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European Gas Shocks and Italian Industrial Activity: Regional and Sectoral Evidence

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Abstract

This thesis investigates the influence of European natural gas market shocks on the Italian industrial sector, focusing on both real firms' activity and price dynamics. The analysis is composed of two dimensions: first, industrial activity, proxied by regional industrial electricity consumption, and second, industrial prices, which are measured through sectoral producer price indices (PPI). This dual approach helps understand how energy shocks propagate through the economy. The empirical strategy relies on structural shocks that are identified using a Bayesian Vector Autoregression (BVAR), following Adolfsen et al. (2025), which distinguishes between supply, economic activity, inventory, and unconstrained shocks. These shocks are incorporated into a panel Local Projections framework (Jordà, 2005) to estimate impulse response functions over a 12-month horizon. The analysis exploits both regional and sectoral variation while controlling for fixed effects and seasonal patterns. The results show that the transmission of gas market shocks to the Italian industrial sector is heterogeneous across shock types. Economic activity shocks emerge as the most robust and economically meaningful driver of industrial electricity consumption, generating positive and persistent responses. In contrast, supply and inventory shocks produce weaker and largely transitory effects, which become less pronounced once seasonality is accounted for. Heterogeneity analysis indicates that differences between high- and low-intensity regions exist but are not characterized by a stable amplification pattern. On the price side, the response of producer prices is generally small in magnitude and differs from the quantity-based results. Supply shocks generate short-lived cost-push effects followed by reversals, while economic activity shocks do not lead to immediate inflationary pressures. Inventory and residual shocks are associated with more persistent negative price adjustments. Overall, the evidence suggests a limited and delayed pass-through of gas shocks to industrial prices, with firms partially absorbing cost effects. Taken together, the findings highlight the importance of demand-driven channels in shaping industrial responses to energy shocks and point to a disconnect between quantity and price adjustments. The results contribute to the understanding of energy shock transmission in Europe and provide new evidence on the role of industrial structure and energy intensity in mediating these effects.

Prefazione

Questa tesi analizza l'impatto degli shock del mercato europeo del gas naturale sul settore industriale italiano, concentrandosi sia sull'attività reale delle aziende sia sulle dinamiche di prezzo. L'analisi si articola in due dimensioni: la prima riguarda l'attività industriale, approssimata dal consumo elettrico industriale a livello regionale e, in secondo luogo, i prezzi industriali, misurati attraverso gli indici dei prezzi alla produzione (PPI). La strategia empirica si basa su shock strutturali identificati mediante un VAR bayesiano (BVAR) introdotto da Adolfsen et al. (2025), in cui vengono distinti quattro tipi di shock: offerta, attività economica, di scorte e shock non vincolati. Questi shock sono integrati in un framework di Local Projections (Jordà, 2005) in un contesto panel al fine di stimare le risposte agli impulsi su un orizzonte di 12 mesi. L'analisi sfrutta sia la variazione regionale sia quella settoriale, controllando per effetti fissi e per la stagionalità. I risultati mostrano che la trasmissione degli shock del mercato al settore industriale italiano è eterogenea a seconda del tipo di shock. Gli shock di attività economica emergono come il canale più robusto ed economicamente rilevante, generando risposte positive e persistenti. Al contrario, gli shock di offerta e di scorte producono effetti più deboli e transitori. L'analisi dell'eterogeneità mostra come la differenza tra regioni ad alta e bassa intensità energetica esista, ma non evidenzia un meccanismo stabile di amplificazione. Dal lato dei prezzi, la risposta degli indici dei prezzi di produzione è generalmente contenuta e differisce dai risultati dell'analisi sulle quantità. Gli shock di offerta generano effetti di costo di breve durata, seguiti da inversioni, mentre gli shock di attività economica non producono pressioni inflazionistiche immediate. Gli shock di scorte e quelli residuali sono associati ad aggiustamenti di prezzo negativi e più persistenti. Nel complesso, i risultati suggeriscono un pass-through limitato e ritardato, con le imprese che assorbono parzialmente l'effetto. Nel complesso, l'analisi evidenzia l'importanza dei canali legati alla domanda nel modellare la risposta industriale agli shock energetici e mostra una disconnessione tra gli aggiustamenti nelle quantità e nei prezzi. I risultati contribuiscono alla comprensione della trasmissione degli shock energetici a livello europeo e forniscono nuove evidenze sul ruolo ricoperto dalla struttura industriale e dell'intensità energetica nel mediare tali effetti.

1 Introduction

The energy market plays a central role in modern economies, as recent fluctuations in energy prices clearly illustrate. It influences several macroeconomic variables such as production costs, industrial activity, and inflation dynamics, thereby affecting both firms' behavior and aggregate economic performance. Among energy commodities, natural gas has become particularly important in the European market over the past two decades, mainly because of its extensive use in heating, electricity generation, and industrial production. Its relevance has progressively increased as European economies have shifted toward energy sources that are perceived as relatively cleaner compared to other fossil fuels, further reinforcing its centrality in the energy mix.

In manufacturing processes, natural gas represents a key input, making industrial activity highly exposed to its price fluctuations. This exposure is particularly evident in energy-intensive industries, where energy costs constitute a significant share of total production costs. Sectors such as glass, cement, and steel depend heavily on natural gas and fossil fuels for their production processes, implying that changes in prices directly influence firms' production costs and, consequently, their production decisions (Borge-Diez et al., 2023). As a result, fluctuations in gas prices can translate into changes in industrial output, cost structures, and ultimately pricing behavior.

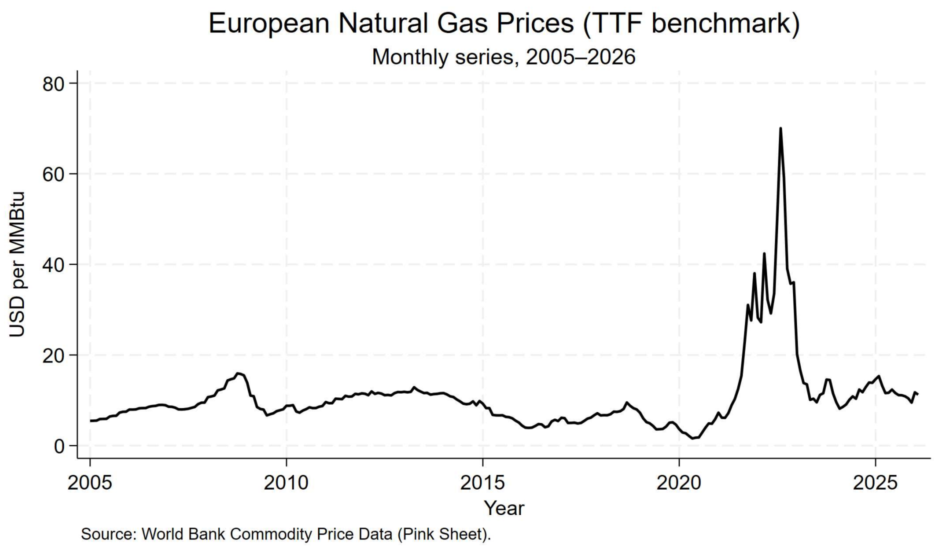


Figure 1: European natural gas prices based on the Dutch TTF benchmark, 2005–2026.

As shown in Figure 1, which represents the evolution of European natural gas prices using the Dutch TTF benchmark, the gas market in Europe has experienced a substantial structural change in recent years. Historically, gas prices have been relatively stable and largely determined by long-term contracts and regulated infrastructure, which contributed to limiting short-term volatility. Over time, however, the market has become increasingly exposed to global supply and demand conditions influenced by geopolitical developments (Correljé, 2016; Neumann and von Hirschhausen, 2015). The gradual liberalization of gas markets and the increasing integration with global energy markets have reduced the role of rigid contractual arrangements, making prices more responsive to international shocks. This increased integration made the European energy market more exposed and, at the same time, more vulnerable to external disturbances.

This vulnerability became especially visible during the recent energy crisis. After the COVID-19 pandemic in 2020, which led to a sharp contraction in economic activity and energy demand, the subsequent recovery phase was accompanied by strong pressures on energy markets. These tensions were further exacerbated by the sharp reduction in Russian gas supplies following the Russian invasion of Ukraine in 2022, which disrupted established supply channels and created significant uncertainty in European energy markets. As a consequence, natural gas prices reached unprecedented levels, as shown in the figure. This disruption in the energy markets raised concerns about the macroeconomic effects of energy shocks on industrial production and inflation dynamics (Emiliozzi et al., 2025). Although prices declined after the peak of the crisis, volatility remains higher than what was observed before, suggesting a structural change in the dynamics of energy markets. This sharp increase in prices had severe consequences for European economies, particularly for the industrial sector. Firms faced substantially higher production costs, which influenced both industrial output and producer prices, forcing adjustments in production decisions and pricing strategies (Borge-Diez et al., 2023; Emiliozzi et al., 2025).

In macroeconomic research, understanding the transmission of energy shocks has long been a central topic. A large body of literature has examined the economic effects of energy price fluctuations, focusing on their impact on output, inflation, and other key macroeconomic variables. More recently, there have been contributions that emphasized the importance of distinguishing between different types of energy shocks, such as supply disruptions, demand-driven shocks, or changes in inventories. This distinction is crucial because different shocks may have heterogeneous effects on the economy and may operate through different transmission channels. Structural approaches have therefore been used to identify such shocks and analyze their influence on the economy. In particular, structural approaches based on vector autoregressions have developed frameworks to identify shocks in the European markets and analyze their macroeconomic effects in a systematic way (Adolfsen et al., 2025).

This thesis contributes to the literature by studying how structural shocks originating from the European natural gas market affect the Italian industrial sector along two main dimensions. The first dimension concerns industrial activity, which is measured through regional industrial electricity consumption. Electricity consumption is a widely used proxy in the literature, as electricity demand closely tracks manufacturing activity and production intensity, providing a timely and reliable indicator of industrial dynamics (Lehmann, 2024). The second dimension concerns industrial prices, which are measured using sectoral producer price indices (PPI) for Italian industries. By focusing on both quantities and prices, the analysis is able to capture different aspects of the adjustment process and provide a more comprehensive assessment of how energy shocks propagate through the industrial sector.

The empirical analysis focuses on different types of European gas shocks, which are identified using a Bayesian VAR framework, following the approach proposed by Adolfsen et al. (2025). This identification strategy allows the separation of structurally different disturbances affecting the gas market. The effects on industrial activity and prices are estimated using the Local Projection method proposed by Jordà (2005). This approach allows the estimation of impulse response functions that trace the dynamic impact of gas market shocks over time, providing a flexible framework to analyze the timing, magnitude, and persistence of the responses.

By combining regional electricity consumption data with sectoral producer price indices, this thesis identifies both quantity and price adjustments of the Italian industrial sector following gas market disturbances. This double perspective allows for a more comprehensive understanding of how energy shocks affect industrial production and pricing behavior, highlighting the different channels through which these shocks propagate.

The remainder of this thesis is structured as follows. Section 2 describes the data and the empirical methodology in detail. Section 3 presents the empirical results, including descriptive statistics, local projection estimates, impulse response functions, as well as robustness and heterogeneity checks. Section 4 concludes.

2 Data and Methodology

2.1 European Gas Market Shocks

In this section, the gas market shocks and their construction are described. They are derived from the structural model developed by Adolfsen et al. (2025). The authors identify three economically meaningful disturbances in the European gas market: a supply shock, an economic activity shock, and an inventory shock. In addition, they consider a fourth residual shock that captures other unexplained dynamics. The original model is estimated over a long historical sample, while this thesis analyzes only the period between 2018 and 2023 due to the limited availability of industrial electricity consumption data for Italian regions.
The identification of the shocks relies on a Bayesian Vector Autoregressive (BVAR) model estimated on key indicators of the European gas market. The variables considered are:

Gas quantities:
defined as the total gas supplied in Europe. It is the sum of imports and domestic production, minus exports.

Gas inventories:
the amount of gas stored in European facilities.

Gas prices:
measured using the Dutch Title Transfer Facility (TTF) day-ahead price.

Euro-area industrial production:
an indicator of the business cycle and of the cyclical demand for gas.

Both gas quantities and inventories show strong seasonality, primarily driven by heating needs. To avoid this influence, the series are seasonally adjusted using the X-13 ARIMA method.

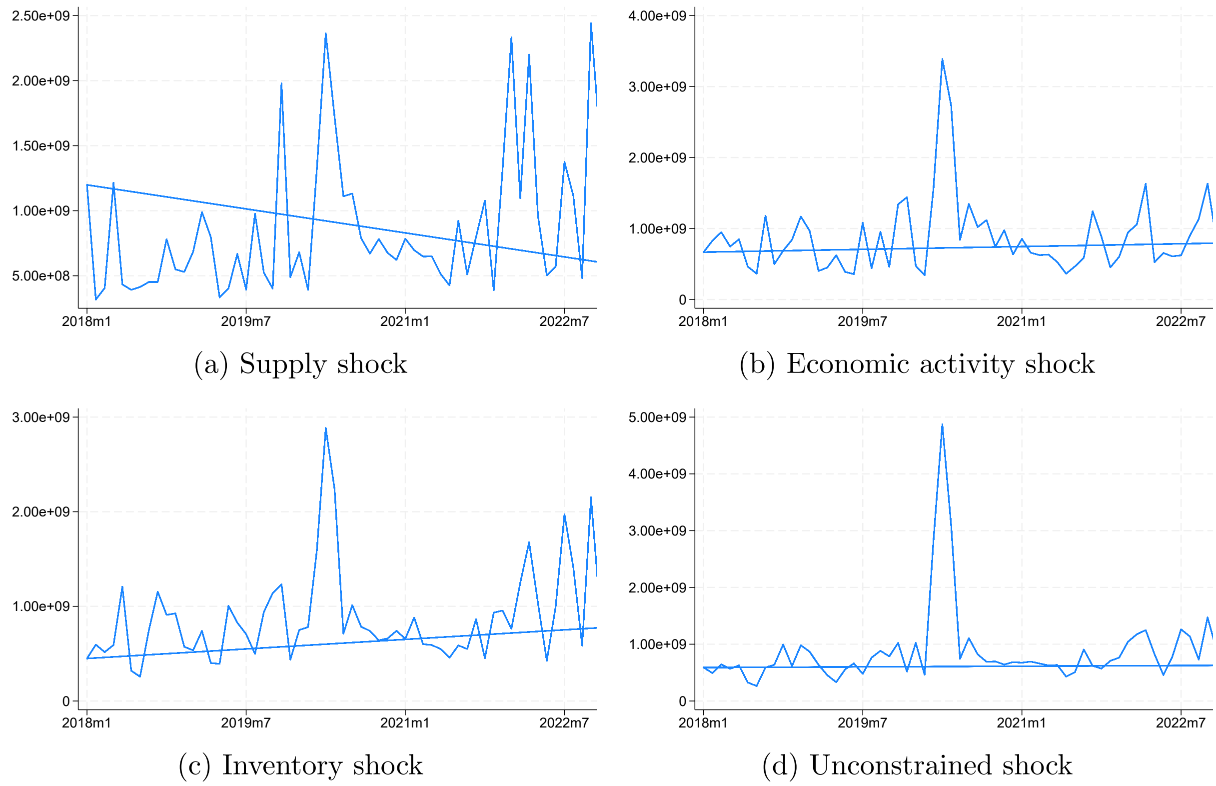
To identify the gas shocks, a dynamic structure of a monthly Bayesian VAR with 12 lags is used, estimated over the 2006–2023 period. In this thesis, only shocks from 2018 onward are used, but the estimation over the full period is performed by the original authors to ensure a long sample and robust identification.

