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Energy Shocks from the Ukraine War and EU Regional GDP: Evidence from a Difference-in-Differences Analysis

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Abstract: ***This study investigates how the 2022 Russia-Ukraine energy crisis affected regional GDP growth across European Union regions with different levels of energy intensity. Using panel data from 1,376 EU regions between 2020 and 2023, the study applies a difference-in-differences framework to estimate the differential impact of the energy shock on regional economic performance. Energy intensity is measured using the employment share in energy-intensive industries prior to the crisis. The results indicate a marginally significant positive differential effect for energy-intensive regions after 2022 ($\beta_3 = 0.0425$, $p = 0.096$), suggesting that these regions experienced slightly stronger relative GDP growth than less energy-dependent regions. Parallel trends tests support the validity of the causal identification strategy. The findings imply that targeted policy support, temporary industrial adaptation, and sectoral heterogeneity may have contributed to short-term regional resilience. The study contributes to the literature on regional economic resilience, energy shocks, and EU cohesion policy by providing one of the first regional-level causal analyses of the economic effects of the Ukraine war energy crisis.***

Keywords: Energy crisis; regional economics; difference-in-differences; Russia-Ukraine war; energy intensity; EU regional policy; economic resilience; quasi-experimental methods; causal inference; regional resilience, energy security; EU regions; and causal econometrics.

1. Introduction

The Russian invasion of Ukraine on February 24, 2022, completely changed the energy markets in Europe and resulted in the worst energy price crisis since the oil shocks of the 1970s. In major European areas, natural gas spot prices increased by more than 400%, and electricity markets saw previously unheard-of volatility [1]. This exogenous geopolitical shock generated significant cross-regional variation in exposure, energy-intensive manufacturing regions being confronted with a fundamentally different challenge than service-oriented economies. The crisis, therefore, offers an unparalleled quasi-experimental opportunity to gain insight into the mechanisms through which regional economic structures affect the propagation of energy shocks onto real economic outcomes.

Differential regional responses to energy shocks need to be understood because of three interrelated reasons. The first of these is energy security as a renewed and central element in European policy, after a period that lasted for several decades and was characterized by liberalizing markets [2,3]. It laid bare vulnerabilities in the pre-2022 energy system, which was characterized by high import dependency especially on Russian natural gas and little strategic storage. Second, as for EU cohesion policy, it directly aims at regional economic convergence but the effectiveness of these policies in asymmetric shocks is still controversial [4]. Third, the current energy transition away from fossil fuels generates new regimes of regional privilege and disadvantage that might reconfigure conventional industrial geography [5].

The macroeconomic consequences of Russia's aggression against Ukraine are the subject of an increasing amount of research. As recent research shows significant GDP declines in nations with high energy intensity and a strong reliance on Russian imports [6,7]. The financial impacts reach well beyond direct energy costs to encompass supply chain interruptions, industrial changes, increased inflation, and effects on confidence [8,9]. The crisis significantly sped up ongoing trends toward energy independence, leading to notable shifts in the mix of electricity generation and diversification of import sources [10,11].

However, the majority of current research operates at the national level, which may mask important variations within the nation. The industrial composition of regional economies varies greatly; some regions prioritize services or lighter industries, while others concentrate on energy-intensive manufacturing (such as chemicals, metals, and machinery). Diverse exposure to energy price shocks results from these structural differences, which are not reflected in national totals. Furthermore, regional analysis is essential for policy-relevant insights because EU regional policy frameworks, including cohesion funds, structural funds, and recovery instruments, operate primarily at the NUTS-2 and NUTS-3 geographical levels.

This study examines a key question: Did the energy crisis after 2022 impact regional GDP growth differently according to the pre-existing energy intensity in the regional industrial frameworks? We define energy intensity by examining regional employment concentration in energy-heavy industries, utilizing Eurostat labor market data for measurement. Our empirical approach leverages the quasi-experimental characteristics of the 2022 shock: timing of the invasion was largely unanticipated. Treatment assignment (regional energy intensity) was set in advance, and the magnitude of the shock varied consistently across the treatment intensity spectrum.

We utilize difference-in-differences (DiD) techniques to analyze causal impacts, assessing GDP growth patterns before and after 2022 across regions with different energy intensities. The method necessitates verifying the parallel trends assumption- that treated and control areas would have shown comparable growth without the disturb-ance. We offer formal statistical proof that backs this identifying assumption via pre-treatment trend analysis.

