Discussion Paper Series – CRC TR 224

Discussion Paper No. 730
Project B 07

The Labor Market Impact of the Energy Crisis: Evidence from Germany

Katia Gallegos Torres[1]
Jakob Lehr[2]

February 2026

[1]IAB Nuremberg, ZEW Mannheim
[2]University of Mannheim

Support by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TR 224 is gratefully acknowledged.

The Labor Market Impact of the Energy Crisis: Evidence from Germany

Katia Gallegos Torres* Jakob Lehr†

February 3, 2026

Abstract

This paper studies the impact of the 2022 energy price shock on German manufacturing using newly available administrative data. We construct a Bartik-type exposure measure based on pre-shock energy use and relate it to sector-, establishment-, and region-level outcomes. While highly exposed sectors experienced sizable declines in production, we find no evidence of adverse effects on employment. Instead, we consistently document negative effects on wages. Our baseline estimates suggest that moving from the 25th to the 75th percentile of the exposure distribution at the four-digit sector level is associated with an average annual wage loss of about 2.5% over 2022–2023, corresponding to roughly €1,250 per worker. These average effects mask substantial heterogeneity, with considerably larger wage declines for new hires. At the local labor market level, we find evidence of spillovers from manufacturing to other sectors.

Keywords: Energy Crisis, Manufacturing, Labor Markets, Ex-Post Analysis
JEL Classification: Q40, Q41, O12, L60, J31

*IAB Nuremberg, ZEW Mannheim
†University of Mannheim

[1]**Acknowledgement:** We thank Ulrich Wagner for his detailed feedback on a previous version of this manuscript. Additionally, we thank seminar participants at the EAERE 2025, EEA 2025, VfS 2025, the Innsbruck-Munich Applied Micro Workshop 2025, and internal seminars at ZEW, IAB, and the University of Mannheim. We presented an earlier version under the title *The Socio-Economic Impact of the Energy Crisis: Evidence from Germany*. Jakob Lehr gratefully acknowledges funding by the German Research Foundation (DFG) through CRC TR 224 (Project B07). Declarations of interest: none. Correspondence to jakob.lehr@uni-mannheim.de

1 Introduction

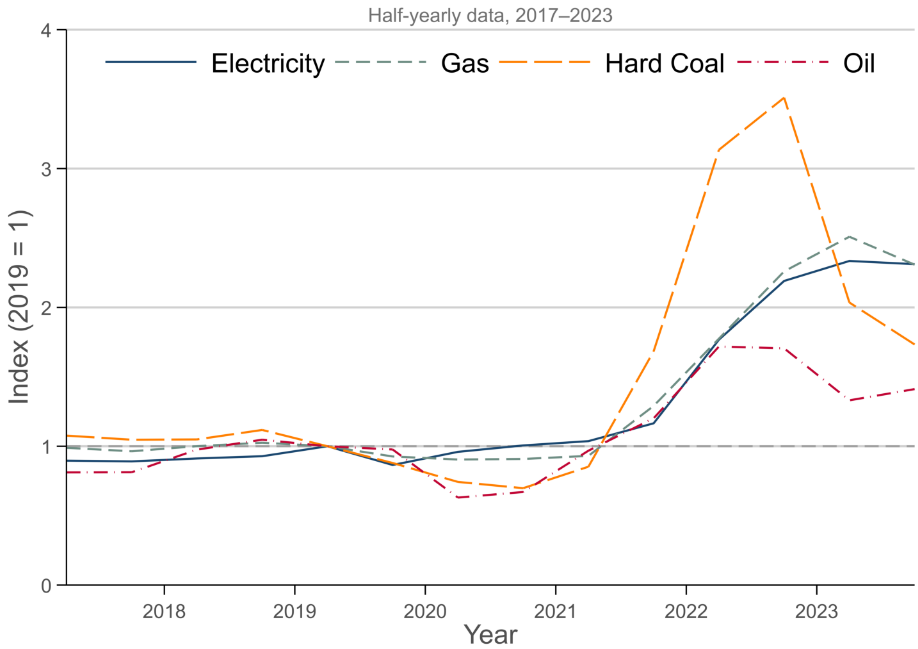
In 2022, after the Russian aggression against Ukraine escalated, Europe faced a severe negative energy supply shock. Germany—Europe's largest economy—appeared particularly vulnerable to this shock for at least two reasons. First, Germany had built up a heavy reliance on Russian energy imports over decades, especially natural gas. This dependence led to a sharp and persistent increase in industrial energy prices for coal, oil, gas, and electricity, as illustrated in Figure 1. Second, the comparatively energy-intensive manufacturing sector accounts for a larger share of GDP in Germany compared to other similarly developed countries.[1] These vulnerabilities were echoed by then German Chancellor Olaf Scholz, who warned that an embargo on Russian gas could put "hundreds of thousands of jobs at risk" and push "entire industries to the brink" (Politico, 2022). Such pessimistic views were not uncontroversial, however. For example, a group of economists judged the consequences of a gas embargo to be "manageable" (Bachmann et al., 2024). While an embargo was never implemented, imports of Russian gas ceased almost completely after key parts of the pipeline infrastructure were destroyed in late summer 2022. Controversy over the shock's economic consequences, remains to this day.

This paper uses newly available administrative micro-level data to provide the first comprehensive ex-post analysis of the energy price shock's effects on the manufacturing sector. The analysis focuses on labor market outcomes (central to contemporaneous policy debates) but also examines effects on economic activity and documents the regional fallout of the shock. Beyond the immediate question of how the shock affected the German labor market, the broader issue of how high energy prices influence employment and wages remains crucial. First, because energy scarcity, and therefore higher prices, is likely to persist in the medium term due to the Russian aggression; and second, because policies aimed at steering the economy to net-zero emissions, such as carbon pricing, will further raise production costs in fossil-fuel-intensive industries. For instance, carbon prices near estimates of the social cost of carbon (around \$185 per ton of CO_2; Rennert et al., 2022) would imply an increase in EU ETS prices by more than a factor of ten relative to the average price between 2010 and 2020. While the need to decarbonize is uncontested, minimizing the socio-economic disruptions observed during previous structural transformations is also a key priority (Autor et al., 2020a; Autor et al., 2013, 2014; Dauth et al., 2014; Dippel et al., 2021). Insights gained from analyzing the recent energy price shock can help inform this transition.

We draw on detailed plant-level fuel consumption data from the German census of the manufacturing industry (AFiD), which we combine with aggregate shifts in fuel prices to construct a measure for plants' exposure to the energy price shock. This exposure measure depends on pre-shock energy use, fuel mix, and electricity and gas consumption bands (Bartik, 1991). We

[1] More than half of Germany's natural gas demand in 2021 was met through imports from Russia (BP, 2021). Because gas-fired power plants are often the marginal electricity generators, electricity and gas prices closely co-move. 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).

Figure 1: Industrial Energy Price Index (2019 = 1), 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.

use administrative social security data from the *German Institute for Employment Research* (IAB) to evaluate post-shock labor market outcomes by regressing changes in outcomes on the exposure measure. Because the manufacturing census (AFiD) cannot be directly merged with IAB data, we aggregate both the plant-level exposure measure and labor market outcomes to either the four-digit economic sector level or the level of 223 local labor markets.[2] Drawing on the *Integrated Employment Biographies* (IEB)—individual-level data covering the universe of socially insured workers in Germany—we construct employment and wage measures at the respective levels of aggregation. In addition, we use the *Establishment History Panel* (BHP)—an establishment-level dataset provided by the IAB—which contains detailed labor market outcomes such as employment and various moments of the establishment-level wage distribution.[3] The plant-level data allows us to validate the sector-level findings and to conduct further heterogeneity analyses, for instance by plant characteristics or by examining effects on the plant-level wage distribution. Thanks to the availability of multiple pre-treatment periods in the IAB datasets, we can evaluate pre-trends, i.e., we can test whether the exposure measure was uncorrelated with sectoral trends prior to 2022 (Goldsmith-Pinkham et al., 2020).

We first document large heterogeneity in exposure across sectors and regions. For example, the four-digit sector at the 75$^{\text{th}}$ percentile of the exposure distribution ("manufacture of plastic

[2]For the exposure measure, we use plants' fuel consumption from 2018 to "predict" their additional energy costs in 2022—holding 2018 consumption fixed—aggregate these predicted costs to the four-digit sector level, and then rescale the sector totals using 2018 sectoral employment, as we will describe in detail in Section 2.

[3]Throughout the paper, we use the terms "plant" and "establishment" interchangeably.

packing goods") is seven times more exposed than the sector at the 25$^{\text{th}}$ percentile ("manufacture of machinery for paper and paperboard production"). These differences carry over to the regional level, albeit in a less pronounced form. For instance, the interquartile coefficient at the local labor-market level is only slightly above two. To motivate our main analysis of labor-market effects, we examine how production evolved across sectors with different exposure to the price shock. Based on a monthly four-digit sector level production index, we show that in 2023 production in sectors in the most exposed quartile was 10–15 percentage points (pp.) lower than in the least affected quartile.

Our main analysis shows that the price shock did not negatively affect overall employment but significantly depressed wages. We estimate that a 100% increase in shock exposure reduced average real wages by approximately 0.35% at the sector level, averaged over 2022 and 2023. This magnitude implies that moving from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of the exposure distribution results in an average reduction in mean wages of roughly 2.5%, corresponding to an earnings loss of about €1,250 annually. Examining heterogeneities, we find that the decline in average wages for new hires is more than twice as large as the average effect. By contrast, for long-tenure workers the effect is roughly half as large as the average effect. While wage responses vary substantially by tenure, differences across task groups (abstract versus routine) are small. Workers performing abstract tasks experience a slightly larger relative wage decline and, because their baseline wages are approximately 50% higher, a substantially larger absolute decrease.

Using establishment-level data, we confirm both the employment and wage effects of the shock. We further show that the effects are relatively homogeneous across different moments of the establishment's wage distribution: the shock shifted the establishment-level wage distribution downward without increasing within-establishment wage inequality. Finally, analyzing the shock across 223 local labor markets allows us to study effects beyond manufacturing and test for spillovers. While manufacturing wages respond most strongly to regional exposure, wages outside manufacturing—particularly in services—also decline, suggesting spillovers in local labor markets.

Related Literature and Contribution First, our paper contributes to a growing literature on the consequences of the recent energy crisis. For example, the fiscal, price, income, and growth effects of the energy price shock have been analyzed using macroeconomic models (e.g., Auclert et al., 2023; Bachmann et al., 2024; Krebs and Weber, 2024). Another branch of the literature employs micro-level data at the household or regional level to examine the distributional consequences of the shock and to evaluate policy measures implemented to cushion the impact of the shock (e.g., Behr et al., 2025; Fabra et al., 2025; Fetzer et al., 2024b; Levell et al., 2025). Few papers have analyzed the effect of the price shock on the manufacturing sector based on micro data. Using French manufacturing data at the firm- and sector-level respectively, Lafrogne-Joussier et al. (2023) and Arquié and Thie (2023) study the pass-through of energy costs to product prices. Employing shift–share designs based on pre-crisis fuel shares, both papers find evidence of full pass-through. Closely related to our work, 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, measuring exposure by energy costs as a share of total costs. They find no evidence of lower employment or increased exit but document higher prices and adjustments to firms' capital stock, with heterogeneity by firm size.[4] We contribute to this literature by providing a comprehensive ex-post analysis of the effects of the price shock on the German manufacturing sector, based on micro data at the sectoral, establishment and regional levels. We combine various administrative datasets and focus on labor market outcomes. The effects on the labor market were subject of particularly controversial debates at the time. Our results show that the cost shock was partly passed through to wages, but like Fetzer et al. (2024a), we do not detect an adverse employment effect.

Second, the paper contributes to the broader literature on the impact of energy cost on the manufacturing sector. This literature focuses mainly on environmental and economic outcomes (Abeberese, 2017; André et al., 2023; Fontagné et al., 2024; Ganapati et al., 2020; Gerster and Lamp, 2024; Graevenitz and Rottner, 2022; Marin and Vona, 2021). While these papers document a consistently negative effect of energy costs on energy use and, therefore, emissions, the evidence on economic performance is mixed. Some papers focus explicitly on labor-market effects, which aligns with the focus of our paper. For example, using sector- and individual-level data, Yamazaki (2017) and Yip (2018) find negative effects of the carbon tax introduced in 2008 in British Columbia on both employment and wages. Curtis (2018) shows that adverse labor-market effects of a regional cap-and-trade program in the US were concentrated among new hires. Negative effects of energy prices on employment have also been documented by Bretschger and Jo (2024) and Marin and Vona (2021) for France and by Kahn and Mansur (2013) for the US. In contrast, Martin et al. (2014) and Hille and Möbius (2019) do not find negative effects of energy prices on manufacturing employment. For Germany, Mertens et al. (2022) use firm-level energy price variation to estimate rent-sharing elasticities in the German manufacturing sector. They show that energy-driven increases in input costs adversely affect wages but not regular employment. Using the European Labor Force Survey Marin and Vona (2019) take a pan-European perspective to analyze the impact of energy prices on hours worked by skill group. Their findings suggest that energy price increases are skill-biased against manual workers. This result contrasts with an observed negative correlation between energy prices and the skill premium at the aggregate level, which has been rationalized through an energy–skill complementarity (Kehrig and Ziebarth, 2017; Polgreen and Silos, 2009). We contribute to this literature in several ways. Unlike most previous studies, which rely on relatively modest price movements over time to estimate contemporaneous responses, the 2022 price shock allows us to construct a single, well-defined exposure measure that we fix at baseline. Hence, we can assess pre-trends and track sectoral outcome trajectories over time in response to a one-time shock. Moreover, the richness of our employment data allows us to study adjustment margins and heterogeneities. For instance, declines in employment may result from layoffs or reduced hiring, and wage declines may reflect wage cuts for incumbent workers or lower wages for new

[4]Earlier work has used more aggregated data to investigate the effects of historical oil price shocks on, among other, (regional) wages (Kehrig and Ziebarth, 2017; Polgreen and Silos, 2009) or on macroeconomic fluctuations (Barsky and Kilian, 2004).

hires. Consistent with Curtis (2018), we show that wages for new hires decline disproportionately, while wages for long-tenured workers also decline, albeit to a much lesser extent. In contrast to Marin and Vona (2019), we do not find that workers with routine tasks are disproportionately affected; if anything, wages of workers performing abstract tasks decline slightly more, in line with energy–skill complementarities.

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 and Autor et al., 2013, 2014, for 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 would benefit the transition to carbon neutrality, as public support for climate policy is likely to erode otherwise. We contribute to this literature by mapping the shock to the local level. We document a strong correlation between the shock and regional concentrations of carbon-intensive industries and we present suggestive evidence of spillovers from manufacturing to other sectors in local labor markets. These results indicate that adjustment pressures in some industries can extend beyond the directly affected sectors, with implications for the broader local economic system.

The remainder of the paper is structured as follows: Section 2 introduces the data, outlines the empirical approach and provides a brief background on the policy response. Section 3 presents descriptive results and Section 4 reports the main findings. Section 5 discusses the results and concludes.

2 Data, Empirical Specification and Policies

2.1 Data and Construction of Treatment Variable

We combine information from the German manufacturing census with administrative worker-level data for the universe of workers subject to social security contributions to analyze the effects of the energy supply shock at the (i) sectoral, (ii) establishment and (iii) regional levels. We describe the respective data sources and the construction of variables in detail below.

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 plants) for the year 2018.[5] Both modules provide information at the plant level, covering the universe of plants that belong to a manufacturing firm with at least 20 employees. The energy use module provides detailed information about plant-level fuel use in physical units and by fuel type. The industrial plants module contains information on indicators of economic performance such as sales, number of employees, and total wagebill. We combine the plant-level information from AFiD with time series data for industrial fuel prices published by the German Statistical Office extending until 2023.[6] For gas and electricity, there are separate price series depending on plants' consumption level. This is important because both the price levels before the shock and the change resulting from the shock differed across plants depending on their consumption levels (cf. Figure A1 for the evolution of net gas and electricity prices by consumption band).[7] We draw on this combined dataset to construct the sector-level exposure as follows:

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

The inner sum approximates the additional energy costs for plant i resulting from the price shift. To do so, we multiply the 2018 consumption of fuel f by plant i in sector s and consumption band b ($Fuel^{2018}_{i,f,s,b}$) by the change in the price of fuel f between 2018 and the second half of 2022, using consumption-band–specific price trends ($\Delta P_{f,b}$). Specifically, we use the change in the net price plus levies but excluding deductible taxes. The outer sum aggregates across all plants within a four-digit economic sector s. Expression 1 thus provides an approximation of the increase in sectoral energy expenditures incurred across plants under the assumption of a homogeneous price shift and fixed 2018 consumption levels. Assuming 2018 consumption levels ensures that expression 1 is not contaminated by endogenous consumption adjustments.

To account for differences in the size of economic sectors, we scale expression 1 by the number of employees in 2018. We refer to expression 2 below as our sector-level exposure measure.

$$Exposure_s = \frac{AdditionalCosts_s}{\sum_{i \in S} L^{2018}_i} \tag{2}$$

Expression 2 can be interpreted as the additional energy costs per worker (headcount) in sector s, that result from fuel price changes, assuming 2018 consumption levels. 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 plant sizes within sectors, measured by their gas and electricity consumption. This intensity treatment follows the logic of a shift-share instrument. Indeed, if information for actual energy expenditures for 2022

[5]We currently have access to AFiD data only for pre-shok years until 2020. The specific versions of data have the following DOIs: 10.21242/43531.2020.00.03.1.1.0 ("AFiD Modul Energieverbrauch"), 10.21242/42111.2020.00.01.1.1.0 ("AFiD Modul Industriebetriebe").