The BVAR is estimated using standard Minnesota priors, which stabilize models with many parameters and are frequently used in applied macroeconomic research. The reduced-form model is:

$$Y_t = A_0 + \sum_{l=1}^{12} A_l Y_{t-l} + B\varepsilon_t$$

with Y_t denoting the vector of endogenous variables and ε_t the vector of structural shocks.

The identification of the shocks is performed via sign restrictions. Each variable reacts to a shock in a way consistent with economic theory, not by imposing exact numerical responses but only directional restrictions.



(a) Supply shock

(b) Economic activity shock

(c) Inventory shock

(d) Unconstrained shock

Figure 2: European gas market shocks (monthly mean, 2018–2023).

Gas Supply Shock The gas supply shock captures an unexpected reduction in the physical availability of gas in the European market. This includes technical failures, geopolitical disruptions, and interruptions in pipeline flows; this thesis concentrates only on the shocks identified by the model, independently of their historical origin.

When there is a negative supply disturbance, the available gas becomes scarce, causing an increase in gas prices. Gas inventories are also depleted. The shock is subject to the following restrictions:

- Gas quantities: decrease
- Gas inventories: decrease
- Gas prices: increase
- Industrial production: unrestricted

The gas supply shock is characterized by a highly irregular pattern, with frequent month-to-month fluctuations. The series shows high short-run volatility, in particular around 2020, but the overall magnitude of its fluctuations remains limited when compared to other shocks. Positive realizations correspond to negative supply disturbances, but they do not appear to be associated with large persistent deviations.

Economic Activity Shock The economic activity shock reflects changes in gas demand driven by fluctuations in industrial production. When industrial production expands, gas demand increases and puts upward pressure on prices.

When production intensifies, demand for gas increases and consumes both ongoing supply and stored resources. Quantities may eventually increase in response to higher demand, but the model predicts a negative short-run effect due to the immediate drawdown of storage. This type of shock has greater persistence than the supply shock, since it is driven by macroeconomic dynamics rather than temporary disruptions.

The restrictions are:

- Industrial production: increase
- Gas prices: increase
- Gas inventories: decrease
- Gas quantities: decrease

The economic activity shock is characterized by larger movements in magnitude than the supply shock. The series shows a pronounced peak around early 2020, which dominates the time profile and reflects a major disruption in economic activity. Variations in economic activity occur less frequently, but they have stronger effects, as highlighted by the vertical scale. The pattern followed by this type of shock underlines how demand-driven shocks tend to generate strong, episodic deviations rather than continuous high-frequency variations.

Inventory Shock Inventory shocks are interpreted as precautionary increases in gas demand driven by expectations of tighter market conditions for future supply. Market participants accumulate gas in storage, which causes an increase in both quantities and prices. These effects are usually short-lived, as conditions tend to normalize rapidly.

The restrictions are:

- Gas inventories: increase
- Gas quantities: increase
- Gas prices: increase

Inventory shocks display temporary movements, with amplitudes larger than those observed for the supply shock and smaller than the peak reached by the economic activity shock. A peak is visible around 2020, followed by renewed volatility during the 2022–2023 period. The observed behavior is consistent with the idea that inventory shocks arise when precautionary storage decisions are taken due to uncertainty.

Unrestricted Shock The model includes a fourth shock capturing remaining variations in the gas market that are not explained by the three structural shocks. Although it is not the focus of this thesis, it contributes to the completeness of the structural decomposition.

The residual component may be influenced by weather conditions, unobserved global energy shocks, measurement errors or statistical noise, and idiosyncratic market fluctuations. Unconstrained shocks show the largest volatility among the series. A large spike is visible around 2020, followed by additional sizeable movements in subsequent years. These fluctuations are not systematically aligned with those observed for the other shocks. The pattern reflects the residual nature of the shock, potentially influenced by weather-related effects and other unobserved factors.

The Role of the 1,000 Draws A key methodological component of the model concerns the role of uncertainty in the estimation of structural shocks. In Bayesian estimation, parameters are not treated as fixed but as random variables with a posterior distribution. To account for this uncertainty, the authors generate 1,000 random draws from the posterior distribution of the shocks. Each draw is a plausible realization of the shock series consistent with the estimated BVAR.

These draws serve to measure estimation uncertainty, since they allow the construction of confidence bands for impulse responses and avoid reliance on a single realization. This is preferable to a single point estimate and increases robustness; it is also consistent with Bayesian inference. These 1,000 draws do not represent different countries, regions, or scenarios, but only uncertainty in the estimation of the structural shocks.

In this thesis, the shocks are used at a monthly frequency. Since they are provided daily in the original paper, the empirical strategy aggregates them first into daily averages and then into monthly shocks. They are then matched with monthly industrial electricity consumption data. The resulting monthly shocks vary over time but are common across Italian regions. This transformation preserves the structural content of the shocks and aligns them with the data frequency.

2.2 Industrial Electricity Consumption Data

The unit of observation is an Italian region i, observed at monthly frequency over the period 2018–2023. Industrial electricity consumption is the dependent variable and is used as a proxy for industrial activity. The variable, expressed in first differences, measures the monthly change in electricity consumption (GWh). The shocks described above vary over time but are common across regions, as they originate from European-wide gas market dynamics.

2.3 Empirical Framework for Industrial Activity

In this section, the empirical strategy used to assess the impact of European gas market shocks on Italian industrial activity is described. The analysis exploits the regional dimension of the data together with its time variation within a panel data framework. The empirical analysis adopts the Local Projections (LP) methodology proposed by Jordà (2005) to estimate the dynamic response of regional industrial activity to European gas market disturbances. This framework is well suited to the present setting, as it allows impulse responses to be estimated without imposing strong dynamic restrictions. Moreover, LPs can be flexibly implemented in a panel setting when controls and fixed effects are included.

The analysis is done by implementing a sequence of panel local projections that are estimated separately for each forecast horizon $h = 1, \ldots, 12$. For each horizon, the future variations of regional industrial electricity consumption are regressed on the European gas market shock. Since electricity consumption shows a strong seasonal pattern, the empirical strategy addresses seasonality using specifications with month-of-year dummy variables. The comparison between these specifications helps distinguish genuine shock-driven responses from seasonal fluctuations.

The gas market shocks are expressed in standardized form so that the coefficients can be interpreted as the average response of regional industrial electricity consumption to a one standard deviation European gas shock at a given horizon.

The analysis is intended to highlight the persistence, the timing and the importance of different types of European gas shocks. The focus is also on how the estimated dynamics are affected when seasonality is included in the controls.

The baseline panel local projection specification estimated for each horizon $h = 1, \ldots, 12$ is the following:

$$\Delta y_{i,t+h} = \beta_h \, shock_t + \gamma_i + \delta_m + \varepsilon_{i,t+h} \tag{1}$$

where $\Delta y_{i,t+h}$ denotes the change in industrial electricity consumption (in GWh) in region i at horizon h, $shock_t$ is the standardized European gas market shock at time t, γ_i are region fixed effects, and δ_m are month-of-year fixed effects capturing seasonal patterns. Standard errors are clustered at the regional level.

2.4 Producer Price Index Data

This section describes the construction of the sectoral dataset and the econometric framework used to estimate the dynamic response of Italian producer prices (PPI) to European gas market shocks. The analysis is conducted using a monthly panel of industrial sectors and follows the Local Projections (LP) approach employed in the previous section, adapted to a sectoral price-setting environment.

Data construction and sectoral classification The empirical analysis relies on monthly Italian producer price indices disaggregated by industrial sector. Sectoral identifiers are defined according to the official ATECO 2007 classification (updated in 2021). A dedicated ATECO classification file is employed to ensure consistency across sectors. Each observation is uniquely identified by sector (ATECO code), month, and corresponding producer price index.

The use of the ATECO classification permits the identification of industrial sectors and the construction of the sectoral panel, while sector fixed effects control for time-invariant structural characteristics such as technological intensity and market structure.

The final panel includes monthly observations from 2018 to 2023 and is fully consistent with the period analyzed in the previous section for electricity consumption.

Dependent variable The dependent variable is the monthly log change in the producer price index:

$$\Delta p_{s,t} = \Delta \log(PPI_{s,t}) \tag{2}$$

Using log differences rather than levels improves the stationarity properties of the dependent variable, allows the interpretation of coefficients as approximate percentage changes, and ensures consistency with the empirical strategy adopted in the previous section.

For each forecast horizon $h = 1, \ldots, 12$, future changes are constructed as $\Delta p_{s,t+h}$, enabling the estimation of dynamic impulse responses through local projections.

Gas market shocks The explanatory variables correspond to the same standardized European gas market shocks introduced earlier in the analysis. They are derived from the structural BVAR model of Adolfsen et al. (2025) and include supply, economic activity, inventory, and unconstrained shocks.

All shocks are standardized to have zero mean and unit variance. Consequently, the estimated coefficients measure the response of sectoral PPI to a one-standard-deviation structural shock.

Importantly, the shocks are externally identified at the European level and are not constructed from Italian sectoral prices. This feature supports their exogeneity and limits concerns related to reverse causality or sector-specific price dynamics driving the results.

2.5 Empirical Framework for Producer Prices

Econometric Specification Dynamic responses are estimated using the Local Projection (LP) method proposed by Jordà (2005). For each horizon h, the following regression is estimated:

$$\Delta p_{s,t+h} = \beta_h Shock_t + \gamma_s + \delta_m + \varepsilon_{s,t+h} \tag{3}$$

where s denotes the industrial sector, t denotes time (monthly frequency), γ_s are sector fixed effects, and δ_m are month-of-year fixed effects (m = 1,. . . ,12) capturing common seasonality. The coefficient β_h represents the impulse response at horizon h.

Sector fixed effects control for time-invariant structural differences across industries, such as technological characteristics and energy intensity. Month-of-year dummies account for seasonal patterns in producer prices. Standard errors are clustered at the sector level to address serial correlation and heteroskedasticity within sectors over time.

The use of Local Projections ensures direct comparability with the quantity-based LP framework employed in the analysis of industrial activity, while adapting the specification to sectoral price dynamics.

In order to facilitate the interpretation of the dynamic effects, cumulative impulse responses are reported in the results section. These responses represent the cumulative change in producer prices up to horizon h, obtained by summing the future log changes of the dependent variable.

Identification strategy The identification of causal effects relies on the external construction of European gas shocks within a structural BVAR framework. Since these shocks are identified at the European level and are exogenous to Italian sectoral prices, they provide variation that is plausibly orthogonal to sector-specific price innovations.

Conditional on sector fixed effects and month-of-year dummies, the estimated coefficients capture the causal effect of European gas market disturbances on Italian producer prices.

3 Results

3.1 Descriptive Statistics

Table 1: Regional distribution of industrial electricity consumption

Region	Mean (GWh)	Std. Dev.	Share (%)
Lombardia	1061.5	181.8	35.18
Veneto	316.0	51.8	10.47
Friuli-Venezia Giulia	267.1	36.7	8.85
Piemonte	171.6	28.0	5.69
Emilia-Romagna	171.3	27.2	5.68
Sicilia	147.1	22.9	4.87
Umbria	134.5	23.4	4.46
Toscana	122.3	13.9	4.05
Sardegna	118.6	15.2	3.93
Puglia	94.9	11.1	3.15
Campania	81.1	8.4	2.69
Lazio	73.8	8.1	2.45
Liguria	45.2	4.0	1.50
Abruzzo	45.1	7.4	1.49
Basilicata	42.3	9.5	1.40
Marche	38.6	6.2	1.28
Trentino-Alto Adige	37.5	6.2	1.24
Valle d'Aosta	27.0	4.7	0.89
Molise	16.5	3.8	0.55
Calabria	5.6	4.1	0.18

Table 1 reports the distribution of industrial electricity consumption across Italian regions. The data show a strong geographical concentration. Lombardia alone accounts for over one third (35%) of total national industrial electricity consumption over the sample period. It is followed by Veneto (10.5%) and Friuli-Venezia Giulia (8.9%), but at a considerable distance. It is important to underline how the first five regions together account for more than 65% of total national industrial electricity consumption, indicating that industrial activity is heavily clustered in a limited number of regions, all located in Northern Italy.

At the opposite end of the distribution, regions such as Calabria (0.18%), Molise (0.55%), and Valle d'Aosta (0.89%) contribute only marginally to total industrial electricity demand, highlighting a wide gap in both scale and industrial development.

Table 2: High vs Low electricity intensity regions

Group	Mean (GWh)	Std. Dev.	Observations
Low intensity	41.3	22.8	600
High intensity	260.5	282.3	600

We also classify regions into high- and low-intensity groups. High-intensity regions have an average monthly consumption of about 260 GWh, compared to 41.3 GWh in the low-intensity group. The standard deviation is considerably larger among high-intensity regions (282.3) than among low-intensity ones (22.8), suggesting higher volatility and stronger cyclical exposure in more industrialized areas.

