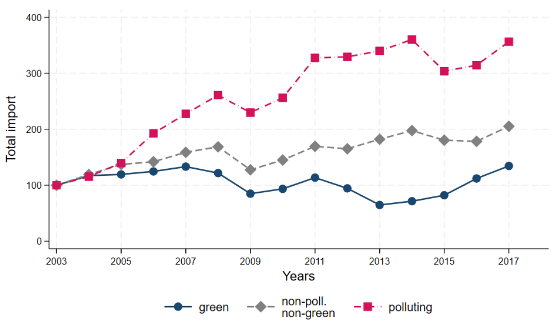
Figure 2: Trends in inspected controls by industry type



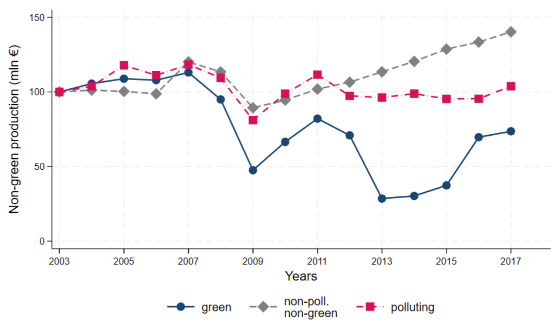
(a) Energy Purch. / Turnover



(b) Machinery Investment / Value Added



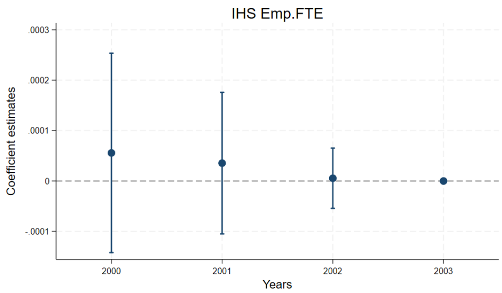
(c) Total import



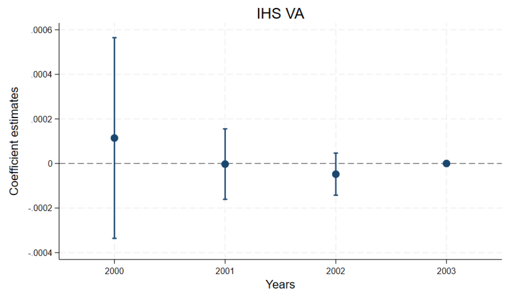
(d) Non-green production

Notes. Authors' elaboration on SBS, BACI and PRODCOM data. Panel A compares the dynamic – i.e. setting taking 2003 as base year = 100 – in energy purchases over turnover between green, polluting and non-polluting-non-green industries. Panel B does so for machinery investment over value added. Panel C does so for total import. Panel D does so for total non-green production. We weight Panel C and D by total production to account for size.

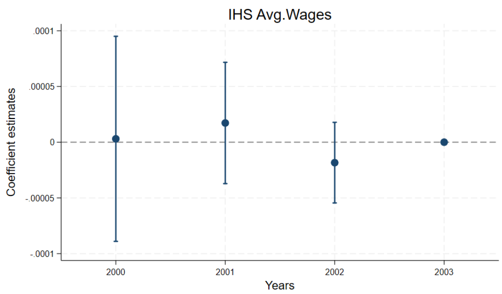
Figure 3: Parallel trends: inspected outcomes and green patents instrument.



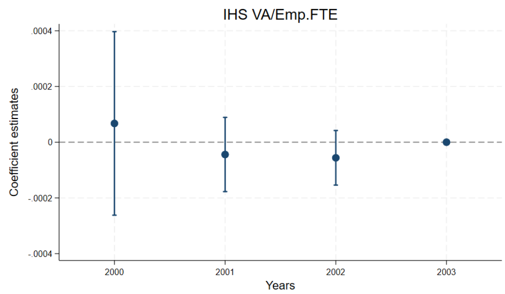
(a) Employment (FTE)



(b) Value added



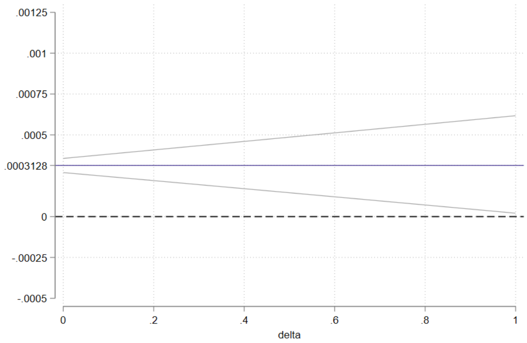
(c) Avg. wages



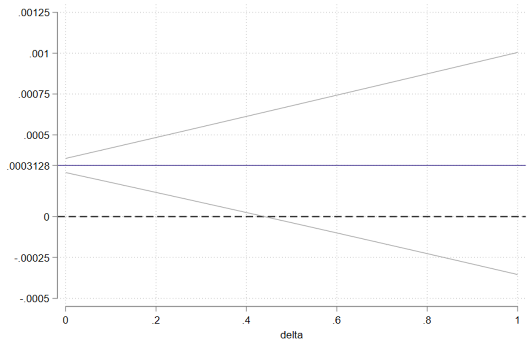
(d) Labour Productivity

Notes. These figures show 95% confidence intervals of the average value of the green patents shift-share in the pre-sample period, interacted with year dummies, on each outcome of interest. The omitted year is 2003. Controls include the IHS of investment intensity, total import and energy costs, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects and weigh the estimates by the country-sector production. The sample is restricted to those industries with green potential. The confidence intervals are based on clustered standard errors at the country-sector level.

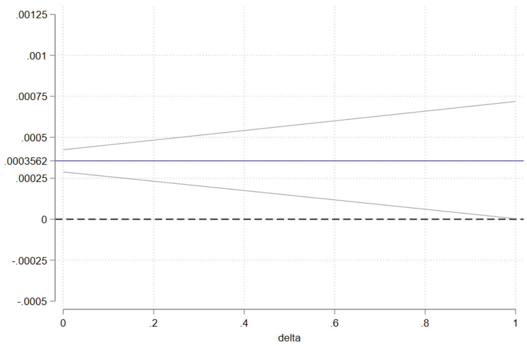
Figure 4: Sensitivity to violations of the exclusion restriction. Green patents instrument.



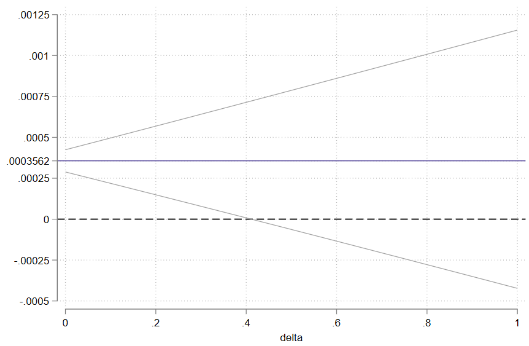
(a) Employment (FTE). max $\delta = \hat{\beta}$



(b) Employment (FTE). max $\delta = \frac{IQR\,gp}{IQR\,pat} \times \hat{\beta}$



(c) VA. max $\delta = \hat{\beta}$



(d) VA. max $\delta = \frac{IQR\,gp}{IQR\,pat} \times \hat{\beta}$

Notes. These figures show 90% confidence intervals about the baseline coefficients of green production on FTE employment and value added (columns (3) and (7) in Panel A of Table 2) for different priors about a potential violation of the exclusion restriction. Priors are described by the parameter delta reported on the horizontal axis. In sub-figures (a) and (c) the dynamic of δ is simply bounded to $\hat{\beta}$. In sub-figures (b) and (d), the dynamic of δ is bounded by the ratio of IQR of green production and green patents and $\hat{\beta}$. The confidence intervals are based on clustered standard errors at the country-sector level.

Tables

Table 1: Green industry potential on employment, value added, average wages and productivity.

	(1)	(2)	(3)	(4)
Panel A:	*Employment (FTE, IHS)*	*Value Added (IHS)*	*Avg. wages (IHS)*	*Labour Prod. (IHS)*
$Green_j * year_t$	0.0088*	0.0195***	0.0055***	0.0110*
	(0.0048)	(0.0063)	(0.0017)	(0.0057)
$Polluting_j * year_t$	-0.0091***	-0.0144***	-0.0014	-0.0069**
	(0.0033)	(0.0055)	(0.0010)	(0.0035)
N	44040	44040	44040	44040
Panel B:				
$Green_j * year_t$	-0.0042	0.0246**	0.0079***	0.0287***
	(0.0055)	(0.0097)	(0.0028)	(0.0085)
$HighGreen_j * year_t$	0.0172***	0.0162**	0.0039**	-0.0005
	(0.0063)	(0.0075)	(0.0019)	(0.0061)
$Polluting_j * year_t$	-0.0091***	-0.0144***	-0.0014	-0.0069**
	(0.0033)	(0.0055)	(0.0010)	(0.0033)
N	44040	44040	44040	44040
Controls	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: Dependent variables: the IHS of employment in full time equivalent; the IHS of value added; the IHS of average wages; the IHS of labour productivity. $Green_j * year_t$ is a dummy variable that identifies if an industry j has green potential or not, interacted with a time trend. $HighGreen_j * year_t$ is a dummy variable that identifies if an industry j has high green potential or not, interacted with a time trend. $Polluting_j * year_t$ is a adummy variable that identifies if an industry j is potentially polluting intensive or not, interacted with a time trend. *Panel A* shows the estimates related to green, which include high green, and polluting industries. *Panel B* shows the estimates also related to high green, net of green, industries. Controls include the IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects. Estimates are weighted by country-sector production. Country-sector clustered standard errors in parentheses. Number of countries: 21. Number of 4-digit sectors: 199. * p<0.10, ** p<0.05, *** p<0.01.

Table 2: Green production on employment, value added, average wages and productivity.

