Mass layoffs across 15 economies reveal unequal reallocation costs of the green transition*

Stefano Lombardi†, César Barreto†, Alexander Hijzen†, Oskar Nordström Skans†,

Patrick Bennett, Antoine Bertheau, Winnie Chan, Domenico Depalo, Jonas Fluchtmann,

Andrei Gorshkov, Jonathan Hambur, Benjamin Lochner, Jordy Meekes, Tahsin Mehdi,

Balázs Muraközy, Gulnara Nolan, Kjell Salvanes, Rune Vejlin

The global shift toward low-carbon, environmentally sustainable growth is widely seen as essential for mitigating climate change.[1–9] However, little is known about how the resulting economic restructuring will affect workers, although such knowledge is essential for designing effective climate policy and maintaining broad societal support for decarbonization.[10,11] Existing research shows that job loss generates long-lasting economic scars,[12–17] but evidence on whether workers displaced from high-emission industries face systematically worse outcomes than other displaced workers remains scarce. We analyze the reallocation costs of job loss in high-carbon emission sectors and in the rest of the economy using harmonized matched employer–employee registers from fifteen economies ($N = 757{,}839{,}979$), from which we construct a sample of workers displaced in mass layoffs matched to comparison workers ($N = 16{,}668{,}400$). Workers displaced from high-emission industries suffer persistently larger income losses than comparable workers displaced from other industries. A detailed subgroup analysis shows that workers in high-emission sectors tend to have characteristics associated with smaller penalties—they are longer-tenured, higher-skilled men of higher socioeconomic status employed at higher-paying firms—yet they are disproportionately employed in rural areas, contracting industries, and large mass-layoff events, all labor market conditions that amplify losses. Despite institutional differences, these findings are consistent across countries and suggest climate policy should combine place-based and targeted interventions to mitigate the reallocation costs of decarbonization.

*Lombardi: VATT Institute for Economic Research, Institute for Evaluation of Labour Market and Education Policy (IFAU), IZA, Uppsala Center for Labor Studies (UCLS). Barreto: OECD, Friedrich-Alexander-Universit at Erlangen-Nurnberg (FAU). Hijzen: OECD, Institute for Labor Economics (IZA). Nordström Skans: Uppsala University, UCLS, IZA, IFAU. Bennett: University of Liverpool, Institute for Employment Research (IAB), FAU, IZA. Bertheau: Norwegian School of Economics (NHH). Chan: Statistics Canada Fluchtmann: OECD. Gorshkov: Uppsala University. Hambur: Federal Reserve Bank of Australia. Lochner: FAU, IAB. Meekes: Leiden University. Mehdi: Statistics Canada Muraközy: University of Liverpool. Nolan: Federal Reserve Bank of Australia. Salvanes: NHH, IZA. Vejlin: Åarhus University.

†Co-first authors.

Introduction

Many nations worldwide, along with the scientific community, view global warming as an existential threat to humankind that must be addressed through the green transition—that is, through policies aimed at shifting toward low-carbon, environmentally sustainable models.[1,2] As of end of 2025, global warming projections over this century are 2.3-2.5°C, far from meeting the Paris Agreement of staying well below 2°C while aiming for 1.5°C.[3] How to reach the target in a timely manner therefore continues being object of intense political and scientific debate.[4–9]

While the green transition is not expected to reduce aggregate employment, it will require substantial worker reallocation across firms, occupations, and local labor markets. Despite broad scientific consensus on the need for decarbonization, the reallocation costs borne by displaced workers as industrial restructuring takes place remain an often overlooked aspect of this process. Understanding how these costs are distributed across worker groups is crucial for designing targeted mitigation policies and for ensuring the political feasibility of the transition. Workers who bear the largest losses may be more likely to oppose climate policies, contributing to political polarization and support for views such as climate change denial.[18] From a policy perspective, these distributional concerns are particularly salient because, unlike reallocation driven by technological progress, the green transition is not necessarily perceived as delivering immediate economic gains, potentially increasing the political cost of policies associated with job displacement.

Differences in post-displacement outcomes between workers from high-emission sectors and those from the rest of the economy are unlikely to reflect an inherent penalty associated with high carbon emissions. Instead, they are likely driven by variation in worker characteristics and in the types of firms, industries, and local labor markets in which workers are employed. This is in line with previous research documenting that job loss has lasting consequences[12–15,19] that vary substantially across workers and labor markets,[16,17] with consequences extending beyond labor market outcomes for displaced workers.[20–23] Yet, evidence on the reallocation costs faced by workers in the context of the green transition remains scarce, as the existing research does not account for the disparate consequences of job loss for workers within and across high-emission sectors and the rest of the economy, nor does it incorporate an international perspective.[24] This limits our understanding of the reallocation costs of decarbonization and our ability of targeting mitigation policies, in a context where cross-country coordination is essential.

Our paper studies the economic consequences of job loss in high-carbon emission sectors versus the rest of the economy (henceforth, low-emission sectors) across 15 countries. The analysis relies on harmonized administrative employer–employee registers linking workers to their employer and providing detailed information on labor market histories and demographics over the course of their careers. The underlying data comprises $N = 757{,}839{,}979$ worker-year observations, corresponding to full population coverage in 10 countries and large representative samples in the remaining countries (Extended Data Table 1). The large sample size allows us to identify sufficiently many workers displaced for plausibly exogenous reasons and to conduct group-level analyses with adequate statistical power. In particular, to limit bias from voluntary separations and anticipatory behavior, we focus on job separations occurring in correspondence of mass layoffs and plant closures. This yields an analysis sample of $N = 16{,}668{,}400$ person-year observations (Extended Data Table 1).

Our empirical approach consists of an event study model that contrasts the labor income trajectories of workers that lose their job in high emission industries to those of osbervationally similar workers employed in the same industries but who do not lose their job, before and after the displacement year.[25] Because job loss generally leads to earnings declines, we benchmark the reallocation costs associated with job loss in high-emission industries by contrasting them with those experienced by workers in low-emission industries. We refer to the resulting differential losses as to *high-emission penalties*, which we meta-analyze across the 15 countries.[26,27] See Extended Data Figure 1 and Supplementary Table A.1 for the definition of high- and low-emission industries.

Following displaced workers over time allows us to analyze their recovery trajectories and to attribute income losses to joblessness, wage reductions, and transitions to lower-quality employers. The analysis of post-layoff income dynamics and their sources across emission sectors has immediate policy implications, as their initial magnitude, persistence, and underlying drivers may call for very different policy instruments. For instance, if the goal is to contrast large immediate income losses quickly, job search assistance or hiring subsidies might generally be better suited than relatively long training programs that tend to take time to be effective. Moreover, if the labor income losses are primarily driven by joblessness, job search assistance might be preferred over retraining.[28–30]

Our results document sizable high-emission penalties that persist for up to five years after displacement. These losses are not driven by differential employment declines, but instead reflect disproportionately large wage reductions among workers previously employed in high-emission sectors. A complementary country-level analysis shows that, despite substantial cross-country differences in overall displacement losses and some heterogeneity in emission-specific effects, high-emission penalties exhibit only moderate variation across countries. We further show that differences in worker and firm composition across countries account for a limited part of the observed cross-country differences in income losses.

Having documented the average consequences of job loss across displaced workers, we examine which job loss characteristics drive such average high-emission penalties. We use four categories of pre-displacement characteristics—workers, firms, labor market, and occupation—each characterized by detailed job loss features. Together with the analysis of the economic consequences of job loss across each characteristic, we jointly examine pre-displacement sorting along the same dimensions, which provides a direct metric for evaluating workers' exposure to characteristics associated with differential losses within and across emission sectors.

The results reveal substantial heterogeneity in both the high-emission penalty and sorting patterns. Workers in high-emission sectors tend to exhibit characteristics associated with relatively smaller income losses following displacement, yet they are disproportionately employed in local labor markets where job loss entails larger income declines. Consistent with this pattern, within-country compositional differences between high- and low-emission sectors on average account for a large share of the high-emission penalty.

Results

Income losses following displacement are persistent and disproportionately large in high-emission sectors

Figure 1 reports point estimates and 95% confidence intervals from the event studies of workers in high and low emission sectors, between four years before and five years after job loss. For each emission group, the model compares the labor market outcomes of workers that lose their job in a mass layoff to those of similar workers that do not experience such an event, before and after the event time. All estimates are separately estimated by country and then aggregated (see Methods). Sample size is $N = 16{,}668{,}400$ worker-year observations evenly split between displaced workers and matched controls. Data sources and sample described in Extended Data Table 1 and 2.

The figure reports estimated job loss coefficients on income (measured as the percentage change relative to the pre-displacement average) and employment. The left figures show estimates by emission sector, while the right ones report high-emission differentials (penalties). All estimates–along with those for wages and firm pay premia discussed later–are reported in Supplementary Tables A.2—A.6. Country-level estimates are reported in Suppplementary tables A.7—A.14.

According to Figure 1, workers do not exhibit anticipatory behavior before displacement. In the Methods section we provide further evidence in favor of the parallel trends assumption required for the unbiased estimation of the model coefficients. We therefore interpret the estimates as emission group- and time-specific job loss effects on the outcome under study.

Panel A of Figure 1 shows that losing a job in high emission sectors (in red) comes with a substantial and persistent high-emission income penalty compared to losing a job in low emission industries (in blue). Workers displaced in high emission sectors experience a 51 % income drop the year they lose their job ($\beta_{high,k=0} = -0.507$; 95% CI: -0.508, -0.505; $p = 0.000$) and 39 % income losses if they lose their job in low emission sectors ($\beta_{low,k=0} = -0.395$; 95% CI: -0.396, -0.393; $p = 0.000$). Hence, while workers in both groups are severely hit by job displacement, those employed in high emission industries suffer disproportionally larger income losses. The corresponding high-emission penalty—the difference between the two coefficients—is 11.2 % ($\beta_{penalty,k=0} = -0.112$; 95% CI: -0.114, -0.110; $p = 0.000$), equivalent to €2883 (in 2015 Euros).

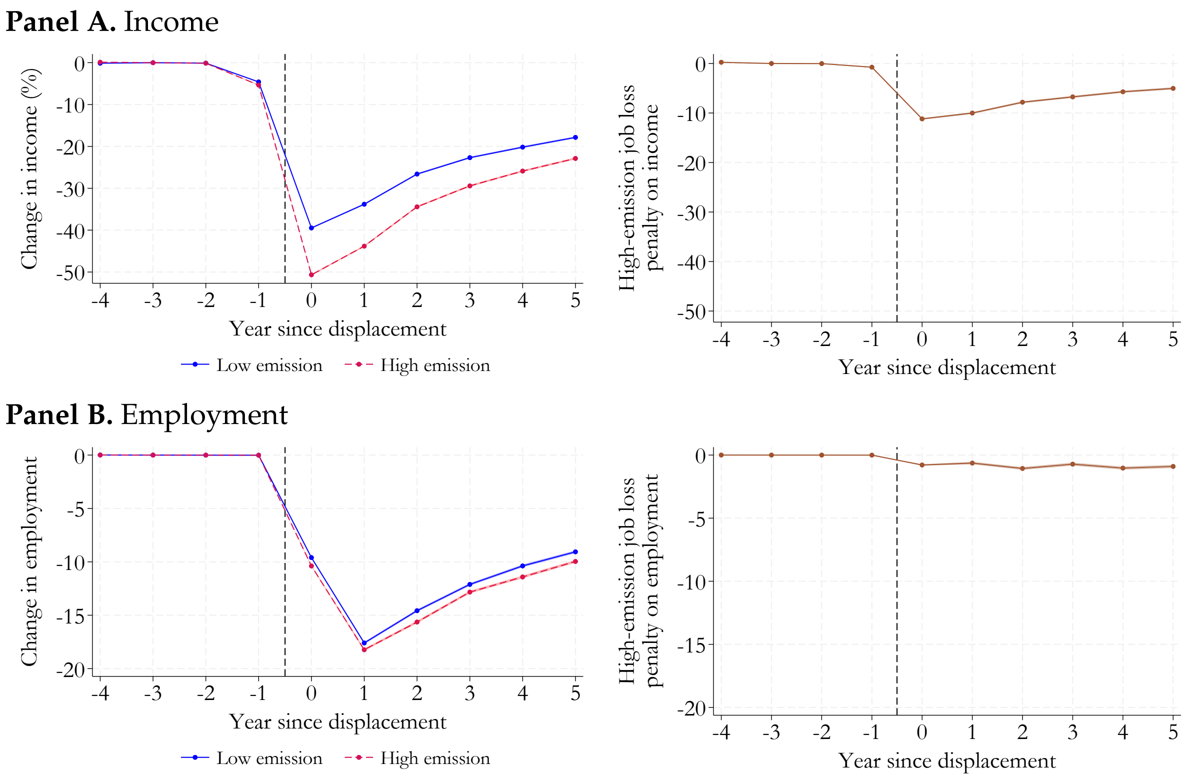


Fig. 1: Evolution of income and employment in high and low emission sectors before and after job displacement. Event study estimates by emission sector (left) and difference between high- and low-emission sectors (right). Income (Panel A) measured as percentage change from the pre-displacement level; employment (Panel B) is an indicator for positive income. The model specification includes worker and calendar-year fixed effects, event-time indicators interacted with displacement status (and included as main effects), calendar-year indicators, and a cubic in age. All regressors are fully interacted with the emission sector indicator. Country-specific estimates are obtained from balanced samples of displaced and matched comparison workers and then aggregated across countries (see Methods). The sample size is $N = 16{,}668{,}400$ observations.

Over time, the displaced workers in both high and low emission sectors experience a gradual income recovery, which is however only partial ($\beta_{high,k=5} = -0.229$; 95% CI: -0.231, -0.226; $p = 0.000$). And while the high-emission penalty in income reduces from about 11 % to 5 % due to the gap in wages closing down ($\beta_{penalty,k=5} = -0.050$;

95% CI: -0.053, -0.048; $p = 0.000$), the gap closes only sluggishly and partially.

