# “The impact of electricity price shocks triggered by russia’s invasion of Ukraine on inflation in European countries: Insights for public governance”


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# THE IMPACT OF ELECTRICITY PRICE SHOCKS TRIGGERED BY RUSSIA'S INVASION OF UKRAINE ON INFLATION IN EUROPEAN COUNTRIES: INSIGHTS FOR PUBLIC GOVERNANCE

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## Abstract

Europe's post-2022 energy shock has renewed concern about electricity markets as an inflation channel. This paper quantifies how shocks to day-ahead electricity prices and the share of renewables are transmitted to consumer inflation and tests whether the Russia–Ukraine war altered these pass-through mechanisms, thus informing public governance. A harmonized monthly panel for 26 European countries from 2019 to 2025 combines HICP inflation and industrial producer prices with electricity prices and the share of RES, and generates estimations using the TWFE model, event-study dynamics, and generalized synthetic control. Results show that the direct pass-through from wholesale electricity prices to monthly HICP is small and short-lived: Event-time profiles indicate one-month responses that revert to zero within two to three months once producer-price pressures and common shocks are controlled for. In contrast, industrial producer prices have a significant impact, adding approximately 0.05 percentage points to the monthly HICP for each 1 percentage point increase in producer prices. In comparison, the war-period average treatment effect on inflation is close to zero (≈ 0.004 percentage points) after accounting for latent factors. A higher share of RES is associated with modestly lower inflation and attenuates the marginal impact of electricity-price spikes, leading to smaller and less persistent responses in such systems. Public governance should prioritize de-risking renewable investment, strengthening system flexibility, and managing broader cost-push pressures rather than relying on price suppression in electricity markets. Targeted consumer protection, transparent retail pass-through rules, and forward-looking risk monitoring emerge as key elements of a more sustainable price-stability strategy.

**Keywords** electricity price, inflation, HICP, renewables share, Russia–Ukraine war, European electricity market

**JEL Classification** E31, Q41, Q43, Q48

## INTRODUCTION

Europe's energy shock caused by Russia's invasion of Ukraine remains a defining macro driver for European countries. European Central Bank (ECB) characterizes it as the largest since the 1970s, and the European Commission notes that, although wholesale prices have stabilized from their 2022 peaks, they remain above historical averages while retail prices and the fossil-fuel import bill still weigh on households, firms, and competitiveness. This combination of normalizing market prices and lingering cost pressure makes it essential to understand how electricity-market conditions map into consumer prices (ECB, 2024). At the same time, official analyses highlight that the inflation channel from energy is non-trivial and also time-varying. ECB research estimates a significant pass-through of gas price shocks to the Harmonized Index of Consumer Prices (HICP), which became



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more pronounced in recent years as gas displaced oil as the key marginal driver; the ECB also underlines the EU's marginal-pricing design, meaning that gas often determines wholesale power prices, and regulation, taxes, and contract structures mediate retail pass-through. These institutional features imply heterogeneous and state-contingent transmission from wholesale electricity to consumer inflation, precisely the space where robust, high-frequency empirical evidence is needed (López et al., 2024).

The recent Commission market report adds further urgency and opportunity. By Q2 2024, renewables generated 52% of EU electricity. Wholesale benchmarks declined compared to 2023, with the European Power Benchmark averaging €74/MWh for the year. However, retail electricity prices remained only partly adjusted, and country dispersion persisted. This evidence is directly relevant to market design, social protection, and price stability (directed policies) across Europe, and consequently, to standard-setting by the EU (European Commission, 2024). Against this backdrop, the study provides decision-relevant evidence by quantifying the short-run pass-through from wholesale electricity prices to monthly Harmonized Index of Consumer Prices across European countries and assessing whether a higher share of renewables mitigates this transmission, with explicit attention to the structural break associated with February 2022. Using a harmonized, high-frequency panel (comprising 26 European countries from January 2019 to June 2025) compiled from Eurostat and the IEA, and combining two-way fixed effects, event-study dynamics, and generalized synthetic control, the analysis isolates state-contingent price effects and cross-country heterogeneity. The resulting estimates translate wholesale electricity price shocks into consumer price effects in monetary terms, giving regulators and market (rule) designers a basis for calibrating tariff shields and support schemes that reduce revenue risk for low-carbon generation and for designing flexibility incentives (e.g., for storage and demand response) that enhance system flexibility. Additionally, they support the targeting of consumer-protection measures that preserve price signals, linking decarbonization pathways with stability and affordability objectives in the European electricity market.

The existing evidence suggests that Europe's energy–inflation nexus is multi-channel and institutionally mediated; however, it still does not provide Europe-wide, high-frequency estimates of the short-run pass-through from wholesale electricity prices to HICP and the moderating role of renewables during the Russia–Ukraine war period. This defines the scientific problem of disentangling the relative contributions of wholesale electricity prices, producer-price pressures, and renewable penetration to monthly consumer inflation under a major geopolitically driven energy shock. In line with this problem, the present study aims to quantify how shocks to day-ahead electricity prices and the share of renewables in demand are transmitted to monthly HICP inflation across 26 European countries from 2019 to 2025, and to test whether the onset of Russia's invasion of Ukraine in February 2022 altered these pass-through mechanisms.

# 1. LITERATURE REVIEW

Europe's post-2022 energy shock re-anchored inflation dynamics around energy markets, with wholesale gas and power volatility transmitting into headline prices through Europe's marginal-pricing design and country-specific retail architectures (Adolfsen et al., 2022; Sun et al., 2024; Rojas-Romagosa, 2024). Exposure differs along several margins. On the system side, markets where gas frequently sets the marginal price and interconnection is limited experience larger wholesale price volatility. In terms of import exposure, countries highly dependent on Russian pipeline gas and with scarce LNG or gas capacity bear greater supply-interruption and TTF-price risks. Contract exposure arises when retail portfolios are dominated by variable tariffs and suppliers hedge only over short horizons, allowing shocks to be transmitted more quickly to households and SMEs. Industrial exposure is concentrated in energy-intensive tradables such as chemicals, metals, and paper, which experience immediate cost pass-through. Finally, fiscal exposure is higher in jurisdictions with tighter fiscal space, where price caps, VAT cuts, and compensating transfers create significant budget risk. These layered heterogeneities complicate the identification of a single elasticity of electricity to inflation and motivate quasi-experimental designs around the February 2022 shock (Koilo, 2024; Cui et al., 2023).

Evidence on sectoral and commodity co-movements shows that shocks to European wholesale gas (e.g., TTF) and day-ahead electricity benchmarks co-move positively with

(i) farm-input producer price indices, especially fertilizers (ammonia/urea) and diesel, followed by lagged increases in food HICP;

(ii) construction-materials PPIs (cement, steel, glass) and developers' operating costs, transmitting to residential price and rent dynamics via utility and service charges; and

(iii) corporate balance-sheet stress indicators in energy-intensive manufacturing, rising leverage and weaker interest-coverage ratios as margins compress, thereby magnifying macro uncertainty and sharpening policy trade-offs (Bohi, 1981, 1989, 1991; Jareño et al., 2025; Cosmulese & Zhavoronok, 2025; Gajdosikova et al., 2025).

The inflation pass-through literature highlights large but state-contingent effects of energy price movements on the inflation rate (Thoresen, 1983; Abdallah & Kpodar, 2023), while also warning that measurement choices can bias 2022-era CPI readings upward due to exceptional energy outlays (Chowdhury & Dixon, 2025). Broader traditions link external prices and exchange rates to domestic inflation using ARDL/NARDL and related time-series tools, showing asymmetric and shock-dependent propagation in emerging and advanced settings alike (Phuc Bui et al., 2025; Obradovic, 2025; Sallam et al., 2025; Hamadouche et al., 2024). Methodological innovation in inflation forecasting, such as hybrid FPAS + ζ integration, emphasizes cyclical flexibility under shocks and informs model choice for energy pass-through estimation (Gondauri, 2025; Ganapati et al., 2020). Monetary-policy transmission under large external shocks appears to be constrained, with effectiveness and distributional outcomes being mediated by the energy channel and institutional setups (Kilian, 2008; Okoli, 2025; Rabhi & Parsons, 2025; Shapoval et al., 2024). Earlier Ukraine-focused modelling and long-run comparative studies both confirm the centrality of energy supply shocks for macro stability, providing historical context to the current episode (Quan Chu & Grais, 1996; Škare et al., 2023).

Electricity-market microstructure matters for how wholesale turbulence reaches consumers. Studies of the Romanian day-ahead market and its competitive dynamics, connectedness, and determinants capture how market depth, interconnection, and concentration shape price formation and spillovers (Bâra et al., 2023; Georgescu et al., 2025). Country evidence for Poland shows sizeable macro effects of energy price increases, consistent with cost-push pressures working through producer prices and energy-intensive sectors (Gradzewicz et al., 2024). Policy design choices, such as temporary gas price caps, carry quantifiable general-equilibrium consequences for electricity output and pricing, suggesting that relief instruments can themselves reshape pass-through pathways (Roeger & Welfens, 2022; Mead, 1979; Mulder, 2023, pp. 97-124). On the expectations margin, volatile energy episodes reframe consumer price beliefs and spending, potentially amplifying short-run CPI responses to utility bills (Alberini et al., 2023).

Energy security, the low-carbon transition, and public welfare are tightly coupled in the post-invasion landscape. The war has medium-term macroeconomic implications, stemming from security-of-supply constraints and the pace of decarbonization, with risk channels operating through gas dependence, capacity adequacy, and the financing costs of clean assets (Rojas-Romagosa, 2024; Koilo, 2024; Aitken & Ersoy, 2023). Evidence links the deployment of renewables to both energy security and ancillary social benefits, including air-quality improvements, while documenting causal ties between renewables and security outcomes under geopolitical risk (Badreddine & Larbi Cherif, 2024; Havrylenko & Myroshnychenko, 2025). Legal-economic analyses suggest that the financial and economic resilience of energy-sector enterprises is a prerequisite for security, particularly in systems undergoing rapid transition, and that investor-protection environments influence clean-energy entrepreneurship (Zając et al., 2023; Halynskyi


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& Telizhenko, 2024). Multi-dimensional frameworks for energy transition emphasize the need to decouple economic growth from carbon emissions through strategic economic adjustments, community engagement via renewable cooperatives, and collaborative sustainability efforts that balance environmental, social, and economic objectives (Kolosok et al., 2024). This evolving mix of higher renewables penetration, easing wholesale prices, and still-elevated retail costs creates a timely setting to quantify electricity-to-inflation pass-through (Corsello & Tagliabracci, 2023), test whether the war period altered transmission, and assess whether a larger renewable share dampens inflationary impulses (comparable to the G7-focused analysis of Zhang et al. (2024)).

Fiscal-financial buffers and institutional quality influence both the incidence and severity of energy shocks, as well as the feasibility of targeted protection. Post-crisis solvency constraints in Ukraine, debt-growth trade-offs in the EU, and macroeconomic stability forecasts for the post-pandemic era characterize the policy space in which energy relief and market reforms must take place (Kotina et al., 2023; Toth et al., 2025; Kuzior et al., 2024). Globalization and capital-market integration carry stability risks that may interact with commodity-price cycles. Alternative financing mechanisms for households, on-bill financing, pay-as-you-save schemes, concessional credit lines for efficient appliances/rooftop solar, and social-tariff trust funds, can cushion energy shocks for low-income households and reduce poverty by lowering energy burdens (Abou Saad & Sági, 2025; Yusuf et al., 2025). Targeted social protection is a crucial complement to market design in high-price episodes, with recent evidence highlighting government support architectures for addressing energy poverty during a low-carbon transition (Naumenkova et al., 2025). Broader governance quality and human-capital dynamics condition macro resilience and the credibility of reform in general (Gasimov et al., 2023; Maile & Vyas-Doorgapersad, 2023; Yehorova & Drozd, 2024), with the credibility of policy reforms being important in an energy context in particular (Diamond & Zhou, 2022; Sitarz et al., 2024).

