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Summary

Governments across the globe are implementing stricter environmental policies to combat climate change and promote sustainability. This study contributes to the growing literature exploring the influence of environmental policy on skill-biased employment across various occupations. Specifically, we examine the causal effect of the revised version of Environmental Policy Stringency Index (EPS) and its components on skill-biased employment, focusing on occupations such as managers, professionals, technicians, and manual workers across 21 European economies from 2008 to 2020. Using the Method of Moments Quantile Regression (MMQR), the findings reveal that stringent environmental policies affect employment shares across different occupational categories. Skilled workers tend to benefit more from such policies, with a notable increase in the employment of professionals across all policy measures and a more differentiated impact among technicians and managers. In contrast, manual workers are generally adversely affected by environmental policies. These asymmetric effects on occupations exacerbate labour market inequalities, including disparities in employment levels and potential earnings. This research highlights the importance of designing tailored policies to mitigate adverse labour market outcomes while facilitating a transition to sustainable economic practices.

Keywords: Environmental policy stringency; Skilled workers; Employment; Method of Moments Quantile Regression

JEL Classification: Q58, J24

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Skill-Biased Employment and the Stringency of Environmental Regulations in European Countries*

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Abstract

Governments across the globe are implementing stricter environmental policies to combat climate change and promote sustainability. This study contributes to the growing literature exploring the influence of environmental policy on skill-biased employment across various occupations. Specifically, we examine the causal effect of the revised version of Environmental Policy Stringency Index (EPS) and its components on skill-biased employment, focusing on occupations such as managers, professionals, technicians, and manual workers across 21 European economies from 2008 to 2020. Using the Method of Moments Quantile Regression (MMQR), the findings reveal that stringent environmental policies affect employment shares across different occupational categories. Skilled workers tend to benefit more from such policies, with a notable increase in the employment of professionals across all policy measures and a more differentiated impact among technicians and managers. In contrast, manual workers are generally adversely affected by environmental policies. These asymmetric effects on occupations exacerbate labour market inequalities, including disparities in employment levels and potential earnings. This research highlights the importance of designing tailored policies to mitigate adverse labour market outcomes while facilitating a transition to sustainable economic practices.

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1. Introduction

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The risks posed by climate change at both individual and social level are already severe and are going to rise further in absence of a very rapid reduction of greenhouse gas emissions and removal of carbon dioxide from the atmosphere. Therefore, more stringent climate polices for more ambitious environmental targets are urgently called for. Such policies, however, have many other implications beside the mitigation of the economic losses from extreme weather and other climate change related events. For instance, there is a wide concern in many business sectors about the costs of climate and other environmental regulations due to possible related competitive disadvantages that would bring about reductions in economic activities and job losses. Such a worry has not been completely dissipated so far. Indeed, whether and how environmental regulation affects production levels and unemployment remains a very controversial issue also in the academic debate where the presence of papers reporting negative effects is still important (see, for instance, Greenstone, 2002; Walker, 2011; Curtis, 2018). Nonetheless, many papers do not find significant evidence of changes in total employment caused by environmental restrictive policies (Morgenstern et al., 2002; Berman and Bui, 2011; among the others) and, according to the so-called Porter hypothesis, a more stringent environmental regulation could even increase firms' productivity and competitiveness if it forces firms to shift towards more efficient processes (Porter and van der Linde, 1995). However, even when environmental regulation occurs to be negatively correlated to production and employment, it results in differentiated impacts and in a reallocation of employment among industries and types of occupation, rather than in a generalized jobs lost (Walker, 2011; Hafstead and Williams III, 2016; Liu et al., 2017; Liu et al., 2021; Zheng et al. 2022; Li and Jin, 2024), As this reallocation of workers is accompanied by changes in the demand for different skills, shedding further lights on whether and how environmental regulation can induce such changes is crucial to inform the policy makers and identify training and educational policies that supplement the transition towards a sustainable economy (Vona et al., 2018).

In this paper we address this issue by estimating how the environmental policies adopted by 21 European countries in the period from 2008 to 2020 affected the labor market and, particularly, the employment shares across different types of occupations. Environmental policies are proxied by the OECD Environmental Policy Stringency Index (EPS), i.e. the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behaviors[1]. The OECD EPS index covers 13 policy instruments, mainly focussed on climate change and air pollution, and can be dissected in three different sub-components: market-based policies (MBP), non-market-based policies (NMBP), and technological support policies (TSP). In order to identify the asymmetric effects of environmental policies on different types of employment, we refer to the International Standard Classification of Occupations (ISCO) and focus on four groups, i.e. Managers, Professionals, Technicians, and Manual workers. Specifically, we conduct quantile regressions related to the effect of EPS, MBP, NMBP and TSP on the percentages of Managers, Professionals, Technicians, and Manual workers over countries' populations. The effects of environmental policies are scrutinized by disentangling the point estimates (the so-called 'location', i.e., the effect evaluated at the mean of dependent variable distribution or along the quintile distribution) and the 'scale' value (i.e. a measure of the variance of the effects along the employment-to-population distribution).

Our analysis allows us to appreciate a number of differentiated results. Indeed, we show that skilled workers appear to benefit from environmental policies as we note a rise of professionals for each type of measure, while for technicians and managers, the effects are more mixed. For the latter, the impact is generally small. On the contrary, manual workers are generally penalized by environmental

[1]. A deeper analysis of the OECD EPS index is provided by Kruse et al. (2022).

policies. We also find that different environmental policies have different effects on employment. Indeed, non-market-based policies produce negative employment effects (except for professionals), while technological support policies produce positive employment effects (except for manuals). Finally, we note mixed impacts on the variance of employment-to-population ratio.

This research contributes to the growing literature dealing with the differentiated effects of environmental regulation in the labor market. On this issue Zhong et al. (2021) build a theoretical model based on Cobb-Douglas production function employing high and low skilled workers and show that environmental regulation may generate two effects: a "compliance cost effect" affecting positively the employment of high skilled and negatively the employment of low skilled workers, and an "innovation offset effect" that generates a positive effect on both skilled and unskilled employment. As a consequence, the number of high skilled workers tends to grow in response to strengthening of environmental regulation while the number of low skilled workers tend first to go down and then to recover, following a U shape pattern. The authors conducted also an empirical test on provincial dynamic panel data in China that validates their model.

Skill-biases in employment dynamics are well documented also in other studies on the effects of environmental policies. Vona et al. (2018), for instance, report the effect of environmental regulation in a panel of US metropolitan and nonmetropolitan areas showing that, even if no effect arises on overall employment, the demand of some identified categories of green skills (namely, technical and engineering skills) results to be positively (but moderately) affected. In a similar vein, Bowen et al. (2018) estimate the share of jobs that would benefit from green transition in the US, showing that only a small share of the workers that could be involved in the green transition (which they estimate to be about 20% of US workers) will require specific green skills. Zheng et al. (2022), instead, find that environmental regulation in China caused a significant fall of the labour demand in pollution-intensive sectors. However, they also observe a negative effect on corporate salaries coupled with a positive effect on per capita salaries which allow them to argue that the negative effects of environmental regulation are mainly borne by low-skilled workers. Niggli and Rutzer (2021) explored how environmental regulation impacts at the occupational employment, using ISCO 3-digit aggregation level within the manufacturing sector across 19 European countries. A decline in labour demand was observed for occupations with low green potential, whereas an increase was noted for those with high green potential. Moreover, Consoli et al. (2016) analyse labour force characteristics of green and non-green occupations revealing that green jobs – that are those that we expect to benefit more from environmental policies - present a higher content of human capital such as formal education, work experience and on-the-job training. A shift from low skilled to high skilled jobs is also confirmed by Bu et al. (2022) - who focus on the Chinese Carbon Emission Trading pilot program and document an increase in the proportion of high educated workforce coupled with a decrease in the proportion of production workers– and Marin and Vona (2019) who find that climate policies in the EU have favoured those jobs characterized by a higher content of technical skills and have been biased against low skilled manual workers. Vandeplas et al. (2022) argue that the transition costs caused by the subsequent reallocations in the labour market should be mitigated by suitable policy actions.