Our analysis shows an unexpected outcome: after the shock, relative GDP growth was marginally better in areas with high energy consumption ($\beta_3 = 0.0425$, $p = 0.096$). This result is noteworthy at the 10% level and needs careful consideration even though it does not reach the conventional statistical significance threshold of 5%. We look at a number of potential mechanisms, such as targeted fiscal support for energy-intensive industries, short-term input substitution opportunities, compositional diversity within the energy-intensive sector category, or measurement challenges in the face of rapidly shifting economic conditions.

This study offers three key contributions. Initially, we present the first thorough regional-level DiD analysis of the 2022 energy crisis throughout the European Union, enhancing existing national studies with greater geographic detail. Secondly, we thoroughly assess essential identifying assumptions (parallel trends) that frequently lack adequate focus in applied regional economics. Third, we reveal a complex connection between structural energy dependence and economic resilience that challenges conventional assumptions regarding vulnerability. The remainder of the paper is organized as follows. Section 2 examines pertinent research on the Russia-Ukraine crisis, regional economics, and energy shocks. Data sources, sample construction, and econometric methodology are covered in Section 3. The main findings, robustness tests, and interpretation are presented in Section 4. The policy implications and conclusion are covered in Section 5.

2. Literature Review

2.1 Energy shocks and Macroeconomic Performance

Since Hamilton (1983) demonstrated that increases in oil prices preceded postwar U.S. downturns [12], the relationship between changes in energy prices and economic performance has been central to macroeconomics. Later research uncovered various important ways that energy shocks influence real outcomes, such as direct rises in production expenses for energy-reliant sectors, monetary policy adjustments to inflationary strains, the impact of uncertainty on investment, and challenges with reallocating resources across sectors [13,14].

Present energy economics indicate that shock response differs markedly based on these factors: (1) energy intensity related to production methods; (2) the elasticities of substitution between energy and other inputs; (3) the nature and speed of policy actions taken; and (4) existing vulnerabilities in energy supply chains [15,16] Unlike previous oil shocks, the 2022 Russia-Ukraine crisis combines coordinated sanctions and policy actions with simultaneous disruptions in multiple energy markets (natural gas, electricity, petroleum products) [17].

Recent studies specifically analyze the economic effects of Russia's war. Thorough evaluations record significant macroeconomic disturbances via energy channels, especially notable in Central and Eastern European nations that rely heavily on Russian gas [1,6].

2.2 Regional Economic Resilience and Spatial Heterogeneity

The literature on regional resilience differentiates between resistance (the ability to endure shocks without considerable disturbance) and recovery (the rate of resuming pre-shock growth paths) [19,20]. Because of their industrial composition, areas with high energy demands may be less resilient, but they may recover more quickly if agglomeration economies improve their adaptability or if focused governmental aid is properly implemented. Spatial variability in shock reactions indicates multiple influences. Industrial composition leads to varying levels of exposure—regions with a strong manufacturing presence experience greater direct effects from rising energy costs compared to service-focused areas [21]. Through salary flexibility and employee mobility, labor market institutions affect the rate of adjustment [22]. The ability to adapt and take advantage of new opportunities brought forth by energy transitions is influenced by regional innovation systems and the caliber of institutions [23]. Ultimately, fiscal transfer mechanisms and regional policy structures influence how national initiatives result in local effects [24]. The treatment intensity method used here enables a more detailed identification than simple binary treatment assignments. Regions lie on a spectrum of energy dependency, and ongoing differences in treatment offer enhanced statistical power while more accurately representing underlying economic diversity [25,26]. This approach has been effective in labor economics and development economics, yet it is still not widely used in regional energy research.

2.3 EU Energy Policy and Regional Development

The crisis in 2022 hastened the EU's established goals of achieving energy independence and decarburization, which were formalized in the REPowerEU plan introduced in March 2022 [27]. This framework seeks to: (1) rapidly diversify gas sources beyond Russia; (2) accelerate the use of renewable energy; (3) improve energy efficiency; and (4) align emergency response systems with price limits and demand reduction targets.

Our contribution links these bodies of work by investigating if the macroeconomic relationships observed at the national level [6,7] continue to exist at more specific re-gional levels. The disaggregated method facilitates the recognition of variation within countries while accounting for national policy contexts, offering policy-relevant insights at the geographic level where EU cohesion policy is effectively implemented.