Overall, these descriptive statistics highlight the structural asymmetries that characterize Italian regions and motivate the heterogeneity analysis conducted in the following sections. Regions with larger industrial activity may react differently to European gas shocks compared to regions with smaller industrial bases.

3.2 Baseline Local Projections and Seasonality

The local projections show how Italian regional industrial electricity consumption is influenced by European gas market shocks. It is also clear how seasonality plays an important role in the patterns of consumption and in the shaping of the estimated dynamics. When we compare the baseline specifications and models with monthly dummies the seasonal patterns are revealed.

In the gas supply shocks the baseline specification suggests a weak and unstable response of industrial electricity consumption and delayed effects with significant responses at medium and longer horizons. In the early horizons the coefficients are not statistically significant (-0.387 at lead 1, -0.399 at lead 3). This coefficient at six months is positively related to the shock (7.563) with significance at 5% level, while it becomes negative at twelve months with a significance at the 10% level (-2.341). However, when there is the control for monthly seasonality, the magnitude and the persistence of responses are reduced. The coefficient at lead 1 becomes positive, but remains small (1.998) and significant at the 10% level. On the longer horizons the responses are weak or not relevant. This suggests that supply shocks in the baseline model are not robust and are driven by seasonality and their influence on industrial activity is likely to be driven by seasonal comovement.

A different picture emerges from the analysis about economic activity shocks. In the baseline specification there is a greater response of industrial activity. At lead 1 a positive effect is observed (3.524) that is significant at the 10% level. After, the values take a zig-zag path, going first down at lead 3 (-6.183) with significance at the 10% level, and then becoming strongly positive at lead 6 (6.802) with significance at the 5% level. At the twelfth month the estimated response becomes insignificant at conventional levels . When control dummies are included the estimated effects remain economically meaningful, but with a more stable pattern. The response remains positive and statistically significant (3.276) at lead 1, while the large oscillations observed in the baseline specification are less strong. A positive and significant at standard levels effect reappears at the twelve-month horizon (0.710) with significance at the 5% level.

This underlines how demand driven shocks are the most robust channel through which European gas market shocks influence Italian industrial activity. Unlike supply shocks, the effects of the economic activity shocks survive the seasonality controls indicating more of a macroeconomic transmission rather than a spurious correlation.

Inventory shocks show a weaker response than the economic activity ones. In the baseline specification the estimated coefficients have a delayed and sign changing pattern. At lead 1 the response is small (-0.306) and statistically insignificant, while at lead 3 a negative effect emerges (-2.938) with significance at the 10% level. This response is then followed by a positive effect on the twelve-month horizon (5.124). When monthly seasonality is added the dynamics change substantially: the estimated effects are more concentrated in shorter horizons and have less magnitude than before. Positive and weakly significant responses are observed at lead 1 (2.036) and at lead 3 (1.061). At the twelve-month horizon there still stands a positive effect (1.623) with significance at the 5% level. This analysis suggests that inventory shocks may have transitory effects on industrial activity, consistent probably with precautionary storage behavior in response to uncertainty, but their macroeconomic relevance appears limited when seasonality controls are added.

The comparison between the baseline specification and models that include seasonality controls highlights the crucial role that seasonal dynamics play in shaping the estimated response. Supply and inventory shocks exhibit fragile and non-persistent effects, while when seasonality is controlled for, economic activity shocks emerge as the most economically meaningful driver of regional industrial electricity consumption. These results highlight how demand-side mechanisms are important in the transmission of European gas market shocks to Italian industrial activity.

3.3 Impulse Response Functions

In order to illustrate the effects of the European gas market shocks on Italian regional industrial electricity consumption, the results of the Local Projections are graphically depicted through impulse response functions (IRFs). They provide a convenient representation of the response over time of industrial activity, allowing timing, magnitude and persistence effects to be clearly visualized. Each coefficient traces the cumulative response of the dependent variable after the shock. The response at horizon h represents the sum of the estimated effects from the impact period up to month h, allowing the adjustment to be visualized graphically.

In this thesis, the IRFs are constructed using the Local Projection methodology proposed by Jordà (2005). For each forecast horizon $h = 1, \ldots, 12$, a separate panel regression is estimated, and the corresponding coefficient β_h measures the average response of regional industrial electricity consumption h months after the shock. This approach allows for flexible dynamics and accommodates fixed effects without imposing a specific parametric dynamic structure across horizons.

The impulse responses are computed for standardized shocks, so each IRF traces the response of industrial electricity consumption to a one-standard-deviation European gas market shock. Since the shocks are common across regions, identification relies on their time variation within the panel framework, after controlling for region fixed effects and seasonal factors. Monthly dummy variables are included to control for seasonality in electricity demand.

The inclusion of region fixed effects does not change the pattern of the impulse responses, confirming that the estimated dynamics are not influenced by time-invariant differences of Italian regions.

In the figures, the horizontal axis reports the forecast horizon in months, while the vertical axis shows the cumulative change in industrial electricity consumption (GWh) at each horizon. The shaded grey area represents a 90 percent confidence interval based on clustered standard errors. When zero is not included in the confidence bands, the response is statistically significant at the 10 percent level.

The impulse response functions represent the effect of a one-standard-deviation gas market shock. In economic terms, the cumulative responses after 12 months correspond to a change of approximately 10–12 GWh in monthly industrial electricity consumption in the case of demand-driven shocks. Since the average monthly consumption in the sample is around 150 GWh, the variation is roughly 7–8% relative to the mean level.

The magnitude of other shocks is lower, typically between 3–5% of the monthly average consumption level.

Using the cumulative response to a shock helps summarize the overall effect over time and reduced the oscillatory behavior of standard IRFs. They allow a clearer interpretation of medium and long run impact.

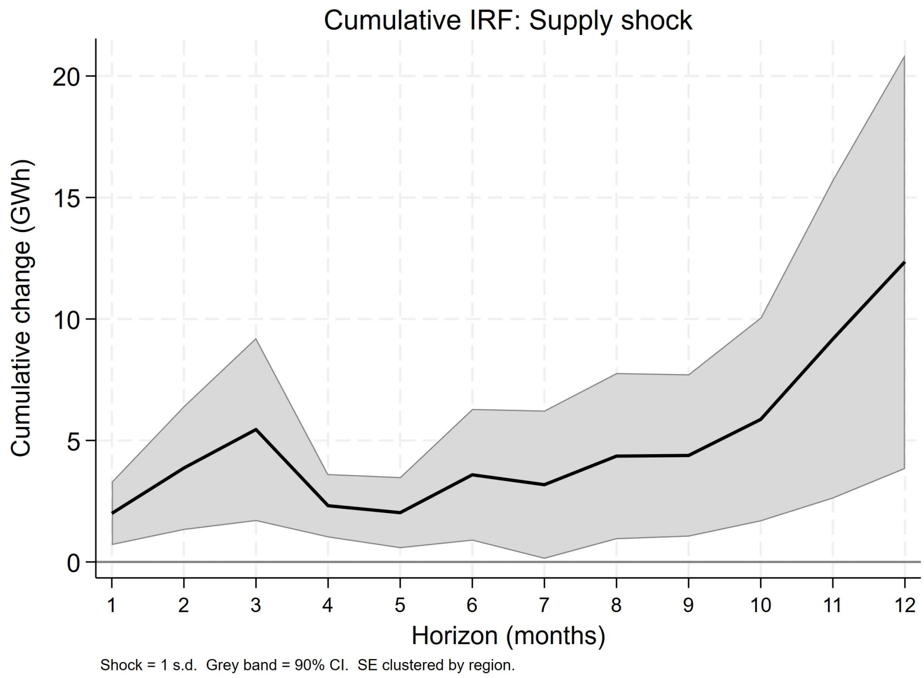


Figure 3: Cumulative impulse response of electricity consumption to a supply shock

Supply shock From Figure 3 we can see how the response to a supply shock is relatively limited and unstable. In the short run, the effect remains statistically imprecise, with the confidence bands around zero, while at longer horizons the cumulative response becomes slightly positive, although with a modest magnitude.

This pattern suggests that supply disturbances do not translate into strong or persistent changes in Italian industrial electricity consumption.

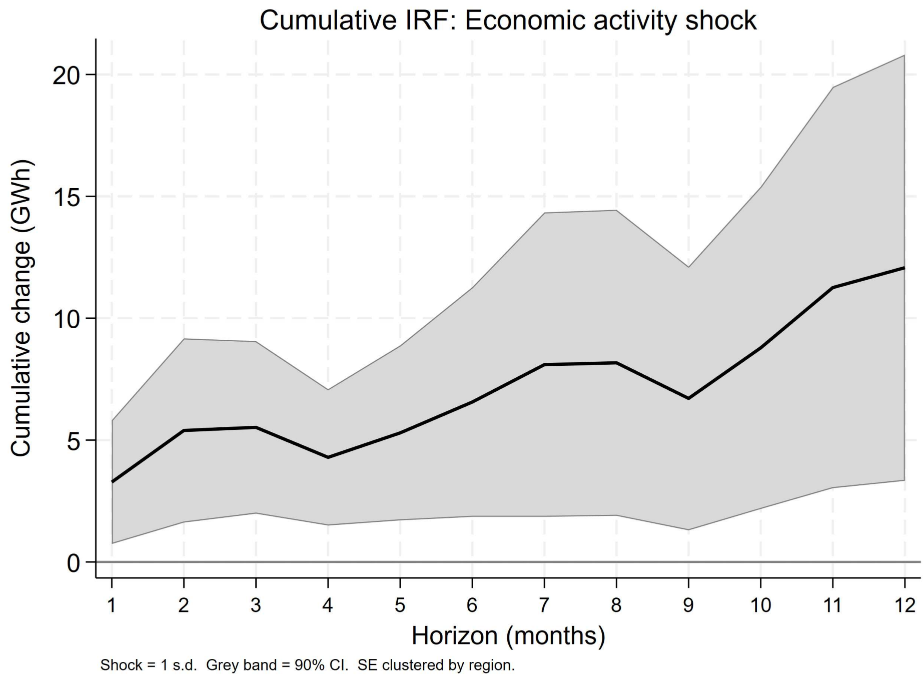


Figure 4: Cumulative impulse response of electricity consumption to an economic activity shock

Economic activity shock The cumulative response shows a clearer and more persistent pattern. Industrial electricity consumption increases progressively following a demand-driven shock. The cumulative effect grows steadily over time, suggesting that stronger economic activity can lead to an increase in industrial energy demand.

This result is also consistent with the interpretation of electricity consumption as a proxy for industrial production. When economic activity expands, firms increase output and energy use, which leads to higher electricity consumption.

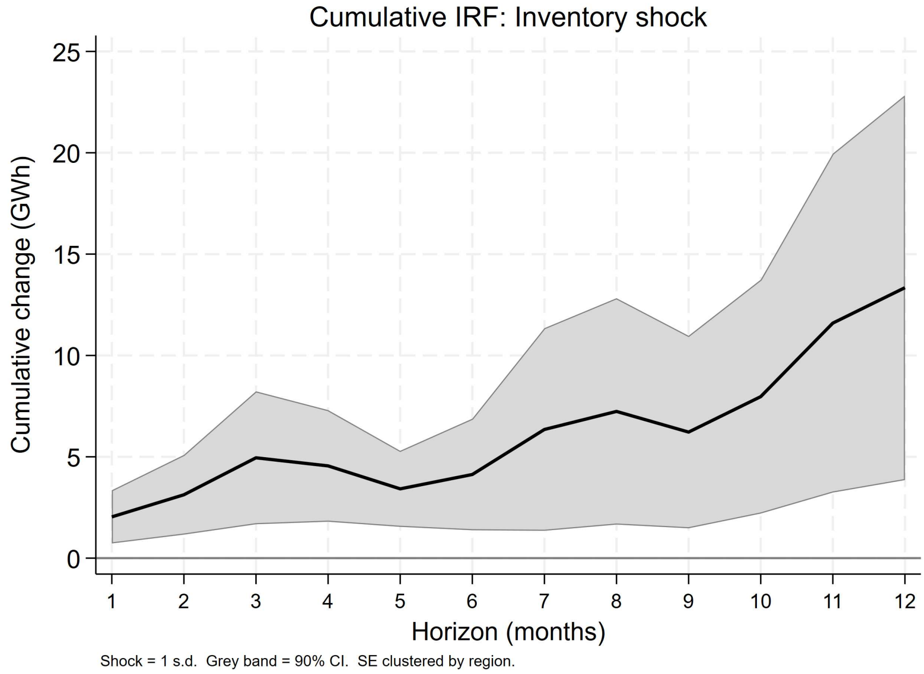


Figure 5: Cumulative impulse response of electricity consumption to an inventory shock

Inventory shock Inventory shocks generate weak cumulative responses even if the point estimates slightly increase over time. The confidence bands remain wide and tend to be around zero, indicating that there is a limited degree of statistical precision in the estimation.

These dynamics are consistent with the interpretation of the shock as a precautionary adjustment driven by expectations about the future rather than immediate changes. As a result, electricity consumption is modestly influenced by this type of shock.

