

Revisiting Fundamentals of the European Gas Market: The Role of Supply Substitution

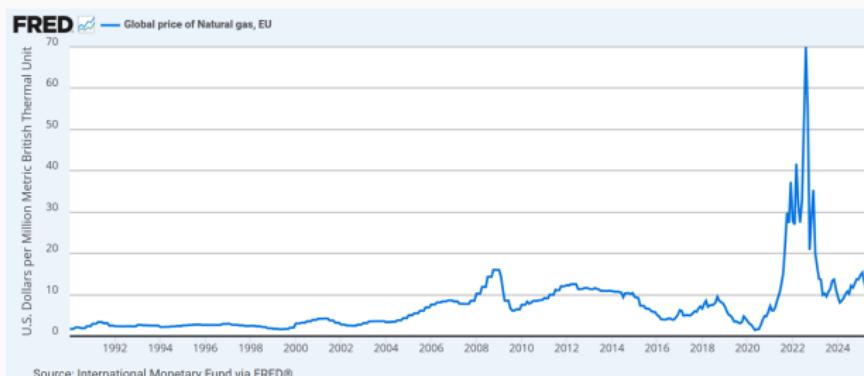
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Introduction

- Economic activity relies on **energy consumption**.
- Natural Gas (NG) was the **second most consumed** energy source in 2021.
- **2022 energy crisis** marked the highest NG prices.



Introduction

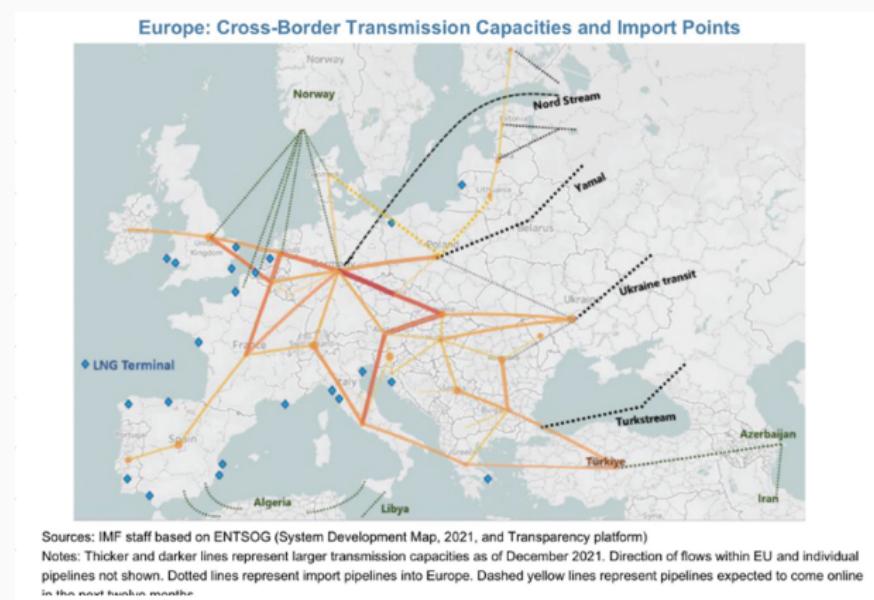
- Renewed attention to the **structural drivers** of the European gas market
- Apply Structural VAR models developed for crude oil:
 - European NG market: *Adolfsen et al. 2024, Güntner et al. 2024 or Boeck et al. 2025.*
 - American NG market: *Rubaszek et al. 2021 or Farag 2024*
- But all of them ignore that **supply composition** affects the price formation.

Introduction

- This paper:
 1. Identifies structural drivers of the European NG market using a Bayesian SVAR with sign restrictions.
 2. Allow the model to capture substitution effects between two types of supply: pipeline gas and liquefied natural gas (LNG).
 3. Examine whether NG shocks affect the valuation of (sectoral) European companies.