Our research is particularly close to Marin and Vona (2019) as both of us are among the very few papers that evaluate skill-biased employment dynamics due to environmental policies focusing on European countries. Further, we both focus on the same occupational groups, i.e. managers (ISCO 1), professionals (ISCO 2), technicians (ISCO 3) and manual workers (ISCO 7, 8 and 9). However, while their analysis is conducted on 14 EU countries and 15 industrial sectors over the period 1995–2011, we cover the entire economy of 21 European countries, including non EU countries like Switzerland and Norway, over the period 2008-2020. Most importantly, in Marin and Vona (2019) the stringency of climate policy is proxied by energy prices while we use the OECD EPS which both represents a more general index of environmental regulation's stringency and, above all, allows us to take into account different regulatory approaches, namely market-based, non-market-based, and those based on technological support. Under this respect our paper also contributes to that stream of literature investigating pros and cons of alternative environmental policy instruments (Goulder and Parry, 2008). In particular, our specific research question is very close to those of Jing et al. (2023) and Sun and Zhang (2024) who consider the heterogeneous effects of alternative types of environmental regulation on the employment skill structure in China.

The remain of the paper if organized as follows. The following section lays out some theoretical background about the econometric methodology employed for the study. Section 3 focuses on the empirical analysis by showing the data and explaining the preliminary tests and the empirical methodology that have been employed. The main results are presented and discussed in Section 4 while in Section 5 we show some additional insights coming from an analysis run only on specific sectors. Section 6 concludes and offers some policy implication.

2. Theoretical background

Environmental policies serve as a crucial instrument that governments employ to enforce social standards and foster sustainable economic development by mitigating the adverse externalities of pollution caused by production and business activities. These policies can potentially drive changes in production technologies, thus affecting labour demand. However, such shifts may lead to varying impacts across different occupational groups.

Previous research on environmental regulation has identified four distinct approaches in the literature regarding economic and empirical models. The first perspective adopts the Human Capital Theory (HCT) by Becker (1964), which proposes that individuals' investment in education and upskilling elevates productivity and growth. From this perspective, environmental regulations can potentially create new jobs in sectors like renewable energy, energy efficiency, or sustainability advisory, but these jobs require different skills, contrary to conventional sectors that do not require them. This can potentially favour high-skilled workers who are more open to adaptability. The second perspective (Doeringer and Piore, 1971) employs the Labour Market Segmentation (LMS) theory that states that the labour market has different segments based on skills, education, experience etc, that give different opportunities and wages to workers. Environmental regulation could create new segments in the labour market, rewarding more high-skilled labour and leaving low-skilled labour for precarious jobs. The LMS theory has been recently used by Janikowska and Jebreel (2022). The third perspective adopts the Environmental Kuznets Curve (EKC) hypothesis (Grossman and Krueger, 1995). This hypothesis adapts the Kuznets' inverse U-shaped relationship between per capita income and inequality to assert that with increased economic growth, environmental degradation initially increases and then decreases. Using that theory, we can say that environmental regulation can shift EKC, potentially impacting different skill groups differently. For instance, high-skilled could get more employment in green sectors due to new opportunities, while manual workers could face job losses from polluting sectors during this transition. Abdullahi and Maji. (2019) used supporting arguments from the EKC hypothesis to understand the impact of environmental regulation on labour market dynamics in Sub-Saharan Africa. Lorente and Álvarez-Herranz (2016) support the EKC hypothesis and found that environmental regulation positively impacts labour market dynamics by reducing ecological degradation. Finally, the last perspective employs the aforementioned Porter Hypothesis (Porter, 1991; Porter and Linde, 1995) arguing that environmental regulation could stimulate innovation and competitiveness and create new markets for green technologies and services, potentially benefiting skilled workers in innovation-driven sectors.

Based on such theoretical and empirical frameworks, and in the vein of Vona et al. (2018), Marin and Vona (2019) and Zheng et al. (2021), we are going to estimate the following economic model

$$EMP = f(EPS, GTI, WAG, GDP, INV, TO) \qquad (1)$$

in order to figure out the effect of environmental policy stringency (*EPS*) on employment (*EMP*), taking also into account also the effects of a number of covariates (*GTI, WAG, GDP, INV* and *TO*). The exact content of all these variables and the econometric specification of (1) will be better explained in the following section.

3. Empirical analysis

3.1 Data

The annual panel data of 21 European countries[2] (Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland) are selected, covering the time span from 2008-2020[3].

The employment variables are defined according to the International Standard Classification of Occupations (ISCO), which allows us to identify four groups of occupations, such as Managers (ISCO 1), Professionals (ISCO 2), Technicians (ISCO 3), and Manual workers (ISCO, 7, 8, and 9)[4]. The related yearly values are obtained from "The European Union Labor Force Survey" (Eurostat Database).

The principal explanatory variable is the updated version of the Environmental Policy Stringency Index (EPS), which describes the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behavior. The EPS is also considered in terms of the three different sub-components: market-based policies (MBP), non-market-based policies (NMBP), and technological support policies (TSP). The specific instruments employed in constructing this indicator are depicted in Figure 1. EPS data was derived from the Organization for Economic Co-operation and Development (OECD). For more information regarding the methodology behind the calculation of this index, see Kruse et al. (2022)[5].

[Figure 1 about here]

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[2] Data on different groups of occupations from Eurostat are not available for Iceland. Moreover, data on the environmental policy stringency index (OECD) are missing for Bulgaria, Croatia, Cyprus, Latvia, Lithuania, Malta, and Romania.

[3] We restrict our analysis to the years 2008–2020, as data from Eurostat, the Labor Force Survey employs the NACE rev. 2 classification from 2008 onwards, while data from OECD (Environmental Policy Stringency Index) is only available until 2020.

[4] The exclusion from our empirical estimation of occupational groups, such as clerical (ISCO 4) service occupations (ISCO 5), and agricultural occupations (ISCO6), is due to data unavailability for Manufacturing, Construction, and Mining sectors which are included in our empirical analysis.

[5] Niggli and Rutzer (2021) use the first version of the OECD EPS index (Botta and Kozluk, 2014) to investigate the heterogeneous effect of environmental policy on an ad hoc categorization of occupational skills within the manufacturing sector of 19 European countries during the period 1992-2010.

Figure 2 shows the revised EPS index scores for 1990 and 2020 in the OECD countries under scrutiny. Theoretically, its values range from 0 to 6, with 6 representing the highest stringency level and 0 being the lowest. However, we note a certain degree of heterogeneity of EPS across countries and different evolution over time. In 2020, France and Switzerland displayed the highest levels of EPS, being 4.89 and 4.5, respectively. On the contrary, the lowest levels emerged from some Eastern and Southern European countries, such as Spain, the Slovak Republic, and Hungary. All countries also displayed a consistent increase in the EPS levels in the time range 1990-2020. In this regard, we cite the case of Denmark, Norway, Estonia, and Slovenia, which are among the countries experiencing the sharpest increase in the EPS level.

[Figure 2 about here]

A set of control variables - i.e., green technological innovation (GTI), economic dimension (GDP), wage rate (WAG), public investment (INV), and trade openness (TO) - are included to control for other sources of variability of the outcomes. Data for such variables were collected from "The World Development Indicator" (The World Bank).

Table 1 synthesizes the full set of variables considered in our analysis. In addition, it includes also the acronym used in the manuscript, a brief description of such variables, and their sources.

[Table 1 about here]

To enhance our understanding of the distinctive features of variables, we perform a comprehensive investigation of descriptive statistics in Table 2. We report the main statistics of both raw and transformed data. Notably, we normalize occupational data and use logarithm transformation of all covariates. The former was necessary because of the variability of occupational levels across countries. Without controlling for such an issue, the distribution of the occupational levels would be guided by the country size, thus conducting to misleading conclusions. For this reason, empirical analyses are carried out on normalized data, as obtained by dividing the raw occupational levels by the country-level yearly population. In addition, we consider logarithm transformation of covariates, which may help and homogenize the interpretation of estimation results.

As expected, the average value of manual workers is greater than other occupations (around 2392 thousand), while managers display the lowest average value (around 489 thousand). The comparison of raw and normalized values stresses the importance of correcting the occupational data by population levels, to achieve the goal of putting aside the country-size effect. The variability across average values (i.e., the ratio between maximum and minimum values) is very high in the case of raw data (up to 140 in the case of technicians) while it decreases to a few units in the case of normalized data (around 7 in the case of managers, and less for other occupations).

The environmental stringency varies considerably even between EU countries. Table 2 depicts that EPS values range from a minimum of 1.80 (the lowest level of EPS in 2008) to a maximum of 4.89 (the highest level in 2020). Non-market-based instruments, on average, demonstrate stronger stringency than market-based instruments and technology support programs, while the latter show the highest levels of variability across years and countries (being included in the range of 0.5-5.5).

Finally, Table 2 reports statistics of control variables. We note a relatively high level of variability in terms of green technological innovation, trade openness, and wage rate, while differences are more limited in terms of economic dimension and public investments.

[Table 2 about here]

3.2 Preliminary tests

The initial stage of our empirical investigation consists of running several statistical analyses to characterize the used data.