The larger labor income losses of workers displaced in high- as opposed to low-emission sectors can be explained by a combination of reduced employment and lower wages of the re-employed workers. Identifying the relative importance of these channels in high- and low-emission sectors can help inform which policy instruments are most appropriate for closing the high-emission penalty. Panel B of Fig. 1 shows that the high-emission penalty in income does not reflect differences in re-employment rates, since the latter follow nearly identical dynamics in high- and low-emission groups from the year of job loss ($\beta_{high,k=0} = -0.104$; 95% CI: -0.104, -0.103; $p = 0.000$, and $\beta_{low,k=0} = -0.096$; 95% CI: -0.097, -0.095; $p = 0.000$) throughout the post-event period up to five years later ($\beta_{high,k=5} = -0.100$; 95% CI: -0.101, -0.098; $p = 0.000$, and $\beta_{low,k=5} = -0.091$; 95% CI: -0.092, -0.089; $p = 0.000$). Extended Data Figure 2 and Supplementary Tables A.5, A.6 confirm that the high-emission penalties in income are driven by wage differences between displaced workers from high- and low-emission industries, and that these differences are largely accounted for by persistent gaps in lost firm pay premia.

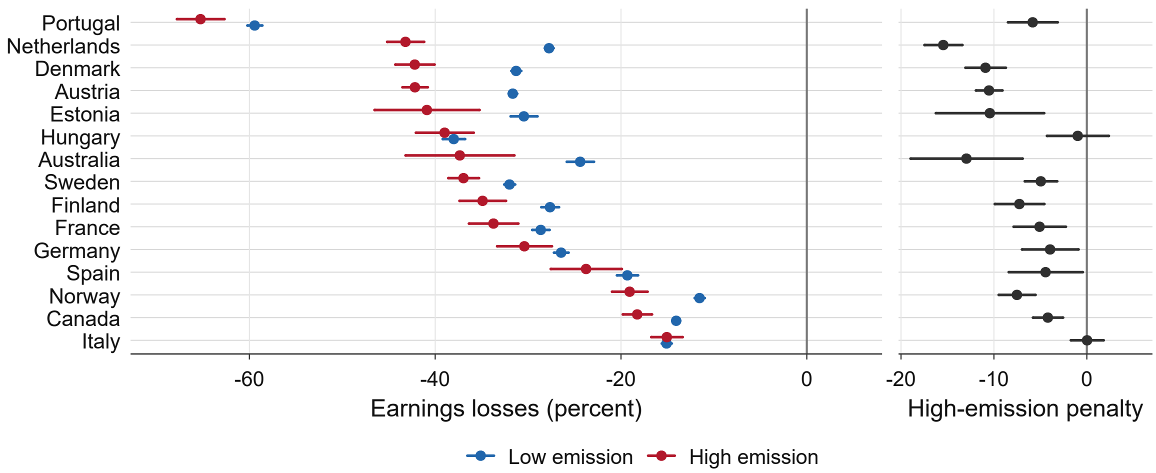
Cross-country differences in high-emission penalties are moderate

To explore the extent to which the estimates presented so far reflect cross-country heterogeneities, Figure 2 reports country-level yearly losses in income (Panel A) and employment (Panel B) averaged in the five years following displacement. Wage and firm pay premia losses are included in Extended Data Figure 3, and Supplementary Tables A.15 and A.16.

Despite the existing cross-country variation, the bulk of the countries is characterized by high-emission sector income losses in the 35-45% range: $\beta_{high,NLD} = -0.432$; 95% CI: -0.452, -0.412; $p = 0.000$; $\beta_{high,DNK} = -0.422$; 95% CI: -0.443, -0.401; $p = 0.000$; $\beta_{high,AUT} = -0.422$; 95% CI: -0.435, -0.408; $p = 0.000$; $\beta_{high,EST} = -0.409$; 95% CI: -0.465, -0.353; $p = 0.000$; $\beta_{high,HUN} = -0.390$; 95% CI: -0.421, -0.359; $p = 0.000$; $\beta_{high,AUS} = -0.374$; 95% CI: -0.432, -0.315; $p = 0.000$. $\beta_{high,SWE} = -0.370$; 95% CI: -0.386, -0.353; $p = 0.000$; $\beta_{high,FIN} = -0.349$; 95% CI: -0.374, -0.324; $p = 0.000$; $\beta_{high,FRA} = -0.337$; 95% CI: -0.364, -0.311; $p = 0.000$; $\beta_{high,DEU} = -0.304$; 95% CI: -0.333, -0.275; $p = 0.000$.

The income losses in high emission sectors are positively correlated with those in the low emission ones, and also with the resulting high-emission penalty (Supplementary Figure A.1). High-emission income penalties range between about 5 and 10% in most countries: $\beta_{penalty,DNK} = -0.109$; 95% CI: -0.131, -0.088; $p = 0.000$; $\beta_{penalty,AUT} = -0.105$; 95% CI: -0.119, -0.091; $p = 0.000$; $\beta_{penalty,EST} = -0.104$; 95% CI: -0.162, -0.046; $p = 0.000$; $\beta_{penalty,AUS} = -0.130$; 95% CI: -0.190, -0.069; $p = 0.000$;

Panel A. Labor earnings



Panel B. Employment

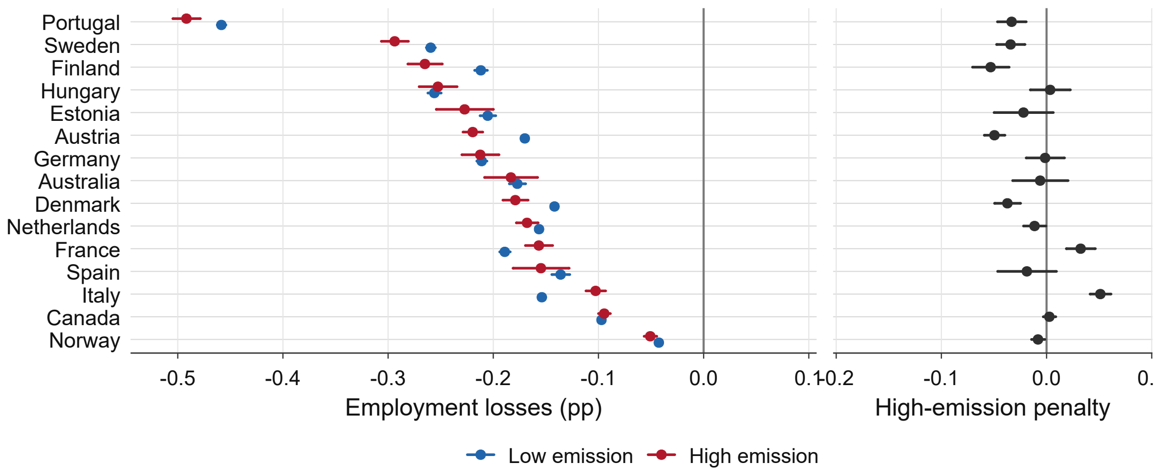


Fig. 2: Average country-level outcome losses in the five years following displacement. Country-specific average income (Panel A) and employment (Panel B) losses in the five years following displacement, by emission sector (left) and difference between high- and low-emission sectors (right). Income measured as percentage change from the pre-displacement level; employment is an indicator for positive income. The model specification includes displacement status and post-displacement indicators interacted and included as main effects, calendar-year fixed effects, and a cubic in age. All regressors are fully interacted with the emission sector indicator. Country-specific estimates are obtained from balanced samples of displaced and matched comparison workers.

$\beta_{penalty,SWE} = -0.050$; 95% CI: -0.067, -0.032; $p = 0.000$; $\beta_{penalty,FIN} = -0.073$; 95% CI: -0.099, -0.046; $p = 0.000$; $\beta_{penalty,FRA} = -0.051$; 95% CI: -0.079, -0.023; $p = 0.000$; $\beta_{penalty,DEU} = -0.040$; 95% CI: -0.070, -0.009; $p = 0.010$; $\beta_{penalty,ESP} = -0.044$; 95% CI: -0.084, -0.005; $p = 0.028$; $\beta_{penalty,NOR} = -0.075$; 95% CI: -0.095, -0.056; $p = 0.000$; $\beta_{penalty,CAN} = -0.042$; 95% CI: -0.058, -0.026; $p = 0.000$; $\beta_{penalty,PRT} = -0.058$; 95% CI: -0.085, -0.032; $p = 0.000$, with the exception The Netherlands, Hungary, and Italy ($\beta_{penalty,NLD} = -0.155$; 95% CI: -0.175, -0.134; $p = 0.000$; $\beta_{penalty,HUN} = -0.010$; 95% CI: -0.043, 0.023; $p = 0.561$; $\beta_{penalty,ITA} = 0.000$; 95% CI: -0.017, 0.018; $p = 0.976$).

The high-emission penalties in employment are similarly homogeneous across countries and between about 0 and 5%, with the exception of Italy and France ($\beta_{high,ITA} = 0.051$; 95% CI: -0.112, -0.094; $p = 0.000$; $\beta_{high,FRA} = 0.032$; 95% CI: -0.169, -0.144; $p = 0.000$). The same holds for the wage penalties, where with the exception of the Netherlands for none of the countries we can reject the equality of the high-emission coefficient to -5 log points at the 5% level (Extended Data Figure 3 and Supplementary Table A.16).

As discussed in the Methods section, in all countries our sampling approach selects displaced workers observationally similar to the comparison workers before the event event occurs (Extended Data Table 2, Supplementary Table A.17). However, differences in sample composition across countries might still exist and potentially drive the cross-country differential job loss effects, hindering the interpretation of the meta-analyzed estimates. This does not appear to be the case, since when comparing income losses in high or low emission sectors across countries, only XXX% (SE = XXX, $p =$ XXX) of the differential losses is explained by cross-country discrepancies in workers, firms, or labor market characteristics (Extended Data Figure 4, Supplementary Table A.18).

High-emission sector workers have more favorable worker characteristics but sort into local labor markets characterized by larger income losses.

Across countries, workers in high-emission sectors suffer larger income losses than workers in the rest of the economy (Supplementary Table A.19 reports high-emission penalties aggregated across countries). We next analyze the factors contributing to this high-emission penalty. There is no clear reason why employment in high-emission sectors should inherently lead to larger earnings losses following displacement. Instead, the penalty reflects that job displacement has heterogeneous consequences across workers, firms, and local labor market environments,[16,17] and that high-emission sectors disproportionately expose workers to characteristics associated with larger losses.

Since the high-emission penalty may reflect both differences in how income losses vary with job loss features and differences in how workers sort across those features, Figure 3 jointly analyzes these two components, expressed as high–low emission differentials. High-emission penalties (y-axis) are based on emission-specific average yearly income losses in the five years after displacement; sorting (x-axis) is measured as the high–low emission group differential for each job loss feature. To capture the fact that the job loss features operate along two dimensions—the high-emission income penalty and differential sorting—which jointly determine the contribution of each characteristic to the average high-emission penalty, the size of each dot is proportional to the absolute value of the product of the group-specific high-emission penalty and the corresponding high–low emission differential in sorting.

To keep the analysis tractable, the heterogeneities do not include interactions between characteristics. For each job loss characteristic (e.g. income quartiles) we show the category with the largest high-emission penalty (in absolute value), recoding categories so that the penalty is positive. Extended Data Figures 5, 6 and Supplementary Table A.20 show income losses and sorting across all categories of the job loss features.

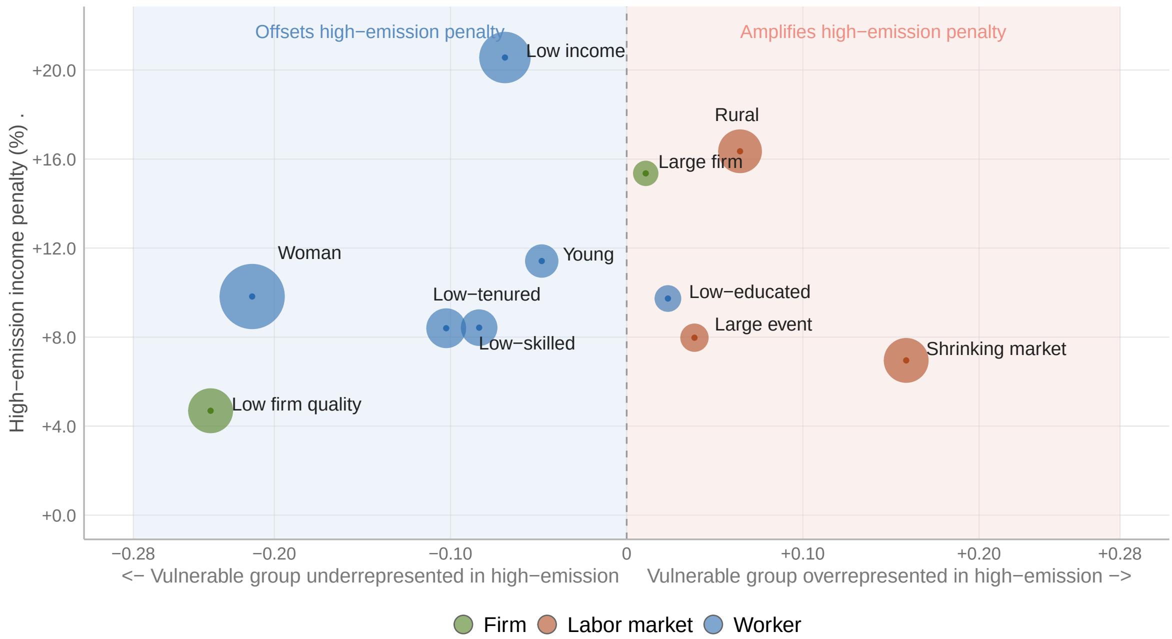


Fig. 3: Heterogeneous high-emission penalties on income and differential sorting between high- and low-emission groups. High-emission job-loss effects on income (y-axis) plotted against the differential share in high- versus low-emission sectors by worker, firm, and labor market characteristics (x-axis). Each dot represents one estimate for a specific sample subgroup defined by a pre-displacement characteristic. High-emission penalties obtained by separately regressing for each country and categorical variable income on job loss indicator interacted with post-displacement indicator and their main effects, fully-interacted with the levels of the categorical variable. The size of each dot is proportional to the absolute value of the product of the job-loss effect for the given worker group and the corresponding differential sorting between high- and low-emission sectors. For each job-loss characteristic, only the largest high-emission penalty (in absolute value) is shown; the corresponding variable is recoded so that the high-emission penalty is positive. The full set of emission-sector-specific and high-emission-specific job-loss estimates is reported in Extended Data Table 3, and the corresponding sorting estimates are reported in Extended Data Table 6. Estimates are aggregated across all countries (see Methods section).