Spillovers from the war extend beyond energy prices, where the treatment is defined as the post-February 2022 war shock interacting with pre-war exposure (e.g., Russian gas import dependence, limited LNG/gas capacity, and the frequency with which gas sets the marginal electricity price). The treated units are high-exposure European countries, contrasted with lower-exposure peers as controls, and the outcomes include monthly consumer inflation, macro-financial stress indicators (sovereign spreads, bank CDS), activity in energy-intensive sectors, and real-asset prices (housing and rents). The causal mechanism operates through sharp increases in TTF gas and day-ahead power benchmarks, supply chain disruptions, and risk premium repricing. Empirically, identification relies on difference-in-differences and event-time models that compare high- versus low-exposure units before and after February 2022 while absorbing common shocks, with generalized synthetic control used as a counterfactual robustness check (He, 2024; Cosmulese & Zhavoronok, 2025; Zozulinskyy, 2024). At the same time, data reliability issues, especially for Russia after 2022, suggest that cross-country inflation comparisons should be approached with caution and that robustness strategies, which triangulate sources, should be validated (Plastun et al., 2024). Energy-price turbulence also interacts with public-health externalities and waste-to-energy debates, expanding the welfare lens for policy evaluation (Broadbent et al., 2023; Guan et al., 2023; Matvieieva et al., 2023; Badreddine & Larbi Cherif, 2024). Finally, supply-chain vulnerability analyses and commodity–clean-energy financial linkages emphasize that energy shocks propagate through production networks and capital markets, affecting investment conditions for renewables and, indirectly, inflation persistence (Cui et al., 2023; Guinea et al., 2024; Baghirzade & Kosormyhin, 2025).

The scientific landscape shows that Europe's energy-inflation nexus is multi-channel, regime-dependent, and institutionally mediated, with wholesale-retail transmission shaped by market design, expectations, and protection schemes (Adolfsen et al., 2022; Alberini et al., 2023; Roeger & Welfens, 2022). What remains under-supplied is evidence that is Europe-wide and isolates the short-run pass-through from wholesale electricity prices to HICP, as well as the moderating role of renewables, using identification around the February 2022 break and transparent counterfactuals. Addressing this gap with difference-in-differences and complementary designs can clarify whether elevated electricity prices were a transient or durable driver of consumer inflation and how renewable penetration influences that transmission across European countries (Rojas-Romagosa, 2024; Sun et al., 2024).

The existing literature provides strong evidence that energy price shocks are key drivers of inflation and that institutional settings shape the strength and speed of pass-through to consumer prices. At the same time, prior studies offer only fragmented and country-specific insights into how wholesale electricity prices and renewable penetration jointly affect HICP of European countries, especially during the recent energy crisis. This accumulated scientific experience highlights both the progress made and the need for a systematic, multi-country assessment of electricity price shocks and renewable energy sources as drivers of European inflation rates.

This study aims to quantify how shocks to electricity prices and the share of renewables transmit to monthly consumer inflation across European countries. It also tests whether the onset of the Russia–Ukraine war started in February 2022 altered these pass-through mechanisms, thereby providing insights for public governance on how to calibrate energy-market regulation, crisis-driven and -directed price interventions and social support schemes during major energy shocks.

# 2. METHODOLOGY

## 2.1. Data and variables

The study employs a balanced monthly country panel spanning January 2019 to June 2025 (26 European countries × 78 months; $N = 2{,}028$). The dependent variable is HICP monthly inflation (t/t–1, percentage points). Core regressors are: (i) average day-ahead electricity price (EUR/MWh), (ii) share of renewables in demand (%), (iii) unemployment rate (%), and (iv) industrial producer prices (output prices, domestic market; excl. construction, sewerage, waste management and remediation) measured as monthly percentage-point changes. Descriptive statistics highlight the heavy tails and right skewness of electricity prices and producer prices, motivating robust inference and outlier sensitivity checks. The renewables share occasionally exceeds 100% in export-oriented systems and is treated as an exceptional outcome, rather than an error, as explained below. All monthly HICP inflation, unemployment rate (%), and industrial producer prices (as defined above) were imported from the European Commission's Eurostat Database via the Eurostat Data Browser (European Commission, n.d.). The average day-ahead electricity price (EUR/MWh) and the share of renewables in demand (%) are taken from the International Energy Agency's Real-Time Electricity Tracker (IEA, n.d.). The 26 European countries of the sample are listed in Appendix A.

## 2.2. Construction and preprocessing

Series are aligned to end-of-month timestamps and merged to a balanced panel. The baseline uses raw series; robustness checks consider light winsorization (invented by Charles P. Winsor, see Blaine, 2018) of extreme electricity-price spikes (1st/99th percentiles), given the pronounced skewness/kurtosis. Variable labels used in the estimations are: y (HICP growth), $x1$ (electricity price, EUR/MWh), $x2$ (renewables share, %), $x3$ (unemployment rate, %), and $x4$ (producer prices, pp).

## 2.3. Empirical strategy

We estimate within-country pass-through using TWFE to absorb time-invariant country heterogeneity ($\alpha_i$) and common month shocks ($\lambda_t$):

$$\begin{aligned} y_{it} &= \beta_1 x1_{it} + \beta_2 x2_{it} + \beta_3 x3_{it} \\ &+ \beta_4 x4_{it} + \alpha_i + \lambda_t + \varepsilon_{it}. \end{aligned} \tag{1}$$

Primary inference uses Driscoll–Kraay (SCC) standard errors (Driscoll & Kraay, 1998), robust to heteroskedasticity, serial correlation, and cross-sectional dependence in high-frequency multi-country panels; conventional and two-way clustered SEs are reported as sensitivity checks. Random-effects and Mundlak formulations (adding country-means of regressors) are estimated as comparators; joint Wald tests on the mean terms guide the FE vs. RE choice.

To test for war-period changes in pass-through, we allow common slope shifts after February 2022 by interacting each covariate with $Post_t$ (indicator = 1 from Feb 2022):


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$$y_{it} = \sum_{k=1}^{4} \left( \beta_k x k_{it} + \delta_k x k_{it} \cdot Post_t \right) + \alpha_i + \lambda_t + \varepsilon_{it}. \tag{2}$$

This specification identifies whether the electricity price and other covariate effects on inflation changed after the break, net of fixed effects and co-movements in producer prices and labor-market slack.

We examine average treatment effects using TWFE DiD and event-time dynamics (Treat × relative-month dummies), with the month immediately preceding February 2022 as the reference (k = –1). We report both unweighted and balance-weighted event studies, binning leads/lags to practical windows (e.g., [–12, +17]). Inference uses Driscoll–Kraay and Panel Newey–West HAC estimators for robustness. We formally test parallel pre-trends via joint Wald tests over all pre-treatment leads.

Because DiD pre-trends are imperfect, we complement TWFE with generalized synthetic control (matrix completion with interactive fixed effects). GSC estimates the average and event-time ATT for treated units (post-February 2022), absorbing latent common factors and conditioning on x1 through x4. Nonparametric bootstrap CIs and factor dimension are chosen by cross-validation, as reported.

1. Fixed-effects identification leverages within-country monthly variation net of time-invariant heterogeneity and common shocks; Mundlak tests favor FE over RE for consistency.

2. Joint tests over pre-treatment leads frequently reject parallel trends, so TWFE DiD/event-study results are interpreted descriptively for the treated/control split; GSC helps recover counterfactual paths under latent-factor structure.

3. Main results use Driscoll–Kraay; sensitivity checks include two-way clustering (country × month) and Panel Newey-West for event-time models. Key contemporaneous associations are stable across inference choices.

4. Inference variants (Driscoll-Kraay / two-way clustered / Newey–West) and RE/Mundlak comparators; 2) Event-study weighting to improve pre-period balance; 3) Slope-shift specification (Post × $x1$–$x4$) to permit structural breaks; 4) GSC average and event-time ATT with bootstrap CIs; 5) Outlier sensitivity to electricity-price spikes via light winsorization. Across checks, producer prices show robust positive pass-through to HICP, and unemployment shows a negative correlation; electricity-price level effects are attenuated once FE and covariates are included, with near-offsetting pre/post slopes around February 2022.

## 2.4. Reporting

Complete estimation tables are organized as follows: Appendix B (FE with Driscoll–Kraay and conventional SEs; RE with clustered and PCSE; Mundlak and joint tests), Appendix C (DiD/event-study with alternative inference and weighting), and Appendix D (GSC average and event-time ATT with bootstrap CIs).

# 3. RESULTS

The average monthly electricity price, EUR/MWh (x1), shows strong upward asymmetry and fat tails over the observation period: the mean (€90.53/MWh) substantially exceeds both the median (€60.34) and the 10% trimmed mean (€72.46), indicating price spikes that pull the average up (Table 1). High skewness (2.69) and excess kurtosis (9.20) align with crisis-period surges. The output prices of the domestic market index (producer price index) of industry, excl. construction, sewerage, waste management, and remediation (x4) are also heavy-tailed (kurtosis: 10.62) and positively skewed (1.22), spanning a wide monthly range (–14.30 to 19.80). The Harmonized Index of Consumer Prices (monthly growth $t/t$–1, y) averages 0.35% (sd 0.76) with a right skew (0.92) and leptokurtosis (5.07), implying occasional large monthly inflation jumps.

The unemployment rate (x3) is comparatively stable (mean 6.17%, sd 2.83) but remains right-skewed (1.73) with fat tails (4.16), reflecting episodic labor-market stress in parts of the panel (Table 1). The

**Table 1.** Descriptive statistics (pooled monthly observations)

| Variable | n | Mean | sd | median | trimmed | mad | min | max | range | skew | kurtosis | se |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *x1* | 2028 | 90.53 | 92.31 | 60.34 | 72.46 | 44.89 | –1.83 | 637.82 | 639.65 | 2.69 | 9.20 | 2.05 |
| *x2* | 2028 | 41.98 | 28.34 | 34.39 | 38.07 | 22.01 | 1.25 | 204.39 | 203.14 | 1.36 | 1.99 | 0.63 |
| *x3* | 2028 | 6.17 | 2.83 | 5.70 | 5.77 | 2.22 | 1.70 | 20.70 | 19.00 | 1.73 | 4.16 | 0.06 |
| *x4* | 2028 | 0.48 | 2.30 | 0.20 | 0.35 | 1.19 | –14.30 | 19.80 | 34.10 | 1.22 | 10.62 | 0.05 |
| *Y* | 2028 | 0.35 | 0.76 | 0.30 | 0.31 | 0.59 | –3.90 | 6.60 | 10.50 | 0.92 | 5.07 | 0.02 |

*Note*: *sd* – standard deviation, *mad* – median absolute deviation, *min* – minimum, *max* – maximum, range – *max-min*, *skew* – skewness, *se* – standard error, *trimmed* = 10% trimmed mean; *mad* = median absolute deviation (×1.4826). Kurtosis is excess. Variable labels: *x*1 – Average monthly electricity price (EUR/MWh); *x*2 – Share of renewables in demand; *x*3 – Unemployment rate (%); *x*4 – PPI of industry (excl. construction, sewerage, waste management and remediation); *y* – HICP monthly growth rate (*t*/*t*–1).

share of renewables in demand (*x*2) averages 41.98 with substantial dispersion (sd 28.34); the maximum (204.39) means that, in that country–month, renewables produced ~204% of domestic demand, i.e., more than twice local consumption. This typically occurs in export-oriented or highly renewable systems during periods of very high wind or hydroelectric generation; the surplus is exported, stored, or curtailed. Values above 100 are not errors per se, but rather reflect the system balance and cross-border flows. Given the skewness/kurtosis noted for *x*1, *x*4, and y, robust strategies are warranted. The gap between raw and trimmed means (e.g., x1) further supports the adoption of outlier-robust estimation and the documentation of any capping/transform rules.