	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Panel A:	*Employment (FTE, IHS)*		*Value Added (IHS)*	
$Gp_{cj,t}$	0.0008*	0.0031***	0.0012**	0.0036***
	(0.0005)	(0.0009)	(0.0005)	(0.0012)
Cost per job		29102		
Panel B:	*Avg. wages (IHS)*		*Labour Prod. (IHS)*	
$Gp_{cj,t}$	-0.0001	-0.0000	0.0004	0.0004
	(0.0001)	(0.0003)	(0.0003)	(0.0007)
N	5503	5503	5503	5503
CD F-Stat		588.5		588.5
FS coeff.		0.124***		0.124***
Controls	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: Dependent variables: the IHS of employment in full time equivalent; the IHS of value added; the IHS of average wages; the IHS of labour productivity. The endogenous variable, $Gp_{cj,t}$, refers to the sold production in country c, of industry j at time t that is green. The instrumental variable refers to the shift-share instrumental variable related to green patents. *Panel A* shows the estimates related to employment in full time equivalent and value added. *Panel B* shows the estimates related to average wages and labour productivity. Columns (1) and (3) show OLS estimates, while columns (2) and (4) show 2SLS ones. Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient, refer to 2SLS estimates. Controls include the IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects. Estimates are weighted by country-sector production. The sample is restricted to those industries with green potential. Country-sector clustered standard errors in parentheses. Number of countries: 21. Number of 4-digit sectors: 22. * p<0.10, ** p<0.05, *** p<0.01.

Table 3: Balance table of covariates Green production higher than median.

Variable	Low Gp (1)	High Gp (2)	Diff. (2-1)
Machinery Investment / Value Added (IHS)	0.188	0.092	0.016
	(0.113)	(0.077)	(0.013)
Total Import (IHS)	17.611	16.680	0.018
	(2.585)	(1.572)	(0.063)
Energy Purchases / Turnover (IHS)	0.018	0.014	0.000
	(0.032)	(0.021)	(0.002)
Non-green Production (mln)	37817.398	7823.334	2064.516
	(46649.160)	(7148.811)	(1929.975)
Green Production (mln)	3.716	1600.643	98.690**
	(8.638)	(2296.595)	(42.114)
Observations	3332	2178	5510

Notes: Low green production implies a level of green production below or equal to the median. High green production implies a level of green production above the median. Country-sector and year fixed effects are included. Country-sector clustered standard errors in parentheses. Estimates are weighted by country-sector production. Number of countries: 21. Number of 4-digit sectors 22. * p<0.10, ** p<0.05, *** p<0.01.

Table 4: Green production on employment, value added, average wages and productivity. Long-term change.

	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Panel A:	Δ *Employment (FTE, IHS)*		Δ *Value Added (IHS)*	
$\Delta\ Gp_{cj,t}$	0.0013**	0.0024**	0.0023***	0.0031**
	(0.0006)	(0.0010)	(0.0005)	(0.0013)
Cost per job		38227		
Panel B:	Δ *Avg. wages (IHS)*		Δ *Labour Prod. (IHS)*	
$\Delta\ Gp_{cj,t}$	-0.0001	0.0000	0.0010**	0.0008
	(0.0001)	(0.0002)	(0.0004)	(0.0006)
N	329	329	329	329
CD F-Stat		131.3		131.3
FS coeff.		0.170***		0.170***
Controls	✓	✓	✓	✓

Notes: Dependent variables: the change of IHS of employment in full time equivalent; the the change of IHS of value added; the change of IHS of average wages; the change of IHS of labour productivity. The endogenous variable, $\Delta\ Gp_{cj,t}$, refers to the change in sold production in country c, of industry j between t and t-1 that is green. The instrumental variable refers to the change of the shift-share instrumental variable related to green patents. *Panel A* shows the estimates related to employment in full time equivalent and value added. *Panel B* shows the estimates related to average wages and labour productivity. Columns (1) and (3) show OLS estimates, while columns (2) and (4) show 2SLS ones. Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient, refer to 2SLS estimates. Controls include the lag of IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production. Estimates are weighted by the lagged country-sector production. The sample is restricted to those industries with green potential. Robust standard errors in parentheses. Number of countries: 20. Number of 4-digit sectors: 22. * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Green production on employment, value added, average wages and productivity. Green production shift-share.

	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Panel A:	*Employment (FTE, IHS)*		*Value Added (IHS)*	
$Gp_{cj,t}$	0.0008*	0.0006	0.0012**	0.0011**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Cost per job		141451		
Panel B:	*Avg. wages (IHS)*		*Labour Prod. (IHS)*	
$Gp_{cj,t}$	-0.0001	-0.0001	0.0004	0.0005
	(0.0001)	(0.0002)	(0.0003)	(0.0004)
N	5503	5503	5503	5503
CD F-Stat		6271.5		6271.5
FS coeff.		0.145***		0.145***
Controls	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: Dependent variables: the IHS of employment in full time equivalent; the IHS of value added; the IHS of average wages; the IHS of labour productivity. The endogenous variable, $Gp_{cj,t}$, refers to the sold production in country c, of industry j at time t that is green. The instrumental variable refers to the shift-share instrumental variable related to green production. *Panel A* shows the estimates related to employment in full time equivalent and value added. *Panel B* shows the estimates related to average wages and labour productivity. Columns (1), (3), (5) show OLS estimates, while columns (2), (4), (6) show 2SLS ones. Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient, refer to 2SLS estimates. Controls include the IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects. Estimates are weighted by country-sector production. The sample is restricted to those industries with green potential. Country-sector clustered standard errors in parentheses. Number of countries: 21. Number of 4-digit sectors 22. * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Green production on employment, value added, average wages and productivity. Countries heterogeneity.

	Green patents shift-share - 2SLS					
	Whole Sample	*EU-15 Sample*	*EU-12 Sample*	*Whole Sample*	*EU-15 Sample*	*EU-12 Sample*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Employment (FTE, IHS)*			*Value Added (IHS)*		
$Gp_{cj,t}$	0.0031***	0.0034***	1.0481	0.0036***	0.0039***	2.7482
	(0.0009)	(0.0009)	(4.7603)	(0.0012)	(0.0012)	(12.1923)
Cost per job	29102	22116				
Panel B:	*Avg. wages (IHS)*			*Labour Prod. (IHS)*		
$Gp_{cj,t}$	-0.0000	0.0002	-0.1745	0.0004	0.0005	1.7310
	(0.0003)	(0.0003)	(0.6927)	(0.0007)	(0.0007)	(7.5934)
N	5503	3749	1299	5503	3749	1299
CD F-Stat	588.5	385.3	0.1	588.5	385.3	0.1
FS coeff.	0.124***	0.122***	0.171	0.124***	0.122***	0.171
Controls	✓	✓	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the IHS of employment in full time equivalent; the IHS of value added; the IHS of average wages; the IHS of labour productivity. The endogenous variable, $Gp_{cj,t}$, refers to the sold production in country c, of industry j at time t that is green. The instrumental variable refers to the shift-share instrumental variable related to green patents. *Panel A* shows the estimates related to employment in full time equivalent and value added. *Panel B* shows the estimates related to average wages and labour productivity. All columns show 2SLS estimates, with Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects. Estimates are weighted by country-sector production. The sample is restricted to those industries with green potential. Depending on the column, the sample is not restricted, restricted to EU 15 countries, restricted to EU 12 countries. Country-sector clustered standard errors in parentheses. Number of countries: 20. Number of 4-digit sectors 22. * p<0.10, ** p<0.05, *** p<0.01.

Table 7: Green production on employment, value added, average wages and productivity. Countries heterogeneity. Green production shift-share.

	Green production shift-share - 2SLS					
	Whole Sample	*EU-15 Sample*	*EU-12 Sample*	*Whole Sample*	*EU-15 Sample*	*EU-12 Sample*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Employment (FTE, IHS)*			*Value Added (IHS)*		
$Gp_{cj,t}$	0.0006	0.0007	0.0085*	0.0011**	0.0012**	-0.0065
	(0.0005)	(0.0005)	(0.0048)	(0.0005)	(0.0005)	(0.0134)
Cost per job	141451	105556	33850			
Panel B:	*Avg. wages (IHS)*			*Labour Prod. (IHS)*		
$Gp_{cj,t}$	-0.0001	-0.0000	0.0032*	0.0005	0.0005	-0.0099
	(0.0002)	(0.0002)	(0.0019)	(0.0004)	(0.0004)	(0.0072)
N	5503	3749	1299	5503	3749	1299
CD F-Stat	6271.5	4221.9	107.4	6271.5	4221.9	107.4
FS coeff.	0.145***	0.145***	0.035***	0.145***	0.145***	0.035***
Controls	✓	✓	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the IHS of employment in full time equivalent; the IHS of value added; the IHS of average wages; the IHS of labour productivity. The endogenous variable, $Gp_{cj,t}$, refers to the sold production in country c, of industry j at time t that is green. The instrumental variable refers to the shift-share instrumental variable related to green production. *Panel A* shows the estimates related to employment in full time equivalent and value added. *Panel B* shows the estimates related to average wages and labour productivity. All columns show 2SLS estimates, with Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects. Estimates are weighted by country-sector production. The sample is restricted to those industries with green potential. Depending on the column, the sample is not restricted, restricted to EU 15 countries, restricted to EU 12 countries. Country-sector clustered standard errors in parentheses. Number of countries: 20. Number of 4-digit sectors 22. * p<0.10, ** p<0.05, *** p<0.01.

Table 8: Green production on employment, value added, average wages and productivity. RNGA heterogeneity.

