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Summary

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Keywords: Green industrialisation, Local job multipliers, Employment effects of the green transition, Shift-share IV design, Difference-in-differences

JEL classification: J21, O14, R11

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The Local Job Multipliers of Green Industrialization.*

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May 29, 2025

Abstract

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1 Introduction

In the aftermath of the Covid crisis, green deal plans became popular around the world to reconcile employment growth and the transition to carbon neutrality through coordinated investments in infrastructures, skills and specific industries (Rodrik, 2014; Tagliapietra & Veugelers, 2020). A key element of this new strategy is to foster green industrial productions, e.g., electric vehicles, batteries and PV panels, also leveraging a re-shoring of the associated value chains through local content requirements. Although the logic of green deal plans is clear and resonates with that of a so-called “Big Push” (Murphy et al., 1989; Rosenstein-Rodan, 1943), there is not enough evidence in support of the claim that green industrialization creates a large number of well-paid jobs. EU countries are an interesting case to study the effect of green industrialization on local labour markets. On the one hand, European countries gradually lost their comparative advantage in specific green productions in favour of China. On the other hand, EU governments are planning to implement a combination of trade tariffs, local content requirement and industrial subsidies to re-shore green productions, for example through the Net Zero Industry Act (NZIA). Against this backdrop, a trade-off emerges between creating green jobs through industrial policies and making green goods more affordable to achieve carbon neutrality. Investigating the extent to which green productions boost job creation, and thus allow to gain political support for the green transition (Bergquist et al., 2020; Cavallotti et al., 2025; Vona, 2023), is a first crucial step to assess the potential effects of green industrial policies.

This paper is the first to contribute to this debate providing new evidence on the effect of green industrialization on employment growth for EU NUTS2 regions over the period 2003-2017. Because the local effects of manufacturing activities are widespread, we estimate both a direct effect of green industrialization on local manufacturing employment and an indirect job multiplier effect (Moretti, 2010). The second key contribution of our paper is to rely on a novel measure of green regional penetration that combines granular country-product data on green industrial production (Bontadini & Vona, 2023; Frattini et al., 2024) with regional employment shares disaggregated at the level of 2-digit manufacturing industries. Similarly to the literature on the China shock (Autor et al., 2013), we allocate green production shocks, at various time frequencies, to regions using their lagged industrial structure. We use a shift-share instrumental variable (SSIV) design to mitigate endogeneity concerns (Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020). Specifically, our SSIV design leverages technology improvements in non-EU countries to identify plausibly exogenous variation in the opportunity to produce green goods locally. The intuition is that regions with stronger initial green capabilities can better exploit global improvements in green technologies to activate or expand green productions.[1] To

[1]This strategy is conceptually aligned with SSIVs that leverage exposure to technological shocks to study long-term

identify the labour market effects of the green transition, we use technology, supply-side shocks that may potentially lead to different results compared to an analysis exploiting policy shocks. However, this approach is commonly used to circumvent data limitations by a few recent studies evaluating the labour market impacts of renewable energy generation (Fabra et al., 2024; Scheifele & Popp, 2025). The third key novelty of our paper is to evaluate supply-side green shocks for the much larger manufacturing sector, where green innovations are produced and multiplier effects are more likely to emerge.

Our study on the local employment effect of green productions can be framed as a test of recent theoretical models revisiting the job creation and destruction effects of new technologies (Acemoglu & Restrepo, 2019; Autor et al., 2022; Gregory et al., 2022). The main argument of these models is that new technologies are mainly labour-saving on existing tasks, where a learning process towards standardization has been accomplished, and labour-augmenting on new tasks, that are, by definition, ill-structured and less routinised. Previous research shows that the bulk of employment in green activities requires new tasks, either within established occupations or through the emergence of new occupations (Elliott et al., 2024; Saussay et al., 2022; Vona et al., 2018, 2019). Thus, we expect green industrial production to be more labour-intensive than other kinds of production within the manufacturing sector.[2] The economic geography literature provides additional reasons to expect positive local multipliers of green production. First, high and medium-tech activities, such as green ones, pay higher wages that boost local employment through pecuniary externalities (Moretti, 2011). Second, new work and innovative activities, such as green ones, are more likely to attract complementary upstream and downstream activities locally (Carlino & Kerr, 2015; Lin, 2011). In the green economy, for instance, Popp et al. (2021) and Fabra et al. (2024) show that job creation effects on construction activities are particularly important as building new infrastructures is an essential element of green industrialization.

Our favourite shift-share specification reveals that, conditional on pre-existing industrial and country-specific trends as well as on time-invariant regional characteristics, green industrialization increases the employment-to-(economically) active population ratio. New jobs are created both in manufacturing (the "treated sector") and in non-manufacturing activities (the pure multiplier effects). However, while the former effect is as expected persistent, the latter fades away in the long-run, i.e., after five years, and it is heterogeneous across sub-sectors, being positive for construction and utilities and negative on the service sector. However, inspecting the time profile of the multiplier effect more closely, the muted long-term effect of green industrialization on the employment-to-active population masks posi-

employment dynamics in local labour markets (Acemoglu & Restrepo, 2020; Acemoglu et al., 2022; Autor & Dorn, 2013).

[2] Although not directly examining green activities, the recent paper of Autor et al. (2022) finds that several new job titles, a measure of new task, are related to the green economy. The related paper of Saussay et al. (2025) combines the rich textual description of job vacancy data and patent abstracts to show that green technologies are more labour augmenting than other technologies, but also that, over time, they are becoming more labour-saving.

tive effects on both total employment and the active population, resulting in agglomeration effects that eventually increase the tightness of local labour markets. When netting out such agglomeration effect, estimates reveal that green industrialization affects both total and non-manufacturing employment also in the long-term. Moreover, in line with previous research (Popp et al., 2021; Vona et al., 2018), we find that greening of labour markets exacerbates job polarization, as the positive effect of green production is concentrated on workers with tertiary education, especially those employed in STEM -Science, Technology, Engineering and Math (STEM) jobs, and basic education (lower-secondary or less), particularly in the construction sector.

Interpreting our effects as Local Average Treatment Effect (LATE), we quantify their economic relevance using the variation in green production explained by SSIV. In doing so, we find that the historical increase in green industrialization accounted for by the plausibly exogenous technological shocks accounts for approximately one-tenth of a percentage point of the increase in the local employment-to-active population after three years. This effect is twice as large when we purge the total employment effect from the induced agglomeration effects.

A legitimate threat to the plausibility of our identification strategy is the violation of the parallel trend assumption, which is difficult to detect in a SSIV design where the instrument is a linear combination of multiple instruments (Goldsmith-Pinkham et al., 2020). Violations of the parallel trend assumptions are a key issue in the related paper of Popp et al. (2021), where regions receiving more green subsidies under the American Recovery and Reinvestment Act were also growing faster before the policy. Following Goldsmith-Pinkham et al. (2020), we apply the most recent diagnostic tests for SSIV designs to detect the potential presence of pre-trends for the whole instrument and its components, i.e., the baseline employment shares of the 2-digit NACE sectors that receive the highest weights in the SSIV.[3] Overall, these diagnostic tests exclude that severe pre-trends undermine the credibility of our favourite specifications. This is corroborated also by checking the sensitivity of our results to the inclusion of different sets of controls, such as automation exposure, population density and demographic characteristics. Finally, we lend further credibility to our research design providing formal testing about the relevance of the SSIV (Lee et al., 2022) and the validity of the monotonicity assumption.[4]

We then extend our main results in two directions of paramount importance for the green transition. In our first extension, we simulate what could happen with a policy-driven big push by investigating

[3] Within the framework of Goldsmith-Pinkham et al. (2020), these correspond to the sectors with the highest Rotemberg weights.

[4] Lending further support to the monotonicity assumption is necessary in our setting because green innovation shocks in other countries can both increase green production in EU countries with better green technological capabilities (the main assumption behind our identification strategy) or decrease them due to a competitiveness effect.

the effect of large green production shocks, which serve as proxies for a policy-driven fiscal stimulus, in a staggered difference-in-differences (DiD) design (Roth et al., 2023). We find that the effect on total employment is approximately ten times larger than the LATE effect, which is not surprising given the larger size of the shocks and the fact that we estimate an Average Treatment Effect (ATT) rather than a LATE. Moreover, the effect of large green industrialization shocks are persistent on non-manufacturing employment, even without purging from induced agglomeration effects. These effects seem not invalidated by the presence of pre-trends. Remarkably, by decomposing the ATT in cohort-specific effects (Callaway & Sant'Anna, 2021), we find that early shocks have significantly larger employment effects. Overall, this resonates with the facts that green production has become more labour-saving over time (Saussay et al., 2025), and that Europe lost his comparative advantage in critical green products, making large shocks less frequent.

In our second extension, we investigate the differential effect of the green industrialization shock for regions more vulnerable to the green transition. In fact, it is critical to consider how the green transition would affect regions that may be poorly equipped for it. We identify such "brown" regions using the regional employment share in polluting industries at baseline. We find that green multipliers are not statistically different for browner regions. Indeed, while browner regions may have less green technological capabilities, they are usually poorer (Weber, 2020) and thus characterised by higher labour supply elasticity (Austin et al., 2018). This finding lends support to green industrial policies as a place-based policy for distressed communities in the context of the green transition (Bartik et al., 2019; Iammarino et al., 2019; Vona, 2023).

This paper contributes to the voluminous literature that evaluates job multiplier effects of various activities, exploiting either fiscal or supply-side shocks (Chodorow-Reich, 2019; Moretti, 2010; Nakamura & Steinsson, 2014; Wilson, 2012). A burgeoning literature evaluates the job multiplier effects of the green transition. The seminal study of Vona et al. (2019) follows the empirical strategy of Moretti (2010), estimating the indirect job creation effects of a new green job in US metropolitan areas. The main finding is that the green job multiplier is large compared to other sectors and in line with job multipliers of high-tech activities. Popp et al. (2021) uses similar data, but concentrates on a fiscal push, i.e. the green subsidies within the American Recovery and Reinvestment Act (ARRA). Green job multipliers appear more uncertain in this case, due to the presence of pre-trends, and become large and persistent only for regions with a greater prevalence of green skills, mostly technical and engineering ones.[5] Taken together, these findings suggest that green job multipliers are expected to be

[5]Another recent evaluation of the labour market impact of green subsidies is the paper of Wald et al. (2024), which evaluates job multipliers of the French Energy Efficiency Obligations scheme, a large-scale energy retrofit program, finding a modest job multiplier. Their results are, however, difficult to compare with ours as they focus on short-term effects and on the construction sector.

larger for regions with better pre-existing green capabilities. We build on these findings by exploiting differential exposure to green technology shocks as a function of the initial regional capabilities. We also complement US-based studies considering different countries, the entire EU, and isolating the effects of large green production shocks.

Another strand of literature focuses on the energy sector within the green transition, covering different geographies: Spanish (Fabra et al., 2024) and Brazilian municipalities (Scheifele & Popp, 2025), NUTS3 regions in four EU countries (Cappa et al., 2024) and the US commuting zones (Chan & Zhou, 2024).[6] Like us, these studies use a supply-side shock, such as the building of a wind farm or renewable energy penetration, to identify local labour market effects, either in an event study setup or exploiting the local suitability to wind or solar as an instrument. While the size and the persistence of effects are mixed, the two peer-reviewed papers suggest that job creation effects are probably short-lived, stronger for solar and concentrated in the construction phase of the plant (Fabra et al., 2024; Scheifele & Popp, 2025). Our research complements this work focusing on a larger, yet overlooked, part of the energy transition: green manufacturing production. Because green goods are tradable and high-tech, we expect larger and more persistent job multipliers than those related to the renewable energy generation – although a precise comparison of the effect remains difficult.

Lastly, this paper contributes to the literature on the so-called just transition. Several papers focus on the decline of coal (Hanson, 2023; Haywood et al., 2024; Rud et al., 2024; Weber, 2020), highlighting its persistent negative effects on both workers and regions. Rather than focusing on the consequences of the decline of polluting industries, we focus on the potential solutions by examining the extent to which a green industrial push can alleviate the consequences of job losses in left-behind regions hosting pollution-intensive industries. As shown by a few recent papers in political science (Bergquist et al., 2020; Bolet et al., 2024; Cavallotti et al., 2025), giving new green opportunities to left-behind brown workers and regions is essential to enhance the political acceptability of the green transition. Our results are encouraging on the feasibility of this strategy within the EU context.

The rest of the paper is organized as follows. Section 2 describes the data used and shows a few descriptive facts. Section 3 discusses the empirical framework associated with the SSIV. Section 4 presents the main results, the validation of the SSIV, and the sensitivity of the results to different specifications. Section 5 presents the results of the two extensions. Section 6 concludes.

[6] A parallel strand of literature focuses on the local job creation effect of fossil fuel energy (Black et al., 2005; Feyrer et al., 2017; Marchand, 2012; Weber, 2012), finding modest employment effects.

2 Data and descriptives

2.1 Measuring green production

We measure green manufacturing production using granular product-level data from the PRODCOM dataset by Eurostat. For the manufacturing sector, the PRODCOM dataset provides detailed information on the value of production for around 4,000 products annually from 1995 to 2017. We then follow Bontadini and Vona (2023) to identify a list of products that reduce harmful environmental impacts in their usage, e.g., bicycles and wind turbines. This list is obtained by excluding double-usage products from a list of 902 green products contained either the OECD's Combined List of Environmental Goods (CLEG) or the German Statistical Office's list of green goods, which follows Eurostat's criteria for defining environmental goods (Eurostat, 2016). Because PRODCOM data are only available in Eastern European countries from 2003 on, we start our analysis in 2003.

For this paper, we slightly revise the list of green goods by applying the following changes. First, we expande the list to include a set of new products whose environmental benefits are now established.[7] Second, we include batteries, which were excluded in the original list due to their double usage, given their growing importance in energy transition. Third, we include nuclear energy and biofuels as they are considered part of the broad portfolio of low-carbon technologies in the official EU taxonomy.[8] Fourth, we addressed and corrected prior ambiguities in the previous classification.[9] Lastly, we broadened the scope to include not only final green products, but also their constituent components, with particular attention to those used in energy-efficient building.[10] This slightly revised list contains 188 green products for each country.[11] We then aggregate the green production of each product at the 2-digit NACE-by-country level, and deflate green and non-green production using the price indexes provided by the 2019 release of EUKLEMS.

2.2 Green regional penetration

While data on green production are available at the industry-by-country level, our goal is to estimate the impact of green industrialization on local EU labour markets, both directly (on manufacturing

[7] Examples of these goods are: 2720235 Lithium-ion accumulators (excl. spent); Indicator panels incorporating light emitting diodes (LED).

[8] See, for instance, here.

[9] For example excluding goods such as 33204100 - Installation of medical and surgical equipment - and 33204200 - Installation services of professional electronic equipment.

[10] For example including goods such as 23991930 - Mixtures and articles of heat/sound-insulating materials n.e.c. - and 26405190 - LED backlight modules for LCDs of headings 8525 to 8528 (excl. for computer monitors).

[11] The reason why the number of green goods in the current list (188) is lower than the lists of Bontadini and Vona (2023) and Frattini et al. (2024) (221) has to do with the fact that we employ newly raw PRODCOM data which Eurostat harmonized up to 2007, hence aggregating directly quite a few green goods. More details on the data cleaning process as well as the full list of green products (Table A21) can be found in the Appendix A.6.

jobs) and indirectly (on other sectors' jobs). Similarly to the approach followed by the China shock literature (Autor et al., 2013), we allocate country-sector green production to regions using information of the regional employment structure. Specifically, we exploit the Structural Business Statistics (SBS) data by Eurostat, which provides NUTS2 manufacturing employment by 2-digit NACE sector, and the EU Labour Force Survey (LFS) that provides NUTS2 total employment. The measure of green regional penetration reads as follows:

$$GRP_{rt} = \sum_j \frac{L_{rjt}}{L_{cjt}} \cdot \frac{GP_{cjt}}{L_{rt}}, \tag{1}$$

where GP_{cjt} is green production in country c, manufacturing industry j at time t. $\frac{L_{rjt}}{L_{cjt}}$ are the employment shares of manufacturing industry j in region r and country c at time t. Note that within-country, cross-regional differences in green production for industry j (e.g., bicycles) stem uniquely from variation in these shares. Finally, we compute green industrialization shocks relative to the size of the local economy rescaling for the regional employment ($1/L_{rt}$) and hence obtaining a measure of green regional penetration per worker (GRP henceforth).

We explore the time profile of the effect of green industrialization by taking time differences of Equation 1 at various intervals of length k:

$$\Delta GRP_{rt_k} = \sum_j \frac{L_{rjt-k}}{L_{cjt-k}} \cdot \frac{\Delta GP_{cjt_k}}{L_{rt-k}}, \tag{2}$$

where ΔGP_{cjt_k} refers to the change of green production in country c, industry j, between t and $t-k$. To capture initial exposure to green shocks, the employment shares, as well as the total regional employment, refer to the initial period $t-k$.

2.3 Green patents

We seek to isolate arguably exogenous variation in green production exploiting improvements in green technology in non-EU countries. For this purpose, we build a measure of initial exposure to green innovations using patent applications in the European Patent Office (EPO).[12] Information on patent applications are retrieved from the PATSTAT dataset, and we treat as green all patents that contain at least one green technology class, i.e. the so-called Y02 tag under the Cooperative Patent Classification (CPC). To smoothen yearly fluctuations in patent activities and obtain an accurate proxy of green technological exposure, we construct the stock of green patent applications until year t using the

[12]See Popp (2019) for a recent review on the use of patents to measure green innovation.

perpetual inventory method (Verdolini & Galeotti, 2011).[13] We assign green patents to country-NACE industry pairs using the crosswalk provided by PATSTAT.

2.4 Final dataset

We gather data from the EU Labour Force Survey (LFS) to construct measures of regional employment (our dependent variable) for specific sectors (manufacturing, utilities, construction, services) and skill categories (by educational attainment). We divide employment measures by the active population to account for the effect of green industrialization on both job creation and labour force participation. We use LFS data for our dependent variables as SBS data -which are used to map green production shocks in manufacturing to region- do not contain information on the service sector. Moreover, we collect various data on NUTS2 characteristics to control for confounders in the econometric analyses, e.g., population density, share of female, foreign-born and population by educational attainment. As an additional control, in an extension, we also use data on regional exposure to automation from Anelli et al. (2021).

Our final dataset is a balanced panel of 278 NUTS2 regions for 28 countries that spans from 2003 to 2017 and contains information on the variables discussed above.[14] Table A4 provides basic statistics related to the main data, while Appendix A.6 provides extensive details on the construction of the final dataset.

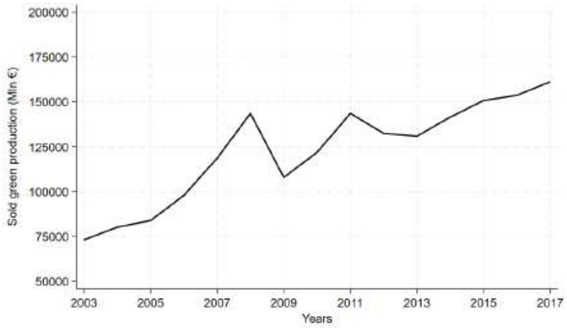
2.5 Descriptive evidence

Figure 1 shows that EU green production exhibits an upward trend during the period of our analysis (panel a). A similar upward trend is also observed for the green regional penetration (Table A4 in the Appendix). Importantly, the long-term growth rate of green production (+120%) outperformed that of non-green production (+74%), particularly so after the 2008 financial crisis (panel b). However, regions attracting green productions do not do so at the detriment of non-green production (see Figure A1). Consistently with previous findings on the size of the green economy (Elliott & Lindley, 2017; Saussay et al., 2022; Vona et al., 2019), the share of green over total production remained quite small, accounting for just 3.3% in 2017 (panel c). Lastly, a three-year change in GRP positively correlates with that of regional employment (panel d). This positive unconditional correlation between green industrialization shocks and employment growth further motivates the econometric analysis of the next section.

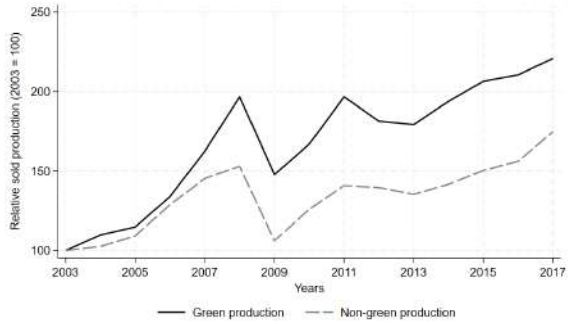
[13] The formula is $K_{i,t} = PAT_{i,t} + (1-\delta)K_{i,t-1}$, where $\delta = 0.1$ is the depreciation rate, $PAT_{i,t}$ is the number of green patents in CPC class i at time t. The initial stock (1991) is calculated as $K_{i,t_0} = PAT_{i,t_0}(1-\delta)$.

[14] The countries in the analysis are: AT, BE, BG, CY, CZ, DE, DK, EL, ES, FI, FR, HR, HU, IE, IS, IT, LU, LV, MT, NL, NO, PL, PT, RO, SE, SI, SK, UK. We exclude EE and LT for data availability. Further, we exclude the following regions: FRY1 (Guadalupe); FRY2 (Martinique); FRY3 (Guayane); FRY4 (Reunion); FRY5 (Mayotte); ES70 (Canarias); PT20 (Azores); PT30 (Madeira). A full list of the NUTS2 regions in the dataset is listed in Table A22.

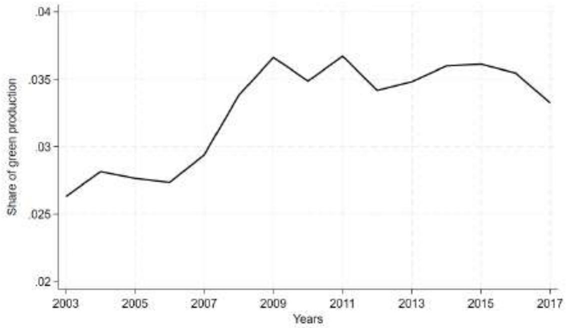
Figure 1: Green and total production over time



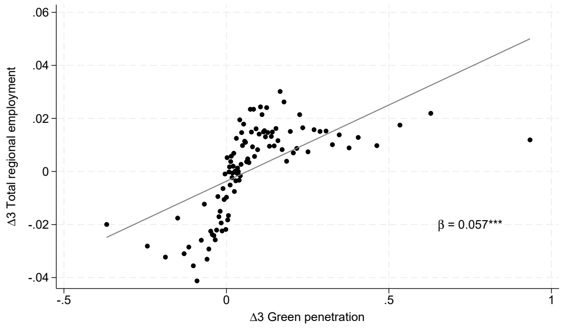
(a) Sold green production level



(b) Sold green vs non-green production



(c) Green share of production



(d) GRP and total regional employment

Notes. These plots show the evolution over time of total and green production in absolute levels in panel (a), in relative levels in panel (b), and of the share of green production in panel (c).

