Employment Effects of EU-ETS Prices*

Christofer Schroeder†

European Central Bank

January 27, 2026

For the most recent version, click here

Abstract

This paper studies the employment effects of carbon pricing under the European Union's Emissions Trading System (EU-ETS). I refer to standard methods from the literature to define and measure the environmental properties of jobs along two dimensions: how "green" a job is, and how polluting it is. I then leverage a series of shocks to EU-ETS prices to estimate their dynamic impacts on employment. The panel local projections estimates reveal that an exogenous 1% increase in EU-ETS prices leads to a roughly 0.2% decline in employment after one and a half years. Impacts on employment in more polluting jobs are estimated to be even stronger, while impacts on employment in greener jobs are also estimated to be negative, albeit less pronounced. Two factors play an important role in shaping these responses: the allocation of free emissions allowances and the stringency of employment protection legislation. When relatively fewer emissions are covered by free allowances, the negative employment effects of EU-ETS price shocks are stronger. Similarly, when employment protection is greater, the estimated impact is more muted. These findings underscore the economic consequences of carbon pricing, offering valuable insights for policymakers balancing climate objectives with labour market considerations.

JEL classification: E24, J21, H23, Q54, Q58

Keywords: climate change, carbon pricing, employment, green jobs, polluting jobs

*I thank Agostino Consolo, Björn Fischer, Miles Parker, Jirka Slacalek, David Sondermann, and seminar participants at the ECB for valuable comments and feedback. This paper should not be reported as representing the views of the European Central Bank (ECB). The views expressed are those of the author and do not necessarily reflect those of the ECB. Any remaining errors are my own.

†Contact: christofer.schroeder@ecb.europa.eu

1 Introduction

A large body of evidence documents the expected negative impacts of climate change. On the one hand, the physical risks associated with global warming and extreme weather events have been shown to be significant (Tol, 2018). These physical risks call for policies aimed at mitigating the sources of climate change. On the other hand, climate change policies also carry transition risks and potential negative economic consequences. Of the menu of options available to policy makers, market-based mechanisms, including the European Union's Emissions Trading System (EU-ETS), are often cited as the most efficient set of tools for mitigating emissions (de Mooij et al., 2012). The literature generally finds that the EU-ETS has been successful in reducing carbon emissions in member countries, but evidence of its economic impacts, including on employment, is mixed (Dechezleprêtre et al., 2023; Känzig, 2025; Känzig and Konradt, 2024).

This paper studies the impact of carbon pricing on employment in Europe. Going beyond existing studies that estimate their impact on aggregate employment, this paper focuses on the impacts of carbon pricing on employment in "greener" or more polluting jobs. To set the stage, this paper first presents a broad set of stylized facts describing the environmental characteristics of European labour markets — or how green or polluting jobs are in Europe. This paper then turns to an empirical analysis estimating the dynamic impact of movements in prices of EU-ETS certificates on employment in greener and more polluting jobs at the country level.

I find that EU-ETS prices tend to have a negative impact on employment. In the aggregate, exogenous shocks to EU-ETS prices are estimated to have persistent, negative effects on employment over the two years following impact. Estimates of the effects on employment in greener jobs are similarly negative, yet less precise. The impacts on employment in more polluting jobs are estimated to be particularly strong, especially for jobs which are associated with a high *direct* emissions intensity. Across countries, I study how these results are driven by two factors: employment protection and the allocation of free emissions allowances. Countries with relatively low levels of employment protection see particularly strong, negative impacts of EU-ETS prices on employment, both in the aggregate, and in greener and more polluting jobs. Similarly, countries with a low ratio of free emissions allowances to actual emissions drive the overall negative employment effects.

Conceivably, carbon pricing may have different impacts on employment in different types of jobs. In particular, carbon pricing may spur innovation in green technologies, increasing relative demand for greener jobs, while negatively impacting pollution intensive activity and the demand for more polluting jobs (Martinez-Fernandez et al., 2010). This *substitution* effect may or may not be dominated by a *scale* effect impacting overall economic activity and the demand for labour. To take these potential channels to the data, this paper applies the methodology developed by Vona et al. (2018) to define and measure the environmental characteristics of jobs. Each occupation is assigned a continuous score along two dimensions: green intensity and pollution intensity, as described in detail in Section 2. Greener jobs include those with a higher degree of greener tasks, while more polluting jobs are defined as those which are more concentrated in higher emissions-intensive sectors.

Debates surrounding the consequences of carbon pricing for labour markets often lack a clear picture of their environmental characteristics. To provide a basic description of these for the European setting, and to motivate the later empirical analysis, this paper first presents a set of general stylized facts. First, it shows that the vast majority of workers in Europe work in jobs which are neither very green nor very polluting. Second, it shows that the green and pollution intensity of the average job vary across countries. Third, average green and pollution intensity varies for workers of different characteristics. Workers in greener jobs are more likely to be men, highly educated, and to work in urban areas. Workers in more polluting jobs are also more likely to be men, less educated, and to work in rural areas. Fourth, average green intensity has been increasing over time as more workers become employed in greener jobs. At the same time, average pollution intensity has been decreasing. As the measures of pollution intensity constructed in this paper vary over time, this decrease could be due to lower employment in more polluting jobs or due to a decline in average pollution intensity *within* jobs. The fifth stylized fact shows that the later effect largely drives the decline in overall average pollution intensity.

This paper then turns to an empirical analysis of the impacts of EU-ETS prices on employment. To capture exogenous movements in EU-ETS certificate prices, I rely on a series of shocks identified by Känzig (2025) and described in detail in Section 2. I estimate the dynamic impact of these EU-ETS price shocks on country-level employment using a panel local projections approach as in Jordà and Taylor (2016). The baseline results show that EU-ETS prices are estimated to have a persistent, negative impact on aggregate employment. In terms of magnitude, the results suggest that a 1% increase in EU-ETS prices leads to a peak cumulative decline in employment of roughly 0.2% after one and a half years. These results are qualitatively and quantitatively in line with those in the existent literature (Konradt and Mangiante, 2025). In addition to the impacts on aggregate employment, I also estimate the impacts on employment in greener and more polluting jobs. The results, though less precisely estimated, indicate that EU-ETS price shocks also lead to negative impacts on employment in these types of jobs. The estimated effects are particularly strong for employment in polluting jobs measured on the basis of direct emissions intensities. In these jobs, EU-ETS price shocks are estimated to lead to a roughly 1% reduction in employment — or about five times larger than the estimated elasticity for aggregate employment. I show that this pattern of results is robust to controlling for additional, potentially confounding factors, alternative approaches to computing the standard errors, alternative identification strategies using instrumental variables, and different thresholds used for defining what is a green job.

Given the diverse nature of the countries considered in the sample, I test for heterogeneous effects at the country level. I focus on two potentially relevant dimensions. First, I study how effects vary by the allocation of free emissions allowances under the EU-ETS. EU-ETS emissions certificates are primarily distributed via auction. Each year, however, a certain amount of additional allowances are freely allocated to emitters in an attempt to mitigate the risk of carbon leakage. Due to the institutional features which stipulate how free allowances are allocated, countries vary in the share of actual emissions which are covered by free allowances, indicating differences in the effective price of emissions faced in a country. The heterogeneity analysis suggests that the baseline results are largely driven by countries with fewer free emissions allowances relative to actual emissions. In countries with a high ratio of free allowances to emissions, shocks to EU-ETS prices are estimated to have a considerably smaller impact on aggregate employment, as well as employment in greener or more polluting jobs.

I also study how effects vary with the degree of employment protection across countries. In countries with relatively stronger employment protection legislation, economically relevant shocks, such as those to EU-ETS prices, may be expected to have more muted impacts than in countries with relatively weaker employment protection. The results suggest that this is indeed the case. In countries with relatively weaker employment protection, shocks to EU-ETS prices are estimated to have a significant, negative effect on employment over the two years following impact. This is true for aggregate employment, and employment in greener and more polluting jobs. In countries with relatively stronger employment protection, on the other hand, shocks to EU-ETS prices are estimated to have a considerably smaller impact on all employment outcomes considered.

The environmental characteristics of jobs referenced in this paper are, of course, not observable features but rather constructed measures which incorporate judgment and a number of assumptions. In particular, sectoral emissions underlying the measure of pollution intensity presented in this paper can be measured in various ways. The most widely referenced measures of emissions capture direct emissions, or those stemming from resources controlled by a particular country or sector. These emissions are also referred to as scope 1 emissions. Direct emissions, however, do not account for the emissions associated with the energy used to power economic activity in a particular country or sector. These emissions are referred to as indirect emissions, or scope 2 emissions. Indirect emissions are often ignored in in the literature and accounting for them may provide us with a more accurate measure of how polluting a job is. In all analyses included in this paper, I present results measuring how polluting a job is both on the basis of direct emissions alone — or, pollution *intensities* — as well as when also accounting for indirect emissions — or, pollution *multipliers*.

This paper contributes to the literature in a number of ways. First, it contributes to a literature studying the macroeconomic impacts of the EU-ETS. The EU-ETS is generally found to have been successful in reducing carbon emissions (Känzig and Konradt, 2024; Schroeder and Stracca, 2025) but evidence of its economic consequences is mixed. Dechezleprêtre et al. (2023) use firm level data to show that the EU-ETS has reduced carbon emissions by 10-20% while having little impact on firms' profits and employment. At the macro level, Känzig (2025), Känzig and Konradt (2024), and Konradt and Mangiante (2025) also find that the EU-ETS has lead to a reduction in emissions yet at the cost of a fall in economic activity, including a reduction in employment. The existent literature, however, focuses entirely on employment in the aggregate. This paper shows that employment effects of EU-ETS price shocks depend to an important degree on jobs' environmental characteristics.

This paper also contributes to a literature studying the green transition and its interaction with labour markets. Bowen et al. (2018) and Vona et al. (2018) propose methodologies for measuring how green or "brown" (polluting) jobs in the US labour market are. Bluedorn et al. (2023) translate these measures to other countries, including European economies. The authors show, among other things, that employment in greener and more polluting jobs is concentrated among small subsets of workers, and that stronger environmental policies are associated with a higher share of green intensive jobs. This paper complements these findings, expanding the definition of polluting jobs to include indirect emissions, as well as exploring the impact of a particular environmental policy mechanism in a more empirically rigorous way. It also shows how employment impacts from environmental policies — in this case the EU-ETS — can vary across countries, depending to an important degree on the allocation of free allowances and the strength of employment protection legislation.

The analyses and findings presented in this paper carry important implications for the broader policy debate on climate change and the institutions for which it is relevant. For one, this paper's findings can be used to inform policy makers of the potential labour market impacts of future developments in EU-ETS prices. In the face of a higher price on carbon, positive policy actions may range from those encouraging the development of green skills and the acceleration of investment in green technologies, to the targeted support for workers in particularly polluting jobs. This paper's findings, however, are to be viewed in context. First, the estimates presented in this paper are of short-term employment effects and are not indicative of permanent impacts. Second, green and polluting jobs are defined in this paper based on a job's fixed environmental characteristics in 2011. Pollution intensity and multipliers have been trending downward *within* jobs, as shown in Section 3, while there is evidence that jobs are becoming greener as more and more green tasks are incorporated into occupational profiles (Bachmann et al., 2024). Any potential effects of EU-ETS prices on these shifts in environmental characteristics within jobs are ignored in this paper.[1]

The rest of this paper is structured as follows. Section 2 describes the data and the methodology used to define and measure the environmental characteristics of jobs. Section 3 presents

[1]There is evidence that EU-ETS prices significantly reduce emissions which may explain the decline in pollution intensities and multipliers observed in the data (Känzig and Konradt, 2024; Schroeder and Stracca, 2025). Studying the impacts of the EU-ETS on the share of green tasks within jobs offers a fruitful avenue for future research.

a number of stylized facts of the environmental characteristics of European labour markets. Section 4 contains an empirical analysis of the impact of EU-ETS prices on employment, first detailing the empirical approach before presenting and discussing the results. Section 5 concludes.