	2SLS			
	(1)	(2)	(3)	(4)
Panel A:	*Employment (FTE, IHS)*	*Value Added (IHS)*	*Avg. wages (IHS)*	*Labour Prod. (IHS)*
$Gp_{cj,t}$	0.0021	0.0011	-0.0007	-0.0010
	(0.0020)	(0.0012)	(0.0005)	(0.0019)
$Gp_{cj,t} * SRNGA_{cj,t0}$	0.0014	0.0031***	0.0009*	0.0018
	(0.0019)	(0.0011)	(0.0005)	(0.0018)
$Gp_{cj,t}$ +	0.0034***	0.0042***	0.0002	0.0008*
$Gp_{cj,t} * SRNGA_{cj,t0}$	(0.0003)	(0.0006)	(0.0002)	(0.0004)
N	5503	5503	5503	5503
CD F-Stat	155.4	155.4	155.4	155.4
Cost per job	26603			
Controls	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: Dependent variables: the IHS of employment in full time equivalent; the IHS of value added; the IHS of average wages; the IHS of labour productivity. The endogenous variable, $Gp_{cj,t}$, refers to the sold production in country c, of industry j at time t that is green. The endogenous variable is interacted with $SRNGA_{cj,t0}$, a dummy equal one if the symmetric relative comparative advange measure of a country-sector pair is greater than one at baseline.The instrumental variable refers to the shift-share instrumental variable related to green patents. All columns show 2SLS estimates, with Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects. Estimates are weighted by country-sector production. The sample is restricted to those industries with green potential. Country-sector clustered standard errors in parentheses. Number of countries: 21. Number of 4-digit sectors 22. * p<0.10, ** p<0.05, *** p<0.01.

Table 9: Direct and indirect green production on employment, value added, average wages and productivity. IO domestic linkages.

	2SLS							
	Green		Non-green		Green		Non-green	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:	*Employment (FTE, IHS)*				*Value Added (IHS)*			
$Gp_{cj,t}$	0.0023***	0.0023**			0.0037***	0.0040***		
	(0.0008)	(0.0010)			(0.0013)	(0.0009)		
Up $Gp_{cj,t}$	0.0042**		0.0013		-0.0017		-0.0001	
	(0.0021)		(0.0013)		(0.0030)		(0.0014)	
Down $Gp_{cj,t}$		0.0025**		-0.0001		-0.0021		-0.0015
		(0.0012)		(0.0008)		(0.0017)		(0.0010)
Cost per job	13977	18852						
Panel B:	*Avg. wages (IHS)*				*Labour Prod. (IHS)*			
$Gp_{cj,t}$	0.0006*	0.0005***			0.0014**	0.0016***		
	(0.0004)	(0.0002)			(0.0006)	(0.0006)		
Up $Gp_{cj,t}$	-0.0037***		-0.0022***		-0.0060***		-0.0013	
	(0.0008)		(0.0003)		(0.0022)		(0.0008)	
Down $Gp_{cj,t}$		-0.0018***		-0.0013***		-0.0046***		-0.0014**
		(0.0004)		(0.0002)		(0.0011)		(0.0005)
N	5149	5149	35640	35640	5149	5149	35640	35640
CD F-Stat	204.4	259.8	32053.4	44074.5	204.4	259.8	32053.4	44074.5
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the IHS of employment in full time equivalent; the IHS of value added; the IHS of average wages; the IHS of labour productivity. $Gp_{cj,t}$, refers to the direct sold production in country c, of industry j at time t that is green. *Up* $Gp_{cj,t}$ refers to the indirect and upstream sold production in country c, of industry j at time t that is green. *Down* $Gp_{cj,t}$ refers to the indirect and downstream sold production in country c, of industry j at time t that is green. Each variable is instrumented with its shift-share instrumental variable related to green patents. *Panel A* shows the estimates related to employment in full time equivalent and value added. *Panel B* shows the estimates related to average wages and labour productivity. Columns (1), (2), (5) and (6) show estimates for green potential industries, while columns (3), (4), (7) and (8) show the ones related to non-green ones. Cragg-Donald (CD) F statistic for weak identification refer to all 2SLS estimates. Controls include the IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects. Estimates are weighted by country-sector production. Country-sector clustered standard errors in parentheses. Number of countries: 21. Number of 4-digit sectors: 22 (columns 1, 2, 5, 6); 176 (columns 3, 4, 7, 8). * p<0.10, ** p<0.05, *** p<0.01.

Appendices

A Main data sources management

A.1 Measure of green production - additional details

PRODCOM data. The PRODCOM dataset provides information on sold production at a very high level of dis-aggregation across quite a few European countries over a considerable period of time.[43] However, its use presents three important challenges. The first is that product coverage changes over time due to product code entry and exit. Second, product codes change over time due to statistical redefinition, with codes merging into a single new one or one code splitting into several, either new or existing. Third, in 2008, the NACE industry classification changed from NACE rev. 1.1 to NACE rev. 2, causing some products to change industries at the 4-digit. As a result, by aggregating data at the 4-digit industry level, as we do in this study, combining changes in product codes and industry classification may confuse changes in production within an industry with a mere statistical re-classification. We deal with these issues by closely following Bontadini and Vona (2023) methodology to harmonize the PRODCOM data over time. The methodology identifies chains of product codes that change over time due to statistical reclassification and attributes a "synthetic code" to each chain that does not change over time. Then, these synthetic codes can be easily paired with a NACE rev. 2 industry code at the 4-digit level since these are the first 4 digits of the PRODCOM codes from 2008 onwards. Because the synthetic codes do not change over time, we can allocate production values to NACE rev. 2 industries for the years preceding their introduction, covering the whole time-span of the PRODCOM data (1995-2017).

A key advantage of the Bontadini and Vona (2023) procedure is that it yields a time-consistent measure of green production, taking into account that green products may split into a green and a non-green product or merged with a non-green product. An example in the PRODCOM dataset is wind turbines. Until 2007, wind turbines were classified under a residual heading "generating sets n.e.c.", which contained both green and non-green products. Only after 2008 did the code split into a non-green product, "generating sets (excluding wind-powered and powered by spark-ignition internal combustion piston engine)", and a green product, "generating sets, wind-powered". Consequently, we have information on the production of wind-powered generating sets only after the year in which the split occurred (2008), while before then, wind turbines were lumped together with other generating sets. A similar issue applies when green and non-green products are merged into a unique synthetic code.

Finally, the PRODCOM data has some missing values at the product level. Whenever possible, we impute these by applying the average growth rate to fill the years between two non-missing observations. Unfortunately, the issue remains for trailing and leading missing values. However, this is mitigated by

[43] https://ec.europa.eu/eurostat/comext/newxtweb/.

the fact that our analysis is carried out at 4-digit NACE rev. 2. Unless all products underlying a given NACE 4-digit code are all missing (as it is the case, for example for Poland before 2003) we perform our aggregations treating the missing values as zeros.

Green goods list. As we discussed in the main text, Bontadini and Vona (2023) PRODCOM list of green potential goods is the union of the CLEG list and the German list, net of manually inspected goods with double usage.[44] For example, pipes and water tanks may be considered green when used for water and waste management purposes, but they will not be green when used for other activities, such as textile production that involves intensive water consumption (Bontadini & Vona, 2023). Among the goods with double usage that they exclude there are tanks, industrial ovens, baskets, and mats. The goods with double usage that they keep on the list are thermostats and apparatus equipment for meteorology and chemical analysis of water. These products are included in all three lists composing the CLEG list, indicating a consensus around their green potential.

We refer the interested reader to Bontadini and Vona (2023) for additional details.

A.2 Patents - additional details

A key challenge when working with patent and production data is that the former are not classified across industries in the same way as the latter. PATSTAT provides information on all patents filed, classified in the cooperative patent classification (CPC). This easily allows the identification of green patents with the Y02 marker. However, it does not map straightforwardly into the NACE rev.2 classification we use for green production. We, therefore, rely on the methodology provided by Lybbert and Zolas (2014), LZ henceforth. This procedure is compiled with an algorithm performing text analysis of patent and industry description, computing the probability of a CPC and NACE rev.2 being connected and using these as weights for the resulting many-to-many correspondence.[45] The LZ methodology has been used extensively in the literature on innovation (Belderbos et al., 2021; Castellani et al., 2022; Domini et al., 2022) and green innovation (Franco & Marin, 2017; Fusillo, 2023; Wurlod & Noailly, 2018). However, it is important to give a sense of how the procedure works in practice. To illustrate this, let us take the example of the manufacture of engines and turbines (NACE rev.2 code 2811), which includes the production of wind turbines, along with many other non-green products. The LZ crosswalk links this industry with the patents related to wind motors (F03D, not classified as strictly green), as well as to climate mitigation technologies related to energy generation, transmission, or distributions (Y02E). Naturally, the 2811 NACE industry encompasses much more than just the production of wind turbines. As a result, other CPC patents are linked to it. These include both green patents such as climate mitigation technologies

