# Climate Policies and Skill-Biased Employment Dynamics: Evidence from EU countries

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## ABSTRACT

The political acceptability of climate policies is undermined by job-killing arguments, especially for the least-skilled workers. However, evidence for distributional impacts for different workers remains scant. We examine the associations between climate policies, proxied by energy prices and a stringency index, and workforce skills for 14 European countries and 15 industrial sectors over the period of 1995-2011. We find that, while the long-term decline in employment in most carbon-intensive sectors is unrelated to policy stringency, climate policies have been skill biased against manual workers and have favoured technicians and professionals. This skill bias is confirmed using a shift-share instrumental variable estimator.

## KEY WORDS

Climate policies, workforce skills, cluster analysis, multiple exposure to structural shocks

## JEL

J24, Q52.

# Climate Policies and Skill-Biased Employment Dynamics: Evidence from EU countries*

## 1 Introduction

Concerns about international competitiveness and job losses have often characterized the political debate over climate policies. The withdrawal of the US from the Paris Agreement is only the latest episode of a political discourse that, especially among the conservative parties, has exploited the *job-killing argument* to block the approval of ambitious climate policies (Coglianese et al., 2013). Cragg et al. (2013) showed that US Congressional representatives are less inclined to vote for climate policies if they were elected from areas that are both poorer and have a pollution-intensive industrial structure. While the job-killing argument is less popular in the European debate, generous exemptions have been adopted in all countries to shelter polluting industries from international competition (Ekins and Speck, 1999). According to Martin et al. (2014), policymakers have overstated the relocation risk brought about by the European Emission Trading Scheme (EU-ETS), which is the flagship EU policy on climate change mitigation. Empirical evidence has not disconfirmed these concerns: in most cases, air quality regulations and energy prices (a proxy for carbon tax) have modest negative employment effects, concentrated on polluting and energy-intensive industries (e.g., Greenstone, 2002; Kahn and Mansur, 2013; Walker, 2013). Although such negative effects can be offset by well-designed tax recycling schemes (Yamazaki, 2017), direct subsidies to the green economy (Vona et al., 2018b) and induced innovations (Horbach and Rennings, 2013; Gagliardi et al., 2016), climate policies can still have large distributional consequences for different groups of workers, undermining their political acceptability.

Of particular importance is assessing whether the labour market impacts of climate policies reinforce or not the well-known secular trend of skill upgrading, induced by globalization and automation (Autor and Acemoglu, 2011; Goss et al., 2014; Lu and Ng, 2013; Autor et al., 2015). Regarding information and communication technologies (ICT henceforth), firms exposed to stringent climate policies could adopt technologies and organizational practices that require different worker competencies. Ultimately, whether climate policies and the greening of our economies induce changes in skill demand, and the extent to which these changes are aligned with those of on-going technological transformations are empirical issues that our paper seeks to answer.

The first step of our research is to provide an exploratory look at the way in which the adoption of climate policies interacts with other labour market trends in shaping long-

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term changes in the workforce composition. Indeed, reemployment opportunities for displaced workers depend on their skill sets and should be less hopeful for workers whose competencies are offshored or automated. Conversely, workers equipped with the competencies needed in new green jobs will benefit from the expansion in the demand for green goods and services induced by such policies (Vona et al., 2018b).

We contribute in three ways to the scant empirical literature on the distributional impacts of environmental policies across different workers' groups, which has mostly been limited to the US (Walker, 2013; Vona et al., 2018a). First, we enlarge the breadth and generality of previous works by considering a more aggregated level of analysis. More specifically, we examine the associations between climate policies and workforce skills for 14 European countries and 15 industrial sectors over the period of 1995-2011. Similar to previous research on the impact of ICT (Michaels et al, 2014), this approach allows us to examine within-sector cross-country differences in the associations between climate policies and labour demand divided by skill group.

Second, we build a unique dataset containing information on exposure to climate policies, green innovations and other structural changes, essentially trade and (ICT and non-ICT) capital investments (section 2). On the one hand, this dataset allows us to isolate the effects of climate policies on workforce skills in our econometric analyses. On the other hand, we gain descriptive insights into how climate policies interact with other structural transformations in the labour market. We use cluster analysis to describe the overlap of different labour market changes and thus the potentially cumulative effects of present and future climate policies (section 3).

Third, we estimate the long-term effects of climate policies on workforce skills addressing the issue of the endogeneity of climate policies using a standard shift-share methodology for the two main policies of interest (section 4). Our favourite measures of climate policies are sectoral energy prices, following the methodology of Sato et al. (2015), and the composite EPS index, synthetizing the plethora of environmental policies adopted by EU countries in a unique index suitable for instrumentation (Botta and Kozluk, 2014). Our results indicate that properly accounting for endogeneity changes only the magnitude of the estimated effects and that, if any, OLS estimates are downwardly biased.

More generally, there are three main results of our analysis. First, the cluster analysis shows that clusters exposed to climate policies (with higher GHG emissions intensity) and to other structural transformations (i.e., trade exposed) are not necessarily at a disadvantage, compared to other clusters. Second, we estimate a decline in employment in most emission-intensive sectors that occur independently on policy stringency. Third, both the cluster and the econometric analyses emphasize a pronounced skill bias in favour of technicians and against manual workers. The bias is stronger for energy prices, high-tech sectors, and the combined effects of all climate policies, explaining up to 2/3 of the increase in the share of technicians over the sample period. Before delving into the cores of sections 2 (data and descriptive), 3 (cluster analysis and taxonomy of exposure to multiple shocks) and 4 (econometric analysis and main results) of the paper, the next subsection discusses in greater detail our contribution with respect to the previous literature.

## 1.1 Related literature

Our paper contributes to the active literature on the impacts of environmental policies on competitiveness (Dechezleprêtre and Sato, 2017), of which labour market impacts are an expression. Two contrasting hypotheses explicitly or implicitly tested are: the Pollution Haven hypothesis (e.g., Levinson and Taylor, 2008); and the Porter hypothesis (e.g., Porter and van der Linde, 1995). The former focuses on the increase in compliance costs induced by unilateral environmental policies that eventually lead to a relocation of pollution-intensive industries towards countries with less stringent policies. The latter emphasizes the dynamic incentives of strict, but flexible, environmental policies for green innovation (weak version) and competitiveness (strong version).

Both hypotheses have important implications for labour market outcomes. As emphasized by the partial equilibrium model of Berman et al. (2001), the extent to which the Pollution Haven effect translates into job losses depending on the size of the scale effect induced by compliance costs, the labour intensity of abatement technologies and the degree of competition in product markets. To illustrate, if the decrease in labour demand associated with a reduction in the scale of production of polluting sectors is greater than the increase in labour demand required in abatement technologies, the aggregate effect is negative. Morgenstern et al. (2002) showed that the scale effect is small since firms have market power in polluting industries, and consequently, the increase in compliance costs can be passed on to consumers with negligible effects on total demand. For the sake of simplicity, the Porter hypothesis can be nested within this framework by allowing for innovation in abatement technologies, including both end-of-pipe and cleaner technologies (Frondel et al., 2007; Horbach et al., 2012), to spur a green comparative advantage, possibly leading to net job creation.[1] Overall, the aggregate effect of environmental policies on labour demand remains a largely unresolved empirical issue. On the one hand, the literature isolating the effects on most cost-exposed polluting industries has generally found negative employment effects. On the other hand, the literature focusing on employment, environmental policies and green innovation has generally found a positive correlation.[2] The main difficulty in reconciling the empirical findings of the two literature streams is that it is easier to derive a reduced-form specification, identify a reliable control group and thus obtain the causal effects in the first strand of literature than in the second.[3] Moreover, job destruction in polluting sectors can be offset by job creation in upstream suppliers of green technologies and services, which are difficult to assess in reduced-form econometric models. Finally, the timing of the effect is important because the offsetting mechanisms through innovation are likely to be effective in the medium to long term, while the increase in compliance costs occurs immediately (e.g., Lanoie et al. 2008)

These research strands have so far focused on the aggregate employment impacts, while the impact of structural transformations can be highly skill biased. Looking at skill-biased impacts has been crucial to understanding the inequality-enhancing effects of globalization, ICTs and other policy reforms, especially market liberalization (Autor and Acemoglu, 2011; Goss et al., 2014). In developed countries, all of these transformations have: i) been mildly labour-saving, especially in manufacturing; ii) reduced the demand for unskilled labour and routine jobs; and iii) increased the demand for highly skilled labour and abstract jobs, especially for non-routine interactive skills, compared to non-

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[1] Obviously, the theoretical mechanisms that support the Porter hypothesis are more sophisticated than this simple linkage effect. A good survey of the literature appears in Ambec et al. (2013).

[2] Reviewing the findings of these two strands of literature is beyond the scope of these papers, and the picture provided here is to a certain extent a drastic simplification due to space limitations. Examples of the first set of "negative" results are: Greenstone (2002); Walker (2011); Kahn and Mansur (2013) and Marin and Vona (2017); examples of the second set of "positive" results, especially for cleaner technologies, are Rennings et al. (2004); Horbach and Rennings (2013); Gagliardi et al. (2016) and Vona et al. (2017).

[3] Estimating the impacts of environmental policies on innovation and then that of innovation on employment is not an easy task, given the presence of pervasive endogeneity issues in estimating both equations and the difficulties in finding reliable exclusion restrictions for identification purposes.

routine cognitive skills.[4] The theoretical rationale to account for these patterns is the so-called Routine-Replacing Technical Change hypothesis, according to which ICT technologies replace routine cognitive tasks in the workplace and facilitate the fragmentation of global value chains and the relocation of manual tasks in developing countries. At the same time, the combined effects of ICT technologies and increased international competition have disproportionately benefited talented workers through a combination of complementarity effects, the scalability of intangible investments and increased market size.

By analogy with these first-order structural changes, a key and yet unexplored question is whether the labour market impacts of environmental policies are biased towards certain workers' groups and whether the direction of the bias is similar to that of these changes. Answering these questions not only is crucial for examining the labour market distributional impacts of climate policies, but it is also important for the acceptability and the design of environmental policies. Indeed, identifying the losers and supporting them during the transition to a new job will significantly increase the political acceptability of climate policies. Further, training workers with the skills required by green jobs would reduce the costs of coping with climate policies.

A chief difficulty is that we do not have clear theoretical insights, but only conjectures, into the relationship between climate policies (as a proxy of the demand of greener productions) and skill demand. Consequently, our paper aims at identifying data-driven patterns, which could provide basic insights and calibrations for theoretical contributions regarding the skill-biased effects of climate policies. An example is the paper by Hafstead and Williams III (2018), which, using a search and matching general equilibrium model, showed that an aggregate, modest effect of a carbon tax masks a substantial relocation of labour between clean and dirty sectors. Because relocation costs are typically proportional to skill gaps (e.g., Gathmann and Schönberg, 2010), an extension of this model could take advantage of our findings to express relocation costs as a function of such skill gaps.[5]

[4] In the seminal paper by Autor, Levy and Murnarne (2003), a key distinction within the high-skill group is that between non-routine cognitive skills, e.g., math, engineering and science, and non-routine interactive skills, e.g. language and social skills.

