Earnings lost in the *green* transition: The costs of phasing out coal-fired power generation*

Vaios Triantafyllou †

January 16, 2026

Abstract

In this paper, I study the impact of Germany's coal phase-out policy on workers. Using confidential matched employer–employee microdata and a triple difference-in-differences design, I compare workers in electricity generation and coal mining to workers in other industries, across districts with differential baseline dependence on coal-fired power generation, before and after the introduction of the legislation. I find an 8.6% decline in annual labor earnings and a 5.4% reduction in annual days in employment, driven almost entirely by workers in electricity generation. Affected workers were 1.2 p.p. more likely to move into unemployment. The effects were concentrated among middle-aged and less-educated workers, those with shorter job and labor market tenures, and workers in occupations requiring lower experience levels. In an event-study framework around plant closures, I show that workers separating from their establishments experienced larger wage losses compared to those staying, and transitioned into *greener* but lower-paying establishments. While workers did not transition to other districts or sectors, they were partially absorbed by *greener* firms, primarily in those districts where *green* technologies were already abundant.

*I appreciate the comments and suggestions of Fernando Aragon, Michele Belot, Antonio Bento, Edoardo Bollati, Julieta Caunedo, Mark Curtis, Katia Gallegos Torres, Garth Heutel, Bart de Koning, Todd Gerarden, Takuma Habu, Johannes Heidelberger (*Federal Network Agency*), Markus Janser, Simon Janssen, Philipp Kircher, Nicolas Koch, Rocco Macchiavello, Michael Oberfichtner, Leonardo Peñaloza-Pacheco, Juan Pablo Rud, Nick Sanders, Paul Stainier, and Reed Walker. Importantly, I would like to thank Nadine Fetsch, Pascal Hess and the *Education, Training, and Employment Over the Life Course (BQE)* department for generously hosting me at the *Institute for Employment Research (IAB)* and providing access to the data. I also appreciate comments from participants in seminars at Cornell University, the Association of Environmental and Resource Economists Annual Summer Conference, the International Renewable Energy Agency 2024 International Energy Workshop, the 22nd Conference on Research on Economic Theory and Econometrics (CRETE), the European Association of Labour Economists Conference, the Energy Modelling Hub Annual Forum 2024, the International Workshop on Empirical Methods in Energy Economics, the 15h International Ph.D. Workshop "Perspectives on (Un-)Employment", the Eastern Economic Association 51st Annual Conference, LSE Environment Camp 2025, as well as the European Association of Environmental and Resource Economists 2025 Annual Conference. Lastly, I would like to acknowledge the generous funding received from the Cornell Department of Economics.

†Cornell University. E-mail: vaios.tria@gmail.com.

1 Introduction

Over the past decade, governments and international organizations have made extensive efforts to reduce greenhouse gas (GHG) emissions by regulating and attempting to transform the most carbon-intensive economic industries (European Commission, 2023b). These efforts are naturally concentrated in the *green* transition of the energy sector, which is responsible for 75% of global emissions, and particularly of electricity generation, which contributes to one-third of the overall energy use (Center for Climate and Energy Solutions, 2019; Climate Watch, 2022).

However, phasing out conventional energy sources implies a large number of plant closures with potential adverse impacts on workers, raising the question of what the distributional consequences of this transition are. Moreover, the transition away from conventional forms of energy generation, especially coal, implies the loss of jobs across their supply chains, from mining to transportation and generation, only part of which will be absorbed by the ramp-up of generation from renewable technologies. While renewables create jobs in the short term with the manufacturing and installation of equipment for new generation units, it is not clear that this trend will be maintained in the long term (International Labour Organisation, 2018; International Renewable Energy Agency, 2022). Hence, the European Union has pledged to dedicate 55 Billion Euros between 2021 and 2027 to implement a just energy transition in the context of the *European Green Deal*. These funds go towards supporting the reallocation, either within or outside the energy sector, of impacted workers, but also towards the affected regions at large (European Commission, 2021).

In the context of this *green* transition, Germany has put forward a plan to phase out the generation of energy from coal. Germany depends on coal for roughly 30% of its electricity generation, while coal amounted to more than 25% of the country's energy supply as of 2015. Hence, a timely and coordinated phase-out is pivotal for the safety of jobs in the supply chain of coal, but also for the security of the supply in the grid (International Energy Agency, 2022; Günther and Haucap, 2014). In the case of Germany, the move away from coal is especially challenging, because nuclear power has already been phased out. Nuclear power is an efficient source of energy generation that is low in carbon intensity and does not depend on weather or other conditions. This leaves renewables, such as wind and solar power, which are intermittent in nature, along with natural gas as the viable alternatives. Hence, the need to maintain a balance between energy availability and emissions in Germany is amplified by the phase-out of coal (Federal Office for the Safety of Nuclear Waste Management, 2023). More importantly for workers, a careful phase-out plan is needed as those employed in the supply chain of coal tend to be older and less educated, with skills that are not easily transferable to other sectors (European Commission, 2023a).

German authorities began discussions for the future of the electricity market in 2014, and in 2016 ordered 5 lignite plants to shut down sequentially between 2016 and 2019 in exchange for undisclosed compensation. However, it was not until 2020 that an official law was passed, stipulating public tenders to take coal plants offline and corresponding support packages for affected operators and workers (Federal Network Agency, 2021a). This two-step process provides a framework to examine how a phase-out announcement affected workers between 2015 and 2019, in the absence of direct support measures.

To study the effects of the German government's coal phase-out plan on workers, I work with four main sources of data. First, I utilize data on plant-level generation and capacity for all coal plants in Germany. Second, I use data on the specific notices and closure dates of coal plants. Third, I use confidential employer-employee matched microdata, following workers over time for the period in question, and observing their annual wage earnings, days worked, as well as demographic and skill-related characteristics. Lastly, I employ a geo-located dataset on *green* installations over time to track the ramp-up of renewable energy generation during the same period.

I follow two approaches in my estimation. First, I utilize the announcement of the phase-out, i.e. the beginning of a concrete policy discussion, as a cut-off in a triple difference-in-differences framework. Workers plausibly did not anticipate the coal phase-out policy announcement and, therefore, had no reason to adjust their labor market behavior before that. Subsequently, I use a balanced panel of workers to compare the evolution of my outcomes of interest for those employed in electricity and mining (treated) to ones in other industries (non-treated), across districts with differential reliance on coal fired-power generation at baseline, before and after the announcement. In this part, I also present estimates based on a simple difference-in-differences specification, comparing workers in treated versus not treated industries, only within regions with coal plants or mines. Second, to get closer at estimating the actual impact of plant closures, I employ an event-study analysis, where I normalize the time to zero around the year of the first closure of a coal plant in a district. To do so, I restrict my data to only districts containing a plant that closed at any point during the period of interest and compare affected workers to non-affected ones. In this approach, I utilize the robust estimator proposed by Sun and Abraham (2021) to avoid comparisons with already treated workers, given the staggered fashion of plant closures.

Four main results stem from my analysis using the preferred triple difference-in-differences specification. First, my estimations show that the policy announcement led to a 8.6% decline in annual labor earnings and a 5.4% reduction in annual days in employment for affected workers between 2015 and 2019. Second, I find that the effect was concentrated among workers in electricity and not mining, i.e. in more downstream economic activities. Third, affected workers were 1.2 p.p. more likely to move into unemployment. Fourth, the effects were concentrated among middle-aged and less-educated workers, those with shorter job and labor-market tenures, and workers in occupations requiring lower experience levels.

To shed light on the mechanisms driving my results, I turn to the effects around the time of plant closures and I look at the labor market trajectories of workers following that. In an event-study framework around plant closures, I show that workers separating from their establishments experienced larger wage losses compared to those staying in the same establishments. Furthermore, I show that workers were more likely to transition to other establishments within the same industries and districts, showing no geographic or sectoral mobility. Workers were also more likely to transition into *greener* but lower-paying establishments, particularly in districts where *green* technologies were already abundant.

I carry out three robustness exercises to verify that the results are not driven by sample selection or indirect industry exposure. First, using the full unbalanced worker panel yields effects that closely match the baseline balanced panel estimates, indicating that labor market entry and exit do not affect the findings. In a second robustness exercise, I exclude all upstream industries that supply more than 5 percent of inputs to coal or electricity generation to ensure the control group is not indirectly exposed to the policy. The results remain virtually unchanged, suggesting that the baseline control group provides a clean counterfactual. As an additional falsification test, I assign "treatment" to workers in heavy industries, which are in principle unaffected by the policy, and exclude workers in mining and electricity. This placebo produces no significant dynamic effects, confirming that the empirical strategy does not mechanically generate spurious declines in unrelated sectors. Together, these exercises show that the main results are stable across alternative samples and specifications, reinforcing that the documented effects reflect the true impact of the policy announcement on workers.

My results contribute to four main strands of literature. First, I contribute to the literature on the labor market impacts of environmental regulation. Environmental regulation has been shown to lead to losses in long-term earnings for workers, as was the case in the aftermath of the Clean Air Act (CAA) in the United States. Following the CAA, workers in treated plants, within affected industries, experienced more than $5.4 billion in forgone earnings in the form of transitional costs, while they re-allocated to different sectors (Walker, 2013). Moreover, Marin and Vona (2019) find that climate policies over the past 20 years in Europe have been skill-biased, disproportionately affecting manual workers, while benefiting more skilled technicians. However, the degree to which a climate policy affects workers also depends on the level of labor mobility; When workers have the option to transition to the same or different industries in locations that are comparatively less affected by the legislation, they can mitigate some of the costs (Castellanos and Heutel, 2023). In the case of Germany's coal phase-out, while workers transition to new establishments, they are not geographically mobile and still face reductions in earnings.[1]

Second, I contribute to the literature on the effects of the transition away from conventional fuels on workers more broadly. This literature is concerned with how the transition, not necessarily as imposed through environmental legislation, impacts affected workers. It has been documented that a reduction in the demand for coal can have spillovers into non-mining industries, as well as increase welfare expenditures in the affected regions (Black et al., 2002, 2003, 2005). Specifically for coal mining communities, it has been shown that a decline in the demand for coal can have

[1] For a more comprehensive review of the economic literature, see, for instance, Greenstone (2002); Walker (2011); Dechezleprêtre and Sato (2017); Hafstead and Williams (2018, 2019); Curtis and Lee (2019); Horbach (2020); Popp et al. (2021).

long-lasting effects on affected regions, resulting in out-migration (Morris et al., 2019; Hanson, 2022; Krause, 2023). However, Colmer et al. (2024) find that reallocation does not necessarily mitigate transitional costs for affected workers. Also, Rud et al. (2024) find long-lasting impacts for displaced miners as a result of the decline of coal in the UK. Additionally, Garnache et al. (2025) find that oil workers faced significant reductions in both annual earnings and employment as a result of transitioning away from oil in the Norwegian context. In this paper, I look at the transition out of energy generation from coal which, although spatially correlated with coal mining, is substituted by renewable generation, creating jobs that can potentially absorb affected workers.

Third, I contribute to the literature on plant closures and the subsequent impacts on workers. Jofre-Monseny et al. (2018) look at the effects of the closures of manufacturing plants in Spain and quantify how job losses in closed plants translate to job losses in the affected industry at large. They find that only 0.6-0.7 jobs are lost in the affected industry for each direct loss due to the plant closure. Jacobson et al. (1993) find that high-tenure workers displaced from distressed firms suffer long-term earnings losses averaging 25% per year. Specifically for Germany, relevant literature has studied the closures of coal mines, a process that lasted from the 1990s until a decade ago. It has been shown that higher-educated, middle-aged workers faced the highest welfare losses, with unemployment being only a small part of these losses (Haywood et al., 2024). However, the short-term impacts of phasing out the generation of energy from coal, rather than coal mining, have not yet been studied in this context.

Fourth, I contribute to the growing literature on workers, skills, and the *green* transition. There is evidence that workers struggle to transition from *brown* to *green* jobs, especially those who are older and lack a college education (Curtis et al., 2024). Therefore, given the high growth of *green* jobs, training workers to assist them in this transition is key to phasing out conventional energy generation (Popp et al., 2022; Curtis and Marinescu, 2023; Barreto et al., 2024; Chateau et al., 2018; Causa et al., 2024). In this paper, I aim to contribute to this literature by looking at the wage penalty that workers undergoing those transitions have to face.[2]

The rest of the paper is organized as follows: Section 2 provides context about the electricity industry in Germany, as well as details on the timeline of the phase-out and the institutional framework. Section 3 describes the data I use in my analysis. Section 4 outlines the empirical strategy implemented to estimate the impacts on workers. Section 5 outlines the main results of my estimates. Section 6 explores the labor market trajectories of workers following plant closures, shedding light on the mechanisms driving my main results. Section 7 presents several robustness exercises and addresses a potential threat to identification. Finally, Section 8 concludes.

[2] For a more comprehensive review of this literature please refer to Lehr et al. (2012), Consoli et al. (2016), Bowen et al. (2018), Dechezleprêtre et al. (2021), Tyros et al. (2023), Fabra et al. (2024), Arenas-Arroyo et al. (2025), Villani et al. (2026).

2 Context and institutional framework

2.A Background on the German electricity industry

The *green* transition in Germany kicked off with the *Energiewende*, a long-term plan of the Federal Government to transform the electricity industry and achieve lower emissions, reliability of the energy supply, and affordable energy prices (German Federal Government, 2010). Among the goals of the *Energiewende* were the push for electricity generation from renewable sources, the complete phase-out of generation from nuclear power (which has already been completed), as well as the phase-out of coal. The official package of *Energiewende* was passed in 2010, and in its primary form did not include the phase-out of nuclear power. This was only added in the transition plan following the Fukushima nuclear disaster in 2011.

The phase-out of nuclear energy becomes particularly relevant when studying the shift away from conventional sources of energy, such as coal. Nuclear energy is very efficient and has no dependency on weather conditions. Hence, in the absence of this option, the only alternatives to substitute conventional energy generation are renewable energy, which is inherently intermittent, and natural gas. Therefore, the absence of the nuclear option in the case of Germany places even more strain on the coal phase-out process and calls for a carefully designed transition (Reuters, 2023).

Historically, Germany has faced surplus electricity generation in the North due to excess wind power and favorable weather conditions, while there is a lack of energy generation in the South. Several efforts have been made to expand the network in order to achieve a balance in the supply of electricity (Federal Ministry for Economic Affairs and Climate Action (BMWK), 2024; Reuters, 2022). In order to better manage this supply, and avoid putting strain on the grid, operators wishing to close down their plants have been required to notify the regulating body of their intention at least a year in advance, as of 2013. This is a requirement for all operators, irrespective of the energy source of the plant. Following this notification (*Stilllegungsanzeige*, or StA by its German acronym), the *Federal Network Agency (BNetzA)*, the agency responsible for regulating energy markets, along with the *Transmission System Operator (TSO)* assess the grid stability and the degree to which the plant is *system-relevant*. Based on that, plants are either allowed to close, or required to remain in a grid reserve (also referred to as network reserve). What this means, essentially, is that they are no longer allowed to sell electricity in the market, but are required to supply the grid, in case of shortages in the network (Federal Network Agency, 2015; Federal Network Agency, 2024).

However, not all plants are required to file such a notice before closing. More specifically, only plants that exceed 10 Megawatts (MW) in installed capacity are required to file a notice, as smaller ones are unlikely to be classified as being *system-relevant* anyway. Additionally, for a plant to be required to file a notice, it has to be technically and legally capable of generating electricity. More specifically, if a vital part of a plant is broken, such a notification is not required. Additionally, if the permit of the plant expires, or the emission permit provided by the local authority (in the case of a conventional plant) or the general permit (in the case of a nuclear plant) expires, a notification is not required either (Federal Ministry of Justice and Consumer Protection, 2016).

2.B Electricity generation from coal

Based on data from *BNetzA*, as of 2024, there were a total of 143 fully operational generators in Germany, while 89 had been permanently shut down.[3] Two types of coal-fired power plants operate in Germany, namely lignite (or *brown coal*) and *hard coal* power plants. Lignite is the lower-quality fuel among the two types, with the higher carbon intensity (U.S. Geological Survey, 2024). Of the operational generators, 64% are *hard coal* generators, while the rest operate on lignite. Also, 65% of the fully retired ones used to operate on *hard coal*. Table A.1 presents the summary statistics for operational and retired coal plants by type of fuel. Of the operational plants, lignite generators have a higher average installed capacity, while the opposite is true for fully retired ones.

As part of its reporting, *BNetzA* has introduced several sub-categories of both operational and closed power generators. Operational ones are categorized as (a) in operation, (b) temporarily returned to market, or (c) in reserve after having notified the regulator. Permanently closed generators are classified as (a) having closed with StA notification, (b) having closed without StA notification, or (c) having shut down based on the *Coal Phase-out Act* (after 2020), a law that is further explained in Section 2.C. The spatial distribution of those generators, which I categorize as fully operational throughout the period of interest, fully retired, or operational until 2019, can be seen in Figure 1.

All generators that went into the reserve or were retired following 2019 are depicted as operational. In my analysis, I define coal districts, i.e. the dark shaded districts of Figure 1, as those that contain any type of power generator, including generators that were retired, went into the reserve, or remained fully operational throughout the time period (or a coal mine).[4] For context, 68 out of the 400 administrative districts (*Kreis*) of Germany are defined as treated.