Figure 3 shows that the largest high-emission income penalties are suffered by low-income workers ($\beta = -0.206$; 95% CI: -0.212, -0.200; $p = 0.000$) located in rural areas ($\beta = -0.163$; 95% CI: -0.167, -0.160; $p = 0.000$) and employed in large firms ($\beta = -0.154$; 95% CI: -0.158, -0.150; $p = 0.000$). Large high-emission penalties are also concentrated among women ($\beta = -0.098$; 95% CI: -0.100, -0.096; $p = 0.000$) and young ($\beta = -0.114$; 95% CI: -0.119, -0.109; $p = 0.000$), low-tenured ($\beta = -0.084$; 95% CI: -0.087, -0.081; $p = 0.000$), low-skilled, ($\beta = -0.084$; 95% CI: -0.087, -0.082; $p = 0.000$), and low-educated workers ($\beta = -0.097$; 95% CI: -0.104, -0.091; $p = 0.000$), displaced in large mass layoffs ($\beta = -0.070$; 95% CI: -0.072, -0.067; $p = 0.000$).

Figure 3 further relates the differential high-emission penalties to the differential sorting of workers across job loss features. Estimates on the negative side of the x-axis correspond to vulnerable worker groups for whom the differential sorting in high- vs. low-emission sectors operates in a favorable manner. For instance, women are a vulnerable group, as they face a positive high-emission penalty. However, sorting offsets the contribution of this group to the overall (average) high-emission penalty, since the share of women is disproportionately large in *low*-emission sectors (high- vs. low-emission share, $s_{women} = -0.213$). Likewise, with the exception of the high-school educated ($s_{lowEduc} = 0.023$), all other worker characteristics associated with larger penalties—plotted in blue—are underrepresented in high-emission sectors: low tenure ($s_{lowTenure} = -0.102$), low skill ($s_{lowSkill} = -0.084$), low income ($s_{lowIncome} = -0.069$), and young ($s_{young} = -0.048$). High-emission workers are also less likely to be employed in firms paying low pay premia ($s_{lowFirmQuality} = -0.236$).

On the contrary, workers in high-emission sectors are more likely to display market level job loss characteristics—plotted in red—associated with high-emission penalties. They are disproportionately concentrated in shrinking labor markets, rural areas, and subject to large mass layoff events ($s_{shrinkingLM} = 0.159$, $s_{rural} = 0.064$, and $s_{largeEvent} = 0.038$), all job loss characteristics that amplify high-emission penalties.

Overall, looking at the whole Figure 3 and comparing the size of the dots across job loss features, the five categories contributing the most to the average high-emission penalty are being low-income, woman, and employed in a low-quality firm (characteristics offset the high-emission penalty component), and being employed in a rural area and in a shrinking market (exacerbating the high-emission penalty).

Extended Data Figures 5, 6 and Supplementary Table A.20 illustrate that, across all job loss features, workers who lose a job in high-emission sectors are virtually always worse off than a workers displaced in the rest of the economy, with variation in the high-emission penalties across features being largely driven by heterogeneous income losses in high-emission sectors. In addition, when considering the joint contribution of all observable characteristics to the average high-emission penalty, Extended Data Figure 7 and Supplementary Table A.21 show that about two thirds of the high-emission income penalty is explained by compositional differences in worker, firm, and labor market characteristics across high- and low-emission sectors.

Supplementary Figure A.2 additionally reports heterogeneous income losses by occupation-specific task content for the subset of countries for which occupation information is available. Although the largest high-emission penalties are observed in occupations with high cognitive task content, workers in high-emission sectors are disproportionately concentrated in manual occupations, reducing the contribution of task content to the average high-emission penalty.

Discussion

Most countries have committed to the Paris Agreement and view the shift toward low-carbon, environmentally sustainable models as a central tool to address climate change. Yet, we know relatively little about how the necessary restructuring of economies will affect workers in high-carbon emission sectors. A faster and sustainable transition cannot overlook the job loss and reallocation costs it will generate, nor the possibility that these costs will be uneven across workers. The goal of our analysis is to understand these reallocation costs and their sources, which is essential for designing effective mitigation policies.

Our analysis exploits detailed population-wide registers from 15 countries that link workers to their employers over their careers and capture job loss independently of workers' choices through separations due to mass layoffs and plant closures.[15] When analyzing the income dynamics of displaced workers, we show that even though all workers experience large losses after job displacement, losing a job in a high-emission sector entails an an immediate additional penalty of about 8% compared to losing a job elsewhere. This initial high-emission penalty is far from being short-lived: it remains sizable even 5 years after displacement.

What drives this persistent high-emission income losses differential? Workers in high- and low-emission sectors are equally likely to find a new job after displacement, but 5 years after job loss those displaced in high-emission industries see an additional 5% wage reduction on top of the 10% wage losses suffered by other displaced workers. This persistent high-emission wage penalty is largely driven by re-employment in lower-quality firms that pay relatively low wages to their workforce.

We further leverage the granularity of the data to analyze heterogeneities in income losses following displacement.[16,17] While a worker who loses a job in a high-emission sector is virtually always worse off than a worker displaced in other sectors, we also document substantial variation in these high-emission penalties, with the most disproportionately affected workers being the relatively young and old, people with low socioeconomic status, women, employees of large rural firms, and those displaced in large mass-layoff events.

To properly interpret this heterogeneity in high-emission income penalties, we analyze the extent to which displaced workers are over- or under-represented in jobs characterized by large high-emission penalties. On the one end, workers in high-emission sectors display worker- and firm-level characteristics generally associated with *lower* high-emission penalties: they are, to a larger extent, high-tenured, high-SES, experienced and highly productive men employed at high-paying firms compared to workers in other industries. On the other hand, they are relatively less educated and disproportionately exposed to labor market conditions associated with higher penalties:

they are more likely to work in rural areas, in contracting sectors, and to be caught in larger mass-layoff events.

How can policy close the documented high-emission penalty? Taken together, our results suggest that the workers who suffer the largest losses are those who previously accrued substantial rents. These workers tend to be low educated and geographically concentrated—both in terms of labor markets and firm characteristics. Hence, a combination of place-based policies,[31] retraining, and hiring subsidies targeted toward lower-educated workers may help counteract the disproportionately large losses in high-emission sectors.[28,29]

So far, we have discussed the reallocation costs of job loss through a cross-country meta-analysis that highlights recurrent patterns of the transition. Our harmonized research design also allows us to complement this analysis by examining heterogeneities across countries. Although differences in high-emission penalties exist—and some countries stand out—the aggregate findings reflect remarkably similar patterns across economies, even in the presence of very different institutions. While we caution against extrapolating these patterns to other settings, and recognize that evidence-based policy design must account for country-specific contexts, our results offer grounds for optimism: more homogeneous patterns across countries can facilitate cross-country coordination, which is needed for enhancing both the political feasibility and the global fairness of the transition.

Methods

Data and definitions

Definition of high-carbon emission industries. The classification of high-emission sectors is based on Eurostat data for 27 EU countries, the UK, Norway, Iceland, and Switzerland, covering 2-digit ISIC Rev.4 industries over 2009–2020. Sectoral greenhouse gas (GHG) emission intensity is measured as CO_2-equivalent emissions per unit of value added (tonnes per million EUR). A sector is classified as high-emission if its average GHG intensity ranks in the top two deciles of the cross-country distribution in at least 10 of the 32 countries. At this cutoff, the frequency distribution shows a sharp break, with a decline of more than 50% in the number of sectors and around 20% in GHG intensity (Extended Data Figure 1). We exclude sewerage and waste collection, as the sector is not expected to contract and is essential for the net-zero transition. Agriculture is also excluded, since mass layoffs are more likely to reflect seasonal rather than structural adjustments, and employment projections do not indicate declining growth.[32] Results are robust to these exclusions (Supplementary Table XXX).

Matched employer-employee registers. The analysis uses register data from 12 European countries—Austria, Denmark, Estonia, Finland, France, Germany, Hungary, Italy, the Netherlands, Norway, Portugal, Spain, Sweden—as well as from Canada and Australia. While the registers are originally collected for taxation and other administrative purposes, they can be accessed for research under country-specific rules and GDPR regulations. The matched employer-employee data link workers to their employers and co-workers longitudinally using pseudonymized unique identifiers. With the exception of Australia, France, Germany, Hungary, Italy and Spain the registers cover the full population of resident workers and firms each year for roughly 20 years between 2000 and 2019. In the remaining countries, the data consist of large, representative samples of workers' labor market histories. Extended Data Table YYY describes the observation window and data sources for each country. We discuss robustness checks and additional analyses in the Empirical approach section.

Data harmonization and definition of index workers. Privacy restrictions prevent us to analyze the data on one environment. Therefore, we proceed in three steps. First, in line with a small but growing literature that uses matched employer-employee registers from different countries, we harmonize the research design by applying identical sampling restrictions, variables definitions, and statistical estimation strategy across all countries.[15,33] The data is then analyzed separately on each country-specific secure sever by using a common set of codes prepared centrally. Finally, we process and meta-analyze locally the country-level estimates exported from the servers.

We restrict the observation window to the pre-2020 period to ensure that our estimates are not influenced by the COVID-19 pandemic. We omit the self-employed and apprentices from the pool of workers. In cases where an employed person holds multiple jobs within a year, we assign that worker to a single employer by selecting the job with the highest annual earnings. With the exception of Australia, Canada, Estonia and Portugal, employers are identified based on establishment (plant-level) identifiers rather than through firm-level ones. We allow workers to be employed in either single- or multi-establishment firms.

Out of all selected individuals, the index workers are the private sector employees separating from their employer in correspondence of a mass layoff event and the observationally similar individuals who do not (see the Empirical Strategy section).

Labor market outcomes. Earnings are adjusted for inflation and measured in real 2015 EUR. They are defined as the pre-tax labor income sources—regular wage, overtime, and bonuses—from potentially multiple jobs. We winsorize earnings at the top 0.1% of the yearly distribution to limit the influence of outliers. In countries where earnings are censored above a certain ceiling, we impute them according to the standard approach in the literature.[34] Employment is an indicator variable defined based on having strictly positive annual earnings. We use the number of employees at the end of the year to define firm size. Whenever possible, daily wages are derived by dividing annual earnings from the main employer by the number of days worked for the employer during the year. We follow the standard practice in the literature and assign zero earnings and missing daily wages during periods of non-employment.[13,15]

Industry, occupation, worker demographics, and labor market. Job tenure is defined as the number of years a worker is continuously employed at the current firm. Education is coded in four groups according to ISCED 2011 classification: less than high school (ISCED 0–2), high school or equivalent vocational education (ISCED 3–4), short-cycle tertiary education and Bachelor's or equivalent (ISCED 5–6), and Master's and above (ISCED 7–8). Workers' demographics include gender and age.

We use industry information to assign workers to the emission sector where they work. Three-digit industry is measured with NACE revision 2 classification. We harmonize 3-digit occupations using the ISCO-08 classification whenever occupation information is available in the registers of the given country. Each occupation is further classified in terms of its dominant task. In line with existing literature, task content is calculated with O*NET data that characterizes each job according to five task groups: non-routine cognitive analytical, non-routine cognitive personal, routine cognitive, non-routine manual, routine manual.[35,36]

In terms of labor market characteristics, when the analysis uses firm regional area, we adopt a NUTS 2 level of aggregation, and then we adopt the mapping XXX to define whether a given worker is based in either a rural or urban area. We measure the size of the event as XXX and classify it into two groups: above-median and below-median XXX. Employment trends are measured as XXX and are similarly split into above- and below-median values.

Workers' ability and firm pay premia We measure firm pay premia and worker ability with fixed effects estimated via an Abowd–Kramarz–Margolis model for monthly income.[37] The estimated workers' fixed effects are interpreted as the persistent component of the worker's wage that is portable across jobs, net of firm-quality and time-varying worker's characteristics. The estimated firm fixed effects are interpreted as a measure of firm quality; they capture the average pay premium that a firm pays to all its workers relative to the other firms in the data, holding the previously mentioned measure of worker ability constant.[38] To limit known incidental parameters issues,[39] we estimate the model using the largest possible set of workers and firms connected by job-to-job moves, before restricting it to the sub-sample of index workers.

Empirical strategy

Job displacement and mass layoff events Job displacement—or job loss—is defined as a job separation occurring in correspondence with a mass-layoff event, where employment in an establishment with at least 30 employees declines by at least 30% between a baseline year $t^* - 1$ and t^*.[12,13,15] The definition of mass layoff therefore includes plant closures. To limit the influence of restructuring events, such as mergers and acquisitions, we require that no more than 25% of displaced employees move to the same establishment the year following the event.[40] Overall, this definition of displacement ensures that job separations are plausibly exogenous, involuntary, and unrelated to workers' performance or individual career plans.

Selection of displaced and comparison workers The empirical approach quantifies the income, employment, and wage losses associated with job loss by comparing the labor market outcomes of displaced workers to those of suitable comparison workers, collectively referred to as index workers. All index workers are sampled to be at most 60 years old, have two or more years of job tenure, and work in establishments with at least 30 employees in baseline year $t^* - 1$. Displaced workers are those who separate from their employer during the mass-layoff window between $t^* - 1$ and t^* and are not recalled to the same employer in the following six years. If a worker experiences multiple displacement events, we focus on the first one. Comparison workers are sampled in the same way, except that they never displaced.

Because displaced and non-displaced workers may still differ along characteristics other than job loss itself, we match each displaced worker to one comparison worker using the following procedure.[15,41] First, we match exactly on baseline year, 1-digit industry, high-emission sector indicator, and sex. Then, within each exact-match cell, we estimate a propensity score via a probit model of displacement on observable characteristics—log annual earnings in the three years prior to displacement, log employer size, age, tenure, and task content when available (all measured in $t^* - 1$). We then use 1:1 nearest-neighbor matching to assign each displaced worker one control worker.