[5] Empirically, relocation costs associated with environmental policies are difficult to estimate due to data limitations. An exception is the paper by Walker (2013), who estimated the long-term earning losses of approximately 20% for workers displaced by the Clean Air Act, the main command-and-control environmental policy in the US. His main finding is that these losses are very heterogeneous, being particularly large for older workers, women and those forced to change sectors. In contrast with these

To the best of our knowledge, research on the skill biasedness of environmental policies is still scant and mostly limited to the US. Indirect evidence has been provided in three cross-sectional studies analysing the skill biasedness of green productions. Using the US Green Goods and Services Survey available for 2010 and 2011, Becker and Shadbegian (2009) and Elliott and Lindley (2017) found that plants producing green goods and services employ a lower share of production workers. Consoli et al. (2016) examined the skill difference between green and non-green jobs using standard skill measures, such as education and routine task intensity, based on data from the Occupational Information Network (O*NET), which contains detailed information about the skills and tasks content of approximately 1000 occupations. They generally found modest differences but also a bias towards higher skills for green jobs (see also Bowen et al., 2018). Vona et al. (2018a) was the first paper providing a direct test of the effect of recent amendments to the Clean Air Act on skill demand in US regions over the period of 2006-2014. Moving from the nuanced results of Consoli et al. (2016) for standard skill measures, they also used O*NET to identify the skills that are significantly different for green jobs, compared to other jobs. The key finding is that skill gaps tend to be relevant, especially for engineering and technical skills, including monitoring. Taking stock of these findings, we expect climate policies to amplify the long-term skill upgrading of the workforce, with a more pronounced effect for engineering and technical skills.

# 2 Data, measures and descriptive statistics

## 2.1 Data and measures

We use standard data sources that, to the best of our knowledge, we are the first to combine in a unique dataset. Our final dataset includes 15 sectors: 13 manufacturing sectors, “mining and quarrying”, and “electricity, gas and water supply”, classified according to the NACE rev. 1.1 classification.[6] Due to missing data on key variables described below, we focus on 14 countries only.[7] The resulting dataset is a balanced panel for 15 industrial sectors and 14 countries.

findings, Curtis (2018) showed that the negative employment effects of the NOx Budget Trading Program are concentrated among younger cohorts.

[6] We excluded ‘construction’ (NACE F), which is very different from other sectors in two important dimensions. First, it is an outlier in terms of employment. Second, it is sheltered by other shocks, such as international competition and automation.

[7] The countries are Austria, Belgium, the Czech Republic, Germany, Denmark, Spain, Finland, France, Hungary, Ireland, Italy, the Netherlands, Sweden and the United Kingdom. Over the period of 1995-2011,

Our primary measure of sectoral exposure to climate policies is emissions intensity. The data source is the World Input Output Dataset (WIOD), which allows us to compute both the direct GHG emissions until 2009 ($CO_2$, $N_2O$ and $CH_4$ aggregated according to their global warming potential) of the sector and the indirect GHG emissions through the purchase of electricity from the power sector (using input-output technical coefficients). To account for the direct and indirect exposures, our measure of GHG is the sum of the direct and indirect emissions (from the power sector) per unit of the sectoral value added.[8] Because sectors producing green goods and technologies can benefit from climate policies and be sources of job creation through an increase in the demand for green machines and services, we build a second measure of exposure to climate policies, namely, the stock of climate-related patent applications at the European Patent Office from REGPAT as a proxy for green comparative advantage.[9] Climate-related patents are identified based on their IPC and CPC codes according to the taxonomy developed by the OECD (ENV-TECH indicator) and are related to renewable energy sources, energy efficiency, carbon capture and storage, emission mitigation technologies (e.g., energy storage, hydrogen-based fuels, fuel cells) and efficient combustion technologies. We use the IPC-ISIC concordance proposed by Lybbert and Zolas (2014) to attribute climate-related patents to each sector. Importantly, patents are assigned to sectors that manufacture the green technology, rather than to the sectors that use it, thus capturing comparative advantage in green technologies. We measure environmental patent intensity by rescaling the patent stock by the number of hours worked in the sectors.

On the labour market side, we use the European Labour Force Survey to retrieve, for each industry, information about the total and the share of hours for workers by different "skill groups". [10] Our favourite measure of skills is the share of workers employed in a certain occupational group, while our alternative measure breaks down the workforce by

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these countries contribute to approximately 73.7% of employment and 92.3% of value added of the EU27 in the selected sectors. Data on ICT and non-ICT capital from EUKLEMS are not available for Bulgaria, Cyprus, Estonia, Greece, Lithuania, Latvia, Malta, Poland, Portugal, Romania and Slovakia. Moreover, data on import penetration (OECD) are missing for Luxembourg, while data on EPS (OECD) are not available for Slovenia.

[8] We use emissions, rather than energy intensity: the two measures show a correlation of 0.91 in our sample.

[9] The stock is built with the perpetual inventory method, using the EPO patent count sorted by priority year from 1977. We apply a 20% depreciation rate.

[10] The Labour Force Survey employs the NACE rev 1.1. classification until 2007 and the NACE rev. 2 classification from 2007 onwards. We build a country-specific weighted concordance table between the two classifications, exploiting the double coding of information for 2007.

educational categories. This choice reflects the findings of the recent literature in labour economics emphasizing that occupational categories have greater predictive power than educational categories for labour market outcomes (Acemoglu and Autor, 2011), which is also consistent with the Routine-Replacing Technical Change hypothesis mentioned in section 1.1. We focus our analysis on four occupational groups: managers (ISCO 1), professionals (ISCO 2), technicians (ISCO 3) and manual workers (ISCO 7, 8 and 9). The paper by Vona et al. (2018a), which empirically identifies the skills relevant for green and brown jobs, motivates the separate inclusion of professionals, managers and technicians. Indeed, engineering and design skills emerge as the most important skills for both the green and polluting sectors. We include the share of managers because both Vona et al. (2018a) and Martin et al. (2012) found managerial skills to be important for environmentally friendly productions. Routine manual workers are included because they are both intensively employed in polluting industries and negatively affected by trade and technology shocks (Autor and Dorn, 2013; Autor et al., 2015). The second skill measure breaks down different levels of educational attainment as follows: low skill (secondary International Standard Classification of Education, ISCED, level or less), medium skill (upper secondary ISCED level) and high skill (tertiary ISCED level).[11]

EU-KLEMS provides information about ICT and non-ICT capital and labour productivity (until 2007), while we retrieved from OECD STAN (data available until 2009) the share of imports over total production, which is a conventional measure of import competition. As discussed in the introduction, ICT technologies and globalization have large labour market impacts, and a key goal of our analysis is to understand the extent to which these impacts overlap with those of climate policies.

To capture climate policies that increase the price of emissions, we compute the share of total direct GHG emissions released by establishments that participate in the European Emission Trading Scheme (EU-ETS), using information on verified emissions of EU-ETS plants (classified by sector) from the EU ETS registry and total sectoral GHG emissions from WIOD. In the absence of other carbon pricing policies, we follow previous research using historical energy prices to proxy for the likely effects of climate policies on firms' competitiveness (Aldy and Pizer, 2015; Marin and Vona 2017; Sato et

[11] For occupational groups not considered in our analysis, such as clerical (ISCO 4) and service occupations (ISCO 5), it is worth mentioning that they represent a tiny proportion of employment in the sectors considered by our analysis, i.e., 10.6% of the average industry workforce.

al., 2015). We follow Sato et al.'s (2015) methodology and estimate energy prices (country, sector and year specific) by combining country-level time-varying tax inclusive prices for each energy source (from IEA) with the sector-country-year specific energy mix (from WIOD). Finally, other climate and environmental policies are multi-dimensional, consisting of a mix of subsidies, taxes and emission limits. To account for multi-dimensionality, we use the OECD dataset on environmental policy stringency (EPS; see Botta and Koźluk, 2014). To avoid double counting of the EU-ETS stringency, we re-calculated the aggregated indicator without the components of $CO_2$ tax and $CO_2$ trading (labelled as *EPS_no_ETS*), following the same procedure described by Botta and Koźluk (2014). For instrumentation purposes, we use the aggregate EPS index, which incorporates the measure of EU-ETS stringency (labeled simply *EPS*).

In what follows, our data are organized in long intervals delimited by 1995, 1999, 2003, 2007, and 2011 to capture medium- to long-term associations between climate policies and labour market outcomes.[12] Since some variables are available until 2007 only, our descriptive analysis is performed for the time span of 1995-2007, while the econometric part also uses the last year because we fix the exposure to various shocks during the initial period.

## 2.2 Descriptive evidence

Table 1 summarizes the main data sources and the acronyms of the variables that are used throughout the paper, and it presents basic descriptive statistics for our variables of interest.

[Table 1 about here]

As a first glance towards understanding the associations between climate policies and labour market outcomes, we correlate both the levels (Table 2) and long-term changes (Table 3) of our variables of interest. We highlight in italics the correlations that are not significantly different from zero (5% level). Examining the levels, the patterns for the two measures of exposure to climate policies are completely different. On the one hand, higher emissions per worker are associated with lower exposure to other shocks, namely, import

[12] Clearly, we checked that our results are unaffected by the particular years selected to delimit the windows, and we perform extensive robustness checks using moving average transformations.

penetration and ICT capital investment, and lower skill intensity. On the other hand, as expected, higher green patent intensity is positively associated with ICT capital investments, as well as demand for highly educated workers, professionals, technicians and managers.

[Table 2 and Table 3 about here]

When we examine long-term 1995-2007 changes, we do not find any co-movements between our measures of exposure to climate policies and other structural shocks. Across the board, any increase in the exposure to structural transformations (ICT capital, trade or emissions intensity) leads to a decrease in hours worked. Interestingly, sectors becoming more intensive in green patents do not display any positive and significant changes in employment, while they reinforce their skill biasedness toward graduate workers and professionals.

Finally, we observe another interesting pattern for the climate-related changes in demand for skills. In contrast with findings of Vona et al. (2018a), sectors that become cleaner reduce their relative demands for technicians and middle skills and increase that for unskilled and manual workers. The behaviour of sectors changing their emissions intensities is at odds with the common wisdom that employment contractions are usually accompanied by skill upgrading. An explanation of this unexpected pattern requires a more careful treatment of the overlap among different structural shocks, which is the goal of the cluster analysis in the next section.

# 3 A taxonomy of exposure to multiple structural transformations

Isolating the associations between climate policies and workforce composition is challenging due to the contemporaneous presence of other structural drivers that have well-known biased effects on labour demand. Climate policies can either reinforce or mitigate the skill-biased effect of these changes. To consider in a compact way the overlapping of different shocks, we develop a taxonomy of sectors based on their degree of exposure to structural drivers affecting labour market outcomes. Cluster analysis is the most natural method for allowing the data reveal this taxonomy, if any.[13]

### 3.1 Cluster analysis: methodology

The variables used to build the clusters are the following: i) the capital deepening and the technological level of the sector are captured using both non-ICT and ICT capital stocks per hour worked; ii) exposure to international competition is captured by import penetration; and iii) GHG intensity and the stock of EPO climate-related patents per hours worked are, respectively, our primary and secondary proxies for exposure to climate policies.[14]

Note that the distribution of clustering variables is skewed and characterized by the presence of outliers. Therefore, as a preliminary step in the search for a meaningful sectoral taxonomy, we transform each variable in percentile ranks to avoid the formation of clusters driven by extreme values.