2 Data

2.1 Constructing the dataset

This paper exploits a novel dataset constructed using data from multiple sources. First, I merge quarterly cross-sections of microdata from the European Union's Labour Force Survey (EU-LFS). The EU-LFS is a quarterly survey administered by national statistical authorities across Europe and harmonised to be comparable across countries. Its main focus is to capture information on respondents' labour market status, and its responses are used to construct aggregate headline labour market statistics. Microdata on individual and household survey responses from the EU-LFS are made available for scientific use from Eurostat. Beyond labour market participation and employment status, the EU-LFS contains detailed information on the occupation, sector, and region of work, as well as a host of additional demographic characteristics.

Next, I merge on a time series of exogenous movements in EU-ETS prices developed by Känzig (2025) and used in Konradt and Mangiante (2025) and Konradt and Weder di Mauro (2023). The EU-ETS operates as a cap and trade system. In line with the EU's climate target, the cap — or total number of issued emissions certificates — is reduced over time such that emissions fall. Emissions certificates are allocated amongst participating firms who are required to surrender enough certificates to match their verified emissions each year. Emissions certificates can be traded on a number of spot and futures markets. Känzig (2025) constructs a series of surprises in EU-ETS certificate prices by calculating the daily change in futures prices within narrow windows around regulatory announcements concerning the supply of emissions certificates. Focusing on price movements within narrow windows around announcements helps to alleviate the concern that these announcements may be influenced by broader macroeconomic conditions. The implicit assumption is that macroeconomic conditions are unlikely to change significantly within a sufficiently narrow window. Känzig (2025) then uses this series of price surprises as an instrument to uncover a time series of carbon price shocks estimated using VAR techniques. I collapse the original daily time series of estimated shocks to the quarterly frequency by summing within each quarter to match the frequency of the EU-LFS. Figure B1 in Appendix B plots the time series of these identified EU-ETS price shocks. The shocks are broadly centered around zero and range from a roughly 2% decrease to a 3% increase in carbon prices at the quarterly frequency.

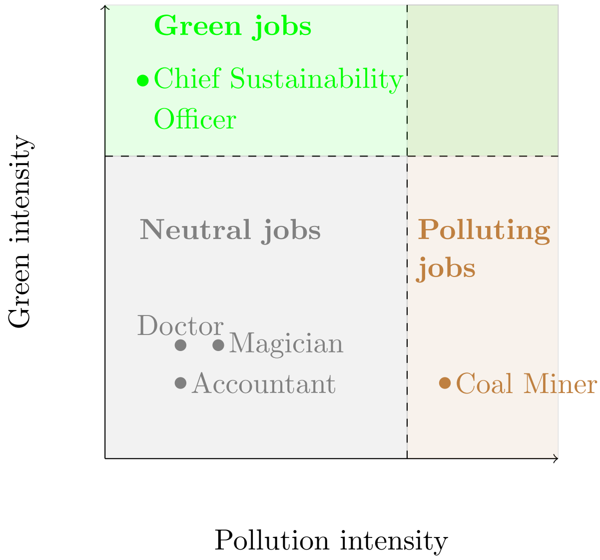
2.2 Measuring the Environmental Characteristics of Jobs

The occupational and sectoral identifiers in the EU-LFS can be used to define and measure the environmental characteristics of jobs. To do so, I follow the methodology developed by Vona et al. (2018) and applied by Bluedorn et al. (2023), Elliott et al. (2024), and Scholl et al. (2023). Each occupation is assigned a continuous score along two dimensions: green intensity and pollution intensity. Figure 1 presents a conceptual illustration of how a few selected jobs could be described along these two dimensions. Although "green" or "polluting" jobs often feature in the public discourse as mutually exclusive categories, the methodology presented here allows, in principle, for a job to have both a positive green intensity score as well as a positive pollution intensity score. The space defined by these two dimensions can be demarcated into four rough categories: green jobs, which have a high green- and low pollution intensity; pollution-intensive jobs, which have a high pollution- and low green intensity; neutral jobs, which have a low green- and pollution intensity, and green- and pollution-intensive jobs, which have a high green- and pollution intensity. I outline below the steps followed in detail to construct the continuous measures of green and pollution intensity. In the empirical analysis which follows, I consider binary measures of green and polluting jobs defined using thresholds discussed in Section 4.

Green intensity Green intensity and pollution intensity are measured in different ways. The green intensity of a job is defined according to the tasks typically carried out in that job. Dierdorff et al. (2009) develop a taxonomy of "green tasks" for occupations listed in the O*Net database of occupations for the US labour market. For each occupation in O*Net, the database contains detailed information on the skills and qualifications typically required, as well as the associated tasks. The green intensity for each occupation is simply calculated as the ratio of green tasks to the overall number of tasks associated with that job.

$$\text{Green intensity}_{soc8} = \frac{\#\ \text{Green tasks}_{soc8}}{\#\ \text{Total tasks}_{soc8}} \tag{1}$$

Figure 1: Conceptual illustration of the environmental characteristics of jobs



Notes: This figure presents a conceptual illustration of how a number of examples of jobs could be described along the dimensions of green intensity and pollution intensity. Green intensity and pollution intensity are defined and calculated as described in Section 2.2. The figure does not plot actual green intensity and pollution intensity scores as observed in the data but rather a simplified, illustrative example.

Jobs in the O*Net database are classified according to the Standard Occupational Classification System (SOC) at the 8-digit level. This occupational classification system was developed and is used to classify jobs in the US labour market. Examples of SOC occupations which have a relatively high green intensity score include Environmental Engineers (17-2081.00), Solar Photovoltaic Installers (47-4099.01), or Recycling and Reclamation Workers (51-9199.01).

In Europe, and in the EU-LFS, jobs are classified according to the International Standard Classification of Occupations (ISCO). To map the information on occupational task profiles in O*Net to the data from the EU-LFS, I construct a crosswalk between SOC and ISCO. This requires making a number of assumptions and computational choices for which I follow the previous literature.[2] First, I compute green intensity scores for all 8-digit SOC occupations in O*Net as in equation (1). I then aggregate these scores to the 6-digit level by taking the unweighted average green intensity of each 8-digit occupation associated with a 6-digit SOC occupation. I then apply a standard crosswalk mapping 6-digit SOC to 3-digit ISCO occupations provided by the US Bureau of Labor Statistics (BLS).[3] For each 3-digit ISCO occupation, I

[2] See Scholl et al., 2023 for a detailed overview and discussion of the mapping of the green intensity measure developed by Vona et al., 2018 for SOC occupations to ISCO occupations.

[3] See: https://www.bls.gov/soc/isco_soc_crosswalk.xls

compute a green intensity score using the green intensity scores from its associated 6-digit SOC occupations. Crosswalking between SOC and ISCO does not map occupations 1:1 across classifications. When many SOC occupations are mapped to one ISCO occupation, I compute the employment-weighted average of green intensity scores of 6-digit SOC occupations using employment shares in the US labour market from the BLS.[4] The derived measure of green intensity can therefore be interpreted as the employment-weighted share of green tasks as a percentage of total tasks. Appendix Section A.1 in Appendix A provides a detailed illustrative example of the above described steps in computing green intensity.

One of the main advantages of the EU-LFS is the availability of data over a relatively long period of time. For some countries, microdata are available stretching back to 1995. This long horizon, however, spans numerous revisions to some of the classification systems relied upon in this paper. In 2010, the latest version of ISCO — ISCO-08 — was adopted, replacing the previous version which had been in place since 1988, ISCO-88. At the same time, SOC-2010 replaced SOC-2000. Occupations in waves of the EU-LFS between 1995-2010 are coded according to ISCO-88 while occupations in later waves are coded according to ISCO-08. Direct crosswalks between SOC-2010 and ISCO-88 do not exist. To construct consistent green intensity measures for jobs in the EU-LFS waves up to 2010, I first map 6-digit SOC-2010 occupations to SOC-2000. Occupations across these two version of the SOC do not always map 1:1. When one SOC-2000 occupation maps to multiple SOC-2010 occupations, I calculate a weighted average of green intensities of each associated SOC-2010 occupation, weighting by US employment shares. I then crosswalk these 6-digit SOC-2000 occupations to 4-digit ISCO-88 occupations using the crosswalk provided by Hardy et al. (2018). Again, I weight the green intensity scores of SOC occupations by employment shares for ISCO-88 occupations which map to multiple SOC-2000 occupations. Finally, I aggregate the ISCO-88 scores at the 4-digit level to the 3-digit level.

Pollution intensity Lacking a taxonomy of "polluting tasks", the pollution intensity of a job is calculated using data on sectoral emissions and employment. First, for each country and in each year, I compute the average emissions intensity for each broad sector defined according to the Statistical Classification of Economic Activities in the European Community (NACE) classification system. Next, I compute the share of workers employed in each sector for each

[4]When mapping from SOC-2010 to ISCO-08 I use 2016 employment shares as this year falls roughly in the middle of the considered time span following the 2008 ISCO revision. When mapping from SOC-2000 to ISCO-88, as described below, I weight by 2005 employment shares.

3-digit ISCO occupation. Finally, I calculate the pollution intensity for each occupation as the average of sectoral emissions intensities weighted by the share employed in each sector. Formally, pollution intensity for each occupation o, in each country c, in each year t is calculated as

$$\text{Pollution intensity}_{o,c,t} = \sum_{s=1}^{S} (\text{Emissions intensity}_{s,c,t})(\text{Share employed}_{o,s,c,t}) \tag{2}$$

across sectors s. The derived measure of pollution intensity can therefore be interpreted as the employment-weighted share of sectoral emissions intensities for each occupation. This measure is higher for occupations in which a larger share of workers work in pollution-intensive sectors. Section A.2 in Appendix A provides a detailed illustrative example of the steps described above for computing pollution intensity. Importantly, I calculate this measure using country- and year-specific sectoral emissions data such that the measure can vary for the same occupation across countries and time. Trends in pollution intensity can therefore be driven by shifts in employment between less and more polluting jobs, and changes in pollution intensity *within* jobs as discussed in Section 3. In the empirical analysis that follows in Section 4, and to allow for comparisons with the time-invariant measure of green intensity, I consider constant measures of pollution intensity calculated holding sectoral emissions intensities constant at their 2011 levels.

In 2008, the NACE sectoral classification system underwent a major revision reflecting broader structural changes across sectors. NACE codes in earlier waves of the EU-LFS adhere to the previous version, NACE Rev. 1, while codes in later waves adhere to the revised version, NACE Rev. 2. The exact timing of the transition from NACE Rev. 1 to NACE Rev. 2 varies across countries, and in some cases, waves of the EU-LFS contain codes from both versions. To ensure a consistent measure of pollution intensity over time, I map NACE Rev. 1 employment to NACE Rev. 2 using correspondence tables published by the European Commission and Eurostat (2008). Sectors in NACE Rev. 1 and Rev. 2 do not map 1:1. For NACE Rev. 2 sectors which map to many NACE Rev. 1 sectors, I compute the sum of employment across the associated NACE Rev. 1 sectors. For NACE Rev. 1 sectors which map to many NACE Rev. 2 sectors, I compute NACE Rev. 2 employment by dividing the associated NACE Rev. 1 employment by the number of NACE Rev. 2 sectors mapped to.

Sectoral emissions can be computed in a number of ways. In this paper, I consider two different measures. First, I consider the average *direct* emissions intensities of a number of pollutants which are regulated by the European Environment Agency (EEA) using annual data provided by Eurostat. These pollutants include nitrous oxides (NO_x), non-methane volatile organic compounds (NMVOCs), airborne particulates (PM_{10} and $PM_{2.5}$), sulfur dioxide (SO_2), and carbon dioxide (CO_2). Direct emissions — often referred to as scope 1 emissions — capture the emissions directly emanating from producers in each sector and country. They do not, however, account for the emissions caused to produce the energy required for production in a particular sector, or by a sector's upstream suppliers. These emissions are often referred to as indirect, or scope 2 and 3 emissions. To capture these, I also consider data on emissions multipliers — the sum of direct and indirect emissions — from the IMF's Climate Change Indicators Dashboard. These data are available at the country-year-sector level, but only for emissions of CO_2. Sectors in these data are defined according to the International Standard Industrial Classification of All Economic Activities (ISIC) classification system. To merge these data to those from the EU-LFS, I apply a correspondence table provided by the Statistics Division of the United Nations.[5] I then compute the pollution multiplier for each occupation using (2), replacing the emissions intensities with emissions multipliers. I refer to the first measure considering direct emissions as *pollution intensity*, and the latter measure, considering direct and indirect emissions, as the *pollution multiplier*.

