The Socio-Economic Impact of the Energy Crisis: Evidence from Germany

Katia Gallegos Torres* Jakob Lehr†

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Abstract

This paper examines the impact of the 2022 energy price shock on Germany's manufacturing sector. Using shifts in fuel prices and detailed energy consumption data from the German manufacturing census, we construct an exposure measure at the fine-grained four-digit sector level. Combining this shock with multiple administrative datasets, we document significant adverse effects on economic activity, a negative effect on wages but no impact on employment. Finally, we map the price shock to 400 districts to characterize its spatial distribution and assess its regional consequences. The insights from our analysis are highly relevant in the context of the structural changes required for transitioning to carbon neutrality.

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*IAB Nuremberg, ZEW Mannheim
†University of Mannheim
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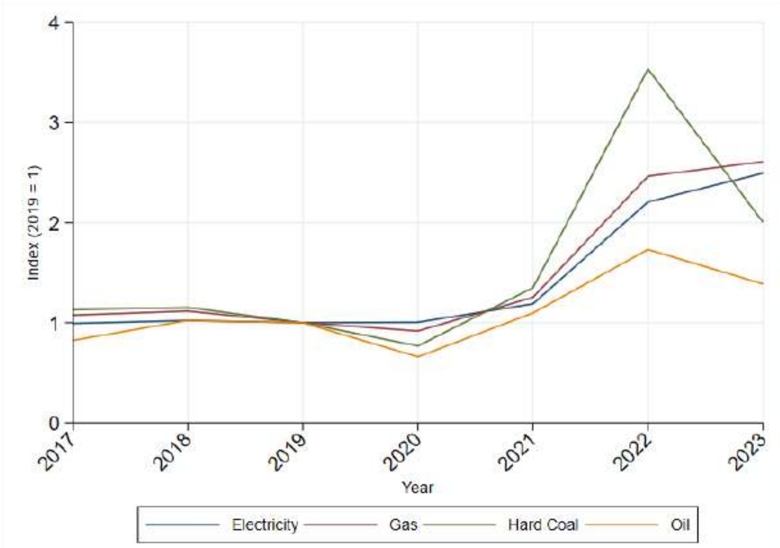
1 Introduction

Russia's invasion of Ukraine in February 2022 triggered an energy crisis in Europe. Due to a heavy reliance on Russian energy imports—built up over decades—the German economy appeared particularly vulnerable to this shock.[1] Moreover, the comparatively energy-intensive manufacturing sector plays a more important role in Germany than other similarly developed countries, with natural gas being the single most important energy source for German manufacturing firms.[2] Against this backdrop, German Chancellor Olaf Scholz feared that an embargo on Russian gas could place "hundreds of thousands of jobs at risk" and push "entire industries to the brink" (Politico, 2022). In contrast to these pessimistic views—articulated by the German government—macro-simulations by Bachmann et al. (2024) deemed the consequences of a gas embargo "manageable". While there was no majority support for a gas embargo, imports of Russian gas ceased almost completely over the course of 2022 causing energy prices to spike in late 2022, and by 2023 prices for gas, coal and electricity were still more than 100% higher than in 2019 (cf. Figure 1).

Figure 1: Price Index (2019 = 1) for Industrial Energy Use in Germany



Notes: The figure shows the evolution of industrial energy prices in Germany by energy source—electricity, gas, coal, and oil—at a half-yearly frequency. All prices are normalized by the respective values for the first half of 2019. Source: Statistisches Bundesamt (Destatis – Federal Statistical Office of Germany), Daten zur Energiepreisentwicklung, December 2023, EVAS Nos. 61241, 61411, 61421, 61111, 61231, published 31 January 2024, GENESIS-Online., own calculations.

Three years after the energy supply shock hit the German economy, this paper provides the first comprehensive ex-post analysis of the shock's effects on the manufacturing sector. The analysis covers its impact on production, employment, wages, prices, and the regional distribution of

[1] For instance, more than half of Germany's natural gas demand in 2021 was met through imports from Russia (BP, 2021).

[2] For example, manufacturing value added as a percentage of GDP in 2021 was 18.9% in Germany, compared to 9.7% in France (World Bank, 2024). Natural gas accounts for approximately one-third of industrial energy use, followed by electricity (one-fifth) and coal (one-sixth) (Federal Statistical Office, 2024)

effects, which arise from the geographical distribution of industrial structures.

Russia's war against Ukraine represents a turning point ("Zeitenwende") for Germany in multiple dimensions, particularly concerning energy. It marks a structural break in energy supply: energy will most likely be scarcer and, consequently, more expensive in the medium term. This development accelerates and intensifies pre-existing trends resulting from the aim to reduce CO_2 emissions and the policy measures taken to achieve this objective, e.g., carbon pricing. Therefore, analyzing the current price shock can provide valuable insights into the potential impacts of future climate policies. For example, it can shed light on how sectors adapt to higher energy prices, who bears the burden of higher prices, which regions are affected, and not least, the implications of all this for public attitudes, i.e., political support for decarbonization, which we measure by voting behavior.

Our analysis draws on multiple administrative datasets at the establishment-, sector-, and regional-levels. First, we use detailed data on establishment-level fuel consumption by fuel type from the German Census of the manufacturing industry (AFiD) for the pre-shock period, which we combine with aggregate shifts in fuel prices to construct a measure for establishments' exposure to the energy price shock. We then aggregate this establishment-level measure to fine-grained four-digit economic sectors to obtain a sector level intensity treatment variable, which depends both on a sector's energy intensity and its fuel mix, as different fuel prices followed different trajectories (cf. Figure 1).[3] We combine this intensity treatment with sectoral data on economic performance indicators, which extend through 2023 allowing us to evaluate the effect of the price shock in the first and second years of its occurrence (2022–2023). For the main analysis of the shock's impact on labor market outcomes, we draw on the Integrated Employment Biographies (IEB) from the German Institute for Employment Research (IAB), i.e., individual-level data covering the universe of socially insured workers in Germany. We use this data to construct sectoral aggregates for wages and employment, distinguishing, e.g., between task groups, incumbent workers, and new hires. In addition to the sector-level data, we use the Establishment History Panel (BHP)—an establishment-level dataset provided by the IAB—which contains detailed information on relevant labor market outcomes, including the number of employees and various moments of the establishment-level wage distribution. Finally, we also use the IEB to map the energy price shock to the regional level.

We draw on the logic of shift-share instruments to construct our treatment intensity measure, which varies with sectoral energy intensity, fuel mix, and plant size distribution, since gas and electricity price series are available and differ across respective consumption bins. We then focus on differential changes in outcomes depending on treatment intensity. Thanks to the availability of data for multiple pre-treatment periods, we can evaluate pre-trends, i.e., we can test whether, prior to 2022, the exposure measure was uncorrelated with sectoral trends (Goldsmith-Pinkham et al., 2020). Evidence of parallel trends prior to 2022 supports the central identifying assumption

[3] Specifically, we use establishments' fuel consumption from 2018 to "predict" the additional energy costs in 2022, assuming consumption levels from 2018, aggregate to the four digit sector level and rescale the sector aggregate with the number of employees in the respective sector in 2018.

that, in the absence of treatment, trends would have remained the same post-treatment.

First, we show descriptively large heterogeneity in exposure across four-digit economic sectors. For example, our exposure measure at the 75^{th} percentile of the distribution is seven times higher than at the 25^{th} percentile ("manufacture of plastic packing goods" and "manufacture of machinery for paper and paperboard production"). These heterogeneities carry over—albeit less pronounced—to the regional level due to the presence of industrial clusters. For instance, the same inter-quartile-coefficient at the district-level is approximately three.

Second, to motivate our main analysis of the impact of the price shock on labor market outcomes, we first show in a motivational exercise that the price shock had an adverse effect on economic activity. Specifically, using a monthly production index at the four-digit sector level, we show that in 2023, production in sectors within the most affected quartile was 10-15 percentage points (pp.) lower than in the least affected quartile. Results based on annual data on real turnover confirm this finding. Additionally, we show that annual producer prices in the affected sectors increased sharply—indicating that costs were (partly) passed through.

We then analyze the labor market effects of the energy supply shock at the sector and establishment level. Across both datasets we do not find an adverse effect on employment but we find a consistent negative effect on wages. For example, we estimate that in 2023 a 100% increase in shock exposure reduced average wages by 0.43% at the sector level and by 0.37% at the establishment level. Taking the sector-level estimates, the magnitude implies that moving from the 25^{th} to the 75^{th} exposure percentile results in an average reduction in the mean wage by approximately 2.8%. We find that the decline in the average sectoral wage is largely driven by adverse effects on wages for new hires and workers with short tenure, whereas the negative effect on wages of long-tenure workers amounts to roughly half of the average effect. While there is substantial heterogeneity in wage responses by tenure, we do not document meaningful differences across task groups (abstract versus routine). Consistent with this, the plant-level data indicate relatively homogeneous effects across different moments of establishments' wage distributions; in other words, the shock shifted the entire distribution downward without increasing within-plant wage inequality.

At the district-level, we first show that shock exposure is strongly correlated with regional clusters of carbon-intensive industries. We document that these regions are characterized by a relatively higher share of workers with vocational training, a lower share of individuals with academic degrees, lower levels of in- and out-migration, and a slightly older population. We further correlate regional shock exposure with voting outcomes as a proxy for public attitudes. Our results show that support for climate policies—as measured by Green Party vote shares—tends to be lower in these regions, while support for climate-skeptic parties is higher. Importantly, these correlations are present both before and after the shock, indicating no causal effect of the energy price shock on voting behavior. Consistent with the sector-level analysis, we also find evidence of a negative effect on local average wages in manufacturing.

Related Literature and Contribution. First, the paper contributes to the growing literature on the consequences of the recent energy crisis. For example, Bachmann et al. (2024) and Auclert et al. (2023) analyze the fiscal, price, and income effects of the energy price shock using macroeconomic models. Departing from this macro approach, Fetzer et al. (2024b) employ property-level data from the UK to examine differential exposure to the price shock across regions and socioeconomic groups, as well as the heterogeneous effects of potential policy responses. Lafrogne-Joussier et al. (2023) use firm-level data (2018–2022) to estimate the pass-through of energy costs to product prices. Using a shift-share design based on pre-crisis fuel shares they find evidence for complete pass-through. Similarly, Arquié and Thie (2023) analyze pass-through in the French manufacturing sector with sector-level data, confirming complete pass-through in less competitive sectors (high-markup sectors) but lower pass-through in sectors with more intense competition. Fetzer et al. (2024a) combine firm-level administrative and survey data from the UK to assess firms' responses to the energy price shock along various margins. They measure firms' exposure to the cost shock by firms' energy costs as a share of total costs. Overall, they find no evidence of lower employment or increased exit but observe higher prices and adjustments to firms' capital stock with heterogeneities, e.g., by firms' size. We contribute to this literature by providing a comprehensive ex-post analysis of the effect of the price shock on Germany, Europe's largest economy, which appeared particularly vulnerable given its large manufacturing sector and dependence on Russian gas imports. Our results on pass-through are consistent with those of Lafrogne-Joussier et al. (2023) and Arquié and Thie (2023) for France, and we extend the literature to labor market consequences by analyzing employment and wage effects using comprehensive establishment-level and individual-level administrative microdata.

Second, the paper contributes to the broader literature on the impact of energy cost on the manufacturing sector. Fontagné et al. (2024) use firm-level data from the French manufacturing sector (1996–2019) and a shift-share approach based on baseline fuel shares to estimate the effects of energy prices on energy use, production, employment, and prices. They find that while higher energy prices improve energy efficiency, they also lead to reductions in output, employment, and exports. Similarly, Marin and Vona (2021), also focusing on the French manufacturing industry, show that higher energy prices lower energy consumption but cause modest employment losses concentrated in energy-intensive sectors. André et al. (2023) analyze firm-level data from ORBIS, which they combine with sector-country-year level energy price data to differentiate between the short- and medium-term effects of energy prices on firms' productivity.[4] Some papers focus explicitly on various labor market consequences of energy prices. For instance, Yamazaki (2017) and Yip (2018) document negative effects on employment and wages resulting from the carbon tax introduced in 2008 in British Columbia, based on sector-level and individual-level data, respectively. Cox et al. (2014) combine firm-level data from Germany with sector level electricity prices to estimate cross-price elasticities between electricity and heterogeneous labor, finding

[4] Other related papers include Ganapati et al. (2020) who estimate energy cost pass-through in US manufacturing, Abeberese (2017) analyze the impact of electricity prices on manufacturing firms in India and Gerster and Lamp (2024) exploit electricity price variation from tax exemption rules to estimate their effects on firms production and input decisions.

negative unconditional cross-price elasticities. Mertens et al. (2022) use firm level energy price variation to estimate rent-sharing elasticities in the German manufacturing sector and Marin and Vona (2019) take a pan-European perspective: they use data from 15 economic sectors across 14 European countries and the European Labor Force Survey to analyze the impact of energy prices on hours worked by skill group. Their findings imply that energy price increases are skill-biased against manual workers. The price shock of 2022 provides a unique opportunity to extend the literature on the consequences of energy costs on manufacturing. Unlike previous studies that relied on relatively modest price movements over time, the current price shock allows us to construct a single measure of shock exposure—which we fix at baseline. This setting allows for an assessment of pre-trends first and then for tracking sectoral outcome trajectories over time in response to this well-defined shock.

Third, this paper contributes to the emerging literature on the consequences of the structural changes required for moving towards carbon neutrality and its impact on affected communities. By mapping the energy price shock to local labor markets using the universe of workers subject to social security contributions, it aligns closely with Hanson (2023), who maps energy-intensive manufacturing to U.S. labor markets. Although the green transition is in its early stages, evidence from previous structural transformations, particularly globalization, highlights profound effects across industrialized nations (cf. Dauth et al. (2014) for the labor market effects in Germany, Autor et al. (2013, 2014) for the US and Dippel et al. (2021) and Autor et al. (2024, 2020a) for effects on attitudes and voting behavior in Germany and the US). A pertinent concern is that the structural changes driven by decarbonization may result in economic, social, and political costs akin to those experienced by regions undergoing structural transformation in previous decades. Indeed, avoiding these painful experiences could be necessary to transition to carbon neutrality, as public support for climate policy is likely to erode otherwise. Therefore, we focus, among other things, on voting behavior in affected regions as a measure for political preferences and find—in line with the hypothesis mentioned above—that the vote shares for the green party are lower in regions with a higher share of carbon-intensive jobs. However, we do not find an increase of this pre-existing difference due to the shock.

The remainder of the paper is structured as follows: Section 2 introduces the datasets and outlines the empirical approach. Section 3 presents descriptive results, and Section 4 reports the main findings. Finally, Section 5 discusses the results and concludes.

2 Data and Empirical Approach

2.1 Data

For this project we combine multiple datasets for various levels of analysis, i.e., establishment-, sector- and regional-level.

Census of the Manufacturing Industry
To construct a measure for exposure to the energy price shock we draw on the German census

of the manufacturing industry called AFiD (*"Amtliche Firmen in Deutschland"*). The AFiD-data consists of different modules, of which we combine the *"AFiD Modul Energieverbrauch"* (energy use module) and *"AFiD Modul Industriebetriebe"* (industrial establishments) for the year 2018.[5] Both modules provide information at the establishment level, covering the universe of establishments that belong to a manufacturing firm with at least 20 employees. The energy use module provides detailed information about establishment level fuel use in physical units and by fuel type. The industrial establishment module contains information on indicators of economic performance such as sales, number of employees, and total wagebill.[6] We combine the establishment-level information with time series data for industrial fuel prices published by the German Statistical Office extending until 2023. There are separate time series by consumption bins for gas and electricity consumption. This is important because both the price levels before the shock and the change resulting from the shock differed across establishments depending on their energy consumption (cf. Figure A2 for the evolution of gas and electricity prices by consumption bin).[7] We draw on this combined dataset to construct the sectoral price shock exposure as follows:

$$AdditionalCosts_s = \sum_{i \in S} \underbrace{\sum_{f \in F} Fuel_{i,f,s}^{2018} \times \Delta P_f}_{\text{establishment } i\text{'s exposure}} \tag{1}$$

The inner sum approximates the additional energy costs for establishment i resulting from the price shift by multiplying establishment i's 2018 consumption of fuel f with the change in fuel f's price between 2018 and the second half of 2022. The outer sum aggregates across all establishments within a four-digit economic sector s.[8] Expression 1 thus yields an approximation of the increase in sectoral energy expenditures. Assuming 2018 consumption levels makes sure that expression 1 is not contaminated by endogenous consumption adjustments of establishments and could be used in a shift-share instrumental variable approach.