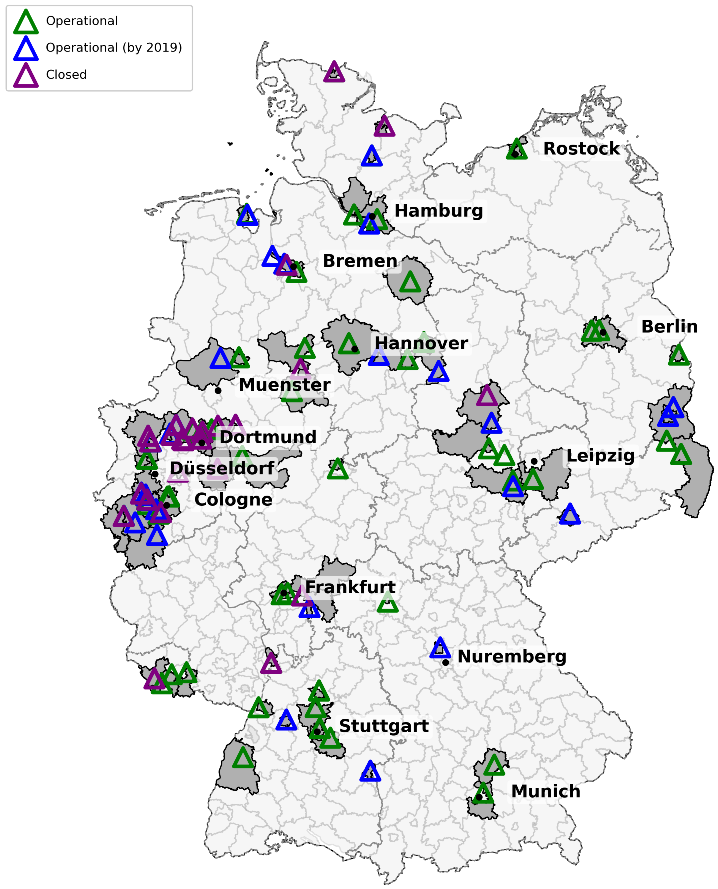
2.C Coal phase-out and the security standby

In December 2014, the *Climate Action Programme 2020*, a cross-sector program that aimed to decarbonize the economy overall, was passed into law. The plan specified that a reduction of 2 Million tons of carbon dioxide equivalent was to be achieved through decarbonizing the electricity sector in particular. Subsequently, in October 2014, the German *Federal Ministry for Economic Affairs and Energy* released a *Green Paper* that served to kick off a public debate between power producers, consumers, and other major stakeholders regarding setting up a blueprint for the future of the electricity industry in Germany.

[3] A coal-fired power plant may contain multiple generators, and individual generators can shut down while others continue operating.

[4] Section A.1 of the Appendix provides more details on the coal mining industry in Germany.

Figure 1: Map of coal plants and administrative districts containing one



Notes: The purple triangles represent coal generators that entered the reserve following the announcement of the policy or were retired between 2014 and 2019. The green triangles represent coal generators that remained operational throughout the period in question. The blue triangles represent generators that were operational by the end of 2019. A total of 232 generators are included in this map. Only plants over 10 MW are reported. District boundaries are also rendered with districts in dark gray representing districts that contain at least one coal power plant, in any of the three categories, while districts in white representing districts without any coal power plant. Source: Own elaboration based on plant-level geographical information obtained from the *Federal Network Agency (BNetzA)*

The debate lasted for just over six months and the main concern was how to maintain the balance between the so-called *reserve function* and the *dispatch function* of the electricity market (Federal Ministry for Economic Affairs and Energy, 2014).[5] In June of 2015, the Ministry released a *White Paper* summarizing the public discussion and announcing the decision in favor of, among other measures, the creation of additional levels of security for energy supply (Federal Ministry for Economic Affairs and Energy, 2015).

In 2016, with the *Energy Industry Act* (*Energiewirtschaftsgesetz* or EnWG, by its German acronym) two concrete steps to phase-out coal were codified. First, the *brown coal* standby was created, by ordering 8 generators totaling 2.7 GW of installed capacity to shut down temporarily over a 4-

[5] The *reserve function* refers to the market's capability to ensure adequate supply at any given moment; The *dispatch function* refers to its ability to optimize the use of the capacity only at times when needed.

year period starting in 2016, with the obligation to be re-activated if needed, and be permanently shut down after that (Görg Law Offices, 2016; Federal Network Agency, 2021b).[6] These were only lignite-fired plants which corresponded to 13% of all lignite-fired generation in the country (Reuters, 2015; Power Magazine, 2015). The coal plants that were ordered to temporarily enter the coal reserve were two generators in each of the *Frimmersdorf*, *Niederaussem*, and *Jaenschwalde* plants, as well as one in the *Neurath* plant, and one in the *Buschhaus* plant, at different times between 2016 and 2019 (Federal Ministry of Justice and Consumer Protection, 2016).

The operators of the above plants all received (confidential) remuneration in exchange for standing by.[7] This move was perceived as the first concrete plan to phase out coal, pushing other plants to close down as well.

Second, a *capacity reserve* was planned to be created in 2020. According to this, several plants amounting to 2 Gigawatts (GW) of installed capacity would be taken off the grid and would serve to respond to unexpected or extreme circumstances.[8] Plants in the *capacity reserve* would not be allowed to operate, but would be required to immediately supply the grid if the *TSO* deems there are no other alternatives to balance supply and demand (Federal Ministry for Economic Affairs and Energy, 2020). Between 2014 and 2020, a total of 33 other generators permanently shut down, without receiving any support package. It was only in 2020 that the official *Act to Reduce and End Coal-Fired Power Generation (KVBG)* was passed into law, outlining a plan for the complete phase-out of coal by 2038 and the commissioning of open tenders where coal-plant operators would bid to take their generators into the *capacity reserve*. The first such tender took place in 2020 (Federal Government of Germany, 2020; Federal Network Agency, 2021a; Öko-Institut and Prognos, 2017).

Back in 2015, of the 700,000 people employed in energy, roughly 20,000 people were employed in the lignite industry. One fifth of the lignite industry employees were directly employed in coal power plants, while the rest were in lignite mining. According to the *German Institute for Economic Research (DIW Berlin)*, the expected impact of the coal phase-out would be a reduction of more than 20% in the total employment of the lignite industry by 2030 (German Institute of Economic Research, 2019). It is also important to note that affected workers are represented by the Trade Union for mining, chemicals and energy industries (IG BCE), the third largest trade union in Germany, which negotiates collective agreements on behalf of workers. The trade union has been a fierce critic of the phase-out policy (Clean Energy Wire, 2020).[9]

[6] Section 13g of the EnWG

[7] After inquiring with the *Executive Office of the President* of *BNetzA*, I was informed that the deals that were reached between the German government and the operators of those plants are not publicly available. To the best of my knowledge, there were no specific stipulations for workers over and above what collective agreements with worker unions and German labor law stipulate for any type of plant closure.

[8] Section 13e of the EnWG

[9] It has been documented that, over time, collective agreement coverage in Germany has declined (Rieder and Schnabel, 2025). Figure A.4 presents the trends over time for the share of firms covered by any type of either industry-wide or firm-level collective agreement, separately for electricity and mining and for firms in other sectors. As is evident, while historically the electricity sector has been heavily unionized, it saw a disproportional drop, particularly in industry-wide collective agreements over time.

Despite the official law being passed in 2020, the announcement of the policy and the creation of a reserve had consequences that started to kick in prior to 2020. The intended consequences were the plants entering the reserve, while the unintended ones were the movement of workers, who plausibly foresaw the imminent threat to energy production from coal and decided to hedge against that risk or were laid off. Given that there was no comprehensive plan in place to mitigate any potential consequences until 2020, I aim to study the impacts of this announcement on local labor markets by limiting the reference timeline to 2009-2019.[10]

3 Data and descriptive evidence

3.A Data sources

I utilize five distinct sources of data in my analysis, as outlined below:

Plant-level generation and capacity for coal. Data on annual plant-level electricity generation measured in Megawatt hours (MWh) was obtained through *ENTSO-E*, the *European Association for the Cooperation of Transmission System Operators (TSOs)* for electricity via Energy Charts (2025). This dataset only includes energy production facilities using coal to generate electricity (and heat) in Germany with installed capacity over 100 MW.

Administrative timeline of plant openings and closures. Through *BNetzA*, I have obtained two lists of power generating facilities. The first list includes all operational plants that have either remained operational ever since their commissioning, or went into a reserve. This dataset includes information on the full address of the plant, the commissioning date, the status of the plant, the main source of electricity generation, as well as the installed capacity in MW. It includes information on all types of power generation facilities (both conventional and renewable) that exceed 10 MW of installed capacity. The second dataset includes information on the closed plants, with the complete address, source of generation, commissioning and closing date, type of closure (relating to an obligation to inform the authority before the closure), as well as the installed capacity in MW. I also utilize the official list of notices provided by the plants to *BNetzA*, a year prior to closure.

Complete labor market biographies. I have obtained access to the complete labor market biographies of workers in Germany. The data access was provided via on-site use at the *Institute for Employment Research (IAB)* of the *German Federal Employment Agency (BA)*. This is the weakly anonymized version of *Integrated Labour Market Biographies (IEB)* which combines several data sources and contains information on individuals in Germany who are either subject to social security contributions, receive unemployment benefits, are registered as actively looking for a job, or participate in some sort of labor market program launched by the German government (Graf et al., 2023).

[10] In the period after 2019, due to the energy crisis in Europe, several of the plants returned to the market to secure supply, thereby complicating the setup for the evaluation of the second phase of the policy.

Within this dataset, I can observe the district of residence, the district where the place of work of the individuals is located, biographical information on the background of the individuals, their labor market earnings, the time for which they have been in employment or unemployment (on an episode basis), as well as information on the classification of their occupation and the classification of the economic activity of the establishment at which they are employed.[11] Additionally, I can observe the reason for termination of employment, where relevant.[12]

Renewable installation data. I obtain data on all renewable installations through the *Market master data register* (or *Marktstammdatenregister (MaStR)* in German), the official register for the German energy sector maintained by *BNetzA*. *MaStR* provides unit-level information on all registered electricity generation assets in Germany and is continuously updated in real time. For each generation unit, the registry reports key characteristics such as a unique unit identifier, display name, energy carrier, gross installed capacity, commissioning date, registration date, and current operational status (e.g. in operation, temporarily shut down, decommissioned, or in planning). The main difference with the administrative dataset used for coal plants is that *MaStR* includes detailed information on solar and battery installations, even for units with power below 1kW.

District-level information. District-level information including regional GDP, the district population, as well as shares of employment in different sectors, was obtained through the regional database of the *Federal and State Statistical Office* of Germany.

3.B Role of the coal industry and success of the policy

As Figure A.2 (a) shows, electricity in Germany has historically been contributing roughly 40% to total emissions, 10 percentage points higher than the equivalent value worldwide. After 2015, there is an apparent drop in the share of electricity in overall emissions for Germany, driven by the coal phase-out policy studied in this paper, and the *green* transition of electricity generation in the country overall.

Furthermore, Figure A.2 (b) shows that carbon intensity of the electricity industry in Germany is largely driven by coal. More specifically, generation from coal has historically been contributing to more than 90% of electricity-related emissions with oil and gas together contributing less than 20%. However, again consistent with the phase-out policy, after 2015, the share of coal in electricity-related emissions dropped below 80%, albeit still the dominant source.

The policy was successful in achieving the specified targets of emissions reductions in the electricity sector, through placing 8 large generators in a reserve, as well as through several additional generators closing down. This paper studies how such a successful environmental policy trans-

[11] An episode essentially refers to a job spell, i.e. defines a period of time for which the individual is employed at a specific establishment.

[12] In working with IEB, I followed Wolfgang and Eppelsheimer (2020) and Stueber et al. (2023) to transform the raw, episode-based data into a panel, deal with wages of marginal workers, wages above the assessment ceiling, as well as deal with parallel episodes and keep the main one for each worker. More details on the processing of the employer-employee matched microdata is available in Section II of Appendix B.

lated to effects in the local labor markets, and how workers responded to such a drastic change in their industry.

3.C The transition out of coal

As expected, the aforementioned reduction in emissions was driven by an equally drastic reduction in generation of electricity from coal. Figure 2 (a) shows the change in electricity generation from coal-fired plants in Terawatt hours (TWh), which dropped by roughly 48% between 2015 and 2020, as shown in the "Overall" curve that draws from nationwide data. Two additional curves show the generation from aggregated plant level data, split into generation from the 5 large plants that went into the reserve and other plants, some of which closed down, possibly foreseeing the imminent decline of the industry. As is evident, the largest reduction was achieved through plants that closed down without having any agreement with the government, raising the question of what the labor market impacts of this process were.[13] In all cases, there is a bounce-back after 2020 due to the re-opening of coal plants, driven by the *Global Energy Crisis* and the subsequent spike in gas prices starting in 2021 (International Energy Agency, 2025).

Figure 2 (b) shows the evolution of average daily wages within coal districts, separately for workers employed in electricity and mining and for workers in all other industries. Up to 2014, wages in the two groups follow broadly parallel upward trends. After 2014, however, the trajectories diverge: wage growth in electricity and mining flattens, while wages in other industries continue to rise. This divergence coincides with the onset of the coal phase-out process and suggests that workers directly exposed to the decline of coal generation experienced weaker wage growth relative to other workers in the same local labor markets.

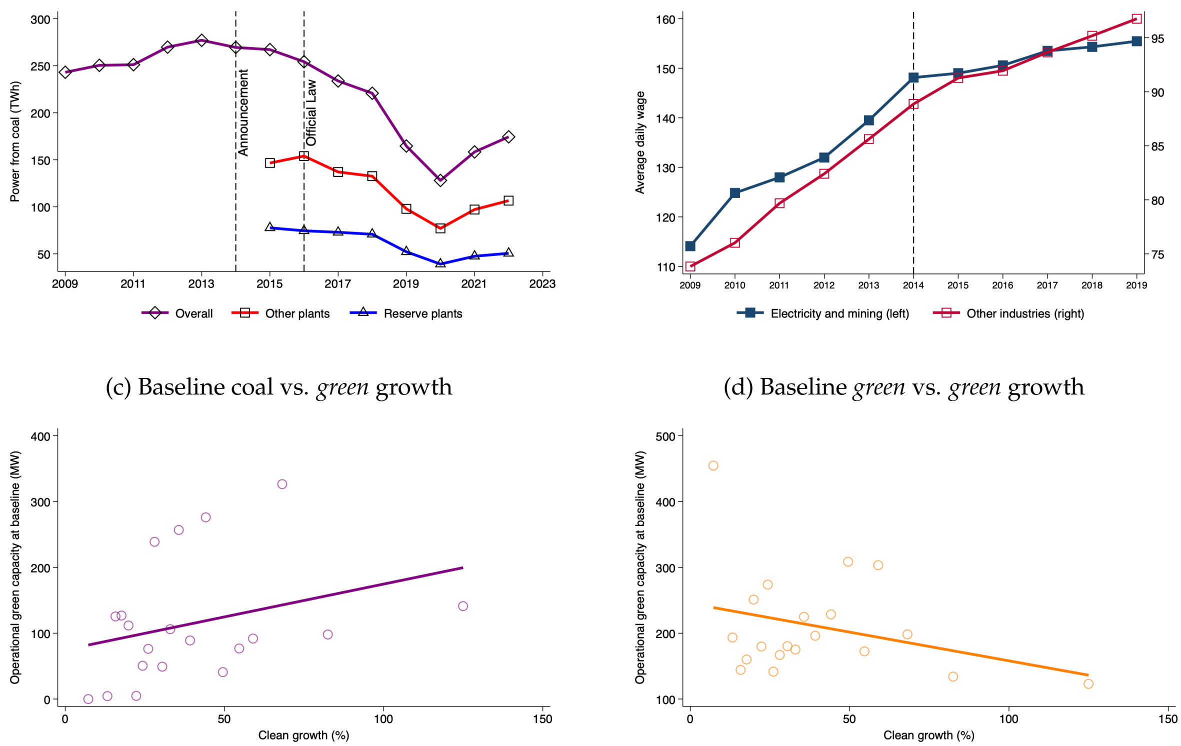
At the same time, though, there was in increase in renewable installations in those same districts. Figures 2 (c) and 2 (d) explore how baseline energy capacity relates to subsequent clean-energy expansion across districts. Panel (c) plots baseline operational coal capacity in 2014 against the growth of clean installations between 2015 and 2019, revealing a positive correlation: areas with larger coal capacity at baseline tend to experience larger growth in clean energy installations. Panel (d) shows the same relationship for baseline clean capacity, which is instead negatively correlated with subsequent clean growth, consistent with diminishing returns to expansion in already *green*-intensive areas. Taken together, these patterns suggest that regions historically specialized in coal generation were also those that expanded clean capacity most rapidly during the transition, highlighting a reallocation of energy investment rather than simple spatial persistence of *green* production.

Taken together, these trends document a rapid decline in coal generation alongside rising renewable investment and diverging wage trends within coal districts. This transition creates conditions under which workers tied to coal-intensive activities are likely to experience weaker wage

[13] The plant-level data in Figure 2 (a) is presented from 2015 onwards because *ENTSO-E* only makes plant-level generation available for that period.

growth and increased pressure to reallocate, either across sectors or into expanding clean-energy activities within the same local labor markets.