2.3 Descriptive Statistics

In this paper, I focus on a baseline sample drawn from the quarterly dataset described above. The sample includes employed individuals aged 25-64 between Q1 2007 - Q4 2019 from 23 countries in the European Union. These include: Austria, Belgium, Cyprus, the Czech Republic, Germany, Denmark, Estonia, Greece, Spain, Finland, France, Croatia, Hungary, Ireland, Italy, Lithuania, Latvia, the Netherlands, Poland, Portugal, Romania, Sweden, and Slovakia.[6] The sample includes roughly 27 million individual observations. Table 1 presents descriptive statistics of the measures of green and pollution intensity for the sample considered in this paper. It shows a number of important facts. First, the green intensity of the average worker's job is about 4% while the median worker's job has a green intensity of zero. This means that the median job is not associated with any green tasks, and that the distribution of green intensity is heavily skewed to the right. Second, accounting for indirect emissions, pollution multiplier

[5] See: https://unstats.un.org/unsd/classifications/Econ

[6] Bulgaria, Luxembourg, Malta, and Slovenia are not included in the baseline sample as ISCO codes for these countries are only available at the 1- or 2-digit level.

Table 1: Descriptive statistics

	Mean	25th percentile	50th percentile	75th percentile	Standard deviation
Green intensity (%)	3.95	0.00	0.00	4.04	7.36
Pollution intensity (kg/Euro)	0.04	0.01	0.03	0.06	0.06
Pollution multiplier (kg/Euro)	0.42	0.15	0.30	0.55	0.40

Notes: This table presents descriptive statistics of the green intensity, pollution intensity, and pollution multiplier derived in this paper as described in Section 2.2. The sample includes all employed individuals aged 25-64 between Q1 2007 - Q4 2019 in Austria, Belgium, Cyprus, Germany, Estonia, Greece, Spain, Finland, France, Ireland, Italy, Lithuania, Latvia, the Netherlands, Poland, Portugal, Romania, Sweden, and Slovakia.

are higher than pollution intensities for the average job, as well as along the distribution. This is evident by the higher pollution multipliers at the 25th, 50th, and 75th percentiles. Indirect emissions increase pollution multipliers by a factor of about 10 across the distribution compared to pollution intensities.

Table 2 lists the five jobs with the highest green intensity, pollution intensity, and pollution multiplier in the sample. Amongst the greenest jobs are both white collar (Services Managers, Manufacturing, Mining, Construction, and Distribution Managers, Engineering Professionals, and Life Science Technicians & Related Associated Professionals) and blue collar (Refuse Workers) jobs as shown in Panel A. Panels B and C present the top five polluting jobs. Since the measures of pollution intensity and pollution multiplier vary by country and year, Table 2 focuses only on the top five polluting jobs in Germany in 2018. A number of the occupations in Panel B are those with a large share employed in the transportation sector (Locomotive Engine Drivers and Related Workers, Travel Attendants, Conductors & Guides, and Ship & Aircraft Controllers and Technicians) given its relatively high emissions intensity, not only in Germany.[7] Panel C presents a slightly different set of occupations with some overlap to those in Panel B. Process Control Technician remains the most polluting-intensive occupation when considering both direct and indirect emissions and Locomotive Engine Drivers and Related Workers continues to feature in the top five. The remaining occupations in Panel C are those with a high share of workers employed in the agricultural sector. This reflects the fact that indirect emissions are relatively high in agriculture.

[7] The occupations listed in Table 2 also highlight some of the limitations of the applied methodology for measuring the pollution intensity of jobs. While transport by rail is a relatively low-emissions mode of transportation, the occupation 'Locomotive Engine Drivers and Related Workers' is defined as a particularly high polluting job due to the fact that a large share of these jobs are found in the transportation sector which is a highly polluting sector. Lacking more detailed emissions data within sectors, the measures proposed in this paper should, at a minimum, be considered to be rough measures of a job's environmental characteristics.

Table 2: Five greenest and most polluting jobs in the sample

Panel A: Green intensity

ISCO-08 code	Occupation	Green intensity (%)
132	Manufacturing, Mining, Construction, and Distribution Managers	38
143	Services Managers	36
961	Refuse Workers	34
214	Engineering Professionals	32
314	Life Science Technicians and Related Associated Professionals	21

Panel B: Pollution intensity, Germany (2018)

ISCO-08 code	Occupation	Pollution intensity (kg/Euro)
313	Process Control Technicians	0.19
831	Locomotive Engine Drivers and Related Workers	0.14
811	Mining and Mineral Processing Plant Operators	0.12
511	Travel Attendants, Conductors, and Guides	0.12
315	Ship and Aircraft Controllers and Technicians	0.11

Panel C: Pollution multiplier, Germany (2018)

ISCO-08 code	Occupation	Pollution multiplier (kg/Euro)
313	Process Control Technicians	1.57
131	Production Managers in Agricultre, Forestry, and Fishing	0.83
613	Mixed Crop and Animal Producers	0.81
831	Locomotive Engine Drivers and Related Workers	0.78
612	Animal Producers	0.77

Notes: This table presents the five occupations with the highest measured green intensity, pollution intensity, and pollution multipliers in the data. Since the measures of pollution intensity and pollution multiplier vary by country and year, the table presents the top five polluting jobs in Germany in 2018.

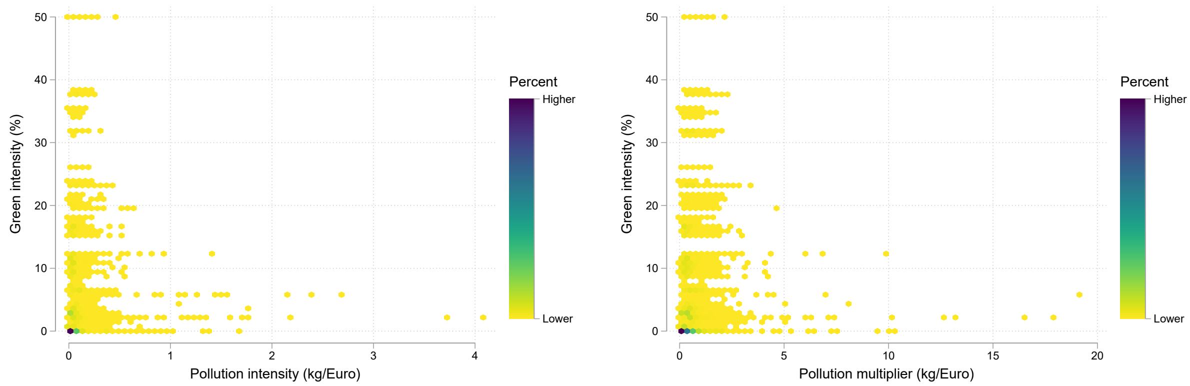
3 Environmental Characteristics of European Labour Markets

This section presents a number of stylized facts of the environmental characteristics of labour markets in Europe using the measures detailed in Section 2.2. The first stylized fact is that the vast majority of workers work in jobs that are not very green nor very polluting. Figure 2 presents binned bivariate histograms for the sample of workers based on the green intensity and pollution intensity (Panel 2a) or pollution multiplier (Panel 2b) of their jobs. The sample is highly concentrated near the origin of the two dimensional space in both panels. Applying the terminology from Figure 1 in Section 2.2, the vast majority of workers work in relatively neutral jobs.

The data also show that, on average, jobs which are greener tend to also be less polluting, while jobs that are more polluting tend to be less green. There are no workers in the sample working in jobs in the upper right corner of the two-dimensional environmental characteristic space in jobs that are both greener and more polluting. Although the methodology used in this paper allows, in principle, for jobs to be both greener and more polluting, a high share of workers working in such jobs, along with a high share working in relatively neutral jobs, would call into question the ability of the proposed measures to reliably distinguish between "green" and "polluting" jobs as is often the case in the public discourse. The patterns present in the data suggest, however, that these measures broadly capture two distinct environmental dimensions of jobs.

Figure 2: Histogram of environmental characteristics in the sample

(a) Green intensity and pollution intensity (b) Green intensity and pollution multiplier



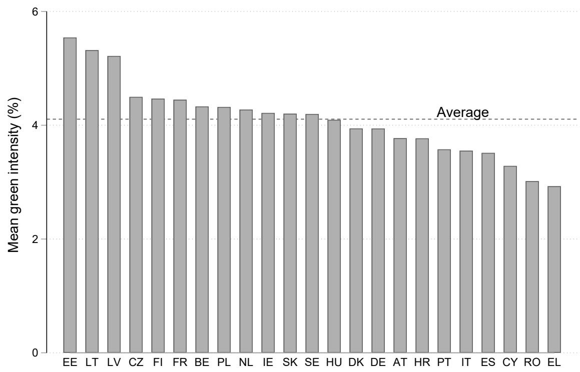
Notes: This figure plots binned bivariate histograms for the sample of workers based on the environmental characteristics of their jobs. The y-axis in both panels plots green intensity. The x-axis plots pollution intensity (Panel 2a) or the pollution multiplier (Panel 2b) of workers' jobs in the sample. The observations in the data are grouped into 70 bins along both axes. Dark blue areas represent bins with a higher percentage of the total sample, while yellow areas represent bins with a lower percentage.

The second stylized fact is that average environmental characteristics of jobs vary across countries. Panel 3a in Figure 3 plots the mean green intensity of employment across countries in the sample while Panel 3b plots the mean pollution intensity and mean pollution multiplier. The dashed horizontal lines represent cross country averages. Aside from exhibiting variance in averages across countries, the data offer a number of additional insights. First, some countries with a relatively high average green intensity of employment also have a relatively high pollution intensity of employment. This is the case, for instance, in Estonia, Latvia, and the Czech Republic. Second, accounting for indirect emissions provides a slightly different ordering of countries in terms of average pollution multipliers. Poland, for instance, is recorded as having the highest average pollution intensity. Accounting for indirect emissions, however, Estonia records a higher average pollution multiplier.[8] Despite these differences, the ranking of countries in terms of pollution intensity and pollution multipliers is broadly similar.

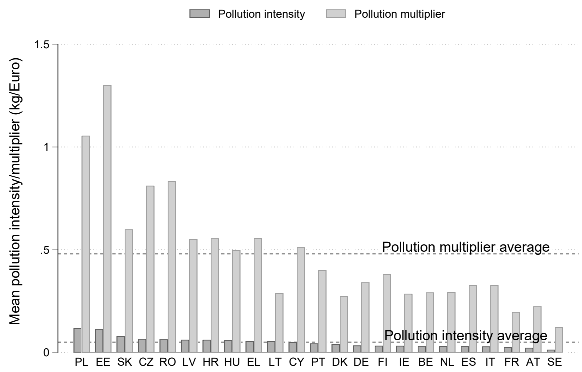
[8]The differences in pollution intensities and pollution multipliers largely reflect differences in the source of energy across countries. In Estonia, for instance, oil shale — a particularly pollution intensive source of energy — has traditionally accounted for more than 70% of energy production (International Energy Agency, 2019).

Figure 3: Average environmental characteristics across countries

(a) Green intensity



(b) Pollution intensity and pollution multipliers

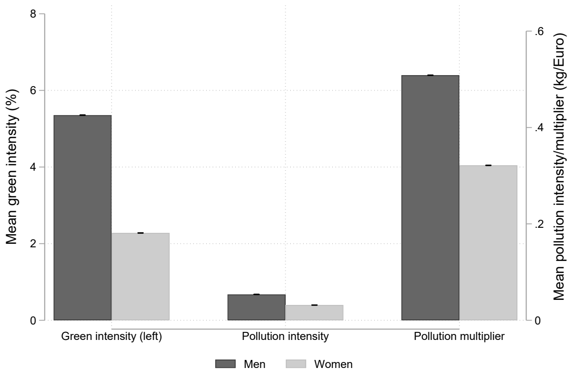


Notes: This figure plots the mean green intensity of employment across countries in the sample in Panel 3a and the mean pollution intensity and pollution multipliers of employment in Panel 3b. The dashed horizontal lines represent cross country averages of each measure.

