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Journal of Environmental Economics and Management 98 (2019) 102253

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

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ARTICLE INFO

Article history:
Received 28 June 2018
Revised 10 May 2019
Accepted 7 August 2019
Available online 12 August 2019

JEL classification:
J24
Q52

Keywords:
Climate policies
Workforce skills
Employment impacts
Cluster analysis
Energy prices
Shift-share instruments

ABSTRACT

The political acceptability of climate policies is undermined by job-killing arguments, especially for the least-skilled workers. However, evidence of the distributional impacts for different workers remains scant. We examine the associations between climate policies, proxied by energy prices, and workforce skills for 14 European countries and 15 industrial sectors over the period 1995–2011. Using a shift-share instrumental variable estimator and controlling for the influence of automation and globalization, we find that climate policies have been skill biased against manual workers and have favoured technicians. The long-term change in energy prices accounted for between 9.2% and 17.5% (resp. 4.2% and 8.0%) of the increase (resp. decrease) in the share of technicians (resp. manual workers).

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., 2014). 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 produced 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 taxes) have modest negative employment effects that are concentrated

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https://doi.org/10.1016/j.jeem.2019.102253
0095-0696/

among polluting and energy-intensive industries (e.g. Greenstone, 2002; Kahn and Mansur, 2013; Walker, 2011). Although such negative effects can be offset by well-designed tax recycling schemes (Yamazaki, 2017), direct subsidies to the green economy (Vona et al., forthcoming) 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 the policies' political acceptability.

Of particular importance is assessing whether the labour market impacts of climate policies reinforce the well-known secular trend of skill upgrading induced by globalization and automation (Acemoglu and Autor, 2011; Goos et al., 2014; Lu and Ng, 2013; Autor et al., 2013). Regarding information and communication technology (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 examination of how the adoption of climate policies interacts with other labour market trends in shaping long-term changes in workforce composition. Indeed, reemployment opportunities for displaced workers depend on their skill sets and are likely less promising 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., forthcoming).

We contribute in three ways to the scant empirical literature on the distributional impacts of environmental policies across different worker groups, which has mostly been limited to the US (Walker, 2011; Vona et al., 2018). First, we expand the breadth and generality of previous works by considering a more aggregated level of analysis. Specifically, we examine the associations between climate policies and workforce skills for 14 European countries and 15 industrial sectors over the period 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 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 assign each sector-country pair to a group representing the combined exposure to different structural transformations, including those related to climate change (section 3). In this way, we are able to capture the overlap of such structural transformations and thus the potentially cumulative effects of present and future climate policies.

Third, we estimate the effects of climate policies, proxied by energy prices as in Sato et al. (2019), on workforce skills. In doing so, we isolate the effects of energy prices by controlling for time invariant sector-by-country characteristics as well as for sector-, country- and cluster-specific time trends. We address the residual concerns regarding the endogeneity of energy prices (i.e., time-varying omitted variables, such as quantity discounts) using a standard shift-share instrument. We find that properly accounting for endogeneity changes only the magnitude of the estimated effects and that, if anything, ordinary least squares (OLS) estimates are downward biased.

There are three main notable results from 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 relative to other clusters. Second, the large increase in energy prices that occurred between 1995 and 2011 did not exacerbate the employment decline of polluting sectors. Third, the main finding of our paper is that a weak and insignificant effect of energy prices on total employment masks significant heterogeneity across occupational groups, with a pronounced skill bias in favour of technicians and against manual workers. The historical increase in energy prices explains only a modest fraction (i.e., between 4.2% and 8.0%) of the large decline in the share of manual workers' employment between 2011 and 1995. By contrast, the effect of energy prices on technicians ranges between 9.2% and 17.5%. Compared to other structural transformations, a peculiar aspect of climate policies is that the bias in favour of abstract occupations is concentrated among technical occupations (ISCO 3), such as Physical and Engineering Science Technicians, Process Control Technicians and Government Regulatory Associate Professionals.

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 (Berck and Hoffmann, 2002). The following two contrasting hypotheses are tested: 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 and Bui (2001), the extent to which the Pollution Haven effect translates into job losses depends 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. Morgenstern et al. (2002) showed that the scale effect is small since firms have market power in polluting industries. Consequently, the increase in compliance costs can be passed on to consumers with negligible effects on total demand. The Porter hypothesis can be nested within this framework by allowing for innovation in abatement technologies that creates a green comparative advantage, possibly leading to net job creation (see, e.g., Fankhaeser et al., 2008).

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 (e.g., Greenstone, 2002; Walker, 2011; Kahn and Mansur, 2013; Marin and Vona, 2017).[1] On the other hand, the literature focusing on green innovation has generally found a positive correlation between employment and policies (e.g., Rennings et al., 2004; Horbach and Rennings, 2013; Gagliardi et al., 2016; Vona et al., forthcoming). The main difficulty in reconciling the empirical findings of the two streams of literature 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. 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 operating 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 strands of the literature have thus far focused on the aggregate employment impacts, but the impact of structural transformations can be highly skill biased. Examining skill-biased impacts has been crucial to understanding the inequality-enhancing effects of globalization and ICT (Acemoglu and Autor, 2011; Goos et al., 2014). In developed countries, all of these transformations have reduced the demand for unskilled labour and routine jobs while increasing that for highly skilled labour and abstract jobs, especially those that require social skills (Deming, 2017).

Analogous to these first-order structural transformations, a key and yet unexplored question is whether the labour market impacts of environmental policies are biased towards certain groups of workers and whether the direction of the bias is similar to that of these changes. Answering these questions is crucial for two reasons. First, identifying the losers and supporting them during the transition to a new job would significantly increase the political acceptability of climate policies (Vona et al., forthcoming). Second, training workers with the skills required by green jobs would reduce the costs of coping with climate policies by easing the adoption and the development of green innovations.

Despite the active policy debate on green jobs and skills (Martinez-Fernandez et al., 2010; Deschenes, 2013), empirical research on the skill biasedness of environmental policies remains scant and mostly limited to the US. Indirect evidence has been provided in three cross-sectional studies analysing the skill biasedness of green production. 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 on the skill and task 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. (2018) was the first paper to provide a direct test of the effect of recent amendments to the Clean Air Act on skill demand in US regions over the period 2006–2014. Extending the nuanced results of Consoli et al. (2016) obtained using standard skill measures, they also used O∗NET to identify the skills that are significantly different between green jobs and 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.[2] Due to missing data on key variables described below, we focus on 14 EU countries only.[3] The resulting dataset is a balanced panel for 15 industrial sectors and 14 countries over the period 1995–2011.[4]

[1] For the UK and Germany, however, existing research finds no negative employment effect even in polluting industries (Cole and Elliott, 2007; Martin et al., 2014; Petrick and Wagner, 2014).

[2] 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 drivers, such as international competition and automation.

[3] 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 1995–2011, these countries accounted for 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.

[4] We limit our analysis to the period 1995–2011, as data from WIOD (i.e., energy mix and total hours worked) is only available (with NACE rev. 1.1 classification) until 2011.