Figure 2: The transition out of coal and local economic adjustment



(a) Generation of electricity from coal

(b) Wages within coal districts

(c) Baseline coal vs. *green* growth

(d) Baseline *green* vs. *green* growth

Notes: Panel (a): The top curve shows the total electricity generation from coal over time for all plants that are above 10 MW of capacity. The bottom curve shows the generation of electricity over time for the 5 large plants that went into the stand-by. The curve in the middle shows the generation over time for other plants, some of which closed down during this period without any agreement with the government. Plant-level data is not available before 2015, hence the breakdown by type of plant only goes back to 2015. Panel (b): The two curves show the evolution of average daily wages separately for workers in electricity and mining (left y-axis) and all other workers (right y-axis), as defined based on their industry of work in 2014. Panel (c): This figure shows the correlation between baseline operational coal capacity in MW in 2014 and the growth of clean installations between 2015 and 2019. Panel (d): This figure shows the correlation between baseline operational clean capacity in MW in 2014 and the growth of clean installations between 2015 and 2019. Source: Panel (a): Own rendering based on plant level generation and capacity data obtained from the *Federal Network Agency (BNetzA)* and the *European Network of Transmission System Operators for Electricity (ENTSO-E)* Transparency Platform through energy-charts.com. Panel (b): Own rendering based on data from the *Integrated Labour Market Biographies (IEB)*. Panel (c): Own rendering based on data from *Marktstammdatenregister (MaStR)*. Panel (d): Own rendering based on data from *Marktstammdatenregister (MaStR)*.

3.D Demographic and labor force characteristics

Next, I turn to the demographic and labor force characteristics of workers in different districts, based on their treatment status, i.e. containing or not a coal plant, as well as based on the types of plants they contain, i.e. only operational plants throughout the period I am studying, only closed plants throughout the period, or a mix of the two (or a plant that went into the reserve). Table A.2 shows demographic characteristics as well as educational attainment for the three types of coal-containing districts, as well as for control ones at baseline, i.e. in 2014. As can be seen, districts containing coal power plants are, on average, larger in terms of population compared to ones that do not, but quite balanced in terms of age distribution. Additionally, purely operational districts have a higher share of people with intermediate degrees than both purely closed and mixed coal plant-type districts.

Table A.3 demonstrates the unemployment rates and share of part-time employees for each of those districts. Overall, districts containing coal plants have higher unemployment rates, especially pronounced in districts with only closed coal plants or with a mix of the two. Additionally, Table A.4 shows employment characteristics of the different types of districts. While closed plant districts on average have smaller labor forces compared to other plant-containing districts, shares of employment in mining, electricity, and waste management average roughly 2% of the total across those districts.

Similarly, Table A.5 provides information separately for workers in treated industries and workers in untreated ones at baseline, i.e. in 2014, and only within districts that contain either a power plant or a coal mine, based on the employer-employee matched data. The main takeaways of this table are that workers in treated industries are on average significantly higher paid than their counterparts in untreated industries, with a mean of $61,204.05 annual labor earnings compared to $36,959.04 for the latter group. Additionally, on average they worked a total of 363.01 days in 2014 compared to 322.13 for ones in untreated economic activities. Furthermore, they have longer experience in the labor market overall, as well as longer tenure within their present job. However, the two groups are not significantly different in terms of school leaving qualification and age, nor do they display any significant difference in separation probabilities from their establishment at baseline.

4 Empirical strategy

4.A Effect of the announcement

In attempting to investigate and quantify the impacts on workers, I define German administrative districts as having been, ex-ante, impacted by the policy or not. Impacted districts are the ones that contained any type of coal power plant at baseline, i.e. in 2014. I am using 2014 as my baseline as this was the last year before the discussion on the creation of a reserve kicked off.

Given that in the *IEB* dataset I can follow individuals over time, I can look at several outcomes after the discussion had started and the announcement was made, comparing treated workers to non-treated ones, within impacted districts. I assign treatment status to individuals who worked or resided in any of the impacted districts at baseline based on the economic activity of their firm.[14] More specifically, I consider electricity and mining to be the industries affected by the

[14] While I believe that the place of work, as opposed to the place of residence, is the relevant variable, it seems that the two coincide in the vast majority of cases in my sample. Specifically, only 0.9% of observations for workers in

policy. However, the most important limitation of my data is that the highest disaggregation of electricity-related economic activities I can observe is that of *Electric power generation, transmission, and distribution* and its sub-categories, which do not distinguish between renewable and conventional sources, or coal in particular. On the contrary, in mining, which I also consider to be directly affected, I can observe specifically *Mining of coal and lignite*.[15] People who were unemployed at baseline are included in the control group. To estimate the impact of this announcement on workers, I utilize the following difference-in-differences specification:

$$\log y_{idst} = \alpha + \beta \cdot I_{ids} \cdot \mathbb{1}_{t \geq 2015} + \kappa_t + age^2_{idst} + \Gamma[X'_{ds} \times \kappa_t] + [\rho_s \cdot t] + \phi_{ids} + \varepsilon_{idst} \tag{1}$$

Where y_{idst} is the outcome of interest for individual i in district d of state s at time t, namely the probability of being unemployed, the average daily wages, the days of employment each year, or the total labor earnings of the worker. I_{ids} is an indicator for whether or not worker i worked in a treated economic activity in 2014, taking a value of 1 if the worker was employed either in electricity generation, transmission, and distribution or in coal and lignite mining at baseline, and 0 otherwise. Additionally, $\mathbb{1}_{t \geq 2015}$ is an indicator for whether the year is before or after, and including, 2015; I also control for square age of individuals in order to capture potential nonlinearities, especially as some of the outcomes might follow hump-shaped relationships, increasing at earlier ages and reversing when individuals are older. In some of the specifications I interact baseline characteristics of districts X_{ds} that include baseline GDP, baseline employment in electricity and baseline employment in manufacturing with time fixed effects κ_t; I also allow for state-specific linear time trends, $\rho_s \cdot t$, by interacting each state indicator with a linear time variable. This flexibly absorbs unobserved factors that evolve smoothly over time within a state. Lastly, I add individual fixed effects ϕ_{ids}, time fixed effects κ_t, as well as a random error term ϵ_{idst}, clustered on the district level. I refrain from including economic activity, district, or firm fixed effects, as those are potentially outcomes of the policy in question and would therefore be *bad controls*.

Based on the above, $I_{ids} \times \mathbb{1}_{t \geq 2015}$ only takes a value of 1 in the case that a worker is observed after 2014 who resided in an impacted district and was working in a directly affected economic activity at the time the policy was announced, and zero otherwise. Therefore, I am exploiting variation across industries, comparing individuals who worked in treated industries in 2014 and those that did not, and over time to estimate the impact of the announcement of the coal phase-out policy. My identification strategy relies on two assumptions, namely (a) that workers did not

treated industries have a district of work that is different than the district of residence, while this is true for only 0.6% of observations for workers in untreated industries. Hence, for employed workers, I utilize the place of work, while for unemployed ones I replace this variable (which is empty) with the place of residence. The results remain the same if I simply use the place of residence for all workers.

[15] Given that the economic activity categories relating to electricity do not provide any information on the means of generation, the treated category includes both workers in economic activities relating to conventional energy, as well as those in renewables. If one considers workers who in 2014 were employed in firms developing and utilizing renewable resources to not be negatively affected by the policy in question, the baseline results could be interpreted as a lower bound on workers in the supply-chain of coal.

anticipate this policy announcement before 2015 and therefore did not take any action to reallocate to different jobs or firms, either within or outside the electricity industry, or otherwise adjust their labor market behavior and (b) that there are no other time-varying shocks that differentially affect workers based on treatment status. In other words, in absence of this policy announcement, and conditioning on the outcomes of the two groups having evolved in a parallel fashion prior to 2014, this parallel trend would have persisted beyond that date.

Hence, and in order to corroborate the second assumption outlined above, I also employ the equivalent dynamic version of Equation 1, where I interact the treatment with time dummies, as opposed to looking at the simple difference-in-differences specification. More specifically, I utilize the following specification for the period between 2009 and 2019:

$$\log y_{idst} = \alpha + \sum_{t \neq 2014} \beta_t \cdot I_{ids} \cdot D_t + \sum_{t \neq 2014} \kappa_t \cdot D_t + age^2_{idst} + \Gamma[X'_{ds} \times t] + [\rho_s \cdot \kappa_t] + \phi_{ids} + \varepsilon_{idst} \tag{2}$$

As can be seen in Equation 2, the omitted time period is 2014, which serves as the baseline period relative to which any change is measured.

Furthermore, to alleviate concerns that the difference-in-differences estimates resulting from Equations 1 and 2 might be capturing more general trends affecting the electricity sector in Germany, I proceed to estimate a triple difference-in-differences specification, comparing workers along three dimensions. Namely, utilizing the same cutoff for the introduction of the legislation, as well as the industry of work at baseline, as before, I also introduce a continuous variable for the share of electricity generated by coal in each region. For regions without coal plants, this would take a value of 0, and workers in those districts would serve as pure controls. For districts containing coal plants, the variable would take value between 0 and 1, proxying for the dependence of the district on coal-fired power generation. Hence, in contrast to Equations 1 and 2 that only include treated districts, Equations 3 and 4 are estimated on the full sample, including all 400 districts. Hence, I estimate the following regression:

$$\begin{aligned} \log y_{idst} = \alpha + \beta_2 \cdot C_{ds} \cdot I_{ids} \cdot \mathbb{1}_{t \geq 2015} + \gamma_2 \cdot I_{ids} \cdot \mathbb{1}_{t \geq 2015} + \delta_2 \cdot C_{ds} \cdot \mathbb{1}_{t \geq 2015} \\ + \kappa_t + age^2_{idst} + \Gamma[X'_{ds} \times \kappa_t] + [\rho_s \cdot t] + \phi_{ids} + \varepsilon_{idst} \end{aligned} \tag{3}$$

Here, C_{ds} is the pre-policy coal reliance of each district, while all other variables remain the same. As before, I proceed to also estimate the dynamic version, as follows:

$$\begin{aligned} \log y_{idst} = \alpha + \sum_{t \neq 2014} \beta_{2t} \cdot C_{ds} \cdot I_{ids} \cdot D_t + \sum_{t \neq 2014} \gamma_{2t} \cdot I_{ids} \cdot D_t + \sum_{t \neq 2014} \delta_{2t} \cdot C_{ds} \cdot D_t + \\ \sum_{t \neq 2014} \kappa_{2t} \cdot D_t + age^2_{idst} + \Gamma[X'_{ds} \times \kappa_t] + [\rho_s \cdot t] + \phi_{ids} + \varepsilon_{idst} \end{aligned} \tag{4}$$

In Equations 3 and 4 I compare the change in outcomes of electricity sector workers relative to other workers before and after the introduction of the coal phase-out legislation, across districts with varying pre-policy coal reliance. The coefficient β_{2t} on the triple interaction captures how much more (or less) affected electricity workers were in regions that were more coal-intensive prior to the policy. The identification assumption here is that, absent the legislation, the difference in outcome trends between electricity and non-electricity workers would not have systematically differed across districts with different initial coal intensities. In other words, there were no other shocks correlated with coal intensity that differentially affect electricity workers after the policy, aside from the coal phase-out itself.

Figure A.3 of the Appendix presents the predictors of the presence of a coal plant, as well as of the coal share in electricity in 2014 (mapping to the third dimension added in Equations 3 and 4). As can be seen, the share of coal in a region is significantly predicted by the age profile of workers, as well as by the share of workers in electricity. Both of those predictors are included as controls.

4.B Effect of plant closures and transition probabilities

Lastly, it is important to stress that the policy was not adopted by all districts at the same time. As we have different plants exiting at different points in time after 2014, either to enter the reserve or retiring altogether, the adoption of the policy was staggered. However, the above specification aims to estimate the impact of the announcement of the policy, as opposed to the direct impact of the closures themselves. The announcement was a strong signal that the national German energy policy is taking drastic steps towards phasing out the generation of electricity from coal, hence companies and workers started to take actions to hedge their risk exposure directly after the announcement (as mentioned in Section 2, the official legislation was not passed until 2020.)

Therefore, I employ a third approach looking into the effects of the plant closures themselves. Here, I only keep the districts that contain only plants that eventually closed (i.e. I drop districts with operational plants, reserve plants, or without any plants) and compare the evolution of the outcomes of interest relative to the timing of the closure of the first plant in the district for workers in treated versus non-treated industries. Given that the closures were arguably anticipated, I only utilize this approach to provide suggestive evidence on the labor market trajectories of workers to different industries, firms, or occupations. The specification I estimate is as follows:

$$y_{idst} = \alpha + \sum_{k \neq -1} \beta_{3t} \cdot \mathbb{1}\{t - T_d = k\} + \kappa_t + age^2_{idst} + \Gamma[X'_{ds} \times \zeta_t] + [\rho_s \cdot t] + \phi_{ids} + \varepsilon_{idst} \tag{5}$$

Where y_{idst} is either the average daily earnings or a transition probability $\mathbb{P}(\text{Separation})_{idst}$. Here, k indexes event time relative to the closure of the first coal-fired power plant in district d, defined as $k = t - T_d$, where t denotes calendar time and T_d is the year in which the first coal plant closure occurs in district d, taking values from -3 to 3, i.e. from three years before to three years after closure. Following standard practice in event study designs, I normalize the coefficient in the year immediately preceding closure ($t = -1$) to zero and use it as the reference period. Given the staggered timing of plant closures across districts, estimating dynamic effects using a traditional two-way fixed effects DiD estimator may lead to biased comparisons between treated units and units that have already been treated in the presence of heterogeneous treatment effects. I therefore estimate Equation 5 using the interaction weighted event study estimator of Sun and Abraham (2021), which constructs cohort-specific comparisons based on the timing of the first plant closure and identifies dynamic treatment effects by comparing treated workers in electricity and coal mining to workers in never-treated industries.

5 Effects of the policy announcement

5.A Overall effects

As a first step, I utilize different versions of Equations 1 and 3 to look at the average impact of the announcement on annual labor earnings, annual days in employment, average daily wages, and the probability of being unemployed for all affected workers. In my baseline estimates, I utilize a balanced panel of workers that are present in all periods. As a robustness, I estimate the effects in the full sample, an exercise described in Section 7. The results are presented in Figure 3. I progressively add controls in different specifications, while in my preferred specification, I control for person fixed effects, square age, baseline characteristics of the district interacted with time fixed effects, as well as state by time trends. Baseline characteristics include district-level GDP, share of electricity in employment, and share of manufacturing in employment.

Panel (a) of Figure 3 shows a sizable decline in annual labor earnings for workers in treated industries relative to controls. In the preferred specification, treated workers experience a reduction of about 8.6 percent compared to their baseline difference in 2014. This decline is stable across specifications as progressively richer sets of controls are added, and is slightly smaller in magnitude when using the triple-difference specification. Panel (b) shows that treated workers also experience a decline of 5.4 percent in annual days in employment, though the magnitude is more modest than for earnings, suggesting that reduced labor supply or employment interruptions account for only part of the earnings loss.

Panel (c) shows that average daily wages also decline following the announcement, pointing to a wage component of the adjustment rather than employment alone. The estimated effects are again stable across specifications and slightly smaller under the triple-difference design. Panel (d) complements these results by showing an increase in the probability of unemployment for treated workers, on the order of 1.2 percentage points relative to controls. Together, these patterns indicate that the announcement led to both lower wages and higher employment instability for workers in affected industries.

Finally, comparing the baseline difference-in-differences estimates to the triple-difference specifications highlights the role of local coal exposure. Across outcomes, estimates from the triple-difference design are consistently smaller in absolute value. This pattern is consistent with the policy shock operating through local labor market conditions rather than reflecting purely sector-wide trends.

Figure 3: Estimated effect of the policy announcement on workers

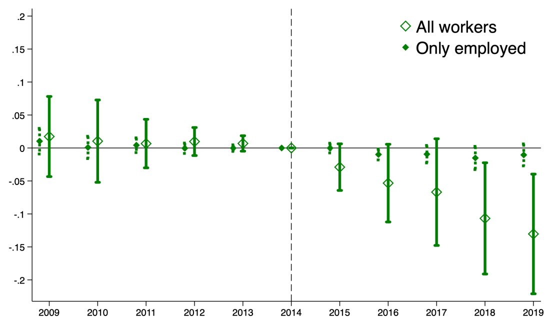
Notes: This figure reports coefficients of different versions of Equations 1 and 3, where the dependent variable is the log of total labor earnings, log of annual days in employment, log average daily wages, and probability of being unemployed for workers. The controls included in each regression are presented. Standard errors are clustered on the district level. Regression coefficients for all outcomes but the probability of being unemployed are reported using the transformation $\exp(\beta) - 1$ so as to represent a percentage difference between the changes in control and treatment relative to the baseline. The 90% confidence intervals are presented. Source: Own estimates based on the *Integrated Labour Market Biographies (IEB)*.

The estimates presented so far capture only the average effect of the policy announcement. I therefore turn to the dynamic triple-difference specification described in Equation 4, which allows a comparison of the evolution of outcomes between treated and control workers before and after the announcement, relative to the baseline year, and across districts with different baseline coal shares. To do this, I separate workers into two different groups, (a) all workers in my sample and (b) workers that remained employed throughout the time period, i.e. excluding those who went into unemployment at any point in time. Figure 4 reports the resulting coefficients for total labor earnings and days in employment.