The role of the comparison workers in the empirical approach is to provide valid counterfactual trajectories for what would have happened to the displaced workers absent job loss. Under the assumption that displaced and comparison workers' potential outcomes evolve with same trends (parallel trends assumption), the quasi-experimental job loss estimates of interest can be given a causal interpretation.[42,43] Although this assumption cannot be fully tested with the data, we discuss how it can be empirically supported (see Validity of the event study).

Event study model The estimation sample is composed by the displaced and matched comparison workers. For each country, we separately estimate the following dynamic difference-in-differences (or event-study) model:

$$y_{eit} = \alpha_i + \lambda_{et} + X'_{it}\theta_e + \sum_{k=-4}^{5} \gamma_{ek}\mathbf{1}\{k = t^*_i + k\} + \sum_{k=-4}^{5} \beta_{ek}\mathbf{1}\{k = t^*_i + k\} \times Displaced_i + \varepsilon_{eit} \tag{1}$$

where y_{eit} is a labor market outcome of worker i at calendar year t in emission sector e (high-emission or rest of the economy), and k indexes the number of years relative to displacement year t^*.

The coefficients of interest β_{ek} capture the time- and emission sector-specific change in the outcome of the displaced workers relative to the comparison workers. The worker fixed effects α_i control for time-invariant unobserved worker-level heterogeneity, the calendar year indicators λ_{et} capture business cycle fluctuations, the fixed effects γ_{ek} account for hump-shaped earnings profiles, X'_{it} includes a cubic polynomial specification for age, and ε_{it} is the idiosyncratic error term. Standard errors are clustered at the matched workers pair level to account for the matching estimation.[44]

Equation (1) can be estimated by either splitting the sample by emission sector e or by fully interacting the right-hand-side by an indicator for being employed in a high-emission sector in $t^* - 1$. Point estimates in the two approaches are numerically identical but standard errors are not. The interacted model is more flexible, as it allows correlation between emission sectors via the variance-covariance matrix jointly estimated. We therefore estimate the fully-interacted model, whose triple interaction coefficient directly corresponds the high-emission penalty of interest.

Heterogeneous high carbon-emission penalties To allow average losses to differ across emission sectors and along job loss characteristics measured in $t^* - 1$, we reclassify the pre- and post-displacement time into two overall periods and add a emission group indicator (previously absorbed by the α_i terms). We then fully interact the model with one job loss categorical feature at a time (e.g., age groups, education categories) preserving displaced-matched comparison workers pairs to maintain the balancedness of the sample.[44] This leads to a two-by-two difference-in-differences specification fully interacted by emission group and job loss characteristic. The coefficients of interest capture group-specific yearly losses averaged in the 5-year post-period.

Validity of the event study design Figure 1 panels indicate that workers do not exhibit anticipatory behavior before the job-loss event. The estimated coefficients for income are close to 0 four years ($\beta_{k=-4}$ = XXX, 95% CI XXX–XXX, p = XXX), two years ($\beta_{k=-2}$ = XXX, 95% CI XXX–XXX, p = XXX), and one year ($\beta_{k=-1}$ = XXX, 95%

CI XXX–XXX, p = XXX) before job loss. We fine similar lack of differential pre-job loss trends in wages between workers losing their job and the comparison workers ($\beta_{k=-4}$ = XXX, 95% CI XXX–XXX, p = XXX; $\beta_{k=-2}$ = XXX, 95% CI XXX–XXX, p = XXX; $\beta_{k=-1}$ = XXX, 95% CI XXX–XXX, p = XXX). Employment and firm quality outcomes mechanically show no pre-event trends the three years before job loss since, according to the sampling scheme that selects workers sufficiently attached to the labor market, workers are restricted to be stably employed before the event year. Supplementary Tables A.7—A.14 confirm the lack of anticipatory effects when analyzing the pre-trends in each country separately. Extended Data Table 2 and Supplementary Table A.17 further show that displaced workers and comparison workers are observationally similar before the event occurs in terms of age, job tenure, and firm size, income, and wage.

All in all, the evidence favors lack of anticipatory trends and supports the validity of the event study design. The post-event estimates can therefore be interpreted as job loss effects on the labor market outcomes of interest.

Differential observed characteristics across countries and other validation tests To test the extent to which cross-country unbalance in pre-displacement characteristics drive job loss differences across countries, we decompose income losses separately by emission sector as follows.[15] In each country we estimate individual-level difference-in-differences between displaced workers and matched pairs between $t^* - 3$ and $t^* + 3$. We then regress the individual-level income losses on job displacement characteristics W, using the same features of the heterogeneous effects analysis (Figure 3). The country-level coefficients and group shares are used to decompose $\Delta_{c-c'}$—the average income loss gap between country c and c' (Norway)—as (omitting e subscripts):

$$\Delta_{c-c'} = \underbrace{\sum_{w \in W} (E[w_{i,c}] - E[w_{i,c'}])\beta_w^{c'}}_{\text{Explained by } W \text{ composition}} + \underbrace{\sum_{w \in W} (\beta_w^{c} - \beta_w^{c'})E[w_{i,c'}]}_{\text{Residual}} \tag{2}$$

where the first component captures how much of the cross-country differences in job loss are attributable to average differences in the observable characteristics of W.

Extended Data Figure 4 shows that compositional differences in high emission sectors (Panel A) and in low emission sectors (Panel B) play a limited role in explaining the existing cross-country differences in income losses due to displacement. We use a similar decomposition approach to compare income losses between emissions sectors of the same country (Extended Data Graph 7 and Supplementary Table A.21).

In addition, we present a set of validation exercises and robustness checks that assess whether particular research design choices influence the results. First, using the sub-sample of countries for which we have occupation information we show that the income losses are not driven by occupation-specific differential emissions, therefore supporting the idea that our sector-specific measure of emissions captures a relevant level of emission heterogeneity (Panel E of Supplementary Table A.20). Second, we test how excluding transport from the sample affects the results, and find that our baseline definition—which classifies transport as a high-emission sector—yields a conservative lower bound of the high-emission penalty (Supplementary Table XXX, column XXX). Lastly, we repeat the analysis by including workers up to 50 years to assess whether early retirement drives the results, and test whether the choice of XXX leads to differential conclusions (Supplementary Table XXX, column XXX). Overall, the results are robust to the alternative sampling choices.

Meta-analysis of country-level estimates We aggregate country-level estimates using an inverse-variance approach equivalent to a fixed-effect meta-analysis:[26,27]

$$\hat{\beta}_{meta} = \sum_c w_c \hat{\beta}_c \cdot \left(\sum_c w_c \right)^{-1} \tag{3}$$

with c indexing countries and $w_c = \frac{1}{\hat{Var}(\hat{\beta}_c)}$. Statistical inference of the aggregated estimates is made using $SE_{meta}(\hat{\beta}_{meta}) = \sqrt{1/\sum_c w_c}$.

Recall that we estimate a triple difference-in-differences—across displaced versus comparison workers, before versus after displacement, and high- versus low-emission sectors. This specification yields, for each country, both emission-sector–specific losses and their difference (the high-emission penalty). To preserve the identity between the sector-specific differential losses and the triple-interaction coefficient, we compute w_c once, using weights from the low-emission group, and apply them to both the group-specific estimates and the high-emission penalty.

Acknowledgments

We would like to thank Francesco Vona, Andrea Bassanini, Andrea Garnero and participants to the 8th Linked Employer-Employee Data Workshop (Copenhagen), the 2025 SkiLMeeT Conference (Sofia), the WeLaR Conference (Brussels), the IZA/OECD Workshop "Applications Using Linked Employer-Employee Data" (Paris), and IFAU Uppsala for useful comments and discussions.

Lombardi gratefully acknowledges funding from the OP Research Foundation (decision no. 20240292) and the Research Council of Finland (decision no. 350399).

Author contributions

Lombardi and Barreto are co-first authors. Lombardi wrote the codes shared with all co-authors, wrote the draft of the manuscript, processed and meta-analyzed results obtained by all other co-authors, and produced results for Finland. Barreto wrote the codes shared with all co-authors and produced estimates for Estonia, France, Spain and Portugal and made comments to the draft of the manuscript. Barreto, Lombardi, Hijzen, and Skans jointly designed the study, and developed the methodology. This project is part of LinkEED at the OECD, founded and managed by Hijzen, who was the OECD team co-lead responsible in this project in collaboration with Barreto. Lombardi was the academic team lead author in the project. All other authors are in alphabetical order. XXX, and XXX provided comments the draft of the manuscript. XXX produced estimates from the XXX administrative records; produced estimates from the XXX administrative records; ...

References

[1] D. I. Armstrong McKay, A. Staal, J. F. Abrams, R. Winkelmann, B. Sakschewski, S. Loriani, I. Fetzer, S. E. Cornell, J. Rockström, and T. M. Lenton. "Exceeding 1.5 C global warming could trigger multiple climate tipping points". *Science* 377.6611 (2022), eabn7950.

[2] K. R. Van Daalen, C. Tonne, J. C. Semenza, J. Rocklöv, A. Markandya, N. Dasandi, S. Jankin, H. Achebak, J. Ballester, H. Bechara, et al. "The 2024 Europe report of the Lancet Countdown on health and climate change: unprecedented warming demands unprecedented action". *The Lancet Public Health* 9.7 (2024), e495–e522.

[3] A. Olhoff, W. F. Lamb, T. Kuramochi, J. Rogeli, M. den Elzen, J. Christensen, T. Fransen, M. Pathak, and D. Tong. "Emissions Gap Report 2025: Off target– Continued collective inaction puts global temperature goal at risk". United Nations Environment Programme. 2025.

[4] L. T. Keyßer and M. Lenzen. "1.5 C degrowth scenarios suggest the need for new mitigation pathways". *Nature communications* 12.1 (2021), 2676.

[5] P. Achakulwisut, P. Erickson, C. Guivarch, R. Schaeffer, E. Brutschin, and S. Pye. "Global fossil fuel reduction pathways under different climate mitigation strategies and ambitions". *Nature communications* 14.1 (2023), 5425.

[6] M. Weitzel and J. A. Ordonez. "Aligning intermediate climate targets with long-term decarbonisation ambition". *npj Climate Action* 4.1 (2025), 65.

[7] T. Arvanitopoulos, S. Bulian, C. Wilson, A. J. Jordan, J. Tosun, and N. Vasilakos. "Climate policy portfolios that accelerate emission reductions". *Nature Communications* (2026).

[8] J. Vogel and J. Hickel. "Is green growth happening? An empirical analysis of achieved versus Paris-compliant CO2–GDP decoupling in high-income countries". *The Lancet Planetary Health* 7.9 (2023), e759–e769.

[9] J. Infante-Amate, E. Travieso, and E. Aguilera. "Green growth in the mirror of history". *Nature Communications* 16.1 (2025), 3766.

[10] A. Dechezleprêtre, A. Fabre, T. Kruse, B. Planterose, A. Sanchez Chico, and S. Stantcheva. "Fighting climate change: International attitudes toward climate policies". *American Economic Review* 115.4 (2025), 1258–1300.

[11] M. E. Dabla-Norris, M. T. Helbling, S. Khalid, H. Khan, G. Magistretti, A. Sollaci, and M. K. Srinivasan. *Public perceptions of climate mitigation policies: Evidence from cross-country surveys*. International Monetary Fund, 2023.

[12] L. S. Jacobson, R. J. LaLonde, and D. G. Sullivan. "Earnings Losses of Displaced Workers". *American Economic Review* 83.4 (1993), 685–709. DOI: 10.17848/wp92-11. URL: http://research.upjohn.org/up_workingpapers/11 (visited on 11/08/2020).

[13] J. F. Schmieder, J. Heining, and v. W. Till. "The Costs of Job Displacement over the Business Cycle and Its Sources: Evidence from Germany" (2020), 91.

[14] M. Lachowska, A. Mas, and S. A. Woodbury. "Sources of Displaced Workers' Long-Term Earnings Losses". *American Economic Review* 110.10 (2020), 3231–3266. ISSN: 0002-8282. DOI: 10.1257/aer.20180652. URL: https://pubs.aeaweb.org/doi/10.1257/aer.20180652 (visited on 12/14/2020).

[15] A. Bertheau, E. M. Acabbi, C. Barceló, A. Gulyas, S. Lombardi, and R. Saggio. "The unequal consequences of job loss across countries". *American Economic Review: Insights* 5.3 (2023), 393–408.

[16] A. Gulyas and K. Pytka. "Understanding the Sources of Earnings Losses After Job Displacement: A Machine-Learning Approach". Working paper. 2019.

[17] S. Athey, L. K. Simon, O. N. Skans, J. Vikstrom, and Y. Yakymovych. "The heterogeneous earnings impact of job loss across workers, establishments, and markets". *arXiv preprint arXiv:2307.06684* (2023).

[18] D. Gelles. "The U.S. under Trump: Alone in Its Climate Denial". *The New York Times* (2025). URL: https://www.nytimes.com/2025/05/19/climate/trump-climate-denial.html.

[19] H. Illing, J. Schmieder, and S. Trenkle. "The gender gap in earnings losses after job displacement". *Journal of the European Economic Association* 22.5 (2024), 2108–2147.

[20] D. Sullivan and T. von Wachter. "Job Displacement and Mortality: An Analysis Using Administrative Data". *The Quarterly Journal of Economics* 124.3 (2009), 1265–1306. DOI: 10.1162/qjec.2009.124.3.1265.

[21] M. Rege, K. Telle, and M. Votruba. "Parental Job Loss and Children's School Performance". *The Review of Economic Studies* 78.4 (2011), 1462–1489. DOI: 10.1093/restud/rdr002.

[22] K. Huttunen and J. Kellokumpu. "The Effect of Job Displacement on Couples' Fertility Decisions". *Journal of Labor Economics* 34.2 (2016), 403–442. DOI: 10.1086/683645.

[23] K. Huttunen, J. Møen, and K. G. Salvanes. "Job loss and regional mobility". *Journal of Labor Economics* 36.2 (2018), 479–509.

[24] C. Barreto, R. Grundke, and Z. Krill. “The cost of job loss in carbon-intensive sectors: Evidence from Germany”. *OECD Economics Department Working Papers* (2023).

[25] J. M. Wooldridge. *Econometric analysis of cross section and panel data*. MIT press, 2010.

[26] K. Rice, J. P. Higgins, and T. Lumley. “A re-evaluation of fixed effect (s) meta-analysis”. *Journal of the Royal Statistical Society Series A: Statistics in Society* 181.1 (2018), 205–227.