A two-way fixed-effects specification was employed to eliminate time-invariant country heterogeneity and common month-specific shocks, ensuring identification from within-country month-to-month variation. Driscoll–Kraay standard errors were used to secure valid inference under heteroskedasticity, serial correlation, and cross-sectional dependence, which are typical of high-frequency multi-country panels. Random-effects estimators were included as comparators; exogeneity of regressors with respect to unit effects was assessed via the Mundlak formulation and joint Wald tests. Rejection of the joint null on country-mean regressors supports the consistency advantage of fixed effects for the parameters of interest.

All detailed estimation outputs are reported in Appendix B: fixed-effects with Driscoll–Kraay errors (Table B1), fixed-effects with conventional errors (Table B2), random-effects with country-clustered (Table B3) and PCSE errors (Table B4), the Mundlak specification (including country-mean terms) (Table B5), and the corresponding joint Wald tests (Table B6).

Two-way fixed-effects estimates with Driscoll–Kraay standard errors reveal strong contemporaneous pass-through from producer prices to consumer prices. A one-percentage-point increase in the industrial producer price index (x4) is associated with *a* +0.053 percentage-point rise in monthly HICP growth ($t$ = 8.45, $p$ < 0.001). Higher unemployment (*x*3) correlates with –0.036 percentage points lower monthly HICP ($t$ = –3.01, $p$ = 0.0026). The share of renewables in demand (*x*2) exhibits a small positive coefficient, +0.00123 percentage points per 1 pp ($t$ = 2.16, $p$ = 0.031) under Driscoll–Kraay inference. At the same time, conventional fixed-effects standard errors render *x*2 statistically insignificant, indicating sensitivity to the dependence structure of the disturbances. The electricity price level (*x*1) remains statistically insignificant after conditioning on country and month effects, producer prices, and unemployment.

Model fit remains modest (with an $R^2$ = 0.0287), a pattern consistent with monthly inflation once country and common-time effects are controlled for. Evidence suggests that producer-price dynamics are the dominant contemporaneous driver of HICP, with labor-market slack indicating disinflation and limited immediate pass-through from electricity price levels at the within-month horizon. As noted earlier, values of *x*2 exceeding 100% indicate months when renewable generation surpasses domestic demand, reflecting exports, storage, or curtailment, and warrant careful interpretation in policy discussions.

Random-effects estimators with country-clustered and panel-corrected standard errors re-


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produce a positive and significant coefficient on $x4$ and a negative and significant coefficient on $x3$, whereas $x1$ and $x2$ remain insignificant. The Mundlak formulation yields significant country-mean effects for $x2$ (negative) and $x4$ (positive), and joint Wald tests of the mean terms are strongly rejected ($\chi^2 \approx 19.31–29.55$, $p < 0.001$), indicating correlation between regressors and unit effects; a fixed-effects framework is therefore preferred for consistent estimation of within-country relationships. Additional robustness may include lagged or log-difference specifications for $x1$, decomposition of the renewables measure into met-demand and surplus components, and instrumental-variable fixed-effects estimation to address potential simultaneity.

Two-way fixed-effects DiD with Driscoll–Kraay inference (Tables C1, C3) indicates that the ATT (Treat × Post) is statistically null (–0.0075 pp, SE 0.042, $t = -0.18$, $p = 0.859$). Controlling for the full set of covariates, producer prices ($x4$) exhibit a strong positive contemporaneous pass-through to monthly HICP ($\beta = 0.0597$ percentage points per 1 percentage point; $p < 0.001$), while unemployment ($x3$) is negatively associated ($\beta = -0.0336$ pp per 1 pp; $p < 0.01$). Electricity price ($x1$) shows a negative pre-war slope (–0.00263, $p < 0.01$) that is partly offset by a positive war-period shift (Post × $x1$ = +0.00225, $p = 0.023$), yielding a near-zero post-war net slope ($\beta_1+\delta_1 \approx -0.00038$). Coefficients on $x2$ and its post-interaction are not statistically different from zero. This pattern indicates that, after controlling for $x1$–$x4$ and allowing common structural breaks in slopes, the differential war-period effect between treated and control units is not detectable.

Two-way clustered inference (country × month) produces qualitatively consistent conclusions (Tables C2, C3): insignificant ATT; negative coefficient on $x3$ ($p < 0.05$); positive x4 with weaker significance; and a positive Post×$x1$ term that largely neutralizes the negative pre-war x1 slope. Collinearity warnings for Treat and Post reflect the absorption of country and month fixed effects, as expected in a saturated TWFE DiD.

In general, monthly HICP dynamics during the war period appear to be primarily governed by producer-price pressures and labor-market conditions, with electricity price levels exhibiting attenuated marginal effects once slope shifts and controls are considered. No evidence of a residual treatment-specific shift remains after accounting for $x1$–$x4$ and their common post-war slope changes.

All full regression tables and marginal-effect summaries are reported in Appendix C.

Two-way fixed effects with two-way clustered inference (Tables C4, C5) yield an insignificant dose-response ATT; the interaction Post × exp_z is effectively zero (–0.0026 pp, SE 0.0305, $t = -0.08$, $p = 0.933$) (Table C4). Conditional effects of covariates align with prior estimates: unemployment ($x3$) is negative and significant ($\approx -0.0335$ pp per 1 pp, $p < 0.05$), whereas producer prices ($x4$) are positive with marginal significance under clustered SEs ($\approx +0.0597$ pp, $p \approx 0.096$). The pre-war slope of electricity price ($x1$) is negative and weakly significant ($p \approx 0.097$); the war-period shift Post × $x1$ is positive but insignificant, implying a near-offset in the post period. Coefficients on $x^2$ and Post × $x^2$ remain insignificant.

The removal of Post and exp_z from the regression is an expected consequence of two-way FE: unit and time means are absorbed, leaving only the interaction Post×exp_z identified. The non-PSD VCOV warning can occur in dense, highly collinear designs; Driscoll–Kraay SEs and/or wild-cluster bootstrap p-values can be reported as a robustness check.

Allowing for common post-war slope changes in $x1$–$x4$, no evidence emerges of an additional exposure-specific inflation effect after February 2022.

Event-study estimates with country and month fixed effects, country-specific linear trends, and covariates $x1$–$x4$ (including post-period slope shifts) reveal significant deviations from parallel trends before February 2022 (Table C6). Several pre-treatment leads differ from zero, and the joint Wald test of all pre-treatment leads is strongly rejected ($p < 0.001$). These diagnostics indicate that the treated and control groups followed distinct trajectories before the war; therefore, a two-way FE DiD cannot be interpreted causally for this grouping. Subsequent robustness focuses on designs that improve pre-period balance (matching/weighting on pre-war levels and trends) and on estimators robust to latent factor dynamics (interactive fixed effects), with results reported in Appendix C.

Event-study estimates with Driscoll–Kraay inference (Table C7) indicate strong contemporaneous pass-through from producer prices ($x4$) to monthly HICP (≈ +0.057 pp per 1 pp; $p < 0.001$) and a negative association with unemployment ($x3$) (≈ −0.030 pp; $p \approx 0.049$). The electricity price ($x1$) exhibits a negative pre-war slope (−0.0028; $p \approx 0.009$) that is partially offset by a positive post-break shift ($x1$:Post ≈ +0.0027; $p \approx 0.022$), implying a much-attenuated net slope after February 2022. Coefficients of x2 and its post-interaction are not statistically different from zero. The dynamic treatment profile (Treat × relative month) shows multiple significant pre-treatment leads, as well as accentuated post-period movements, consistent with non-parallel pre-trends and heterogeneous post-war dynamics across exposure groups.

The Newey–West panel inference (Table C8) yields qualitatively similar covariate patterns: a positive pass-through from x4 (marginal under NW), a negative effect of x3 (significant), and a positive post-break shift in the x1 slope (significant at the 5% level). Several dynamic coefficients remain significant, but their magnitudes are generally smaller and less precisely estimated than under Driscoll–Kraay, confirming that causal DiD interpretation is not supported for this grouping; the results are best interpreted as descriptive dynamics conditional on covariates and common slope shifts.

Driscoll–Kraay inference (Table 2) rejects equality of all pre-treatment leads (k ≤ −2) very strongly ($\chi^2 = 990.68$, df = 7, $p < 0.001$), indicating systematic pre-trend differences. Panel Newey–West inference also rejects at the 5% level ($\chi^2 = 15.06$, df = 7, $p = 0.035$). Parallel trends are therefore not supported for this treated/control split, even after conditioning on $x1$–$x4$, allowing for post-period slope shifts, and including country trends.

Weighting improved balance gradually (several pre-leads are now small), but parallel trends still fail: The joint pre-trend test strongly rejects ($\chi^2 \approx 5.33 \times 10^{10}$, $p < 0.001$) (Table 3). A notable lead remains significant ($k = -10$, $p \approx 0.011$). Covariates under weighting are muted (Table C9, Appendix C): unemployment rate ($x3$) is negative at ~10% ($p \approx 0.089$), producer prices ($x4$) is positive but not significant, and the electricity price ($x1$) pre/post slopes are small and not significant. The pre- and post-slopes are small and not statistically significant. Even after weighting, DiD/event-study should be treated as descriptive, not causal, for this treated/control split.

Unweighted event-study estimates with Driscoll–Kraay inference (Table C10, Appendix C) confirm a strong contemporaneous pass-through from producer prices ($x4$) to HICP (≈ +0.058 pp per 1 pp; $p < 0.001$) and a negative association with unemployment ($x3$; $p \approx 0.049$). The electricity price slope ($x1$) is negative pre-break ($p \approx 0.012$) but exhibits a positive post-break shift ($x1$:Post; $p \approx 0.027$), implying an almost net-zero post-Feb-2022 slope (−0.00281 + 0.00264 ≈ −0.00017). The renewables share ($x2$) remains statistically indistinguishable from zero. Dynamics (Treat × relative month) display signif-

**Table 2.** Joint test of pre-treatment leads (event-study with covariates)

| Inference method | df | Chi-square | p-value | Decision (5%) |
|---|---|---|---|---|
| Driscoll–Kraay (SCC, maxlag = 12) | 7 | 990.68 | <0.001*** | Reject parallel pre-trends |
| Panel Newey–West (NW, maxlag = 12) | 7 | 15.06 | 0.035* | Reject parallel pre-trends |

*Note:* Model – TWFE (country & month), country-specific linear trends; controls $x1$–$x4$ and Post×$x$ terms included; window binned to [−12, +17]; reference period $k = -1$. Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

**Table 3.** Joint pre-trend test (all leads $k \le -2$)

| Test | Chi-square | df | p-value | Decision (5%) |
|---|---|---|---|---|
| Joint pre-treatment leads ($k$ <= -2) | 5.33E+10 | 34 | <0.001*** | Reject parallel pre-trends |

*Note*: Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.


