Renewable Energy Supply Shocks from Wind Electricity*

Paula Patzelt†
LSE

This version: August 30, 2025

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 shift from fossil fuels to renewable electricity, business cycle dynamics may persistently change.

JEL codes: E31, E32, Q42, Q43.
Keywords: Business cycle, prices, energy supply, energy shocks, wind energy.

*For helpful comments and discussions I am grateful to Clare Balboni, Maarten De Ridder, Jonathon Hazell, Ethan Ilzetzki, Stephen Jarvis, Diego Känzig, Ricardo Reis, Emiliano Rinaldi, and Silvana Tenreyro. I also thank seminar participants at LSE Macroeconomics, Norges Bank, RES PhD conference, CESifo/ifo Junior Workshop on Energy and Climate Economics, RES Easter Training School, LSE Environment Camp, LSE EEE Hour, and Frankfurt Summer School. First draft: August 2024.

†Contact: `p.h.patzelt@lse.ac.uk`.

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.[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

[1]See Känzig (2021), Känzig (2023) and Bai et al. (2024) for empirical contributions, amongst others. Recent theoretical work shows that supply shocks can generate demand-like responses under certain conditions (Cesa-Bianchi and Ferrero, 2021, Guerrieri et al., 2022, Kharroubi and Smets, 2024).

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 falls, 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.[3] Second, while oil prices adjust flexibly with quick passthrough to consumer prices such as petrol, electricity prices for consumers are much less flexible. Depending

[2] These include: 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.

[3] These differences persist as transmission networks and trading across largely national bidding zones remain limited.

on contract conventions and end-user consumption volumes, retail electricity prices may 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 only responds persistently positively to electricity. 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.

This paper's main contribution to the literature is identifying energy supply shocks focused on electricity prices and based on renewables rather than fossil fuels, 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.[4] 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.[5]

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 de-

[4]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.

[5]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.

pend 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.[6] Additional studies have expanded to other countries and examined asymmetric generation effects on prices.[7] 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,[8] as well as energy demand and consumption.[9] Weather instruments have also been applied to non-energy issues such as health and voting.[10] 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.

[6]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.

[7]Examples 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.

[8]Examples 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.

[9]See 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.

[10]Examples 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.

The paper proceeds as follows. Section 2 introduces wind as a 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 shocks as instruments to analyse electricity price change effects on other prices, economic activity, and exploring heterogeneity across shock characteristics and state dependence. 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 share in consumption baskets, wholesale electricity prices correlate strongly with overall inflation.[11] 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.

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 ex-

[11] The EA average weight of electricity in HICP was 3% in 2024. See appendix figure B.1 for the correlation between electricity and aggregate inflation.

ceptions.[12]

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.[13] 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 turn negative for brief periods. Conversely, when wind speeds are low, market prices are determined by marginal non-renewable generation.

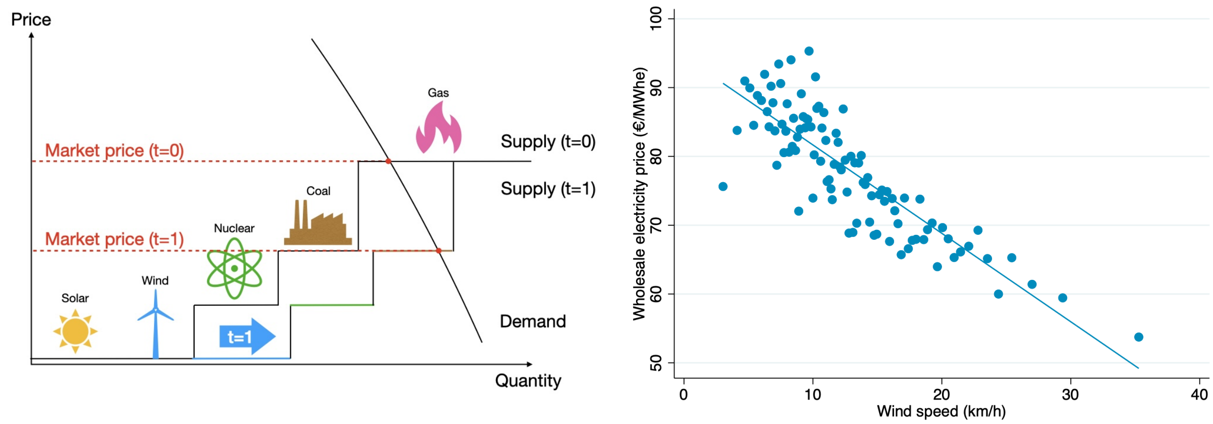
Since wind represents 21% of electricity generation on average and is projected to increase further, price effects can be sizeable but vary by country according to wind reliance. The quantitative impact also depends on current market conditions and supply curve po-

[12]Within the sample, only Germany-Luxembourg forms a cross-border zone, while Italy is divided into nine separate bidding zones, Sweden into four, and Denmark into two. Portugal and Spain represent an intermediate case: formally separate zones that are effectively integrated through well-developed cross-border networks and extensive trading, resulting in identical wholesale prices over 90% of the time.

[13]The EU has agreed policy adjustments to the pricing system to reduce the dependence of consumer electricity price on fossil fuels. The merit order will stay in place, but move to a corridor system for market prices with bounds on the marginal prices, somewhat weakening the direct relationship between marginal costs and the market price during extreme price swings. For more information, see for example https://www.consilium.europa.eu/en/policies/electricity-market-reform/.

Figure 1: Merit order pricing in wholesale electricity markets

(a) In theory: wind is inframarginal **(b)** In practice: wind relevance



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.

sition. When demand is fully satisfied by renewables, additional wind has minimal price impact. However, when equilibrium requires significant fossil fuel use, the effect depends on whether additional wind changes the marginal source. If wind shifts equilibrium to a different marginal source, or if marginal costs are convex at high levels, supply curve shifts can substantially impact prices, creating asymmetric effects.

2.4 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 B.2 by country), though not necessarily linear due to the cube relationship between wind speed and extractable power.[14] The sample is restricted to wind speeds within standard usable ranges where possible, though this rarely constrains averaged data.

[14] Extractable 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).

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.[15] Using meteorological data directly avoids concerns about capacity build-up and market-based utilisation changes.

2.5 Wholesale and retail prices

Ideally, one would study retail rather than wholesale electricity prices, 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.[16]

Passthrough from wholesale to retail prices varies substantially across countries and consumer types (see appendix figure B.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.[17] Germany represents an extreme case with 12-month household price guarantees that delayed adjustments even during the energy crisis, while countries like Spain have more flexible contracts that track wholesale prices closely. 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.

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.

2.6 The Ukraine energy crisis

The sample period includes the European energy crisis triggered by Russia's invasion of Ukraine in February 2022, which fundamentally disrupted energy markets and prompted unprecedented policy interventions. European electricity prices reached record highs

[15]Higher 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.

[16]The HICP electricity subindex could proxy retail prices, but its construction varies across countries and time, especially regarding new versus existing contracts.

[17]For example, even within Germany, passthrough varies with competition levels across market segments (Duso and Szücs, 2017).

during 2022 and early 2023, driven mainly by reduced Russian energy supplies and soaring natural gas prices.

European governments responded with extensive fiscal measures to protect consumers and businesses from extreme electricity prices, though the scope and design of interventions varied significantly across countries using subsidies, tax reductions, or consumption vouchers. For example, Germany implemented retail price caps during 2023 covering 80% of previous-year household consumption, while Spain and Portugal negotiated the "Iberian exception" limiting wholesale prices through a price cap on gas electricity generation.

During the crisis period, one can therefore expect both heightened public awareness of electricity prices due to extensive media coverage and weakened passthrough from wholesale to retail prices due to policy measures. To address this challenge, I conduct a sample split analysis comparing responses during the energy crisis and the pre-period. As shown in section 4.3, the main findings are not driven by the crisis period, suggesting they reflect structural features of electricity markets rather than extraordinary circumstances.

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.[18] While the relationship to electricity demand is not obvious, depending on heating and cooling needs across industries and consumers, such effects cannot be excluded.

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

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 capacity[19] within sample countries as of February 2025, shown in appendix figure B.4. These locations are provided by Global Energy Monitor using OpenStreetMap data.[20]

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. 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:

$$wind_{c,t}^{turbines} = \sum_{g} wind_{g,c,t} \times \frac{capacity_{g,c}}{\sum_g capacity_{g,c}} \tag{1}$$

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.[21] The regression residual constitutes the wind electricity supply shock:

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

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

[19] 10MW capacity corresponds to approximately 3-5 onshore turbines or 1-2 offshore turbines, servicing roughly 10,000-15,000 households annually. This threshold is a limitation of available data.

[20] See appendix A for details on sources, selection, and limitations.

[21] Controlling for wind elsewhere is not essential for instrument power nor the main results for macroeconomic effects. See the first stage in appendix table D.4 and main macroeconomic effects in appendix figure D.13 when using the residual of capacity-weighted wind at turbines, controlling only for the seasonal fixed effects. Similarly, controlling for average national wind instead of filtering on non-turbine locations yields almost exactly identical results. Wind turbines require open spaces and are unpopular neighbours due to noise pollution and visual effects, leading to installation in low population density areas. To address concerns about unequal demand effects across space, appendix figure B.5 shows the locations of turbine farms and population density side by side for the example of Germany with the most installed turbines, showing only a small negative relationship around the most populous cities.

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.

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 B.6 shows the resulting average and country-specific shock series. Their variation is contained within 2km/h, avoiding dependence on extreme wind speed swings.

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:

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

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.[22] 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.

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.[23]

The strength of the instrument improves over time and should increase further as the share of wind in electricity generation grows with the green energy transition.[24] 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.[25]

3.4 Robustness

To ensure robustness of results to the specific shock identification approach, I present several alternative shocks that address different aspects of the identification challenge while maintaining the reliance on wind's inframarginal role for prices. These alternative approaches yield positively correlated shock series functioning as strong instruments in panel specifications, and produce qualitatively similar responses of macroeconomic variables.[26]

One approach to strengthen the exogeneity assumption is to rely exclusively on wind at offshore turbines, controlling for wind over the country's land area. This method provides greater confidence in excluding direct demand effects, as offshore locations are unpopulated and cannot directly affect consumption behaviour. However, this approach comes at the cost of significantly reduced instrument power, as most European wind

[22]See appendix table D.1 for detailed results of the first stage in the panel and by country.

[23]Wind shares in electricity generation by country are shown in appendix figure B.3 The first stage is weakest for Italy, where the national average price poorly represents its fragmented bidding zones and where wind constitutes the lowest share of electricity generation capacity in the sample. Alternatively, varying shares of home production not captured by market prices or significant differences in the ability to substitute between sources and origins of electricity could explain the variation.

[24]See appendix table D.5 for the first stage results of the baseline panel specification by subsample, showing a continuous increase in the effect of turbine wind speeds on wholesale prices and instrument strength.

[25]See figure B.7 for recent trends and projections of electricity generation from the IEA's WEO.

[26]See appendix C for details on alternative shock construction and D.4 for results using these shocks.

turbines are onshore such that offshore represents less than 10% of total installed wind capacity on average.[27]

Another alternative would be to use national average wind speeds regardless of turbine locations. To address exogeneity concerns through potential demand impacts of wind speeds, I construct surprises that are orthogonal to previous patterns in wind and contemporaneous temperature and solar radiation, removing weather-related demand effects. This strategy yields shocks that provide strong instruments, but are correlated across countries. Using these surprises as instruments for electricity price changes yields broadly similar results to the baseline, although weaker in size and significance.

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 one. Appendix figure D.14 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.

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). I estimate the following specification in the cross-country panel for different outcome variables $y_{c,t}$:

$$\log(y_{c,t+h}) = \alpha^h + \beta^h \Delta \log(p^e_{c,t}) + \sum_{l=1}^{2} \gamma^h_l \log(y_{c,t-l}) + \sum_{l=1}^{2} \delta^h_l \Delta \log(p^e_{c,t-l}) + \eta^h_c + \theta^h_t + \psi^h i_{c,t} + \epsilon_{c,t+h} \quad (4)$$

[27] Appendix table D.3 presents first-stage results using only offshore wind, showing considerably weaker statistical power as expected. Appendix figure D.12 shows main results using offshore wind shocks as instruments, yielding qualitatively similar results compared to onshore wind shocks, except for the direct effect on HICP electricity which is close to zero.

The coefficient of interest, β^h, captures the impact of a one percentage point change in electricity prices on the outcome variable $y_{c,t+h}$ 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 the 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 out of the EA, I also control for the policy rate $i_{c,t}$.

When comparing to effects of oil price changes, time fixed effects are not available since oil prices do not vary across countries. I hence compute impulse responses to oil price changes interacted with the country-specific weight of oil in HICP from the pre-period, and apply the same specification to electricity for comparison.[28]

The results presented in this section show the impact of price changes β^h at horizon h rather than cumulative effects, providing a clear picture of how electricity price shocks propagate through the economy over time. Alternative shock measures, outcomes, and reduced-form results are presented in appendix D.

