

Renewable energy supply shocks from wind electricity*

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Abstract

This paper identifies electricity supply shocks by exploiting the fact that variations in wind speed at turbine locations are exogenous with respect to macroeconomic outcomes and drive electricity prices in European wholesale markets inframarginally. Instrumenting electricity price changes with these wind supply shocks, I find that higher electricity prices raise inflation and reduce electricity use as expected, but generate surprising effects on economic activity. Unemployment rises, but industrial production also rises over time, and the effect on GDP is negligible. As these effects differ markedly from the impact of oil price shocks, they suggest that as economies electrify and shift electricity generation toward renewables, business cycle dynamics may persistently change.

JEL codes: E31, E32, Q42, Q43.

Keywords: Business Cycle, Prices, Energy Supply, Energy Shocks, Wind Energy.

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1 Introduction

Advanced economies are undergoing a fundamental energy transition that shifts economic activity from fossil fuels toward electricity through widespread electrification of transport, heating, and industrial processes. Globally, the electricity share in total energy demand is projected to nearly double from approximately 20% today to 34% by 2050, with the US projected to reach 40% and the EU 50% (International Energy Agency, 2024). As electricity demand rises while fossil fuel consumption declines, electricity becomes an increasingly important supply input across the economy. While the supply shock literature has focused primarily on transport disruptions and fossil fuels, electricity supply shocks may operate through mechanisms that are less well understood, especially as generation increasingly relies on intermittent renewables.¹ This paper asks how supply shocks to electricity affect the economy and whether they operate through fundamentally different transmission mechanisms than traditional fossil fuel shocks.

There are several challenges to identifying exogenous electricity supply shocks for causal analysis. First, electricity prices reflect variations in both supply and demand, making it difficult to isolate supply-side effects. Second, while electricity prices differ across countries, they also co-move significantly because fossil inputs as marginal generation sources are traded on global markets, such that much of the price variation is across time, not just space. Third, since electricity is typically generated by multiple sources simultaneously, an electricity price increase is hard to distinguish from broader energy market developments such as spikes in gas or oil prices.

This paper overcomes these challenges by constructing electricity supply shocks from variations in wind speeds at turbine locations. According to merit order pricing in wholesale markets, wind and other renewable generation is used to satisfy electricity demand first, such that changes in wind electricity generation shift the entire electricity supply curve. However, exploiting this inframarginal role requires addressing any confounding effects of wind on electricity demand. While wind itself has limited direct effects on demand apart from extreme fluctuations, it exhibits significant seasonal variations that coincide with demand patterns and correlates negatively with temperature, which affects electricity demand through heating and cooling needs.

To isolate supply-relevant variation, I construct shocks from wind speeds at turbine locations weighted by their capacity, controlling for patterns in electricity demand. This

¹See Känzig (2021), Känzig (2023) and Bai et al. (2024) for empirical contributions, amongst others.

approach focuses on wind which is used for electricity supply, but controls for seasonal fluctuations in demand and wind in non-generating areas to capture any common demand effects that are constant across space. I validate this approach using alternative identification strategies, relying on wind only at offshore turbines or using national wind speeds and controlling for demand impacts explicitly. The resulting wind electricity supply shocks provide strong instruments for wholesale electricity price changes in countries with significant wind electricity shares, but especially in a cross-country panel, while passing conventional diagnostic checks for shocks.

I use these wind supply shocks to examine the macroeconomic effects of electricity price changes across a panel of 17 European countries from 2015 to 2024.² The focus on Europe is motivated by three factors: rapid expansion of renewable capacity, significant reliance on wind generation with substantial variation across countries, and distinct national electricity markets that provide identifying variation. I estimate standard instrumental variable local projections to determine the dynamic effects on key macroeconomic variables, then explore the drivers of these responses and compare them with oil price shock effects.

The results show significant and persistent passthrough from wholesale electricity prices to both energy and non-energy prices, consistent with the electricity weight in consumption baskets. However, this transmission varies markedly across countries due to varying retail contract structures.

More surprisingly, the effects on macroeconomic activity do not follow classic supply shock predictions. While unemployment initially rises and electricity consumption stays flat, industrial production exhibits significant positive responses at longer horizons instead of the expected negative effects, and real GDP remains largely unaffected. These effects are driven primarily by smaller price changes and not explained by the recent energy crisis.

Electricity differs structurally from fossil fuels in three key ways: First, while fuel prices are determined globally, electricity generation relies on them only partly and hence electricity prices vary significantly between countries depending on the electricity generation mix. Second, while oil prices adjust flexibly with quick passthrough to consumer prices such as petrol, electricity prices for consumers are much less flexible. Depending on contract conventions and end-user consumption volumes, retail electricity prices may

²The countries with consistently available data for the sample period are: Austria, Belgium, Croatia, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, the Netherlands, Poland, Portugal, Romania, Spain, and Sweden.

either track wholesale prices closely or remain fixed over extended periods. Third, electricity is generated with both dispatchable and non-plannable intermittent renewables, generating higher price volatility particularly at high frequency, compared to the relatively stable supply of most fuels which are easily storable.

The structural differences between electricity and fuels translate into different macroeconomic effects, highlighting how the energy transition will alter business cycle dynamics. Electricity and oil shocks generate similar price impacts proportional to their expenditure weights, but differ in persistence and implications for economic activity, as unemployment reacts in different directions and industrial production responds persistently positively to electricity price increases. As the composition of energy supply shocks shifts from fossil fuels toward electricity, macroeconomic responses to energy disruptions will likely change substantially. Additionally, while this analysis focuses on unit price changes, the energy transition may also increase electricity price volatility due to greater reliance on intermittent renewable sources.

Literature This paper’s main contribution to the literature is identifying supply shocks specific to electricity prices, using variation in renewables rather than relying on fossil fuel market instruments, expanding the toolbox of cost-push shocks in macroeconomics.

The existing literature on energy supply shocks focuses almost exclusively on oil prices, typically identified using structural vector autoregression (SVAR) models with various identifying assumptions. Early contributions used oil production shortfalls to instrument oil prices (Hamilton, 2003), later replaced by Kilian’s (2008) influential exogenous oil supply shocks identified using OPEC production data. To differentiate explicitly between oil supply and demand shocks, Baumeister and Hamilton (2019) employ Bayesian VARs reflecting uncertainty about identifying assumptions in the structural model. Känzig (2021) identifies oil supply news shocks from high-frequency movements in oil futures around OPEC announcements. Other energy supply shocks concern fossil fuels, particularly natural gas. Casoli, Manera and Valenti (2022) and Boeck and Zörner (2023) use different identifying restrictions in VARs to recover gas supply shocks and study their effects on inflation and expectations, while Alessandri and Gazzani (2023) construct high-frequency supply shocks from European gas market news. Kilian and Zhou (2023) analyse different energy products in the US and identify shocks jointly through sign restrictions, and Ganepola, Shubita and Lee (2023) use natural gas prices and supply to the UK as supply factors determining electricity prices.

Theoretical literature has recently revealed that supply shocks can yield demand-like aggregate responses under certain conditions, such as cross-sectoral elasticities, incomplete markets, and the heterogeneity of economic agents (Cesa-Bianchi and Ferrero, 2021, Guerrieri et al., 2022, Kharroubi and Smets, 2024). These insights highlight that when estimating empirically, the effects depend critically on the scope of the disruption, the selectivity of impacts across agents, heterogeneity across sectors, and the speed of transmission through different market segments. I contribute by providing electricity shocks which speak to all of those dimensions and exhibit partially demand-like effects, as they are particularly prone to generating Keynesian supply shock effects given electricity’s low substitutability in production.

While renewables have previously been exploited for their role in driving prices, existing literature in energy economics largely focuses on the effects of generated renewable electricity on prices at high frequency. Many papers examine Germany as an early European promoter of non-fossil electricity. Sensfuß, Ragwitz and Genoese (2008) analyse renewable electricity generation effects on German wholesale prices, including welfare and policy analysis of support payments. Cludius et al. (2014) evaluate German renewable energy promotion policies, while Maciejowska (2020) uses quantile analysis to study nonlinear price effects of wind and solar generation. Most recently, Hirth, Khanna and Ruhnau (2024) use wind electricity generation as instrument for electricity prices to elicit demand elasticity, and Liebensteiner, Ocker and Abuzayed (2025) use imports of wind-generated electricity, each at hourly frequency. Additional studies have expanded to other countries and examined asymmetric generation effects on prices.³ I contribute by exploiting this relationship directly with wind speeds at generation sites and providing a plausible exogenous supply instrument for prices at lower frequency for macroeconomic analysis. Using exogenous weather independent of capacity investment decisions ensures isolating supply components for macroeconomic analysis.

Lastly, a substantial literature also uses weather variables as instruments in a variety of settings in economics not restricted to energy or macroeconomics. Weather has been used to study both energy production and prices,⁴ as well as energy demand and con-

³Examples include Mulder and Scholtens (2013) on wind’s role in Dutch electricity prices, Csereklyei, Qu and Ancev (2019) for Australia, Woo et al. (2016) for the US, Tselika, Tselika and Demetriades (2024) on asymmetric wind effects in Denmark and Sweden, and Nibedita and Irfan (2022) on asymmetric effects in Indian wholesale markets.

⁴Examples include Fisher-Vanden, Mansur and Wang (2015) on extreme weather impacts on electricity production, Heinen, Khadan and Strobl (2019) on consumer prices, Ito and Reguant (2016) on wind farm output, and Natalini, Bravo and Newman (2020) on energy price conflict repercussions.

sumption.⁵ Weather instruments have also been applied to non-energy issues such as health and voting.⁶ To ensure that the exclusion restriction holds in my setting, I use regional variation in wind over-weighting supply-relevant locations to construct national shocks based on the relevantly exogenous variation.

The paper proceeds as follows. Section 2 introduces wind as relevant determinant of electricity prices by detailing market structures. Section 3 presents the construction and evaluation of exogenous wind electricity supply shocks. Section 4 employs the shock as instrument to analyse electricity price change effects on other prices, economic activity, and heterogeneity across shock characteristics. Finally, section 4.4 compares electricity and oil price shocks in terms of their characteristics and macroeconomic effects.

2 Electricity markets in Europe

2.1 The importance of electricity

Electrification is increasing electricity's share in firm production costs and household expenditures, including the adoption of heat pumps, electric vehicles, industrial automation, and the rise of data-intensive industries. Although electricity represents a significant but moderate average share in consumption baskets at 3%, wholesale electricity prices correlate strongly with overall inflation (figure C.1). Electricity is upstream to virtually all sectors, while exposure varies dramatically, with the share of electricity in energy use ranging from 6% in construction to 59% in information and communication.

Electricity can hence speak to several dimensions of supply shock complexity discussed in theoretical literature. It is an important factor in production such that supply shocks present significant disruptions, it has selective impacts across households and firms, heterogeneity across sectors, and varying speed of transmission by market segment. Storage of electricity is limited such that it must be produced and consumed almost simultaneously, making supply disruptions immediately visible in wholesale prices. The shift toward renewable generation sources like wind also changes the nature of these

⁵See Considine (2000) on climate effects on energy demand and carbon emissions, Lee and Chiu (2011) on temperature effects on electricity demand, Nguyen and Vo (2020) on fuel consumption, and Atalla, Bigerna and Bollino (2018) on energy demand elasticities.

⁶Examples include Fan and Wang (2020) analysing health outcomes of coal plant closures using temperature instruments, and Stokes (2016) using wind mill proximity as exogenous variation in voting behaviour against climate policies.

shocks, introducing intermittency and different price dynamics than fossil fuel-based systems.

2.2 The merit order principle

Wholesale markets within the EU are organised according to bidding zones, the largest areas within which electricity can be traded without capacity allocations, sharing a common wholesale price. These zones largely coincide with national borders with some exceptions.⁷

Most wholesale electricity trading occurs through long-term pre-purchase agreements, while short-term deviations from expected demand and supply drive the remaining trading on spot markets. I focus on the day-ahead section as most liquid spot market, where providers buy and sell electricity for the following day in short windows based on expected production and consumption profiles.

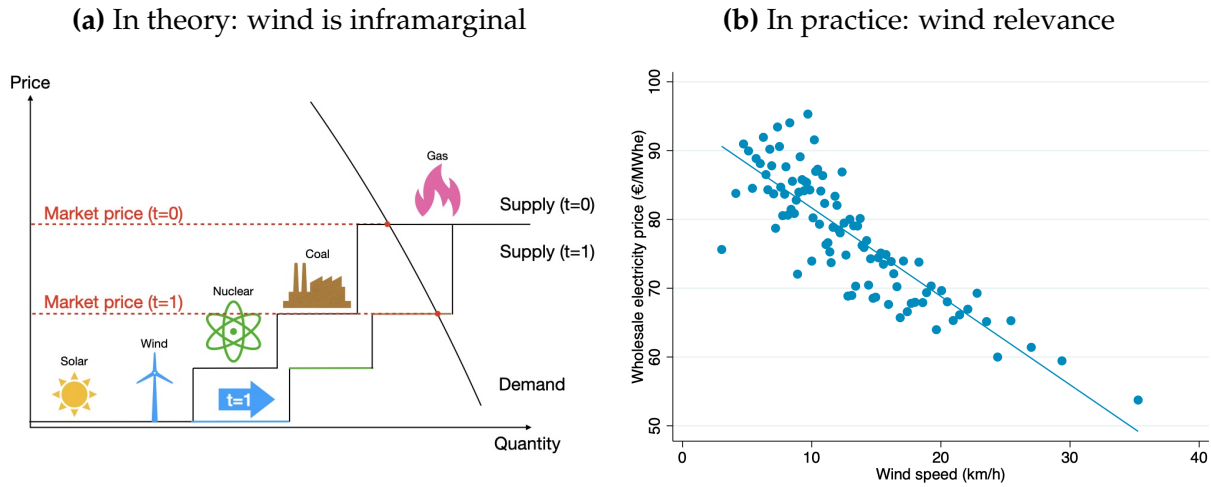
Within each bidding zone, wholesale electricity prices are directly affected by renewable electricity generation through the merit order pricing principle. The merit order stipulates that electricity is sourced from providers in ascending order of marginal costs until demand is met, as shown in figure 1a. The market price is determined by the last producer required to satisfy demand, with the highest marginal cost setting the market price. Renewables have near-zero marginal costs and are therefore always used first to satisfy electricity demand.

2.3 The role of wind

Wind electricity is inframarginal for wholesale market prices: when more wind electricity is generated, the near-zero portion of the supply curve extends outward, shifting steeper sections with increasing marginal costs from non-renewables to the right, as illustrated in figure 1a. Increased wind electricity thus reduces market prices by replacing higher-cost non-renewable generation. This inframarginal role can be observed in practice as a strong negative correlation between daily national wind speeds and wholesale prices in figure 1b. When renewable electricity supply is abundant, daily prices approach zero and intra-day prices can become negative. Conversely, when wind speeds are low, market prices

⁷Within the sample, Germany-Luxembourg forms a cross-border zone, Italy is divided into nine separate bidding zones, Sweden into four, Denmark into two. Portugal and Spain are separate but effectively integrated with almost identical prices.

Figure 1: Merit order pricing in wholesale electricity markets



Note: Panel a) shows a stylised illustration of demand and supply in wholesale electricity markets for bidding zones in the EU. The supply function has the distinctive feature of large step sizes between different electricity generation sources, but in reality will have small differences of marginal costs between generators within a particular source. Panel b) shows the relationship between daily national average wind speeds and the wholesale electricity day-ahead price across sample countries in a binscatter plot with 100 quantiles.

are determined by marginal non-renewable generation.

Since wind represents 21% of electricity generation on average and is projected to increase further, price effects can be sizeable but vary by country according to wind reliance. The quantitative impact also depends on current market conditions and supply curve position. When demand is fully satisfied by renewables, additional wind has minimal price impact. However, when equilibrium requires significant fossil fuel generation, the effect can be large if additional wind changes the marginal source or marginal costs are convex at high levels, creating asymmetric effects.

2.4 Wholesale and retail prices

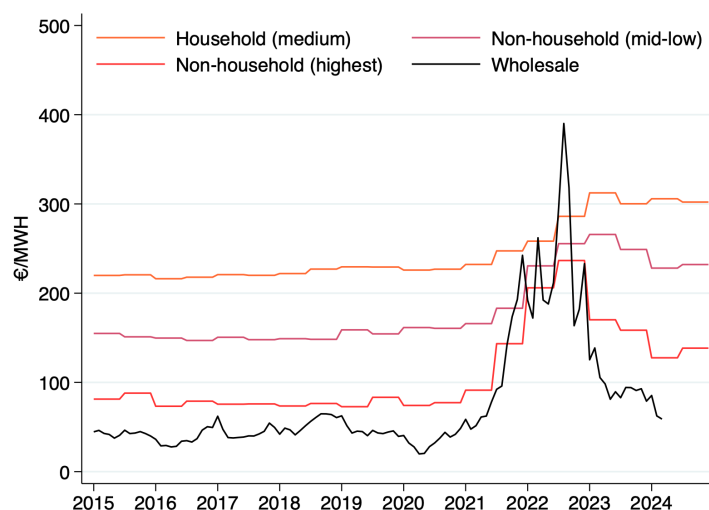
Studying retail rather than wholesale electricity prices might be preferable, as retail prices directly affect outcomes and decisions. However, consistent cross-country retail price data is unavailable at high frequency and published only semi-annually by Eurostat. The HICP electricity is an imperfect proxy for retail prices since its construction varies in the treatment of new and existing contracts across countries and time.

Passthrough from wholesale to retail prices varies substantially across countries and consumer types (see appendix figure C.2). Household prices are typically higher and

more stable than firm prices due to taxes and distribution charges, with cross-country differences reflecting varying contract structures and regulatory frameworks.⁸ Firm prices relate closely to wholesale prices across all countries, particularly for high-consumption bands, with the largest industrial consumers participating directly in wholesale markets. See average prices in figure 2.

Given superior data availability and the close relationship between wholesale and firm retail prices, I focus on wholesale price changes. Consumers experience these changes through electricity bills with varying lags depending on country- and volume-specific contract standards, so initial responses should be driven primarily by large commercial consumers and only a subset of households.

Figure 2: Wholesale and retail electricity prices



Note: The figure shows the development of wholesale and retail prices for selected electricity consumer groups on average across sample countries. Retail prices are available only bi-annually from Eurostat. Household prices in red (medium band DC, 2,500 kWh to 4,999 kWh); mid-low consumption non-household prices in blue (industry, services, offices, agriculture, etc; mid-low band IC, 500 MWh to 1,999 MWh), high-consumption non-household prices in purple (highest band IG, 150,000 MWh or over), all including any taxes and levies, and wholesale prices in black.

⁸For example, Germany has standard 12-month household price guarantees, leading to delayed price adjustment.

3 Wind electricity supply shocks

Using wind as a supply shock to electricity prices in a macroeconomic context presents one key challenge: eliminating confounding demand effects. The resulting shock series must isolate wind variation that drives wholesale price changes while remaining orthogonal to macroeconomic effects unrelated to electricity prices. Wind itself is unlikely to have strong direct demand effects on electricity or general consumption, particularly excluding extreme weather. However, wind exhibits strong seasonal patterns and significant negative correlations with temperature and solar radiation.⁹ While the relationship to electricity demand is not obvious, depending on heating and cooling needs across industries and consumers, such effects cannot be excluded.