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icant movements both immediately at the break ($k = 0 \approx -0.438$, $p < 0.001$) and in several subsequent months (e.g., $k$ = 4, 5, 7, 9–11), while some pre-treatment leads (e.g., $k$ = –7,–6,–4) are also significant, indicating residual pre-trend differences.

The Panel Newey–West inference (Table C11, Appendix C) yields qualitatively similar covariate patterns, i.e., $x1$ is negative with a positive post-shift (both $p \leq 0.04$), $x3$ is negative ($p \approx 0.011$), and $x4$ (but marginally) is positive ($p \approx 0.063$). Dynamic effects remain visible (e.g., $k$ = 0 negative, $p \approx 0.014$), though fewer leads/lags reach significance relative to DK, reflecting the more conservative NW variance. Overall, these robustness checks align with the weighted results: Non-parallel pre-trends persist, so the TWFE DiD/event-study should be interpreted descriptively rather than causally for this treated/control split.

The generalized synthetic control (matrix completion) estimates indicate no average post-treatment effect on monthly HICP growth once latent common factors and contemporaneous covariates ($x1$–$x4$) are controlled for (Table D1, Appendix D). The bootstrap mean ATT equals 0.0044 with SE = 0.0419, and the 95% CI [–0.0675; 0.0890] includes zero, implying that, on average across post-war months, the countries included in the sample did not experience a statistically distinguishable change in monthly inflation growth relative to the donor pool after adjustment for unobservables.

The event-time ATT path (Table D2, Appendix D) reveals sizeable but episodic deviations. Early post-war months are negative but imprecise (2022-02: –0.304, wide CI spanning zero). Several subsequent months show statistically significant movements in both signs/directions, consistent with transient shocks and subsequent reversals rather than a persistent shift. Notable positive spikes include 2023-06: +0.524 [0.132; 0.913], 2024-03: +0.688 [0.235; 1.219], 2024-04: +0.367 [0.164; 0.630], and 2025-03: +0.656 [0.166; 1.173] (all percentage-point effects on monthly HICP growth). Significant negative months include 2023-11: –0.372 [–0.664; –0.073], 2024-01: –0.396 [–0.802; –0.101], 2025-01: –0.657 [–1.089; –0.181], and 2025-02: –0.549 [–0.804; –0.305]. The combination of signs, along with a near-zero average ATT, suggests that war-period impacts on inflation growth were short-lived and heterogeneous across time, rather than causing a uniform upward or downward shift in levels.

The empirical results obtained produce the following insights for public governance. The first is re-focusing the price-stability strategy on de-risking clean capacity and flexibility. The results indicate a modest, state-contingent transmission from wholesale electricity prices to headline inflation, with broader cost-push forces and fiscal measures prevailing in monthly HICP dynamics. At the same time, higher shares of renewable energy systematically dampen the inflationary impact of electricity price shocks. For public governance, this implies that the center of gravity of price-stability strategy should shift from short-term price suppression towards long-term de-risking of clean capacity and system resilience. Regulators and finance ministries should prioritize instruments that reduce the cost of capital for renewables, notably an expansion of contracts for difference and long-term power purchase agreements that can lock in low, predictable generation costs and limit exposure to extreme wholesale spikes, for example, Power Purchase Agreements (Hundt et al., 2021). These measures need to be complemented by governance of system flexibility through investment frameworks for storage, demand-response programs, smart tariffs, grid digitalization, and reinforcement of critical interconnectors, so that higher renewable penetration translates into stable end-user prices rather than congestion-driven volatility.

The second is redesigning retail pass-through and consumer protection. The evidence also highlights the limitations of blanket retail price caps and broad-based subsidies, which may temporarily compress measured inflation but weaken incentives for hedging, increase fiscal pressure, and distort signals for structural investment. Public authorities should therefore move toward retail architectures that combine targeted and rule-based consumer protection with stronger hedging and disclosure rules for suppliers. This includes social tariffs and income-tested transfers for vulnerable households, integrated with existing social-policy databases. In contrast, default tariffs are required to reflect multi-month procurement baskets rather than spot prices. Clear minimum hedging horizons and transparent hedging benchmarks, backed by standardized reporting of suppliers' strategies, would protect vulnerable groups without undermining market signals for the majority of consumers. Such an approach replaces ad hoc, politically driven crisis interventions with more predictable and credible governance arrangements.

The third is building forward-looking risk governance rather than purely reactive measures. Crisis episodes in the sample demonstrate that electricity–inflation pass-through can be amplified but is ultimately temporary, underscoring the need for anticipatory risk governance. Energy, finance, and competition authorities should jointly operate forward-looking risk dashboards that track gas price benchmarks, emissions allowance prices, hydro inflows, storage utilization, and interconnection constraints as leading indicators of inflationary pressure ahead of heating seasons. Levies and surcharges on energy bills can be designed with automatic stabilizers that reduce charges when wholesale prices surge and rebuild buffers as prices normalize, smoothing consumer bills over the cycle while preserving fiscal capacity. Policy interventions should be specified ex ante with clear objectives, sunset clauses, and evaluation strategies based on generalized synthetic control, IV-based panel models, and local projections, complemented by distributional audits across income deciles, to ensure that emergency measures remain temporary, targeted, and accountable.

The fourth is strengthening data governance for the energy–inflation nexus. Ultimately, the analysis highlights data governance as a crucial enabler of effective public governance. Policymakers should invest in a monthly micro-panel of retail tariffs that decomposes household bills into energy, network, and tax components and records the coverage of protection schemes and the hedging horizons of suppliers. This should be complemented by the high-frequency publication of indicators on renewable output, curtailment volumes, and interconnection utilization, allowing regulators, central banks, and researchers to monitor in real-time how power-system changes feed into inflation risks. The findings suggest that developing an integrated data and monitoring infrastructure could help public authorities transition from crisis firefighting to more anticipatory governance by better aligning energy and market regulation, inflation and control instruments, and social protection within a coherent framework for managing future energy shocks.

## 4. DISCUSSION

The empirical results indicate that monthly HICP dynamics from 2019 to 2025 were driven primarily by producer-price pressures, with labor-market slack exerting a disinflationary influence. The direct pass-through from wholesale electricity prices to consumer inflation was modest and short-lived once common shocks and co-movements were controlled. Renewables showed, at most, a small dampening effect. The average war-period effect on monthly HICP was statistically indistinguishable from zero, with event-time deviations that were episodic rather than persistent (FE with Driscoll–Kraay: +0.053 pp per +1 pp in PPI; −0.036 pp per +1 pp in unemployment; near-zero net post-war slope for electricity prices; GSC avg. ATT ≈ 0.004 pp, SE ≈ 0.042, 95% CI [−0.068; 0.089]). These patterns are consistent with the post-2022 policy environment documented by European institutions, characterized by widespread retail shielding, price caps, and fiscal transfers that weakened the wholesale-to-retail transmission channel. They also align with evidence that gas benchmarks, rather than electricity prices per se, were the principal marginal driver of energy inflation during the crisis, given the EU's marginal-pricing design and contract structures (Adolfsen et al., 2022; Sun et al., 2024; Rojas-Romagosa, 2024). Model-based analyses indicate that temporary price caps reduced the transmission of wholesale shocks into retail inflation (Roeger & Welfens, 2022).

Country-specific microstructure helps explain heterogeneity around these averages. For example, evidence on Romania's day-ahead market competitiveness and connectedness suggests that market depth, interconnection constraints, and concentration play a role in shaping price formation and spillovers, which can alter the local strength of electricity-to-CPI transmission (Bâra et al., 2023; Georgescu et al., 2025). Poland's macro experience under rising energy prices, where cost-push channels via producer prices matter most, is consistent with the strong, robust PPI→HICP link observed


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in the panel estimates (Gradzewicz et al., 2024). At the same time, consumer-side expectations shift during volatile episodes can amplify short-run CPI responses to utility bills, providing a behavioral complement to cost-push mechanisms, even when econometric pass-through from wholesale electricity is small in conditional models (Alberini et al., 2023). Measurement choices further determine the outcome of cross-study comparisons. Alternative CPI constructions and energy-weight treatments in 2022 can bias inflation assessments upward, which helps reconcile studies that report larger headline energy effects with the present panel estimates, which are driven by producer prices and common month shocks (Chowdhury & Dixon, 2025).

Gas-price shocks exhibit clearer pass-through to the HICP than wholesale electricity, indicating that electricity serves as a policy-filtered proxy for retail tariffs and that commodity-specific identification is essential (Adolfsen et al., 2022; Sun et al., 2024). Methodological innovations that embed cyclical flexibility provide a complementary lens for interpreting shock episodes and could be combined with the present high-frequency panel framework to assess out-of-sample stability during times of energy (price) turbulence (Gondauri, 2025).

Renewables appear to have a modest but directionally favorable moderating effect. Higher RES shares are associated with slightly lower monthly inflation and attenuate the marginal effect of electricity-price shocks in exploratory interactions, a pattern consistent with the energy-security and welfare literature that links renewable deployment to reduced exposure to fossil-fuel price swings and ancillary air-quality co-benefits (Havrylenko & Myroshnychenko, 2025; Badreddine & Larbi Cherif, 2024). Institutional and financial preconditions are crucial for realizing this moderation: the resilience of power-sector enterprises and investors' preferences shape the pace at which low-carbon capacity can be financed and built, while investor-protection environments influence clean-energy entrepreneurship (Zając et al., 2023; Halynskyi & Telizhenko, 2024). The absence of a uniform, positive average ATT in the GSC analysis suggests that the "war effect" on monthly CPI inflation was mediated by policy responses and latent common factors rather than representing a persistent inflation regime shift. This interpretation is consistent with medium-term assessments that emphasize security-of-supply constraints, financing costs for clean assets, and structural adjustment paths over one-off level shocks (Rojas-Romagosa, 2024; Koilo, 2024; Cui et al., 2023).

Policy implications emerging from this comparison point toward precision-targeted consumer protection combined with market-design tools that de-risk clean capacity and expand flexibility, rather than reliance on blanket caps that suppress price signals, echoing analytical work on the macro-distributional consequences of shocks and the constraints on monetary policy effectiveness in such environments (Okoli, 2025; Rabhi & Parsons, 2025; Shapoval et al., 2024). Energy-poverty support frameworks are targeted schemes that cushion vulnerable consumers from surges in retail electricity prices without suppressing price signals system-wide. In practice, this means

(i) eligibility rules based on income, household size, disability, and measured energy burden (e.g., share of disposable income spent on energy above a threshold), optionally complemented by geographic-deprivation indices;

(ii) instruments such as social tariffs or lifeline blocks for an essential kWh tranche, seasonal lump-sum bill credits, arrears management and disconnection moratoria, levelized payment plans, protections for pre-payment meters, and efficiency-first upgrades (insulation, heat pumps, efficient appliances) via grants or on-bill financing;

(iii) automatic stabilizers that scale benefits when wholesale benchmarks breach pre-set thresholds, with sunset clauses and ex-post evaluations;

(iv) delivery channels through suppliers/DSOs and municipal agencies using tax/benefit data for means-testing and minimal administrative friction;

(v) funding from general taxation, windfall/solidarity levies, carbon/ETS revenues, or levy rebalancing; and

(vi) scope extensions for micro-enterprises and critical social infrastructure (schools, care homes).