[6]Fuel types are electricity purchased from the grid, gas, coal, oil, district heat and wood.

[7]We assign plants to bands based on their consumption in 2018 and then use the respective time series. The fuel price time series are obtained from the Federal Statistical Office of Germany (Destatis), *Daten zur Energiepreisentwicklung*, available at this link.

were available in the AFiD data, expression 2 could be used as an instrument for the change in actual energy costs per worker.

This measure offers several advantages over simpler alternatives, such as relying on energy expenditure shares from before the shock as in Fetzer et al. (2024a). First, it captures variation resulting from differential price trends across fuel types. Second, by using data on physical energy consumption from a baseline year, the exposure measure accounts for the fact that larger consumers typically payed lower energy prices. Hence, using energy expenditure shares instead 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 bands for gas and electricity accounts for differential price trends by size: smaller consumers faced a smaller increase in prices compared to larger consumers in relative terms.[8]

Integrated Employment Biographies (IEB) In our baseline analysis of labor market effects, we draw on the Integrated Employment Biographies (IEB), which cover the universe of socially insured workers in Germany.[9] This worker-level data includes information on workers' employment history, their wage, educational background, tasks, their 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 employment figures and mean wages separately by workers' task group and tenure at the sector level. We also aggregate those at the local labor market level to obtain regional wages and employment figures.

To map the sector-level shock to the regional level, we make use of information on individuals' sector affiliation and their place of work. Specifically, we multiply expression 2, which defines sectoral exposure as additional energy costs per worker, by the number of workers in sector s in region r and then sum across all manufacturing sectors in region r to obtain the regional exposure:

$$AdditionalCosts_r = \sum_{s \in r} L_s \times Exposure_s \tag{3}$$

To address the possibility that this value can be high in densely populated regions even when manufacturing does not play a significant role in the respective region, we rescale expression 3 with the total number of socially insured employees (SVPB) in the region (not only those from the manufacturing sector). Hence, our regional exposure measure is defined as follows:

$$Exposure_r = \frac{AdditionalCosts_r}{L_r} \tag{4}$$

where L_r is the total number of socially insured employees in region r. The exposure measure could thus be interpreted as the additional energy costs per SVPB in a region.

Establishment History Panel (BHP) To corroborate the sector-level results with plant-level estimates and investigate heterogeneities, we use the BHP from the IAB (Ganzer et al., 2024).

[8]This presumably reflects 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.

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

The BHP is constructed by aggregating worker-level information to the establishment level (which is done by the Research Data Center of the IAB). For our analysis, we draw on the 100% sample of the BHP for the period 2018–2023. We restrict the sample to establishments in the manufacturing sector and to those with at least 20 employees to align with the manufacturing census. The BHP contains, among other things, information on establishments' economic sector, their location, the number of employees, and various moments of the wage distribution—for example, the mean, median, and the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles. This information complements the aggregate employment and wage figures calculated at the sectoral and regional levels using the IEB, as it allows us to gauge effects on within-establishment wage dispersion. Moreover, the availability of plant-level data allows us to investigate heterogeneity by plant characteristics such as size.

2.2 Empirical Specification

To estimate the effect of the energy price shock on the various units of analysis, we relate changes in outcomes to the respective exposure measure. Specifically, we estimate the following model:

$$\Delta y_{s,j,t} = y_{s,j,t} - y_{s,j,2021} = \beta_0 + \sum_{\substack{\tau=2018 \\ \tau\neq 2021}}^{2023} \beta^{\tau} ln(Exposure_s) \times \mathbb{1}\{t = \tau\} + \gamma_{j,t} + \varepsilon_{s,j,t} \tag{5}$$

The dependent variable, $\Delta y_{s,j,t}$ in equation 5, is the change in the outcome of sector/plant s, nested in industry j, between year t and 2021—the year preceding the shock.[10] 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 by industry fixed effects ($\gamma_{j,t}$). 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. Finally, $\varepsilon_{s,j,t}$ denotes a random disturbance term.[11]

2.3 Policy Measures in Response to the Energy Crisis

This subsection provides a brief overview of how the German government responded to the energy crisis. Subsection A.2 in the Appendix offers a more detailed discussion of the measures implemented between 2022 and 2023. In general, the German government responded to the energy crisis by introducing a range of support schemes targeting both households and industry. For industry, (i) the *Energiekostendämpfungsprogramm* (energy cost reduction program), introduced in July 2022, and (ii) the energy price brakes were likely most relevant. The *Energiekostendämpfungsprogramm* had a total volume of approximately €5 billion to provide state aid to energy-intensive firms. Firms could claim state aid for energy price increases exceeding a

[10] We follow Autor et al. (2020b) and Autor et al. (2014) closely in aggregating two-digit sectors into eleven broader industries. Table A1 in the Appendix shows the mapping of two-digit sectors to these eleven industries.

[11] For the regional-level analysis, we employ a slightly modified version of equation 5, as specified in equation 6.

doubling relative to the corresponding reference month in 2021 (January–December 2021).[12] The scheme ran out when the energy price brakes entered into force in January 2023. The price brakes were not specifically targeted at industry, let alone at energy-intensive segments of the industry. For industrial consumers, the net gas price was capped at 7 ct/kWh for 70% of historical consumption and at 13 ct/kWh for 70% of historical electricity consumption. Both these caps were well above historical price levels for large industrial consumers and marginal energy prices remained unaffected.[13]

While both measures plausibly dampened the impact of the shock, their designs did not shield firms from at least a doubling of energy prices and left the prices of marginal units largely unchanged. Because the price brakes were broad-based measures accessible to presumably almost all industrial energy users, we do not expect them to confound our empirical analysis. The *Energiekostendämpfungsprogramm* may differ in this respect, as eligibility was contingent on firm-specific energy intensity. It is therefore plausible that the amount of state aid received by a sector increases with our exposure measure. Depending on the magnitude of the cushioning effect and the strength of its correlation with exposure, our estimates for 2022 may thus represent a lower bound relative to the undampened effect.

3 Descriptive Statistics

Price Shock and Manufacturing Census Data We first describe the distribution of the exposure measure across 220 four-digit sectors. To this end, Figure 2 plots the logarithm of the shock as defined in expression 2. Each bar in the plot represents a four-digit sector, and the same color indicates that four-digit sectors belong to the same broad industry. The figure illustrates substantial heterogeneity across sectors. For example, the predicted energy cost increase per worker is €1,004 at the 25$^{\text{th}}$ percentile ("manufacture of machinery for paper and paperboard production") and €7,386 at the 75$^{\text{th}}$ percentile ("manufacture of plastic packing goods"). The figure also highlights considerable variation in shock exposure within industries, as bars of the same color appear at different levels. Our empirical specification leverages this within-industry variation for identification.[14]

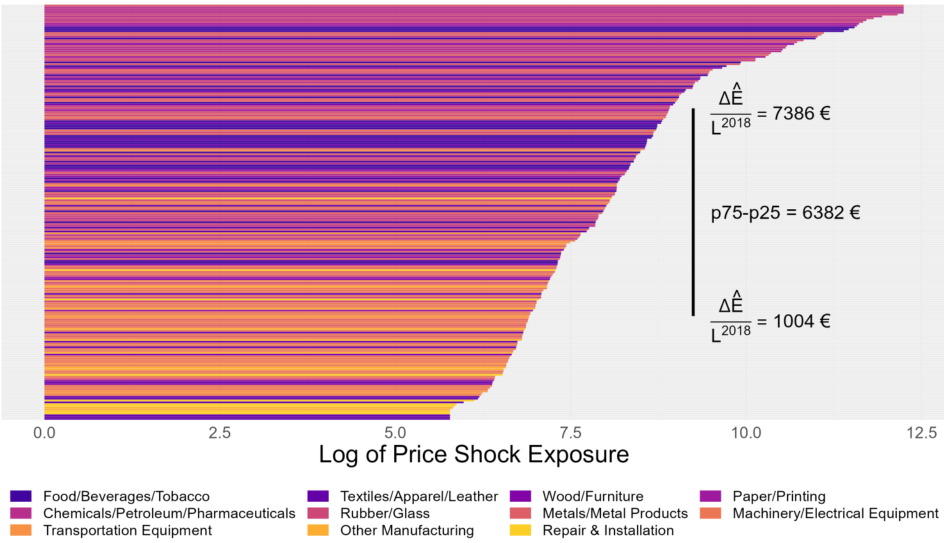
To illustrate how key sectoral characteristics—such as employment or the number of workers—vary with the degree of sectoral exposure, we report medians of these variables, as retrieved from the German census data for 2018, within each quartile of the exposure distribution (see Table

[12]For example, compensation was limited to the difference between a firm's net gas or electricity price in August 2022 and twice the respective price in August 2021. Moreover, from September onward, compensation was limited to at most 70% of the quantity consumed in the corresponding reference month.

[13]For comparison, net gas prices averaged between 1.5 and 2 ct/kWh for large industrial consumers (annual gas consumption exceeding 277 GWh) and net electricity prices for large industrial consumers (annual electricity consumption exceeding 20 GWh) averaged between 4 and 6 ct/kWh in 2019. (cf. Statistisches Bundesamt (Destatis), *Statistischer Bericht: Daten zur Energiepreisentwicklung*, August 2025, EVAS-Nr. 61241, Ergänzung zur Datenbank GENESIS-Online, Tabelle 61241-05 (*Erdgas – Abgabe an Nicht-Haushalte, EUR/kWh*) and Tabelle 61241-16 (*Strom – Abgabe an Nicht-Haushalte, EUR/kWh*), veröffentlicht am 30.09.2025.)

[14]At the industry level, Chemicals/Petroleum/Pharmaceuticals is the most exposed, followed by Paper/Printing and Metals/Metal Products. In contrast, the least exposed industry is Repair & Installation. See Figure A2 in the Appendix.

Figure 2: Log of Sectoral Price Shock Exposure



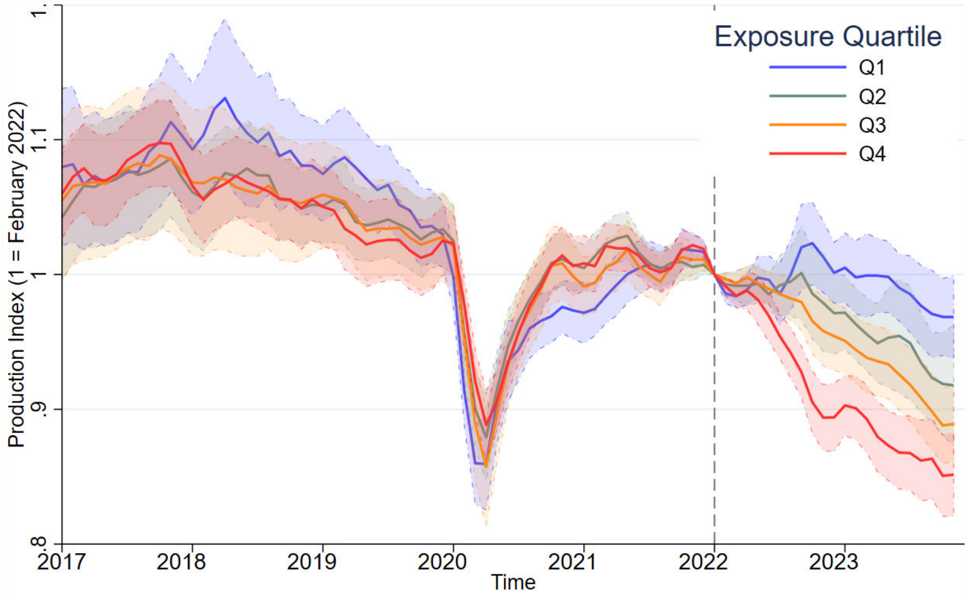
Notes: The figure shows the logarithm of the exposure measure, defined as the predicted increase in energy costs per worker in a four-digit sector. Sectors within the same two-digit sector are represented by the same color. The black vertical lines span from the 25^{th} to the 75^{th} percentile. Source: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

A2 in the Appendix). One can glean from the table that, while the median of sectors' turnover is relatively evenly distributed across exposure quartiles, the median number of employees is smallest in the most exposed quartile. Relatedly, the median turnover per worker increases monotonically from the least to the most exposed quartile, as do the median number of workers per plant and turnover per plant. These patterns plausibly reflect the concentration of the shock in the heavy, capital-intensive segments of the manufacturing industry.

To grasp the impact of the price shock on economic activity—and to motivate the subsequent main analysis of labor market outcomes—we plot the quartile-specific means of a production index in Figure 3. The production index is a data product provided by the statistical office and is constructed from a monthly survey of manufacturing plants reporting output in values and quantities. It therefore captures real economic activity at the four-digit industry level.[15] We normalize the index to February 2022 and plot its evolution for the five years preceding the shock and for the two post-shock years that we analyze. The figure shows that, prior to the COVID shock in 2020, economic activity evolved similarly across exposure quartiles, particularly among the three most exposed quartiles. Economic activity collapsed by approximately 15pp. in 2020 when COVID hit, followed by a swift recovery during the second half of the year. The least exposed sectors experienced the largest drop and a somewhat slower recovery, which may be related to these sectors being the most labor-intensive sectors and hence more exposed to COVID (cf. Table A2). Since mid-2022, economic activity across exposure quartiles has diverged markedly. The decline increases monotonically from the least to the most exposed quartile: by

[15] Specifically, we use the following data product from Destatis: "Produktionsindex für das Verarbeitende Gewerbe: Deutschland, Monate, Original- und bereinigte Daten, Wirtschaftszweige" (version BV 4.1), which can be downloaded here. Last retrieved on 12 September 2024.

Figure 3: Production Index by Exposure Quartile (Monthly Index)



Notes: 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). The vertical dashed-line marks the beginning of the Russian aggression against Ukraine in February 2022. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018) and industrial energy price data and the production index (BV 4.1) from the Federal Statistical Office.

late 2023, economic activity was about 15pp. below its level from February 2022 in the most exposed quartile (red line). In the least exposed quartile, economic activity was less than 5pp. below its February 2022 level (blue line). This descriptive evidence points to an adverse effect on economic activity as a result of the energy shock, which we take as motivation for the following analysis.

Sector-Level Employment Data Table 1 provides summary statistics based on the IEB data, aggregated to 220 four-digit sectors.[16] One can see from the table that the average sector employs approximately 27,000 individuals (row 1), with more than 90% in full-time positions (row 2) and over two-thirds of workers are engaged in routine tasks (row 3), while the rest is performing abstract tasks (row 4). The average annual wage is approximately €50k, with considerable variation across sectors. For example, at the 25$^{\text{th}}$ percentile, the average wage is €42k, and at the 75$^{\text{th}}$ percentile, it is €58k. In general, workers engaged in abstract tasks earn, on average, roughly €22k or 50% more than workers performing routine tasks. The table also shows 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 sectoral average wage of newly hired workers is €43k—substantially below the overall average across sectors and, by construction, below the sectoral average wage of the complementary subgroup (i.e., workers who were not newly hired), who earn €51k. Workers who leave their jobs earn an average annual wage of €45k, slightly higher than that of new hires but well below the overall average.

[16]While there are about 10 more four-digit sectors, we are unable to retrieve aggregates for some of them from the micro data due to confidentiality restrictions. Moreover, we impose the requirement that a sector must employ at least 350 employees at baseline.

To visualize the cross-sectional correlation between shock exposure and mean wages for routine and abstract employment we use binned scatterplots shown in Figure A3 in the Appendix. These figures reveal a clear positive correlation between wages and exposure, possibly reflecting a compensating wage differential for workers in energy and pollution intensive industries (Cole et al., 2009).

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

	Mean	SD	p25	p50	p75	N
# Employees	26,615	44,211	4,264	9,622	29,802	220
# FT Employees	24,807	41,368	4,026	8,741	28,596	220
# Employees (Routine)	18,818	29,963	3,255	7,215	21,668	220
# Employees (Abstract)	7,796	15,252	1,029	2,652	8,265	220
Mean Wage (€ per Year)	50,268	11,387	42,234	48,268	58,447	220
Mean Wage (Routine, € per Year)	43,982	9,270	37,017	42,730	50,071	220
Mean Wage (Abstract, € per Year)	67,055	12,940	57,465	65,139	76,473	220
Share of New Hires	0.13	0.06	0.10	0.12	0.15	220
Mean Wage (New Hires, € per Year)	43,440	9,930	36,462	42,275	48,766	220
Mean Wage (No new Hires, € per Year)	51,241	11,483	43,106	48,946	59,253	220
Mean Wage (Leavers, € per Year)	45,468	10,431	38,668	43,684	51,577	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 annual wage, mean annual 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: Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (IAB).

Establishment-Level Data Table 2 presents summary statistics from the BHP. We restrict the dataset to establishments with at least 20 employees, consistent with the inclusion criteria of the manufacturing census. After imposing this restriction and removing outlier observations, the dataset contains 41,662 unique establishments.[17] Row 1 of Table 2 reports the number of employees per establishment. The median establishment employs 52 workers, while the mean is 135, well above the 75$^{\text{th}}$ percentile. This reflects that the plant-size distribution is heavily right-skewed. Rows 2 to 5 summarize moments of the establishment-level wage distribution, measured in euros per year. The average establishment-level annual mean wage is approximately €43.6k, the median is about €41.7k and wages at the 75$^{\text{th}}$ percentile amount to roughly €50k. As a general rule, larger establishments tend to pay higher wages, which explains why sectoral average wages exceed average establishment-level wages. The average of wages at the 25$^{\text{th}}$ percentile of the within-establishment wage distribution (fourth row) is €34.6k, whereas the corresponding average for the 75$^{\text{th}}$ percentile (fifth row) amounts to €48.5k. This difference indicates meaningful within-establishment wage dispersion. Table 2 also report the average share of new hires (entrants) and separations (exits). Both rates amount to approximately 14%, which is slightly above the corresponding figures at the sector level (cf. Table 1). This can be explained by somewhat lower worker turnover in larger establishments. Moreover, the table shows that the average establishment in the sample was around 30 years old in 2020 and that roughly 28% of establishments employ at least 100 workers. Finally, the last row indicates that both the mean and median establishment belong to a sector in the second exposure quartile, meaning they fall

[17] Specifically, we define outliers as extreme changes relative to 2021 in log employment, log wages, or entry and exit rates, where an extreme change is defined as being below the 2^{nd} or above the 98^{th} percentile.

into the second-least-exposed category. This reflects the fact that sectors in the highest exposure quartiles tend to consist of fewer but larger establishments (cf. Table A2 in the Appendix).