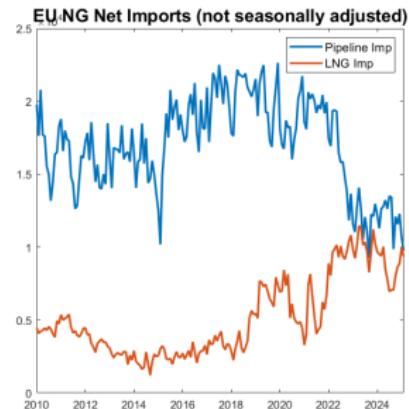
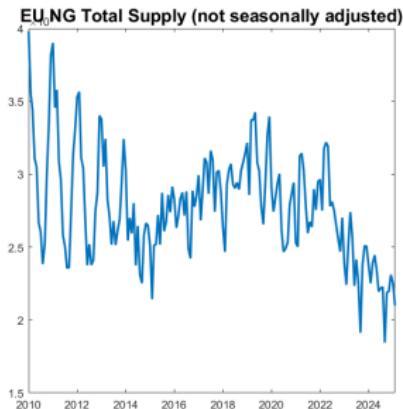
Why is supply composition important?

- Natural gas, produced primarily outside the EU, must be transported to Europe either by ship (as LNG) or via pipeline.



Why is supply composition important?

- Ignoring supply composition can lead to an **underestimation of supply-side** dynamics (*Moll et al. 2023; Hamilton 2023*).
- *Why?* because substitution between pipeline gas and LNG obscures the underlying drivers of total supply.



▶ Details

Data

Data is obtained from the following sources:

- Joint Organization Data Initiative (JODI)¹ ²:
 - **Cheap NG Supply:**
 $Pipeline\ Imports - Pipeline\ Exports + Domestic\ Production$
 - **LNG NG Supply:** $LNG\ Imports - LNG\ Exports$
 - **Change in inventories:** $NG\ Inventories_t - NG\ Inventories_{t-1}$
- Eurostat: manufacturing **industrial production** in the EU19.
- World Bank Commodity Price (WBCP): **Nominal EU NG price** (in \$).
- Federal Reserve Economic Data (FRED): **CPI** in the USA.

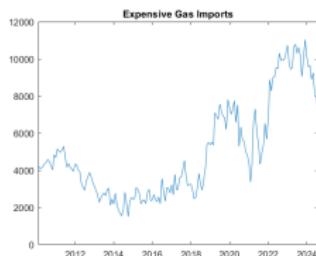
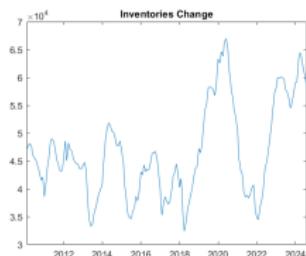
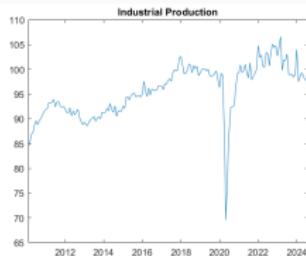
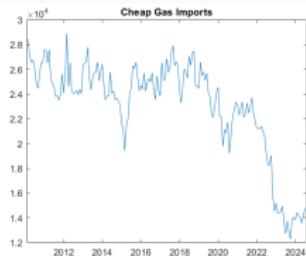
¹All of them are seasonally adjusted using ARIMA X13 TRAMO-SEATS.

²Selected countries: DE, FR, ES, IT, BE, NL, DK, PT, CH, AT, CZ, HU, GR, LT, FI.

Data

- Data is collected in a vector of endogenous variables:

$$y_t = [q_{\text{pip}}, ip, p, s, q_{\text{LNG}}]$$



- Univariate unit root test strongly reject stationarity. All variables are expressed in log-growths.

Structural relationships

- Pipeline and LNG supply:

$$q_t^{pip} = \gamma_{qp} p_t + \mathbf{b}_1' x_{t-1} + \varepsilon_t^{\text{pipeline supply}}$$

$$q_t^{LNG} = \beta_{qp} p_t + \mathbf{b}_5' x_{t-1} + \varepsilon_t^{\text{LNG supply}}$$

- Industrial activity:

$$ip_t = \alpha_{yp} p_t + \mathbf{b}_2' x_{t-1} + \varepsilon_t^{\text{aggregate demand}}$$

- Gas (flow) demand:

$$Q_t = \alpha_{py} ip_t + \alpha_{pq} p_t + \mathbf{b}_3' x_{t-1} + \varepsilon_t^{\text{flow demand}},$$