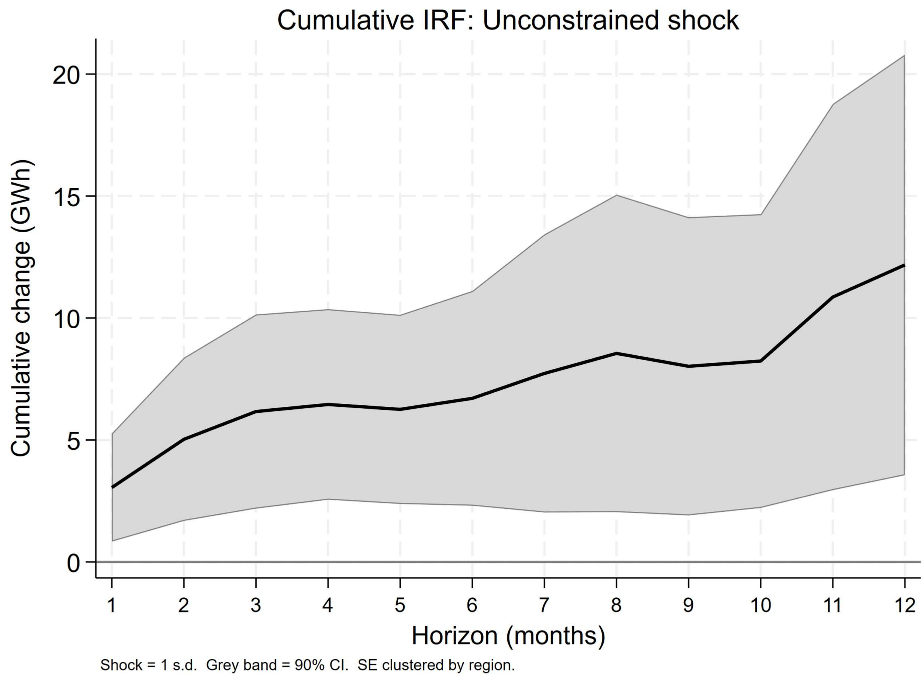


Figure 6: Cumulative impulse response of electricity consumption to an unconstrained shock

Unconstrained shock The cumulative response to the unconstrained shock shows a gradual increase over time, but with uncertainty. The confidence bands remain wide and reflect the residual nature of the shock.

The results suggest that this type of shock plays a limited role in shaping the dynamics of industrial electricity consumption, since it captures variations that are not explained by the structurally identified components of the gas market model.

Overall interpretation Overall, the results suggest that European gas market shocks have a moderate effect on Italian industrial electricity consumption. Demand-driven shocks generate stronger and more persistent responses, while supply and inventory shocks produce weaker and more volatile dynamics.

3.4 Robustness: Lagged Dependent Variables

To verify the stability of the baseline results, we extend the local projection specification by adding three lags of the dependent variable and three lags of the shock. This analysis aims to control for persistence in regional industrial electricity consumption, which could bias the estimated impulse responses.

Industrial electricity demand is characterized by dynamic adjustment processes, influenced by production decisions that are usually planned over time and may exhibit inertia. By including lagged dependent variables and lagged shocks, the effect of gas market shocks can be isolated from both the internal persistence of industrial activity and the serial correlation of the shock process.

The robustness specification therefore takes the following form:

$$\Delta y_{i,t+h} = \beta_h shock_t + \sum_{k=1}^{3} \theta_{h,k} shock_{t-k} + \sum_{k=1}^{3} \phi_{h,k} \Delta y_{i,t-k} + \gamma_i + \delta_m + \varepsilon_{i,t+h}$$

where three lags of electricity consumption and three lags of the shock are included together with region fixed effects and month-of-year dummies. Standard errors remain clustered at the regional level to account for within-region serial correlation.

The dependent variable $\Delta y_{i,t+h}$ represents the future change in industrial electricity consumption in region i, measured h months after the realization of the shock at time t. For each horizon h, a separate regression is estimated in order to capture the dynamic response through the coefficient β_h.

The variable $shock_t$ represents the standardized European gas market shock observed at time t. Because of the standardization of the shocks, the coefficient β_h measures the response of regional industrial electricity consumption to a one-standard-deviation change in the corresponding gas market disturbance.

The terms $\sum_{k=1}^{3} \phi_{h,k} \Delta y_{i,t-k}$ capture the first three lags of the dependent variable, while $\sum_{k=1}^{3} \theta_{h,k} shock_{t-k}$ represent lagged values of the shock. Together, they control for persistence and gradual adjustment in industrial electricity consumption as well as for serial correlation in gas market disturbances. By including both lagged dependent variables and lagged shocks, we ensure that the estimated responses are not driven by inertia or omitted dynamic components.

The term γ_i captures region fixed effects, which absorb time-invariant structural differences across Italian regions, such as industrial composition, infrastructure, or long-run energy intensity. The term δ_m captures month-of-year fixed effects (m = 1,. . . ,12) and controls for common seasonal fluctuations in electricity demand across regions.

Finally, $\varepsilon_{i,t+h}$ is the error term. Standard errors are clustered at the regional level to account for within-region serial correlation.

Table 3: Robustness LP with shock lags (1–3) and dependent-variable lags (1–3): selected horizons

	$h = 1$	$h = 3$	$h = 6$	$h = 12$
Supply shock	2.839**	2.628*	2.439**	-2.815*
Econ. activity	2.093**	3.231***	0.653	-1.162
Inventory shock	2.663**	3.593*	-0.854	1.874*
Unconstrained	3.975**	3.618*	-1.773	2.718**

Region FE and month-of-year fixed effects included. Standard errors clustered by region. Entries report the contemporaneous shock coefficient β_h. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Results

Supply shock

When lagged dependent variables and lagged shocks are included in the regressions, the inclusion of lags does not materially change the qualitative pattern of the response to a supply shock. The contemporaneous coefficients β_h continue to display instability across different horizons. The short-run coefficients remain positive and statistically significant at some horizons, but the pattern continues to show sign reversals and very limited persistence. The results underline how industrial electricity consumption is mainly subject to temporary adjustment rather than sustained changes. The inclusion of lags therefore does not alter the interpretation of supply-driven disturbances.

Economic activity shock

From Table 3 it is clear how the economic activity shock remains the most robust channel of transmission. After controlling for persistence in the shocks and the dependent variable, the contemporaneous coefficients β_h remain significant at standard levels for several horizons. Some oscillations persist, but the overall pattern continues to show economically meaningful effects. This suggests that demand-driven shocks have a stronger and more persistent impact on industrial electricity consumption, consistent with their macroeconomic origin rather than simple short-term cost fluctuations.

Inventory shock

Controlling for lagged variables does not identify a stable dynamic response for inventory shocks. The contemporaneous coefficients β_h still show sign changes, even if they remain statistically significant at some horizons. These results underline that inventory disturbances reflect temporary adjustments rather than a persistent transmission channel.

Unconstrained shock

The unconstrained shock continues to display irregular patterns with statistically significant *positive* contemporaneous coefficients at multiple horizons and isolated negative effects. Some contemporaneous coefficients remain significant at specific horizons, but the absence of a systematic dynamic structure supports the interpretation of this shock as a residual component capturing unobserved influences.

Overall, the robustness analysis confirms the main results of the baseline regressions. The inclusion of lagged dependent variables and lagged shocks again shows how economic activity shocks represent the most stable and economically meaningful driver of regional industrial electricity consumption, while the other shocks generate mainly transitory and short-term effects with coefficients that are highly unstable across horizons.

3.5 Heterogeneity across Regions

In this section, the baseline analysis is extended to account for regional heterogeneity. The previous results establish the average response of regional industrial electricity consumption to European gas shocks, without explicitly considering differences in industrial composition and energy intensity across regions. However, Italian regions differ substantially in their industrial structure, as shown in Table 1. Regions with a higher concentration of energy-intensive industries may exhibit a stronger reaction to the same shock, particularly because these shocks may operate not only through energy costs but also through broader macroeconomic demand channels.

To investigate this dimension, the Local Projection framework is augmented by introducing a dummy variable identifying regions with higher average industrial electricity consumption. This extension allows the dynamic response of electricity consumption to differ between high- and low-intensity regions, while maintaining region fixed effects and month-of-year fixed effects as in the baseline specification.

Formally, for each horizon $h = 1, \ldots, 12$, the following specification is estimated:

$$\Delta y_{i,t+h} = \beta_h Shock_t + \theta_h (Shock_t \times High_i) + \gamma_i + \delta_m + \varepsilon_{i,t+h} \tag{4}$$

where $High_i$ is a dummy variable equal to one for regions whose average electricity consumption is above the median level of energy intensity. The coefficient β_h measures the response of low-intensity regions, while θ_h captures the differential effect for high-intensity regions. The total effect for high-intensity regions is therefore given by $\beta_h + \theta_h$.

High- vs Low-Intensity Regions

The heterogeneity analysis extends the baseline specification by explicitly allowing for differences between low- and high-energy-intensive regions in the regression. The interaction term captures whether the effects of European gas shocks are amplified or attenuated in regions with higher average electricity consumption (the total response for high-intensity regions corresponds to the baseline effect plus the interaction term).

Table 4: Heterogeneity Effects by Electricity Intensity (Supply Shock)

h	Low	SE (Low)	High	SE (High)	Diff (High−Low)	p-value
1	2.416	0.939	1.581	0.893	-0.834	0.284
2	-1.183	0.921	4.565	2.170	5.748	0.066
3	1.079	0.541	-0.279	0.678	-1.358	0.165
4	2.096	1.478	-8.322	4.299	-10.418	0.079
5	0.318	0.444	-1.039	0.410	-1.357	0.059
6	-4.558	2.625	7.574	3.943	12.131	0.063
7	3.821	2.329	-4.561	1.942	-8.381	0.040
8	-0.996	0.810	3.665	1.313	4.661	0.031
9	1.517	0.759	-1.062	0.732	-2.579	0.061
10	-1.523	1.031	-0.248	0.772	1.275	0.297
11	1.746	0.748	3.768	1.606	2.023	0.047
12	1.870	1.036	-1.549	1.332	-3.419	0.125

Notes: Low is the baseline effect (β_h). High is the total effect for high-intensity regions ($\beta_h + \theta_h$). Diff is the interaction term (θ_h). p-value refers to the test of $\theta_h = 0$. Region fixed effects and month-of-year fixed effects included. Standard errors are clustered by region.

Supply shock The response remains unstable, characterized by sign reversals across different horizons. The interaction term is occasionally statistically significant, but its direction changes between positive and negative effects, indicating that the differential effect alternates between amplification and attenuation. There is no persistent or systematic heterogeneity pattern. This suggests that supply disturbances mainly generate temporary adjustment dynamics rather than structural regional differences in transmission.

Table 5: Heterogeneity Effects by Electricity Intensity (Economic Activity Shock)

h	Low	SE (Low)	High	SE (High)	Diff (High−Low)	p-value
1	0.570	0.230	5.983	3.060	5.414	0.110
2	-1.590	1.296	5.854	2.591	7.444	0.059
3	5.147	2.775	-5.864	3.585	-11.011	0.079
4	1.061	0.769	-3.612	1.626	-4.673	0.053
5	-1.838	1.101	3.825	1.947	5.663	0.064
6	-4.151	2.457	6.656	3.745	10.807	0.080
7	3.085	1.742	-0.105	0.858	-3.190	0.057
8	2.368	1.316	-1.921	1.255	-4.289	0.077
9	-1.022	0.547	-0.927	0.347	0.095	0.845
10	-2.796	1.803	5.191	2.406	7.987	0.055
11	3.738	1.864	0.285	0.865	-3.453	0.097
12	0.212	0.166	1.208	0.519	0.996	0.043

Notes: Low is the baseline effect (β_h). High is the total effect for high-intensity regions ($\beta_h + \theta_h$). Diff is the interaction term (θ_h). p-value refers to the test of $\theta_h = 0$. Region fixed effects and month-of-year fixed effects included. Standard errors are clustered by region.

Economic activity shock The economic activity shock remains the most economically interpretable disturbance. In the baseline specification, the response of low-intensity regions is statistically significant at some short- and medium-term horizons. The interaction term is significant in several horizons, indicating that regional electricity intensity influences the transmission mechanism, but the sign of the differential effect is not uniform over time: high-intensity regions show stronger responses at some horizons, while in others the response is attenuated. Overall, these results suggest that the demand channel is more informative than the other shocks, but the regional amplification mechanism varies across horizons rather than operating in a constant direction.

Table 6: Heterogeneity Effects by Electricity Intensity (Inventory Shock)

h	Low	SE (Low)	High	SE (High)	Diff (High−Low)	p-value
1	2.538	1.057	1.535	0.772	-1.003	0.187
2	-0.800	0.716	2.964	1.364	3.764	0.068
3	3.771	1.950	-1.649	1.342	-5.419	0.064
4	0.554	0.196	-1.281	0.904	-1.835	0.073
5	-1.215	0.563	-1.601	1.067	-0.386	0.577
6	-1.771	0.934	2.213	1.526	3.984	0.102
7	0.793	0.421	3.075	2.144	2.282	0.238
8	1.191	0.671	1.101	0.576	-0.090	0.899
9	2.212	1.185	-4.038	2.038	-6.250	0.051
10	-1.707	1.038	1.862	0.951	3.569	0.053
11	2.778	1.260	3.117	1.392	0.339	0.519
12	-2.509	1.634	5.755	2.747	8.265	0.060

Notes: Low is the baseline effect (β_h). High is the total effect for high-intensity regions ($\beta_h + \theta_h$). Diff is the interaction term (θ_h). p-value refers to the test of $\theta_h = 0$. Region fixed effects and month-of-year fixed effects included. Standard errors are clustered by region.

Inventory shock Inventory shocks display temporary and oscillatory effects. Several interaction coefficients are marginally significant, but without a consistent sign across horizons. This lack of persistence supports the interpretation of this disturbance as reflecting precautionary storage adjustments rather than sustained macroeconomic forces.

Table 7: Heterogeneity Effects by Electricity Intensity (Unconstrained Shock)

h	Low	SE (Low)	High	SE (High)	Diff (High−Low)	p-value
1	0.033	0.433	6.066	2.850	6.033	0.076
2	-0.281	0.593	4.188	1.754	4.469	0.061
3	3.458	1.703	-1.575	1.337	-5.033	0.073
4	2.425	1.238	-1.850	1.411	-4.275	0.094
5	-2.116	1.180	1.612	1.121	3.728	0.086
6	-3.213	1.810	3.950	2.267	7.163	0.074
7	2.272	1.339	-0.390	0.755	-2.662	0.029
8	1.473	0.810	0.491	0.588	-0.982	0.097
9	-0.523	0.391	0.254	0.305	0.777	0.188
10	-0.864	0.654	1.160	0.602	2.025	0.080
11	1.333	0.537	3.159	1.375	1.826	0.061
12	0.844	0.334	1.610	0.484	0.765	0.006

Notes: Low is the baseline effect (β_h). High is the total effect for high-intensity regions ($\beta_h + \theta_h$). Diff is the interaction term (θ_h). p-value refers to the test of $\theta_h = 0$. Region fixed effects and month-of-year fixed effects included. Standard errors are clustered by region.