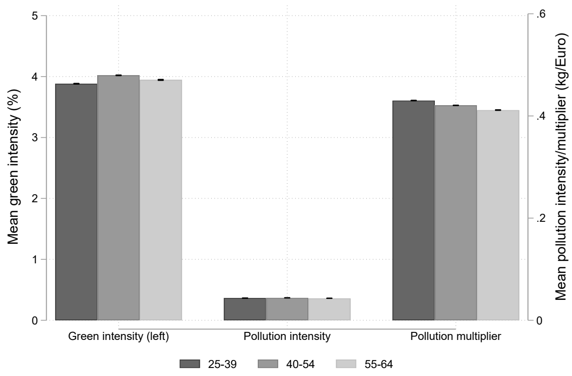
The third stylized fact is that the average environmental characteristics of jobs vary for workers of different characteristics. Figure 4 plots the average green intensity, pollution intensity, and pollution multiplier of jobs for workers by gender, age, education, and degree of urbanization in the region of employment. The data show that men tend to hold jobs that are both greener and more polluting than women. Younger workers (aged 25-39) work in jobs that are somewhat less green, and slightly more polluting —- particularly when considering pollution multipliers. Higher educated workers — or those with at least a tertiary level education — hold jobs with a considerably higher average green intensity than less educated workers. Higher educated workers also tend to hold jobs that are less polluting than less educated workers. Among these less educated workers, those with at most an upper secondary level of education hold the most polluting jobs, while workers with at most a lower secondary level of education hold jobs that are on average less polluting. This pattern is particularly clear when considering polluting multipliers. Finally, workers in cities hold jobs that are, on average, greener than workers in less urban areas. Conversely, workers in rural areas tend to hold more polluting jobs, on average, than workers in more urban areas. Together, these findings are in line with those from the literature, including Bluedorn et al. (2023) and Causa et al. (2024) who study broader samples, covering non-European advanced countries and developing countries.

Figure 4: Average environmental characteristics by worker characteristics

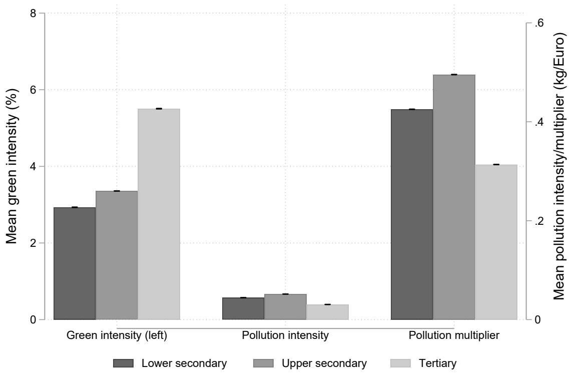
(a) Gender



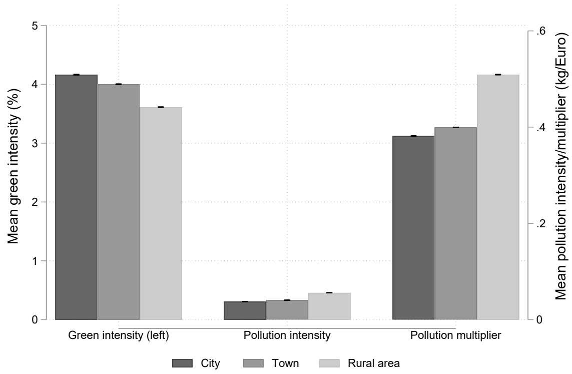
(b) Age



(c) Education



(d) Urbanisation



Notes: This figure plots the average environmental characteristics of jobs various subsets of the sample based on worker characteristics. Panel 4a plots averages for men and women. Panel 4b plots averages for age groups. Panel 4c plots averages for groups defined by their highest level of educational attainment. Panel 4d plots averages for groups defined by the degree of urbanisation of their place of work. In all panels, the averages of green intensity are plotted against the left y-axis, while the averages of pollution intensity and pollution multipliers are plotted against the right y-axis.

The patterns shown in Figure 4 can be partly explained by differences in the likelihood to work in managerial positions.[9] Indeed, men, older workers, the more educated, and those working in cities are all more likely to be employed in managerial positions than their counterparts (see Figure B2 in Appendix B). At the same time, managerial positions have, on average, a higher green intensity and a lower pollution intensity or pollution multiplier. Table B1 in Appendix B shows that workers in managerial positions have, on average, a 13 percentage points higher green intensity than workers in non-managerial positions. Managers also have a lower average pollution intensity or pollution multiplier than non-managers. The results also show that working in a

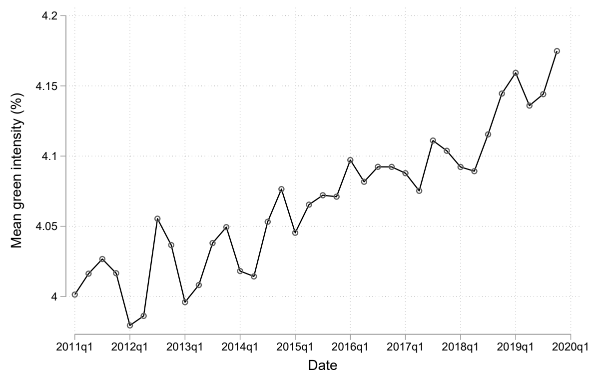
[9] Managerial positions are defined as those in ISCO major group 1 ("Managers").

managerial position can explain a particularly significant share of the variation in green intensity in the sample at around 20%.

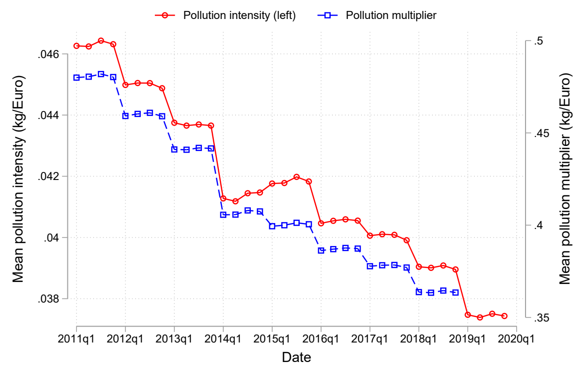
The stylized facts presented up to this point characterize the environmental characteristics of European labour markets in the cross section. The fourth stylized fact shows that the average green intensity of employment has been steadily increasing over time, while the average pollution intensity and pollution multiplier of employment have been decreasing. These trends are plotted in Figure 5. The measure of green intensity constructed in this paper is constant over time. As such, the increasing trend shown in Panel 5a can only be the result of increasing employment in relatively greener jobs. The measures of pollution intensity and pollution multipliers considered in the paper do vary over time. Their downward trend could therefore be due to a number of factors. First, it could be the case, as with the trend in green intensity, that employment is decreasing in relatively more polluting jobs. Second, it could be the case that jobs themselves are becoming less polluting. Due to the methodology used to measure pollution intensity and pollution multipliers, this *within* job decrease could be either due to less employment in relatively more polluting sectors, or decreases in pollution intensity or pollution multipliers within sectors.

Figure 5: Average environmental characteristics over time

(a) Green intensity



(b) Pollution intensity and pollution multipliers

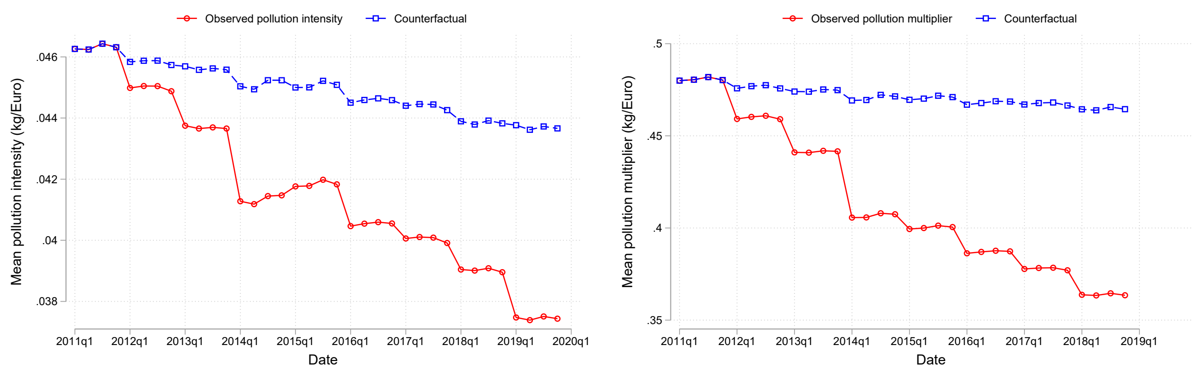


Notes: This figure plots the mean green intensity of employment across time in the sample in Panel 5a and the mean pollution intensity and pollution multiplier in Panel 5b.

The fifth stylized fact is that the decline in average pollution intensity and pollution multipliers is largely due to declines in pollution intensity and multipliers within sectors. To show this, I start by computing counterfactual measures of pollution intensity and multipliers for each job holding sectoral emissions constant at their 2011 levels.[10] The trends in average observed and counterfactual pollution intensities and multipliers are shown in Figure 6. In contrast to the trends in the average observed measures in Panels 6a and 6b, the trends in the corresponding average counterfactual measures remain relatively flat. That is, by shutting down the effect of decreasing sectoral emissions intensities and multipliers, average pollution intensity and multipliers remain more or less constant. This suggests that the decrease in average pollution intensity and multipliers is largely due to decreases in emissions intensities and multipliers within sectors.

Figure 6: Average polluting intensity and multipliers over time

(a) Pollution intensity (b) Pollution multiplier



Notes: This figure plots mean pollution intensity in Panel 6a and mean pollution multipliers in Panel 6b across time. Each panel also plots the trend in the average of a counterfactual measure, computed holding sectoral emissions intensities or multipliers constant at their 2011 levels.

4 Employment Effects of ETS Prices

4.1 Empirical Model

This part of the paper presents an empirical analysis of the impact of EU-ETS prices on employment. The baseline empirical approach consists of a series of panel local projections following Jordà and Taylor (2016)

$$y_{i,t+h} - y_{i,t-1} = \alpha_i^h + \beta^h ETS_t + \sum_{l=1}^{L} \theta_l^h \Delta y_{i,t-l} + X_{i,t}' \gamma^h + \epsilon_{i,t}^h \tag{3}$$

[10]It is well documented that emissions intensities and multipliers have been falling in many European countries; see, for instance, Crippa et al. (2025) for a long-run overview of developments in greenhouse gas emissions between 1970-2024 using data from the Emissions Database for Global Atmospheric Research (EDGAR).

$y_{r,t}$ is the log outcome in country i, time (quarter) t, at horizon $h = 1 \dots H$. α_i^h is a country fixed effect. ETS_t is a series of shocks to EU-ETS prices as estimated by Känzig (2025) and described in Section 2.1. In the baseline specification, I include $L = 4$ lags of the change in the outcome variable on the right hand side. Controlling for these lags improves inference as it obviates the need to correct standard errors for serial correlation in the residuals (Montiel Olea and Plagborg-Møller, 2021). The vector $X_{i,t}$ contains additional, time-varying controls at the country level. In the baseline specification, I control for four lags of the change in log real GDP, four lags of the exogenous variable, ETS_t, a linear time trend, and fixed effects for each of the four quarters of the year to account for seasonality. β^h is the main parameter of interest capturing the cumulative impact of EU-ETS price shocks on the outcome variable at horizon h. $\epsilon_{i,t}^h$ is the error term. I compute standard errors of the parameter estimates following Driscoll and Kraay (1998) to allow for heteroskedasticity, and serial- and cross-sectional correlation in the error term.