First, we test the normality of the data using the Jarque and Bera test. Then, we run a battery of tests to examine, in turn, the existence of cross-sectional dependence, slope homogeneity, the presence of unit root, and cointegration analysis. Related results are summarized in the Appendix (Tables A1-A5).

Our analysis revealed that the null hypothesis of the normally distributed data is rejected, with very few exceptions (Table A1). This suggests the importance of adopting an estimation method able to relax the normality assumption when studying the relationship between the variables of interest.

Our findings also validate the existence of cross-sectional dependence (Table A2). The statistical significance of all variables in this analysis, in fact, results in the rejection of the null hypothesis at the 1% and 10% significance levels (few exceptions emerge from the Pesaran CD test).

The null hypothesis regarding the homogeneity of slopes is also rejected with a significance level of 1%, providing evidence of heterogeneity in the data, which may reflect distinctive characteristics of the economies under scrutiny (Table A3).

Following the presence of cross-sectional dependency and slope heterogeneity in the data, we conducted unit root and cointegration studies (Table A4). Regarding the former, due to the results of the two previous tests, the literature suggests the use of the second-generation Cross-Sectional augmented Im-Pesaran-Shin (CIPS) test to evaluate the stationarity characteristics of the variables (Pesaran, 2007). The null hypothesis of the CIPS panel unit root test is that the series contains a unit root. The outcomes of the unit root analysis have revealed that only the variables EPS, MBP, GTI, and INV are stationary at the level, while the remaining ones are stationary at the first difference.

Following the unit root results displayed in Table A4, we investigated the cointegration relationship among covariates using the various cointegration approaches proposed by Pedroni (1999), Kao (1999) and Westerlund (2007). The findings provide substantial evidence of a durable, enduring relationship among the variables in all models throughout the analysed EU countries (Table A5). The presence of these enduring associations enables the calculation of long-term elasticity estimates.

3.3 Empirical methodology

Following the evidence that emerged from the aforementioned statistical analysis, this study relies on the method of moments-quantile regression (MMQR) technique introduced by Machado and Silva (2019)[6]. The adoption of the MMQR has several advantages for our study. First, it deals with the non-normality of the data distribution, which is crucial considering the results that emerged from the Jarque and Bera test, and provides estimates at specific location, scale, and quantiles. Second, it accounts for time-invariant country-specific unobserved heterogeneity, by including fixed effects in the model, and examines the distributional heterogeneous impact of independent variables on the various quantiles of dependent variables.

[6] Similar technique is used e.g. by Safi et al. (2024), Umar and Safi (2023) and Lee et al. (2023).

MMQR is frequently employed to estimate the conditional median or different quantiles of the dependent variable based on specific conditions of the independent variables, unlike traditional ordinary least-squares regression (OLS) models that provide estimates of the conditional mean.

Moreover, the MMQR model is more effective than standard OLS regression as it deals with endogeneity and irregularities in the data. The traditional OLS regression model calculates the on-average effect of predictor variables on predicted variables; conversely, MMQR model outcomes display how explanatory variables influence dependent variables at different quantiles. Furthermore, unlike the classical OLS estimator, MMQR estimators are not restricted by standard distribution assumptions. (Wang et al., 2024). MMQR integrates asymmetric and nonlinear interactions under moment restrictions (Huang et al., 2022). This innovative approach examines the distributional and heterogeneous characteristics of various quantile values (Sarkodie and Strezov, 2019), assisting researchers in achieving a more comprehensive analytical perspective and emphasizing potential differences and trends among variables across varying conditions. The proposed method is noteworthy for its simplicity, as it consistently produces non-overlapping estimates during quantile evaluation. For this reason, the following demonstrates the estimate of conditional quantiles $Q_y(\frac{\tau}{X}X_{it})$ for a location-scale variant model:

$$Y_{it} = \beta_i + X_{it}'\gamma + (\emptyset_i + Z_{it}\alpha)\, U_{it} \tag{2}$$

In the above equation Y_{it} represents the dependent variable (EMP), whereas X_{it} denotes predicators (EPS, MBP, NBMP, TSP, GTI, GDP, WAG, INV, and TO), while $\alpha, \beta, \gamma, \emptyset$ are parameters to be observed. The scale coefficient $(\emptyset_i + Z_{it}\alpha) = 1$ demonstrates the fixed effect of quantile. U_{it} is an unobserved random variable distributed over the cross-sectional, $i = 1 \dots n,$ indicates the individual i fixed effect, and Z is a $K -$ vector of unknown components of X.

$$X_i, = X_i, (Z)\; i = 1, \dots\dots n, \tag{3}$$

For a specified constant value of i, the random variable X_{it} provides a distribution that is both identical and independent, as well as independent across heterogeneous values of t. Following the conditions outlined by Machado and Silva (2019), the variable U_{it} is presumed to be independent and identically distributed throughout time for each unit i. Furthermore, it is essential to note that U_{it} is unrelated to the variable X_{it}. This is necessary for the moment described in the study mentioned above.

The MMQR formulation incorporating all the relevant parameters for our model is specified as follows:

$$QEMP_{itj}\,(\tau|X_{it}) = \vartheta_{i\tau j} + \vartheta_{1\tau j} lnEPS_{it} + \vartheta_{2\tau j} lnGTI_{it} + \vartheta_{3\tau j} lnGDP_{it} + \vartheta_{4\tau j} lnINV_{it} + \vartheta_{5\tau j} lnWAG_{it} + \vartheta_{6\tau j} lnTo_{it} + \varepsilon_{itj} \tag{4}$$

where $QEMP_{itj}\,(\tau|X_{it})$ represents the conditional quantile of the dependent variable employment of specific occupation, the subscript "i" refers to the cross-sectional unit (in this study, 22 selected European countries), j represents different categorized occupations such as Managers, Professionals, Technicians, and Manual workers. In contrast, "t" means the time series (2008-2020) index. The vector X_{it} represents explanatory variables, including environmental policy stringency index (EPS), green technological innovation (GTI,), economic dimension (GDP), public investment (INV), wage rate (WAG), and trade openness (TO). The error term of the model is denoted by ε_{itj}. The estimated coefficients are represented by $\vartheta_1$to ϑ_6, and ϑ_i represents the intercept.

To examine the empirical relationship between Market-Based Policy (MBP), Non-Market-Based Policy (NMBP), Technology Support Policy (TSP), and occupational level employment (EMP), we furtherly consider the following equations

$$QEMP_{itj}\ (\tau|X_{it}) = \gamma_{i\tau j} + \gamma_{1\tau j} lnMBP_{it} + \gamma_{2\tau j} lnGTI_{it} + \gamma_{3\tau j} lnGDP_{it} + \gamma_{4\tau j} lnINV_{it} + \gamma_{5\tau}\ lnWAG_{it} + \gamma_{6\tau j} lnTo_{it} + \mu_{itj} \quad (5)$$

$$QEMP_{itj}\ (\tau|X_{it}) = \delta_{i\tau j} + \delta_{1\tau j} lnNMBP_{it} + \delta_{2\tau j} lnGTI_{it} + \delta_{3\tau}\ lnGDP_{it} + \delta_{4\tau j} lnINV_{it} + \gamma_{5\tau j} lnWAG_{itj} + \gamma_{6\tau j} lnTo_{it} + \epsilon_{itj} \quad (6)$$

$$QEMP_{itj}\ (\tau|X_{it}) = \varphi_{i\tau j} + \varphi_{1\tau j} lnTSP_{it} + \varphi_{2\tau j} lnGTI_{it} + \varphi_{3\tau j} lnGDP_{it} + \varphi_{4\tau j} lnINV_{it} + \varphi_{5\tau j} lnWAG_{it} + \varphi_{6\tau j} lnTo_{it} + \epsilon_{itj} \quad (7)$$

where EPS in equation (4) is replaced, respectively, by MBP, NMBP and TSP, and the estimated coefficients have been relabelled by $\gamma_1 - \gamma_6, \delta_1 - \delta_6, \varphi_1 - \varphi_6$, while $\gamma_i, \delta_i, \varphi_i$ represents the intercepts. All the other variables are the same defined in equation (4).

4. Results

This section provides empirical results obtained from the MMQR model, their interpretation, and the subsequent discussion (Tables 3-6). They allow us to uncover the heterogeneous impact of environmental policy stringency and the related sub-components on different occupations. For the sake of brevity, the results related to the quantiles are not shown in the Tables but they are summarized in Figure 3[7].

When commenting our estimates, we firstly focus on the first row of each Table which resume the relationship of interest in our study, i.e. how the environmental stringency index and its sub-components affect the employment levels. The effects of covariates are briefly described at the end of the paragraph.