Our primary measure of sectoral exposure to climate policies is emissions intensity, measured in terms of actual greenhouse gas emissions. The data source is the World Input Output Dataset (WIOD), which allows us to compute both the direct GHG emissions (CO_2, N_2O and CH_4 aggregated according to their global warming potential) of the sector-country and the (indirect) GHG emissions embodied in the electricity purchased from the power sector (using input-output technical coefficients), as the cost of climate policy in the power sector is usually passed-through to industrial and final consumers (see, e.g., Sijm et al., 2006). Our measure is the sum of the direct and indirect emissions (from the power sector) per unit of the sectoral value added.[5] Because sectors producing green goods and technologies can benefit from climate policies and can 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.[6] 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 (see Haščič and Migotto, 2015). We use the IPC-ISIC concordance proposed by Lybbert and Zolas (2014) to attribute climate-related patents to each sector. In this way, patents are assigned to sectors that manufacture the green technology rather than to the sectors that use it, thus capturing the 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 (EU-LFS) to retrieve, for each industry, information about the total hours worked and the share of hours worked by workers in different “skill groups”.[7] Our favoured measure of skills is the share of workers employed in a certain occupational group, while our alternative measure breaks down the workforce by educational category. 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). 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. (2018), which empirically identifies the skills relevant for green and brown jobs, motivates the separate inclusion of professionals, managers and technicians. 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. (2018) and Martin et al. (2012) found managerial skills to be important for environmentally friendly production. Routine manual workers are included because they are both intensively employed in polluting industries and negatively affected by trade and technology drivers (Autor and Dorn, 2013; Autor et al., 2013). 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).[8]

EU-KLEMS provides information on ICT and non-ICT capital and labour productivity (until 2007). We retrieved from OECD STAN (data available until 2009) import penetration measured as the ratio of imports to total domestic consumption (i.e., net imports plus gross domestic production), which is a conventional measure of import competition. As discussed in the introduction, ICTs 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.

While several environmental policies potentially affect sectoral performance, most of them vary at the country or EU level, and thus, their effects is difficult to isolate from those of other country-specific factors. Further, the stringency of the flagship climate policy of the EU, i.e., the Emission Trading Scheme, was weak over the period considered in our analysis. We hence focus on energy prices that, following an active strand of the literature (Deschenes, 2013; Aldy and Pizer, 2015; Marin and Vona, 2017; Sato et al., 2019), can be used to proxy for what would happen if an ambitious carbon pricing scheme were adopted. We follow the methodology of Sato et al. (2019) 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). Our measure of energy prices is thus a weighted average of prices for different energy sources.[9]

We assess the robustness of our results to the inclusion of other environmental policies by including, in an extension of our main specification, the OECD index of Environmental Policy Stringency (EPS), which aggregates a wide array of policies such as subsidies, taxes and emission limits (see Botta and Koźluk, 2014, for details).

[5] We use emissions rather than energy intensity. The two measures show a correlation of 0.91 in our sample.

[6] 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.

[7] 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.

[8] The occupational groups not considered in our analysis, such as clerical (ISCO 4) and service occupations (ISCO 5), represent a tiny proportion of employment in the sectors considered by our analysis, i.e., 10.6% of the average industry workforce.

[9] Specifically:

$$p_{ijt}^{E} = \sum_{k} \phi_{ijt}^{k} p_{it}^{k}$$

where ϕ_{ijt}^{k} is the share of energy source k (electricity, gas, coal, oil) in country i and sector j, while p_{it}^{k} is corresponding price of energy source k (see Sato et al., 2019, for details).

Since some variables are available only until 2007 (i.e., ICT and non-ICT capital), our descriptive analysis in the next section is performed for the period 1995–2007, while the econometric part in section 4 also uses more recent years up to 2011 because we set the exposure to various structural drivers at the initial period.

2.2. Preliminary 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.

As a first attempt to understand 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 (p-value < 0.05). 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 drivers, namely, import 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 and demand for highly educated workers, professionals, technicians and managers.

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

We observe another interesting pattern for the climate-related changes in demand for skills. In contrast with findings of Vona et al. (2018), sector-country pairs that become cleaner reduce their relative demands for technicians and middle-skilled workers and increase their demands 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 drivers, which is the goal of the cluster analysis in the next section.

3. A taxonomy of exposure to multiple structural transformations

Isolating the association 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 transformations, we develop a taxonomy of sector-country pairs based on their degree of exposure to structural drivers affecting labour market outcomes. Cluster analysis is the most natural method for allowing the data to reveal this taxonomy (e.g., Consoli and Rentocchini, 2015). For the sake of exposition, in the cluster analysis, we organize the data in long intervals delimited by 1995, 1999, 2003 and 2007.[10]

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 our primary and secondary proxies, respectively, for exposure to climate policies.[11]

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 into percentile ranks to avoid the formation of clusters driven by extreme values.

The aim of cluster analysis is to identify groups of observations (country-sector pairs) that are distinct, that is, those 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). First, we perform hierarchical clustering to identify the "optimal" number of clusters (Milligan and Cooper, 1985) by assessing how distinct the clusters are. Second, 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. Our favoured clustering algorithm is the average linkage algorithm, which computes the Euclidean distance in clustering variables across all possible pairs of individuals across different clusters and aims to minimize distances within the clusters and, at the same time, maximize distances across clusters. This procedure provides six main clusters, which are described in the following sub-sections (see Appendix A for technical details).

[10] We checked that our results are unaffected by the particular years selected to delimit the windows.

[11] 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.

Table 1
Definition of variables.

Variable	Source	Years	Description	Mean	Median	SD
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	21.079
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 (CO_2, CH_4 and N_2O expressed in CO_2-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	0.066
Technicians	EU LFS	1995–2011	Share of technicians (ISCO 3)	0.1483	0.125	0.1128
Manual	EU LFS	1995–2011	Share of manual workers (ISCO 7, 8 and 9)	0.5903	0.615	0.1601
High education	EU LFS	1995–2011	Share of workers with tertiary (ISCED) education	0.1903	0.1653	0.122
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	0.262	0.1585
Hours worked	WIOD	1995–2011	Hours worked by employed and self-employed workers	251.1599	117.8889	335.7974
Energy price	IEA; WIOD	1995–2011	Sector-country-year specific price of energy inputs. The price is the weighted average of country-year energy-source-specific energy prices, using country-sector-year-specific energy mix as weight.	0.2484	0.3165	0.2298
Environmental Policy Stringency (EPS)	OECD EPS Indicator	1995–2011	Environmental Policy Stringency indicator. The indicator has been standardized to range between 0 and 1.	0.4488	0.1671	0.4811

Table 2
Correlation between measures of structural drivers and labour force composition in levels (pooled panel for years 1995, 1999, 2003 and 2007).

	ICT capital intensity (log)	Non-ICT capital intensity (log)	Import penetration	Climate patent stock per empl	GHG/VA (log)
ICT capital intensity (log)	1.0000				
Non-ICT capital intensity (log)	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	
GHG/VA (log)	−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 share	0.6708	0.3665	0.1415	0.4474	−0.2125
Middle education share	−0.1983	−0.2276	0.0265	0.2574	0.1207
Low education share	−0.2034	*−0.0021*	−0.1054	−0.4866	*0.0115*

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

Table 3
Correlation between measures of structural drivers and labour force composition (long differences 1995–2007).

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

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

3.2. Profiling of clusters

Table 4 provides a description of the cluster taxonomy by reporting the average percentiles (and the median values in parentheses) of clustering variables across the six different clusters, to which we attribute a label.[12]

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 (Fig. 1). Theoretically, we expect that being exposed to multiple structural drivers is worse than being exposed to a single driver because all structural transformations (except perhaps green innovations) are potentially labour saving.

Clusters 1 (*Brown Global Low-tech*) and 2 (*Brown Medium-tech*) are both characterized by a moderate level of GHG emissions intensity. The main difference is that cluster 1 is open to trade and is extremely low tech, while cluster 2 is medium tech and relatively sheltered from international competition. Over time, we observe a convergence of these two clusters in terms of capital deepening and green patents. Emissions intensity, in contrast, 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 Appendix A). Importantly, the *Brown Medium-tech cluster* is the largest in terms of average employment share (31.2%), while the *Brown Global Low-tech* cluster is the fourth largest (14.8%).