[27] J. Chandler, M. Cumpston, T. Li, M. J. Page, V. Welch, et al. “Cochrane handbook for systematic reviews of interventions”. *Hoboken: Wiley* 4.1002 (2019), 14651858.

[28] D. Card, J. Kluve, and A. Weber. “Active labour market policy evaluations: A meta-analysis”. *The economic journal* 120.548 (2010), F452–F477.

[29] D. Card, J. Kluve, and A. Weber. “What works? A meta analysis of recent active labor market program evaluations”. *Journal of the European Economic Association* 16.3 (2018), 894–931.

[30] B. Crépon and G. J. Van Den Berg. “Active labor market policies”. *Annual Review of Economics* 8.1 (2016), 521–546.

[31] D. Neumark and H. Simpson. “Place-based policies”. *Handbook of regional and urban economics*. Vol. 5. Elsevier, 2015, 1197–1287.

[32] F. Borgonovi, E. Lanzi, H. Seitz, R. Bibas, J. Fouré, H. Plisiecki, and L. Atarody. “The effects of the EU Fit for 55 package on labour markets and the demand for skills”. *OECD Social, Employment and Migration Working Papers* (2023).

[33] A. S. Hermansen, A. Penner, I. Boza, M. M. Elvira, O. Godechot, M. Hällsten, L. F. Henriksen, F. Hou, Z. Lippényi, T. Petersen, et al. “Immigrant–native pay gap driven by lack of access to high-paying jobs”. *Nature* 644.8078 (2025), 969–975.

[34] D. Card, J. Heining, and P. Kline. “Workplace heterogeneity and the rise of West German wage inequality”. *The Quarterly Journal of Economics* 128.3 (2013), 967–1015. ISSN: 0033-5533, 1531-4650. DOI: 10.1093/qje/qjt006. URL: http://qje.oxfordjournals.org/cgi/doi/10.1093/qje/qjt006 (visited on 09/06/2016).

[35] D. Acemoglu and D. Autor. “Skills, tasks and technologies: Implications for employment and earnings”. *Handbook of labor economics*. Vol. 4. Elsevier, 2011, 1043–1171.

[36] P. Lewandowski, R. Keister, W. Hardy, and S. Górka. “Ageing of routine jobs in Europe”. *Economic Systems* 44.4 (2020), 100816.

[37] J. M. Abowd and F. Kramarz. “The Analysis of Labor Markets using matched employer-employee data”. *the analysis of labor markets usin MEE.pdf*. Vol. 3. Handbook of Labor Economics. Elsevier, 1999.

[38] P. Kline. “Firm wage effects”. *Handbook of Labor Economics* 5 (2024), 115–181.

[39] P. Kline, R. Saggio, and M. Sølvsten. “Leave-out estimation of variance components”. *Econometrica* 88.5 (2020), 1859–1898.

[40] T. Hethey-Maier and J. F. Schmieder. “Does the Use of Worker Flows Improve the Analysis of Establishment Turnover? Evidence from German Administrative Data”. NBER Working Paper, No. 19730. 2013.

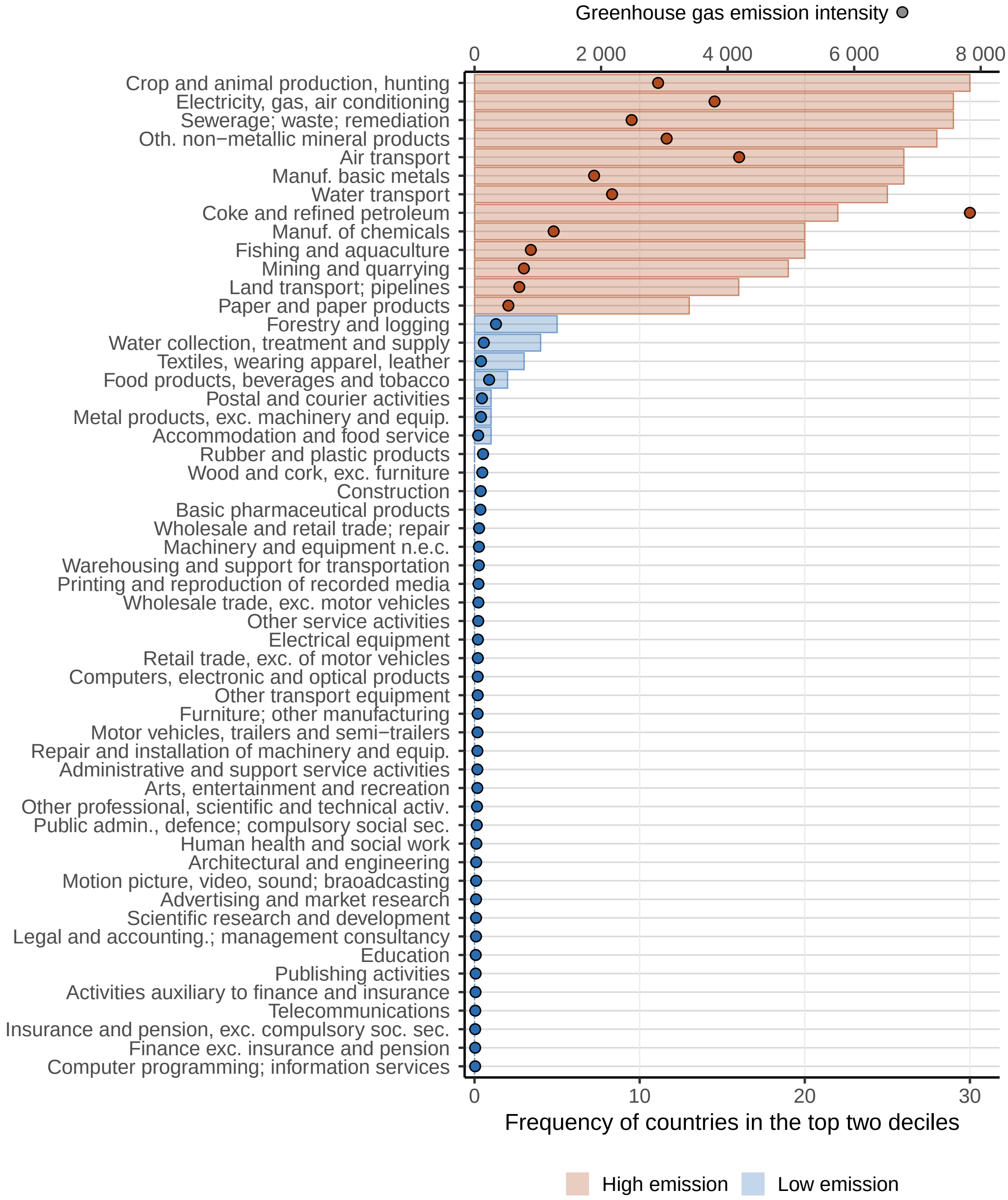
[41] J. F. Schmieder, T. Von Wachter, and J. Heining. “The costs of job displacement over the business cycle and its sources: evidence from Germany”. *American Economic Review* 113.5 (2023), 1208–1254.

[42] J. D. Angrist and J.-S. Pischke. “The credibility revolution in empirical economics: How better research design is taking the con out of econometrics”. *Journal of economic perspectives* 24.2 (2010), 3–30.

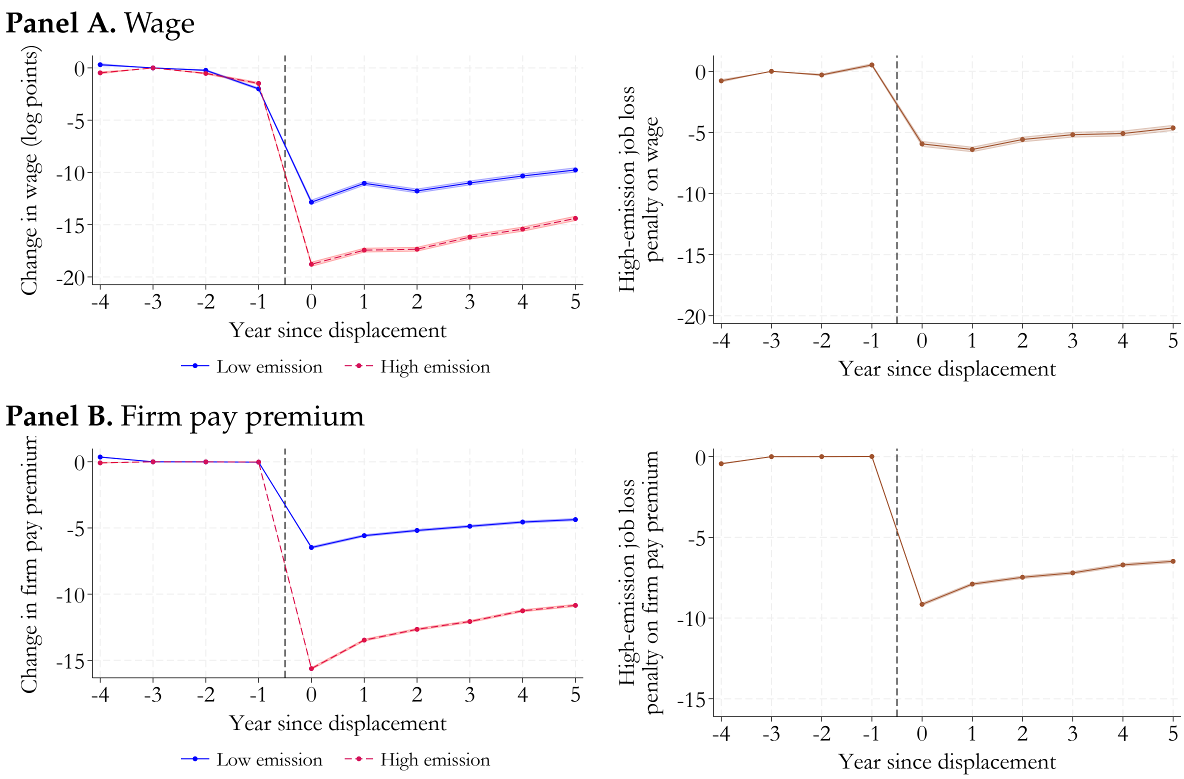
[43] G. W. Imbens and D. B. Rubin. *Causal inference in statistics, social, and biomedical sciences*. Cambridge university press, 2015.

[44] A. Abadie and J. Spiess. “Robust post-matching inference”. *Journal of the American Statistical Association* 117.538 (2022), 983–995.

Extended Data

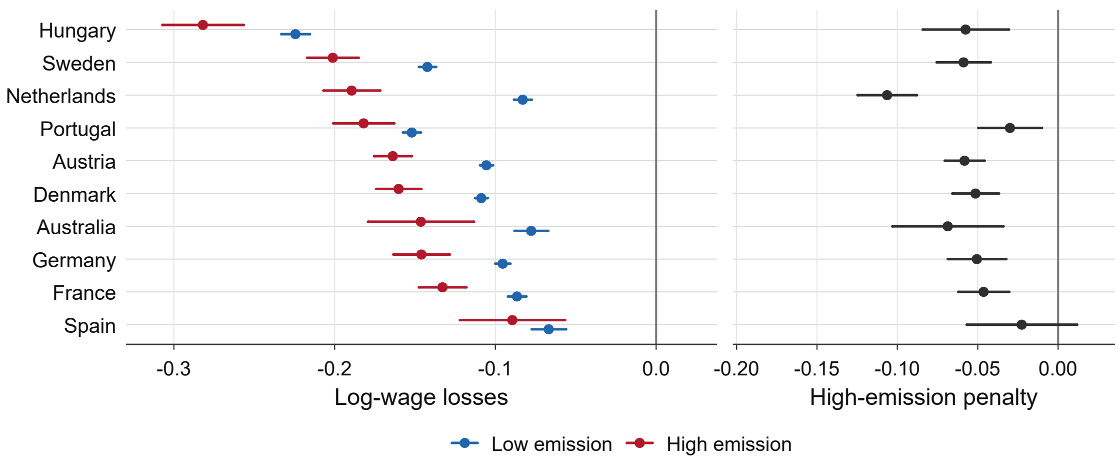


Extended Data Fig. 1: Classification of industries into high emission and rest of the economy. High-emission industry classification and corresponding greenhouse gas emission intensity and high-emission industry frequency across EU-27 and the additional countries considered. See Methods.

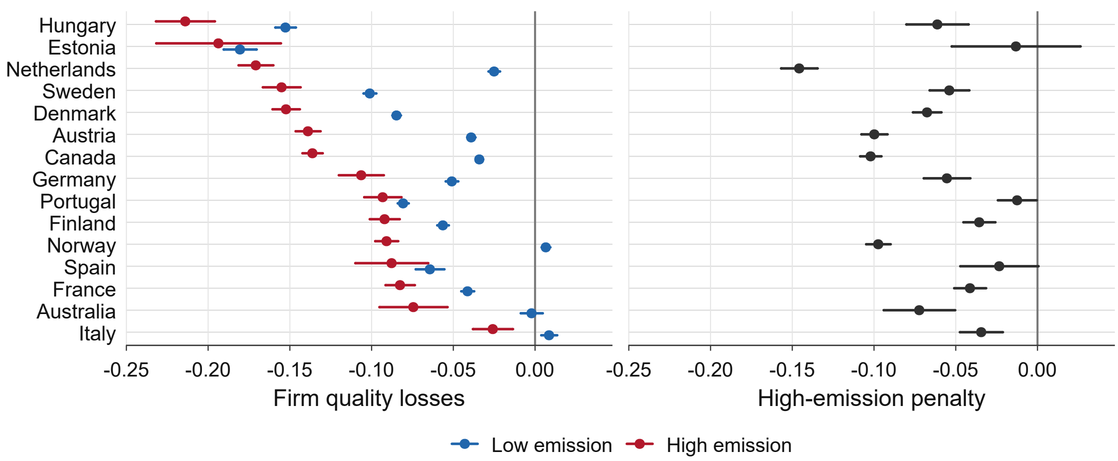


Extended Data Fig. 2: Evolution of labor market outcomes in high and low emission sectors before and after job displacement. Event study estimates of the job loss on displaced workers' labor market outcomes, by emission sector. Estimates aggregated across all countries (see Methods section).