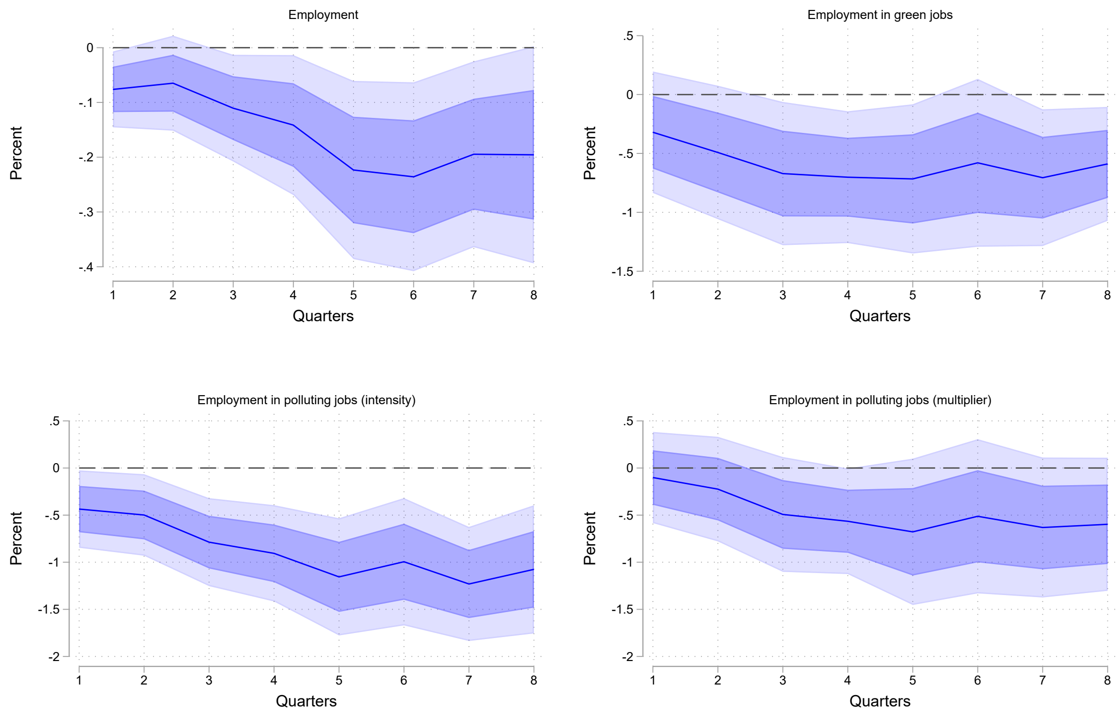
I consider the following four outcomes: aggregate employment, employment in green jobs, and employment in polluting jobs defined on the basis of either pollution intensities or pollution multipliers. Constructing these outcomes requires setting thresholds along the continuous environmental characteristics measures beyond which jobs are categorized in to these groups. I set these thresholds as follows. In the baseline specification, green jobs are defined as jobs with a green intensity greater than zero. Polluting jobs on the basis of pollution intensities are defined as those jobs with a pollution intensity greater than 0.027 kg/Euro, corresponding to the median job. Similarly, polluting jobs defined according to pollution multipliers are defined as those jobs with a pollution multiplier greater than the median, or 0.3 kg/Euro.

4.2 Results

Baseline Figure 7 presents estimates of the baseline specification in the form of impulse response functions for each of the four outcome variables considered. The estimates are plotted over a horizon of 8 quarters, or two years. Point estimates at each horizon are surrounded by 68% (dark blue) and 90% (light blue) confidence intervals. The estimates are scaled such that they represent the percent change in the outcome given a 1% increase in EU-ETS prices. Starting in the top left panel, EU-ETS prices are estimated to have a persistent and negative cumulative impact on aggregate employment in the sample. The estimates are largely significant at the 10% level over the two years following impact. These results are closely in line with those from

[Konradt and Mangiante (2025)](#). The results plotted in the upper right panel show that shocks to EU-ETS prices are also estimated to have had a negative impact on employment in green jobs. Though the estimates are less precise, the results suggest that any substitution effects towards employment in green jobs are dominated by a negative labour demand effect.

Figure 7: Dynamic impacts of shocks to EU-ETS prices



Notes: This figure plots the impulse response functions from a one percent increase in EU-ETS prices in model (3) on employment, employment in green jobs, and employment in polluting jobs, defined either on the basis of pollution intensities or pollution multipliers. Point estimates at each horizon are surrounded by 68% (dark blue) and 90% (light blue) confidence intervals. Standard errors are calculated following Driscoll and Kraay (1998).

The bottom two panels in Figure 7 plot the estimated impacts on employment in polluting jobs. EU-ETS price shocks are estimated to have had a negative impact on employment in polluting jobs that remains relatively persistent over the two years following impact. In particular, the estimates in the bottom left panel where polluting jobs are defined on the basis of pollution intensities, suggest that a one percent increase in EU-ETS prices leads to a roughly 1% reduction in employment in these jobs after one year — about five times larger than the estimated impact for aggregate employment. The estimates in the bottom right panel plot the impulse response function for employment in polluting jobs when these are defined on the basis of pollution multipliers. The estimated impacts are somewhat smaller in magnitude than those obtained when following the pollution intensity definition, and are not always statistically significant at the 10% level. This more muted impact falls in line with the fact that EU-ETS certificates are only required to offset direct emissions.

Together, the baseline results suggest that EU-ETS prices lead to a decrease in employment over the short-term, in the aggregate and in both green and polluting jobs. These findings are, however, to be viewed in context. First, the estimates presented in this section are of short-term effects and do not indicate permanent impacts. Second, green and polluting jobs are defined based on a job's fixed environmental characteristics in 2011. Any potential effects of EU-ETS prices on pollution intensity and multipliers or green intensity within jobs are not captured by the estimates shown here.

That EU-ETS prices have a negative impact on employment in green jobs suggests that any potential substitution effects towards employment in these jobs are dominated by negative scale effects. This finding can be rationalized in a number of ways. First, it could be the case that the skills required in green jobs are such that they are not quickly or easily filled in the labour market. This is supported by the findings in Bluedorn et al. (2023) and is broadly consistent with the evidence of differences between the characteristics of workers in green and polluting jobs shown in Section 3. Second, it could be the case that adjustments in the demand for green jobs are dependent on investment in green technologies which may take time to be realized.

Robustness I run a number of robustness checks to test the sensitivity of the baseline results to the assumptions and modeling choices imposed. The results of these tests are presented in Appendix B. First, I estimate (3) when also controlling for a number of other potentially confounding factors in the vector $X_{i,t}$. These include: four lags of the country-specific HICP, four lags of the interest rate on 10-year government bonds, and an indicator variable covering the period of the European sovereign debt crisis (Q2 2011 - Q1 2012). The impulse response functions are plotted in Figure B3. The pattern of results is broadly in line with those from the baseline specification.

Second, I estimate the baseline specification and compute bootstrapped standard errors. The impulse response functions are plotted in Figure B4. Bootstrapping helps to address concerns arising from the fact that (3) treats the shock variable ETS_t as observed when it is in fact a generated regressor with an unknown distribution. The pattern of results is, again, broadly in line with those from the baseline specification. The bootstrapped standard errors are in fact somewhat smaller than the Driscoll and Kraay (1998) standard errors suggesting that the sampling error in ETS_t does not pose a significant threat to inference in this setting.

Third, instead of including the shock variable ETS_t directly in (3), I use it as an instrument for the average quarterly EU-ETS allowance price per metric ton of carbon which takes its place in the local projections. The impulse response functions are plotted in Figure B5. Using ETS_t as an instrument also helps to address concerns surrounding its inclusion as a generated regressor in the baseline specification. Again, the pattern of results is broadly in line with those from the baseline specification.

Fourth, I explore the sensitivity of the estimated impacts on green employment by changing the threshold at which a job is classified as green. In addition to the baseline definition by which all jobs with a non-zero green intensity are classified as green jobs, I also consider the cases in which green jobs are defined as those with a green intensity at or above the 75th (4% share of green tasks), 90th (11%), or 95th (17%) percentiles of the green intensity distribution. The impulse response functions are plotted in Figure B6. The results obtained when defining green jobs as those above the 75th and 90th percentiles are broadly similar to those from the baseline specification. Only when green jobs are defined as those above the 95th percentile do the estimates suggest a positive effect on green employment in the very short run that largely hovers around zero and is statistically insignificant over the remaining horizon. These results provide evidence to suggest that there may be a small group of specialized, highly-green jobs for which EU-ETS prices may have non-negative employment effects in the short-run.

Heterogeneity The impacts of EU-ETS prices on employment may vary across countries in the sample. To test for heterogeneous effects at the country level, I estimate the following state dependent local projections model following Cloyne et al. (2023)

$$y_{i,t+h} - y_{i,t-1} = \alpha_i^h + \beta^h ETS_t + \sum_{l=1}^{L} \theta_l^h \Delta y_{i,t-l} + X'_{i,t}\gamma^h + ETS_t X'_{i,t}\xi^h + \mu^h Z_{i,t} + \lambda^h ETS_{i,t} Z_{i,t} + \epsilon_{i,t}^h \tag{4}$$

$Z_{i,t}$ is a state variable for country i at time t. The remaining variables are defined as in (3). λ^h is the main parameter of interest capturing the differential impact of EU-ETS prices by the value of the state variable. Including the interaction term $ETS_t X'_{i,t}$ on the right hand side (4) allows the impact of EU-ETS prices to vary not only by the state variable, but with the controls as well, limiting potential bias from omitted variables.

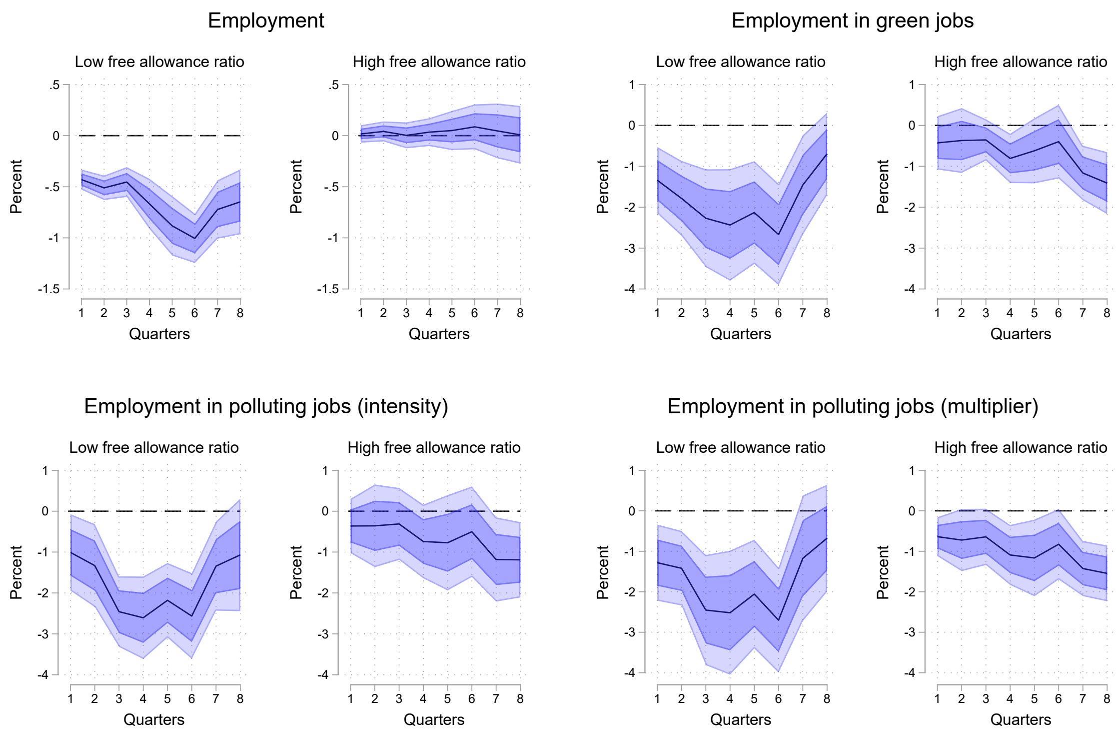
I study the heterogeneity in effects along two dimensions. First, I study how effects vary by the allocation of free emissions allowances under the EU-ETS. In addition to emissions certificates which are auctioned, each year some amount of certificates are freely allocated to emitters, primarily in the manufacturing sector. The stated aim of the free allocation of some certificates is to mitigate the risk of carbon leakage (European Commission, 2011). The share of total allowances which have been allocated freely, and the exact way in which these allocations have been determined, has varied over the history of the EU-ETS. For the most part, however, allocations have been determined according to product- and sector-specific benchmarks based on average emissions intensities. Benchmarks do not vary across countries and have occasionally been updated to reflect the general decline in emissions intensities. The share of total emissions covered by free allowances, therefore, varies across countries, signaling a degree of heterogeneity in the effective price of emissions.