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 and some Textile, Rubber and Plastics producers (Table A2), and it is the second in terms of size with an average of 20.6% of

[12] In the bottom part of the table, we test the differences in five clustering variables across clusters by running five separate linear regressions with a clustering variable as the dependent variable and cluster dummies as independent variables. Not surprisingly, as the cluster analysis seeks to maximize the differences in clustering variables across clusters, the cluster dummies are jointly (F-test) significantly different from zero for all of the clustering variables, and they explain a significant proportion of the overall variance (R squared > 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).

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	15.84	67.23	19.76	47.8	164	0.1477
	(0.169)	(1.069)	(0.582)	(0.023)	(1.121)		
2 Brown Medium-tech	23.72	32.71	24.48	36.54	57.15	144	0.3120
	(0.239)	(2.452)	(0.215)	(0.104)	(1.627)		
3 Green Global High-tech	64.09	45.4	77.16	62.3	15.4	166	0.2062
	(1.031)	(3.328)	(0.726)	(0.779)	(0.315)		
4 Exposed to Automation	65.5	62.39	32.21	34.12	38.34	121	0.1950
	(0.901)	(4.844)	(0.301)	(0.085)	(0.881)		
5 Black Exposed to Mult. Drivers	68.03	79.97	74.06	72.33	69.45	116	0.0724
	(1.212)	(10.590)	(0.660)	(1.655)	(3.249)		
6 Black High-tech	73.53	83.03	19.64	85.12	85.73	129	0.0667
	(1.662)	(19.493)	(0.182)	(4.794)	(11.170)		
Total	50	50	50	50	50	840	1
	(0.575)	(3.819)	(0.436)	(0.290)	(1.265)		
F test of joint significance of cluster dummies	332.73***	520.09***	407.15***	392.07***	785.62***		
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	–	–		

Notes: For each cluster, we report the average percentile of each variable and the median value of the 'true' variable in parentheses. To estimate the F-test of the joint significance of cluster dummies, we run simple OLS regressions with the selected variable as the dependent variable and cluster dummies as independent variables, which are jointly tested. Scheffe's test of multiple comparison is derived from the analysis of variance (ANOVA) model.

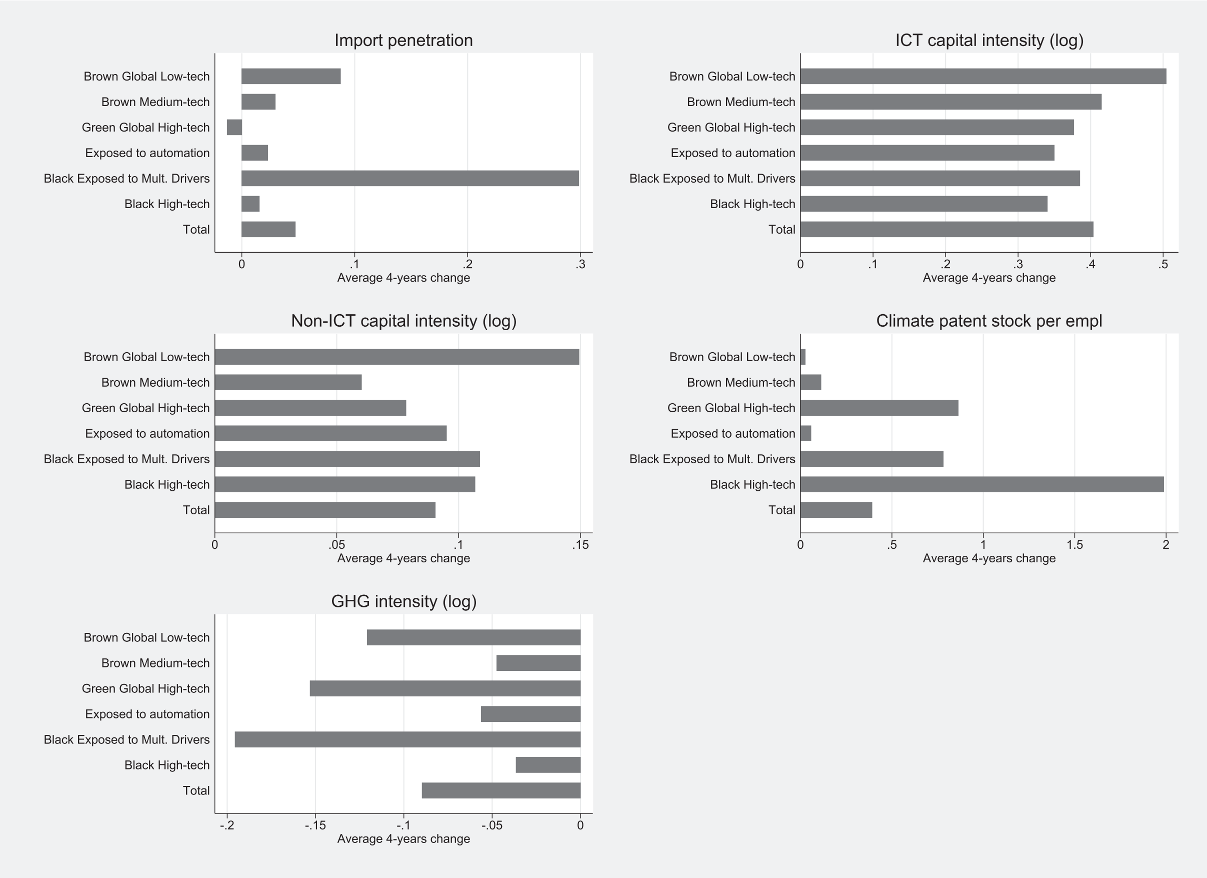

Fig. 1. Average period-to-period growth in clustering variables by beginning-of-period cluster weighted by beginning-of-period hours worked (1995–1999; 1999–2003; 2003–2007).

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 from international competition and climate-related transformations. 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 Drivers* and *Black High-tech*) are the most emission-intensive clusters, but they represent, on average, a remarkably smaller share of hours worked (7.2% and 6.7%, respectively). Both score high on all of the dimensions, especially climate-related ones; the only notable difference is that the *Black High-tech* cluster has been fully sheltered from 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 the best performer in terms of increases in green patent intensity, while cluster 5 is an outlier in terms of increased trade exposure.

3.3. *The taxonomy at work*

Before moving to our econometric analysis, in which we use cluster dummies to flexibly control for exposure to multiple structural drivers, we assess here the composition and dynamics of different clusters in terms of workforce skills. Table 5 shows that the differences in labour force composition across clusters go in the expected directions, following a general technology-skill complementarity argument.

However, as evident in last three rows of the table, the 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 insignificant, especially for managers.

Fig. 2 reports the trends in our skill measures across different clusters. We observe that, as expected, hours worked declined mostly in clusters exposed to multiple drivers and international competition (1, 3, 5), with the exception of the small cluster 6,

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 Exposed to Mult. Drivers	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***
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

Notes: For each cluster, we report the weighted (with hours worked) average of each variable. To estimate the F-test of joint significance of cluster dummies, we run simple OLS regressions with the selected variable as the dependent variable and cluster dummies as independent variables, which are jointly tested. Scheffe's test of multiple comparison is derived from the analysis of variance (ANOVA) model.

which experienced the largest employment decline. Further, while pronounced skill upgrading is widespread, we do not observe any striking pattern clearly associated with climate-related factors, except for the switch from manual workers to technicians in the "black" cluster 6.

The fact 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 lagged cluster dummies (Panel A) and then on lagged clustering variables (Panel B). Only cluster 1 experienced a significant decrease in employment relative to the other clusters. Importantly, the explanatory power of the initial cluster dummies (Panel A, column 1) is greater than that of the time-varying lagged clustering variables (Panel B, column 1), justifying the use of cluster dummies to account for exposure to multiple drivers. Finally, the signs of the two proxies for exposure to climate policies are in line with our expectations: 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 drivers, 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 section describes the methodology used to estimate this association and the main results of the paper.