We cluster our country-sector pairs for each of the four years for which all data are available: 1995, 1999, 2003 and 2007. The aim of cluster analysis is to identify groups of observations that are distinct, that is, that: i) are different from the others; and ii) group together observations that are homogeneous within the cluster. We adopt a two-step procedure to identify the optimal composition of clusters, as suggested in Hair et al. (2009). As a first step, we perform hierarchical clustering to identify the 'optimal' number of clusters (Milligan and Cooper, 1985) by assessing how distinct the clusters are (see Appendix A). As a second step, we use the resulting clusters (and corresponding centroids) as a starting point for the optimal re-attribution of observations into clusters by means of non-hierarchical clustering.[15] Our favourite clustering algorithm is the average linkage algorithm, which computes the distance (squared Euclidean distance) in clustering variables across all possible pairs of individuals across different clusters and aims at minimizing distances within the clusters and, at the same time, maximizing

[13] For a similar use of cluster analysis to build a taxonomy based on skill diversity, see Consoli and Rentocchini (2016).

[14] Other variables could have been included as clustering variables, such as the total patent stock and investments in intangible capital, but at the cost of increasing complexity and losing observations.

[15] Hierarchical clustering techniques sequentially split clusters and do not allow for the re-allocation of observations across different branches of the clustering tree. Non-hierarchical clustering techniques are more flexible and allow for re-allocation of observations to render clusters more homogeneous and distinct.

distances across clusters. This procedure provides six main clusters, which are described in the following sub-sections (see Appendix A for details).

### 3.2 Profiling of clusters

Table 4 provides the description of the cluster taxonomy by reporting the average percentiles (and the median values in parentheses) of clustering variables across the six different clusters. These figures are the basis for understanding the typical features of observations belonging to different clusters and attributing a label to each cluster.

[Table 4 about here]

To evaluate the differences in clustering variables across clusters, we run five linear regressions with a clustering variable as a dependent variable and all of the cluster dummies as independent variables. Not surprisingly, given that the cluster analysis seeks to maximize the differences in clustering variables across clusters, cluster dummies are jointly (F-test) significantly different from zero for all of the clustering variables, and they explain a significant proportion of the whole variance (R squared far greater than 0.6). In the last row of the table, we also enlist pairs of clusters for which clustering variables are not significantly different (based on Scheffe's test). Note that this outcome is more frequent for ICT capital (6 of 15 possible pairwise comparisons) than for the other four clustering variables, especially the climate-related ones, corroborating the well-known fact that ICT is a general-purpose technology with a broad range of applications (Helpman, 1998).

We now discuss the features of the six clusters by combining information about the clustering variables (Table 4) with the dynamics of the clustering variables across different clusters (Figure 1). Theoretically, we should expect that being exposed to multiple shocks is worse than being exposed to a single shock because all structural transformations (except perhaps green innovations) are potentially labour saving.

[Figure 1 about here]

Clusters 1 (*Brown Global Low-tech*) and 2 (*Brown Medium-tech*) are both characterized by a medium pollution intensity. The main difference is that cluster 1 is opened to trade and is extremely low tech, while cluster 2 is medium tech and is relatively sheltered by international competition. Over time, we observe a catching-up of these two clusters regarding capital deepening and green patents. Emissions intensity, instead, declined twice as fast in cluster 1 as in cluster 2. The first cluster contains a combination of diverse sectors, including Textile and Transport Equipment, while the second cluster is more concentrated in a few sectors, such as Basic Metals, Food and Wood production (Table A2 of the Appendix A).[16] Importantly, the *Brown Medium-tech* cluster is the largest in terms of average employment share (31.2%), while the *Brown Global Low-tech* (14.8%) cluster is the fourth largest.

The third cluster (*Green Global High-tech*) resembles the second with two notable differences: i) a significantly larger share of green knowledge; and ii) a very modest GHG emissions intensity. This cluster contains the Machinery and Equipment producers, as well as some Textile, Rubber and Plastics producers (Table A2), and it is the second in terms of size with an average of 20.6% in total employment. Notably, the cluster becomes significantly greener over time, in terms of both green patents and emissions intensity.

Cluster 4 (*Exposed to Automation*) is also a large cluster with 19.5% of total employment on average. It collects observations that remain relatively, but not fully, sheltered by international competition and climate-related transformations. For this reason, we use it as a benchmark category in our regression analysis. For all of the clustering variables, the observed growth rates for this cluster resemble those experienced by other clusters.

The last two clusters (*Black and Exposed to Multiple Shocks* and *Black High-tech*) are the most polluting ones, but they represent, on average, a remarkably smaller share of hours worked (7.2% and 6.7%, respectively). Both cluster 5 and cluster 6 score high along all of the dimensions, especially climate-related ones; the only notable difference is that cluster 6 has been fully sheltered by international competition. Both clusters are very concentrated sector-wise: Chemicals and Mining for cluster 5; and Coke, Petroleum, Nuclear and Electricity Generation for cluster 6. Concerning the trends over time, cluster 6 is by and large the best performer in terms of increases in green patent intensity, while cluster 5 is an outlier in terms of increased trade exposure.

[16] Interesting, the chi-square independence test presented in Table A2 shows that both sectors and countries are not randomly assigned to clusters. While this assignment is expected for sectors, the results for countries highlight country-specific features in the incidence of structural transformations in the labor market.

## 3.3 The taxonomy at work

Before moving to our econometric analysis, in which use cluster dummies to flexibly control for exposure to structural shocks, we assess here the composition and dynamics of different clusters in terms of workforce skills. In Table 5, we observe that the composition of the labour force is different across clusters, and the differences go in the expected directions, following a general technology-skill complementarity argument. However, as evident in last three rows of the table, cluster dummies explain only a small proportion of the variance in our measures of skills, except for manual workers, and the pairwise differences across clusters are often not statistically significant, especially for managers.

[Table 5 and Figure 2 about here]

Figure 2 reports the trends in our skill measures across different clusters. According to the previous discussion, cluster 5 and, to a lesser extent, cluster 1 should be those at a higher risk of job loss since they are affected by a larger number of labour-saving shocks. We observe that hours worked declined mostly in clusters exposed to multiple shocks and international competition (1, 3, 5), although it is cluster 6 that experienced the largest employment decline. Visually, a pronounced skill upgrading is widespread, but we do not observe any striking pattern clearly related to climate-related factors, except for the switch from manual workers to technicians in cluster 6.

[Table 6 about here]

That the clusters do not reveal pronounced differences in employment patterns is also confirmed in Table 6, in which we regress the 4-year long-term changes (1995-1999, 1999-2003, 2003-2007, 2007-2011) in employment on initial cluster dummies (columns 1-2) and then on clustering variables (columns 3-4). Indeed, only cluster 1 experienced a significant decrease in employment, compared to other clusters. Importantly, the explanatory power of the initial cluster dummies alone (column 1) is greater than that of time-varying lagged clustering dummies (column 3), justifying the use of cluster dummies to consider in a flexible way the exposure to multiple shocks. Finally, the signs of the two proxies for exposure to climate policies are in line with those expected from our discussion in section 1.1: negative and significant for GHG intensity and positive and significant for green patent intensity.

We can conclude that cluster analysis provides a flexible method to control for exposure to multiple shocks, but a fully-fledged assessment of the associations of climate policies and skill-biased employment dynamics should directly include our two proxies for exposure to these policies. The next describes the methodology used to estimate such an association and the main results of the paper.

# 4 Link between climate policies and labour market outcomes

## 4.1 Empirical strategy

In this section, we study the associations between climate policies and labour market outcomes through standard econometrics tools. Our starting point is the following equation, weighted for the initial employment level of the country-sector cell to account for differences in size:

$$\Delta Y_{ijt}^{k} = \beta_1 \overline{ETS\_string}_{ijt} + \beta_2 \overline{En\_Price}_{ijt} + \beta_3 \log(EI)_{ij,t=95} + \\ +\beta_4 \log(EI)_{ij,t=95} \times \overline{EPS\_no\_ETS}_{it} + \sum_{d=1}^{6} 1_{\{i,j\} \in C_{d,t=95}} + \mu_{it} + \theta_j + \varepsilon_{ijt}, \quad (1)$$

where:

i) Our dependent variable is the 4-year change in share of labour of type $k$, i.e., $\Delta Y_{ijt}^{k}$. There are two advantages to using a long difference estimator. First, we directly estimate the permanent changes in workforce skills. Second, first differencing removes time-invariant the fixed characteristics of the country-sector pair and transforms $Y_{ijt}^{k}$ into a stationary variable.[17]

ii) The independent variables of interest are the three policies: the EU-ETS ($\overline{ETS\_string}_{ijt}$); energy prices ($\overline{En\_Price}_{ijt}$); and an index of all of the other policies except for the EU-ETS ($\overline{EPS\_no\_ETS}_{it}$).

[17] We use the Harris-Tzavalis stationarity test, which is designed for panels such as ours that have small T and large N. The null hypothesis of the unit root is rejected for all of our dependent variables in first differences, while it is not rejected for total employment in levels.

iii) $1_{\{i,j\} \in C_{d,t=95}}$ are five cluster dummies (the omitted category being cluster 4 "Exposed to automation") that consider the initial exposure and overlapping of the various structural changes discussed above. Using the initial cluster avoids the problem of endogeneity related to cluster switching, which is however not as frequent as shown in Tables A3 and A4 in Appendix A.

iv) We include the initial level of GHG intensity in logs ($\log(EI)_{ij,t=95}$) to capture the differential performance of a country-sector pair within a given cluster, depending on the initial level of GHG emission.

v) $\mu_{it}$ is a full set of country-specific year dummies that account non-parametrically for a broad range of country-specific time trends (e.g., differential effect of the great recession, general level of technology and competencies), which are likely to be correlated with both $\Delta Y_{ijt}^{k}$ and our variables of interest. Note that estimating the autonomous influence of $\overline{EPS\_no\_ETS}_{it}$ is not possible when including country-by-time dummies.[18]

vi) $\theta_j$ are sector dummies absorbing observable and unobservable sector-specific trends. We assume these trends to be linear because cluster dummies and non-parametric country trends are already intended to capture deviations from long-term sectoral patterns, such as globalization and automation.

vii) $\varepsilon_{ijt}$ is a standard error term.

Before turning to the issue of policy endogeneity, we discuss the functional form used for the three policy variables. An important issue is whether to include the policies in differences or in levels. Compared to the policy changes, policy levels have a first-order effect on the cost structure and thus on industry competitiveness, labour demand and workforce skills. For instance, the effect on costs of a given change in energy prices depends on the initial levels of energy prices. To capture synthetically both the levels and the difference effect, we compute the average of the policy of interest between the initial and final years of the time interval used for the corresponding long-difference; e.g., $\overline{En\_Price}_{ijt}$ is the average energy price between time t and time t-4.

[18] An alternative specification with orthogonal country and time dummies, in addition to $\overline{EPS\_no\_ETS}_{it}$, delivers qualitatively similar results. However, the interpretation of the coefficient associated with $\overline{EPS\_no\_ETS}_{it}$ is cumbersome here because it also captures the nonlinear component of the country-specific trends.

Another important choice regards the interactions between the policy variables, on the one hand, and the index of emissions intensity discussed above, on the other. To avoid multicollinearity, we decide to include only the interaction between $\overline{EPS\_no\_ETS}_{it}$ and the initial GHG emission intensity of the sector-country pair. Indeed, unlike energy prices and ETS stringency, the EPS index varies only at the country level, so it is not possible to identify its autonomous effect once we include non-parametric country trends. This choice is corroborated by an additional econometric exercise in which we estimate variants of equation 1 with only one policy at a time and its interaction with GHG intensity. The results, reported in Table B2 of Appendix B, justify our choice as long as, in most cases, the interactions between $\overline{ETS\_string}_{ijt}$ (or $\overline{En\_Price}_{ijt}$), on the one hand, and initial pollution (or energy intensity), on the other, are not statistically significant at conventional levels.