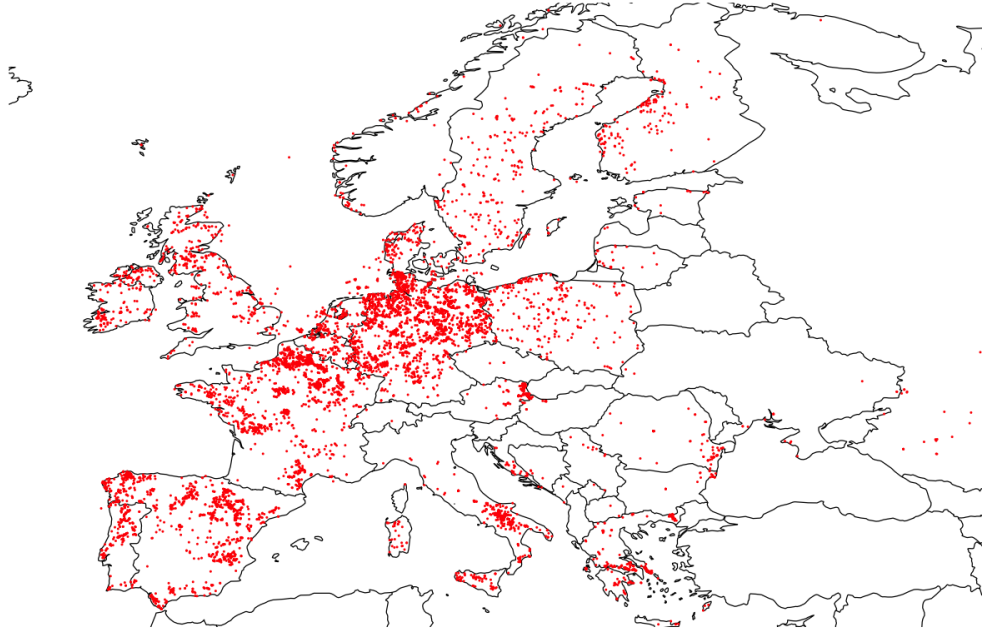
3.1 Shock construction

The approach exploits variation in wind within countries, focusing on locations of wind farms. I use locations of all operational wind farms exceeding 10MW capacity¹⁰ within sample countries, shown in appendix figure 3. These locations are provided by Global Energy Monitor using OpenStreetMap data. Since reliable time-varying capacity data at the turbine level is unavailable, locations and capacities are measured as of February 2025. The implications of this measurement choice for instrument strength and exogeneity, including further details on sources, selection, and limitations are discussed in appendix B.

⁹For example, temperature has been shown to affect trading behaviour and stock returns (Cao and Wei, 2005).

¹⁰10MW corresponds to approximately 3-5 onshore or 1-2 offshore turbines, servicing roughly 10,000-15,000 households annually.

Figure 3: Wind turbine farm locations above 10MW capacity



Note: Locations of wind turbine farms with installed capacity of at least 10MW across European countries. Data provided by the Global Wind Power tracker show installed capacity operational as of February 2025.

Construction of wind supply shocks proceeds in two steps. First, I match each wind farm to average monthly wind in its geographical 0.25° grid cell location over time from Copernicus ERA5. Generation-relevant wind is computed as the capacity-weighted average wind speed across all grid cells g within a country c containing at least 10MW installed wind capacity:

$$wind_{c,t}^{turbines} = \sum_g wind_{g,c,t} \times \frac{capacity_{g,c}}{\sum_g capacity_{g,c}} \quad (1)$$

Second, to control for highly seasonal patterns in electricity demand, I regress capacity-weighted wind at turbine locations on calendar month fixed effects $\eta_{c,m}$ separately by country. In addition, I control for wind in grid cells without wind turbines in the country, $wind_{c,t}^{else}$. If wind is similarly correlated with other weather conditions across space within a country or demand effects are constant across space, this should account for any additional demand effects not captured by constant seasonal patterns. The regression residual

constitutes the wind electricity supply shock:

$$wind_{c,t}^{turbines} = \alpha + \beta_c wind_{c,t}^{else} + \eta_{c,m} + \epsilon_{c,t}, \text{ such that } wind_{c,t}^{shock} \equiv \hat{\epsilon}_{c,t} \quad (2)$$

This approach isolates wind in electricity-generating locations, weighted by installed capacity to maximise instrument power while minimising demand contamination. It yields a monthly shock measure to correspond to the frequency of any outcome variables of interest but could similarly be constructed as a daily series.

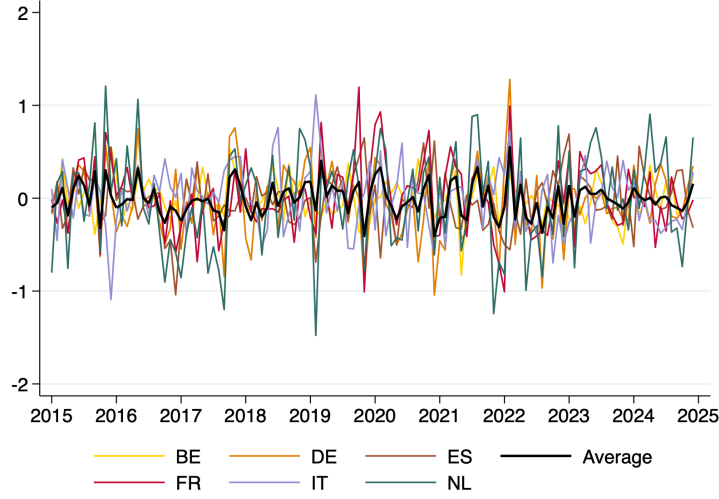
While electricity demand volumes affect wind shock impacts on prices – with smaller effects when demand is low and renewables sufficient – this influences instrument strength across market states without threatening exogeneity. Further, concerns about endogenous turbine installation in high-price locations are mitigated by using sub-national data within countries with national bidding zones and equalised prices.

I use wind speeds rather than wind electricity generation to construct electricity price shocks to avoid concerns about capacity build-up and market-based utilisation changes. While the energy literature normally relies on generation since the relationship with wind speeds is non-linear, generation capacity becomes endogenous over time and is therefore problematic for studying longer-horizon responses.

3.2 Diagnostics

The shocks exhibit no obvious patterns across countries or time, appearing closer to white noise, as expected for macroeconomic shock series. Appendix figure 4 shows the resulting average and country-specific shock series. Their variation is contained within 2km/h, avoiding dependence on extreme wind speed swings.

Figure 4: Wind electricity supply shocks by country



Note: Monthly wind electricity supply shocks as residuals from capacity-weighted turbine location wind speed controlling for wind speed in non-turbine locations as detailed in equation 2. Shown for the six largest countries in the sample and as simple average across all 21 countries.

Following Ramey (2016), I conduct several diagnostic tests to ensure the series constitutes a true shock. The national shocks exhibit only limited autocorrelation at one and two-month lags, which are included in any specifications assessing effects of instrumented electricity price changes. The shocks are not forecastable using macroeconomic or meteorological variables at the national level, confirming their exogenous nature. Additionally, the shocks show no significant correlation with other structural shocks. The correlation with Känzig (2021) oil supply news shocks is negative but small (-0.07) and insignificant, similar to correlations with other non-energy shocks such as Kerssenfischer (2022) monetary policy and information shocks.

3.3 Relevance

The first-stage specification regresses monthly wholesale price changes on the contemporaneous wind shock:

$$\Delta \log(p_{c,t}^{ws}) = \alpha + \beta wind_{c,t}^{shock} + \eta_c^h + \theta_t^h + \mu_{c,t} \quad (3)$$

I focus on price changes rather than levels to capture the higher volatility of wholesale electricity prices compared to other energy products, which makes changes more suitable for identifying shock impacts on macroeconomic variables.

In the panel, an additional km/h of excess wind in turbine locations decreases wholesale prices by 5.90pp compared to the previous month, as shown in table 1. In terms of standard deviations, this implies that a 1SD shock moves prices by 0.084 SDs. I evaluate instrument strength using F-statistics compared to the standard critical value of 10 for valid inference. The instrument is strong, even with conservative Driscoll-Kraay standard errors that account for both serial and cross-sectional dependence, resulting in an F-statistic of 22.

Table 1: Monthly first stage results by country and in cross-country panel

	BE	DE	ES	FR	IT	NL	Panel		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Wind shock	-2.53 (7.90)	-14.72*** (4.85)	-23.95*** (6.97)	-16.70*** (5.34)	0.06 (5.59)	-4.69 (3.05)	-8.25*** (1.48)	-5.90*** (1.01)	-5.90*** (1.26)
Observations	119	119	119	119	119	119	1945	1945	1945
R ²	0.001	0.069	0.087	0.065	0.000	0.018	0.014	0.570	0.014
Country FEs							Yes	Yes	Yes
Time FEs								Yes	Yes
F-statistic	0	9	12	10	0	2	31	34	22
Standard errors	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	DK

Note: The table shows results of the specification in equation (3). The dependent variable for all columns is the percentage change in wholesale prices from the previous month, restricted to the geography as indicated in the column headers. The wind shock coefficients represent the effect of 1km/h weighted turbine wind on the percentage point change in wholesale prices compared to the previous month. Standard errors in parentheses are computed as robust or as Driscoll-Kraay standard errors with 3 lags. See results for all countries in appendix table E.1. See for the persistence of effects appendix figure E.1.

Country-specific coefficient estimates are also negative, but instrument strength varies significantly. The instrument is strong in wind-reliant countries such as Germany and Spain and weak in countries with low shares of wind in electricity generation, such as Italy and Belgium.¹¹

The strength of the instrument improves over time and should increase further as the

¹¹See wind generation shares by country in figure C.3.

share of wind in electricity generation grows with the green energy transition.¹² Wind electricity provided less than 18% of electricity in Europe in 2023, but the International Energy Agency’s World Energy Outlook projects this share to reach 40% by 2035 and 46% by 2050.¹³

3.4 Robustness

To ensure robustness of results to the specific shock identification approach, I present two alternative shocks. Using either of these as instruments for electricity price changes yields broadly similar results to the baseline, although weaker in size and significance (figure E.13 and D.2).

One alternative relies exclusively on wind at offshore turbines, controlling for wind over the country’s land area. This method increases confidence in excluding direct demand effects, as offshore locations are unpopulated and cannot directly affect consumption behaviour. However, since offshore wind capacity is less than 10% of total wind capacity on average, offshore-only shocks have significantly reduced instrument power (table E.2).

The second alternative is to use national average wind speeds regardless of turbine locations. To remove weather-related demand effects, I construct surprises orthogonal to previous patterns in wind and contemporaneous temperature and solar radiation. This strategy yields shocks that provide strong instruments, but are correlated across countries.

To check sensitivity to the demand-related control, I drop wind in non-turbine cells or instead use national average wind when constructing the shock. The first and second stage are largely insensitive to these choices (table E.3, figure E.14), suggesting limited demand effects. Appendix figure C.4 further shows locations of wind turbines and population density for the example of Germany, with a small negative correlation between turbine density and population around major cities.

As a placebo test, I apply the baseline identification strategy to countries excluded from the sample due to their lack of installed wind turbines. Slovenia and Slovakia both have no installed wind generation capacity, such that wind in these countries has no explanatory power for changes in electricity prices, with a first-stage F-statistic below

¹²See table E.4 for the first stage by subsample, showing increasing effect magnitude and instrument strength.

¹³See figure C.5.

one. Appendix figure E.15 shows impulse responses using average wind over the land area, producing insignificant estimates around zero for the main variables of interest and confirming that wind has no significant demand impact generating macroeconomic responses.

Since the sample includes the European energy crisis triggered by Russia's invasion of Ukraine in February 2022, I test whether results are robust to excluding this period. The crisis presented a severe disruption of energy markets and prompted unprecedented fiscal policy interventions to protect consumers and businesses from extreme electricity prices, though the scope and design of interventions varied significantly across countries. The disruption heightened attention to electricity prices, while policy responses weakened passthrough from wholesale to retail prices. The main findings are not driven by the crisis period, suggesting they reflect structural features of electricity markets rather than extraordinary circumstances. Instead, responses during the crisis are closer to theoretical predictions than during the pre-period (figure E.6).

4 Causal macroeconomic effects of electricity prices

Having established the relevance and validity of wind shocks as instruments, I now use them to isolate exogenous variation in electricity price changes and study their effects on other prices, macroeconomic activity, and energy markets. To capture the dynamic causal effects, I estimate impulse responses using instrumental variable local projections as proposed by Jordà, Schularick and Taylor (2015) for different outcome variables $y_{c,t}$ in the cross-country panel.

$$\log(y_{c,t+h}) = \alpha^h + \beta^h \Delta \log(p_{c,t}^e) + \sum_{l=1}^2 \gamma_l^h \log(y_{c,t-l}) + \sum_{l=1}^2 \delta_l^h \Delta \log(p_{c,t-l}^e) + \eta_c^h + \theta_t^h + \psi^h i_{c,t} + \epsilon_{c,t+h} \quad (4)$$

The coefficient of interest, β^h , captures the impact of a one percentage point (pp) change in electricity prices on the outcome $y_{c,t+h}$ at horizon h months ahead. It shows an average effect across countries during the sample period from 2015–2024.

As controls, I include two lags of the dependent and independent variables to account for remaining autocorrelation in the shock series and persistence in outcome variables. Country fixed effects η_c^h control for systematic differences in outcomes across countries,

and time fixed effects η_t^h account for any common shocks, such that the remaining variation is across countries in each month. To account for differences in monetary policy reactions between countries in or outside of the EA, I also control for the policy rate $i_{c,t}$.¹⁴

Alternative shock measures, outcomes, and reduced-form results are presented in appendix E.

4.1 Average macroeconomic effects

This section presents the main results from instrumenting electricity price changes with wind shocks in the European panel, examining their transmission through prices and effects on economic activity in figures 5 and 6, revealing two key findings. First, electricity price shocks propagate through energy markets and have modest but persistent effects on general price levels, with initial effects giving way to second-round adjustments as rigid pricing structures eventually respond. Second, the effects on economic activity present a complex pattern defying expectations for supply shocks: unemployment initially increases as expected, but industrial production reacts significantly positively at longer horizons after an initial decline, while GDP effects remain insignificant.

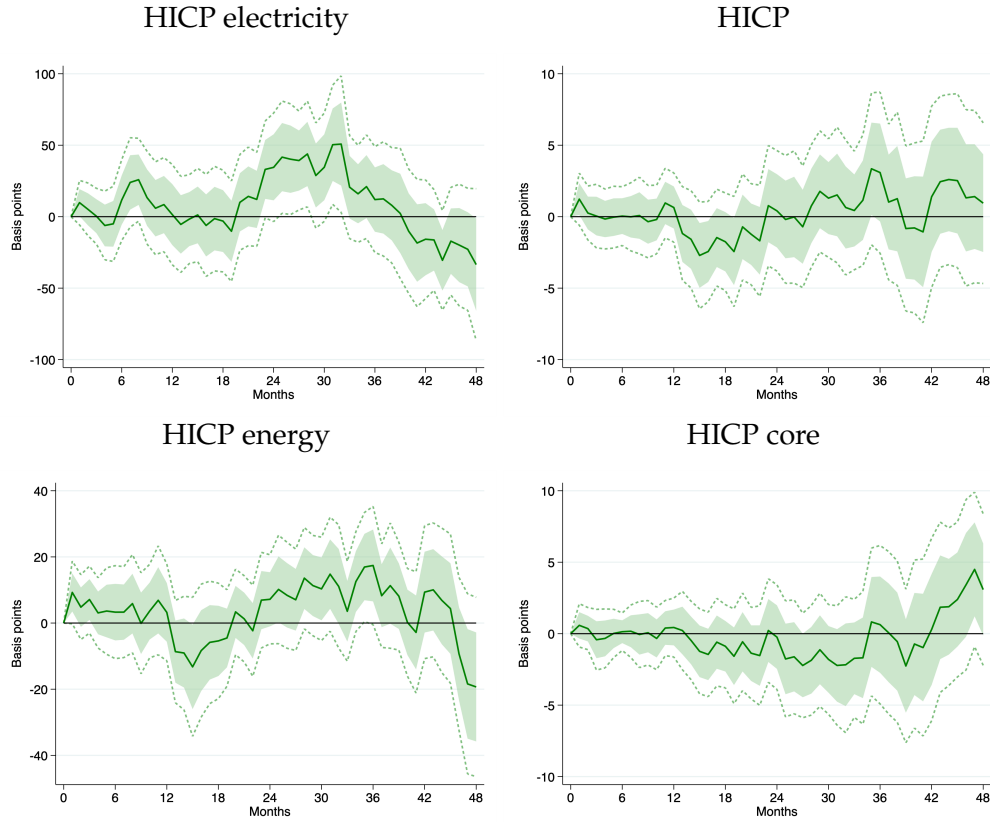
Following a 1pp wholesale price increase, HICP electricity shows a complex pattern of transmission over a four-year horizon. The response peaks at 25 basis points (bp) after six months, declines through month 12, then exhibits a second rise around months 18-24 before gradually falling. This pattern reflects the complex transmission from wholesale to retail prices, highlighting how contractual rigidities and regulatory structures insulate consumers from wholesale price volatility on average, as discussed in section 2.4. While the individual point estimates are rarely statistically significant, the persistent positive responses over the first two years suggest economically meaningful passthrough.

The general consumer price level shows an initial marginally significant increase of up to 2bp in the first quarter, slightly below electricity's 3% average expenditure weight. This immediate response fades during the first year, with the price level more likely to decline than rise in the second year, suggesting that any initial inflationary pressure from electricity shocks dissipates relatively quickly. Prices increase again during the third year when HICP electricity and rigid retail prices adjust.

Electricity price changes create broader energy market effects that persist longer than retail electricity price impacts. HICP energy shows robust and significant responses, with

¹⁴See Miyamoto, Nguyen and Sergeyev (2024) for how monetary policy can impact the effect of oil supply shocks.

Figure 5: Effects of wholesale electricity price changes on other prices

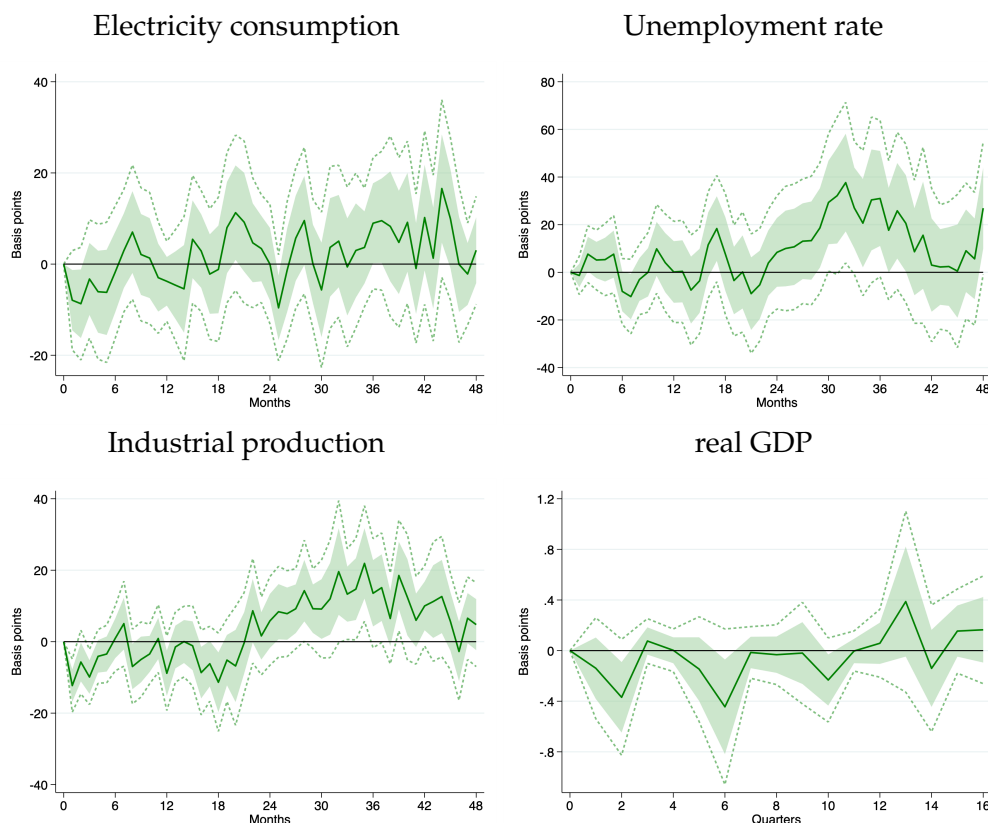


Note: Impulse responses to 1-month wholesale electricity price changes instrumented by wind shocks. Local projection estimated in the panel with country and time fixed effects, 2 lags, and Driscoll-Kraay standard errors with 3 lags, according to equation (4). Error bands represent 68% and 90% confidence intervals.

consistent increases up to 10bp maintained throughout the first year before reversing during the second year. This pattern indicates strong transmission through wholesale energy markets even when retail electricity prices show limited average passthrough. Second round effects likely through adjusting retail prices are also visible for energy prices and persist into year four.¹⁵

The spillover effects extend beyond energy markets, affecting broader price dynamics. Core HICP (excluding energy and food) initially increases by 1bp following electricity price rises, suggesting meaningful transmission to non-energy prices despite the small magnitudes. While these core price effects are not statistically significant, their pattern aligns with an initial passthrough and later spillovers from adjusted retail electricity prices in the fourth year after the shock.