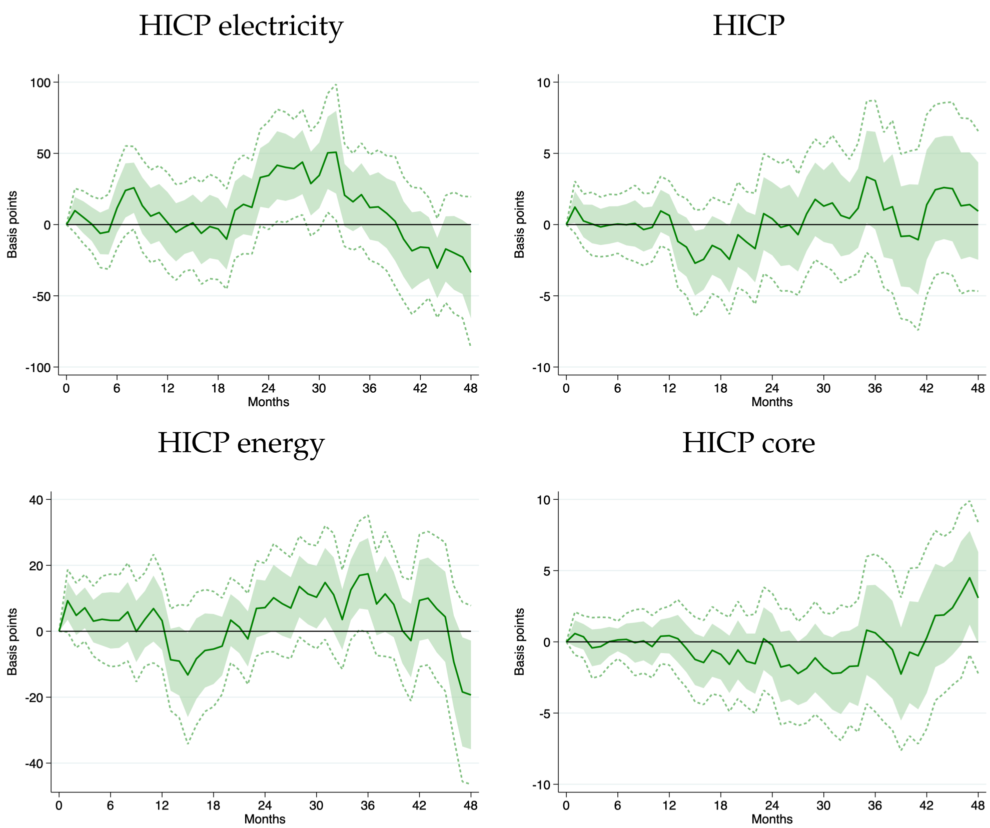
4.1 Average macroeconomic effects

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. Figures 2 and 3 show impulse responses to a 1pp wholesale electricity price increase of prices and activity respectively, 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: unemployment initially increases as expected, but industrial production reacts significantly positively at longer horizons after an initial decline, while GDP effects remain insignificant. This mixed pattern defies expectations

[28]The resulting specification for oil is as follows: $\log(y_{c,t+h}) = \alpha^h + \eta_c^h + \theta_t^h + \beta^h \left(\Delta \log(p_t^o) \times weight^o_{c,t-12}\right) + \sum_{l=1}^{2} \gamma_l^h \log(y_{c,t-l}) + \sum_{l=1}^{2} \delta_l^h \Delta \log(p_{t-l}^o) + \psi^h i_{c,t} + \epsilon_{c,t+h}$. This approach is similar to the methodology for price shocks in Patzelt and Reis (2024). 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.

for supply shocks.

Figure 2: 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.

Following a 1pp wholesale price increase, HICP electricity shows a complex pattern of transmission over a four-year horizon. The response peaks at around 25 basis points after six months, declines through month 12, then exhibits a second rise around months 18-24 before gradually falling. This pattern reflects the complex and incomplete nature of 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 2.5. 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 2 basis points 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 consistent increases up to 10 basis points 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.[29]

The spillover effects extend beyond energy markets, affecting broader price dynamics. Core HICP (excluding energy and food) initially increases by 1 basis point 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.

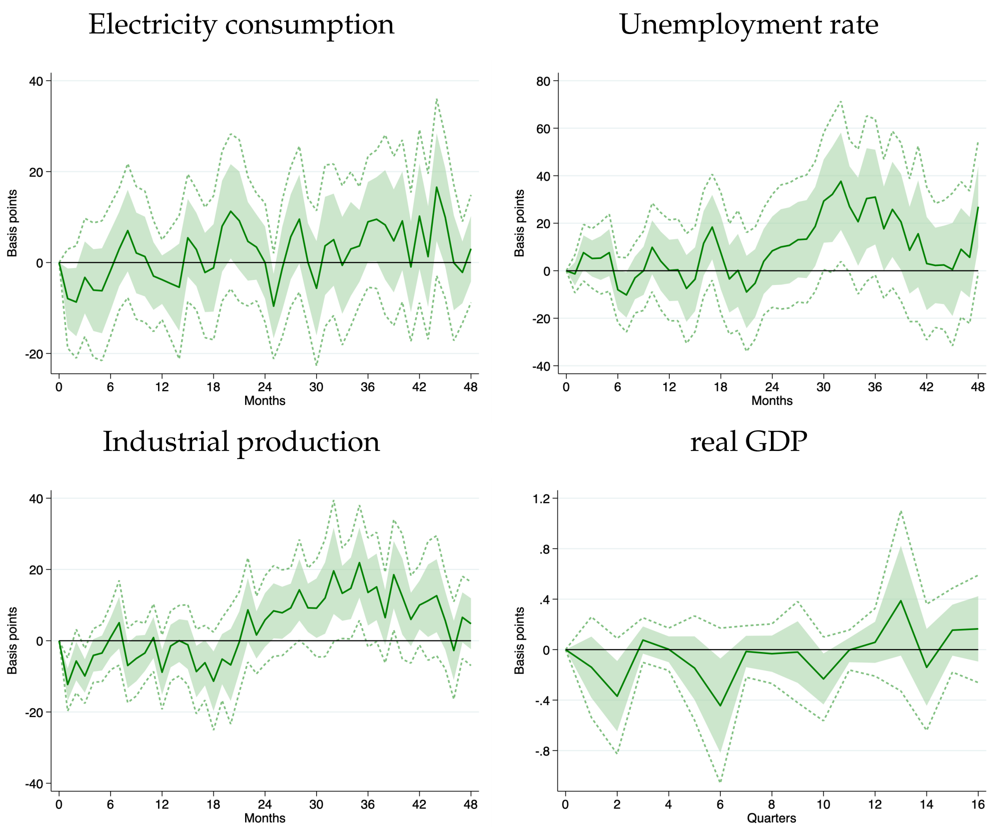
Electricity supply shocks generate complex effects on economic activity that fundamentally diverge from theoretical predictions. Figure 3 reveals a nuanced pattern where initial responses consistent with supply shock theory give way to sustained positive effects that challenge standard economic intuition.

Electricity consumption initially shows the expected negative response to higher prices, declining by up to 7 basis points 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 10 bp throughout the first year, but grows over time and becomes significant up to 40 bp in years three and four, reflecting rigid labour market structures in Europe.

Industrial production, after showing modest initial declines around 10 bp, becomes strongly and persistently positive from year two onwards, reaching 15-25 basis points and

[29] Coal and especially gas prices also rise following electricity price shocks, speaking to their substitutability with electricity.See additional energy price impacts in appendix figure D.3.

Figure 3: 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.

maintaining these elevated effects through year four.[30] 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.[31]

Figure D.9 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. Using more time-series and less cross-sectional variation, effects on retail electricity prices are more significant, leading to a more pronounced and significant 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 in D.10 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 became weaker in the 2010s and 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. 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.

[30] This pattern is qualitatively quite consistent also when using other versions of the wind electricity shocks to instrument for electricity price changes, as shown in appendix D.4.

[31] For sector level effects on value added, see appendix figure D.8.

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 and resulting wholesale-to-retail pass-through.

Producer prices react more strongly and statistically significantly to wholesale electricity price increases, as shown in figure 4a. The energy PPI sub-index shows the largest response, with prices spiking immediately after the shock by up to 30 bp and continuing to rise over two years after the shock, proving the more direct impact on commercial electricity users. Passthrough of energy producer prices to overall producer prices consequently is also more pronounced than to retail prices, with an initial statistically significant price increase of 3 bp after a 1 pp wholesale electricity price jump.

Retail price responses vary significantly by country, which is largely explained by differences in retail market structures leading to variation in consumer exposure to wholesale electricity price changes.[32] Figure 4b shows retail price responses separately for countries with more flexible or rigid retail electricity prices, revealing a more pronounced and significant increase in both HICP electricity and the overall HICP over the first year in countries where retail and wholesale prices are strongly correlated. Where retail prices are less flexible, the peak effect on prices is delayed by 1-2 years in comparison.

4.3 State- and 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 three dimensions of heterogeneity that help explain the puzzling average results and reveal important asymmetries in transmission mechanisms.

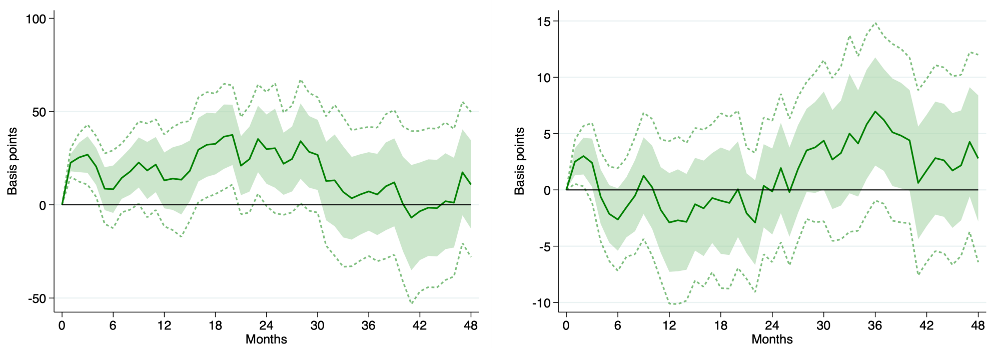
Figure 5a reveals that transmission mechanisms operate differently depending on shock direction, with decreases potentially creating more persistent adjustments but in-

[32] As shown in figure B.2, firm electricity prices track wholesale prices closely in most countries, but consumer exposure varies significantly due to differences in regulation, standard contractual terms, retail market competition, wholesale cost shares in retail prices, and consumer switching behaviour. The energy crisis, which prompted differential policy measures to shield consumers from rising energy prices, further complicated passthrough dynamics. Appendix figure D.5 shows passthrough to HICP electricity separately by country. However, country-specific results should be interpreted cautiously given varying instrument strength. Additional country-specific impacts for overall HICP and industrial production are shown in appendix figures D.6 and D.7.

Figure 4: Transmission of wholesale electricity price changes to retail prices

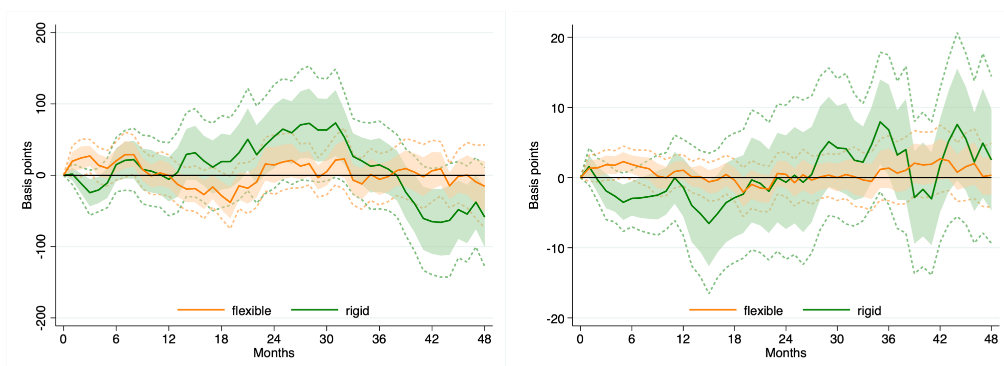
(a) Producer prices

PPI energy | PPI



(b) Retail prices by flexibility

HICP electricity | HICP



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 4b splits countries into 2 groups based on the correlation of wholesale and retail electricity prices for various consumer groups, as shown in table B.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.

creases leading to more pronounced passthrough to retail prices.[33] Price increases generate stronger HICP responses within the first year, while price decreases produce larger delayed responses in years three and four. Industrial production exhibits the puzzling pattern for both directions, but the surprising positive effects emerge earlier following price decreases than increases. Unemployment 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 5b reveals 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. This suggests that substantial electricity price increases trigger the expected adjustment mechanisms, while smaller shocks prompt more gradual, persistent adjustments, such as efficiency improvements or production reorganisation.

Figure 5c 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.[34] 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.

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 seem to drive the aggregate results. These findings suggests that substantial cost pressures could trigger efficiency improvements, technological upgrades, or production reorganisation.

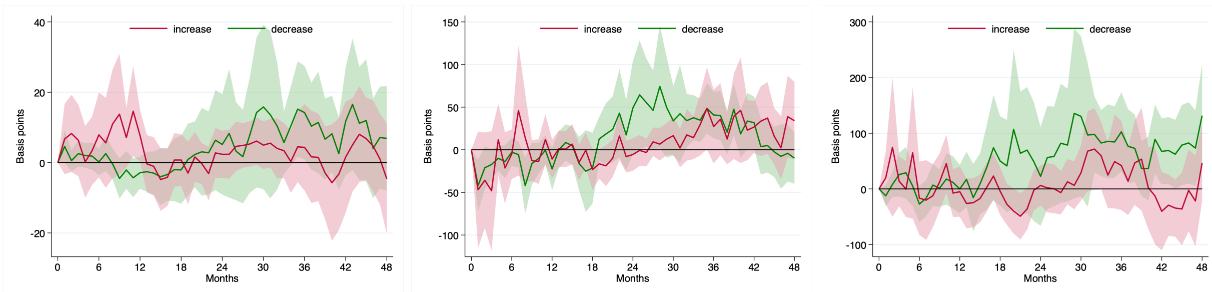
[33]These patterns are consistent with established findings about asymmetric retail price passthrough.See for example Peltzman (2000) and Borenstein, Cameron and Gilbert (1997) for references.

[34]Since the crisis period until the end of the sample constitutes less than four years, I estimate impulse responses only for half the horizon when estimates can still be made relatively precisely.