4. Effect of climate policies on skill-biased employment dynamics

There are three types of issues that make the identification of the effect of climate policies on employment problematic. First, the effect of other structural transformations is likely to dominate that of climate policies. Second, not only are there several climate policies that can be evaluated, but both the initial level and the change in such policies are likely to matter for employment dynamics. Third, the identification of the effect of climate policies is problematic given the unavoidable presence of omitted variables.

4.1. Estimation equation

To illustrate the strategy that we adopt to tackle these three issues, let us introduce our estimation equation:

$$\Delta Y_{ijt} = \beta_1 p^E_{ij,t-1} + \beta_2 \Delta p^E_{ij,t} + \gamma log(GHG/VA)_{ij,1995} + \phi^c_{ij,1995} + \mu_{i,t} + \theta_{j,t} + \varepsilon_{ij,t}, \tag{1}$$

where our dependent variable ΔY_{ijt} is the change in the share of hours worked in occupation-specific occupation groups (e.g., technicians) or the change in the logarithm of total hours worked in country i, sector j and year t, while $\varepsilon_{ij,t}$ is a standard error term. All regressions are weighted by initial (1995) hours worked in the sector-country pair.

The main variable of interest is the energy price $p^E_{ij,t}$. We include both the lagged level and the contemporaneous change in energy prices, as they both can influence the firm's adjustment of its skill mix. Following Jaeger et al. (2018), we will show that the effect of the lagged level of energy prices is a good proxy for the cumulative effect of past price changes on the choice of the current skill mix (see Section 4.3). To address the issue of having multiple environmental policies, we also present the results of an extended specification of equation (1) in which we add the index of Environmental Policy Stringency (EPS) developed at the OECD.

We include five initial cluster dummies $\phi^c_{ij,1995}$ (the omitted category is cluster 4 *Exposed to automation*) that account in a flexible way for the overlapping of the various structural transformations discussed above. The use of initial cluster dummies

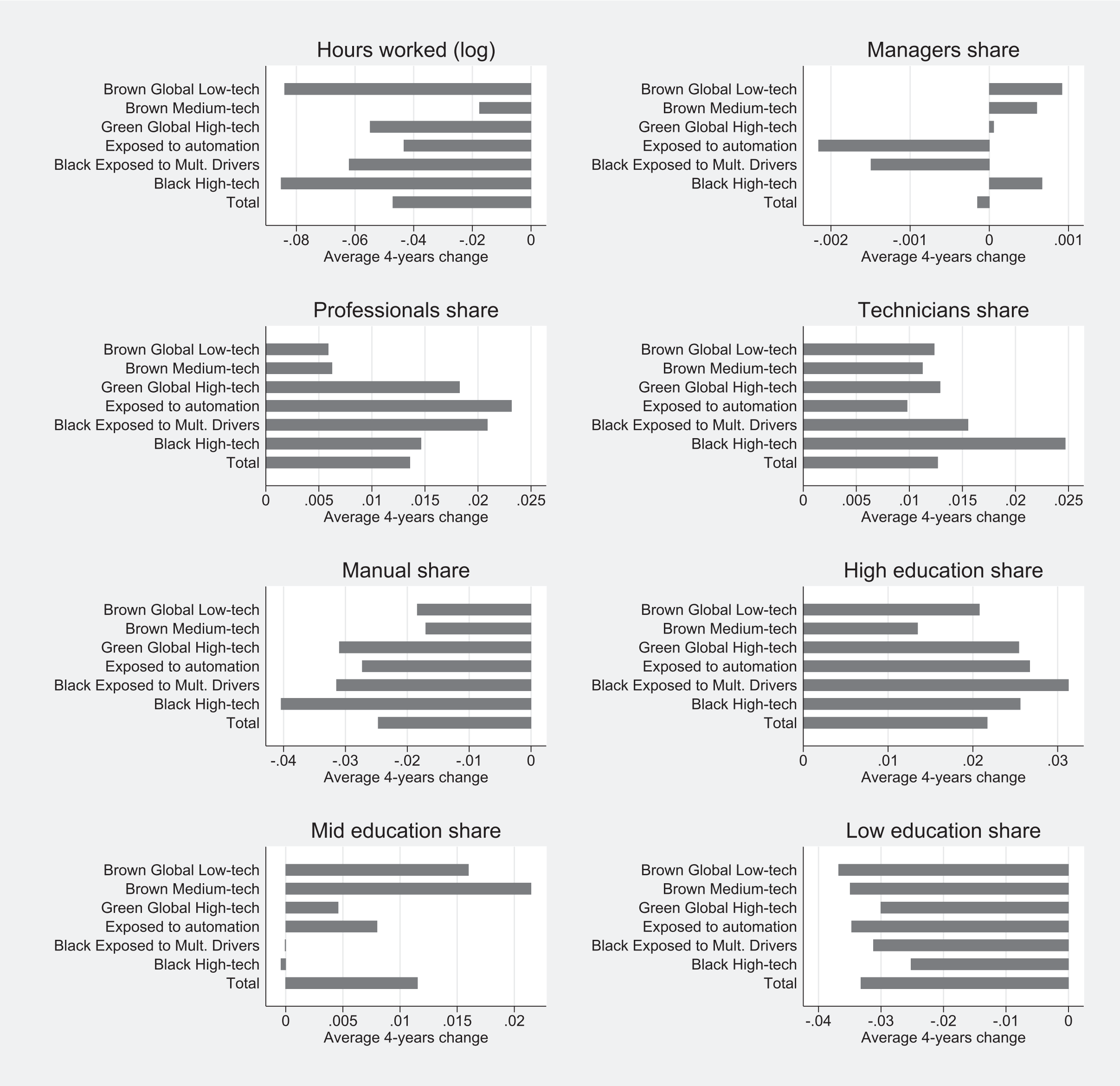

Fig. 2. Average period-to-period growth in labour-related measures by beginning-of-period cluster weighted by beginning-of-period hours worked (1995–1999; 1999–2003; 2003–2007; 2007–2011).

avoids endogeneity problems related to cluster switching, which is, however, not a frequent outcome, as shown in the transition matrices presented in Tables A3 and A4 of Appendix A. In addition to the cluster dummies, we also include country-by-year $\mu_{i,t}$ and sector-by-year $\theta_{j,t}$ dummies that control in a flexible way for trends that have either a sector- (e.g., technological diffusion) or country-specific (e.g., the debt crisis) component. We further adjust for the permanent influence of the initial GHG intensity (in logs) to capture an additional component of the labour market dynamics of emission-intensive sectors that goes beyond the inclusion of cluster, country and sector dummies. GHG intensity allows us to fully isolate the labour market effects of climate policies from the labour market trends of emission-intensive sectors. Finally, as a general rule, we use a log transformation for those variables (e.g., GHG/VA, total employment) with highly skewed distributions, with few outliers possibly driving the results. By contrast, energy prices (in constant US Dollars – base year 2005 – per kilogram of oil equivalent – KOE) and the occupational shares vary between 0 and 1, and their distributions are nearly Gaussian; hence, we do not adopt a log-transformation in these cases.

Given the first-difference specification of equation (1), the main source of data variation left to identify the effect of energy prices is the change in employment within a country-sector pair. We further partial out the country-, sector- and cluster-specific (time-varying) components of this variation by including flexible trends for sectors and countries and linear trends for clusters.

Table 6
Predictive power of cluster dummies vs. clustering variables.