Panel A. Log-wage

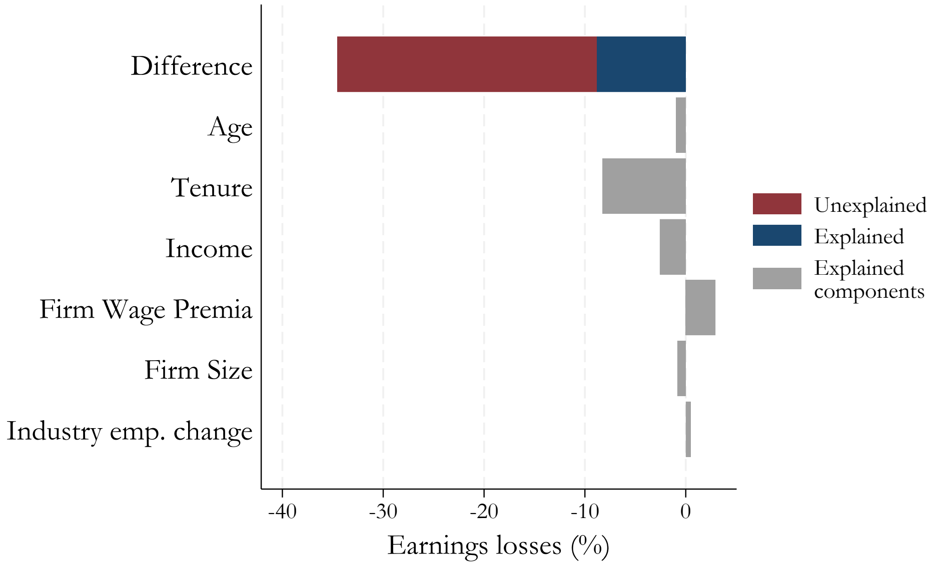


Panel B. Firm pay premium

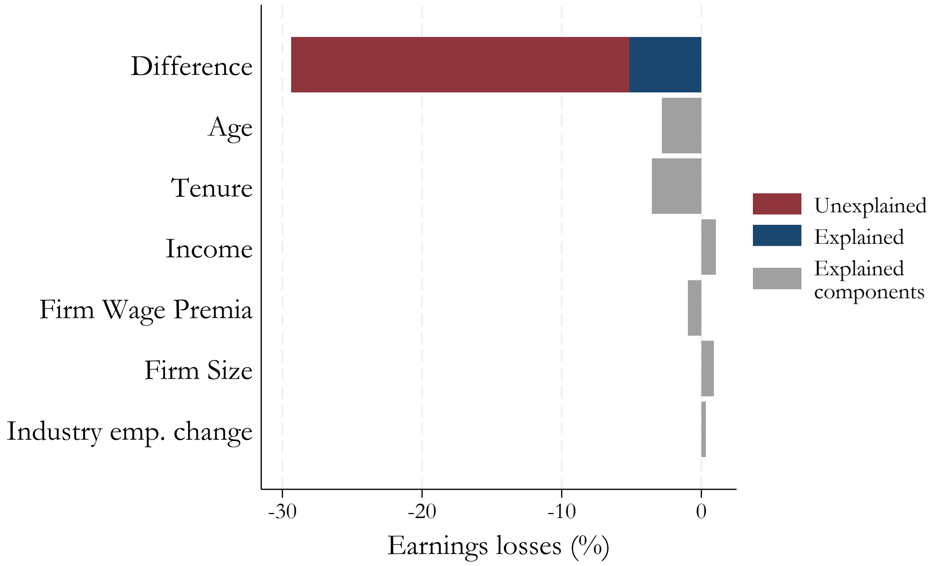


Extended Data Fig. 3: Average effects in the five years following job loss, by country. Country-level Job loss effects on labor earnings (Panel A), employment (Panel B) and log-wage (Panel C). Averaged 5-year post-event period effects.

Panel A. Income gap across countries, high emission

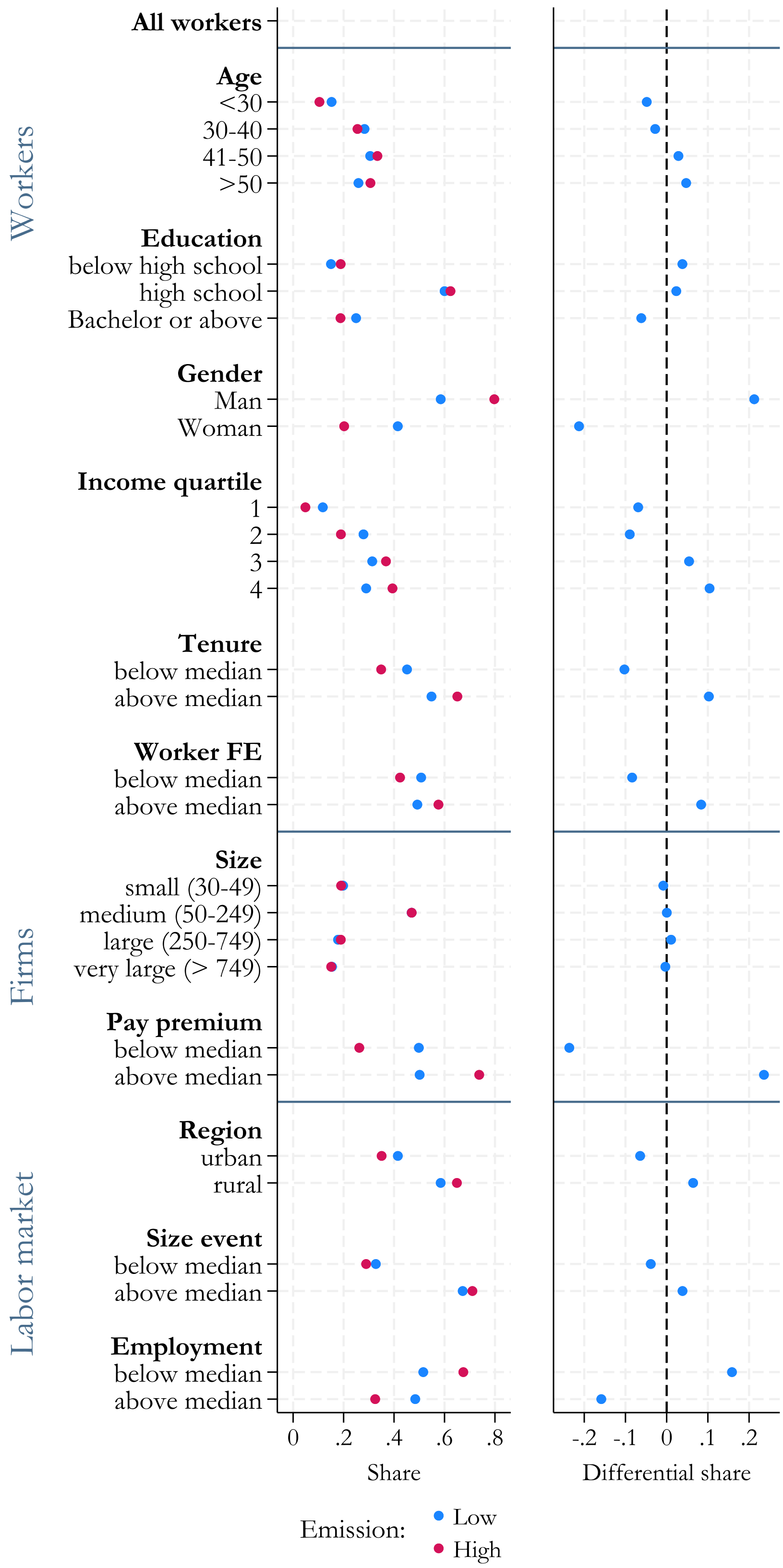


Panel B. Income gap across countries, low emission

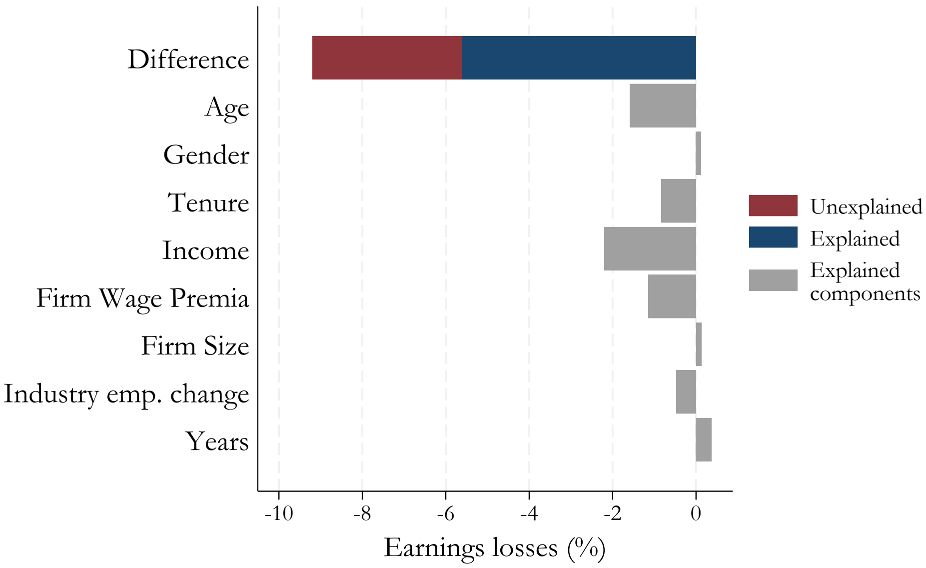


Extended Data Fig. 4: Sources of differential income losses across countries in high- and low-emission emission sectors. Decomposition of emission sector-specific gap in earnings losses across countries. The estimates were obtained by separately computing the difference in post-layoff income gap between each country and Norway and later aggregating the income gap and its components across countries (see Methods section). The decomposition excludes countries without full-population data as it was not possible to estimate firm pay premia in those cases.

Extended Data Fig. 5: Heterogeneous post-displacement income losses. Post-layoff percent change in income by emission sector (left), difference between high and low emission sectors job loss effects (center), and difference in the share of workers in high vs. low emission group (right). Each row presents estimates for a specific sample sub-group defined by a pre-displacement characteristic. Estimates aggregated across all countries (see Methods section).



Extended Data Fig. 6: Share of job losers in worker, firm, and market characteristic. The share sum up to one within high or low emission sector. The left panel shows shares separately by emission sector. The right panel reports the difference between high and low emission. All shares were obtained separately by country and later aggregated (see Methods section).



Extended Data Fig. 7: Sources of within-country differential income losses between high vs. low emission sectors. Within-country difference in income losses between high vs. low emission sectors decomposed into a component explained by compositional differences across sectors and a component that remains unexplained by difference in observable characteristics. All estimates were obtained separately by country and later aggregated (see Methods section). The decomposition excludes countries without full-population data as it was not possible to estimate firm pay premia in those cases.

Country	Source registers: Obs.	Source registers: Universe	Matched sample obs.	Years	Employer	Education, wage, occupation
Australia	11,099,820	10% sample	292,200	2002–2019	Firm	No, Yes, Yes
Austria	54,133,568	Yes	1,174,060	2000–2019	Estab.	No, Yes, No
Canada	219,660,691	Yes	4,672,400	2001–2019	Firm	No, No, No
Denmark	48,382,269	Yes	1,083,000	2000–2019	Estab.	Yes, Yes, Yes
Germany	51,016,849	10% sample	630,480	2000–2019	Estab.	Yes, Yes, Yes
Spain	7,733,207	4% sample	137,280	2006–2019	Estab.	Yes, Yes, No
Estonia	10,896,117	Yes	207,620	2003–2019	Firm	No, No, No
Finland	21,461,502	Yes	389,660	2000–2019	Estab.	Yes, No, Yes
France	44,728,913	8% sample	648,840	2002–2019	Estab.	No, Yes, No
Hungary	21,515,214	50% sample	389,740	2003–2017	Estab.	No, Yes, Yes
Italy	19,025,501		1,249,860			
Netherlands	98,936,166	Yes	1,488,580	2006–2019	Firm	No, Yes, No
Norway	48,855,647	Yes	1,131,480	2002–2019	Estab.	Yes, Yes, Yes
Portugal	43,942,692	Yes	1,009,060	2002–2019	Firm	Yes, Yes, Yes
Sweden	56,451,823	Yes	784,820	2002–2018	Estab.	Yes, Yes, Yes

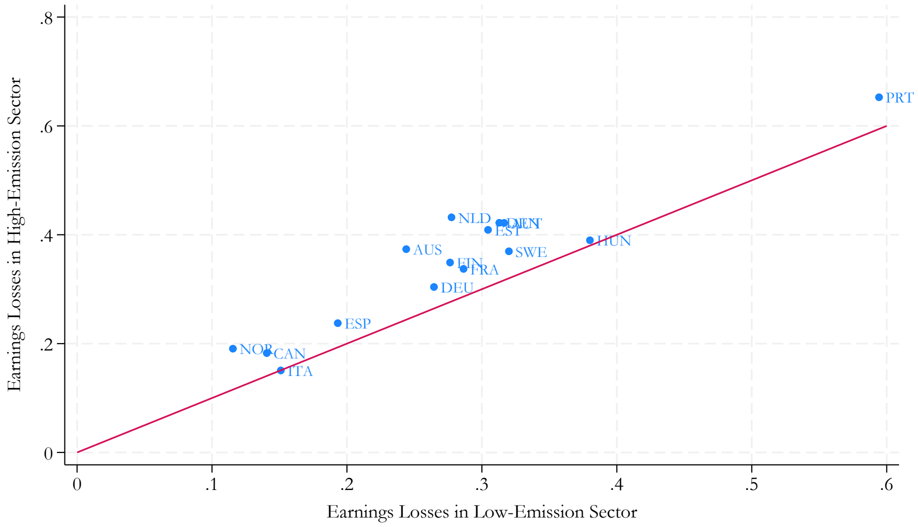
Extended Data Table 1: Overview of data sources. Number of observations corresponds to the total number of worker-year rows in the start registers ($N = 757,839,979$) and in the matched samples used to estimate the event study models for income and employment ($N = 15,289,080$).