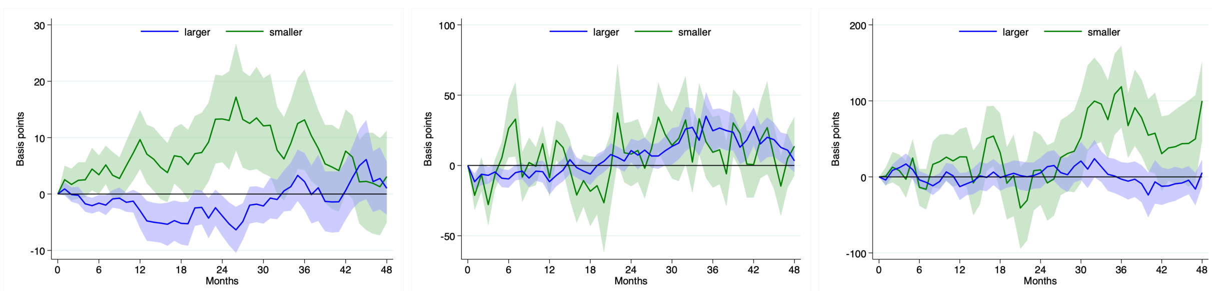
Figure 5: Comparing effects by shock, state, and energy product

(a) Electricity price change: increase or decrease

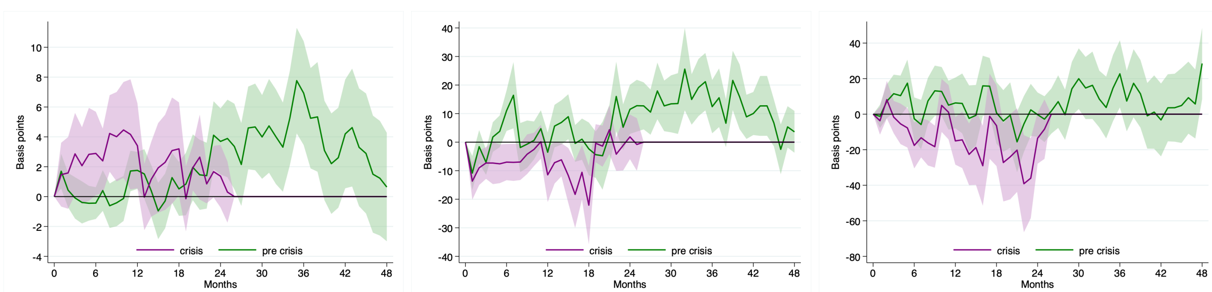
HICP Industrial production Unemployment rate



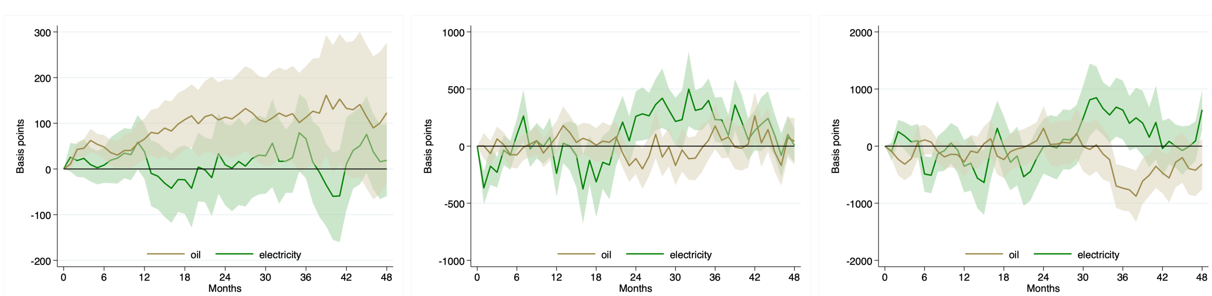
(b) Size of electricity price change: above or below 75th percentile



(c) Electricity price change: energy crisis



(d) Comparing electricity and oil price changes (per unit of HICP weight)



HICP Industrial production Unemployment rate

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, and c) compares 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. Panel d) 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. 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/oil price shocks have similar macroeconomic effects?

Figure 5d compares impulse responses to a 1pp Brent oil price change instrumented by Känzig (2021) oil supply news shocks with a 1pp electricity price change instrumented with wind shocks.[35] The specification mirrors equation (4), but interacts both energy products with their respective shares in country-specific HICP, allowing direct comparison of price effects per unit of expenditure exposure.

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 9 basis points for oil (roughly 10% overall energy weight) versus 3 basis points for electricity (3% electricity weight).[36]

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 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.[37]

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

[35]The shocks show no obvious relationship (see appendix figure D.1), since OPEC is highly unlikely to adjust oil supply based on European wind conditions. The correlation between shocks is slightly negative, close to zero, and statistically insignificant. Appendix section D.5 presents reduced-form effects of oil shocks on macroeconomic variables over the sample period. See appendix figure D.11 for a comparison of the responses of all main macroeconomic variables.

[36]Obtain these numbers by multiplying the point estimates from the graph with the average HICP weights for each energy product, for oil $160 * 0.06$, and for electricity $90 * 0.03$.

[37]See appendix figure D.16 for industrial production responses over longer periods and in subsamples.

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. This also suggests that different production sectors are affected disproportionately based on their electrification levels and energy intensity in production. Finally, the differences between electricity and oil, and the evolving nature of these relationships over time, indicates that historical oil shock analysis may provide limited guidance for understanding electricity price effects in an increasingly electrified economy. As the energy transition progresses, understanding these differential transmission mechanisms becomes crucial for both monetary policy and macroeconomic forecasting.

5 Conclusion

Electricity prices represent an increasingly important component of energy costs in Europe, yet identifying exogenous changes has remained challenging, with literature relying primarily on oil price instruments. This paper demonstrates that wind can serve as exogenous driver of electricity price changes when carefully extracting electricity supply-relevant variation. The shock measure, constructed from wind at turbine locations while controlling for broader demand patterns, provides a strong instrument for electricity price changes without requiring a structural model or restrictive assumptions.

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 more volatile and diverse electricity price shocks will affect increasingly electrified economies with varying generation mixtures.

Due to electrification and the energy transition, wind electricity shocks will only become more important for European business cycles. Increasing reliance on wind electricity, expected to double over the next ten years (International Energy Agency, 2024), will strengthen the power of wind shocks as instruments for electricity prices. The phase-out of fossil fuels will shift the overall composition of energy supply shocks towards electricity, fundamentally altering business cycle dynamics if the patterns documented over the past decade persist.

References

Alessandri, Piergiorgio, and Andrea Gazzani. 2023. "Natural gas and the macroeconomy: not all energy shocks are alike." *Bank of Italy Temi di Discussione (Working Paper) No*, 1428.

Atalla, Tarek, Simona Bigerna, and Carlo Andrea Bollino. 2018. "Energy demand elasticities and weather worldwide." *Economia Politica*, 35: 207–237.

Bai, Xiwen, Jesús Fernández-Villaverde, Yiliang Li, and Francesco Zanetti. 2024. "The causal effects of global supply chain disruptions on macroeconomic outcomes: evidence and theory." *CESifo Working Paper No. 10930*.

Baumeister, Christiane, and James D Hamilton. 2019. "Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks." *American Economic Review*, 109(5): 1873–1910.

Betz, Albert. 2013. "The maximum of the theoretically possible exploitation of wind by means of a wind motor." *Wind Engineering*, 37(4): 441–446.

Boeck, Maximilian, and Thomas O Zörner. 2023. *Natural Gas Prices and Unnatural Propagation Effects: The Role of Inflation Expectations in the Euro Area.* SSRN.

Borenstein, Severin, A Colin Cameron, and Richard Gilbert. 1997. "Do gasoline prices respond asymmetrically to crude oil price changes?" *The Quarterly journal of economics*, 112(1): 305–339.

Cao, Melanie, and Jason Wei. 2005. "Stock market returns: A note on temperature anomaly." *Journal of Banking & Finance*, 29(6): 1559–1573.

Casoli, Chiara, Matteo Manera, and Daniele Valenti. 2022. "Energy shocks in the Euro area: disentangling the pass-through from oil and gas prices to inflation." *Fondazione Eni Enrico Mattei Working Paper 1399*.

Cesa-Bianchi, Ambrogio, and Andrea Ferrero. 2021. "The transmission of Keynesian supply shocks." *CEPR Discussion Paper No. DP16430*.

Cludius, Johanna, Hauke Hermann, Felix Chr Matthes, and Verena Graichen. 2014. "The merit order effect of wind and photovoltaic electricity generation in Germany 2008–2016: Estimation and distributional implications." *Energy economics*, 44: 302–313.

Considine, Timothy J. 2000. "The impacts of weather variations on energy demand and carbon emissions." *Resource and Energy Economics*, 22(4): 295–314.

Csereklyei, Zsuzsanna, Songze Qu, and Tihomir Ancev. 2019. "The effect of wind and solar power generation on wholesale electricity prices in Australia." *Energy Policy*, 131: 358–369.

Duso, Tomaso, and Florian Szücs. 2017. "Market power and heterogeneous pass-through in German electricity retail." *European Economic Review*, 98: 354–372.

Emeis, Stefan. 2018. *Wind energy meteorology: atmospheric physics for wind power generation.* Springer.

Fan, Maoyong, and Yi Wang. 2020. "The impact of PM 2.5 on mortality in older adults: evidence from retirement of coal-fired power plants in the United States." *Environmental Health*, 19: 1–13.

Fisher-Vanden, Karen, Erin T Mansur, and Qiong Juliana Wang. 2015. "Electricity shortages and firm productivity: evidence from China's industrial firms." *Journal of Development Economics*, 114: 172–188.

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning. 2022. "Macroeconomic implications of COVID-19: Can negative supply shocks cause demand shortages?" *American Economic Review*, 112(5): 1437–1474.

Hamilton, James D. 2003. "What is an oil shock?" *Journal of econometrics*, 113(2): 363–398.

Heinen, Andréas, Jeetendra Khadan, and Eric Strobl. 2019. "The price impact of extreme weather in developing countries." *The Economic Journal*, 129(619): 1327–1342.

Hirth, Lion, Tarun M Khanna, and Oliver Ruhnau. 2024. "How aggregate electricity demand responds to hourly wholesale price fluctuations." *Energy Economics*, 135: 107652.

International Energy Agency. 2024. "World Energy Outlook 2024." International Energy Agency, Paris.

Ito, Koichiro, and Mar Reguant. 2016. "Sequential markets, market power, and arbitrage." *American Economic Review*, 106(7): 1921–1957.

Jordà, Òscar, Moritz Schularick, and Alan M Taylor. 2015. "Betting the house." *Journal of international economics*, 96: S2–S18.

Känzig, Diego R. 2021. "The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements." *American Economic Review*, 111(4): 1092–1125.

Känzig, Diego R. 2023. "The unequal economic consequences of carbon pricing." National Bureau of Economic Research.

Kerssenfischer, Mark. 2022. "Information effects of euro area monetary policy." *Economics Letters*, 216: 110570.

Kharroubi, Enisse, and Frank Smets. 2024. "Energy shocks as Keynesian supply shocks: implications for fiscal policy." *Available at SSRN 4842330*.

Kilian, Lutz. 2008. "Exogenous oil supply shocks: how big are they and how much do they matter for the US economy?" *The review of economics and statistics*, 90(2): 216–240.

Lee, Chien-Chiang, and Yi-Bin Chiu. 2011. "Electricity demand elasticities and temperature: Evidence from panel smooth transition regression with instrumental variable approach." *Energy Economics*, 33(5): 896–902.

Liebensteiner, Mario, Fabian Ocker, and Anas Abuzayed. 2025. "High electricity price despite expansion in renewables: How market trends shape Germany's power market in the coming years." *Energy Policy*, 198: 114448.

Maciejowska, Katarzyna. 2020. "Assessing the impact of renewable energy sources on the electricity price level and variability–A quantile regression approach." *Energy Economics*, 85: 104532.

Mulder, Machiel, and Bert Scholtens. 2013. "The impact of renewable energy on electricity prices in the Netherlands." *Renewable energy*, 57: 94–100.

Natalini, Davide, Giangiacomo Bravo, and Edward Newman. 2020. "Fuel riots: Definition, evidence and policy implications for a new type of energy-related conflict." *Energy Policy*, 147: 111885.

Nguyen, Gam Thi, and Thang T Vo. 2020. "Short-run and long-run gasoline demand elasticities: a case study of Australia." *International Energy Journal*, 20(3): 299–310.

Nibedita, Barsha, and Mohd Irfan. 2022. "Analyzing the asymmetric impacts of renewables on wholesale electricity price: Empirical evidence from the Indian electricity market." *Renewable Energy*, 194: 538–551.

Olea, José Luis Montiel, and Carolin Pflueger. 2013. "A robust test for weak instruments." *Journal of Business & Economic Statistics*, 31(3): 358–369.

Patzelt, Paula, and Ricardo Reis. 2024. "Estimating the rise in expected inflation from higher energy prices." Centre for Macroeconomics (CFM).

Peltzman, Sam. 2000. "Prices rise faster than they fall." *Journal of political economy*, 108(3): 466–502.

Ramey, Valerie A. 2016. "Macroeconomic shocks and their propagation." *Handbook of macroeconomics*, 2: 71–162.

Sensfuß, Frank, Mario Ragwitz, and Massimo Genoese. 2008. "The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany." *Energy policy*, 36(8): 3086–3094.

Stokes, Leah C. 2016. "Electoral backlash against climate policy: A natural experiment on retrospective voting and local resistance to public policy." *American Journal of Political Science*, 60(4): 958–974.

Tselika, Kyriaki, Maria Tselika, and Elias Demetriades. 2024. "Quantifying the short-term asymmetric effects of renewable energy on the electricity merit-order curve." *Energy Economics*, 132: 107471.

Woo, Chi-Keung, Jack Moore, Brendan Schneiderman, Tony Ho, Arne Olson, Lakshmi Alagappan, Kiran Chawla, Nate Toyama, and Jay Zarnikau. 2016. "Merit-order effects of renewable energy and price divergence in California's day-ahead and real-time electricity markets." *Energy Policy*, 92: 299–312.

Appendix

A Data

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.[38] 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.

Data on wind turbine locations is provided by nonprofit organisation Global Energy Monitor's[39] Global Wind Power Tracker, which collects information from OpenStreetMap on all wind turbines 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 should limit the power of the shock as an instrument in earlier years of the sample, when the shock measure overweights locations with not yet installed wind turbines. Its implications for exogeneity should however be limited as long as we can assume that population or production locations have not moved away from such locations to make way for wind farms, which seems plausible.

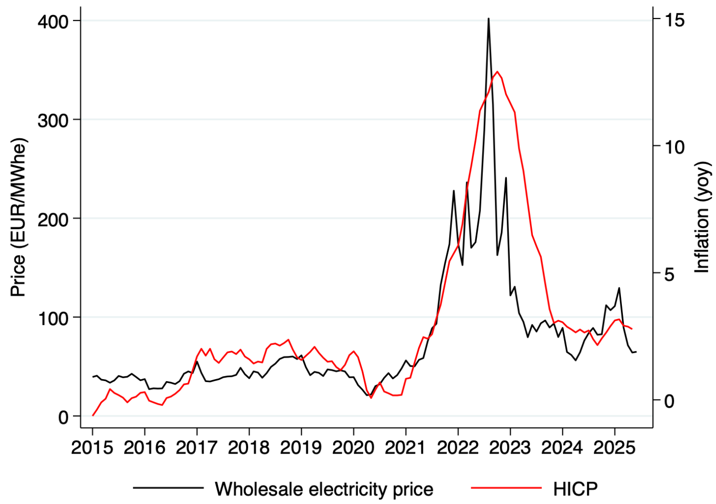
Grid-level weather data including wind speed at 100m elevation, solar radiation and temperature by 0.25° (≈ 28km) grid cell is taken from the Global Wind Atlas using EU Copernicus ERA5 data and provided as monthly averages.