To account for differences in the sizes of economic sectors, we scale expression 1 with the number of employees in 2018 and define expression 2 below as our measure of sectoral exposure to the price shock.

$$Exposure_s = \frac{ExcessCosts_s}{\sum_{i \in S} L_i^{2018}} \tag{2}$$

Expression 2 can be interpreted as the additional energy costs resulting from the fuel price changes per employee in sector s, assuming consumption levels from 2018. Exposure intensity thus depends on the energy intensity of production in a given sector, the sector-specific fuel mix—since fuel prices did not evolve uniformly (cf. Figure 1)—and the distribution of establishment sizes within sectors, measured by their gas and electricity consumption (cf. Figure A2 in the Appendix).

This measure offers several advantages over simpler alternatives, such as relying on energy

[5]We currently have access to AFiD data only up to the year 2020.

[6]For a detailed description of the energy use module see Petrick et al. (2011)

[7]We assign establishments to bins based on their consumption in 2018 and then use the respective time series. The fuel price time series can be downloaded here.

[8]Fuel types are electricity purchased from the grid (prices by consumption bins), gas (prices by consumption bins), coal, oil, district heat and wood.

expenditure shares from before the shock. First, it captures variation resulting from differential price trends across fuel types. Second, using physical consumption data from a baseline year, the measure accounts for the fact that larger consumers typically pay lower energy prices, which implies that using expenditure shares would not sufficiently reflect the existing heterogeneity in energy intensity across sectors. Third, and related to the previous point, relying on price shifts by consumption bins for gas and electricity accounts for differential trends by size: smaller consumers faced a smaller increase in prices compared to larger consumers, presumably reflecting different contract structures, e.g., smaller consumers rely more on medium-term fixed-price contracts whereas larger consumers rely more on short-term contracting leading to higher price volatility.

Sector Level Outcome Data

To assess the impact of price shock on a broad range of economic performance indicators, we combine various datasets published by the German Statistical Office at the four-digit economic sector level and merge the shock exposure measure constructed from the establishment level data as detailed above.[9] Data from the German Statistical Office on these various outcomes is available through 2023, providing coverage for two post-treatment years. The dataset includes information on firms' turnover, total employment, wage bill, investment, and prices. Additionally, we use a production index constructed by the Statistical Office, which accounts for output price changes and seasonal patterns at the four-digit sector-month level. This high-frequency data allows us to assess how the shock affected economic activity over time in more detail.

Establishment History Panel

We use the "Establishment History Panel" (BHP) from the IAB to investigate the labor market consequences (Ganzer et al., 2024). The BHP is constructed from individual-level information for the universe of workers subject to social security contributions by aggregating respective information at the level of a establishment (which is done by the Research Data Center of the IAB). For our analysis, we draw on a 50% sample of the BHP for the period 2018–2023, i.e., it covers two "post-treatment" years. We restrict the sample to establishments in the manufacturing sector. The BHP contains information about establishments' economic sector, their location, the number of employees, and different moments of the wage distribution, e.g., the mean, median, and the 25^{th} and 75^{th} percentiles. Furthermore, we add information about worker flows in and out of establishments to study employment adjustment patterns.

Integrated Employment Biographies (IEB)

We draw on the Integrated Employment Biographies (IEB), which cover the universe of socially insured workers in Germany.[10], The worker-level data include information on workers' economic sector (at the four-digit level), as well as their place of work and residence at the district level. From these data, we construct mean wages by task group and for new hires, and we use it to map sectoral exposure back to 400 districts across Germany.

[9] The data on annual outcomes can be downloaded here (production, employment, investment), here (input costs) and here (prices) and the monthly production index has been downloaded here.

[10] The IEB is the basis for other standard employment datasets in Germany (e.g., Schmucker et al., 2023).

To map the shock to the regional level, we draw on expression 2, which defines sectoral exposure as additional energy costs per worker and we multiply this measure by the number of workers in sector s in district d and then sum across all manufacturing sectors to obtain the regional exposure. Expression 3 describes the procedure:

$$AdditionalCosts_d = \sum_{s \in d} L_s \times Exposure_s \tag{3}$$

To address the possibility that this value can be high in densely populated districts even when manufacturing does not play a significant role in respective district, we rescale it with the total number of socially insured employees in the district d (not only those from the manufacturing sector).

2.2 Empirical Specification

To estimate the effect of the energy price shock on our various units of analysis (sector-, regional-, or establishment-level outcomes), we relate changes in outcomes to the sectoral/regional exposure measure. Below we present the most parsimonious version of the model:

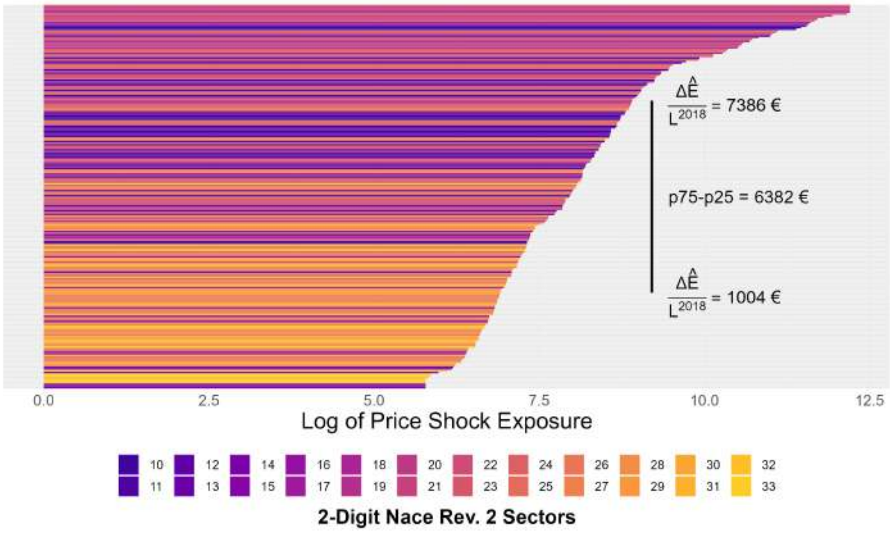
$$\Delta y_{i,t} = y_{i,t} - y_{i,2021} = \beta_0 + \sum_{\tau=2018, \tau \neq 2021}^{2023} \beta^{\tau} ln(Exposure_s) \times \mathbb{1}\{t = \tau\} + \gamma_t + \varepsilon_{i,t} \tag{4}$$

The dependent variable, $\Delta y_{i,t}$, represents the change in the logarithm of unit i's outcome between year t and 2021—the year preceding the shock. Our focus is on the vector of coefficients, β, which collects the coefficients on the interactions between the time-invariant log exposure measure (cf. expression 2) and year dummies, conditional on year fixed effects (γ_t). Each coefficient in β is a year-specific elasticity, i.e., it is an estimate of the percentage change in y associated with a 1% increase in the exposure measure. The coefficients corresponding to the periods before 2021 capture pre-trends, while those for the years after 2021 measure the effects of the price shock. Specification 4 may be augmented with additional fixed effects, such as two-digit sector-year fixed effects or federal-state-year fixed effects. Finally, $\varepsilon_{i,t}$ denotes a random disturbance term.

3 Descriptive Statistics

Price Shock and Sector-Level Data We first describe the distribution of the exposure measure (price shock) across 220 four-digit sectors. To this end, Figure 2 plots the logarithm of the shock—as defined in expression 2—which we constructed using the establishment-level manufacturing census. Each bar in the plot represents a four-digit sector, and the same color indicates that two four-digit sectors belong to the same two-digit sector. The figure illustrates substantial heterogeneity across these sectors. For example, the predicted energy cost increase per worker (the exposure measure) is 1,004€ at the 25^{th} percentile ("manufacture of machinery for paper and paperboard production") and €7,386 at the 75^{th} percentile ("manufacture of plastic packing goods") and the upper part of the figure indicates a long right tail. The figure also highlights

Figure 2: Log of Sectoral Price Shock Exposure



Notes: The figure shows the logarithm of the exposure measure, defined as the predicted increase in energy costs per worker in a four-digit sector. Sectors within the same two-digit sector are represented by the same color. The black vertical lines span from the 25^{th} to the 75^{th} percentile. Data sources include the "Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2019)" and industrial energy price data from the Federal Statistical Office.

considerable variation in shock exposure within two-digit sectors, as bars of the same color appear at different levels.[11] At the two-digit level, the "refining" industry (19) is the most exposed sector, followed by "manufacture of chemicals and chemical products" (20) and "manufacture of basic metals" (24). In contrast, the least exposed industry is "repair, maintenance, and installation of machinery and equipment" (33).

While the main analysis focuses on the labor market impact of the price shock, we also examine its effects on broader economic performance indicators. For this, we draw on data at the four-digit sector level. Table 1 presents descriptive statistics for key variables at the sector level for the year 2021. The first row shows that the average 4-digit sector generates an annual turnover of approximately €9.8 billion and employs around 30,000 workers with both median being substantially lower. The mean turnover per worker as a reduced-form measure of labor productivity is €314,000. The wide interquartile range ($\approx$€150,000) suggests substantial heterogeneity in production technologies across sectors, which is expected to be reflected in varying factor shares. In addition, the table provides information on investment, export share, the number of establishments per sector, the average number of workers per establishment and descriptive statistics for the proce shock exposure measure, as defined in expression 2.[12] The exposure measure exhibits significant right skewness, with the mean exceeding the median by more than a factor of five. Furthermore, the interquartile range (IQR) is approximately 6,200€, highlighting the substantial variation in exposure across sectors. To illustrate how the indicators described

[11] Figure A1b in the Appendix further emphasizes this within-sector variation by sorting the bars within each two-digit sector and stacking them in blocks by two-digit sector.

[12] This measure is available for 220 sectors; however, information for the variables above is sometimes missing for smaller sectors.

in Table 1 vary with the degree of sectoral exposure, we divide the data into exposure quartiles and report the means and medians of the variables for each quartile (see Tables A1 and A2 in the Appendix). The tables reveal that turnover is relatively evenly distributed across exposure quartiles. However, both the average and median number of employees per sector differ markedly: for example, the most exposed sectors employ, on average, only half as many workers as sectors in the other quartiles. This pattern is also reflected in turnover per worker, for which both the mean and median steadily increase from the first to the fourth exposure quartile. Export shares appear relatively uniform across quartiles. In contrast, the number of establishments tends to be lower, and the average number of workers per establishment is higher in more exposed sectors. These patterns plausibly reflect the concentration of the shock in the heavy, capital-intensive segments of the manufacturing sector.

Table 1: Summary Statistics of Sector Level Data (2021)

	Mean	SD	p25	p50	p75	N
Turnover (in Mio.)	9,765.62	29,706.73	1,287.43	3,779.84	9,908.38	204
# Employees	30,580	53,157	4,884	12,120	39,104	204
Turnover (in k) per Employee	314.28	232.79	195.64	247.46	352.22	204
Investment (in Mio.)	293.11	836.34	32.48	109.78	296.26	204
Export Share	0.41	0.20	0.26	0.43	0.56	201
# establishments	225	352	40	91	213	201
Employees per establishment	184	360	90	125	197	201
Shock Exposure	14.99	36.45	1.07	3.04	7.28	204

Notes: The table shows summary statistics of key variables at the 4-digit sector level for the year 2021. The number of observations varies by variable, as the Statistical Office does not publish data for sectors with few firms. The last row provides summary statistics for the shock. Source: "Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2018)", sectoral outcome data, and industrial energy price data from the Federal Statistical Office.

Individual-Level Data Table 2 provides summary statistics based on data for the universe of workers subject to social security contributions, aggregated to 220 four-digit sectors. The first row shows that the average sector employs approximately 27,000 individuals, with more than 90% in full-time positions.[13] Over two-thirds of workers are engaged in routine tasks, while the remainder are involved in abstract tasks. The average daily wage across all sectors is €138, with considerable variation across sectors—at the 25^{th} percentile, the average wage is €116, and at the 75^{th} percentile, it is €160—and across task types: workers engaged in abstract tasks earn, on average, roughly €60 more than those performing manual tasks.

In addition, one can glean from the table that approximately 13% of workers in the average sector were newly employed, i.e., they were not working in their current establishment in the previous year. The average daily wage for newly hired workers is €119—substantially below the sectoral average and, by construction, below the average wage of the complementary subgroup (those not newly hired), who earn €140. Workers who leave their jobs earn an average daily wage of €124, slightly higher than that of new hires but well below the sectoral average.

[13] The number of employees is very similar to the figures reported in Table 1, which is based on sector-level data from the statistical office. The statistical office does not report figures for smaller sectors, which explains the difference in observations and the slightly higher average employment reported in Table 1.

Table 2: Summary Statistics of Sector Level Employment Data (2021)

	Mean	SD	p25	p50	p75	N
Employment	26,624	44,227	4,264	9,631	29,805	220
FT Employment	24,816	41,382	4,028	8,744	28,598	220
Employment (Routine)	18,889	30,059	3,260	7,237	21,694	220
Employment (Abstract)	7,820	15,321	1,032	2,663	8,283	220
Daily Wage	137.74	31.28	115.74	132.34	160.20	220
Daily Wage (Routine)	120.39	25.46	101.12	116.71	137.33	220
Daily Wage (Abstract)	183.57	35.59	156.77	178.12	209.26	220
Share of New Hires	0.13	0.06	0.10	0.12	0.15	220
Daily Wage (New Hires)	119.06	27.34	100.09	115.31	134.40	220
Daily Wage (No new Hires)	140.40	31.55	117.92	134.11	162.87	220
Daily Wage (Leavers)	123.84	28.65	105.16	118.29	140.90	220

Notes: The table presents summary statistics of the following four-digit sector level aggregates: number of workers, number of full time workers, number of workers with routine tasks, with abstract tasks, the mean daily wage, mean daily wages by task-group, the share of new hires and average wages among new hires and those who switch employer. The year is 2021. Source: IAB Integrated Employment Biographies

Establishment-Level Data Table 3 presents summary statistics from the Establishment History Panel (BHP). We have restricted our dataset to include establishments with at least 20 employees since this aligns with the inclusion criteria for the German manufacturing census, which we used to construct the price shock. After applying this restriction, the dataset includes approximately 22,500 establishments per year. Row 1 of table 3 reports the number of employees per establishment: the average establishment employs about 127 workers, while the median establishment employs just 48. Rows 2 to 5 describe moments of the establishment-level wage distribution, measured in euros (€) per calendar day. The average establishment-level mean wage is €118, while the median is €109. The average wage at the 25^{th} percentile of the within-establishment wage distribution is €94, and €132 at the 75^{th} percentile. One can further see from the table that the average establishment in the sample was established in 1990 and that roughly 10% of establishments employ at least 250 workers. On average, both the mean and median establishment belong to a sector in the second exposure quartile, meaning they belong to the second least exposed quartile. This reflects that sectors in the higher exposure quartiles tend to consist of fewer but larger establishments.

Regional-Level Data Finally, the heat map in Figure 3 illustrates the regional distribution of the shock across 400 districts (thin black lines demarcate the Federal States). Each color corresponds to one of six exposure bins. At the regional level, the shock is defined as the predicted increase in energy costs in the manufacturing sector per employee subject to social security contributions (SVPB). The differential exposure arises from the unequal spatial distribution of industries. The pattern reflects well-known industrial structures. For example, dark colors can be observed in the Ruhr area and Saarland—regions associated with heavy industry. The most exposed district on the map is "Salzgitter" in Lower Saxony—home to major steel production. The second most exposed district is "Altötting", located in southeastern Bavaria and known as part of the "Bavarian Chemical Triangle" and the third is "Ludwigshafen am Rhein", which hosts one of the world's largest chemical production sites. Moreover, Figure 3 highlights substantial within-state variation.

Table 3: Summary Statistics from the Establishment History Panel (2021)

	Mean	SD	p25	p50	p75	N
# Employees	126.91	624.15	29.00	48.00	105.00	22447
Mean Wage (€ per Calendar Days)	118.77	37.22	93.11	113.60	137.25	22447
Median Wage (€ per Calendar Days)	109.23	35.11	85.03	103.95	125.37	22447
Wage P25 (€ per Calendar Days)	94.41	28.69	74.12	90.62	109.15	22447
Wage P75 (€ per Calendar Days)	132.32	45.85	100.36	123.94	153.53	22447
Year of Founding	1990	13.58	1975	1991	2002	22447
Share of Large Plants (#L $>$ 249)	0.10	0.29	0.00	0.00	0.00	22447
Shock Exposure Quartile	2.15	0.97	1.00	2.00	3.00	22447

Notes: The table presents summary statistics for plant-level employment, wages (mean plant level wage, median plant level wage, P25 and P75) and the year a plant was established, the share of large plants (at least 250 employees) and the energy price shock exposure quartile. The year is 2021. Source: "Establishment History Panel 1975–2023 (BHP 7523 v1)". Research Data Centre of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB). DOI: 10.5164/IAB.BHP7523.de.en.v1.