Table 2: Summary Statistics from the Establishment History Panel (2021)

	Mean	SD	p25	p50	p75	N
# Employees	135	600	31	52	113	41,662
Mean Wage (€ per Year)	43,589	13,538	34,182	41,706	50,450	41,662
Median Wage (€ per Year)	40,032	12,758	31,189	38,087	46,000	41,662
Wage P25 (€ per Year)	34,613	10,446	27,170	33,235	39,993	41,662
Wage P75 (€ per Year)	48,526	16,665	36,927	45,464	56,312	41,662
Share of Entrants	0.14	0.10	0.07	0.12	0.18	41,662
Share of Exits	0.15	0.48	0.08	0.12	0.18	41,662
Year of Founding	1990	13	1975	1991	2001	41,662
Share of Large Plants (#L > 99)	0.28	0.45	0.00	0.00	1.00	41,662
Shock Exposure Quartile	2.15	0.97	1	2	3	41,662

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.

Regional-Level Data We show the regional fallout of the shock across 223 labor markets in Figure 4 (thin black lines demarcate the Federal States). Each color corresponds to one of six exposure bins. 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*, the *Saarland* and around *Ludwigshafen*—regions associated with heavy industry. The most exposed labor market region on the map, however, is *Altötting*, located in southeastern Bavaria within the "Bavarian Chemical Triangle". Figure A4 in the Appendix plots the logarithm of labor markets' exposure (similar to Figure 2). As expected, the distribution is substantially more compressed compared to that of sectors. For example, the labor market at the 25$^{\text{th}}$ percentile (*Hannover*) experienced a predicted energy cost increase of €1,252 per SVPB, compared to 3,052€ at the 75$^{\text{th}}$ percentile (*Baden-Baden*).[18]

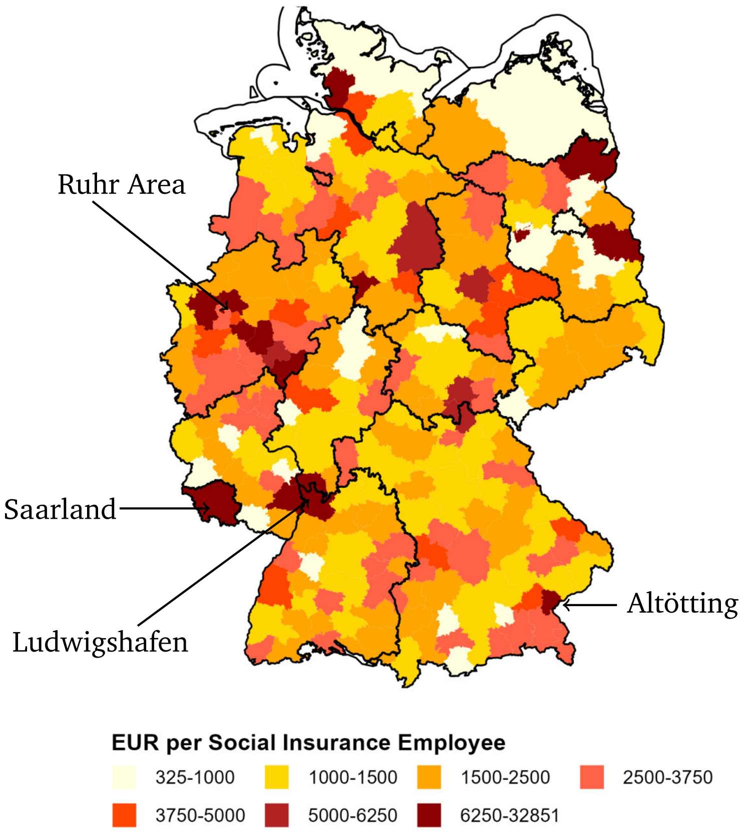
Exposure can be defined at different levels of spatial aggregation, involving trade-offs between signal-to-noise ratios and the scope for within-region spillovers. In our analysis of regional labor market effects, we measure exposure at the level of 223 local labor markets. To assess within–labor-market heterogeneity in exposure, we also construct exposure measures at the level of 400 districts, all nested within labor markets (cf. Figure A5 in the Appendix). If adjacent districts within the same labor market face markedly different exposure, workers displaced from shrinking energy-intensive industries may find alternative employment opportunities in close geographic proximity. Conversely, limited within–labor-market heterogeneity could potentially imply more costly adjustment, requiring greater geographic mobility.

We decompose the variance of the log exposure measure across districts into within– and between–labor-market components, finding that more than 40% of district-level variance comes

[18]Additionally, Figure A7 in the Appendix confirms a close correlation between the logarithm of shock exposure and the logarithm of CO_2 emissions per employee at the regional level. This correlation supports the relevance of the analysis in the broader decarbonization context: the shock primarily affected those regions that will need to adjust the most in order to decarbonize.

from within labor market variation. This substantial local heterogeneity suggests that adjustment may be facilitated by nearby outside options.

Figure 4: Exposure at Labor Market Level: Predicted Additional Energy Costs per SVPB



Notes: The map visualizes the energy price shock exposure at the 223 local labor market level, defined as the predicted increase in energy costs per employee subject to social security contributions (SVPB) in a given labor market. Each labor market 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 labor market by industry using the workers' place of work. Thin black lines delineate federal state boundaries. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018); industrial energy price data, and Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (IAB).

4 Main Results: Effects on Employment and Wages

This section presents the main analysis of the labor-market impact of the price shock at the (i) sector, (ii) establishment, and (iii) regional level.

4.1 Sector-Level Results

Table 3 presents the main results from estimating equation 5 using sectorally aggregated data. The dependent variable in the first three columns is the change in log employment relative to 2021. Column 1 reports results for total employment, and columns 2 and 3 for routine and abstract employment, respectively. In column 4 the dependent variable is the share of abstract employment (in pp.) and in columns 5 to 7, the dependent variable is the log change in wages for the respective worker groups. All specifications include year-by-industry fixed effects. At the bottom of the table, we report the baseline mean of the dependent variable in levels, the number of observations, and the number of unique sectors. For ease of interpretation, we rescale coefficients such that they reflect the change in the dependent variable resulting from a 100% increase in the explanatory variable.

Table 3: Sector-Level Results: Response to a 100% Increase in Exposure

	Δ Log Employment			Δ Share (pp)	Δ Log Wages		
	All (1)	Routine (2)	Abstract (3)	Abstract (4)	All (5)	Routine (6)	Abstract (7)
Δ 2018	0.181	0.003	0.665	0.114	0.128	0.049	0.075
	(0.515)	(0.554)	(0.515)	(0.075)	(0.124)	(0.120)	(0.147)
Δ 2019	0.343	0.205	0.622	0.081	0.022	0.010	-0.099
	(0.420)	(0.428)	(0.446)	(0.054)	(0.101)	(0.102)	(0.142)
Δ 2020	0.349	0.335	0.366	0.012	-0.083	-0.082	-0.196
	(0.264)	(0.266)	(0.304)	(0.039)	(0.097)	(0.085)	(0.132)
Δ 2022	-0.047	0.014	-0.427	-0.081^{*}	-0.257^{**}	-0.201^{*}	-0.367^{***}
	(0.222)	(0.223)	(0.270)	(0.043)	(0.112)	(0.104)	(0.135)
Δ 2023	0.243	0.400	-0.402	-0.150^{**}	-0.446^{***}	-0.387^{***}	-0.490^{***}
	(0.330)	(0.320)	(0.446)	(0.064)	(0.145)	(0.139)	(0.164)
Mean of Y	26,615	18,818	7,796	27	50,268	43,982	67,055
# of Obs.	1,100	1,100	1,100	1,100	1,100	1,100	1,100
# of Sectors	220	220	220	220	220	220	220
Year-Ind.-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows point estimates from estimating equation 5. The unit of observation is a four-digit economic sector. Standard errors, clustered at the four digit sector level, 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, as well as the mean of the dependent variable in levels. All dependent variables are differences relative to 2021. With the exception of the middle column (fourth column) all outcomes are logged. In the middle column the dependent variable is the change in the share (in pp.) of abstract workers. 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* (2018) and Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (IAB). Significance levels are indicated as * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

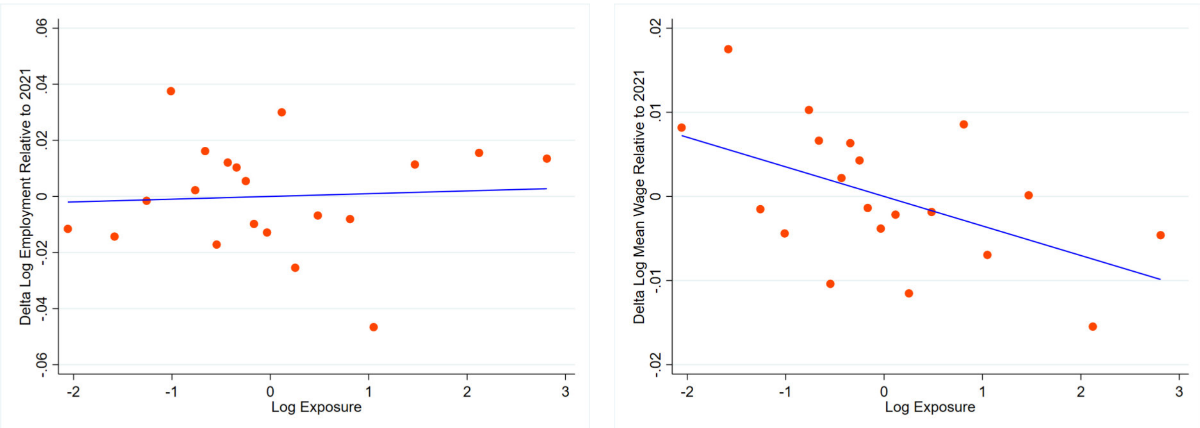
The first three columns do not provide any indication of adverse effects of the price shock on sector-level employment; neither the overall effect (column 1) nor the subgroup effects are statistically significant (columns 2 and 3). Reassuringly, all pre-treatment coefficients are also statistically insignificant, and their pattern does not suggest the presence of any pre-existing trends in sector-level employment. However, when looking at the point estimates in the post period, one can see opposing signs for routine and abstract employment, which may hint at a change in the composition of the workforce. To assess whether the shock affected the skill composition of employment, we examine the change in the share of abstract employment in total employment (in pp.) as the dependent variable (column 4). The results show a small but significant decrease in the share of workers with abstract tasks in the post-shock years. This finding would be consistent with an energy–skill complementarity discussed in previous literature (Kehrig and Ziebarth, 2017; Polgreen and Silos, 2009), whereby increases in energy prices reduce demand for skilled labor relative to unskilled labor.

Turning to average wages in column 5, we find negative and significant effects in 2022 and 2023. The point estimates suggest that a 100% increase in a sector's exposure to the energy cost shock reduced average wages by 0.26% in 2022 and by 0.45% in 2023. For reference, going from the

25th to the 75th percentile of the exposure variable corresponds to an increase in the treatment variable by a factor of seven. Again, the pre-treatment coefficients are all statistically insignificant and close to zero, providing support for the parallel trends assumption. From columns 6 and 7, one can see that the impact of the input price shock on wages was relatively similar for workers in both task groups, with abstract-task workers experiencing a slightly larger relative decrease. Since their baseline wages are approximately 50% higher than those for routine-task workers, as shown at the bottom of the table, the absolute wage change for abstract-task workers is substantially larger.[19]

Finally, we use binned scatterplots to assess visually whether the estimated effects of shock exposure on employment and wages occur along the entire exposure distribution rather than being driven by outliers (cf. Figure 5). For this purpose, we pool observations across the two post-treatment years. The flat relationship in Subfigure 5a reflects the absence of an employment response. By contrast, Subfigure 5b shows a clear negative relationship between exposure and wages across the full distribution. In the Appendix, we present the corresponding binned scatterplots for the pre-treatment period, which confirm flat pre-trends (cf. Figure A8).

Figure 5: Changes in Post-Treatment Outcomes and Shock Exposure



(a) Δ Log Employment (Post-Years) **(b)** Δ Log Wage (Post-Years)

Notes: The binned scatterplots display changes in outcomes relative to 2021, pooled across the post-treatment years (2022–2023), and plotted against log shock exposure, conditional on industry-by-year fixed effects. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Lander: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018) and Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (IAB).

Magnitude To interpret the magnitude of the wage response, we relate the implied wage change to the approximate additional energy costs per worker, i.e., our exposure measure. Put differently, we ask what share of these additional energy costs is absorbed through lower wages. Taking the average effect on wages across both post-treatment years, the coefficients in column 5 of Table 3 imply a decline in the average sectoral wage of approximately 0.35% in response to a 100% increase in exposure. For ease of interpretation, we consider an increase from the 25th to the 75th percentile of the exposure distribution, which corresponds to an increase in the explanatory variable by a factor of seven, as shown in Figure 2. Taking the point estimates at face value, this

[19] This is also confirmed by Figure A10 in the Appendix, which plots the coefficients from estimating the baseline specification on changes in wages instead of log wages.

increase implies a reduction in the average sectoral wage of about 2.5%, which—evaluated at the mean of the dependent variable—corresponds to roughly €1,250 per year. More directly, when we estimate the effect on changes in wages instead of log wages, we find an average effect of approximately €260 over the two post-treatment years for a 100% increase in exposure (cf. Figure A10 in the Appendix). This corresponds to roughly €1,800 when multiplied by a factor of 7. Moving from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of the exposure distribution implies an absolute increase in approximated energy costs per worker by roughly 6,400€ (cf. Figure 2). Hence, one interpretation of the magnitude is that about 20–30% of these additional energy costs was absorbed through wage adjustments.

Another way to put the magnitude of the wage response into perspective is to relate it to the response of economic activity by estimating the elasticity between output per worker and wages ("rent-sharing elasticities"). Since we lack micro-level data on production for the post-shock period, we combine our sectoral information on gross output from 2018, retrieved from the census data, with the production index underlying Figure 3. In other words, we anchor production levels to 2018 and use the index to compute post-shock production. We then estimate the elasticity of wages with respect to output per worker, using the exposure measure as an instrument for changes in output per worker. We outline our approach in more detail in Subsection B.1 in the Appendix, and the corresponding results are presented in Table B1. The elasticities reported in the table vary depending on the specification between 0.15 and 0.3, implying that an increase in output per worker by one-percent leads to an increase in wages by 0.15–0.3%. These estimates accord well with recent findings on rent-sharing elasticities in the German manufacturing sector by Mertens et al. (2022).[20]

Mechanism Next, we investigate the adjustment mechanisms underlying the observed decrease in average sector-level wages. For instance, wages for incumbent workers in exposed sectors might grow slower 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 four groups: newly hired individuals; all individuals who were not newly hired; individuals with long-standing employer–employee relationships ("long tenure"); and employees leaving their establishment, for whom we focus on their last wage.

Table 4 presents the results for the four subsamples described above. For comparison, column 1 reproduces the main sector-level effects on average wages, corresponding exactly to the results reported in column 5 of Table 3. Column 2 reports the effect on wages of newly hired workers. In both post treatment years, the point estimates are roughly twice as large as the main effect in column 1. 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.[21] In column 3 we

[20]Interestingly, the estimates by Mertens et al. (2022) are local average treatment effects from exploiting variation in rents (defined as value-added per worker) induced by energy price fluctuations since they instrument endogenous rents with a shift–share instrument based on plant-level fuel shares. Moreover, they show that their effects are entirely driven by energy price increases, which also aligns with our setting.

[21]On average, approximately 13% of workers in a sector are new hires each year (cf. Table 3)

show the effect on all individuals who were not newly hired (the complementary sub-group). For 2023, this effect is about 20% smaller than the main effect (column 1) but remains statistically significant and substantial.

By definition, all "not newly hired" include workers hired in the previous year, and thus lower wages for new hires in 2022 feed into the sectoral average wage for the "not newly hired" in 2023. 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 hit in 2022. Column 4 reports the corresponding coefficients. The post-treatment effects for long-tenure workers are negative in both years, but are only about half as large as the baseline effect reported in the first column. 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. Finally, another potential mechanism is the outflow of particularly high-wage earners. In column 5, the dependent variable is the average of individuals' last wages before changing employers. If high-wage earners indeed left more exposed sectors disproportionately, one would expect the post-treatment coefficients to be positive.[22] This, however, is not supported by the data: all pre- and post-treatment coefficients are close to zero and statistically insignificant.

4.2 Establishment-Level Results

We now seek to corroborate the results presented above using establishment-level data from the BHP. Table 5 reports results for changes in employment and wages measured at the establishment level. Note that, because the unit of observation differs, the estimates need not align quantitatively with the sector-level results.[23]

The dependent variable in columns 1–3 of Table 5 is the log change in establishment-level employment, while columns 4–6 report results for changes in mean wages at the establishment level. At the bottom of the table, we report the mean of the dependent variable, the number of unique establishments, the number of observations, and the number of unique sectors (clusters). The most parsimonious specifications in columns 1 and 4 include only year-by-industry fixed effects. We then add year-by–federal state fixed effects to control for regional trends (columns 2 and 5). Finally, we also control for establishment age by interacting the year with establishment age (columns 3 and 6).