First, we look at the effects of the general EPS index (Table3)[8]. We note a very small negative (-0.0002) and not statistically significant effect on Managers, focusing on both the point estimate (the so-called 'location', i.e., the effect evaluated at the mean of dependent variable distribution) or along the quantile distribution. On the contrary, the effect is positive for both professionals and technicians (location is equal to +0.06 and +0.022, respectively. Both are statistically significant at a 1% level). Quite interestingly, the 'scale' value (i.e., a measure of the variance of the effects along the employment-to-population distribution) is positive for Professionals (+0.031) and negative for Technicians (-0.0228). The empirical findings suggest that the positive effect for professionals is characterized by a rise of inequality across time and countries in terms of the professional employment-to-population ratio. In other words, the effect is positive on average, but the effect is greater in those countries and years where the ratio was higher. The contrary for Technicians, which have been characterized by a reduction of inequality across time and countries of the technician employment to population ratio. In other words, the effects were positive on average, but it was stronger in countries and years where the technician employment to population ratio was smaller. Finally, we comment on the effect of EPS on manual workers. Our estimates reveal a negative impact

[7] The full set of estimates at the quantile levels are available upon request.

[8] Being the model based on a linear-log specification, the impact of a covariate on the outcome variables can be inferred by multiplying the estimated coefficient with a correcting factor. It is determined by calculating the natural logarithm of (1+*a*), where *a* is the percentage change in the covariate. For example, if one considers an increase of 10% in the covariate, this implies a correcting factor equal to 0.0953. Thus, the employment-to population ratio increases (in absolute terms) by 0.0953*δ_1 because of a 10%-increase in the EPS index.

of EPS on the manual workers to population ratio (-0.0719, statistically significant at 1% level). The 'scale estimate' is positive but not statistically significant.

To sum up, except for the 'quasi-zero' effect on managers, the EPS index is associated with asymmetric effects on the level of employment to population ratio. There was a rise in more skilled occupations and a decrease in less skilled ones (i.e. manual workers). This points in the direction of raising inequalities in the labor markets in terms of skilled-‘unskilled' employment because of Environmental policies. Presumably, we could expect also a widening of earnings inequality, as our estimates suggested asymmetric effects on labor demand for skilled and 'unskilled' workers.

[Table 3 about here]

Now we focus on specific EPS measures. First, we comment on the effects of MBP on occupational levels (Table 4). We note a negative and statistically significant impact on managers (-0.00211, significant at 10% level). The scale effects are also negative, suggesting that such effect was asymmetric along the distribution, with a more detrimental impact in the higher quantiles of the managers-to-population ratio distribution. On average, the impact on professionals was positive (+0.0185, significant at 1% level). The related 'scale' estimate was also positive, suggesting stronger positive effects on the right part of the distribution. On the contrary, the average impact on technicians was negative, but small in magnitude (-0.000809) and statistically not significant. The 'scale' estimate is also negative and statistically significant, with stronger changes at the tails of the distribution. Finally, we remark on the negative effect of MBP on manual workers (-0.0184, significant at 1% level), while the 'scale' is small in magnitude and not significant in a statistical sense.

[Table 4 about here]

Second, we look at NMBP (Table 5), which determines a negative and small effect on manager employment (-0.00879). On the contrary, professionals are positively affected by the application of NMBP. The magnitude of the 'location' estimate is +0.0536 (significant at 1% level). Finally, both technicians and manual workers are negatively affected by NMBP (-0.0289 and -0.0277, both statistically significant, at 1% and 10% respectively). Quite interestingly, the 'scale' estimate is always small and statistically not significant, suggesting NMBP determines relatively small redistribution across countries and years in the employment-to-population ratio, for each type of considered occupation.

[Table 5 about here]

Finally, TSP (Table 6) determines relatively small but statistically significant effects on each type of occupation here analyzed. The effect is positive for managers (+0.00173, significant at 5% level), professionals (+0.0041, significant at 5% level), and technicians (+0.00902, significant at 1% level). The latter is the greatest positive impact from TSP, suggesting that support for technological innovation determines a complementary effect on the labor demand of skilled workers, particularly technicians. On the contrary, TSP is associated with a decrease in manual workers (-0.00927, significant at 1% level), thus suggesting a substitution effect. The 'scale' estimates are statistically significant only for managers and professionals. In both cases, the sign of the estimated coefficients is positive, thus indicating a widening across countries and years of manager and professional employment-to-population ratio.

[Table 6 about here]

As anticipated, estimates at quantile levels are summarized in the Figure 3. It illustrates the comparison among the heterogenous environmental policy stringency on different groups of occupational levels. The effect size varies from the lowest to the upper quantiles (10-90).

The effect of general EPS on managers is different across quantiles. The impact of EPS on managers is direct and negative but statistically insignificant at the 10th, 20th, 30th, and 40th quantiles, respectively. In contrast, the coefficient values are considerably positive with higher quantile levels, i.e., from 50th to 90th quantiles. On the contrary, the effect is positive for professionals across all the quantiles from 10^{th} to 90^{th}, while positive for technicians at lower and middle quantiles but negative at higher quantiles. Finally, we comment on the effect of EPS on manual workers. Our estimates reveal a negative impact of EPS on the manual workers to population ratio across all the quantiles.

Now, we focus on specific EPS components. First, we examine MBP's effects on different occupational levels. The estimated results showed a statistically significant negative impact of MBP on managers and manual workers across all quantiles from the 10th to the 90^{th}. On the other hand, the coefficient of MBP is positive for professionals across all quantiles, 10^{th} to $90^{th,}$ but negative for technicians at lower quantiles and positive for 50^{th} to 90^{th} quantiles, respectively.

Second, regarding NMBP, which determines a negative effect on managers, technicians, and manual workers across all quantiles from the 10th to the 90^{th}. On the contrary, professionals are positively affected by applying NMBP at all quantiles.

Finally, the study confirmed that the heterogeneous influence of TSP on different groups of occupational levels is different across quantiles. The impact of TSP on managers, professionals, and technicians is positive at 20th to 90th for managers, 40th to 90th for professionals, negative for professionals at 10th to 30th quantiles, and positive for technicians at 10^{th} to 90^{th}. On the contrary, TSP is associated with decreased manual workers across all quantiles (10-90).

All in all, our estimates indicate that environmental policies affect the labor market and particularly, the employment share across different types of occupations. Skilled workers appear to benefit from such policies. We note a rise of professionals for each type of measure, while for technicians and managers, the effects are more mixed. For the latter, the impact is generally small. On the contrary, manual workers are generally penalized for environmental policies. The asymmetric effects on occupations wide labor market inequalities, including employment levels, and presumably earnings inequality. We find that different environmental policies have different effects on employment. NMBP produces negative employment effects (except for professionals), while TSP produces positive employment effects (except for manuals). Finally, we note mixed impacts on the variance of employment-to-population ratio (the so-called 'scale' effect).

[Figure 3 about here]

We conclude this section by commenting briefly on the role of the control variables on the outcomes. Such effects can be inferred from the rows 2-6 of Tables 3-6. They depict the heterogeneous impact of WAG, GDP, INV, and TO on different groups of occupational levels. The following are the empirical findings obtained by MMQR. First, the estimated results depict that the effect of wage rate on managers, professionals, and technicians is positive and statistically significant, while this effect is negative for manual workers. Secondly, the findings observed that GDP significantly and positively affects all occupational levels of employment. Thirdly, regarding the public investment variable, the study confirmed that the heterogeneous influence of public investment on professionals differs. The effect of public investment on professionals is both negative and positive. On the contrary, the wage rate positively affects managers, technicians, and manual workers. In addition, the empirical findings showed a negative connection between GTI and managers, while there is a positive association between green technological innovation and professionals, technicians, and manual workers. Finally, regarding the trade openness variable, the effect of TO on managers is negative. On the contrary, professionals are positively affected by the trade activities. Further, the current study confirmed the heterogeneous impact of trade activities on technicians and manual workers.