Displaced:	Income No	Income Yes	Age No	Age Yes	Tenure No	Tenure Yes	Firm size No	Firm size Yes	Observations No	Observations Yes
Panel A: High-emission (all)										
Australia	11.13	11.14	37.99	38.20	3.86	3.95	5.60	5.56	13,800	13,800
Austria	10.45	10.46	41.58	41.49	8.73	8.66	5.15	5.08	52,780	52,780
Canada	10.87	10.86	43.24	43.07	4.36	4.24	5.79	5.66	255,700	255,700
Denmark	12.62	12.62	43.94	44.03	8.45	8.28	4.78	4.72	38,480	38,480
Germany	10.49	10.49	43.90	43.98	9.73	9.62	4.96	4.94	20,150	20,150
Spain	10.29	10.28	45.18	45.24	7.83	7.57	5.64	5.54	6,410	6,410
Estonia	9.25	9.27	42.36	41.96	4.53	4.55	4.92	4.89	8,040	8,040
Finland	10.50	10.50	42.50	42.43	7.87	7.89	4.83	4.83	22,680	22,680
France	10.39	10.36	41.67	41.62	9.98	9.95	6.05	5.98	32,620	32,620
Hungary	14.57	14.56	43.63	43.65	4.90	4.98	4.85	4.77	20,100	20,100
Italy	10.17	10.18	42.57	42.54	12.90	13.04	5.73	5.68	63,590	63,590
Netherlands	10.46	10.46	44.69	44.66	4.37	4.44	4.89	4.83	46,610	46,610
Norway	12.96	12.97	41.40	41.52	6.63	6.56	5.08	5.03	66,250	66,250
Portugal	9.23	9.21	42.70	42.70	11.69	11.48	4.79	4.69	40,600	40,600
Sweden	12.70	12.69	43.48	43.47	8.11	8.13	4.64	4.59	38,850	38,850
Panel B: Rest of economy										
Australia	10.87	10.87	36.56	36.65	3.91	3.94	5.45	5.41	132,300	132,300
Austria	10.31	10.31	40.51	40.59	7.87	7.89	5.06	5.02	534,250	534,250
Canada	10.47	10.46	40.81	40.61	4.23	4.16	5.30	5.32	2,080,500	2,080,500
Denmark	12.49	12.49	42.99	43.10	7.10	7.20	5.00	4.95	503,020	503,020
Germany	10.37	10.38	43.62	43.66	8.26	8.27	4.93	4.91	295,090	295,090
Spain	10.03	10.02	42.24	42.30	7.25	7.17	5.68	5.64	62,230	62,230
Estonia	9.05	9.07	42.57	42.49	4.64	4.50	5.04	4.92	95,770	95,770
Finland	10.45	10.46	40.86	40.86	6.39	6.49	4.74	4.71	172,150	172,150
France	9.98	9.98	39.37	39.31	5.86	5.81	5.13	5.12	291,800	291,800
Hungary	14.55	14.54	39.99	40.00	4.79	4.79	5.18	5.14	174,770	174,770
Italy	9.88	9.89	41.31	41.32	10.88	10.79	6.21	6.16	561,340	561,340
Netherlands	10.06	10.06	41.38	41.40	3.85	3.86	5.55	5.48	697,680	697,680
Norway	12.48	12.52	38.32	38.56	4.57	4.59	4.86	4.78	499,490	499,490
Portugal	9.12	9.14	40.15	40.13	9.66	9.71	5.28	5.23	463,930	463,930
Sweden	12.68	12.68	42.51	42.53	7.25	7.26	4.95	4.91	353,560	353,560

Extended Data Table 2: Predetermined characteristics by country and displacement group. Average characteristics measured before actual or potential displacement by country. The panels summarize information in high- and low-emission sectors of the economy. Income and firm size are measured in log form; age and job tenure in years; income measured in $t = -3$ and deflated thousand EUR. The last column reports the emission-specific number of worker-year observations used for estimation.

A Supplementary Figures and Tables

Panel A. Income losses in high- and low-emission groups



Panel B. High-emission penalty by high-emission income losses

Figure A.1: Income losses and high-emission penalty by country. Country-level yearly post-displacement job loss effects on in high- vs. low-emission sectors (Panel A), and high-emission penalty vs. earnigns losses in low-emission sectors (Panel B).

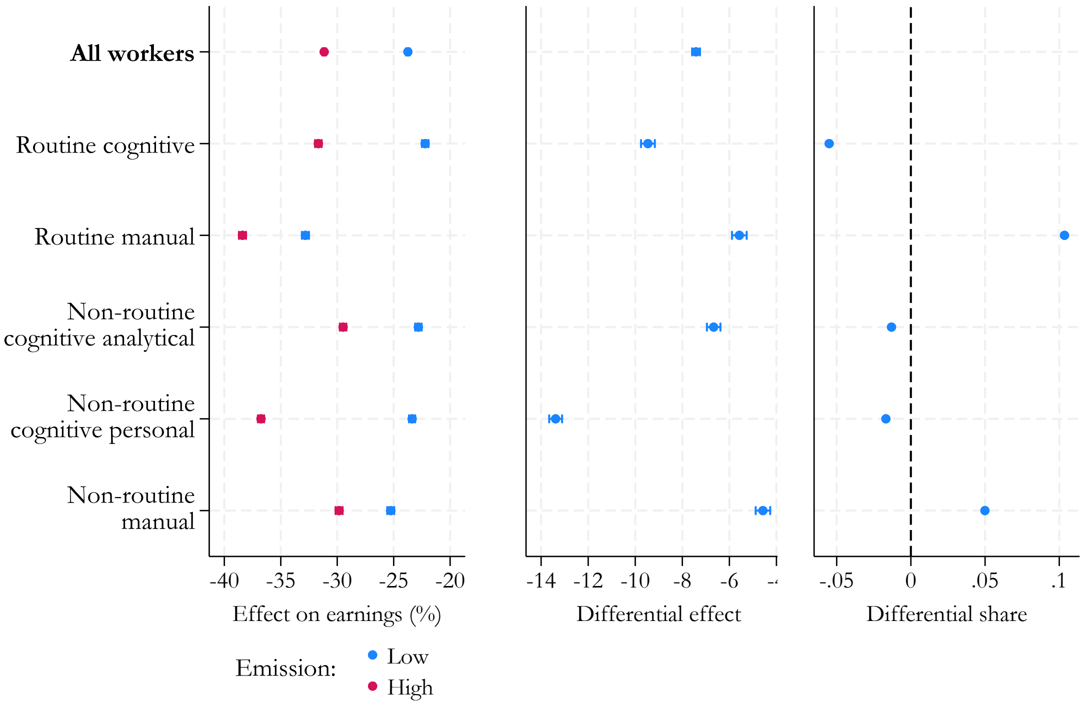
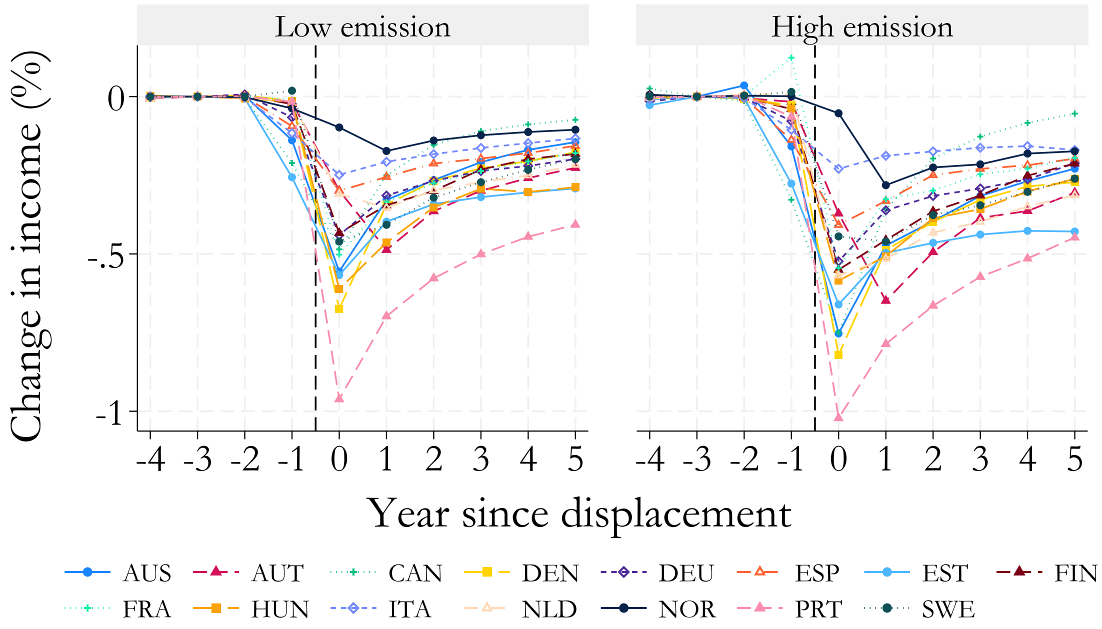


Figure A.2: Heterogeneous effects by occupational-level tasks. Average job loss effects in the five years after the event. For each characteristic, the job loss effect is taken in deviation from the corresponding reference category (the first, omitted, one). The left panel shows such conditional effects by emission sector. The central panel reports the differential high- vs. low-emission conditional effects; the right panel the high-low emission differential share of workers in the given characteristic. All estimates were obtained separately by country and later aggregated (see Methods section).

Panel A. Income



Panel B. Employment

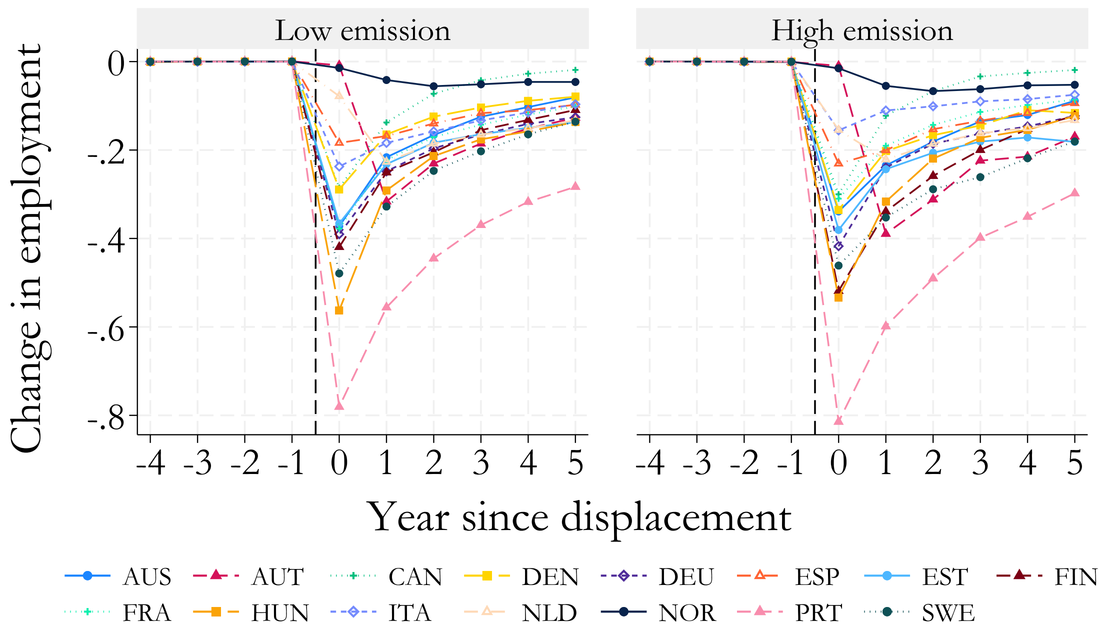
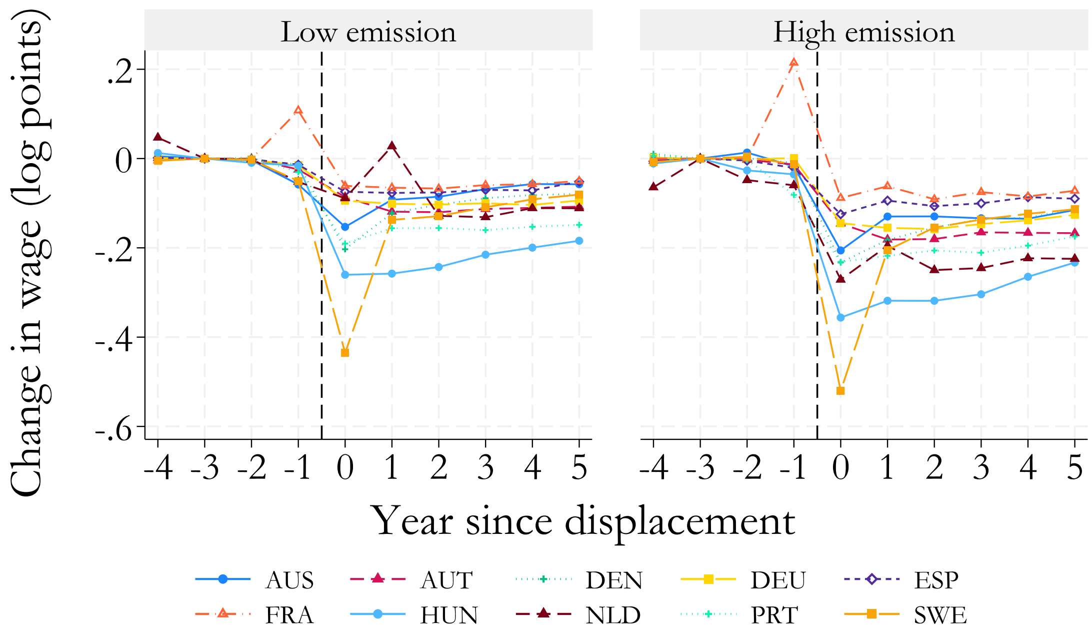