Green industrial production is known to be highly concentrated in a few high-to-medium tech manufacturing sectors (Bontadini & Vona, 2023; Frattini et al., 2024).[15] An analogous pattern, although less pronounced, is observed across regions. Figure 2 provides a visual insight on the high concentration of green productions across regions (panel a). Out of 278 NUTS2 regions, only 102 have an average GRP value higher than the mean (0.503). Using a standard locational Gini coefficient, the spatial concentration of green activities is 0.444, compared to a concentration of non-green manufacturing activities of 0.413. In line with the cross-country evidence of Bontadini and Vona (2023), the darkest green regions are observed in Denmark (Midtjylland, Syddanmark and Nordjylland among others) and Germany (Oberpfalz, Mittelfranken and Tübingen among others). In other countries, some green industrial regions are also observed in Austria (Oberösterreich and Steiermark), Spain (País Vasco), Sweden (Småland med öarna and Östra Mellansverige) and Italy (Friuli-Venezia Giulia, Emilia-Romagna and Lombardia).[16]

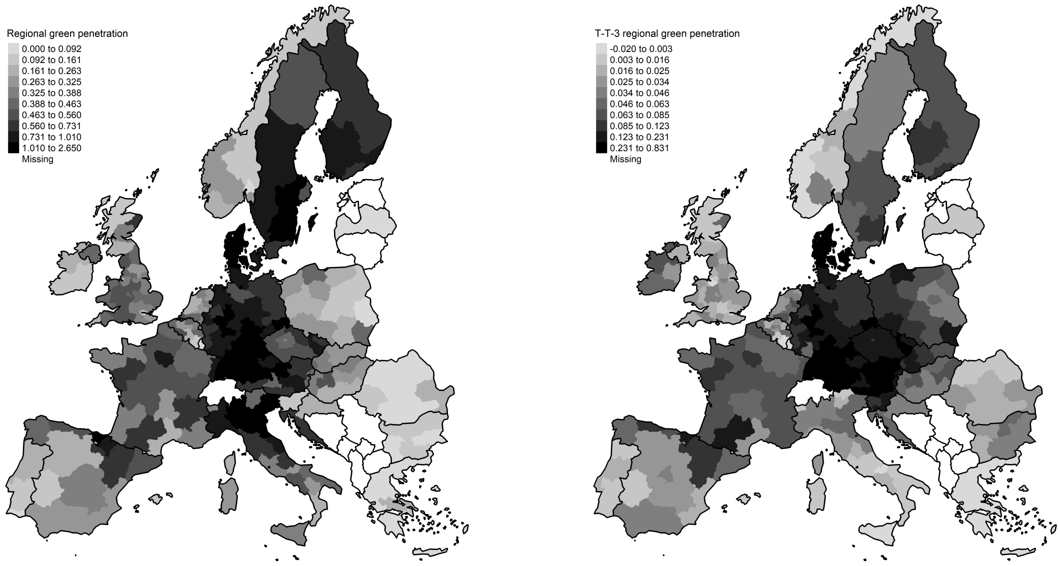
Finally, green production shocks disproportionally occur in regions that are already green (panel

[15] Table A1 shows that, at 2-digit NACE level, only 7 sectors (33 - Repair and installation of machinery and equipment; 26 Manufacture of computer, electronic and optical products; 30 Manufacture of other transport equipment; 27 Manufacture of electrical equipment; 28 Manufacture of machinery and equipment n.e.c.; 16 Manufacture of wood and of products of wood and cork; 29 Manufacture of motor vehicles) out of 24 produce green goods without being identified as polluting.

[16] See Table A2 for details.

b of Figure 2). The largest increases are indeed observed in Denmark, Austria and Germany, and in a few regions of Spain, France and Poland (see Table A3 for details). The path-dependency in green production is captured by a high and statistically significant correlation between the three-year change in GRP and its initial level (0.311, significant at the 1% level), conditional on year fixed effects. As a result, pre-existing differences in green regional penetration could contaminate the estimated effects of green industrialization shocks on local employment growth.

Figure 2: Green penetration by NUTS2 region, levels and three years change



(a) Average value

(b) Three-year change

Notes. These maps show the average green penetration (panel (a)) and its five-year change (panel (b)) by NUTS2 regions in the EU. The average refers to the whole period, from 2003 to 2017. Levels correspond to deciles. Average values are weighted by the share of the regional population over the EU one.

3 Empirical strategy

We adopt the following specification to estimate the local labour market effects of green industrialization shocks:

$$\Delta L_{rt_k} = \alpha + \beta \Delta GRP_{rt_k} + \gamma \mathbf{X'}_{rt_0} \times \tau_t + \tau_t + \eta_c + \epsilon_{rt}. \tag{3}$$

ΔL_{rt_k} is the change between t and $t-k$ (with $k = 3$ in our favourite specification) in regional employment over the active population. ΔGRP_{rt_k} is the change in the green regional penetration per worker defined in Equation 2. τ_t and η_c are, respectively, time and country dummies that control for global shocks and country-specific time trends. ϵ_{rt} is the error term. To improve the representativeness of our estimates, we weight the regressions using the baseline shares of the regional population over the EU one.

$\mathbf{X'}_{rt_0}$ is a vector of key control variables, which are taken at baseline t_0 (the average value between 2000 and 2003) and interacted with year dummies to allow for non-linear effects of initial conditions on employment dynamics.[17] In our favourite specification, these controls are the share of employment in manufacturing and the non-green regional penetration, constructed as in Equation 1 for the whole manufacturing sector. The first accounts for the so-called missing share component identified as a key confounding factor by the recent literature on shift-share instrumental variable design (Borusyak et al., 2022). Without controlling for the initial degree of industrialization, sector-specific industrial shocks, such as those used in our work, could mechanically capture differential employment trends for regions at different stage of industrial development. Likewise, the latter accounts for the size of industrial production in the region. In some robustness checks, we expand the set of controls to other potential confounders (see Section 4.2).

In Equation 3, the effect of green production shocks on employment growth is identified net of country and industry-specific trends. Yet, it is difficult to believe that GRP shocks are as good as randomly assigned (Borusyak et al., 2022). First, GRP is subject to measurement error because, within 2-digit NACE sectors, green production is also highly concentrated in a handful of 4-digit sectors (Bontadini & Vona, 2023), for which we cannot observe the employment shares at the NUTS2 level. This classical measurement error typically results in attenuation bias of the OLS estimates. Secondly, omitted variable bias is a common issue in analyses where labour market outcomes are regressed on indicators of structural transformations (Acemoglu & Restrepo, 2020; Autor et al., 2013). Specifically to the green transition, regions hosting green production facilities tend to be high-tech and have a solid skill base, thus already positioned on robust economic paths (Popp et al., 2021; Vona et al., 2019). Meanwhile, green investments may be jointly undertaken with automation investments, which reduce labor demand (Acemoglu & Restrepo, 2020, 2022; Graetz & Michaels, 2018). Due to these intricacies, it is difficult to determine a clear direction of the bias due to omitted variables.

To tackle these potential sources of endogeneity, we instrument the change in GRP with a shift-share instrumental variable (SSIV) leveraging differences in the regional green patent exposure.

$$\Delta IVGpat_{rt_k} = \sum_j \frac{L_{rj,t_0}}{L_{cjt_0}} \times \frac{\Delta Gpat^{NonEU}_{cjt}}{L_{rt_0}}. \tag{4}$$

$\frac{L_{rjt_0}}{L_{cjt_0}}$, the share component, are the employment shares of manufacturing industry j in region r and country c at time t_0 (avg. between 2000 and 2003). $\Delta Gpat^{NonEU}_{cjt}$, the shift component, is the change in the stock of EPO green patents by non-EU based inventors between t and t_k allocated to country-sector

[17]We take the controls at baseline to avoid "bad control" problems (Angrist & Pischke, 2009).

pair (c, j).[18] The shift is allocated to a country-sector pair (c, j) proportionally to the initial patent stock of that country in this sector over the EU green patent stock at time t_0 (2002).[19] Therefore: $\Delta Gpat_{cjt}^{NonEU} = \Delta Gpat_{jt}^{NonEU} \times Gpat_{cjt_0} / \sum_c Gpat_{cjt_0}$, where $\Delta Gpat_{tj}^{NonEU}$ is the change in the stock of green patents by non-EU based inventors in sector j.

The intuition behind this instrument is that regions with stronger green technological capabilities are able to benefit relatively more from a global green technology push.[20] Note that this instrument is similar to a shift-share design that leverages variation in the baseline exposure to new technologies of the workforce (Acemoglu & Restrepo, 2020; Acemoglu et al., 2022). The main difference is that here capabilities are measured using patents rather than workforce skills. Our instrument is also in line with models and empirical evidence highlighting path-dependency in green knowledge creation (Acemoglu et al., 2012; Aghion et al., 2016; Popp, 2002). In our setup, the use of third-country inventions helps navigating the trade-off between instrument strength, as implied by path-dependency, and exogeneity.

To give a first insight on the instrument's relevance, Figure 3 shows the raw correlation between the three-year change in the green patent SSIV and the three-year change in GRP. As one could expect, the correlation is quite strong and positive. This result is corroborated by a formal test of the strength of the excluded instrument in the full two-stage least square model based on Equation 3 (i.e., Kleibergen-Paap F-statistic = 53.4, see for example Table 1).

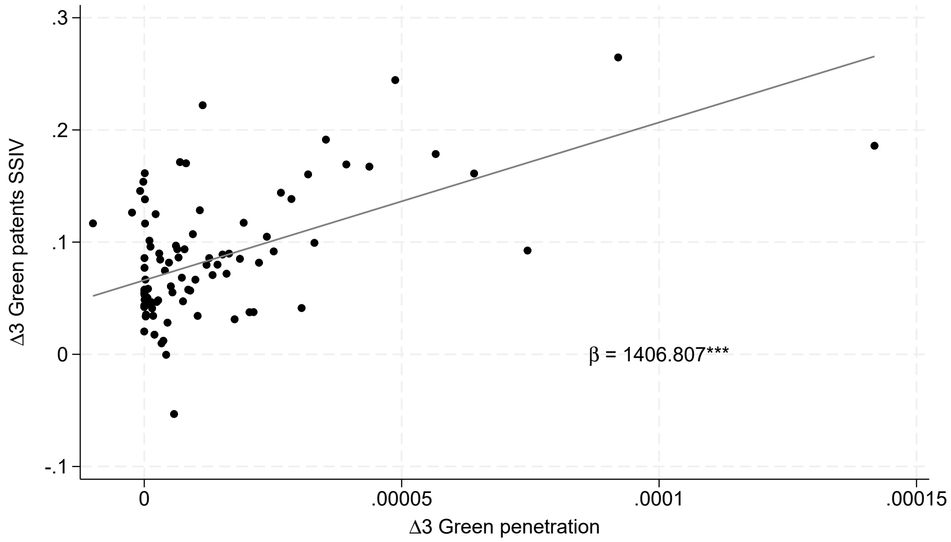
Modern treatment of SSIV requires a careful validation of the plausibility of the underlying identifying assumptions (Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020). Section 4.1 is dedicated to the discussion and testing of such identifying assumptions, supporting the validity of our empirical strategy.

[18]We take all inventors that do not reside in the EU and further exclude cross-countries patents if one of the inventors is based in the EU.

[19]In recent research using shift-share instruments, the use of baseline shares is recommended to mitigate endogeneity concerns (Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020).

[20]For a practical example consider the following. A new patent application related to wind technologies filed by Chinese inventors, the shift, is deemed to positively benefit regions that already have a relative advantage in wind patents, such as Danish ones, through various channels. First, foreign competition typically stimulates domestic inventors closer to the technological frontier (e.g., Vestas?????), while selecting out those farther away (Acemoglu et al., 2006). Second, it can complement domestic invention if patents result from broad international collaborations, making local producers more productive. Third, even if invention abroad are destructive to local producers, regions with a pre-existing technological advantage are more likely to perform relatively better than regions without it.

Figure 3: Correlation between green penetration and green patents SSIV in three-year changes.



Notes. This graph shows the raw correlation between the average three-year change in regional green penetration and the average three-year change in the green patents SSIV. We weight the two variables by the share of regional population over the EU one.

4 Main results

Table 1 reports the OLS (odd columns) and 2SLS (even columns) estimates of the relationship between regional employment in different macro sectors and green manufacturing penetration. Panel A presents results for total, manufacturing and non-manufacturing regional employment, while Panel B focuses on construction, services and agriculture plus mining regional employment.[21] For almost all macro-sectors, our estimates show a positive and highly statistically significant effect of the triennial change in green regional penetration on the three-year change in the employment-to-active population ratio. Estimated coefficients are almost an order of magnitude larger in our favourite 2SLS specification, where technology shocks are used to instrument production shocks. The lower OLS coefficient stems from an attenuation bias due to measurement error, but also reflects stronger employment effects on compliers. That is: a stronger effect on regions where higher green technological capabilities at baseline attract green production shocks.

The estimated coefficients can be interpreted as the effects of a 1'000€ three-year increase in green production per worker on the employment-to-the active population. However, the median three-year increase in green production per worker is only 46€ in our data (see Table A4), thus the coefficients should be multiplied by 0.046 to obtain a reasonable range of variation. In our favourite 2SLS specification of column 2, a three-year change in green regional penetration implies a change in the employment-to-population share of 0.008 ($0.046 \times \hat{\beta}$). Still, this quantification is inconsistent with an

[21]Non-manufacturing is the sum of employment in construction, services and utilities. Given its small size and for the sake of space, we do not report here the results related to utilities, but we discuss them in the next sub-sections.

Table 1: Green penetration on regional employment

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Total*		*Manufacturing*		*Non-manufacturing*	
$\Delta\ GRP_{r,t3}$	0.028***	0.166***	0.010***	0.053***	0.022***	0.126***
	(0.007)	(0.038)	(0.003)	(0.015)	(0.008)	(0.036)
Panel B:	*Construction*		*Services*		*Agric.+ Min.*	
$\Delta\ GRP_{r,t3}$	0.007***	0.076***	0.016**	0.039	-0.004	-0.013
	(0.002)	(0.014)	(0.007)	(0.030)	(0.007)	(0.030)
N	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1658.106***		1658.106***		1658.106***
KP F-Stat		53.4		53.4		53.4
CD F-Stat		79.4		79.4		79.4
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta\ GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and t-3. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * p<0.10, ** p<0.05, *** p<0.01.

accurate LATE interpretation of the 2SLS coefficients. Indeed, only part of the median three-year increase in green production is accounted for by exogenous green technology shocks. This part can be quantified using the first-stage coefficient and is equal to 0.007 (7€).[22] Using only the three-year change in GRP explained by the instrument, our favourite specification implies an effect of green industrialization shocks on the share of employment-to-active population of 0.0011, or slightly more than one tenth of a percentage point if compared to the median employment-to-active population (0.0011/0.923).[23]

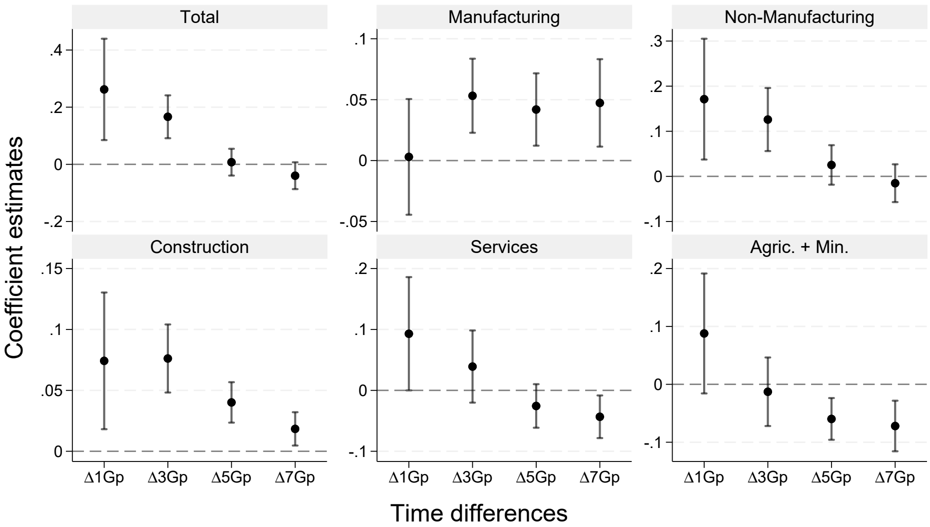
Moving to specific sectors in the rest of Table 1, we observe a similar employment effect in terms of magnitude in both the manufacturing sector, which receives the positive green industrialization shocks, and the non-manufacturing sector, which benefits indirectly from these shocks through the multiplier effect. Outside manufacturing, we observe additional job creation especially in the construction sector, in line with previous literature (Cappa et al., 2024; Fabra et al., 2024; Popp et al., 2021). We interpret

[22]This number is obtained multiplying the median value of the green patents SSIV (0.0000041) by the first-stage coefficient of the SSIV instrument (1658.106).

[23]Note that the bias of the OLS becomes smaller when using this accurate quantification. For the OLS regression, the effect should be quantified using the median three-year change in green regional penetration (0.046), thus the implied change in the employment-to-population is 0.0013.

this result as the additional multiplier effect of infrastructural investments complementary to the green transition. Another interesting result is that the overall effect in column 2 of Panel A is smaller than the sum of the effects in manufacturing (col. 4) and non-manufacturing (col. 6). This is because total employment also includes primary industries (mining and agriculture), for which the estimated effect of green industrialization is negative and statistically significant (Panel B col. 6). This result suggests that green industrialization accelerates the secular reallocation of labour from primary sectors to manufacturing and construction.

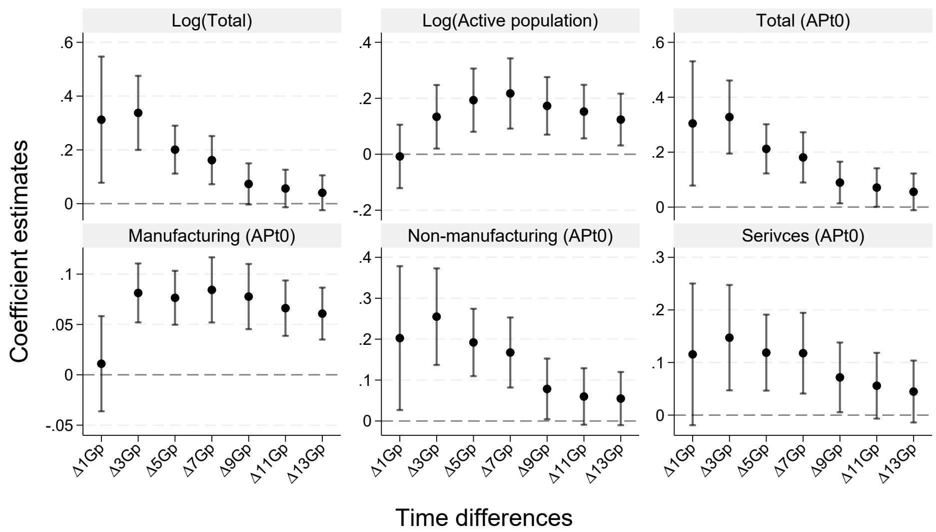
Figure 4: 2SLS estimates of green penetration on regional employment. Green patents SSIV.



Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3 and on Equation 4 by looking at one-, three-, five- and seven-year changes. KP F-stats: 11.0; 53.4; 140.3; 160.7. CD F-stats: 14.9; 79.4; 174.8; 191.8.

Next, we explore the time profile of the green industrialization effect estimating the model of Equation 3 varying the time difference $t - t_k$. Figure 4 plots the main coefficients of the favourite 2SLS specification. Specifically, each sub-plot reports the time-varying coefficients for each of the macro-sectors. For total employment over active population, the effect is at the peak after one-year and then gradually declines to become statistically insignificant at the five-years difference. Not surprisingly, this pattern is driven by the non-manufacturing sector, which represents the bulk of the local employment in most regions. Outside manufacturing, the effects on construction employment remain statistically significant up to seven-years, although decreasing in magnitude. On the other hand, services employment effects are more short-lived and achieve statistical significance only at the one-year difference, become insignificant at the three- and five-years differences, to then turn negative at seven-years. In contrast, we observe a stable job creation effect in manufacturing, implying that green industrial policy may be able to create stable manufacturing jobs in the local economy. Lastly, the effects on primary activities quickly become negative, reinforcing the reallocation hypothesis.

Figure 5: 2SLS estimates of green penetration on regional employment and active population. Green patents SSIV. Longer time horizon and decomposition.

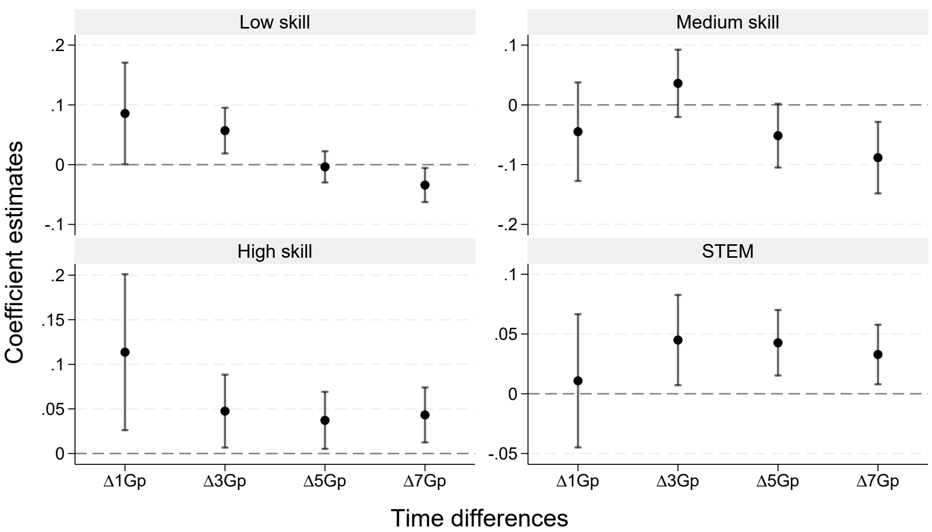


Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3 and on Equation 4 by looking at three-, five-, seven-, nine-, eleven- and thirteen- year changes. KP F-stats: 11.0; 53.4; 140.3; 160.7; 129.7; 176.0; 232.5. CD F-stats: 14.9; 79.4; 174.8; 191.8; 324.3; 333.9; 234.2.