In nearly all large territorial states, one finds districts in the highest and lowest exposure bins.

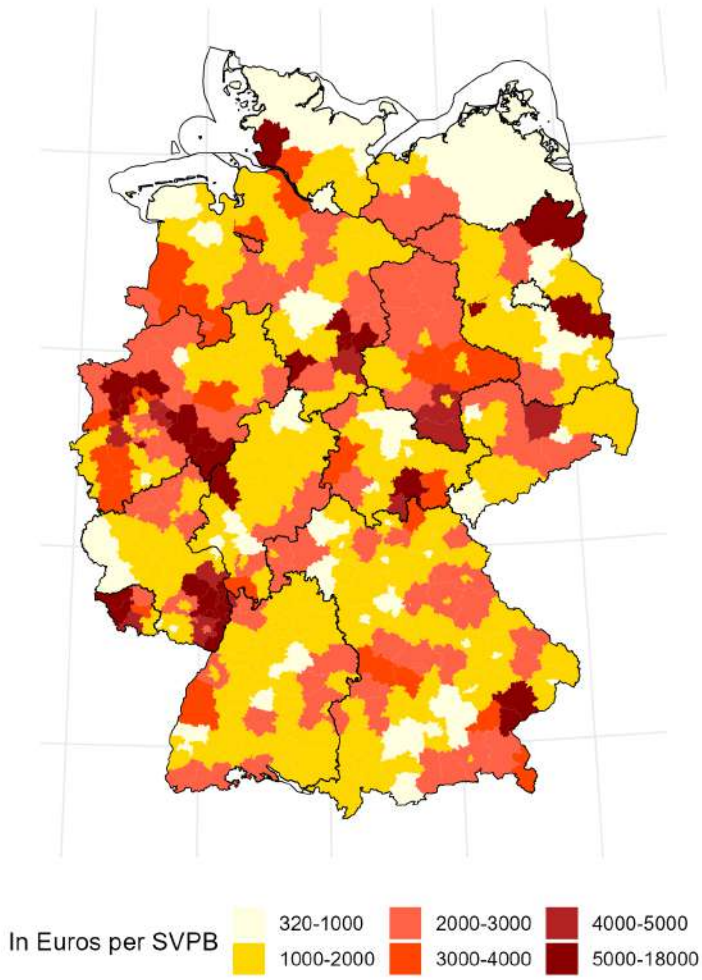
Figure A8 in the appendix plots the logarithm of districts' exposure (similar to Figure 2). The distribution is more compressed compared to that of sectors but still shows significant heterogeneities. For example, the district at the 25^{th} ("Bayreuth") percentile experienced a predicted energy cost increase of 1,158€ per SVPB, compared to 2,497€ at the 75^{th} percentile ("Deggendorf").

For the figures cited above, we used individuals' place of residence to allocate the sectoral shock to districts. An alternative would be to use the place of work. Figure A9 in the appendix shows regional exposure based on workplace location. While the correlation between the two measures is very high (see Figure A10a), the shock is more concentrated in certain districts when using workplace location (see bins in Figures A9 and density plots in Figure A10b). For example, using place of work makes "Ludwigshafen am Rhein" the most exposed district, while neighboring districts are much less affected. Since many workers in Ludwigshafen live in surrounding areas, using place of residence spreads the shock more evenly (see Figure A9). Depending on the research question, one approach may be more appropriate than the other; for most of the analysis in this paper, we rely on place of residence.

4 Results

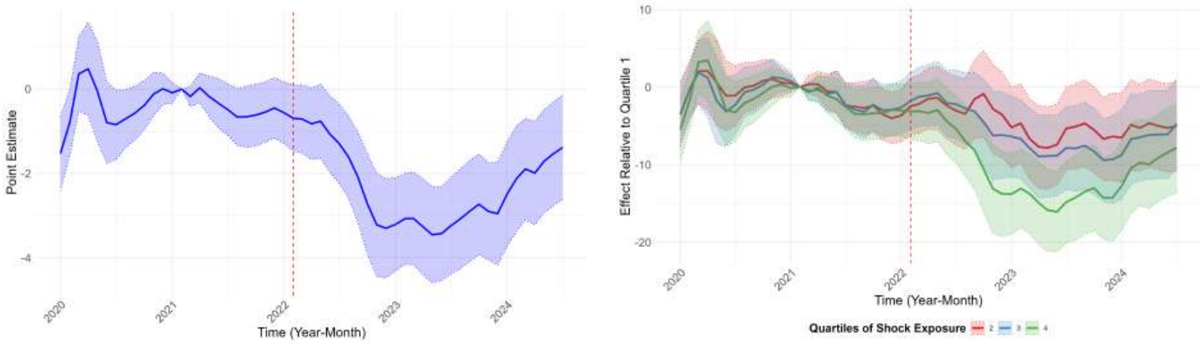
This section presents the results. We start with a motivational analysis using a monthly sector-level production index. Since we expect that the negative energy supply shock caused a reduction of economic activity, thereby potentially impacting firms' labor demand, our initial focus is on establishing an adverse effect of the price shock on economic activity. We then turn to our main analysis of labor market outcomes—employment and wages—using data from the universe of workers subject to social security contributions and comprehensive establishment-level data from the BHP. Finally, we analyze the effects of the energy price shock using regional data.

Figure 3: Exposure at District Level: Additional Energy Costs per SVPB



Notes: The map visualizes exposure by district, defined as the predicted increase in energy costs per employee subject to social security contributions (SVPB) in a given region. Each region is classified into one of six exposure bins (see legend). To map the sectoral shock to regions, we used the number of workers in a district by industry using the workers' place of residence. Thin black lines delineate federal state boundaries. Data sources include "the Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2019)", industrial energy price data from the Federal Statistical Office, and IAB employment data for the universe of SVPBs.

Figure 4: Sectoral Price Shock and Economic Activity (Monthly Production Index)



(a) EV: Log Exposure Intensity **(b)** EV: Exposure Quartile Dummies

Notes: Both plots show point estimates connected by solid lines, along with 95% confidence intervals (shaded areas), obtained from estimating equation 4. The unit of observation is the 4-digit sector level, and the outcome variable is the change in a production index (BV 4.1, published by the German Statistical Office). In Subfigure 4a, the explanatory variable is the logarithm of the exposure measure, while in Subfigure 4b, the explanatory variables are dummy indicators for a sector's exposure quartile. The vertical red dashed-lines mark the beginning of the invasion of Ukraine in February 2022. Standard errors are clustered at the 4-digit sector level. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2019) and industrial energy price data and the production index (BV 4.1) from the Federal Statistical Office.

4.1 Motivational Analysis: Effects on Economic Activity

Figure 4a plots the point estimates (connected by the thick blue line) along with 95% confidence intervals (shaded in blue), obtained from estimating equation 4 with changes in the monthly production index as the dependent variable.[14] The vertical red line marks February 2022, the onset of the Russian invasion of Ukraine. We normalized the outcome with respect to February 2021, meaning all effects are to be interpreted relative to this date. We chose one year before the war because tensions were already building up during 2021 which might raise concerns about anticipation.

Despite this potential anticipation, when looking to the left of the vertical red dashed-line, no systematic pattern is discernible, suggesting that sectors later differentially exposed to the energy price shock experienced no systematic differences in their economic developments prior to the shock. Indeed, most pre-shock coefficients are statistically indistinguishable from zero, which is reassuring as it supports the central identifying assumption of parallel trends. Focusing on the period around the vertical line, one can observe a gradual decline in point estimates beginning in late 2021, continuing until May 2022, when the coefficients start collapsing until the end of 2022. By November 2022—when energy imports from Russia had almost entirely ceased and energy prices peaked—the point estimate falls below –3. Recall that the dependent variable is an index normalized to 100 and not log-transformed. Thus, the point estimate suggests that a 100% increase in a sector's exposure corresponds to a drop in the production index of approximately 3 pp. (which is also 3% in case of the production index) by the end of 2022. For instance, this implies that moving from the median sector (with an exposure measure amounting to 2,954€ per

[14]The production index has been seasonally and calendar-adjusted using the "Berliner Verfahren (BV 4.1)" by the German Statistical Office to account for factors such as the number of trading days and holidays.

worker) to the 75^{th} percentile (7,386€ per worker) is associated with an estimated 4.5% decline in production. The point estimates remain around –3 throughout 2023 but begin to recover by the end of the year until mid-2024, when the sample period ends. By June 2024, the point estimate reaches approximately -1.7, suggesting that the difference in economic activity by price shock exposure had halved relative to the low point in mid-2023.

Figure 4b presents estimates using exposure quartile dummies instead of the continuous exposure measure. We omit the indicator for the least exposed quartile from the regression specification, so the estimates are to be interpreted relative to this group. As before, no clear pre-trends are evident; notably, the three plotted quartiles' trajectories closely align prior to 2022. The sharp decline in point estimates observed in Figure 4a, which began in May 2022, appears primarily driven by the most exposed quartile (green line). By the end of 2022, production in the most exposed quartile was nearly 15% lower compared to the least exposed quartile. In contrast, the second most exposed quartile (blue line) experienced a more gradual decline throughout 2022, with its economic activity approximately 8% below that of the least exposed quartile by mid-2023. The third most exposed quartile (red line) showed a decline of about 6% around the same time. The recovery observed in Figure 4a, which began at the end of 2023, is primarily driven by the most exposed quartile and, to a lesser extent, by the second most exposed quartile, while the red line remains largely horizontal through 2024.

These initial results show a clear negative effect of the price shock on production. This effect was qualitatively expected and, as such, strengthens confidence in our exposure measure. Section A.2 in the appendix provides a more detailed examination of sector-level responses, such as the pass-through of energy costs, using annual sector-level data. In our main results, we now primarily focus on labor market outcomes.

4.2 Main Results: Effects on Employment and Wages

We now turn to the labor market impact of the price shock using individual-level data from the IAB, aggregated to the four-digit sector level, and establishment-level data.

Sector-Level Results. Table 4 presents the main results from estimating equation 4 using sectorally aggregated data. Columns 1 and 2 focus on the employment response, while columns 3 and 4 examine wage adjustments. The annual effects of shock exposure are estimated conditional on year fixed effects in the odd-numbered columns, whereas the even-numbered columns control for sectoral shocks through the inclusion of sector-by-year fixed effects.[15] To ease the readability of the table, we have rescaled our estimates such that the coefficients can be interpreted as the change in the dependent variable in response to a 100% increase in the explanatory variable.

The results in columns 1 and 2 do not indicate any adverse effects of the price shock on sector-level employment. Three out of four post-treatment coefficients are even positive, but statistically

[15] We aggregate the 24 two-digit NACE sectors into 14 broader industries, following closely Autor et al. (2014) and Autor et al. (2020b), who control for trends within 11 industries. Table A3 in the appendix provides an overview of this aggregation.

Table 4: Sector-Level Results: Response to a 100% Increase in Exposure

	Log Employment		Log Wages	
	(1)	(2)	(3)	(4)
Delta 2018	-0.381	0.222	-0.174	0.166
	(0.465)	(0.542)	(0.116)	(0.129)
Delta 2019	-0.366	0.390	-0.274***	0.099
	(0.412)	(0.464)	(0.102)	(0.113)
Delta 2020	0.101	0.472	0.066	-0.055
	(0.291)	(0.323)	(0.085)	(0.105)
Delta 2022	0.232	-0.002	0.035	-0.226*
	(0.264)	(0.255)	(0.141)	(0.122)
Delta 2023	0.162	0.327	-0.250	-0.434***
	(0.352)	(0.330)	(0.158)	(0.146)
# of Observations	1,100	1,100	1,100	1,100
# of Sectors	220	220	220	220
Year-FE	Yes		Yes	
Year-Sector-FE		Yes		Yes

Notes: The table shows point estimates from estimating versions of equation 4. The unit of observation is a four-digit economic sector. Standard errors are given in parentheses. We do not include additional control variables. Fixed effects and number of observations are given at the bottom of the table. All dependent variables are are log differences to 2021. The sample is restricted to four-digit sectors with at least 350 employees. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Lander: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2019) and IAB Integrated Employment Biographies. Significance levels are indicated as * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

indistinguishable from zero and generally small in magnitude. Reassuringly, all pre-treatment coefficients are also statistically insignificant, and their pattern does not suggest the presence of any pre-existing trends in sector-level employment. Turning to average wages, we again find no statistically significant impact in the post-treatment period based on the most parsimonious specification (cf. column 3). However, the pre-treatment coefficients provide some evidence against the parallel-trends assumption. Once sectoral shocks are controlled for (column 4), the significant pre-treatment coefficient disappears, with the 2019 estimate even changing sign. Instead, the point estimates for the post-treatment period become statistically significant. Specifically, they suggest that a 100% increase in a sector's exposure to the energy cost shock reduced average wages by 0.23% in 2022 and by 0.43% in 2023.

Establishment-Level Results We now seek to corroborate the results presented above using establishment-level data from the BHP. Table 5 presents results for the same outcomes and based on the same specification as in the sectoral analysis. Note, however, that the results may differ from the sector-level estimates due to differences in aggregation. For instance, employment adjustments by smaller establishments may have limited impact on aggregate sector-level employment, yet still influence the establishment-level estimates, which capture the average percentage change at the establishment level.[16] Conversely, adjustments in small sectors can affect sector-level estimates, but since these sectors contain relatively few establishments, their influence on the establishment-level estimates is more limited.

[16]Despite using establishment level data we cluster standard errors at the level of the shock, i.e., the four-digit sector level.

Table 5: Plant-Level Estimates: Response to a 100% Increase in Exposure

	Log Employment		Log Wages	
	(1)	(2)	(3)	(4)
Delta 2018	0.285	0.451	-0.175	0.081
	(0.318)	(0.349)	(0.114)	(0.094)
Delta 2019	0.137	0.356	-0.245***	-0.081
	(0.265)	(0.288)	(0.073)	(0.054)
Delta 2020	0.034	0.182	0.047	-0.013
	(0.122)	(0.114)	(0.042)	(0.051)
Delta 2022	0.106	0.215*	-0.063	-0.210***
	(0.099)	(0.112)	(0.053)	(0.049)
Delta 2023	-0.118	0.308	-0.217**	-0.369***
	(0.174)	(0.189)	(0.085)	(0.089)
# of Observations	105,715	105,715	105,715	105,715
Year-FE	Yes		Yes	
Year-Sector-FE		Yes		Yes

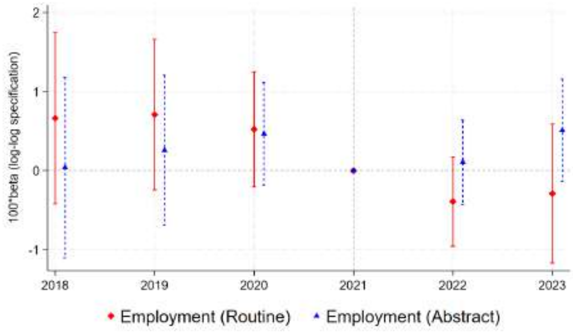
Notes: The table shows point estimates from estimating versions of equation 4. The unit of observation is at the plant-level. Standard errors are given in parentheses and clustered at the four-digit-sector level. We do not include additional control variables. Fixed effects and number of observations are given at the bottom of the table. All dependent variables are log differences to 2021. The sample is restricted to plants with at least 20 employees. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2019) and "Establishment History Panel 1975–2023 (BHP 7523 v1)". Research Data Centre of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB). DOI: 10.5164/IAB.BHP7523.de.en.v1. Significance levels are indicated as * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 5 shows that the establishment-level estimates broadly confirm the findings based on the sectoral aggregates. In particular, we do not observe any adverse employment effects. As before, the post-treatment coefficients in columns 1 and 2 are mostly positive, with the coefficient in column 2 capturing the differential change between the baseline and 2022 even being marginally significant. Reassuringly, we do not find any statistically significant effects in the pre-treatment period. Overall, these results provide no evidence in support of the hypothesis that the energy price shock had adverse effects on employment. Turning to wages, we again find a negative and statistically significant pre-treatment coefficient for 2019 in column 3, along with a negative——and this time statistically significant——post-treatment coefficient for 2023 of similar magnitude as in table 4. The inclusion of sector-by-year fixed effects again absorbs the pre-trends. In column 4, all pre-treatment coefficients are small, do not indicate any pattern, and are statistically insignificant. The post-treatment coefficients, by contrast, are negative and significant, indicating—consistent with the sector-level estimates—a growing adverse impact of the price shock on wages. The point estimate for 2022 suggests that a 100% increase in exposure depressed mean establishment-level wages by 0.21%, while the estimate for 2023 implies a reduction of 0.37%, which aligns with results in Table 4.