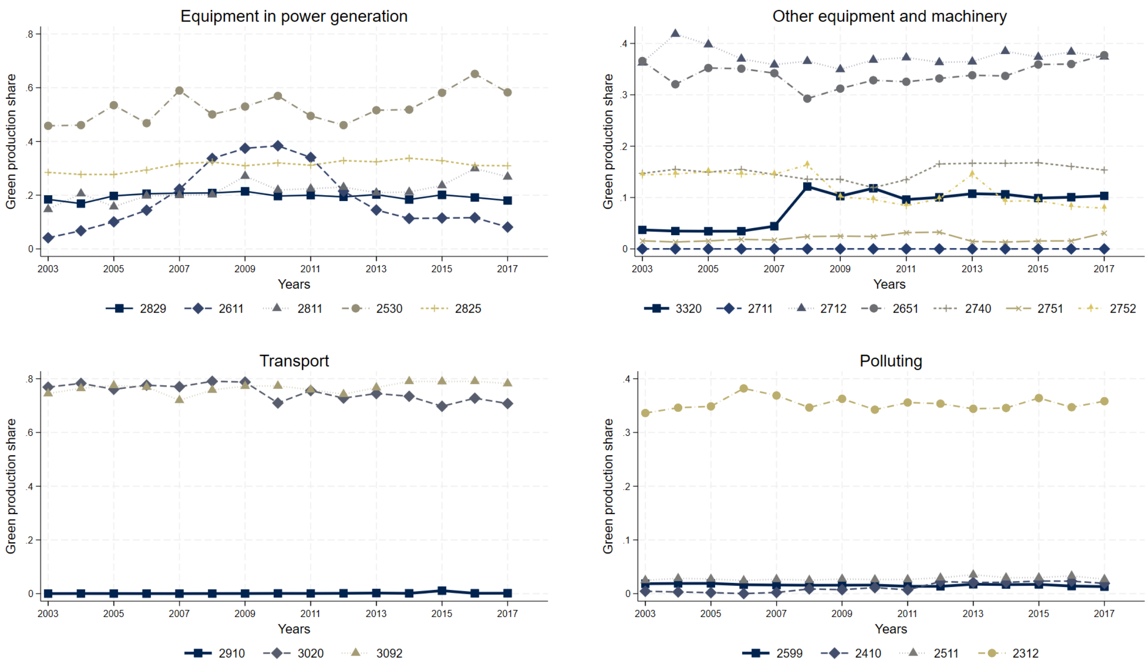
[44] The CLEG list is itself the union of the following lists: the Plurilateral Environmental Goods and Services (PEGS) list developed by the OECD itself, the list suggested by the Asian Pacific Economic Cooperation (APEC) forum and the list stipulated by the WTO Friends group.

[45] LZ provide the methodology for CPC to ISIC rev. 4, which is very close to NACE rev. 2

related to transportation (Y02T), as well as non-green patents related to combustion engines (F02 CPC class). Similarly, a CPC technological class is likely to be relevant to more than one industry, leading to the need for a many-to-many match. Using the LZ methodology, we can attribute weights to CPC classes to allocate patents across industries and to obtain a continuous measure of green technologies associated with each industry, paralleling what we achieve for sold production relying on PRODCOM data.

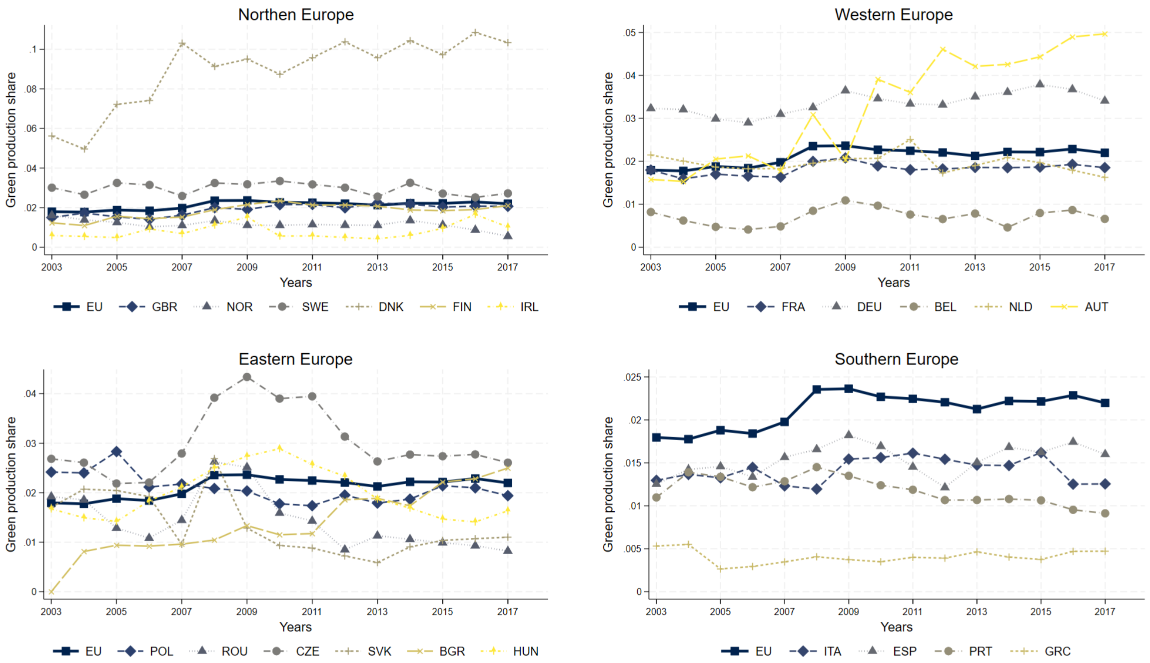
B Additional descriptives

Figure B1: Trends in green production by industry



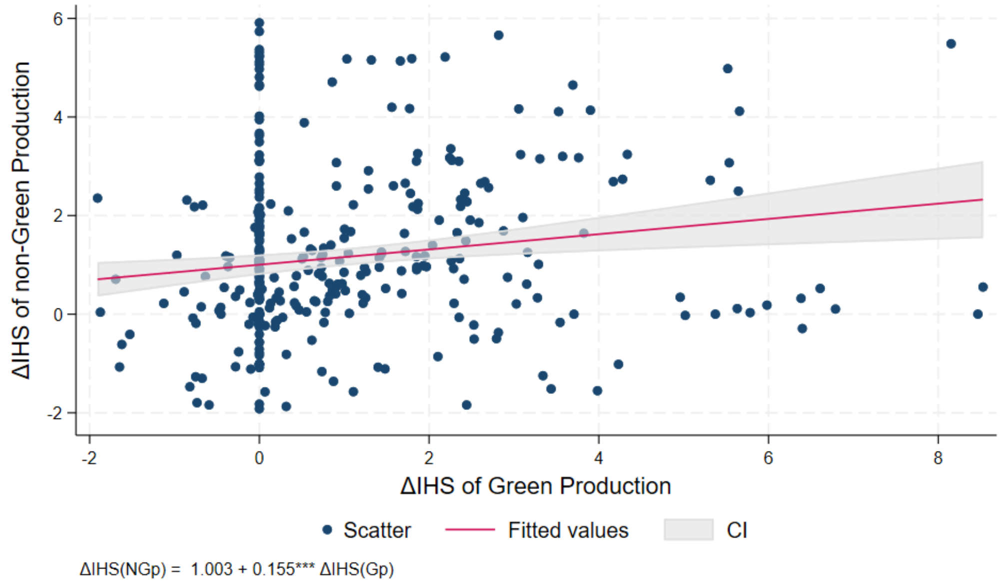
Notes. Authors' elaboration on PRODCOM data. Green production share corresponds to green production divided by total output, measured in PRODCOM, i.e. sold production. The industry codes correspond to Power Generation; steam generators (2530), electronic components (2611), engines and turbines (2811) 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).

Figure B2: Trends in green production by country



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

Figure B3: Correlation between long-term change in non-green production and green production.



Notes. The figure shows the correlation between the long-term change of the IHS-transformed non-green production and the IHS-transformed green one.

Extensive margin estimating equation Table 1 provides results estimated through a simple OLS model. More specifically, we estimate the following equation:

$$IHS(y_{cj,t}) = \alpha + \beta Green_j * year_t + \theta Polluting_j * year_t + \delta \boldsymbol{X'_{cj,t}} + \tau_t + \sigma_{cj} + \epsilon_{cj,t} \tag{6}$$

where $IHS(y_{cj,t})$ is the inverse hyperbolic sine of one of the four dependent variables: employment in FTE, average wages, value added and labour productivity. $Green_j * year_t$ is a dummy variable that identifies whether the 4-digit industry j is potentially green, interacted with a time trend. Recall that potentially green industries are defined as those that produce green goods at least once in our period. This dummy captures the differential trend of potentially green sectors with respect to other industries (the omitted category), thus highlighting the possible future benefits of reallocating inputs towards green manufacturing sectors. Likewise, $Polluting_j * year_t$ is a dummy variable that identifies whether industry j is polluting intensive, interacted with a time trend. $\boldsymbol{X'_{cj,t}}$ is the set of control variables that we describe in the paper that reflects exposure to other structural shocks. To reiterate, these controls include machinery investment over value added, total imports, and energy purchases over turnover. For all these variables, we take the IHS transformation. Moreover, we include the level of sold non-green manufacturing production. This is a proxy of size. We include non-green production in the initial period and interacted with year fixed effects.[46] Lastly, the model includes year and country-sector fixed effects, τ_t and σ_{cj} respectively. We weigh the estimates by the total level of production.

[46] Specifically, we take the average of its value between 2000 and 2003.