There are several concerns in interpreting the policy coefficients as causal. First, lobbying efforts have warranted generous policy exemptions in sectors in which emission reductions were most needed. This issue is particularly relevant for the EU-ETS and the other policies included in the EPS index. Second, energy prices are also correlated with the error term because quantity discounts render the price of energy lower for large consumers. Moreover, changes in the energy mix are likely to be correlated with changes in the input mix, including the skill mix.

Our strategy is to overcome these issues with instrumental variables that are standard in the literature for two of three endogenous variables, that is, energy prices and the EPS index. For the third variable, ETS stringency, since instrumenting is not straightforward[19], we slightly amend equation 1, replacing the measures of ETS stringency and the variable $\overline{EPS\_no\_ETS}_{it}$ with the standard index ($\overline{EPS}_{it}$), including the score for carbon trading schemes:

$$\Delta Y_{ijt}^{k} = \beta_1 \overline{EPS}_{it} + \beta_2 \overline{En\_Price}_{ijt} + \beta_3 \log(EI)_{ij,t=95} + \beta_4 \log(EI)_{ij,t=95} \times \overline{EPS}_{it} + \\ + \sum_{d=1}^{6} 1_{\{i,j\} \in C_{d,t=0}} + \mu_{it} + \mu_j + \varepsilon_{ijt}. \quad (2)$$

[19] Since the EU-ETS is a European policy, an ideal instrument for $\overline{ETS\_string}_{ijt}$ does not exist at the country-by-sector level because industrial groups directly lobby at the EU level to alter the effective stringency of the ETS.

The instrument of the interaction term $\log(EI)_{ij,t=95} \times \overline{EPS}_{it}$ is built as a combination of two variables. The average GHG of non-EU, high-income OECD countries (US, Japan, Canada, South Korea, New Zealand, Australia) in 1995 is the instrument for $\log(EI)_{ij,t=95}$, while we use the EPS in all EU countries except for *i* as an instrument for $\overline{EPS}_{it}$. The exclusion restriction is satisfied by construction since we switch off the time-varying idiosyncratic characteristics of each specific country-sector pair. At the sector level, the average GHG exposure in other countries should reflect deep technological factors, rather than idiosyncratic country characteristics. At the country and time levels, the policy variation in all of the other countries isolates the EU-driven, arguably more exogenous, component of national climate policies.

The instrument of energy prices exploits a classical shift-share logic (Bartik, 1991) that becomes common in related papers estimating the impacts of energy prices (Lin, 2008; Marin and Vona, 2017; Sato et al., 2015). The instrument is obtained by multiplying the vector of sectoral shares of each energy source (coal, gas, electricity, etc.) at time 0 (1995 in our case) by the vector of the time-varying prices of each source at the national level. The exclusion restriction is satisfied as long as two conditions hold: i) the national prices for each source are independent of sector-level idiosyncratic demand shocks; and ii) the initial energy mix of the sector does not affect long-term employment dynamics. The inclusion of sector dummies, capturing sector-level time trends, and of country-year dummies, implicitly capturing the idiosyncratic country-specific features of large energy consumers (e.g., utilities), ensures that these conditions are satisfied.

To provide context to our results, Table B1 in the Appendix shows that all of our policy measures increased substantially over time. The average energy price increased by a remarkable 78%, while EPS stringency tripled between 1995 and 2011. ETS stringency jumped from zero to a positive value between 2003 and 2007 with the beginning of the first phase (2005) and then further increased in 2011 with the beginning of the second phase (2008).

## 4.2 Estimation results

Table 7 presents the OLS estimations of equation 1, while Table 8 contains the IV counterpart. In both tables, the results are presented for the changes in five dependent variables: the log of total hours worked and the shares of hours worked by managers, professionals, technicians and manual workers. Clearly, while the IV specification provides a better estimation of the causal effects of climate policies, the OLS specification has a number of advantages worth mentioning. Above all, it allows for separately identifying the coefficient associated with the EU-ETS. Moreover, it is amenable to extensions to include the other variable that, as we discussed above, could shape the associations between climate policies and employment dynamics, that is, green patent intensity. Finally, it is of its own interest for evaluating the extent to which the OLS coefficients are biased.

[Table 7 and Table 8 about here]

Both Table 7 and Table 8 clearly highlight the two main findings of our paper. First, climate policies do not add to the observed decline in employment for polluting industries, as attested by the negative and significant coefficient of the initial GHG intensity, which resonates with the historical decline in energy-intensive industries in Europe (Rosés and Wolf, 2018). If anything, a more stringent EPS mitigates such a decline as shown by the positive and significant coefficient associated with the interaction between EPS and GHG intensity. Second, the missing association between climate policies and total employment masks significant heterogeneity across occupational groups. Similar to other structural transformations in the labour market, climate policies create winners and losers across occupations within a given industry, rather than directly affecting the total level of industrial employment.

Broadly speaking, the skill bias of climate policies is aligned with that of globalization and automation: manual workers are the losers for all policies considered, while abstract professions (especially when considering energy prices) and managers (especially for ETS stringency) are the winners. A peculiar aspect of climate policies is the pronounced bias in favour of technical occupations (ISCO3), such as Physical and Engineering Science Technicians, Process Control Technicians and Government Regulatory Associate Professionals, in agreement with findings of Vona et al. (2018a) for the Clean Air Act in the USA. Indeed, the share of technicians significantly increases with energy prices and the EPS index.

For energy prices, we can directly compare the IV and OLS results.[20] Interestingly, the OLS coefficients underestimate the skill-bias effects, especially for technicians and manual workers. By retaining only the exogenous variation in energy prices, the shift-share instrument dampens the sources of organizational inertia, slowing the skill upgrading required by energy-saving technologies and organizational practices. For the other two policies, a direct comparison between OLS and IV is not possible because we estimate the ETS inside the EPS index.

The magnitude of the estimated coefficients allows us to assess the policy relevance of our estimates. We use the IV specification to quantify the main effects of interest. Among the different policies, energy price has the strongest effect on workforce skills. An increase of 10% in the mean energy price explains 17.9% of the average increase in the share of technicians. The corresponding effects are slightly smaller but still economically significant: for professionals, 13.2% of their increase; and for manual workers, 13.1% of their decrease. The effects on technicians and manual workers are reinforced by the increase in EPS. For an industry at the mean level of GHG intensity, the average 4-year increase in EPS accounts for 17.3% of the increase in the share of technicians and 14.2% of the decline in the share of manual workers. In summary, 2/3 of the increase in the share of technicians and slightly more than ¼ of the decrease of the share of manual workers are explained by climate policies.

This pronounced skill bias in favour of technical, scientific and engineering skills (i.e., engineers are a substantial proportion of professionals) bears policy relevance given the increase in carbon prices planned by European countries, both at the national (i.e., carbon taxes) and EU levels (i.e., carbon price floors). Our results indicate that investing in technical and engineering skills can significantly reduce the socio-economic costs of a high carbon price scenario. On the one hand, expanding the supply of such skills will decrease the hourly wages of technical workers and thus production costs. On the other hand, retraining manual workers for middle-skill technical jobs for clean and energy-saving tasks will provide fresh opportunities to workers who bear the bulk of the costs of all of the recent structural transformations in the labour market.

[20] Note that both instruments are strong, as testified to by an F of 270.9 for the instrument of energy price and 181.9 for the instrument of $\log(EI)_{ij,t=95} \times \overline{EPS}_{it}$.

An interesting result that deserves further examination is the mitigating effect of EPS on total employment in polluting industries. We examine how the combined effects of the initial GHG intensity ($\hat{\beta}_3 \log(EI)_{ij,t=95} + \hat{\beta}_4 \log(EI)_{ij,t=95} \times \overline{EPS}_{it}$) varies by replacing the averages values $\overline{EPS}_{it}$ and $\log(EI)_{ij,t=95}$ within each decile of initial GHG intensity. We find that the monotonicity of the relationship is preserved: the fraction of the employment decrease explained by GHG intensity is nearly 0 at the first decile, while it is 11.7% at the median and 44.1% for the most polluting observations at the $9^{\text{th}}$ decile. To interpret this result, note that there is a modest but negative correlation (-0.11) between initial GHG intensity and EPS stringency, as well as a positive and significant correlation between the green patent stock per capita and EPS stringency (0.30). Taken together, this evidence suggests that green tech leaders might be more willing to adopt stringent climate policies that can mitigate the long-term employment decline in polluting industries.

We formally test this conjecture in estimating an augmented specification with a full set of interactions between EPS policy stringency (interacted with initial GHG intensity) and a "green tech" dummy variable equal to one for countries sufficiently close to the green technological frontier.[21] For the sake of parsimony, we include only the interaction of the green tech dummy with EPS and the initial GHG terms. Since it would be nearly impossible to find satisfactory instruments for all of the interactions, we estimate this equation with OLS.

[Table 9 about here]

Table 9 presents the results of this exercise. Examining the interaction terms between EPS and the green-tech dummy, the only statistically significant result corroborates our main findings, that is, the share of technicians increases more with climate policies in countries closer to the green technological frontier. Examining the interaction terms between GHG intensity and the green-tech dummy, we find no support for our hypothesis that green high-tech countries are able to mitigate the negative relationship between initial GHG intensity and total employment. This outcome is in contrast with the positive association

[21] We define the green tech dummy equal to one for a country sufficiently close to the green technological frontier in sector *j*. The green technological frontier is defined as the ratio between the green patent stock per capita and the maximum green patent stock in this sector year. The threshold defining the green tech dummy is set at a jump in the distribution of the variable "distance to the green frontier", i.e., distance=0.67.

between employment and the green patent stock per worker that we found in Table 6. This finding indicates that the inclusion of country-by-year and cluster dummies killed this positive and significant association. Further research is required to better understand whether this result is reliable or not, considering the problems in our measurement of green leadership, or whether it is a mismatch between green inventors and polluting industries.[22]

Appendix B replicates Table 7 and Table 8 for different dependent variables: labour productivity (value added per hour worked or gross output per hour worked) and the shares of high-, medium- and low-skilled workers defined in terms of educational attainment as, respectively, university graduates, high-school graduates and lower secondary graduates or less (Tables B3 and B4). The main takeaways from these tables are that climate policies have no effect on labour productivity and that skill biases are less evident when using an education-based measurement of skills. While the second finding corroborates previous research in labour economics that suggests using task- and occupation-based measures of skills, instead of education-based ones (Acemoglu and Autor, 2011), the first is not fully consistent with findings of Albrizio et al. (2017), who used Total Factor Productivity and a distance-to-the-frontier specification of productivity growth. We leave a more detailed examination of the effects of climate policies on labour productivity to future research.