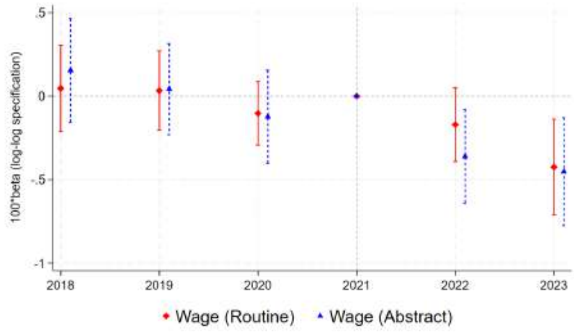
4.3 Labor Market Effects: Heterogeneities, Mechanism and Robustness

Thus far, the results suggest a negative effect of exposure to the price shock on wages, while we do not find any evidence of adverse employment effects. We now seek to deepen our analysis

Figure 5: Effects by Type of Worker: Routine vs. Abstract



(a) Employment



(b) Wages

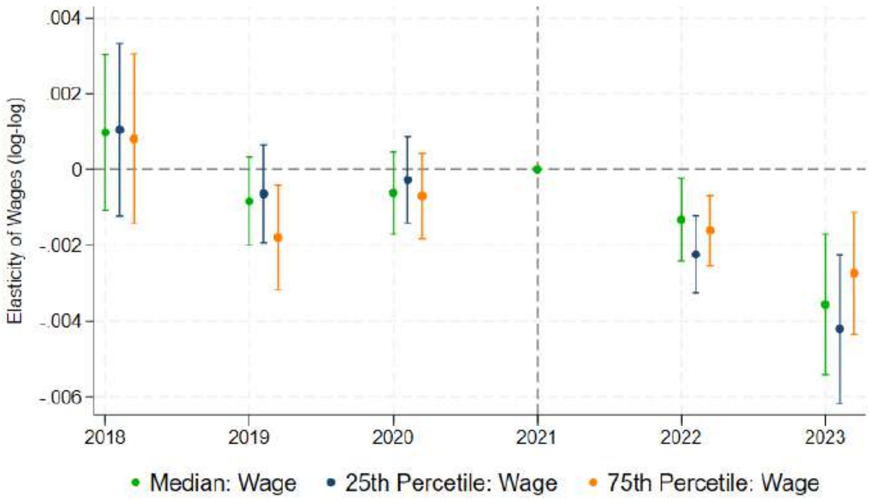
Notes: Figure 5a presents point estimates from estimating equation 4, conditional on year-sector fixed effects. The dependent variable is the log change in the number of routine (red) and abstract (blue) workers relative to 2021. Subfigure 5b displays the corresponding estimates, using the log change in average wages by task group relative to 2021 as the dependent variable. The unit of observation is the four-digit economic sector. Dots/Triangles represent point estimates, and vertical lines indicate 95% confidence intervals. Standard errors are clustered at the four-digit sector level. The sample is restricted to sectors with at least 350 employees. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2019) and industrial energy price data and the Integrated Employment Biographies from the IAB.

by examining heterogeneities, exploring potential mechanisms, and probing the robustness of our findings. Using sector-level data, we investigate heterogeneities by worker type (abstract vs. routine tasks). We use the BHP to analyze heterogeneities by establishment characteristics and effects on within-establishment wage inequality. To shed light on underlying mechanisms, we consider wage offers, wages among long-tenure workers and the average wages of establishment leavers. Finally, we assess the robustness of our estimates towards a discretized exposure measure (exposure quartiles).

Heterogeneities Figure 5 presents the employment and wage effects separately for workers engaged in routine (red) and abstract (blue) tasks. The empirical specification underlying the results in Figure 5 controls for sectoral shocks by including sector-year fixed effects. Subfigure 5a shows the estimated effects on employment. As can be seen from the figure, neither the number of routine workers nor that of abstract workers decreased in response to the energy price shock and all pre- and post-shock coefficients are statistically insignificant. Subfigure 5b plots the effects on average sectoral wages for routine and abstract workers. As for employment, there exists little heterogeneity. Reassuringly, pre-trends are flat in both groups. The estimated coefficients for the post-period point to a drop of average wages on impact, i.e., in 2022, and wages continued to fall in 2023. Both post-treatment point estimates are close to the average effect reported in column 4 of table 4.

Related to the above split between workers engaged in abstract and routine tasks, we now use the BHP data to analyze within establishment wage inequality by looking at the effects of the price shock on different moments of the wage distribution: the 25^{th} percentile, the median, and the 75^{th} percentile. Figure 6 plots the corresponding point estimates. Overall, one can see that the effects strongly co-move before and after the shock. We do not discern any pattern pre-treatment. In contrast, post coefficients are negative and significant on impact, dropping further in 2023. In both post-treatment years, the point estimate capturing the effect on wages at the 25^{th} percentile is the largest. While the confidence intervals of all point estimates clearly overlap, one might interpret this as a weak indication of a larger effect among lower-wage workers. These results—indicating a relatively homogeneous impact of the price shock on wages—align with the analysis for abstract and routine workers. For example, from table 2, one can glean that workers with abstract tasks earn an average wage that is ≈50% above that of routine workers, i.e., we expect abstract workers at the upper end of the establishments' wage distribution and routine workers at the lower end.

Figure 6: Effects along the within establishment Wage Distribution



Notes: The figure presents point estimates from estimating equation 4, controlling for year-sector fixed effects. The dependent variables are the log changes relative to 2021 in the establishment-level median wage (green), the 25^{th} percentile wage (blue), and the 75^{th} percentile wage (orange), estimated separately. The unit of observation is the establishment. Dots represent point estimates, and vertical lines indicate 95% confidence intervals. Standard errors are clustered at the four-digit sector level. The sample is restricted to establishments with at least 20 employees. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2019) and industrial energy price data. Research Data Centre of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB). DOI: 10.5164/IAB.BHP7523.de.en.v1.

Subsection A.3 in the appendix presents additional heterogeneity analyses based on establishment characteristics. Specifically, we distinguish between small and large establishments (fewer or more than 250 employees) and by establishment age. Figures A3 and A4 suggest that overall heterogeneities are limited. The wage effects provide some suggestive evidence of a stronger negative impact among smaller establishments. In the case of employment, some effects are estimated less precisely, and the presence of pre-trends in certain subsamples warrants a cautious interpretation.

Mechanism: Hires and Leavers Our results indicate a consistently negative effect on mean wages. Several mechanisms could account for the observed adjustment in average sector- or establishment-level wages. For instance, wages for incumbent workers in exposed sectors might grow more slowly compared to less exposed sectors; high-wage individuals may leave a sector or establishment; or newly hired workers may receive lower wage offers. To shed light on these potential channels, we estimate the effect of the price shock on sectoral average wages separately for five groups: newly hired individuals, all individuals who were not newly hired, individuals with long-standing employer–employee relationships, the last wage of plant leavers and the new wage of plant leavers. Table 6 presents the results. For comparison, column 1 reproduces the main sector-level effects on average wages, corresponding exactly to the results reported in column 4 of Table 4. Column 2 reports the effect on wages of newly hired workers, which show a substantial post-shock decline. In 2022, the point estimate is roughly twice as large as the main effect (column 1), and in 2023 it is nearly three times as large. Since the number of new hires is much smaller than the total workforce, the effect is estimated with lower precision, i.e., the standard errors are much larger.[17] In column 3 we show the effect on all individuals who were not newly hired, which is the complementary subgroup to new hires. This effect is slightly smaller than the main effect (column 1) but remains statistically significant, suggesting that the adjustment did not exclusively operate through new hires. Still, because all "not newly hired" include workers hired in the previous year, lower wages for new hires in 2022 in exposed sectors contribute to a smaller coefficient for the "not newly hired" in 2023 in the same sector. To further separate out the dynamic effect of lower wage offers, we compute average sectoral wages for a balanced panel of individuals continuously employed with the same employer between 2017 and 2023, i.e., with at least five years of tenure when the shock occurred in 2022. Column 4 reports the corresponding coefficients. Although the post-treatment effects for these long-tenure workers are negative in both years, they are roughly half the size of the main effect. Thus, while the estimates suggest that long-standing incumbents also experienced modest earnings losses, a relevant part of the adjustment occurred through lower wages for new hires and for workers with relatively short tenure.

Columns 5 and 6 present results for two supplementary outcomes: First, column 5 shows the effect on the average sectoral wage of individuals who changed employers. The underlying idea is that a decrease in a sector's average wage could result from high-wage earners exiting the sector. If this was the case, the post-treatment coefficients would be positive.[18] This, however, is not supported by the data: all pre- and post-treatment coefficients are close to zero and statistically insignificant. Finally, column 6 reports point estimates of the effect on the first wage earned after changing employers, with wages still assigned to the sector of the previous employer.[19] The rationale is that workers in an exposed sector may face poorer outside options when changing employers, even if they transition into a completely different sector. While the post-treatment coefficients are not statistically different from zero, the point estimates are consistent with this

[17] On average, approximately 13% of workers in a sector are new hires each year (cf. Table 4)

[18] For illustration, consider an individual i who worked for employer $e$in sector s in 2022 and switched to employer j in sector o in 2023. The relevant wage is the final wage earned at e in sector s. We assign this wage to the year 2023 because it affects the average wage in sector s in that year, because individual i may no longer be part of the sector's workforce.

[19] For example, consider an individual i who worked for employer e in sector s in 2022 and switched to employer j in sector o in 2023. The dependent variable is the first wage earned with the new employer j, but it is assigned to the sector of the previous employer s.

idea. For instance, the 2023 estimate is approximately twice as large as the main effect on the average sectoral wage.

Table 6: Response of Log Wages to a 100% Increase in Exposure in Subsamples

	All	Hires	No Hires	Long Tenure	Leaver (t-1)	Leaver (t)
	(1)	(2)	(3)	(4)	(5)	(6)
Delta 2018	0.166	-0.556	0.235*	0.098	-0.089	-0.264
	(0.129)	(0.523)	(0.139)	(0.117)	(0.391)	(0.714)
Delta 2019	0.099	-0.098	0.097	0.006	0.192	0.400
	(0.113)	(0.479)	(0.114)	(0.094)	(0.409)	(0.628)
Delta 2020	-0.055	-0.036	-0.049	-0.059	0.296	-0.364
	(0.105)	(0.508)	(0.110)	(0.091)	(0.362)	(0.566)
Delta 2022	-0.226*	-0.555	-0.226*	-0.134	0.092	-0.553
	(0.122)	(0.451)	(0.127)	(0.099)	(0.294)	(0.441)
Delta 2023	-0.434***	-1.125**	-0.329**	-0.193	-0.084	-0.691
	(0.146)	(0.476)	(0.152)	(0.121)	(0.333)	(0.568)
# of Observations	1,100	1,100	1,100	1,100	1,100	1,100
# of Sectors	220	220	220	220	220	220
Year-Sector-FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports point estimates and standard errors from estimating equation 4, controlling for year–sector fixed effects. The dependent variables are the log change in average sector-level wages relative to 2021 for various subsamples. Column 1 reports the effect on the overall average wage; column 2 on the average wage among newly hired workers; column 3 on the average wage for all workers who were not newly hired; and column 4 on the average wage from a balanced panel of workers continuously employed in the same plant since at least 2017. Columns 5 and 6 focus on workers transitioning to new plants. In column 5, the dependent variable is the last wage an individual earned with their previous employer, assigned to the sector of that employer and shifted forward by one year (e.g., for a worker i who moved from plant a to plant b between 2022 and 2023, the wage earned at plant a in 2022 is assigned to the sector of plant a in 2023). Column 6 reports coefficients where the dependent variable is the first wage earned with the new employer, but still assigned to the sector of the previous employer. The unit of observation is the four-digit economic sector. Standard errors are clustered at the four-digit sector level. The sample is restricted to sectors with at least 350 employees. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Lander: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2019) and industrial energy price data and the Integrated Employment Biographies from the IAB. Significance levels are indicated as * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Robustness Finally, we assess the robustness of our main results towards using a discretized exposure measure. Specifically, we assign each four-digit sector to one of four exposure quartiles and regress the outcome variables on quartile dummies interacted with year dummies, omitting the dummies for the least exposed quartile. The coefficients then capture differential trends in outcomes by exposure quartile relative to the least exposed group.

Figures A5 and A6 in the appendix present the results for wages and employment, using both the sector-level and the establishment-level data. For employment, we do not observe differential trends by exposure quartile when using sector-level data (cf. Subfigure A6a). While all post-shock coefficients are negative, they are close to zero. Using the BHP yields positive but also insignificant point estimates for the post period. Some caution is warranted, however, as there appears to be a slight downward trend in employment prior to the shock when using the BHP. It is nevertheless reassuring that this pre-trend is similar across the three upper quartiles, suggesting parallel pre-trends among establishments from sectors in the upper 75% of the exposure distribution, i.e., only the reference group—establishments in the least exposed quartile—deviates. Overall, the estimates are consistent with our earlier conclusion that the energy price shock did not result in adverse employment effects.

Figure A5 presents the corresponding results for wages. Using sector-level data, the negative effect appears to be primarily driven by sectors in the most exposed quartile. For example, the point estimate for 2023 suggests that average wages in the most exposed sectors were approximately 2% lower than they would have been in the absence of the shock. This magnitude broadly aligns with the effects estimated using the continuous treatment variable: the point estimates in Table 4 indicate that a 100% increase in exposure is associated with a wage decrease of approximately 0.43%. Moving from the 25^{th} to the 75^{th} percentile corresponds to an exposure increase by factor seven, which—taking the estimates at face value—would imply a wage decline of roughly 3%. Post-treatment coefficients for the second and third most exposed quartiles are also negative, though statistically insignificant, suggesting wage declines of around 1% relative to the baseline category.

At the establishment level (Subfigure A5b), we observe a similar pattern: the largest absolute effects are found in the most exposed quartile, with statistically significant wage reductions in both post-treatment years. In particular, the 2023 estimate implies a decrease in average establishment-level wages of approximately 1.5% relative to the control group. Thanks to smaller standard errors in the establishment-level data compared to the sector-level data, we also detect statistically significant effects among establishments in the third most exposed quartile. The estimates suggest wage reductions of around 0.5% in 2022 and 0.8% in 2023 and for the second most exposed quartile, the point estimates are also negative but not statistically significant. With regard to pre-trends, the estimates for 2019 and 2020 are small and statistically insignificant. The point estimates for 2018, however, are statistically significant. Importantly, all three pre-treatment estimates are very similar in magnitude, which suggests that the deviation is driven by the control group (i.e., establishments in the least exposed quartile), while the wage trajectories of the three most exposed quartiles were largely parallel before the shock. This contrasts with the post-treatment period, during which wage effects clearly vary with the intensity of exposure.

4.4 Regional Exposure

After analyzing the effects of the shock at the sector level we now turn to the regional level. For this, we map the shock to 400 districts as described in subsection 2.[20] As can be seen from the heat map in Figure 3, shock exposure is high in regions characterized by heavy industry. Figure A7 provides a formal depiction of this relationship, showing the correlation between the logarithm of shock exposure and the logarithm of CO_2 emissions per employee at the regional level. This correlation highlights the analysis's relevance within the broader decarbonization context.

We begin with a purely descriptive analysis of the relationship between the log of shock exposure and local economic characteristics—such as workforce composition, education, and other socio-

[20]Currently, we do not yet have regional data available that would allow us to measure the effects of the shock at the regional level, since these has not been published yet. An exception is real GDP growth rates at the federal-state level. Figure A11 in the appendix plots the corresponding correlations.

demographic indicators—using binned scatter plots. We then examine the impact of the shock on local labor markets and analyze whether this affected public attitudes measured by voting behavior.

Correlated Regional Characteristics Figure A12 in the appendix shows binned scatter plots. From the first row of subfigures one can glean that exposure is weakly positively correlated with the share of workers in the primary sector, strongly positively correlated with the share of workers in the secondary sector, and negatively correlated with the share employed in the tertiary sector.[21] The second row of subfigures, which displays correlations by qualification levels, further reflects the underlying labor force structure across sectors. More exposed regions exhibit a higher share of workers with vocational training and a lower share with academic degrees, whereas the share of individuals without formal education appears largely uncorrelated with exposure. Similarly, the share of students and the proportion of females are lower in more exposed regions. Interestingly, these regions are also characterized by lower mobility: both in-migration and out-migration rates are negatively correlated with exposure. Finally, the population in more exposed areas tends to be somewhat older on average.

Regional Exposure and Labor Market Outcomes In the previous section, we documented a negative impact of the price shock on wages and an insignificant effect on employment. This result holds across both establishment-level and individual-level data. We now use the regional-level data to estimate the effect of regional exposure on both outcomes. Whereas the previous analyses identified effects based on variation in treatment intensity across four-digit industries within the manufacturing sector, this specification relies on variation in exposure across regions, which allows us to examine the labor market outcomes for sectors other than manufacturing. Respective estimates may capture potential spillover effects. For instance, the trajectory of the service sector in an region with heavy energy intensive manufacturing may be different from that in a region specialized in light manufacturing.