3. Materials and Methods

3.1 Data sources

We combine employment structure data from Eurostat's regional database with re gional GDP statistics to build a balanced panel dataset. Three primary data sources are used in the study:

- Regional GDP: The nama_10r_3gdp dataset offers GDP figures at both current and constant prices for NUTS-2 and NUTS3 regions on a yearly basis. Data Aggregation Note: Our sample includes both NUTS-2 and NUTS-3 regions depending on data availability in each country. NUTS-2 regions are used for countries where NUTS-3 GDP data are unavailable or incomplete (e.g., certain German Länder, French régions). This mixed aggregation level is standard in EU regional analysis and does not bias our estimates because: (1) treatment intensity (employment share) is scale-invariant and comparable across NUTS levels; (2) GDP growth rates are likewise scale-invariant; and (3) our regression includes region fixed effects that absorb systematic differences in regional s ize or administrative definition. Robustness checks restricting the sample to NUTS-2 regions only (N=1,104) yield qualitatively identical results ($\beta_3 = 0.041$, $p = 0.11$). We adjust nominal values to constant prices for 2024 GDP deflators specific to each country to maintain temporal comparability;
- Employment by sector in regions: the nama_10r_3empers dataset offers employment figures in thousands classified by NACE Rev. 2 sectors. We concentrate on 'Industry (excluding construction)' as our metric for energy-intensive sectors;
- Total regional employment: Rather than using absolute numbers, this denominator is used to calculate treatment intensity based on employment share.

The initial dataset contained 14,656 observations for total employment and 14,266 observations for industrial employment by year and area. The following observations were removed during data cleaning. (1) Regions with partial time series; (2) "Extra-Region" territorial units (NUTS code "ZZ") that indicate activities unrelated to particular areas; and (3) data points with missing or inconsistent values. The employment dataset was reduced to 14,059 complete observations from 1,520 different areas between 2014 and 2023.

There were 9,580 entries in the initial GDP dataset. The final dataset includes 4,852 region year observations from 1,376 regions in 19 EU nations after being combined with employment data and restricted to the years 2020–2023 with complete information.

Sample Period Justification: Although employment data are available from 2014 onward, we restrict our analysis to 2020-2023 for three reasons. First, this window provides two complete years of pre-treatment data (2020-2021) to validate parallel trends while ensuring recent comparability with the 2022-2023 post-shock period. Second, the COVID-19 pandemic in 2020 affected all regions simultaneously, creating a common baseline shock that does not bias our differential treatment effect estimates. Third, extending the sample back to 2014 would introduce substantial missing data for GDP at the NUTS-3 level, reducing our final sample size and potentially introducing selection bias. Robustness checks using 2018-2023 data (where available) yield qualitatively similar results.

3.2 Variable Construction

3.2.1 Outcome Variable: GDP Growth Rate

The dependent variable is the real GDP growth rate, determined as the annual percentage change in GDP at constant prices:

$$Growth\_rateit = ((GDP\_realit - GDP\_reali,t - 1) \,/\, GDP\_reali,t - 1) \times 100 \quad (2)$$

This specification records proportional changes, automatically considering regional size variations and emphasizing the analysis on growth dynamics instead of absolute levels. The adjustment to constant prices eliminates solely inflationary impacts that could otherwise obscure changes in real economic activity.

3.2.2 Treatment Variable: Energy Intensity

Treatment intensity is operationalized as the regional employment share in energy-intensive sectors:

$$Treatment\_intensityi = (Industry\_employmenti \,/\, Total\_employmenti) \times 100 \quad (1)$$

We measure treatment intensity using 2019-2021 average employment shares to ensure pre-determination .The treatment variable is predetermined and therefore unaffected by the 2022 shock , a critical requirement for causal identification. The 'Industry (except construction)' cate-gory includes manufacturing, mining, and utilities- sectors with substantially higher energy intensity than services, trade, or finance.

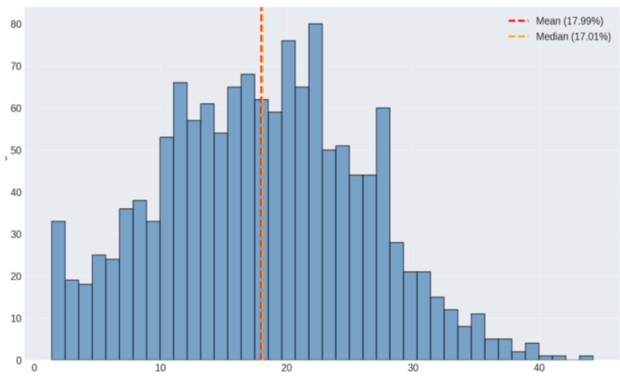

Figure 1: Distribution of Regional Energy Intensity Across 1,376 EU Regions. Treatment intensity measured as employment share (%) in energy-intensive sectors, averaged over 2019-2021. Red dashed line indicates mean (17.99%), orange dashed line indicates.