Figure 6: Effects of electricity price changes on economic activity



Note: Impulse responses to 1-month wholesale electricity price changes instrumented by wind shocks. Local projection estimated in the panel with country fixed effects, 2 lags, and Driscoll-Kraay standard errors with 3 lags, according to equation (4). Error bands represent 68% and 90% confidence intervals.

¹⁵Coal and gas prices also rise, see appendix figure E.4.

Electricity supply shocks generate complex effects on economic activity that fundamentally diverge from theoretical predictions. Figure 6 reveals a nuanced pattern where initial responses consistent with supply shock theory give way to sustained positive effects that challenge standard economic intuition.

Electricity consumption initially shows the expected negative response to higher prices, declining by up to 7bp during the first year. However, this response is not persistent despite lagged retail price increases. The unemployment rate exhibits the expected increase consistent with higher input costs reducing complementary labour demand. The effect is marginal at short horizons, rising by up to 10bp throughout the first year, but grows over time and becomes significant up to 40bp in years three and four, reflecting rigid labour market structures in Europe.

Industrial production, after showing modest initial declines around 10bp, becomes strongly and persistently positive from year two onwards, reaching 15-25bp and maintaining these elevated effects through year four. A positive response is particularly puzzling given that industrial production captures electricity-intensive manufacturing sectors that should be most adversely affected by higher electricity costs. Instead, the results suggest an expansion of activity after an initial adjustment period.

Real GDP shows more muted responses throughout, with small negative effects in early quarters giving way to modest positive effects in the fourth year, all statistically and economically insignificant. The minimal GDP effects compared to the large industrial production and employment changes suggest significant compositional shifts within the economy.¹⁶

Figure E.11 shows the main macroeconomic responses to electricity price changes over a longer sample, using a subsample of countries that were early adopters of wind electricity. Effects on retail electricity prices are more significant, leading to more pronounced passthrough to the overall price index. The response of industrial production follows the same pattern as in the baseline but is somewhat muted, while the unemployment rate increases more unambiguously and persistently.

Repeating the analysis for subsamples (figure E.12) reveals that effects used to be much closer to supply shock predictions and have altered over time. In the 2000s, the HICP increased significantly, with effects steadily building for 3.5 years after the initial shock, and industrial production reacted as initially expected, with a small increase followed by a sustained and significant decline. This relationship faded in the 2010s and

¹⁶See effects on sectoral value added in appendix figure E.10.

partially reversed after 2020, which reflects the limited average effect over the broad but shorter main sample.

Theory predicts that higher input costs should reduce both employment and production, yet electricity price increases appear to stimulate industrial activity while still constraining labour markets in recent periods. The minimal GDP effects despite larger changes in industry suggest that electricity shocks trigger significant reallocation across economic activities rather than aggregate expansion or contraction (akin to Baqaee and Farhi (2022)). The sustained positive industrial production effects, combined with rising unemployment, point to productivity-enhancing adjustments such as automation, energy efficiency improvements, or shifts toward less labour-intensive but more electricity-efficient production processes. These patterns are consistent with recent theoretical and empirical work showing that energy price increases can induce long-run efficiency improvements through capital investment, generating positive output effects at longer horizons despite initial disruptions (Gamtessa and Olani, 2018, André et al., 2023).

4.2 Wholesale-retail price transmission

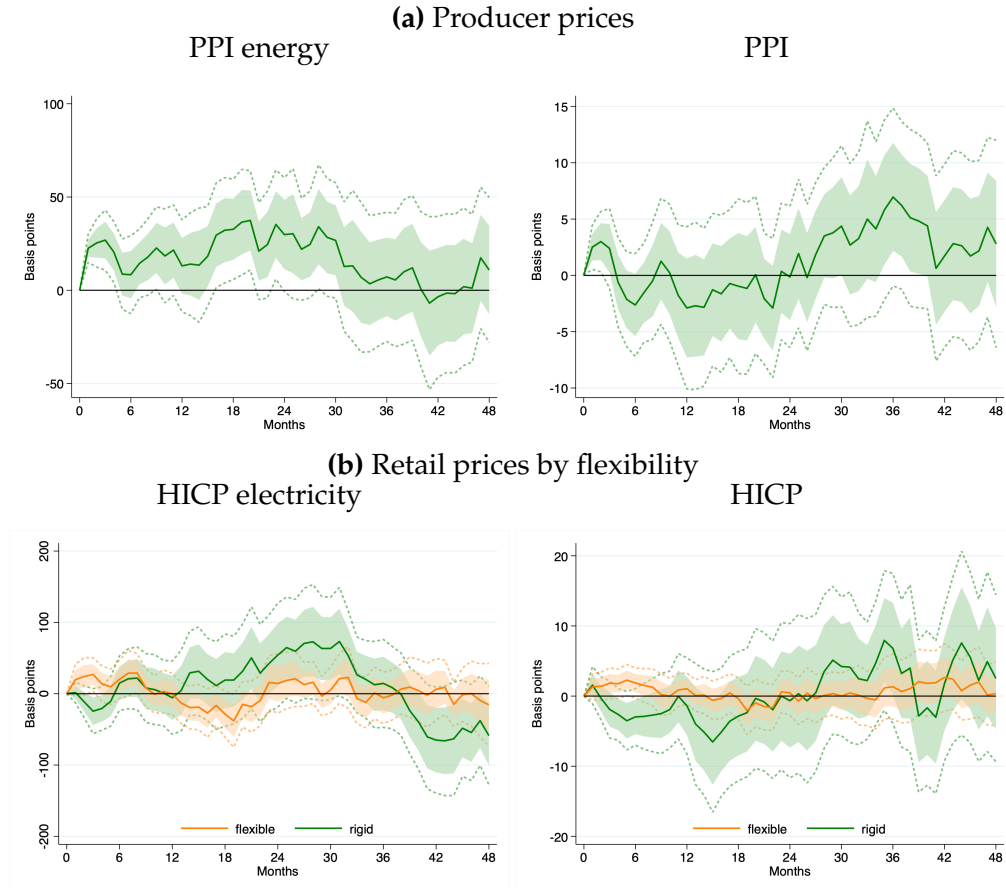
The average responses to wholesale price increases conceal significant heterogeneity in price transmission, both across segments of the economy and countries with vastly different retail market structures.

Producer prices react more strongly and statistically significantly to wholesale electricity price increases, as shown in figure 7a. The energy PPI sub-index shows the largest response, with prices spiking immediately after the shock by up to 30bp and continuing to rise over two years after the shock. Passthrough of energy producer prices to overall producer prices is more pronounced than to retail prices, with an initial statistically significant price increase of 3bp after a 1pp wholesale electricity price jump.

Retail price responses vary significantly by country, reflecting differences in consumer exposure to wholesale prices.¹⁷ Figure 7b shows retail price responses separately for countries with more flexible or rigid retail electricity prices, revealing a stronger and significant increase in both HICP electricity and the overall HICP over the first year in countries where retail and wholesale prices are highly correlated. Where retail prices are less flexible, the peak effect on prices is delayed by 1-2 years. This aligns with evidence from within Spain showing stronger passthrough after the introduction of real-time retail

¹⁷See figure E.7 for responses of HICP electricity by country.

Figure 7: Transmission of wholesale electricity price changes to retail prices



Note: Impulse responses to 1-month wholesale electricity price changes instrumented by wind shocks. Local projection estimated in the panel with country and time fixed effects, and 2 lags according to equation (4). Panel 7b splits countries into 2 groups based on the correlation of wholesale and retail electricity prices for various consumer groups, as shown in table C.1. The countries in the flexible retail price group are BE, DK, ES, FI, GR, IE, IT, RO, and SE. Countries in the rigid retail price group are AT, DE, FR, HR, HU, NL, PL, and PT. Driscoll-Kraay standard error bands using 2 lags represent 68% and 90% confidence intervals.

pricing (Garzon and Hierro, 2024).

4.3 Shock-dependent effects

The analysis thus far has assumed linear average effects of electricity prices on macroeconomic outcomes. However, effects likely depend on the type of shock and the market conditions when it occurs. This section examines heterogeneity that helps explain the puzzling average results and reveals important asymmetries in transmission mechanisms.

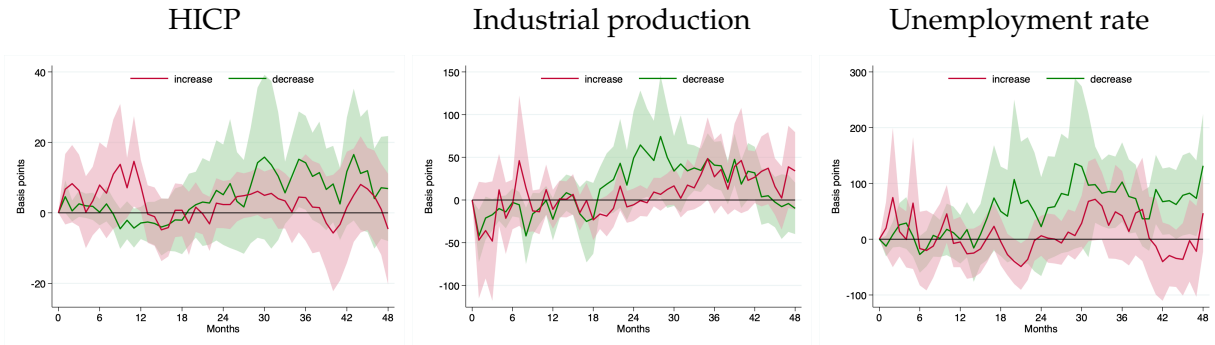
Figure 8a reveals that transmission mechanisms operate differently depending on shock direction. Price increases generate stronger HICP responses within the first year, consistent with findings about asymmetric retail price passthrough (Peltzman, 2000, Borenstein, Cameron and Gilbert, 1997). However, both increases and decreases produce the lagged persistent adjustments in prices and industrial production, which for price decreases lead to larger price effects and earlier positive effect son industrial production. Unemployment also increases following both price increases and decreases, but responds more strongly and significantly to price decreases, with effects reaching statistical significance in years two through four.

Comparing responses to price changes above and below the 75th percentile in figure 8b shows that the price level effects of large shocks are smaller by unit initially and revert over time. Both larger and smaller shocks produce the same pattern in industrial production with significant decreases over the first six months but more than offsetting increases in the months following, which is sharper following large shocks. Unemployment responds primarily to smaller price changes, with large shocks having smaller impact apart from the initial increase.

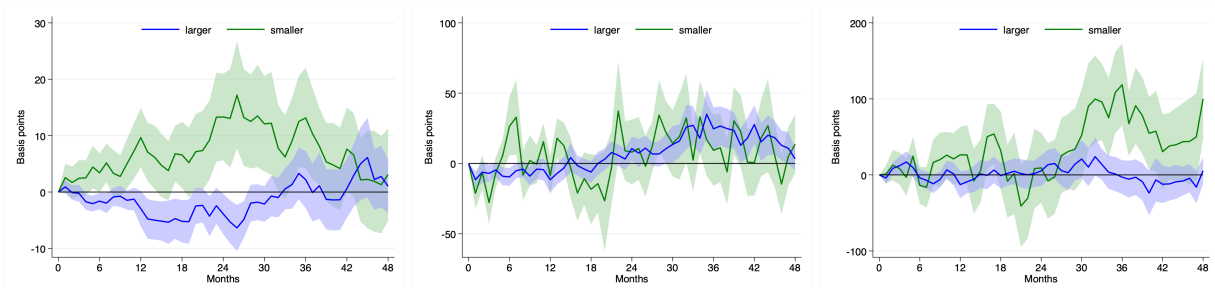
These asymmetries provide partial insight into the counterintuitive activity effects. Instead of crisis periods or large changes in prices, it is smaller changes during normal market conditions that drive the aggregate results. The findings suggest that substantial cost pressures trigger the expected short-term adjustment mechanisms through capacity underutilisation, while smaller shocks prompt more gradual, persistent adjustments, such as technological upgrades, production reorganisation, or efficiency improvements, as found in Gamtessa and Olani (2018) and Känzig and Williamson (2024).

Figure 8: Comparing effects by shock and energy product

(a) Electricity price change: increase or decrease



(b) Size of electricity price change: above or below 75th percentile



Note: Impulse responses to a 1pp electricity price change instrumented with wind shocks. Local projection estimated as specified in equation (4), using sample splits according to the stated criteria in panels a-c). Panel a) separates price increases and decreases, b) compares price changes with absolute size above the 75th percentile to all others. The first column of graphs shows impacts on the log HICP index, the second column shows effects on the log industrial production index, and the third column shows effects on the log of the unemployment rate. Driscoll-Kraay standard error bands represent 68% confidence intervals.

4.4 Comparing electricity and oil price shocks

As electrification progresses for both households (heat pumps, electric vehicles) and firms (automation, data and AI use), electricity increasingly replaces fossil fuels. Does this energy transition also imply different dynamics following energy price shocks, or do electricity and fuel price shocks have similar macroeconomic effects?

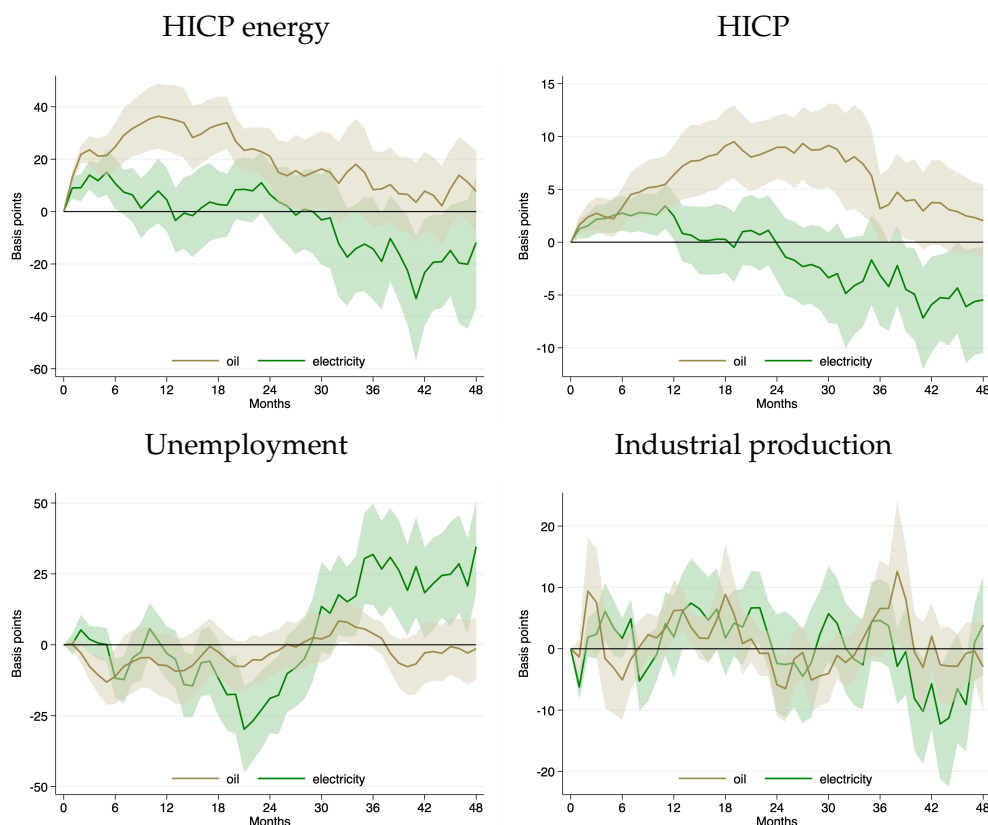
Since oil prices are global, I interact oil price changes with country-specific pre-period HICP weights and apply the same specification to electricity for comparison of effects per unit of expenditure exposure. The resulting specification for oil is as follows:

$$\begin{aligned} \log(y_{c,t+h}) = & \alpha^h + \eta_c^h + \theta_t^h + \beta^h (\Delta \log(p_t^o) \times weight_{c,t-12}^o) \\ & + \sum_{l=1}^2 \gamma_l^h \log(y_{c,t-l}) + \sum_{l=1}^2 \delta_l^h \Delta \log(p_{t-l}^o) + \psi^h i_{c,t} + \epsilon_{c,t+h} \end{aligned} \quad (5)$$

Figure 9 compares impulse responses to Brent oil price changes instrumented by Känzig (2021) oil supply news shocks with electricity price changes instrumented by wind shocks. The shocks show no obvious relationship (figure E.2), their correlation is small, negative, and insignificant.¹⁸

¹⁸See appendix E.5 for details and additional results.

Figure 9: Comparing effects of electricity and oil price changes (per unit of HICP weight)



Note: This figure compares electricity price changes to Brent oil prices instrumented by oil supply news shocks in brown, interacting each energy price change with the previous year's weight in HICP to compare using time fixed effects. Impulse responses to 1pp changes in energy prices: wholesale electricity prices instrumented by wind shocks in green, and Brent oil prices instrumented by oil supply news shocks in brown. Local projection estimated in the panel with country fixed effects, macroeconomic controls, and 2 lags as specified in equation (4). Driscoll-Kraay standard error bands represent 68% confidence intervals.

While both energy types generate similar price responses during the first year, oil price effects are more persistent and continue increasing in the following years. When scaled by expenditure weights, the responses align with economic intuition, as the broader energy market presence of oil creates proportionally larger aggregate price impacts. The unscaled peak responses align with expenditure weights: approximately 9bp for oil (roughly 10% overall energy weight) versus 3bp for electricity (3% electricity weight).¹⁹

Surprisingly, neither electricity nor oil price increases generate expected negative activity responses over this European sample period, but the patterns differ markedly. Electricity price changes generate significantly more positive industrial production effects

¹⁹Obtained by multiplying the point estimates with the average HICP weights.

than oil. This could indicate lower flexibility in usage of electricity, or more scope for efficiency and productivity improvements using electricity compared to fuels. Longer subsample analysis reveals that the minimal effects of oil shocks represent a change from the 2000s and 2010s, when oil shocks did produce negative activity effects consistent with Känzig’s original findings for world industrial production (appendix figure E.17).