Table B1: Green and polluting production by 2-digit industries

NACE	LABEL	Mean green prod. 2003	Mean green prod. 2017	Mean green share 2003	Mean green share 2017	Share of total green production	Average GHG intensity
26	Manufacture of computer, electronic and optical products	19390,24	21069,96	0,057	0,071	0,272	0,3
28	Manufacture of machinery and equipment n.e.c	12399,02	28827,53	0,042	0,038	0,265	0,54
27	Manufacture of electrical equipment	10048,01	18734,26	0,083	0,075	0,187	0,3
30	Manufacture of other transport equipment n.e.c	6977,39	13290,54	0,266	0,253	0,127	0,61
33	Repair and installation of machinery and equipment	1284,2	4918,52	0,007	0,012	0,04	0,74
29	Manufacture of motor vehicles, trailers and semi-trailers	73,35	455,4	0,003	0,002	0,004	0,61
31	Furniture	0	0	0	0	0	0,74
32	Other manufacturing	0	0	0	0	0	0,74
16	Products of wood, cork, straw, plaiting	0	0	0	0	0	0,88
22	Rubber and plastic products	0	0	0	0	0	0,94
13	Textiles	0	0	0	0	0	0,97
14	Wearing apparel	0	0	0	0	0	0,97
15	Leather and related products	0	0	0	0	0	0,97
17	Paper and paper products	0	0	0	0	0	1,18
18	Printing and reproduction of recorded media	0	0	0	0	0	1,18
10	Food products	0	0	0	0	0	1,45
11	Beverages	0	0	0	0	0	1,45
12	Tobacco products	0	0	0	0	0	1,45
	Polluting industries						
19	Coke and refined petroleum products	0	0		0	0	44,99
23	Other non-metallic mineral products	3239,65	4667,11	0,025	0,028	0,052	7,78
20	Chemicals and chemical products	0	0	0	0	0	5,11
21	Basic pharma. products, preparations	0	0	0	0	0	5,11
24	Fabricated metal products, exc. machinery	180,9	1141,549	0,002	0,005	0,007	4,23
25	Basic metals	2367,24	4091,83	0,036	0,045	0,046	4,23
	Summary	Tot.: 55960	Tot.: 97196,7	Avg.: 0,022	Avg.: 0.022	Tot.: 1	Avg.: 3,64

Notes: Authors' elaboration on PRODCOM data. Production values are deflated to have data at constant prices, with 2015 as the base year. Columns 1 and 2 report the mean value of green production for each industry in 2003 and 2017, respectively. Columns 3 and 4 report the mean green share of production of each industry for the years 2003 and 2017, respectively. Coke and refined petroleum products were not included in PRODCOM until 2005. Column 5 reports the share that green production of each industry represents in total green production. Columns 6 report the average GHG intensity for each industry computed with WIOD. Polluting industries are identified as the 5 industries with the highest average GHG intensity. The last row reports either the average or the total of each column.

Table B2: Distribution of green production shares across green industries at 4 digits NACE

Nace	Label	Mean	Median	Max	SD	Share of *Gp*
High green potential industries						
3092	Manufacture of bicycles and invalid carriages	0.77	0.77	1.00	0.18	3.19
3020	Manufacture of railway locomotives and rolling stoc	0.74	0.71	1.00	0.13	9.82
2530	Manufacture of steam generators, except central heating hot water boilers	0.53	0.56	1.00	0.29	1.97
2712	Manufacture of electricity distribution and control apparatus	0.37	0.41	1.00	0.13	14.80
2312	Shaping and processing of flat glass	0.35	0.35	1.00	0.14	4.83
2651	Manufacture of instruments and appliances for measuring, testing, etc	0.34	0.36	1.00	0.09	19.44
2825	Manufacture of non-domestic cooling and ventilation equipment	0.31	0.33	0.89	0.10	10.23
2811	Manufacture of engines and turbines, except aircraft, vehicle and cycle engines	0.22	0.14	1.00	0.27	9.74
2829	Manufacture of other general-purpose machinery n.e.c.	0.20	0.17	1.00	0.11	7.69
2611	Manufacture of electronic components	0.18	0.12	1.00	0.20	5.08
2740	Manufacture of electric lighting equipments	0.15	0.15	0.56	0.08	2.80
2752	Manufacture of non-electric domestic appliances	0.12	0.05	0.50	0.12	0.58
3320	Installation of industrial machinery and equipment	0.09	0.08	0.28	0.06	4.62
Marginally green industries						
2511	Manufacture of metal structures and parts of structures	0.03	0.03	0.13	0.02	2.23
2751	Manufacture of electric domestic appliances	0.02	0.01	1.00	0.05	0.43
2670	Manufacture of optical instruments and photographic equipment	0.02	0.00	0.08	0.03	0.12
2351	Manufacture of cement	0.02	0.00	0.64	0.03	0.28
2599	Manufacture of other fabricated metal products n.e.c.	0.02	0.01	0.29	0.02	0.58
2410	Manufacture of basic iron and steel and of ferro-alloys	0.01	0.00	0.66	0.05	0.90
2899	Manufacture of other special-purpose machinery n.e.c.	0.01	0.00	0.15	0.02	0.28
2910	Manufacture of motor vehicles	0.00	0.00	0.51	0.01	0.41
2711	Manufacture of electric motors, generators and transformers	0.00	0.00	0.00	0.00	0.00

Notes: Authors' elaboration on PRODCOM data. Production values are deflated to have data at constant prices, with 2015 as base year. Mean, median, maximum and standard deviation are computed over all available countries and years (2003–2017), changes in the average green share for 2003–2017. The last column reports for each industry the share it represents in total green production across all industries, countries and years

C Alternative specifications

Table C1: Green production on employment, value added, average wages and productivity. Controls inclusion.

	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Employment (FTE, IHS)*			*Value Added (IHS)*		
$Gp_{cj,t}$	0.0032***	0.0031***	0.0031***	0.0041***	0.0040***	0.0036***
	(0.0008)	(0.0008)	(0.0009)	(0.0011)	(0.0011)	(0.0012)
Cost per job	28774	29330	29102			
Panel B:	*Avg. wages (IHS)*			*Labour Prod. (IHS)*		
$Gp_{cj,t}$	-0.0001	-0.0000	-0.0000	0.0010	0.0008	0.0004
	(0.0004)	(0.0003)	(0.0003)	(0.0006)	(0.0006)	(0.0007)
N	5503	5503	5503	5503	5503	5503
CD F-Stat	609.1	671.3	588.5	609.1	671.3	588.5
FS coeff.	0.126***	0.133***	0.124***	0.126***	0.133***	0.124***
Non-green prod.		✓	✓		✓	✓
Controls			✓			✓
Country-Sector FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the IHS of employment in full time equivalent; the IHS of value added; the IHS of average wages; the IHS of labour productivity. The endogenous variable, $Gp_{cj,t}$, refers to the sold production in country c, of industry j at time t that is green. The instrumental variable refers to the shift-share instrumental variable related to green patents. *Panel A* shows the estimates related to employment in full time equivalent and value added. *Panel B* shows the estimates related to average wages and labour productivity. Columns show 2SLS estimates. With Cragg-Donald (CD) F statistic for weak identification and the first stage coefficient. Controls include the IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects. Estimates are weighted by country-sector production. The sample is restricted to those industries with green potential. Country-sector clustered standard errors in parentheses. Number of countries: 21. Number of 4-digit sectors: 22. * p<0.10, ** p<0.05, *** p<0.01.

Table C2: Green production on employment, value added, average wages and productivity. Alternative set of fixed effects.

	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Panel A:	*Employment (FTE, IHS)*		*Value Added (IHS)*	
$Gp_{cj,t}$	0.0011***	0.0056**	0.0014***	0.0063**
	(0.0004)	(0.0026)	(0.0004)	(0.0030)
Cost per job		16269		
Panel B:	*Avg. wages (IHS)*		*Labour Prod. (IHS)*	
$Gp_{cj,t}$	0.0002	0.0008*	0.0003**	0.0001
	(0.0001)	(0.0005)	(0.0001)	(0.0011)
N	5510	5510	5510	5510
CD F-Stat		129.3		129.3
FS coeff.		0.068*		0.068*
Controls	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓
Sector-Year FE	✓	✓	✓	✓

Notes: Dependent variables: the IHS of employment in full time equivalent; the IHS of value added; the IHS of average wages; the IHS of labour productivity. The endogenous variable, $Gp_{cj,t}$, refers to the sold production in country c, of industry j at time t that is green. The instrumental variable refers to the shift-share instrumental variable related to green patents. *Panel A* shows the estimates related to employment in full time equivalent and value added. *Panel B* shows the estimates related to average wages and labour productivity. Columns (1) and (3) show OLS estimates, while columns (2) and (4) show 2SLS ones. Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient, refer to 2SLS estimates. Controls include the IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We include country-year and sector-year fixed effects. Number of countries: 21. Number of 4-digit sectors: 22. Estimates are weighted by country-sector production. The sample is restricted to those industries with green potential. Country-sector clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table C3: High green production on employment, value added, average wages and productivity.

	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Panel A:	*Employment (FTE, IHS)*		*Value Added (IHS)*	
$Gp_{cj,t}$	0.0008*	0.0022***	0.0013**	0.0035***
	(0.0004)	(0.0008)	(0.0005)	(0.0010)
Cost per job		20959		
Panel B:	*Avg. wages (IHS)*		*Labour Prod. (IHS)*	
$Gp_{cj,t}$	-0.0000	0.0003	0.0005**	0.0013***
	(0.0001)	(0.0003)	(0.0002)	(0.0003)
N	3285	3285	3285	3285
CD F-Stat		394.4		394.4
FS coeff.		0.138***		0.138***
Controls	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: Dependent variables: the IHS of employment in full time equivalent; the IHS of value added; the IHS of average wages; the IHS of labour productivity. The endogenous variable, $Gp_{cj,t}$, refers to the sold production in country c, of industry j at time t that is green. The instrumental variable refers to the shift-share instrumental variable related to green patents. *Panel A* shows the estimates related to employment in full time equivalent and value added. *Panel B* shows the estimates related to average wages and labour productivity. Columns (1) and (3) show OLS estimates, while columns (2) and (4) show 2SLS ones. Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient, refer to 2SLS estimates. Controls include the IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects. Estimates are weighted by country-sector production. The sample is restricted to those industries with high green potential. Country-sector clustered standard errors in parentheses. Number of countries: 21. Number of 4-digit sectors: 13. * p<0.10, ** p<0.05, *** p<0.01.

Table C4: Green production on employment, value added, average wages and productivity. Two way clustering.