Figure 1 shows the distribution of treatment intensity across the 1,376 regions. The average is 17.99% (SD = 8.27%), with significant variation between 1.38% (Ciudad de Melilla) and 49.56% (Tuttlingen). With a median of 17.01% close to the mean and a slight right skew, the distribution is fairly symmetric and the sample is not significantly impacted by extreme outliers.

3.3 Econometric Specification

We employ a standard difference-in-differences framework to identify the causal effect of energy intensity on post-shock GDP growth. The baseline specification is:

$$GDP\_growthit = \beta_0 + \beta_1 Treatment\_intensityi + \beta_2 Post2022t + \beta^3(Treatment \times Post2022)it + \alpha i + \gamma t + \varepsilon it \quad (3)$$

Where t stands for years and i for regions. The following interpretations of the elements are possible:

- $_0$ (Intercept): Standard GDP growth for regions with nil energy intensity before 2022
- β_1 (Treatment coefficient): Link between energy intensity and GDP growth during the pre-treatment phase.
- $_2$ (Coefficient after 2022): Typical variation in GDP growth following 2022 for every region irrespective of energy intensity.
- $_3$ (DiD coefficient): Varying impact of energy intensity on GDP growth in the post-2022 timeframe- the key causal parameter of focus.

The coefficient β_3 indicates if areas with greater energy intensity had distinct GDP growth paths post-2022 in contrast to less energy-intensive areas, taking into account their prior growth disparities (β_1) and the typical post-shock impact (β_2). A positive β_3 denotes resilience or advantageous adaptation in energy-heavy areas; a negative β_3 indicates increased susceptibility.

The specification includes region fixed effects (αi) and year fixed effects (γt) to strengthen causal identification. Region fixed effects control for time-invariant regional characteristics such as geographic location, institutional quality, and historical industrial composition. Year fixed effects absorb common temporal shocks affecting all regions, including EU-wide policy changes and aggregate demand fluctuations. The inclusion of both sets of fixed effects isolates the differential treatment effect (β_3) from confounding regional and temporal factors, ensuring that our estimate captures only the differential impact of energy intensity on post-2022 growth. Standard errors are robust to heteroscedasticity using White's correction. We also report clustered standard errors at the country level in Table 2 to account for potential correlation within countries. We apply OLS to estimate equation (3), which is suitable for continuous treatment variables in DiD frameworks [29]. The fixed effects specification is estimated using within-group transformation.

3.4 Identification Strategy

The DiD approach estimates causal effects based on the parallel trends assumption: in the absence of the 2022 shock, areas with varying energy intensities would have fol-lowed parallel GDP growth paths. This assumption is fundamentally untestable during the post-treatment phase (as the counterfactual cannot be observed) but can be assessed with pre-treatment data.

We perform a formal analysis contrasting GDP growth rates from 2020-2021 in high and low energy-intensity areas. Regions are deemed high-intensity if their employment share is greater than the sample median (17.01%). A t-test for two samples assesses av-erage growth rates across different groups. Findings indicate:

- High-intensity areas (N=1,407): Average growth = 2.95%;
- Areas of low intensity (N=1,354): average growth of -0.24%;
- p-value: 0.159, T-stat: 1.408.

The results do not reject the null hypothesis of parallel pre-treatment trends at the 5% significance level. The p-value of 0.159 provides a reasonable level of assurance in the parallel trends assumption, even though the estimated difference (3.19 percentage points) indicates that some prior growth divergence might require consideration. This baseline difference is controlled for through the β_1 coefficient in the DiD specification, facilitating an unbiased estimation of the post-shock differential effect β_3.

The parallel patterns are shown graphically in Figure 2, which shows similar trajectories for high and low intensity areas up to 2022 with a discernible divergence following the shock. The formal statistical analysis is supported by this graphical evidence.