To shed further light on the time profile of multiplier effects, we decompose the effect of the green industrialization on the numerator (total or sectoral employment) and the denominator (active population) of our dependent variable. While doing so, we extend the inspected time horizon, looking up until thirteen-year changes. Figure 5 shows the outcome related to this exercise. The top-left and top-centre figures show that, in the short term, green manufacturing penetration impacts more on total employment rather than on active population. However, in the long-term the effect of green industrialization on active population becomes stronger and more persistent, while the one on total employment gradually declines. The former dynamic (i.e., an agglomeration effect) eventually exceeds the latter accounting for the negative seven-year effect on total employment-to active population found in Figure 4. The top-right figure lends further support to this finding, using as dependent variable the change in total employment over an active population fixed at baseline. Quantitatively, the size of the three-year effect on total employment doubles when keeping the active population at baseline. Purging the effect of agglomeration by sector, the three bottom figures show that the multiplier effects remain positive in the long-term, although vanishing over time in the services sector. Moreover, it is remarkable the stability of the coefficients associated with manufacturing employment, which are consistently positive and significant after thirteen years. Overall, green industrialization triggers agglomeration effects that increase the population in search of employment and thus the tightness of the local labour market. Net of these induced agglomeration effects, local job multipliers persist in the long-run, differently from what was found in studies estimating the local employment effect of renewable energy generation (Fabra et al., 2024; Scheifele & Popp, 2025). This is not surprising as green industrial production is a tradable activity, typically creating supply-side linkages and local spillovers (Moretti, 2011).

Finally, we investigate the quality of the jobs created, using Equation 3 to estimate the skill-biased effect of green industrialization. The caveat here is that, due to data limitations, we can only measure skills using educational attainments. We look at the effect on low- (lower secondary education and less), middle- (higher secondary education) and high- (tertiary education) skill workers. Given the documented importance of Science, Technology, Engineering and Math (STEM) skills for the green transition (Popp et al., 2024; Vona et al., 2018), we define STEM employees as the number of workers employed in science and technology activities and with tertiary education. Figure 6 and Table A13 in the Appendix align with previous findings in the literature showing a positive and persistent impact of green industrialization, especially on college graduate and STEM workers. Despite declining over time, the job creation effect is also strong on workers with basic education, which is again consistent with findings of Popp et al. (2021) for the US and the high low-skill intensity of construction jobs. In contrast, we find no significant effect on middle skill workers. Figure A6 in the Appendix confirms these results even when netting out agglomeration effects.

Figure 6: 2SLS estimates of green regional penetration on regional skill level. Green patents SSIV.



<u>Notes</u>. These graphs replicate and extend the 2SLS estimation based on Equation 3, including additional the interaction with the regional skill level, and on Equation 4 by looking at one-, two-, three-, five- and seven-year changes. KP F-stats: 11.0; 53.4; 140.3; 160.7. CD F-stats: 14.9; 79.4; 174.8; 191.8.

To summarize, we observe a modest multiplier effect of green industrialization in the medium-term that gradually disappears in the long-run. Medium-term multipliers are mostly concentrated in the construction sector. In turn, the service sector positively benefits from short-term multipliers, which then fade away because green industrialization increases the labour supply and thus the tightness of local labour market. As a long-term pay-off of green industrialization, more exposed regions remain endowed with a larger base of manufacturing and construction activities, as well as of STEM and college graduate workers.

4.1 Validation of shift-share instrument

In this sub-section, we discuss the identifying assumptions that support our SSIV design. Moreover, we present the results associated to the validity of this research design.

The credibility of our instrument rests on the exclusion restriction that, conditional on industry-specific and country trends, pre-existing green technological capabilities affect regional employment dynamics only through green production shocks. Because shift-share instruments are implicitly a linear combination of multiple instruments (Goldsmith-Pinkham et al., 2020), the exogeneity assumption (and the related parallel trend assumption) can be violated both for the whole instrument and for each of the shares used to build it. More specifically, Goldsmith-Pinkham et al. (2020) suggest to decompose SSIV into a weighted average of just-identified estimates derived from individual instruments. The resulting weights, known as Rotemberg weights, quantify the contribution of each instrument to the overall 2SLS estimate and allow testing for plausible violations of the parallel trend assumption not only for the whole instrument, but also for components identified as more important by the decomposition.

Following Goldsmith-Pinkham et al. (2020), we rely on the identifying assumption that the initial sectoral shares used to assign the green technology shocks to regions are exogenous. In doing so, we begin by showing the top-five industries that, according to the Rotemberg weights (Goldsmith-Pinkham et al., 2020), contribute more to the overall 2SLS coefficient. Table A5 shows that three of the top-five industries are among the highest in terms of green production (28, 27, and 26 - see Table A1), while two only have marginal green production (20 and 29). The top five industries receive more than three quarters of the absolute weight in the estimator (0.771). In particular, the first two (28 and 27) account for about half of it (0.551/1). This is consistent with the high-degree of concentration in green production (Table A1. Table A5 also shows the baseline (avg. 2000-2003) employment share within manufacturing of these sectors and reports example of green goods that fall within these sectors.

Based on this finding, we assess the plausibility of the parallel trend assumption for the whole SSIV instrument as well as for the top-five sectors identified by the Rotemberg weights. As in Goldsmith-Pinkham et al. (2020), we regress the pre-sample (from 2000 to 2003) dependent variables in levels either on the green patents-SSIV at t_0 or on one of the 2-digit employment shares of top-five sectors at t_0, interacted with year fixed effects. To mimic the main specification of equation 3, we include in these regressions region and year fixed effects, country linear trends, and the previously discussed controls interacted with year fixed effects. We weight estimates by the share of baseline regional population. The reference year is 2000.

Figure A4 shows the results of this empirical exercise. For the aggregate instrument, we detect some signs of positive pre-trends in total employment, particularly in 2002, which may lead to an upward bias in our estimates. However, inspecting the plots for each sector individually, these pre-trends do not arise in the sector where the shock originates (manufacturing), but are concentrated in the construction sector. Indeed, manufacturing, services and, to a lesser extent, the primary sector all exhibit parallel employment trends before 2003. Inspecting the five sectors with the highest Rotemberg weights further mitigates concerns regarding the violation of the parallel trend assumption. Across the board, most subfigures show rather flat pre-trends. A few notable exceptions are sectors 20 (Manufacture of chemicals and chemical products, which is only marginally green) and 26 (Manufacture of computer, electronic and optical products), which show negative pre-trends in services employment, possibly leading to a downward bias in our estimates. To be sure that these key sectors do not drive our main results, we further validate our SSIV design by excluding them one-by-one from the instrument and replicating the main analysis accordingly. Tables A7, A8, A9, A10 and A11 reassure us that our main results are not driven by any of these key sectors, as the estimates remain qualitatively in line with the main ones.

We also assess the balance of the aggregate SSIV and each employment share identified by the Rotemberg weights along the two key controls present in the estimating equation: the share of employment in manufacturing and the non-green regional penetration. Specifically, we regress the baseline value of the green patents-SSIV (or of each of the 2-digit manufacturing employment shares of top-5 sectors by Rotemberg weights) on the baseline value of the employment share in manufacturing and the regional non-green manufacturing penetration, including country fixed effects and weighting for the share of regional population over the EU one. Table A6 highlights that both the aggregate SSIV and most shares (excluding 26, 28 and 29) positively correlate with the employment share in manufacturing. On the other hand, only the aggregate SSIV and sector 29 positively correlate with non-green manufacturing penetration. This supports our choice of including these controls non-parametrically in Equation 3.

We further assess the relevance of our instrument by applying the methodology of Lee et al. (2022) to adjust the t-statistics of the second-stage coefficients.[24] Table A12 shows that almost all the coefficients of interest of Table 1 have high enough adjusted t-statistics to preserve statistical significance at the

[24] Lee et al. (2022) address the issue of invalid inference in IV estimations caused by weak instruments, challenging the reliance on arbitrary thresholds like F-stat > 10. Lee et al. (2022) introduce the tF procedure, a robust inferential method for instrumental variable regressions that adjusts t-statistics and confidence intervals using the first-stage F-statistic. The resulting procedure usually leads to more demanding t-statistics.

1% level. The only exception is the one related to non-manufacturing employment, which, however, does so at a 5% level.

Another issue concerns the interpretation of the IV estimates as Late Average Treatment Effects (LATE, Imbens and Angrist, 1994). To interpret SSIV estimates as LATEs, the monotonicity assumption must hold. In our specific case, it requires that the SSIV variable has a positive effect on green production on all the regions. This is not obvious as, for example, a green invention in China could reduce green production in Europe through a business stealing effect. Although this assumption cannot be tested directly, we perform a Monte Carlo simulation where we re-estimate 1,000 times our main coefficient of Table 1 by redrawing regions with repetition and thus implicitly excluding a few regions at the time. We then plot the estimated first-stage coefficients obtained for each sub-sample to detect large deviations from the central value that we estimated for the whole sample. Figure A5 shows that the distribution of the coefficients of the first stage is consistently positive - thus excluding large violations of the monotonicity assumption - and roughly centred around the baseline estimated value of the first-stage coefficient. Overall, these pieces of evidence provide solid support to the credibility of our identification strategy.

4.2 Robustness checks

In this subsection, we assess the robustness of our main estimated effects (Table 1) to different versions of the main specification. These additional results are included in the Appendix for the sake of space.

Table 1 does not report the results related to utilities. Despite being a small sector in terms of employment (average 0.7%), the utilities sector contains activities that are linked to green manufacturing, such as the production, transmission and distribution of electricity. Hence, we would expect to find positive multipliers of GRP on utilities employment. Figure A7 shows that this is actually the case. Remarkably, the time profile of the effects is similar to that of manufacturing employment, suggesting that greener regions experience long-term job growth in the utilities sector as well.

Next, we augment our main specification of Equation 3 including a richer set of potential confounders that were identified as important by the related literatures on the China shock (Autor et al., 2013) and local job multipliers (Chodorow-Reich, 2019; Moretti, 2010; Vona et al., 2019). More specifically, we include the following variables at baseline: population density, median age, the share of female population, the share of foreign population, and the share of the population with at least secondary and tertiary education. Table A14 shows that the estimated coefficients remain quantitatively in line with the main ones.

Our main specification controls for time-invariant regional characteristics, country-level and broad industry-level trends, but not for pre-existing regional trends unrelated to green industrialization. To assess whether our results survive the inclusion of such trends, Table A15 replaces the country-level fixed effects either with NUTS1 or NUTS2 region fixed effects.[25] We find that the estimated coefficients remain statistically significant at conventional level and increase with respect to our favourite specification with country fixed effects.

As discussed before, one source of bias in the OLS estimates is that green investments may be carried out jointly with automation investments that reduce labour demand (Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018). Hence, controlling for automation investment in our main specification can help avoid a potential source of omitted variable bias. To do so, we measure the exposure to automation at the regional level as in Anelli et al. (2021) and include it as a control variable.[26] Table A16 shows that the main estimates are robust the inclusion of this control, which, as expected, is negatively associated with employment growth.

Lastly, we change the level of clustering of the standard errors from NUTS2 to NUTS1. This accounts for possibly larger interdependencies between local labour markets (Manning & Petrongolo, 2017). Table A18 shows that the significance level of the regional green manufacturing penetration coefficients remains within accepted ranges, except for the construction sector.

5 Extensions

This final section extends our analysis into two policy-relevant directions. First, we concentrate on large shocks in green industrial production that more closely resemble the case of a sudden push in green industrial policy. Second, we assess the effect of green industrialization in regions that are specialized in pollution-intensive activities and thus may also experience substantial job losses from the green transition.

5.1 Large shocks to green manufacturing penetration

While our data show an upward trend in green productions, higher than the trend in non-green ones (Figure 1), the green industrialization expansion studied so far cannot be considered a "big push" (Murphy et al., 1989; Rosenstein-Rodan, 1943). Indeed, our study spans a historical period where EU countries lost their initial comparative advantage in some key green products, notably solar PV.

[25]Specifically, in a first-difference model, this demanding specification allows employment to follow a different linear trend in each region, independently on green industrialization.

[26]It is worth mentioning that there is no perfect overlap of NUTS2 regions between the main data and the automation exposure one. See Appendix A.6 for details. For consistency, we re-estimate the main results restricting the sample to those NUTS2 regions for which we have automation data and show it in Table A17. Estimates are in line with the main ones.

In this context, creating local jobs out of green activities may be easier due to the absence of general equilibrium effects associated, for instance, to the increased tightness of local labour markets, especially for workers with green-specific skills.

Taking stock from the related paper of Aghion et al. (2023) on the local labour market effect of automation in France, we mimic the effect of a big green push in a staggered difference-in-difference (DiD) design, where the treatment is a large positive shock to the local green economy. More formally, we estimate the following two-way fixed effects model.

$$L_{rt} = \alpha + \sum_{p=-5}^{7} \beta_p GP_{rp} + \gamma \mathbf{X'}_{rt_0} \times \tau_t + \tau_t + \eta_r + \sigma_c \times year + \epsilon_{rt}, \tag{5}$$

where L_{rt} and $\mathbf{X'}_{rt_0}$ are, respectively, one of the outcome variables and of the controls already discussed in Equation 3. τ_t and η_r are year and region fixed effects, and $\epsilon_{r,t}$ is the error term.

GP_{rp} is a dummy variable equal to 1 for treated regions, defined as regions r experiencing an increase in green regional penetration between t and $t-1$ above the 90$^{\text{th}}$ percentile. We assume that, once a region experiences such a shock, is treated thereafter and we exclude always treated units (Callaway & Sant'Anna, 2021). As in an DiD event study design, the effect of the treatment is decomposed in a series of leads (up to five years) and lags (up to seven years) relative to the region's year of exposure.[27] Figure A8 provides a sense of the staggered design, showing the fraction of treated regions by cohort. Around 2/3 of large green shocks are observed between 2006 and 2008, before Chinese competition in green production deteriorates the pre-existing EU advantage.

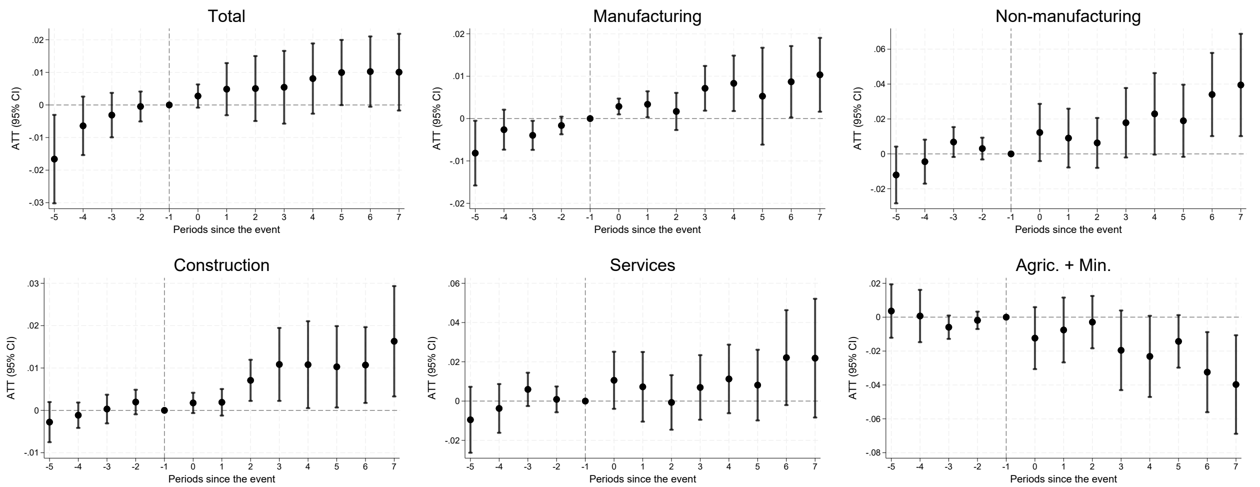
Importantly, this staggered DiD approach does not rely on the technologically-driven source of identifying variation of the SSIV, and hence does not need to be interpreted as a LATE. Assuming that large shocks to green manufacturing penetration are plausibly exogenous, a DiD set-up can be interpreted as an Average Treatment effects on the Treated (ATT). The plausibility of the ATT interpretation rests on the assumption of conditional parallel trends, that can be indirectly tested in an event study design.

Recent DiD literature has shown that, within a staggered design, the two-way fixed effects (TWFE) models may not yield a transparent weighted average of treatment effects when these effects are heterogeneous (see Roth et al. (2023) for an excellent review). To account for this issue, we choose the regression adjustment framework proposed by Callaway and Sant'Anna (2021) (CS henceforth), where the outcome variable is depurated by the controls included in the main specification of Equation 3. As an additional advantage, the CS estimator relaxes the assumption of treatment homogeneity and

[27]Note that, since our sample starts in 2003 and we define treatment based on shocks in regional green manufacturing penetration between t and $t-1$, the first non-missing year in the estimating sample is 2004.

thus allows to estimate group-time ATTs, with groups determined by the initial treatment time of each unit, before aggregating the results. In the main results, we use never-treated regions as the control group, but changing the control group with not-yet-treated regions does not substantially affect our results (Figure A9 in the Appendix).

Figure 7: Large shocks to green manufacturing penetration. Event study estimates.

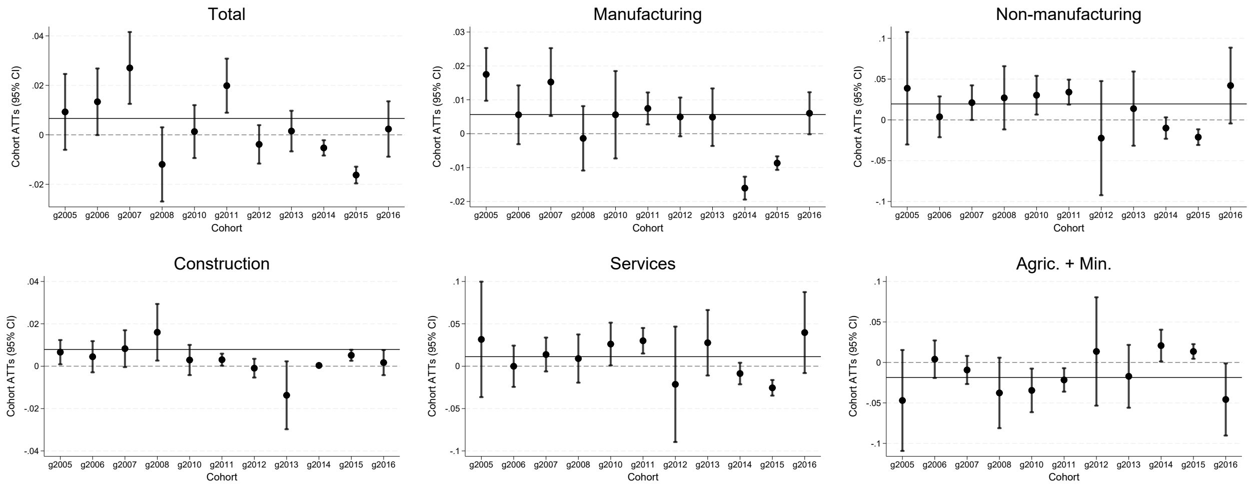


Notes. These plots show the results of the event study specification for several outcomes employing a regression adjustment from Callaway and Sant'Anna (2021). The positive spike in green regional penetration is defined as a change higher than the 90^{th} percentile in the one-year change of green regional penetration. The first spike identifies the beginning of treatment. Standard errors are clustered at the NUTS2 level.

We display the results of our favourite CS estimator in Figure 7. The results are qualitatively in line with those of the main specification, but the effects are as expected larger, slower to emerge and more persistent also outside manufacturing. More specifically, the coefficients become statistically significant only after five-years, pointing to increases the total employment-to active population ratio by 1.1 pp (0.01/0.092) - an effect ten times larger than the LATE one. Moreover, we do not observe a decline in the employment-to-active population in the services sector and, netting out the agglomeration effect as in Section 4, we find long-term statistically significant effects on all sectors (Figure A11). Reassuringly, most of the sub-plots show no signs of the presence of pre-trends or, for total employment, a negative pre-trend for regions receiving large green shocks, making us confident that violations of the conditional parallel trends assumption are not severe in our setup. Finally, both the TWFE and CS estimators show somewhat similar patterns (Figure A10), consistent with the fact that negative weights account for a small fraction of the total ATTs in our case (Table A19).

Further, exploiting the properties of the CS estimator, we decompose the ATT into cohort-specific ATTs. Figure 8 reveals that the earliest-treated groups mostly exhibit positive ATT, driving the bulk of the aggregate impact. In contrast, later-treated cohorts display more volatile ATTs: some still show positive ATT estimates, while others show estimates that hover around zero or even negative.

Figure 8: Large shocks to green manufacturing penetration. Cohort-specific ATTs.



Notes. These figures show the ATT by cohort, with cohort being identified by the year of exposure to treatment, a positive shock in regional green manufacturing penetration between t and $t-1$ above the 90th percentile. The solid black line represents the aggregate ATT.

This evidence suggests that it may be more difficult to reconcile future efforts to promote green industrialization with job creation. This evidence also aligns with the gradual loss of EU's advantage in green products and with the fact that most recent green technologies are becoming more labour-saving (Saussay et al., 2025).

5.2 Evaluating the impacts on vulnerable regions

One of the main goals of the EU green deal is to achieve a so-called "just transition". That is: the policy-driven green transition must not exacerbate regional inequalities, especially on regions more dependent on polluting industries. Place-based policies for left-behind regions are usually advocated by economists on the ground of their high labour supply elasticity (Austin et al., 2018; Bartik et al., 2019). Regions hosting polluting industries and coal mines can be a good target for such policies are they are usually poorer and already on a declining trajectory (Hanson, 2023; Vona, 2023; Weber, 2020). Recent political-economy research suggests that providing opportunities in the green economy to communities that depend on polluting industries helps mitigate their opposition to the green transition (Bergquist et al., 2020; Bolet et al., 2024; Cavallotti et al., 2025).