- Inventories (precautionary demand):

$$s_t = \psi_1 q_t^{pip} + \psi_2 p_t + \psi_3 q_t^{LNG} + \mathbf{b}_4' x_{t-1} + \varepsilon_t^{\text{precautionary demand}}$$

Identification through sign restrictions

- Structural elasticities in \mathbf{A} matrix follow economic sign assumptions:

Parameter	Interpretation	Restriction
γ_{qp}	Pipeline supply elasticity	> 0
β_{qp}	LNG supply elasticity	> 0
α_{yp}	Price effect on activity	< 0
α_{qy}	Income elasticity of demand	> 0
α_{qp}	Price elasticity of demand	< 0
ψ_1, ψ_2, ψ_3	Inventory elasticities	none

- Restrictions are implemented as truncated priors on \mathbf{A} .
- Ensures \mathbf{A}^{-1} (impact matrix) yields economically consistent responses.

Structural and impact matrices

Contemporaneous elasticities

$$\mathbf{A} = \begin{pmatrix} 1 & 0 & -\gamma_{qp} & 0 & 0 \\ 0 & 1 & -\alpha_{yp} & 0 & 0 \\ 1 & -\alpha_{py} & -\alpha_{qp} & -1 & 1 \\ -\psi_1 & 0 & -\psi_2 & 1 & -\psi_3 \\ 0 & 0 & -\beta_{qp} & 0 & 1 \end{pmatrix}$$

- Under: $\gamma_{qp} > 0$ $\beta_{qp} > 0$ $\alpha_{yp} < 0$ $\alpha_{qy} > 0$ $\alpha_{qp} < 0$

Structural and impact matrices

Contemporaneous elasticities

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Impact matrix

$$sign(\mathbf{A}^{-1}) = \begin{pmatrix} + & + & + & ? & ? \\ + & + & - & ? & + \\ - & + & + & + & - \\ ? & ? & - & + & ? \\ ? & + & + & ? & + \end{pmatrix}$$

Each column of \mathbf{A}^{-1} represents the contemporaneous effect of a particular structural shock on the vector of endogenous variables.

Each row of \mathbf{A}^{-1} represents the contemporaneous effect of the vector of structural shocks on a particular variable.

Methodology: SVAR framework

- The model is formulated as a Structural VAR (SVAR):

$$\mathbf{A}y_t = \mathbf{B}x_{t-1} + u_t, \quad u_t \sim N(0, \mathbf{D})$$

- The parameters of the model are:
 - \mathbf{A} contains contemporaneous elasticities among endogenous variables.
 - \mathbf{B} captures autoregressive coefficients.
 - \mathbf{D} is the variance covariance matrix of structural shocks.
- The reduced form can be recovered:

$$y_t = \Phi x_{t-1} + \varepsilon_t, \quad \Phi = \mathbf{A}^{-1}\mathbf{B}, \quad \Omega = \mathbf{A}^{-1}\mathbf{D}(\mathbf{A}^{-1})'$$

- Estimated using **Bayesian methods** with **sign restrictions**
Baumeister et al. 2015 & Baumeister et al. 2019.

Methodology: Priors and identification

- Joint prior decomposed as:

$$p(\mathbf{A}, \mathbf{B}, \mathbf{D}) = p(\mathbf{A}) p(\mathbf{D} | \mathbf{A}) p(\mathbf{B} | \mathbf{A}, \mathbf{D})$$

- Elements of \mathbf{D} follow inverse-Gamma priors; rows of \mathbf{B} follow multivariate normal priors.
- Priors on \mathbf{A} reflect economic knowledge via truncated Student-t distributions.
- Following BH (2015, 2019), priors on elasticities remain informative under set identification.
- Remark: Priors incorporate information not given by the likelihood. They can incorporate information from the literature to ensure plausible structural elasticities.