Dep. var: △ log(hours worked)	(1)	(2)	(3)
Panel A – Lagged cluster dummies			
1 Brown Global Low-tech	−0.0824***	−0.0769***	−0.0142
	(0.0315)	(0.0267)	(0.0151)
2 Brown Medium-tech	−0.0115	−0.0106	0.0114
	(0.0148)	(0.0141)	(0.0138)
3 Green Global High-tech	−0.0118	0.0055	−0.0384
	(0.0203)	(0.0127)	(0.0238)
4 Exposed to Automation	[base cat]	[base cat]	[base cat]
5 Black Exposed to Mult. Drivers	−0.0087	0.0021	0.0324
	(0.0146)	(0.0153)	(0.0224)
6 Black High-tech	0.0020	0.0126	0.0560*
	(0.0187)	(0.0222)	(0.0290)
Controls	Year dummies	Country, sector and year dummies	Year-specific country and sector dummies
R squared	0.143	0.223	0.413
N	840	840	840
Panel B – Lagged clustering variables			
Import penetration	−0.0112	−0.0111	−0.0006
	(0.0095)	(0.0089)	(0.0021)
log(ICT K intensity)	−0.0135	0.0221*	−0.0045
	(0.0135)	(0.0119)	(0.0121)
log(Non-ICT K intensity)	0.0183	0.0075	0.0099
	(0.0122)	(0.0111)	(0.0091)
Climate patent stock per empl	0.0095***	0.0095***	0.0134***
	(0.0032)	(0.0027)	(0.0027)
log(GHG/VA)	−0.0106*	−0.0130**	−0.0129
	(0.0057)	(0.0063)	(0.0088)
Controls	Year dummies	Country, sector and year dummies	Year-specific country and sector dummies
R squared	0.132	0.240	0.436
N	840	840	840

Notes: OLS regressions on stacked differences (1995–1999; 1999–2003; 2003–2007; 2007–2011) weighted by hours worked in 1995. Standard errors clustered by sector-country in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2. Endogeneity issues

The set of controls described above are included in equation (1) to mitigate endogeneity concerns in the estimation of energy price effects. However, it is unlikely that these controls fully absorb the biases associated with variables that are difficult to observe and vary at the country-by-sector level.

First, negative (positive) demand shocks reduce (increase) the demand for inputs, including labour, and contemporaneously increase (decrease) energy prices through *ex post* reductions (increases) in quantity discounts. In a study of the structure of energy prices in French manufacturing plants, Marin and Vona (2017) find that the incidence of quantity discounts is not constant over time and varies substantially both within and between sectors. Because quantity discounts are ultimately correlated with unexpected demand shocks, this finding suggests that demand shocks are unlikely to be absorbed by the set of controls included in equation (1).

The second source of omitted variable bias is associated with unobservable technological shocks. In particular, we expect changes in the energy mix (a proxy for technology) to be correlated with changes in the input mix, including the skill mix. Clearly, the consequences of a change in the price of, e.g., coal on the input mix are at least partly unobservable to econometricians, who largely ignore the specific technological relations linking the demand of skills, on the one hand, and the type of capital equipment and organizational practices required when using a specific energy source, on the other.

Taking both sources of bias into account, it is not straightforward to formulate predictions on the direction of the estimation bias for the effect of energy prices on workforce skills. For total employment, Marin and Vona (2017) show that OLS underestimates (in absolute terms) the negative effect of energy prices because the component of technological shocks that is correlated with energy prices is relatively more energy-saving than labour-saving and thus more than offsets the bias associated with unobservable demand shocks. In their study, this implies that the job destruction effect induced by higher energy prices is larger in the IV than in the OLS estimation.[13] If, as indicated by research in labour economics (e.g. Jaimovich and Siu, 2018),

[13] Typically, the elasticity of employment to energy prices estimated in previous studies ranges between −0.10 and −0.23 and is higher in energy-intensive sectors (Deschenes, 2013; Kahn and Mansur, 2013; Marin and Vona, 2017). A recent contribution by Hille and Möbius (2019) decomposes the overall impact of energy prices on sector-level employment effect of energy prices into different effects: cost to comply with regulation, factor shift and demand. Their dynamic panel GMM estimator finds a negligible overall net effect of energy prices on manufacturing employment, with a large cost effect that more than compensates for the (negative) demand effect and factor shift effect.

the pace of skill upgrading is accelerated by recessions and negative shocks, we expect larger employment contractions to be associated with larger skill shifts. Thus, the skill-biased effects should be magnified when using an appropriate IV estimator.

We instrument energy prices by exploiting a classical shift-share logic (Bartik, 1991) that has become common in related papers estimating the impacts of energy prices (Linn, 2008; Marin and Vona, 2017). Specifically, the instrument is obtained by multiplying the vector of sector-country specific shares of each energy source (coal, gas, electricity, oil) at time 0 (1995 in our case) by the vector of the time-varying prices of each source at the national level. That is:

$$IVp^E_{ijt} = \sum_s \phi^k_{ij,t=1995} p^k_{i,t} \tag{2}$$

where $\phi^k_{ij,t=1995}$ is the initial *share* of energy source k in country i and sector j,[14] while $p^k_{i,t}$ is the national *shift* in the price of energy source k. Since we have two endogenous variables in equation (1), we instrument the change in energy prices with the change in IVp^E_{ijt}.

Such instruments only retain the exogenous variation in energy prices and thus mitigate both sources of omitted variable bias. The exclusion restrictions are satisfied as long as two conditions hold: i) the national prices for each source are independent of sector-level idiosyncratic demand and supply shocks, and ii) the initial energy mix of the sector does not affect long-term employment dynamics.

These assumptions are impossible to test explicitly. The inclusion of sector-specific and country-specific trends, which capture the idiosyncratic features of an energy market (e.g., the political power of large utilities) potentially correlated with energy prices, mitigate concerns associated with violations of the first assumption. However, to lend further credibility to our IV estimations, we will explore the robustness of our results to the exclusion of the electricity sector, i.e., the one that most likely influences national energy prices and policies, and to the use of a variant of this instrument where world energy price shifts replace national price shifts.

As suggested by a recent paper by Goldsmith-Pinkham et al. (2018), the plausibility of the second assumption can be assessed by exploiting the fact that a Bartik instrument is equivalent to using a linear combination of initial shares (i.e., energy source shares in our case) as instruments. Therefore, a researcher can not only explicitly use over-identification tests to assess the exogeneity of all instruments, but (more important) she can also study the extent to which important covariates are balanced with respect to initial energy source shares. Indeed, non-parallel pre-trends or significant imbalances in the covariates' distribution depending on the initial shares are more likely to indicate imbalances in unobservable variables potentially correlated with the dependent variable.

Appendix B presents the detailed results of these analyses that we briefly summarize here. Table B1 shows that initial energy source shares are not balanced with respect to the clustering variables (Panel A), but they become more balanced when we used cluster dummies as in equation (1), with the notable exception of cluster 3 *Green Global High-tech*. Since excluding this cluster allows us to achieve a satisfactory balance (Panel C), we perform a robustness check by excluding it when estimating energy price effects (Panel C of Table C1 in Appendix C). Second, we do not observe significant pre-trend differences across sector-country pairs with different energy mixes (in 1995) during the period 1990–1994 (see Tables B2 and B3), although we can only conduct these tests on total hours worked and education-based skill measures due to data limitations on occupational shares in the EU-LFS.[15] The effects of energy prices on these variables are not statistically significant (see in particular Table B2).

To provide context for our results, Fig. 3 shows that all of our policy measures increased substantially over time. The average energy price increased by a remarkable 78%, while average EPS stringency (our secondary policy measure) tripled between 1995 and 2011. Such large increases in energy prices represent an ideal test of the resilience of EU labour markets in advance of the future adoption of ambitious climate policies.