The response of unemployment also differs: it marginally increases after electricity price increases but decreases after oil price increases. The differential employment responses suggest fundamental differences in either the substitutability of energy inputs with labour in production or the income effects from energy price shocks that prompt extensive margin labour supply responses.

These findings reveal three critical insights about macroeconomic implications of the energy transition. First, the magnitude of immediate price effects can be explained by current expenditure shares, but persistence patterns reflect underlying market structures – oil’s flexible pricing versus electricity’s contractual rigidities. Second, neither energy type currently behaves like traditional supply shocks in terms of real activity effects, with electricity responses being particularly notable given the consistent positive industrial production effects. Finally, the differences between electricity and oil, and the evolving nature of these relationships over time, indicate that historical oil shock analysis may provide limited guidance for understanding electricity price effects in an increasingly electrified economy.

5 Conclusion

Electricity prices represent an increasingly important component of energy costs, yet identifying exogenous changes is challenging, with literature relying primarily on oil price instruments. This paper demonstrates that wind can serve as exogenous driver of electricity price changes when extracting supply-relevant variation. The shock measure, constructed from wind at turbine locations while controlling for demand patterns, provides a strong instrument for electricity price changes.

The results reveal significant passthrough from wholesale electricity to other prices, but no consistent negative effects on economic activity. While unemployment rises with some lag, industrial production responds positively to higher electricity prices after an initial decline. These counterintuitive effects are structural features of electricity markets rather than crisis-period exceptions, creating an important puzzle for future research on

sectoral heterogeneity, energy substitution patterns, and the role of efficiency investments in driving them.

Comparing with oil, both shocks affect aggregate prices proportionally to their expenditure shares and neither generates the negative activity effects predicted by classic supply shock theory. However, the unexpected responses are more pronounced and persistent for electricity. Crucially, electricity prices remain local rather than global and transmit to retail prices more indirectly, making them particularly important for understanding how diverse electricity price shocks will affect increasingly electrified economies with varying generation mixtures.

As wind electricity capacity doubles over the next decade (International Energy Agency, 2024) and fossil fuels are phased out, wind shocks will increase in power and the overall composition of energy supply shocks will shift towards electricity, fundamentally altering business cycle dynamics. Understanding these differential transmission mechanisms becomes crucial for both monetary policy and macroeconomic forecasting.

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Appendix

A Related literature

The existing literature on energy supply shocks focuses almost exclusively on oil prices, typically identified using structural vector autoregression (SVAR) models with various identifying assumptions. Early contributions used oil production shortfalls to instrument oil prices (Hamilton, 2003), later replaced by Kilian's (2008) influential exogenous oil supply shocks identified using OPEC production data. To differentiate explicitly between oil supply and demand shocks, Baumeister and Hamilton (2019) employ Bayesian VARs reflecting uncertainty about identifying assumptions in the structural model. Känzig (2021) identifies oil supply news shocks from high-frequency movements in oil futures around OPEC announcements. Other energy supply shocks concern fossil fuels, particularly natural gas. Casoli, Manera and Valenti (2022) and Boeck and Zörner (2023) use different identifying restrictions in VARs to recover gas supply shocks and study their effects on inflation and expectations, while Alessandri and Gazzani (2023) construct high-frequency supply shocks from European gas market news.

Recent theoretical advances in supply shock analysis have revealed that such disruptions can generate seemingly contradictory demand-like responses depending on cross-sectoral elasticities, incomplete markets, and the heterogeneity of economic agents (Cesa-Bianchi and Ferrero, 2021, Guerrieri et al., 2022, Kharroubi and Smets, 2024). When estimating effects of supply shocks empirically, these insights highlight that the effects depend critically on the scope of the disruption, the selectivity of impacts across households and firms, heterogeneity across sectors, and the speed of transmission through different market segments. I contribute to the discussion by providing an electricity supply shock which can speak to all of these dimensions and does exhibit partially demand-like effects.

The role of renewables in electricity pricing is well-established in energy economics, where literature focuses on demonstrating and quantifying renewable electricity generation effects on prices through merit order mechanisms at high frequency. Many papers examine Germany as an early European promoter of non-fossil electricity. Sensfuß, Ragwitz and Genoese (2008) analyse renewable electricity generation effects on German wholesale prices, including welfare and policy analysis of support payments. Cludius et al. (2014) evaluate German renewable energy promotion policies, while Maciejowska (2020) uses quantile analysis to study nonlinear price effects of wind and solar genera-

tion. Most recently, Hirth, Khanna and Ruhnau (2024) use wind electricity generation as instrument for electricity prices to elicit demand elasticity, and Liebensteiner, Ocker and Abuzayed (2025) use imports of wind-generated electricity, each at hourly frequency. Additional studies have expanded to other countries and examined asymmetric generation effects on prices.²⁰ I contribute to this literature by exploiting the merit order relationship to provide instrument relevance of renewables for electricity prices at lower frequencies, using exogenous weather independent of capacity investment decisions to isolate supply components for macroeconomic analysis.

Finally, a substantial literature uses weather variables as instruments to answer diverse questions not restricted to energy or macroeconomics. Weather has been used to study both energy production and prices,²¹ as well as energy demand and consumption.²² Weather instruments have also been applied to non-energy issues such as health and voting.²³ To ensure the exclusion restriction holds in my setting, I use regional variation in wind overweighting supply-relevant locations to construct national shocks, differentiating between demand and supply effects of weather to isolate relevant electricity supply variation.

B Data

The main sample includes 17 European countries: Austria, Belgium, Croatia, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, the Netherlands, Poland, Portugal, Romania, Spain, and Sweden. The countries are determined by the requirements of significant installed wind generation capacity and data availability. The sample period is constrained by consistent data availability for wholesale electricity prices across countries.

²⁰Examples include Mulder and Scholtens (2013) on wind's role in Dutch electricity prices, Csereklyei, Qu and Ancev (2019) for Australia, Woo et al. (2016) for the US, Tselika, Tselika and Demetriades (2024) on asymmetric wind effects in Denmark and Sweden, and Nibedita and Irfan (2022) on asymmetric effects in Indian wholesale markets.

²¹Examples include Fisher-Vanden, Mansur and Wang (2015) on extreme weather impacts on electricity production, Heinen, Khadan and Strobl (2019) on consumer prices, Ito and Reguant (2016) on wind farm output, and Natalini, Bravo and Newman (2020) on energy price conflict repercussions.

²²See Considine (2000) on climate effects on energy demand and carbon emissions, Lee and Chiu (2011) on temperature effects on electricity demand, Nguyen and Vo (2020) on fuel consumption, and Atalla, Bigerna and Bollino (2018) on energy demand elasticities.

²³Examples include Fan and Wang (2020) analysing health outcomes of coal plant closures using temperature instruments, and Stokes (2016) using wind mill proximity as exogenous variation in voting behaviour against climate policies.

Electricity price and production data is made available publicly in the EU. Hourly electricity wholesale day-ahead prices by bidding zone are sourced from ENTSO-E, the European Network of Transmission System Operators for Electricity, and has been aggregated to daily prices by load and country by independent energy think tank Ember.²⁴ In addition to the standard macroeconomic variables used, national electricity retail prices are available semi-annually by consumer category and usage band from Eurostat. They also provide the annual installed electricity generation capacity by source and country, and monthly electricity generation.

Grid-level weather data including wind speed at 100m elevation, solar radiation and temperature by 0.25° ($\approx 28\text{km}$) grid cell is taken from the Global Wind Atlas using EU Copernicus ERA5 data and provided as monthly averages.

Data on wind turbine locations is provided by nonprofit organisation Global Energy Monitor's²⁵ Global Wind Power Tracker, which collects information from OpenStreetMap on all wind farms exceeding 10MW capacity including their locations, capacity, operating status and operational/shutoff dates. The data is collected from user entries and therefore prone to errors and missing values on details. Manual checks against official data for installed capacity for Germany indicate that the data provides a roughly accurate picture of installed wind capacity at least there, but some uncertainty of the accuracy cannot be excluded.

Due to limitations on details of operating dates, I use all wind turbine installations at the latest available date after the main sample, February 2025, instead of tracking installation over time. This measurement choice has two implications.

First, it reduces instrument power in earlier sample years by assigning weight to locations that did not yet have operational turbines. Wind speed variation at these locations did not affect electricity generation or prices at the time, introducing classical measurement error that attenuates the first-stage relationship. The instrument is therefore strongest in recent years when measured capacities accurately reflect actual generation capacity, and estimated effects may represent lower bounds if early-sample attenuation biases coefficients toward zero. The stronger first-stage results in later subsamples shown in table E.4 are consistent with this interpretation.

Second, one might be concerned that overweighting regions with recent capacity growth could introduce bias if these regions differ systematically in ways correlated with macroe-

²⁴Prices for Ireland are available from October 2018 after a change in the system, and for Croatia from October 2017.

²⁵<https://globalenergymonitor.org>

conomic outcomes. However, several features of the identification strategy mitigate this concern. The instrument relies on deviations in wind speed from location-specific seasonal means, which remain exogenous to economic conditions regardless of why capacity was installed at a given location. The transmission channel operates through national wholesale prices rather than regional economic conditions, so bias would require wind speed deviations in high-growth regions to correlate with national outcomes through channels other than electricity prices, which seems implausible given the spatial aggregation. Results in the extended sample for early-adopter countries (figure E.11), where the 2025 capacity weights more closely approximate historical capacity, show qualitatively similar patterns, providing further reassurance that the time-invariant weights do not drive the main findings.

B.1 Wind speeds and wind electricity generation

I use wind speeds rather than wind electricity generation to construct electricity price shocks. The first stage captures wind speed impacts on electricity production, which are strong and positive (see appendix table C.2 by country), though not necessarily linear due to the cube relationship between wind speed and extractable power.²⁶ The sample is restricted to wind speeds within standard usable ranges where possible, though this rarely constrains averaged data.

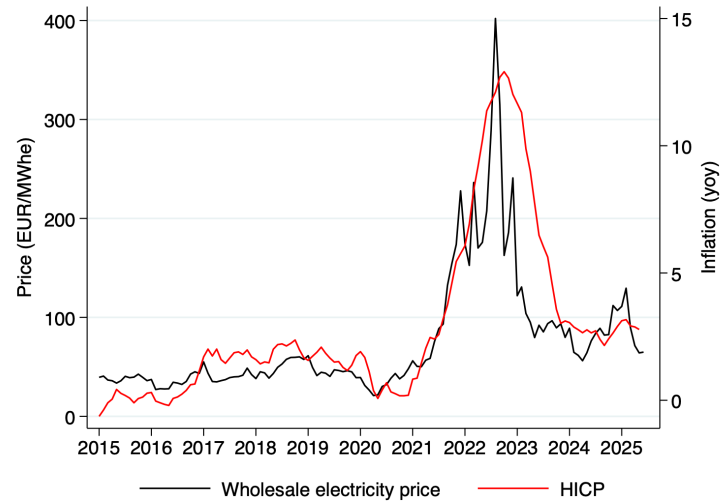
While wind electricity generation is commonly used in energy economics, using it directly would be problematic for studying longer-horizon responses as renewable capacity becomes endogenous over time.²⁷ Using meteorological data directly avoids concerns about capacity build-up and market-based utilisation changes.

²⁶Extractable power from wind follows Wind power density = $1/2\rho U^3$, where U is wind speed and ρ is air density. Modern turbines typically operate between 3-25 m/s cut-off speeds and can theoretically extract up to 59.26% of wind energy (Betz criterion, Betz (2013)), achieving around 40% in practice. For technical details, see Emeis (2018).

²⁷Higher renewable generation reduces prices via merit order, lowering profits for all producers, which reduces investment incentives and affects future capacity and price trajectories. Additionally, operators may shut off windmills when wholesale prices turn negative.

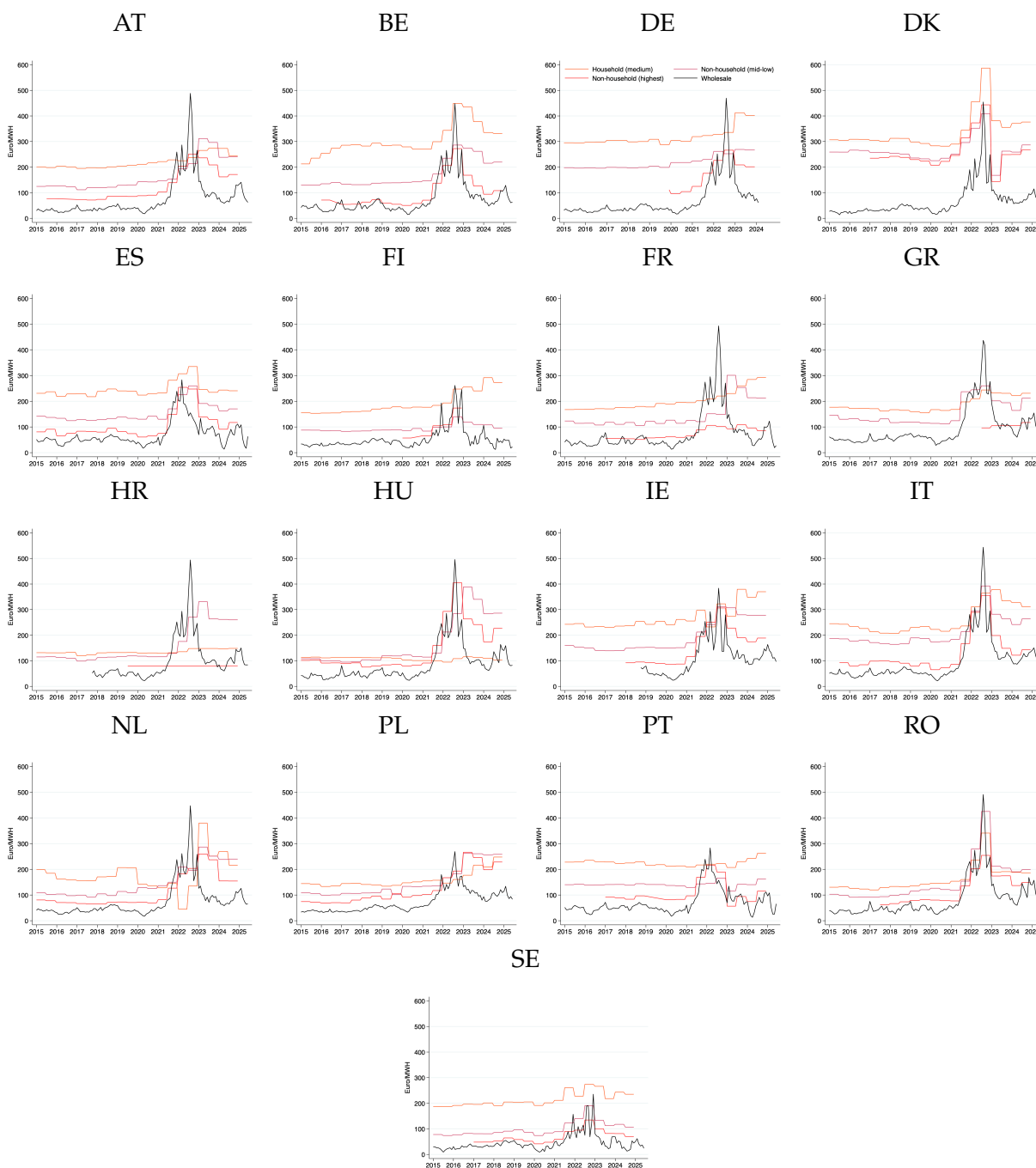
C Descriptives

Figure C.1: Electricity prices and inflation



Note: The figure shows the year-on-year inflation rate using the HICP and wholesale electricity prices, averaged across the European countries in the sample.

Figure C.2: Wholesale and retail electricity prices



Note: These figures show the development of wholesale and retail prices for selected electricity consumer groups. Retail prices are available only bi-annually from Eurostat. Household prices in red (medium band DC, 2,500 kWh to 4,999 kWh); mid-low consumption non-household prices in blue (industry, services, offices, agriculture, etc; mid-low band IC, 500 MWh to 1,999 MWh), high-consumption non-household prices in purple (highest band IG, 150,000 MWh or over), all including any taxes and levies, and wholesale prices in black.

Table C.1: Correlation of wholesale and retail prices by consumer type and band

	Firm (mid-low)	Firm (highest)	Household (medium)
AT	0.49	0.81	0.45
BE	0.75	0.97	0.73
DE	0.59	0.89	0.37
DK	0.77	0.85	0.96
ES	0.77	0.90	0.83
FI	0.81	1.00	0.40
FR	0.20	0.67	0.26
GR	0.91	-0.65	0.73
HR	0.49	1.00	0.47
HU	0.55	0.91	-0.39
IE	0.72	0.95	0.32
IT	0.92	0.98	0.70
NL	0.53	0.67	-0.20
PL	0.65	0.77	0.45
PT	0.33	0.89	-0.09
RO	0.94	0.91	0.94
SE	0.93	0.90	0.78

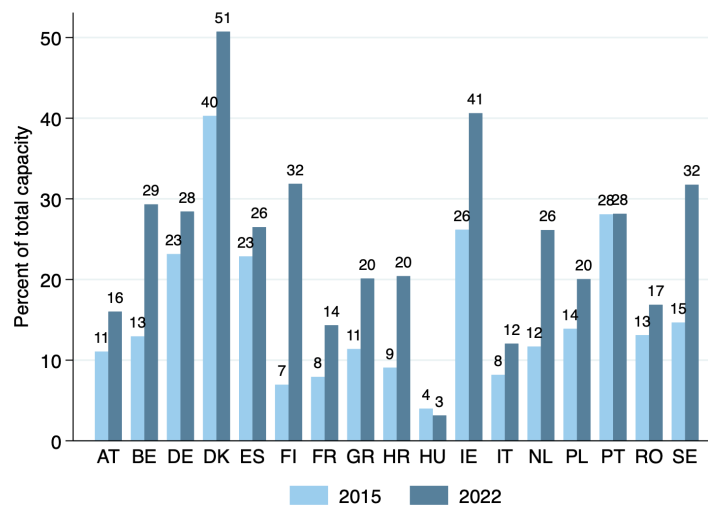
Note: Correlation of half-yearly retail prices by consumer category and usage with average wholesale electricity prices during the same period by country in the sample from 2015H1-2024H2. Medium household band defined as DC (2,500 kWh to 4,999 kWh), mid-low firm band as IC (500 MWh to 1,999 MWh), and high firm band as IG (150,000 MWh or over), all including any taxes and levies.

Table C.2: Wind electricity generation and wind speed by country

	AT	BE	DE	DK	ES	FI	FR	GR	HR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Average wind speed	27.42*** (1.83)	21.05*** (2.44)	294.46*** (20.95)	23.95*** (2.35)	161.18*** (9.15)	20.26*** (4.41)	104.96*** (10.30)	8.29** (4.13)	4.24*** (0.75)
Constant	-42.05*** (6.32)	-61.19*** (14.55)	-1092.58*** (136.05)	-56.27*** (17.98)	-391.46*** (46.01)	-81.93** (32.38)	-349.11*** (56.88)	13.08 (21.67)	-6.04 (4.10)
Observations	120	120	120	120	120	96	120	120	73
R ²	0.647	0.457	0.715	0.510	0.690	0.227	0.497	0.035	0.315

	HU	IE	IT	NL	PL	PT	RO	SE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average wind speed	2.40*** (0.10)	18.32*** (0.82)	65.35*** (4.50)	37.17*** (7.06)	42.11*** (3.64)	39.50*** (2.54)	25.64*** (1.35)	46.72*** (6.73)
Constant	-5.77*** (0.48)	-51.69*** (5.95)	-184.29*** (23.02)	-125.86*** (46.84)	-121.43*** (20.61)	-101.49*** (13.14)	-55.41*** (5.76)	-162.17*** (49.75)
Observations	120	75	108	120	120	120	120	120
R ²	0.821	0.903	0.684	0.235	0.565	0.690	0.801	0.343

Note: Correlation of monthly national wind electricity generation and average wind speed across country land area conditional on a constant.