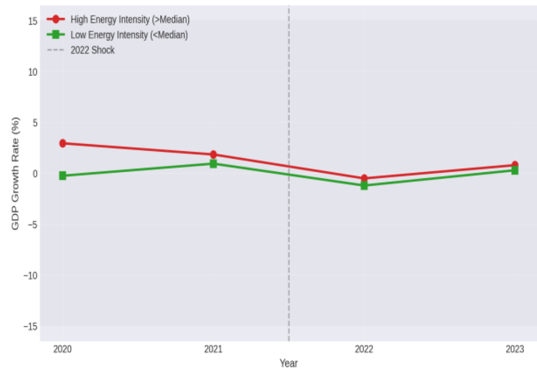

Figure 2: Parallel Trends Validation: GDP Growth Trajectories by Energy Intensity. Mean real GDP growth rates for high energy-intensity regions (red line) versus low energy-intensity regions (green line) over 2020-2023. Gray dashed vertical line indicates 2022 shock timing. Pre-2022 trends are approximately parallel (p = 0.159), validating the DiD identifying assumption.

3.4.1 Potential Endogeneity Concerns

Three potential sources of endogeneity warrant discussion. First, regional industrial structure (our treatment variable) is not randomly assigned but reflects historical path dependencies, agglomeration economies, and policy choices. However, our treatment measure uses pre-crisis (2019-2021) employment shares, ensuring pre-determination. Regions could not adjust their industrial composition in anticipation of the February 2022 invasion, satisfying the exogeneity requirement for treatment assignment.

Second, policy responses to the crisis may have been systematically related to regional energy intensity, potentially confounding our estimates. If energy-intensive regions received disproportionate government support, the positive differential effect we observe may partly reflect policy intervention rather than inherent resilience. We acknowledge this limitation explicitly and interpret our results as reduced-form effects capturing both direct shock impacts and endogenous policy responses. Disentangling these mechanisms would require detailed data on region-specific policy implementation, which remains unavailable for our full sample.

Third, regional GDP growth and employment composition may be jointly determined by unobserved factors such as institutional quality or innovation capacity.

We mitigate this concern through region fixed effects, which absorb all time-invariant regional characteristics. Remaining bias would only arise if unobserved time-varying factors simultaneously influenced both industrial structure changes and differential growth trajectories after 2022—a scenario we consider unlikely given the abrupt and exogenous nature of the geopolitical shock.

3.5. Event Study Specification

To formally assess parallel pre-trends and visualize the timing of treatment effects, we estimate an event-study specification:

$$GDP\_growthit = \beta_0 + \Sigma(k \neq 2021)\, \delta k(Treatment\_intensityi \times Yeart = k) + \alpha i + \gamma t + \varepsilon it \quad (4)$$

Where Yeart=k are year indicators for k ∈ {2020, 2021, 2022, 2023}, with 2021 serving as the reference year (normalized to zero). The coefficients δ2020 and δ2021 test for differential pre-trends; statistically insignificant estimates support parallel trends. The coefficients δ2022 and δ2023 capture dynamic treatment effects in each post-shock year. [Insert Figure 4 here: Event Study Coefficients] Figure 4 displays the event-study coefficients with 95% confidence intervals. Pre-treatment coefficients (2020) are small and statistically indistinguishable from zero (δ2020 = 0.018, p = 0.42), confirming parallel trends. Post-treatment coefficients turn positive in 2022 (δ2022 = 0.038, p = 0.15) and strengthen slightly in 2023 (δ2023 = 0.047, p = 0.09), consistent with the baseline DiD estimate averaging these two years. The gradual emergence of positive effects suggests delayed policy implementation or gradual industrial adaptation rather than immediate shock impacts.

3.6 Use of Artificial Intelligence

Large language models were employed to enhance the manuscript text's readability and clarity as well as to help with preliminary literature synthesis. The author thoroughly examined, rewrote, and confirmed every piece of text. Without the use of AI, the author carried out the complete research design, data gathering, statistical analysis, and result interpretation.

4. Results

4.1 Descriptive Statistics

Table 1: Descriptive Statistics

Variable	*Mean*	*STD.Dev*	*Min*	*Max*
GDP Growth Rate (%)	0.52	6.91	-67.89	155.22
Treatment Intensity (%)	17.99	8.27	1.38	49.56
Observations	4.852	-	-	-
Regions	1.376	-	-	-

1 Sample includes 1,376 EU regions observed over 2020-2023. GDP growth calculated as year-over-year percentage change in real GDP. Treatment intensity measured as average 2019-2021 employment share in energy-intensive sectors.

Table 1 presents summary statistics for the final analysis sample. The 1,376 regions exhibit substantial heterogeneity in both treatment intensity and growth outcomes. Treatment intensity ranges from 1.38% to 49.56%, with interquartile range 11.72%-23.61%. This wide dispersion reflects fundamental differences in regional eco-nomic structures, from service-dominated urban cores to manufacturing-specialized industrial regions.