	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Panel A:	*Employment (FTE, IHS)*		*Value Added (IHS)*	
$Gp_{cj,t}$	0.0008*	0.0031***	0.0012*	0.0036***
	(0.0005)	(0.0008)	(0.0006)	(0.0012)
Cost per job		29102		
Panel B:	*Avg. wages (IHS)*		*Labour Prod. (IHS)*	
$Gp_{cj,t}$	-0.0001	-0.0000	0.0004	0.0004
	(0.0001)	(0.0003)	(0.0003)	(0.0007)
N	5503	5503	5503	5503
CD F-Stat		590.0		590.0
FS coeff.		0.124***		0.124***
Controls	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: Dependent variables: the IHS of employment in full time equivalent; the IHS of value added; the IHS of average wages; the IHS of labour productivity. The endogenous variable, $Gp_{cj,t}$, refers to the sold production in country c, of industry j at time t that is green. The instrumental variable refers to the shift-share instrumental variable related to green patents. *Panel A* shows the estimates related to employment in full time equivalent and value added. *Panel B* shows the estimates related to average wages and labour productivity. Columns (1) and (3) show OLS estimates, while columns (2) and (4) show 2SLS ones. Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient, refer to 2SLS estimates. Controls include the IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects. Estimates are weighted by country-sector production. The sample is restricted to those industries with green potential. Country-sector and year clustered standard errors in parentheses. Number of countries: 21. Number of 4-digit sectors: 22. * p<0.10, ** p<0.05, *** p<0.01.

Table C5: Green production on employment, value added, average wages and productivity. $ln + \epsilon$ transformation.

	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Panel A:	*Employment (FTE, IHS)*		*Value Added (IHS)*	
$Gp_{cj,t}$	0.0008*	0.0031***	0.0011**	0.0038***
	(0.0005)	(0.0008)	(0.0006)	(0.0012)
Cost per job		29158		
Panel B:	*Avg. wages (IHS)*		*Labour Prod. (IHS)*	
$Gp_{cj,t}$	-0.0001	0.0001	0.0003	0.0006
	(0.0001)	(0.0003)	(0.0002)	(0.0006)
N	5503	5503	5503	5503
CD F-Stat		577.7		577.7
FS coeff.		0.123***		0.123***
Controls	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: Dependent variables: the natural log of employment in full time equivalent; the natural log of value added; the natural log of average wages; the natural log of labour productivity. The endogenous variable, $Gp_{cj,t}$, refers to the sold production in country c, of industry j at time t that is green. The instrumental variable refers to the shift-share instrumental variable related to green patents. *Panel A* shows the estimates related to employment in full time equivalent and value added. *Panel B* shows the estimates related to average wages and labour productivity. Columns (1) and (3) show OLS estimates, while columns (2) and (4) show 2SLS ones. Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient, refer to 2SLS estimates. Controls include the natural log of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects. Estimates are weighted by country-sector production. The sample is restricted to those industries with green potential. Country-sector clustered standard errors in parentheses. Number of countries: 21. Number of 4-digit sectors: 22. * p<0.10, ** p<0.05, *** p<0.01.

Table C6: Green production on employment, value added, average wages and productivity. Green potential industries dummy.

	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Panel A:	*Employment (FTE, IHS)*		*Value Added (IHS)*	
$Gp_{cj,t}$	0.0007	0.0037***	0.0011**	0.0041***
	(0.0005)	(0.0012)	(0.0005)	(0.0013)
Cost per job		24639		
Panel B:	*Avg. wages (IHS)*		*Labour Prod. (IHS)*	
$Gp_{cj,t}$	-0.0001	-0.0003	0.0004	0.0004
	(0.0001)	(0.0005)	(0.0003)	(0.0007)
N	43561	43561	43561	43561
CD F-Stat		3965.8		3965.8
FS coeff.		0.105***		0.105***
Controls	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: Dependent variables: the IHS of employment in full time equivalent; the IHS of value added; the IHS of average wages; the IHS of labour productivity. The endogenous variable, $Gp_{cj,t}$, refers to the sold production in country c, of industry j at time t that is green. The instrumental variable refers to the shift-share instrumental variable related to green patents. *Panel A* shows the estimates related to employment in full time equivalent and value added. *Panel B* shows the estimates related to average wages and labour productivity. Columns (1) and (3) show OLS estimates, while columns (2) and (4) show 2SLS ones. Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient, refer to 2SLS estimates. Controls include the IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We further include a dummy that identifies green industries interacted with year trends.We include country-sector and year fixed effects. Estimates are weighted by country-sector production. Country-sector clustered standard errors in parentheses. Number of countries: 21. Number of 4-digit sectors: 199. * p<0.10, ** p<0.05, *** p<0.01.

Table C7: Direct and indirect green production on employment, value added, average wages and productivity. IO European linkages.

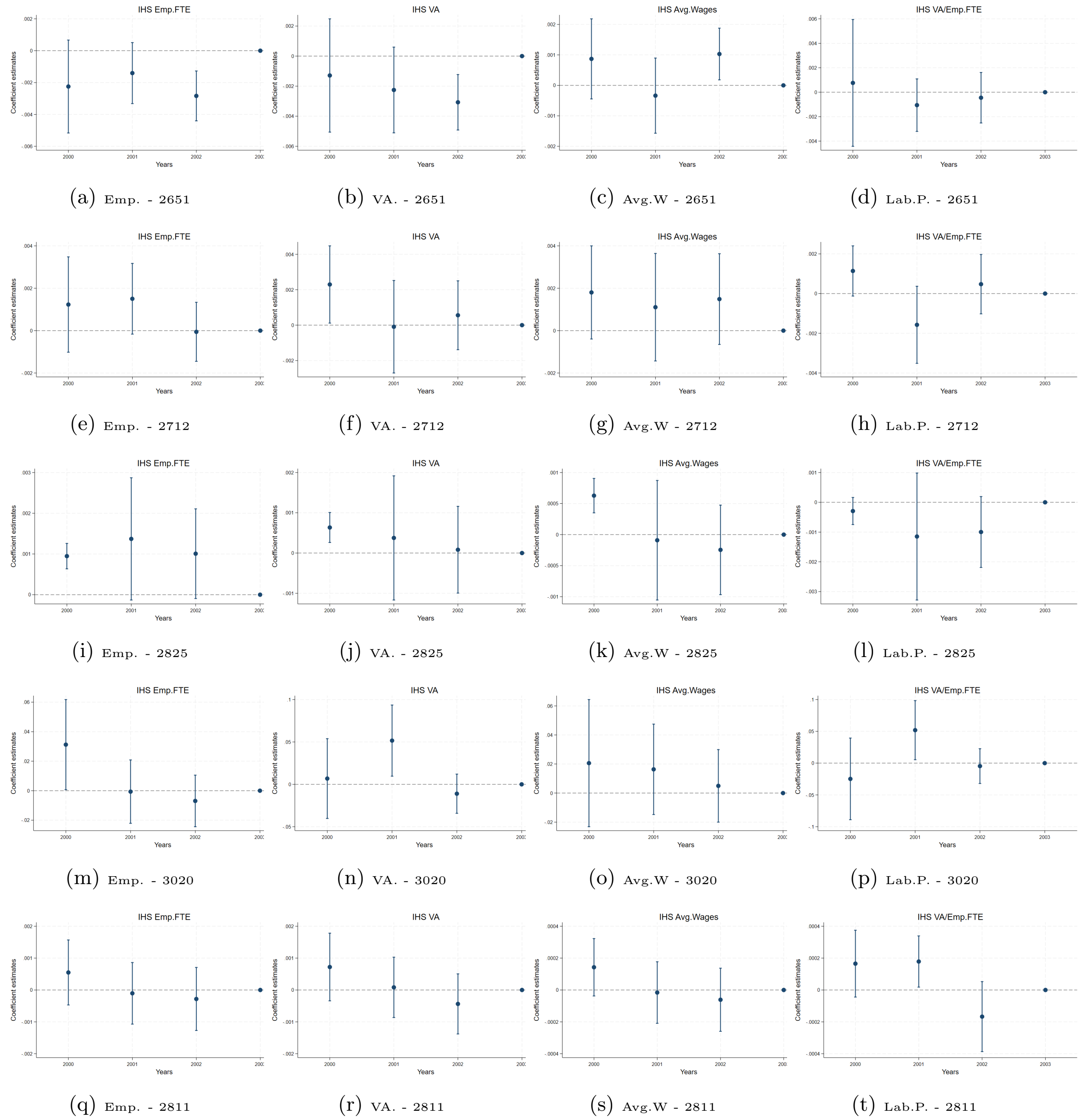
	2SLS							
	Green		Non-green		Green		Non-green	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:	*Employment (FTE, IHS)*				*Value Added (IHS)*			
$Gp_{cj,t}$	0.0023***	0.0026***			0.0033***	0.0039***		
	(0.0007)	(0.0009)			(0.0012)	(0.0009)		
$Up\ Gp_{cj,t}$	0.0078***		0.0011		0.0017		0.0001	
	(0.0028)		(0.0018)		(0.0039)		(0.0021)	
$Down\ Gp_{cj,t}$		0.0080		-0.0031		-0.0086		-0.0076*
		(0.0052)		(0.0034)		(0.0069)		(0.0039)
Cost per job	9002	8606						
Panel B:	*Avg. wages (IHS)*				*Labour Prod. (IHS)*			
$Gp_{cj,t}$	0.0004	0.0005**			0.0010*	0.0013**		
	(0.0004)	(0.0002)			(0.0006)	(0.0006)		
$Up\ Gp_{cj,t}$	-0.0044***		-0.0018***		-0.0062*		-0.0009	
	(0.0011)		(0.0005)		(0.0032)		(0.0011)	
$Down\ Gp_{cj,t}$		-0.0085***		-0.0052***		-0.0169***		-0.0045***
		(0.0022)		(0.0008)		(0.0050)		(0.0016)
N	5149	5149	35640	35640	5149	5149	35640	35640
CD F-Stat	217.3	254.6	20417.5	22291.3	217.3	254.6	20417.5	22291.3
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the IHS of employment in full time equivalent; the IHS of value added; the IHS of average wages; the IHS of labour productivity. $Gp_{cj,t}$, refers to the direct sold production in country c, of industry j at time t that is green. $Up\ Gp_{cj,t}$ refers to the indirect and upstream sold production in country c, of industry j at time t that is green. $Down\ Gp_{cj,t}$ refers to the indirect and downstream sold production in country c, of industry j at time t that is green. Each variable is instrumented with its shift-share instrumental variable related to green patents. *Panel A* shows the estimates related to employment in full time equivalent and value added. *Panel B* shows the estimates related to average wages and labour productivity. Columns (1), (2), (5) and (6) show estimates for green potential industries, while columns (3), (4), (7) and (8) show the ones related to non-green ones. Cragg-Donald (CD) F statistic for weak identification refer to all 2SLS estimates. Controls include the IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects. Estimates are weighted by country-sector production. Country-sector clustered standard errors in parentheses. Number of countries: 21. Number of 4-digit sectors: 22 (columns 1, 2, 5, 6); 176 (columns 3, 4, 7, 8). * p<0.10, ** p<0.05, *** p<0.01.