Columns 1–3 confirm that pre-2021 employment trends were unrelated to the shock. This holds

[22]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 employer e in sector s. We assign this wage to the year 2023 because it affects the average wage in sector s in that year, since individual i is no longer part of the sector's workforce.

[23]For example, employment adjustments in small establishments may have only a limited effect on aggregate sector-level employment, yet still matter for the establishment-level estimates, which capture the average percentage change at the establishment. Conversely, adjustments occurring in small sectors may influence the sector-level estimates, but their effect on the establishment-level results is more muted because such sectors contain relatively few establishments.

Table 4: Log Wage Response to a 100% Increase in Exposure (Sector Level)

	All (1)	Hires (2)	No Hires (3)	Long Tenure (4)	Leaver (5)
Δ 2018	0.128	-0.429	0.174	0.026	-0.145
	(0.124)	(0.493)	(0.133)	(0.126)	(0.334)
Δ 2019	0.022	-0.117	0.010	-0.078	0.207
	(0.101)	(0.446)	(0.100)	(0.097)	(0.390)
Δ 2020	-0.083	-0.102	-0.071	-0.095	0.173
	(0.097)	(0.468)	(0.105)	(0.087)	(0.309)
Δ 2022	-0.257**	-0.567	-0.259**	-0.160	0.093
	(0.112)	(0.408)	(0.127)	(0.101)	(0.274)
Δ 2023	-0.446***	-0.949**	-0.369**	-0.197*	-0.161
	(0.145)	(0.463)	(0.148)	(0.112)	(0.321)
Mean of Y	138	119	140	147	125
# of Observations	1,100	1,100	1,100	1,100	1,100
# of Sectors	220	220	220	220	220
Year-Ind.-FE	Yes	Yes	Yes	Yes	Yes

Notes: This table reports point estimates and standard errors from estimating equation 5, 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 (2018) and industrial energy price data and Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (IAB). Significance levels are indicated as * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

across all three specifications. In the post period, we again do not find evidence of an adverse effect on employment. On the contrary, we find positive point estimates, which even become statistically significant in 2023. For instance, the estimate in column 1 suggests that increasing exposure by 100% leads to a 0.27% increase in employment, corresponding to approximately 0.37 additional employees for the average establishment. We discuss and qualify this employment result later when presenting heterogeneities by establishment-size and results using a discretized exposure measure (quartile dummies). To preview the corresponding results: the positive employment effect is driven by small establishments and by differential trends between establishments from the least-exposed quartile on the one hand and establishments from the three most-exposed quartiles on the other hand. Therefore, our cautious conclusion from the employment results in columns 1–3 is that there is no evidence for an adverse employment effect.

Turning to wages in columns 4–6 of Table 5, the point estimates for the pre-shock years do not indicate pre-trends in wages. Again, the estimates are insensitive to the inclusion of region-by-year fixed effects (column 5) and age controls (column 6). In the post period, we find negative and highly significant point estimates on impact. For example, in 2022 average establishment-level wages decreased by 0.1% in response to a 100% increase in exposure. As in the sector-level analysis, this effect is larger in 2023, implying a decline in mean establishment-level wages of

Table 5: Establishment-Level Results (BHP): Response to a 100% Increase in Exposure

	Log Employment			Log Mean Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ 2018	-0.037	-0.021	-0.023	-0.011	0.010	0.010
	(0.253)	(0.250)	(0.250)	(0.096)	(0.083)	(0.082)
Δ 2019	-0.010	0.007	0.004	-0.098	-0.089	-0.090
	(0.219)	(0.214)	(0.214)	(0.062)	(0.056)	(0.055)
Δ 2020	0.003	0.005	0.002	-0.017	-0.022	-0.022
	(0.088)	(0.089)	(0.088)	(0.045)	(0.043)	(0.043)
Δ 2022	0.103	0.109	0.112	-0.110***	-0.117***	-0.116***
	(0.077)	(0.076)	(0.076)	(0.040)	(0.041)	(0.041)
Δ 2023	0.278**	0.289**	0.293**	-0.239***	-0.256***	-0.254***
	(0.130)	(0.129)	(0.128)	(0.072)	(0.071)	(0.070)
Mean of Y	136	136	136	43,604	43,604	43,604
# of Unique Plants	40,220	40,220	40,220	40,220	40,220	40,220
# of Observations	173,287	173,287	173,287	173,287	173,287	173,287
# of Sectors	220	220	220	220	220	220
Year-Ind.-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-State-FE		Yes	Yes		Yes	Yes
Establishment-Age			Yes			Yes

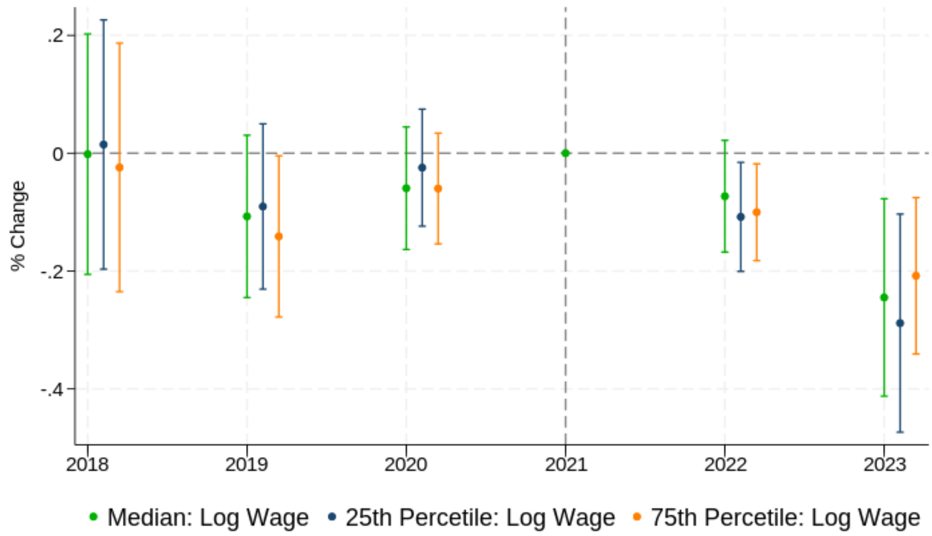
Notes: The table shows point estimates from estimating versions of equation 5. The unit of observation is at the plant-level. Standard errors are given in parentheses and clustered at the four-digit-sector level. Fixed effects, number of observations and number of sectors (cluster) are given at the bottom 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 (2018); industrial energy price data; 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 * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

approximately 0.25%, corresponding to about €110 when evaluated at the mean of the dependent variable (€43.6k). Similar to the sector-level results we visualize the relationship between the shock and changes in the establishment-level outcomes in the pre- and post-periods using binned scatterplots (cf. Figure A9 in the Appendix). As for the sector-level results, the negative effect on wages appears as a rotation of the wage distribution.

Heterogeneity We first ask whether the shock had differential effects depending on workers' position in the establishment-level wage distribution. To answer this, we estimate the effect on wages at the 25th, 50th, and 75th percentiles of the establishment-level wage distribution. Figure 6 plots the coefficients from the corresponding regressions from which 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 as in the main results in Table 5. In both post-treatment years, the point estimate capturing the effect on wages at the 25th percentile (blue) is the largest but differences are small and confidence intervals of all point estimates clearly overlap. Overall, the estimates suggest a shift in the establishment-level wage distribution but do not indicate a change in wage dispersion, i.e., a change in within-establishment wage inequality.

Next, we investigate heterogeneities by establishment and regional characteristics. We start by dividing the sample between large and small establishments (above or below 100 employees). For instance, one may hypothesize that large establishments are better positioned to adjust to shocks

Figure 6: Effects Along the Establishment-Level Wage Distribution



Notes: The figure presents point estimates from estimating equation 5, 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$^{\text{th}}$ percentile wage (blue), and the 75$^{\text{th}}$ 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 (2018); industrial energy price data; 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.

or to lobby for support. We then divide establishments according to whether they are located in more or less industrialized districts and labor markets, measured by the share of employees in industry (above or below the respective medians). Industrial workers in regions with a high industry share may have better outside options, hence employers ability to pass through the cost shock to wages could be constraint. Tables A4 (employment) and A5 (wages) in the Appendix report the results from the splits.

Table A4 shows that the positive effect on employment documented in Table 5 is driven entirely by small establishments. This provides a meaningful qualification regarding the aggregate relevance of the effect: the average number of employees in the sample of small establishments is only 45, compared to 366 among large establishments. Hence while only about one-quarter of the establishments meet our definition of large (>100 workers), these large establishments still employ almost three-quarter of workers. Turning to regional differences, we do not find evidence of heterogeneous employment responses depending on whether establishments are located in more or less industrialized districts or labor markets.

For wages, the effect appears to be relatively homogeneous across establishment size (Table A5). If anything, it tends to be larger among large establishments. Recall that larger energy consumers also experienced a greater relative increase in electricity and gas prices, so the differences between large and small establishments may also reflect differences in exposure depending on size. With regard to regional differences, we find that the wage effect tends to be muted among establishments located in more industrialized districts, consistent with the hypothesis concerning outside options stated above. When splitting the sample by the larger geographic units—labor markets—the pattern remains qualitatively similar, although the difference becomes smaller.

Robustness: Discretized Exposure Subsection B.2 in the Appendix presents results based on a discretized exposure measure using the sector- and establishment-level data.[24] Specifically, we estimate the average effect on employment and wages for exposure quartiles relative to the least-exposed quartile. Figure B2 plots the estimates for employment (Subfigure a) and wages (Subfigure b). For employment, no systematic pattern is visible prior to treatment. In the post-treatment period, the point estimates suggest a positive employment effect of nearly identical magnitude across all three more-exposed quartiles. In other words, employment contracted in sectors within the least-exposed quartile relative to the other three quartiles. The three most-exposed quartiles behaved similar to each other in both post-treatment years. For wages, Subfigure (b) confirms flat pre-trends and a negative effect on wages in the post period. In contrast to the employment effect, the negative wage effect increases in magnitude when moving up the exposure distribution.

Additional Analysis: Temporary Work The absence of a negative employment effect—both in the sector and establishment-level data—may be somewhat surprising, though it is in line with similar estimates for the UK (Fetzer et al., 2024a). Our results are also consistent with Mertens et al. (2022), who find no effect of energy price fluctuations on regular employment in German manufacturing, looking at the period 2003–2017. However, they document that the expenditure share on "temporary work" declines when energy prices rise. Unfortunately, temporary workers are not observed in the BHP; therefore, the effects we estimate using this dataset do not capture potential adjustments along this margin.[25] However, information on temporary employment is available in the *Betriebspanel*, an annual survey of establishments conducted by the IAB that covers roughly 15,000 establishments across all sectors of the economy (Bellmann et al., 2024). When restricting the sample to manufacturing and applying the same sample restriction as for the BHP (at least 20 employees), the number of unique establishments amounts to roughly 1,600, compared to more than 40,000 in the BHP.

We report our analysis based on the *Betriebspanel* in Subsection B.3 of the Appendix. We construct two measures of temporary work: (i) the share of temporary workers in total employment, and (ii) a dummy for whether an establishment employs any temporary workers. The table shows consistent negative effects of the energy price shock on both measures in 2023. However, we also find significant effects in 2020, suggesting that establishments' responses to the Covid-19 shock with respect to temporary work are related to their exposure to the energy price shock. Overall, given the small sample size and some significant estimates in the pre-treatment years, we view the results as suggestive evidence of a negative effect of the energy price shock on temporary employment. This would be consistent with previous literature and intuition, as temporary work

[24]For the sake of completeness, we also show the corresponding estimates using the sector-level data.

[25]Temporary agency work is reported as a separate sector (NACE 78.20). Unfortunately, we do not know to which sectors the workers actually supply their labor.

is plausibly the most flexible margin for adjusting labor input.

4.3 Regional-Level Estimates

To complement the sector- and establishment-level analysis, we map the shock to 223 labor market regions as described in Subsection 2 and estimate the effect of regional exposure on employment and wages. While the earlier analysis focused exclusively on the manufacturing sector, the regional approach also allows us to estimate effects on wages and employment in non-manufacturing industries and thereby capture potential regional spillovers from manufacturing into other sectors. Because the regional shock is constructed by mapping additional manufacturing energy costs per worker to regions, exposure will mechanically be higher in regions with a larger manufacturing employment share. However, we seek to compare regions with broadly similar economic structures—particularly with respect to the degree of industrialization—that differ in their exposure to the shock due to differences in the composition of manufacturing sectors and, consequently, in energy intensity or fuel mixes. To make these comparisons, we augment equation 5 to include an interaction between years and the baseline share of industrial workers:

$$\Delta y_{l,r,t} = \beta_0 + \sum_{\tau=2018,\tau\neq 2021}^{2023} \beta^{\tau} ln(Exposure_l) \times \mathbb{1}\{t=\tau\} + \gamma_{r,t} + indsh_l \times year_t + \varepsilon_{l,r,t} \quad (6)$$

Table 6: Regional Results: Employment and Wage Responses to a 100% Exposure Increase

	Δ Log Employment			Δ Log Wages		
	All (1)	Manu. (2)	No Manu. (3)	All (4)	Manu. (5)	No Manu. (6)
Δ 2018	0.236	0.868*	0.084	0.179	-0.220	0.210
	(0.210)	(0.525)	(0.213)	(0.119)	(0.222)	(0.133)
Δ 2019	0.154	0.244	0.177	0.104	-0.188	0.101
	(0.153)	(0.451)	(0.159)	(0.113)	(0.205)	(0.121)
Δ 2020	0.212*	0.486	0.177	-0.036	-0.394**	0.023
	(0.112)	(0.362)	(0.131)	(0.084)	(0.169)	(0.083)
Δ 2022	-0.202*	-0.476	-0.114	-0.172**	-0.210	-0.142*
	(0.119)	(0.295)	(0.102)	(0.079)	(0.137)	(0.084)
Δ 2023	-0.244	-0.291	-0.204	-0.322***	-0.595***	-0.195**
	(0.188)	(0.395)	(0.163)	(0.083)	(0.185)	(0.095)
Mean of Y	118,125	26,297	91,829	43,770	48,357	41,340
# of Labor Markets	223	223	223	223	223	223
# of Observations	1,115	1,115	1,115	1,115	1,115	1,115
Ind. Empl. Share	Yes	Yes	Yes	Yes	Yes	Yes
Year-East-FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows point estimates from estimating versions of equation 6. The unit of observation is a labor market region. 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 log differences to 2021. The dependent variables in the first three columns are changes in employment (all, manufacturing employment and non-manufacturing employment) and in the last three columns changes in average wages (all, manufacturing wages and non-manufacturing wages). 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 * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6 presents the results from the regional-level analysis. Each column reports estimates for a different outcome. The first column shows the effect on total employment, the second on manufacturing employment, and the third on non-manufacturing employment. Columns 4 to 6 report the corresponding estimates for wages.[26] In columns 1–3, the point estimates capturing post-shock employment effects are negative throughout, though statistically insignificant in most cases. The only exception is the estimate for overall employment in 2022, which is negative and significant at the 10% level. Overall, despite the uniformly negative point estimates, the lack of statistical significance lets us conclude that there is no clear evidence of adverse effects on regional employment.

For the average regional wage, we find a significant negative effect in 2022 and 2023 (column 4), implying a 0.17% and 0.32% decline in response to a 100% increase in exposure. For reference, moving from the 25th to the 75th percentile of the regional exposure distribution corresponds to an increase in exposure by a factor of 2.5 (cf. Figure A4 in the Appendix). Thus, evaluated at the regional mean wage, this implies a reduction of approximately €270 annual earnings across the two post-shock years.[27] This effect is driven by both; manufacturing and non-manufacturing wages. Mirroring the negative wage effects in manufacturing that we documented at the sector and plant level, we also find negative effects on average manufacturing wages at the regional level (column 5). Both post-shock point estimates are larger in absolute value than the average effects reported in column 4, and the estimate for 2023 is highly significant, implying a reduction in regional manufacturing wages of about 0.6% in response to a 100% increase in exposure. Interestingly, we also find negative and statistically significant—though smaller—effects for non-manufacturing wages (column 6). These findings suggest that the shock may have spilled over from manufacturing to other sectors within local labor markets.[28]

To assess which segments of the local economy are affected by spillovers from the shock, we estimate the effects of regional exposure on regional wages and employment by one-digit industry. Table A6 in the Appendix shows that the negative effect for wages outside manufacturing is driven primarily by service sectors, in particular “Trade, transport and storage, hospitality” (5) and “Information and communication, credit and finance” (6). For employment (Table A7), the pattern is qualitatively similar. We find negative point estimates in the post periods for both sectors mentioned before. In addition we also find a strong negative effect on “Other Services”. Overall, we interpret these results as indication for regional spillovers from the manufacturing sector to other industries, in particular the service sector. Such spillovers could, for example, take the form of negative demand effects arising from manufacturing plants that reduce production or investment in anticipation of deteriorating economic conditions. In contrast to the negative wage (and partly employment) effects observed in service industries, we do not find any response in labor market outcomes in “Public Administration; Social Security, Education and Training; Health and Social Services” (8), which is the sector where the least spillovers may be expected.

[26]We winsorize outcomes at the 1st and 99th percentiles.

[27]We obtain this figure by multiplying the mean wage (€43,770) by 0.0025—the average of the estimated coefficients for 2022 and 2023—and by 2.5, corresponding to the interquartile increase in exposure.