5. Further analysis on specific economic sectors

This section describes the results of a further analysis which restricts our investigation to specific economic sectors. While the benchmark analysis was based on the entire economy, the impact of EPS would be particularly effective for economic sectors that are more responsive to the application of such policies. Thus, we investigated how EPS and its sub-components affected occupational levels in the construction, manufacturing, and transportation sectors (e.g. Marin and Vona, 2019). Related results are displayed in the Appendix (Tables A6-A9)[9]. Our findings point in the direction of composite effects across economic sectors, especially for Managers, Professionals, and Technicians. Focusing on Managers, the analysis confirms that EPS is, on average, ineffective for the employment-to-population ratio. On the contrary, the negative effect of MBP is stronger in the manufacturing sector, while the positive impact of TSP is much stronger in the transportation and storage sector. Looking at the Professionals, the analysis confirms that, when statistically significant, environmental policies play a positive role in occupations both in the manufacturing and transportation sectors. However, EPS and its sub-components emerge as negative roles for professionals employed in the construction sector. Turning our attention to the technicians, we note the positive effect of EPS emerged from the benchmark analysis, which is confirmed only for the construction and transportation sectors. Looking at the EPS sub-components, we find that the location effect is statistically significant only for the transportation sector. In this regard, MBP and TSP have a positive effect on technician occupations, while NMBP has a negative impact. We conclude by focusing on manual workers. The within-sector analysis confirms the negative impact of environmental policies on manual workers, both looking at the general index and its sub-components. Such negative effects appear stronger in the manufacturing sector.

On the one hand, the within-sector analysis highlights the presence of heterogeneous responses of economic sectors to the solicitation of environmental policies, at least for skilled occupations. On the other hand, it is confirmed the negative effect of EPS and its sub-components for manual workers, whatever the economic sector analyzed.

6. Conclusions

In this paper we have seen how the stringency of environmental policies adopted by 21 European countries in the period spanning from 2008 to 2020 has affected the employment rates across Managers, Professionals, Technicians, and Manual workers. Namely, environmental policies have been proxied by the OECD Environmental Policy Stringency Index (EPS) which allows also to distinguish between market-based policies (MBP), non-market-based policies (NMBP), and technological support policies (TSP). To obtain our results we have employed a MMQR model that has allowed us to estimate the effect of such policies both at the average and at different deciles of the distribution of our dependent variables. Our findings shed further light on the heterogeneous

[9] For the sake of brevity, we only show location and scale effects, while quantile effects are available upon request.

impact that the environmental policy stringency causes on different types of occupation and allow us to highlight a couple of evidences which might suggest some interesting policy implications.

Firstly, we show that the stringency of environmental policy seems not to affect managers while it has a positive effect on the shares of employed professionals and technicians, and a negative impact on manual workers. These findings are consistent with those received by previous studies that report a shift from unskilled to skilled jobs (e.g. Bowen et al., 2018; Vona et al., 2018; Marin and Vona, 2019; Bu et al., 2022). However, our paper points out that technical skills and specializations, that typically characterize technicians and professionals, would result to be more important than managerial qualifications as the latter can be probably employed in a wider array of sectors and activities, regardless of their environmental content. Quite interestingly, this represents a useful information for policymakers seeking for educational and training policies that can effectively help the green transition.

Secondly, when we move to the analysis of the single sub-components of the environmental policy index, we observe that all of them are significant in terms of effects generated on skills' reallocations. Furthermore, we observe that non-marked based policies, which are typically regarded as less efficient than marked based policies, present an additional flaw as they negatively affect technical jobs that, conversely, result to depend positively on the stringency of the other environmental policies. This evidence might probably deserve some further theoretical investigations.

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List of Tables:

Table 1. Variable description

Variable	Acronym	Description	Source
Managers	**MNG**	Ratio of Managers/Population	EU LFS
Professionals	**PROF**	Ratio of Professionals/Population	EU LFS
Technicians	**TECH**	Ratio of Technicians/Population	EU LFS
Manual workers	**MANW**	Ratio of Manual workers/Population	EU LFS
Environmental Policy Index	**EPS**	Environmental Policy Stringency Index (0-6)	OECD
Market-Based Policy	**MBP**	Market-based environmental regulation stringency (0-6)	OECD
Non-Market Based Policy	**NMBP**	Non-Market based environmental regulation stringency (0-6)	OECD
Technological Support Policy	**TSP**	Technological Support Policy (0-6)	OECD
Green Technological Innovation	**GTI**	Environmental-related technologies % of total technologies.	OECD
Economic Dimension	**GDP**	GDP per capita (constant 2010 US$)	World Bank
Public Investment	**INV**	Gross fixed capital formation (% of GDP)	World Bank
Trade Openness	**TO**	The ratio of exports plus imports over GDP (%)	World Bank
Wage Rate	**WAG**	Total (% of total employment)	World Bank
Notes: EU LFS denotes The European Union Labor Force Survey			

Table 2. Descriptive statistics

	Raw data						Transformed data					
Variables	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**	**Transformation**	**Mean**	**Std. dev.**	**Minimun**	**Maximum**	**Skewness**	**Kurtosis**
MNG	488.981	257.700	556.655	51.000	2226.800	Population ratio	0.0279	0.0107	0.0083	0.0593	0.6059	3.3151
PROF	1494.195	739.400	1626.546	84.700	8077.900	Population ratio	0.0853	0.0262	0.0371	0.1446	0.4257	2.2334
TECH	1450.803	636.200	2012.592	67.900	9326.600	Population ratio	0.0699	0.0209	0.0245	0.1300	0.0881	2.7746

MANW	2392.126	1090.100	2775.086	196.300	10953.60	Population ratio	0.1228	0.0279	0.0718	0.1943	0.5169	2.3885
EPS	3.205	3.111	0.539	1.806	4.889	Logarithm	1.1507	0.1692	0.5908	1.5869	-0.101	2.6490
MBP	1.777	1.500	0.912	0.500	4.167	Logarithm	0.4524	0.4926	-0.6931	1.4271	0.2055	2.1293
NMBP	5.236	5.500	0.476	2.750	6.000	Logarithm	1.6506	0.1055	1.0116	1.7917	-3.184	16.9912
TSP	2.603	2.750	1.214	0.500	5.500	Logarithm	0.8056	0.6149	-0.6931	1.7047	-1.101	3.5650
GTI	110.818	102.074	44.156	45.419	252.495	Logarithm	2.4936	0.3025	1.3937	3.2748	-0.201	3.7318
GDP	84.578	85.169	6.117	63.011	93.832	Logarithm	10.4568	0.5537	9.3523	11.5478	-0.127	1.9485
INV	26.683	26.719	1.206	23.695	29.011	Logarithm	3.0675	0.2002	2.3691	3.9940	-0.525	6.8932
TO	12.661	12.360	3.863	4.030	26.440	Logarithm	4.6286	0.4012	3.8159	5.5314	0.0263	1.8545
WAG	21.913	22.008	4.417	10.687	54.274	Logarithm	4.4348	0.0771	4.1433	4.5415	-1.761	6.7905

Notes: raw data of occupations are expressed in thousands.

Table 3. MMQR estimates: Environmental policy stringency indicator

	Managers		Professionales		Technicians		Manual workers	
	Location	**Scale**	**Location**	**Scale**	**Location**	**Scale**	**Location**	**Scale**
EPS	-0.000235	0.00307	0.0604***	0.0310**	0.0224***	-0.0228***	-0.0719***	0.00134
GTI	-0.00761***	0.00247*	-0.0127	0.00174	0.00770**	0.00470*	0.0125**	0.00149
WAG	0.0134	-0.00461	0.00103	-0.000561	0.00432***	0.00123*	-0.00868***	0.000197
GDP	-0.00231***	-0.00136***	0.0943**	-0.0102	0.109***	0.0176	0.017	-0.0620***
INV	0.0202***	0.00386	-0.00475	0.0041	0.0175**	0.0145***	0.0431***	0.0142**
TO	-0.00143	0.000366	0.0145*	-0.000917	0.000653	0.000394	-0.00614	0.00508**

Notes: ***, **, and * denote the significance level at 1%, 5%, and 10% respectively.

Table 4. MMQR estimates: Market-based policy indicator

	Managers		Professionales		Technicians		Manual workers	
	Location	**Scale**	**Location**	**Scale**	**Location**	**Scale**	**Location**	**Scale**
MBP	-0.00211*	-0.00155**	0.0185***	0.00970***	-0.000809	-0.0055***	-0.0184***	0.00118
GTI	-0.00767***	0.00227	-0.0114**	0.00205	0.00798**	0.00154	0.0110**	0.00185
WAG	-0.00244***	-0.00133***	0.00302**	0.000871	0.00461***	0.00065	-0.0108***	0.000738
GDP	0.0182*	0.00088	0.104***	-0.0283**	0.131***	0.000531	-0.00337	-0.0857***
INV	0.0214***	0.00535**	-0.0117	-0.00034	0.0192**	0.0168***	0.0494***	0.0103*
TO	-0.00246	-0.000618	0.0161***	0.00334	-0.00266	-0.00136	-0.00615	0.00681**

Notes: ***, **, and * denote the significance level at 1%, 5%, and 10% respectively.