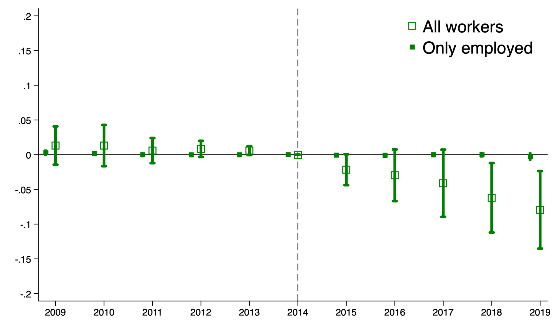
Prior to the announcement, outcomes evolve similarly across treated and control workers. In contrast, following the announcement, the two groups begin to diverge sharply. For workers who remained continuously employed, the decline in outcomes is smaller and recovers by the end of the sample period. When including workers who transition into unemployment, however, the effects are substantially larger and persist through 2019, indicating that employment separations play an important role in the adjustment process.

Figure 4: Estimated dynamic effect of the policy announcement on workers

(a) DDD Total labor earnings



(b) DDD Days in employment



Notes: This figure reports coefficients of a dynamic triple difference-in-differences regression based on Equation 4, where the dependent variable is the log of total labor earnings or annual days in employment. The regression includes all controls. Standard errors are clustered on the district level. Regression coefficients are reported using the transformation $\exp(\beta) - 1$ so as to represent a percentage difference between the changes in control and treatment relative to the baseline. The 90% confidence intervals are also plotted. Source: *Integrated Labour Market Biographies (IEB)*.

Figure A.5 reports similar dynamic estimates from a simple difference-in-differences specification estimated within affected regions, i.e. based on Equation 2. The simple difference-in-differences estimates shown in the appendix exhibit some pre-trends, which could partly reflect differential sectoral adjustment in the aftermath of the 2008–09 financial crisis. Existing evidence suggests that employment in Germany's export-oriented sectors, such as manufacturing, which is part of the control group in this analysis, experienced more pronounced employment and earnings volatility during that time. On the other hand, electricity and utilities were relatively less affected during this period (OECD, 2010; Rinne and Zimmermann, 2012; Dustmann et al., 2014). To the extent that these sector-specific dynamics persist during the pre-announcement period, they may generate spurious pre-trends in a simple difference-in-differences framework. The triple-difference specification addresses this concern by netting out sector-specific time shocks and differences in baseline exposure to coal. Consistent with this interpretation, the triple-difference estimates display flatter pre-trends and smaller, but more credible, post-announcement effects.

Taken together, the dynamic results indicate that the adverse labor market impacts of the announcement emerge only after 2014 and are driven both by reduced earnings of workers that transitioned to other establishments and by transitions into unemployment.

5.B Effects along the supply chain

One of the most interesting dimensions of the effects of environmental policies that push for the transition away from conventional fuels, is the effect along the supply chain. Figure 5 shows dynamic difference-in-differences estimates of the policy announcement's effects on workers in electricity and coal mining, for total labor earnings and days in employment, distinguishing between all workers and those continuously employed. Pre-announcement coefficients are close to zero in both industries, indicating parallel trends. After the announcement, statistically significant negative effects emerge in electricity, while estimates for coal mining are noisily estimated and not statistically significant throughout.

Figure 5: Estimated dynamic effect of the policy announcement on workers by industry

Notes: This figure reports coefficients of a dynamic triple difference-in-differences regression based on Equation 4, where the dependent variable is the log of total labor earnings or annual days in employment. The regression includes all controls. Standard errors are clustered on the district level. Regression coefficients are reported using the transformation $\exp(\beta) - 1$ so as to represent a percentage difference between the changes in control and treatment relative to the baseline. The 90% confidence intervals are also plotted. Source: *Integrated Labour Market Biographies (IEB)*.

The post-announcement decline in total labor earnings is driven by workers in the electricity sector. Earnings losses are larger and more persistent when all workers are included than when conditioning on continued employment, indicating that employment exits account for an important share of the adjustment. In contrast, although point estimates for coal mining are often negative, wide confidence intervals prevent rejecting zero effects, implying no statistically detectable impact in that sector over the period considered.

Results for days in employment point in the same direction. Electricity exhibits significant and sustained reductions in employment days, particularly in the full sample, whereas effects among continuously employed workers are zero. For coal mining, estimates remain statistically insignificant for both samples, suggesting limited detectable changes in employment duration. Overall, the figure indicates that the announcement's labor market effects are concentrated in electricity rather than coal mining.

5.C Heterogeneity based on worker characteristics

Figure 6 documents substantial heterogeneity in the impact of the policy announcement across workers. Here, I focus on average daily wages as the primary outcome, as this measure isolates changes in earnings conditional on employment and provides a clearer benchmark for assessing adjustment costs at the worker level. The figure reveals a clear pattern: the adverse effects are concentrated among groups with weaker attachment to the labor market or lower ex-ante resilience, while more established workers experience smaller and often statistically indistinguishable effects. Across all panels, estimates are generally negative, but both their magnitude and precision vary meaningfully with observable characteristics, offering insight into the channels through which the announcement affected workers' outcomes.

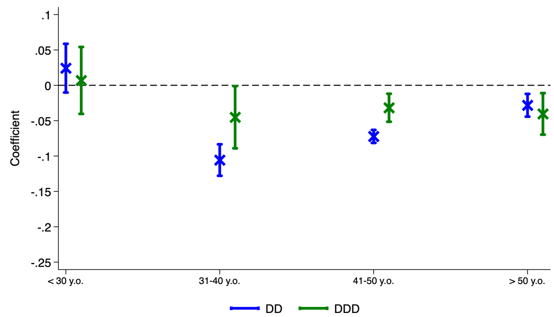
Starting with age in Panel (a), the negative effects are most pronounced for workers in the middle of the distribution. Those aged between 31 and 40 y.o. experience the largest declines, suggesting that they are particularly exposed to policy-induced uncertainty or adjustments. The effect attenuates steadily with age. Workers in their forties and above still experience losses, but of smaller magnitude.

Panel (b) shows the gradient by baseline educational level, or maximum educational attainment. Workers with lower educational attainment bear the largest negative impact, while the estimated effects become smaller as education increases. For the most educated groups, the coefficients are close to zero, indicating relative insulation from the announcement. This suggests that education operates as a buffer, either because higher-educated workers possess more transferable skills, are employed in segments of the sector less directly exposed, or face better outside options when firms adjust employment in response to policy signals.

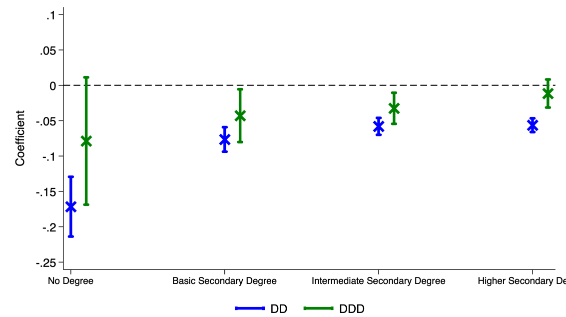
Panels (c) and (d) highlight the importance of tenure, both at the job and at the labor-market level. Workers with short job tenure experience negative effects, while those with longer tenure see substantially muted responses. The same pattern holds when tenure is measured more broadly as overall labor-market attachment: workers with limited cumulative experience are hit hardest, whereas long-tenured workers exhibit coefficients close to zero. This is consistent with firms adjusting primarily at the margin, by reducing hours, wages, or employment prospects for newer or less protected workers, rather than for incumbents with accumulated firm-specific human capital or stronger implicit contracts.

Figure 6: Heterogeneity in estimated effect of the policy announcement on workers

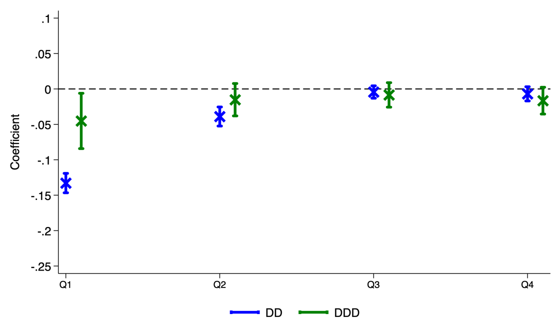
(a) By age bin



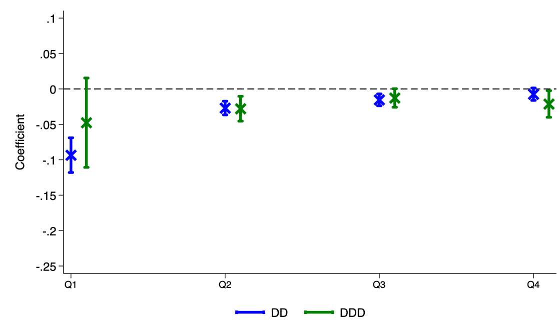
(b) By education level



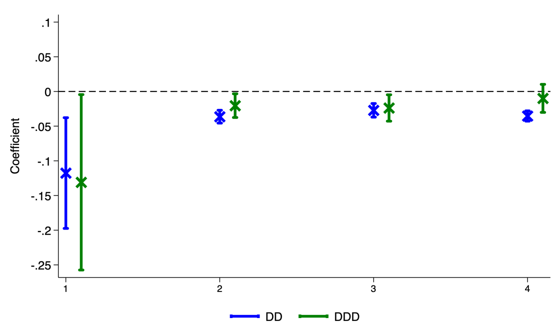
(c) By job tenure



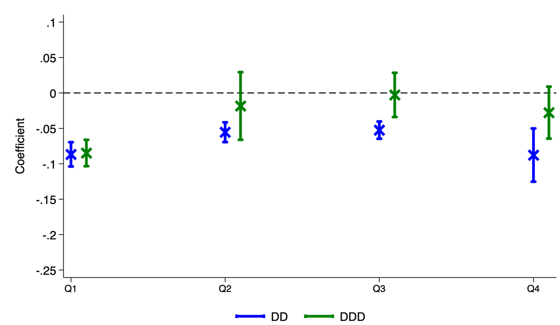
(d) By labor market tenure



(e) By experience level



(f) By population density



Notes: Panel (a): This figure presents heterogeneity by age bin at baseline. Panel (b): This figure presents heterogeneity by highest educational attainment at baseline. Panel (c): This figure presents heterogeneity by quartile of baseline job tenure. Panel (d): This figure presents heterogeneity by quartile of baseline labor market tenure. Panel (e): This figure presents heterogeneity by baseline experience requirement. This is one of the four experience level requirements reported in the Occupational Panel. Panel (f): This figure presents heterogeneity by quartile of baseline population density. This figure reports coefficients of a version of Equations 1 and 3, where the dependent variable is the log average daily wage for workers. All controls are included. Standard errors are clustered on the district level. Regression coefficients are reported using the transformation $\exp(\beta) - 1$ so as to represent a percentage difference between the changes in control and treatment relative to the baseline. The 90% confidence intervals are also plotted. Source: *Integrated Labour Market Biographies (IEB)*.

Panel (e) reinforces this interpretation by showing heterogeneity by experience level. The workers in occupations with the lowest experience level requirement face large declines, while the effects shrink markedly with experience requirement and eventually become negligible. Experience level appears to function as a form of insurance against policy-driven shocks, potentially reflecting both higher productivity and greater adaptability within firms. Finally, panel (f) shows that workers in low-density areas experience more negative effects than those in denser labor markets. In thicker labor markets, workers may find it easier to reallocate across firms or sectors, dampening the local impact of the announcement, whereas in sparsely populated areas adjustment costs are higher and outside options more limited.

Taken together, the figure paints a coherent picture: the policy announcement primarily affected workers who are middle-aged, less educated, in occupations with lower experience requirement, and more weakly attached to their jobs and local labor markets. The results are consistent with an adjustment process in which firms respond to anticipated policy changes by scaling back opportunities for such workers, while shielding more established employees. This heterogeneity provides intuition for why average effects may mask substantial distributional consequences and underscores that the short-run labor-market costs of policy announcements are borne disproportionately by workers with fewer buffers against economic change.

6 Plant closures and labor market trajectories

While the previous section focused on the effect of the policy announcement, such estimates mask potentially rich dynamics in workers' labor market outcomes around the actual closures of coal-fired power plants. To capture the timing and persistence of wage effects, I now turn to an event-study framework centered on the year of the first plant closure in a district. This approach allows me to trace the evolution of wages before and after closures, assess the presence of pre-trends, and distinguish short-run from medium-run adjustment patterns. I do that within the plant-closure event study framework using a version of Equation 5. Given that plant closures were anticipated, the usual event study identifying assumptions do not necessarily hold in this case. Hence, I only interpret the results of this section as suggestive of the mechanisms that might be driving the estimated results presented above.

6.A Impact on wages

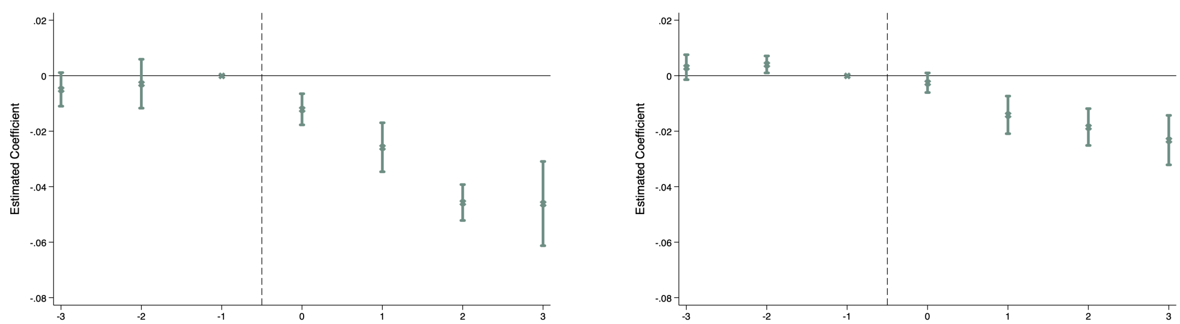
Figure 7 presents the estimated coefficients from an event-study specification around plant closures, separately for *leavers* in Panel (a) and *stayers* Panel (b). The horizontal axis denotes event time relative to the closure year, with the year immediately preceding closure omitted as the reference period. The vertical axis reports percentage changes in average daily wages, with 90% confidence intervals.[16]

[16] Wunder and Zeydanli (2021) utilize the Socio-Economic Panel to demonstrate that workers anticipate the effects of an imminent plant closure in the year before the actual closure date. This *lead effect* is expected to be particularly

In both panels, wages evolve similarly between treated and control workers prior to closure, with estimates close to zero and statistically insignificant, indicating no evidence of differential pre-trends. Following the closure, wages decline for both groups. Among *leavers*, wage losses emerge immediately and grow over time, reaching economically meaningful magnitudes of around 5% in the years after separation. *Stayers* also experience wage declines, though the magnitude is smaller, around 2%, and the adjustment appears more gradual.

Figure 7: Effect on wages after plant closures by separation status

(a) *Leavers* (b) *Stayers*



Notes. This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 5, where the dependent variable is the log average daily wage for workers. Regression coefficients are reported using the transformation $\exp(\beta) - 1$ so as to represent a percentage difference between the changes in control and treatment relative to the baseline. Standard errors are clustered on a district level. The 90% confidence intervals are also plotted. Source: *Integrated Labour Market Biographies (IEB)*.

These patterns highlight distinct mechanisms through which plant closures affect workers. For *leavers*, wage losses are consistent with displacement costs, including the loss of firm-specific human capital and potentially transitions into lower-paying jobs or sectors. For *stayers*, the negative effects operate within the firm, reflecting task reallocation, occupational downgrading, or reduced rents as remaining activities wind down, firms contract and reorganize during the shutdown process. The absence of pre-trends strengthens the causal interpretation, while the persistence of post-closure wage declines suggests that the adjustment costs of plant closures extend well beyond the immediate employment shock.

6.B Worker transitions

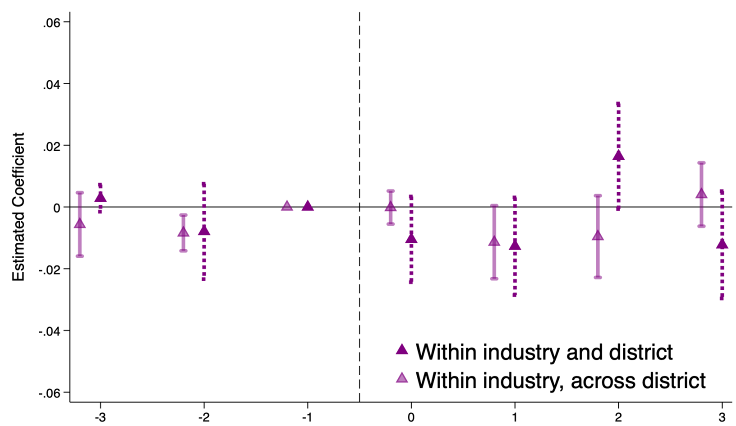
Therefore, I proceed to investigate worker transitions, by looking at the probability that a worker changes establishments from one year to the next, as well as the characteristics of those establishments. This is particularly relevant as it has been shown that large parts of wage losses in the German context generally can be attributed to employer characteristics, and more specifically to workers moving to lower-paying firms (Schmieder et al., 2023).

salient in the case of closures of plants generating electricity given the notice that operators have to provide to *BNetzA* a year before the closure. An alternative specification where $t = -2$ is used as the baseline yields similar results.