[28]At the regional level, no data exists that would allow us to measure the effects of the shock on economic activity directly. An exception is real GDP growth rates at the federal-state level. Figure A6 in the Appendix plots the corresponding correlations for the post-shock years (2022 and 2023).

5 Discussion and Conclusion

This study provides the first ex-post analysis of the impact of the 2022 energy price shock on Germany focusing on labor market outcomes. After energy imports, particularly natural gas, from Russia nearly ceased in late summer 2022, industrial energy prices soared. This triggered a controversial debate about the consequences for the German economy, particularly the labor market. For our analysis, we uniquely combine information from the manufacturing census with administrative employment data from the IAB to study the effect of the shock at the sector, establishment, and regional level. Using a Bartik-type treatment intensity measure, we find a consistent adverse effect on wages but no negative employment effects, indicating that adjustment occurred primarily through labor income rather than employment quantities. For instance, our estimates imply that moving from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of the exposure distribution is associated with an annual earnings loss of around 2.5% in the post-shock period. This corresponds to roughly €1,250 per year, or about 20–30% of the approximated additional energy costs per worker resulting from the energy price shift.

Beyond the immediate question of how the price shock affected the German economy, this episode can also inform how the manufacturing sector may respond to ambitious climate policies. For example, raising carbon prices near levels of the estimated social cost of carbon would imply an increase in EU-ETS prices by a factor of ten relative to the average price in the previous decade and therefore may have similar impacts on the energy-intensive segments of the economy (Rennert et al., 2022).

One lesson from previous structural transformations is that adverse shocks in specific industries can trigger broader regional decline along many socioeconomic dimensions. We map our sector-level shock to the level of local labor markets and find indeed indication for spillovers in local labor markets. On the positive side though, our descriptive evidence shows that the regional exposure measure is far less dispersed than at the sectoral level, and that highly exposed labor markets are not concentrated in particular parts of Germany but rather scattered across the country (cf. Figures 4 and A4). This may be encouraging, as it suggests that workers could find employment opportunities outside energy-intensive industries without having to migrate over long distances.

For several reasons, our estimates may represent a lower bound on the effect of energy prices on manufacturing. First, if firms pass through higher energy costs to product prices (Lafrogne-Joussier et al., 2023), downstream sectors that rely on these products as inputs will receive an indirect treatment. Our estimates capture the direct effect on manufacturing over and above any such indirect effects on downstream sectors. Second, the German government introduced measures to cushion the shock to the manufacturing sector. To the extent that these measures were effective, our estimates constitute a lower bound relative to a counterfactual scenario without any policy response. Future work using plant- or firm-level outcome data may address these questions. For example, detailed information on intermediate inputs, their energy intensity, and plant-level variation in sourcing could allow for the estimation of indirect effects and information on state aid received by individual plants could be used to assess the magnitude of cushioning effects. Moreover, plant-level data would enable estimation of the degree of substitutability between energy inputs and other factors of production. Much of the controversy surrounding the effects of the price shock on manufacturing stemmed from different assumptions about this degree of substitutability. Quantifying the role of each of these factors in explaining how Germany's economy responded to the energy price shock is left for future research.

References

Abeberese, Ama Baafra (Dec. 2017). "Electricity Cost and Firm Performance: Evidence from India". *The Review of Economics and Statistics* 99.5, pp. 839–852. DOI: 10.1162/REST_a_00641. eprint: https://direct.mit.edu/rest/article-pdf/99/5/839/1918618/rest_a_00641.pdf.

André, Christophe, Hélia Costa, Lilas Demmou, and Guido Franco (May 2023). *Rising energy prices and productivity: short-run pain, long-term gain?* OECD Economics Department Working Papers 1755. OECD Publishing. DOI: 10.1787/2ce493f0-en.

Arquié, Axelle and Malte Thie (Sept. 2023). *Energy, Inflation and Market Power: Excess Pass-Through in France*. Working Papers 2023-16. CEPII.

Auclert, Adrien, Hugo Monnery, Matthew Rognlie, and Ludwig Straub (2023). *Managing an energy shock: Fiscal and monetary policy*. NBER Working Paper. National Bureau of Economic Research. DOI: 10.3386/w31543.

Autor, David, David Dorn, Gordon Hanson, and Kaveh Majlesi (Oct. 2020a). "Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure". *American Economic Review* 110.10, pp. 3139–83. DOI: 10.1257/aer.20170011.

Autor, David, David Dorn, Gordon H. Hanson, Gary Pisano, and Pian Shu (Sept. 2020b). "Foreign competition and domestic innovation: Evidence from US patents". *American Economic Review: Insights* 2.3, pp. 357–74. DOI: 10.1257/aeri.20180481.

Autor, David H., David Dorn, and Gordon H. Hanson (Oct. 2013). "The China syndrome: Local labor market effects of import competition in the United States". *American Economic Review* 103.6, pp. 2121–68. DOI: 10.1257/aer.103.6.2121.

Autor, David H., David Dorn, Gordon H. Hanson, and Jae Song (Sept. 2014). " Trade adjustment: Worker-level evidence". *The Quarterly Journal of Economics* 129.4, pp. 1799–1860. DOI: 10.1093/qje/qju026. eprint: https://academic.oup.com/qje/article-pdf/129/4/1799/30631720/qju026.pdf.

Bachmann, Rüdiger, David Baqaee, Christian Bayer, Moritz Kuhn, Andreas Löschel, Benjamin Moll, Andreas Peichl, Karen Pittel, and Moritz Schularick (2024). "What if? The macroeconomic and distributional effects for Germany of a stop of energy imports from Russia". *Economica* 91.364, pp. 1157–1200. DOI: https://doi.org/10.1111/ecca.12546. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecca.12546.

Barsky, Robert B. and Lutz Kilian (Dec. 2004). "Oil and the Macroeconomy Since the 1970s". *Journal of Economic Perspectives* 18.4, pp. 115–134. DOI: 10.1257/0895330042632708.

Bartik, Timothy J. (1991). *Who Benefits from State and Local Economic Development Policies?* W.E. Upjohn Institute.

Behr, Sophie M., Till Köveker, and Merve Kücük (2025). *Understanding energy savings in a crisis: The role of prices and non-monetary factors*. eng. DIW Discussion Papers 2112. Berlin.

Bellmann, Lutz, Martin Gensicke, Susanne Kohaut, Iris Möller, Barbara Schwengler, Nicole Tschersich, and Matthias Umkehrer (2024). *IAB Establishment Panel (IAB-BP) 1993–2023*. Tech. rep. 27 p. Nürnberg: FDZ-Datenreport 10/2024 (en). DOI: 10.5164/IAB.FDZD.2410.en.v1.

BP (2021). *Statistical Review of World Energy 2021, 70th edition*. Accessed: 2024-12-31.

Bretschger, Lucas and Ara Jo (2024). "Complementarity between labor and energy: A firm-level analysis". *Journal of Environmental Economics and Management* 124, p. 102934. DOI: https://doi.org/10.1016/j.jeem.2024.102934.

Bundesamt für Wirtschaft und Ausfuhrkontrolle (BAFA) (July 2022). *Merkblatt zum Energiekostendämpfungsprogramm*. Version 7. URL: https://www.bafa.de/SharedDocs/Downloads/DE/Energie/ekdp_merkblatt.pdf (visited on 3/8/2025).

Bundesministerium der Finanzen (Oct. 2022). *Mit Entschlossenheit durch die Energiekrise*. URL: https://www.bundesfinanzministerium.de/Monatsberichte/2022/10/Inhalte/Kapitel-2b-Schlaglicht/2b-mit-entschlossenheit-durch-die-energiekrise.html (visited on 3/8/2025).

Cole, Matthew A., Robert J. R. Elliott, and Joanne K. Lindley (2009). "Dirty Money: Is There a Wage Premium for Working in a Pollution Intensive Industry?" *Journal of Risk and Uncertainty* 39.2, pp. 161–180. DOI: 10.1007/s11166-009-9077-x.

Curtis, E. Mark (Mar. 2018). "Who Loses under Cap-and-Trade Programs? The Labor Market Effects of the NOx Budget Trading Program". *The Review of Economics and Statistics* 100.1, pp. 151–166. DOI: 10.1162/REST_a_00680. eprint: https://direct.mit.edu/rest/article-pdf/100/1/151/1918692/rest_a_00680.pdf.

Dauth, Wolfgang, Sebastian Findeisen, and Jens Suedekum (2014). "The rise of the East and the Far East: German labor markets and trade integration". *Journal of the European Economic Association* 12.6, pp. 1643–1675. DOI: https://doi.org/10.1111/jeea.12092. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jeea.12092.

Dippel, Christian, Robert Gold, Stephan Heblich, and Rodrigo Pinto (May 2021). "The effect of trade on workers and voters". *The Economic Journal* 132.641, pp. 199–217. DOI: 10.1093/ej/ueab041. eprint: https://academic.oup.com/ej/article-pdf/132/641/199/41954563/ueab041.pdf.

Erdgas-Wärme-Soforthilfegesetz (Nov. 19, 2022).

Fabra, Natalia, Clément Leblanc, and Mateus Souza (2025). *Unpacking the Distributional Implications of the Energy Crisis: Lessons from the Iberian Electricity Market*. eng. CESifo Working Paper 12093. Munich.

Federal Statistical Office (2024). *Energieverbrauch im verarbeitenden Gewerbe*. Accessed: 2024-12-31.

Fetzer, T., C. Palmou, and J. Schneebacher (2024a). *How do Firms Cope with Economic Shocks in Real Time?* Discussion Paper 19608. Paris & London: CEPR.

Fetzer, Thiemo, Ludovica Gazze, and Menna Bishop (July 2024b). "Distributional and climate implications of policy responses to energy price shocks*". *Economic Policy* 39.120, pp. 711–756. DOI: 10.1093/epolic/eiae038. eprint: https://academic.oup.com/economicpolicy/article-pdf/39/120/711/59647939/eiae038.pdf.

Fontagné, Lionel, Philippe Martin, and Gianluca Orefice (Feb. 2024). "The many channels of firm's adjustment to energy shocks: evidence from France". *Economic Policy* 39.117, pp. 5–43. DOI: 10.1093/epolic/eiae011. eprint: https://academic.oup.com/economicpolicy/article-pdf/39/117/5/57075366/eiae011.pdf.

Ganapati, Sharat, Joseph S. Shapiro, and Reed Walker (Apr. 2020). "Energy Cost Pass-Through in US Manufacturing: Estimates and Implications for Carbon Taxes". *American Economic Journal: Applied Economics* 12.2, pp. 303–42. DOI: 10.1257/app.20180474.

Ganzer, A., A. Schmucker, and S. Wolter (2024). *Establishment History Panel 1975-2023*. FDZ-Datenreport 09/2024 (en). Nürnberg: FDZ, p. 117. DOI: 10.5164/IAB.FDZD.2409.en.v1.

Gerster, Andreas and Stefan Lamp (June 2024). "Energy Tax Exemptions and Industrial Production". *The Economic Journal* 134.663, pp. 2803–2834. DOI: 10.1093/ej/ueae048. eprint: https://academic.oup.com/ej/article-pdf/134/663/2803/59146757/ueae048.pdf.

Gesetz zur Einführung einer Strompreisbremse (Dec. 20, 2022).

Gesetz zur Einführung von Preisbremsen für leitungsgebundenes Erdgas und Wärme (Dec. 20, 2022).

Gesetz zur temporären Senkung des Umsatzsteuersatzes auf Gaslieferungen über das Erdgasnetz (Oct. 25, 2022). https://dejure.org/BGBl/2022/BGBl._I_S._1743.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift (Aug. 2020). "Bartik Instruments: What, When, Why, and How". *American Economic Review* 110.8, pp. 2586–2624. DOI: 10.1257/aer.20181047.

Graevenitz, Kathrine von and Elisa Rottner (2022). *Do Manufacturing Plants Respond to Exogenous Changes in Electricity Prices? Evidence From Administrative Micro-Data*. ZEW Discussion Paper 22-038. Mannheim: ZEW – Leibniz Centre for European Economic Research.

Hanson, Gordon H (2023). *Local labor market impacts of the energy transition: prospects and policies*. Tech. rep. National Bureau of Economic Research.

Hille, Erik and Patrick Möbius (2019). "Do energy prices affect employment? Decomposed international evidence". *Journal of Environmental Economics and Management* 96, pp. 1–21. DOI: https://doi.org/10.1016/j.jeem.2019.04.002.

Kahn, Matthew E. and Erin T. Mansur (2013). "Do local energy prices and regulation affect the geographic concentration of employment?" *Journal of Public Economics* 101, pp. 105–114. DOI: https://doi.org/10.1016/j.jpubeco.2013.03.002.

Kehrig, Matthias and Nicolas L. Ziebarth (Apr. 2017). "The Effects of the Real Oil Price on Regional Wage Dispersion". *American Economic Journal: Macroeconomics* 9.2, pp. 115–48. DOI: 10.1257/mac.20150097.

Krebs, Tom and Isabella Weber (June 2024). *Can Price Controls Be Optimal? The Economics of the Energy Shock in Germany*. IZA Discussion Papers 17043. Institute of Labor Economics (IZA). DOI: None.

Lafrogne-Joussier, R., J. Martin, and I. Mejean (2023). *Energy cost pass-through and the rise of inflation: Evidence from French manufacturing firms*. Discussion Paper 18596. Paris & London: CEPR.

Levell, Peter, Martin O'Connell, and Kate Smith (2025). *The Welfare Effects of Price Shocks and Household Relief Packages: Evidence from an Energy Crisis*. CEPR Discussion Paper 19939. Paris and London: CEPR.

Marin, Giovanni and Francesco Vona (2019). "Climate policies and skill-biased employment dynamics: Evidence from EU countries". *Journal of Environmental Economics and Management* 98, p. 102253. DOI: https://doi.org/10.1016/j.jeem.2019.102253.

Marin, Giovanni and Francesco Vona (2021). “The impact of energy prices on socioeconomic and environmental performance: Evidence from French manufacturing establishments, 1997–2015”. *European Economic Review* 135, p. 103739. DOI: https://doi.org/10.1016/j.euroecorev.2021.103739.

Martin, Ralf, Laure B. de Preux, and Ulrich J. Wagner (2014). “The impact of a carbon tax on manufacturing: Evidence from microdata”. *Journal of Public Economics* 117, pp. 1–14. DOI: https://doi.org/10.1016/j.jpubeco.2014.04.016.

Mertens, Matthias, Steffen Müller, and Georg Neuschäffer (2022). *Identifying rent-sharing using firms’ energy input mix*. IWH Discussion Papers 19/2022. Halle Institute for Economic Research (IWH).

Polgreen, Linnea and Pedro Silos (2009). “Crude substitution: The cyclical dynamics of oil prices and the skill premium”. *Journal of Monetary Economics* 56.3, pp. 409–418. DOI: https://doi.org/10.1016/j.jmoneco.2009.03.002.

Politico (2022). “Olaf Scholz warns against Russia energy embargo”. *Politico*. Accessed: 2025-01-01.

Rennert, Kevin, Frank Errickson, Brian C. Prest, Lisa Rennels, Richard G. Newell, William Pizer, Cora Kingdon, Jordan Wingenroth, Roger Cooke, Bryan Parthum, David Smith, Kevin Cromar, Delavane Diaz, Frances C. Moore, Ulrich K. Müller, Richard J. Plevin, Adrian E. Raftery, Hana Ševčíková, Hannah Sheets, James H. Stock, Tammy Tan, Mark Watson, Tony E. Wong, and David Anthoff (2022). “Comprehensive evidence implies a higher social cost of CO_2”. *Nature* 610.7933, pp. 687–692. DOI: 10.1038/s41586-022-05224-9.

Schmucker, Alexandra, Stefan Seth, and Philipp vom Berge (2023). *Sample of Integrated Labour Market Biographies (SIAB) 1975 - 2021*. Tech. rep. 02/2023 (en). Nürnberg: FDZ Datenreport. DOI: 10.5164/IAB.FDZD.2302.en.v1.

World Bank (2024). *Manufacturing, value added (% of GDP)*. https://datacatalog.worldbank.org/public-licensescc-by. Manufacturing refers to industries belonging to ISIC divisions 15-37. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. Data are based on World Bank national accounts and OECD National Accounts data files.

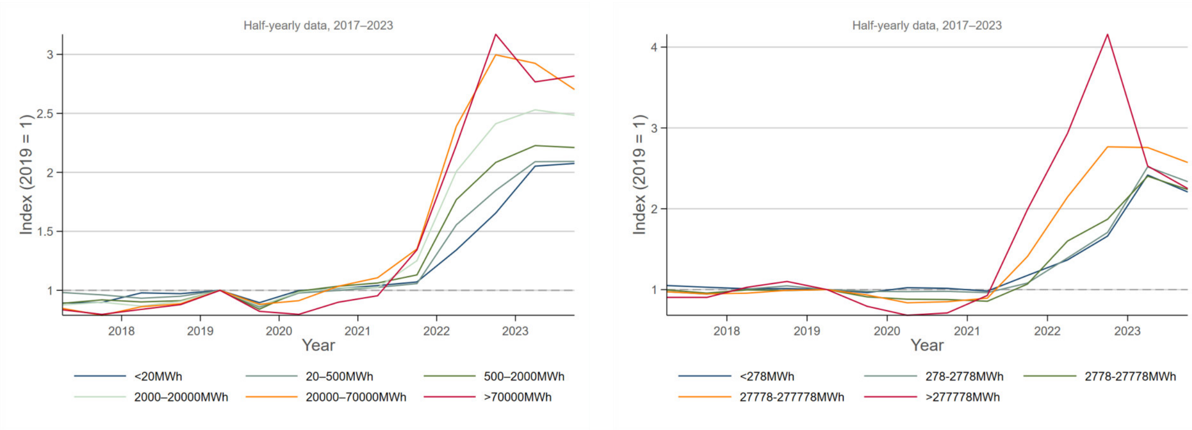
Yamazaki, Akio (2017). “Jobs and climate policy: Evidence from British Columbia’s revenue-neutral carbon tax”. *Journal of Environmental Economics and Management* 83, pp. 197–216. DOI: https://doi.org/10.1016/j.jeem.2017.03.003.