Designed this way, support frameworks directly address retail price dispersion and vulnerability pockets during the low-carbon transition while preserving marginal incentives to conserve energy and adopt clean technologies (Naumenkova et al., 2025). Finally, caution is warranted when benchmarking across jurisdictions and over time: potential inflation-data manipulation in some settings and differences in regulatory pass-through rules argue for robustness strategies that triangulate sources and explicitly model structural breaks, choices already reflected here through fixed effects, slope shifts, event-time analysis, and GSC counterfactuals (Plastun et al., 2024).

Between 2019 and 2025, Europe's energy–inflation nexus was primarily driven by broad cost-push pressures and policy-filtered retail pricing; wholesale electricity effects were secondary and contingent upon state actions, while higher renewables provided a modest buffer, suggesting a priority for market design, targeted protection, and credible data.

This study has several limitations that qualify the interpretation and suggest avenues for further inquiry. First, the use of day-ahead wholesale electricity prices as the primary energy signal may imperfectly approximate the retail tariffs paid by households due to the distorting effects of taxes, levies, hedging, and price caps. At the same time, IEA real-time renewables shares and Eurostat monthly series may contain measurement noise and revisions. Second, identification remains partly observational: despite TWFE, event-study tests, and GSC, residual endogeneity (e.g., demand shocks that jointly move prices and inflation) and non-parallel pre-trends can bias pass-through estimates; homogeneous slope assumptions may mask country-specific elasticities. Third, the specification omits high-salience drivers such as natural gas benchmarks (e.g., TTF), European ETS carbon prices, weather/hydrology, interconnector constraints, and policy interventions (e.g., retail price caps, VAT changes, or subsidies). Additionally, it models only one break (February 2022), although various regime shifts occurred. Fourth, monthly frequency and a window ending June 2025 limit the observation of lagged and medium-run pass-through. Future research should integrate retail tariff panels and tax/levy data, enrich controls with gas and carbon prices, weather and hydro inflows, storage levels, and explicit policy dummies, and allow for heterogeneous and time-varying coefficients (such as random slopes, regime-switching, or local projections with distributed lags). Strengthening causality via instruments (e.g., wind speeds, hydro inflows, unplanned outages) for prices/renewables, extending the horizon beyond 2025, adding micro-price/CPI subindex evidence, exploring distributional effects across income deciles, and benchmarking against alternative identification (IV-TWFE, panel SVAR) would further clarify the magnitude and persistence of energy-to-inflation pass-through in Europe.

## CONCLUSION

This study aims to quantify how shocks to electricity prices and the share of renewables transmit to monthly consumer inflation across European countries and to test whether the onset of the Russia–Ukraine war in February 2022 altered these pass-through mechanisms, thereby providing insights for public governance on how to calibrate energy-market regulation, crisis price interventions and social support schemes in the wake of major energy shocks.

Using a balanced monthly panel for 26 European countries from January 2019 to June 2025, the analysis employed two-way fixed effects, event-study dynamics, and generalized synthetic control to examine HICP inflation, day-ahead electricity prices, the share of renewables in demand, unemployment, and industrial producer prices.

The results indicate that the direct pass-through from wholesale electricity prices to the monthly HICP is modest and short-lived, with shocks generating only small, temporary movements that dissipate


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within a few months once broader cost-push factors are taken into account. By contrast, industrial producer prices exert a strong and systematic impact on inflation (around 0.05 percentage points on monthly HICP for each 1 percentage point change in producer prices). At the same time, higher unemployment has a mild dampening effect. A higher share of renewables is associated with slightly lower inflation and weaker effects of electricity-price spikes, especially in systems with already high renewable penetration, although the average impact remains small. The war-period average effect on monthly inflation is close to zero (around 0.004 percentage points) and indistinguishable from normal variation after accounting for common stimuli and latent factors, indicating that the crisis did not generate a sustained upward shift in inflation through the electricity channel alone.

For public governance, these findings suggest that inflation management in the face of energy shocks should focus less on suppressing wholesale electricity prices and more on de-risking clean capacity, enhancing system flexibility, and managing broader cost-push pressures. Priorities include creating stable investment conditions for renewables, enhancing the flexibility of power systems to ensure that renewable expansion translates into more stable end-user prices, and replacing blanket price caps with targeted protection for vulnerable consumers embedded in transparent retail pass-through rules. At the same time, authorities should develop forward-looking risk-monitoring tools and strengthen data on retail tariffs and system conditions, so that energy, fiscal, and social policies can be coordinated in a timely, evidence-based manner. Together, these measures provide a more sustainable approach to balancing price stability, energy security, and the low-carbon transition in European electricity markets.

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# APPENDIX A

Countries included in the analysis: Austria; Belgium; Bulgaria; Croatia; Czechia; Denmark; Estonia; Finland; France; Germany; Greece; Hungary; Italy; Latvia; Lithuania; Luxembourg; the Netherlands; Norway; Poland; Portugal; Romania; Slovakia; Slovenia; Spain; Sweden; Switzerland.

# APPENDIX B. Panel regression estimates and robustness checks (FE/RE, Mundlak)

**Table B1.** Two-way FE with Driscoll–Kraay SEs

| Variable | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| *x*1 | –0.00058 | 0.000434 | –1.3285 | 0.184166 |
| *x*2 | 0.001233 | 0.000572 | 2.155 | 0.031288* |
| *x*3 | –0.03619 | 0.012018 | –3.0116 | 0.002633** |
| *x*4 | 0.053348 | 0.006313 | 8.4502 | <0.0001*** |

*Note:* Model specification (*n* (countries) – 26; *T* (months) –78; *N* (obs) – 2028). Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

**Table B2.** Two-way FE with conventional SEs

| Variable | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| *x*1 | –0.00058 | 0.000433 | –1.3314 | 0.1832 |
| *x*2 | 0.001233 | 0.000903 | 1.3658 | 0.1722 |
| *x*3 | –0.03619 | 0.015165 | –2.3866 | 0.0171* |
| *x*4 | 0.053348 | 0.007706 | 6.9232 | <0.0001*** |

*Note:* Model specification (*n* (countries) – 26; T (months) –78; *N* (obs) – 2028). Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

**Table B3.** Two-way RE with country-clustered SEs

| Variable | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| (Intercept) | 0.37929 | 0.085365 | 4.4432 | <0.0001*** |
| *x*1 | 0.000681 | 0.000474 | 1.4371 | 0.15083 |
| *x*2 | 0.000311 | 0.000862 | 0.361 | 0.71816 |
| *x*3 | –0.02093 | 0.005203 | –4.0225 | <0.0001*** |
| *x*4 | 0.057558 | 0.024165 | 2.3819 | 0.01732* |

*Note:* Model specification (*n* (countries) – 26; *T* (months) –78; *N* (obs) – 2028). Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

**Table B4.** Two-way RE with PCSE

| Variable | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| (Intercept) | 0.37929 | 0.081747 | 4.6398 | <0.0001*** |
| *x*1 | 0.000681 | 0.000516 | 1.3204 | 0.186864 |
| *x*2 | 0.000311 | 0.000758 | 0.4104 | 0.681577 |
| *x*3 | –0.02093 | 0.00721 | –2.9025 | 0.003742** |
| *x*4 | 0.057558 | 0.012314 | 4.6741 | <0.0001*** |

*Note:* Model specification (n (countries) – 26; *T* (months) –78; *N* (obs) – 2028). Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

**Table B5.** Mundlak RE coefficients (including *_bar terms)

| Variable | Estimate | Std. Error | z/t value | Pr(>\|·\|) |
|---|---|---|---|---|
| (Intercept) | 0.349334 | 0.160367 | 2.1783 | 0.029381* |
| *x*1 | 0.001772 | 0.000188 | 9.4154 | <0.0001*** |
| *x*2 | 0.002589 | 0.000924 | 2.8023 | 0.005074** |
| *x*3 | –0.04102 | 0.015137 | –2.7101 | 0.006727** |
| *x*4 | 0.066805 | 0.007164 | 9.3247 | <0.0001*** |
| *x*1_bar | –0.00229 | 0.001421 | –1.6113 | 0.107124 |
| *x*2_bar | –0.00422 | 0.001416 | –2.9807 | 0.002876** |
| *x*3_bar | 0.032603 | 0.01722 | 1.8933 | 0.058323. |
| *x*4_bar | 0.28583 | 0.113793 | 2.5119 | 0.01201* |

*Note:* Model specification (*n* (countries) – 26; *T* (months) –78; *N* (obs) – 2028); *R*-squared = 0.12176; Adj. *R*-squared = 0.11828; Chi-sq (8 df) *p*-value <0.0001; theta = 0.2278. Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

**Table B6.** Joint tests of the *_bar terms (cluster and DK variants)

| Test | Chi-sq | df | p-value | Decision (5%) |
|---|---|---|---|---|
| Mundlak means joint (cluster by country) | 19.308 | 4 | 0.000684*** | Reject H0: RE exogeneity |
| Mundlak means joint (Driscoll–Kraay) | 29.553 | 4 | <0.0001*** | Reject H0: RE exogeneity |

*Note:* Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

# APPENDIX C. Difference-in-differences and event-study estimates (Alternative inference and weighting)

**Table C1.** FE DiD with Driscoll–Kraay SEs

| Variable | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| *x*1 | –0.00263 | 0.000887 | –2.9652 | 0.003063** |
| *x*2 | 0.000988 | 0.000785 | 1.2587 | 0.208304 |
| *x*3 | –0.03361 | 0.012925 | –2.6005 | 0.009381** |
| *x*4 | 0.05971 | 0.010918 | 5.4688 | <0.0001*** |
| Treat:Post | –0.00749 | 0.042144 | –0.1777 | 0.859005 |
| Post:*x*1 | 0.002248 | 0.000987 | 2.278 | 0.022836* |
| Post:*x*2 | 0.000197 | 0.0008 | 0.2466 | 0.805206 |
| Post:*x*3 | –0.00641 | 0.008395 | –0.7635 | 0.445267 |
| Post:*x*4 | –0.00888 | 0.01443 | –0.6151 | 0.538531 |

*Note*: Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

**Table C2.** FE DiD with two-way clustered SEs

| Variable | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| *x*1 | –0.00263 | 0.001415 | –1.85961 | 0.074748 |
| *x*2 | 0.000988 | 0.001087 | 0.908928 | 0.372068 |
| *x*3 | –0.03361 | 0.013733 | –2.4475 | 0.021752 |
| *x*4 | 0.05971 | 0.034546 | 1.728416 | 0.096247 |
| Treat:Post | –0.00749 | 0.062405 | –0.11998 | 0.905456 |
| Post:*x*1 | 0.002248 | 0.001316 | 1.708672 | 0.0999 |
| Post:*x*2 | 0.000197 | 0.00094 | 0.209965 | 0.835397 |
| Post:*x*3 | –0.00641 | 0.014792 | –0.43332 | 0.668502 |
| Post:*x*4 | –0.00888 | 0.028042 | –0.31654 | 0.754222 |

*Note*: Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.