# 5 Concluding remarks

Our paper investigates the effects of climate policies on the demand for workers with different skills. We find that the skill bias of climate policies mostly consists of a substitution of technical and professional workers for manual ones. While the main skill-bias pattern is broadly consistent with that of other structural transformations, such as globalization and the ICT revolution, we observe for climate policies a more marked re-direction toward technical and scientific skills (i.e., non-routine cognitive skills), compared to managerial and social skills (i.e., non-routine interactive skills). Since this result is broadly consistent with that of Vona et al. (2018a) for US regions, we argue that

[22] Producers of green technologies are often not in the most polluting sectors, as confirmed by the low weighted correlation between initial GHG intensity and the green patent stock per capita, i.e., 0.17.

training investments for greening our economy should start from the technical and scientific disciplines.

Importantly, a highly heterogeneous effect of climate policies across workers' groups does not match the induced decrease in total employment. Climate policies did not contribute to the swift decline in employment in polluting industries, in contrast with the findings of the micro-econometric literature. This gap between macro and micro findings reveals once again an aggregation bias in the evaluation of the economic effects of environmental policies (e.g., Levinson and Taylor, 2008; Dechezleprêtre and Sato, 2017). Nevertheless, the mechanisms through which modest to large effects for the treated companies in polluting sectors translate into negligible effects at the sector-level are not clear. In our paper, we investigate the mediating effects of green technology, but we do not find conclusive evidence after controlling for sector and country effects.

This paper is a first step toward understanding of distributional labour market impacts of environmental policies. Although we find evidence of distributional impacts in terms of changes in demand for different groups of workers, the next step should be to examine earnings' effects. In this work, we refrain from examining the impact of climate policies on earnings for two reasons. First, estimating wage premiums for specific skill categories at the industry level introduces additional sources of bias related to compositional effects and self-selection regarding unobservable workers' characteristics. Second, institutional differences in wage-setting rules across EU countries should be considered, which would add another layer of complexity to our analysis. This analysis is left for future research using matched employer-employee data that are better suited for an analysis of earnings' dynamics (see Walker, 2013).

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# Tables and figures

Table 1 – Definition of variables

| Variable | Source | Years | Description | Mean | Median | Standard deviation |
|---|---|---|---|---|---|---|
| ICT capital intensity | EU KLEMS | 1995-2007 | Stock of ICT capital per hour worked. | 1.4125 | 0.5748 | 3.3224 |
| Non-ICT capital intensity | EU KLEMS | 1995-2007 | Stock of non-ICT capital per hour worked. | 9.2597 | 3.8193 | 21.0790 |
| Import penetration | OECD STAN | 1995-2009 | Import / (Output + Import – Export). | 0.5672 | 0.4358 | 1.4739 |
| Climate patent stock per empl | OECD-REGPAT; Lybbert and Zolas (2014); OECD-ENVTECH | 1995-2011 | Stock of EPO patent applications in climate-related technologies. Patents are attributed to the sectors according to the IPC-ISIC concordance table proposed by Lybbert and Zolas (2014). Climate related technologies are identified following the IPC- and CPC-based taxonomy proposed by the OECD ENVTECH Indicator. | 2.5391 | 0.3805 | 6.0176 |
| GHG/VA | WIOD | 1995-2009 | Greenhouse gas emissions (CO2, CH4 and N2O expressed in CO2 equivalent tons) per real value added. The numerator also includes emissions embodied in the purchase of electricity (based on input-output estimates). | 5.4161 | 0.7988 | 26.2186 |
| Managers | EU LFS | 1995-2011 | Share of managers (ISCO 1) | 0.0751 | 0.0649 | 0.0447 |
| Professionals | EU LFS | 1995-2011 | Share of professionals (ISCO 2) | 0.0783 | 0.0562 | 0.0660 |
| Technicians | EU LFS | 1995-2011 | Share of technicians (ISCO 3) | 0.1483 | 0.1250 | 0.1128 |
| Manual | EU LFS | 1995-2011 | Share of manual workers (ISCO 7, 8 and 9) | 0.5903 | 0.6150 | 0.1601 |
| High education | EU LFS | 1995-2011 | Share of workers with tertiary (ISCED) education | 0.1903 | 0.1653 | 0.1220 |
| Mid education | EU LFS | 1995-2011 | Share of workers with upper secondary (ISCED) education | 0.5201 | 0.5084 | 0.1656 |
| Low education | EU LFS | 1995-2011 | Share of workers with secondary or lower (ISCED) education | 0.2895 | 0.2620 | 0.1585 |
| Hours worked | WIOD | 1995-2011 | Hours worked by employed and self employed workers | 251.1599 | 117.8889 | 335.7974 |
| Environmental Policy Stringency (EPS) | OECD EPS Indicator | 1995-2011 | Environmental Policy Stringency indicator (CO2 tax and CO2 trading excluded). The indicator has been standardized to range between 0 and 1 | 0.4488 | 0.1671 | 0.4811 |
| ETS stringency | EU ETS Registry; WIOD | 1995-2011 | Ratio between GHG emissions of establishments that participate to the EU ETS over total GHG emissions of the sector | 0.4839 | 0.0000 | 0.4321 |
| Energy price | IEA; WIOD | 1995-2011 | Sector-country-year specific price of energy inputs. The price is the weighted average of country-year fuel specific energy prices, using country-sector-year specific energy mix as weight. | 0.2484 | 0.3165 | 0.2298 |

Table 2 – Correlation between measures of shocks and labour force composition (levels for years 1995, 1999, 2003 and 2007)

| | log(ICT capital intensity) | log(Non-ICT capital intensity) | Import penetration | Climate patent stock per empl | log(GHG/VA) |
|---|---|---|---|---|---|
| log(ICT capital intensity) | 1.0000 | | | | |
| log(Non-ICT capital intensity) | 0.6763 | 1.0000 | | | |
| Import penetration | 0.0886 | *-0.0018* | 1.0000 | | |
| Climate patent stock per empl | 0.5005 | 0.3371 | 0.0670 | 1.0000 | |
| log(GHG/VA) | -0.1805 | 0.1671 | -0.1621 | *0.0357* | 1.0000 |
| Managers | 0.3385 | 0.1346 | 0.0774 | 0.1039 | *-0.0350* |
| Professionals | 0.6127 | 0.2932 | 0.1399 | 0.3530 | -0.2452 |
| Technicians | 0.4324 | 0.2501 | 0.0702 | 0.3334 | -0.0913 |
| Manual | -0.6571 | -0.3923 | -0.0889 | -0.3894 | 0.1109 |
| High education | 0.6708 | 0.3665 | 0.1415 | 0.4474 | -0.2125 |
| Mid education | -0.1983 | -0.2276 | *0.0265* | 0.2574 | 0.1207 |
| Low education | -0.2034 | *-0.0021* | -0.1054 | -0.4866 | *0.0115* |

Correlations weighted by hours worked. Correlation coefficients not significant at 5% level in italics

Table 3 – Correlation between measures of shocks and labour force composition (long differences 1995-2007)

| | Δ log(ICT capital intensity) | Δ log(Non-ICT capital intensity) | Δ Import penetration | Δ Climate patent stock per empl | Δ log(GHG/VA) |
|---|---|---|---|---|---|
| Δ log(ICT capital intensity) | 1.0000 | | | | |
| Δ log(Non-ICT capital intensity) | 0.2189 | 1.0000 | | | |
| Δ Import penetration | 0.1513 | *0.1085* | 1.0000 | | |
| Δ Climate patent stock per empl | *-0.0541* | *0.0383* | *0.0334* | 1.0000 | |
| Δ log(GHG/VA) | *-0.0065* | -0.1870 | *-0.1282* | 0.1366 | 1.0000 |
| Δ log(hours worked) | -0.2494 | -0.3454 | -0.2038 | *-0.1236* | -0.1482 |
| Δ Managers | 0.259 | *0.0767* | *-0.0036* | *-0.0234* | *-0.0695* |
| Δ Professionals | *-0.1341* | *-0.0352* | *-0.0423* | *0.1198* | *-0.0719* |
| Δ Technicians | *0.1233* | *0.0248* | *-0.0438* | *-0.0701* | 0.2587 |
| Δ Manual | -0.1712 | *-0.0455* | *0.0276* | *-0.0138* | -0.1847 |
| Δ High education | 0.1890 | *-0.0494* | *0.0430* | 0.1587 | *0.0305* |
| Δ Middle education | *-0.0076* | *-0.0305* | *-0.0576* | *-0.0454* | 0.2252 |
| Δ Low education | *-0.1302* | *0.0614* | *0.0174* | *-0.0749* | -0.2116 |

Correlations weighted by hours worked in 1995. Correlation coefficients not significant at 5% level in italics

Table 4 – Definition and profiling of clusters (average percentile of clustering variables, median value of variables in parenthesis)

| Cluster | ICT K intensity | Non-ICT K intensity | Import penetration | Climate patent stock per empl | GHG/VA | n | Empl share |
|---|---|---|---|---|---|---|---|
| 1 Brown Global Low-tech | 18.43<br>(0.169) | 15.84<br>(1.069) | 67.23<br>(0.582) | 19.76<br>(0.023) | 47.8<br>(1.121) | 164 | 0.1477 |
| 2 Brown Medium-tech | 23.72<br>(0.239) | 32.71<br>(2.452) | 24.48<br>(0.215) | 36.54<br>(0.104) | 57.15<br>(1.627) | 144 | 0.3120 |
| 3 Green Global High-tech | 64.09<br>(1.031) | 45.4<br>(3.328) | 77.16<br>(0.726) | 62.3<br>(0.779) | 15.4<br>(0.315) | 166 | 0.2062 |
| 4 Exposed to Automation | 65.5<br>(0.901) | 62.39<br>(4.844) | 32.21<br>(0.301) | 34.12<br>(0.085) | 38.34<br>(0.881) | 121 | 0.1950 |
| 5 Black and Exposed to Multiple Shocks | 68.03<br>(1.212) | 79.97<br>(10.590) | 74.06<br>(0.660) | 72.33<br>(1.655) | 69.45<br>(3.249) | 116 | 0.0724 |
| 6 Black High-tech | 73.53<br>(1.662) | 83.03<br>(19.493) | 19.64<br>(0.182) | 85.12<br>(4.794) | 85.73<br>(11.170) | 129 | 0.0667 |
| Total | 50<br>(0.575) | 50<br>(3.819) | 50<br>(0.436) | 50<br>(0.290) | 50<br>(1.265) | 840 | 1 |
| F test of joint significance of cluster dummies | 332.73*** | 520.09*** | 407.15*** | 392.07*** | 785.62*** | | |
| R squared of the regression | 0.6299 | 0.7162 | 0.6989 | 0.6374 | 0.6167 | | |
| Not statistically different (p-value>0.05) clusters according to Scheffe's test | 1-2, 3-4, 3-5, 4-5, 5-6 | 5-6 | 2-6 | - | - | | |

Figure 1 – Average period-to-period growth in clustering variables by beginning-of-period cluster