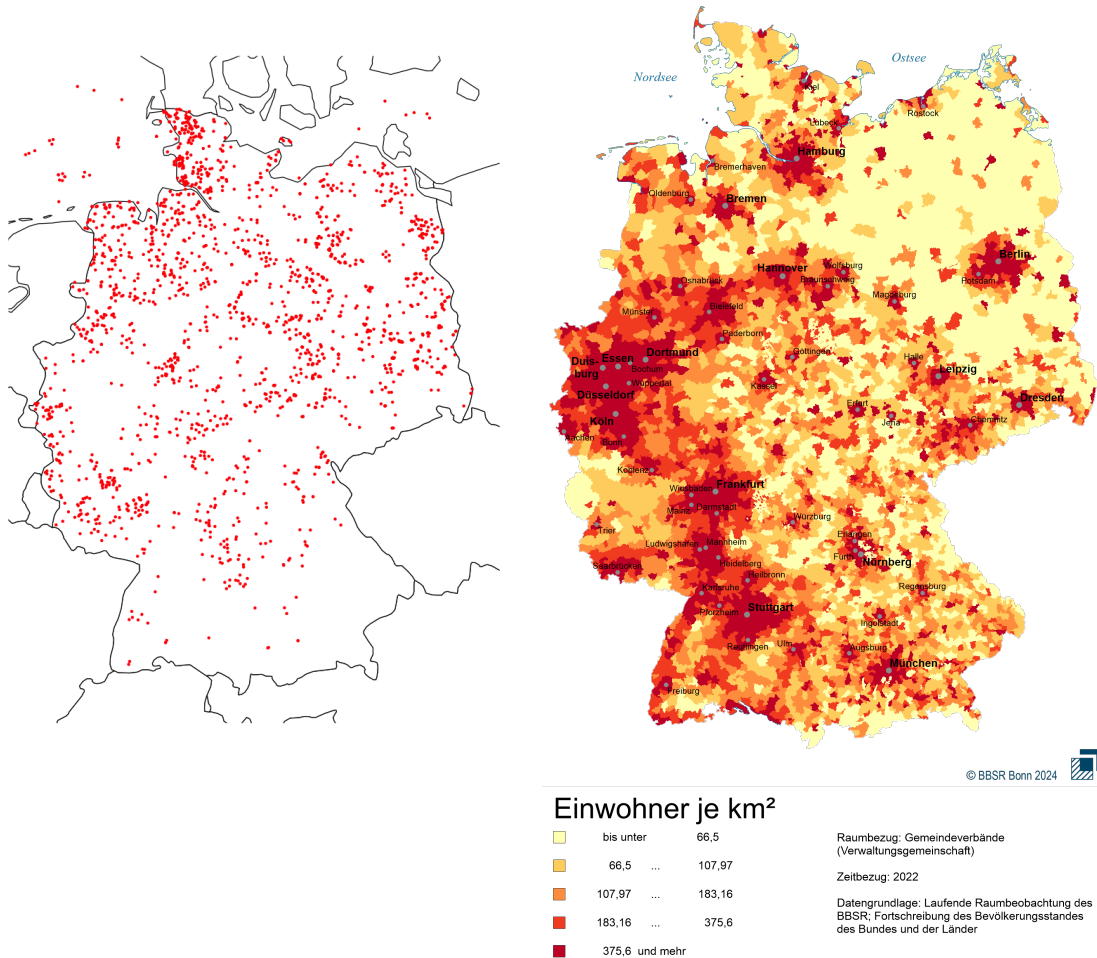
Figure C.3: Wind in electricity generation capacity

Note: Share of wind electricity in total electricity generation capacity in percent, measured as megawatts of net maximum electrical capacity of all main activity producers. Data from Eurostat.

Figure C.4: Wind farm locations and population density in Germany

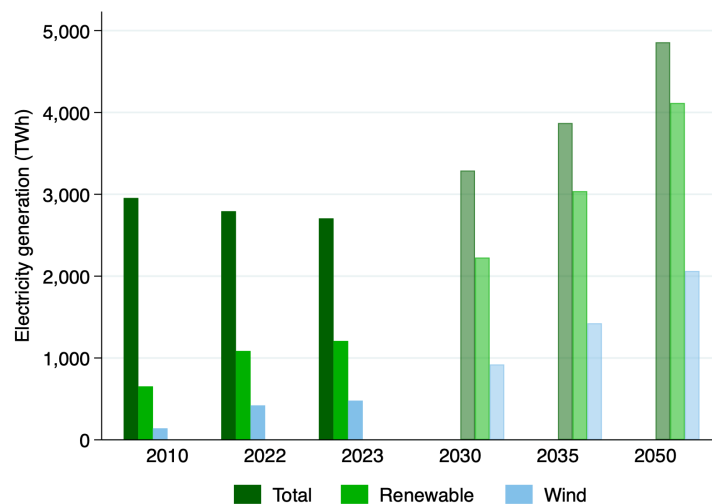
(a) Wind turbine farm locations

(b) Population density (inhabitants/ km^2)



Note: Panel a) shows locations of wind turbine farms with installed capacity of at least 10MW across Germany. Data provided by the Global Wind Power tracker show installed capacity operational as of February 2025. Panel b) shows population density as the number of people per square kilometre by NUTS3 region, using data for 2022 provided by INKAR.

Figure C.5: Recent and projected share of wind and renewables in electricity generation in Europe



Note: Data from the International Energy Agency's World Energy Outlook 2024 for Europe. Solid colours show past annual averages, transparent colours show projections by the IEA.

D Alternative shock identification using national surprises

D.1 Construction

One method of isolating the demand-exogenous portion of wind and ensure that wind shocks are unforecastable is to construct wind surprises relative to a wind expectation based on previous patterns in wind and contemporaneous demand-relevant correlated weather. I construct a simple model of monthly wind to form expected wind speeds, using past wind speed from both the previous month to account for serial correlation and the same month in the previous year to account for changing seasonal patterns. In addition, I include contemporaneous controls for temperature and solar radiation, and a seasonal fixed effect by calendar month to capture persistent seasonal variation. This is estimated separately by country to allow for different coefficients.

$$wind_t = \gamma temp_t + \delta solar_t + \rho_1 wind_{t-1} + \rho_{12} wind_{t-12} + \eta_{month} + \epsilon_t, \text{ such that } wind_{c,t}^{shock} \equiv \hat{\epsilon}_{c,t}$$

Including contemporaneous weather into the wind model ensures that any direct response of demand to the remaining wind surprise is limited, as the remaining surprise wind is orthogonal to contemporaneous temperature and solar radiation by construction. Average monthly wind likely only has a small direct effect on demand, given that most variation is from small changes in wind of 1-2km/h, even once excluding more extreme daily wind speeds. However, wind is negatively correlated with both temperature and solar radiation, so a month with lower wind speeds is likely to be a warmer and sunnier month, which might induce changes in electricity demand, but also indirect changes in consumption patterns.²⁸ The relation of temperature and electricity demand however is not obvious, as it depends on different heating and cooling needs both by industry and consumers, such that one can also expect systematic differences between European countries, hence the model is estimated separately by country.

Including the recent history and typical seasonal patterns of national wind in the model acts as a simple proxy for wind forecasting models that forward price contracts are based on. Since most electricity trading happens in forward agreements years in advance, prices for these are based on seasonal patterns and climate forecasts. These are much more sophisticated than the regression model used here, but based on outdated

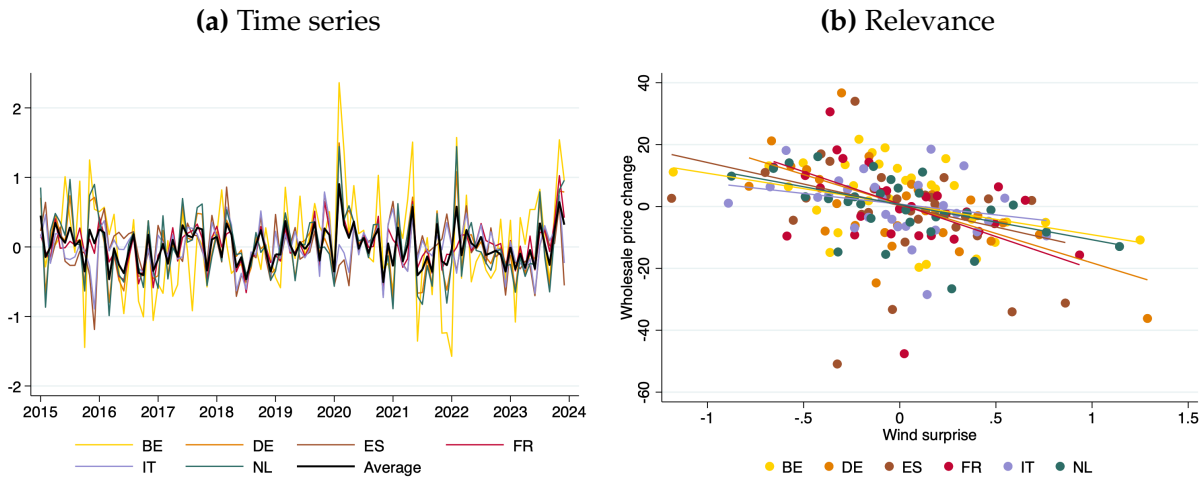
²⁸For example, temperature has been shown to affect trading behaviour and thereby stock returns (Cao and Wei, 2005)

information from years before. Changes in wholesale prices on the spot market therefore are more likely to reflect deviations of the renewable electricity generation from what was expected, insofar as changes are driven by renewables.

D.2 Results

The resulting wind surprise series constructed as the deviation of actual monthly average wind speed from the model expectation is shown for the six largest countries in the left panel of figure D.1. They exhibit some correlation across countries but minimal autocorrelation at one to two lags. Relevance of these wind surprises for the variable of interest of wholesale electricity price changes is shown visually in the right panel of figure D.1. Monthly wind surprises are clearly negatively correlated with a change in wholesale prices. Relevance is consistently given across countries, with the exception of Italy (which has split bidding zones and the lowest wind electricity share in the sample). This relationship is also not just reliant on outliers of extreme wind surprises, as most variation stems from 1-2km/h wind more or less than expected for the month.

Figure D.1: Wind surprises by country



Note: Monthly wind surprises as deviations of actual wind from the model expectation described in equation D.1 by country. Panel a) shows the time series of wind surprises in km/h, while panel b) shows a binscatter plot with 30 quantiles by country, relating wind surprises in km/h and the percentage change in wholesale prices compared to the previous month.

Instrument strength of the wind surprises is tested in the first stage of instrumenting for the monthly percentage change in average wholesale prices compared to the

previous month with the constructed shock series for the current month, $wind_{c,t}^{shock} = wind_{c,t} - \mathbb{E}[wind_{c,t}]$ according to equation 3. Table D.1 summarises the first stage results by country and in the cross-country panel. Here the coefficients for the wind surprise can be interpreted as the effect of a 1km/h monthly wind surprise on wholesale prices in terms of percentage point change compared to previous month. As expected, the coefficient is negative for all countries, but the surprise series has varying instrument power. Differences seem clearly related to shares of wind in electricity generation as shown in figure C.3, but could also be due to varying shares of home production which is not captured by market prices, or significant differences in the ability to substitute between sources and geographical origins of electricity. In the panel of all eleven countries of the sample in columns (7) and (8) exploiting cross-country variation, the instrument is strong and robust F-statistic well above the required level for inference, even with more conservative estimation of standard errors.

Table D.1: Monthly first stage results: wind surprises

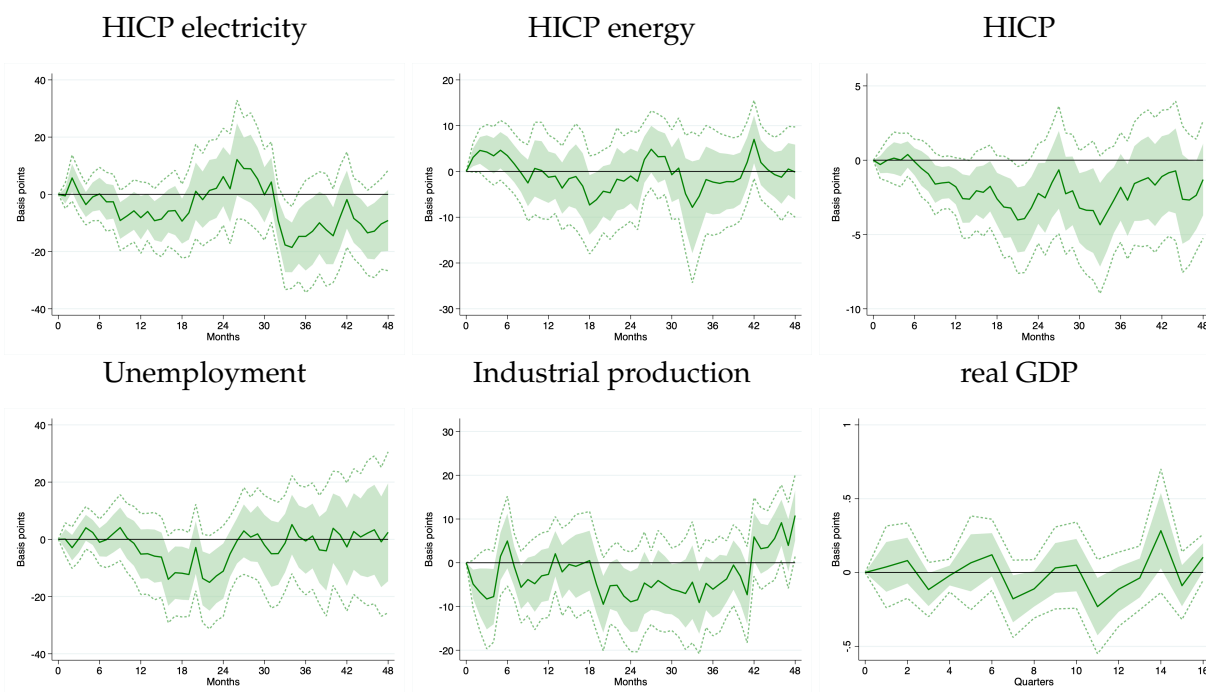
	BE	DE	ES	FR	IT	NL	EA panel		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Wind surprise	-9.93*** (2.47)	-19.03*** (3.28)	-13.89** (6.09)	-20.97*** (6.43)	-6.93* (3.79)	-11.42*** (2.53)	-12.07*** (0.95)	-12.07*** (1.32)	-7.98*** (1.25)
Observations	119	119	119	119	119	119	1945	1945	1945
R ²	0.091	0.139	0.038	0.064	0.015	0.084	0.063	0.062	0.046
Country FEs							Yes	Yes	Yes
Time FEs									Yes
F-statistic	16	34	5	11	3	20	162	84	41
Standard errors	Robust	Robust	Robust	Robust	Robust	Robust	Robust	DK	DK

Note: The table shows results of the specification in equation 3, with the wind shocks as surprises to expected wind as modelled in equation D.1, without controlling for wind in non-turbine grid cells. The dependent variable for all columns is the percentage change in wholesale prices from the previous month, restricted to the geography as indicated in the column headers. Standard errors in parentheses robust or Driscoll-Kraay with 3 lags.

Using wind surprises as instruments for wholesale electricity prices instead of the baseline turbine-weighted wind shocks yields similar conclusions for average macroeconomic effects. Price responses overall are similar if slightly more muted, and the activity responses are less marked, with a more delayed positive impact on industrial production and no significant effect on unemployment. This can partially be ascribed to the lower cross-country variation as shocks are more correlated across countries when not condi-

tioning on windmill locations.

Figure D.2: Macroeconomic effects of electricity prices instrumented by wind surprises



Note: Impulse responses to 1-month changes in electricity prices instrumented by wind surprises. GDP impulse responses estimated for 1-quarter changes instrumented with the sum of shocks over the quarter. Local projection estimated in the panel with country fixed effects and 2 lags as specified in equation (4), without controlling for wind in non-turbine grid cells. Driscoll-Kraay standard errors with 3 lags. Error bands represent 68% and 90% confidence intervals.

E Additional results

E.1 First stage

Table E.1: Monthly first stage results by country

	AT	BE	DE	DK	ES	FI	FR	GR	HR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Wind shock	7.91*	-2.53	-14.72***	-12.57***	-23.95***	-17.77***	-16.70***	-2.69	3.59
	(4.16)	(7.90)	(4.85)	(3.99)	(6.97)	(6.28)	(5.34)	(3.90)	(8.56)
Observations	119	119	119	119	119	119	119	119	86
R^2	0.021	0.001	0.069	0.060	0.087	0.043	0.065	0.005	0.004
F-statistic	4	0	9	10	12	8	10	0	0
	HU	IE	IT	NL	PL	PT	RO	SE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Wind shock	1.88	-40.70	0.06	-4.69	-4.21	-33.28*	23.64	-27.22***	
	(6.85)	(35.09)	(5.59)	(3.05)	(5.57)	(18.94)	(15.39)	(8.86)	
Observations	119	74	119	119	119	119	119	119	
R^2	0.001	0.016	0.000	0.018	0.003	0.021	0.019	0.053	
F-statistic	0	1	0	2	1	3	2	9	

Note: The table shows results of the specification in equation 3 by country, excluding country and time fixed effects. The dependent variable for all columns is the percentage change in wholesale prices from the previous month, instrumented by capacity-weighted wind at turbines, and restricted to the country as indicated in the column headers. Robust standard errors in parentheses.

Table E.2: Monthly first stage results: capacity-weighted wind at offshore turbines

	BE	DE	ES	FR	IT	NL	Panel		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Residuals	-0.95 (4.76)	-6.31** (2.99)	-7.62* (4.10)	-3.88 (3.59)	1.22 (2.76)	-3.48 (2.71)	-6.66*** (1.24)	-3.08*** (1.06)	-3.08** (1.27)
Observations	119	119	119	119	119	119	1264	1264	1264
R^2	0.000	0.031	0.028	0.007	0.002	0.011	0.022	0.562	0.008
Country FEs							Yes	Yes	Yes
Time FEs								Yes	Yes
F-statistic	0	4	3	1	0	2	29	8	6
Standard errors	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	DK

Note: The table shows results of the specification in equation 3 when the shock is constructed according to equation 2 but using only wind turbines located offshore and hence controlling for average wind across the entire land area of the country. The dependent variable for all columns is the percentage change in wholesale prices from the previous month, restricted to the geography as indicated in the column headers. Standard errors in parentheses are computed as robust or Driscoll-Kraay with 3 lags.