Using data from the European Commission's Union Registry, I calculate for each country, in each year, the ratio of freely allocated allowances to verified emissions.[11] These data are available for all of the countries and years covered by the baseline sample, except for Croatia. In each year, I split the sample of countries at the median value of this ratio and classify countries that lie above as 'high free allowance' countries, and countries that lie below as 'low free allowance' countries. As such, $Z_{i,t}$ becomes an indicator variable equal to one if country i is a high free allowance country at time t and zero otherwise. The estimates of the β^h's trace the impulse response function for the low free allowance countries, while the sum of the β^h and λ^h estimates

[11] These data can be viewed through the European Environment Agency's EU-ETS data viewer, available here: https://www.eea.europa.eu/en/analysis/maps-and-charts/emissions-trading-viewer-1-dashboards. Verified emissions are those which have been measured and verified by independent third-parties.

trace the impulse response function for the high free allowance countries.

Figure 8: Dynamic impacts of shocks to EU-ETS prices by free allowance allocation



Notes: This figure plots the impulse response functions from a one percent increase in EU-ETS prices in model (3) on employment, employment in green jobs, and employment in polluting jobs, defined either on the basis of pollution intensities or pollution multipliers. The estimates are plotted separately for high and low free allowance countries. High free allowance countries are defined as those with a ratio of freely allocated allowances to verified emissions above the median in a particular year; low free allowance countries are defined as those with a ratio below the median. Point estimates at each horizon are surrounded by 68% (dark blue) and 90% (light blue) confidence intervals. Standard errors are calculated following Driscoll and Kraay (1998).

Figure 8 plots the resulting impulse response functions by the ratio of free allowances. The results show a clear pattern. Shocks to EU-ETS prices have a significant, negative impact on all of the employment outcomes considered for low free allowance countries, or countries which face a relatively higher effective price of emissions. For countries with a high free allowance ratio, however, the estimated effects are much smaller in magnitude and often, especially over early horizons, indistinguishable from zero at conventional levels of significance. These results suggest that the allocation of free allowances plays an important role shaping the employment response to EU-ETS price shocks.

I also study how effects vary by the level of employment protection across countries. Employment in countries where jobs are more protected by legislation may exhibit a more muted response to EU-ETS price shocks than in countries with a lower degree of protection. Here, I draw on data from the OECD's Indicators of Employment Protection.[12] These indicators aggregate regulations surrounding the dismissal and hiring of workers in to harmonized indices. I focus on the summary index of employment protection for individual and collective dismissals of workers on regular contracts (EPRC). The index is available for most of the countries and years covered by the baseline sample.[13] In each year, I split the sample of countries at the median value of this index and and classify countries that lie above as 'high employment protection countries', and countries that lie below as 'low employment protection countries'. I again estimate (4) where $Z_{i,t}$ now becomes an indicator variable equal to one if country i is a high employment protection country at time t and zero otherwise.

The impulse response functions for high and low employment protection countries are presented in Figure 9. The results show a clear pattern. Shocks to EU-ETS prices have a significant, negative impact on all of the employment outcomes considered for countries with low employment protection. For countries with high employment protection, however, the estimated effects are much smaller in magnitude. For employment in green jobs, the estimated impacts are small and largely insignificant at the 10% level. For employment in polluting jobs, the estimates are less precise and largely indistinguishable from zero; only at later horizons does a negative, cumulative impact materialize. These results suggest that employment protection legislation plays an important role shaping employment responses to EU-ETS price shocks.

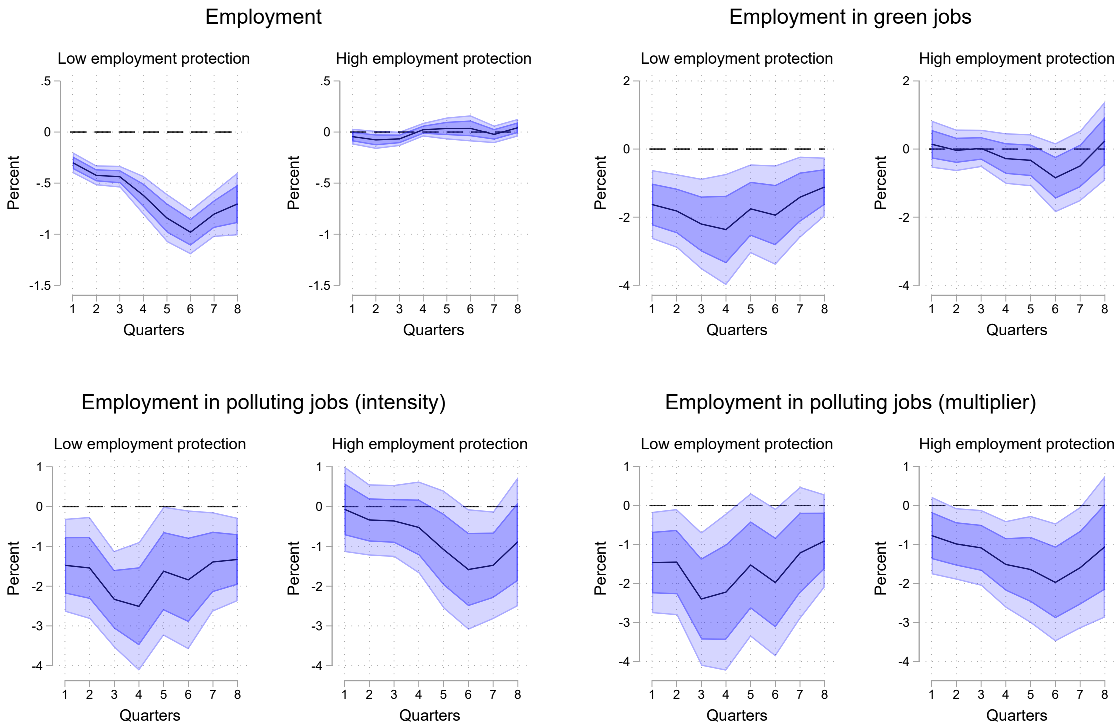
5 Conclusion

This paper studies European labour markets through the lens of their environmental properties. I construct a large dataset and apply standard methodologies to define jobs along two dimensions: green intensity and polluting intensity. I then document a number of stylized facts. These show that the vast majority of workers in Europe work in jobs that are not very green nor very polluting. The average environmental characteristics of jobs vary across countries and over time. They also vary for different subsets of workers in a meaningful way. I then turn to

[12]See: https://www.oecd.org/en/data/datasets/oecd-indicators-of-employment-protection.html

[13]Cyprus, Croatia, and Romania are not covered by the OECD's Employment Protection Indicators, while data for Lithuania and Latvia are only partially available over the time span considered.

Figure 9: Dynamic impacts of shocks to EU-ETS prices by level of employment protection



Notes: This figure plots the impulse response functions from a one percent increase in EU-ETS prices in model (3) on employment, employment in green jobs, and employment in polluting jobs, defined either on the basis of pollution intensities or pollution multipliers. The estimates are plotted separately for high and low employment protection countries. High employment protection countries are defined as those with an EPRC index value above the median in a particular year; low employment protection countries are defined as those with an index value below the median. Point estimates at each horizon are surrounded by 68% (dark blue) and 90% (light blue) confidence intervals. Standard errors are calculated following Driscoll and Kraay (1998).

an empirical analysis of the impact of shocks to EU-ETS prices on employment. I find that exogenous increases in EU-ETS certificate prices lead to a negative impact on employment over a period of two years. Estimates of the impact on green and polluting jobs, though less precise, suggest that effects on employment are also negative in these types of jobs. These negative effects on aggregate employment are driven to an important degree by two factors: the allocation of free allowances and employment protection legislation. When relatively fewer emissions are covered by freely allocated allowances, the negative employment effects of EU-ETS price shocks are stronger. Similarly, when employment protection legislation is tighter, the estimated impact is more muted.

The analyses and findings presented in this paper carry important implications for the broader policy debate on climate change and the green transition, and the institutions for which it is relevant. While these findings can be informative of potential future impacts of EU-ETS prices on the labour market, they should be viewed in light of the limitations discussed in this paper. They also highlight a number of areas for future research. First, further analysis of the impacts of EU-ETS prices on employment in green and polluting jobs would benefit from a theoretical framework, clearly illustrating the potential scale and substitution channels touched on in this paper, and detailing the parameters on which they depend. Second, alternative data sources, including job descriptions from online vacancy postings, could be exploited to determine the impact of EU-ETS prices on the share of green tasks within jobs. Third, the analyses presented in this paper could be extended to cover the gradual phasing-out of free allowances under the original ETS and the introduction of EU-ETS 2 to estimate the impacts of prices in this separate, parallel market. Finally, it will be important to follow and understand how the introduction of the EU's Carbon Border Adjustment Mechanism (CBAM) will impact this paper's findings.

References

Bachmann, R., Janser, M., Lehmer, F., & Vonnahme, C. (2024). *Disentangling the Greening of the Labour Market: The Role of Changing Occupations and Worker Flows*, IAB-Discussion Paper 12/2024.

Bluedorn, J., Hansen, N.-J., Noureldin, D., Shibata, I., & Tavares, M. M. (2023). Transitioning to a Greener Labor Market: Cross-country Evidence from Microdata. *Energy Economics*, *126*.

Bowen, A., Kuralbayeva, K., & Tipoe, E. L. (2018). Characterising Green Employment: The Impacts of 'Greening' on Workforce Composition. *Energy Economics*, *72*, 263–275.

Causa, O., Nguyen, M., & Soldani, E. (2024). *Lost in the Green Transition? Measurement and Stylized Facts*, OECD Economics Department Working Papers No. 1796.

Cloyne, J. S., Jordà, Ò., & Taylor, A. M. (2023). *State-Dependent Local Projections: Understanding Impulse Response Heterogeneity*, NBER Working Paper No. 30971.

Crippa, M., Guizzardi, D., Pagani, F., Banja, M., Muntean, M., Schaaf, E., Quadrelli, R., Risquez, M. A., Taghavi-Moharamli, P., Köykkä, J., Grassi, G., Rossi, S., Melo, J., Jacome Felix Oom, D., Branco, A., Suárez-Moreno, M., Sedano, F., San-Miguel, J., Manca, G., . . . Pekar, F. (2025). *Ghg emissions of all world countries* (tech. rep.). Luxembourg, Publications Office of the European Union.

Dechezleprêtre, A., Nachtigall, D., & Venmans, F. (2023). The Joint Impact of the European Union Emissions Trading System on Carbon Emissions and Economic Performance. *Journal of Environmental Economics and Management*, *118*, 102758.

de Mooij, R. A., Keen, M., & Parry, I. W. (2012). *Fiscal Policy to Mitigate Climate Change: A Guide for Policymakers*. International Monetary Fund.

Dierdorff, E. C., Norton, J. J., Drewes, D. W., Koustalis, C. M., Rivkin, D., & Lewis, P. (2009). *Greening of the World of Work: Implications for O*NET-SOC and New and Emerging Occupations* (tech. rep.). National Center for O*Net Development.

Driscoll, J. C., & Kraay, A. C. (1998). Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. *The Review of Economics and Statistics*, *80*(4), 549–560.

Elliott, R. J. R., Kuai, W., Maddison, D., & Ozgen, C. (2024). Eco-innovation and (Green) Employment: A Task-Based Approach to Measuring the Composition of Work in Firms. *Journal of Environmental Economics and Management*, *127*.

European Commission. (2011). Commission Decision of 27 April 2011 determining transitional Union-wide rules for harmonised free allocation of emission allowances pursuant to Article 10a of Directive 2003/87/EC of the European Parliament and of the Council (notified under document C(2011) 2772).

European Commission and Eurostat. (2008). *NACE Rev. 2 – Statistical Classification of Economic Activities in the European Community* (tech. rep.). Luxembourg, Office for Official Publications of the European Communities.

Hardy, W., Keister, R., & Lewandowski, P. (2018). Educational Upgrading, Structural Change and the Task Composition of Jobs in Europe. *Economics of Transition*, *26*(2), 201–231.

International Energy Agency. (2019). *Energy Policies of IEA Countries: Estonia 2019* (tech. rep.). Paris, OECD Publishing.