Unconstrained shock The residual shock exhibits irregular dynamics. Some interaction terms are statistically different from zero, but the pattern lacks a coherent structure, consistent with the interpretation that the residual disturbance captures heterogeneous influences rather than a clearly identifiable transmission channel.

Overall, the heterogeneity analysis confirms that European gas shocks affect regional industrial activity and electricity consumption, but it does not reveal a clear and stable amplification mechanism in high-intensity regions. Differences between high- and low-intensity regions exist, particularly for demand-driven shocks, but the magnitude and direction of these differences vary across horizons. The evidence suggests that regional industrial structure influences short-run adjustment dynamics while leaving the core transmission mechanism identified in the baseline specification largely unchanged.

3.6 Producer Price Responses

The cumulative impulse responses indicate that producer price reactions are relatively small in magnitude, although statistically significant at several horizons. The sign and persistence of the effects differ across shocks, indicating a heterogeneous transmission mechanism.

To illustrate the transmission of European gas market shocks to industrial prices, the dynamic responses of the producer price index (PPI) are represented through cumulative impulse response functions.

The impulse responses show the cumulative change in sectoral producer prices following a one-standard-deviation gas market shock. The horizontal axis reports the forecast horizon in months, while the vertical axis reports the cumulative percentage change in producer prices. The shaded area represents the 90 percent confidence interval.

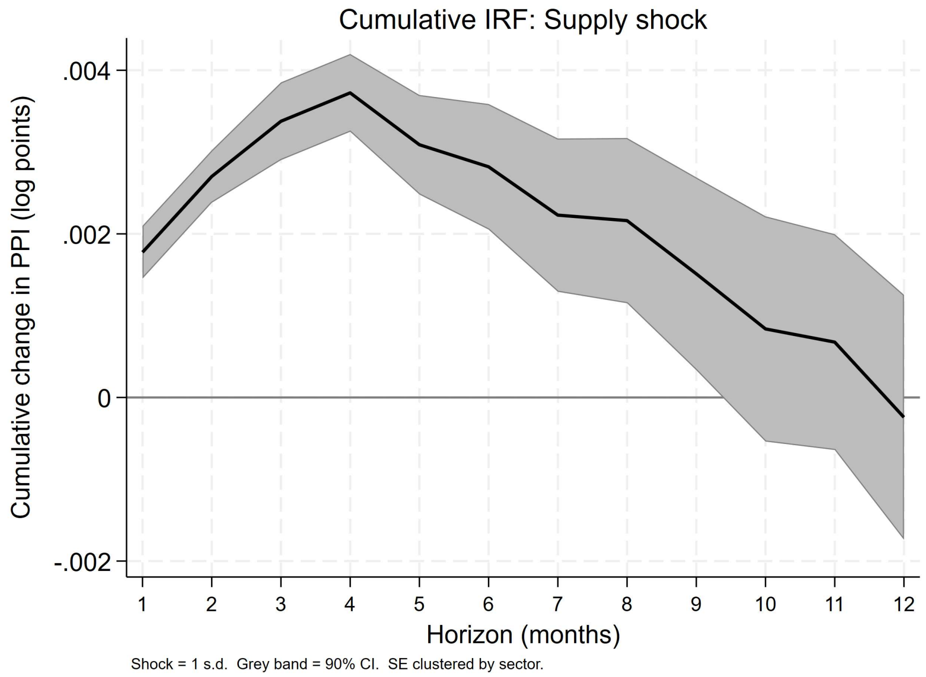


Figure 7: Cumulative impulse response of producer prices to a supply shock

Supply shock Figure 7 shows how producer prices react to a supply shock, initially increasing and then gradually reverting over time. In the early horizons the response is positive, with prices increasing by approximately 0.3–0.4%, indicating that a reduction in gas supply temporarily increases production costs and therefore producer prices.

This effect gradually declines and becomes statistically insignificant at longer horizons.

This behaviour suggests that supply disturbances mainly generate short-run cost pressures without persistent changes in industrial prices.

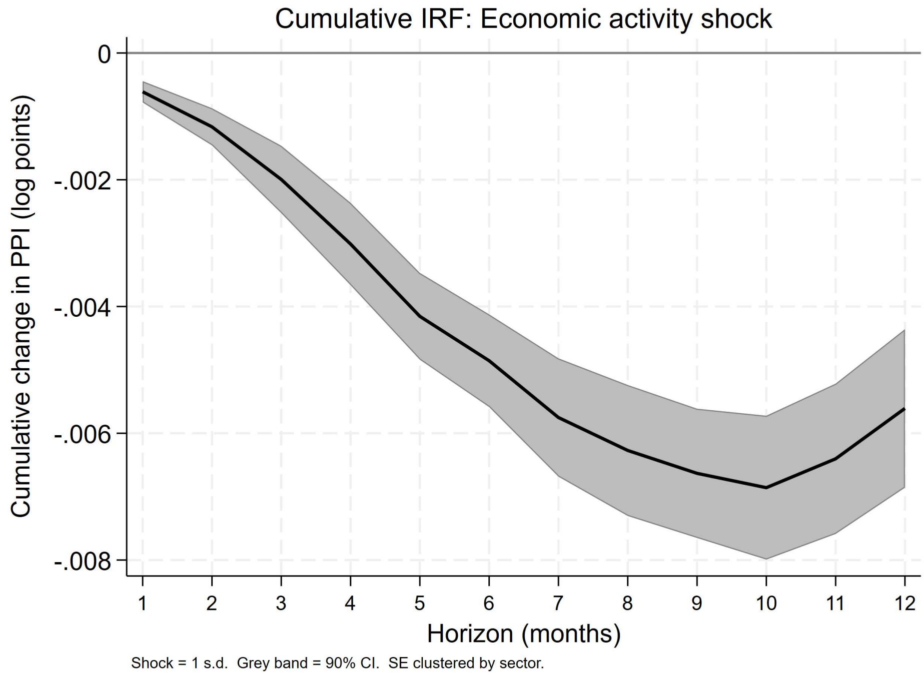


Figure 8: Cumulative impulse response of producer prices to an economic activity shock

Economic activity shock The response of producer prices to an economic activity shock is negative and relatively persistent. As shown in Figure 8, the cumulative effect becomes increasingly negative, reaching approximately -0.6 to -0.7% around horizon 10.

This pattern indicates that demand-driven shocks may be associated with lower producer prices in the medium run when economic activity strengthens. One possible explanation is that higher activity improves production efficiency and increases capacity utilization, thereby reducing unit production costs.

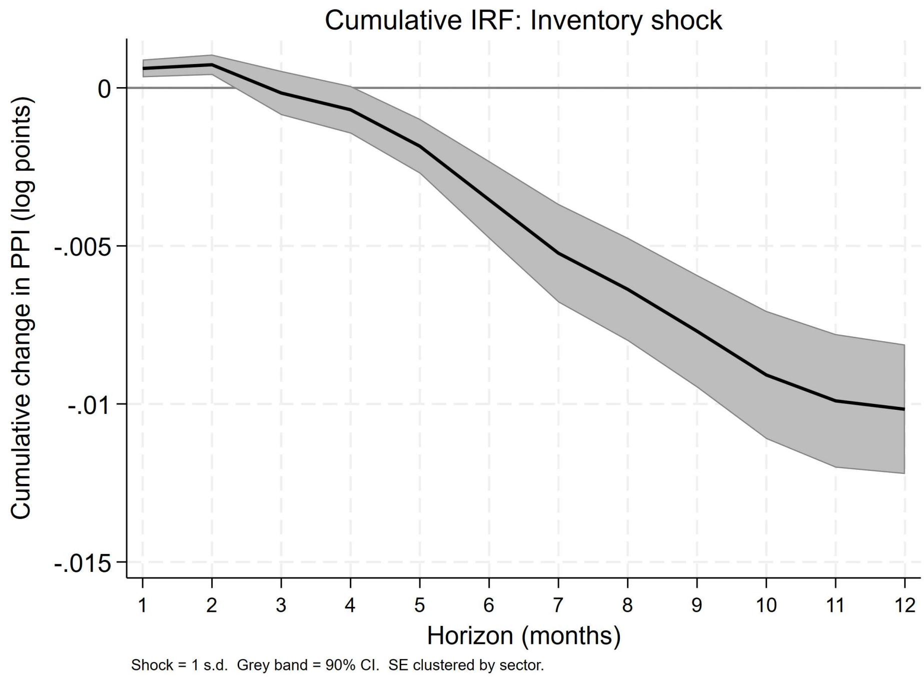


Figure 9: Cumulative impulse response of producer prices to an inventory shock

Inventory shock Inventory shocks generate the strongest response among the gas market shocks considered. Producer prices decline steadily over time, reaching almost -1% after twelve months.

This pattern suggests that adjustments in gas inventories play an important role in price dynamics. Changes in inventory conditions may influence expectations about future gas availability and costs, which are then transmitted along the industrial supply chain.

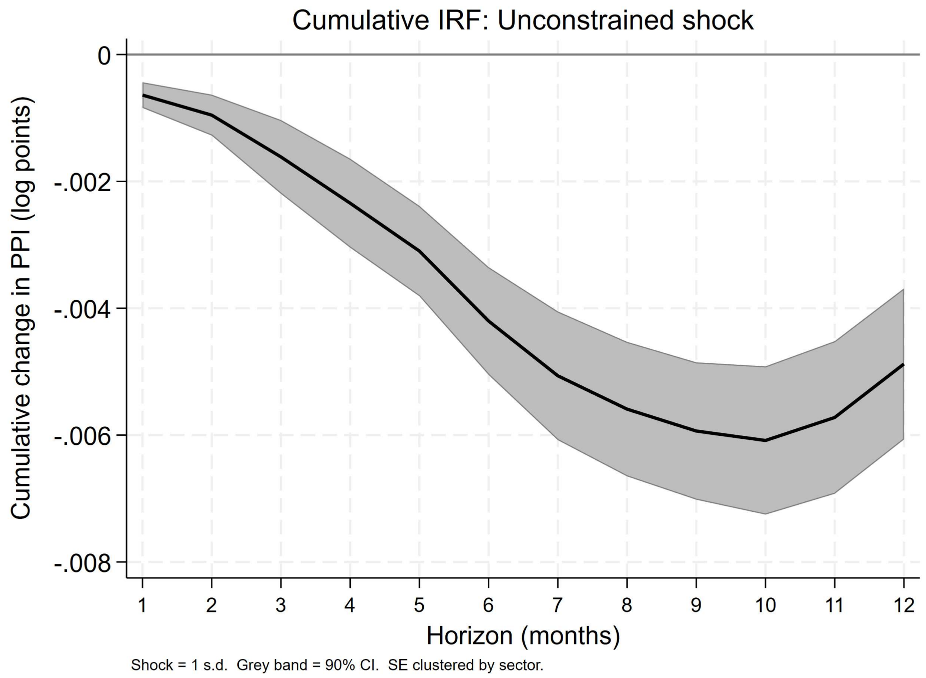


Figure 10: Cumulative impulse response of producer prices to an unconstrained shock

Unconstrained shock Unconstrained shocks also produce a negative response in producer prices, although the magnitude is smaller. The cumulative response gradually declines and reaches around -0.5% after one year.

Since this shock captures residual components of gas market fluctuations, the results suggest that unexplained disturbances still affect industrial prices, but with a more limited impact compared with structurally identified shocks.

3.7 Comparison between Quantity and Price Responses

What this chapter has shown is that PPI responses differ substantially from the quantity responses described in the first part of the thesis. Industrial electricity consumption reacts primarily through a demand-driven expansion channel, while producer prices exhibit weaker and often negative cumulative responses.

Supply shocks generate only temporary cost pressures, with producer prices increasing in the short run before gradually reverting over time. In contrast, economic activity shocks are associated with a persistent negative response in producer prices, suggesting that stronger economic activity may improve production efficiency and capacity utilization, thereby reducing unit production costs.

Inventory shocks produce the strongest cumulative decline in producer prices, indicating that changes in gas storage conditions and expectations about future energy availability may affect the industrial supply chain. Residual shocks also generate negative adjustments, although their magnitude remains relatively small.

Overall, the evidence suggests that European gas shocks only partially translate into Italian producer price dynamics. Industrial activity responds through higher production levels, while cost pressures appear to be partially absorbed through margin adjustments, resulting in a limited pass-through to producer prices.

4 Conclusion

The aim of this thesis was to investigate the transmission of European natural gas market shocks to the Italian industrial sector. The analysis develops along two complementary dimensions: first, industrial activity is proxied by regional industrial electricity consumption, and second, industrial prices, which are measured through sectoral producer price indices. Regional and sectoral data are combined with the structural gas shocks identified by Adolfsen et al. (2025).

To estimate the dynamic response of industrial activity and producer prices to European gas shocks, we rely on the Local Projection methodology proposed by Jordà (2005). The shocks are derived from a structural Bayesian VAR model and are distinguished into supply shocks, economic activity shocks, inventory shocks and the residual disturbances are categorized as unconstrained shocks.

The analysis identifies a transmission of the effects of gas shocks to the Italian industrial sector, but with differences between quantities and prices. Demand-driven shocks have the strongest influence, and they are associated with economic activity. These types of shocks generate positive and relatively persistent effects on industrial energy demand, consistent with the idea that stronger economic conditions increase production and therefore electricity use. Instead, supply and inventory shocks produce weaker and unstable responses in industrial activity.

The second part of the analysis shows that producer prices exhibit a different pattern. The cumulative impulse responses indicate that price adjustments are small and often negative. Among the shocks, supply ones generate only temporary cost pressures that increase prices in the short run. Economic activity and inventory shocks show negative cumulative responses, which could suggest that improvements in production efficiency may offset the cost effects associated with energy market disturbances.

Taken together, these findings suggest that European gas shocks influence the Italian industrial sector primarily through changes in production activity rather than through the pass-through to industrial prices. Adjusting output appears easier for firms than adjusting prices, which indicates that cost shocks are at least partially absorbed within production margins.

This study contributes to the literature on energy shocks and macroeconomic transmission by providing new evidence on the regional and sectoral effects of European gas market disturbances. However, several limitations remain: the analysis focuses on a relatively short sample period and uses a proxy for industrial activity. Future research could adopt longer sample periods, firm-level data, or alternative measures of industrial production and energy intensity.