Methodology: Posterior and estimation

- Likelihood assumes normal structural innovations:

$$p(Y_T | \mathbf{A}, \mathbf{D}, \mathbf{B}) = (2\pi)^{-\frac{Tn}{2}} |\det(\mathbf{A})|^T \det(\mathbf{D})^{-\frac{T}{2}}$$
$$\times \exp \left\{ -\frac{1}{2} \sum_{t=1}^T (\mathbf{A}y_t - \mathbf{B}x_{t-1})' \mathbf{D}^{-1} (\mathbf{A}y_t - \mathbf{B}x_{t-1}) \right\}$$

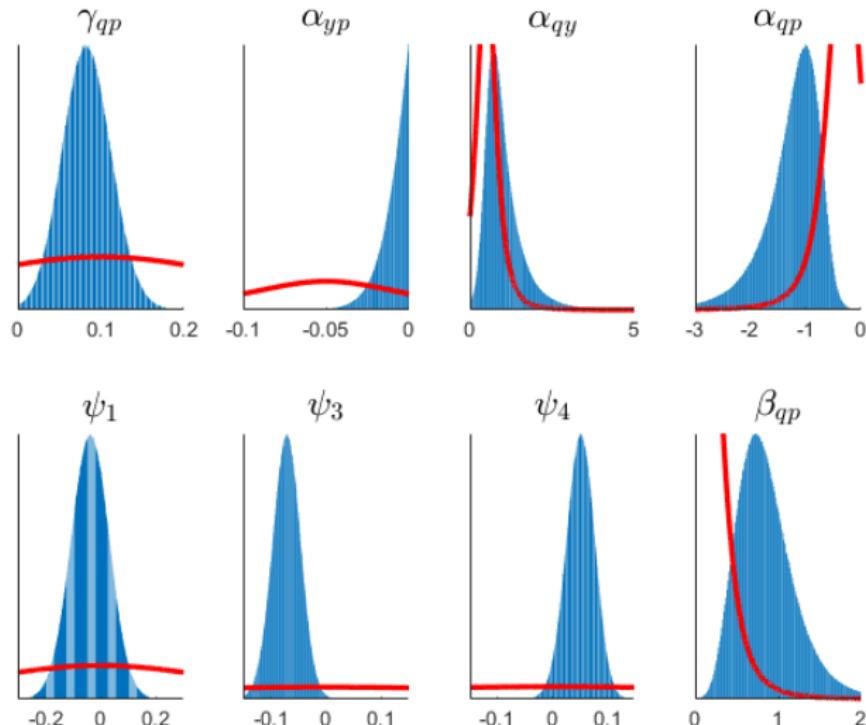
- The MCMC used for drawing from the posterior:

- *Gibbs-Sampler step*: Posteriors for \mathbf{B} and \mathbf{D} are conditionally conjugate (Normal–Gamma).
- *Metropolis hasting step*: \mathbf{A} is sampled numerically under sign restrictions.