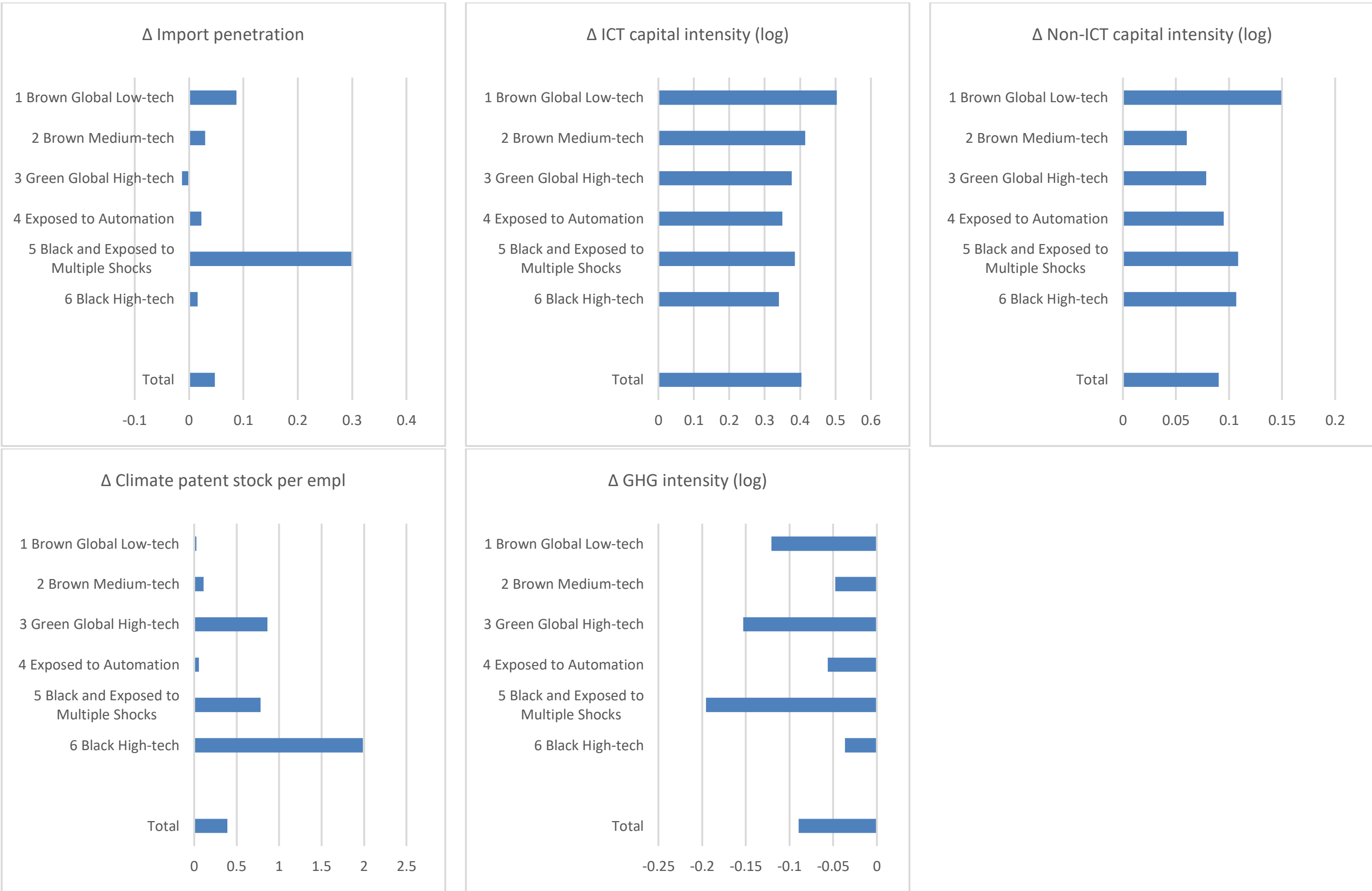


Table 5 – Labour market characteristics of clusters

| Cluster | Managers | Professionals | Technicians | Manual | High-education | Mid-education | Low-education |
|---|---|---|---|---|---|---|---|
| 1 Brown Global Low-tech | 0.0607 | 0.0396 | 0.1045 | 0.7022 | 0.1023 | 0.5760 | 0.3218 |
| 2 Brown Medium-tech | 0.0608 | 0.0293 | 0.0889 | 0.6850 | 0.1031 | 0.4640 | 0.4330 |
| 3 Green Global High-tech | 0.0831 | 0.1162 | 0.1749 | 0.5188 | 0.2504 | 0.4993 | 0.2503 |
| 4 Exposed to Automation | 0.0772 | 0.0799 | 0.1260 | 0.5998 | 0.1906 | 0.4838 | 0.3256 |
| 5 Black and Exposed to Multiple Shocks | 0.0933 | 0.1091 | 0.1869 | 0.4810 | 0.2556 | 0.4839 | 0.2604 |
| 6 Black High-tech | 0.0744 | 0.0913 | 0.1757 | 0.5144 | 0.2255 | 0.5324 | 0.2421 |
| Total | 0.0718 | 0.0685 | 0.1291 | 0.6105 | 0.1696 | 0.4977 | 0.3327 |
| F test of joint significance of cluster dummies | 9.27*** | 58.63*** | 43.42*** | 83.43*** | 79.77*** | 2.89** | 20.77*** |
| R squared of the regression | 0.0399 | 0.1990 | 0.1906 | 0.3307 | 0.2811 | 0.0584 | 0.1306 |
| Not statistically different (p-value>0.05) clusters according to Scheffe's test | 1-2, 1-4, 1-5, 1-6, 2-4, 2-5, 2-6, 3-4, 3-5, 3-6, 4-5, 4-6, 5-6 | 1-2, 3-4, 3-5, 3-6, 4-5, 4-6, 5-6 | 1-2, 1-4, 2-4, 3-4, 3-5 | 1-2, 3-4, 3-5 | 1-2, 3-4, 3-5, 5-6 | 2-3, 2-4, 2-5, 2-6, 3-4, 3-5, 3-6, 4-5, 4-6, 5-6 | 1-3, 1-4, 1-5, 3-4, 3-5, 4-5, 5-6 |

Figure 2 – Average period-to-period growth in labour-related measures by beginning-of-period cluster

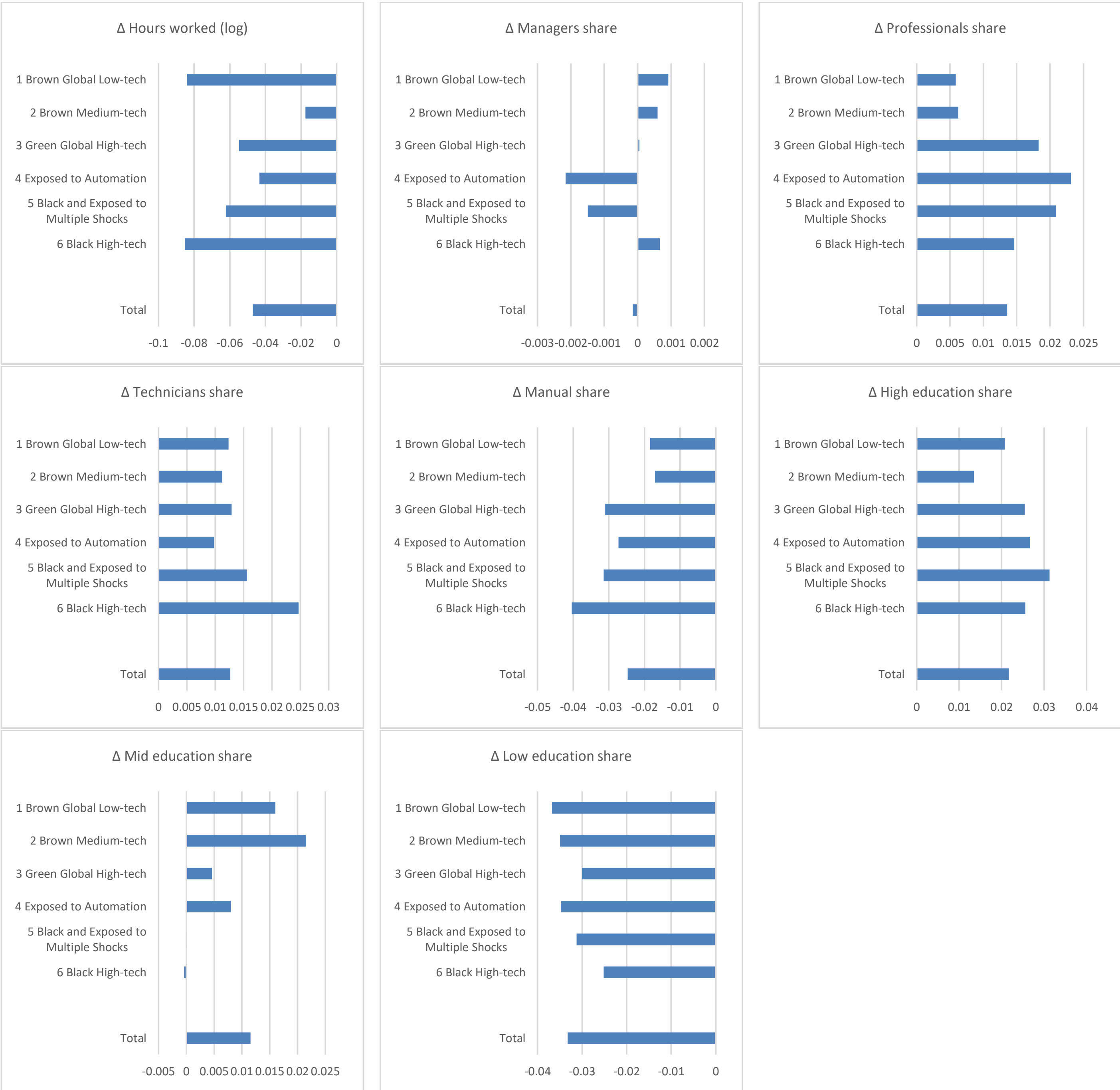

Table 6 – Predictive power of cluster dummies vs clustering variables

| Dep. var: Δ log(hours worked) | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| 1 Brown Global Low-tech | -0.0824*** | -0.0769*** | | |
| | (0.0315) | (0.0267) | | |
| 2 Brown Medium-tech | -0.0115 | -0.0106 | | |
| | (0.0148) | (0.0141) | | |
| 3 Green Global High-tech | -0.0118 | 0.00555 | | |
| | (0.0203) | (0.0127) | | |
| 4 Exposed to Automation | [base cat] | [base cat] | | |
| 5 Black and Exposed to Multiple Shocks | -0.00870 | 0.00210 | | |
| | (0.0146) | (0.0153) | | |
| 6 Black High-tech | 0.00196 | 0.0126 | | |
| | (0.0187) | (0.0222) | | |
| Import penetration | | | -0.0112 | -0.0111 |
| | | | (0.00951) | (0.00890) |
| log(ICT K intensity) | | | -0.0135 | 0.0221* |
| | | | (0.0135) | (0.0119) |
| log(Non-ICT K intensity) | | | 0.0183 | 0.00753 |
| | | | (0.0122) | (0.0111) |
| Climate pat. stock per empl. | | | 0.00948*** | 0.00947*** |
| | | | (0.00316) | (0.00269) |
| log(GHG/VA) | | | -0.0106* | -0.0130** |
| | | | (0.00573) | (0.00626) |
| Controls | Year dummies | Country, sector and year dummies | None | Country, sector and year dummies |
| R squared | 0.143 | 0.223 | 0.132 | 0.240 |
| N | 840 | 840 | 840 | 840 |

OLS regressions on stacked differences (1995-1999; 1999-2003; 2003-2007; 2007-2011) weighted by hours worked in the first year of each time window. Standard errors clustered by sector-country in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Table 7 – Baseline estimates

| | (1) Δ log(hours worked) | (2) Δ Managers | (3) Δ Professionals | (4) Δ Technicians | (5) Δ Manual |
|---|---|---|---|---|---|
| Log of GHG intensity (1995) | -0.0385** | 0.000752 | 0.00146 | -0.00910** | 0.00826** |
| | (0.0168) | (0.00218) | (0.00303) | (0.00408) | (0.00394) |
| Average (t, t-4) energy price | -0.0824 | -0.00583 | 0.0402*** | 0.0374* | -0.0524** |
| | (0.0749) | (0.0116) | (0.0125) | (0.0226) | (0.0256) |
| Average (t, t-4) ETS stringency | -0.0310 | 0.0121* | 0.00731 | -0.00131 | -0.0221** |
| | (0.0425) | (0.00656) | (0.0109) | (0.0131) | (0.00993) |
| Average (t, t-4) EPS | 0.0668*** | -0.00202 | -0.00310 | 0.0179** | -0.0130** |
| x Log of GHG intensity (1995) | (0.0219) | (0.00330) | (0.00487) | (0.00691) | (0.00612) |
| R squared | 0.522 | 0.486 | 0.491 | 0.378 | 0.415 |
| N | 840 | 840 | 840 | 840 | 840 |

OLS regressions on stacked differences (1995-1999; 1999-2003; 2003-2007; 2007-2011) weighted by hours worked in the first year of each time window. Standard errors clustered by sector-country in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. All regressions include country-specific time dummies, sector dummies and initial (1995) cluster dummies.