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A Appendix

Table A1: Local Projections: baseline vs monthly seasonality (Supply shock)

	Baseline (no seasonality)				Monthly seasonality (*i.month*)			
	L1	L3	L6	L12	L1	L3	L6	L12
Std. supply shock	-0.387	-0.399	7.563**	-2.341*	1.998*	0.400	1.508*	0.161
	(0.388)	(0.493)	(3.361)	(1.128)	(0.792)	(0.350)	(0.790)	(0.332)
Observations	1180	1140	1080	960	1180	1140	1080	960

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A2: Local Projections: baseline vs monthly seasonality (Economic activity shock)

	Baseline (no seasonality)				Monthly seasonality (*i.month*)			
	L1	L3	L6	L12	L1	L3	L6	L12
Std. econ. activity shock	3.524*	-6.183*	6.802**	0.390	3.276*	-0.358	1.252	0.710**
	(1.723)	(3.205)	(3.157)	(0.255)	(1.543)	(0.525)	(0.750)	(0.338)
Observations	1180	1140	1080	960	1180	1140	1080	960

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A3: Local Projections: baseline vs monthly seasonality (Inventory shock)

	Baseline (no seasonality)				Monthly seasonality (*i.month*)			
	L1	L3	L6	L12	L1	L3	L6	L12
Std. inventory shock	-0.306	-2.938*	2.215*	5.124**	2.036*	1.061*	0.221	1.623**
	(0.383)	(1.505)	(1.239)	(2.262)	(0.797)	(0.577)	(0.358)	(0.680)
Observations	1180	1140	1080	960	1180	1140	1080	960

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A4: Robustness LP (Supply shock): including lags of the shock (1–3) and lags of the dependent variable (1–3)

	(1) $f1$	(2) $f2$	(3) $f3$	(4) $f4$	(5) $f5$	(6) $f6$	(7) $f7$	(8) $f8$	(9) $f9$	(10) $f10$	(11) $f11$	(12) $f12$
Standardized value (supply)	2.839**	2.612**	2.628*	-5.438*	-0.764*	2.439**	0.170	-1.247	1.024*	-1.382	5.070*	-2.815*
	(1.084)	(1.150)	(1.417)	(2.770)	(0.423)	(1.102)	(0.898)	(0.997)	(0.588)	(1.107)	(2.639)	(1.383)
L.Standardized value (supply)	1.293	1.771	-3.663*	-0.957*	2.578**	-0.764	1.916***	-1.822*	-2.452	5.085*	0.256	-5.417**
	(0.774)	(1.104)	(2.044)	(0.483)	(1.116)	(0.535)	(0.588)	(0.875)	(1.466)	(2.764)	(0.686)	(2.367)
L2.Standardized value (supply)	1.738	-3.374*	-1.445***	2.751**	-0.773	1.942***	-1.062*	-2.816	5.466*	0.0339	-4.320**	-0.411
	(1.049)	(1.948)	(0.503)	(1.134)	(0.610)	(0.580)	(0.550)	(1.723)	(2.883)	(0.723)	(1.709)	(0.937)
L3.Standardized value (supply)	-3.801*	-1.404***	0.882	1.598	1.397***	-2.030**	-2.307	7.491**	-1.586	-4.843**	-2.813*	6.375*
	(2.022)	(0.476)	(0.645)	(1.320)	(0.412)	(0.942)	(1.363)	(3.530)	(1.182)	(1.850)	(1.540)	(3.105)
L.Δ Consumo elettrico	-0.122***	-0.0236	0.551***	-0.418***	-0.0105**	0.0295***	0.466***	-0.636***	0.0139***	-0.0181***	0.855***	-0.769***
	(0.00816)	(0.0170)	(0.0137)	(0.0209)	(0.00376)	(0.00365)	(0.0124)	(0.0133)	(0.00316)	(0.00230)	(0.0138)	(0.0189)
L2.Δ Consumo elettrico	-0.0958***	0.545***	-0.000742	-0.413***	0.0443***	0.503***	-0.111***	-0.656***	-0.000339	0.838***	-0.0225***	-0.694***
	(0.0171)	(0.0221)	(0.00523)	(0.0228)	(0.00605)	(0.00999)	(0.0110)	(0.0215)	(0.00318)	(0.0145)	(0.00312)	(0.0218)
L3.Δ Consumo elettrico	0.493***	0.00604	-0.0249***	-0.386***	0.532***	-0.0622***	-0.0782***	-0.721***	0.861***	-0.0376***	0.0101***	-0.658***
	(0.0198)	(0.00909)	(0.00405)	(0.0239)	(0.00659)	(0.00766)	(0.00574)	(0.0231)	(0.0144)	(0.00384)	(0.00214)	(0.0128)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1100	1080	1060	1040	1020	1000	980	960	940	920	900	880

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Robustness LP (Economic activity shock): including lags of the shock (1–3) and lags of the dependent variable (1–3)

	(1) $f1$	(2) $f2$	(3) $f3$	(4) $f4$	(5) $f5$	(6) $f6$	(7) $f7$	(8) $f8$	(9) $f9$	(10) $f10$	(11) $f11$	(12) $f12$
Standardized value (econact)	2.093**	2.356*	3.231***	-3.684**	0.205	0.653	3.538*	-0.259	-2.562*	-1.572*	6.913**	-1.162
	(0.999)	(1.232)	(1.069)	(1.554)	(0.582)	(0.534)	(1.945)	(0.299)	(1.332)	(0.813)	(2.914)	(0.678)
L.Standardized value (econact)	0.676	1.707**	-3.312***	0.869	0.190	3.501*	-0.364	-4.755**	0.239	7.074**	-1.675**	-2.255
	(0.522)	(0.678)	(1.115)	(0.720)	(0.718)	(1.838)	(0.434)	(2.179)	(0.542)	(3.026)	(0.719)	(1.311)
L2.Standardized value (econact)	2.295**	-2.690**	0.292	-0.818	4.394*	-0.635	-4.500**	-0.423	7.120**	-1.117*	-1.364	-3.243*
	(0.829)	(0.986)	(0.784)	(0.598)	(2.199)	(0.532)	(1.906)	(0.630)	(3.078)	(0.630)	(1.125)	(1.699)
L3.Standardized value (econact)	-2.114**	0.265	0.00899	4.561*	-2.253*	-2.846**	2.798**	6.879**	-3.056**	-3.054*	-3.091**	6.065*
	(0.852)	(0.530)	(0.665)	(2.249)	(1.145)	(1.271)	(1.151)	(3.015)	(1.380)	(1.631)	(1.286)	(3.002)
L.Δ Consumo elettrico	-0.123***	-0.0236	0.553***	-0.422***	-0.00961**	0.0372***	0.465***	-0.642***	0.0117***	-0.0142***	0.862***	-0.770***
	(0.00791)	(0.0171)	(0.0128)	(0.0200)	(0.00410)	(0.00461)	(0.0128)	(0.0124)	(0.00227)	(0.00271)	(0.0127)	(0.0194)
L2.Δ Consumo elettrico	-0.0964***	0.545***	-0.000616	-0.418***	0.0506***	0.514***	-0.118***	-0.668***	0.00280	0.848***	-0.0171***	-0.699***
	(0.0165)	(0.0222)	(0.00491)	(0.0227)	(0.00723)	(0.00986)	(0.0116)	(0.0202)	(0.00300)	(0.0141)	(0.00281)	(0.0228)
L3.Δ Consumo elettrico	0.494***	0.00344	-0.0251***	-0.388***	0.540***	-0.0564***	-0.0862***	-0.729***	0.868***	-0.0314***	0.0116***	-0.663***
	(0.0188)	(0.0103)	(0.00403)	(0.0237)	(0.00625)	(0.00746)	(0.00626)	(0.0219)	(0.0128)	(0.00382)	(0.00220)	(0.0131)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1100	1080	1060	1040	1020	1000	980	960	940	920	900	880

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Robustness LP: Inventory shock with shock lags (1–3) and dependent-variable lags (1–3)

	(1) $f1$	(2) $f2$	(3) $f3$	(4) $f4$	(5) $f5$	(6) $f6$	(7) $f7$	(8) $f8$	(9) $f9$	(10) $f10$	(11) $f11$	(12) $f12$
z_shock_inv	2.663**	1.108**	3.593*	-1.710	-1.129	-0.854	3.484	-0.398	0.604	-5.760*	7.663*	1.874*
	(1.116)	(0.429)	(1.731)	(1.047)	(0.789)	(0.817)	(2.519)	(0.563)	(0.740)	(3.130)	(3.787)	(0.913)
L.z_shock_inv	-1.825*	2.941	-0.454	-2.598*	-0.888	4.877	1.016	-3.128**	-6.708*	12.11*	1.109	-7.880**
	(0.945)	(1.936)	(0.571)	(1.447)	(0.887)	(3.280)	(0.686)	(1.456)	(3.584)	(6.210)	(0.683)	(3.545)
L2.z_shock_inv	5.574*	-0.160	-3.081*	-1.121	5.710	-0.0761	-4.866**	-5.615*	13.90*	-1.807	-6.253**	1.802*
	(2.829)	(0.873)	(1.741)	(0.717)	(3.477)	(1.045)	(1.962)	(2.933)	(6.921)	(1.660)	(2.780)	(0.949)
L3.z_shock_inv	-3.025	-2.817**	0.921	4.695*	-1.993	-2.858**	1.947**	9.640**	-4.878*	-3.708**	1.722*	2.754*
	(1.804)	(1.129)	(0.956)	(2.556)	(1.483)	(1.119)	(0.849)	(4.470)	(2.718)	(1.484)	(0.962)	(1.513)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1100	1080	1060	1040	1020	1000	980	960	940	920	900	880

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A7: Robustness LP: Unconstrained shock with shock lags (1–3) and dependent-variable lags (1–3)

	(1) $f1$	(2) $f2$	(3) $f3$	(4) $f4$	(5) $f5$	(6) $f6$	(7) $f7$	(8) $f8$	(9) $f9$	(10) $f10$	(11) $f11$	(12) $f12$
z_shock_unc	3.975**	0.647	3.618*	0.231	-0.0920	-1.773	2.254	0.415	2.608*	-6.769*	6.102*	2.718**
	(1.828)	(0.469)	(1.898)	(0.659)	(0.546)	(1.133)	(1.651)	(0.715)	(1.298)	(3.481)	(3.144)	(1.268)
L.z_shock_unc	-4.521*	3.156	1.303**	-3.415**	-2.494	4.684	2.696**	-2.650	-9.660*	11.88*	3.372**	-7.779*
	(2.288)	(2.198)	(0.463)	(1.290)	(1.576)	(2.883)	(1.019)	(1.559)	(4.737)	(6.187)	(1.255)	(4.072)
L2.z_shock_unc	7.153*	0.819	-4.942**	-0.807	6.395*	0.549	-6.139**	-6.339**	15.45*	-0.404	-8.483*	-0.109
	(3.664)	(0.796)	(1.980)	(1.092)	(3.680)	(0.398)	(2.668)	(2.999)	(7.653)	(1.284)	(4.164)	(0.801)
L3.z_shock_unc	-2.586	-3.179***	1.902*	4.099	-2.223	-3.146**	2.681**	9.464**	-5.769*	-5.382**	2.142	4.216**
	(1.758)	(1.061)	(1.019)	(2.509)	(1.363)	(1.406)	(1.151)	(4.383)	(3.278)	(2.246)	(1.539)	(1.765)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1100	1080	1060	1040	1020	1000	980	960	940	920	900	880

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A8: Heterogeneity Local Projections (High vs Low electricity intensity) — Supply shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$f1$	$f2$	$f3$	$f4$	$f5$	$f6$	$f7$	$f8$	$f9$	$f10$	$f11$	$f12$
z_shock_supply	2.416**	-1.183	1.079*	2.096	0.318	-4.558*	3.821	-0.996	1.517*	-1.523	1.746**	1.870*
	(0.939)	(0.921)	(0.541)	(1.478)	(0.444)	(2.625)	(2.329)	(0.810)	(0.759)	(1.031)	(0.748)	(1.036)
z_shock_supply × *High*	-0.834	5.748*	-1.358	-10.42*	-1.357*	12.13*	-8.381**	4.661**	-2.579*	1.275	2.023**	-3.419
	(0.757)	(2.946)	(0.939)	(5.623)	(0.675)	(6.152)	(3.794)	(2.004)	(1.295)	(1.190)	(0.950)	(2.129)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1180	1160	1140	1120	1100	1080	1060	1040	1020	1000	980	960

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Heterogeneity Local Projections (High vs Low electricity intensity) — Economic activity shock

	(1) $f1$	(2) $f2$	(3) $f3$	(4) $f4$	(5) $f5$	(6) $f6$	(7) $f7$	(8) $f8$	(9) $f9$	(10) $f10$	(11) $f11$	(12) $f12$
z_shock_econact	0.570**	-1.590	5.147*	1.061	-1.838	-4.151	3.085*	2.368*	-1.022*	-2.796	3.738*	0.212
	(0.230)	(1.296)	(2.775)	(0.769)	(1.101)	(2.457)	(1.742)	(1.316)	(0.547)	(1.803)	(1.864)	(0.166)
z_shock_econact × *High*	5.414	7.444*	-11.01*	-4.673*	5.663*	10.81*	-3.190*	-4.289*	0.0947	7.987*	-3.453*	0.996**
	(3.231)	(3.711)	(5.922)	(2.264)	(2.875)	(5.838)	(1.573)	(2.297)	(0.477)	(3.912)	(1.976)	(0.459)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1180	1160	1140	1120	1100	1080	1060	1040	1020	1000	980	960

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Heterogeneity Local Projections (High vs Low electricity intensity) — Inventory shock

	(1) $f1$	(2) $f2$	(3) $f3$	(4) $f4$	(5) $f5$	(6) $f6$	(7) $f7$	(8) $f8$	(9) $f9$	(10) $f10$	(11) $f11$	(12) $f12$
z_shock_inv	2.538**	-0.800	3.771*	0.554**	-1.215**	-1.771*	0.793*	1.191*	2.212*	-1.707	2.778**	-2.509
	(1.057)	(0.716)	(1.950)	(0.196)	(0.563)	(0.934)	(0.421)	(0.671)	(1.185)	(1.038)	(1.260)	(1.634)
z_shock_inv × *High*	-1.003	3.764*	-5.419*	-1.835*	-0.386	3.984	2.282	-0.0901	-6.250*	3.569*	0.339	8.265*
	(0.734)	(1.948)	(2.756)	(0.965)	(0.681)	(2.317)	(1.873)	(0.702)	(3.003)	(1.726)	(0.515)	(4.133)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1180	1160	1140	1120	1100	1080	1060	1040	1020	1000	980	960