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

[39] https://globalenergymonitor.org

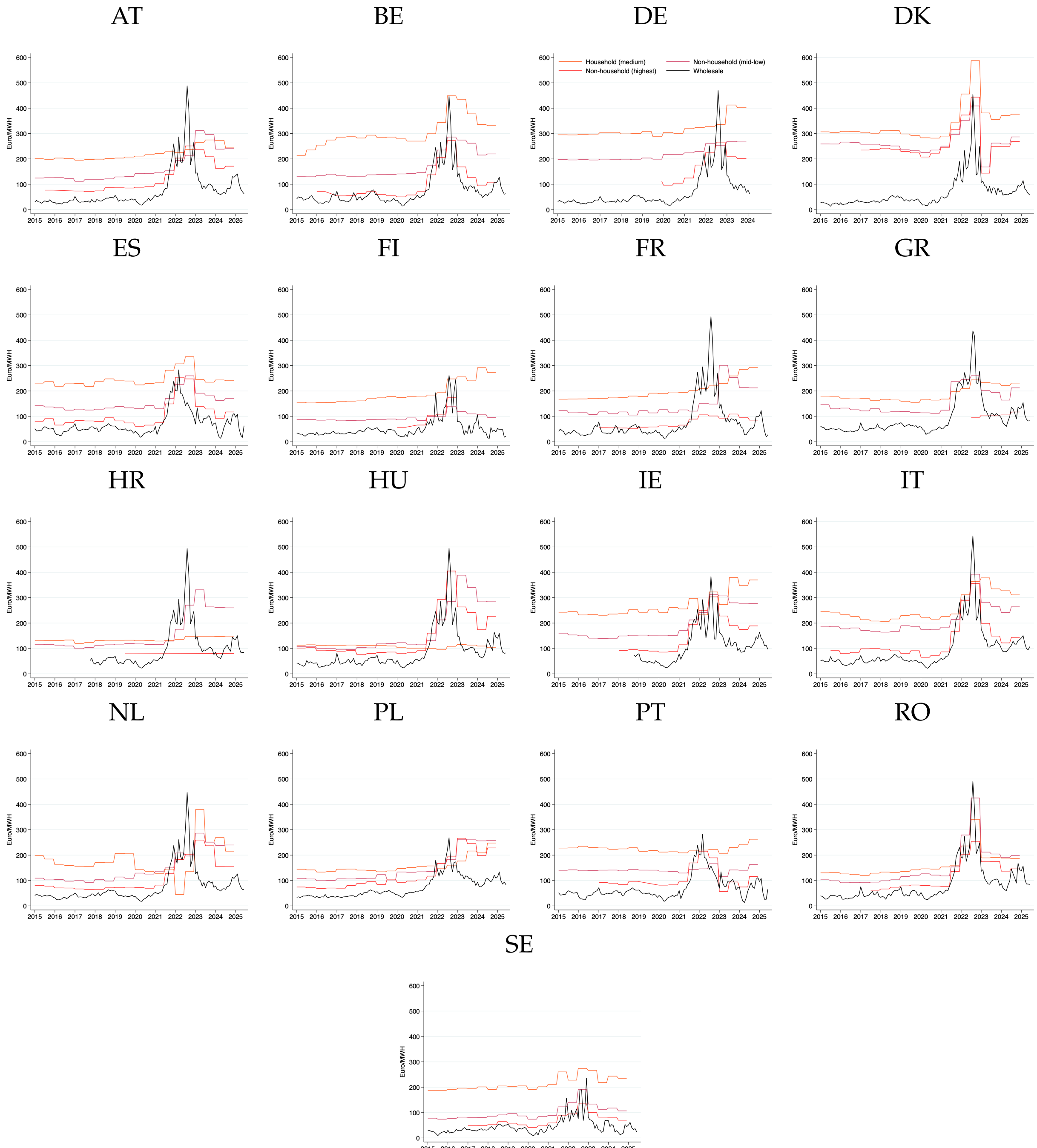
B Descriptives

Figure B.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 B.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 B.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.

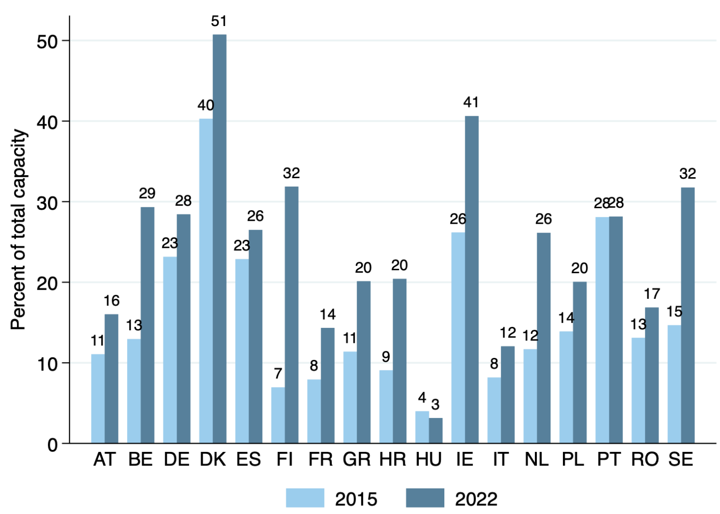
Table B.2: Wind electricity generation and wind speed by country

	AT	BE	DE	DK	ES	FI	FR	GR	HR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Average wind speed	27.42***	21.05***	294.46***	23.95***	161.18***	20.26***	104.96***	8.29**	4.24***
	(1.83)	(2.44)	(20.95)	(2.35)	(9.15)	(4.41)	(10.30)	(4.13)	(0.75)
Constant	-42.05***	-61.19***	-1092.58***	-56.27***	-391.46***	-81.93**	-349.11***	13.08	-6.04
	(6.32)	(14.55)	(136.05)	(17.98)	(46.01)	(32.38)	(56.88)	(21.67)	(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***	18.32***	65.35***	37.17***	42.11***	39.50***	25.64***	46.72***
	(0.10)	(0.82)	(4.50)	(7.06)	(3.64)	(2.54)	(1.35)	(6.73)
Constant	-5.77***	-51.69***	-184.29***	-125.86***	-121.43***	-101.49***	-55.41***	-162.17***
	(0.48)	(5.95)	(23.02)	(46.84)	(20.61)	(13.14)	(5.76)	(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

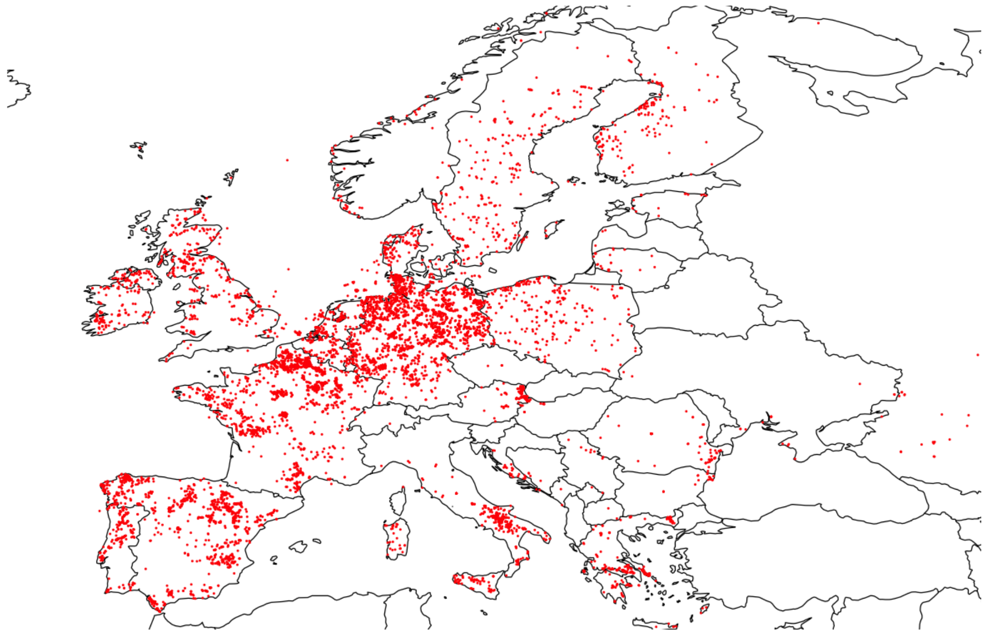
Note: Correlation of monthly national wind electricity generation and average wind speed across country land area conditional on a constant.

Figure B.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.

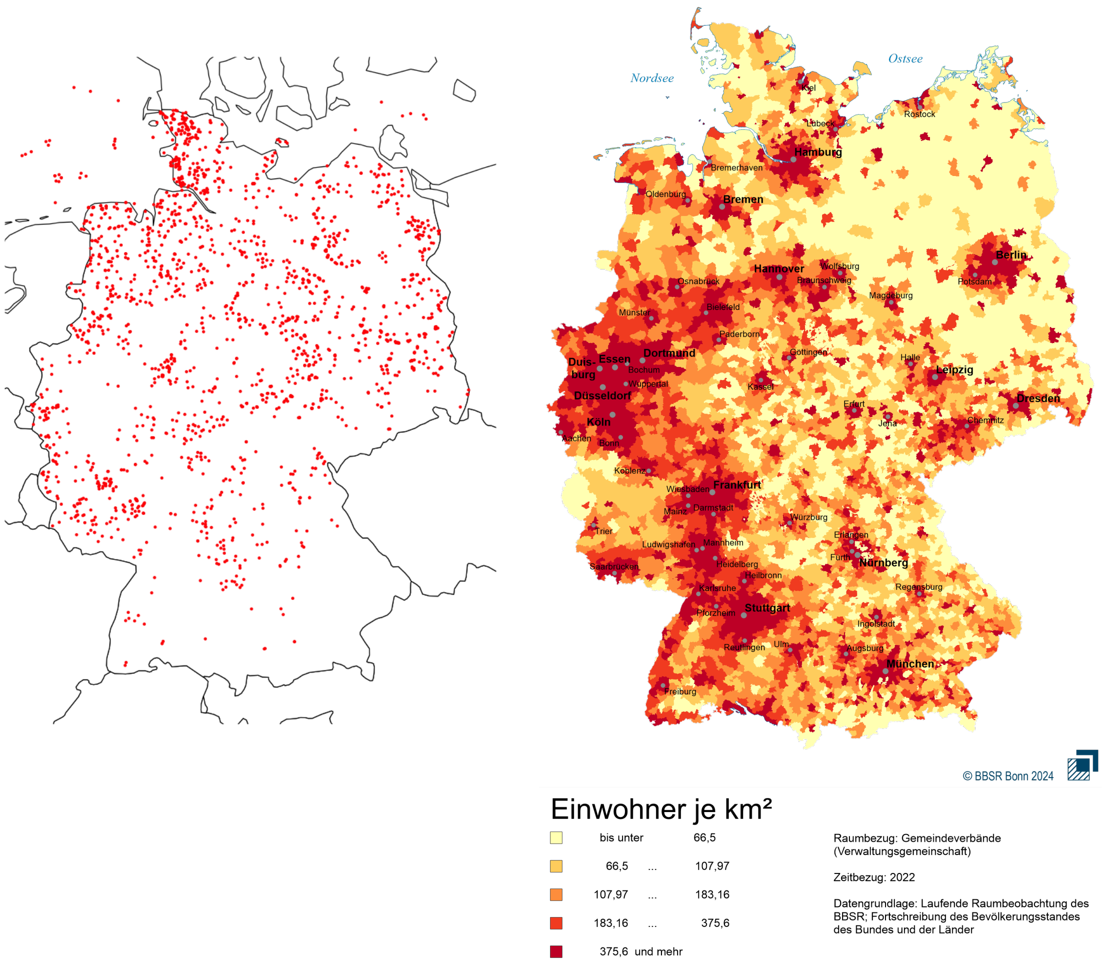
Figure B.4: Wind turbine farm locations above 10MW capacity



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.

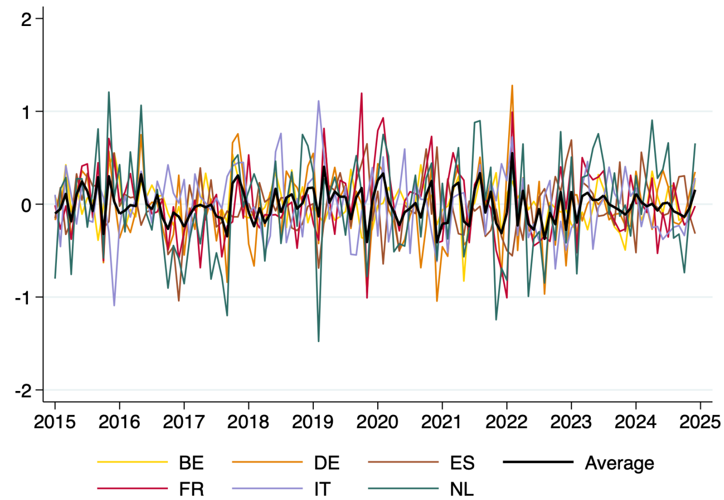
Figure B.5: Wind farm locations and population density in Germany

(a) Wind turbine farm locations **(b)** Population density (inhabitants/km^2)



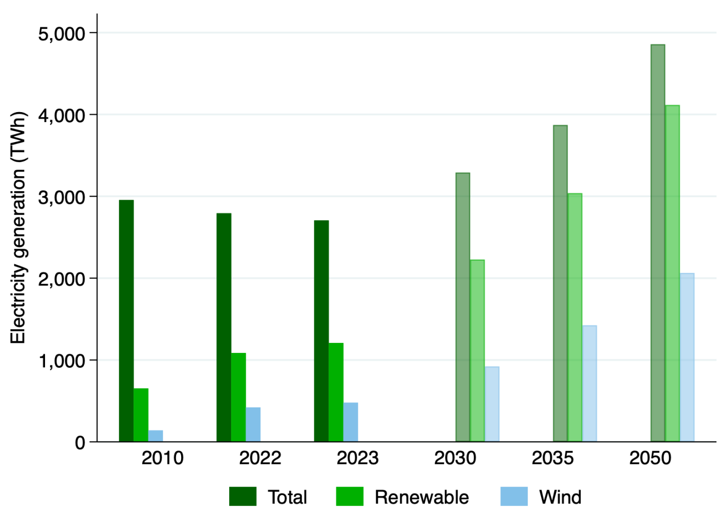
Note: Panel a) shows locations of wind turbine farms with installed capacity of at least 10MW across Germany. Data provided by the Global Wind Power tracker show installed capacity operational as of February 2025. Panel b) shows population density as the number of people per square kilometre by NUTS3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

Figure B.6: 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.