Jordà, Ò., & Taylor, A. M. (2016). The Time for Austerity: Estimating the Average Treatment Effect of Fiscal Policy. *Economic Journal*, *126*(590), 219–255.

Känzig, D. (2025). *The Unequal Economic Consequences of Carbon Pricing*, mimeo.

Känzig, D., & Konradt, M. (2024). Climate Policy and the Economy: Evidence from Europe's Carbon Pricing Initiatives. *IMF Economic Review*, (72), 1081–1124.

Konradt, M., & Mangiante, G. (2025). *The Unequal Costs of Carbon Pricing: Economic and Political Effects across European Regions*, mimeo.

Konradt, M., & Weder di Mauro, B. (2023). Carbon Taxation and Greenflation: Evidence from Europe and Canada. *Journal of the European Economic Association*, *21*(6), 2518–2546.

Martinez-Fernandez, C., Hinojosa, C., & Miranda, G. (2010). *Greening Jobs and Skills: Labour Market Implications of Addressing Climate Change*, OECD Local Economic and Employment Development (LEED) Working Paper Series 2010/02.

Montiel Olea, J. L., & Plagborg-Møller, M. (2021). Local Projection Inference is Simpler and More Robust than You Think. *Econometrica*, *89*(4), 1789–1823.

Scholl, N., Turban, S., & Gal, P. (2023). *The Green Side of Productivity: An International Classification of Green and Brown Occupations*, OECD Productivity Working Papers No. 33.

Schroeder, C., & Stracca, L. (2025). Pollution Havens? Carbon Taxes, Globalization, and the Geography of Emissions. *IMF Economic Review.*

Tol, R. S. J. (2018). The Envrionmental Impacts of Climate Change. *Review of Envrionmental Economics and Policy*, *12*(1), 4–25.

Vona, F., Marin, G., Consoli, D., & Popp, D. (2018). Envrionmental Regulation and Green Skills: An Empirical Exploration. *Journal of the Association of Environmental and Resource Economists*, *5*(4), 713–753.

A Green- and pollution intensity of Jobs: Detailed Examples

This appendix provides detailed examples of the methodology used to construct the green intensity and pollution intensity measures as described in Section 2.2.

A.1 Green intensity

O*Net is a database of occupations in the US labour market maintained by the US Department of Labor. Each occupation in O*Net is associated with a set of commonly associated tasks. In 2010, the O*Net Green Task Development Project identified a number of new green occupations and taxonomy of green tasks for both these new occupations as well as existing occupations. One of the new green occupations identified was that of a Chief Sustainability Officer (SOC: 11-1011.03). One of its green tasks is, for example, to "conduct sustainability- or environment related risk assessments". An example of an existing occupation in O*Net that is associated with a green task is a Financial Analyst (SOC: 13-2051.00) which is associated with the green task "(to) forecast or analyze financial costs associated with climate change or other environmental factors, such as clean water supply and demand".

Tables A1, A2, and A3 show how the green intensity scores for the 8-digit SOC occupations Chief Sustainability Officer and Financial and Investment Analyst can be mapped in to the 3-digit ISCO 08 occupations in the EU-LFS. Specifically, table A1 shows how the green intensity score is calculated as the ratio of green tasks to total tasks for each 8-digit SOC occupation. Table A2 then shows how the green intensity score for each 6-digit SOC occupation is calculated as the average of green intensity scores from each corresponding 8-digit SOC occupation. Finally, Table A3 shows how the scores are crosswalked to 3-digit ISCO-08 occupations. The green intensity score for each 3-digit ISCO-08 occupation is calculated as the employment weighted average of scores from each 6-digit SOC occupation which maps to it. I chose to weight by employment from 2016 as it falls roughly in the middle of the considered time span in this paper's empirical analyses.

Table A1: Green intensity for 8-digit SOC occupations

8-digit SOC	8-digit SOC Title	Green tasks	Total tasks	Green intensity$_{soc8}$
11-1011.03	Chief Sustainability Officer	18	18	1
13-2051.00	Financial and Investment Analyst	6	18	0.3

Table A2: Aggregating green intensity from 8-digit SOC to 6-digit SOC

8-digit SOC	8-digit SOC Title	Green intensity$_{soc8}$	6-digit SOC	6-digit SOC Title	Green intensity$_{soc6}$
11-1011.03	Chief Sustainability Officer	1	11-1011	Chief Executive	0.5
11-1011.03	Chief Executive	0	11-1011	Chief Executive	0.5
13-2051.00	Financial and Investment Analyst	0.3	13-2051	Financial and Investment Analyst	0.3

Table A3: Crosswalking green intensity from 6-digit SOC to 3-digit ISCO

6-digit SOC	6-digit SOC Title	Green intensity$_{soc6}$	Employment$_{2016,soc6}$	3-digit ISCO	3-digit ISCO Title	Green intensity$_{isco3}$
11-1011	Chief Executive	0.5	223,260	112	Managing Director & Chief Executive	0.15
11-1021	General & Operations Manager	0.1	2,188,870	112	Managing Director & Chief Executive	0.15
11-1011	Chief Executive	0.5	223,260	111	Legislator & Senior Official	0.19
11-1021	General & Operations Manager	0.1	2,188,870	111	Legislator & Senior Official	0.19
11-1031	Legislator	0	53,670	111	Legislator & Senior Official	0.19
11-2031	Public Relations & Fundraising Manager	0	63,970	111	Legislator & Senior Official	0.19
11-9161	Emergency Management Director	0	9,570	111	Legislator & Senior Official	0.19
11-9199	Manager, All Other	0.4	403,670	111	Legislator & Senior Official	0.19
13-2051	Financial and Investment Analyst	0.3	281,610	241	Finance Professional	0.06
13-2011	Accountant & Auditor	0	1,246,540	241	Finance Professional	0.06
13-2031	Budget Analyst	0	54,700	241	Finance Professional	0.06
13-2041	Credit Analyst	0	72,930	241	Finance Professional	0.06
13-2052	Personal Financial Advisor	0.1	201,850	241	Finance Professional	0.06
13-2061	Financial Examiner	0	49,750	241	Finance Professional	0.06
13-2082	Tax Preparer	0	70,030	241	Finance Professional	0.06

A.2 Pollution intensity

Table A4 shows in detail how pollution intensity is calculated for one particular occupation, in one country, in one year in the data: Legislators & Senior Officials in Germany in 2019. First, the share of workers in the occupation employed in each NACE sector is calculated. Next, the pollution intensity is calculated as the average emissions intensity across sectors weighted by the share employed in each sector.

Table A4: Computing pollution intensity for Legislators & Senior Officials in Germany in 2019

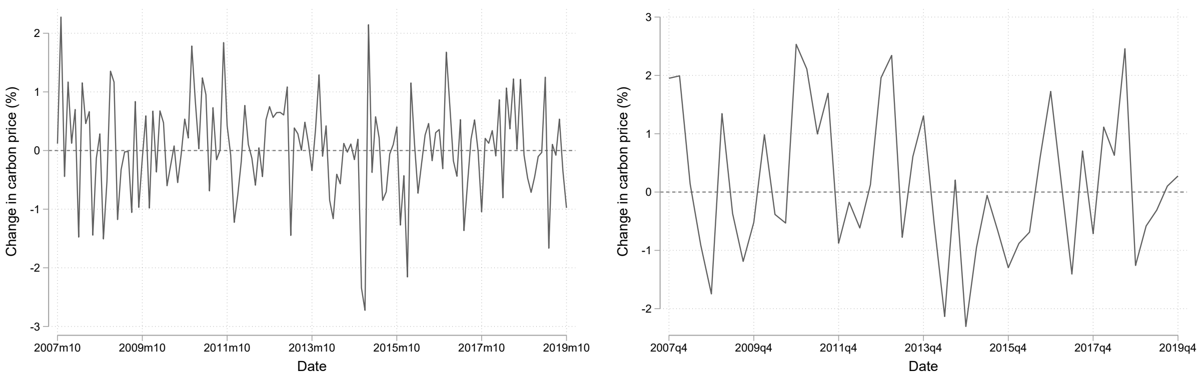
ISCO-3	ISCO-3 Title	Total employment	Shared employed in sector	NACE2 sector	Emissions intensity (kg/Euro)	pollution intensity
111	Legislator & Senior Official	39,997	0.03	Manufacturing	0.05	0.01
111	Legislator & Senior Official	39,997	0.01	Wholesale & Retail Trade	0.01	0.01
111	Legislator & Senior Official	39,997	0.01	Transportation & Storage	0.1	0.01
111	Legislator & Senior Official	39,997	0.02	Accommodation & Food Service Activities	0.01	0.01
111	Legislator & Senior Official	39,997	0.03	Professional, Scientific, & Technical Activities	0.004	0.01
111	Legislator & Senior Official	39,997	0.01	Administrative & Support Service Activities	0.002	0.01
111	Legislator & Senior Official	39,997	0.63	Public Administration & Defence, Compulsory Social Security	0.005	0.01
111	Legislator & Senior Official	39,997	0.02	Education	0.005	0.01
111	Legislator & Senior Official	39,997	0.06	Human Health & Social Work Activities	0.006	0.01
111	Legislator & Senior Official	39,997	0.01	Arts, Entertainment, & Recreation	0.004	0.01
111	Legislator & Senior Official	39,997	0.17	Other Service Activities	0.02	0.01

B Additional Tables and Figures

This appendix presents additional tables and figures not appearing in the main text.

Figure B1: Time series of identified shocks to EU-ETS prices from Känzig (2025)

(a) Monthly shocks (b) Quarterly shocks



Notes: This figure plots the time series of identified shocks to EU-ETS prices from Känzig (2025). Panel B1a plots the original monthly shocks as computed by the author and available here: https://github.com/dkaenzig/carbonpolicyshocks. Panel B1b plots the time series of shocks aggregated to the quarterly frequency, summing the monthly shocks in each quarter. The shocks are scaled such as to represent the percentage change in EU-ETS prices.

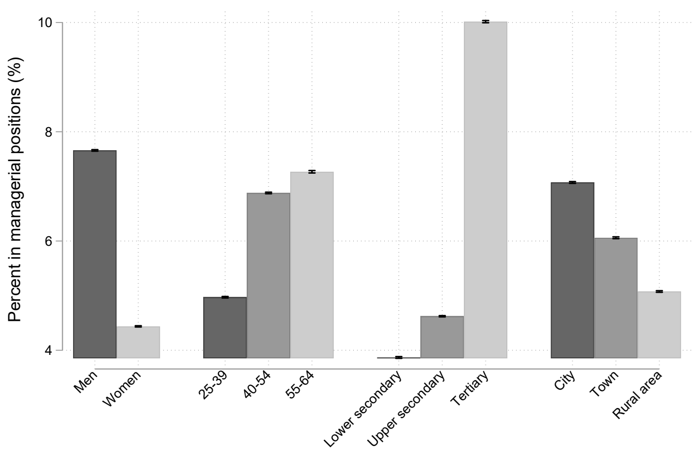
Table B1: Regressing measures of environmental characteristics on managerial status

	(1) Green intensity	(2) Pollution intensity	(3) Pollution multiplier
Managerial position	13.59	-0.00591	-0.0241
	(0.00532)	(0.0000462)	(0.000401)
R^2	0.197	0.001	0.000