4.3. Estimation results

Table 7 contains the main results of this study obtained by estimating equation (1) in three ways: i) OLS (Panel A), ii) our preferred approach, the just-identified IV (Panel B); and iii) the over-identified IV, where we can explicitly test for the exogeneity of all instruments (Panel C). Comparing the three panels, our results indicate a downward bias in the OLS estimates of the effect of energy prices on sectoral employment. Although the job destruction effect is larger and negative in the IV specifications, the joint effect of energy prices changes and levels is not statistically significant at conventional levels making the job killing hypothesis unlikely, especially so given the substantial historical increase in energy prices documented in Fig. 3.[16]

A downward bias in the OLS estimates of the skill-biased effect is also observed for the contemporaneous change in energy prices, especially for technicians and manual workers. In contrast, the magnitude of the estimated coefficient of lagged energy prices remains unchanged across the different occupational groups (columns 2–5). The plausibility of our identification strategy is further confirmed by the stability of the coefficients in the two IV specifications (Panels B and C) and by the failure to reject the null hypothesis of exogeneity for our main variables of interest, namely the employment shares of different occupational

[14] Jaeger et al. (2018) and Marin and Vona (2017) suggest the use of a pre-sample energy mix to reduce endogeneity concerns. Unfortunately, sector/country specific energy mix from WIOD is only available from 1995 onwards.

[15] Data on hours worked, total and by education-based skill measures, for 1990–1995 were retrieved from the EU-KLEMS database.

[16] The p-value of the Chi square test of joint significance of $\Delta p^E_{ij,t}$ and $p^E_{ij,t-1}$ is 0.37.

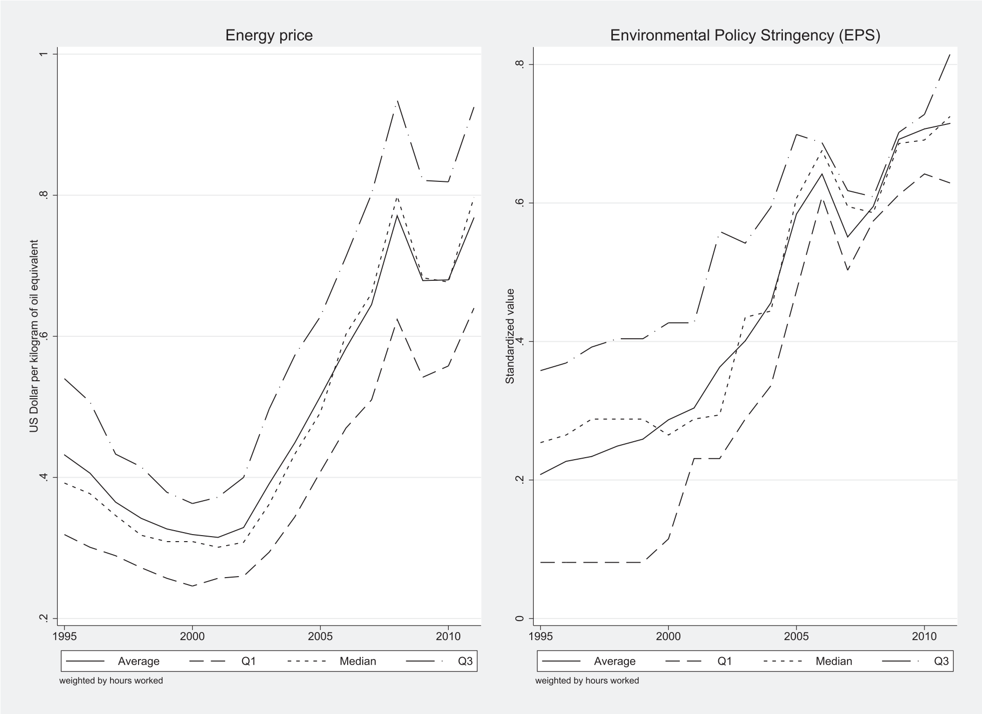

Fig. 3. Trends in policy stringency measures.

groups (Panel C, columns 2–5). In both the just-identified and the over-identified specifications, the instruments remain strong with F-statistics above the usual cut-off of ten (Stock and Yogo, 2002). Table B4 in Appendix B presents the complete details of the first-stage results for both the just-identified and the over-identified specifications.

The novel finding of our paper is that a weak and insignificant effect of energy prices on total employment masks significant heterogeneity across occupational groups. On the aggregate employment impact, this finding contrasts with those obtained using plant-level data (Marin and Vona, 2017) or finer levels of geographical aggregation (Kahn and Mansur, 2013), which highlight a modest negative employment effect of higher energy prices. However, this conforms to the fact that the competitiveness and employment impacts of environmental policies are larger in micro- than in macro-studies (Smith, 2015; Dechezleprêtre and Sato, 2017). While macro-analyses of policy impacts generally fail to identify causal effects, micro-studies estimate a causal but partial equilibrium (or local) effect that does not account for the offsetting effect of employment reallocation across regions and firms.

Regarding the skill-biasedness of the impacts, climate policies create winners and losers across occupations within a given industry. Broadly speaking, the skill bias of climate policies is aligned with that of globalization and automation: manual workers are the losers (column 5), while abstract professions are the winners (columns 2–4). A peculiar aspect of climate policies is, however, that the pronounced bias towards abstract occupations is concentrated among technical occupations (ISCO 3), such as Physical and Engineering Science Technicians, Process Control Technicians and Government Regulatory Associate Professionals. In our preferred IV specification of Panel B, the share of technicians increases significantly with both the change and the lagged level of energy prices. Furthermore, while the effects of both the change and the level of energy prices are statistically insignificant on managers, we find a positive effect on the share of professionals only for the lag of energy prices. This finding is consistent with those Vona et al. (2018) for the US Clean Air Act but with the important difference that the bias is towards low-level technical skills rather than high-level engineering skills.

Thus far, we have interpreted the effect of the contemporaneous change in energy prices as a short-term effect and the effect of the lagged price level as a long-term effect. To corroborate this interpretation and examine in greater detail the dynamic adjustment of employment to energy price changes, we follow the approach proposed by Jaeger et al. (2018) by noting that the current choice of the skill mix is the result of current and past energy price shocks. We augment the specification in equation (1) with lagged changes in energy prices up to year $t - m$ (and adjust the year of the lagged level of energy prices and the instruments accordingly).[17]

[17] These additional variables are instrumented in a straightforward way, by multiplying the vector of national price changes in year t with the vector of the energy source shares in 1995. Table B5 reports first-stage regressions for the specifications in Table 8. Each instrument is a good predictor of the endogenous variable in the same period, which means that there is sufficient heterogeneity in the 'shifts' (i.e., national source-specific energy prices).

Table 7
Baseline estimates.