Table 5. MMQR estimates: Non-Market based policy indicator

	Managers		Professionales		Technicians		Manual workers	
	Location	**Scale**	**Location**	**Scale**	**Location**	**Scale**	**Location**	**Scale**
NMBP	-0.00879	0.00125	0.0536***	0.00487	-0.0289***	-0.00277	-0.0277*	0.00415
GTI	-0.00821***	0.00294*	-0.00825*	0.00134	0.00603*	0.000371	0.00967*	0.00126
WAG	-0.00209***	-0.00144***	0.000581	0.000517	0.00539***	0.00127**	-0.00907***	0.00061
GDP	0.0164*	-0.00174	0.128***	0.0138	0.140***	-0.0116	-0.037	-0.0492***
INV	0.0190***	0.00397	0.0057	0.00779	0.0149**	0.0126***	0.0355***	0.00805
TO	-0.0011	0.000379	0.00488	-0.00423	-0.00126	0.000897	0.00411	0.00379

Notes: ***, **, and * denote the significance level at 1%, 5%, and 10% respectively.

Table 6. MMQR estimates: Technological support policy indicator

	Managers		Professionales		Technicians		Manual workers	
	Location	**Scale**	**Location**	**Scale**	**Location**	**Scale**	**Location**	**Scale**
TSP	0.00173**	0.00143***	0.00410**	0.00669***	0.00902***	-0.00178	-0.00927***	6.50E-05
GTI	-0.00808***	0.00260*	-0.0130***	0.00108	0.00556	0.00309	0.0141***	0.00244
WAG	-0.00236***	-0.00144***	0.00183	0.000212	0.00441***	0.000191	-0.00951***	0.000438
GDP	0.0118	-0.00522	0.145***	0.0175	0.122***	0.00721	-0.0402	-0.0411***
INV	0.0198***	0.00327	-0.00247	0.00449	0.0164	0.0139	0.0415***	0.0122**
TO	-0.00102	0.00031	0.0076	-0.00125	-0.000275	0.000195	0.00114	0.00509*

Notes: ***, **, and * denote the significance level at 1%, 5%, and 10% respectively.

List of Figures:

Fig. 1. The modified version of EPS index. Source: Kruse et al. (2022)

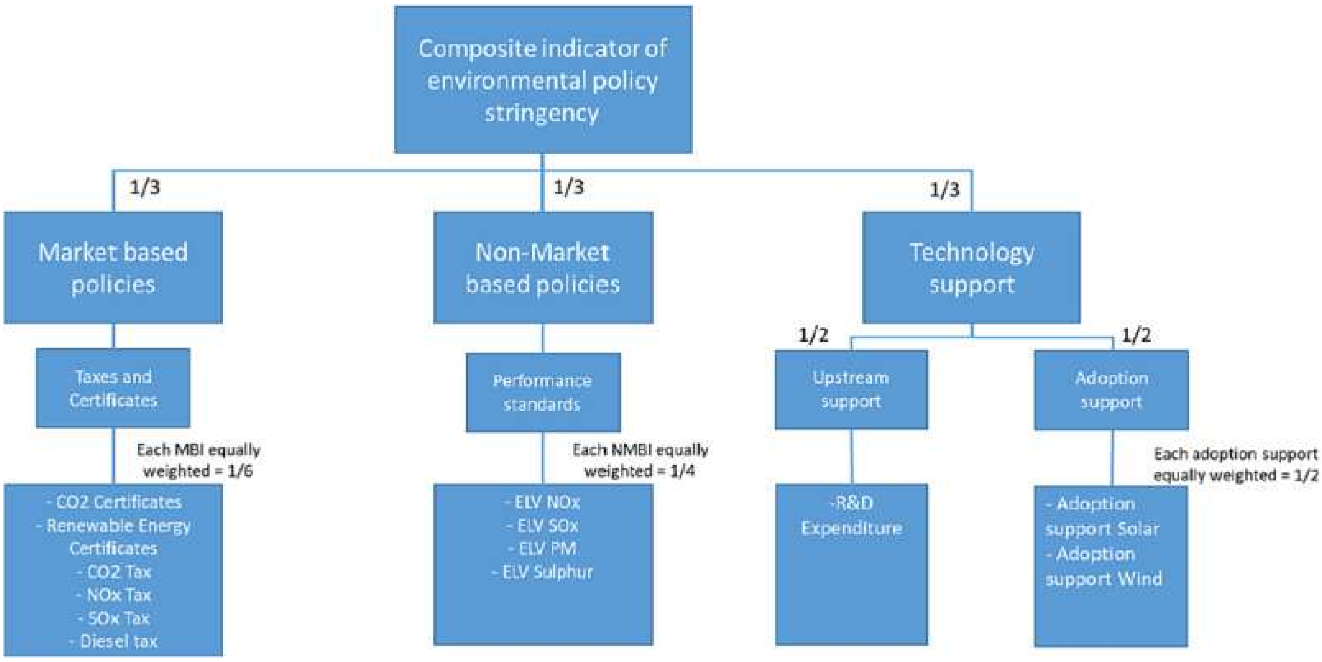


Figure 2. The modified EPS index in 21 European countries.

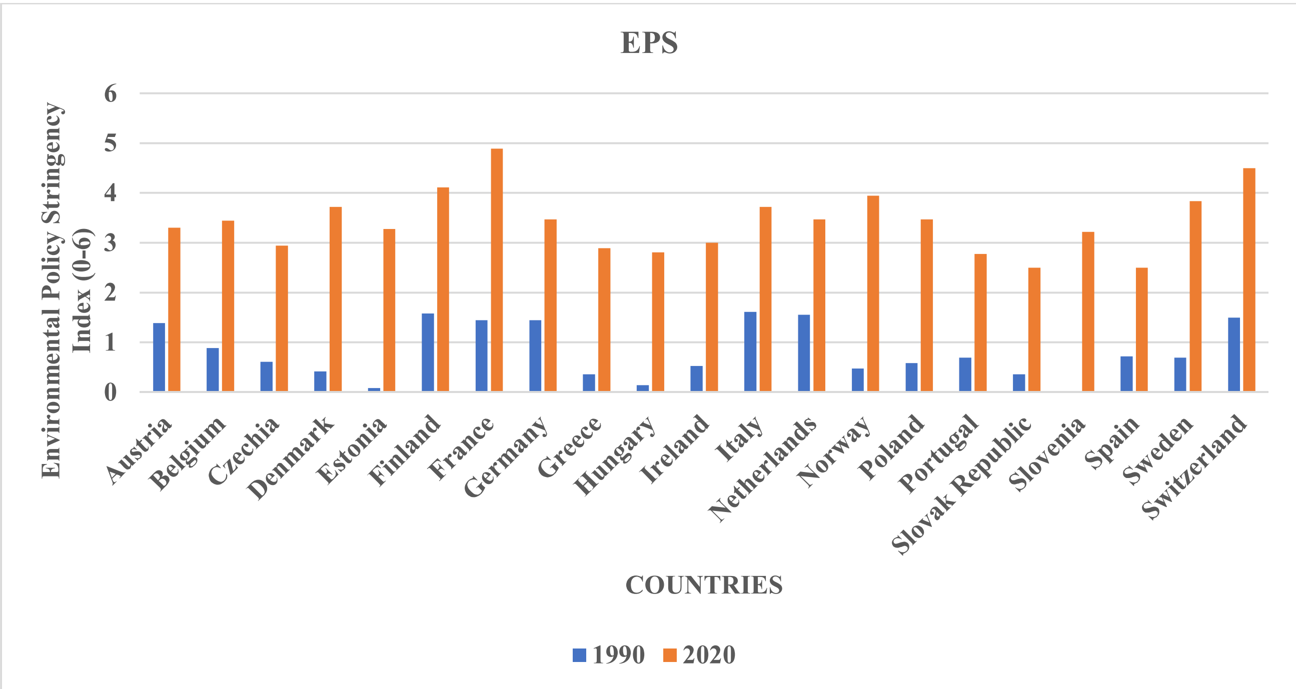
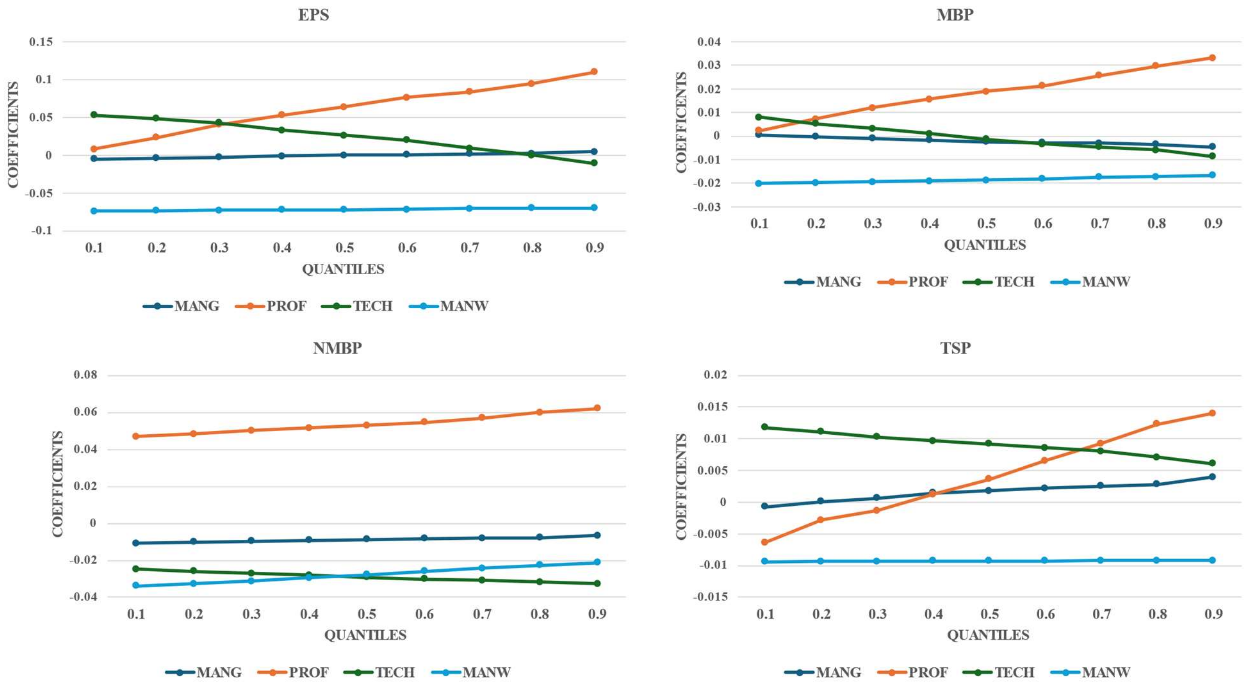