Inspired by these considerations, we construct a measure of the potential disadvantages created by the green transition which relies on the degree of specialization in polluting industries at baseline (2000-2003). More specifically, we measure brown exposure as the ratio between regional employment in polluting industries and the total regional employment: $BP_{r,t_0} = \sum_j \frac{L_{r,j=poll,t_0}}{L_{r,t_0}}$.[28] The average value

[28] In line with Bontadini and Vona (2023) and the literature cited there, the polluting industries are: 24 - manufacture of basic metals; 25 - manufacture of fabricated metal products; 21 - manufacture of basic pharmaceutical products; 20 - manufacture of chemicals and chemical products; 23 - manufacture of other non-metallic mineral products; 19 -

of BP_{r,t_0} is 0.044, signalling that the average share of employment in polluting industries is rather small (see Table A4). We measure elevated brown penetration by identifying those NUTS2 regions that have BP_{r,t_0} above the 75$^{\text{th}}$ percentile.

Figure A13 shows NUTS2 regions by brown exposure (a) and those identified as having a high degree of brown exposure (b). Notable clusters emerge in the West of France, North of Italy and Czech Republic. Table A20 shows balancing tests between brown and non-brown NUTS2 regions. Brown-specialized regions tend to have lower population density, slightly higher median age, and a higher (lower) share of low (high) skill workers. They also have higher employment in manufacturing and non-green regional penetration at baseline, while they do not show differences in terms of three-year changes in green regional penetration and regional green patents exposure. Lastly, and somehow unexpectedly, brown-specialized regions have a higher probability of being exposed to large shocks to regional green penetration.

Econometrically, we assess the differential effect of green industrialization on brown regions by adding the interaction between the high-brown exposure dummy variable and the three years change in GRP to our main specification of Equation 3. Table 2 shows the results of this empirical exercise, where almost none of the interaction coefficients are statistically significant. For instance, the effect of green industrialization on total employment growth is slightly lower in brown specialized regions, but the coefficient associated to the interaction term is far from being statistically significant. The only exception to this pattern is the more pronounced negative reallocation effect of green penetration in brown regions on agriculture and mining employment.

When restricting the sample to brown-exposed regions and expanding to other time differences (Figure A14), estimates are in line with the main sample although job creation effects on manufacturing are less precisely estimated (Figure 4). However, netting out agglomeration effects makes the estimated coefficients statistically significant also for brown regions (Figure A15- except in the very long-term (after nine-years). The result that brown-exposed and non-brown exposed regions equally benefit from green industrialization shocks is confirmed using the DiD-large shock specification (see Figure A16), where we estimate the ATT separately for the two groups of regions against the common control group of never treated. In brown-exposed regions, although the ATTs are estimated less precisely due to decrease in sample size, a weaker effect in manufacturing is offset by a stronger effect outside manufacturing.

The main policy implication of these results is that brown exposed regions can still benefit from the green industrialization. Large job creation effects outside manufacturing can be accounted for by

manufacture of coke and refined petroleum products and the entire mining sector (i.e. sectors from 05 to 08, excluding sector 09 which pertains services related to the mining sector).

Table 2: Green penetration and brown specialization interaction on regional employment

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Total*		*Manufacturing*		*Non-manufacturing*	
$\Delta\ GRP_{r,t3}$	0.023***	0.211***	0.007**	0.044**	0.022**	0.067
	(0.007)	(0.066)	(0.003)	(0.021)	(0.009)	(0.079)
$*\ BP\ SPEC_{r,t0}$	0.019	-0.046	0.010***	0.011	0.000	0.094
	(0.012)	(0.087)	(0.003)	(0.025)	(0.012)	(0.106)
Panel B:	*Construction*		*Services*		*Agric.+ Min.*	
$\Delta\ GRP_{r,t3}$	0.006***	0.069**	0.017**	-0.011	-0.006	0.100
	(0.002)	(0.030)	(0.008)	(0.065)	(0.008)	(0.070)
$*\ BP\ SPEC_{r,t0}$	0.004	0.015	-0.003	0.076	0.008	-0.151**
	(0.005)	(0.044)	(0.008)	(0.074)	(0.008)	(0.070)
N	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
KP F-Stat		11.1		11.1		11.1
CD F-Stat		16.6		16.6		16.6
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta\ GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and *t-3*. The instrumental variable refers to the shift-share instrumental variable related to green patents. The endogenous and instrumental variable are interacted with a dummy variable equal to 1 if a NUTS2 has a value of brown exposure higher than the 75^{th} percentile at baseline (avg. 2000-2003). Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * p<0.10, ** p<0.05, *** p<0.01.

the larger labour supply elasticity of more vulnerable regions (Austin et al., 2018). This result is also in line with evidence that green and brown activities utilize a similar set of skills (Saussay et al., 2022; Vona et al., 2018)

6 Conclusions

This paper offers new insights on the effects of green industrialization on local labour markets in EU countries. While previous work focused on green energy (Cappa et al., 2024; Chan & Zhou, 2024; Fabra et al., 2024; Scheifele & Popp, 2025) or on green fiscal policies (Popp et al., 2021; Wald et al., 2024), we are, to the best of our knowledge, the first to estimate the local multiplier effect of green industrialization. Within a causal empirical framework, we show that regional green manufacturing penetration creates jobs in the local economy and such effect is more persistent than those estimated for renewable energy generation. Importantly, we show that the effect is less likely to be contaminated by pre-existing trends, which were an issue in the related study of Popp et al. (2021).

The aggregate effect on the employment-to-active population masks various structural changes in the local economy. First, we observe a strong and persistent effect on manufacturing employment. Green manufacturing production also increases the share of STEM workers in the local labour market, enhancing the general attractiveness of greener regions. Second, the multiplier effect outside manufacturing is more evident and persistent on construction and utilities, while it is short-lived in the services sector. This finding underscores the crucial role of infrastructural investments for the green transition. Third, green industrialization accelerates labour reallocation away from the primary sector and triggers agglomeration forces that increase the tightness of local labour markets. Both reallocation and agglomeration effects are in line with the fact that greener regions become more attractive locations to live and work. Fourth, we observe a skill-bias of green industrial activities in favour of high- (especially STEM) and low-skilled workers, which aligns with previous research (Marin and Vona, 2019; Vona et al., 2018). The change in the skill composition is partly driven by induced changes in the local industrial structure. On the one hand, green industries are high-to-medium tech and thus their expansion increases the demand of STEM workers. On the other hand, the expansion of construction allows to absorb workers laid off from the primary sector and the inflow of new workers.

Although we do not exploit specific green policies to identify local labour market effects, our findings can be used to improve the design of green industrial policies. In particular, the two main extensions of our analysis provide further food for thought for policy makers. On the positive side, our results suggest that green industrialization can be a promising part of place-based policies for left-behind brown regions. On the negative side, large green industrialization shocks are less frequent in recent years and, when they occur, create less jobs. This implies that green subsidies, possibly combined with local content requirement, are less likely to be effective in creating local jobs in the future. What remains unclear is whether a lower effectiveness is due to the lack of competitiveness of EU countries in green industries or to the fact that green technologies are becoming more labour-saving. These issues certainly deserve further research.

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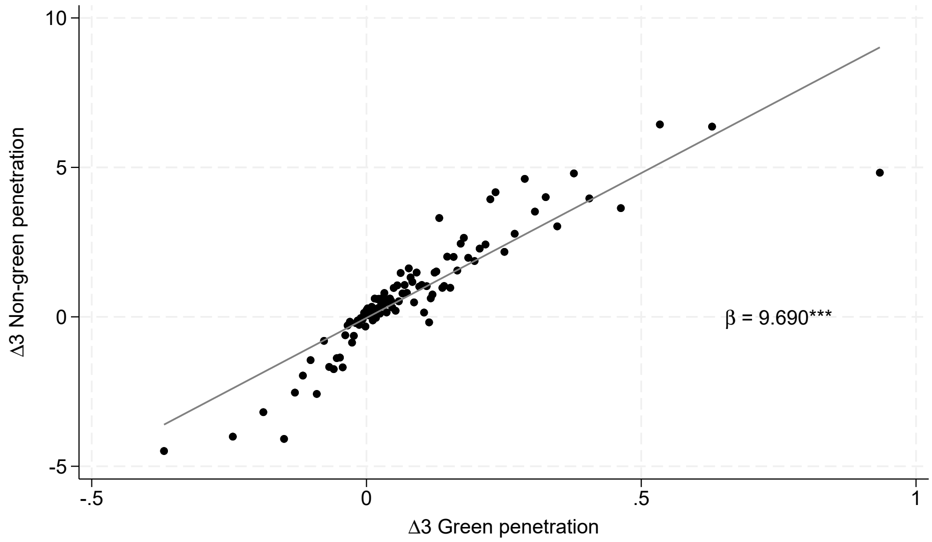
A Appendix

A.1 Descriptive statistics

Figure A1: GRP and NGRP



Notes. This graph shows the raw correlation between the average three-year change in regional non-green penetration and the average three-year change in regional green penetration. We weight the two variables by the share of regional population over the EU one.

Table A1: Green and polluting production by 2-digit industries

NACE2D	Label	Share Gp	Tot. Gp	Mean Gp	SD Gp	Max Gp	GHG int.
	Potentially green industries						
33	Repair and installation of machinery and equipment	0.1844	383554.854	711.605	1368.634	8106.562	0.740
26	Manufacture of computer, electronic and optical products	0.1804	294572.305	541.493	1432.731	11602.843	0.300
30	Manufacture of other transport equipment	0.1764	239995.366	441.168	916.273	7482.641	0.610
27	Manufacture of electrical equipment	0.1299	383540.545	705.038	1798.052	14265.906	0.300
28	Manufacture of machinery and equipment n.e.c.	0.0836	524287.359	963.764	2317.087	17440.078	0.540
16	Manufacture of wood and of products of wood and cork	0.0015	2308.279	4.911	10.564	68.902	0.880
29	Manufacture of motor vehicles	0.0003	2422.361	4.923	25.723	251.283	0.610
	Non-green industries						
10	Manufacture of food products	0.0000	0.000	0.000	0.000	0.000	1.450
11	Manufacture of beverages	0.0000	0.000	0.000	0.000	0.000	1.450
12	Manufacture of tobacco products	0.0000	0.000	0.000	0.000	0.000	1.450
13	Manufacture of textiles	0.0000	0.000	0.000	0.000	0.000	0.970
14	Manufacture of wearing apparel	0.0000	0.000	0.000	0.000	0.000	0.970
15	Manufacture of leather and related products	0.0000	0.000	0.000	0.000	0.000	0.970
17	Manufacture of paper and paper products	0.0000	0.000	0.000	0.000	0.000	1.180
18	Printing and reproduction of recorded media	0.0000	0.000	0.000	0.000	0.000	1.180
22	Manufacture of rubber and plastic products	0.0000	0.000	0.000	0.000	0.000	0.940
31	Manufacture of furniture	0.0000	0.000	0.000	0.000	0.000	0.740
32	Other manufacturing	0.0000	0.000	0.000	0.000	0.000	0.740
	Polluting industries						
24	Manufacture of basic metals	0.0216	63525.056	126.544	202.420	1024.372	4.230
25	Manufacture of fabricated metal products	0.0137	75930.470	139.578	262.518	1956.398	4.230
21	Manufacture of basic pharmaceutical products	0.0000	0.000	0.000	0.000	0.000	5.110
20	Manufacture of chemicals and chemical products	0.0163	60694.073	280.991	590.525	3945.616	5.110
23	Manufacture of other non-metallic mineral products	0.0314	95324.577	186.545	312.939	1473.388	7.780
19	Manufacture of coke and refined petroleum products	0.0000	0.000	0.000	0.000	0.000	44.990

Notes: Authors' elaboration on PRODCOM data. Production values are deflated to have data at constant prices, with 2020 as the base year. Column 1 reports the share that green production of each industry represents in total green production. Column 2 reports total sold green production from 2003 to 2017, with data in million of €. Column 3 and 4 report the mean and standard deviation of green production from 2003 to 2017, with data in million of €. Column 5 reports the maximum value of an industry-year of sold green production, with data in million of €. 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.

Table A2: Top NUTS2 regions by average green manufacturing penetration.

Region	GRP	Region	GRP
DK - Midtjylland	2.650	DE - Sachsen-Anhalt	0.771
DK - Syddanmark	2.547	FR - Alsace	0.771
DE - Oberpfalz	2.141	DE - Schleswig-Holstein	0.759
DE - Mittelfranken	2.127	SE - Västsverige	0.752
DK - Nordjylland	2.032	CZ - Střední Morava	0.731
DE - Tübingen	1.805	AT - Vorarlberg	0.730
DE - Schwaben	1.728	DE - Münster	0.726
DE - Stuttgart	1.658	SE - Sydsverige	0.720
DE - Freiburg	1.573	ES - Aragón	0.720
DE - Bremen	1.510	DE - Köln	0.712
DE - Karlsruhe	1.498	AT - Wien	0.704
AT - Oberösterreich	1.491	FI - Etelä-Suomi	0.702
DE - Unterfranken	1.473	FR - Rhône-Alpes	0.700
DE - Hamburg	1.436	CZ - Moravskoslezsko	0.700
DE - Detmold	1.407	HR - Jadranska Hrvatska	0.699
DE - Arnsberg	1.364	AT - Kärnten	0.689
DE - Dresden	1.300	FR - Midi-Pyrénées	0.681
DE - Oberfranken	1.278	AT - Niederösterreich	0.676
DE - Oberbayern	1.237	DE - Leipzig	0.662
ES - País Vasco	1.231	DE - Berlin	0.661
DE - Gießen	1.228	FI - Itä-Suomi	0.640
SE - Småland med öarna	1.216	IT - Toscana	0.636
IT - Friuli-Venezia Giulia	1.214	DE - Brandenburg	0.623
IT - Emilia-Romagna	1.185	ES - La Rioja	0.614
SE - Östra Mellansverige	1.148	AT - Tirol	0.606
IT - Lombardia	1.054	UK - North Eastern Scotland	0.603
DE - Thüringen	1.047	IT - Umbria	0.601
IT - Veneto	1.021	IT - Abruzzo	0.599
DE - Kassel	0.999	DE - Mecklenburg-Vorpommern	0.573
DE - Niederbayern	0.992	DE - Trier	0.571
AT - Steiermark	0.986	CZ - Severovýchod	0.566
DE - Chemnitz	0.977	FR - Pays de la Loire	0.562
FI - Länsi-Suomi	0.966	CZ - Jihovýchod	0.557
ES - Comunidad Foral de Navarra	0.953	FR - Limousin	0.557
DK - Sjælland	0.940	UK - Shropshire and Staffordshire	0.551
IT - Piemonte	0.931	ES - Principado de Asturias	0.549
SE - Norra Mellansverige	0.931	UK - East Wales	0.548
DE - Saarland	0.931	FR - Bourgogne	0.547
IT - Marche	0.922	SE - Övre Norrland	0.545
DE - Düsseldorf	0.920	DE - Lüneburg	0.539
DE - Weser-Ems	0.915	FR - Centre (FR)	0.539
DE - Braunschweig	0.911	UK - Hampshire and Isle of Wight	0.535
DE - Hannover	0.877	CZ - Jihozápad	0.531
DE - Darmstadt	0.849	UK - Dorset and Somerset	0.529
IT - Liguria	0.847	HU - Közép-Dunántúl	0.528
FR - Ile de France	0.825	FR - Franche-Comté	0.521
DE - Rheinhessen-Pfalz	0.819	FR - Haute-Normandie	0.514
DK - Hovedstaden	0.805	IT - Campania	0.509
DE - Koblenz	0.788	ES - Cantabria	0.505
SE - Mellersta Norrland	0.783	CZ - Severozápad	0.504
FI - Etelä-Suomi	0.778	BE - Prov. Hainaut	0.503

Notes. This table shows the NUTS2 regions for which their average green manufacturing penetration from 2003 to 2017 is higher than the average across NUTS regions.

Table A3: Top NUTS2 regions by the average three-year change in green manufacturing penetration.

Region	**Δ_3 GRP**	**Region**	**Δ_3 GRP**
DK - Midtjylland	0.831	DE - Saarland	0.152
DK - Syddanmark	0.680	FR - Midi-Pyrénées	0.141
DK - Nordjylland	0.536	DE - Schleswig-Holstein	0.140
AT - Oberösterreich	0.506	PL - Podkarpackie	0.139
AT - Steiermark	0.364	PL - Dolnośląskie	0.136
DE - Tübingen	0.361	CZ - Severozápad	0.135
DE - Oberpfalz	0.352	CZ - Střední Čechy	0.134
DE - Stuttgart	0.336	DE - Koblenz	0.134
DE - Schwaben	0.334	SK - Západné Slovensko	0.128
DE - Mittelfranken	0.331	SI - Vzhodna Slovenija	0.127
AT - Vorarlberg	0.313	DE - Düsseldorf	0.125
DK - Sjælland	0.298	DE - Darmstadt	0.123
AT - Wien	0.296	ES - Comunidad Foral de Navarra	0.121
DE - Bremen	0.296	PL - Opolskie	0.119
DE - Freiburg	0.290	DE - Berlin	0.116
DE - Dresden	0.286	PL - Śląskie	0.114
DE - Gießen	0.283	SK - Stredné Slovensko	0.114
DE - Unterfranken	0.279	FI - Länsi-Suomi	0.113
DE - Hamburg	0.278	DE - Leipzig	0.112
DE - Karlsruhe	0.276	PL - Zachodniopomorskie	0.111
AT - Kärnten	0.259	CZ - Praha	0.111
AT - Niederösterreich	0.249	DE - Münster	0.109
DE - Detmold	0.248	ES - Aragón	0.109
DE - Oberbayern	0.247	SE - Småland med öarna	0.107
CZ - Střední Morava	0.238	DE - Mecklenburg-Vorpommern	0.107
DE - Arnsberg	0.237	PL - Wielkopolskie	0.105
DK - Hovedstaden	0.233	SI - Zahodna Slovenija	0.102
AT - Tirol	0.231	FR - Pays de la Loire	0.098
DE - Oberfranken	0.231	DE - Sachsen-Anhalt	0.098
CZ - Severovýchod	0.209	DE - Trier	0.098
PL - Pomorskie	0.201	FR - Ile de France	0.096
CZ - Jihozápad	0.194	ES - La Rioja	0.093
DE - Kassel	0.194	SK - Bratislavský kraj	0.091
DE - Niederbayern	0.190	DE - Köln	0.090
AT - Salzburg	0.178	FI - Etelä-Suomi	0.090
DE - Braunschweig	0.176	PL - Lubuskie	0.089
CZ - Jihovýchod	0.170	ES - Principado de Asturias	0.088
AT - Burgenland	0.170	DE - Brandenburg	0.087
DE - Thüringen	0.169	DE - Lüneburg	0.086
CZ - Moravskoslezsko	0.167	FR - Poitou-Charentes	0.084
DE - Hannover	0.164	PL - Kujawsko-pomorskie	0.084
DE - Weser-Ems	0.161	FR - Alsace	0.082
ES - País Vasco	0.159	FI - Itä-Suomi	0.082
FR - Alsace	0.082		

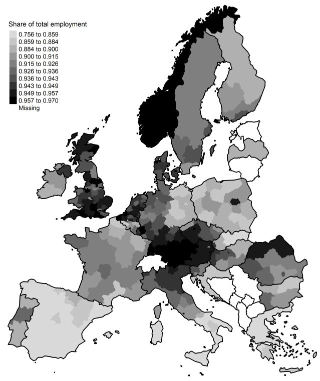
Notes. This table shows the NUTS2 regions for which their three-year average green manufacturing penetration from 2003 to 2017 is higher than the average across NUTS regions.

Table A4: Descriptive statistics of main variables

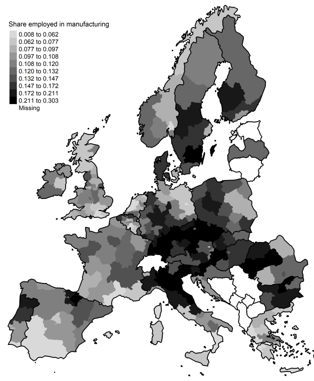
	Mean	SD	Min	p50	Max
Outcomes					
Total employment over active pop.	0.9104	0.0524	0.6295	0.9224	0.9829
t-t_3 Total employment over active pop.	0.0011	0.0349	-0.1842	0.0032	0.1514
Manufacturing employment over active pop.	0.1312	0.0583	0.0000	0.1227	0.3332
t-t_3 Manufacturing employment over active pop	-0.0057	0.0155	-0.1463	-0.0054	0.0965
Non-manufacturing employment over active pop.	0.6886	0.1199	0.0573	0.7027	0.9529
t-t_3 Non-manufacturing employment over active pop.	0.0109	0.0535	-0.8496	0.0126	0.7649
Construction employment over active pop.	0.0675	0.0177	0.0000	0.0663	0.1828
t-t_3 Construction employment over active pop.	-0.0020	0.0132	-0.1020	-0.0005	0.0521
Services employment over active pop.	0.6133	0.1214	0.0000	0.6266	0.8678
t-t_3 Services employment over active pop.	0.0121	0.0497	-0.8469	0.0114	0.7648
Agriculture + mining employment over active pop.	0.0906	0.1042	-0.1640	0.0661	0.8609
t-t_3 Agriculture + mining employment over active pop.	-0.0042	0.0494	-0.7685	-0.0025	0.8489
Green penetration and green patents SSIV					
Regional green penetration	0.548829	0.468924	0.000000	0.416036	4.595836
t-t_3 regional green penetration	0.082808	0.175823	-0.901374	0.046272	2.551368
Regional green patents SSIV	0.000060	0.000077	0.000000	0.000036	0.000512
t-t_5 regional green patents SSIV	0.000012	0.000021	-0.000049	0.000004	0.000187
Controls					
Population density (t0)	448.4507	961.3419	2.8500	173.4750	9519.3584
Median age (t0)	38.7253	2.6659	31.3500	38.9750	50.1882
Share of female population (t0)	0.5178	0.0084	0.4892	0.5175	0.5545
Share of foreign-born population (t0)	0.0459	0.0437	0.0015	0.0348	0.3660
Share of population with lower secondary edu. (t0)	0.3977	0.1606	0.1085	0.3690	0.8468
Share of population with upper secondary edu. (t0)	0.3926	0.1373	0.0958	0.3792	0.6943
Share of population with tertiary edu. (t0)	0.1535	0.0682	0.0497	0.1519	0.4280
Share employed in manufacturing (t0)	0.1556	0.0618	0.0102	0.1475	0.3372
Regional non-green penetration (t0)	8.2605	6.7683	0.0000	6.1283	39.7887
Polluting activities exposure (t0)	0.0440	0.0205	0.0022	0.0392	0.1188

Notes. This table shows the descriptive statistics of the main variables used in the analysis.