	△ log(hours worked)	△ Managers	△ Professionals	△ Technicians	△ Manual
Panel A – OLS estimates					
△ Energy price	0.0432	−0.0017	−0.0139	−0.0007	0.0241
	(0.0480)	(0.0111)	(0.0107)	(0.0178)	(0.0243)
Energy price (t-1)	−0.0122	−0.0017	0.0059**	0.0130**	−0.0102
	(0.0162)	(0.0025)	(0.0025)	(0.0055)	(0.0066)
log of GHG intensity (1995)	−0.0005	−0.0000	−0.0001	0.0001	0.0003
	(0.0030)	(0.0003)	(0.0004)	(0.0005)	(0.0007)
R squared	0.495	0.437	0.441	0.372	0.313
N	3360	3360	3360	3360	3360
Panel B – IV baseline estimates					
△ Energy price	−0.0205	0.0036	−0.0109	0.0630**	−0.0599
	(0.0877)	(0.0197)	(0.0195)	(0.0313)	(0.0407)
Energy price (t-1)	−0.0305	−0.0016	0.0081**	0.0141**	−0.0135**
	(0.0217)	(0.0030)	(0.0032)	(0.0057)	(0.0062)
log of GHG intensity (1995)	−0.0008	−0.0000	−0.0001	0.0002	0.0002
	(0.0028)	(0.0003)	(0.0004)	(0.0005)	(0.0007)
N	3360	3360	3360	3360	3360
F test of excluded IV	58.31	58.31	58.31	58.31	58.31
Panel C – IVs decomposed in their different energy source components					
△ Energy price	0.0044	−0.0049	−0.0095	0.0454	−0.0380
	(0.0789)	(0.0179)	(0.0192)	(0.0293)	(0.0420)
Energy price (t-1)	−0.0258	−0.0039	0.0074**	0.0149**	−0.0115*
	(0.0231)	(0.0031)	(0.0034)	(0.0059)	(0.0065)
log of GHG intensity (1995)	−0.0007	−0.0000	−0.0001	0.0002	0.0003
	(0.0028)	(0.0003)	(0.0004)	(0.0005)	(0.0007)
N	3360	3360	3360	3360	3360
F test of excluded IV	33.14	33.14	33.14	33.14	33.14
Sargan test of overid (J stat)	11.42	3.601	2.091	8.633	8.984
p-value of the Sargan test	0.0761	0.731	0.911	0.195	0.174

Notes: Regressions weighted by hours worked in 1995. Standard errors clustered by sector-country in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include year-specific country dummies, year-specific sector dummies and initial (1995) cluster dummies.

Table 8 presents the results of this extension for three specifications including, one, two or three lags of energy price changes. We stopped at three lags because adding further lags reduces the strength of the instruments below the usual cut-off of ten. The upshot of these regressions is that the effect of the lagged level of energy prices is very persistent and remains statistically significant even with a lag of four years. Further corroborating our main finding, the effect of the sum of the coefficients associated with energy prices is statistical significant for manual workers and technicians only. Overall, these results support our interpretation that the effect of lagged energy prices approximates well past cumulative changes in energy prices.

The analysis of the adjustment process suggests that we can use our main specification in Table 7 to quantify the estimated effects. To discipline such quantification, note that our data indicate a catching-up in energy prices whereby larger increases occurred in sector-country pairs with lower initial prices. We thus build an upper and a lower bound of the price effect corresponding to the 1st quartile (0.31 US dollars per kilogram of oil equivalent – koe) and the 3rd quartile (0.62 USD/koe) of the energy price distribution, respectively. Using an auxiliary regression of the change in energy prices on the lagged level of energy prices plus year, sector and country dummies, we compute the short-term predicted change in energy prices at the 1st and the 3rd quartile of the distribution. The upper and lower bounds of the short-term effect are obtained by multiplying these predicted changes by the estimated coefficient of the energy price change (Panel B of Table 7). Similarly, we compute the upper (resp. lower) bound of the cumulative effect of past price changes by multiplying the estimated coefficient of the lagged energy price by the inter-quartile change (resp. the 90th – 0.82 USD/koe – to 75th – 0.62 USD/koe – change) in energy prices.

In Table 9, the long-term effect is the sum of the current and the cumulative past changes, and we compare it with the historical change in the employment shares for each occupation group (column 3). Focusing on technicians and manual workers for whom the long-term effects are statistically significant across different specifications, the effect is remarkably larger for the former than for the latter group. The historical increase in energy prices explains only a modest fraction (i.e., between 4.2% and 8.0%) of the large decline in the share of manual workers' employment between 2011 and 1995. By contrast, the effect of energy prices on technicians ranges between 9.2% and 17.5%.

4.4. Extensions

We summarize here the results of a series of additional regressions that have two main aims: i) providing further support for the plausibility of our empirical strategy and ii) extending and reinforcing our main results. For the sake of space, we relegate all details of these analyses to Appendix C.

Table 8
Dynamic adjustment model.

	△ log(hours worked)	△ Managers	△ Professionals	△ Technicians	△ Manual
Panel A – One lag					
△ Energy price	−0.0481	0.0026	−0.0196	0.0630*	−0.0537
	(0.102)	(0.0229)	(0.0230)	(0.0324)	(0.0441)
△ Energy price (t-1)	0.0933	0.0189	0.0624**	0.0191	−0.0325
	(0.0864)	(0.0250)	(0.0253)	(0.0310)	(0.0434)
Energy price (t-2)	−0.0256	−0.0027	0.0075**	0.0122**	−0.0129**
	(0.0233)	(0.0031)	(0.0034)	(0.0060)	(0.0059)
log of GHG intensity (1995)	0.0000	0.0002	−0.0002	0.0005	−0.0002
	(0.0029)	(0.0003)	(0.0004)	(0.0006)	(0.0007)
Cumulative effect of △ Energy price	0.0452	0.0215	0.0428	0.0820*	−0.0861
	(0.126)	(0.0279)	(0.0306)	(0.0460)	(0.0581)
N	3150	3150	3150	3150	3150
F test of excluded IV	45.66	45.66	45.66	45.66	45.66
Panel B – Two lags					
△ Energy price	−0.0550	0.0049	−0.0166	0.0600*	−0.0371
	(0.1134)	(0.0232)	(0.0241)	(0.0344)	(0.0471)
△ Energy price (t-1)	0.1051	0.0155	0.0684**	0.0180	−0.0065
	(0.0986)	(0.0287)	(0.0299)	(0.0389)	(0.0515)
△ Energy price (t-2)	0.0223	0.0192	−0.0024	−0.0226	−0.0335
	(0.1103)	(0.0255)	(0.0284)	(0.0492)	(0.0537)
Energy price (t-3)	−0.0298	−0.0052*	0.0059	0.0127*	−0.0152**
	(0.0236)	(0.0031)	(0.0037)	(0.0071)	(0.0069)
log of GHG intensity (1995)	−0.0000	0.0001	−0.0003	0.0004	−0.0000
	(0.0030)	(0.0003)	(0.0004)	(0.0005)	(0.0007)
Cumulative effect of △ Energy price	0.0722	0.0396	0.0495	0.0554	−0.0771
	(0.146)	(0.0344)	(0.0373)	(0.0511)	(0.0615)
N	2940	2940	2940	2940	2940
F test of excluded IV	27.38	27.38	27.38	27.38	27.38
Panel C – Three lags					
△ Energy price	−0.0506	0.0025	−0.0165	0.0612*	−0.0312
	(0.113)	(0.0241)	(0.0249)	(0.0347)	(0.0486)
△ Energy price (t-1)	0.0919	0.00896	0.0735**	0.0068	0.0192
	(0.0996)	(0.0308)	(0.0315)	(0.0370)	(0.0528)
△ Energy price (t-2)	0.0230	0.0326	−0.0025	−0.0318	−0.0297
	(0.1393)	(0.0312)	(0.0372)	(0.0603)	(0.0672)
△ Energy price (t-3)	0.0426	−0.0319	0.0171	0.0312	−0.0127
	(0.1381)	(0.0249)	(0.0325)	(0.0436)	(0.0530)
Energy price (t-4)	−0.0296	−0.0063	0.0058	0.0158**	−0.0207***
	(0.0248)	(0.0040)	(0.0044)	(0.0071)	(0.0078)
log of GHG intensity (1995)	0.0009	−0.0000	−0.0003	0.0006	−0.0001
	(0.0031)	(0.0003)	(0.0004)	(0.0005)	(0.0007)
Cumulative effect of △ Energy price	0.107	0.0122	0.0716	0.0675	−0.0543
	(0.173)	(0.0379)	(0.0439)	(0.0545)	(0.0734)
N	2730	2730	2730	2730	2730
F test of excluded IV	13.87	13.87	13.87	13.87	13.87

Notes: Regressions weighted by hours worked in 1995. Standard errors clustered by sector-country in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include year-specific country dummies, year-specific sector dummies and initial (1995) cluster dummies.