Figure 3. Graphical illustration of MMQR quantile estimates from all adopted EPS.



Appendix A:

Table A1. Jarque and Bera Test

Variables	Jarque-Bera	P-value
MNG	17.837	0.000
PROF	14.930	0.000
TECH	0.931	0.627
MANW	16.413	0.000
EPS	1.864	0.393
MBP	10.546	0.005
NMBP	2688.001	0.000
TSP	58.817	0.000
GTI	7.929	0.018
GDP	13.312	0.001
INV	184.935	0.000
TO	14.957	0.000
WAG	304.461	0.000

Table A2. Assessment of cross-sectional dependence.

Variables	BP-LM	Pesaran scaled LM	Pesaran CD
MNG	885.450***	31.933***	9.366***
PROF	996.603***	37.357***	14.672***
TECH	924.403***	33.834***	4.775***
MANW	645.320***	20.216***	6.592***
EPS	354.271***	6.015***	0.634
MBP	441.355***	10.264***	4.080***
NMBP	462.109***	11.276***	0.851
TSP	361.922***	6.388***	1.368
GTI	407.724***	8.623***	3.640***

GDP	661.911***	21.026***	11.788***
WAG	509.935***	13.610***	4.819***
INV	656.612***	20.767***	3.564***
TO	656.049***	20.740***	11.436***

Notes: *** stands for 1% significance level

Table A3. Slope heterogeneity

Managers	**EPS**	**MBP**	**NMBP**	**TSP**
Delta	3.395***	3.285***	3.732***	3.706***
Adj. Delta	5.475***	5.296***	6.018***	5.976***
Professional	**EPS**	**MBP**	**NMBP**	**TSP**
Delta	4.114***	3.638***	4.152***	4.356***
Adj. Delta	6.634***	5.867***	6.696***	7.023***
Technicians	**EPS**	**MBP**	**NMBP**	**TSP**
Delta	4.198***	3.205***	4.297***	4.005***
Adj. Delta	6.769***	5.168***	6.929***	6.459***
Manual Workers	**EPS**	**MBP**	**NMBP**	**TSP**
Delta	4.658***	4.932***	5.113***	5.055***
Adj. Delta	7.511***	7.953***	8.245***	8.150***

Notes: *** stands for 1% significance level.

Table A4. Unit root tests

	CADF		**CIPS**	
Variables	**Level**	**1st difference**	**Level**	**1st difference**
MNG	-1.205	-2.854***	-1.931	-2.905***
PROF	-0.880	-1.365	-0.999	-2.273***
TECH	-1.340	-2.239**	-1.676	-2.316**
MANW	-2.384***	-2.921***	-1.962	-2.962***
EPS	-2.192**	-2.933***	-2.274***	-3.415***
MBP	-2.446***	-3.133***	-2.132**	-3.702***
NMBP	-1.584	-0.935	-1.585	-1.619
TSP	-1.618	-2.719***	-2.023	-3.239**
GTI	-1.767	-2.373***	-2.731***	-4.228***
GDP	-1.461	-1.886	-0.793	-3.198***
WAG	-1.672	-1.964	-1.979	-3.217***
INV	-3.201***	-2.790***	-2.444***	-3.031***
TO	-1.721	-1.855	-1.650	-2.205**

Notes: *** and ** denotes the significance level at 1%. and 5%, respectively.

Table A5. Cointegration analysis

Managers	**EPS**	**MBP**	**NMBP**	**TSP**
Kao	-2.454***	-2.518***	-2.558***	-1.374*
Pedroni	6.644***	6.493***	7.066***	7.229***
Westerlund	4.509***	3.487***	2.711***	2.160**
Professional	**EPS**	**MBP**	**NMBP**	**TSP**
Kao	-2.022**	-2.072**	-2.210**	-2.015**
Pedroni	6.708***	6.793***	6.697***	6.854***
Westerlund	1.981**	3.106***	2.018**	2.276**
Technicians	**EPS**	**MBP**	**NMBP**	**TSP**
Kao	-2.735***	-2.719***	-2.876***	-2.726***
Pedroni	7.291***	7.083***	7.359***	7.226***

Westerlund	3.245***	3.329***	2.415***	2.777***
Manual Workers	**EPS**	**MBP**	**NMBP**	**TSP**
Kao	1.129	1.670**	1.230*	0.694
Pedroni	7.861***	8.100***	7.967***	7.958***
Westerlund	1.509*	2.392***	2.058**	1.177*

Notes: *** stands for 1% significance level.

Table A6. Within sector analysis: Managers

Environmental policy stringency						
	Manufacturing		**Constructions**		**Transportation and Storage**	
VAR.	**location**	**scale**	**location**	**scale**	**location**	**scale**
EPS	-0.000571	0.000740**	-0.000201	0.000756***	-5.33006	0.000267**
GTI	-0.00125***	-0.000156	4.55005	0.000364**	-0.000220	0.000207**
GDP	-0.000580***	-0.000184***	-0.000627***	-0.000217***	-0.000207***	-0.000114***
WAG	0.00397***	0.00215**	0.00130	-0.000207	0.00141***	0.000461
INV	0.00273***	-0.000407	0.00237***	0.000651**	0.000953***	0.000308**
TO	-0.000264	0.000113	-0.000740***	-7.85005	2.25005	-8.19005
Market-based policy						
MBP	-0.000500***	2.95005	-0.000146	-5.52005	-0.000156**	-4.24006
GTI	-0.00127***	-0.000165	3.86e-05	0.000363**	-0.000225*	0.000186**
GDP	-0.000617***	-0.000155**	-0.000638***	-0.000209***	-0.000216***	-0.000113***
WAG	0.00465***	0.00211**	0.00147	0.000306	0.00178***	0.000446
INV	0.00297***	-0.000296	0.00244***	0.000778***	0.00104***	0.000371***
TO	-0.000443	6.47005	-0.000788***	-0.000210	-5.58005	-0.000130*
Non-market-based policy and Managers						
NMBP	-0.000740	0.000815*	0.000746	0.00151***	1.24005	0.000374
GTI	-0.00131***	-2.01006	9.37e-05	0.000471**	-0.000219	0.000236
GDP	-0.000570***	-0.000196***	-0.000649***	-0.000241***	-0.000207	-0.000120
WAG	0.00374***	0.00252***	0.000845	4.09e-05	0.00141	0.000559
INV	0.00260***	-0.000353	0.00246***	0.000856***	0.000955	0.000371
TO	-0.000165	2.50005	-0.000740***	-0.000229*	2.28005	-0.000129
Technological support policy and Managers						
TSP	0.000189	0.000196**	-1.27006	0.000164***	8.07005*	5.61005**
GTI	-0.00131***	-5.39005	4.31005	0.000340*	-0.000242*	0.000230***
GDP	-0.000594***	-0.000168***	-0.000630***	-0.000210***	-0.000209***	-0.000111***
WAG	0.00332**	0.00238***	0.00112	0.000347	0.00135***	0.000536*
INV	0.00265***	-0.000603*	0.00236***	0.000649**	0.000932***	0.000295**
TO	-0.000149	0.000111	-0.000714***	-0.000137	4.09005	-8.46005