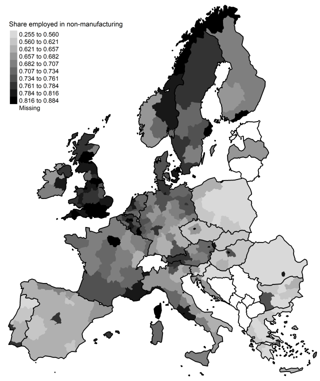
Figure A2: Regional employment



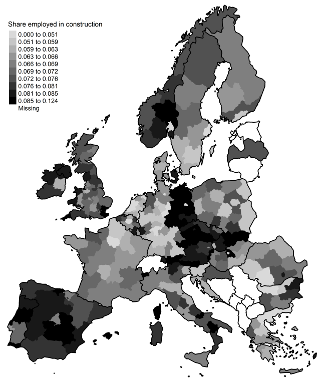
(a) Total employment



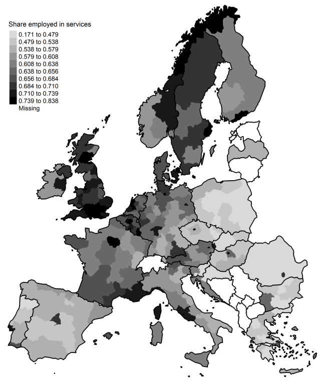
(b) Manufacturing employment



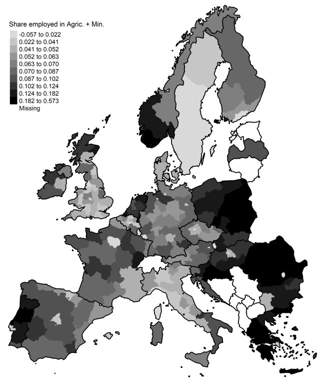
(c) Non-manufacturing employment



(d) Construction employment



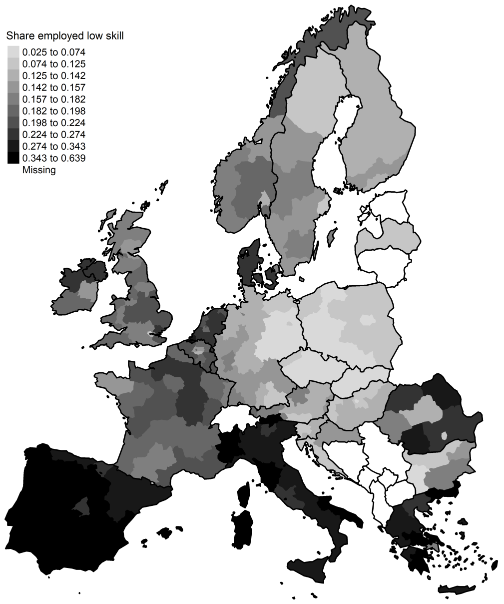
(e) Services employment



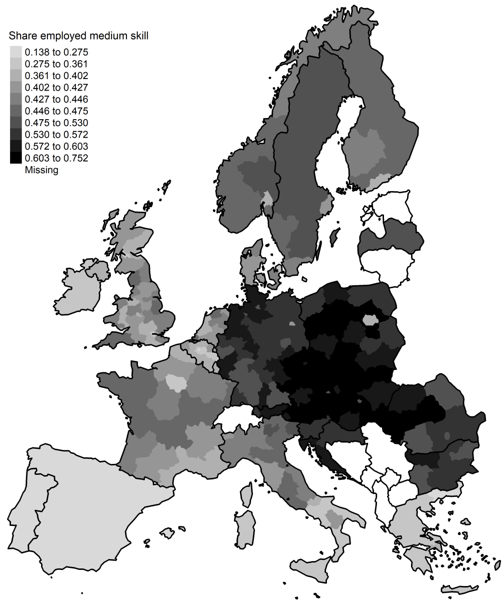
(f) Agric. + Min. employment

__Notes__. These maps show the average outcomes inspected by NUTS2 regions in the EU. The average refers to the whole period, from 2003 to 2017. Deciles do the categorization of the variable. Average values are weighted by the share of the regional population over the EU one.

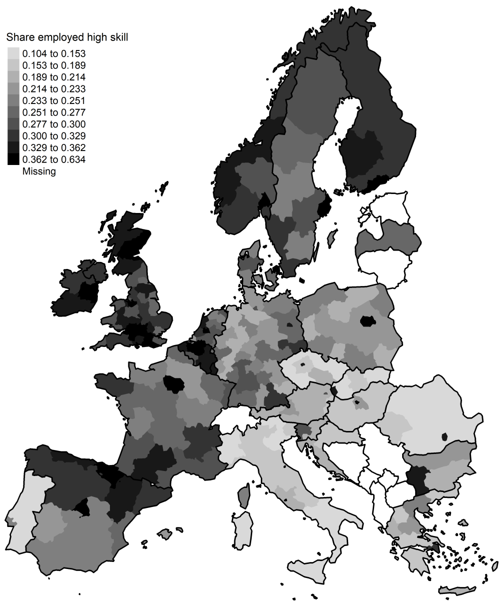
Figure A3: Regional employment by skill level



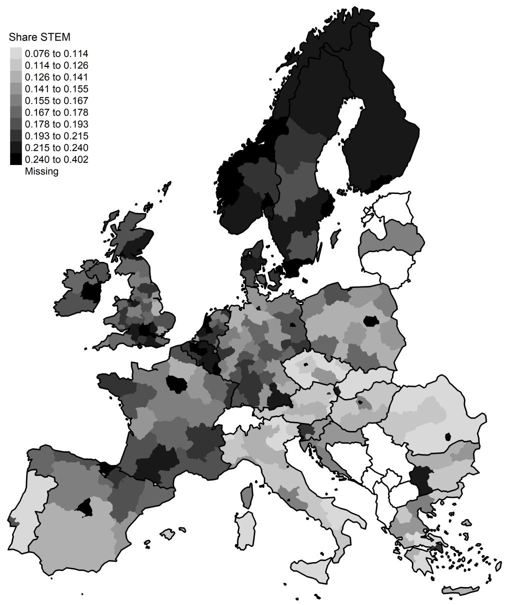
(a) Low skill



(b) Medium Skill



(c) High skill



(d) Regional STEM employment

Notes. These maps show the average skill level and STEM employment by NUTS2 regions in the EU. The average refers to the whole period, from 2003 to 2017. Deciles do the categorization of the variable. Average values are weighted by the share of the regional population over the EU one.

A.2 Green patents SSIV validation

Table A5: Top 5 Rotemberg weights of green patents SSIV

NACE2	Label	Rotemberg weight	Emp. Share (t_0)
28	Manufacture of machinery and equipment n.e.c.	0.301	0.111
27	Manufacture of electrical equipment	0.250	0.109
29	Manufacture of motor vehicles	0.091	0.090
20	Manufacture of chemicals and chemical products	0.066	0.120
26	Manufacture of computer, electronic and optical products	0.063	0.129
PRODCOM	Label		
28211354	Electric furnaces and ovens (excluding induction- and resistance-heated)		
28251431	Machinery and apparatus for filtering and purifying gases		
28112150	Steam turbines for electricity generation		
27201100	Primary cells and primary batteries		
27902060	Light-emitting diodes (LEDs)		
27112680	Photovoltaic AC generators		
29102450	Motor vehicles, with only electric motor for propulsion		
29102430	Motor vehicles, with hybrid propulsion		
29104313	Road tractors for semi-trailers with only electric motor for propulsion		
20595997	Biofuels (diesel substitute)		
26517015	Electronic thermostats		
26515313	Electronic gas or smoke analysers		
26516500	Hydraulic or pneumatic automatic regulating or controlling instruments and apparatus		

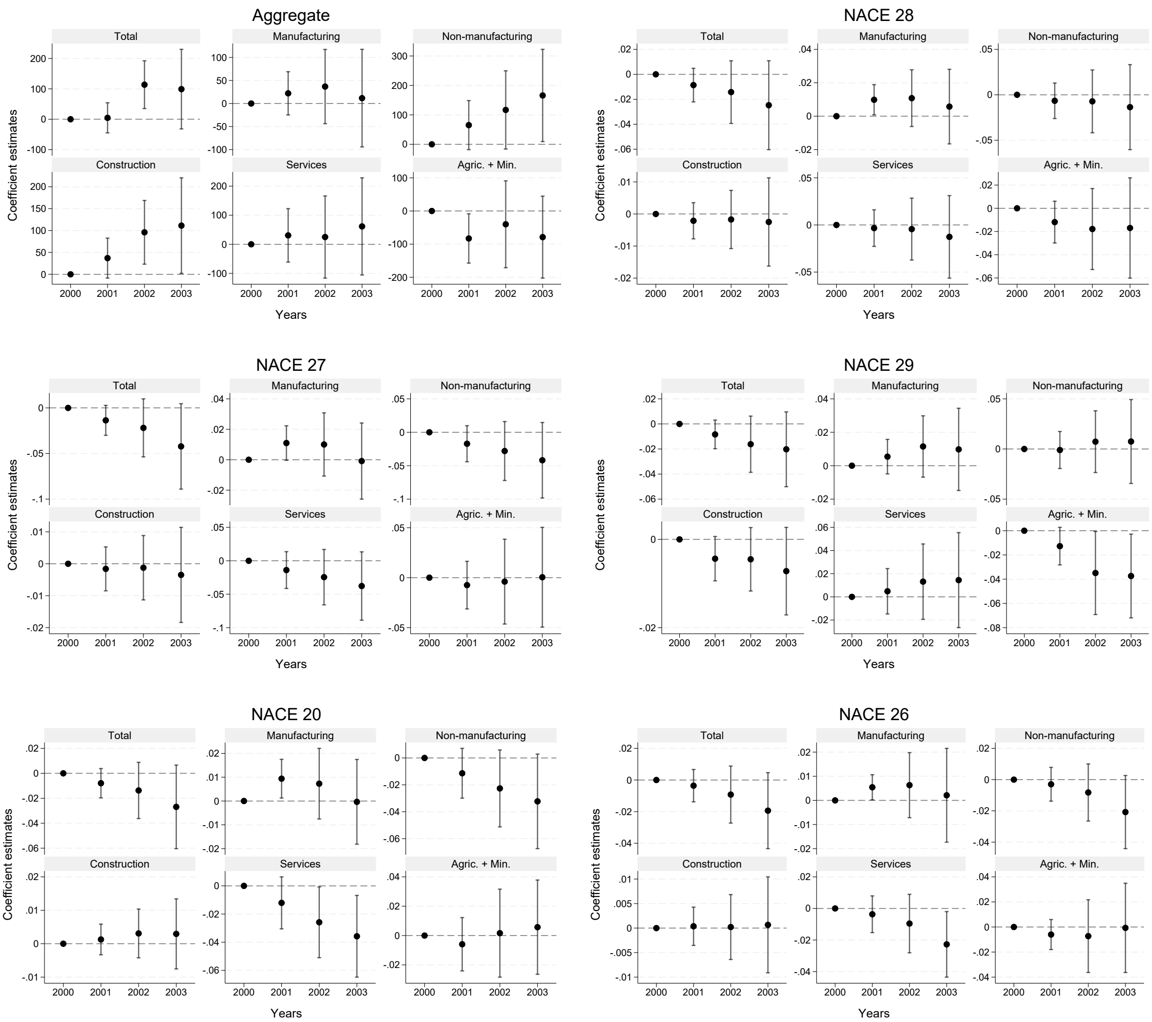
Notes. This table reports 2-digit manufacturing sectors with the highest five Rotember weights associated to the green patents-SSIV (Goldsmith-Pinkham et al., 2020). Further, it reports the baseline (avg. 2000-2003) employment share within manufacturing of these sectors. Lastly, it reports example of green goods that fall within these sectors.

Table A6: Correlation between green patents SSIV, industry employment shares and controls.

	(1) Green patents	(2) NACE 27	(3) NACE 26	(4) NACE 28	(5) NACE 29	(6) NACE 20
Share emp manu$_{r,t0}$	0.0001*	0.7412***	0.1400	0.8849***	0.1467	0.6075
	(0.0000)	(0.2843)	(0.5863)	(0.2208)	(0.3236)	(0.4454)
$NGRP_{r,t0}$	0.0000***	-0.0019	0.0017	-0.0024	0.0087*	-0.0030
	(0.0000)	(0.0024)	(0.0071)	(0.0023)	(0.0046)	(0.0038)
Observations	254	254	254	254	254	254
Country FE	✓	✓	✓	✓	✓	✓

Notes: This table show the balance of the two main covariates for the pre-sample aggregate green patents-SSIV and each of the 2-digit manufacturing employment shares resulting to be within the top 5 Rotemberg weights. We include country fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 254. Due to data availability in baseline employment shares, we exclude the following regions: BG31, BG32, BG33, BG34, BG41, BG42, CY00, HR03, HR04, IS00, LV00, MT00, RO11, RO12, RO21, RO22, RO31, RO32, RO41, RO42, SK01, SK02, SK03, SK04. * p<0.10, ** p<0.05, *** p<0.01.

Figure A4: Parallel trends of the green patents SSIV by industry share



Notes. These figures assess the parallel trend assumption by regressing the green patents-SSIV and each top five Rotemberg weight employment share interacted with year fixed effects on outcomes in levels in the pre-sample period, that is from 2000 to 2003. The reference year is 2000. Regressions include employment share in manufacturing and non-green manufacturing penetration at baseline interacted with year fixed effects, as well as region and year fixed effects and country linear trends. We weight estimates by the share of regional population over the EU one.

Table A7: Green penetration on regional employment. Excluding sector 28

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Total*		*Manufacturing*		*Non-manufacturing*	
$\Delta\ GRP_{r,t3}$	0.044***	0.418***	0.008*	0.131***	0.037***	0.301***
	(0.010)	(0.111)	(0.005)	(0.039)	(0.012)	(0.088)
Panel B:	*Construction*		*Services*		*Agric. + Min.*	
$\Delta\ GRP_{r,t3}$	0.016***	0.147***	0.022**	0.136**	-0.002	-0.014
	(0.004)	(0.038)	(0.011)	(0.063)	(0.012)	(0.060)
N	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		944.643***		944.643***		944.643***
KP F-Stat		19.2		19.2		19.2
CD F-Stat		38.3		38.3		38.3
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta\ GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and t-3. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. To assess possible violations of parallel trends as shown in Figure A4, we exclude NACE2 sector 28. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * p<0.10, ** p<0.05, *** p<0.01.

Table A8: Green penetration on regional employment. Excluding sector 27

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Total*		*Manufacturing*		*Non-manufacturing*	
Δ $GRP_{r,t3}$	0.028***	0.239**	0.012***	0.063*	0.019***	0.191**
	(0.007)	(0.098)	(0.003)	(0.035)	(0.007)	(0.084)
Panel B:	*Construction*		*Services*		*Agric. + Min.*	
Δ $GRP_{r,t3}$	0.006***	0.133***	0.014**	0.030	-0.002	-0.016
	(0.002)	(0.044)	(0.005)	(0.060)	(0.006)	(0.058)
N	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1193.462***		1193.462***		1193.462***
KP F-Stat		11.9		11.9		11.9
CD F-Stat		26.0		26.0		26.0
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, Δ $GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and t-3. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. To assess possible violations of parallel trends as shown in Figure A4, we exclude NACE2 sector 27. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * p<0.10, ** p<0.05, *** p<0.01.

Table A9: Green penetration on regional employment. Excluding sector 29

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Total*		*Manufacturing*		*Non-manufacturing*	
$\Delta\ GRP_{r,t3}$	0.028***	0.152***	0.010***	0.056***	0.022***	0.113***
	(0.007)	(0.037)	(0.003)	(0.015)	(0.008)	(0.037)
Panel B:	*Construction*		*Services*		*Agric. + Min.*	
$\Delta\ GRP_{r,t3}$	0.007***	0.073***	0.016**	0.029	-0.004	-0.017
	(0.002)	(0.013)	(0.007)	(0.033)	(0.007)	(0.032)
N	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		2009.240***		2009.240***		2009.240***
KP F-Stat		55.3		55.3		55.3
CD F-Stat		91.1		91.1		91.1
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta\ GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and t-3. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. To assess possible violations of parallel trends as shown in Figure A4, we exclude NACE2 sector 29. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * p<0.10, ** p<0.05, *** p<0.01.

Table A10: Green penetration on regional employment. Excluding sector 20

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Total*		*Manufacturing*		*Non-manufacturing*	
$\Delta\ GRP_{r,t3}$	0.031***	0.118***	0.010***	0.042***	0.023***	0.089***
	(0.007)	(0.023)	(0.003)	(0.011)	(0.008)	(0.025)
Panel B:	*Construction*		*Services*		*Agric. + Min.*	
$\Delta\ GRP_{r,t3}$	0.008***	0.057***	0.016**	0.023	-0.003	-0.013
	(0.002)	(0.008)	(0.007)	(0.022)	(0.008)	(0.022)
N	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		2225.323***		2225.323***		2225.323***
KP F-Stat		121.6		121.6		121.6
CD F-Stat		132.5		132.5		132.5
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta\ GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and t-3. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. To assess possible violations of parallel trends as shown in Figure A4, we exclude NACE2 sector 20. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * p<0.10, ** p<0.05, *** p<0.01.

Table A11: Green penetration on regional employment. Excluding sector 26

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Total*		*Manufacturing*		*Non-manufacturing*	
Δ $GRP_{r,t3}$	0.032***	0.166***	0.010***	0.040***	0.027***	0.134***
	(0.008)	(0.044)	(0.003)	(0.015)	(0.009)	(0.039)
Panel B:	*Construction*		*Services*		*Agric. + Min.*	
Δ $GRP_{r,t3}$	0.009***	0.085***	0.019***	0.043	-0.005	-0.008
	(0.003)	(0.019)	(0.007)	(0.032)	(0.007)	(0.031)
N	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1735.026***		1735.026***		1735.026***
KP F-Stat		31.5		31.5		31.5
CD F-Stat		65.2		65.2		65.2
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

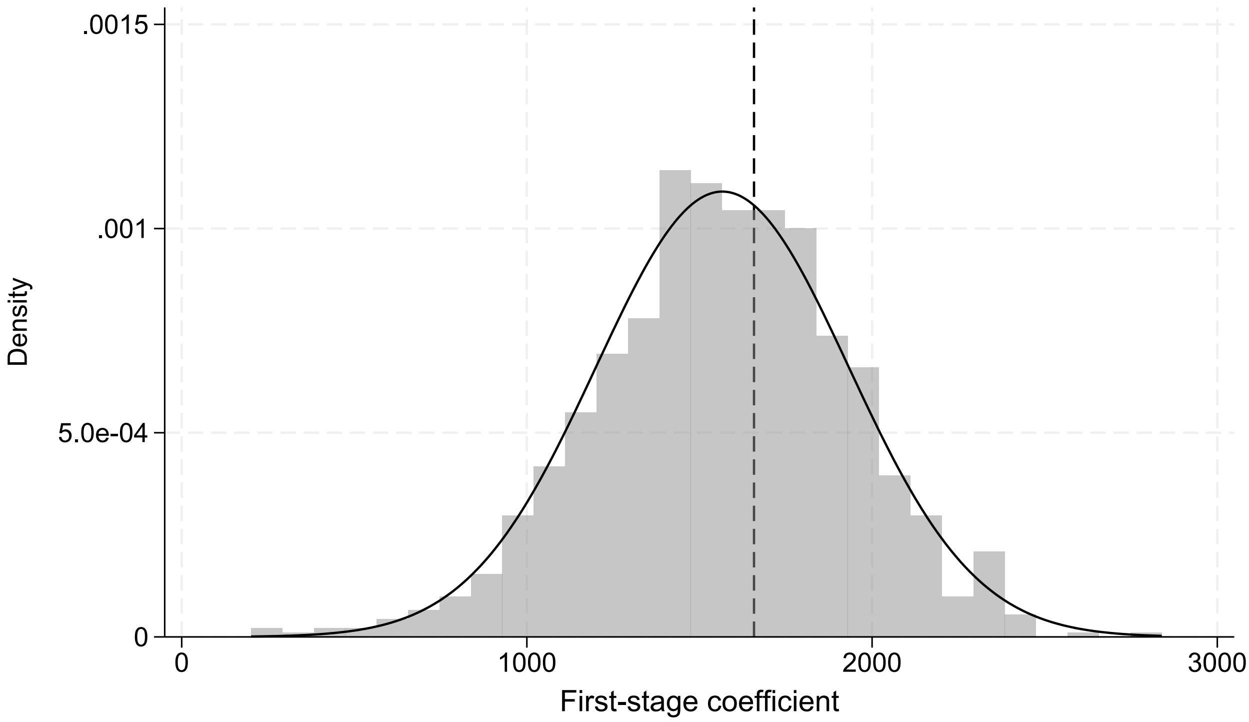
Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, Δ $GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and t-3. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. To assess possible violations of parallel trends as shown in Figure A4, we exclude NACE2 sector 26. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * p<0.10, ** p<0.05, *** p<0.01.

Table A12: Lee et al. (2022) valid t-ratio inference

Panel A:	*Total*	*Manufacturing*	*Non-manufacturing*
Coefficient	0.166	0.053	0.126
Unadj SE	0.028	0.012	0.046
1% CV of |t|	3.138	3.138	3.138
Adj SE	0.034	0.015	0.056
Adj UB	0.255	0.091	0.269
Adj LB	0.078	0.015	-0.017
FS F-stat	80.909	80.909	80.909
Panel B:	*Construction*	*Services*	*Agric. + Min.*
Coefficient	0.076	0.039	-0.013
Unadj SE	0.012	0.042	0.042
1% CV of |t|	3.138	3.138	3.138
Adj SE	0.015	0.051	0.052
Adj UB	0.115	0.171	0.12
Adj LB	0.038	-0.093	-0.146
FS F-stat	80.909	80.909	80.909

Notes: This table applies the methodology from Lee et al. (2022) to estimate valid t-ratio inference for instrumental variables. The estimates the command works on are even columns of Table 1.