Figure B.7: 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.

C Alternative shock identification using national surprises

C.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.

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

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.[40] 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

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

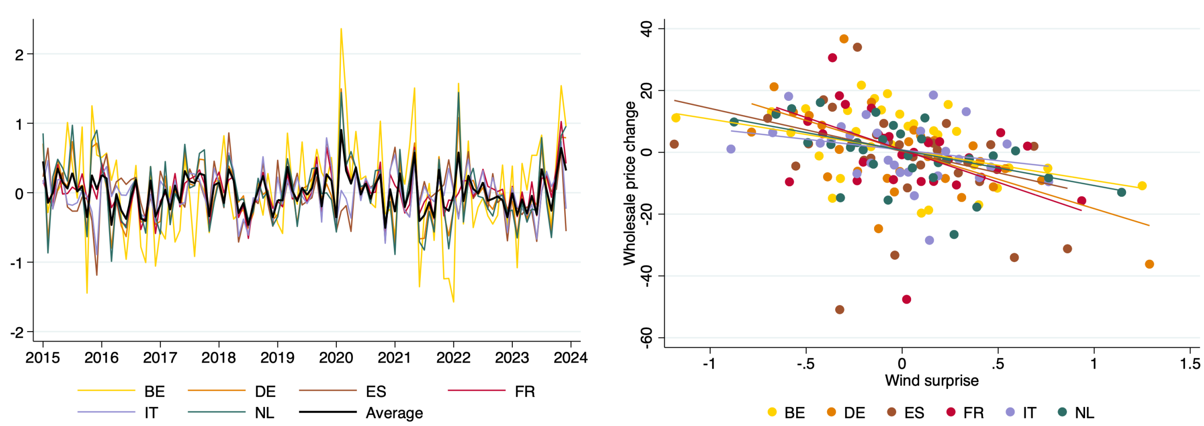
information from years before. Changes in wholesale prices on the spot market therefore are more likely to reflect deviations of the renewable electricity generation from what was expected, insofar as changes are driven by renewables.

C.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 C.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 C.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 C.1: Wind surprises by country

(a) Time series **(b)** Relevance



Note: Monthly wind surprises as deviations of actual wind from the model expectation described in equation C.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 C.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 B.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.

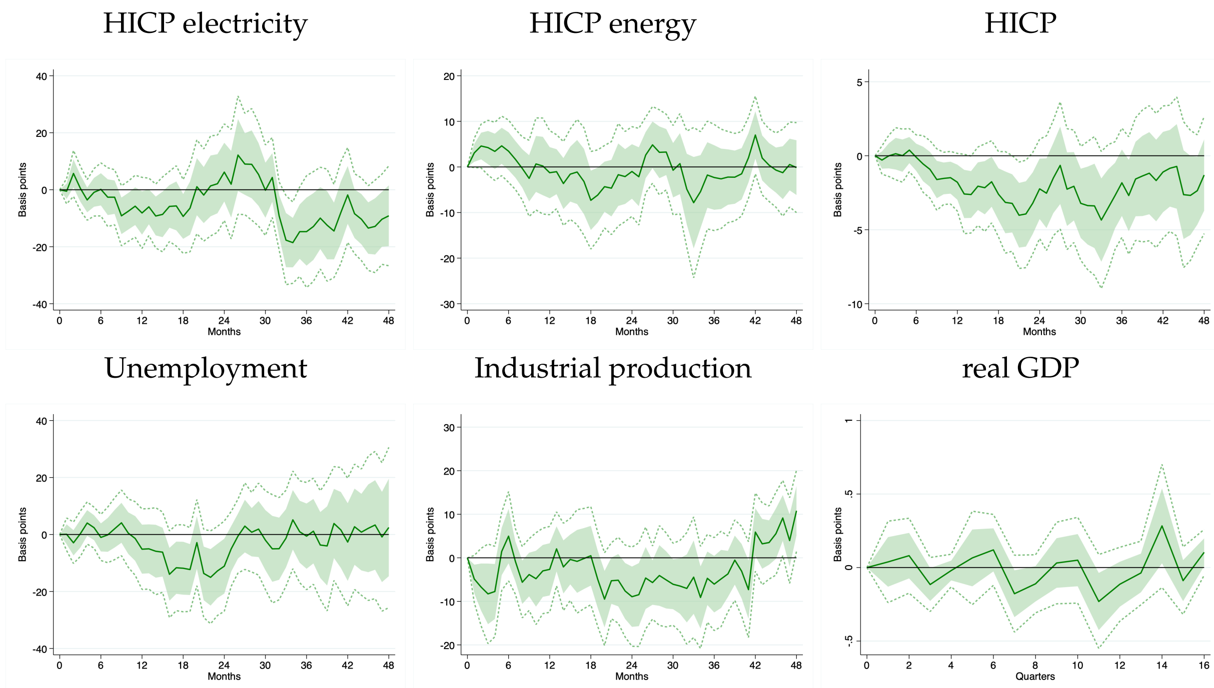
Table C.1: Monthly first stage results: wind surprises

	BE	DE	ES	FR	IT	NL	EA panel		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Wind surprise	-9.93***	-19.03***	-13.89**	-20.97***	-6.93*	-11.42***	-12.07***	-12.07***	-7.98***
	(2.47)	(3.28)	(6.09)	(6.43)	(3.79)	(2.53)	(0.95)	(1.32)	(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 C.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 conditioning on windmill locations.

Figure C.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.

D Additional results

D.1 First stage

Table D.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	-14.72***	-23.95***	-16.70***	0.06	-4.69	-8.25***	-5.90***	-5.90***
	(7.90)	(4.85)	(6.97)	(5.34)	(5.59)	(3.05)	(1.48)	(1.01)	(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 D.2.

Table D.2: 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 D.3: 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	-6.31**	-7.62*	-3.88	1.22	-3.48	-6.66***	-3.08***	-3.08**
	(4.76)	(2.99)	(4.10)	(3.59)	(2.76)	(2.71)	(1.24)	(1.06)	(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 D.4: 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***	-17.10***	-14.56***	-15.59***	-3.31	-7.65***	-11.45***	-7.50***	-7.50***
	(1.68)	(1.97)	(3.51)	(3.67)	(3.12)	(1.23)	(0.69)	(0.59)	(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.

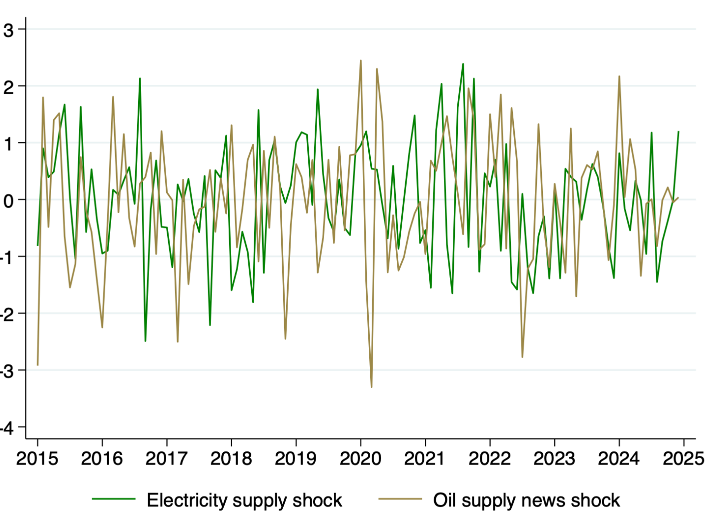
Table D.5: Monthly first stage results in subsamples: capacity-weighted wind at turbines

	2015-2017	2018-2020	2021-2023	2024-2025	Full (2015-2025)
	(1)	(2)	(3)	(4)	(5)
Wind shock	-3.47	-5.24**	-6.92**	-14.74**	-5.90***
	(2.25)	(1.97)	(2.63)	(4.86)	(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.

D.2 Shock diagnostics

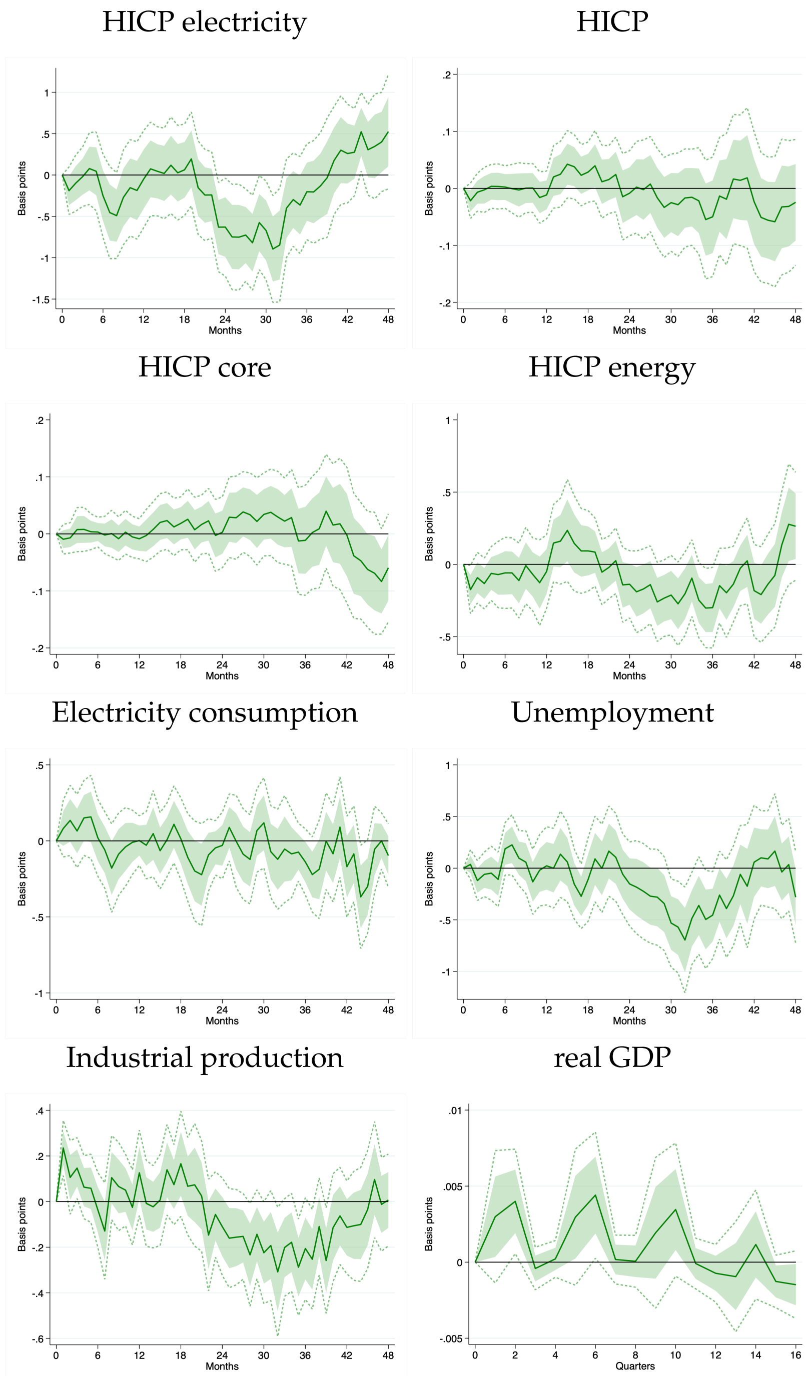
Figure D.1: Electricity and oil supply shocks