Yip, Chi Man (2018). “On the labor market consequences of environmental taxes”. *Journal of Environmental Economics and Management* 89, pp. 136–152. DOI: https://doi.org/10.1016/j.jeem.2018.03.004.

Appendix A Additional Material

A.1 Descriptives

Figure A1: Net Electricity and Gas Price Indices by Consumption Band (2019 = 1)

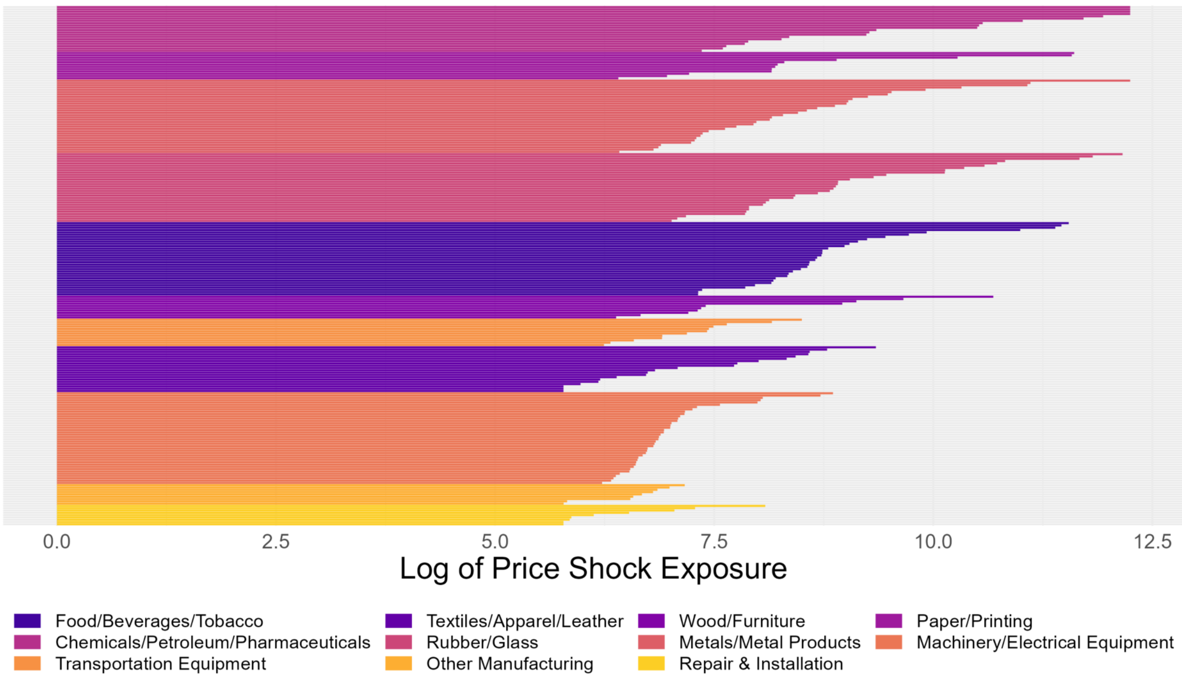


(a) Electricity Price Index

(b) Gas Price Index

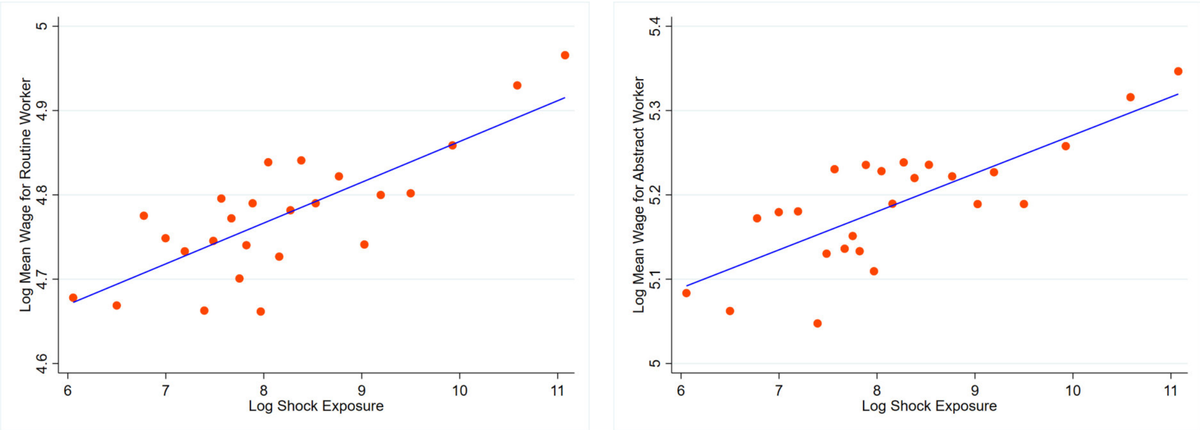
Notes: Subfigure A1a shows an index for the evolution of net industrial electricity prices by consumption bin. Subfigure A1b shows the same for industrial gas prices. Source: Statistisches Bundesamt (Destatis – Federal Statistical Office of Germany), Daten zur Energiepreisentwicklung, December 2023, EVAS Nos. 61241, 61411, 61421, 61111, 61231, published 31 January 2024, GENESIS-Online.

Figure A2: Log Sectoral Exposure - Sorted Industries



Notes: The figure presents the log-transformed exposure measure. Four-digit sectors are sorted within their respective industries. The industry with the lowest exposure is positioned at the bottom, while the one with the highest exposure is at the top. Source:Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018), AFiD-Panel Energieverwendung (2018) and industrial energy price data.

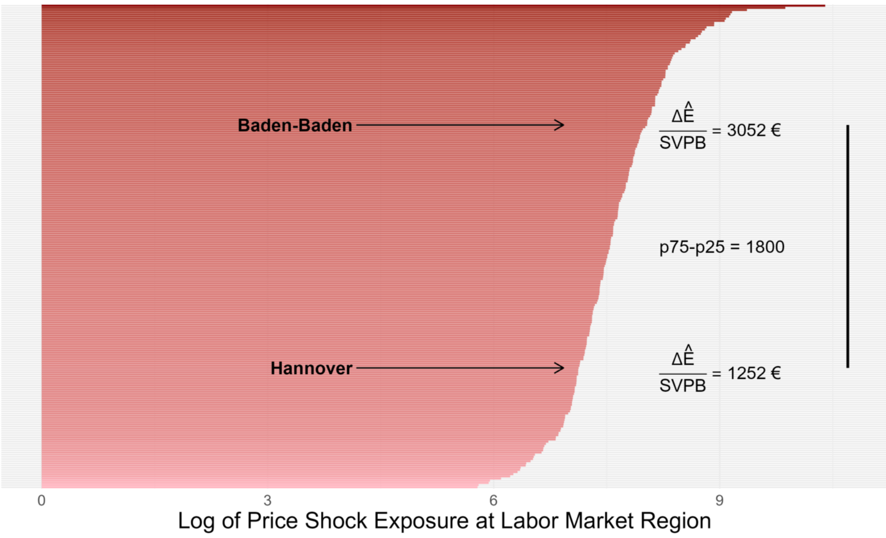
Figure A3: Cross-Sectional Correlation between Average Wage by Task Group and Shock Exposure



(a) Log Average Wage (Routine Employment) **(b)** Log Average Wage (Abstract Employment)

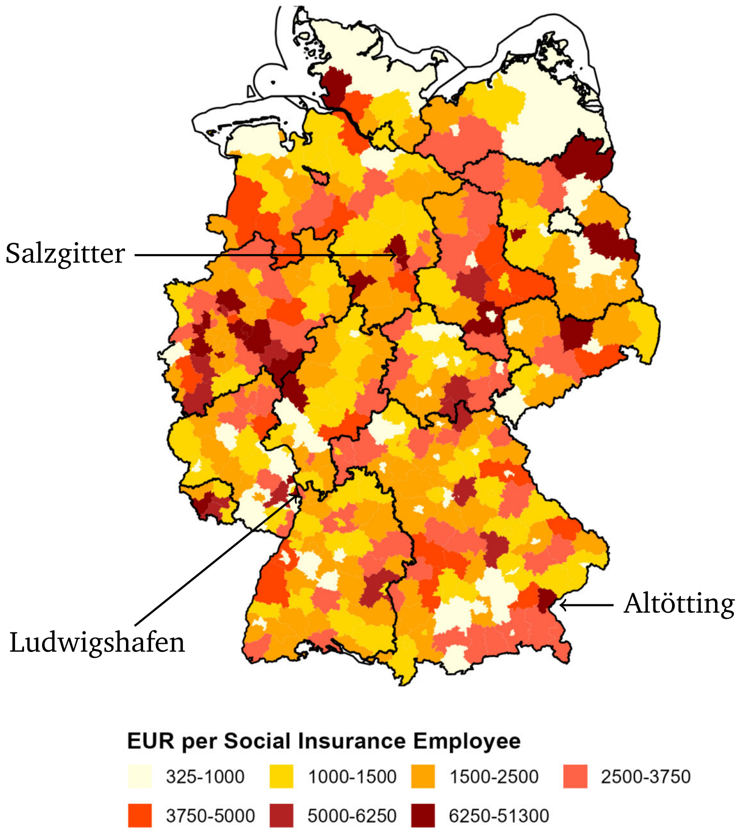
Notes: These figures show the correlation between the sectoral mean wage for routine (Subfigure a) and abstract workers (Subfigure b) and log shock exposure in 2021, conditional on industry fixed effects. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Lander: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018) and Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (IAB).

Figure A4: Log Price Shock Exposure Across Labor Markets



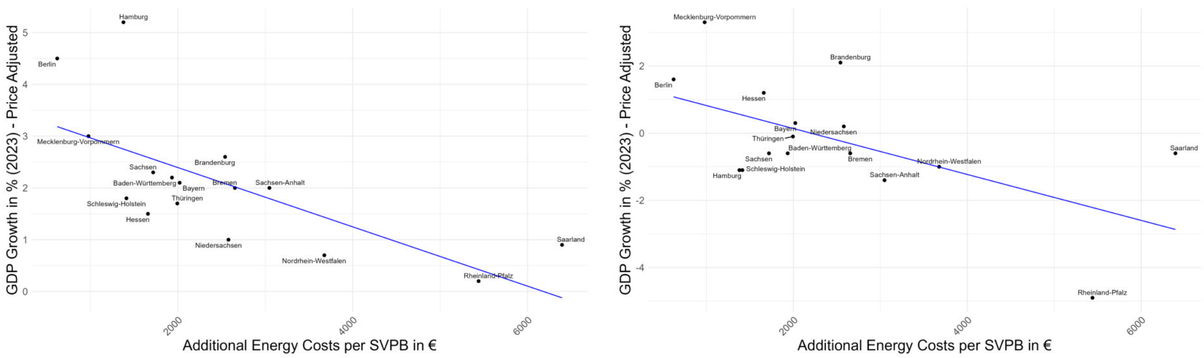
Notes: The figure shows the logarithm of the exposure measure at the labor market region. It is defined as the predicted increase in energy costs per worker liable to social security contributions in a given region. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Lander: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018) and Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (IAB).

Figure A5: Exposure at District Level: Predicted Additional Energy Costs per SVPB



Notes: The map visualizes the energy price shock exposure at the level of 400 districts, defined as the predicted increase in energy costs per employee subject to social security contributions (SVPB). Each district 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 work. Thin black lines delineate federal state boundaries. Arrows point to the three most exposed districts: *Ludwigshafen*, *Altöttingen* and *Salzgitter*. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018); industrial energy price data, and Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (IAB).

Figure A6: Exposure at the Federal State Level and Real GDP Growth

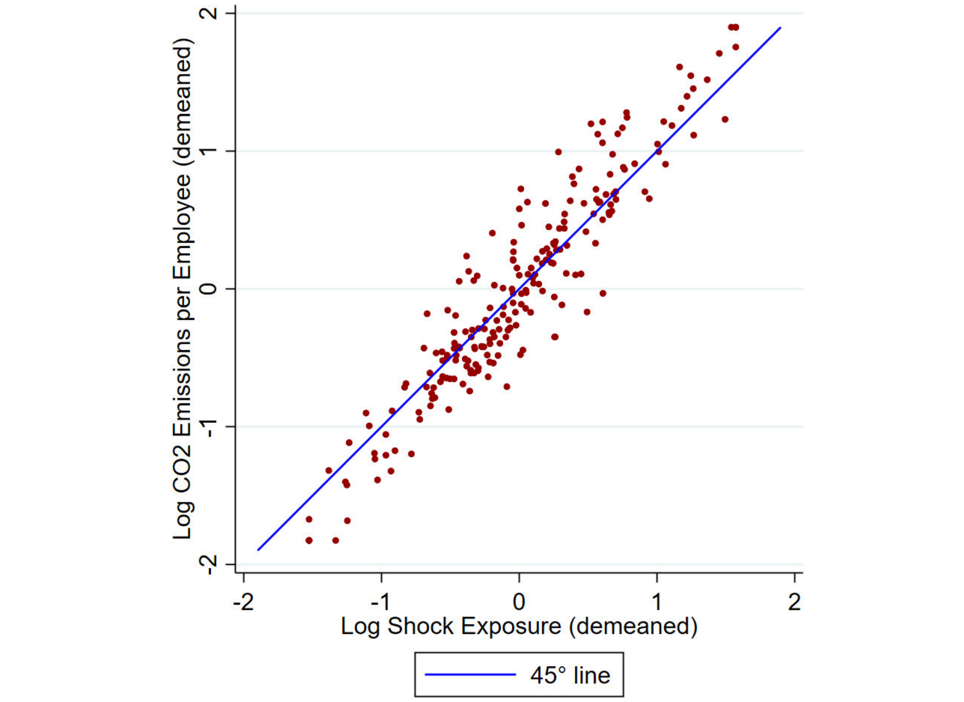


(a) Real GDP Growth in 2022

(b) Real 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 A6a shows GDP growth for 2022 on the y-axis and Figure A6b growth for 2023. Source: 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 and "Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder", "Bruttoinlandsprodukt, Bruttowertschöpfung (BIP)", Statistikportal, accessed December 23, 2024.

Figure A7: Scatterplot: Shock Exposure and CO_2 Emissions per SVPB Across Labor Markets



Notes: The scatterplot 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). Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Lander: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018) and Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (IAB).

Table A1: 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 & furniture	16 Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials; 31 Manufacture of furniture
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 & glass	22 Manufacture of rubber and plastic products; 23 Manufacture of other non-metallic mineral products
Metals & metal products	24 Manufacture of basic metals; 25 Manufacture of fabricated metal products, except machinery and equipment
Machinery & electrical equipment	26 Manufacture of computer, electronic and optical products; 27 Manufacture of electrical equipment; 28 Manufacture of machinery and equipment n.e.c.
Transportation equipment	29 Manufacture of motor vehicles, trailers and semi-trailers; 30 Manufacture of other transport equipment
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.

Table A2: Medians of Four-Digit Sector Level Means by Shock Exposure Quartile

	First Quartile	Second Quartile	Third Quartile	Fourth Quartile
Turnover (in Mio.)	1,974.62	4,810.50	2,666.19	2,821.64
# Employees	9,327	16,808	8,698	7,711
Turnover (in k) per Employee	213.22	223.17	249.87	369.32
Average Wage	42.03	44.26	41.23	47.25
# Plants	70	130	65	53
Turnover per Plant	27,425.28	28,197.90	33,513.52	53,998.68
Employees per Plant	107	122	132	159
Shock Exposure (€ per #L)	722.70	1,506.45	4,557.27	29,063.68

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 (2018) and industrial energy price data.

A.2 Policy Response

Table A3: Policy Measures to Support Households and Industry (2022–2023)

Announced	Measure	Active Period	Content
07.2022	Energiekostendämpfungsprogramm (EKDP)	–12.2022	Subsidy program compensating part of exceptional electricity and gas cost between 02.2022 an 12.2022, targeted to energy intensive establishments in trade exposed sectors.
09.2022	VAT reduction on gas and district heating	10.2022–03.2024	Temporary reduction of VAT from 19% to 7% on gas and district heating for households and businesses, including industry.
09.2022	Economic stabilisation shield ("Abwehrschirm")	2022–2024	Includes several measures including energy price brakes, not targeted to industry, total amount up €200 billion implemented via the Economic Stabilisation Fund (WSF)
10.2022	Erdgas-Wärme-Soforthilfegesetz (EWSG)	12.2022	One-off emergency measure for December 2022, gas and heat costs, financed via the WSF (i.e., part of the "Abwehrschirm") bridging the period before price brakes entered into force.
12.2022	Gas and heat price brake (EWPBG)	01–12.2023	Cap on gas and heat prices for a defined share of historical consumption; financed via the WSF.
12.2022	Electricity price brake (StromPBG)	01–12.2023	Electricity price cap for a defined share of prior consumption; financed via the WSF.

- **Energiekostendämpfungsprogramm (EKDP):** The *Energiekostendämpfungsprogramm* (Energy Cost Relief Programme) was adopted in July 2022 as a temporary state aid measure under the *Guidelines on State Aid for Climate, Environmental Protection and Energy 2022* (CEEAG). It provided direct grants to mitigate exceptional increases in energy procurement costs for eligible energy- and trade-intensive firms. Eligibility was restricted to firms operating in selected sectors (four-digit NACE classification) listed in Annex I of the CEEAG. In addition, firms were required to demonstrate that their energy procurement costs in the most recently completed financial year exceeded 3% of production value.