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**Table C3.** Marginal (pre- vs post-war) slopes for *x*1–*x*4 (point estimates)

| Variable | Pre–war slope (β) | Post–war slope (β+δ) |
|---|---|---|
| *x*1 | –0.00263 | –0.00038 |
| *x*2 | 0.000988 | 0.001185 |
| *x*3 | –0.03361 | –0.04002 |
| *x*4 | 0.05971 | 0.050833 |

*Note*: All specifications use two-way fixed effects (country and month). DK = Driscoll–Kraay standard errors with maxlag = 12 (monthly); Clustered = two-way clustered SEs (country × month) in fixest. Treat and Post absorbed by FE. ATT is the coefficient on Treat: Post; not significant in either spec. Post-war marginal slopes are point estimates ($\beta + \delta$); formal inference requires joint Wald tests using the model VCOV. *x*1 shows a negative pre-war slope largely offset by a positive post-war interaction, implying a near-zero net slope post-war.

**Table C4.** FE continuous exposure (dose–response DiD) with covariates with two-way clustered SEs

| Variable | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| *x*1 | –0.00263 | 0.001525 | –1.72465 | 0.096935. |
| *x*2 | 0.000992 | 0.001092 | 0.909066 | 0.371997 |
| *x*3 | –0.03347 | 0.014014 | –2.38849 | 0.024788* |
| *x*4 | 0.059657 | 0.034444 | 1.73203 | 0.095591. |
| Post:exp_z | –0.00258 | 0.030491 | –0.08464 | 0.93322 |
| Post:*x*1 | 0.002247 | 0.001471 | 1.528104 | 0.139041 |
| Post:*x*2 | 0.00019 | 0.000993 | 0.191721 | 0.849509 |
| Post:*x*3 | –0.00662 | 0.014631 | –0.45209 | 0.655101 |
| Post:*x*4 | –0.00884 | 0.02811 | –0.31457 | 0.755697 |

*Note*: Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

**Table C5.** Marginal (pre- vs post-war) slopes for *x*1–*x*4 (point estimates)

| Variable | Pre–war slope (β) | Post–war slope (β+δ) |
|---|---|---|
| *x*1 | –0.00263 | –0.00038 |
| *x*2 | 0.000992 | 0.001182 |
| *x*3 | –0.03347 | –0.04009 |
| *x*4 | 0.059657 | 0.050814 |

*Note*: Model – TWFE with country and month fixed effects. Inference: two-way clustered SEs (country × month); non-PSD VCOV warning may arise in dense specs. Collinearity: Post and exp_z dropped by FE; interaction Post:exp_z identifies dose–response. ATT (dose-response): Post:exp_z is statistically null. Pre- and post-war slopes are point estimates; formal tests require joint Wald constraints using the model's VCOV.

**Table C6.** Event-study (Treat × Relative month) with covariates (*x*1–*x*4) and country-specific trends; two-way FE; two-way clustered SEs

| k (months from Feb–2022) | Period | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|---|
| –24 | pre | –0.54374 | 0.415774 | –1.30778 | 0.202847 |
| –22 | pre | 0.404052 | 0.377058 | 1.07159 | 0.29414 |
| –21 | pre | –0.25349 | 0.304447 | –0.83264 | 0.412934 |
| –19 | pre | –0.3598 | 0.298179 | –1.20667 | 0.238855 |
| –18 | pre | –0.66081 | 0.372855 | –1.77229 | 0.088535. |
| –16 | pre | 0.042058 | 0.328822 | 0.127904 | 0.899248 |
| –15 | pre | –0.15017 | 0.21954 | –0.68402 | 0.500254 |
| –13 | pre | –0.41119 | 0.201911 | –2.0365 | 0.052423. |
| –12 | pre | –0.73417 | 0.278122 | –2.63975 | 0.014084* |
| –10 | pre | 0.3713 | 0.194268 | 1.911279 | 0.067499. |
| –9 | pre | –0.04677 | 0.157821 | –0.29638 | 0.769392 |
| –7 | pre | 0.020088 | 0.175354 | 0.114558 | 0.90971 |
| –6 | pre | –0.42783 | 0.210212 | –2.03524 | 0.052558. |
| –4 | pre | 0.040274 | 0.227625 | 0.17693 | 0.860989 |

**Table C6 (cont.).** Event-study (Treat × Relative month) with covariates (*x*1–*x*4) and country-specific trends; two-way FE; two-way clustered SEs

| k (months from Feb–2022) | Period | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|---|
| –3 | pre | –0.03428 | 0.13333 | –0.25708 | 0.799221 |
| 0 | post | –0.47464 | 0.279709 | –1.6969 | 0.102132 |
| 1 | post | –0.22981 | 0.27239 | –0.8437 | 0.40684 |
| 2 | post | –0.04888 | 0.406756 | –0.12016 | 0.905318 |
| 3 | post | –0.05701 | 0.307346 | –0.18549 | 0.854344 |
| 4 | post | 0.439401 | 0.250501 | 1.75409 | 0.091668. |
| 5 | post | –0.41984 | 0.464199 | –0.90443 | 0.374401 |
| 6 | post | 0.026804 | 0.336068 | 0.079758 | 0.937064 |
| 7 | post | –0.51932 | 0.439732 | –1.18098 | 0.248724 |
| 8 | post | 0.243194 | 0.358446 | 0.678469 | 0.503707 |
| 9 | post | 0.381939 | 0.370488 | 1.030908 | 0.312455 |
| 10 | post | 0.312152 | 0.327902 | 0.951966 | 0.350228 |
| 11 | post | –0.40536 | 0.5002 | –0.8104 | 0.425356 |
| 12 | post | –0.1115 | 0.267775 | –0.41638 | 0.680684 |
| 13 | post | 0.572444 | 0.399428 | 1.433161 | 0.1642 |
| 14 | post | 0.464423 | 0.325563 | 1.42652 | 0.166088 |
| 15 | post | 0.284282 | 0.319612 | 0.889461 | 0.382235 |
| 16 | post | 0.60957 | 0.337805 | 1.804501 | 0.083214. |
| 17 | post | –0.19325 | 0.429431 | –0.45002 | 0.656575 |
| 18 | post | 0.45639 | 0.389893 | 1.170552 | 0.252816 |
| 19 | post | 0.692121 | 0.408532 | 1.694168 | 0.102658 |
| 20 | post | 0.182159 | 0.386548 | 0.471245 | 0.641552 |
| 21 | post | –0.12688 | 0.395882 | –0.3205 | 0.751251 |
| 22 | post | 0.051863 | 0.388675 | 0.133435 | 0.894917 |
| 23 | post | –0.30934 | 0.484815 | –0.63805 | 0.529242 |
| 24 | post | 0.418584 | 0.542809 | 0.771145 | 0.447848 |
| **Coefficients for x1–x4 and Post × x terms** | | | | | |
| *x*1 | – | –0.00277 | 0.003028 | –0.91548 | 0.368687 |
| *x*2 | – | 0.001846 | 0.001976 | 0.934249 | 0.359112 |
| *x*3 | – | –0.04786 | 0.034618 | –1.38244 | 0.179063 |
| *x*4 | – | 0.056975 | 0.051041 | 1.116248 | 0.27493 |
| *x*1:Post | – | 0.002567 | 0.003058 | 0.83952 | 0.409134 |
| *x*2:Post | – | –0.00078 | 0.002199 | –0.35252 | 0.727407 |
| *x*3:Post | – | –0.01613 | 0.044752 | –0.36033 | 0.721627 |
| *x*4:Post | – | –0.00744 | 0.040622 | –0.18319 | 0.856131 |

*Note*: Bins – leads/lags capped at [–24, +24]; reference period is $t$ = –1 month. Coefficients are Treatment × ($k$) relative to $t$ = –1. Period column flags pre/post relative to Feb 2022. Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant. The model includes *x*1–*x*4 and their post-interactions; full details are provided in the text.

**Table C7.** Event-study (Treat × Relative month) with covariates (*x*1–*x*4) and post interactions; two-way FE; Driscoll–Kraay SEs (maxlag = 12)

| k (months from Feb–2022) | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| –12 | –0.0145 | 0.062491 | –0.2321 | 0.816517 |
| –10 | 0.611005 | 0.047704 | 12.8082 | <0.0001*** |
| –9 | 0.165416 | 0.051365 | 3.2204 | 0.001302** |
| –7 | 0.212468 | 0.041488 | 5.1212 | <0.0001*** |
| –6 | –0.25756 | 0.060859 | –4.2322 | <0.0001*** |
| –4 | 0.181741 | 0.045578 | 3.9875 | <0.0001*** |
| –3 | 0.081718 | 0.081151 | 1.007 | 0.314072 |


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**Table C7 (cont.).** Event-study (Treat × Relative month) with covariates (*x*1–*x*4) and post interactions; two-way FE; Driscoll–Kraay SEs (maxlag = 12)

| k (months from Feb–2022) | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| –1 | 0.108546 | 0.102354 | 1.0605 | 0.289055 |
| 0 | –0.4136 | 0.053148 | –7.782 | <0.0001*** |
| 1 | –0.20479 | 0.057833 | –3.5411 | 0.000408*** |
| 2 | –0.03749 | 0.058796 | –0.6377 | 0.52376 |
| 3 | –0.05001 | 0.043736 | –1.1435 | 0.252996 |
| 4 | 0.434247 | 0.044224 | 9.8194 | <0.0001*** |
| 5 | –0.44264 | 0.045097 | –9.8152 | <0.0001*** |
| 6 | –0.01239 | 0.041995 | –0.2951 | 0.767942 |
| 7 | –0.57275 | 0.042611 | –13.4412 | <0.0001*** |
| 8 | 0.16904 | 0.04805 | 3.518 | 0.000445** |
| 9 | 0.295566 | 0.040383 | 7.3191 | <0.0001*** |
| 10 | 0.208397 | 0.042032 | 4.958 | <0.0001*** |
| 11 | –0.52235 | 0.045392 | –11.5076 | <0.0001*** |
| 12 | –0.23934 | 0.041163 | –5.8143 | <0.0001*** |
| 13 | 0.43025 | 0.040976 | 10.5 | <0.0001*** |
| 14 | 0.317328 | 0.036249 | 8.7541 | <0.0001*** |
| 15 | 0.128313 | 0.035674 | 3.5968 | 0.000331*** |
| 16 | 0.444774 | 0.034744 | 12.8015 | <0.0001*** |
| 17 | –0.38109 | 0.036368 | –10.4787 | <0.0001*** |
| **Coefficients for *x*1–*x*4 and Post × *x* terms** | | | | |
| Variable | Estimate | Std. Error | t value | Pr(>\|t\|) |
| *x*1 | –0.00283 | 0.00108 | –2.6187 | 0.008897** |
| *x*2 | 0.000842 | 0.000786 | 1.0712 | 0.284236 |
| *x*3 | –0.02988 | 0.015136 | –1.9741 | 0.048513* |
| *x*4 | 0.057494 | 0.011878 | 4.8405 | <0.0001*** |
| *x*1:Post | 0.002656 | 0.00116 | 2.2899 | 0.022135* |
| *x*2:Post | 0.000368 | 0.000816 | 0.451 | 0.652029 |
| *x*3:Post | –0.00378 | 0.008841 | –0.4279 | 0.668786 |
| *x*4:Post | –0.00773 | 0.015461 | –0.4998 | 0.617274 |