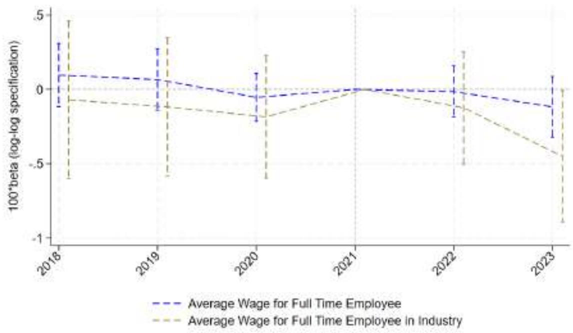
Subfigure 7a presents point estimates from regressions of the log of average wages (blue line) and average wages in the manufacturing sector (brown line) on the log of regional exposure. The specification includes region-by-year fixed effects and controls for the initial share of industrial employment. Including the latter control ensures comparisons between regions with different exposures but similar degrees of industrialization. First, subfigure 7a shows no indication that trends in average (manufacturing) wages differed prior to 2021, depending on the subsequent exposure to the shock. In the post-treatment period, however, the point estimates capturing the effect on average manufacturing wages are negative, with the effect in 2023 being statistically significant. This effect mirrors the previous wage results based on establishment and individual-level data. Note, however, that the outcome here is the average wage in the manufacturing sector in a given district. In contrast, previous estimates are based on variation from within the manufacturing sector. The negative coefficient based on the regional data thus results from the higher share of exposed workers—which saw a relative decline of their wages according to

[21] These patterns are partly mechanical, as the exposure measure is constructed based on industrial energy consumption.

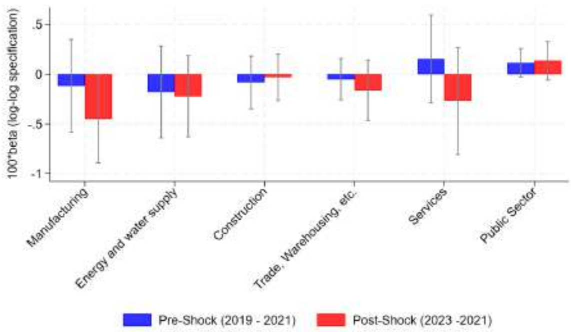
previous estimates—in more exposed regions. The point estimates capturing the effect on overall average wages—which includes manufacturing—also turn negative in both post-treatment years but remain small and statistically insignificant. This suggests that the wage responses in other sectors are muted relative to the response of the manufacturing sector, which is in line with expectations.

Subfigure 7b shows the estimates that capture the response of average wages in different sectors. Blue bars are pre-trend coefficients (with wage changes from 2019 to 2021 as the dependent variable), and red bars are the coefficients capturing post-treatment effects (changes between 2021 to 2023).

Figure 7: Regional Exposure and Wages



(a) Effect on Log Average (Manufacturing) Wage



(b) Effect on Log Average Wages

Notes: Subfigure 7a presents point estimates from a regression of the log change in manufacturing employment relative to 2021 on the regional exposure measure interacted with year dummies. The specification includes macro-region (North, South, East, and West) by year fixed effects, as well as a control for the baseline share of manufacturing employment also interacted with the year. Standard errors are clustered at the level of "Raumordnungsregionen". Subfigure 7b displays the corresponding coefficients for 2019 (pre-trend) and 2023, based on the same empirical specification, for different subsectors. Data sources include the "Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2019)" and industrial energy price data from the Federal Statistical Office.

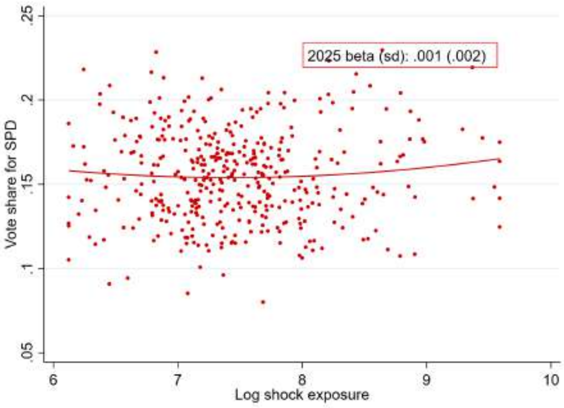
Figure A13 in the appendix presents the corresponding results for employment in manufacturing and other sectors. Consistent with the main findings, we observe statistically insignificant estimates across all pre- and post-treatment years—both for total employment and for employment within the manufacturing sector. Furthermore, there is no evidence of systematic spillover effects on employment in non-manufacturing sectors.

Regional Exposure and Attitudes

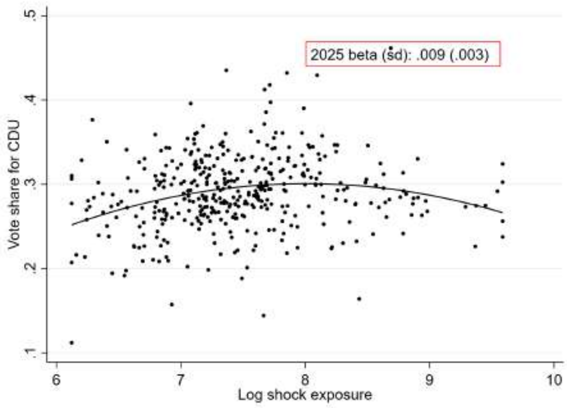
We first describe the relationship between regional exposure and attitudes measured by voting behavior in the most recent federal election held in February 2025. For that, we use scatter plots where the logarithm of regional exposure is plotted on the x-axis against parties' vote shares on the y-axis (see Figure 8). Each dot represents a district and the solid line is the quadratic fit. In the upper right corner, we also include the point estimate and standard error from a linear regression of vote shares on log shock exposure (the slope of a linear fit).

We begin with the two traditional main parties—the Social Democrats (SPD) and the Christian

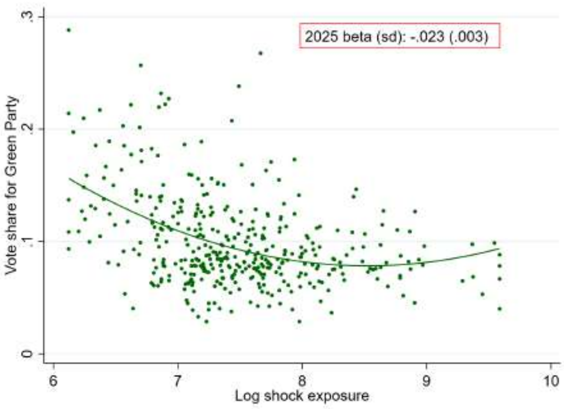
Figure 8: Correlation Between Shock Exposure and Voting Behavior



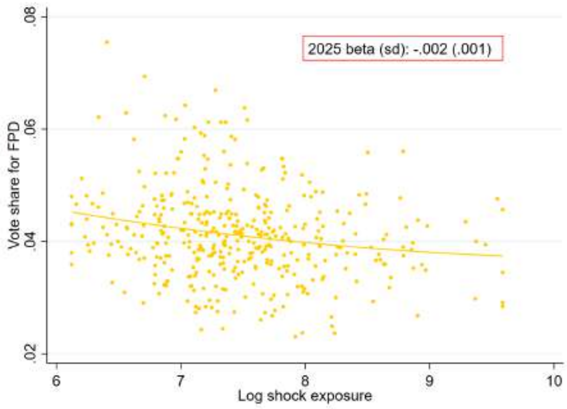
(a) Vote Share for SPD



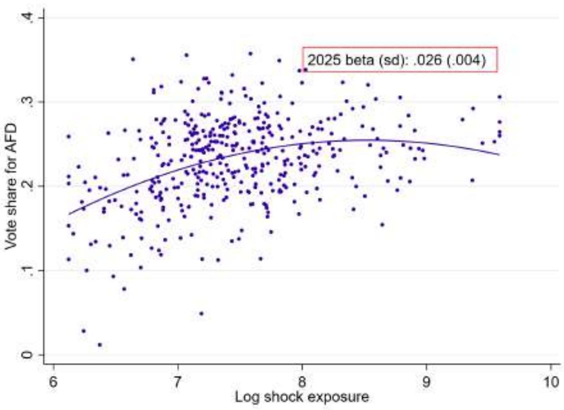
(b) Vote Share for CDU



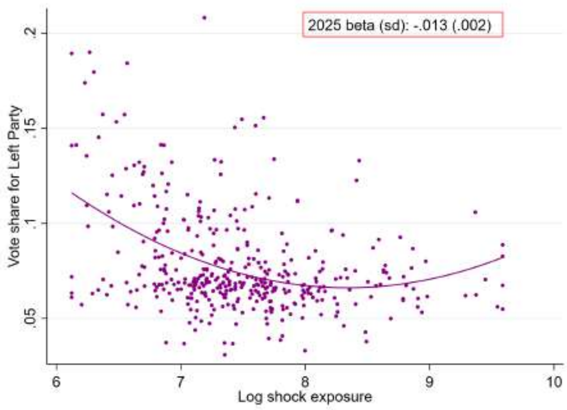
(c) Vote Share for Greens



(d) Vote Share for FDP



(e) Vote Share for AfD



(f) Vote Share for Left

Notes: The scatter plots visualize the correlation between the log of regional exposure and vote shares in the most recent federal election held in 2025. Vote shares have been residualized by macro-regions (North, South, East, and West). The fitted line represents a quadratic fit. In the red boxes we show the coefficient and corresponding standard error from a linear regression of vote shares on regional exposure. Data sources include the "Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2019)" and industrial energy price data from the Federal Statistical Office and data from the federal election officer.

Democrats (CDU)—shown in the top row of Figure 8. As seen in the left subfigure, there is virtually no correlation between SPD vote share and shock exposure. This is somewhat surprising, given that the shock is strongly correlated with industrial employment, and the working class has historically been the SPD's core constituency. The right subfigure, which plots the CDU's vote shares against regional exposure, does not reveal a clear pattern either. While the linear fit yields a positive and statistically significant estimate, the effect size is small—particularly given the comparably high average vote share of 28% for the CDU. The middle row of Figure 8 shows vote shares for the Green Party and the liberal FDP plotted against the shock exposure. The left subfigure indicates a negative and quantitatively meaningful correlation between the shock and the Green Party's votes. The linear slope implies that a 100% increase in exposure is associated with a 2.3pp decline in their vote share, roughly 20% of their average support. As the Green Party is the most consistent and ambitious advocate of climate policy, it is plausible that voters in regions most exposed to such policies—potentially facing job and income risks—are less likely to support them. The right subfigure for the FDP, a party generally associated with a weaker appeal to working-class voters, shows a qualitatively similar negative relationship between exposure and their vote shares. However, the slope coefficient is an order of magnitude lower than that for the Greens. The bottom row of Figure 8 plots vote shares for parties from both ends of the political spectrum against the exposure measure. Subfigure 8e shows a positive correlation between regional exposure and support for the far-right AfD. The estimated linear slope implies that a 100% increase in exposure is associated with a 2.6 percentage point higher vote share for the AfD. Given the party's stance as "climate-skeptic," this finding is consistent with the notion that the AfD attracts greater support in regions where voters are economically dependent on carbon-intensive manufacturing. The final subfigure reveals a negative correlation between exposure and the left party's vote share. While this party has traditionally sought to represent working-class interests, it has become increasingly popular among voters in more urban areas in recent years. This shift aligns with the observed negative correlation between regional exposure and support for the left party.

To move beyond the correlations discussed above and examine whether changes in voting behavior can be causally attributed to the energy price shock, we analyze changes in party vote shares between the most recent election and the previous one held in 2021, as well as changes between the 2017 and 2021 elections to test for pre-trends. Table 7 presents the corresponding results. Each coefficient reported in the table comes from a separate regression. For each party, we report estimates from three specifications: The most parsimonious specification includes only region-fixed effects (columns 1 and 4).[22] The second specification additionally controls for the baseline share of industrial employment (columns 2 and 5). This specification corresponds to the specification used to study regional labor market effects. It reflects the aim to compare similarly industrialized regions that differ in their sectoral composition within manufacturing. The third specification further includes a set of socio-demographic pre-shock controls that are known to

[22]We follow Dauth et al. (2014) and include fixed effects for four regions in Germany: the south (Baden-Wuerttemberg and Bavaria), west (North Rhine-Westphalia, Saarland, Hesse and Rhineland-Palatinate), east (Mecklenburg Pomerania, Brandenburg, Thuringia and Saxony), north (Schleswig-Holstein, Hamburg, Lower-Saxony and Bremen)

correlate with voting behavior.

Table 7: Log Shock Exposure and Change in Vote Share

	Δ CDU Share			Δ SPD Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ 2021 - 2017	0.003	0.006*	0.006	0.002	0.001	0.000
	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Δ 2025 - 2021	-0.002	-0.002	-0.002	-0.008***	-0.003	-0.001
	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)
	Δ Green Share			**Δ FDP Share**		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ 2021 - 2017	-0.013***	-0.004	-0.000	0.003*	-0.000	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Δ 2025 - 2021	0.006***	0.004*	0.003*	-0.000	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
	Δ AfD Share			**Δ Left Share**		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ 2021 - 2017	0.002	-0.003**	-0.003**	0.001	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Δ 2025 - 2021	0.012***	0.002	-0.000	-0.007***	-0.003	-0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
# of Observations	400	400	400	400	400	400
Region-FE	Yes	Yes	Yes	Yes	Yes	Yes
Industrial employment share		Yes	Yes		Yes	Yes
Sociodemographic characteristics			Yes			Yes

*Notes:*he table reports point estimates and standard errors from regressions of changes in federal election vote shares on the regional exposure measure. Each coefficient is obtained from a separate regression. The unit of observation is the German district (Kreis). Standard errors are clustered at the level of "Raumordnungsregionen." The inclusion of control variables is indicated at the bottom of the table. Data sources include the "Research Data Centers of the Federal Statistical Office and the Statistical Offices of the L ¨ander: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2019)" and industrial energy price data from the Federal Statistical Office and data from Germany's federal election office. Stan * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

The top panel of Table 7, which reports results for Germany's two traditional major parties, shows that the energy price shock is largely uncorrelated with changes in the vote share for the center-right CDU. In contrast, column 4 indicates a significant decline in vote shares for the center-left SPD in the most recent election. However, this effect becomes statistically insignificant once we control for the baseline share of employment in manufacturing. This suggests that although SPD support declined in more industrialized regions, the energy price shock itself does not appear to be the driving factor.

The middle panel presents results for the Green Party and the liberal FDP. For both, we find no robust or statistically significant relationship between vote share changes and shock exposure.

In the bottom panel, we observe a sizable increase in vote shares for the far-right AfD. However, this effect is fully accounted for by the baseline industrial employment share, mirroring the pattern observed for the SPD, though with the opposite sign. A similar pattern emerges for the Left Party, where initial correlations also become insignificant after controlling for baseline industry structure.

Taken together, the results in Table 7 indicate that while there are regional voting shifts associated with industrial employment patterns, we do not find evidence that these changes can be causally linked to the energy price shock.

5 Discussion and Conclusion

After energy imports—particularly gas—from Russia nearly ceased in late summer 2022, industrial energy prices rose 1–3 times above their 2019 levels, depending on the fuel type. This raised concerns about a severe economic crisis in Germany. Against this backdrop, this paper offers the first ex-post analysis of the price shock on economic activity, prices, and particularly on labor market outcomes, e.g., wages and employment using fine-grained, four-digit sector-level data as well as administrative establishment and regional-level data. To measure shock exposure, we combine establishment-level data on fuel shares from the German manufacturing census with aggregate fuel price changes between the pre-shock and shock years, which we then aggregate to the four-digit sector level.

In a motivating exercise, we first document a substantial adverse effect of the energy supply shock on economic activity, using a monthly production index. Specifically, we find that in 2023 the output of sectors in the most exposed quartile was 10–15 pp. lower than that of sectors in the least exposed quartile. We corroborate these results with annual data on real output. In addition, we document negative effects on investment and a marked increase in prices. The former finding suggests that the price shock is likely to entail medium-term consequences through reduced investment, while the latter indicates that energy price dynamics may have played a significant role in the surge of aggregate inflation in recent years.

To analyze the labor market consequences, we draw on detailed individual-level employment data aggregated to the sector level as well as establishment-level information on employment and wages. Results from both sources do not provide evidence of negative employment effects but consistently indicate an adverse impact on wages. For instance, our estimates suggest that a 100% increase in a sector's shock exposure reduced average sectoral wages by approximately 0.43%. We further show that the effect for long-tenure workers is roughly half the average, while the effect on wages for new hires is about three times larger. By contrast, the effects are relatively homogeneous across task groups and along the plant-level wage distribution.