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

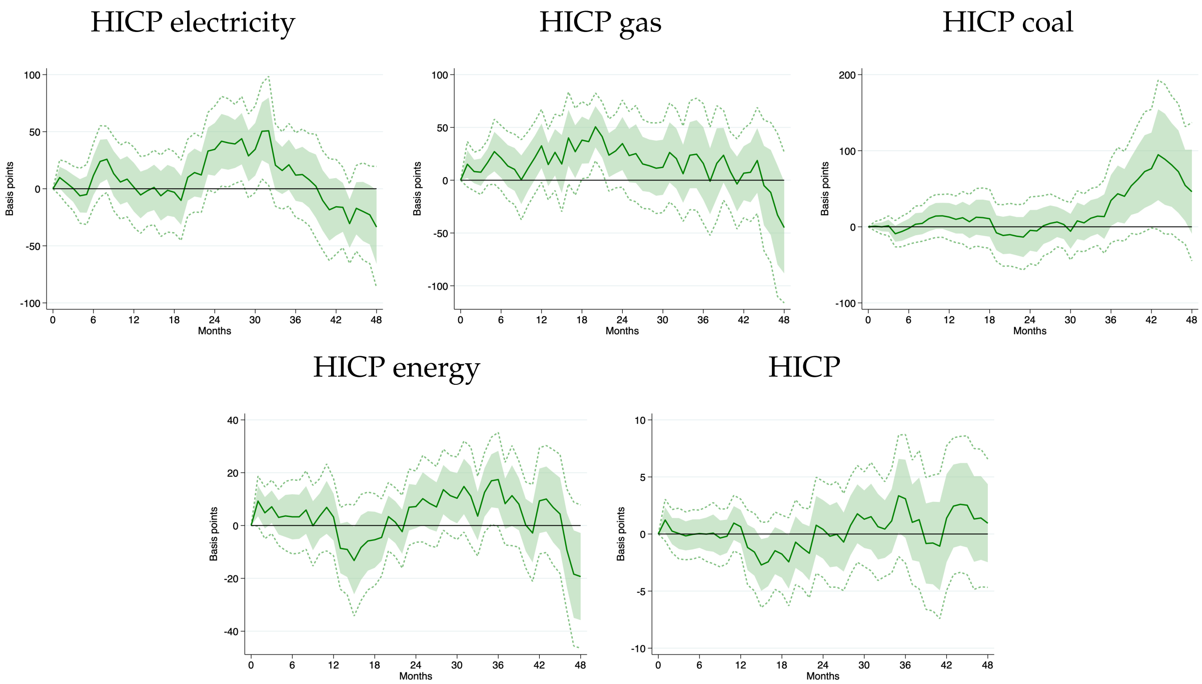
D.3 Macroeconomic effects

Figure D.2: Reduced form macroeconomic effects of turbine wind shocks



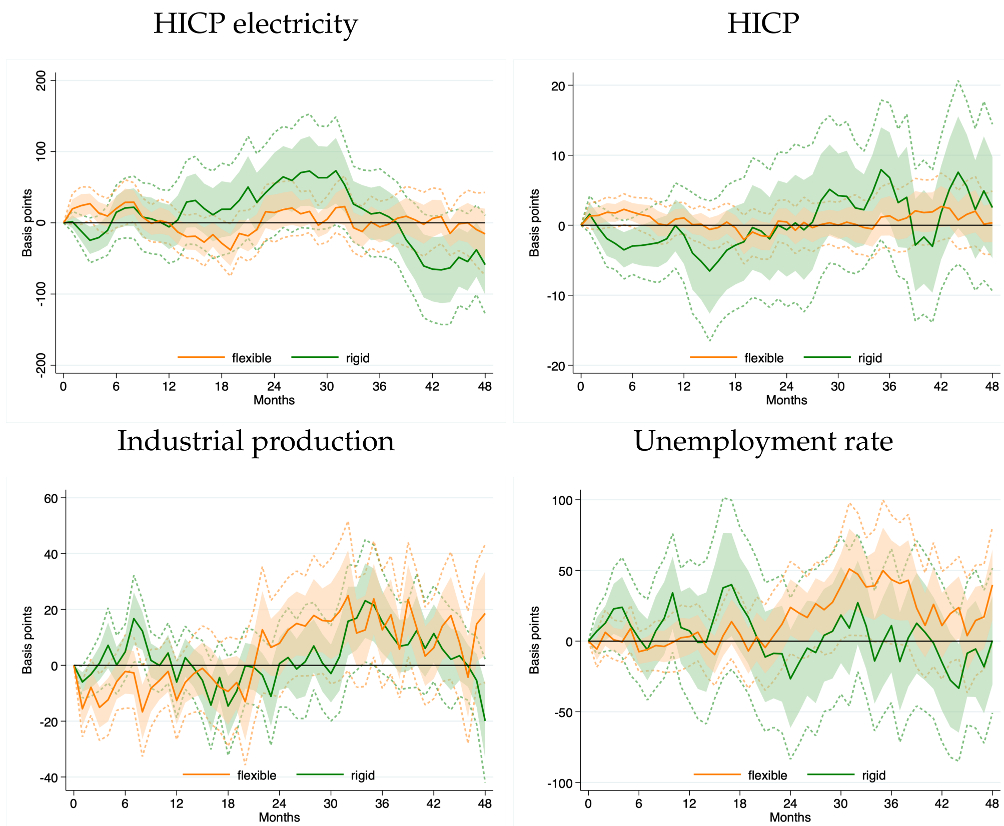
Note: Impulse responses to standardised turbine wind shocks. Local projection estimated according to equation (4) in the panel with country and time fixed effects, policy control, 2 lags, and Driscoll-Kraay standard errors with 3 lags. Error bands represent 68% and 90% confidence intervals respectively.

Figure D.3: Price effects of electricity price changes



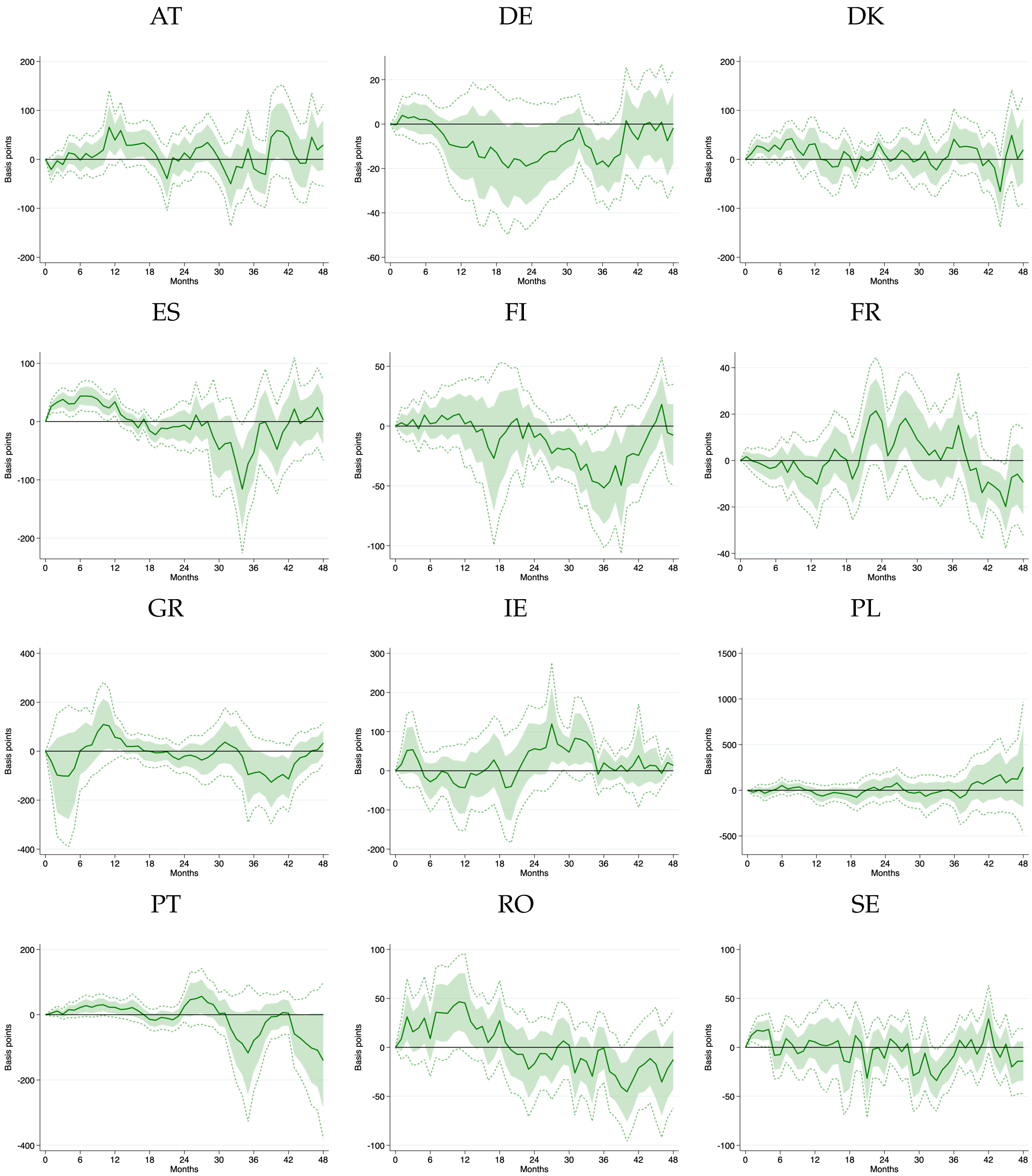
Note: Impulse responses to 1-month wholesale electricity price changes instrumented by wind shocks. Local projection estimated in the panel according to equation 4, and Driscoll-Kraay standard errors with 3 lags. Error bands represent 68% and 90% confidence intervals respectively.

Figure D.4: Passthrough-dependent effects of electricity price increases



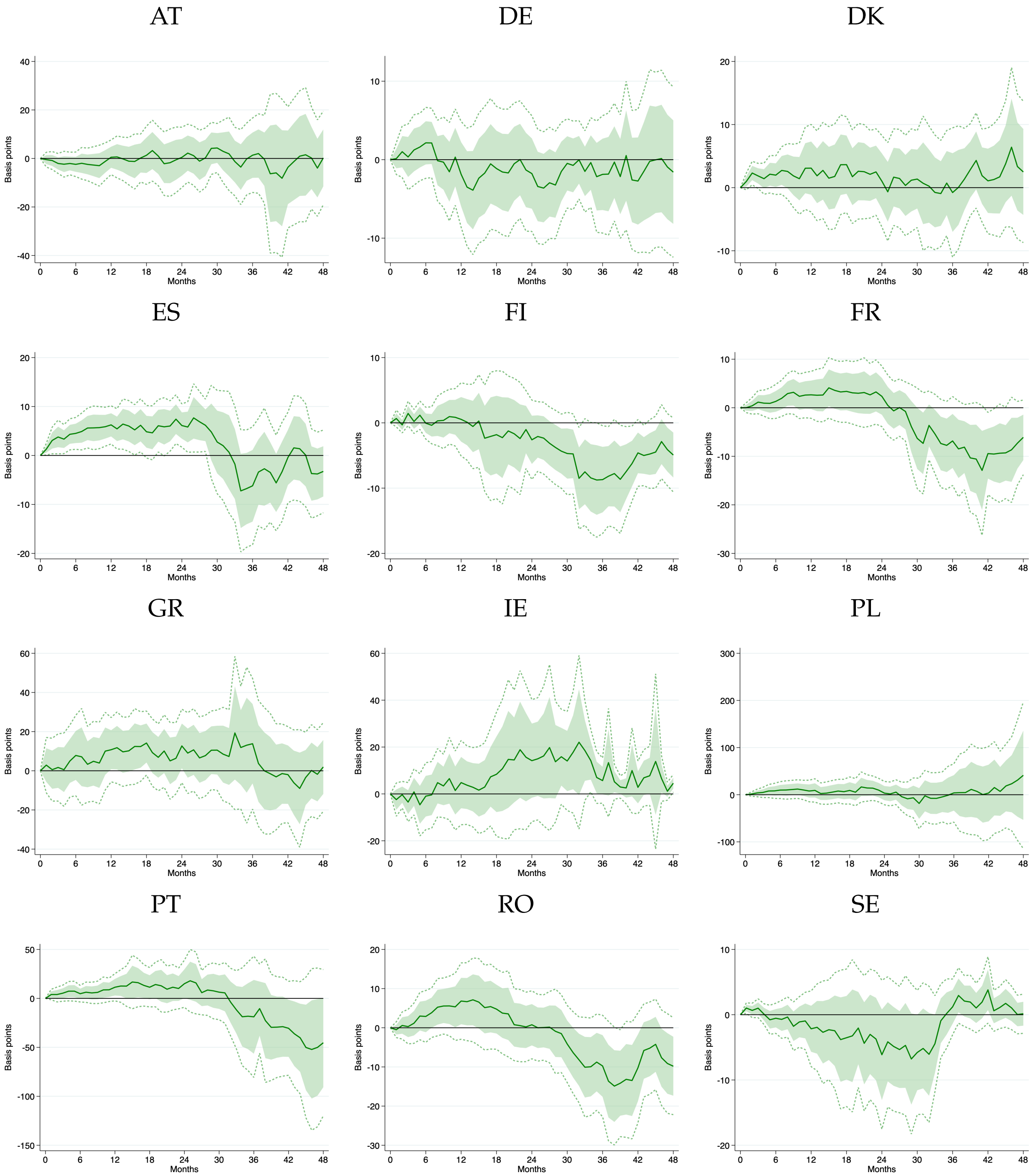
Note: Impulse responses to a 1pp electricity price change instrumented with wind shocks. Local projection estimated in the panel with country fixed effects and 2 lags as specified in equation (4), splitting countries into 2 groups based on the correlation of wholesale and retail electricity prices for various consumer groups, as shown in table B.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 D.5: Effects of electricity price changes on HICP electricity by country



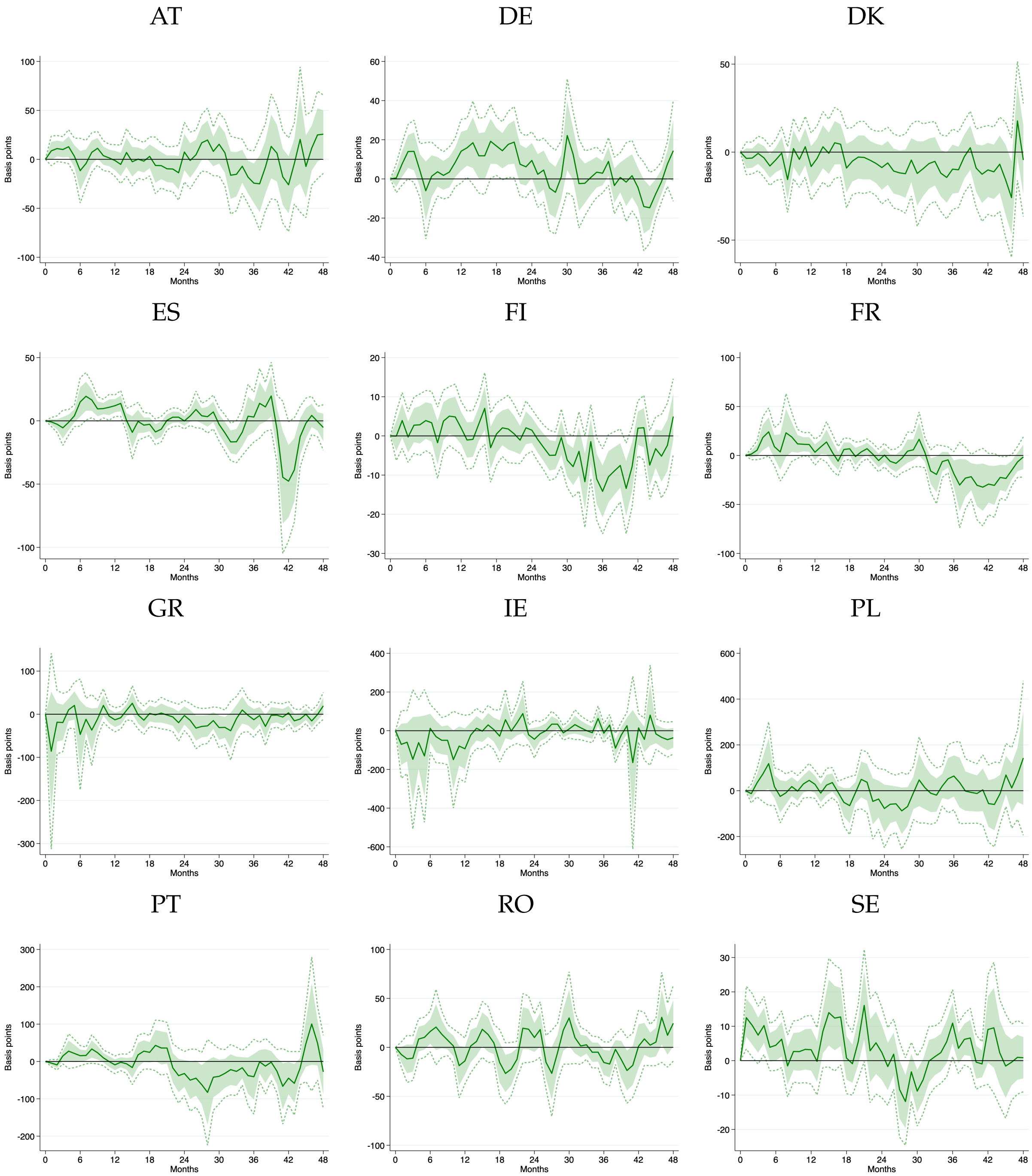
Note: Impulse responses of the log HICP electricity index to wholesale electricity price changes instrumented by wind shocks. Local projection estimated as in 4 but separately by country with 2 lags and robust standard errors. Error bands represent 68% and 90% confidence intervals respectively. Belgium, 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 D.6: Effects of electricity price changes on the price level (HICP) by country