Standard errors in parentheses

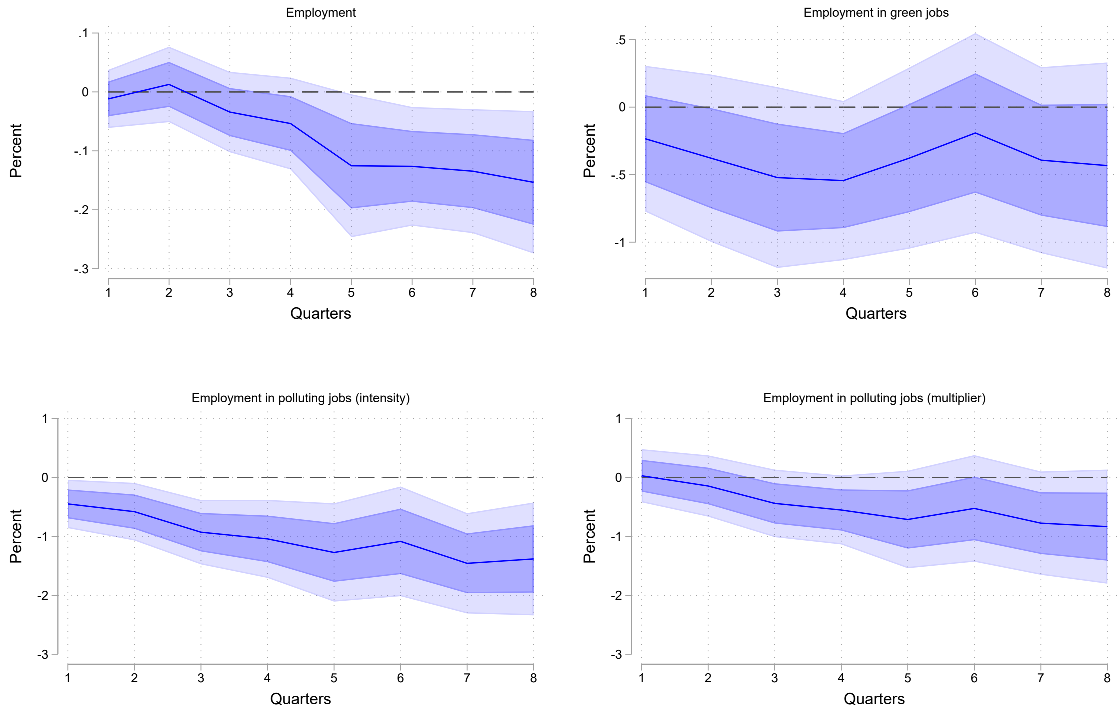
Notes: This table shows regression results from simple OLS regressions of the intensity measure in each column on an indicator variable equal to one if the observation is recorded as working in a managerial position, and zero otherwise. Managerial positions are defined as those in ISCO major group 1 (“Managers”).

Figure B2: Percentage working in managerial positions



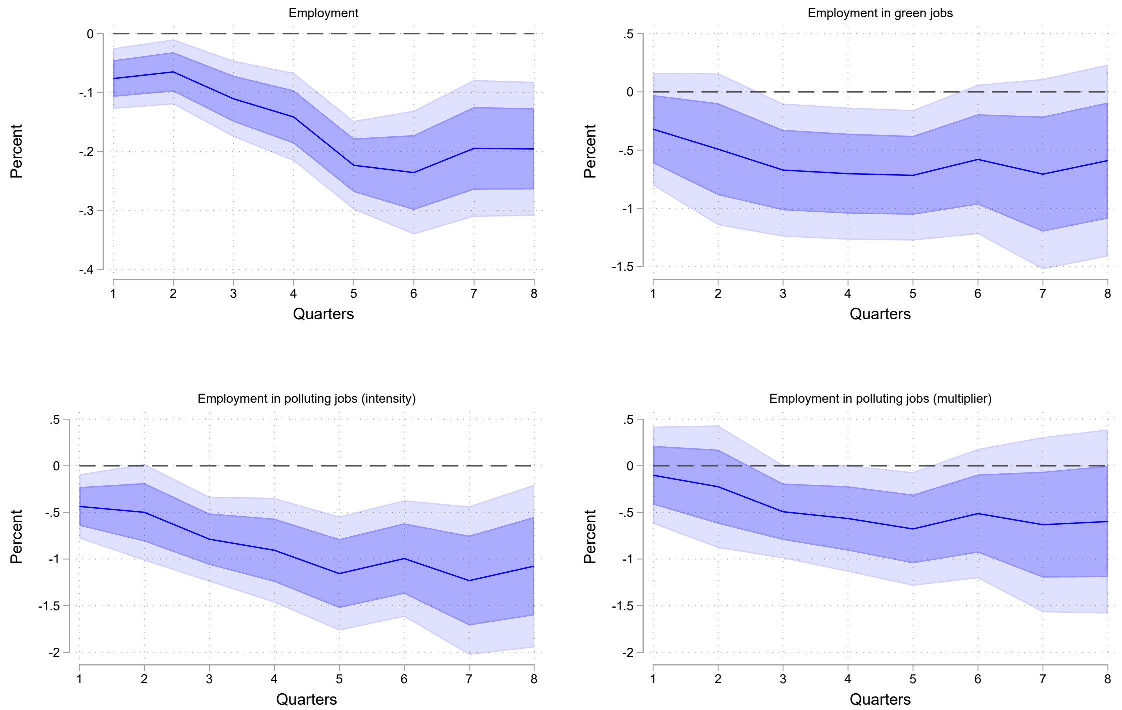
Notes: This figure plots the percentage of workers in the sample working in managerial positions for specific groups of workers. Managerial positions are defined as those in ISCO major group 1 ("Managers").

Figure B3: Dynamic impacts of shocks to EU-ETS prices with additional control variables



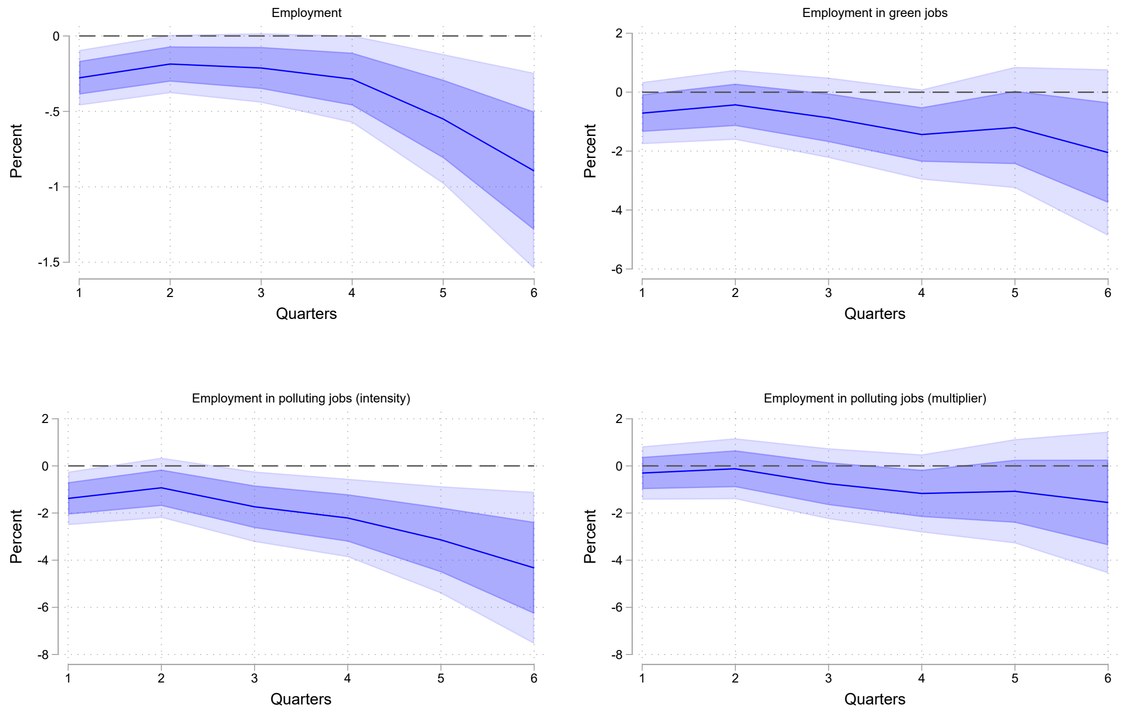
Notes: This figure plots the impulse response functions from a one percent increase in EU-ETS prices in model (3) on employment, employment in green jobs, and employment in pollution intensive jobs, defined either only considering direct emissions, or direct and indirect emissions intensity. Point estimates at each horizon are surrounded by 68% (dark blue) and 90% (light blue) confidence intervals. Standard errors are calculated following Driscoll and Kraay (1998).

Figure B4: Dynamic impacts of shocks to EU-ETS prices with bootstrapped standard errors



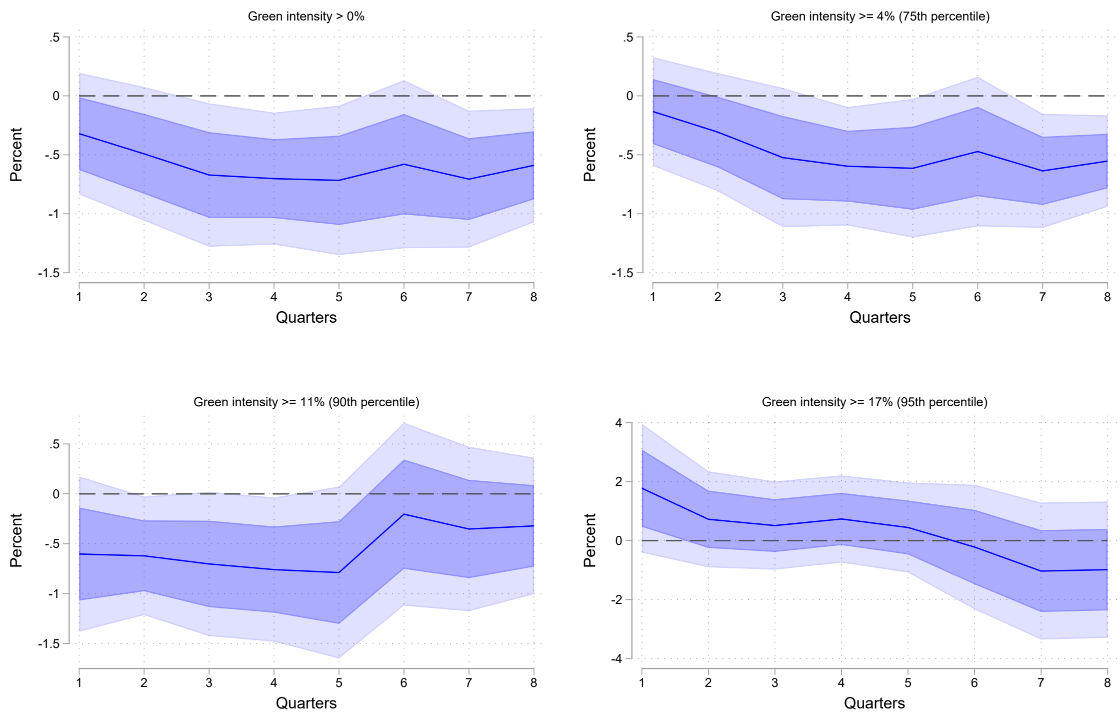
Notes: This figure plots the impulse response functions from a one percent increase in EU-ETS prices in model (3) on employment, employment in green jobs, and employment in pollution intensive jobs, defined either only considering direct emissions, or direct and indirect emissions intensity. Point estimates at each horizon are surrounded by 68% (dark blue) and 90% (light blue) confidence intervals. Standard errors are calculated by bootstrapping.

Figure B5: Dynamic impacts of shocks to EU-ETS prices, IV estimates



Notes: This figure plots the impulse response functions from a one percent increase in EU-ETS prices in model (3) on employment, employment in green jobs, and employment in pollution intensive jobs, defined either only considering direct emissions, or direct and indirect emissions intensity. Point estimates at each horizon are surrounded by 68% (dark blue) and 90% (light blue) confidence intervals. Standard errors are calculated following Driscoll and Kraay (1998).

Figure B6: Dynamic impacts of shocks to EU-ETS prices, different threshold for defining green jobs



Notes: This figure plots the impulse response functions from a one percent increase in EU-ETS prices in model (3) on employment in green jobs defined according to different thresholds on the green intensity of each job. The upper left panel defines green jobs as jobs with a green intensity greater than 0%, as in the baseline results. The upper right panel defines green jobs as jobs with a green intensity greater than or equal to 4%, or the 75th percentile of the green intensity distribution. The bottom left panel defines green jobs as jobs with a green intensity greater than or equal to 11%, or the 90th percentile of the green intensity distribution. The bottom right panel defines green jobs as jobs with a green intensity greater than or equal to 17%, or the 95th percentile of the green intensity distribution. Point estimates at each horizon are surrounded by 68% (dark blue) and 90% (light blue) confidence intervals. Standard errors are calculated following Driscoll and Kraay (1998).