Table A7. Within sector analysis: Professionals

	Manufacturing		**Constructions**		**Transportation and Storage**	
Environmental policy stringency						
VAR.	**location**	**scale**	**location**	**scale**	**location**	**scale**
EPS	0.00380***	0.00195***	-0.000753***	0.000365***	0.00110***	0.000351***
GTI	-0.00143**	-0.000553	1.98e-05	-5.44006	-4.44005	7.84005
GDP	0.000244	-0.000258**	-9.36005***	-2.30e-05	-7.18005***	-2.26005
WAG	0.0104***	0.00541***	0.00133**	-0.000303	0.000694*	-0.000694***
INV	-0.000155	-0.000367	0.000591***	0.000296**	2.87005	7.98005
TO	0.00174***	-0.00104***	-0.000208**	-0.000157**	0.000316***	0.000171***
Market-based policy						

MBP	-0.000204	-0.000546**	-0.000304***	0.000154***	5.23005	-3.22005
GTI	-0.00139**	-0.000505	9.04007	-2.82005	-2.74005	3.74005
GDP	0.000290	-0.000309***	-0.000123***	-2.45005	-5.24005**	-2.04005
WAG	0.0143***	0.00907***	0.00138**	-0.000577	0.00155***	-0.000383
INV	0.000169	-0.000144	0.000719***	0.000258*	5.70005	0.000175
TO	0.00114*	-0.00156***	-0.000264**	-0.000141**	0.000203**	0.000130**
Non-market-based policy						
NMBP	0.00572***	0.00186**	0.000155	8.15005	0.000988***	0.000448***
GTI	-0.000992	-0.000506	2.02e-05	1.08006	4.37005	3.45005
GDP	0.000157	-0.000255**	-0.000109***	-1.34005	-8.07005***	-1.77005
WAG	0.0117***	0.00582***	0.000600	0.000216	0.00130***	-0.000788***
INV	0.000811	-3.46e-05	0.000570***	0.000234**	0.000216	0.000252**
TO	0.00105*	-0.00137***	-0.000116	-0.000228***	0.000147*	0.000106**
Technological support policy						
TSP	0.000841***	0.000800***	-0.000102**	3.06005	0.000206***	7.17005***
GTI	-0.00161**	-0.000582	3.73005	8.98e006	-8.52005	7.48005
GDP	0.000279	-0.000271	-0.000102***	-9.40006	-6.0805**	-4.09005**
WAG	0.0132***	0.00583**	0.000736	0.000207	0.00151***	-0.000678**
INV	-0.000164	-0.000291	0.000576***	0.000244**	3.84005	0.000133
TO	0.00143*	-0.000964	-0.000133	-0.000200***	0.000218***	0.000137**

Table A8. Within sector analysis: Technicians

	Manufacturing		**Constructions**		**Transportation and Storage**	
Environmental policy stringency						
VAR.	**location**	**scale**	**location**	**scale**	**location**	**scale**
EPS	-0.000340	-0.00178*	0.00178**	-0.000357	0.00125***	-0.000512***
GTI	0.00182*	0.000428	0.000804*	0.000332	-4.16006	-4.85005
GDP	0.000421*	1.53e-05	1.08005	9.16005	-0.000257***	-0.000133***
WAG	0.00741	-0.0144***	0.00658***	-0.000202	0.00479***	0.00101**
INV	0.00462*	0.00485***	0.00215**	0.00124	-5.2605	0.000283*
TO	0.00121	0.00149***	-1.34005	0.000418	-0.000749***	-0.000456***
Market-based policy						
MBP	-0.000249	-0.000709**	-0.000426	-0.000321	0.000288***	-0.000154***
GTI	0.00181*	0.000395	0.000816	0.000106	2.1105	-8.8105
GDP	0.000402	-6.83e-05	1.30005	7.86005	-0.000221***	-0.000120***
WAG	0.00770	-0.0143***	0.00919	3.64005	0.00522***	0.000865*
INV	0.00474*	0.00510***	0.00249	0.00170	-0.000144	0.000225
TO	0.00113	0.00134**	-0.000460	5.01005	-0.000766***	-0.000432***
Non-market-based policy						
NMBP	-2.39005	0.000178	0.000159	-0.000558	-0.00126**	-0.000293
GTI	0.00182*	0.000397	0.000838	0.000163	-7.3105	-8.9805
GDP	0.000417	-1.96e-05	3.41005	0.000119	-0.000206***	-9.3505***
WAG	0.00711	-0.0160***	0.00812***	-0.000621	0.00637***	0.000884*
INV	0.00460*	0.00477***	0.00226*	0.00137	-0.000150	-0.000125
TO	0.00126	0.00174***	-0.000247	0.000335	-0.000869***	-0.000301***
Technological support policy						
TSP	0.000233	5.1505	0.000627	8.55005	0.000336***	-3.9805
GTI	0.00176*	0.000323	0.000659	0.000252	-7.8005	8.9906
GDP	0.000410	-3.7305	2.05005	5.74005	-0.000247***	-0.000139***

WAG	0.00693	-0.0159***	0.00770	-0.000192	0.00565***	0.000731*
INV	0.00454*	0.00466***	0.00209	0.00114	-7.0705	0.000117
TO	0.00131	0.00176***	-0.000108	0.000402	-0.000838***	-0.000366***

Table A9. Within sector analysis: Manual workers

	Manufacturing		**Constructions**		**Transportation and Storage**	
Environmental policy stringency						
VAR.	**location**	**scale**	**location**	**scale**	**location**	**scale**
EPS	-0.0340***	-0.00415	-0.0100***	-0.00323***	-0.00292***	0.000612
GTI	0.00509	0.00193	0.00529***	5.23006	0.00163***	6.48-05
GDP	-0.00654***	0.00214***	-0.00228***	-0.000394**	-0.00146***	-0.000285***
WAG	-0.00866	-0.0499***	-0.00445	-0.00646*	0.00421*	-0.00261*
INV	0.0169*	0.00611	0.0195***	0.00334**	0.00484***	0.00125**
TO	0.00233	0.0107***	-0.00541***	-0.000533	-0.000631	-7.9405
Market-based policy						
MBP	-0.00750***	0.00157	-0.00151***	-0.000317	-0.000181	0.000310*
GTI	0.00441	0.00236	0.00511***	0.000465	0.00159***	0.000272
GDP	-0.00749***	0.00176***	-0.00251***	-0.000500***	-0.00152***	-0.000162**
WAG	-0.0212	-0.0656***	-0.00979*	-0.00812**	0.00204	-0.00271**
INV	0.0192**	0.00478	0.0198***	0.00250*	0.00478***	0.000990*
TO	0.00294	0.0129***	-0.00488***	-0.000235	-0.000345	0.000256
Non-market-based policy						
NMBP	-0.00668	0.00578	-0.0162***	0.000852	0.000697	7.7506
GTI	0.00417	0.00242	0.00405***	0.000389	0.00164***	0.000312
GDP	-0.00688***	0.00165***	-0.00202***	-0.000342**	-0.00152***	-0.000175**
WAG	-0.0366*	-0.0502***	-0.00740	-0.0101***	0.00135	-0.00162
INV	0.0142	0.00490	0.0168***	0.00233*	0.00477***	0.00113**
TO	0.00697*	0.0117***	-0.00356***	-7.59006	-0.000277	0.000155
Technological support policy						
TSP	-0.00503***	-0.00103	-0.000909**	-0.000261	-0.000819***	-7.7305
GTI	0.00599	0.00235	0.00540***	0.000812	0.00182***	0.000134
GDP	-0.00692***	0.00198***	-0.00240***	-0.000440**	-0.00148***	-0.000261***
WAG	-0.0352*	-0.0426***	-0.0127**	-0.00723**	0.00223	-0.000812
INV	0.0164*	0.00542	0.0192***	0.00277**	0.00489***	0.00127**
TO	0.00564	0.0116***	-0.00431***	0.000121	-0.000432	-0.000106

Notes: ***, **, and * denote the significance level at 1%, 5%, and 10% respectively

Appendix B:

Supplementary data and code

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