Table E.3: Monthly first stage results: capacity-weighted wind at turbines controlling only for seasonal fixed effects

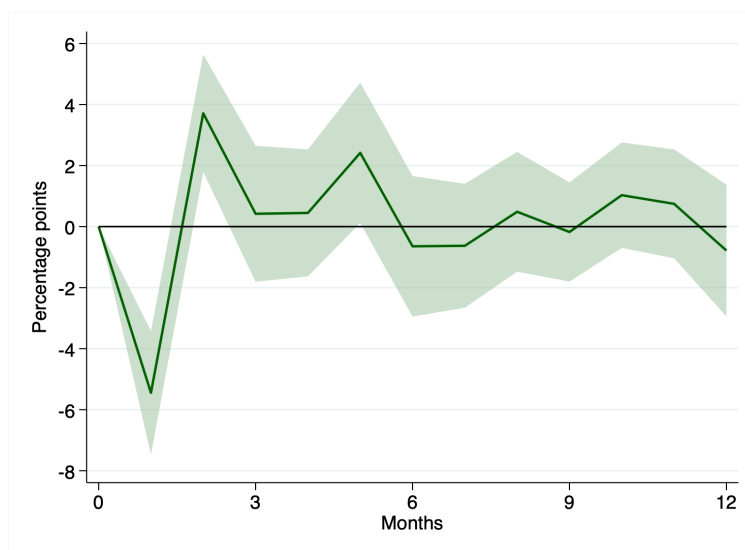
	BE	DE	ES	FR	IT	NL	Panel		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Residuals	-10.12*** (1.68)	-17.10*** (1.97)	-14.56*** (3.51)	-15.59*** (3.67)	-3.31 (3.12)	-7.65*** (1.23)	-11.45*** (0.69)	-7.50*** (0.59)	-7.50*** (0.90)
Observations	119	119	119	119	119	119	1945	1945	1945
R^2	0.182	0.309	0.115	0.151	0.009	0.168	0.107	0.598	0.078
Country FEs							Yes	Yes	Yes
Time FEs								Yes	Yes
F-statistic	36	75	17	18	1	39	275	164	70
Standard errors	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	DK

Note: The table shows results of the specification in equation 3 when the shock is constructed according to equation 2 but controlling only for calendar month fixed effects. The dependent variable for all columns is the percentage change in wholesale prices from the previous month, restricted to the geography as indicated in the column headers. Standard errors in parentheses are computed as robust or Driscoll-Kraay with 3 lags.

Table E.4: Monthly first stage results in subsamples: capacity-weighted wind at turbines

	2015-2017	2018-2020	2021-2023	2024-2025	Full (2015-2025)
	(1)	(2)	(3)	(4)	(5)
Wind shock	-3.47 (2.25)	-5.24** (1.97)	-6.92** (2.63)	-14.74** (4.86)	-5.90*** (1.26)
Observations	527	602	612	204	1945
R^2	0.007	0.021	0.015	0.033	0.014
Country FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
F-statistic	2	7	7	9	22
Standard errors	DK	DK	DK	DK	DK

Note: The table shows results of the specification in equation 3 for the cross-country EA panel. The dependent variable for all columns is the percentage change in wholesale prices from the previous month. Standard errors in parentheses are computed as Driscoll-Kraay with 3 lags.

Figure E.1: Persistence of first stage effects

Note: The figure shows the first stage relationship as described in equation 3 with country and time fixed effects over 12 months, using the baseline capacity-weighted turbine wind shocks and estimating their effects on the change in monthly wholesale electricity prices. Error bands show 68% confidence intervals computed using Driscoll-Kraay standard errors with 3 lags.

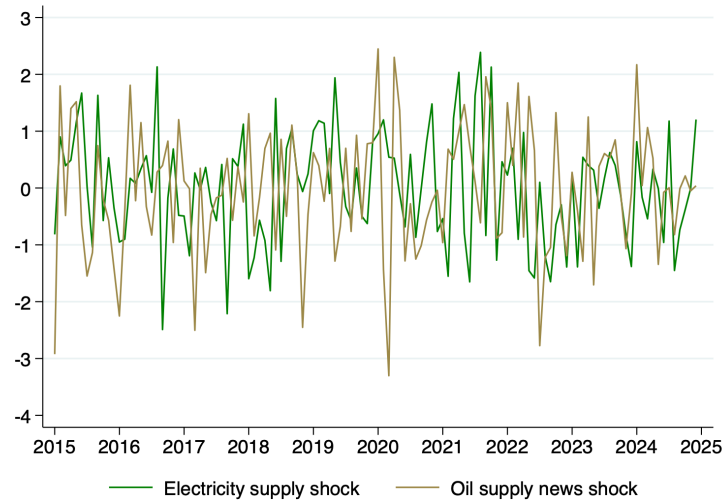
Table E.5: Monthly first stage results in cross-country panel interacted with wind generation shares

	(1)	(2)	(3)
Wind shock	-4.84** (2.29)	-2.88** (1.46)	-2.88* (1.68)
L12.Wind share in generation	-32.81*** (11.47)	-2.98 (11.71)	-2.98 (13.88)
Wind shock $\times$ L12.Wind share in generation	-14.91 (9.41)	-12.22** (5.45)	-12.22** (5.25)
Observations	1707	1707	1707
R^2	0.018	0.586	0.013
Country FEs	Yes	Yes	Yes
Time FEs		Yes	Yes
F-statistic	11	9	8
Standard errors	Robust	Robust	DK

Note: The table shows results of the specification in equation (3) with the addition of the share of wind in electricity generation in the same month of the previous year, separately and interacted with the shock. The dependent variable for all columns is the percentage change in wholesale prices from the previous month. The wind shock coefficients represent the effect of 1km/h weighted turbine wind on the percentage point change in wholesale prices compared to the previous month. Standard errors in parentheses are computed as robust or as Driscoll-Kraay standard errors with 3 lags.

E.2 Shock diagnostics

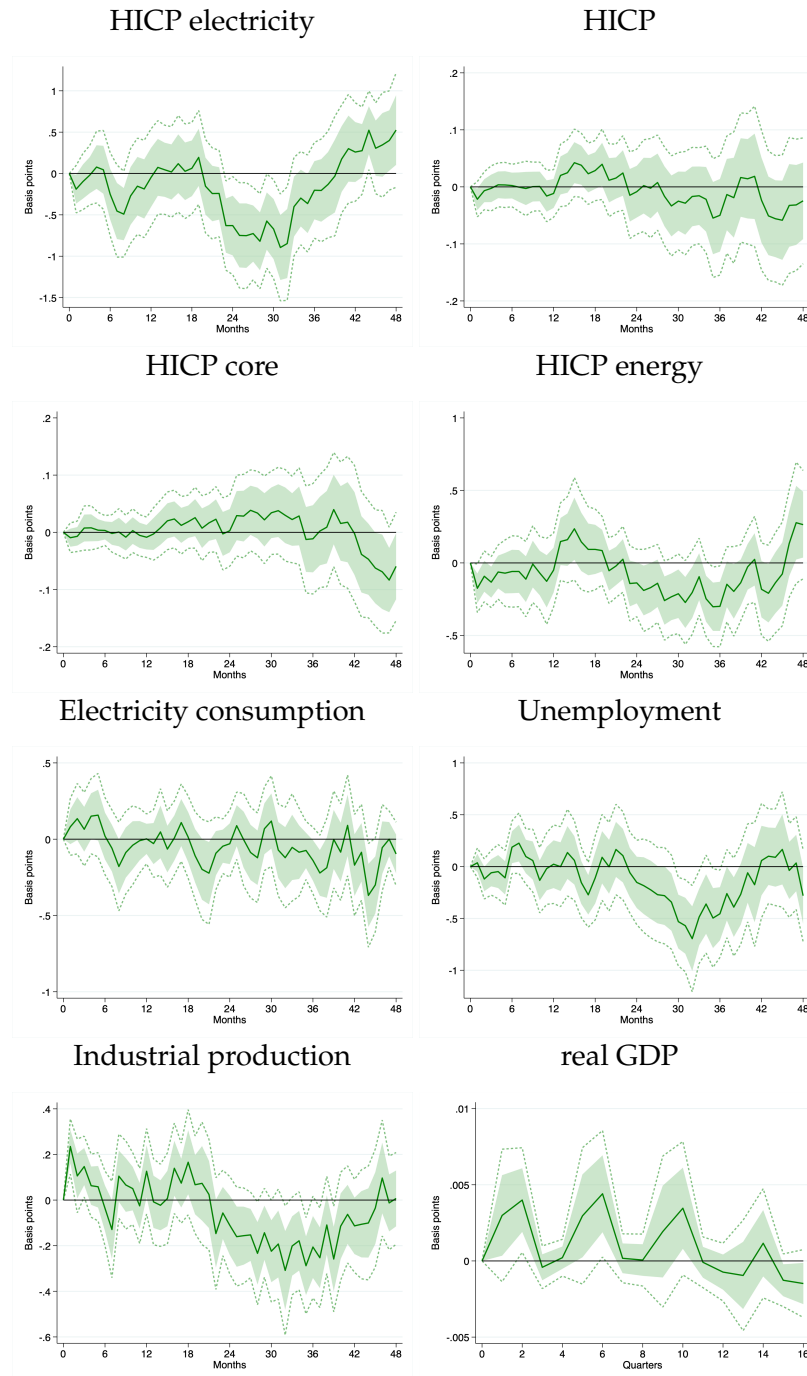
Figure E.2: Electricity and oil supply shocks



Note: Standardised wind electricity supply shocks from wind at turbine farms averaged across sample countries, and standardised Känzig (2021) oil supply news shocks.

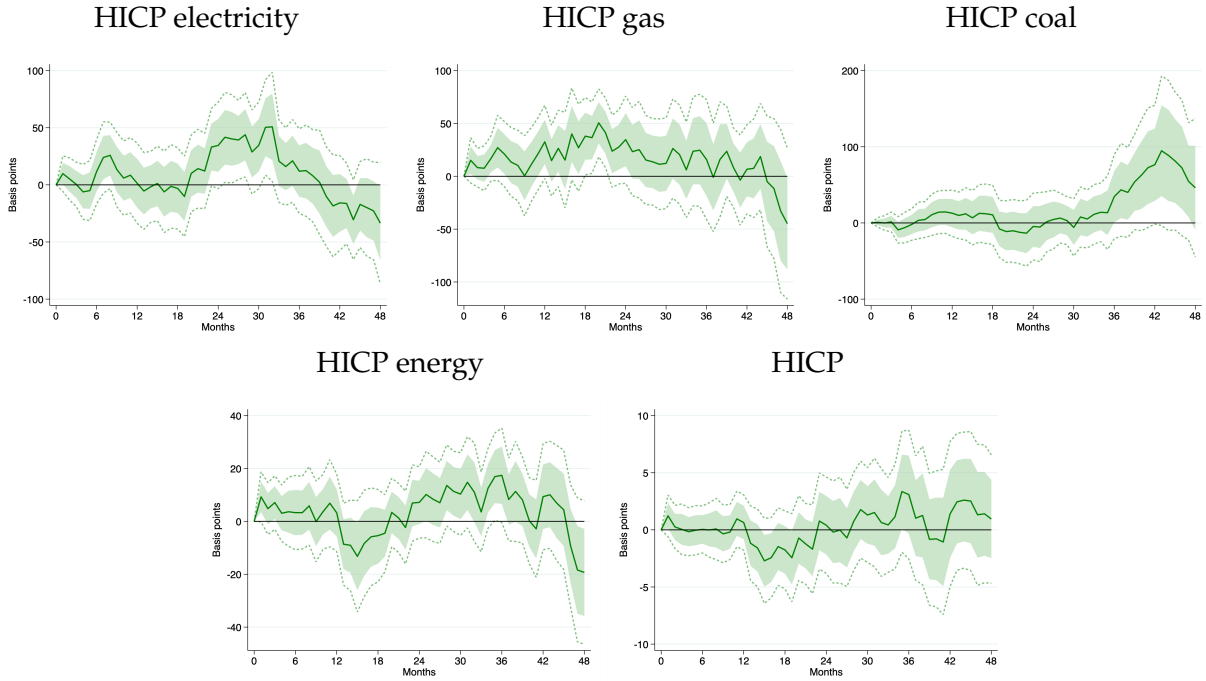
E.3 Macroeconomic effects

Figure E.3: Reduced form macroeconomic effects of turbine wind shocks



Note: Impulse responses to standardised turbine wind shocks. Local projection estimated according to equation (4) in the panel with country and time fixed effects, policy control, 2 lags, and Driscoll-Kraay standard errors with 3 lags. Error bands represent 68% and 90% confidence intervals respectively.

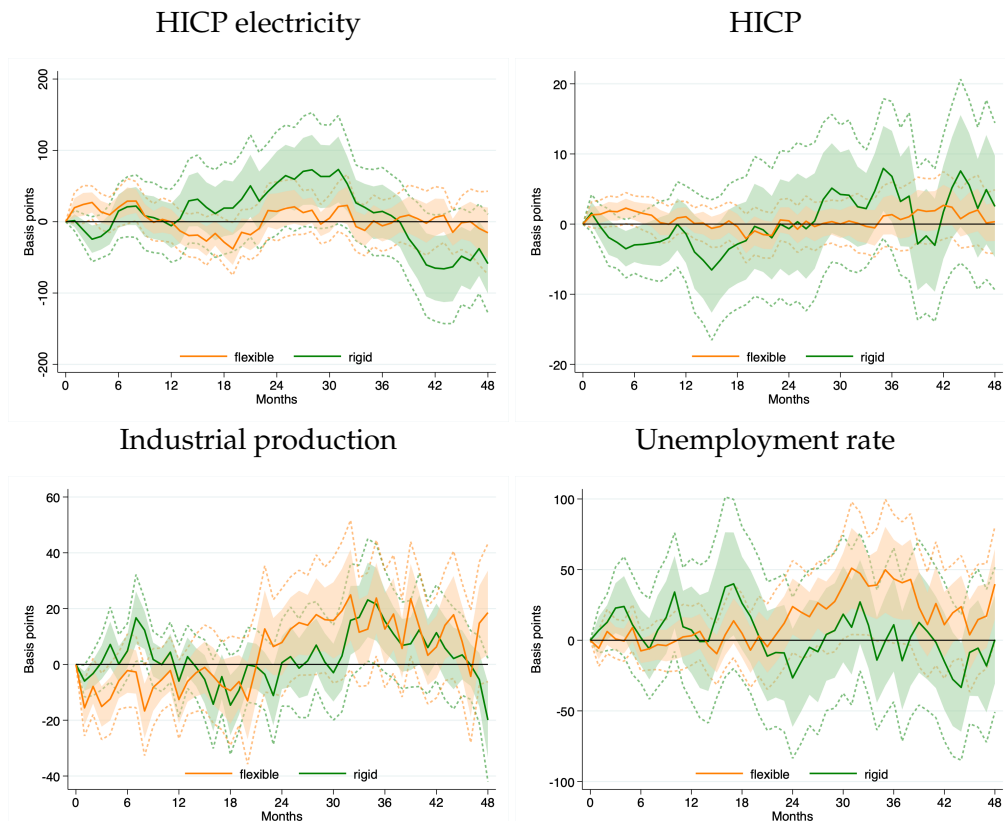
Figure E.4: Price effects of electricity price changes



Note: Impulse responses to 1-month wholesale electricity price changes instrumented by wind shocks. Local projection estimated in the panel according to equation 4, and Driscoll-Kraay standard errors with 3 lags. Error bands represent 68% and 90% confidence intervals respectively.

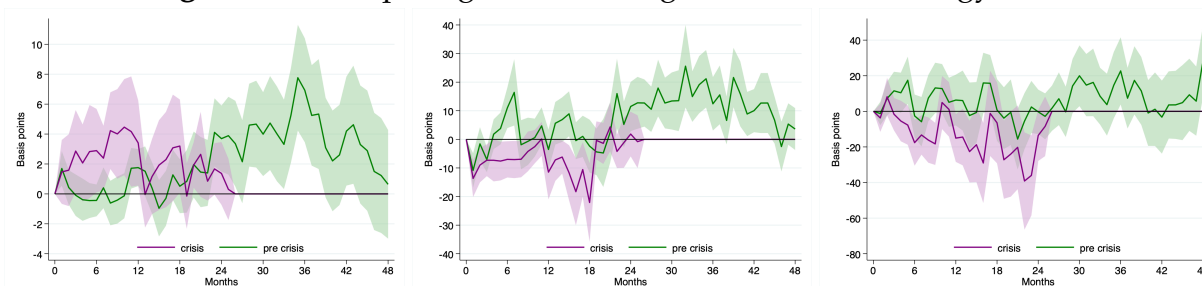
Figure E.6 provides crucial evidence that the puzzling economic activity effects are structural rather than reflecting extraordinary policy interventions. During the energy crisis period, industrial production shows more conventional negative responses where estimates can be made reliably, contradicting rather than explaining the average positive effects. Similarly, unemployment decreases during the crisis period, as opposed to increasing during normal times. These patterns likely reflect extensive policy interventions during the crisis that shielded consumers and firms from electricity price volatility and fundamentally altered transmission mechanisms. Interestingly, despite these policy measures, unit price effects are stronger during the first year within the crisis.

Figure E.5: Passthrough-dependent effects of electricity price increases



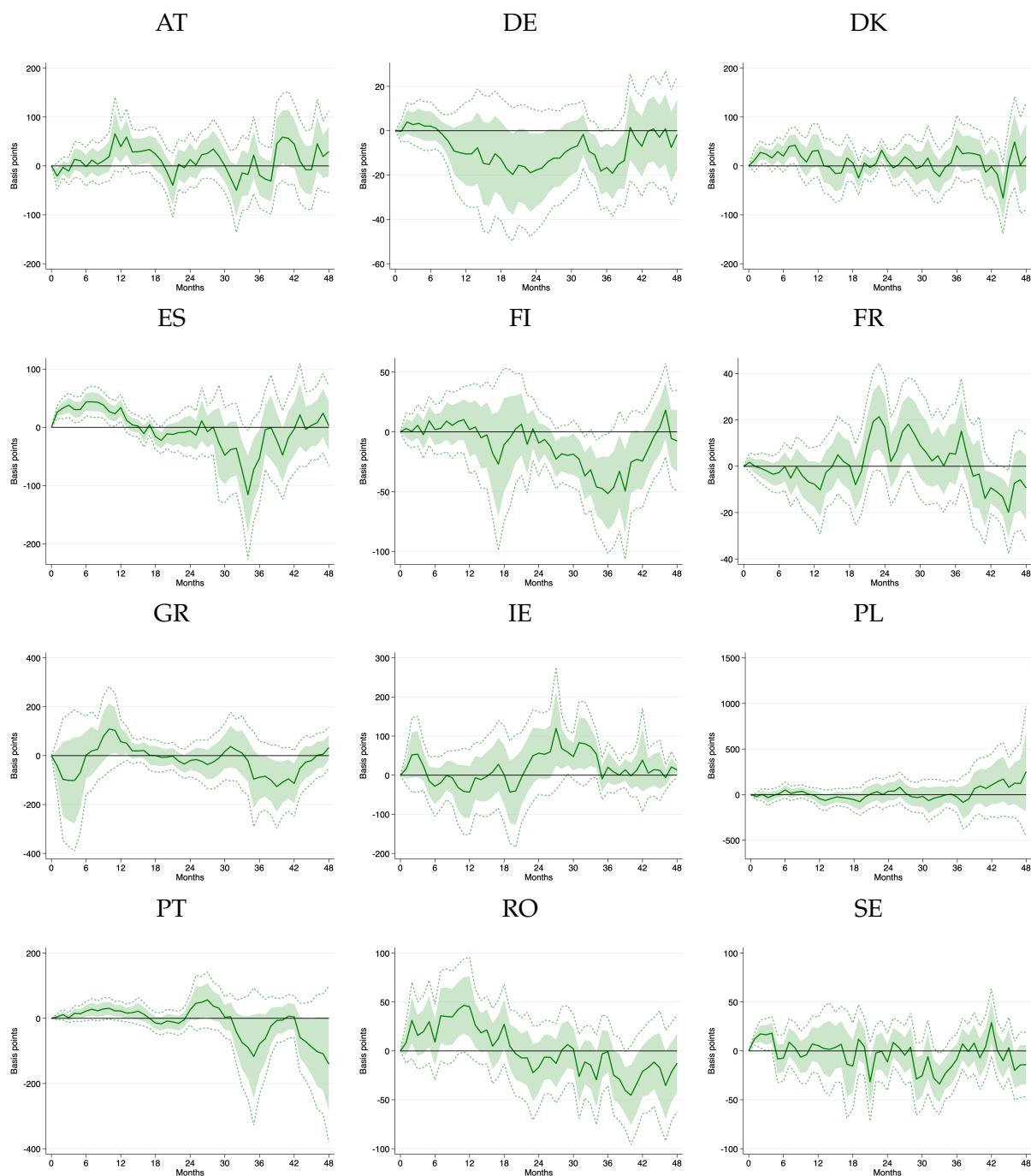
Note: Impulse responses to a 1pp electricity price change instrumented with wind shocks. Local projection estimated in the panel with country fixed effects and 2 lags as specified in equation (4), splitting countries into 2 groups based on the correlation of wholesale and retail electricity prices for various consumer groups, as shown in table C.1. The countries in the flexible retail price group are BE, DK, ES, FI, GR, IE, IT, RO, and SE. The countries in the rigid retail price group are AT, DE, FR, HR, HU, NL, PL, and PT. Driscoll-Kraay standard error bands using 2 lags represent 68% and 90% confidence intervals.