Finally, we map the sectoral shock to 400 districts. Regional patterns reflect well-known industrial clusters. On a purely descriptive level, we observe that more exposed regions are dispersed across the country, suggesting that the shock partially averages out across federal states. This could be good news for potentially displaced workers, as it increases the likelihood of transitioning to a less exposed industry within relatively close geographic proximity. Even without the price shock, this analysis is relevant in light of the anticipated higher energy prices needed to transition toward lower carbon intensity in production. Using post-shock data on labor market outcomes and voting behavior, we first confirm the sector-level employment results. Turning to election outcomes, we do not find evidence of a systematic relationship between a region's exposure to the shock and voting behavior. On a correlational basis, however, we document that regions more exposed to the shock tend to show lower support for stricter climate policies—as measured by Green Party vote shares and higher support for parties skeptical of human-made climate change even prior to the shock.

The results presented in this paper hold important insights for policymakers. First, while affected sectors experienced reduced production, there was no complete collapse, and some recovery has been observed by 2024. This suggests that sectors can adapt to higher energy prices necessary for successful climate policy, particularly if such policies are phased in gradually. The finding that energy costs were passed through highlights that energy cost shocks also impact downstream sectors with some time lag, i.e., they propagate through the economic system. To the extent that downstream sectors were already indirectly affected through pass-through, our main estimates should be interpreted as a lower bound.

We do not find consistent evidence for adverse employment effects, though our analysis covers only the initial years of the shock, and adverse effects might still occur in the longer term and respective years were still characterized by comparatively tight labor markets. However, the observed adverse wage effects indicate that workers bear part of the cost of higher energy prices– not through unemployment, but through reduced wages. For example, point estimates from the sector- and plant-level analyses suggest that average wages decreased by approximately 0.4% in response to a 100% increase in exposure. A back-of-the-envelope calculation, multiplying the increase in exposure from the 25^{th} to the 75^{th} percentile (factor seven), implies an average wage loss of about €1,400–roughly 20% of the estimated energy cost increase per worker (cf. Figure 2).

For future climate policy, this underscores the importance of compensating those adversely affected to maintain broad political support for higher energy prices resulting from carbon pricing instruments. Indeed, our regional-level analysis shows that in regions more exposed to the energy price shock—which are also more carbon-intensive—support for climate policies has already been lower even before the shock.

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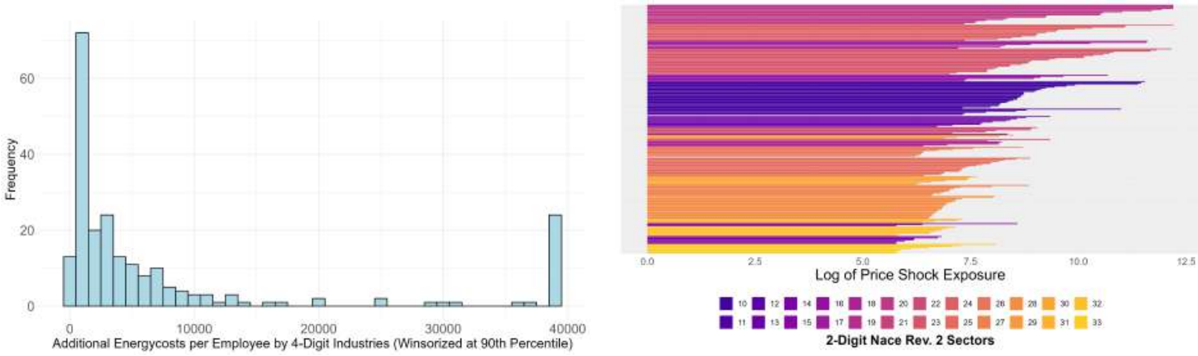
Appendix A Additional Material: Sector-Level

A.1 Descriptives

Figure A1: Sectoral Exposure



(a) Histogram: Winsorized Shock **(b)** Log Shock

Notes: The histogram in Figure A1a shows the exposure measure, defined as the predicted increase in energy costs per worker in a four-digit sector, winsorized at the 90^{th} percentile. Subfigure A1b presents the log-transformed exposure measure. Four-digit sectors are sorted within their respective two-digit sectors, with blocks of two-digit sectors stacked. The two-digit sector with the lowest exposure is positioned at the bottom, while the one with the highest exposure is at the top. Data sources include the “Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2019)” and industrial energy price data from the Federal Statistical Office.

Table A1: Means of Sectors by Exposure Quartile

	First Quartile	Second Quartile	Third Quartile	Fourth Quartile
Turnover (in Mio.)	6,894.66	8,365.34	15,568.95	8,233.53
# Employees	30,325	37,317	37,745	16,933
Turnover (in 1000) per L	218.16	260.73	335.34	442.90
Investment (in Mio.)	141.70	270.34	475.11	285.27
Export Share	0.43	0.41	0.38	0.42
# establishments	279	333	191	100
L per establishment	124.74	152.39	266.09	194.20
Shock Exposure	0.73	1.77	4.79	52.67

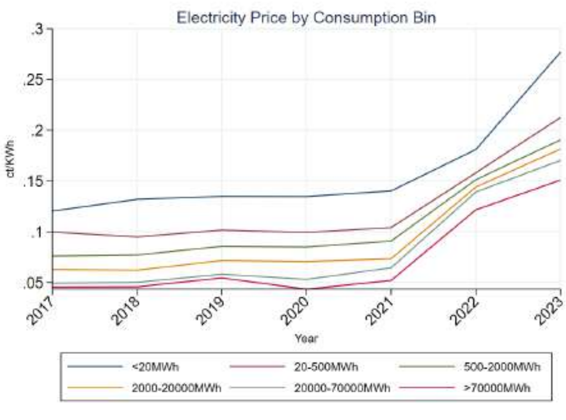
Notes: This table shows the means of four-digit sector level means by shock exposure quartile. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2019) and sectoral outcome data and industrial energy price data from the Federal Statistical Office.

Table A2: Medians of Sectors by Exposure Quartile

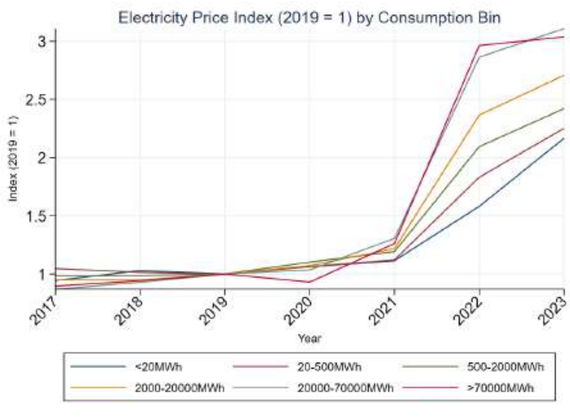
	First Quartile	Second Quartile	Third Quartile	Fourth Quartile
Turnover (in Mio.)	2,260.14	5,670.36	2,584.35	3,210.66
# Employees	10,468	20,578	8,270	9,473
Turnover (in 1000) per L	207.09	227.31	263.20	404.32
Investment (in Mio.)	39.69	149.50	72.83	137.06
Export Share	0.43	0.43	0.35	0.42
# establishments	116	160	62	60
L per establishment	106.37	106.87	135.28	162.29
Shock Exposure	0.74	1.50	4.56	29.06

Notes: This table shows the medians of four-digit sector level means by shock exposure quartile. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2019) and sectoral outcome data and industrial energy price data from the Federal Statistical Office.

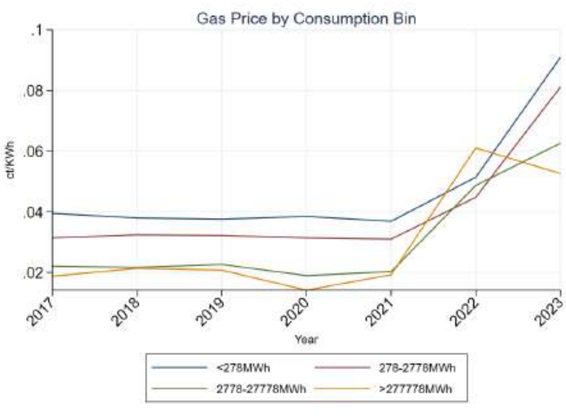
Figure A2: Electricity and Gas Prices by Consumption Bin



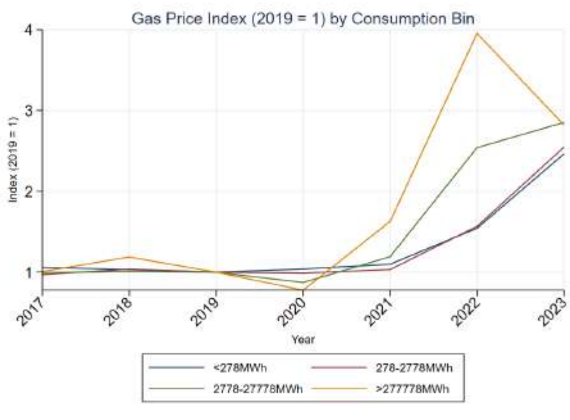
(a) Electricity Price



(b) Electricity Price Index



(c) Gas Price



(d) Gas Price Index

Notes: Subfigure A2a shows the evolution of industrial electricity prices in levels by consumption bin and subfigure A2b shows the corresponding index. Subfigure A2c shows the evolution of industrial gas prices in levels by consumption bin and subfigure A2d shows the corresponding index. Source: Statistisches Bundesamt (Destatis – Federal Statistical Office of Germany), Daten zur Energiepreisentwicklung, December 2023, EVAS Nos. 61241, 61411, 61421, 61111, 61231, published 31 January 2024, GENESIS-Online.

Table A3: Aggregation of NACE Rev. 2 Sectors into Combined Sectors

Aggregated sector	**Included NACE Rev. 2 divisions (full titles)**
Food, beverages & tobacco	10 Manufacture of food products; 11 Manufacture of beverages; 12 Manufacture of tobacco products
Textiles, apparel & leather	13 Manufacture of textiles; 14 Manufacture of wearing apparel; 15 Manufacture of leather and related products
Wood & wood products	16 Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
Paper & printing	17 Manufacture of paper and paper products; 18 Printing and reproduction of recorded media
Petroleum, chemicals & pharmaceuticals	19 Manufacture of coke and refined petroleum products; 20 Manufacture of chemicals and chemical products; 21 Manufacture of basic pharmaceutical products and pharmaceutical preparations
Rubber & plastics	22 Manufacture of rubber and plastic products
Non-metallic mineral products	23 Manufacture of other non-metallic mineral products
Metals (basic & fabricated)	24 Manufacture of basic metals; 25 Manufacture of fabricated metal products, except machinery and equipment
Electronics & electrical equipment	26 Manufacture of computer, electronic and optical products; 27 Manufacture of electrical equipment
Machinery & equipment n.e.c.	28 Manufacture of machinery and equipment n.e.c.
Motor vehicles & other transport equipment	29 Manufacture of motor vehicles, trailers and semi-trailers; 30 Manufacture of other transport equipment
Furniture	31 Manufacture of furniture
Other manufacturing	32 Other manufacturing
Repair & installation of machinery & equipment	33 Repair and installation of machinery and equipment

Notes: The table shows the aggregation of NACE Rev. 2 two-digit sectors into combined sectors used in the analysis. Official titles follow the NACE Rev. 2 classification.

A.2 Additional Analysis at the Sector Level: Annual Economic Performance Indicators and Pass Through of Costs

In this subsection, we draw on aggregate data published by the German Statistical Office to further examine the economic response to the energy price shock. We begin by analyzing indicators of economic performance and then turn to the response of output prices to assess the extent of cost pass-through.

A.2.1 Annual Economic Performance Indicators

Table A4 presents additional results for four outcomes: log real turnover, number of employees, investment, and the Producer Price Index (PPI). Each column corresponds to a separate regression specification (see equation 4). For each outcome, we estimate two versions of the model: one with and one without two-digit sector-by-year fixed effects. Rather than estimating year-specific coefficients, we interact the exposure measure with binary pre-/post-treatment indicators. The pre-treatment period includes 2018–2020, and the post-treatment period covers 2022–2023. The dependent variables are changes relative to 2021. Columns 1 and 2 report the effects on real (deflated) turnover. In column 1, which does not include sector-year fixed effects, the pre-treatment coefficient is statistically insignificant, while the post-treatment coefficient indicates a sizable decline in output. When sector-year fixed effects are included (column 2), the magnitude of the estimated effect decreases and becomes statistically insignificant. Nonetheless, the point estimate remains economically meaningful, suggesting a decline in output of approximately 2% in response to a 100% increase in energy price exposure.

The dependent variable in columns 3 and 4 is the number of employees. Point estimates for the pre- and post-period are insignificant in both specifications, providing no support for the hypothesis that the price shock had adverse employment effects. Columns 5 and 6 provide some evidence of a negative effect on firms' investment. If investments remain lower in the exposed sectors over the medium term, this would imply a gradual decline in the capital stock in the affected sectors. However, upon the inclusion of sector-year fixed effects, the point estimate is close to zero and insignificant. Finally, in columns 7 and 8 we turn to the response of output prices using the sector level PPI as dependent variable. Although these specifications yield significant pre-treatment coefficients, the post-2021 coefficients are about four-times as large as the pre-2021 coefficients. Specifically, respective estimates indicate that a 100% higher exposure is associated with a 4.5-5pp. increase in the producer price index during the post-2021 period. In a refined pass-through analysis presented in the following subsection A.2.2, we are indeed unable to reject the hypothesis that pass-through is 100%. This finding aligns with evidence from France based on both sector- and firm-level data (cf. Arquié and Thie, 2023; Lafrogne-Joussier et al., 2023).

Table A4: Sectoral Effects of Log Shock Exposure

	Real Turnover		Num. Employees		Investment		PPI	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Delta Pre	-0.0107	-0.0078	-0.0062	-0.0032	-0.0137	0.0109	-1.1124***	-1.0833***
	(0.0072)	(0.0113)	(0.0050)	(0.0081)	(0.0139)	(0.0158)	(0.2548)	(0.2933)
Delta Post	-0.0342***	-0.0198	-0.0070	-0.0017	-0.0294**	0.0028	4.9039***	4.6751***
	(0.0102)	(0.0131)	(0.0070)	(0.0084)	(0.0145)	(0.0176)	(0.5765)	(0.7637)
# of Observations	1,020	1,020	1,020	1,020	1,020	1,020	1,020	1,020
# of Sectors	204	204	204	204	204	204	204	204
Year-FE	Yes		Yes		Yes		Yes	
Year-Sector-FE		Yes		Yes		Yes		Yes

Notes: The table shows point estimates from estimating versions of equation 4. The unit of observation is the 4-digit-sector level. The dependent variable is the change in outcomes relative to 2021. The Pre-Dummy is 1 in years prior to 2021 and the Post-Dummy is one in years post 2021. Standard errors are given in parentheses and clustered at the four-digit-sector level. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2019) and sectoral outcome data and industrial energy price data from the Federal Statistical Office. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

In sum, the estimated effects on the sector-level production index presented in the main part of the paper and the additional results presented here (Table A4) provide clear support for the substantial negative impact of the price shock on production. The results further show that firms—in addition to reducing quantities—adjusted prices, i.e., they passed the price shock through to consumers. Moreover, we find some evidence for reduced investment, likely weighing on the medium-term development of the most affected sectors. We proceed by deepening our analysis of pass-through in the subsection below.

A.2.2 Pass-Through of Costs

To extend the results presented above and gauge the degree of cost pass-through, we take an approach similar to Lafrogne-Joussier et al. (2023). Specifically, we first construct an approximation of the percentage change in energy prices at the sectoral level between 2022 and 2018. For that, we proceed as in expression 1, but instead of multiplying establishment energy consumption from 2018 by the price shift, we calculate energy costs for 2018 and 2022 separately, i.e., we multiply energy prices in respective years with 2018 plant level consumption and then aggregate to the secotor level. This yields an approximation of total energy expenditures by each four digit industry for both years which we then divide by total energy use in kWh in 2018 to obtain an approximation of sector-level average energy prices. Finally, we take the log difference of these prices. Note that, for identification, we do not need to get the price levels exactly right; we only need to get the relative changes across sectors correctly.

Since sectors differ in energy intensity, the same price increase implies different cost shocks depending on energy intensity. Therefore, we multiply the logarithmic energy price change by the share of a sector's energy costs in either total material costs or the sum of material and labor costs. The rationale is that, for example, a 100% increase in energy costs implies—all else equal—a 1% increase in marginal costs for a sector where energy costs account for 1% of marginal costs, but a 5% increase for a sector where energy costs account for 5% of marginal costs.