Figure A5: Distribution of the first stage's coefficients. Monte Carlo simulation.



Notes. This figure shows the distribution of the coefficient of the first stage drawn from 1000 different subsamples. The vertical dashed black line correspond to the first-stage coefficient of Table 1.

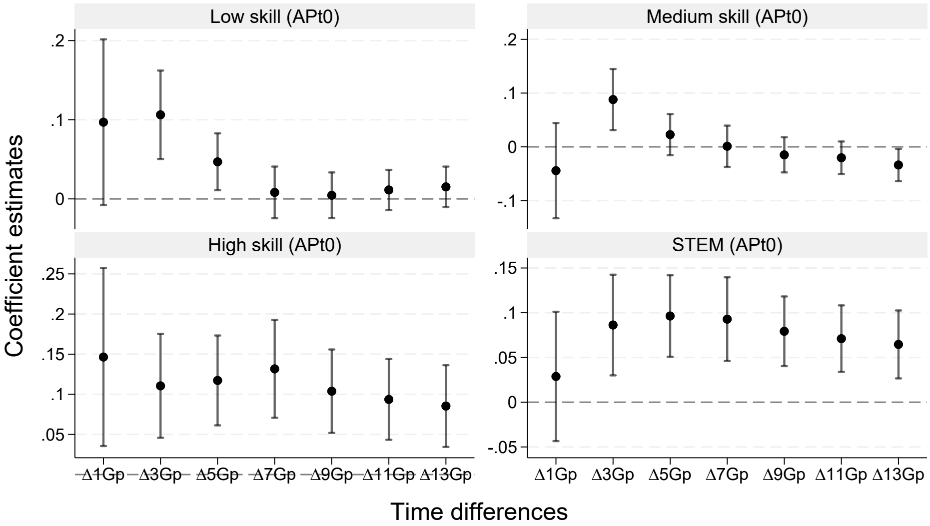
A.3 Additional specifications

Table A13: Green penetration on regional employment by skill level and STEM employment.

	(1)	(2)	(3)	(4)
Panel A:	*Low skill*	*Medium skill*	*High skill*	*STEM*
Δ $GRP_{r,t3}$	0.057***	0.036	0.048**	0.045**
	(0.019)	(0.029)	(0.021)	(0.019)
N	3336	3336	3336	3336
Estimator	2SLS	2SLS	2SLS	2SLS
FS coeff.	1658.106***	1658.106***	1658.106***	1658.106***
KP F-Stat	53.4	53.4	53.4	53.4
CD F-Stat	79.4	79.4	79.4	79.4
Controls	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

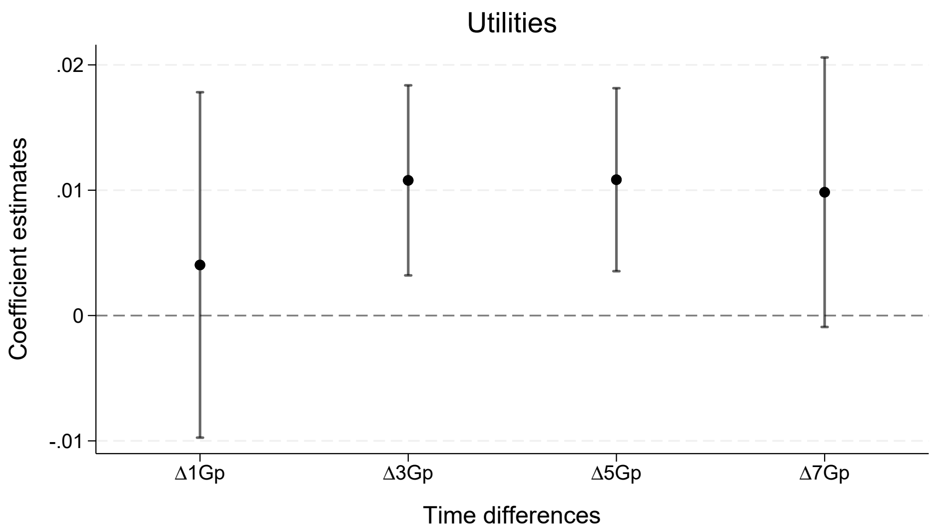
Notes: Dependent variables: the three-year change in regional employment over active population by low, medium and high skill and employment in STEM. Employment with low-skill is given by employed people with less than primary, primary and lower secondary education. Employment with medium-skill is given by employed people with upper secondary and post-secondary non-tertiary education. Lastly, employment with high-skill is given by employed people with tertiary education. STEM employment is given by people with tertiary education and employed in science and technology. The endogenous variable, Δ $GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and t-3. The instrumental variable refers to the shift-share instrumental variable related to green patents. All columns show estimates related to the green patents instrument. All columns report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration measure, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * p<0.10, ** p<0.05, *** p<0.01.

Figure A6: 2SLS estimates of green regional penetration on regional skill level. Green patents SSIV. Longer time horizon and fixed active population.



Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3, including additional the interaction with the regional skill level, and on Equation 4 by looking at one-, two-, three-, five-, seven-, nine-, eleven- and thirteen-year changes. In all graphs active population is kept fixed at baseline (avg. 2000-2003). KP F-Stats: 11.0; 53.4; 140.3; 160.7; 129.7; 176.0; 232.5. CD F-stats: 14.9; 79.4; 174.8; 191.8; 324.3; 333.9; 234.2.

Figure A7: 2SLS estimates of green penetration on regional employment. Green patents SSIV. Utilities employment. Other time differences.



Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3 and on Equation 4 by looking at three-, five- and seven-year changes. Results report estimates related to utilities employment. KP F-stats: 11.0 53.4 140.3 160.7 – CD F-stats: 14.9 79.4 174.8 191.8.

Table A14: Green penetration on regional employment. Extended controls.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Total*		*Manufacturing*		*Non-manufacturing*	
$\Delta\ GRP_{r,t3}$	0.029***	0.205***	0.010***	0.051***	0.023***	0.149***
	(0.007)	(0.040)	(0.003)	(0.014)	(0.008)	(0.041)
Panel B:	*Construction*		*Services*		*Agric. + Min.*	
$\Delta\ GRP_{r,t3}$	0.007***	0.081***	0.016**	0.059	-0.003	0.005
	(0.002)	(0.015)	(0.007)	(0.036)	(0.007)	(0.036)
N	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1611.003***		1611.003***		1611.003***
KP F-Stat		49.7		49.7		49.7
CD F-Stat		71.7		71.7		71.7
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta\ GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and *t-3*. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include population density, median age, share of female population, share of foreign population, share of employed people with secondary education, share of employed people with tertiary education, share of employment in manufacturing and the regional non-green penetration. The share of employment in manufacturing and the regional non-green penetration are interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 270. * p<0.10, ** p<0.05, *** p<0.01.

Table A15: Green penetration on regional employment. NUTS1 and NUTS2 fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Total*		*Manufacturing*		*Non-manufacturing*	
Δ $GRP_{r,t3}$	0.353***	0.459***	0.059***	0.069**	0.259***	0.339***
	(0.091)	(0.148)	(0.022)	(0.031)	(0.073)	(0.114)
Panel B:	*Construction*		*Services*		*Agric. + Min.*	
Δ $GRP_{r,t3}$	0.131***	0.172***	0.114**	0.150**	0.035	0.051
	(0.033)	(0.055)	(0.053)	(0.073)	(0.055)	(0.072)
N	3336	3336	3336	3336	3336	3336
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
KP F-Stat	17.9	10.6	17.9	10.6	17.9	10.6
CD F-Stat	34.3	24.2	34.3	24.2	34.3	24.2
Controls	✓	✓	✓	✓	✓	✓
NUTS1 FE	✓		✓		✓	
NUTS2 FE		✓		✓		✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, Δ $GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and t-3. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show 2SLS estimates related to the green patents instrument including NUTS 1 and year fixed effects, while columns (2), (4) and (6) show the ones related to the green patents instrument including NUTS 2 and year fixed effects. All columns report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 278. * p<0.10, ** p<0.05, *** p<0.01.

Table A16: Green penetration on regional employment. Automation controls

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Total*		*Manufacturing*		*Non-manufacturing*	
Δ $GRP_{r,t3}$	0.041***	0.149***	0.019***	0.063***	0.034***	0.134***
	(0.007)	(0.048)	(0.003)	(0.021)	(0.008)	(0.044)
Δ *Robot penetration*$_{r,t3}$	-0.009**	-0.016***	-0.005**	-0.009***	0.000	-0.007
	(0.004)	(0.005)	(0.002)	(0.003)	(0.003)	(0.005)
Panel B:	*Construction*		*Services*		*Agric. + Min.*	
Δ $GRP_{r,t3}$	0.010***	0.086***	0.025***	0.024	-0.012**	-0.049
	(0.003)	(0.023)	(0.006)	(0.032)	(0.006)	(0.029)
Δ *Robot penetration*$_{r,t3}$	0.001	-0.004*	-0.001	-0.001	-0.004*	-0.001
	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
N	2173	2173	2173	2173	2173	2173
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1207.878***		1207.878***		1207.878***
KP F-Stat		21.6		21.6		21.6
CD F-Stat		39.3		39.3		39.3
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, Δ $GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and *t-3.* The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. The additional control is the 3 years change in regional automation exposure. Besideds this last one, all the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. Region clustered standard errors in parentheses. Number of regions: 207. * p<0.10, ** p<0.05, *** p<0.01.

Table A17: Green penetration on regional employment. Balanced sample by automation data

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Total*		*Manufacturing*		*Non-manufacturing*	
Δ $GRP_{r,t3}$	0.043***	0.162***	0.018***	0.057***	0.043***	0.140***
	(0.008)	(0.037)	(0.003)	(0.015)	(0.010)	(0.033)
Panel B:	*Construction*		*Services*		*Agric.+ Min.*	
Δ $GRP_{r,t3}$	0.011***	0.071***	0.034***	0.056**	-0.019**	-0.035
	(0.003)	(0.013)	(0.008)	(0.025)	(0.008)	(0.021)
N	2484	2484	2484	2484	2484	2484
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1708.035***		1708.035***		1708.035***
KP F-Stat		56.1		56.1		56.1
CD F-Stat		99.3		99.3		99.3
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, Δ $GRP_{r,t5}$, refers to the change in the green penetration measure in region r between t and t-3. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. The sample is restricted depending on availability of automation data at the regional level.Region clustered standard errors in parentheses. Number of regions: 207. * p<0.10, ** p<0.05, *** p<0.01.

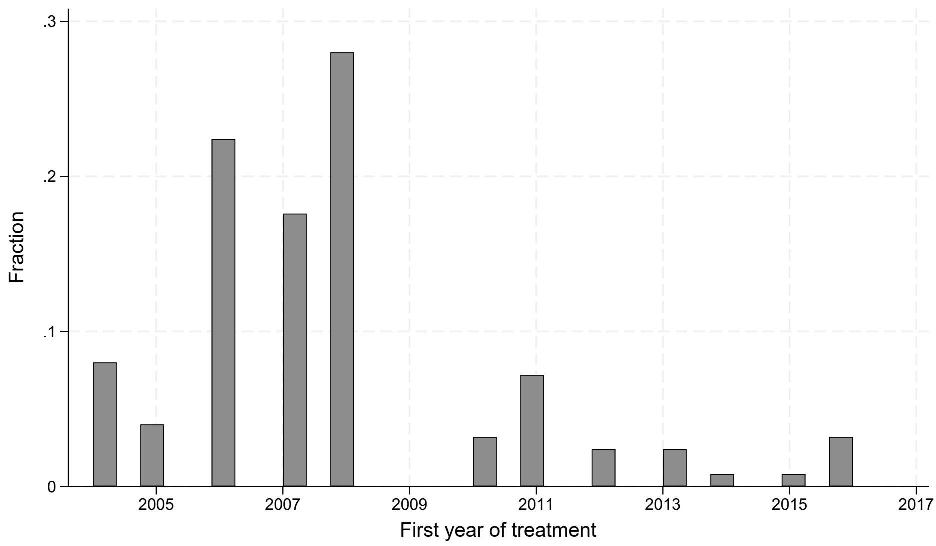
Table A18: Green penetration on regional employment. NUTS 1 clustered standard errors

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	*Total*		*Manufacturing*		*Non-manufacturing*	
$\Delta\ GRP_{r,t3}$	0.028***	0.166***	0.010***	0.053***	0.022**	0.126**
	(0.010)	(0.053)	(0.004)	(0.019)	(0.011)	(0.052)
Panel B:	*Construction*		*Services*		*Agric. + Min.*	
$\Delta\ GRP_{r,t3}$	0.007**	0.076***	0.016*	0.039	-0.004	-0.013
	(0.003)	(0.019)	(0.009)	(0.040)	(0.009)	(0.037)
N	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
FS coeff.		1658.106***		1658.106***		1658.106***
KP F-Stat		38.3		38.3		38.3
CD F-Stat		79.4		79.4		79.4
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Dependent variables: the three-year change in regional employment over active population in: total; manufacturing; non-manufacturing (utilities, construction, services); construction; services; agriculture + mining. The endogenous variable, $\Delta\ GRP_{r,t3}$, refers to the change in the green penetration measure in region r between t and *t-3*. The instrumental variable refers to the shift-share instrumental variable related to green patents. Columns (1), (3) and (5) show OLS estimates, while columns (2), (4) and (6) show the ones related to the green patents instrument. Columns (2), (4) and (6) report the Kleibergen-Paap (KP) and the Cragg-Donald (CD) F statistic for weak identification, as well as the first stage coefficient. Controls include the share of employment in manufacturing and the regional non-green penetration, interacted with year fixed effects. All the controls are taken at baseline, that is their average value between 2000 and 2003. We include country and year fixed effects. Estimates are weighted by the share of regional population over the EU one, at baseline. NUTS 1 clustered standard errors in parentheses. Number of regions: 278. Number of NUTS1: 100. * p<0.10, ** p<0.05, *** p<0.01.

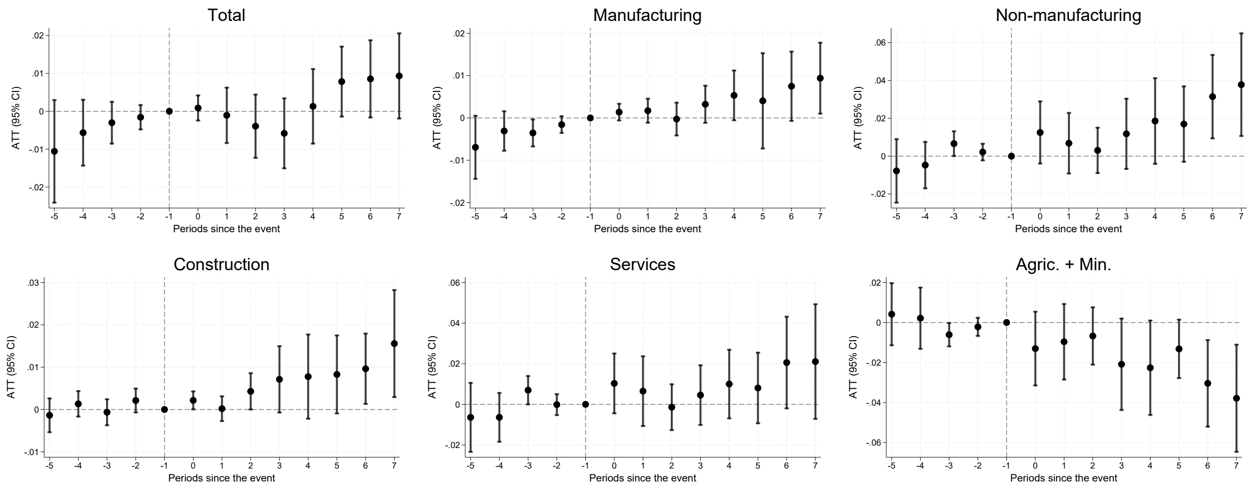
A.4 Large shocks staggered DiD

Figure A8: Large shocks to green regional penetration - first year of treatment



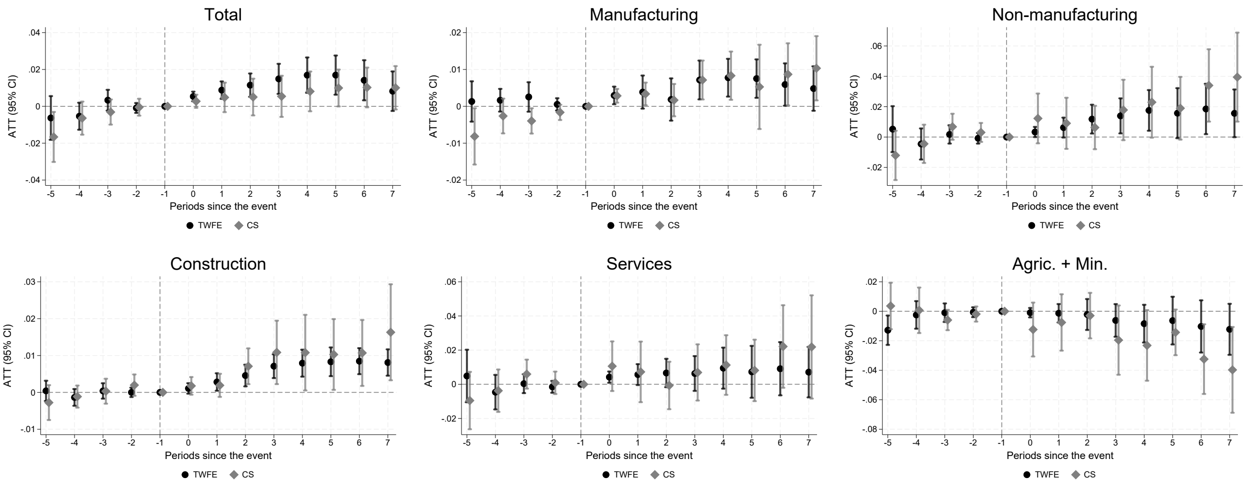
Notes. This figure shows the fraction of municipalities that are treated over the total number by year.

Figure A9: Large shocks to green manufacturing penetration. Event study estimates. Not-yet treated control group.



Notes. These plots show the results of the event study specification for several outcomes employing the regression adjustment estimator from Callaway and Sant'Anna (2021). The positive spike in green regional penetration is defined as a change higher than the 90th percentile in the one-year change of green regional penetration. The first spike identifies the beginning of treatment. Standard errors are clustered at the NUTS2 level. Not-yet-treated regions compose the control group.

Figure A10: Large shocks to green manufacturing penetration. Event study estimates. TWFE and CS.



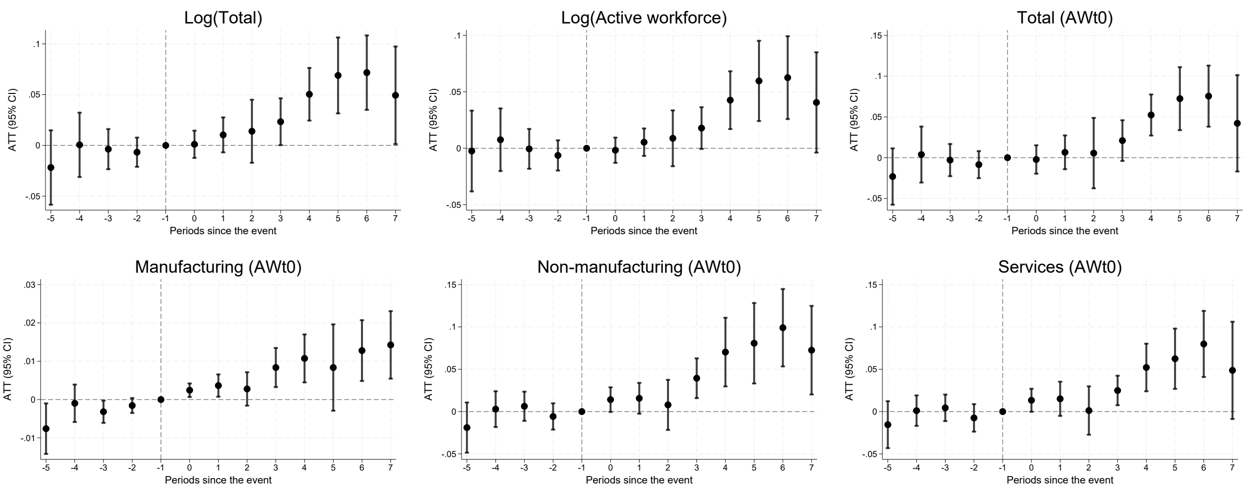
Notes. These plots show the results of the event study specification for several outcomes employing both a two-way fixed effects estimator and the regression adjustment one from Callaway and Sant'Anna (2021). The positive spike in green regional penetration is defined as a change higher than the 90$^{\text{th}}$ percentile in the one-year change of green regional penetration. The first spike identifies the beginning of treatment. Standard errors are clustered at the NUTS2 level.

Table A19: Positive and negative weights from the TWFE regression

	N ATTs	Sum ofweights
Positive Weights	1141	1.0614
Negative Weights	135	-.0614
Total	1276	1

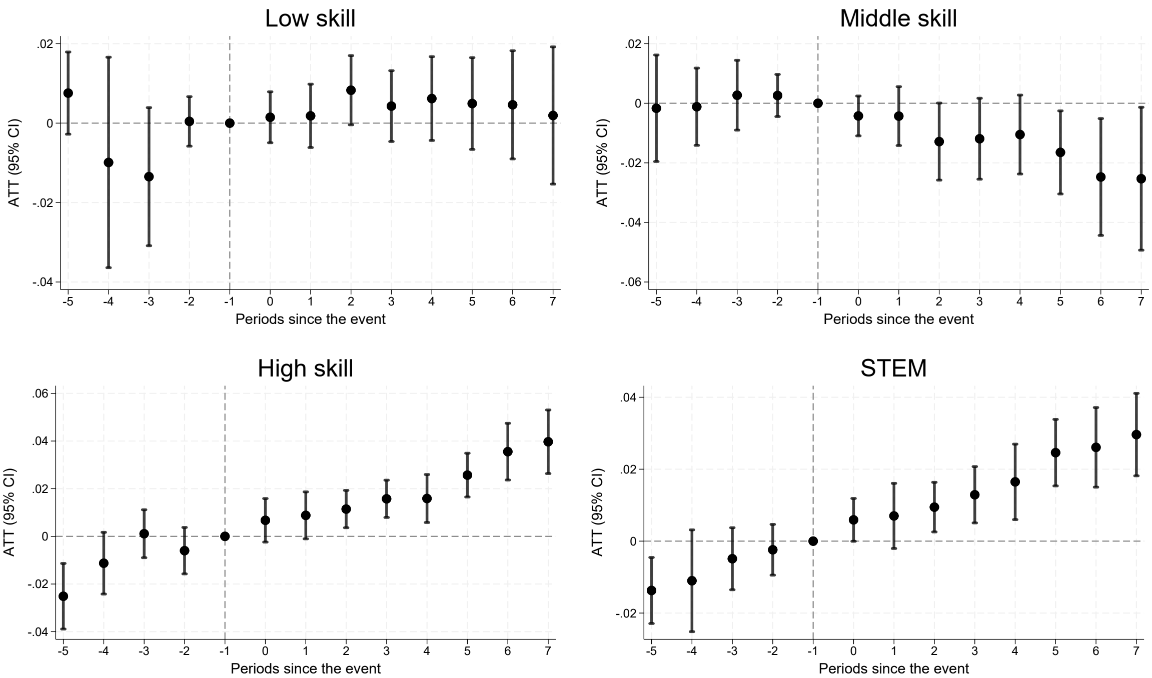
Notes. This table shows the weights attached to the two-way fixed effects regressions computet as in De Chaisemartin and d'Haultfoeuille (2020).