▶ Convergence

Results: Posterior of A

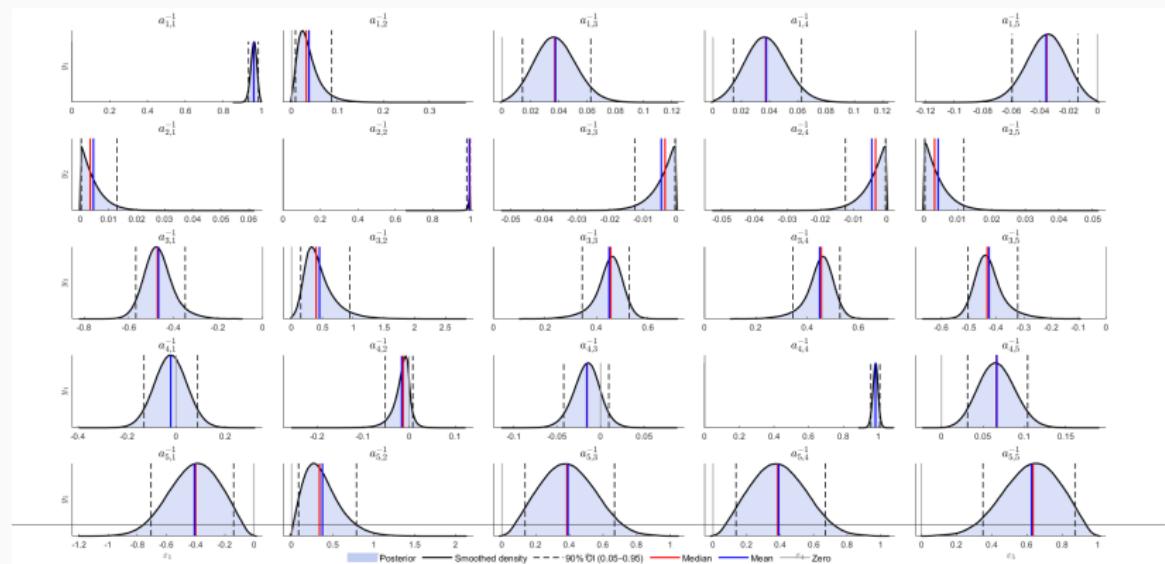
► Posterior formula



Results: Identification

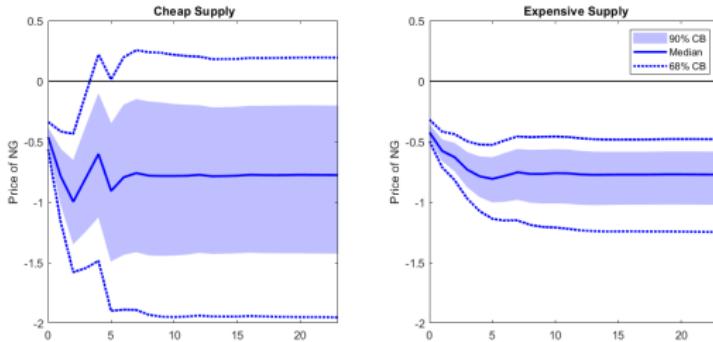
$$\begin{pmatrix} \varepsilon_{q\text{pip},t} \\ \varepsilon_{ip,t} \\ \varepsilon_{p,t} \\ \varepsilon_{s,t} \\ \varepsilon_{q\text{LNG},t} \end{pmatrix} = \begin{pmatrix} + & + & + & + & - \\ + & + & - & - & + \\ - & + & + & + & - \\ ? & ? & ? & + & + \\ - & + & + & + & + \end{pmatrix} \begin{pmatrix} u_t^{\text{pipeline supply}} \\ u_t^{\text{aggregate demand}} \\ u_t^{\text{flow demand}} \\ u_t^{\text{precautionary shock}} \\ u_t^{\text{LNG supply}} \end{pmatrix}$$

Reduced form shocks \mathbf{A}^{-1} Structural shocks

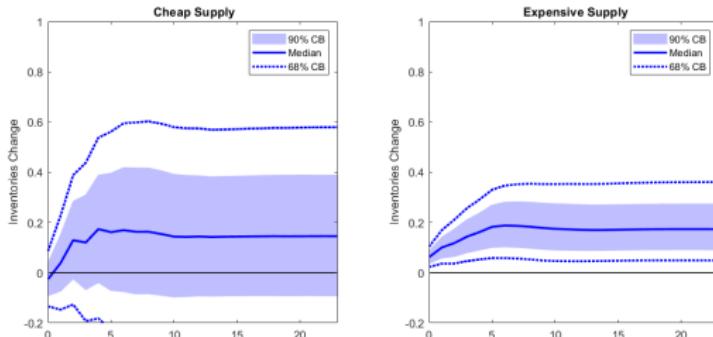


Results: (cumulative) IRF of two supplies

- Cheap supply disruptions have positive transitory effects on the price.