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Heterogeneity Local Projections (High vs Low electricity intensity) — Unconstrained shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$f1$	$f2$	$f3$	$f4$	$f5$	$f6$	$f7$	$f8$	$f9$	$f10$	$f11$	$f12$
z_shock_unc	0.0330	-0.281	3.458*	2.425*	-2.116*	-3.213*	2.272	1.473*	-0.523	-0.864	1.333**	0.844**
	(0.433)	(0.593)	(1.703)	(1.238)	(1.180)	(1.810)	(1.339)	(0.810)	(0.391)	(0.654)	(0.537)	(0.334)
$z\_shock\_unc \times High$	6.033*	4.469*	-5.033*	-4.275*	3.728*	7.163*	-2.662**	-0.982*	0.777	2.025*	1.826*	0.765***
	(3.213)	(2.241)	(2.649)	(2.422)	(2.060)	(3.790)	(1.130)	(0.563)	(0.568)	(1.093)	(0.915)	(0.250)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1180	1160	1140	1120	1100	1080	1060	1040	1020	1000	980	960

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Panel Local Projections on sectoral PPI (log changes): Supply shock (full horizons)

	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12
Supply shock	0.001160***	0.000636***	0.000437**	0.000404**	-0.000936***	-0.000295*	-0.000772***	-0.000108	-0.000655***	-0.000691***	0.000031	-0.000755***
	(0.000189)	(0.000197)	(0.000292)	(0.000179)	(0.000155)	(0.000173)	(0.000165)	(0.000127)	(0.000137)	(0.000181)	(0.000197)	(0.000142)

Notes: Dependent variable is $\Delta \log(\mathrm{PPI}_{s,t+h})$. Sector FE and month dummies included. Standard errors clustered at sector level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A13: Panel Local Projections on sectoral PPI (log changes): Economic activity shock (full horizons)

	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12
Economic activity shock	-0.000474***	-0.000126	-0.000467**	-0.000554***	-0.001131***	-0.000345*	-0.000812***	-0.000537***	-0.000315*	-0.000521***	0.000089	0.000760***
	(0.000131)	(0.000137)	(0.000219)	(0.000151)	(0.000141)	(0.000196)	(0.000189)	(0.000198)	(0.000175)	(0.000143)	(0.000149)	(0.000181)

Notes: Dependent variable is $\Delta \log(\text{PPI}_{s,t+h})$. Sector FE and month dummies included. Standard errors clustered at sector level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A14: Panel Local Projections on sectoral PPI (log changes): Inventory shock (full horizons)

	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12
Inventory shock	0.000313*	0.000537***	-0.000965**	-0.000311*	-0.000782***	-0.001348***	-0.001618***	-0.001134***	-0.001282***	-0.001524***	-0.001093***	-0.000432**
	(0.000173)	(0.000159)	(0.000468)	(0.000159)	(0.000186)	(0.000243)	(0.000266)	(0.000137)	(0.000160)	(0.000182)	(0.000193)	(0.000189)

Notes: Dependent variable is $\Delta \log(\text{PPI}_{s,t+h})$. Sector FE and month dummies included. Standard errors clustered at sector level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A15: Panel Local Projections on sectoral PPI (log changes): Unconstrained shock (full horizons)

	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12
Unconstrained shock	-0.001051***	0.000057	-0.000350	-0.000907***	-0.000205	-0.001141***	-0.001085***	-0.000892***	-0.000546***	-0.000830***	-0.000309*	0.000274
	(0.000202)	(0.000217)	(0.000280)	(0.000249)	(0.000160)	(0.000176)	(0.000199)	(0.000172)	(0.000147)	(0.000152)	(0.000166)	(0.000213)

Notes: Dependent variable is $\Delta\log(\mathrm{PPI}_{s,t+h})$. Sector FE and month dummies included. Standard errors clustered at sector level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B Replication Codes

B.1 Master do-file

The following master do-file runs the entire replication package. It defines the file paths, creates output folders, and sequentially executes all the scripts required to reproduce the empirical results.

Listing 1: Master do-file for full replication

```
****************************************************
* MASTER DO-FILE
* Replication package  run everything
****************************************************

clear all
set more off

*----------------------------------------
* PATHS (MODIFY ONLY THIS LINE)
*----------------------------------------
global root global root "C:\your_path\Thesis_replication"

global data "$root\data"
global dofiles "$root\do_files"
global tables "$root\output\tables"
global figures "$root\output\figures"
global logs "$root\output\logs"

*----------------------------------------
* CREATE OUTPUT FOLDERS (SAFE)
*----------------------------------------
cap mkdir "$root\output"
cap mkdir "$tables"
cap mkdir "$figures"
cap mkdir "$logs"

*----------------------------------------
* LOG FILE
*----------------------------------------
capture log close
log using "$logs\master.log", replace

*----------------------------------------
* RUN ALL DO-FILES
*----------------------------------------

do "$dofiles\08_descriptive_statistics.do"
do "$dofiles\01_shock_series.do"
do "$dofiles\02_lp_baseline_seasonality.do"
do "$dofiles\03_irf_electricity_cumulative.do"
do "$dofiles\04_lp_robustness.do"
do "$dofiles\05_lp_heterogeneity.do"
do "$dofiles\06_lp_ppi_robustness.do"
do "$dofiles\07_irf_ppi_cumulative.do"

*----------------------------------------
* CLOSE LOG
```

```
*---------------------------------------
capture log close

display as text "ALL REPLICATION FILES COMPLETED SUCCESSFULLY."
```

B.2 Descriptive statistics

This do-file computes the main descriptive statistics for the dataset, including summary statistics and regional distributions of industrial electricity consumption.

```
****************************************************
* File: 01_descriptive_statistics.do
* Purpose: Generate descriptive statistics tables:
* (1) Regional ranking
* (2) High vs Low intensity comparison
* (3) National time series
* Input: dataset_finale_lp.dta
* Output: CSV tables in output folder
****************************************************

version 17.0
clear all
set more off

* Load dataset
use "$data/dataset_finale_lp.dta", clear

*====================================================
* 1) REGIONAL STATISTICS AND RANKING
*====================================================

* Compute mean, standard deviation, and total consumption by region
collapse (mean) mean_cons=consumigwh ///
        (sd) sd_cons=consumigwh ///
        (sum) tot_cons=consumigwh, by(regione)

* Compute national total and regional shares (%)
egen national_total = total(tot_cons)
gen share_percent = 100 * tot_cons / national_total

* Sort regions by descending average consumption
gsort -mean_cons

* Display results
list regione mean_cons sd_cons share_percent, sep(0)

* Export table
export delimited using "$tables/desc_region_ranking.csv", replace

*====================================================
* 2) HIGH VS LOW INTENSITY CLASSIFICATION
*====================================================

use "$data/dataset_finale_lp.dta", clear

* Compute average consumption per region
bys reg_code: egen mean_region = mean(consumigwh)
```

```

* Compute median of regional averages
egen median_intensity = median(mean_region)

* Create high-intensity dummy (1 = above median)
gen high_intensity = mean_region > median_intensity

label define highlbl 0 "Low intensity" 1 "High intensity"
label values high_intensity highlbl

* Compute summary statistics by group
collapse (mean) mean_cons=consumigwh ///
        (sd) sd_cons=consumigwh ///
        (count) N=consumigwh, by(high_intensity)

* Display results
list

* Export table
export delimited using "$tables/desc_high_low.csv", replace

*=====================================================
* 3) NATIONAL TIME SERIES
*=====================================================

use "$data/dataset_finale_lp.dta", clear

* Aggregate total national consumption by date
collapse (sum) national_cons=consumigwh, by(date)

* Summary statistics
summ national_cons

* Export dataset
export delimited using "$tables/desc_national_timeseries.csv", replace
```

B.3 Shock series construction

This do-file constructs the monthly shock series from the original data, including aggregation and standardization of the structural shocks.

```
**************************************************
* File: 01_shock_series.do
* Purpose: Plot time series of gas shocks
* Input: dataset_finale_lp.dta
* Output: PDF graphs of shock series
**************************************************

version 17.0
clear all
set more off

use "$data\dataset_finale_lp.dta", clear
format date %tm

twoway line shock_mean_supply date, ///
    title("European Gas Supply Shock (mean)") ///
    ytitle("Shock (mean)") xtitle("Date") ///
    legend(off)
graph export "$figures/shock_supply_mean.pdf", replace

twoway line shock_mean_econact date, ///
    title("European Economic Activity Shock (mean)") ///
    ytitle("Shock (mean)") xtitle("Date") ///
    legend(off)
graph export "$figures/shock_econact_mean.pdf", replace

twoway line shock_mean_inv date, ///
    title("European Inventory Shock (mean)") ///
    ytitle("Shock (mean)") xtitle("Date") ///
    legend(off)
graph export "$figures/shock_inventory_mean.pdf", replace

twoway line shock_mean_unc date, ///
    title("European Unconstrained Shock (mean)") ///
    ytitle("Shock (mean)") xtitle("Date") ///
    legend(off)
graph export "$figures/shock_unconstrained_mean.pdf", replace
```

B.4 Baseline Local Projections with seasonality

This do-file estimates the baseline Local Projection model including month-of-year fixed effects to control for seasonality.

```
/********************************************************************
LOCAL PROJECTIONS  BASELINE vs SEASONALITY
- Outcome: electricity consumption (f1...f12)
- Shocks: supply, economic activity, inventory
- FE: region
- SE: clustered by region
********************************************************************/

version 17.0
clear all
set more off

*-----------------------------------------
* LOAD DATA
*-----------------------------------------
use "$data\dataset_finale_lp.dta", clear

*-----------------------------------------
* PANEL SETTINGS + MONTH DUMMIES
*-----------------------------------------
xtset reg_code date

capture drop month
gen month = month(dofm(date))
label var month "Month of year (1-12)"

*-----------------------------------------
* INSTALL estout IF NEEDED
*-----------------------------------------
capture which eststo
if _rc ssc install estout, replace

*=========================================
* SUPPLY SHOCK
*=========================================
eststo clear

* Baseline
forvalues h = 1/12 {
    quietly xtreg f`h'_consumo z_shock_mean_supply, fe vce(cluster reg_code)
    eststo base_s`h'
}

* With seasonality
forvalues h = 1/12 {
    quietly xtreg f`h'_consumo z_shock_mean_supply i.month, fe vce(cluster reg_code)
    eststo seas_s`h'
}

esttab base_s1 base_s3 base_s6 base_s12 ///
      seas_s1 seas_s3 seas_s6 seas_s12 ///
      using "$tables\lp_supply_baseline_vs_seasonality.txt", replace ///
      keep(z_shock_mean_supply) ///
      se star(* 0.10 ** 0.05 *** 0.01) ///
```

```
      title("Local Projections: baseline vs monthly seasonality (Supply shock)") ///
      label

*=========================================
* ECONOMIC ACTIVITY SHOCK
*=========================================
eststo clear

* Baseline
forvalues h = 1/12 {
    quietly xtreg f`h'_consumo z_shock_mean_econact, fe vce(cluster reg_code)
    eststo base_e`h'
}

* With seasonality
forvalues h = 1/12 {
    quietly xtreg f`h'_consumo z_shock_mean_econact i.month, fe vce(cluster reg_code)
    eststo seas_e`h'
}

esttab base_e1 base_e3 base_e6 base_e12 ///
      seas_e1 seas_e3 seas_e6 seas_e12 ///
      using "$tables\lp_econact_baseline_vs_seasonality.txt", replace ///
      keep(z_shock_mean_econact) ///
      se star(* 0.10 ** 0.05 *** 0.01) ///
      title("Local Projections: baseline vs monthly seasonality (Economic activity shock)") ///
      label

*=========================================
* INVENTORY SHOCK
*=========================================
eststo clear

* Baseline
forvalues h = 1/12 {
    quietly xtreg f`h'_consumo z_shock_mean_inv, fe vce(cluster reg_code)
    eststo base_i`h'
}

* With seasonality
forvalues h = 1/12 {
    quietly xtreg f`h'_consumo z_shock_mean_inv i.month, fe vce(cluster reg_code)
    eststo seas_i`h'
}

esttab base_i1 base_i3 base_i6 base_i12 ///
      seas_i1 seas_i3 seas_i6 seas_i12 ///
      using "$tables\lp_inventory_baseline_vs_seasonality.txt", replace ///
      keep(z_shock_mean_inv) ///
      se star(* 0.10 ** 0.05 *** 0.01) ///
      title("Local Projections: baseline vs monthly seasonality (Inventory shock)") ///
      label

display as text "DONE: Baseline vs Seasonality LP completed."
```

B.5 Cumulative impulse response functions: electricity

This do-file computes cumulative impulse response functions for industrial electricity consumption.

```
*******************************************************
* CUMULATIVE IRF (Local Projections)  ELECTRICITY CONSUMPTION
* Cleaner graphs for thesis
*******************************************************

#delimit cr
clear all
set more off
version 17

use "$data/dataset_finale_lp.dta", clear

cap drop month
gen month = month(dofm(date))

scalar zcrit = 1.645 // 90% CI

* Clustered SE by region
capture confirm numeric variable reg_code
if _rc != 0 {
    encode reg_code, gen(reg_code_id)
    local CLV "vce(cluster reg_code_id)"
}
else {
    local CLV "vce(cluster reg_code)"
}

* Build cumulative dependent variables: cf1=f1, cf2=f1+f2, ..., cf12=sum_{j<=12} fj
cap drop cf*_consumo
gen cf1_consumo = f1_consumo
forvalues h = 2/12 {
    gen cf‘h’_consumo = cf‘=‘h’-1’_consumo + f‘h’_consumo
}

local shocks "z_shock_mean_supply z_shock_mean_econact z_shock_mean_inv z_shock_mean_unc"

foreach shock of local shocks {

    preserve

    tempfile irf
    tempname P
    postfile ‘P’ int h double beta se using ‘irf’, replace

    forvalues h = 1/12 {
        quietly reg cf‘h’_consumo ‘shock’ i.month, ‘CLV’
        post ‘P’ (‘h’) (_b[‘shock’]) (_se[‘shock’])
    }
    postclose ‘P’
    use ‘irf’, clear

    gen ub = beta + zcrit*se
    gen lb = beta - zcrit*se