Figure E.6: Comparing effects during and before the energy crisis



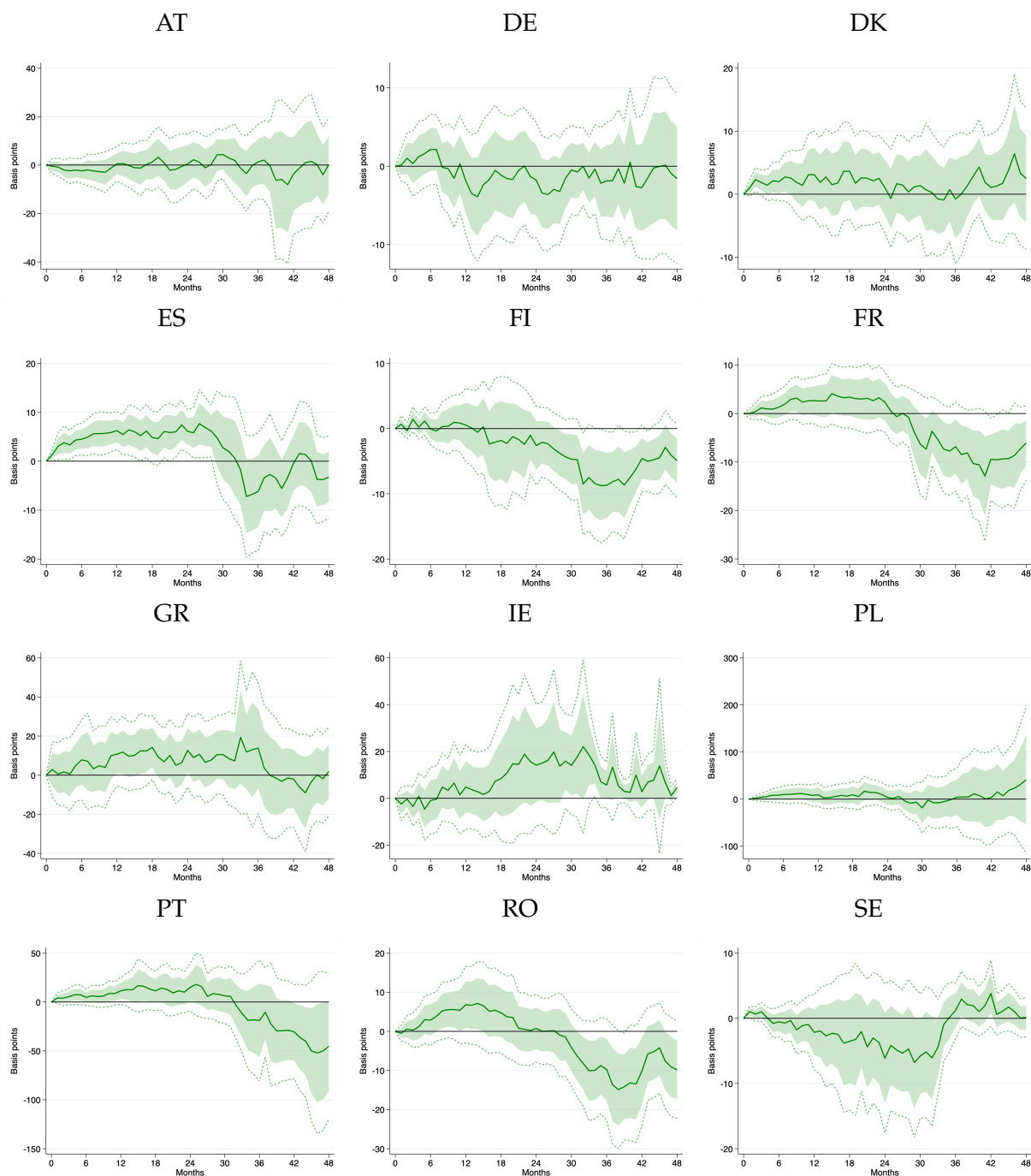
Note: Impulse responses to a 1pp electricity price change instrumented with wind shocks. Local projection estimated as specified in equation (4), using sample splits to compare responses during and after the energy crisis starting September 2021 to the sample before. Impulse responses during crisis are estimated only for two years given the limited duration. Driscoll-Kraay standard error bands represent 68% confidence intervals.

Figure E.7: Effects of electricity price changes on HICP electricity by country



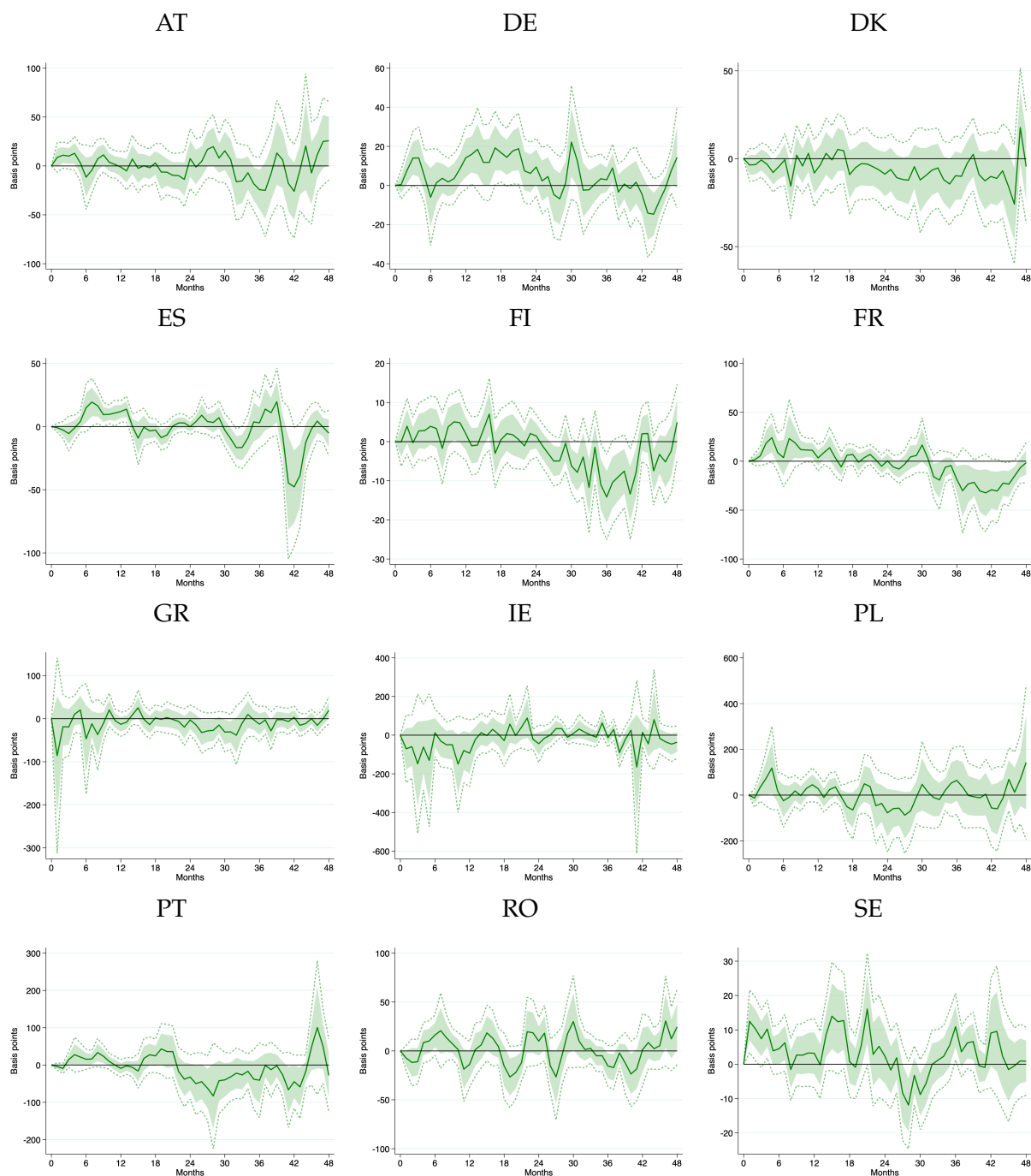
Note: Impulse responses of the log HICP electricity index to wholesale electricity price changes instrumented by wind shocks. Local projection estimated as in 4 but separately by country with 2 lags and robust standard errors. Error bands represent 68% and 90% confidence intervals respectively. Belgium, Croatia, Italy, Hungary and the Netherlands are omitted because the instrument is not strong enough and standard errors are too large to produce readable graphs.

Figure E.8: Effects of electricity price changes on the price level (HICP) by country



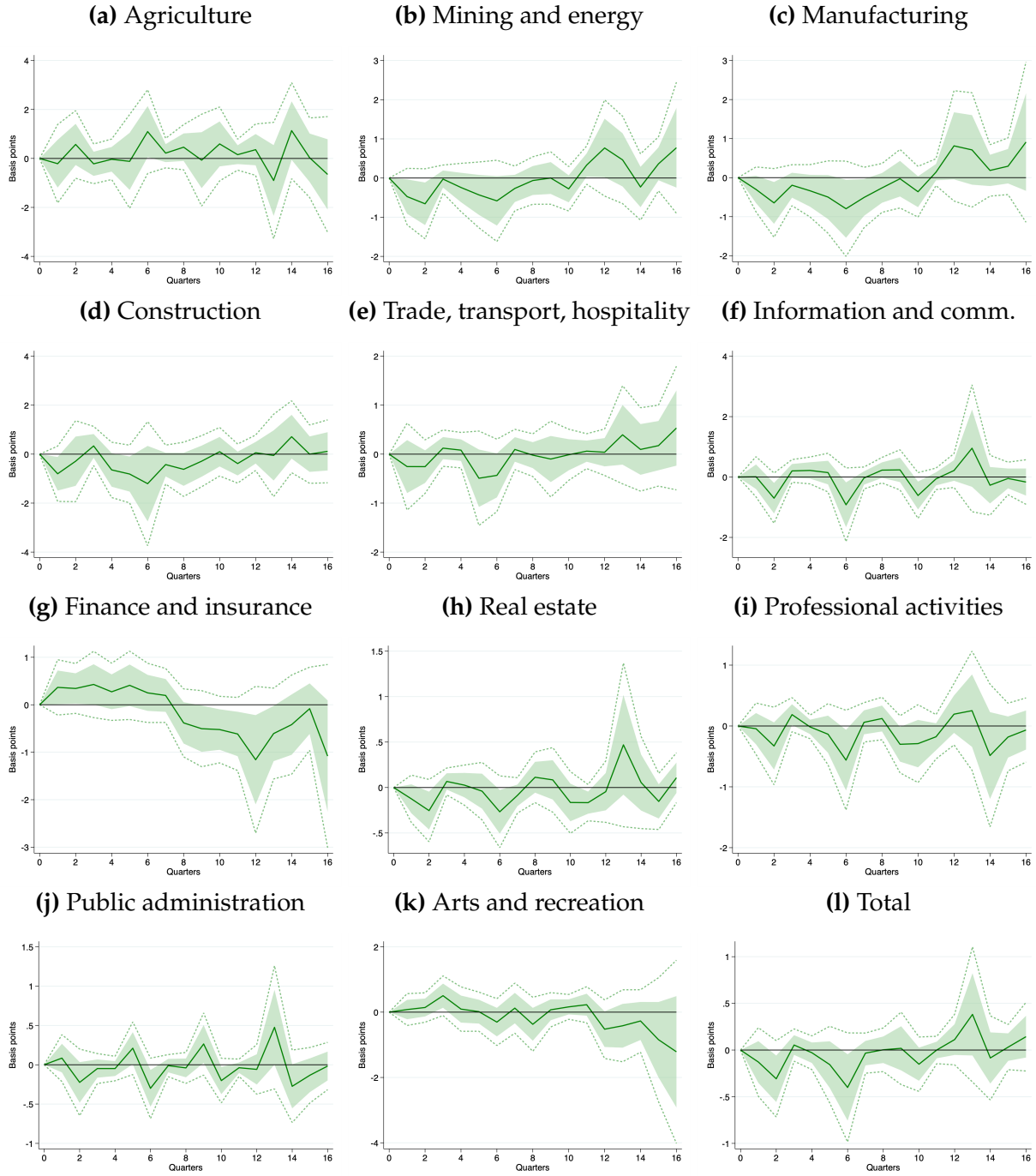
Note: Impulse responses of the log HICP index to wholesale electricity price changes instrumented by wind shocks. Local projection estimated as in 4 but separately by country with 2 lags and robust standard errors. Error bands represent 68% and 90% confidence intervals respectively. Belgium, Croatia, Italy, Hungary and the Netherlands are omitted because the instrument is not strong enough and standard errors are too large to produce readable graphs.

Figure E.9: Effects of electricity price changes on industrial production by country



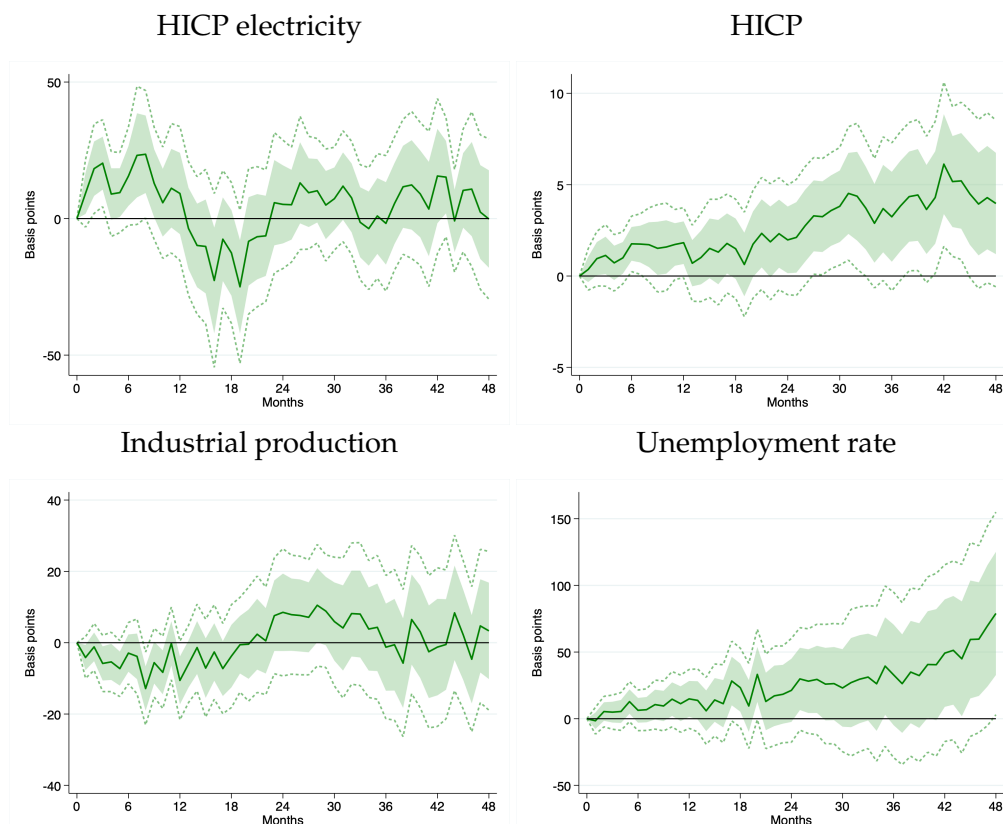
Note: Impulse responses of the log HICP index to wholesale electricity price changes instrumented by wind shocks. Local projection estimated as in 4 but separately by country with 2 lags and robust standard errors. Error bands represent 68% and 90% confidence intervals respectively. Belgium, Croatia, Hungary, Italy, and the Netherlands are omitted because the instrument is not strong enough and standard errors are too large to produce readable graphs.

Figure E.10: Effects of electricity price changes on real gross value added by sector



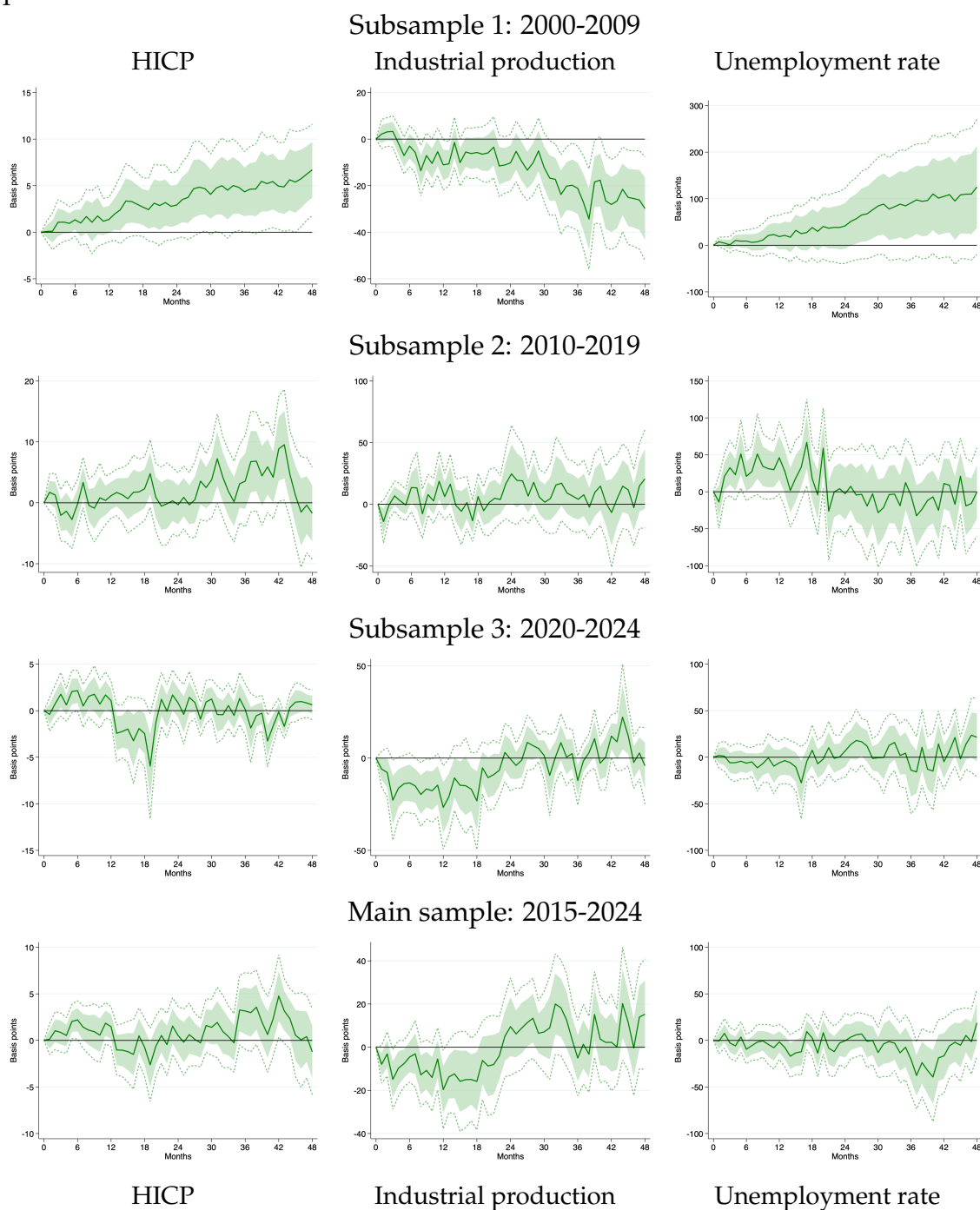
Note: Impulse responses of the log real gross value added by sector to wholesale electricity price changes instrumented by wind shocks. Local projection estimated as in 4 but separately by sector, not seasonally adjusted. Driscoll-Kraay standard errors with 2 lags used to construct 68% and 90% confidence intervals.