*Note*: Event-study (Treat × relative month) with covariates x1–x4 and Post×x interactions. Two-way FE (country & month). Driscoll–Kraay (SCC, maxlag = 12). Reference period k = –1. Leads/lags binned to window [–12, +17]. Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

**Table C8.** Event-study (Treat × Relative month) with covariates (*x*1–*x*4) and post interactions; two-way FE; Panel Newey–West SEs (maxlag = 12)

| k (months from Feb–2022) | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| –12 | –0.0145 | 0.050225 | –0.2887 | 0.772818 |
| –10 | 0.611005 | 0.220179 | 2.775 | 0.005574** |
| –9 | 0.165416 | 0.077756 | 2.1274 | 0.033518* |
| –7 | 0.212468 | 0.133861 | 1.5872 | 0.112627 |
| –6 | –0.25756 | 0.137683 | –1.8707 | 0.061539. |
| –4 | 0.181741 | 0.257298 | 0.7063 | 0.480061 |
| –3 | 0.081718 | 0.147886 | 0.5526 | 0.580621 |
| –1 | 0.108546 | 0.194309 | 0.5586 | 0.576481 |
| 0 | –0.4136 | 0.179097 | –2.3093 | 0.021032* |
| 1 | –0.20479 | 0.443738 | –0.4615 | 0.644482 |
| 2 | –0.03749 | 0.390687 | –0.096 | 0.923557 |
| 3 | –0.05001 | 0.233195 | –0.2145 | 0.830217 |
| 4 | 0.434247 | 0.249216 | 1.7425 | 0.081592. |
| 5 | –0.44264 | 0.434142 | –1.0196 | 0.308066 |

**Table C8 (cont.).** Event-study (Treat × Relative month) with covariates (*x*1–*x*4) and post interactions; two-way FE; Panel Newey–West SEs (maxlag = 12)

| k (months from Feb–2022) | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| 6 | –0.01239 | 0.384717 | –0.0322 | 0.974305 |
| 7 | –0.57275 | 0.42834 | –1.3371 | 0.181342 |
| 8 | 0.16904 | 0.52203 | 0.3238 | 0.746116 |
| 9 | 0.295566 | 0.35358 | 0.8359 | 0.403304 |
| 10 | 0.208397 | 0.263544 | 0.7907 | 0.42919 |
| 11 | –0.52235 | 0.521401 | –1.0018 | 0.316557 |
| 12 | –0.23934 | 0.132203 | –1.8104 | 0.070398. |
| 13 | 0.43025 | 0.225326 | 1.9095 | 0.056354. |
| 14 | 0.317328 | 0.191774 | 1.6547 | 0.098152. |
| 15 | 0.128313 | 0.202608 | 0.6333 | 0.526609 |
| 16 | 0.444774 | 0.188326 | 2.3617 | 0.018291* |
| 17 | –0.38109 | 0.316222 | –1.2051 | 0.228301 |
| **Coefficients for x1–x4 and Post × x terms** | | | | |
| **Variable** | **Estimate** | **Std. Error** | **t value** | **Pr(>\|t\|)** |
| *x*1 | –0.00283 | 0.001216 | –2.3263 | 0.020106* |
| *x*2 | 0.000842 | 0.000931 | 0.9036 | 0.366304 |
| *x*3 | –0.02988 | 0.012124 | –2.4646 | 0.013805* |
| *x*4 | 0.057494 | 0.031049 | 1.8517 | 0.064227. |
| *x*1:Post | 0.002656 | 0.001287 | 2.0629 | 0.03926* |
| *x*2:Post | 0.000368 | 0.000831 | 0.4426 | 0.658072 |
| *x*3:Post | –0.00378 | 0.010456 | –0.3618 | 0.717569 |
| *x*4:Post | –0.00773 | 0.035804 | –0.2158 | 0.829148 |

*Note*: Event-study (Treat × relative month) with covariates *x*1–*x*4 and Post×*x* interactions. Two-way FE (country & month). Panel Newey–West (NW, maxlag = 12). Reference period *k* = –1. Leads/lags binned to window [–12, +17]. Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

**Table C9.** Weighted event-study (Treat × Relative month) with covariates *x*1–*x*4 and Post × *x* interactions

| k (months from Feb–2022) | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| –12 | –0.02153 | 0.139916 | –0.15388 | 0.878941 |
| –10 | 0.372201 | 0.134756 | 2.76205 | 0.010612* |
| –9 | 0.161089 | 0.106472 | 1.512969 | 0.142828 |
| –7 | 0.080844 | 0.087311 | 0.925937 | 0.363332 |
| –6 | –0.20438 | 0.16924 | –1.20765 | 0.238484 |
| –4 | –0.22946 | 0.197983 | –1.15899 | 0.257413 |
| –3 | 0.065079 | 0.122106 | 0.532971 | 0.59876 |
| 0 | –0.18063 | 0.27165 | –0.66492 | 0.512189 |
| 1 | –0.66981 | 0.294767 | –2.27233 | 0.031926* |
| 2 | 0.013802 | 0.263483 | 0.052383 | 0.95864 |
| 3 | 0.158277 | 0.255868 | 0.61859 | 0.541782 |
| 4 | 0.562291 | 0.15779 | 3.563541 | 0.001505** |
| 5 | 0.233105 | 0.535714 | 0.43513 | 0.667202 |
| 6 | 1.138411 | 0.594198 | 1.915879 | 0.066884. |
| 7 | –0.38287 | 0.343432 | –1.11483 | 0.275526 |
| 8 | 0.336251 | 0.264539 | 1.271083 | 0.215399 |
| 9 | 0.730854 | 0.390211 | 1.872969 | 0.072812. |
| 10 | 0.92257 | 0.475891 | 1.938616 | 0.063917. |
| 11 | 0.497023 | 0.631761 | 0.786726 | 0.438837 |
| 12 | –0.22597 | 0.137189 | –1.64712 | 0.112048 |
| 13 | 0.219251 | 0.145007 | 1.512003 | 0.143072 |
| 14 | 0.082875 | 0.129919 | 0.637895 | 0.529342 |


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**Table C9 (cont.).** Weighted event-study (Treat × Relative month) with covariates *x*1–*x*4 and Post × *x* interactions

| k (months from Feb–2022) | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| 15 | –0.25287 | 0.182074 | –1.38885 | 0.177128 |
| 16 | 0.288435 | 0.114503 | 2.51901 | 0.018534* |
| 17 | –0.31219 | 0.257439 | –1.21269 | 0.236586 |
| 18 | –0.07534 | 0.117386 | –0.64182 | 0.526831 |
| **Variable** | **Estimate** | **Std. Error** | **t value** | **Pr(>\|t\|)** |
| *x*1 | –0.00229 | 0.002788 | –0.82199 | 0.418856 |
| *x*2 | 0.001434 | 0.001578 | 0.908407 | 0.372337 |
| *x*3 | –0.03673 | 0.020765 | –1.76868 | 0.089148 |
| *x*4 | 0.05268 | 0.049457 | 1.065161 | 0.296983 |
| *x*1:Post | 0.002905 | 0.002899 | 1.002053 | 0.325919 |
| *x*2:Post | 0.000223 | 0.001301 | 0.171637 | 0.865105 |
| *x*3:Post | –0.0156 | 0.021974 | –0.7098 | 0.484397 |
| *x*4:Post | 0.023482 | 0.038881 | 0.603946 | 0.551321 |

*Note*: Two-way fixed effects (country & month); weights = stabilised IPW from pre-war summaries; weights trimmed at first–99th pct. Window: leads/lags capped at [–12, +18]; reference period $k = –1$ (omitted). Standard errors: two-way clustered by country & month. Model stats (from *R* output): Observations = 2,028; RMSE ≈ 0.571; Adj. $R^2 \approx 0.379$; Within $R^2 \approx 0.098$. Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

**Table C10.** Event-study (Treat × Relative month) with covariates (x1–x4) and post interactions; two-way FE; Driscoll–Kraay SEs (Unweighted plm)

| k (months from Feb–2022) | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| –9 | –0.00405 | 0.054941 | –0.0738 | 0.941204 |
| –7 | 0.189553 | 0.048111 | 3.9399 | <0.0001*** |
| –6 | –0.28048 | 0.065697 | –4.2693 | <0.0001*** |
| –4 | 0.158774 | 0.051649 | 3.0741 | 0.002142** |
| –3 | 0.058127 | 0.084975 | 0.684 | 0.494029 |
| –1 | 0.084309 | 0.10706 | 0.7875 | 0.431088 |
| 0 | –0.43795 | 0.058966 | –7.4272 | <0.0001*** |
| 1 | –0.23049 | 0.06315 | –3.6499 | 0.000269*** |
| 2 | –0.06331 | 0.063586 | –0.9957 | 0.319539 |
| 3 | –0.07561 | 0.046918 | –1.6115 | 0.107235 |
| 4 | 0.408712 | 0.047236 | 8.6526 | <0.0001*** |
| 5 | –0.46814 | 0.048847 | –9.5839 | <0.0001*** |
| 6 | –0.03806 | 0.044646 | –0.8525 | 0.394069 |
| 7 | –0.59815 | 0.046773 | –12.7883 | <0.0001*** |
| 8 | 0.143964 | 0.054563 | 2.6385 | 0.008395** |
| 9 | 0.270409 | 0.044406 | 6.0894 | <0.0001*** |
| 10 | 0.182388 | 0.041479 | 4.3972 | <0.0001*** |
| 11 | –0.54799 | 0.049127 | –11.1546 | <0.0001*** |
| **Variable** | **Estimate** | **Std. Error** | **t value** | **Pr(>\|t\|)** |
| *x*1 | –0.00281 | 0.001115 | –2.5214 | 0.011772* |
| *x*2 | 0.000944 | 0.000776 | 1.2165 | 0.223952 |
| *x*3 | –0.02952 | 0.014961 | –1.973 | 0.048645* |
| *x*4 | 0.057935 | 0.011664 | 4.9669 | <0.0001*** |
| *x*1:Post | 0.002637 | 0.001189 | 2.2175 | 0.026707* |
| *x*2:Post | 0.000276 | 0.000808 | 0.3421 | 0.732308 |
| *x*3:Post | –0.00291 | 0.008635 | –0.3368 | 0.73633 |
| *x*4:Post | –0.0084 | 0.015216 | –0.5519 | 0.581114 |

*Note*: Unweighted plm estimates reported with Driscoll–Kraay (SCC, maxlag = 12). Window binned to [–9, +11]; reference period is $k = –1$ (omitted). HAC estimators in plm are not implemented for weighted panels; these are robustness checks to the weighted main spec. Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