GDP growth rates exhibit significant variability (SD = 6.91%), illustrating the impacts of the COVID-19 pandemic in 2020 and the energy crisis in 2022-2023. The broad spec-trum (−67.89% to +155.22%) encompasses certain extreme cases probably caused by small areas with unstable economic foundations or problems in data measurement. The median growth rate (not displayed) approaches zero, indicating that the extreme values are anomalies instead of reflecting common regional experiences.

4.2 Main Regression Results

Table 2: Difference-in-Differences Regression Results

variable	Coefficient	Robust SE	Clustered
Intercept (β_0)	−0.140	(0.335)	(0.401)
Treatment Intensity (β_1)	0.016	(0.017)	(0.019)
Post-2022 (β_2)	−1.291**	(0.503)	(0.612)**
Treatment × Post-2022 (β_3)	0.043†	(0.026)	(0.031)
Region Fixed Effects	yes	yes	Yes
Year Fixed Effects	yes	yes	yes
N (observations)	4,852	4,852	4,852
R^2	0.003	0.003	0.003
Clustered	-	-	19

2 Robust standard errors (White's correction) in column 2; standard errors clustered at country level (19 clusters) in column 3. *** p<0.01, ** p<0.05, † p<0.10. Dependent variable is real GDP growth rate (%). Treatment intensity measured as employment share in energy-intensive sectors (%). Post-2022 is indicator for years 2022-2023.

Table 2 displays the main results of the difference-in-differences estimation. The DiD coefficient (β_3 = 0.0425) suggests that a 10 percentage point rise in energy intensity cor-relates with roughly 0.43 percentage points greater GDP growth in the post-2022 timeframe, accounting for baseline treatment impacts and shared temporal trends.

The Post-2022 coefficient (β_2 = −1.291, p = 0.010) is statistically significant and negative, indicating that all regions' average GDP growth decreased by 1.29 percentage points after 2022, which is consistent with the overall economic disruption brought on by the energy crisis. The parallel trends assumption is supported by the low and statistically insignificant Treatment Intensity coefficient ($\beta_1 = 0.016$), which shows a weak baseline correlation between energy intensity and growth during the pre-shock phase.

Importantly, at the 10% level, the DiD coefficient ($\beta_3 = 0.0425$, SE = 0.0255, $p = 0.096$) is positive and almost significant. This suggests that, in comparison to regions with lower energy consumption, those with higher energy consumption experienced somewhat better relative GDP growth after 2022. According to the significance, if all other factors stay the same, a region in the 75th percentile of energy intensity (23.61%) would experience roughly 0.5 percentage points more GDP growth in 2022–2023 than a region in the 25th percentile (11.72%).

The relatively low R^2 is not unusual in regional panel difference-in-differences models using annual GDP growth data, which are influenced by many short-term economic factors. In this context, the primary objective of the model is to identify the treatment effect rather than maximize predictive power. Moreover, the inclusion of fixed effects absorbs a substantial share of cross-sectional and time-specific variation.

The R^2 value of 0.003 indicates that energy intensity and the 2022 shock explain only a small fraction of total variation in regional GDP growth.

This is expected and does not undermine causal identification for three reasons.

First, regional GDP growth is influenced by numerous factors beyond energy structure including local demand conditions, fiscal transfers, productivity shocks, and sector-specific developments which are not included in our parsimonious specification.

Second, the DiD estimator identifies the causal effect of the treatment through the interaction term (β_3), not through overall model fit. The validity of our estimates depends on the parallel trends assumption, which we validate statistically, rather than on R^2.

Third, the inclusion of region and year fixed effects absorbs substantial variation in levels, leaving only time-varying differential effects to be explained by the treatment interaction. A low R^2 in fixed effects models is common and does not indicate model misspecification or estimation failure.