Figure 8 presents the probabilities of transitioning to a different establishment within the same industry and district, as well as across districts, within the same industry. I see no effects on the transitions to different districts, i.e. there is no apparent geographic reallocation.

However, transitions spike at the second year after the closure and are within the same industry and district, with an increase of about 2 p.p., compared to baseline. The equivalent event study for transitions across industries, both within the same district and across districts, is shown in Figure A.6 of the Appendix. I see no changes in separation rates towards different industries between control and treatment following the closure of a plant, suggesting that there is not much sectoral mobility, either.

Figure 8: Separation probabilities within the same industry



Notes. This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 5, where the dependent variable is the probability of separating from the establishment. The regression includes all controls. Standard errors are clustered on a district level. The 90% confidence intervals are also plotted. Source: *Integrated Labour Market Biographies (IEB)*.

In Table A.7 of the Appendix, I also present the reasons for termination for the two groups of workers in Figure 8 by relative time to the first closure of a plant in the district. These reasons only concern workers in treated industries that moved to a different firm either within the same district or to a different district, staying in the same industries. The bulk of reasons refer to annual notifications provided by firms to the *Employment Agency*. However, it is evident that, particularly for workers staying within the same industry and district, there is a spike in the share of employment terminations in the first year after the plant closure, in line with the spike that I observe in the transitions to different firms.[17]

While there is a negative effect in terms of daily wages for affected workers, the results presented in Figure 8 seem to point to a direction that contradicts what the environmental literature has traditionally documented for the case of environmental policy. Usually, environmental pol-

[17] The reason for termination appears in the year before the transition is realized, i.e. in the year before the spike is apparent in the corresponding event study. It is plausible to assume that transitions in $t+1$ are induced by the closure itself. Unfortunately, I have no further visibility as to the reason leading to the termination, i.e. whether these were voluntary or not.

icy induces sectoral reallocation of workers as a result of job loss towards sectors of the economy that are less affected (Walker, 2013; Castellanos and Heutel, 2023). Given that in the case of the German coal phase-out policy I observe both *stayers* and *leavers* being negatively affected (albeit differentially) and *leavers* mainly remaining within electricity and mining, I proceed to explore the labor market trajectories of *leavers*, following plant closures.

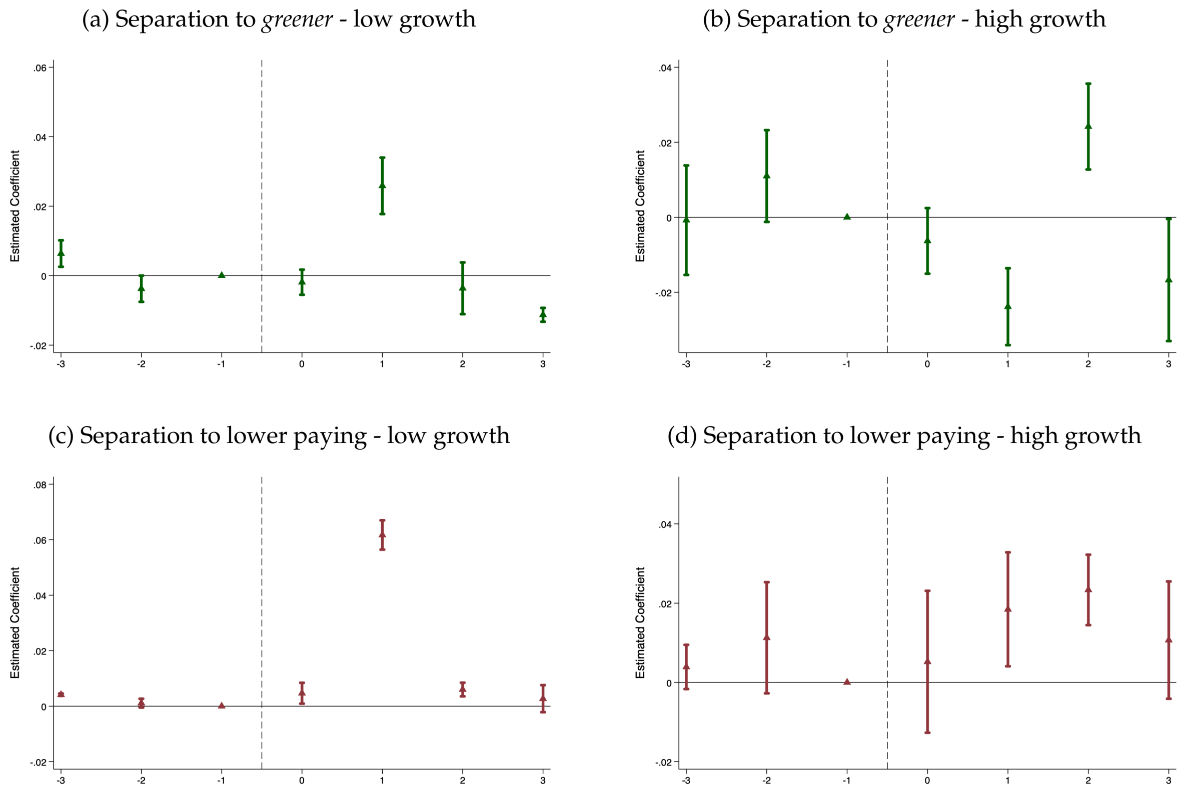
Specifically, I turn to the role of renewables in absorbing workers. Since I have no information on the specific activity of a firm within electricity, I use the *greenness* of a firm as a proxy for that. This is calculated using the *Greenness of jobs Index (GOJI)* developed by Janser (2019). Each occupation is assigned a *greenness* index, which is based on a combination of the occupation and the tasks associated with it. The index is published as part of the *German Occupational Panel* (Bachmann et al., 2024; Janser, 2024; Institue for Employment Research, 2024). Utilizing *GOJI*, I compute the mean *greenness* of firms and estimate whether workers tend to move to firms with a higher share of *green* occupations at baseline.

Panels (a) and (b) of Figure 9 show the probability that workers move to *greener* firms, separately for areas that experienced below median growth of *green* installations in the period following the policy and above, respectively. As can be seen in Panel (a), areas with below median growth see transitions to *greener* firms right after plant closures, consistent with the fact that those areas had already larger shares of installed *green* capacity, as presented in Figure 2. These early *green* transitions coincide with a temporary increase in moves to lower-paying firms, which then dissipates as the immediate adjustment phase ends, as shown in Panel (c).

As renewable expansion progresses in above median growth districts, they are able to absorb more workers in *green* firms, as shown in Panel (b). Hence, by the second year after closure, workers are more likely to transition into *green* firms located in areas with stronger *green* growth. These later transitions are associated with a smaller but persistent probability of moving to lower-paying firms, as shown in Panel (d) indicating a more stable reallocation pattern once *green* capacity has scaled up.

Together, these results suggest that renewable capacity affects the timing and persistence of post-closure reallocation rather than eliminating adjustment costs altogether. Early transitions into *greener* firms occur where *green* capacity already exists and are associated with moves to lower-paying firms. In contrast, as *green* installations expand in high-growth districts, workers increasingly reallocate toward *greener* firms in these areas, with effects on the probability of moving to lower-paying firms that are smaller in magnitude but more persistent. This highlights that renewable expansion shapes where and when workers are absorbed following plant closures, with lasting implications for their firm matches.

Figure 9: Separation probabilities by type of establishment



(a) Separation to *greener* - low growth

(b) Separation to *greener* - high growth

(c) Separation to lower paying - low growth

(d) Separation to lower paying - high growth

Notes. This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 5, where the dependent variable is the probability of separating from the establishment. The regression includes all controls. Standard errors are clustered on a district level. The 90% confidence intervals are also plotted. Source: *Integrated Labour Market Biographies (IEB)*.

7 Robustness and threats to identification

7.A Robustness exercises

I carry out three exercises to ensure the robustness of my results. First, I estimate my baseline results utilizing the unbalanced version of the panel of workers, i.e. not imposing the restriction that only workers that appear in all periods are retained. Figure A.7 presents the results for both annual labor earnings and annual days in employment. The estimates in the full sample are slightly larger, which is expected, given that this sample includes workers who move in and out of the labor force, but the overall story is unchanged. The close match between the two sets of results suggests that the findings are not affected by people entering or leaving the sample, but instead reflect the actual effect of the policy on workers' employment trajectories.

Second, to ensure that the control group is not contaminated by industries that are themselves indirectly exposed to the policy, I re-estimate the dynamic specification after excluding all "adjacent" industries, defined as those supplying more than 5% of inputs to coal or electricity generation based on Germany's 2011 Input-Output matrix, presented in Table A.6. These upstream sectors could plausibly adjust employment or wages in response to the phase-out, which would blur the contrast between treated and control workers. After removing them, however, the results remain virtually unchanged both for earnings and days worked, as can be seen in Figure A.8. This confirms that the main effects are not driven by spillovers into closely linked supplier industries, and that the control group used in the baseline analysis provides a clean counterfactual.

Third, as a falsification test, I assign "treatment" to workers in heavy industries, which are not actually affected by the policy, and re-estimate the full dynamic triple difference-in-differences specification excluding workers in electricity and mining.[18] In this placebo setting, the coefficients are effectively zero throughout the entire pre- and post-period, with no discernible trend break around the announcement date, as can be seen in Figure A.9. The flat estimates confirm that the empirical strategy does not mechanically generate negative effects in unrelated sectors, and that the identification is not driven by nationwide shocks that coincidentally line up with the timing of the policy. This strengthens the interpretation that the documented declines in the main analysis are indeed specific to the workers affected by the coal phase-out announcement, rather than an artifact of model structure or broader macroeconomic dynamics.

7.B Threats to identification

Back in 2015, Germany introduced a minimum wage for the first time. The minimum wage was set at EUR 8.50, effectively impacting approximately 15% of workers who, before January 2015, used to earn below this threshold. The impacts of the introduction of a minimum wage have been extensively studied, showing that there was an increase in regular, at the expense of marginal, employment, with minimal net effects, while it increased earnings, with workers moving to higher-paying and larger establishments (Garloff, 2017; Bruttel, 2019; Caliendo et al., 2020; Dustmann et al., 2022; Bossler and Schank, 2023).

While the timing of the introduction of the minimum wage almost coincides with the introduction of the coal phase-out policy, I do not expect this to differentially affect workers in electricity and mining versus other workers. One potential implication of the introduction of the minimum wage is that heterogeneous effects for lower paying and/or lower skill workers due to the policy introduction might have been mitigated by it, in which case they could be interpreted as a lower bound. However the validity of the main results of the paper should not be impacted by the minimum wage legislation.

Unfortunately, the *IEB* dataset does not allow me to observe hourly wages in order to directly look at affected workers. Rather, I am only able to observe average daily wages. Figure A.10 shows the distributions of average daily wages for control and treatment industries, i.e. electricity and coal mining versus the rest, along with the cutoff of EUR 68 per day (i.e. the equivalent of

[18] Heavy industries here include Manufacturing, Construction, and Water supply, sewerage, and waste management and remediation activities.

the minimum wage introduced multiplied by 8 hours per day for full-time workers). As it can be seen, the shares of the distributions below the threshold remained fairly constant, with no sharp discontinuity after the introduction around this cutoff. This suggests that the minimum wage did not differentially impact the two groups in a significant way.

8 Final remarks

The *green* transition of the electricity industry is the backbone of the fight to limit global GHG emissions and combat climate change. Phasing out electricity generation from coal is pivotal in this effort, especially for countries like Germany which have historically heavily depended on coal to power their economies. However, this transition, and the process of phasing out coal plants, need to take into account the potential adverse effects for workers.

In 2016, Germany codified the coal phase-out policy, which came into full effect with the relevant legislation in 2020. In this paper, I estimate the causal impact of the first announcement on workers who were directly affected. By comparing them to their counterparts who worked in other industries at baseline, and across districts with differential dependence on coal, I find a significant negative effect on wages and days in employment. Additionally, I observe an increase in the probability of being unemployed. I show that workers in downstream economic activities were more severely affected. Moreover, the effects were concentrated among middle-aged and less-educated workers, those with shorter job and labor-market tenures, and workers in occupations requiring lower experience levels. Lastly, workers separating from their establishments experienced larger wage losses compared to those staying, and transitioned into *greener* but lower-paying establishments.

Since 2020, a comprehensive package has been passed into law, accelerating the phase-out and providing financial resources to affected workers; The results of this paper can inform legislators and stakeholders as to the optimal ways to allocate those funds, particularly towards *green* investments and worker re-training, in order to minimize the transitional costs.

References

Arenas-Arroyo, E., Fabian, J., Mengel, F., Schmidpeter, B., and Serafinelli, M. (2025). Demand for green skills in an evolving landscape. Discussion Paper 63/25, RFBerlin.

Bachmann, R., Janser, M., Lehmer, F., and Vonnahme, C. (2024). Disentangling the greening of the labour market: The role of changing occupations and worker flows. Work in progress – Please do not cite or circulate, 12 February 2024.

Barreto, C. et al. (2024). The "clean energy transition" and the cost of job displacement in energy-intensive industries. OECD Social, Employment and Migration Working Papers 310, OECD Publishing, Paris.

Black, D., McKinnish, T., and Sanders, S. (2005). The economic impact of the coal boom and bust. *The Economic Journal*, 115(503).

Black, D. A., McKinnish, T. G., and Sanders, S. G. (2002). The economic impact of the coal boom and bust. *The Economic Journal*, 115(503):449–476.

Black, D. A., McKinnish, T. G., and Sanders, S. G. (2003). Does the availability of high-wage jobs for low-skilled men affect welfare expenditures? evidence from shocks to the steel and coal industries. *Journal of Public Economics*, 87(9-10):1921–1942.

Bossler, M. and Schank, T. (2023). Wage inequality in germany after the minimum wage introduction. *Journal of Labor Economics*, 41(3):267–328.

Bowen, A., Kuralbayeva, K., and Tipoe, E. L. (2018). Characterising green employment: The impacts of 'greening' on workforce composition. *Energy Economics*, 72:263–275.

Bruttel, O. (2019). The effects of the new statutory minimum wage in germany: A first assessment of the evidence. *Journal for Labour Market Research*, 53:10.

Bundesnetzagentur (2024). Kraftwerksliste – erzeugungseinheiten in deutschland (netto-nennleistung $\geq$ 10 mw). https://www.bundesnetzagentur.de/DE/Fachthemen/ElektrizitaetundGas/Versorgungssicherheit/Erzeugungskapazitaeten/Kraftwerksliste/start.html. Accessed: 2024-01-01.

Caliendo, M., Olthaus, R., and Pestel, N. (2020). Long-term employment effects of the minimum wage in germany: New data and estimators. *Labour Economics*, 66:102648.

Castellanos, K. and Heutel, G. (2023). Unemployment, labor mobility, and climate policy. *Journal of the Association of Environmental and Resource Economists*, Forthcoming.

Causa, O., Nguyen, M., and Soldani, E. (2024). Lost in the green transition? measurement and stylized facts. OECD Economics Department Working Papers 1796, OECD Publishing, Paris.

Center for Climate and Energy Solutions (2019). Global emissions. https://www.c2es.org/content/international-emissions/, Last accessed on 2023-08-18.

Chateau, J., Bibas, R., and Lanzi, E. (2018). Impacts of green growth policies on labour markets and wage income distribution: A general equilibrium application to climate and energy policies. OECD Environment Working Papers 137, OECD Publishing, Paris.

Clean Energy Wire (2020). IG BCE - Trade Union for mining, chemicals and energy industries. https://www.cleanenergywire.org/experts/ig-bce-trade-union-mining-chemicals-and-energy-industries. Available online: https://www.cleanenergywire.org/experts/ig-bce-trade-union-mining-chemicals-and-energy-industries. Accessed on January 1, 2024.

Clean Energy Wire (2023). Coal in germany. Retrieved from https://www.cleanenergywire.org/factsheets/coal-germany.

Climate Watch (2022). Global historical emissions. https://www.climatewatchdata.org/ghg-emissions?end_year=2021&start_year=1990, Last accessed on 2023-08-18.

Colmer, J., Lyubich, E., Krause, E., and Voorheis, J. (2024). Transitional costs and the decline of coal: Worker-level evidence. Working Paper.

Consoli, D., Marin, G., Marzucchi, A., and Vona, F. (2016). Do green jobs differ from non-green jobs in terms of skills and human capital? *Research Policy*, 45(5):1046–1060.

Curtis, M. E. and Lee, J. M. (2019). When do environmental regulations backfire? onsite industrial electricity generation, energy efficiency and policy instruments. *Journal of Environmental Economics and Management*, 96(3).

Curtis, M. E. and Marinescu, I. (2023). Green energy jobs in the us: What are they, and where are they? *Environmental and Energy Policy and the Economy*, 4(1).

Curtis, M. E., O'Kane, L., and Park, J. (2024). Workers and the green-energy transition: Evidence from 300 million job transitions. *Environmental and Energy Policy and the Economy*.

Dechezleprêtre, A., Hemous, D., and Sølvsten, M. S. (2021). Labour market transitions to a greener economy. Accessed: 2025-01-11.