Figure A11: Large shocks to green manufacturing penetration. Event study estimates. Agglomeration effects.



Notes. These plots show the results of the event study specification for several outcomes employing the regression adjustment estimator from Callaway and Sant'Anna (2021). The positive spike in green regional penetration is defined as a change higher than the 90$^{\text{th}}$ percentile in the one-year change of green regional penetration. The first spike identifies the beginning of treatment. Standard errors are clustered at the NUTS2 level.

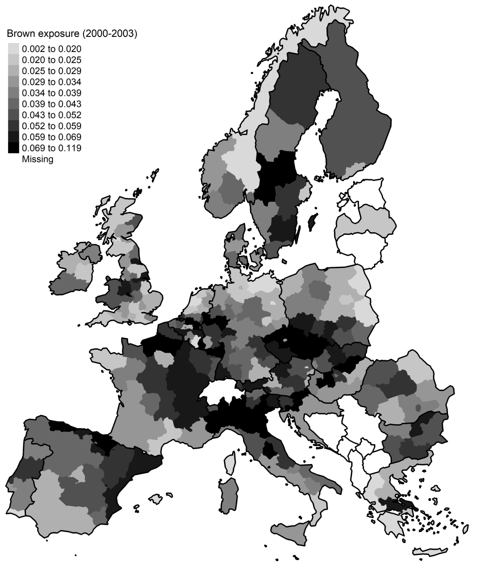
Figure A12: Large shocks to green manufacturing penetration. Event study estimates. Skill-biased employment.



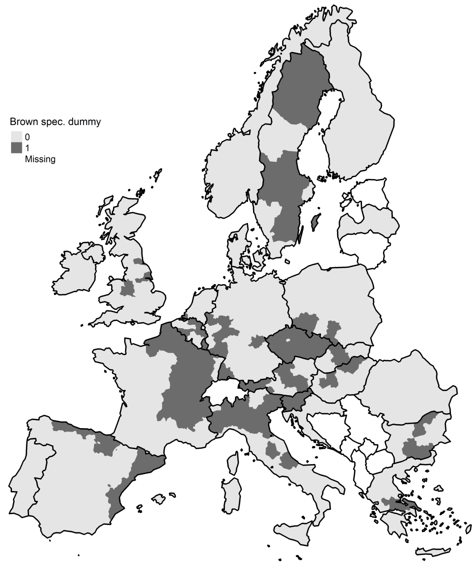
Notes. These plots show the results of the event study specification for several outcomes employing the regression adjustment estimator from Callaway and Sant'Anna (2021). The positive spike in green regional penetration is defined as a change higher than the 90^{th} percentile in the one-year change of green regional penetration. The first spike identifies the beginning of treatment. Standard errors are clustered at the NUTS2 level.

A.5 Brown specialization

Figure A13: Baseline brown exposure by NUTS2 region and dummy that identifies specialization



(a) Baseline level



(b) Dummy above 75$^{\text{th}}$ perc.

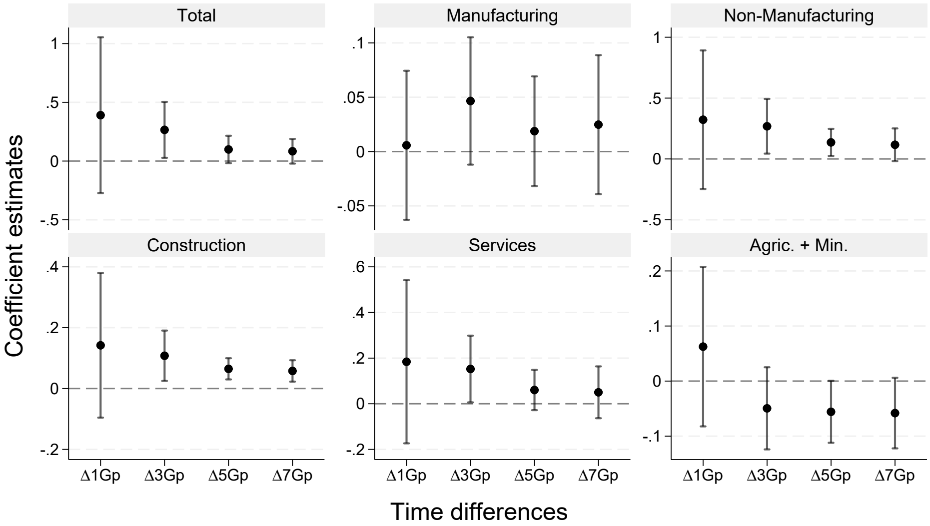
Notes. These maps show the baseline brown exposure (panel (a)) and a dummy that identifies values higher than the 75$^{\text{th}}$ percentile (panel (b)) by NUTS2 regions in the EU. Panel (a) levels correspond to deciles, and are weighted by the share of the regional population over the EU one.

Table A20: Balance table by baseline specialization in brown exposure.

Variable	Not-BP75	BP75	Diff. (BP75-NBP75)
Total employment over active pop.	0.909	0.914	0.0041
	(0.0543)	(0.0462)	(0.0077)
Non-manufacturing employment over active pop.	0.694	0.673	-0.0214
	(0.1330)	(0.0632)	(0.0131)
Population density (t0)	493.477	312.031	-181.4457*
	(1078.0203)	(422.9457)	(99.5077)
Median age (t0)	38.516	39.358	0.8414*
	(2.7258)	(2.3669)	(0.4711)
Share of female population (t0)	0.518	0.517	-0.0009
	(0.0090)	(0.0061)	(0.0010)
Share of foreign-born population (t0)	0.044	0.052	0.0076
	(0.0451)	(0.0389)	(0.0069)
Share of population with lower secondary edu. (t0)	0.385	0.437	0.0519*
	(0.1628)	(0.1470)	(0.0292)
Share of population with upper secondary edu. (t0)	0.392	0.394	0.0014
	(0.1325)	(0.1509)	(0.0266)
Share of population with tertiary edu. (t0)	0.161	0.131	-0.0299***
	(0.0715)	(0.0513)	(0.0110)
Share employed in manufacturing (t0)	0.136	0.217	0.0810***
	(0.0498)	(0.0543)	(0.0109)
Regional non-green penetration (t0)	6.644	13.159	6.5148***
	(5.4745)	(7.8702)	(1.3654)
t-t_3 regional green penetration	0.080	0.093	0.0130
	(0.1671)	(0.1997)	(0.0132)
t-t_3 regional green patents SSIV	0.000	0.000	0.0000
	(0.0000)	(0.0000)	(0.0000)
Pr. large green shock	0.422	0.738	0.3158***
	(0.4939)	(0.4401)	(0.0831)
Observations	3195	975	4170

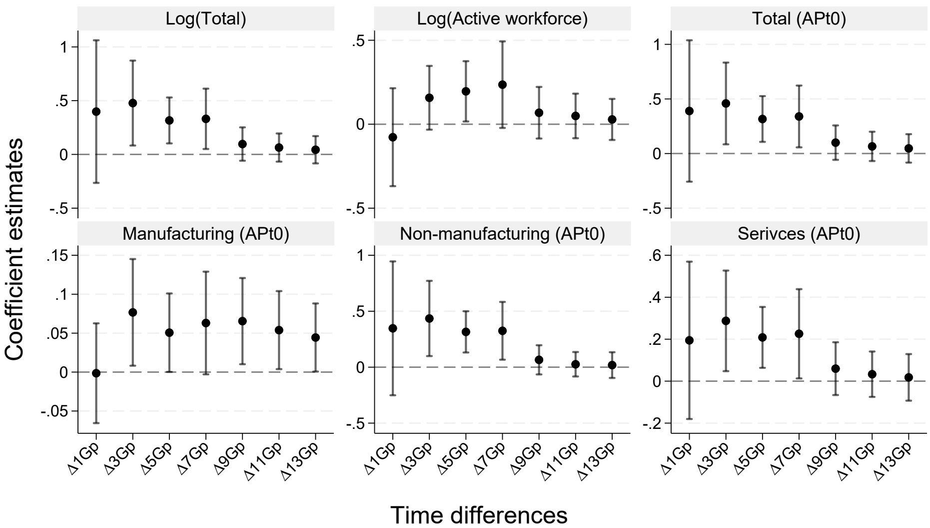
__Notes__. If t0 is present then values are taken at baseline, i.e. an average between 2000 and 2003. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figure A14: 2SLS estimates of green penetration on brown-exposed regional employment. Green patents SSIV.



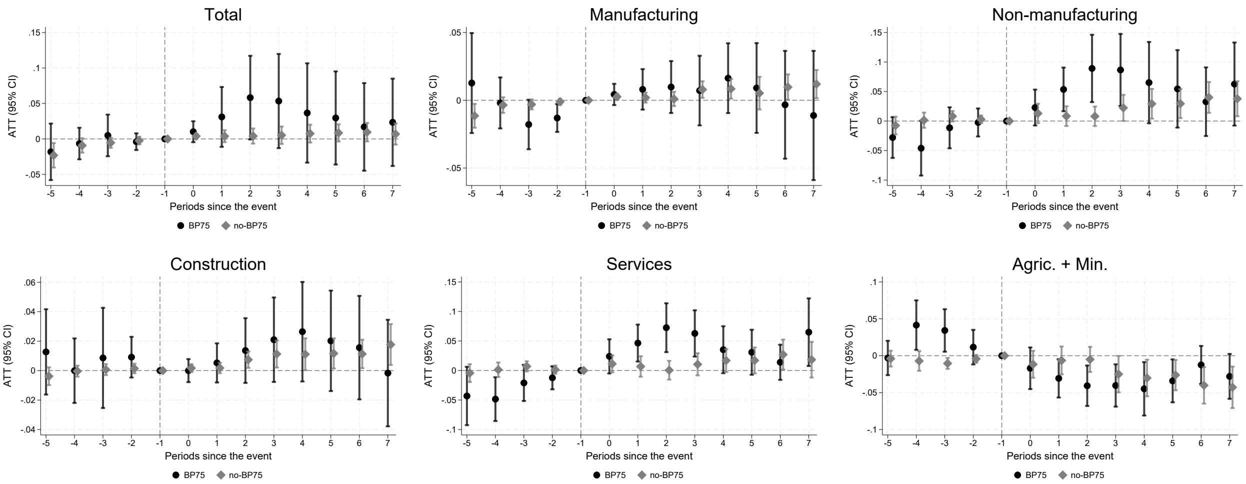
Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3 and on Equation 4 by looking at one-, three-, five- and seven-year changes. The sample is restricted to brown-exposed regions as defined in text. KP F-stats: 1.6; 7.3; 22.0; 25.9. CD F-stats: 2.8; 13.8; 31.6; 25.6.

Figure A15: 2SLS estimates of green penetration on brown-exposed regional employment and active population. Green patents SSIV. Longer time horizon and decomposition.



Notes. These graphs replicate and extend the 2SLS estimation based on Equation 3 and on Equation 4 by looking at three-, five-, seven-, nine-, eleven- and thirteen- year changes. The sample is restricted to brown-exposed regions as defined in text. KP F-stats: 11.0; 53.4; 140.3; 160.7; 129.7; 176.0; 232.5. CD F-stats: 14.9; 79.4; 174.8; 191.8; 324.3; 333.9; 234.2.

Figure A16: Green regional penetration event study estimates. Splitting by brown exposure.



Notes. These plots show the results of the event study specification for several outcomes employing a regression adjustment estimator from Callaway and Sant'Anna (2021). The positive spike in green regional penetration is defined as a change higher than the 90$^{\text{th}}$ percentile in the one-year change of green regional penetration. The first spike identifies the beginning of treatment. The analysis is split by brown exposure. Standard errors are clustered at the NUTS2 level.

A.6 Data sources and cleaning

A.6.1 Main employment data

Total employment. Source: Eurostat - LFS (links: NACER 2 - 2008/2017; NACER 1.1 - 2000 -2007). The data concerns total employment levels by NUTS2 and year, from 2000 to 2017. The division in NACER 2 and NACER 1.1 does not imply any harmonization for employment data. We focus on employment for people older than 15 years old, of both sexes. NUTS2 regional codes have been harmonized to the NUTS 2016 changes. This implies harmonizing changes in regions definitions.[29] Employment data are reallocated for regions affected by splits or merges using proportionate coefficients. Remaining missing data has been interpolated and extrapolated using an inverse distance weighted interpolation.

Manufacturing employment. Source: Eurostat - SBS (links: NACER 2 - 2008/2017; NACER 1.1 - 2000 -2007). The data concerns manufacturing employment, both aggregate and by 2-digit manufacturing industries, levels by NUTS2 and year, from 1995 to 2017. We map 2-digit employment NACER 1.1 data to 2-digit NACER 2 categories using country-specific weights, proportionally redistributing employment values when multiple mappings exist. These weights are calculated from country-product (PRODCOM) levels that leverage details about the crosswalk provided by Eurostat. For example NACER 1.1 sector 29 - Manufacture of machinery and equipment n.e.c. - is allocated as follows: for the 82% to NACER 2 sector 28 - Manufacture of machinery and equipment n.e.c.; for the 5% to NACER 2 sector 33 (Repair and installation of machinery and equipment); for the 9% to NACER 2 sector 27 (Manufacture of electrical equipment); the remaining 4% is allocated to NACER 2 sectors 25 (Manufacture of fabricated metal products, except machinery and equipment), 26 (Manufacture of computer, electronic and optical products) and 32 (Other manufacturing). Across countries, this allocation is mostly stable. For example, the allocation to NACER 2 sector 28 is at minimum 82.65% and at maximum 83.10%. The rest of the data management is identical to that described for total employment.

Utilities employment. Source: Eurostat - SBS (links: NACER 2 - 2008/2017; NACER 1.1 - 2000 -2007). The data concerns utilities employment levels by NUTS2 and year, from 1995 to 2017. The crosswalk between NACER 1.1 and NACER 2 is a simple one-to-one of the NACER 1.1 category E to NACER 2 categories D and E, summed together. The rest of the data management is identical to that described for total employment.

[29] For example, in the UK UKM3 was split into UKM8 and UKM9.

Construction employment. Source: Eurostat - LFS (links: NACER 2 - 2008/2017; NACER 1.1 - 2000 -2007). The data concerns construction employment levels by NUTS2 and year, from 2000 to 2017. The crosswalk between NACER 1.1 and NACER 2 is a simple one-to-one of the NACER 1.1 category F to NACER 2 category F. The rest of the data management is identical to that described for total employment.

Services employment. Source: Eurostat - HTEC (links: NACER 2 - 2008/2017; NACER 1.1 - 2000 -2007). The data concerns services employment levels by NUTS2 and year, from 2000 to 2017. The crosswalk between NACER 1.1 and NACER 2 is a simple one-to-one of the NACER 1.1 categories that identify KIS, summed together, to NACER 2 categories that identify KIS, summed together. KIS identification is defined by Eurostat. The rest of the data management is identical to that described for total employment.

Agriculture plus mining employment. Retrieved indirectly by substracting from total employment employment in manufacturing, utilities, construction and services.

Employment by educational attainment. Source: Eurostat - LFS (link: link). The data concerns employment levels by educational attainment levels by NUTS2 and year, from 2000 to 2017. The levels are the following: less than primary, primary and lower secondary education (ISCED 2011 levels 0-2); upper secondary and post-secondary non-tertiary education (ISCED 2011 levels 3 and 4); tertiary education (ISCED 2011 levels 5-8). The rest of the data management is identical to that described for total employment.

STEM. Source: Eurostat - HRST (link: link). The data concerns employment levels of people with tertiary education (ISCED 2011) and employed in science and technology by NUTS2 and year, from 2000 to 2017. The rest of the data management is identical to that described for total employment.

A.6.2 Green production

Green goods list. Bontadini and Vona (2023) and Frattini et al. (2024) 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.[30] As we discussed in the main text, we refine this list by: including newly items whose environmental benefits are now established; including all batteries, that were excluded due to their potential for double usage; including nuclear energy and biofuels, that enter as part of a

[30]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.

broader low-carbon energy portfolio; excluding ambiguities in the classification arising from dual-use cases; including not only final green products but also their constituent components, with particular attention to those used in energy-efficient housing solutions. Table A21 shows the full list of green goods. The reason why the number of green goods in the current list (188) is lower than the original one (221) has to do with the fact that Eurostat harmonized PRODCOM codes up to 2007. From 2008 we do not harmonize product codes as none of them changes classification up to 2-digit manufacturing industry. Hence, we effectively include more products.

Production. Source: Eurostat - PRODCOM (link: PRODCOM). 8-digit country-product level data is aggregated to country-2-digit industries data from 1995 to 2017. The data is then deflated using 2019 EUKLEMS value added deflators (link all but UK: all; link UK: UK). Non-green production is retrieved by substracting green production from total production.

A.6.3 Patent data

Patent data panel is retrieved from PATSTAT Online database (link: PATSTAT), which is provided by the European Patent Office (EPO). We obtained access by subscription that costs around EUR700/year. For each patent application, the patent office assigns NACE codes associated with it following Van Looy et al. (2014). We classify a patent as green if at least one CPC code associated with it starts with Y.

A.6.4 Economic-Socio-demographic data

Active population. Source: Eurostat - LFS (link: link). The data concerns active population levels of the local population older than 15 years by NUTS2 and year, from 2000 to 2017. The data management is identical to that described for total employment.

Population density. Source: Eurostat - DEMS (link: link). The data concerns population density levels by NUTS2 and year, from 2000 to 2017.

Median age. Source: Eurostat - DEMS (link: link). The data concerns the median age of the population by NUTS2 and year, from 2000 to 2017.

Population by educational attainment. Source: Eurostat - LFS (link: link). The data concerns population by educational attainment levels by NUTS2 and year, from 2000 to 2017. The levels are the following: less than primary, primary and lower secondary education (ISCED 2011 levels 0-2); upper secondary and post-secondary non-tertiary education (ISCED 2011 levels 3 and 4); tertiary education (ISCED 2011 levels 5-8).

A.6.5 Automation exposure data

Data on automation exposure comes from Anelli et al. (2021). Anelli et al. (2021) estimate regional time-varying exposure to automation as $Robot\,Exp_{r,t} = \sum_j \frac{L_{rj,t_0}}{L_{cj,t_0}} \cdot \frac{\Delta Robot_{cj,t_k}}{L_{r,t_0}}$, where $\Delta Robot_{cj,t_k}$ is the change in the operational stock of industrial robots between year t and $t-k$.

A.6.6 Brown employment data

To measure regional brown exposure, we use 2-digit selected manufacturing and mining employment levels at the NUTS2, at baseline (average between 2000 and 2003). The 2-digit manufacturing sectors are: 4 - manufacture of basic metals; 25 - manufacture of fabricated metal products; 21 - manufacture of basic pharmaceutical products; 20 - manufacture of chemicals and chemical products; 23 - manufacture of other non-metallic mineral products; 19 - manufacture of coke and refined petroleum products. These sectors are identified as polluting from Table A1. The 2-digit mining sectors are: 05 - mining of coal and lignite; 06 - Extraction of crude petroleum and natural gas; 07 - mining of metal ores; 08 - other mining and quarrying. The 2-digit mining sector 09 - mining support service activities are not included. Then, regional brown employment is computed as $BP_{r,t_0} = \sum_j \frac{L_{r,j=poll,t_0}}{L_{r,t_0}}$. We then measure elevated regional brown exposure by identifying those NUTS2 regions that have values of this ratio above the 75th percentile.