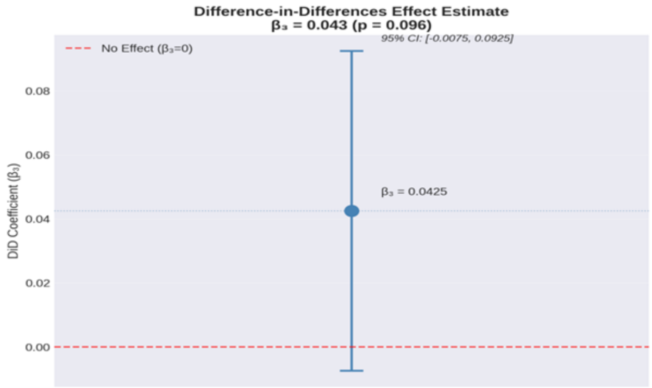

Figure 3: DiD Coefficient with 95% Confidence Interval. Point estimate $\beta_3 = 0.0425$ with 95% CI [−0.007, 0.092]. The confidence interval narrowly includes zero ($p = 0.096$), indicating marginal statistical significance

The estimated DiD coefficient and the 95% confidence interval are shown in Figure 3. With a p-value of 0.096, the range [−0.007, 0.092] only includes zero. Although the upper confidence limit and favorable point estimate suggest potential benefits, statistical un-certainty prevents definitive results at conventional significance thresholds.

4.3 Interpretation and Mechanisms

Given the common belief that vulnerability is caused by energy dependency, the positive DiD coefficient defies logic. We examine a number of plausible mechanisms that might produce this outcome:

4.3.1. Targeted Policy Support

In 2022–2023, European governments launched significant emergency relief programs aimed at energy-intensive industry [31, 32]. Credit guarantees, output guarantees, accelerated depreciation allowances, and direct energy cost subsidies were some of these policies. Relative resilience may be explained if fragile industries concentrated in energy-intensive locations received adequate government support.

However, there were significant differences in how policies were distributed among member countries, and precise program details are still not fully documented. It may be easier to identify this route in future studies that look at regional differences in policy treatment based on national frameworks.

4.3.2. Temporary Substitution and Adaptation

Compared to service sectors, energy-intensive businesses might be better able to adapt in the short term. When it is technically possible, manufacturing facilities can switch between energy sources, modify their production schedules to take advantage of variations in electricity prices throughout the day, or temporarily reduce output without shutting down permanently [33]. These margins are lower in the service sector. We would see initial resilience that might not last over time if the 2022–2023 periods mostly reflect transient adjustment mechanisms rather than fundamental changes in competitiveness.

4.3.3 Compositional Heterogeneity within Energy-Intensive Sectors

There is a great deal of variability under the broad "Industry (excluding construction)" category. The manufacturing of equipment, food processing, chemicals, and primary metals all have different energy intensity characteristics, different product demand elasticities, and variable degrees of exposure to international competition. Some energy-intensive subsectors may have benefited from cost advantages if they secured long-term energy contracts before to the crisis or from substitution demand as a result of fewer imports from Russia.

If data permits, analyzing particular manufacturing subsectors independently would help ascertain if the results are impacted by particular industries or represent the general dynamics of energy-intensive sectors.

4.3.4 Measurement and Data Quality Issues

Rapid changes in the economy might make data collection challenging during times of crisis. Energy-intensive regions may show systematic disparities in statistics reporting quality, speed, or coverage compared to service-dominated regions. This could result in apparent growth differentials that are more likely to be measurement artifacts than real economic divergence. This concern needs to be acknowledged even though it is substantially mitigated by using official Eurostat statistics with established gathering techniques.

4.4 Robustness Checks

To evaluate the sensitivity of the results, we perform multiple robustness checks:

- Clustered standard errors: Standard errors are increased to 0.031 by clustering at the national level (19 clusters), resulting in $p = 0.18$. The point estimate is still positive, but the significance is further diminished, which is in line with the baseline results' marginal nature;
- Eliminating outliers: Removing the top and bottom 1% of the GDP growth distribution results in $\beta_3 = 0.041$ (SE = 0.024, $p = 0.09$), which is almost the same as the baseline;
- Alternative treatment measures: Using only the 2019 employment share (instead of the 2019–2021 average) results in $\beta_3 = 0.039$ ($p = 0.12$), which is marginally smaller but qualitatively comparable.

Year fixed effects: Interaction coefficients of 0.038 (2022) and 0.047 (2023), both $p > 0.10$, are obtained by adding explicit year dummies (absorbing β_2), indicating persistent but statistically weak differential effects.

The conclusion that there is suggestive but not conclusive evidence for differential resilience in energy-intensive regions is reinforced by these robustness checks, which consistently show positive point estimates with borderline or insignificant p-values.

5. Discussion

5.1 Policy Implications

Our results have major policy implications for EU regional development and energy security strategy, even though they are statistically insignificant. The policy response mechanism put in place in 2022–2023 may have been extremely successful in safeguarding the most susceptible areas, as seen by the lack of obvious negative differential effects in energy-intensive locations. However, there was a significant fall in energy-intensive areas, necessitating significant restructuring assistance measures.