Table 8 – Baseline estimates – instrumental variables

| | (1) Δ log(hours worked) | (2) Δ Managers | (3) Δ Professionals | (4) Δ Technicians | (5) Δ Manual |
|---|---|---|---|---|---|
| Log of GHG intensity (1995) | -0.0658*** | -0.00159 | -0.00217 | -0.00777 | 0.0145*** |
| | (0.0236) | (0.00231) | (0.00292) | (0.00477) | (0.00554) |
| Average (t, t-4) energy price | 0.0353 | -0.0139 | 0.0412*** | 0.0494** | -0.0724*** |
| | (0.0916) | (0.0123) | (0.0132) | (0.0233) | (0.0278) |
| Average (t, t-4) EPS (with ETS) | 0.124*** | 0.00254 | 0.00401 | 0.0162** | -0.0267*** |
| x Log of GHG intensity (1995) | (0.0392) | (0.00420) | (0.00471) | (0.00803) | (0.0102) |
| R squared | 0.508 | 0.481 | 0.489 | 0.377 | 0.410 |
| N | 840 | 840 | 840 | 840 | 840 |

IV regressions on stacked differences (1995-1999; 1999-2003; 2003-2007; 2007-2011) weighted by hours worked in the first year of each time window. Standard errors clustered by sector-country in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. All regressions include country-specific time dummies, sector dummies and initial (1995) cluster dummies. F test of excluded IV: 33.35

Table 9 – Role of technology

| | (1) Δ log(hours worked) | (2) Δ Managers | (3) Δ Professionals | (4) Δ Technicians | (5) Δ Manual |
|---|---|---|---|---|---|
| Distant from climate tech frontier, t-4 (dummy) | -0.0307 | 0.0319* | 0.0104 | -0.0396 | 0.0315 |
| | (0.125) | (0.0183) | (0.0380) | (0.0298) | (0.0480) |
| Log of GHG intensity (1995) | -0.0412** | 0.00111 | 0.00148 | -0.0102** | 0.00874** |
| | (0.0169) | (0.00231) | (0.00302) | (0.00403) | (0.00399) |
| Log of GHG intensity (1995) x | -0.00768 | -0.0104 | 0.00132 | 0.00700 | -0.00729 |
| Distant from climate tech frontier, t-4 (dummy) | (0.0361) | (0.00633) | (0.00996) | (0.0111) | (0.0136) |
| Average (t, t-4) energy price | -0.0916 | -0.00665 | 0.0410*** | 0.0354 | -0.0519** |
| | (0.0743) | (0.0116) | (0.0123) | (0.0225) | (0.0257) |
| Average (t, t-4) ETS stringency | -0.0491 | 0.0113* | 0.00877 | -0.00569 | -0.0213** |
| | (0.0410) | (0.00673) | (0.0112) | (0.0131) | (0.00995) |
| Average (t, t-4) EPS | 0.0823*** | -0.00227 | -0.00418 | 0.0224*** | -0.0144** |
| x Log of GHG intensity (1995) | (0.0242) | (0.00373) | (0.00527) | (0.00722) | (0.00644) |
| Average (t, t-4) EPS | 0.164 | -0.0456 | -0.0258 | 0.0866* | -0.0475 |
| x Distant from climate tech frontier, t-4 (dummy) | (0.247) | (0.0307) | (0.0565) | (0.0480) | (0.0667) |
| Average (t, t-4) EPS x Log of GHG intensity (1995) | -0.0486 | 0.0142 | 0.00342 | -0.0254 | 0.0134 |
| x Distant from climate tech frontier, t-4 (dummy) | (0.0687) | (0.0101) | (0.0148) | (0.0172) | (0.0197) |
| R squared | 0.531 | 0.487 | 0.493 | 0.389 | 0.416 |
| N | 840 | 840 | 840 | 840 | 840 |

OLS regressions on stacked differences (1995-1999; 1999-2003; 2003-2007; 2007-2011) weighted by hours worked in the first year of each time window. Standard errors clustered by sector-country in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. All regressions include country-specific time dummies, sector dummies and initial (1995) cluster dummies.

# Appendix A - Details on the cluster analysis

## Optimal number of clusters

The criteria to be used to select the ideal number of clusters are two: i) clusters should be distinct one from the other; and ii) individuals within the cluster should be similar. Even though there is no conclusive test to identify the optimal number of clusters, there are rules of the thumb based on the Pseudo T-squared statistics, the Je(2)/Je(1) statistics and the Chalinski-Harabasz pseudo F statistics (Table A1).[1] These statistics provide indications on how distinct different cluster solutions are. More specifically, Milligan and Cooper (1985) suggest to select the number of clusters for which: i) the Pseudo T-squared is a local minimum (in our case, the 6-clusters solution); ii) the Je(2)/Je(1) statistics is large and a local maximum (6-clusters solution); iii) the Chalinski-Harabasz pseudo F statistics is the largest across different options (4-clusters solution if we exclude *a priori* the 3-clusters solution). Overall, despite the failure to identify a favourite solution based on the Chalinski-Harabasz pseudo F statistics, the other two tests suggest that the 6-cluster solution is the one with the most distinct clusters.

Table A1 - Stopping rules for hierarchical clustering

| N of clusters | Je(2)/Je(1) | Pseudo T squared | Calinski-Harabasz pseudo F |
|---|---|---|---|
| 3 | 0.9885 | 4.69 | 355.48 |
| 4 | 0.8572 | 47.48 | 239.75 |
| 5 | 0.7684 | 7.53 | 202.19 |
| 6 | 0.8448 | 4.23 | 163.47 |
| 7 | 0.8433 | 74.68 | 136.86 |
| 8 | 0.6635 | 130.87 | 139.16 |
| 9 | 0.9428 | 8.8 | 152.46 |

[1] For the purpose of our analysis, we narrow down the range of possible clusters numbers to be between 4 and 8.

Table A2 - Distribution across clusters and: year, sector, country

| | 1 Brown Global Low-tech | 2 Brown Medium-tech | 3 Green Global High-tech | 4 Exposed to Automation | 5 Black and Exposed to Multiple Shocks | 6 Black High-tech |
|---|---|---|---|---|---|---|
| Year<br>*Chi square test of independence: 48.31* | | | | | | |
| 1995 | 54 | 57 | 27 | 20 | 22 | 30 |
| 1999 | 44 | 38 | 39 | 32 | 25 | 32 |
| 2003 | 38 | 27 | 45 | 33 | 33 | 34 |
| 2007 | 28 | 22 | 55 | 36 | 36 | 33 |
| Sector (NACE rev 1.1)<br>*Chi square test of independence: 1760.69* | | | | | | |
| C - Mining and Quarrying | 10 | 4 | | | 37 | 5 |
| 15-16 - Food, Beverages and Tobacco | | 22 | | 32 | 2 | |
| 17-19 - Textiles and Textile; Leather and Footwear | 34 | 5 | 17 | | | |
| 20 - Wood and Products of Wood and Cork | 11 | 32 | 6 | 7 | | |
| 21-22 - Pulp, Paper, Paper, Printing and Publishing | 8 | 4 | | 43 | 1 | |
| 23 - Coke, Refined Petroleum and Nuclear Fuel | 1 | 1 | | 1 | 12 | 41 |
| 24 - Chemicals and Chemical Products | 5 | | 2 | 3 | 46 | |
| 25 - Rubber and Plastics | 12 | 6 | 22 | 16 | | |
| 26 - Other Non-Metallic Mineral | | 22 | | | 3 | 31 |
| 27-28 - Basic Metals and Fabricated Metal | 8 | 26 | 4 | 3 | 13 | 2 |
| 29 - Machinery, Nec | 11 | 4 | 40 | | 1 | |
| 30-33 - Electrical and Optical Equipment | 8 | | 48 | | | |
| 34-35 - Transport Equipment | 24 | 1 | 20 | 11 | | |
| 36-37 - Manufacturing, Nec; Recycling | 32 | 12 | 7 | 5 | | |
| E - Electricity, Gas and Water Supply | | 5 | | | 1 | 50 |
| Country<br>*Chi square test of independence: 407.37* | | | | | | |
| Austria | 6 | 8 | 18 | 7 | 11 | 10 |
| Belgium | 5 | | 23 | 7 | 17 | 8 |
| Czech Republic | 38 | 15 | | 1 | 2 | 4 |
| Germany | 7 | 15 | 8 | 11 | 7 | 12 |
| Denmark | 2 | 1 | 30 | 6 | 7 | 14 |
| Spain | 8 | 18 | 8 | 13 | 4 | 9 |
| Finland | 6 | 5 | 13 | 13 | 9 | 14 |
| France | 3 | 9 | 12 | 16 | 8 | 12 |
| Hungary | 40 | 14 | | | 2 | 4 |
| Ireland | 20 | 10 | 7 | 10 | 8 | 5 |
| Italy | 4 | 29 | 5 | 5 | 8 | 9 |
| Netherlands | 10 | | 18 | 8 | 15 | 9 |
| Sweden | 7 | 6 | 13 | 15 | 12 | 7 |
| United Kingdom | 8 | 14 | 11 | 9 | 6 | 12 |
| Total | 164 | 144 | 166 | 121 | 116 | 129 |

The null hypothesis of the Chi square test is that observations are independently distributed across rows and columns.

## Stability of clusters over time

To evaluate the robustness of our ‘pooled’ clustering, we here evaluate the stability of clusters over time. In Table A3 we show the period-to-period transition matrix (weighted by beginning of period hours worked). Overall, 83.49% of observations (that account for 85.79% of hours worked) remain in the same cluster between two periods. In Table A4 we consider in detail the actual transitions across different clusters and report measures of workforce composition for observations with different transition patterns. Overall, we do not observe clear patterns in these dimensions for observations that change cluster.