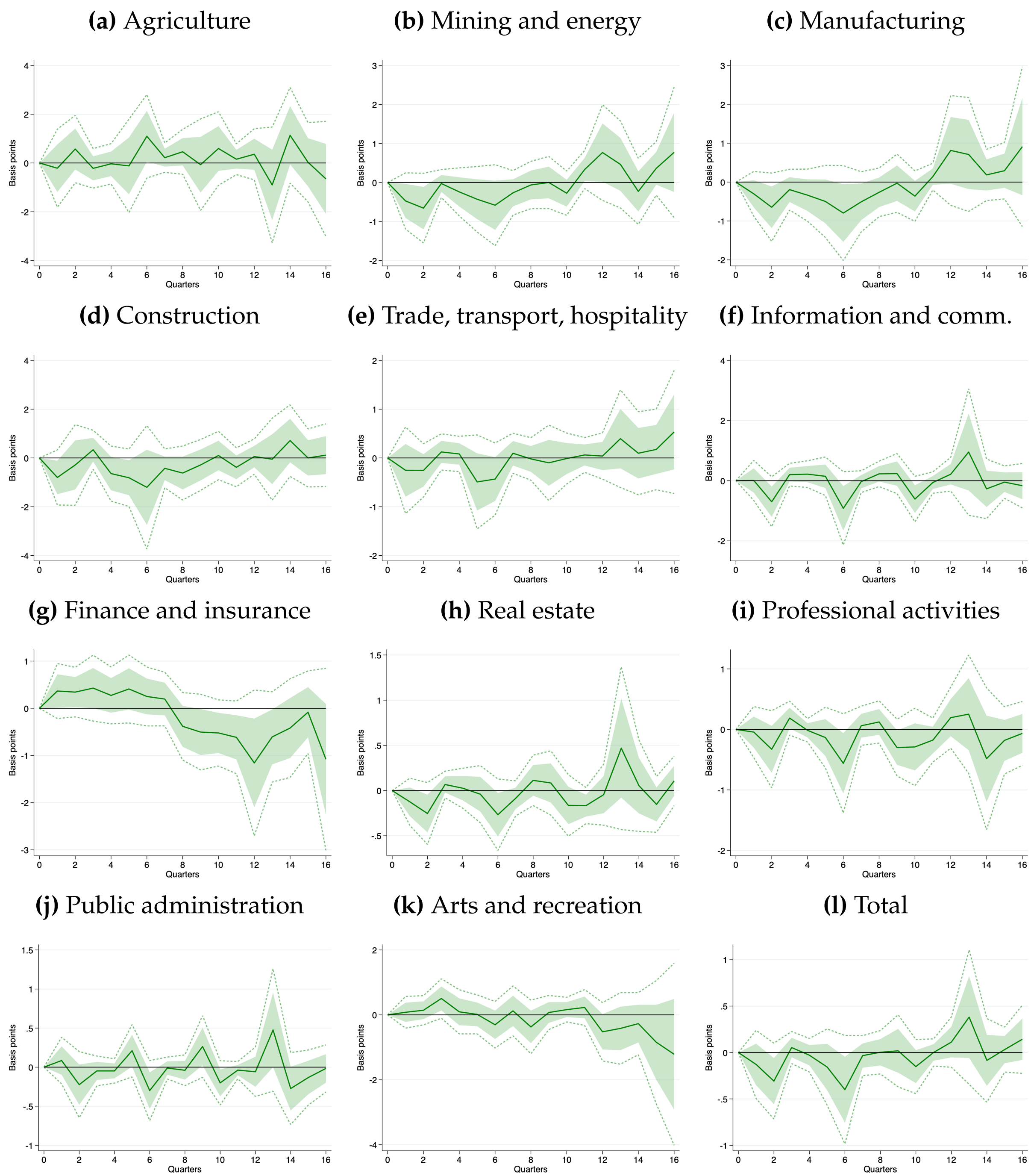
Note: Impulse responses of the log HICP index to wholesale electricity price changes instrumented by wind shocks. Local projection estimated as in 4 but separately by country with 2 lags and robust standard errors. Error bands represent 68% and 90% confidence intervals respectively. Belgium, Croatia, 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 D.7: Effects of electricity price changes on industrial production by country



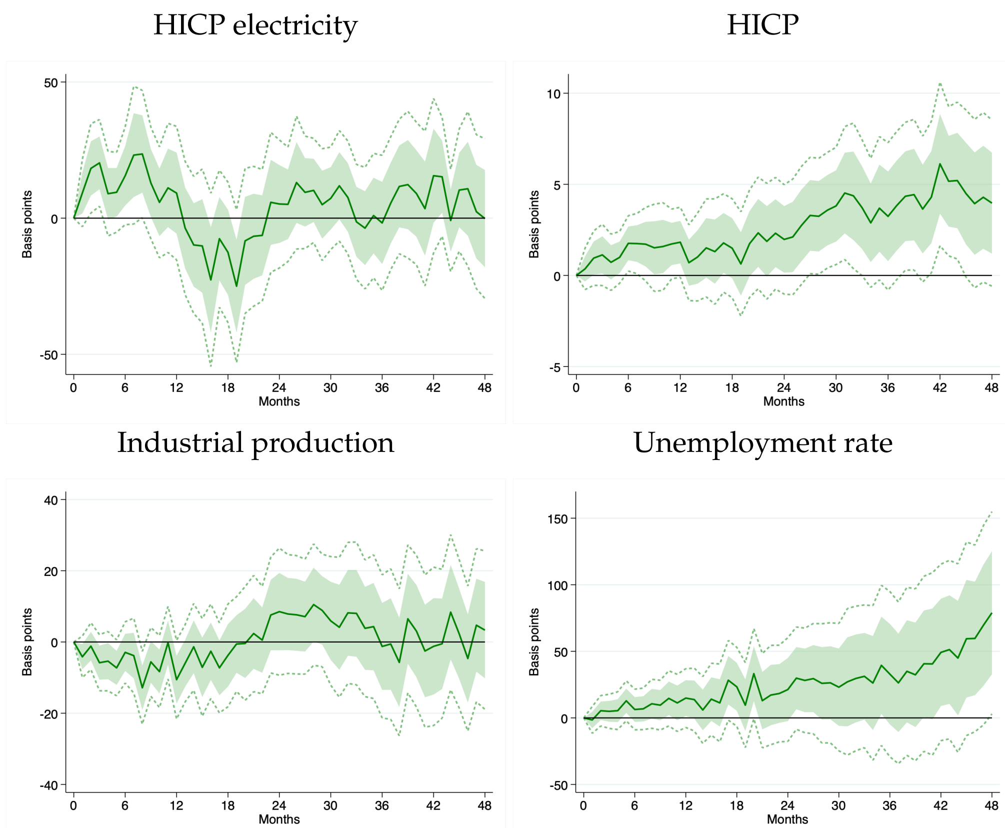
Note: Impulse responses of the log HICP index to wholesale electricity price changes instrumented by wind shocks. Local projection estimated as in 4 but separately by country with 2 lags and robust standard errors. Error bands represent 68% and 90% confidence intervals respectively. Belgium, Croatia, 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 D.8: 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 D.9: Macroeconomic effects of electricity price changes for early adopter countries in extended sample (2000-2024)

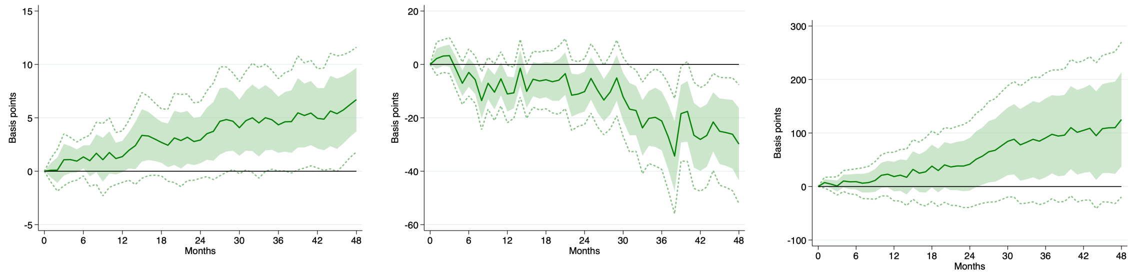


Note: Impulse responses to a 1pp electricity price change instrumented with wind shocks. Local projection estimated in the panel with country fixed effects and 2 lags as specified in equation (4). This panel is restricted to countries that surpassed 10% installed wind electricity generation capacity 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.

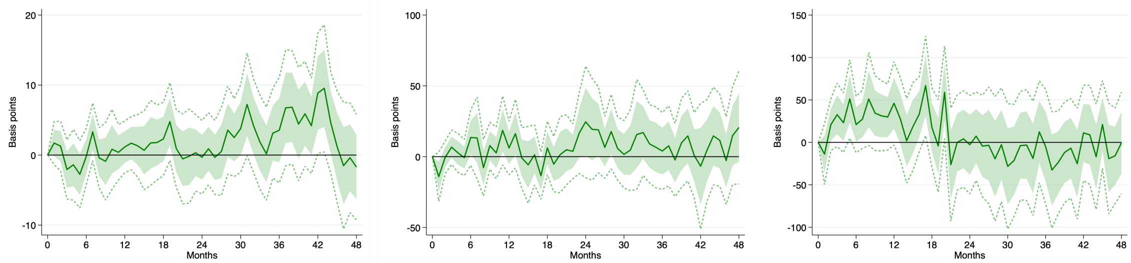
Figure D.10: Macroeconomic effects of electricity price changes for early adopters by subsample

Subsample 1: 2000-2009

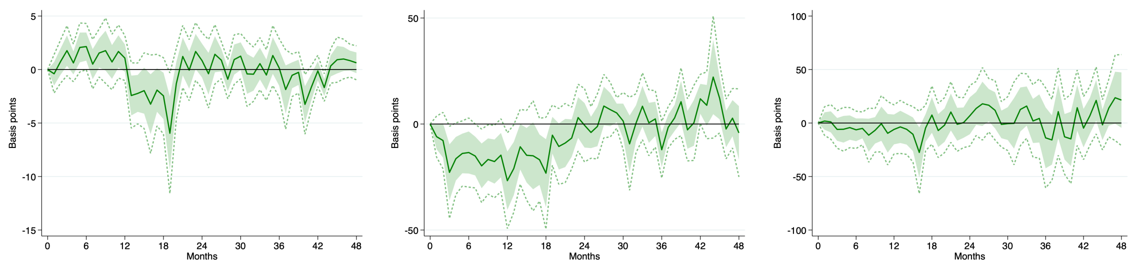
HICP | Industrial production | Unemployment rate



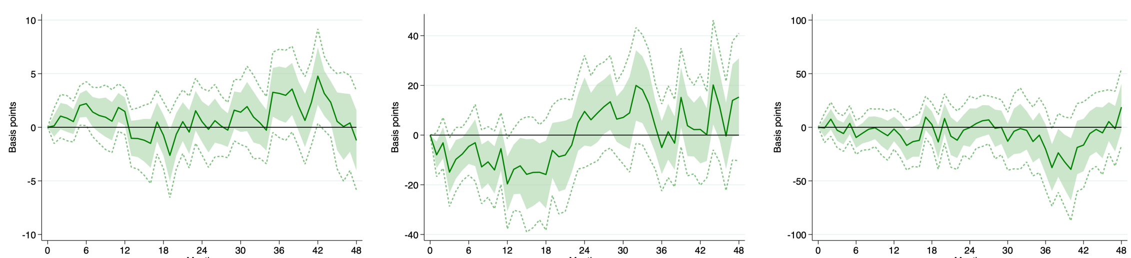
Subsample 2: 2010-2019



Subsample 3: 2020-2024



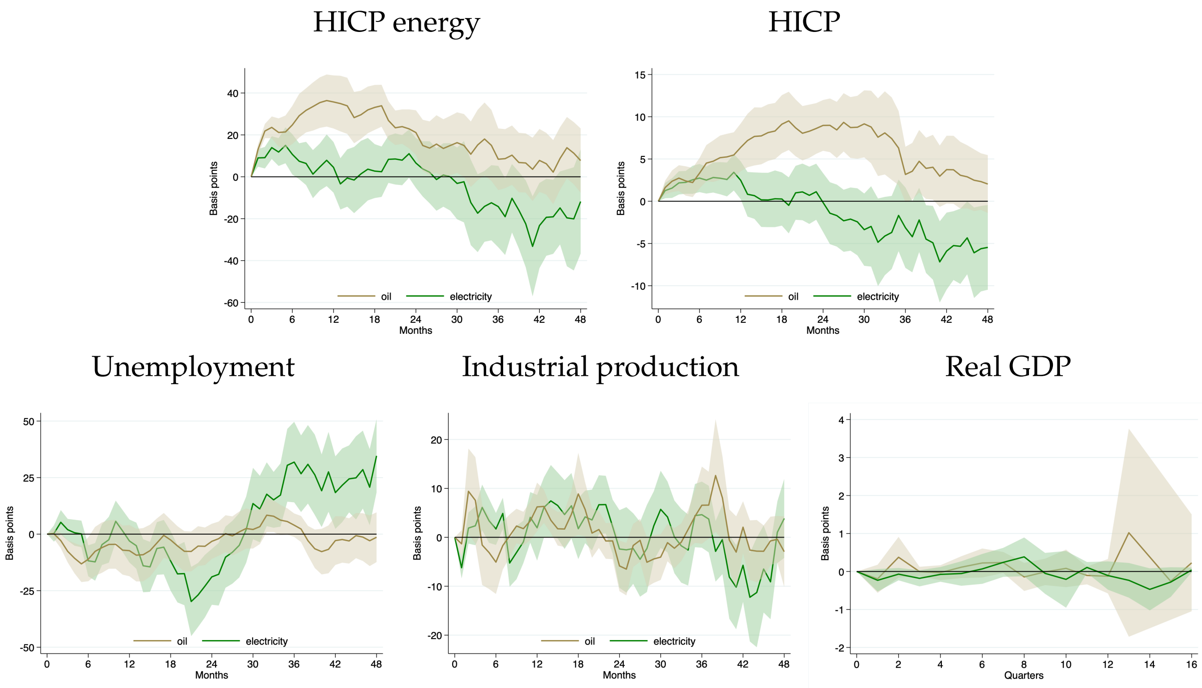
Main sample: 2015-2024



HICP | Industrial production | Unemployment rate

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.