Dechezleprêtre, A. and Sato, M. (2017). The impacts of environmental regulations on competitiveness. *Review of Environmental Economics and Policy*, 11(2):181–360.

Dustmann, C., Fitzenberger, B., Schönberg, U., and Spitz-Oener, A. (2014). From sick man of europe to economic superstar: Germany's resurgent economy. *Journal of Economic Perspectives*, 28(1):167–188.

Dustmann, C., Lindner, A., Schonberg, U., Umkehrer, M., and vom Berge, P. (2022). Reallocation effects of the minimum wage. *The Quarterly Journal of Economics*, 137(1):267–328.

E3G (2018). Why are german coal workers so powerful when there are so few? https://www.e3g.org/publications/why-are-german-coal-workers-so-powerful-when-there-are-so-few1/.

Energiewende Global (2023). Analysis of the historical structural change in the german hard coal mining ruhr area. Retrieved from https://energiewende-global.com/wp-content/uploads/2023/05/Analysis_of_the_historical__structural_change_in_the_German_hard_coal_mining_Ruhr_area.pdf.

Energy Charts (2025). Interactive charts for power generation, consumption, renewables, and more. https://www.energy-charts.info/. Accessed: 25 Dec 2024.

European Commission (2021). The just transition mechanism: making sure no one is left behind. https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal/finance-and-green-deal/just-transition-mechanism_en, Last accessed on 2023-08-18.

European Commission (2023a). Retirement and support packages for older workers in the eu coal sector - a briefing paper on european cases.

European Commission (2023b). Tracking breaches of the 1.5c global warming threshold. https://climate.copernicus.eu/tracking-breaches-150c-global-warming-threshold, Last accessed on 2023-08-18.

Fabra, N., Gutiérrez, E., Lacuesta, A., and Ramos, R. (2024). Do renewable energy investments create local jobs? *Journal of Public Economics*, 239:105212.

Federal Government of Germany (2020). The roadmap for the coal phase-out is set. https://www.bundesregierung.de/breg-de/service/archiv/einigung-zum-kohleausstieg-1712888. Accessed: January 3rd, 2024.

Federal Ministry for Economic Affairs and Climate Action (BMWK) (Accessed 2024). Electricity grids of the future.

Federal Ministry for Economic Affairs and Energy (2014). An electricity market for germany's energy transition (green paper). http://www.pfbach.dk/firma_pfb/gruenbuch-gesamt-englisch_oct_2014.pdf, Last accessed on 2024-01-03.

Federal Ministry for Economic Affairs and Energy (2015). An electricity market for germany's energy transition (white paper). https://www.bmwk.de/Redaktion/EN/Downloads/weissbuch-englisch.pdf?__blob=publicationFile&v=1, Last accessed on 2024-01-03.

Federal Ministry for Economic Affairs and Energy (2020). Energiewende direct - energy transition in germany. https://www.bmwk-energiewende.de/EWD/Redaktion/EN/Newsletter/2020/08/Meldung/direkt-account.html. Accessed: 2023-11-06.

Federal Ministry of Justice and Consumer Protection (2016). Electricity and gas supply act (energy industry act - enwg). https://www.gesetze-im-internet.de/enwg_2005/BJNR197010005.html. Accessed: January 15th, 2024.

Federal Network Agency (2015). Domestic grid reserve. https://www.bundesnetzagentur.de/EN/RulingChambers/Chamber8/RC8_07_Generation%20issues/71_Domestic%20grid%20reserve/71_Domestic%20grid%20reserve.html. Accessed: 2023-11-04.

Federal Network Agency (2021a). Coal phase-out under KVBG Act. https://www.smard.de/page/en/topic-article/5892/206022, Last accessed on 2023-06-19.

Federal Network Agency (2021b). Lignite closure. https://www.bundesnetzagentur.de/EN/RulingChambers/Chamber8/RC8_07_Generation%20issues/73_Lignite%20closure/73_Lignite%20closure.html.

Federal Network Agency (Accessed 2024). Systemrelevante kraftwerke.

Federal Office for the Safety of Nuclear Waste Management (2023). The nuclear phase-out in germany. https://www.base.bund.de/en/nuclear-safety/nuclear-phase-out/nuclear-phase-out_content.html., Last accessed on 2023-08-18.

Garloff, A. (2017). Side effects of the introduction of the german minimum wage on employment and unemployment: Evidence from regional data. Technical report, German Federal Ministry for Economic Affairs and Energy.

Garnache, C., Isaksen, E., and Nareklishvili, M. (2025). Employment and earnings losses in a green transition: Lessons from the oil industry. Unpublished manuscript.

German Federal Government (2010). Energy concept for an environmentally sound, reliable and affordable energy supply. https://cdn.climatepolicyradar.org/navigator/DEU/2010/energy-concept-for-an-environmentally-sound-reliable-and-affordable-energy-supply_ce0f139a23a921c29e1fdbdb92cdd36d.pdf. Accessed: January 3rd, 2024.

German Institute of Economic Research (2019). Phasing-out coal in the german energy sector.

Graf, T., Grießemer, S., Köhler, M., Lehnert, C., Moczall, A., Oertel, M., Schmucker, A., Schneider, A., Seth, S., Thomsen, U., and vom Berge, P. (2023). Weakly anonymous version of the sample of integrated labour market biographies (siab) – version 7521 v1. Technical report, Research Data Centre of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

Greenstone, M. (2002). The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 clean air act amendments and the census of manufactures. *Journal of Political Economy*, 110(6):1175–1219.

Görg Law Offices (2016). Das strommarktgesetz: Ein Überblick. https://www.goerg.de/de/aktuelles/veroeffentlichungen/07-07-2016/das-strommarktgesetz-ein-ueberblick. Accessed: Accessed: 2023-11-06.

Günther, J. and Haucap, J. (2014). The Structure and Development of Energy-intensive Industries in Germany. DIW Data Documentation 2014-072, Deutsches Institut für Wirtschaftsforschung (DIW Berlin).

Hafstead, M. A. and Williams, R. C. I. (2018). Unemployment and environmental regulation in general equilibrium. *Journal of Public Economics*, 160:50–65.

Hafstead, M. A. C. and Williams, R. C. I. (2019). Jobs and environmental regulation. NBER Working Paper 26093, National Bureau of Economic Research.

Hanson, G. H. (2022). Local labor market impacts of the energy transition: Prospects and policies. In *Economic Policy in a More Uncertain World*, pages 155–199. The Aspen Institute, Washington, DC.

Haywood, L., Janser, M., and Koch, N. (2024). The welfare costs of job loss and decarbonization: Evidence from germany's coal phaseout. *Journal of the Association of Environmental and Resource Economists*, 11(3).

Horbach, J. (2020). Impacts of regulation on eco-innovation and job creation. *IZA World of Labor*, (265).

Institue for Employment Research (2024). Vocational training: Occupations with green skills are in high demand. Accessed: 17 February 2025.

International Energy Agency (2022). Germany data explorer. https://www.iea.org/countries/germany, Last accessed on 2023-06-19.

International Energy Agency (2023). Germany - coal. Retrieved from https://www.iea.org/countries/germany/coal.

International Energy Agency (2025). Global energy crisis. https://www.iea.org/topics/global-energy-crisis. Accessed: 23 Dec 2024.

International Labour Organisation (2018). The transition in play: Worldwide employment trends in the electricity sector. https://www.ilo.org/wcmsp5/groups/public/---dgreports/---inst/documents/publication/wcms_625865.pdf, Last accessed on 2023-08-18.

International Renewable Energy Agency (2022). Renewable energy and jobs annual review 2022. https://www.ilo.org/wcmsp5/groups/public/---dgreports/---dcomm/documents/publication/wcms_856649.pdf, Last accessed on 2023-08-18.

Jacobson, L. S., LaLonde, R. J., and Sullivan, D. G. (1993). Earnings losses of displaced workers. *The American Economic Review*, 83(4):685–709.

Janser, M. (2019). *The greening of jobs: Empirical studies on the relationship between environmental sustainability and the labor market*. PhD thesis, Otto-Friedrich-Universität Bamberg.

Janser, M. (2024). Green and brown jobs in transition: Measuring ecological transition and decarbonization using the greenness-of-jobs index (goji). Mimeo.

Jofre-Monseny, J., Sanchez-Vidaly, M., and Viladecans-Marsal, E. (2018). Big plant closures and local employment. *Journal of Economic Geography*, 18:163–186.

Krause, E. (2023). Job loss, selective migration, and the accumulation of disadvantage: Evidence from appalachia's coal country. Working Paper.

Lehr, U., Lutz, C., and Edler, D. (2012). Green jobs? economic impacts of renewable energy in germany. *Energy Policy*, 47:358–364.

Marin, G. and Vona, F. (2019). Climate policies and skill-biased employment dynamics: Evidence from eu countries. *Journal of Environmental Economics and Management*, 98.

Morris, A. C., Kaufman, N., and Doshi, S. (2019). The risk of fiscal collapse in coal-reliant communities. Technical report, Columbia University SIPA and The Brookings Institution.

OECD (2010). Employment outlook 2010: Moving beyond the jobs crisis. Technical report, OECD.

Popp, D., Marin, G., Vona, F., and Chen, Z. (2021). The employment impact of a green fiscal push: Evidence from the american recovery and reinvestment act. *Brookings Papers on Economic Activity*.

Popp, D., Vona, F., Grégoire-Zawilski, M., and Marin, G. (2022). The next wave of energy innovation: Which technologies? which skills? CESifo Working Paper 9878, Center for Economic Studies and ifo Institute (CESifo), Munich.

Power Magazine (2015). Germany moves to idle coal plants, set up capacity reserve. https://www.powermag.com/germany-moves-to-idle-coal-plants-set-up-capacity-reserve/. Accessed: 2023-11-04.

Reuters (2015). Germany outlines plans for reserve power capacity-government paper. https://www.reuters.com/article/germany-powerplants/

germany-outlines-plans-for-reserve-power-capacity-government-paper-idUSL6N0W\P2QE20150323?edition-redirect=uk, Last accessed on 2023-06-19.

Reuters (2022). Winds of change shift germany's economic power northwards.

Reuters (2023). German power mix may get dirtier in 1st non-nuclear winter.

Rieder, A. and Schnabel, C. (2025). Beyond collective agreements: The rise of the wage cushion in germany. IZA Discussion Paper 18153, IZA – Institute of Labor Economics, Bonn, Germany.

Rinne, U. and Zimmermann, K. F. (2012). Another economic miracle? the german labor market and the great recession. *IZA Journal of Labor Policy*, 1(3).

Rud, J.-P., Simmons, M., Toews, G., and Aragon, F. (2024). Job displacement costs of phasing out coal. *Journal of Public Economics*, 236:105167.

Schmieder, J. F., von Wachter, T., and Heining, J. (2023). The costs of job displacement over the business cycle and its sources: Evidence from germany. *American Economic Review*, 113(5):1208–1254.

Stueber, H., Wolfgang, D., and Eppelsheimer, J. (2023). A guide to preparing the sample of integrated labour market biographies (siab, version 7519 v1) for scientific analysis. *Journal for Labour Market Research*, 57(7).

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.

Tyros, S., Andrews, D., and de Serres, A. (2023). Doing green things: skills, reallocation, and the green transition. OECD Economics Department Working Papers 1763, OECD Publishing, Paris.

U.S. Geological Survey (Accessed 2024). What are the types of coal?

Villani, D., Fernández-Macías, E., González-Vázquez, I., and Oshafi, V. (2026). The grey shades of green jobs: Unpacking the occupational approach to green employment. *Ecological Economics*, 240:108833. European Commission – Joint Research Centre, Seville, Spain.

Walker, R. (2013). The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce. *Quarterly Journal of Economics*, 128(4):1787–1835.

Walker, W. R. (2011). Environmental regulation and labor reallocation: Evidence from the clean air act. *American Economic Review*, 101(3):442–447.

Wolfgang, D. and Eppelsheimer, J. (2020). Preparing the sample of integrated labour market biographies (siab) for scientific analysis: a guide. *Journal for Labour Market Research*, 54(10).

Wunder, C. and Zeydanli, T. (2021). The early costs of plant closures: Evidence on lead effects on workers' subjective and objective outcomes. *Journal of Economic Behavior Organization*, 188:489–505.

Öko-Institut and Prognos (2017). Germany's Electric Future: Coal Phase-Out 2035. Technical report, WWF Germany / Öko-Institut / Prognos.

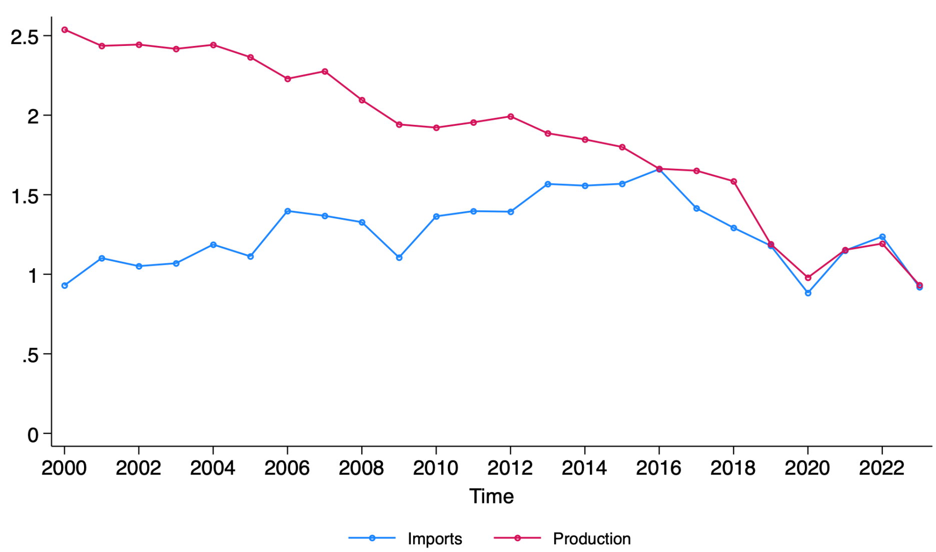
A Appendix

A.1 Background on the coal mining industry

Coal mining has historically been a crucial industry for Germany, as it produced the main input for the largest means of generating electricity in the country. After a gradual process of decline since the 1990s, the workforce employed in coal mines dropped by about 75% by 2003 (E3G, 2018). North Rhine-Westphalia and Saarland were the predominant coal regions, heavily relying on the mining industry. Back in 2007, the State Governments, along with the key stakeholders, made agreements to stop subsidizing *hard coal* mining in those regions, with the last two mines closing in 2018. Lignite mining, on the other hand, remains active, with mines still operating in the states of North Rhine-Westphalia, Brandenburg, Saxony, and Saxony-Anhalt. Unlike *hard coal*, lignite is extracted through opencast mining and continues to power nearby stations, though environmental concerns and political pressures have led to restrictions on expansion in recent years (Energiewende Global, 2023; Clean Energy Wire, 2023).

Figure A.1 shows the evolution of domestic production and imports of coal, combined for both types, since 2000. As can be seen, domestic production has been gradually declining, while imports gradually increased until 2016, substituting domestic production. Both sources of the raw material declined after 2016, which can be directly attributed to the policy in question. Additionally, there is a small spike following 2020, due to the crisis in the electricity market and the re-opening of several coal plants that had entered the reserve. However, as of the beginning of the policy, the total supply was evenly split between domestic sources and imports. This suggests that, while the coal mining industry was in decline, it still constituted a crucial component of electricity generation from coal in the country, supplying almost 50% of the needed raw material (International Energy Agency, 2023). Hence, ex-ante, I expect workers in coal mining to also face the costs of the phase-out. Therefore, I include them in my treated group and consider the effects across the supply chain of coal in the remainder of this paper.

Figure A.1: Coal supply over time (Million TJ)

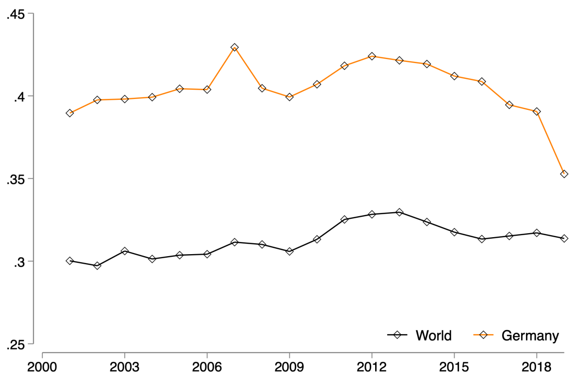


Notes: The red line shows the total domestic production of coal over time in Germany. The blue line shows total imports of coal over time from other countries. Source: Own rendering based on data from the *International Energy Agency (IEA)*.

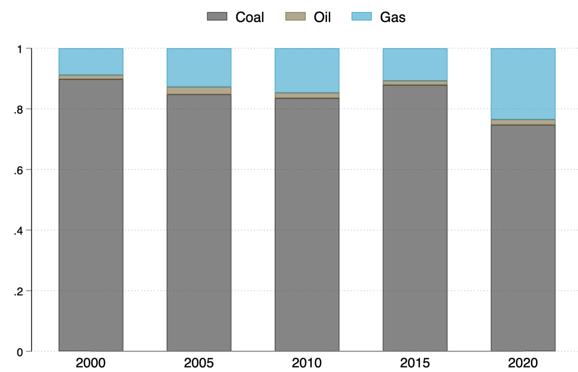
A.2 Descriptives on the electricity industry

Figure A.2: Sources of GHG emissions in Germany

(a) Share of electricity in total GHG emissions



(b) Share of GHG emissions from electricity by source



Notes: Panel (a): The gray line shows the total GHG emissions from electricity in the world as a share of overall GHG emissions. Equivalently, the orange line shows the share of GHG emissions as a share of overall emissions for Germany. Source: Own rendering based on data from *Our world in data*. Panel (b): The stacked bars show the share of coal, oil, and gas in total emissions from electricity in Germany. Source: Own rendering based on data from the *International Energy Agency (IEA)*.