Thus, the specification we estimate reads as follows:

$$\Delta log(PPI_s) = \alpha_0 + \rho \Delta log(Ep_s) \times S_{s0}^E + \varepsilon_s \tag{5}$$

Table A5 presents the results from estimating versions of specification 5. The upper panel of the table focuses on the change in the logarithm of the sectoral PPI between 2023 and 2021, while the lower panel examines the change between 2022 and 2021. In columns 1 and 2, the log energy price change is multiplied by the energy cost share in total material costs (from 2018), and in columns 3 and 4, the log energy price change is multiplied by the energy cost share in total material costs plus the wage bill. Columns 2 and 4 include 2-digit sector dummies, i.e., identification comes from differential shock exposure within two-digit industries, while specifications in columns 1 and 3 include just a constant.

First, one can observe that—–mechanically—–the point estimates in columns 3 and 4 are larger than those in columns 1 and 2. This is because the share of energy costs in total material costs plus the wage bill is strictly smaller than that in material costs alone (i.e., the respective scaling factors). The choice of scaling factor depends on whether labor is considered a flexible input, i.e., a marginal cost component. In any case, using both scaling factors provides reasonable upper and lower bound estimates. Second, absorbing sector fixed effects yields very similar point estimates, suggesting that variation within two-digit sectors is sufficient for identification. Finally, point estimates pertaining to the effect in 2022 tend to be somewhat smaller than those for 2023.

Table A5: Log Change in Approx. Energy Prices and Change in Scaled Log PPI

	(1)	(2)	(3)	(4)
Ln PPI2023 - Ln PPI2021				
Δ EP X $\frac{Ecost}{MatCosts}$	0.8253***	0.7592***		
	(0.0885)	(0.0917)		
Δ EP X $\frac{Ecost}{MatCosts+Wagebill}$			1.1381***	1.0308***
			(0.1589)	(0.1393)
# of Observations	197	197	197	197
# of Sectors	197	197	197	197
Ln PPI2022 - Ln PPI2021				
Δ EP X $\frac{Ecost}{MatCosts}$	0.6819***	0.6371***		
	(0.1439)	(0.1462)		
Δ EP X $\frac{Ecost}{MatCosts+Wagebill}$			0.9887***	0.9000***
			(0.2210)	(0.2245)
# of Observations	197	197	197	197
# of Sectors	197	197	197	197
Sector-FE		Yes		Yes

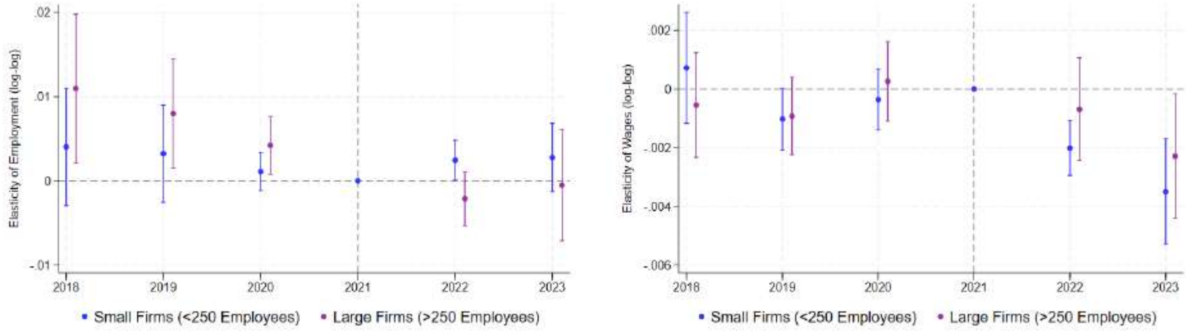
Notes: The table shows point estimates from estimating versions of equation 5. The unit of observation is the 4-digit-sector level. Standard errors are given in parentheses and clustered at the four-digit-sector level. The dependent variable is the log change in the sectoral PPI between 2023 and 2021 (upper panel) and between 2022 and 2021 (lower panel). The explanatory variable is the log change in approximated sectoral energy prices, scaled by the share of energy costs in marginal costs. The latter share is approximated using the share of energy costs in material costs (columns 1 and 2) or the share of energy costs in material plus labor costs. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2019) and sectoral outcome data and industrial energy price data from the Federal Statistical Office. Significance levels are indicated as * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

This is plausible, as the price shock did not occur at the beginning of the year, and some price stickiness is to be expected.

As the discussion above implies, a point estimate of 1 would suggest complete pass-through of costs. The table shows that most point estimates are below 1, and those in columns 1 and 2 are statistically different from 1, although still large in magnitude, suggesting pass-through elasticities between 0.6 and 0.8. The point estimates in columns 3 and 4 are statistically indistinguishable from 1. Recall that labor costs are implicitly assumed to be marginal costs in these specifications. Overall, the table is consistent in showing that a large portion of the cost shock was passed through. This result suggests that the energy price shock has been important for aggregate price inflation in recent years, and the results imply that the shock quickly propagated through the economy to more downstream sectors.

A.3 Additional Figures and Tables

Figure A3: Heterogeneity by establishment Size: Large vs. Small establishments

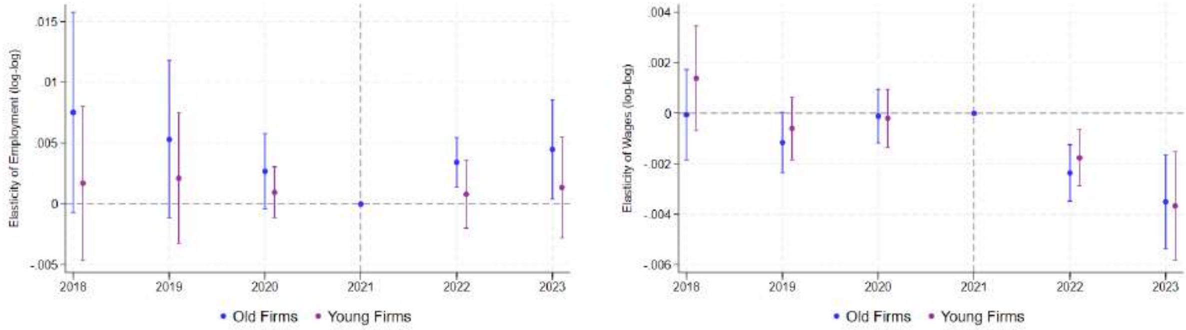


(a) Employment

(b) Wages

Notes: Subfigure A3a presents point estimates from estimating equation 4, using establishment-level data and controlling for year-sector fixed effects. The dependent variable is the log change in employment relative to 2021. Blue markers represent estimates for small establishments (fewer than 250 employees), while purple markers represent estimates for large establishments (at least 250 employees). Subfigure A3b displays corresponding estimates using the log change in mean establishment-level wages as the dependent variable. Dots represent point estimates, and vertical lines indicate 95% confidence intervals. Standard errors are clustered at the four-digit sector level. The sample is restricted to establishments with at least 20 employees. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2019) and industrial energy price data. Research Data Centre of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB). DOI: 10.5164/IAB.BHP7523.de.en.v1.

Figure A4: Heterogeneity by establishment Age: Old vs. Young establishments

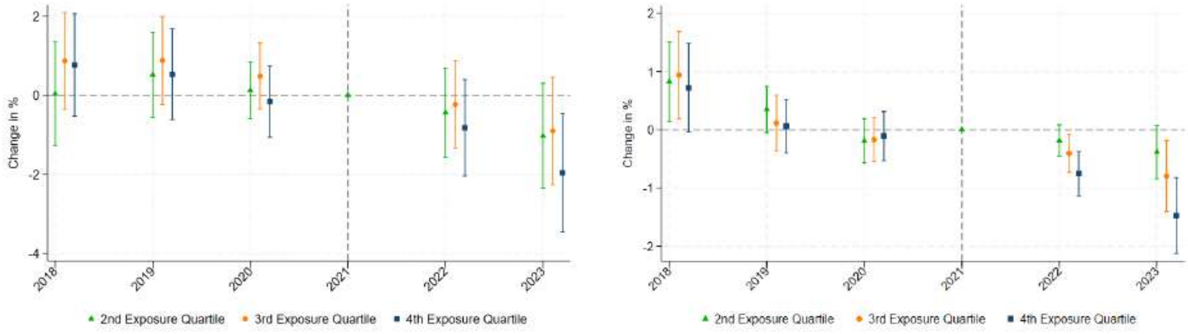


(a) Employment

(b) Wages

Notes: Subfigure A4a presents point estimates from estimating equation 4, using establishment-level data and controlling for year-sector fixed effects. The dependent variable is the log change in employment relative to 2021. Blue markers represent estimates for old establishments (older than median, i.e., established before 1991), while purple markers represent estimates for young establishments. Subfigure A4b displays corresponding estimates using the log change in mean establishment-level wages as the dependent variable. Dots represent point estimates, and vertical lines indicate 95% confidence intervals. Standard errors are clustered at the four-digit sector level. The sample is restricted to establishments with at least 20 employees. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2019) and industrial energy price data. Research Data Centre of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB). DOI: 10.5164/IAB.BHP7523.de.en.v1.

Figure A5: Discretized Exposure Measure: Effect on Wages

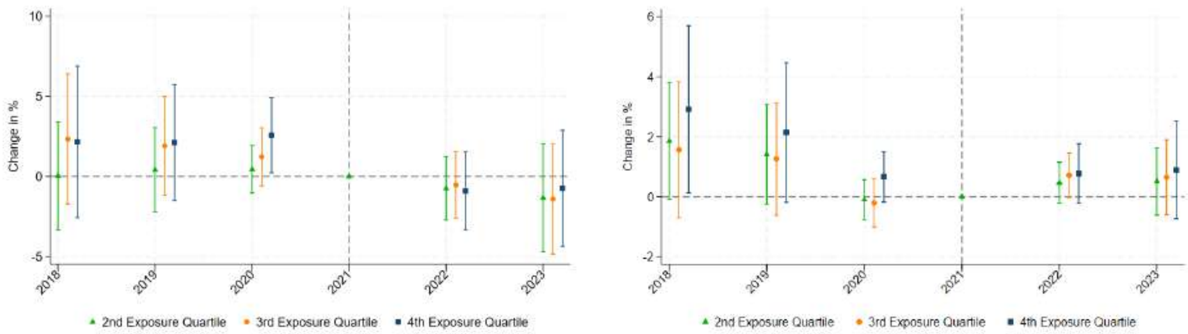


(a) Wages: Sector-Level Data

(b) Wages: BHP

Notes: This figure shows the effects by shock exposure quartile, estimated from equation 4, controlling for sector-year fixed effects. The dependent variable is the log change in mean wages relative to 2021, measured at the four-digit sector level in subfigure A5a and at the establishment level in subfigure A5b. Dots represent point estimates, and vertical lines denote 95% confidence intervals. The estimates reflect differential trends relative to the least exposed quartile. Standard errors are clustered at the four-digit sector level. The sector-level analysis is restricted to sectors with at least 350 employees, and the establishment-level analysis to establishments with at least 20 employees. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2019) and industrial energy price data. Research Data Centre of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB). DOI: 10.5164/IAB.BHP7523.de.en.v1 and the Integrated Employment Biographies from the IAB.

Figure A6: Discretized Exposure Measure: Effect on Employment



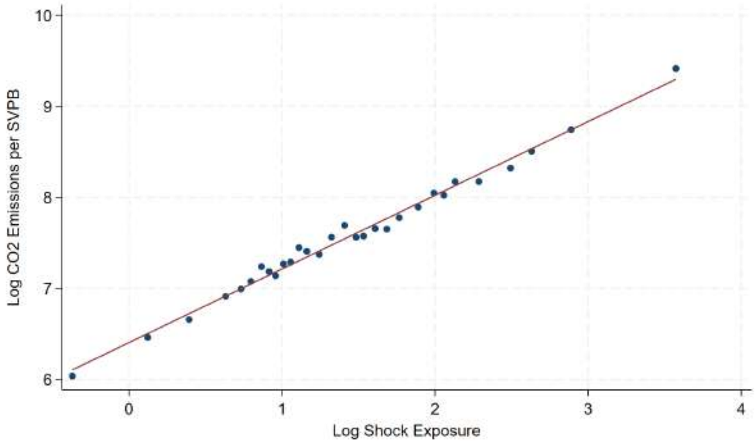
(a) Employment: Sector-Level Data

(b) Employment: BHP

Notes: This figure shows the effects by shock exposure quartile, estimated from equation 4, controlling for sector-year fixed effects. The dependent variable is the log change in employment relative to 2021, measured at the four-digit sector level in subfigure A6a and at the establishment level in subfigure A6b. Dots represent point estimates, and vertical lines denote 95% confidence intervals. The estimates reflect differential trends relative to the least exposed quartile. Standard errors are clustered at the four-digit sector level. The sector-level analysis is restricted to sectors with at least 350 employees, and the establishment-level analysis to establishments with at least 20 employees. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2019) and industrial energy price data. Research Data Centre of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB). DOI: 10.5164/IAB.BHP7523.de.en.v1 and the Integrated Employment Biographies from the IAB.

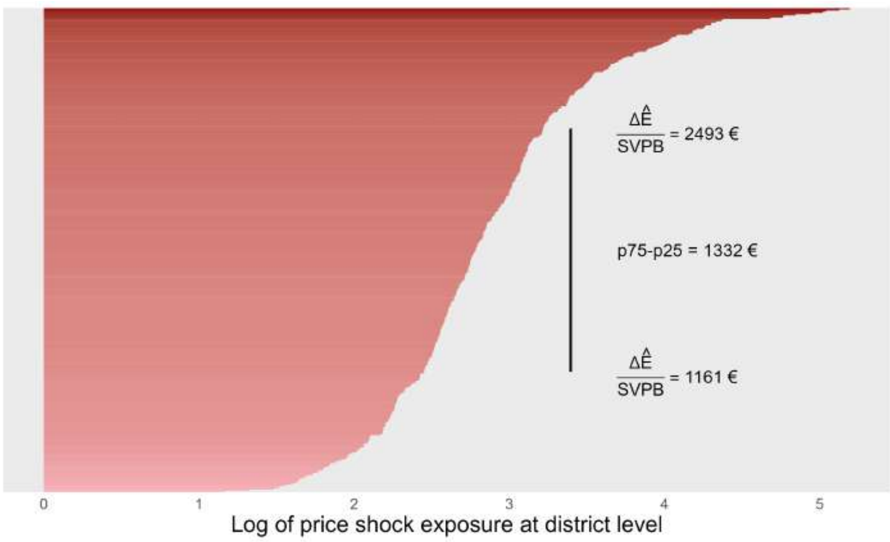
Appendix B Additional Material: Regional Level

Figure A7: Correlation between Log Shock Exposure and Log CO_2 Emissions per SVPB



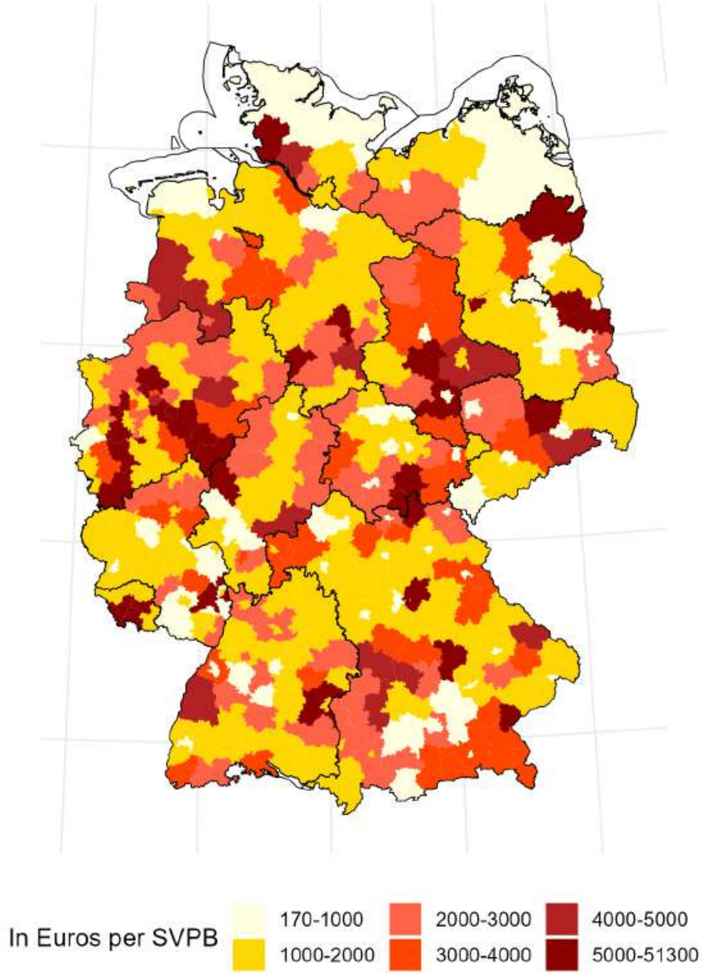
Notes: The binscatter shows the correlation between the logarithm of the regional exposure measure and the logarithm of CO_2 emissions per employee subject to social security contributions at the labor market region level (223 regions). Data sources include "the Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2019)", industrial energy price data from the Federal Statistical Office, and IAB employment data for the universe of SVPBs, own calculations.