Table A21: Green goods list

Code	**Label**
16101010	Railway or tramway sleepers (cross-ties) of wood, not impregnated
16101300	Railway or tramway sleepers (cross-ties) of wood, not impregnated
16103200	Railway or tramway sleepers (cross-ties) of impregnated wood
20595990	Biofuels (diesel substitute), other chemical products, n.e.c.
20595997	Biofuels (diesel substitute)
23121330	Multiple-walled insulating units of glass
23991930	Mixtures and articles of heat/sound-insulating materials n.e.c.
24107500	Railway material (of steel)
24333000	Structures, solely or principally of iron or steel sheet comprising two walls of profil...
25112200	Iron or steel towers and lattice masts
25301150	Vapour generating boilers (including hybrid boilers) (excluding central heating hot wat...
25301230	Auxiliary plant for use with boilers of HS 8402 or 8403
25301330	Parts of vapour generating boilers and super-heater water boilers
25302100	Nuclear reactors

Continued on next page

Table A21 – continued from previous page

Code	Label
25302200	Parts of nuclear reactors
25991131	Sanitary ware and parts of sanitary ware of iron or steel
25992910	Railway or tramway track fixtures and fittings and parts thereof
26112220	Semiconductor light emitting diodes (LEDs)
26112240	Photosensitive semiconductor devices; solar cells, photo-diodes, photo-transistors, etc.
26114070	Parts of diodes, transistors and similar semiconductor devices, photosensitive semicond...
26405190	LED backlight modules for LCDs of headings 8525 to 8528 (excl. for computer monitors)
26511200	Theodolites and tachymetres (tachometers); other surveying, hydrographic, oceanographic...
26511215	Electronic rangefinders, theodolites, tacheometers and photogrammetrical instruments an...
26511235	Electronic instruments and apparatus for meteorological, hydrological and geophysical p...
26511239	Other electronic instruments, n.e.c.
26511270	Surveying (including photogrammetrical surveying), hydrographic, oceanographic, hydrolo...
26511280	Non electronic surveying (including photogrammatrical surveying), hydrographic, oceanog...
26514100	Instruments and apparatus for measuring or detecting ionising radiations
26514200	Cathode-ray oscilloscopes and cathode-ray oscillographs
26514300	Instruments for measuring electrical quantities without a recording device
26514310	Multimeters without recording device
26514330	Electronic instruments and apparatus for measuring or checking voltage, current, resist...
26514355	Voltmeters without recording device
26514359	Non-electronic instruments and apparatus, for measuring or checking voltage, current, r...
26514530	Instruments and apparatus, with a recording device, for measuring or checking electric ...
26514555	Electronic instruments and apparatus, without a recording device, for measuring or chec...
26514559	Non-electronic instruments and apparatus, without a recording device, for measuring or ...
26515110	Thermometers, liquid-filled, for direct reading, not combined with other instruments (e...
26515135	Electronic thermometers and pyrometers, not combined with other instruments (excluding ...
26515139	Thermometers, not combined with other instruments and not liquid filled, n.e.c.
26515235	Electronic flow meters (excluding supply meters, hydrometric paddle-wheels)
26515239	Electronic instruments and apparatus for measuring or checking the level of liquids
26515255	Non-electronic flow meters (excluding supply meters, hydrometric paddle-wheels)
26515313	Electronic gas or smoke analysers
26515319	Non-electronic gas or smoke analysers
26515330	Spectrometers, spectrophotometers... using optical radiations
26515350	Instruments and apparatus using optical radiations, n.e.c.
26515381	Electronic ph and rh meters, other apparatus for measuring conductivity and electrochem...
26515390	Other instruments and apparatus for physical or chemical analysis n.e.c.
26516350	Liquid supply or production meters (including calibrated) (excluding pumps)
26516370	Electricity supply or production meters (including calibrated) (excluding voltmeters, a...
26516500	Hydraulic or pneumatic automatic regulating or controlling instruments and apparatus
26516620	Test benches
26516650	Electronic instruments, appliances and machines for measuring or checking geometrical q...
26516683	Other instruments, appliances,... for measuring or checking geometrical quantities
26516689	Non-electronic measuring machines and instruments (excluding test benches, optical inst...
26517015	Electronic thermostats
26517019	Non-electronic thermostats

Continued on next page

Code	Label
26518200	Parts and accessories for the goods of 26.51.12, 26.51.32, 26.51.33, 26.51.4 and 26.51....
26518550	Parts and accessories for automatic regulating or controlling instruments and apparatus
26702450	Other instruments and apparatus using optical radiation (UV, visible, IR)
26702490	Exposure meters, stroboscopes, optical instruments, appliances and machines for inspect...
27111010	Electric motors of an output <=Â 37,5 W (including synchronous motors <=Â 18 W, univers...
27111095	Photovoltaic DC generators of an output not exceeding 50 W
27111096	Photovoltaic DC generators of an output exceeding 50 W
27112680	Photovoltaic AC generators
27115023	Polycrystalline semiconductors
27116110	Parts suitable for use solely or principally with electric motors and generators, elect...
27123130	Numerical control panels with built-in automatic data-processing machine for a voltage ...
27123150	Programmable memory controllers for a voltage <=Â 1 kV
27123170	Other bases for electric control, distribution of electricity, voltage <=Â 1Â 000 V
27201100	Primary cells and primary batteries
27201110	Manganese dioxide cells and batteries, alkaline, in the form of cylindrical cells (excl...
27201115	Other manganese dioxide cells and batteries, alkaline (excl. spent, and cylindrical cells)
27201120	Manganese dioxide cells and batteries, non-alkaline, in the form of cylindrical cells (...
27201125	Other manganese dioxide cells and batteries, non-alkaline (excl. spent, and cylindrical...
27201130	Mercuric oxide primary cells and primary batteries (excl. spent)
27201140	Silver oxide primary cells and primary batteries (excl. spent)
27201150	Lithium primary cells and primary batteries, in the form of cylindrical cells (excl. sp...
27201155	Lithium primary cells and primary batteries, in the form of button cells (excl. spent)
27201160	Lithium primary cells and primary batteries (excl. spent, and in the form of cylindrica...
27201170	Air-zinc primary cells and primary batteries (excl. spent)
27201175	Dry zinc-carbon primary batteries of a voltage of >= 5,5 V but <= 6,5 V (excl. spent)
27201190	Other primary cells and primary batteries, electric (excl. spent, dry zinc-carbon batte...
27201200	Parts of primary cells and primary batteries (excluding battery carbons, for rechargeab...
27202300	Nickel-cadmium, nickel metal hydride, lithium-ion, lithium polymer, nickel-iron and oth...
27202350	Lithium-ion accumulators (excl. spent)
27401250	Tungsten halogen filament lamps for motorcycles and motor vehicles (excluding ultraviol...
27401293	Tungsten halogen filament lamps, for a voltage >Â 100 V (excluding ultraviolet and infr...
27401295	Tungsten halogen filament lamps for a voltage <=Â 100 V (excluding ultraviolet and infr...
27401510	Fluorescent hot cathode discharge lamps, with double ended cap (excluding ultraviolet l...
27401530	Fluorescent hot cathode discharge lamps (excluding ultraviolet lamps, with double ended...
27402200	Electric table, desk, bedside or floor-standing lamps
27403090	Electric lamps and lighting fittings, of plastic and other materials, of a kind used fo...
27403200	Lighting sets for Christmas trees
27403930	Electric lamps and lighting fittings, of plastic and other materials, of a kind used fo...
27512690	Other electric space heaters
27521400	Non-electric instantaneous or storage water heaters
27902050	Indicator panels incorporating light emitting diodes (LED)
27902060	Light-emitting diode (LED) modules and lamps
27904200	Fuel cells
279900Z1	Parts suitable for use solely or principally with electric motors and generators, elect...

Continued on next page

Table A21 – continued from previous page

Code	Label
28112130	Steam turbines and other vapour turbines (excluding for electricity generation)
28112150	Steam turbines for electricity generation
28112160	Steam turbines and other vapour turbines
28112200	Hydraulic turbines and water wheels
28112400	Generating sets, wind-powered
28113100	Parts for steam turbines and other vapour turbines
28113200	Parts for hydraulic turbines and water wheels (including regulators)
28211354	Electric furnaces and ovens (excluding induction- and resistance-heated); equipment for...
28211362	Dielectric furnaces and ovens, electron beam furnaces, plasma and vacuum arc furnaces, ...
28211470	Parts for industrial or laboratory electric, induction or dielectric furnaces and ovens...
28221130	Pulley tackle and hoists powered by an electric motor (excluding of the kind used for r...
28221250	Winches and capstans powered by an electric motor or internal combustion piston engines...
28221513	Self-propelled works trucks fitted with lifting or handling equipment, powered by an el...
28221515	Self-propelled works trucks fitted with lifting or handling equipment, powered by an el...
28241150	Grinders, sanders and planers, for working in the hand, with self-contained electric mo...
28241185	Electromechanical hand tools, with self-contained electric motor operating with an exte...
28251130	Heat exchange units
28251380	Heat pumps other than air conditioning machines of HS 8415
28251410	Machinery and apparatus for filtering or purifying air (excluding intake filters for in...
28251420	Machinery and apparatus for filtering or purifying gases by a liquid process (excluding...
28251430	Machinery and apparatus for filtering and purifying gases (other than air and excluding...
28251431	Machinery and apparatus for filtering and purifying gases (other than air and excluding...
28251440	Machinery and apparatus for filtering or purifying gases by catalytic process (excludin...
28251441	Machinery and apparatus for filtering or purifying gases by catalytic process (excludin...
28251442	Catalytic converters or particulate filters, whether or not combined, for purifying or ...
28251450	Machinery and apparatus for filtering and purifying gases with stainless steel housing,...
28251470	Machinery and apparatus for filtering or purifying gases including for filtering dust f...
28253070	Parts of refrigerating or freezing equipment and heat pumps, n.e.s.
28291100	Producer gas or water gas generators; acetylene gas generators and the like; distilling...
28291230	Machinery and apparatus for filtering or purifying water
28291270	Machinery and apparatus for solid-liquid separation/ purification excluding for water a...
28298250	Parts for filtering and purifying machinery and apparatus, for liquids or gases (exclud...
28304010	Electric mowers for lawns, parks, golf courses or sports grounds
28992020	Machines and apparatus used solely or principally for the manufacture of semiconductor ...
28992060	Machines and apparatus used solely or principally for the manufacture of flat panel dis...
28993945	Machines and apparatus used solely or principally for (a) the manufacture or repair of ...
29102410	Motor vehicles, with both spark-ignition or compression-ignition internal combustion re...
29102430	Motor vehicles, with both spark-ignition or compression-ignition internal combustion re...
29102450	Motor vehicles, with only electric motor for propulsion
29104142	Motor vehicles for the transport of goods with both compression-ignition internal combu...
29104212	Motor vehicles for the transport of goods with both spark-ignition internal combustion ...
29104213	Motor vehicles for the transport of goods with only electric motor for propulsion
29104311	Road tractors for semi-trailers with both compression-ignition internal combustion pist...
29104312	Road tractors for semi-trailers with both spark-ignition internal combustion piston eng...

Continued on next page

Table A21 – continued from previous page

Code	Label
29104313	Road tractors for semi-trailers with only electric motor for propulsion
29105200	Motor vehicles specially designed for travelling on snow, golf cars and similar vehicles
29312310	Electrical or battery operated lighting or visual signalling of a kind used on bicycles
30201100	Rail locomotives powered from an external source of electricity
30201200	Diesel-electric locomotives
30201300	Other rail locomotives; locomotive tenders
30202000	Self-propelled railway or tramway coaches, vans and trucks, except maintenance or servi...
30203100	Railway or tramway maintenance or service vehicles (including workshops, cranes, ballas...
30203200	Rail/tramway passenger coaches; luggage vans, post office coaches and other special pur...
30203300	Railway or tramway goods vans and wagons, not self-propelled
30204030	Parts of locomotives or rolling-stock
30204050	Mechanical or electromechanical signalling, safety or traffic control equipment for roa...
30204070	Fixtures and fittings and mechanical signalling, safety or traffic control equipment fo...
30209100	Reconditioning of railway and tramway locomotives and rolling-stock
30921000	Bicycles and other cycles (including delivery tricycles), non-motorised
30921030	Non-motorized bicycles and other cycles, without ball bearings (including delivery tric...
30921050	Non-motorized bicycles and other cycles with ball bearings (including delivery tricycles)
30923010	Frames and forks, for bicycles
30923030	Parts of frames, front forks, brakes, coaster braking hubs, hub brakes, pedals crank-ge...
30923060	Parts and accessories of bicycles and other cycles, not motorised (excl. frames, front ...
30923070	Parts and accessories for invalid carriages
30923090	Other parts and accessories of bicycles and other cycles, not motorised
33141120	Repair and maintenance of electric motors, generators and transformers
33141150	Repair and maintenance of electricity distribution and control apparatus
33141900	Repair and maintenance of electrical equipment (excluding electricity distribution and ...
33171100	Repair and maintenance of railway and tramway locomotives and rolling-stock and of mech...
33205020	Installation of electric motors, generators and transformers
33205050	Installation of electricity distribution and control apparatus
33205090	Installation of other electrical equipment, excluding electrical signalling equipment f...

Table A22: NUTS2 regions in the sample list

Code	Label
AT11	AT - Burgenland
AT12	AT - Niederösterreich
AT13	AT - Wien
AT21	AT - Kärnten
AT22	AT - Steiermark
AT31	AT - Oberösterreich
AT32	AT - Salzburg
AT33	AT - Tirol
AT34	AT - Vorarlberg
BE10	BE - Région de Bruxelles-Capitale/Brussels Hoofdstedelijk Gewest

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Table A22 – continued from previous page

Code	Label
BE21	BE - Prov. Antwerpen
BE22	BE - Prov. Limburg (BE)
BE23	BE - Prov. Oost-Vlaanderen
BE24	BE - Prov. Vlaams-Brabant
BE25	BE - Prov. West-Vlaanderen
BE31	BE - Prov. Brabant wallon
BE32	BE - Prov. Hainaut
BE33	BE - Prov. Liège
BE34	BE - Prov. Luxembourg (BE)
BE35	BE - Prov. Namur
BG31	BG - Severozapaden
BG32	BG - Severen tsentralen
BG33	BG - Severoiztochen
BG34	BG - Yugoiztochen
BG41	BG - Yugozapaden
BG42	BG - Yuzhen tsentralen
CY00	CY - Kýpros
CZ01	CZ - Praha
CZ02	CZ - Střední Čechy
CZ03	CZ - Jihozápad
CZ04	CZ - Severozápad
CZ05	CZ - Severovýchod
CZ06	CZ - Jihovýchod
CZ07	CZ - Střední Morava
CZ08	CZ - Moravskoslezsko
DE11	DE - Stuttgart
DE12	DE - Karlsruhe
DE13	DE - Freiburg
DE14	DE - Tübingen
DE21	DE - Oberbayern
DE22	DE - Niederbayern
DE23	DE - Oberpfalz
DE24	DE - Oberfranken
DE25	DE - Mittelfranken
DE26	DE - Unterfranken
DE27	DE - Schwaben
DE30	DE - Berlin
DE40	DE - Brandenburg
DE50	DE - Bremen
DE60	DE - Hamburg
DE71	DE - Darmstadt
DE72	DE - Gießen
DE73	DE - Kassel
DE80	DE - Mecklenburg-Vorpommern

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Table A22 – continued from previous page

Code	Label
DE91	DE - Braunschweig
DE92	DE - Hannover
DE93	DE - Lüneburg
DE94	DE - Weser-Ems
DEA1	DE - Düsseldorf
DEA2	DE - Köln
DEA3	DE - Münster
DEA4	DE - Detmold
DEA5	DE - Arnsberg
DEB1	DE - Koblenz
DEB2	DE - Trier
DEB3	DE - Rheinhessen-Pfalz
DEC0	DE - Saarland
DED2	DE - Dresden
DED4	DE - Chemnitz
DED5	DE - Leipzig
DEE0	DE - Sachsen-Anhalt
DEF0	DE - Schleswig-Holstein
DEG0	DE - Thüringen
DK01	DK - Hovedstaden
DK02	DK - Sjælland
DK03	DK - Syddanmark
DK04	DK - Midtjylland
DK05	DK - Nordjylland
EL30	EL - Attiki
EL41	EL - Voreio Aigaio
EL42	EL - Notio Aigaio
EL43	EL - Kriti
EL51	EL - Anatoliki Makedonia, Thraki
EL52	EL - Kentriki Makedonia
EL53	EL - Dytiki Makedonia
EL54	EL - Ipeiros
EL61	EL - Thessalia
EL62	EL - Ionia Nisia
EL63	EL - Dytiki Ellada
EL64	EL - Sterea Ellada
EL65	EL - Peloponnisos
ES11	ES - Galicia
ES12	ES - Principado de Asturias
ES13	ES - Cantabria
ES21	ES - País Vasco
ES22	ES - Comunidad Foral de Navarra
ES23	ES - La Rioja
ES24	ES - Aragón

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Table A22 – continued from previous page

Code	Label
ES30	ES - Comunidad de Madrid
ES41	ES - Castilla y León
ES42	ES - Castilla-La Mancha
ES43	ES - Extremadura
ES51	ES - Cataluña
ES52	ES - Comunitat Valenciana
ES53	ES - Illes Balears
ES61	ES - Andalucía
ES62	ES - Región de Murcia
ES63	ES - Ciudad de Ceuta
ES64	ES - Ciudad de Melilla
FI19	FI - Länsi-Suomi
FI1B	FI - Etelä-Suomi
FI1C	FI - Etelä-Suomi
FI1D	FI - Itä-Suomi
FI20	FI - Åland
FR10	FR - Ile de France
FRB0	FR - Centre (FR)
FRC1	FR - Bourgogne
FRC2	FR - Franche-Comté
FRD1	FR - Basse-Normandie
FRD2	FR - Haute-Normandie
FRE1	FR - Nord-Pas-de-Calais
FRE2	FR - Picardie
FRF1	FR - Alsace
FRF2	FR - Champagne-Ardenne
FRF3	FR - Lorraine
FRG0	FR - Pays de la Loire
FRH0	FR - Bretagne
FRI1	FR - Aquitaine
FRI2	FR - Limousin
FRI3	FR - Poitou-Charentes
FRJ1	FR - Languedoc-Roussillon
FRJ2	FR - Midi-Pyrénées
FRK1	FR - Auvergne
FRK2	FR - Rhône-Alpes
FRL0	FR - Provence-Alpes-Côte d'Azur
FRM0	FR - Corse
HR03	HR - Jadranska Hrvatska
HR04	HR - Kontinentalna Hrvatska
HU11	HU - Közép-Magyarország
HU12	HU - Közép-Magyarország
HU21	HU - Közép-Dunántúl
HU22	HU - Nyugat-Dunántúl

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Table A22 – continued from previous page

Code	Label
HU23	HU - Dél-Dunántúl
HU31	HU - Észak-Magyarország
HU32	HU - Észak-Alföld
HU33	HU - Dél-Alföld
IE04	IE - Border, Midland and Western
IE05	IE - Southern and Eastern
IE06	IE - Southern and Eastern
IS00	IS - Iceland
ITC1	IT - Piemonte
ITC2	IT - Valle d'Aosta/Vallée d'Aoste
ITC3	IT - Liguria
ITC4	IT - Lombardia
ITF1	IT - Abruzzo
ITF2	IT - Molise
ITF3	IT - Campania
ITF4	IT - Puglia
ITF5	IT - Basilicata
ITF6	IT - Calabria
ITG1	IT - Sicilia
ITG2	IT - Sardegna
ITH1	IT - Provincia Autonoma Bolzano/Bozen
ITH2	IT - Provincia Autonoma Trento
ITH3	IT - Veneto
ITH4	IT - Friuli-Venezia Giulia
ITH5	IT - Emilia-Romagna
ITI1	IT - Toscana
ITI2	IT - Umbria
ITI3	IT - Marche
ITI4	IT - Lazio
LU00	LU - Luxembourg
LV00	LV - Latvia
MT00	MT - Malta
NL11	NL - Groningen
NL12	NL - Friesland (NL)
NL13	NL - Drenthe
NL21	NL - Overijssel
NL22	NL - Gelderland
NL23	NL - Flevoland
NL31	NL - Utrecht
NL32	NL - Noord-Holland
NL33	NL - Zuid-Holland
NL34	NL - Zeeland
NL41	NL - Noord-Brabant
NL42	NL - Limburg (NL)

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Table A22 – continued from previous page

Code	Label
NO01	NO - Oslo og Akershus
NO02	NO - Innlandet
NO03	NO - Sør-Østlandet
NO04	NO - Agder og Rogaland
NO05	NO - Vestlandet
NO06	NO - Trøndelag
NO07	NO - Nord-Norge
PL21	PL - Małopolskie
PL22	PL - Śląskie
PL41	PL - Wielkopolskie
PL42	PL - Zachodniopomorskie
PL43	PL - Lubuskie
PL51	PL - Dolnośląskie
PL52	PL - Opolskie
PL61	PL - Kujawsko-pomorskie
PL62	PL - Warmińsko-mazurskie
PL63	PL - Pomorskie
PL71	PL - Lódzkie
PL72	PL - Swietokrzyskie
PL81	PL - Lubelskie
PL82	PL - Podkarpackie
PL84	PL - Podlaskie
PL91	PL - Mazowieckie
PL92	PL - Mazowieckie
PT11	PT - Norte
PT15	PT - Algarve
PT16	PT - Centro (PT)
PT17	PT - Área Metropolitana de Lisboa
PT18	PT - Alentejo
RO11	RO - Nord-Vest
RO12	RO - Centru
RO21	RO - Nord-Est
RO22	RO - Sud-Est
RO31	RO - Sud-Muntenia
RO32	RO - Bucureşti-Ilfov
RO41	RO - Sud-Vest Oltenia
RO42	RO - Vest
SE11	SE - Stockholm
SE12	SE - Östra Mellansverige
SE21	SE - Småland med öarna
SE22	SE - Sydsverige
SE23	SE - Västsverige
SE31	SE - Norra Mellansverige
SE32	SE - Mellersta Norrland

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Table A22 – continued from previous page

Code	Label
SE33	SE - Övre Norrland
SI03	SI - Vzhodna Slovenija
SI04	SI - Zahodna Slovenija
SK01	SK - Bratislavský kraj
SK02	SK - Západné Slovensko
SK03	SK - Stredné Slovensko
SK04	SK - Východné Slovensko
UKC1	UK - Tees Valley and Durham
UKC2	UK - Northumberland and Tyne and Wear
UKD1	UK - Cumbria
UKD3	UK - Greater Manchester
UKD4	UK - Lancashire
UKD6	UK - Cheshire
UKD7	UK - Merseyside
UKE1	UK - East Yorkshire and Northern Lincolnshire
UKE2	UK - North Yorkshire
UKE3	UK - South Yorkshire
UKE4	UK - West Yorkshire
UKF1	UK - Derbyshire and Nottinghamshire
UKF2	UK - Leicestershire, Rutland and Northamptonshire
UKF3	UK - Lincolnshire
UKG1	UK - Herefordshire, Worcestershire and Warwickshire
UKG2	UK - Shropshire and Staffordshire
UKG3	UK - West Midlands
UKH1	UK - East Anglia
UKH2	UK - Bedfordshire and Hertfordshire
UKH3	UK - Essex
UKI3	UK - Inner London
UKI4	UK - Inner London
UKI5	UK - Outer London
UKI6	UK - Outer London
UKI7	UK - Outer London
UKJ1	UK - Berkshire, Buckinghamshire and Oxfordshire
UKJ2	UK - Surrey, East and West Sussex
UKJ3	UK - Hampshire and Isle of Wight
UKJ4	UK - Kent
UKK1	UK - Gloucestershire, Wiltshire and Bristol/Bath area
UKK2	UK - Dorset and Somerset
UKK3	UK - Cornwall and Isles of Scilly
UKK4	UK - Devon
UKL1	UK - West Wales and The Valleys
UKL2	UK - East Wales
UKM5	UK - North Eastern Scotland
UKM6	UK - Highlands and Islands

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Code	Label
UKM7	UK - Eastern Scotland
UKM8	UK - South Western Scotland
UKM9	UK - South Western Scotland
UKN0	UK - Northern Ireland (UK)

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