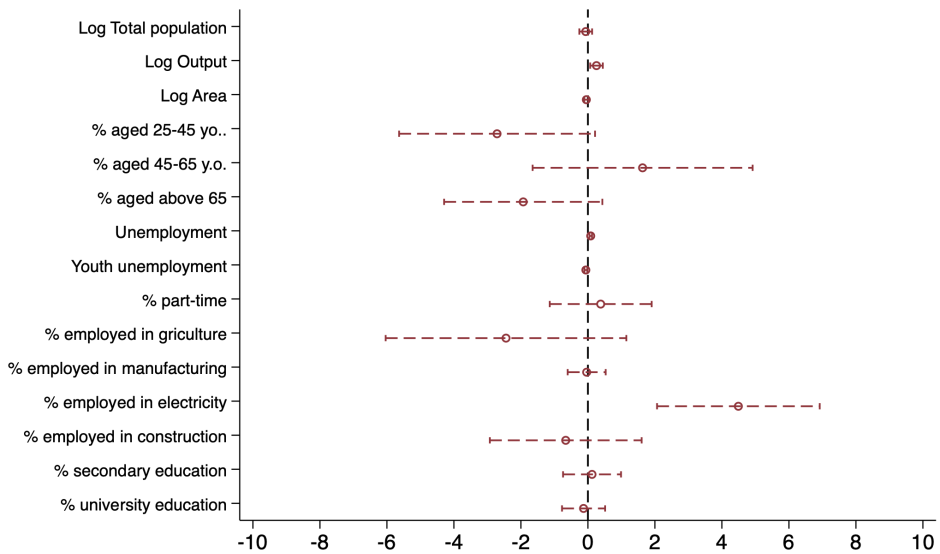
Table A.1: Summary statistics of coal plants in Germany as of 2024

	Lignite		Hard coal	
	Number	Capacity (MW)	Number	Capacity (MW)
Operational	51	390	92	222
Retired	31	152	58	265

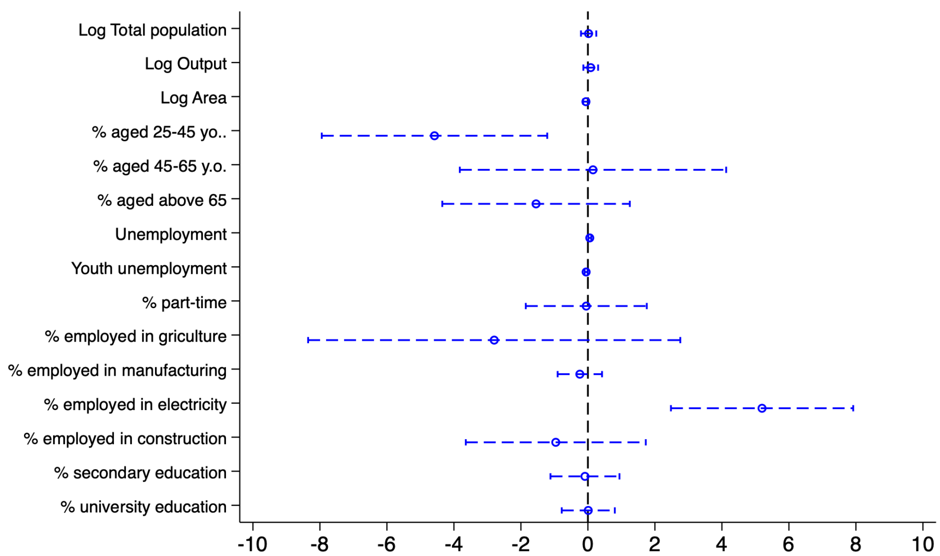
Notes: This table shows the number of generators and the mean capacity in Megawatts (MW) for operational and retired plants, split by lignite and hard coal in each case. These statistics only refer to plants with >10 MW of installed capacity. Source: *Federal Network Agency (BNetzA)*

Figure A.3: Predictors of dependence on coal

(a) Plant existence

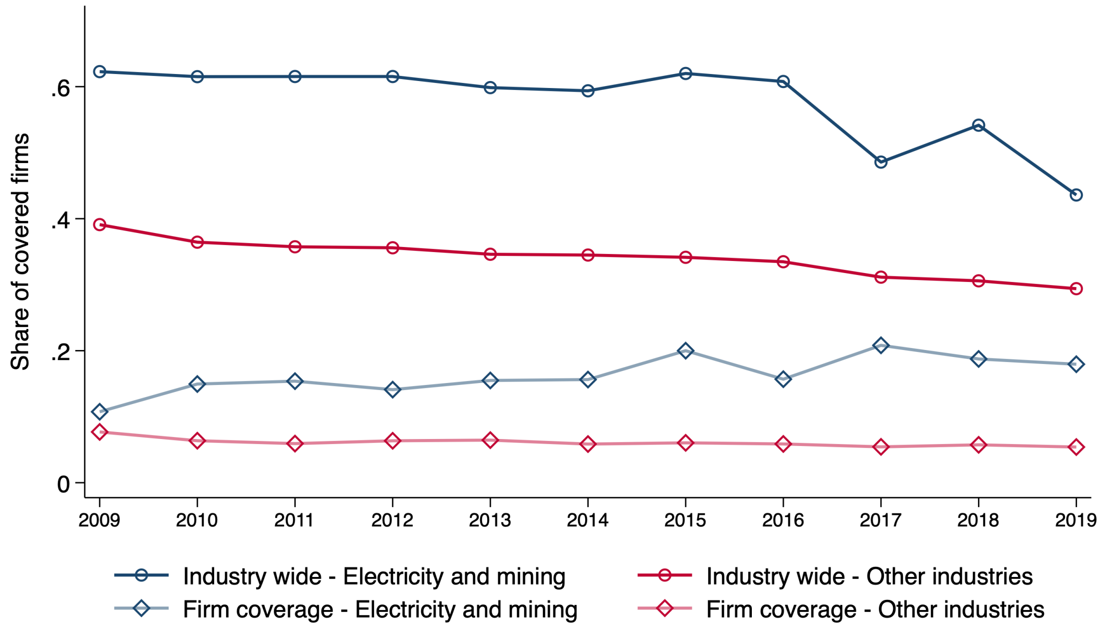


(b) Coal share



Notes: Panel (a) shows predictors of plant existence. Panel (b) shows predictors of coal share.

Figure A.4: Share of firms covered by collective agreements over time



Notes: This figure shows the shares of establishments covered by collective agreements over time. Source: Own elaboration based on the *Integrated Labour Market Biographies (IEB)*

A.3 Population characteristics

Table A.2: Demographic and educational characteristics

	Operational	**Coal** Closed	Mix	**Non-Coal**
Panel A: Demographic Characteristics				
Total population (Thousands)	376.07 (551.06)	372.63 (142.06)	325.27 (193.72)	169.75 (120.59)
Share of women	0.51 (0.01)	0.51 (0.00)	0.51 (0.00)	0.51 (0.01)
Share under 25	0.23 (0.03)	0.24 (0.01)	0.24 (0.02)	0.24 (0.03)
Share 25-45	0.25 (0.03)	0.25 (0.03)	0.24 (0.02)	0.24 (0.02)
Share 45-65	0.30 (0.03)	0.30 (0.03)	0.30 (0.03)	0.31 (0.02)
Share over 65	0.22 (0.03)	0.21 (0.02)	0.22 (0.02)	0.22 (0.02)
Observations	48	6	14	332
Panel B: Education				
No secondary degree	0.06 (0.03)	0.06 (0.02)	0.07 (0.02)	0.06 (0.02)
Secondary degree	0.15 (0.04)	0.18 (0.05)	0.16 (0.03)	0.18 (0.06)
Intermediate degree	0.43 (0.08)	0.39 (0.03)	0.41 (0.05)	0.46 (0.07)
Technical college entrance	0.02 (0.01)	0.03 (0.01)	0.03 (0.01)	0.01 (0.01)
University entrance	0.36 (0.08)	0.37 (0.03)	0.36 (0.05)	0.30 (0.09)
Observations	48	6	14	332

Notes: The table shows the demographic and educational characterization of the population in each type of coal plant-containing district (purely operational, purely closed, and a mix), as well as for control districts. The displayed information is for 2014, i.e. the baseline period in my sample. For some of the variables, information is not available for all districts, hence the discrepancy in the total number of observations. Source: Own elaboration based on data from the *Federal and State Statistical Office* of Germany.

Table A.3: Unemployment and part-time employment characteristics

	Coal			Non-Coal
	Operational	Closed	Mix	
Panel A: Unemployment				
Overall	8.56	10.03	10.70	6.56
	(3.25)	(2.88)	(3.44)	(2.97)
Overall for dependents	7.69	9.07	9.60	5.88
	(2.93)	(2.58)	(3.09)	(2.70)
Men	7.81	9.23	9.64	5.95
	(3.09)	(2.86)	(3.17)	(2.80)
Women	7.52	8.88	9.54	5.82
	(2.81)	(2.32)	(3.07)	(2.63)
Foreigners	16.37	20.52	20.88	13.09
	(5.91)	(5.38)	(6.77)	(5.45)
Youth unemployment	6.50	7.90	8.25	5.30
	(2.56)	(2.62)	(3.21)	(2.62)
Observations	48	6	14	332
Panel B: Employment by type				
Part-time German employees	0.26	0.25	0.26	0.26
	(0.03)	(0.04)	(0.03)	(0.03)
Part-time German women employees	0.45	0.45	0.46	0.47
	(0.04)	(0.03)	(0.03)	(0.04)
Part-time German men employees	0.09	0.09	0.09	0.08
	(0.03)	(0.03)	(0.02)	(0.02)
Part-time foreign employees	0.29	0.27	0.28	0.25
	(0.07)	(0.09)	(0.05)	(0.07)
Part-time foreign men employees	0.18	0.15	0.17	0.15
	(0.07)	(0.07)	(0.06)	(0.07)
Part-time foreign women employees	0.48	0.48	0.48	0.44
	(0.08)	(0.09)	(0.06)	(0.08)
Observations	48	6	14	332

Notes: The table shows the unemployment and part-time employment characterization of the population in each type of coal plant-containing district (purely operational, purely closed, and a mix), as well as for control districts. The displayed information is for 2014, i.e. the baseline period in my sample. For some of the variables, information is not available for all districts, hence the discrepancy in the total number of observations. Source: Own elaboration based on data from the *Federal and State Statistical Office* of Germany.

Table A.4: Employment characteristics

	Coal Operational	Coal Closed	Coal Mix	Non-Coal
Panel A: Total employment by category				
Total Germans (Thousand)	163.14	132.20	112.30	60.17
	(229.14)	(48.00)	(71.96)	(57.68)
German women (Thousand)	75.94	60.08	49.29	27.82
	(112.53)	(22.73)	(30.90)	(27.45)
German men (Thousand)	87.21	72.12	63.00	32.35
	(117.11)	(26.00)	(41.24)	(30.53)
Total foreigners (Thousand)	16.15	11.73	11.25	4.75
	(25.79)	(5.50)	(9.71)	(9.08)
Foreign women (Thousand)	6.52	4.17	3.91	1.78
	(11.06)	(2.11)	(3.54)	(4.01)
Foreign men (Thousand)	9.63	7.57	7.33	2.97
	(14.76)	(3.51)	(6.21)	(5.11)
Observations	48	6	14	332
Panel B: Employment share by industry				
Agriculture	0.01	0.00	0.01	0.01
	(0.01)	(0.00)	(0.01)	(0.01)
Manufacturing	0.20	0.25	0.18	0.25
	(0.09)	(0.14)	(0.05)	(0.10)
Mining, electricity, and waste	0.02	0.02	0.04	0.02
	(0.01)	(0.01)	(0.04)	(0.01)
Construction	0.05	0.04	0.05	0.07
	(0.02)	(0.01)	(0.03)	(0.02)
Trade, hospitality, and transport	0.22	0.21	0.25	0.22
	(0.06)	(0.03)	(0.05)	(0.04)
Information technology	0.03	0.02	0.02	0.02
	(0.03)	(0.01)	(0.01)	(0.02)
Finance and insurance	0.03	0.04	0.02	0.02
	(0.02)	(0.02)	(0.01)	(0.01)
Real estate	0.01	0.01	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)
Other	0.42	0.41	0.42	0.38
	(0.08)	(0.09)	(0.08)	(0.08)
Observations	48	6	14	332

Notes: The table shows the employment characterization of the population in each type of coal plant-containing district (purely operational, purely closed, and a mix), as well as for control districts. The displayed information is for 2014, i.e. the baseline period in my sample. For some of the variables, information is not available for all districts, hence the discrepancy in the total number of observations. Source: Own elaboration based on data from the *Federal and State Statistical Office* of Germany.

Table A.5: Worker characteristics by treatment status within districts containing a coal plant or mine in 2014

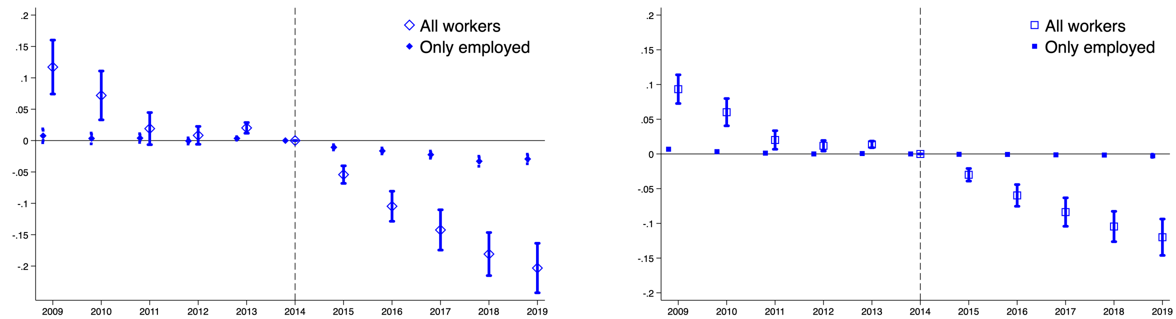
	Untreated industries	**Treated industries**
Share of sex	1.58	1.81
	(0.49)	(0.39)
Year of birth	1969.9	1,969.1
	(9.25)	(8.86)
School leaving qualification	3.35	3.34
	(0.51)	(0.49)
Overall tenure	7,234.43	8,445.66
	(3,179.01)	(3,201.02)
Job tenure	3,327.07	3,792.35
	(2,761.68)	(3,066,36)
$\mathbb{P}$ of separating from establishment	0.1	0.27
	(0.30)	(0.21)
Skill level	2.32	2.58
	(0.87)	(0.80)
Average daily earnings	103.06	168.45
	(61.07)	(38.93)
Annual Labor Earnings	36,959.04	61,204.05
	(22,569.31)	(14,410.02)
Annual Days Employed	322.13	363.01
	(109.93)	(14.34)

Notes: The table shows worker characteristics by treatment status within districts containing a coal plant or mine. The displayed information is for 2014, i.e. the baseline period in my sample. Sex takes a value of 1 for women and a value of 2 for men. School leaving qualification takes values between 1 and 9, with 1 being no lower secondary school qualification, and 9 being entrance qualification for University. Tenure is reported in days worked. Skill level takes values between 1 and 4 with 4 being the highest skill requirement for a job. Source: Own elaboration based on data from the *Integrated Labour Market Biographies (IEB).*

A.4 Main results and mechanisms

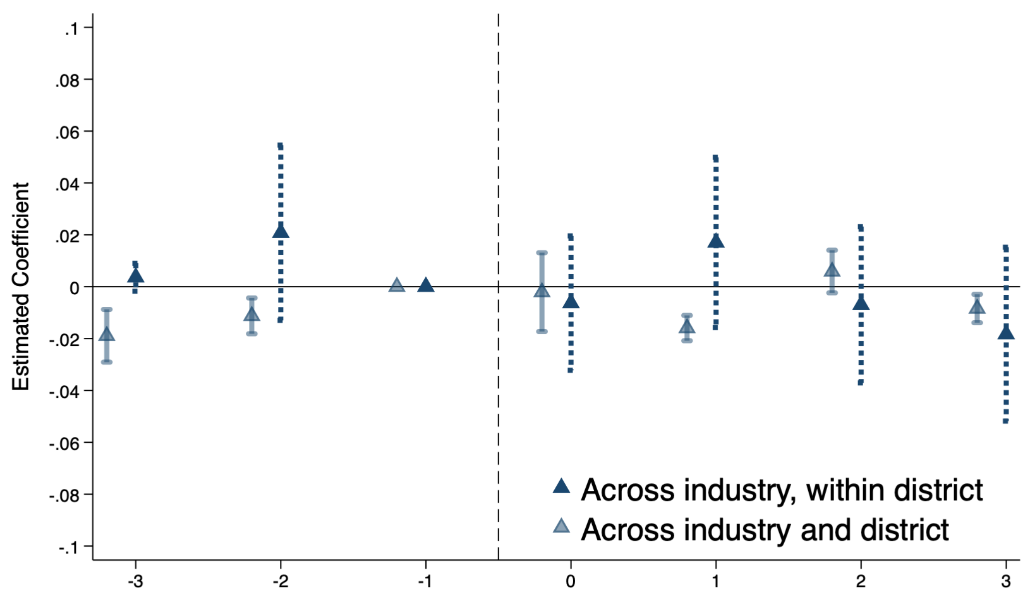
Figure A.5: Estimated dynamic effect of the policy announcement on workers - within affected regions

(a) DD Total labor earnings (b) DD Days in employment



Notes: This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 2, where the dependent variable is the log of total labor earnings or annual days in employment. The regression includes all controls. Standard errors are clustered on the district level. Regression coefficients are reported using the transformation $\exp(\beta) - 1$ so as to represent a percentage difference between the changes in control and treatment relative to the baseline. The 90% confidence intervals are also plotted. Source: *Integrated Labour Market Biographies (IEB)*.