Table C1 presents a first set of robustness checks, where we address some problematic issues of our empirical strategy. To mitigate concerns regarding the influence of specific sectors on national prices, the results in Panel A are obtained using world rather than national energy prices as shifts to build our instrument. While, not surprisingly, both the strength of the excluded instrument and the precision of the estimates decline substantially, we find that the technician-biased employment change is confirmed. The same issue is addressed in Panel B by excluding the power sector from the analysis. The results are again in line with the main results for technicians but are weakened for manual workers.

In Panel C, we exclude the cluster *Green Global High-Tech* that is significantly different from other clusters in terms of initial energy source shares (Table B1). In addition to the fact that the effect on manual workers is smaller, the main notable difference is that the effect on total employment becomes negative and statistically significant. This implies that, once the positive effect of environmental policies on employment in greener sectors is shut down, the effect in the remaining sectors, mostly emission-intensive sectors, is negative as found in more micro-level studies (e.g. Kahn and Mansur, 2013; Marin and Vona, 2017). Finally, Panel D presents the results of an enriched specification in which we further adjust our estimates by controlling for the initial level of all clustering variables (e.g., ICT capital, import penetration). Reassuringly, we do not detect any significant change in the estimated coefficients relative to the main specification; thus, we conclude that cluster dummies account well for differences in clustering variables.

Table 9
Quantification of the effect of energy prices on workforce skills.

	Δ short-term effect/Δ$share_{95,11}$	Δ cumulative effect/Δ$share_{95,11}$	Δtotal effect/Δ$share_{95,11}$
Managers	[0.005, 0.010]	[−0.027, −0.050]	[−0.022, −0.040]
Professionals	[−0.004, −0.009]	*[0.038, 0.070]*	[0.034, 0.062]
Technicians	*[0.025, 0.050]*	*[0.067, 0.124]*	*[0.092, 0.175]*
Manual (negative)	[0.011, 0.023]	*[0.031, 0.057]*	*[0.042, 0.080]*

Notes: In *italics* statistically significant effects. Short-term effects are obtained as follows. First, we regress the change in energy prices on the lagged level of energy prices plus year, sector and country dummies. Second, using the estimated coefficients from this auxiliary regression, we compute the short-term predicted change in energy prices at the 1st and the 3rd quartile of the energy price distribution. Finally, the upper and lower bounds of the short-term effect are obtained by multiplying these predicted changes by the estimated coefficient of the energy price change (Panel B of Table 7). Similarly, we compute the upper (resp. lower) bound of the cumulative past effect by multiplying the estimated coefficient of the lagged energy prices by the inter-quartile change (resp. the 90th to 75th change) in energy prices.

In Table C2, we evaluate whether the precision of our estimated coefficients depends on the methodology chosen to cluster standard errors. As energy price policies vary mostly at the country level and affect sectors only through differences in the energy mix, we adopt two alternative clustering methods: i) by country and ii) two-way clustering (Cameron et al., 2011). The statistical significance of our results does not decline when using different methods; by contrast, the estimated effect of the change in energy prices on the share of manual workers becomes more precise and statistically significant.

Table C3 presents the results of a long-difference specification, where we replace yearly changes with 4-years changes in equation (1). This specification is used as an alternative to the dynamic adjustment model presented in Table 8 to address the nonstationarity of our dependent variables.[18] We find larger long-term impacts than those estimated through equation (1) and a stronger effect on professionals (positive) and total employment (negative). Note, however, that this difference in the magnitude of the effects could be due to the fact that we take arbitrary 4-year windows (1995–1999, 1999–2003, 2003–2007, 2007–2011) rather than exploiting in full our the variation in our data.

In Table C4, we enrich the main specification to account for two additional variables: i) the effect of other environmental policies (Panel A) and ii) the role of green innovation (Panels B and C). For the first extension, the additional policy variables of interest are the interactions between the lagged and the change in the EPS index, on the one hand, and the initial GHG intensity, on the other. Both variables are properly instrumented, with details given in Appendix C. Overall, we find that the biased employment effect of energy prices in favour of technicians is reinforced by other environmental policies. In Panel B, we explore the role of green innovation, proxied by the distance to the sectoral green technological frontier in terms of green patent stock per employee. We do not find any significant association between employment dynamics and the distance to the green frontier. However, our results in Panel C show that, as expected, sectors closer to the frontier are able to transform the challenge of higher energy prices into an opportunity to create jobs (column 1), especially technical jobs (column 4).

Finally, Table C5 replicates Table 7 for different dependent variables: labour productivity (value added per hour worked) and the shares of high-, medium- and low-skilled workers defined in terms of educational attainment, university graduates, high-school graduates and lower secondary graduates or less, respectively. The main takeaways from these tables are that skill biases are not evident when using an education-based measure of skills. Moreover, while polluting sectors experienced lower productivity growth and skill upgrading, an increase in energy prices has a positive short-term effect on productivity growth, which resonates with findings of Albrizio et al. (2017) concerning the effects of the EPS index on TFP growth. We leave a more detailed examination of the effects of energy prices on labour productivity to future research.

5. Concluding remarks

Our paper investigates the effects of energy prices 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, to a lesser extent, professional workers for manual workers. 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) relative to managerial and social skills (i.e., non-routine interactive skills).

This result, which is reinforced when also considering other climate policies, indicates that investing in technical 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. Note that the well-known orientation of the German educational system towards technical and vocational skills may be one of the key factors explaining the German leadership in green production. On the other hand, the debate over a just transition of the workforce (Rosemberg, 2010) can be informed by our findings, which can give guidance for retraining manual workers for middle-skill technical jobs for green tasks. By providing fresh opportunities to workers who bear the bulk of the costs of the low-carbon transition and other structural transformations, such retraining policies will increase the political acceptability of climate policies (Vona et al., forthcoming).

[18] 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. The results are available upon request.

Importantly, energy prices did not contribute to the swift decline in employment in polluting industries, in contrast with the findings from 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 by 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 begin to investigate the mediating effects of green technology, and we find some evidence that the effect of energy prices becomes negative and significant on total employment once greener sectors are excluded.

This paper is a first step towards understanding the distributional labour market impacts of climate 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 the effects on wages, which may be different from that on labour demand, especially in countries with centralized wage-setting institutions. Examining wage effects would be particularly important to assess the distributional impacts, especially on the most vulnerable manual workers. In this work, we refrain from examining the impact of climate policies on wages 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 worker 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 combined with detailed data on the skill requirements of occupations, which are better suited for an analysis of the transitional costs of climate policies as dependent on skill gaps (e.g., Walker, 2011; Gathmann and Schönberg, 2010).

Acknowledgement

We wish to thank Matthew Cole, the editor, and two referees for their constructive comments and suggestions. We also thank Matthieu Glachant, Misato Sato, Arlan Brucal, Chi Man Yip, Robert Elliott for useful comments and discussions. This paper benefits from comments at the following seminars and conferences: Italian Society for Climate Sciences (SISC) Conference 2018 (Venice, Italy), IAERE Conference 2019 (Udine, Italy), SEEDS Workshop (Ferrara, Italy, 2018), Green Growth and Sustainable Development (GGSD, OECD, Paris, France, 2018), EAERE Conference 2019 (Manchester, UK), Seminar at Grantham Institute of LSE (London, UK, 2019), Seminar at the Ecole des Mines (Paris, France, 2019), International Workshop on The Economics of Climate Change and Sustainability (Bologna, Italy, 2019). This work was supported by Horizon 2020 Framework Programme, project INNOPATHS [grant number 730403].

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2019.102253.

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