Table A3 – Period-to-period transition matrix

| | 1 Brown Global Low-tech | 2 Brown Medium-tech | 3 Green Global High-tech | 4 Exposed to Automation | 5 Black and Exposed to Multiple Shocks | 6 Black High-tech |
|---|---|---|---|---|---|---|
| 1 Brown Global Low-tech | 76.47 | 2.21 | 15.44 | 2.94 | 2.94 | 0 |
| 2 Brown Medium-tech | 4.1 | 67.21 | 2.46 | 17.21 | 2.46 | 6.56 |
| 3 Green Global High-tech | 0.9 | 0 | 97.3 | 0.9 | 0.9 | 0 |
| 4 Exposed to Automation | 0 | 1.18 | 5.88 | 87.06 | 5.88 | 0 |
| 5 Black and Exposed to Multiple Shocks | 0 | 0 | 2.5 | 1.25 | 90 | 6.25 |
| 6 Black High-tech | 0 | 1.04 | 0 | 0 | 9.38 | 89.58 |
| Total | 17.46 | 13.81 | 22.06 | 16.03 | 14.92 | 15.71 |

Table A4 – Cluster-to-cluster transition – occupational dimension

| Period-to-period transition | N | Empl share (t-1) | Δ log(hours worked) | Δ Managers | Δ Professionals | Δ Technicians | Δ Manual |
|---|---|---|---|---|---|---|---|
| No change | 526 | 0.8579 | -0.0488 | 0.0036 | 0.0081 | 0.0096 | -0.0169 |
| 1 => 3 | 21 | 0.0228 | -0.1419 | 0.0085 | 0.0082 | 0.0267 | -0.0465 |
| 2 => 4 | 21 | 0.0528 | -0.0054 | 0.0043 | 0.0038 | 0.0112 | -0.0115 |
| 6 => 5 | 9 | 0.0024 | -0.0550 | -0.0192 | 0.0115 | 0.0083 | 0.0142 |
| 2 => 6 | 8 | 0.0089 | -0.0317 | 0.0082 | 0.0150 | 0.0184 | -0.0225 |
| 2 => 1 | 5 | 0.0080 | 0.0947 | 0.0074 | 0.0002 | -0.0044 | -0.0039 |
| 4 => 3 | 5 | 0.0096 | -0.0373 | 0.0090 | 0.0226 | 0.0015 | -0.0420 |
| 4 => 5 | 5 | 0.0045 | -0.0124 | 0.0147 | 0.0259 | 0.0149 | -0.0447 |
| 5 => 6 | 5 | 0.0007 | -0.0375 | 0.0071 | 0.0055 | 0.0639 | -0.0451 |
| Other patterns (12 combinations) | 25 | 0.0325 | -0.0512 | -0.0015 | 0.0155 | 0.0149 | -0.0145 |
| Total | 630 | 1 | -0.0471 | 0.0037 | 0.0083 | 0.0102 | -0.0175 |

# Appendix B – Additional information and results

Table B1 – Separate assessment of different policy measures

| | Average | Min | Q1 | Median | Q3 | Max |
|---|---|---|---|---|---|---|
| | | | EPS | | | |
| 1995 | 0.233 | 0.000 | 0.090 | 0.284 | 0.400 | 0.452 |
| 1999 | 0.289 | 0.000 | 0.090 | 0.323 | 0.452 | 0.581 |
| 2003 | 0.454 | 0.206 | 0.323 | 0.445 | 0.613 | 0.626 |
| 2007 | 0.614 | 0.348 | 0.568 | 0.645 | 0.671 | 0.735 |
| 2011 | 0.756 | 0.510 | 0.710 | 0.729 | 0.832 | 1.000 |
| | | | ETS stringency | | | |
| | Average | Min | Q1 | Median | Q3 | Max |
| 1995 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1999 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2003 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2007 | 0.334 | 0.000 | 0.037 | 0.202 | 0.605 | 1.000 |
| 2011 | 0.412 | 0.000 | 0.043 | 0.341 | 0.825 | 1.000 |
| | | | Energy prices | | | |
| | Average | Min | Q1 | Median | Q3 | Max |
| 1995 | 0.420 | 0.132 | 0.326 | 0.388 | 0.509 | 0.757 |
| 1999 | 0.317 | 0.092 | 0.253 | 0.305 | 0.388 | 0.675 |
| 2003 | 0.369 | 0.100 | 0.290 | 0.360 | 0.456 | 0.760 |
| 2007 | 0.615 | 0.157 | 0.496 | 0.646 | 0.748 | 1.137 |
| 2011 | 0.749 | 0.155 | 0.633 | 0.761 | 0.895 | 1.289 |

Table B2 – Separate assessment of different policy measures

| | (1) Δ log(hours worked) | (2) Δ Managers | (3) Δ Professionals | (4) Δ Technicians | (5) Δ Manual |
|---|---|---|---|---|---|
| | | EPS | | | |
| Log of GHG intensity (1995) | -0.0125 | 0.00426* | -0.00206 | -0.00426 | 0.00591 |
| | (0.0154) | (0.00225) | (0.00271) | (0.00395) | (0.00428) |
| Average (t, t-4) EPS | 0.0203 | -0.00791** | 0.00229 | 0.00758 | -0.00761 |
| x Log of GHG intensity (1995) | (0.0190) | (0.00321) | (0.00372) | (0.00510) | (0.00566) |
| R squared | 0.361 | 0.161 | 0.298 | 0.146 | 0.242 |
| N | 840 | 840 | 840 | 840 | 840 |
| | | Energy prices | | | |
| Log of energy intensity (1995) | -0.0193 | -0.00132 | 0.000443 | -0.000603 | 0.00577 |
| | (0.0175) | (0.00329) | (0.00360) | (0.00389) | (0.00532) |
| Average (t, t-4) energy price | -0.115 | -0.000965 | 0.0470* | 0.00896 | -0.0220 |
| | (0.128) | (0.0248) | (0.0251) | (0.0298) | (0.0383) |
| Average (t, t-4) energy price | 0.0423 | 0.00222 | 0.000477 | 0.00788 | -0.0136 |
| x Log of energy intensity (1995) | (0.0279) | (0.00537) | (0.00535) | (0.00739) | (0.00909) |
| R squared | 0.363 | 0.148 | 0.308 | 0.146 | 0.249 |
| N | 840 | 840 | 840 | 840 | 840 |
| | | ETS | | | |
| Log of GHG intensity (1995) | -0.0120 | 0.000172 | -0.000229 | -0.00105 | 0.00212 |
| | (0.0126) | (0.00126) | (0.00160) | (0.00234) | (0.00252) |
| Average (t, t-4) ETS stringency | -0.269** | 0.0281* | 0.0105 | -0.00668 | -0.0398 |
| | (0.115) | (0.0162) | (0.0291) | (0.0387) | (0.0293) |
| Average (t, t-4) ETS stringency | 0.0833*** | -0.00380 | -0.00426 | 0.00537 | 0.00238 |
| x Log of GHG intensity (1995) | (0.0277) | (0.00415) | (0.00620) | (0.00831) | (0.00656) |
| R squared | 0.381 | 0.158 | 0.299 | 0.145 | 0.251 |
| N | 840 | 840 | 840 | 840 | 840 |

OLS regressions on stacked differences (1995-1999; 1999-2003; 2003-2007; 2007-2011) weighted by hours worked in the first year of each time window. Standard errors clustered by sector-country in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. All regressions include country-specific time dummies, sector dummies and initial (1995) cluster dummies.

Table B3 – Additional dependent variables (OLS)

| | (1) Δ log(Output/L) | (2) Δ log(VA/L) | (3) Δ High-skilled | (4) Δ Medium-skilled | (5) Δ Low-skilled |
|---|---|---|---|---|---|
| Log of GHG intensity (1995) | -0.00617 | -0.0281 | -0.00264 | 0.0113*** | -0.00871*** |
| | (0.0183) | (0.0203) | (0.00241) | (0.00289) | (0.00281) |
| Average (t, t-4) energy price | 0.0395 | 0.136 | 0.0186 | -0.0158 | -0.00280 |
| | (0.137) | (0.151) | (0.0143) | (0.0170) | (0.0168) |
| Average (t, t-4) ETS stringency | 0.0708 | 0.0558 | 0.0154* | 0.00977 | -0.0252** |
| | (0.0765) | (0.0720) | (0.00873) | (0.00682) | (0.00987) |
| Average (t, t-4) EPS | 0.0192 | 0.00154 | -0.00228 | -0.0150*** | 0.0173*** |
| x Log of GHG intensity (1995) | (0.0282) | (0.0239) | (0.00326) | (0.00364) | (0.00381) |
| R squared | 0.187 | 0.186 | 0.282 | 0.263 | 0.294 |
| N | 840 | 840 | 840 | 840 | 840 |

OLS regressions on stacked differences (1995-1999; 1999-2003; 2003-2007; 2007-2011) weighted by hours worked in the first year of each time window. Standard errors clustered by sector-country in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. All regressions include country-specific time dummies, sector dummies and initial (1995) cluster dummies.

Table B4 – Additional dependent variables (IV)

| | (1) Δ log(Output/L) | (2) Δ log(VA/L) | (3) Δ High-skilled | (4) Δ Medium-skilled | (5) Δ Low-skilled |
|---|---|---|---|---|---|
| Log of GHG intensity (1995) | 0.0145 | -0.00772 | -0.00810*** | 0.00684* | 0.00126 |
| | (0.0365) | (0.0386) | (0.00312) | (0.00385) | (0.00351) |
| Average (t, t-4) energy price | -0.252 | -0.0896 | 0.00325 | 0.0103 | -0.0135 |
| | (0.172) | (0.175) | (0.0160) | (0.0226) | (0.0223) |
| Average (t, t-4) EPS (with ETS) | -0.0275 | -0.0432 | 0.00809 | -0.00557 | -0.00252 |
| x Log of GHG intensity (1995) | (0.0652) | (0.0668) | (0.00535) | (0.00611) | (0.00619) |
| R squared | 0.254 | 0.236 | 0.458 | 0.485 | 0.522 |
| N | 840 | 840 | 840 | 840 | 840 |

IV regressions on stacked differences (1995-1999; 1999-2003; 2003-2007; 2007-2011) weighted by hours worked in the first year of each time window. Standard errors clustered by sector-country in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. All regressions include country-specific time dummies, sector dummies and initial (1995) cluster dummies. F test of excluded IV: 33.35

## ABOUT OFCE

The Paris-based Observatoire français des conjonctures économiques (OFCE), or French Economic Observatory is an independent and publicly-funded centre whose activities focus on economic research, forecasting and the evaluation of public policy.

Its 1981 founding charter established it as part of the French Fondation nationale des sciences politiques (Sciences Po), and gave it the mission is to "ensure that the fruits of scientific rigour and academic independence serve the public debate about the economy". The OFCE fulfils this mission by conducting theoretical and empirical studies, taking part in international scientific networks, and assuring a regular presence in the media through close cooperation with the French and European public authorities. The work of the OFCE covers most fields of economic analysis, from macroeconomics, growth, social welfare programmes, taxation and employment policy to sustainable development, competition, innovation and regulatory affairs.

## ABOUT SCIENCES PO

Sciences Po is an institution of higher education and research in the humanities and social sciences. Its work in law, economics, history, political science and sociology is pursued through ten research units and several crosscutting programmes.

Its research community includes over two hundred twenty members and three hundred fifty PhD candidates. Recognized internationally, their work covers a wide range of topics including education, democracies, urban development, globalization and public health.
One of Sciences Po's key objectives is to make a significant contribution to methodological, epistemological and theoretical advances in the humanities and social sciences. Sciences Po's mission is also to share the results of its research with the international research community, students, and more broadly, society as a whole.

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