Figure A.6: Separation probabilities across industries



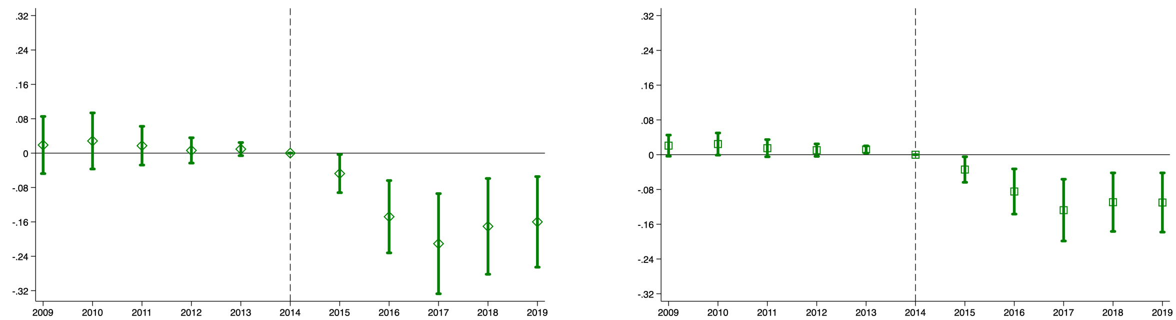
Notes. This figure reports coefficients of a dynamic difference-in-differences regression based on Equation 5, where the dependent variable is the probability of separating from the establishment. The regression includes all controls. Standard errors are clustered on the district level. The 90% confidence intervals are also plotted. Source: *Integrated Labour Market Biographies (IEB)*.

A.5 Robustness exercises

Figure A.7: Estimated dynamic effect of the policy announcement on workers - unbalanced panel

(a) DDD Total labor earnings

(b) DDD Days in employment



Notes: This figure reports coefficients of a dynamic triple difference-in-differences regression based on Equation 4, where the dependent variable is the log of total labor earnings or annual days in employment. The regression includes all controls. Standard errors are clustered on the district level. Regression coefficients are reported using the transformation $\exp(\beta) - 1$ so as to represent a percentage difference between the changes in control and treatment relative to the baseline. The 90% confidence intervals are also plotted. Source: *Integrated Labour Market Biographies (IEB)*.

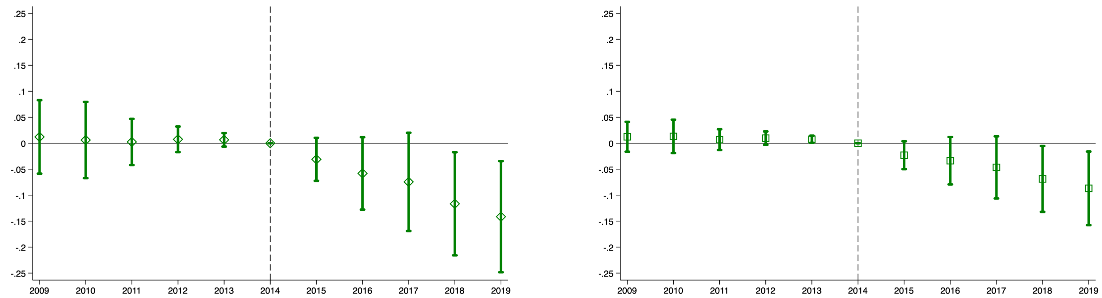
Table A.6: Input shares in coal and electricity generation

Supplier	**Share (%)**
Panel A. Coal	
Repair, maintenance, installation of machinery and equipment	45.25
Specialised construction works	8.89
Metal products	7.89
Metal ores, other mining and quarrying production services	4.61
Electric current, supply of electricity, steam, air conditioning	4.13
Wholesale trade services, except motor vehicles and motorcycles	4.09
Wood, cork, except furniture, articles of straw and plaiting materials	3.91
Investment, security, administrative and support services not elsewhere classified	1.67
Retail trade services, except motor vehicles and motorcycles	1.56
Legal, accounting, management consultancy services	1.41
Panel B. Electricity, steam, air conditioning	
Electric current, supply of electricity, steam, air conditioning	47.84
Public administration and defence services	12.30
Coal	8.07
Electrical equipment	3.23
Coke and refined petroleum products	3.11
Rental and leasing services	2.86
Repair, maintenance, installation of machinery and equipment	2.75
Specialised construction works	2.64
Manufactured gases and distribution services of gaseous fuels	2.27
Wholesale trade services, except motor vehicles and motorcycles	2.24

Notes: This table shows the shares of inputs in the industries of coal and electricity, for the top 10 contributors. Source: 2011 Input-Output table for Germany, provided by the *Federal Statistical Office*.

Figure A.8: Estimated dynamic effect of the policy announcement on workers - excluding adjascent industries

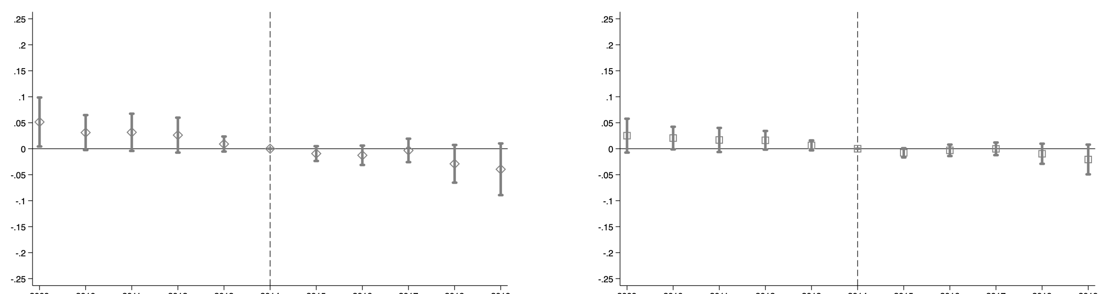
(a) DDD Total labor earnings (b) DDD Days in employment



Notes: This figure reports coefficients of a dynamic triple difference-in-differences regression based on Equation 4, where the dependent variable is the log of total labor earnings or annual days in employment. The regression includes all controls. Standard errors are clustered on the district level. Regression coefficients are reported using the transformation $\exp(\beta) - 1$ so as to represent a percentage difference between the changes in control and treatment relative to the baseline. The 90% confidence intervals are also plotted. Source: *Integrated Labour Market Biographies (IEB)*.

Figure A.9: Placebo exercise using heavy industry as treated

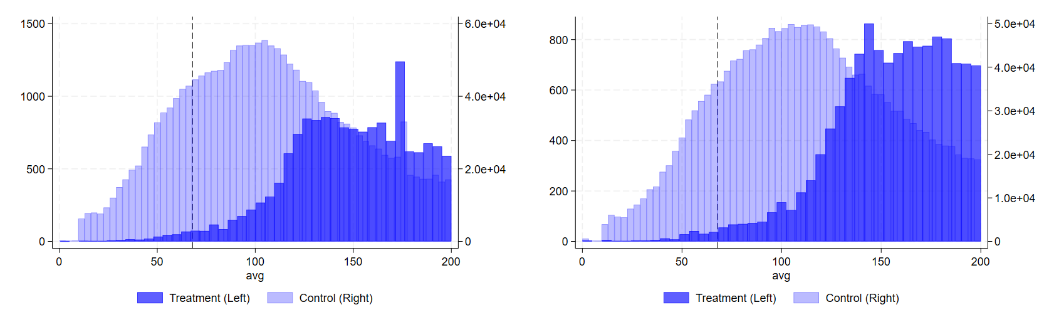
(a) DDD Total labor earnings (b) DDD Days in employment



Notes: This figure reports coefficients of a dynamic triple difference-in-differences regression based on Equation 4, where the dependent variable is the log of total labor earnings or annual days in employment. The regression includes all controls. Standard errors are clustered on the district level. Regression coefficients are reported using the transformation $\exp(\beta) - 1$ so as to represent a percentage difference between the changes in control and treatment relative to the baseline. The 90% confidence intervals are also plotted. Source: *Integrated Labour Market Biographies (IEB)*.

Figure A.10: Wage distributions by control and treatment over time

(c) Wage distribution 2014 (d) Wage distribution 2019



Notes: This figure reports the distributions of wages between EUR 0 and EUR 200 separately for control and treatment economic activities, as well as separately for years 2014 and 2019. Source: *Integrated Labour Market Biographies (IEB)*.

Table A.7: Termination reasons by year relative to first plant closure

Year relative to first closure	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**
Panel A: Leavers within district to same industry							
Deregistration due to end of employment	0.12	0.15	0.03	0.04	0.23	0.13	0.01
Deregistration due to change of health insurance company	0.02	0.01	0.01	0.02	0.02	0.01	0
Deregistration due to change of contribution group	0.02	0.03	0.03	0.02	0.03	0.02	0.05
Deregistration for other reasons	0	0	0	0	0	0.1	0
Deregistration due to change of payroll accounting system / currency changeover	0.08	0.04	0	0	0	0	0.01
Annual notification	0.76	0.76	0.91	0.90	0.70	0.81	0.91
Employment interruption notification due to entitlement to other compensation	0	0.01	0.01	0.01	0.1	0.2	0.02
Employment interruption notification due to parental leave	0	0	0	0.01	0	0	0
Special notification according to § 194 SGB VI	0	0	0	0	0	0	0
Panel B: Leavers within industry to different district							
Deregistration due to end of employment	0.06	0.18	0.14	0.04	0.12	0.26	0.05
Deregistration due to change of health insurance company	0.01	0.01	0.02	0.01	0.02	0.01	0.01
Deregistration due to change of contribution group	0.02	0.01	0.01	0.06	0.03	0.03	0.01
Deregistration for other reasons	0	0	0	0.1	0	0	0
Deregistration due to change of payroll accounting system / currency changeover	0.02	0.03	0	0	0.01	0	0
Annual notification	0.90	0.75	0.82	0.85	0.80	0.68	0.92
Employment interruption notification due to entitlement to other compensation	0	0.01	0	0.02	0.02	0.01	0
Employment interruption notification due to parental leave	0	0	0	0.01	0	0	0
Special notification according to § 194 SGB VI	0	0	0	0	0	0	0.01

Notes: This table presents the share of termination reasons by year relative to the first plant closure, for people who separated from their firms. Source: *Integrated Labour Market Biographies (IEB)*.

B Supplementary appendix

I Power plant dataset processing

2.A.I Plant pre-processing

The main information on power plants (*Kraftwrksliste*) is taken from the website of *BNetzA*, where all plants with installed capacity larger than or equal to 10 MW are reported (Bundesnetzagentur, 2024). This database is split into two groups, namely plants that are currently in operation and plants that have shut down. Below, I describe the steps I have followed to process and clean the plant databases, as well as to map plants to German Administrative Districts (*Kreise*).

I begin by cleaning and re-naming the variables of both databases. For the closed plants, I further split them in plants that closed before and after the end of my period of interest, i.e. 2019. To do so, I utilize the closure date variable and create two additional datasets. First, keeping only plants that closed before or in 2019, I create my closed plant database. Then, by keeping the rest of the plants reported by *BNetzA* as having closed after 2019, I create a database of additional operational plants. Therefore, I end up with three databases, one that contains fully operational plants, one with plants that remained operational throughout the time period of interest, and one that contains plants that closed before the end of my period of interest.

2.A.II Mapping plants to administrative districts

Beginning with the list of fully operational plants, I drop the observations that lack a city address, which refer generally to facilities with installed capacity of less than 10 MW. These are 164 observations out of a total of 2,026, while 2 of them relate to coal. This leaves me with 1,861 operational plants. There are a total of 146 additional operational plants and 114 closed plants, all of which have address information.

After that, I utilize the address fields (Street, Street Number, City, and State) to recover the plant coordinates through the Google Maps API. Using the coordinates, along with the 2019 shapefiles for Germany and the district code dictionary recovered from IAB IEB data, I map plants onto districts, based on whether or not they are contained into the district's polygon. Out of the operational plants, I recover coordinates for all but 2 hydropower plants which are at the German border, and which are subsequently not mapped to any district. Lastly, of the additional operational plants, 146 are mapped onto coordinates, and subsequently onto districts. The same is true for the 114 closed plants.

2.A.III Producing final plant datasets

Lastly, I produce three datasets that are subsequently used to create the treatment variable in the IEB panel. First, I create a dataset of baseline capacity by district, for all types of energy generation. For both the operational and the operational additional plants, I drop any plant that is either commissioned after 2013 or was not mapped onto a district in the process described above. For closed plants, I drop any plant that was either commissioned after 2013 or was closed before 2014. I then append the three datasets. This produces a database of 1,634 plants of all sources of electricity generation. Subsequently, I collapse the total installed capacity by district and energy source. Based on that, I produce a dataset with three variables, the district code, the baseline coal operational capacity and the baseline total operational capacity.

Next, I produce a dataset which categorizes districts based on the type of fully operational plant throughout the time period of interest they contained. For that, I import and append the operational and operational additional plant datasets, only keeping the ones commissioned before or in 2013, and dropping the ones that were not mapped to any district. Subsequently, I only keep plants that are fueled by coal (either hard coal or lignite). I classify plants into 4 categories: (a) plants that were fully operational, (b) plants that were not allowed to close down as they were classified as *system relevant* during the period of interest (namely two generators at the *Walheim* plant), (c) plants that entered the reserve (two generators in each of the *Frimmersdorf*, *Niederaussem*, and *Jaenschwalde* plants, as well as one in the *Neurath* plant, and one in the *Buschhaus* plant), and (d) plants that temporarily closed (the T2 plant in *Neumuenster*). Next, I collapse the dataset on a status by district level, retaining the total operational capacity for each status type by district cell, as well as the first and last year in which a plant was commissioned. Based on that, I create four indicators on whether a district contains any of the four types of plants. Subsequently, and relevant to the analysis presented above, I create three indicators on whether or not a district contains *only* an operational plant or *only* a plant that was in reserve, classified as system relevant, or one that was temporarily shut down.

II Employer-employee data preparation

2.B.I Initial data request

A series of steps is taken to process and restrict the raw data of the *IEB*. Specifically, the initial dataset requested limits the data sources to BeH Employee History, a dataset that follows all employees in Germany, subject to social security contributions and also includes marginal part-time employees, the *Benefit Recipient History (LeH)*, i.e. a dataset that records the histories of unemployment benefits, unemployment assistance, or maintenance allowances for people in Germany, as well as the *MTH Participants-in-Measures Histories*, a dataset recording participation in employment and training measures/programs. Also, the initial data request, only keeps people born between 1942 and 1991, as well as people whose first employment episode is after 2019 or the last employment episode is before 2009. After imposing these initial restrictions, which help with data size limitations, I keep a 70% random sample of all remaining people in the data. This is the baseline dataset which contains roughly 1.2 Billion observations.

2.B.II Episode splitting

I begin with the process of splitting episodes. A single episode is an employment spell that might span several years, while different spells might overlap. I follow established procedures to split episodes by calendar year. Additionally, there are some spells relating to lump-sum payments. I deal with those by reallocating wages from those to the corresponding employment spell for the same person-establishment combination recorded as in the lump-sum payment spell, deleting the lump-sum spells. I then distribute the total income value proportionally according to the duration of the spells among all spells for the person-establishment combination in that year.

2.B.III Variable creation and further restrictions

I proceed by creating several variables and imposing additional restrictions to the data. Those variables mainly have to do with broad groups in educational attainment (both current and maximum attainment), as well as broad occupational categories. Next, I further restrict the data, dropping cases relating to home-based tradespeople, interns, working students, marginally employed, family members (agricutlure), part-time employees, temporary employees, pensioners, as well as those without information on the type of employment.

Next, I deal with parallel spells, where I prioritize employment over unemployment, and in the case of multiple overlapping employment spells in an employer, I retain the one with the highest wage. Additionally I create variables for the tenure in the labor market and the job. I then deflate wages, only keep spells that span the 30th of June (where employment should be recorded) and aggregate employment outcomes for all employment spells to get total labor earnings and days in employment in a year.

Lastly, I restrict my sample only to the years between and including 2009 and 2019, as well as to people of ages between 18 and 65, dropping observations with missing key variables, such as sex, employer (if employed in that year), and place of employment (again if employed). I end up working with a 30% sub-sample of the produced dataset, due to software limitations.