Figure A.3: Income and employment losses in high and low emission sectors

Panel A. Wage



Panel B. Firm pay premium

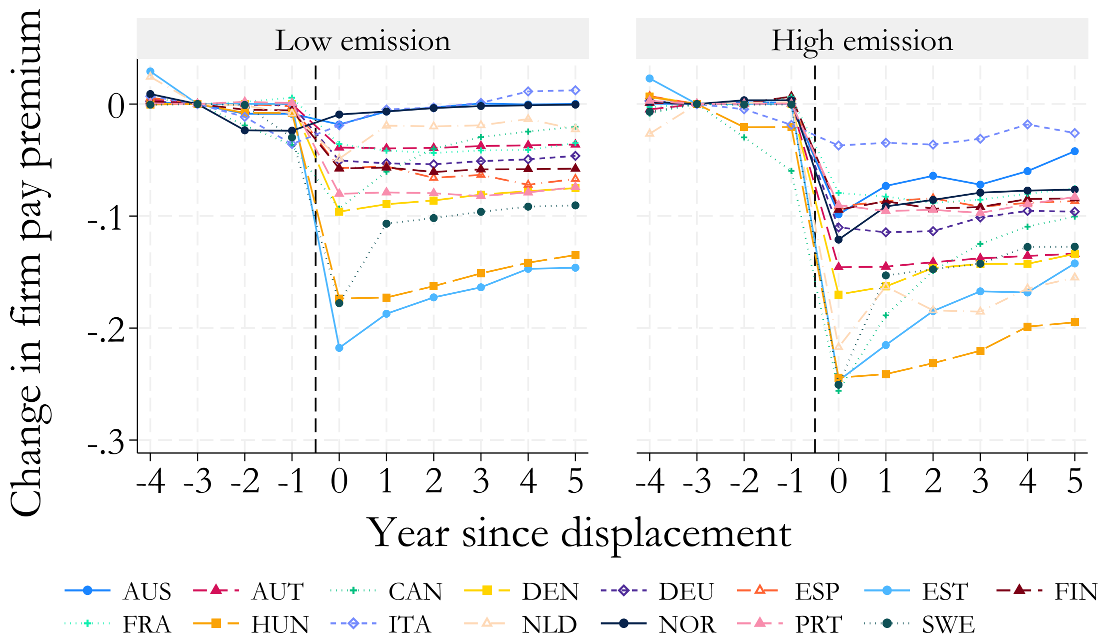
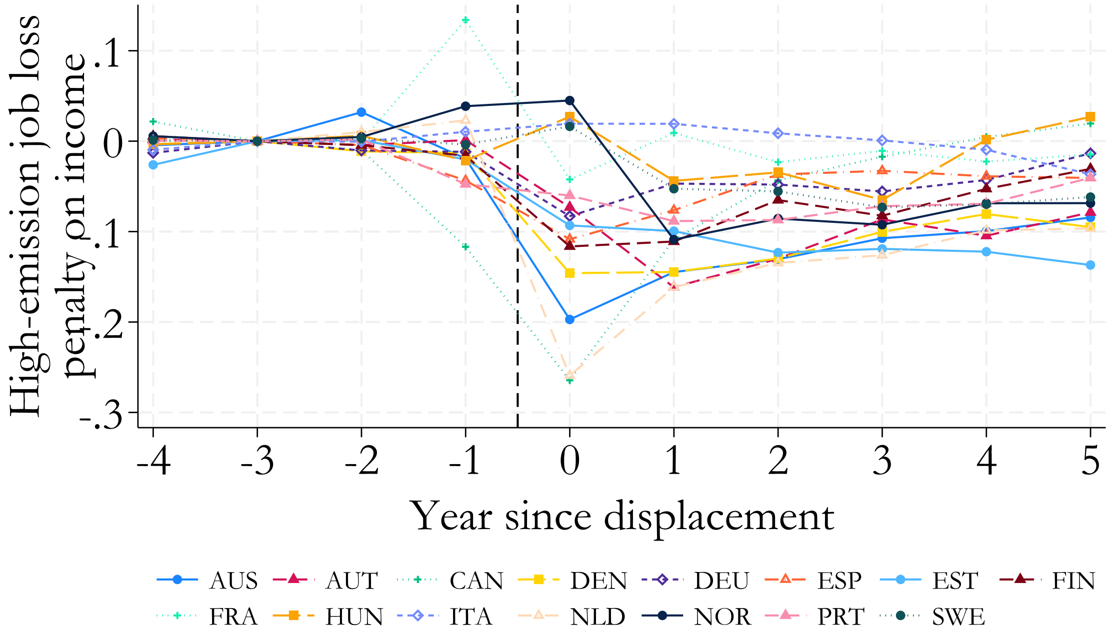


Figure A.4: Wage and firm pay premia losses in high and low emission sectors

Panel A. Income



Panel B. Employment

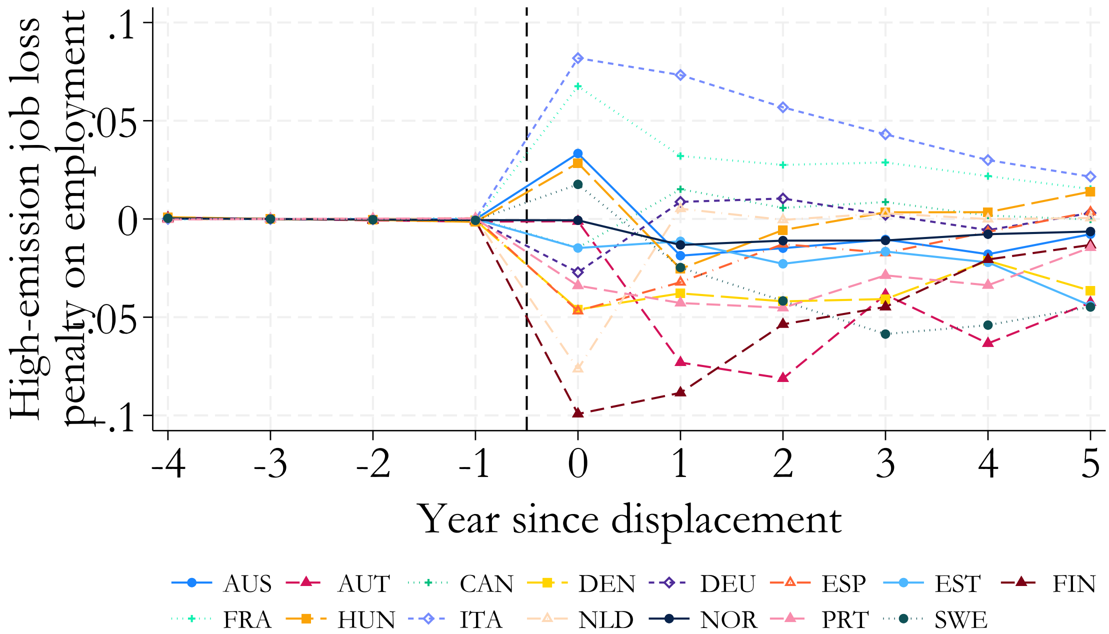
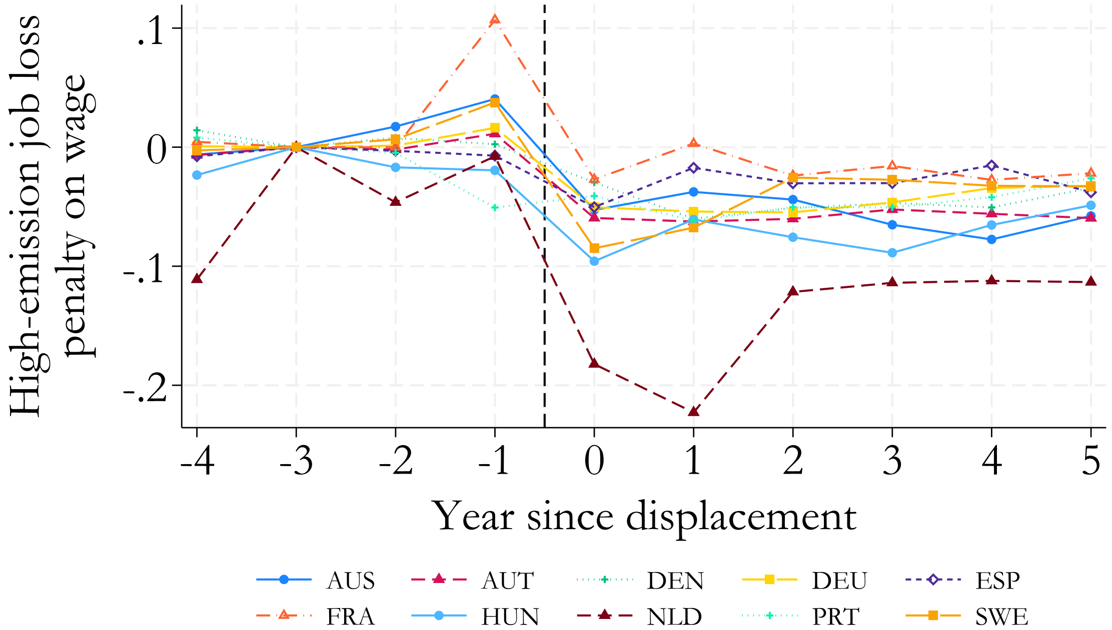


Figure A.5: High emission-job loss penalty on income and employment.

Panel C. Wage



Panel D. Firm quality (wage premium)

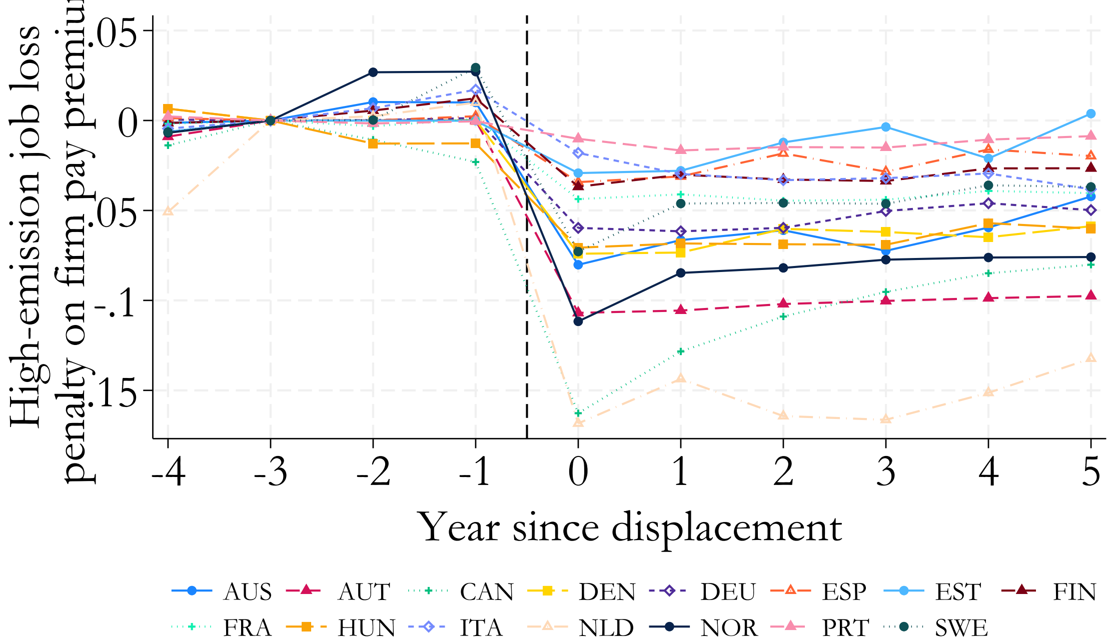


Figure A.6: High emission-job loss penalty on wage and firm pay premia.

Industry	Emission group	Freq.	GHG intensity
Crop and animal production, hunting	High	30	2901.22
Electricity, gas, air conditioning	High	29	3793.79
Sewerage; waste; remediation	High	29	2482.61
Oth. non-metallic mineral products	High	28	3036.30
Air transport	High	26	4182.24
Manuf. basic metals	High	26	1889.56
Water transport	High	25	2173.47
Coke and refined petroleum	High	22	7829.25
Manuf. of chemicals	High	20	1250.23
Fishing and aquaculture	High	20	889.84
Mining and quarrying	High	19	780.33
Land transport; pipelines	High	16	707.58
Paper and paper products	High	13	534.57
Forestry and logging	Low	5	338.88
Water collection, treatment and supply	Low	4	146.72
Textiles, wearing apparel, leather	Low	3	102.15
Food products, beverages and tobacco	Low	2	230.50
Postal and courier activities	Low	1	116.98
Metal products, exc. machinery and equip.	Low	1	101.48
Accommodation and food service	Low	1	57.27
Rubber and plastic products	Low	0	134.55
Wood and cork, exc. furniture	Low	0	122.04
Construction	Low	0	97.72
Basic pharmaceutical products	Low	0	92.72
Wholesale and retail trade; repair	Low	0	71.71
Machinery and equipment n.e.c.	Low	0	68.91
Warehousing and support for transportation	Low	0	67.91
Printing and reproduction of recorded media	Low	0	62.25
Wholesale trade, exc. motor vehicles	Low	0	60.97
Other service activities	Low	0	58.39
Electrical equipment	Low	0	53.19
Retail trade, exc. of motor vehicles	Low	0	51.92
Computers, electronic and optical products	Low	0	50.17
Other transport equipment	Low	0	49.97
Furniture; other manufacturing	Low	0	48.48
Motor vehicles, trailers and semi-trailers	Low	0	46.72
Repair and installation of machinery and equip.	Low	0	44.96
Administrative and support service activities	Low	0	44.85
Arts, entertainment and recreation	Low	0	44.05
Other professional, scientific and technical activ.	Low	0	38.84
Public admin., defence; compulsory social sec.	Low	0	35.40
Human health and social work	Low	0	29.02
Architectural and engineering	Low	0	26.03
Motion picture, video, sound; braoadcasting	Low	0	24.70
Advertising and market research	Low	0	24.04
Scientific research and development	Low	0	23.70
Legal and accounting.; management consultancy	Low	0	23.39
Education	Low	0	18.92
Publishing activities	Low	0	17.54
Activities auxiliary to finance and insurance	Low	0	15.71
Telecommunications	Low	0	11.53
Insurance and pension, exc. compulsory soc. sec.	Low	0	9.60
Finance exc. insurance and pension	Low	0	9.56
Computer programming; information services	Low	0	9.35

Table A.1: Classification of industries into high emission and rest of the economy. High-emission industry classification and corresponding greenhouse gas emission intensity and high-emission industry frequency across EU-27 and the additional countries considered. See Methods.