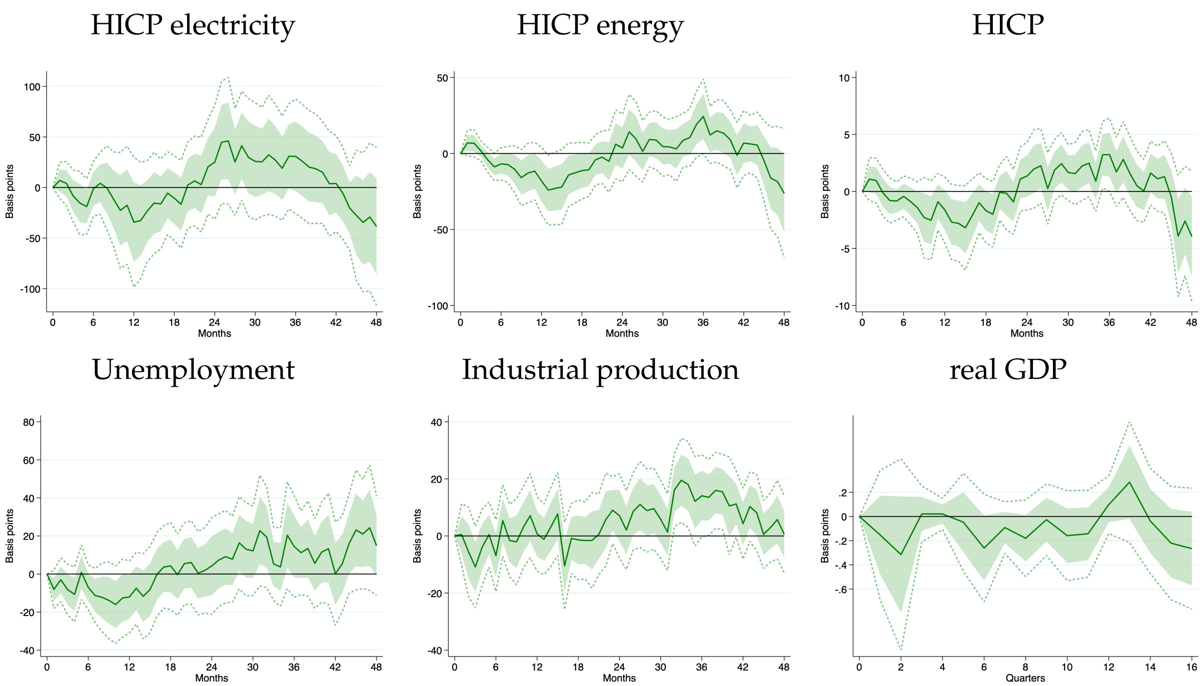
Figure D.11: Effects of price changes: electricity (wind) vs. oil (news)



Note: 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.

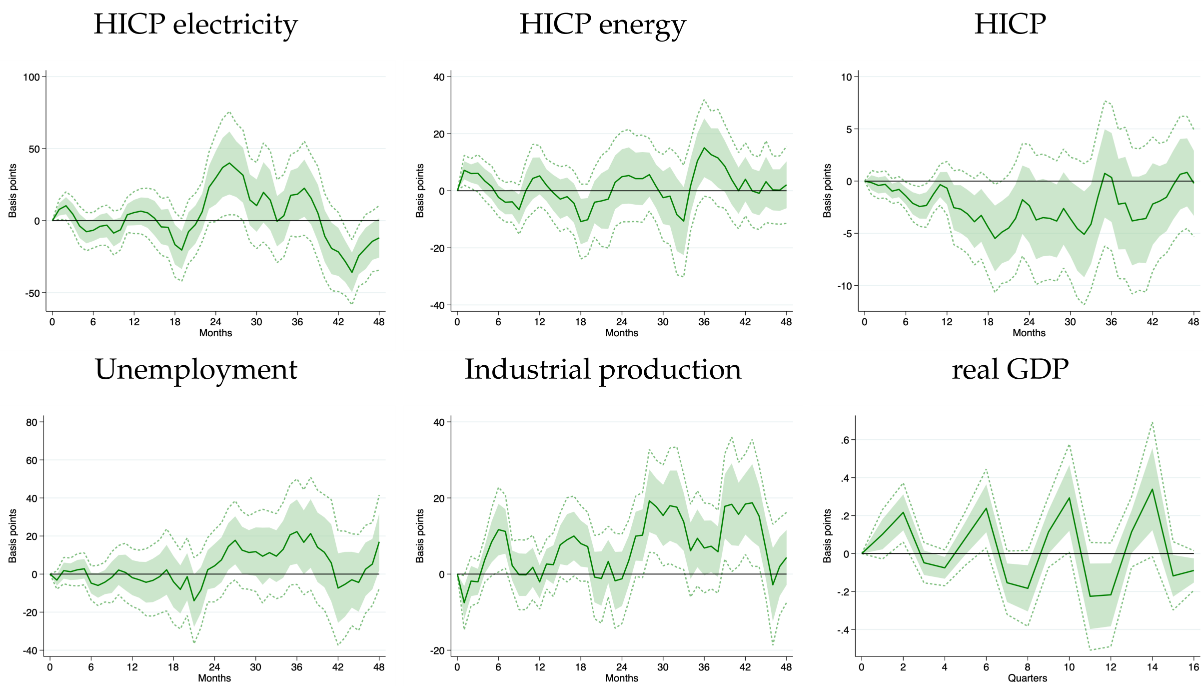
D.4 Results using alternative shock measures

Figure D.12: Macroeconomic effects of electricity prices instrumented by wind at offshore turbines



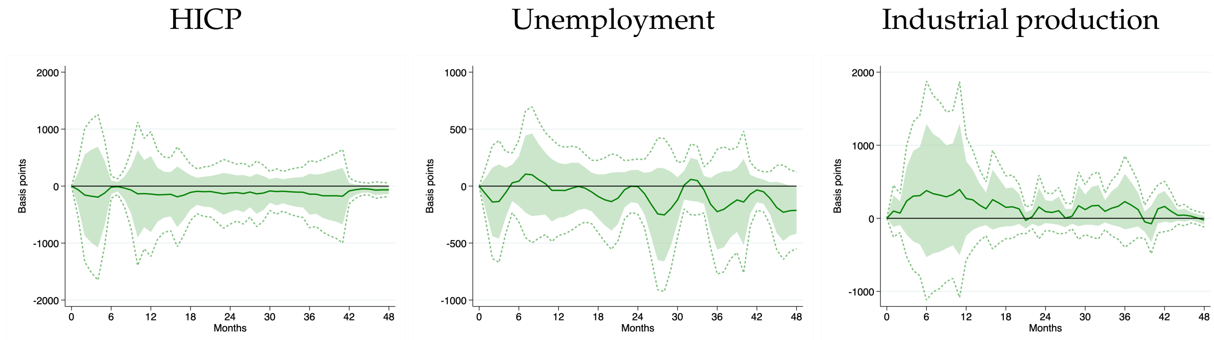
Note: Impulse responses to 1-month changes in electricity prices instrumented by wind at turbines only located offshore. Local projection estimated in the panel with country fixed effects and 2 lags as specified in equation (4), replacing wind in cells without turbines with average wind over all land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

Figure D.13: 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 D.14: 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 lass 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.

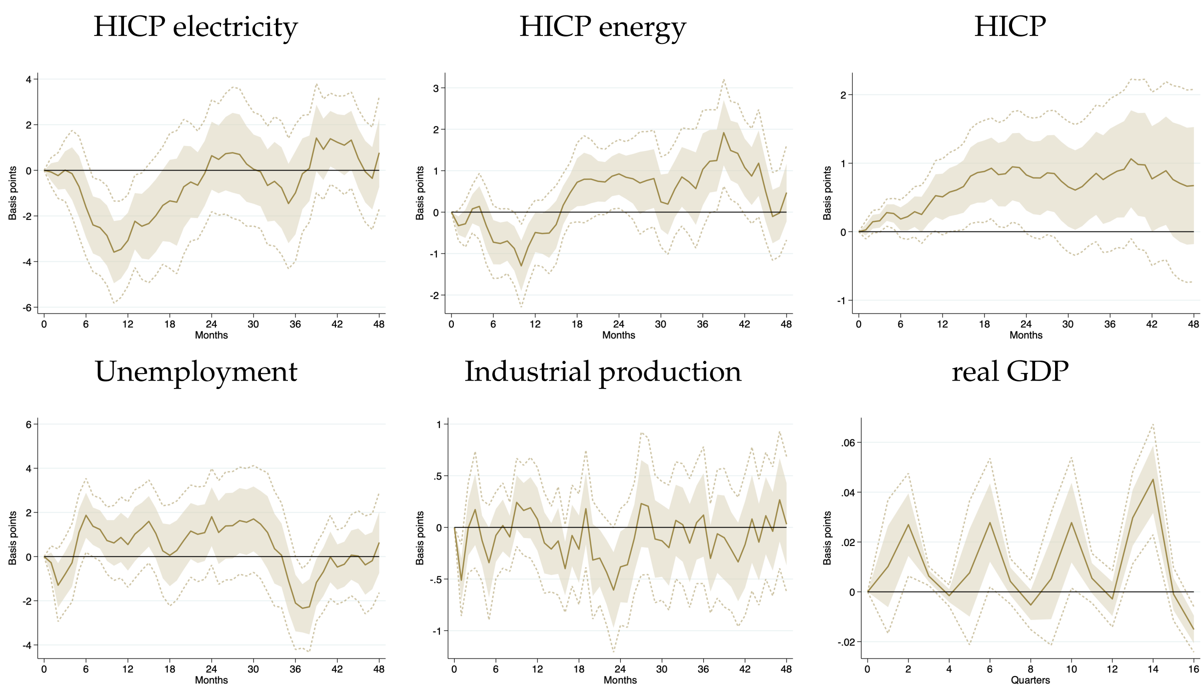
D.5 Effects of oil price shocks

To compare reduced form effects with country-specific shocks, I 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 D.15.

Since positive oil supply news shocks increase oil prices, while positive wind surprises 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.

For analysing the effects of oil price changes, 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

Figure D.15: Reduced form macroeconomic effects of Känzig (2021) oil supply news shocks



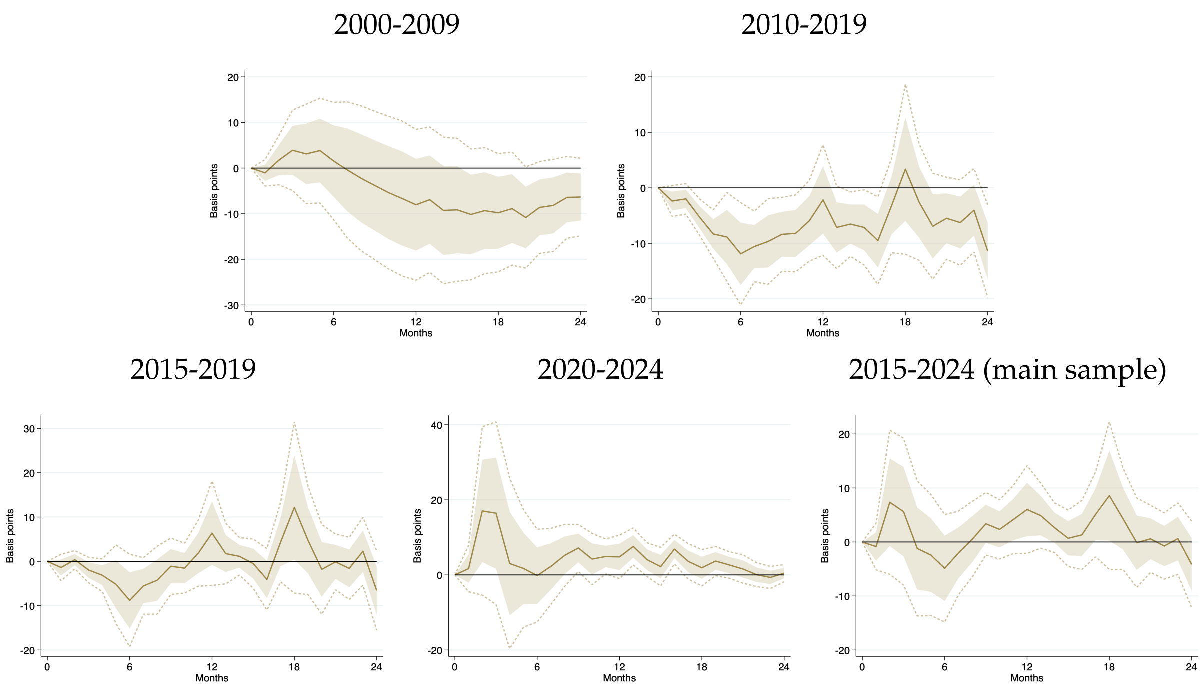
Note: Impulse responses to standardised Känzig (2021) oil supply news shocks, multiplied with pre-sample HICP energy weights by country. GDP impulse responses estimated for 1-quarter changes instrumented with the sum of shocks over the quarter. Local projection estimated in the panel with country and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

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:

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

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 D.16: 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.