D Additional validation of the shift-shares

D.1 Green patents shift-share instrumental variable

Figure D1: Pre-trends for top 5 green industries: green patents shift-share



(a) Emp. - 2651 (b) VA. - 2651 (c) Avg.W - 2651 (d) Lab.P. - 2651

(e) Emp. - 2712 (f) VA. - 2712 (g) Avg.W - 2712 (h) Lab.P. - 2712

(i) Emp. - 2825 (j) VA. - 2825 (k) Avg.W - 2825 (l) Lab.P. - 2825

(m) Emp. - 3020 (n) VA. - 3020 (o) Avg.W - 3020 (p) Lab.P. - 3020

(q) Emp. - 2811 (r) VA. - 2811 (s) Avg.W - 2811 (t) Lab.P. - 2811

Notes. These figures show 95% confidence intervals of the average value of the green patents shift-share in the pre-sample period, interacted with year dummies, on each outcome of interest, for each of the five of the highest sectors in green production. The omitted year is 2003. Controls include the IHS of investment intensity, total import and energy costs, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects and weigh the estimates by the country-sector production. The sample is restricted to those industries with green potential. The confidence intervals are based on clustered standard errors at the country-sector level.

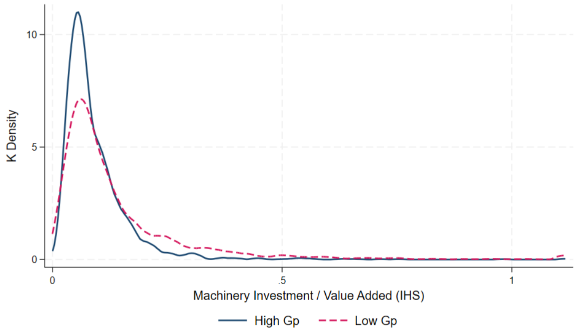
Table D1: Green production on employment, value added, average wages and productivity. Exclusion of industries 2712 or 2651.

	2SLS			
	(1)	(2)	(3)	(4)
Panel A:	*Employment (FTE, IHS)*		*Value Added (IHS)*	
$Gp_{cj,t}$	0.0041***	0.0030***	0.0046***	0.0036***
	(0.0009)	(0.0009)	(0.0008)	(0.0012)
Cost per job	22162	30777		
Panel B:	*Avg. wages (IHS)*		*Labour Prod. (IHS)*	
$Gp_{cj,t}$	0.0001	0.0000	0.0005	0.0006
	(0.0003)	(0.0003)	(0.0009)	(0.0005)
N	5221	5244	5221	5244
CD F-Stat	372.3	1025.6	372.3	1025.6
FS coeff.	0.100***	0.127***	0.127***	0.127***
Controls	✓	✓	✓	✓
Country-Sector FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

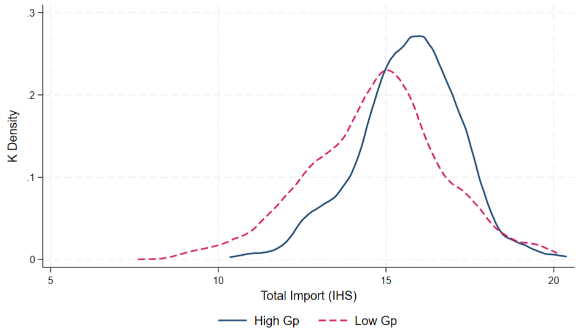
Notes: Dependent variables: the IHS of employment in full time equivalent; the IHS of value added; the IHS of average wages; the IHS of labour productivity. The endogenous variable, $Gp_{cj,t}$, refers to the sold production in country c, of industry j at time t that is green. The instrumental variable refers to the shift-share instrumental variable related to green patents. *Panel A* shows the estimates related to employment in full time equivalent and value added. *Panel B* shows the estimates related to average wages and labour productivity. All columns show 2SLS estimates. Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient, refer to 2SLS estimates. Controls include the IHS of machinery investment over value added, total import and energy purchases over turnover, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects. Estimates are weighted by country-sector production. The sample is restricted to those industries with green potential. In odd columns we exclude industry 2712 - manufacture of electricity distribution and control apparatus- from the analysis. In even columns we exclude industry 2651 - manufacture of instruments and appliances for measuring, testing, etc. - from the analysis. Country-sector clustered standard errors in parentheses. Number of countries: 21. Number of 4-digit sectors: 21. * p<0.10, ** p<0.05, *** p<0.01.

D.2 Balancing covariates - figures

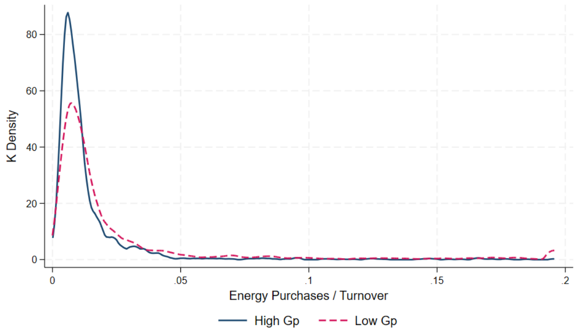
Figure D2: K density plots of covariates, by high and low green production



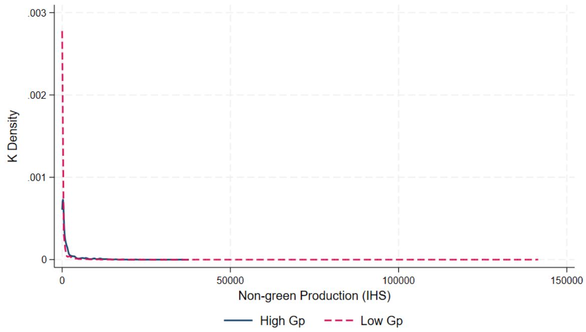
(a) Machinery Investment / Value Added (IHS)



(b) Total Import (IHS)



(c) Energy Purchases / Turnover (IHS)



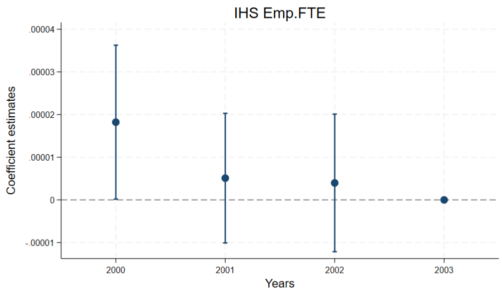
(d) Non-green Production (mln)

Notes. The figures show k-density plots of the four covariates included in the estimating equations, divided by High green production and low green production.

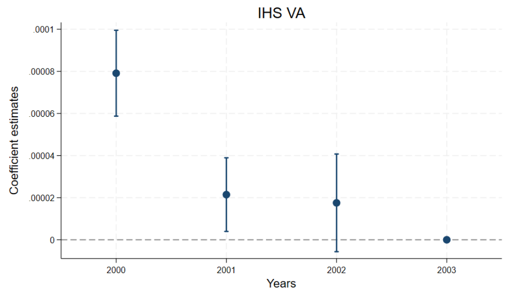
D.3 Green production shift-share instrumental variable

Figures D3 and D4 show the empirical assessment of pre-trends in aggregate and by the top five 4-digit sectors of green production. Figure D3 shows the presence of pre-trends across all outcomes inspected, particularly for value added and labour productivity, suggesting that the estimates relative to these outcomes are downward biased. In Figure D4, sub-figures (e) and (q) show positive pre-trends related to employment. Sub-figures (g), (k) and (o) show positive pre-trends related to average wages. Regarding value added, the aggregate pre-trend is likely due to both sub-figures (f) and (j), and their counterpart in (l) and (h) for labour productivity.

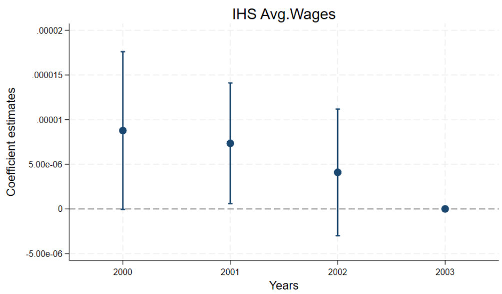
Figure D3: Parallel trends: inspected outcomes and green production instrument.