```

```
    local title "`shock'"
    if "`shock'" == "z_shock_mean_supply" local title "Supply shock"
    if "`shock'" == "z_shock_mean_econact" local title "Economic activity shock"
    if "`shock'" == "z_shock_mean_inv" local title "Inventory shock"
    if "`shock'" == "z_shock_mean_unc" local title "Unconstrained shock"

    twoway ///
        (rarea ub lb h, ///
            fcolor(gs12) fintensity(60) ///
            lcolor(gs8) lwidth(vthin)) ///
        (line beta h, ///
            lcolor(black) lwidth(medthick)) ///
        , ///
        yline(0, lcolor(gs8) lpattern(solid)) ///
        xlabel(1(1)12, labsize(small)) ///
        xtitle("Horizon (months)", size(medsmall)) ///
        ytitle("Cumulative change (GWh)", size(medsmall)) ///
        title("Cumulative IRF: `title'", size(medium)) ///
        legend(off) ///
        note("Shock = 1 s.d. Grey band = 90% CI. SE clustered by region.", size(vsmall)) ///
        graphregion(color(white)) ///
        plotregion(color(white)) ///
        xsize(8) ysize(6)

    local tag = subinstr("`shock'","z_shock_mean_","",.)

    * Export cleaner graphs
    graph export "$figures/CUMIRF_consumo_`tag'_clean.png", replace width(2600)

    * Optional: save numbers
    save "$tables/CUMIRF_numbers_consumo_`tag'_clean.dta", replace

    restore
}

di as txt "DONE: cleaner cumulative IRF graphs saved."
```

B.6 Heterogeneity analysis

This do-file estimates heterogeneous effects across high- and low-intensity regions using interaction terms.

```
/*********************************************************************
HETEROGENEITY ANALYSIS (HIGH vs LOW ELECTRICITY-INTENSITY REGIONS)
- Panel Local Projections (h=1..12)
- Region FE, month dummies, SE clustered by region
- High-intensity = region mean consumption above median (time-invariant)
*********************************************************************/

set more off
capture log close

use "$data/dataset_finale_lp.dta", clear

* estout package (eststo/esttab)
capture which eststo
if _rc ssc install estout, replace

*------------------------------*
* 1) Build High-Intensity dummy
*------------------------------*
capture drop mean_cons median_cons high_intensity

bysort reg_code: egen mean_cons = mean(consumigwh)
egen median_cons = median(mean_cons)
gen high_intensity = (mean_cons > median_cons)
label var high_intensity "High electricity intensity (mean consumption > median)"

*------------------------------*
* 2) Panel settings + month dummies
*------------------------------*
xtset reg_code date

capture drop month
gen month = month(dofm(date))
label var month "Month of year (1-12)"

*------------------------------*
* 3) Program: run heterogeneity LP and save results
*------------------------------*
capture program drop run_het_lp
program define run_het_lp
    version 16.0
    syntax, SHOCKVAR(name) TAG(string)

    tempname R
    matrix `R' = J(12,6,.)
    matrix colnames `R' = b_low se_low b_high se_high b_diff p_diff
    matrix rownames `R' = h1 h2 h3 h4 h5 h6 h7 h8 h9 h10 h11 h12

    eststo clear

    forvalues h = 1/12 {

        quietly xtreg f`h'_consumo ///
            c.`shockvar'##i.high_intensity ///
```

```
          i.month, fe vce(cluster reg_code)

        eststo het_‘tag’_‘h’

        * Low effect (baseline: high_intensity=0)
        quietly lincom _b[‘shockvar’]
        matrix ‘R’[‘h’,1] = r(estimate)
        matrix ‘R’[‘h’,2] = r(se)

        * High effect (Low + interaction)
        quietly lincom _b[‘shockvar’] + _b[1.high_intensity#c.‘shockvar’]
        matrix ‘R’[‘h’,3] = r(estimate)
        matrix ‘R’[‘h’,4] = r(se)

        * Diff (High - Low) and p-value from test
        quietly test 1.high_intensity#c.‘shockvar’
        matrix ‘R’[‘h’,5] = _b[1.high_intensity#c.‘shockvar’]
        matrix ‘R’[‘h’,6] = r(p)
    }

    * Save matrix as dataset for plots / tables
    preserve
        clear
        svmat double ‘R’, names(col)
        gen h = _n
        order h b_low se_low b_high se_high b_diff p_diff

        * 95% CI
        gen ci_low_lo = b_low - 1.96*se_low
        gen ci_low_hi = b_low + 1.96*se_low
        gen ci_high_lo = b_high - 1.96*se_high
        gen ci_high_hi = b_high + 1.96*se_high

        save "$tables/het_‘tag’_results.dta", replace
        export delimited using "$tables/het_‘tag’_results.csv", replace
    restore

    * Export the 12 LP regressions table (optional)
    esttab het_‘tag’_1 het_‘tag’_2 het_‘tag’_3 het_‘tag’_4 ///
           het_‘tag’_5 het_‘tag’_6 het_‘tag’_7 het_‘tag’_8 ///
           het_‘tag’_9 het_‘tag’_10 het_‘tag’_11 het_‘tag’_12 ///
           using "$tables/het_‘tag’_esttab.txt", ///
           replace se star(* 0.10 ** 0.05 *** 0.01) ///
           title("Heterogeneity LP: ‘tag’")

end

*------------------------------*
* 4) Run for each shock
*------------------------------*
run_het_lp, shockvar(z_shock_mean_econact) tag(econact)
run_het_lp, shockvar(z_shock_mean_supply) tag(supply)
run_het_lp, shockvar(z_shock_mean_inv) tag(inv)
run_het_lp, shockvar(z_shock_mean_unc) tag(unc)

*------------------------------*
* 5) One regression sanity check (example)
*------------------------------*
xtreg f1_consumo c.z_shock_mean_econact##i.high_intensity i.month, fe vce(cluster reg_code)
```

```
lincom _b[z_shock_mean_econact]
lincom _b[z_shock_mean_econact] + _b[1.high_intensity#c.z_shock_mean_econact]
test 1.high_intensity#c.z_shock_mean_econact
```

B.7 PPI Local Projections

This do-file estimates the Local Projection models for sectoral producer prices.

```
/*************************************************************************************
PPI  Panel Local Projections (ROBUSTNESS ONLY)  FULL DO-FILE
- Sector panel (ATECO): ateco_id  mdate
- Dep var for LP: f1_ppi ... f12_ppi (future changes of dln_ppi)
- Shocks: z_shock_mean_supply / econact / inv / unc (standardized, monthly)
- Controls: month dummies + 2 lags of dln_ppi
- FE: sector fixed effects
- SE: clustered by sector

Outputs:
- ppi_rob_<shock>.txt
- ppi_rob_irf_<shock>.dta and .csv
*************************************************************************************/

version 17.0
set more off

*----------------------------------------
* 0) LOAD YOUR DATASET
*----------------------------------------
clear all
use "$data/ppi_panel_with_shocks.dta", clear

*----------------------------------------
* 1) BASIC CHECKS
*----------------------------------------
confirm variable ateco_id
confirm variable mdate
confirm variable dln_ppi
confirm variable z_shock_mean_supply
confirm variable z_shock_mean_econact
confirm variable z_shock_mean_inv
confirm variable z_shock_mean_unc

* Panel settings
xtset ateco_id mdate

* Seasonality control
capture drop month
gen month = month(dofm(mdate))
label var month "Month of year (1-12)"

* Ensure esttab exists
cap which esttab
if _rc ssc install estout, replace

*----------------------------------------
* 2) CREATE LP DEPENDENT VARIABLES IF MISSING
*----------------------------------------
forvalues h = 1/12 {
```

```
    capture confirm variable f`h'_ppi
    if _rc {
        capture drop f`h'_ppi
        gen f`h'_ppi = F`h'.dln_ppi
        label var f`h'_ppi "Lead `h' of dln_ppi (future change)"
    }
}

* Quick sanity check
describe f1_ppi f12_ppi
summ f1_ppi f12_ppi

*----------------------------------------
* 3) PROGRAM: ROBUST LP (safe across multiple runs)
*----------------------------------------
capture program drop run_lp_ppi_rob
program define run_lp_ppi_rob
    syntax, shockvar(name) tag(string)

    preserve

    tempname posth
    tempfile tmpres

    postfile `posth' int h double b se using `tmpres', replace

    eststo clear
    forvalues h=1/12 {

        quietly xtreg f`h'_ppi ///
            `shockvar' ///
            L1.dln_ppi L2.dln_ppi ///
            i.month, fe vce(cluster ateco_id)

        eststo rob_`tag'_`h'
        post `posth' (`h') (_b[`shockvar']) (_se[`shockvar'])
    }
    postclose `posth'

    * build IRF dataset for plotting
    use `tmpres', clear
    gen shock = "`tag'"

    gen ub90 = b + invttail(e(df_r), 0.05)*se
    gen lb90 = b - invttail(e(df_r), 0.05)*se
    gen ub95 = b + invttail(e(df_r), 0.025)*se
    gen lb95 = b - invttail(e(df_r), 0.025)*se

    order shock h b se lb90 ub90 lb95 ub95

    save "$tables/ppi_rob_irf_`tag'.dta", replace
    export delimited using "$tables/ppi_rob_irf_`tag'.csv", replace

    * save regression table (12 horizons)
    esttab rob_`tag'_* using "$tables/ppi_rob_`tag'.txt", replace ///
        se star(* 0.10 ** 0.05 *** 0.01) compress

    restore
end
```

```
*-----------------------------------------
* 4) RUN ROBUSTNESS LP FOR EACH SHOCK
*-----------------------------------------
run_lp_ppi_rob, shockvar(z_shock_mean_supply) tag(supply)
run_lp_ppi_rob, shockvar(z_shock_mean_econact) tag(econact)
run_lp_ppi_rob, shockvar(z_shock_mean_inv) tag(inv)
run_lp_ppi_rob, shockvar(z_shock_mean_unc) tag(unc)

*-----------------------------------------
* 5) OPTIONAL: STACK ALL IRFs INTO ONE FILE
*-----------------------------------------
clear
tempfile allirf
save `allirf', emptyok replace

foreach s in supply econact inv unc {
    append using "$tables/ppi_rob_irf_`s'.dta"
    save `allirf', replace
}

use `allirf', clear
save "$tables/ppi_rob_irf_ALL.dta", replace
export delimited using "$tables/ppi_rob_irf_ALL.csv", replace

display as txt "DONE: tables (.txt) + IRF datasets (.dta/.csv) saved."
```

B.8 Cumulative impulse response functions: PPI

This do-file computes cumulative impulse response functions for producer prices.

```
************************************************************
* CUMULATIVE IRF (Local Projections)  PPI
* Cleaner graphs for thesis
*******************************************************

*******************************************************
* CUMULATIVE IRF (Local Projections)  PPI
* Clean and uniform graphs for thesis
*******************************************************

#delimit cr
clear all
set more off
version 17

use "$data/ppi_panel_with_shocks.dta", clear

* If month is not already present, generate it from mdate
cap confirm variable month
if _rc != 0 {
    gen month = month(dofm(mdate))
}

scalar zcrit = 1.645 // 90% CI

* Clustered SE by sector
capture confirm numeric variable ateco_id
if _rc != 0 {
    encode ateco_id, gen(ateco_id_num)
    local CLV "vce(cluster ateco_id_num)"
}
else {
    local CLV "vce(cluster ateco_id)"
}

* Build cumulative dependent variables
cap drop cf*_ppi
gen cf1_ppi = f1_ppi
forvalues h = 2/12 {
    gen cf‘h’_ppi = cf‘=‘h’-1’_ppi + f‘h’_ppi
}

local shocks "z_shock_mean_supply z_shock_mean_econact z_shock_mean_inv z_shock_mean_unc"

foreach shock of local shocks {

    preserve

    tempfile irf
    tempname P
    postfile ‘P’ int h double beta se using ‘irf’, replace

    forvalues h = 1/12 {
        quietly reg cf‘h’_ppi ‘shock’ i.month, ‘CLV’
        post ‘P’ (‘h’) (_b[‘shock’]) (_se[‘shock’])
```

```
    }
    postclose ‘P’
    use ‘irf’, clear

    gen ub = beta + zcrit*se
    gen lb = beta - zcrit*se

    local title "‘shock’"
    if "‘shock’" == "z_shock_mean_supply" local title "Supply shock"
    if "‘shock’" == "z_shock_mean_econact" local title "Economic activity shock"
    if "‘shock’" == "z_shock_mean_inv" local title "Inventory shock"
    if "‘shock’" == "z_shock_mean_unc" local title "Unconstrained shock"

    twoway ///
        (rarea ub lb h, ///
            fcolor(gs10) fintensity(70) ///
            lcolor(gs8) lwidth(vthin)) ///
        (line beta h, ///
            lcolor(black) lwidth(medthick)) ///
        , ///
        yline(0, lcolor(gs8) lpattern(solid)) ///
        xlabel(1(1)12, labsize(small)) ///
        xtitle("Horizon (months)", size(medsmall)) ///
        ytitle("Cumulative change in PPI (log points)", size(medsmall)) ///
        title("Cumulative IRF: ‘title’", size(medium)) ///
        legend(off) ///
        note("Shock = 1 s.d. Grey band = 90% CI. SE clustered by sector.", size(vsmall)) ///
        graphregion(color(white)) ///
        plotregion(color(white)) ///
        xsize(8) ysize(6)

    local tag = subinstr("‘shock’","z_shock_mean_","",.)

    graph export "$figures/CUMIRF_ppi_‘tag’_clean.png", replace width(2600)
    save "$tables/CUMIRF_numbers_ppi_‘tag’_clean.dta", replace

    restore
}

di as txt "DONE: clean cumulative IRF graphs for PPI saved."
```