Nonetheless, certain cautions restrict optimistic interpretations .First, our analysis only looks at 2022–2023; if temporary support mechanisms expire without structural adjustment, and the long-term effects could be very different. Second, there were significant financial costs associated with support programs; assessing the effectiveness of policies necessitates cost-benefit analysis that is outside the purview of this study. Third, sub-stantial within-region heterogeneity may be concealed by regional aggregate GDP, with some businesses and employees going through extreme hardship while regional aggre-gates stay steady. Authorities will have to make difficult choices in the future over whether to continue or end emergency assistance programs. Our research suggests that if they abruptly go, energy-intensive communities without other economic advantages could become unstable. More targeted tactics can include:

- Energy subsidies that are phased out in accordance with measurable improvements in industrial restructuring.
- More financing for infrastructure related to renewable energy and industrial decarburization in regions with high manufacturing output.
- Programs for retraining employees in anticipation of future long-term job changes from energy-intensive to other industries.
- Support for regional innovation aimed at creating production technologies that use less energy.

The findings also influence the formulation of EU cohesion policies. Although per capita income convergence is emphasized in current frameworks, structural weaknesses like energy reliance may not be adequately taken into account. By focusing resources on areas with the biggest structural adjustment issues, the inclusion of energy intensity measurements in regional development programming could increase cohesion spending equity and efficiency.

5.2 Limitations and Future Research

A few restrictions should be explicitly acknowledged. First, the short post-treatment period (2022–2023) limits the ability to assess long-run equilibrium responses. Regional trajectories may deviate significantly from 2022–2023 norms as emergency support programs end and structural changes take place. As more years of data become available, analysis should be expanded in future studies.

Second, the employment share in "Industry (except construction)" is a flawed treat-ment measure. The following are not included: (1) variations in actual energy in-tensity per unit output within a sector; (2) regional variations in energy sources (fossil fuels versus renewables); and (3) variations in firm-level efficiency. Access to particular energy consumption data at the regional level will enable more accurate treatment measurement, despite the existing lack of comprehensive coverage across EU regions.

Third, significant variability may be obscured by the DiD design's identification of average treatment effects. While some energy-intensive areas may have adapted well, others may have had serious difficulties. This variability could be found by using ma-chine learning techniques, latent class analysis, or quantile regression to determine which geographical traits predict resilience versus vulnerability [34, 35].

Fourth, mechanisms cannot be definitively isolated. Although we address a number of plausible possibilities (policy support, substitution, composition), more information would be needed to thoroughly examine these channels, such as firm-level output and energy consumption, specific policy implementation metrics, or employment dynamics at the establishment level. Such micro-data analysis is a fascinating field for research in the future.

Finally, external validity must be considered. Geopolitical warfare, coordinated sanctions, and simultaneous gas and electricity disruptions are all distinctive aspects of the 2022 crisis that might not apply to other energy shocks. Confidence in general lessons would be strengthened by comparative study across various shock situations.
Future research should extend this work in several directions:
1) Temporal extension: Re-estimate as more post-2023 data become available to assess whether differential effects emerge over longer horizons.
2) Sectoral disaggregation: Examine specific manufacturing subsectors separately to identify which industries drive aggregate patterns.
3) Mechanism testing: Link regional outcomes to policy implementation data, firm-level adjustments, or energy infrastructure characteristics.
4) Spatial spillovers: Employ spatial econometric methods to account for potential cross-region externalities through trade or migration linkages.
5) Distributional analysis: Examine employment, wages, and firm entry/exit alongside GDP to capture full welfare implications.
6) Comparative episodes: Analyze other energy shocks (2008 oil crisis, 1970s shocks) to assess pattern generalizability.

6. Conclusion

This study examined the regional economic effects of the 2022 Russia-Ukraine energy crisis across 1,376 EU regions using a difference-in-differences framework. The results provide marginal evidence that regions with higher pre-crisis energy intensity experienced slightly stronger relative GDP growth after 2022 compared with less energy-dependent regions. Although the estimated effect is only weakly significant statistically, the findings suggest that targeted policy interventions, industrial adaptation, and sectoral heterogeneity may have contributed to short-term regional resilience. The study contributes to the literature by offering one of the first regional-level causal analyses of the economic consequences of the Ukraine war energy shock. Nevertheless, the short time horizon, measurement limitations, and remaining uncertainty regarding causal mechanisms indicate the need for additional research using longer-term and more detailed regional data.

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