  Aid was granted exclusively for energy price increases exceeding a doubling relative to the reference period from January to December 2021; cost increases below this were not eligible for support. The maximum aid amount depended on the profit situation of the firm.

  The monthly amount was calculated according to the following formula: $(p_{f,t} - 2p_{f,\text{ref}})\, q_{f,t}\, r_{f,t}$ where $p_{f,t}$ is the average energy price in month t for fuel f, $p_{f,\text{ref}}$ the average price in the 2021 reference period, $q_{f,t}$ the quantity of energy self-consumed in month t, and $r_{f,t}$ the replacement rate. The eligible period covered the months from February to December 2022. For natural gas, during the funding months July and August 2022, the replacement rate was 80% of the volume in the corresponding month of 2021. From September 2022 onwards, for natural gas, electricity, heat, and cooling, the rate was 70% of the corresponding 2021 consumption.

The total volume of the package was 5 billion. For more details cf. *Merkblatt zum Energiekostendämpfungsprogramm*.

- **VAT reduction on gas and district heating:** In October 2022, the *Bundestag* passed the "Act on the Temporary Reduction of the VAT Rate on Gas Deliveries" (*Gesetz zur temporären Senkung des Umsatzsteuersatzes auf Gaslieferungen über das Erdgasnetz* 2022). The law introduced a temporary reduction (October 2022 until March 2024) of the value-added tax on natural gas and district heating for all customers. The measure was primarily aimed at households. Due to input VAT deduction ("Vorsteuerabzug"), allowing firms to deduct VAT paid on inputs—including energy purchases—from the VAT they collect from their customers, the measure did not reduce effective energy costs for industrial customers.

- **Economic stabilisation shield ("Abwehrschirm"):** The "economic stabilization shield" (a.k.a. "Doppelwumms") was announced in late September 2022. Its core element was the provision of credit of up to €200 billion via the Wirtschaftsstabilisierungsfonds (WSF) to finance numerous measures, in particular the energy price brakes (cf. Bundesministerium der Finanzen, 2022).

- **Erdgas-Wärme-Soforthilfegesetz (EWSG):** This measure was a temporary intervention designed to bridge the month of December 2022 ("Dezemberhilfe") until the energy price brakes entered into force. It primarily supported households by covering gas and heating costs. While no exact figures are available, the measure was likely of limited relevance for industry, as gas consumers with an annual consumption exceeding 1.5 GWh were not eligible (cf. *Erdgas-Wärme-Soforthilfegesetz* 2022). The measure was financed through the WSF and thus part of the "Abwehrschirm".

- **Gas and heat price brake (EWPBG):** In December 2022, the Bundestag passed the "Gesetz zur Einführung von Preisbremsen für leitungsgebundenes Erdgas und Wärme", introducing a price brake for a defined share of historical gas consumption. The measure was financed through the Wirtschaftsstabilisierungsfonds (WSF) and was therefore part of the "Abwehrschirm". The price brake entered into force in January 2023 and was phased out in April 2024. For industrial consumers, the net gas price was capped at 7 ct/kWh for 70% of historical gas consumption (cf. *Gesetz zur Einführung von Preisbremsen für leitungsgebundenes Erdgas und Wärme* 2022).

  While this measure clearly supported industry, it nevertheless implied a substantial increase in gas prices even for the subsidized share. For example, according to data from the Federal Statistical Office, net gas prices for large industrial consumers (annual gas consumption exceeding 277 GWh) averaged between 1.5 and 2 ct/kWh in 2019.[29]

- **Electricity price brake (StromPBG):** In December 2022, the Bundestag passed the "Gesetz zur Einführung einer Strompreisbremse", introducing a price brake for a defined share of historical electricity consumption. The measure was financed through the Wirtschaftsstabilisierungsfonds (WSF) and was therefore part of the "Abwehrschirm". The price brake entered into force in January 2023 and was phased out in April 2024. For industrial consumers, the net gas price was capped at 13 ct/kWh for 70% of historical electricity consumption (cf. *Gesetz zur Einführung einer Strompreisbremse* 2022).

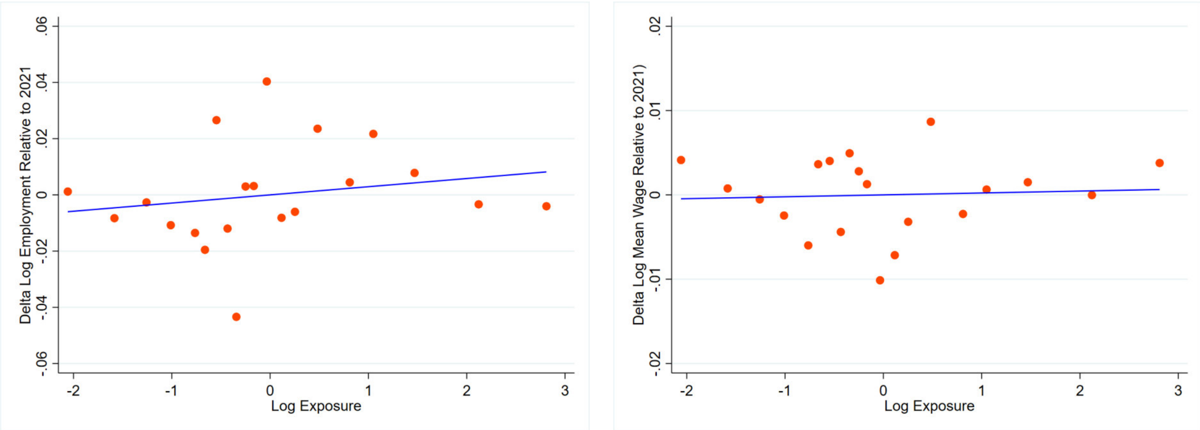
  For comparison, according to data from the Federal Statistical Office, net electricity prices for large industrial consumers (annual electricity consumption exceeding 20 GWh) averaged between 4 and 6 ct/kWh in 2019.[30]

[29]For comparison, pre-crisis net gas prices for large industrial consumers were substantially lower; see Statistisches Bundesamt (Destatis), *Statistischer Bericht: Daten zur Energiepreisentwicklung*, August 2025, EVAS-Nr. 61241, Ergänzung zur Datenbank GENESIS-Online, Tabelle 61241-05 (*Erdgas – Abgabe an Nicht-Haushalte, EUR/kWh*), veröffentlicht am 30.09.2025.

[30]See Statistisches Bundesamt (Destatis), *Statistischer Bericht: Daten zur Energiepreisentwicklung*, August 2025, EVAS-Nr. 61241, Ergänzung zur Datenbank GENESIS-Online, Tabelle 61241-16 (*Strom Abgabe an Nicht-Haushalte - EUR/KWh*), veröffentlicht am 30.09.2025.

A.3 Analysis

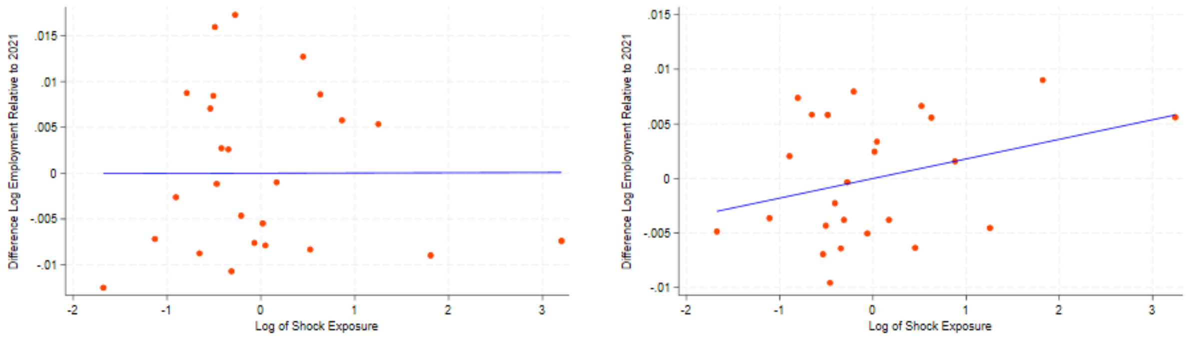
Figure A8: Pre-Treatment Changes in Outcomes and Shock Exposure – Sector Level



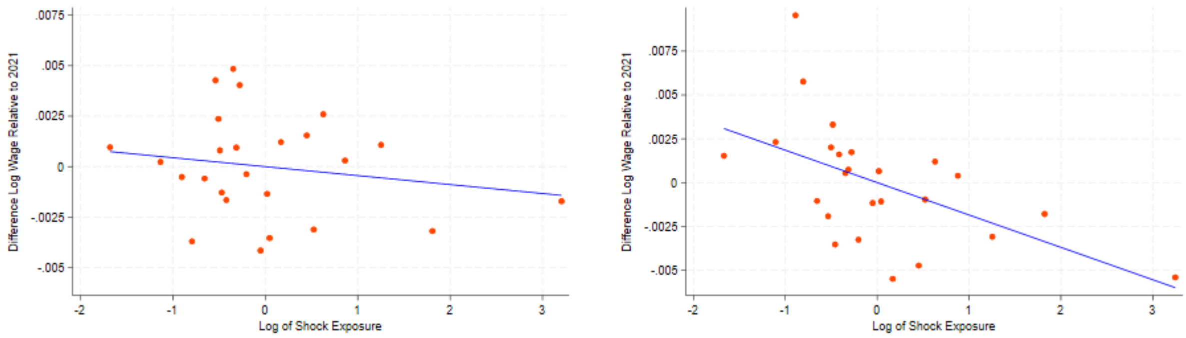
(a) Δ Log Employment (Pre-Years) **(b)** Δ Log Wage (Pre-Years)

Notes: The binned scatterplots display changes in outcomes relative to 2021, pooled across the pre-treatment years (2018–2020), and plotted against log shock exposure, conditional on industry-by-year fixed effects. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Lander: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018) and Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (IAB).

Figure A9: Changes in Outcomes and Shock Exposure – Establishment Level



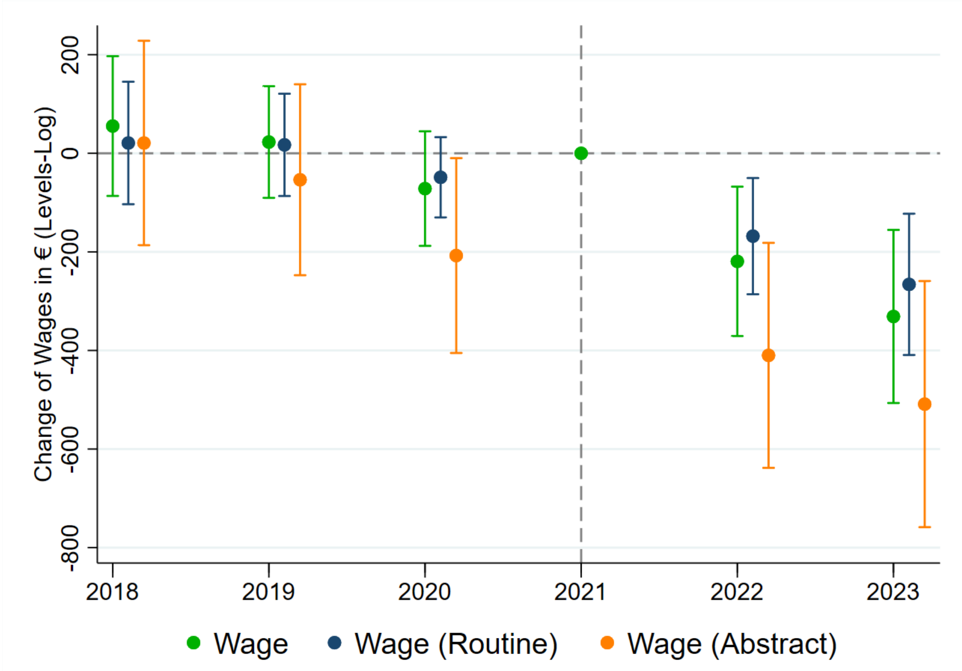
(a) Δ Log Employment (Pre-Years) **(b)** Δ Log Employment (Post-Years)



(c) Δ Log Wage (Pre-Years) **(d)** Δ Log Wage (Post-Years)

Notes: The binned scatterplots display changes in outcomes relative to 2021, plotted against log shock exposure conditional on industry-by-year fixed effects. Observations from the pre-treatment period (2018–2020) are pooled in the upper row, while those from the post-treatment period (2022–2023) are pooled in the bottom row. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018); industrial energy price data; 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.

Figure A10: Effect of a 100% Increase in Exposure on Annual Average Sectoral Wages (in €)



Notes: The figure presents point estimates from estimating equation 5, controlling for year-industry fixed effects. The dependent variables are the changes relative to 2021 in the overall sectoral mean wage (green), the sectoral mean wage for routine workers (blue), and the sectoral mean wage for abstract workers (orange), estimated separately. The unit of observation is the four digit sector. Dots represent point estimates, and vertical lines indicate 95% confidence intervals. Standard errors are clustered at the four-digit sector level. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Lander: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018) and Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (IAB).

Table A4: Sample Splits: Plant-Level Log Employment Response to a 100% Exposure Increase

	Plant Size		Industry Share (District)		Industry Share (LM)	
	(Small)	(Large)	(Low)	(High)	(Low)	(High)
Δ 2018	-0.044	0.327	-0.065	-0.017	-0.036	-0.050
	(0.249)	(0.289)	(0.268)	(0.269)	(0.253)	(0.292)
Δ 2019	-0.020	0.201	-0.055	0.036	0.024	-0.041
	(0.218)	(0.239)	(0.215)	(0.237)	(0.221)	(0.239)
Δ 2020	-0.060	0.135	-0.025	0.019	0.046	-0.049
	(0.083)	(0.119)	(0.084)	(0.108)	(0.088)	(0.111)
Δ 2022	0.185**	-0.060	0.085	0.125	0.108	0.101
	(0.089)	(0.107)	(0.082)	(0.087)	(0.076)	(0.105)
Δ 2023	0.323**	0.118	0.231*	0.322**	0.248**	0.310*
	(0.134)	(0.179)	(0.135)	(0.150)	(0.125)	(0.166)
Mean of Y	45	366	132	139	130	143
# of Unique Plants	28,702	11,518	16,044	24,293	20,703	19,614
# of Observations	119,422	53,865	68,433	104,854	88,778	84,509
# of Sectors	220	220	218	220	220	219
Year-Ind.-FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports point estimates from estimating equation 5. The unit of observation is the plant. The dependent variable is the log change in employment relative to 2021, and the sample is restricted to plants with at least 20 employees. Each regression is estimated on a subsample: (i) plants below or above 100 employees at baseline; (ii) plants located in districts with a manufacturing employment share above or below the median at the district-level; and (iii) plants located in labor markets with a manufacturing employment share above or below the median at the labor-market level. Standard errors, clustered at the four-digit sector level, are reported in parentheses. Means of the dependent variable in levels, the number of unique plants, the number of observations, and the number of sectors (clusters) are provided at the bottom of the table. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018); industrial energy price data; 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 A5: Sample Splits: Plant-Level Log Wage Response to a 100% Exposure Increase

	Plant Size		Industry Share (District)		Industry Share (LM)	
	(Small)	(Large)	(Low)	(High)	(Low)	(High)
Δ 2018	-0.004	-0.078	0.070	-0.060	0.026	-0.045
	(0.103)	(0.089)	(0.089)	(0.105)	(0.090)	(0.105)
Δ 2019	-0.102	-0.116*	-0.065	-0.119	-0.072	-0.121
	(0.064)	(0.069)	(0.061)	(0.075)	(0.060)	(0.074)
Δ 2020	-0.039	-0.021	0.005	-0.042	0.007	-0.050
	(0.052)	(0.054)	(0.037)	(0.057)	(0.040)	(0.061)
Δ 2022	-0.071*	-0.076	-0.175***	-0.062	-0.120**	-0.099**
	(0.038)	(0.063)	(0.049)	(0.041)	(0.050)	(0.039)
Δ 2023	-0.145**	-0.246***	-0.363***	-0.154**	-0.263***	-0.213***
	(0.074)	(0.091)	(0.076)	(0.077)	(0.078)	(0.080)
Mean of Y	40,935	50,253	44,963	42,727	44,186	42,997
# of Unique Plants	28,702	11,518	16,044	24,293	20,703	19,614
# of Observations	119,422	53,865	68,433	104,854	88,778	84,509
# of Sectors	220	220	218	220	220	219
Year-Ind.-FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports point estimates from estimating equation 5. The unit of observation is the plant. The dependent variable is the log change in wages relative to 2021, and the sample is restricted to plants with at least 20 employees. Each regression is estimated on a subsample: (i) plants below or above 100 employees at baseline; (ii) plants located in districts with a manufacturing employment share above or below the median at the district-level; and (iii) plants located in labor markets with a manufacturing employment share above or below the median at the labor-market level. Standard errors, clustered at the four-digit sector level, are reported in parentheses. Means of the dependent variable in €, the number of unique plants, the number of observations, and the number of sectors (clusters) are provided at the bottom of the table. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018); industrial energy price data; 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. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A6: Regional Wage Responses to a 100% Exposure Increase by One-Digit Industry