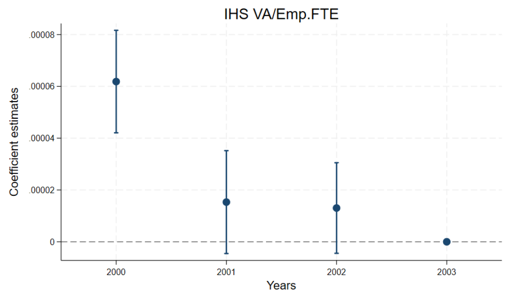
(a) Employment (FTE)



(b) Value added



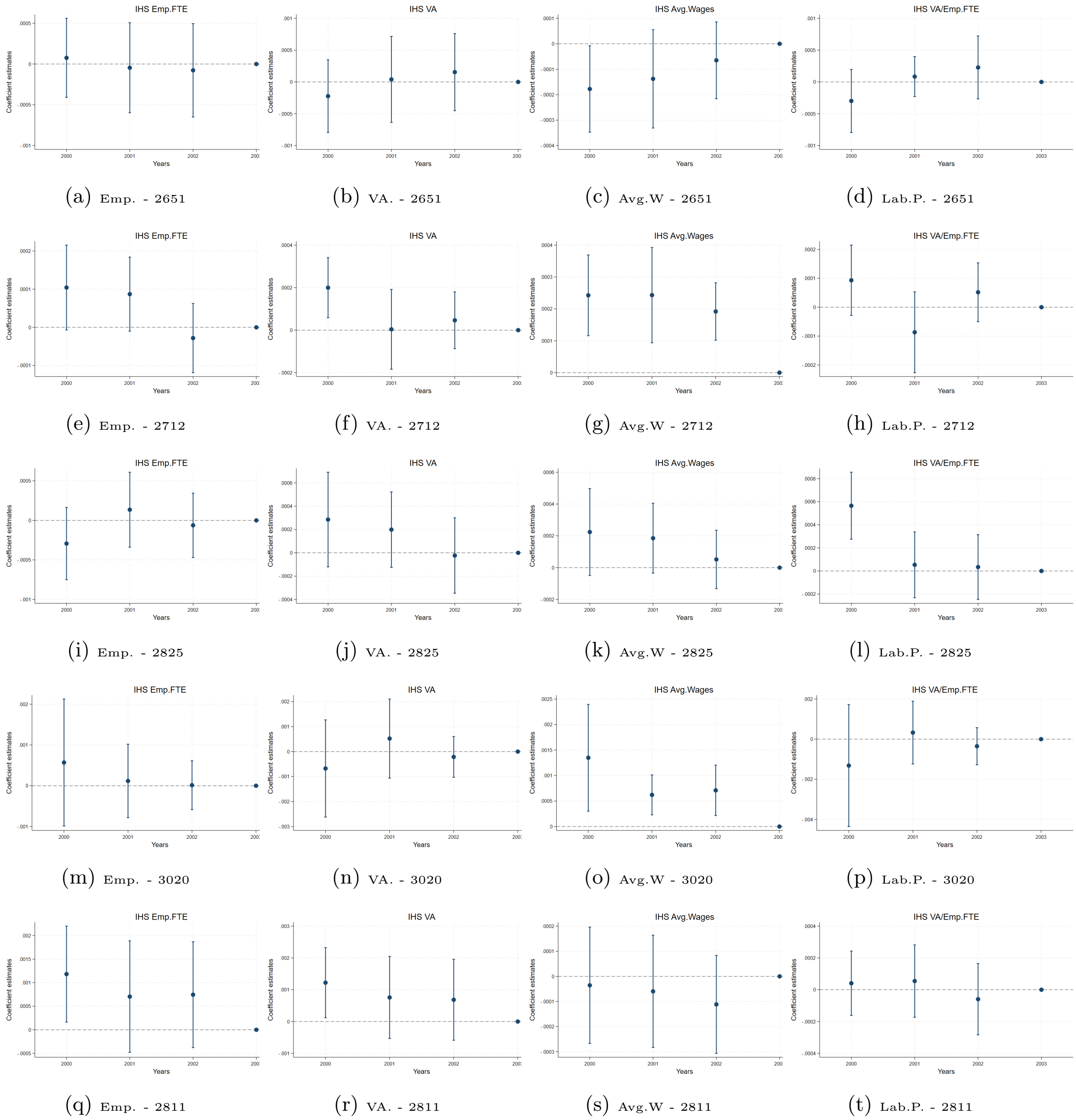
(c) Avg. wages



(d) Productivity

Notes. These figures show 95% confidence intervals of the average value of the green production shift-share in the pre-sample period, interacted with year dummies, on each outcome of interest. The omitted year is 2003. Controls include the IHS of investment intensity, total import and energy costs, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects and weigh the estimates by the country-sector production. The sample is restricted to those industries with green potential. The confidence intervals are based on clustered standard errors at the country-sector level.

Figure D4: Pre-trends for top 5 green industries: green production shift-share



(a) Emp. - 2651 (b) VA. - 2651 (c) Avg.W - 2651 (d) Lab.P. - 2651

(e) Emp. - 2712 (f) VA. - 2712 (g) Avg.W - 2712 (h) Lab.P. - 2712

(i) Emp. - 2825 (j) VA. - 2825 (k) Avg.W - 2825 (l) Lab.P. - 2825

(m) Emp. - 3020 (n) VA. - 3020 (o) Avg.W - 3020 (p) Lab.P. - 3020

(q) Emp. - 2811 (r) VA. - 2811 (s) Avg.W - 2811 (t) Lab.P. - 2811

Notes. These figures show 95% confidence intervals of the average value of the green production shift-share in the pre-sample period, interacted with year dummies, on each outcome of interest, for each of the five of the highest sectors in green production. The omitted year is 2003. Controls include the IHS of investment intensity, total import and energy costs, and the baseline value of non-green production interacted with year dummies. We include country-sector and year fixed effects and weigh the estimates by the country-sector production. The sample is restricted to those industries with green potential. The confidence intervals are based on clustered standard errors at the country-sector level.

D.4 Conley et al. (2012) methodology

To briefly explain the intuition behind the approach of Conley et al. (2012) within our set-up, consider the following equation,

$$IHS(y_{cj,t}) = \alpha + \beta gp_{cj,t} + \gamma IVgpat_{cj,t} + \delta \boldsymbol{X'_{cj,t}} + \tau_t + \sigma_{cj} + \epsilon_{cj,t},$$

where γ is a parameter measuring the size of the violation of the exclusion restriction. The results shown so far rely on the IV assumption that $\gamma = 0$. However, if the exclusion restriction is violated, so that $\gamma \neq 0$, inference about β can still be performed, provided that alternative priors can be formed about γ and conditional on the assumed values of this parameter. This implies estimating the following equation,

$$(IHS(y_{cj,t}) - \gamma IVgpat_{cj,t}) = \alpha + \beta_1 gp_{cj,t} + \delta \boldsymbol{X'_{cj,t}} + \tau_t + \sigma_{cj} + \epsilon_{cj,t}.$$

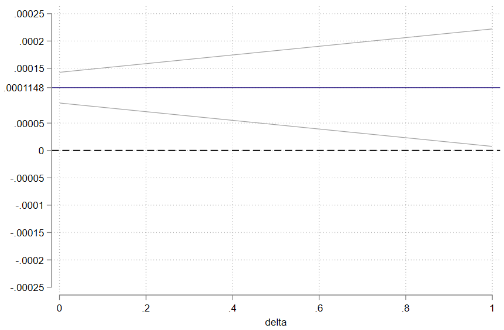
By varying the prior about γ, we can assess how inference about β would be influenced by different degrees of violation of the exclusion restriction of the green patents instrument.[47] In other words, we can assess how strong a violation would have to be for β to become completely uninformative about the causal effect of interest. Conley et al. (2012) emphasize that, because Since the sensitivity of the 2SLS estimator to violations of the exclusion restriction is inversely related to the strength of the instrument, Conley et al. (2012) stress that the same value of γ implies a smaller decrease in the precision of the estimate of β_1 the stronger is the first-stage relationship.

Given this premise, we perform the following. We employ the Union of Confidence Intervals (UCI) approach, which, unlike the local-to-zero approach, does not require distributional assumptions. First, we set $\gamma = \beta$; that is, we set the maximum possible violation of the exclusion restriction to be as big as the effect of the endogenous variable of interest. Alternatively, we set $\gamma = \frac{IQR\,gp}{IQR\,ivgp} \times \beta$; that is, we set the maximum possible violation of the exclusion restriction to be as big as the effect of the endogenous variable of interest, scaled by the respective interquartile ratios. We vary both specifications by a parameter $\delta \in \{0, 0.1, \ldots, 1\}$.

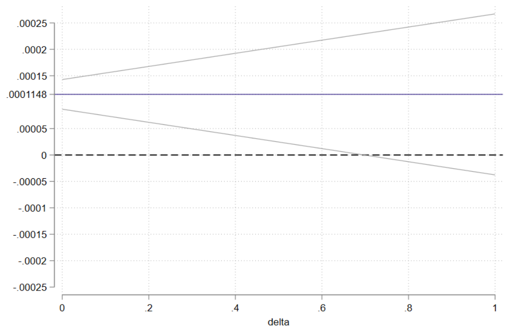
Figure D5 shows the outcome of Conley et al. (2012)'s UCI method, with values of the instrument direct effect bound to that of instrumented green production. In this setting, the green production instrument's direct effect should be about either the same or three/quarters in size as the instrumented green production for the estimated coefficient to be uninformative. We report this methodology applied only to value added given that it is the only 2SLS significant result emerging from Table 5.

[47] The same reasoning that follows can be applied to the green production instrument.

Figure D5: Sensitivity to violations of the exclusion restriction. Green production instrument.Value added



(a) VA. max $\delta = \hat{\beta}$



(b) VA. max $\delta = \frac{IQR\,gp}{IQR\,ivgp} \times \hat{\beta}$

Notes. These figures show 90% confidence intervals about the baseline coefficients of green production on FTE employment and value added (columns (2) and (4) in Panel A of Table 5) for different priors about a potential violation of the exclusion restriction. Priors are described by the parameter delta reported on the horizontal axis. In sub-figures (a) and (c), the dynamic of δ is simply bounded to $\hat{\beta}$. In sub-figures (b) and (d), the dynamic of δ is bounded by the ratio of IQR of green production and green production shift-share and $\hat{\beta}$. The confidence intervals are based on clustered standard errors at the country-sector level.

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