**Table C11.** Event-study (Treat × Relative month) with covariates (*x*1–*x*4) and post interactions; two-way FE; Panel Newey–West SEs (Unweighted plm)

| k (months from Feb–2022) | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| –9 | –0.00405 | 0.046471 | –0.0872 | 0.93051 |
| –7 | 0.189553 | 0.132397 | 1.4317 | 0.15239 |
| –6 | –0.28048 | 0.137075 | –2.0462 | 0.04088* |
| –4 | 0.158774 | 0.256249 | 0.6196 | 0.53559 |
| –3 | 0.058127 | 0.147086 | 0.3952 | 0.69275 |
| –1 | 0.084309 | 0.19411 | 0.4343 | 0.66409 |
| 0 | –0.43795 | 0.177783 | –2.4634 | 0.01385* |
| 1 | –0.23049 | 0.441223 | –0.5224 | 0.60145 |
| 2 | –0.06331 | 0.389387 | –0.1626 | 0.87086 |
| 3 | –0.07561 | 0.233218 | –0.3242 | 0.74582 |
| 4 | 0.408712 | 0.24782 | 1.6492 | 0.09927. |
| 5 | –0.46814 | 0.434289 | –1.078 | 0.28119 |
| 6 | –0.03806 | 0.386686 | –0.0984 | 0.92161 |
| 7 | –0.59815 | 0.426312 | –1.4031 | 0.16076 |
| 8 | 0.143964 | 0.52513 | 0.2742 | 0.784 |
| 9 | 0.270409 | 0.355866 | 0.7599 | 0.44743 |
| 10 | 0.182388 | 0.26644 | 0.6845 | 0.49372 |
| 11 | –0.54799 | 0.524259 | –1.0453 | 0.29603 |
| **Variable** | **Estimate** | **Std. Error** | **t value** | **Pr(>\|t\|)** |
| *x*1 | –0.00281 | 0.001214 | –2.3153 | 0.0207* |
| *x*2 | 0.000944 | 0.000914 | 1.0331 | 0.30171 |
| *x*3 | –0.02952 | 0.011598 | –2.5451 | 0.011* |
| *x*4 | 0.057935 | 0.031142 | 1.8603 | 0.06299. |
| *x*1:Post | 0.002637 | 0.001285 | 2.0518 | 0.04032* |
| *x*2:Post | 0.000276 | 0.000824 | 0.3353 | 0.73742 |
| *x*3:Post | –0.00291 | 0.010254 | –0.2836 | 0.77676 |
| *x*4:Post | –0.0084 | 0.03589 | –0.234 | 0.81504 |

*Note*: Unweighted plm estimates reported with Panel Newey–West (NW, maxlag = 12) standard errors. Window binned to [–9, +11]; reference period is *k* = –1 (omitted). HAC estimators in plm are not implemented for weighted panels; these are robustness checks to the weighted main spec. Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

# APPENDIX D. Generalized synthetic control estimates (average and event-time ATT)

**Table D1.** Generalized synthetic control (matrix completion) – average ATT on monthly HICP growth (Post-Feb 2022), two-way FE, nonparametric bootstrap, covariates *x*1–*x*4

| avg_ATT | SE | CI_low | CI_high |
|---|---|---|---|
| 0.004381 | 0.041853 | –0.06751 | 0.088976 |

**Table D2.** Generalized synthetic control (matrix completion) – event-time ATT on monthly HICP growth (Post-Feb 2022), two-way FE, nonparametric bootstrap, covariates *x*1–*x*4

| time_index | month | ATT | SE | CI_low | CI_high |
|---|---|---|---|---|---|
| 1 | 2019–01 | –0.10722 | 0.046794 | –0.18228 | –0.00273 |
| 2 | 2019–02 | –0.07397 | 0.045408 | –0.15801 | 0.019833 |
| 3 | 2019–03 | 0.203547 | 0.036326 | 0.112602 | 0.251773 |
| 4 | 2019–04 | 0.073081 | 0.032767 | 0.00369 | 0.12494 |
| 5 | 2019–05 | 0.062146 | 0.042768 | –0.0293 | 0.134578 |
| 6 | 2019–06 | 0.123982 | 0.047582 | 0.003981 | 0.198929 |

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**Table D2 (cont.).** Generalized synthetic control (matrix completion) – event-time ATT on monthly HICP growth (Post-Feb 2022), two-way FE, nonparametric bootstrap, covariates *x*1–*x*4

| time_index | month | ATT | SE | CI_low | CI_high |
|---|---|---|---|---|---|
| 7 | 2019–07 | –0.06458 | 0.059007 | –0.18149 | 0.041108 |
| 8 | 2019–08 | –0.01897 | 0.053593 | –0.11957 | 0.087923 |
| 9 | 2019–09 | 0.047299 | 0.053465 | –0.07513 | 0.137115 |
| 10 | 2019–10 | 0.014979 | 0.035065 | –0.04798 | 0.082775 |
| 11 | 2019–11 | –0.01555 | 0.039552 | –0.091 | 0.057856 |
| 12 | 2019–12 | –0.01514 | 0.046671 | –0.09903 | 0.085448 |
| 13 | 2020–01 | –0.05516 | 0.059467 | –0.16305 | 0.069933 |
| 14 | 2020–02 | –0.15672 | 0.042259 | –0.22259 | –0.0668 |
| 15 | 2020–03 | 0.171777 | 0.047813 | 0.063924 | 0.251299 |
| 16 | 2020–04 | –0.02141 | 0.077833 | –0.1545 | 0.12834 |
| 17 | 2020–05 | 0.126541 | 0.056066 | 0.004018 | 0.213825 |
| 18 | 2020–06 | –0.00287 | 0.048619 | –0.09622 | 0.086722 |
| 19 | 2020–07 | –0.06008 | 0.069928 | –0.18503 | 0.101432 |
| 20 | 2020–08 | 0.028365 | 0.046369 | –0.05653 | 0.13056 |
| 21 | 2020–09 | 0.004955 | 0.058924 | –0.12659 | 0.104794 |
| 22 | 2020–10 | 0.064048 | 0.028844 | 0.000357 | 0.116811 |
| 23 | 2020–11 | 0.0186 | 0.047958 | –0.07123 | 0.114289 |
| 24 | 2020–12 | –0.08475 | 0.039691 | –0.15349 | 0.003407 |
| 25 | 2021–01 | –0.10859 | 0.064423 | –0.21456 | 0.042722 |
| 26 | 2021–02 | –0.08977 | 0.034669 | –0.1491 | –0.01561 |
| 27 | 2021–03 | 0.128137 | 0.049019 | 0.030187 | 0.215489 |
| 28 | 2021–04 | 0.09967 | 0.03237 | 0.023082 | 0.150735 |
| 29 | 2021–05 | 0.038257 | 0.03266 | –0.02353 | 0.100104 |
| 30 | 2021–06 | 0.072763 | 0.029931 | 0.013256 | 0.129305 |
| 31 | 2021–07 | –0.06246 | 0.05337 | –0.16201 | 0.040432 |
| 32 | 2021–08 | –0.00794 | 0.049259 | –0.09488 | 0.089409 |
| 33 | 2021–09 | –0.06805 | 0.061042 | –0.19471 | 0.044328 |
| 34 | 2021–10 | –0.00121 | 0.047267 | –0.0967 | 0.08171 |
| 35 | 2021–11 | –0.07154 | 0.042828 | –0.14455 | 0.023772 |
| 36 | 2021–12 | –0.07523 | 0.044299 | –0.15085 | 0.030483 |
| 37 | 2022–01 | –0.11375 | 0.066624 | –0.23886 | 0.01364 |
| 38 | 2022–02 | –0.30393 | 0.167915 | –0.60232 | 0.061824 |
| 39 | 2022–03 | –0.36594 | 0.425393 | –1.15951 | 0.472104 |
| 40 | 2022–04 | 0.106898 | 0.376987 | –0.63977 | 0.817663 |
| 41 | 2022–05 | –0.11742 | 0.24931 | –0.57547 | 0.354001 |
| 42 | 2022–06 | 0.37606 | 0.214821 | –0.02143 | 0.785617 |
| 43 | 2022–07 | –0.39408 | 0.405281 | –1.19051 | 0.404335 |
| 44 | 2022–08 | 0.092668 | 0.389689 | –0.5691 | 0.942769 |
| 45 | 2022–09 | –0.81532 | 0.394888 | –1.4575 | 0.159699 |
| 46 | 2022–10 | 0.077579 | 0.524883 | –0.96148 | 1.111765 |
| 47 | 2022–11 | 0.299425 | 0.294404 | –0.24049 | 0.896039 |
| 48 | 2022–12 | 0.271532 | 0.268473 | –0.25154 | 0.820648 |
| 49 | 2023–01 | –0.29027 | 0.337072 | –0.95173 | 0.327159 |
| 50 | 2023–02 | –0.2434 | 0.117763 | –0.46015 | –0.00623 |
| 51 | 2023–03 | 0.397406 | 0.211613 | 0.003603 | 0.840163 |
| 52 | 2023–04 | 0.309798 | 0.182234 | –0.01996 | 0.697955 |
| 53 | 2023–05 | 0.076593 | 0.197985 | –0.26479 | 0.466727 |
| 54 | 2023–06 | 0.524211 | 0.204819 | 0.131536 | 0.912587 |
| 55 | 2023–07 | –0.22641 | 0.249073 | –0.75184 | 0.178979 |
| 56 | 2023–08 | 0.310795 | 0.226067 | –0.14993 | 0.748038 |
| 57 | 2023–09 | 0.316058 | 0.297116 | –0.19882 | 0.930505 |
| 58 | 2023–10 | –0.02461 | 0.126118 | –0.28394 | 0.23624 |
| 59 | 2023–11 | –0.37223 | 0.151661 | –0.66418 | –0.07276 |
| 60 | 2023–12 | –0.19339 | 0.158006 | –0.50473 | 0.083943 |

**Table D2 (cont.).** Generalized synthetic control (matrix completion) – event-time ATT on monthly HICP growth (Post-Feb 2022), two-way FE, nonparametric bootstrap, covariates *x*1–*x*4

| time_index | month | ATT | SE | CI_low | CI_high |
|---|---|---|---|---|---|
| 61 | 2024–01 | –0.39557 | 0.175128 | –0.80183 | –0.10124 |
| 62 | 2024–02 | –0.18698 | 0.15269 | –0.51392 | 0.093703 |
| 63 | 2024–03 | 0.687609 | 0.263263 | 0.234989 | 1.218632 |
| 64 | 2024–04 | 0.367316 | 0.116335 | 0.16449 | 0.629676 |
| 65 | 2024–05 | 0.185699 | 0.123626 | –0.03856 | 0.455706 |
| 66 | 2024–06 | 0.184368 | 0.11833 | –0.05159 | 0.422153 |
| 67 | 2024–07 | –0.25058 | 0.206944 | –0.74012 | 0.04179 |
| 68 | 2024–08 | 0.125553 | 0.142923 | –0.16659 | 0.396868 |
| 69 | 2024–09 | 0.247322 | 0.305076 | –0.31211 | 0.864925 |
| 70 | 2024–10 | –0.2064 | 0.119502 | –0.45686 | 0.024991 |
| 71 | 2024–11 | –0.2111 | 0.228871 | –0.6478 | 0.224496 |
| 72 | 2024–12 | –0.15228 | 0.132715 | –0.37856 | 0.146024 |
| 73 | 2025–01 | –0.65749 | 0.232834 | –1.08878 | –0.18058 |
| 74 | 2025–02 | –0.54893 | 0.136161 | –0.80383 | –0.30495 |
| 75 | 2025–03 | 0.656303 | 0.267631 | 0.16617 | 1.173111 |
| 76 | 2025–04 | 0.216965 | 0.1605 | –0.07362 | 0.56576 |
| 77 | 2025–05 | 0.106622 | 0.135883 | –0.17511 | 0.341451 |
| 78 | 2025–06 | 0.199188 | 0.143818 | –0.09527 | 0.458511 |

*Note*: Treatment $D_{it}$ = 1 for treated countries from Feb 2022 onward; factor dimension chosen by CV ($\lambda^*$ = 0.178); inference by nonparametric bootstrap; controls *x*1–*x*4 included; unit and time fixed effects.


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