	Δ2018	Δ2019	Δ2020	Δ2022	Δ2023	Emp. share	Obs.	LM
Primary –Agri.& Mining (1)	0.813*	0.465	0.135	-0.111	-0.144	0.02	1,115	223
	(0.433)	(0.427)	(0.213)	(0.270)	(0.420)			
Manufacturing (2)	-0.220	-0.188	-0.394**	-0.210	-0.595***	0.27	1,115	223
	(0.222)	(0.205)	(0.169)	(0.137)	(0.185)			
Energy & water (3)	0.423	0.219	-0.005	-0.102	-0.160	0.02	1,115	223
	(0.325)	(0.258)	(0.176)	(0.194)	(0.251)			
Construction (4)	0.150	-0.054	-0.011	-0.185*	-0.116	0.08	1,115	223
	(0.165)	(0.166)	(0.097)	(0.102)	(0.121)			
Trade, transport & hospitality (5)	0.102	0.015	0.115	-0.340***	-0.480***	0.22	1,115	223
	(0.161)	(0.132)	(0.089)	(0.126)	(0.162)			
Info/Comm., finance & real estate (6)	0.208	0.327	0.173	-0.291	-0.452**	0.04	1,115	223
	(0.225)	(0.222)	(0.187)	(0.197)	(0.204)			
Professional & business services (7)	0.329	0.306	-0.080	-0.321	-0.388	0.10	1,115	223
	(0.432)	(0.352)	(0.281)	(0.204)	(0.305)			
Public admin., education & health (8)	0.219**	0.127	0.052	0.034	0.054	0.22	1,115	223
	(0.099)	(0.102)	(0.063)	(0.070)	(0.089)			
Other services (9)	0.491	0.501	0.123	0.044	-0.200	0.03	1,115	223
	(0.314)	(0.327)	(0.231)	(0.316)	(0.385)			

Notes: The table shows point estimates from estimating versions of equation 5. Unlike the other tables, this table is transposed; that is, each row reports the results from a separate regression. The unit of observation is a labor market region, and the dependent variable is the log change in average employment in a labor market region and one-digit industry relative to 2021. The third-to-last column reports the average share of workers in the corresponding one-digit industry, followed by the number of observations and the number of unique labor market regions. Standard errors are reported in parentheses. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Lander: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018) and Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (IAB). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Regional Employment Responses to a 100% Exposure Increase by One-Digit Industry

	Δ2018	Δ2019	Δ2020	Δ2022	Δ2023	Emp. share	Obs.	LM
Primary – Agri. & Mining (1)	2.296**	1.881*	0.802	0.037	-0.724	0.02	1,115	223
	(1.135)	(0.984)	(0.528)	(0.556)	(0.892)			
Manufacturing (2)	0.868*	0.244	0.486	-0.476	-0.291	0.27	1,115	223
	(0.525)	(0.451)	(0.362)	(0.295)	(0.395)			
Energy & Water (3)	1.433**	0.946	0.426	-0.376	-0.756	0.02	1,115	223
	(0.708)	(0.649)	(0.395)	(0.322)	(0.506)			
Construction (4)	-0.255	0.319	0.170	0.254	0.786**	0.08	1,115	223
	(0.418)	(0.314)	(0.212)	(0.260)	(0.380)			
Trade, Transport & Hospitality (5)	-0.411	-0.229	0.025	-0.438***	-0.487**	0.22	1,115	223
	(0.347)	(0.274)	(0.171)	(0.154)	(0.238)			
Info./Comm., Finance & Real Estate (6)	1.123	0.408	-0.017	-0.041	-0.419	0.04	1,115	223
	(0.687)	(0.524)	(0.284)	(0.349)	(0.539)			
Professional & Business Services (7)	1.042	1.311**	1.166**	0.175	-0.211	0.10	1,115	223
	(0.786)	(0.637)	(0.516)	(0.488)	(0.709)			
Public Admin., Education & Health (8)	-0.339	-0.174	-0.133	0.200	0.036	0.22	1,115	223
	(0.270)	(0.217)	(0.169)	(0.135)	(0.204)			
Other Services (9)	-0.506	-0.345	-0.036	-1.068*	-1.237*	0.03	1,115	223
	(0.515)	(0.484)	(0.347)	(0.545)	(0.721)			

Notes: The table shows point estimates from estimating versions of equation 5. Unlike the other tables, this table is transposed; that is, each row reports the results from a separate regression. The unit of observation is a labor market region, and the dependent variable is the log change in average wages in a labor market region and one-digit industry relative to 2021. The third-to-last column reports the average share of workers in the corresponding one-digit industry, followed by the number of observations and the number of unique labor market regions. Standard errors are reported in parentheses. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Lander: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018) and Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (IAB). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B Supporting Analysis

B.1 Magnitude: Elasticity of Wages with Respect to Output per Worker

To put the magnitude of the wage response into perspective, we estimate the elasticity of wages with respect to output per worker. In the absence of high-quality output data for the post-treatment period, we rely on sectoral information from the 2018 census and combine it with the production index.[31] Specifically, we carry forward 2018 production levels using the index to obtain post-treatment output.

We then use this constructed measure of economic activity and instrument the log change in output (per worker) relative to 2021 with the exposure measure. This way, we isolate variation in economic activity that results from the energy price shock. In the second stage, we relate the predicted change in economic activity during the post-treatment years to the corresponding changes in wages. Specifically, we estimate the following regression using two-stage least squares (2SLS):

$$\text{First stage:} \quad \Delta \ln Y_{s,j,t} = \pi_1 \left(\text{lnexp}_s \times \text{Post}_t\right) + \pi_2 \left(\text{lnexp}_i \times \text{Pre}_t\right) + \gamma_{j,t} + \varepsilon_{s,j,t} \tag{7}$$

$$\text{Second stage:} \quad \Delta \ln(wage_{s,j,t}) = \alpha \, \widehat{\Delta \ln Y_{s,j,t}} + \theta \left(\text{lnexp}_s \times \text{Pre}_t\right) + \gamma_{j,t} + u_{s,j,t} \tag{8}$$

Again $\gamma_{j,t}$ are industry-by-year fixed effects and $\varepsilon_{s,j,t}$ and $u_{s,j,t}$ are error terms. Table B1 presents the results. In columns 1 and 2, the endogenous regressor of interest is the log change in output relative to 2021, while in columns 3 and 4 the explanatory variable is the log change in output per worker. The latter explanatory variable aligns most closely with the rent-sharing literature, which typically measures rents using value added per worker. In the even-numbered columns, we additionally include a linear trend to account for a slight pre-trend in economic activity, by extrapolating this trend linearly into the post-treatment years.

The point estimates in columns 1 and 3 suggest that a 1% increase in economic activity (per worker) leads to a 0.29% and 0.26% increase in the average sectoral wage, respectively. When we control for the pre-trend in economic activity (columns 2 and 4), these effects decrease to 0.19% and 0.14%. The elasticity becomes smaller because extrapolating the pre-trend into the post-treatment years increases the first-stage coefficient. Since wage trends prior to treatment are essentially flat, post-treatment wage effects remain unaffected by the inclusion of a linear trend. As a result, the ratio of the wage effect to the effect on economic activity decreases.

[31] Cf. Figure 3 and Section 3 for information on the production index.

Table B1: Sector-Level: Elasticity of Wages with Respect to Production

	Δ Log Wage			
	(1)	(2)	(3)	(4)
Δ Log Production	0.295**	0.187**		
	(0.129)	(0.082)		
Δ Log Production per #L			0.261**	0.143**
			(0.117)	(0.062)
K-P−F Statistic	8.45	15.61	8.51	18.92
# of Observations	856	856	856	856
# of Sectors	214	214	214	214
Year-Sector-FE	Yes	Yes	Yes	Yes
Linear Trend		Yes		Yes

Notes: The table reports point estimates from estimating versions of equation 8 by means of 2SLS. The dependent variable is the log change in the mean sectoral wage relative to 2021. In columns 1–2, the endogenous regressor of interest is the log change in total production, while in columns 3–4 it is the log change in output per worker. The endogenous regressor is instrumented with the log exposure measure in the post-treatment years. Columns 2 and 4 additionally control for pre-trends by linearly extrapolating pre-treatment trends into the post-treatment period. The unit of observation is a four-digit economic sector. Standard errors are given in parentheses. The number of observations and the number of unique sectors are given at the bottom of the table. 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 (2018) and IAB Integrated Employment Biographies. Significance levels are indicated as * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

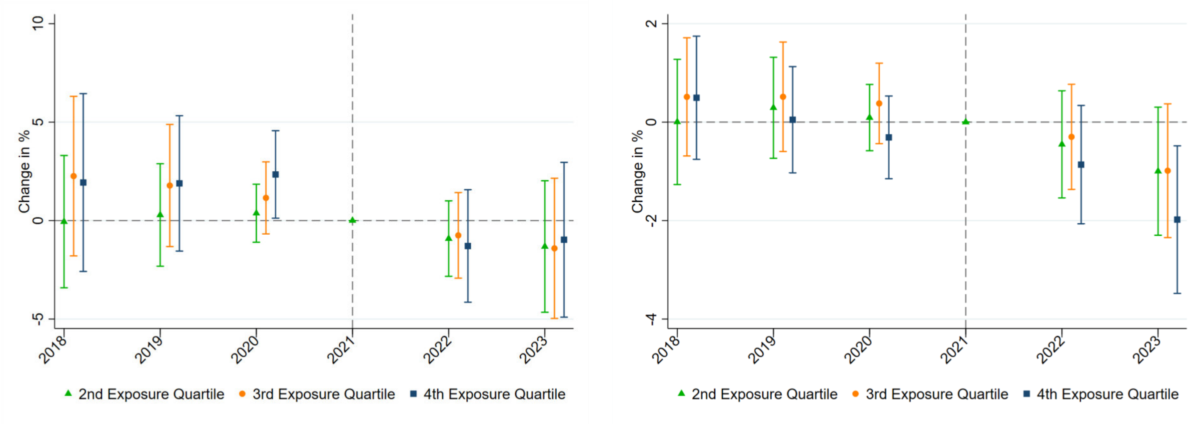
B.2 Robustness: Discretized Exposure

As an additional robustness check, we estimate the effect on sector- and plant-level employment and wages using a discretized exposure measure (exposure quartiles). The specification we take to the data is given below:

$$\Delta y_{s,j,t} = y_{s,j,t} - y_{s,j,2021} = \beta_0 + \sum_{q=2}^{4} \sum_{\substack{\tau=2018 \\ \tau \neq 2021}}^{2023} \beta^{q,\tau} \ \mathbb{1}\{Q_s = q\} \times \mathbb{1}\{t = \tau\} + \gamma_{j,t} + \varepsilon_{s,j,t} \tag{9}$$

In specification 9, we replace the continuous exposure variable with quartile dummies, which we interact with year dummies. We omit the first quartile and hence coefficients capture the differential changes across exposure quartiles relative to the least exposed quartile.

Figure B1: Discretized Exposure Measure: Sector Level

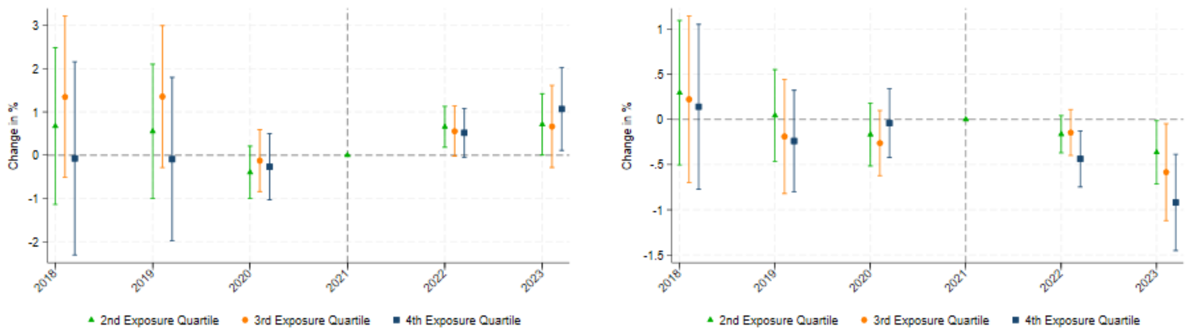


(a) Log Employment **(b)** Log Wages

Notes: This figure shows the effects by shock exposure quartile, estimated from equation 9, controlling for sector-year fixed effects. The dependent variable is the log change in log employment (subfigure B1b) and in log wages (subfigure B1b) relative to 2021, measured at the four-digit sector level. 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 Lander: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018) and Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (IAB).

Subfigure B1 confirms the null effect on employment. All point estimates in the post-treatment period are close to zero and statistically insignificant. Similarly in support of the main results, Subfigure B1b indicates a negative effect on wages. This effect is primarily driven by the most exposed quartile. For example, in 2023, the average wages in sectors from the most exposed quartile were about 2% below the level they would have had in the absence of the shock, under the assumption that the first quartile provides a valid counterfactual.

Figure B2: Discretized Exposure Measure: Establishment Level



(a) Log Employment

(b) Log Wage

Notes: This figure shows the effects by shock exposure quartile, estimated from equation 9, controlling for sector-year fixed effects. The dependent variable is the log change in employment (subfigure B2a) and wages (subfigure B2b) relative to 2021, at the establishment level. 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. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Länder: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018); industrial energy price data; 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.

B.3 Additional Results: IAB Establishment Panel

It is not possible to determine from the administrative employment data in which sectors temporary agency workers are actually deployed.[32] We draw on a survey conducted by the IAB, the "IAB Establishment Panel", which covers roughly 15,000 establishments annually across all sectors of the economy, to analyze the effects of the shock on temporary work.[33] The survey collects information on a wide range of topics, including the number of temporary workers. Because many establishments employ no, or only very few, temporary workers, we calculate the share of temporary workers at the plant level and construct an indicator variable that takes the value one if the plant employs any temporary workers at all.

We then merge the shock-exposure measure using four-digit sector codes and regress changes in the temporary worker share, as well as changes in the indicator, on the shock.

Table B2 reports the results. For both outcomes, we estimate two specifications. In columns 1 and 3, we use all manufacturing plants covered by the survey. This gives us 3,042 unique plants across 201 four-digit sectors. In columns 2 and 4 we restrict the sample to plants with at least 20 employees to match the sample restrictions used in the manufacturing census and the BHP. Restricting the sample to plants with more than 20 employees reduces the sample size by almost 50% to 1,642 unique plants across 181 sectors. From column 1 of Table B2, one can see that the point estimate for 2023 is negative and highly significant, suggesting that a 100% increase in shock exposure reduces the share of temporary employment by approximately 0.32 pp. While this indicates that plants may have adjusted their labor input to the shock by reducing temporary employment, we also find a negative and significant effect in the Covid-year 2020. Temporary work declined substantially in 2020, and the negative coefficient implies that the response of temporary work to Covid was not orthogonal to the energy price shock. Moreover, once we restrict the sample to plants with more than 20 employees, the 2023 effect shrinks by about one-third—suggesting a decrease in temporary work of around 0.2 pp. for a 100% increase in exposure—and becomes statistically insignificant. It remains the largest coefficient in absolute terms across years, however.

The extensive-margin effects shown in columns 3 and 4 suggest a similar pattern to those in columns 1 and 2. The post-treatment coefficients are very similar across both columns. Indeed, from the means of the dependent variables at the bottom of the table, one can conclude that only a few firms with less than 20 employees employ temporary workers. The point estimates for 2023 indicate a decline in the probability of employing temporary workers by slightly more than 2% in response to a 100% increase in exposure. Again, we find a negative and significant effect in 2020, which warrants a cautious interpretation of the results.

[32] There is a separate sector for temporary employment (NACE 78.20, "Temporary employment agency activities" / *Arbeitnehmerüberlassungen*), but the data do not reveal the sectors to which individuals employed by temporary work agencies are assigned.

[33] Specifically, we use the following version of the IAB Establishment Panel: IAB Establishment Panel (IAB-BP), Version 9323 v1. DOI: 10.5164/IAB.IABBP9323.de.en.v1 (cf. Bellmann et al., 2024).

Table B2: Effect on Temporary Workers - Establishement Survey

	Temporary Worker (Share)		Temporary Worker (Dummy)	
	All	#L > 19	All	#L > 19
	(1)	(2)	(3)	(4)
Δ 2018	0.094	0.160	-0.004	-0.004
	(0.125)	(0.196)	(0.009)	(0.014)
Δ 2019	0.087	0.075	-0.002	-0.005
	(0.092)	(0.154)	(0.007)	(0.011)
Δ 2020	-0.176**	-0.146	-0.023***	-0.028**
	(0.082)	(0.129)	(0.008)	(0.012)
Δ 2022	-0.063	0.038	-0.011*	-0.010
	(0.111)	(0.141)	(0.006)	(0.009)
Δ 2023	-0.318***	-0.200	-0.024***	-0.022*
	(0.109)	(0.136)	(0.007)	(0.012)
Mean of Y	2.15	2.98	0.24	0.41
# of Unique Plants	3,042	1,642	3,042	1,642
# of Observations	9,701	5,210	9,701	5,210
# of Sectors	201	181	201	181
Year-Ind.-FE	Yes	Yes	Yes	Yes

Notes: The table shows point estimates from estimating versions of equation 5. The unit of observation is a plant. Standard errors are given in parentheses and clustered at the four-digit sector level. All specifications include industry by year fixed effects. The dependent variable in the first two columns is the share of temporary workers and in the third and forth column it is a dummy indicating whether a plant employs temporary workers. In the second and forth column we restrict the sample to plants with at least 20 emplyees. At the bottom of the table we report the mean of the dependent variable, the number of unique plants, the number of observations and sectors. All dependent variables are are differences to 2021. Source: Research Data Centers of the Federal Statistical Office and the Statistical Offices of the Lander: AFiD-Panel Industriebetriebe (2018) and AFiD-Panel Energieverwendung (2018) and IAB Establishment Panel (IAB BP) – Version 9323 v1, DOI: 10.5164/IAB.IABBP9323.de.en.v1. Significance levels are indicated as * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.