Figure A8: Log Price Shock Exposure Across Districts



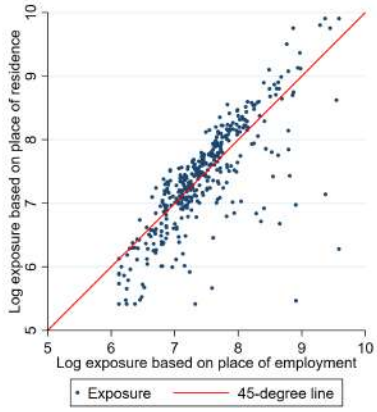
Notes: The figure shows the logarithm of the exposure measure at the district-level. It is defined as the predicted increase in energy costs per worker liable to social security contributions in a given region. Data sources include the "Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2018)", industrial energy price data from the Federal Statistical Office and a anonymous version of integrated labour market biographies from the Research Data Centre of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

Figure A9: Exposure at District Level (using Place of Work): Additional Energy Costs per SVPB

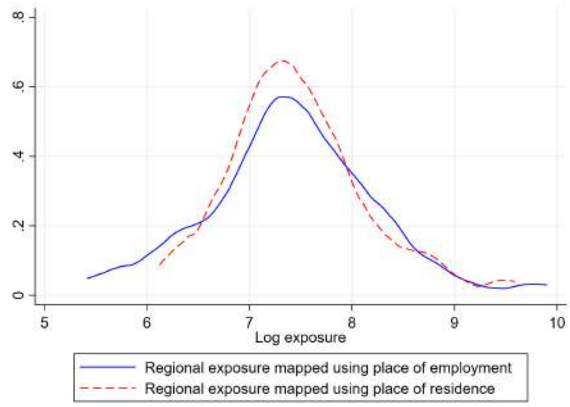


Notes: The map visualizes exposure by district, defined as the predicted increase in energy costs per employee subject to social security contributions (SVPB) in a given region. To map the sectoral shock to regions, we used the number of workers in a district by industry using the workers' locations of work. Each region is classified into one of six exposure bins (see legend). Thin black lines delineate federal state boundaries. Data sources include "the Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2019)", industrial energy price data from the Federal Statistical Office, and IAB employment data for the universe of SVPBs.

Figure A10: Comparison of Regional Shocks using Place of Work or Place of Residence for Mapping



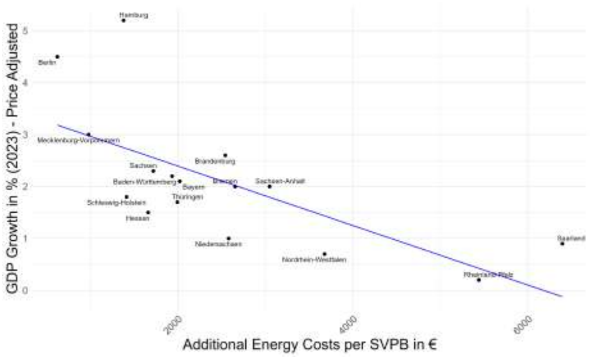
(a) Scatterplot and 45-Degree Line



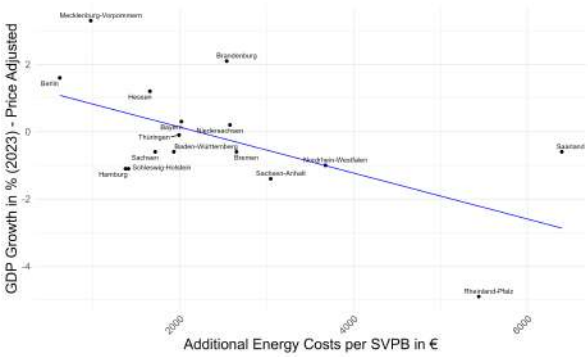
(b) Density of Regional Shocks

Notes: Figure A10a shows the correlation between the district-level shock exposure measure when using the individual place of employment (x-axis) and individuals' place of residence (y-axis) to map the shock from sector to regional level. Figure A10b plots the density of the shocks. Data sources include the "Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2019)" and industrial energy price data from the Federal Statistical Office.

Figure A11: Exposure at the Federal State Level and GDP Growth



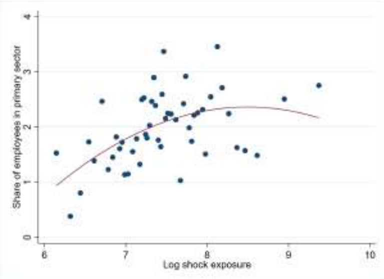
(a) GDP Growth in 2022



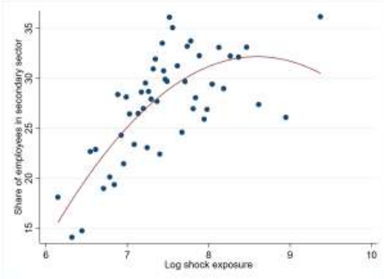
(b) GDP Growth in 2023

Notes: The figures depict the shock exposure, measured as additional energy costs per employee subject to social security contributions at the federal state level (x-axis), plotted against real (price-adjusted) GDP growth at the federal state level (y-axis). Figure A11a shows GDP growth for 2022 on the y-axis and Figure A11b growth for 2023. Data sources include the "Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2019)" and industrial energy price data from the Federal Statistical Office.

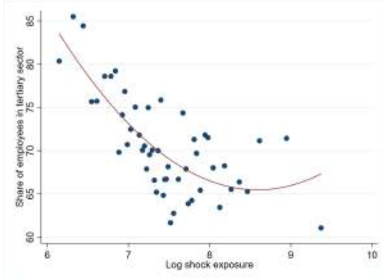
Figure A12: Descriptives: Shock Exposure and Regional Characteristics



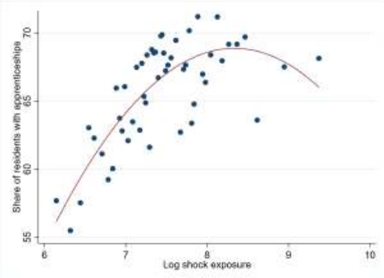
(a) Empl. Share: Primary Sec.



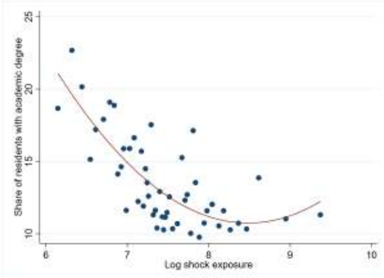
(b) Empl. Share: Secondary Sec.



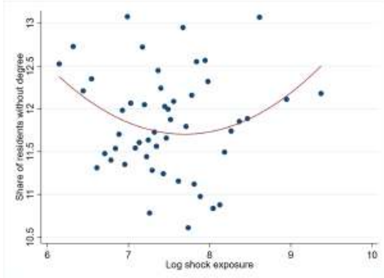
(c) Empl. Share: Tertiary Sec.



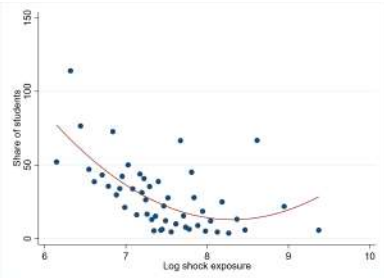
(d) Share: Apprenticeship



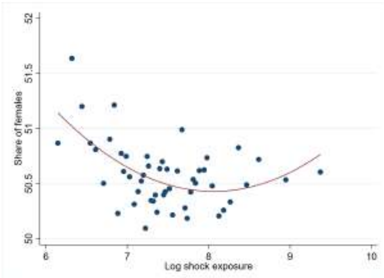
(e) Share: Academics



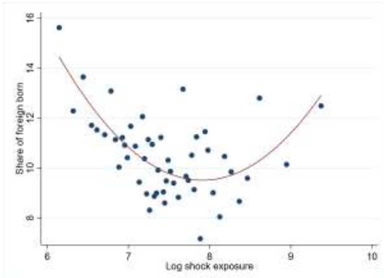
(f) Share: No Formal Education



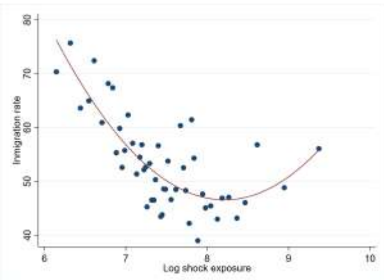
(g) Share: Students



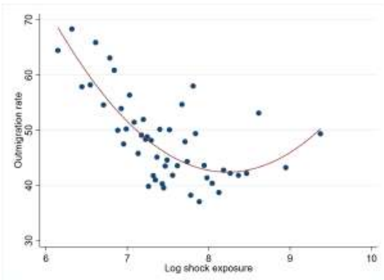
(h) Share: Females



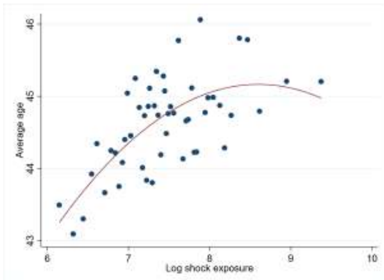
(i) Share: Foreign Born



(j) Inmigration Rate



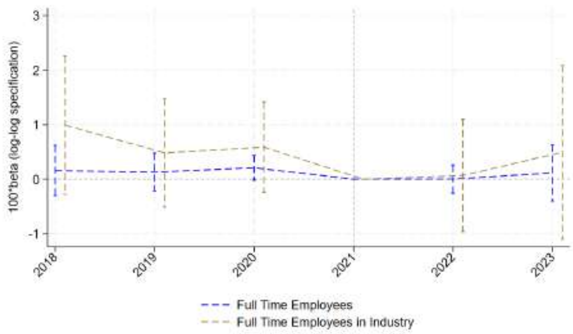
(k) Outmigration Rate



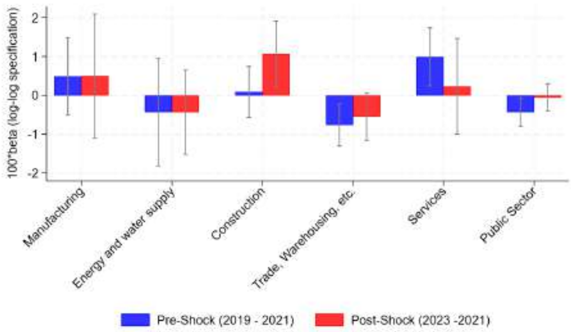
(l) Average Age

Notes: Data sources include the "Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2019)" and industrial energy price data from the Federal Statistical Office.

Figure A13: Regional Exposure and Employment



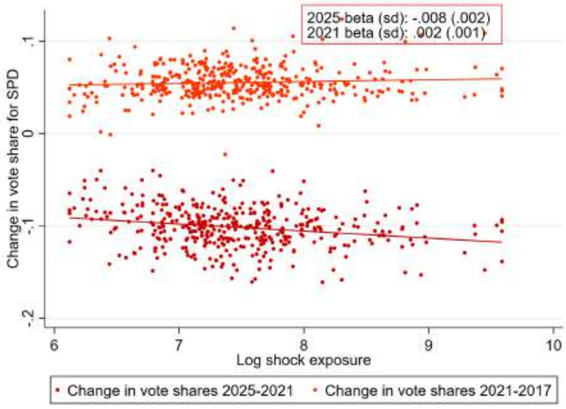
(a) Effect on Log Average (Manufacturing) Employment



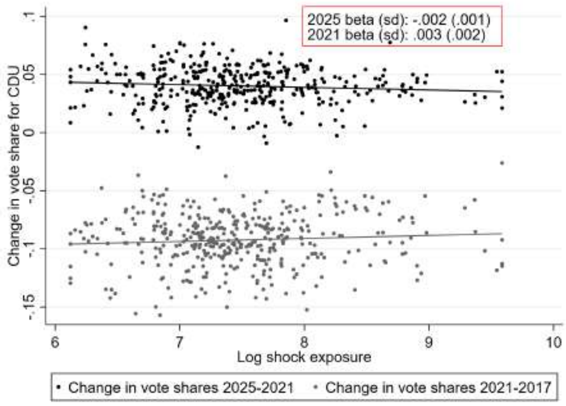
(b) Effect on Log Average Employment

Notes: Data sources include the "Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2019)" and industrial energy price data from the Federal Statistical Office.

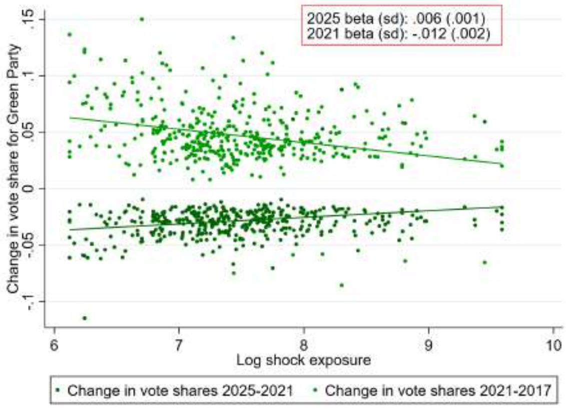
Figure A14: Correlation Between Shock Exposure and Changes in Voting Behavior



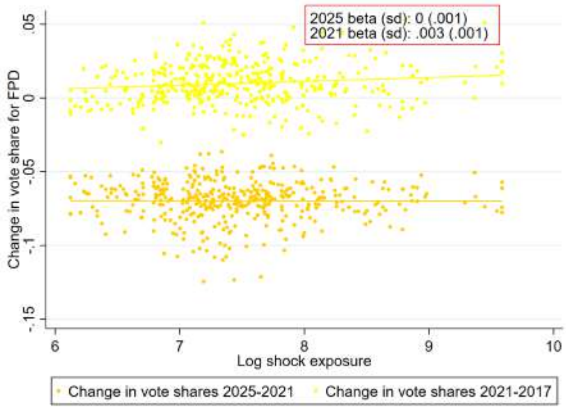
(a) Δ Vote Shares for SPD



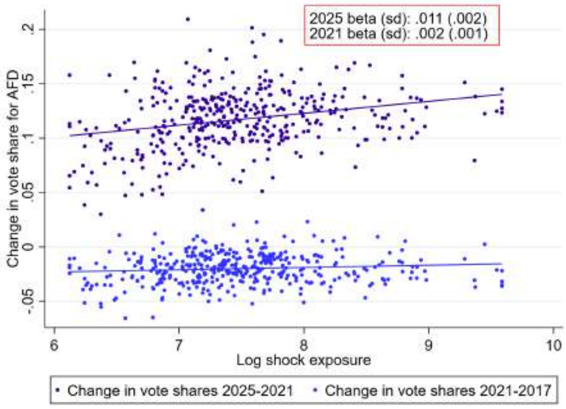
(b) Δ Vote Shares for CDU



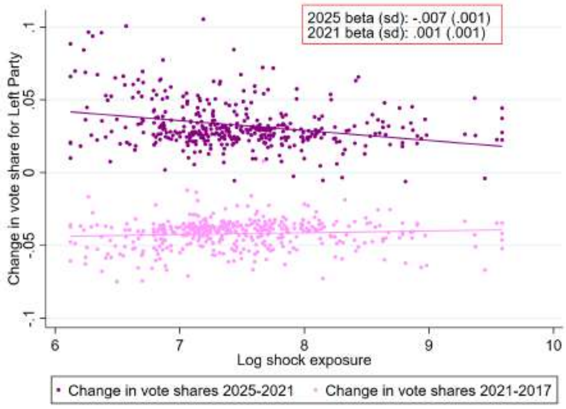
(c) Δ Vote Shares for Greens



(d) Δ Vote Shares for FPD



(e) Δ Vote Shares for AfD



(f) Δ Vote Shares for Left

Notes: The scatter plots visualize the correlation between the log of regional exposure and changes in vote shares between the federal elections in 2021 and 2017 and 2025 and 2021. Changes in vote shares have been residualized by macro-regions (North, South, East, and West). The fitted line represents a linear fit. In the red boxes we show the coefficient and corresponding standard error from the linear regression of changes in vote shares on regional exposure. Data sources include the "Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2019)" and industrial energy price data from the Federal Statistical Office and data from the federal election officer.