Figure E.11: Macroeconomic effects of electricity price changes for early adopter countries in extended sample (2000-2024)



Note: Impulse responses to a 1pp electricity price change instrumented with wind shocks. Local projection estimated in the panel with country fixed effects and 2 lags as specified in equation (4). This panel is restricted to countries that surpassed 10% installed wind electricity generation capacity prior to 2010, which includes Denmark, Finland, Germany, Ireland, Portugal, and Spain. Day-ahead wholesale electricity prices for this period are provided by Bloomberg. Driscoll-Kraay standard error bands represent 68% and 90% confidence intervals respectively.

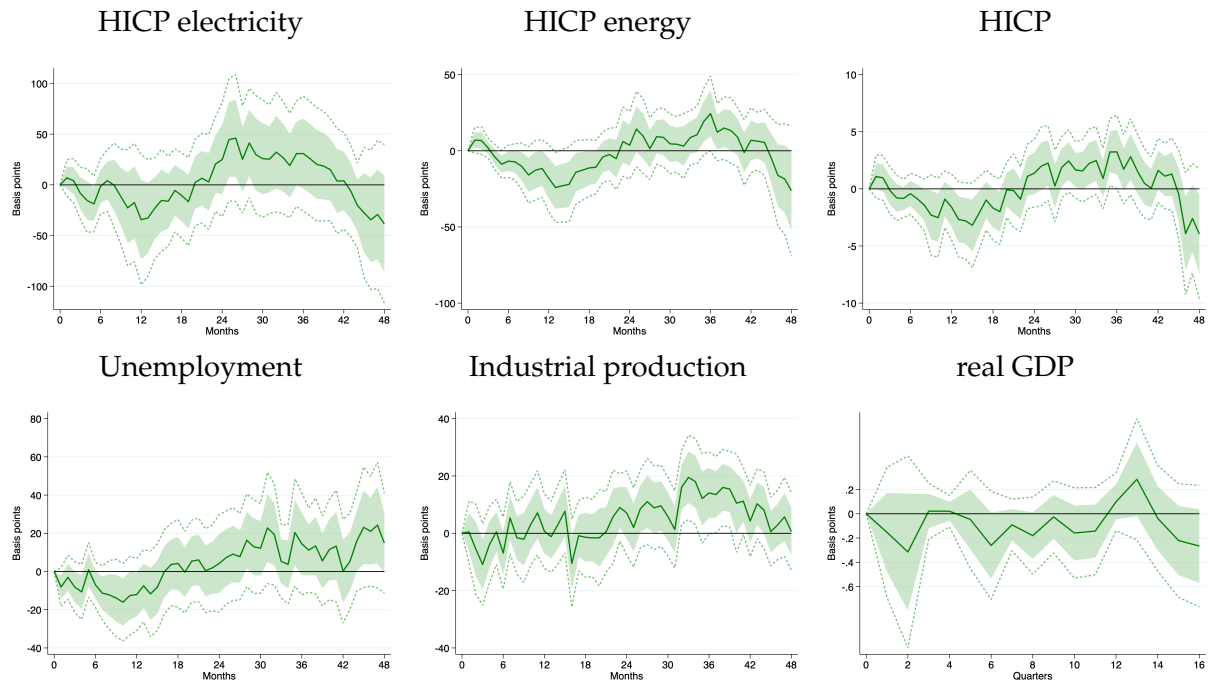
Figure E.12: Macroeconomic effects of electricity price changes for early adopters by subsample



Note: Impulse responses to a 1pp electricity price change instrumented with wind shocks. Local projection estimated in the panel with country fixed effects and 2 lags as specified in equation (4), using sample splits into periods indicated in the subtitles. This panel is restricted to countries that surpassed 10% installed wind electricity generation capacity prior to 2010, which includes Denmark, Finland, Germany, Ireland, Portugal, and Spain. Day-ahead wholesale electricity prices for this period are provided by Bloomberg. Driscoll-Kraay standard error bands represent 68% and 90% confidence intervals respectively.

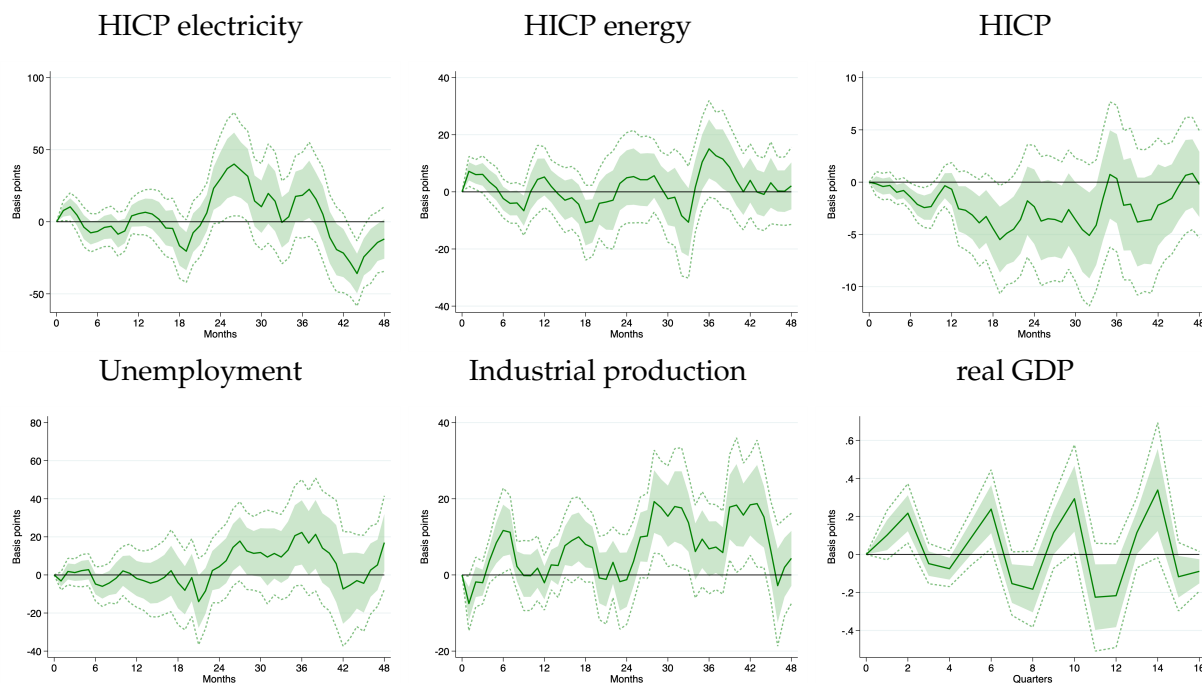
E.4 Results using alternative shock measures

Figure E.13: Macroeconomic effects of electricity prices instrumented by wind at offshore turbines



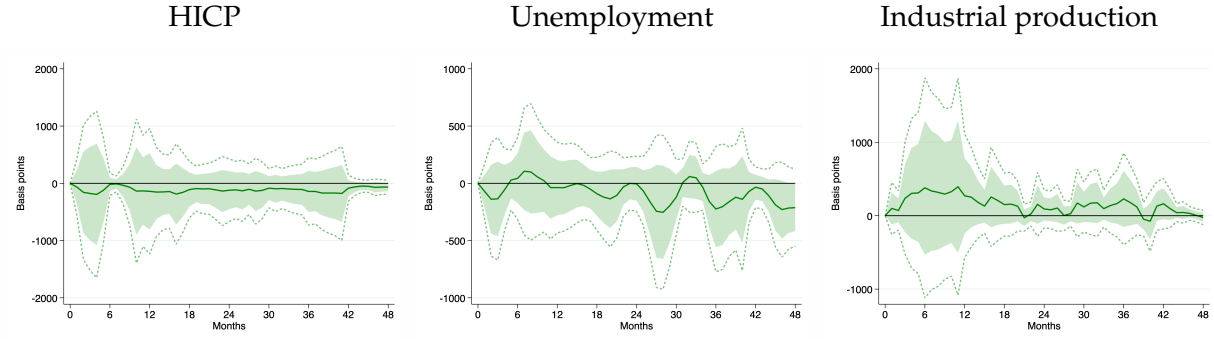
Note: Impulse responses to 1-month changes in electricity prices instrumented by wind at turbines only located offshore. Local projection estimated in the panel with country fixed effects and 2 lags as specified in equation (4), replacing wind in cells without turbines with average wind over all land area. Driscoll-Kraay standard errors with 3 lags. Error bands represent 68% and 90% confidence intervals respectively.

Figure E.14: Macroeconomic effects of electricity prices instrumented by turbine wind controlling for fixed effects only



Note: Impulse responses to 1-month changes in electricity prices instrumented by wind shocks at turbine locations. The shock is constructed according to equation 2 but controlling only for calendar month fixed effects. Local projection estimated in the panel with country fixed effects and 2 lags as specified in equation (4). Driscoll-Kraay standard errors with 3 lags. Error bands represent 68% and 90% confidence intervals respectively.

Figure E.15: Placebo test: Macroeconomic effects of electricity prices instrumented by wind in countries without turbines



Note: Impulse responses to 1-month changes in electricity prices instrumented by average national wind speeds for Slovakia and Slovenia, which have less than 1% installed wind electricity generation in total generation across the sample. Local projection estimated in the panel with time and country fixed effects and 2 lags as specified in equation (4). Driscoll-Kraay standard errors with 3 lags. Error bands represent 68% and 90% confidence intervals respectively.

E.5 Effects of oil price shocks

To compare the effects of electricity and oil price changes, the main text uses a specification interacting each energy form with its country-specific weight in HICP in a panel local projection. The resulting specification for oil is as follows:

$$\log(y_{c,t+h}) = \alpha^h + \eta_c^h + \theta_t^h + \beta^h (\Delta \log(p_t^o) \times \text{weight}_{c,t-12}^o) + \sum_{l=1}^2 \gamma_l^h \log(y_{c,t-l}) + \sum_{l=1}^2 \delta_l^h \Delta \log(p_{t-l}^o) + \psi^h i_{c,t} + \epsilon_{c,t+h} \quad (\text{E.1})$$

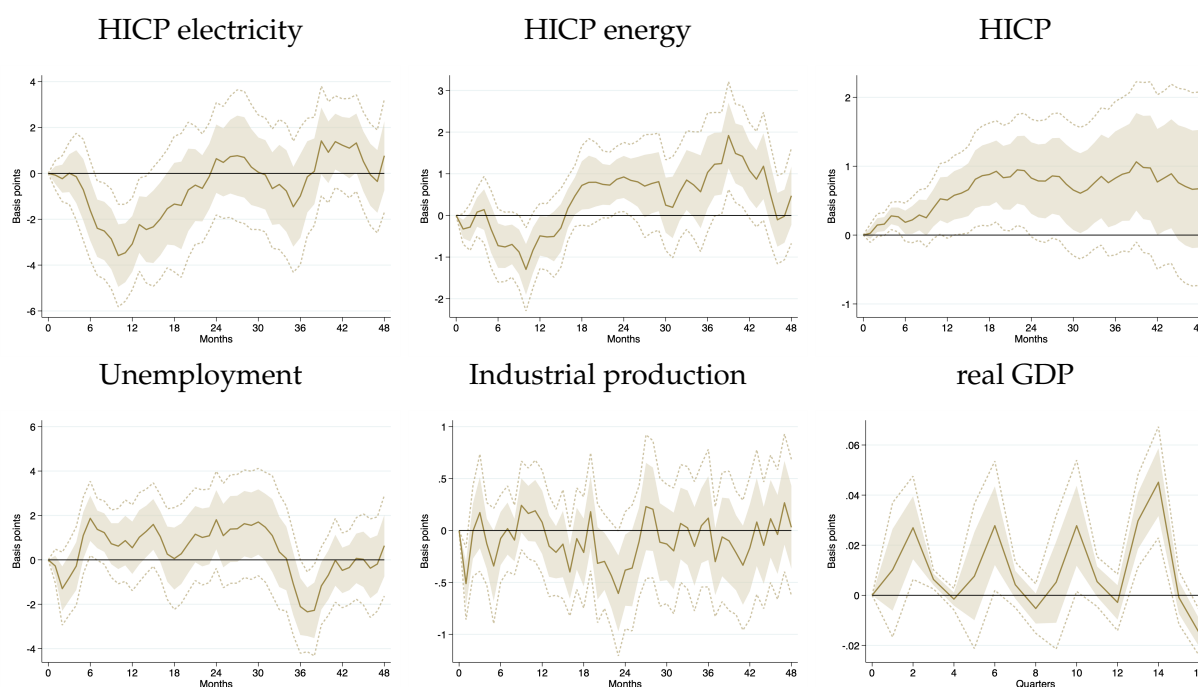
The weight of oil in HICP is computed as the combined weight of liquid fuels, solid fuels, and fuels and lubricants for personal transport equipment, in 2014 before the start of the sample.

To compare reduced form effects with country-specific shocks, I again interact the oil supply news shock with the country-specific pre-sample HICP energy expenditure weights to obtain variation across countries according to their relative exposure to energy prices, as suggested in Patzelt and Reis (2024). Using the resulting shift-share oil shock, I can then compare the main macroeconomic responses to both shocks in the EA using the same panel specification as above in 4, as shown in E.16.

Since positive oil supply news shocks increase oil prices, while positive wind sur-

prises decrease electricity prices, we would expect the impulse responses to mirror each other if oil and electricity had equivalent effects. This is roughly true for prices with the magnitude of effects in line with relative expenditure weights on electricity and oil, but not necessarily for measures of macroeconomic activity. Industrial production never increases after a positive wind shock while effects of oil shocks are more ambiguous, and unemployment increases in response to a positive wind surprise more persistently over a span of almost two years, while the effect of oil supply news is insignificant and subsides faster.

Figure E.16: Reduced form macroeconomic effects of Känzig (2021) oil supply news shocks



Note: Impulse responses to standardised Känzig (2021) oil supply news shocks, multiplied with pre-sample HICP energy weights by country. GDP impulse responses estimated for 1-quarter changes instrumented with the sum of shocks over the quarter. Local projection estimated in the panel with country and time fixed effects, 2 lags, and Driscoll-Kraay standard errors with 3 lags. Error bands represent 68% and 90% confidence intervals respectively.

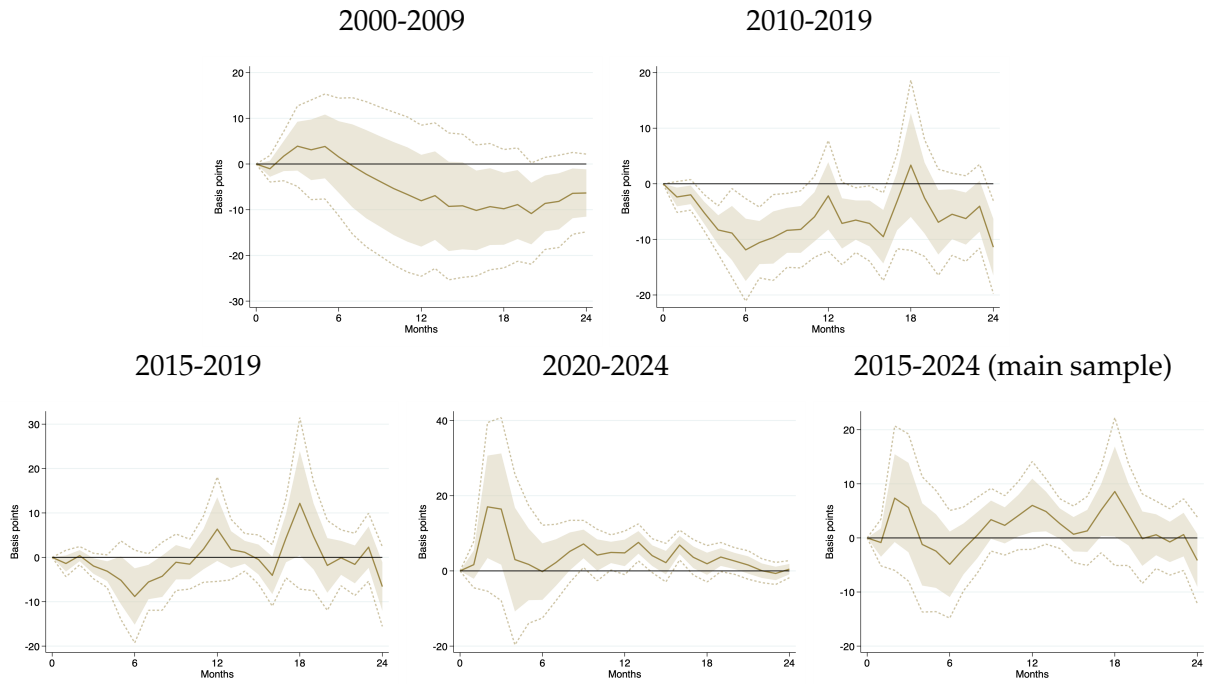
For analysing the effects of oil price changes separately, instead of using time fixed effects which are not available given the nature of global oil prices, I instead control for major macroeconomic developments during the sample period. These include the ECB deposit rate i_t , for common monetary policy, quarterly fiscal surplus $ps_{c,t}$, for fiscal support measures during the energy crisis, and a pandemic dummy C_t , for the most intensive

phase between March 2020 and June 2021 when economic relationships may have been fundamentally altered. The specification for impulse responses to oil price changes is the following:

$$\log(y_{c,t+h}) = \alpha^h + \eta_c^h + \beta^h \Delta \log(p_t^o) + \sum_{l=1}^2 \gamma_l^h \log(y_{c,t-l}) + \sum_{l=1}^2 \delta_l^h \Delta \log(p_{t-l}^o) + \psi^h i_{c,t} + \zeta^h p_{s,c,t} + \phi^h C_t + \epsilon_{c,t+h} \quad (\text{E.2})$$

Applying the same specification to electricity prices instead of including time fixed effects yields similar main results for the impulse responses than the baseline specification does.

Figure E.17: Industrial production effects of oil price changes in subsamples



Note: Impulse responses for the lop industrial production index to 1-month changes in oil prices (euro Brent) instrumented by Känzig (2021) oil supply news shocks. Local projection estimated in the panel with country fixed effects, macroeconomic controls, 2 lags, and Driscoll-Kraay standard errors with 3 lags. Error bands represent 68% and 90% confidence intervals respectively.