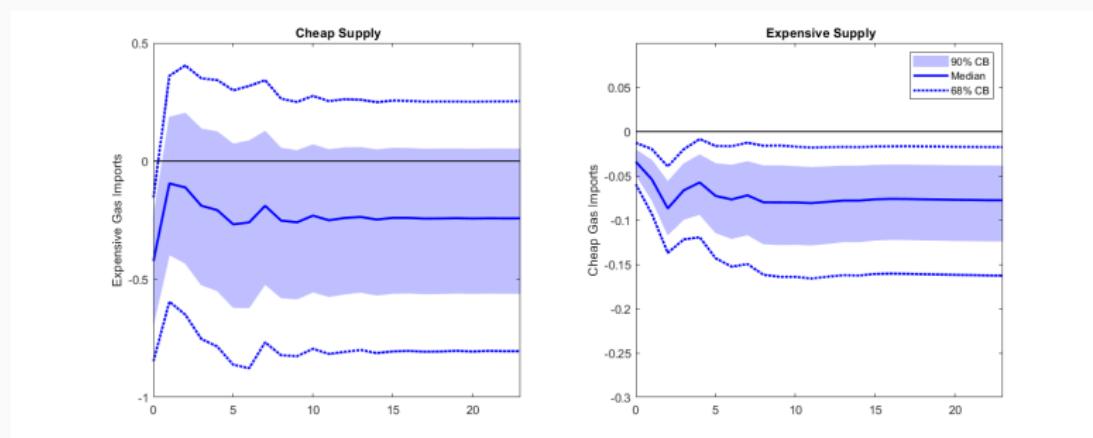


- Expensive supply disruptions have permanent effects on inventories.



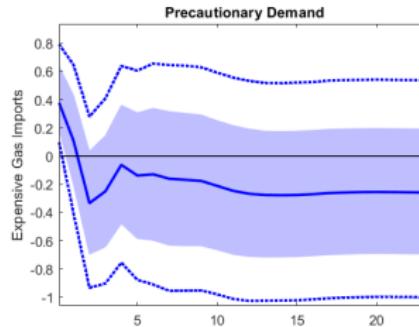
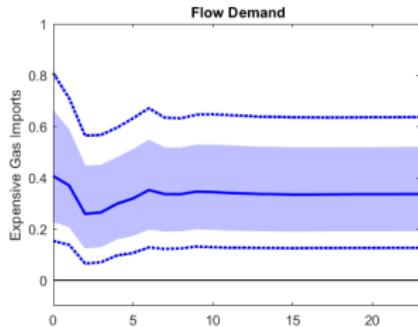
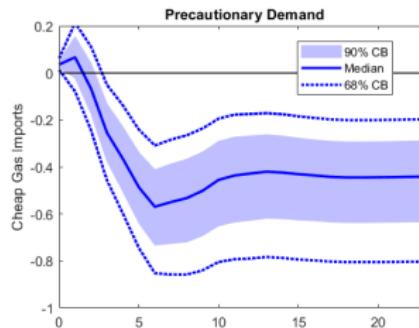
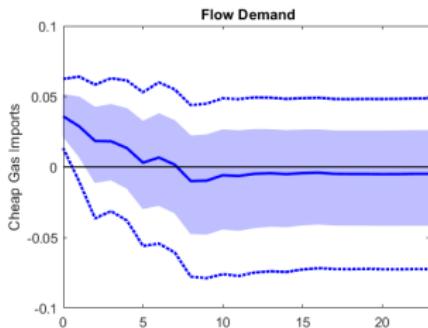
Results: Substitution between two supplies

- Expensive supply shock substitutes cheap NG imports.

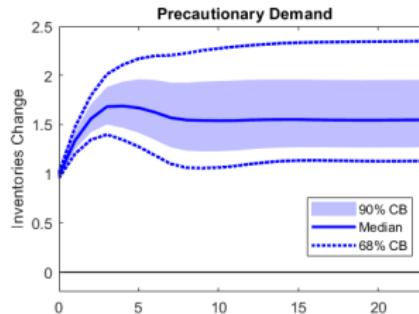
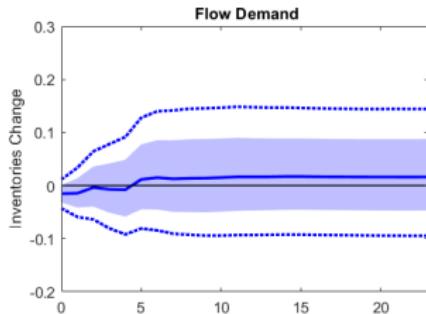
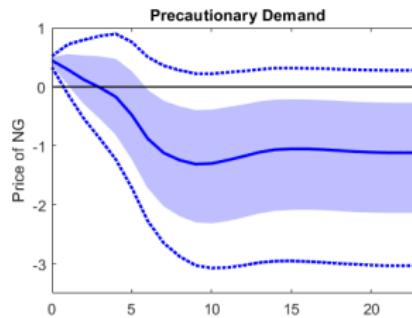
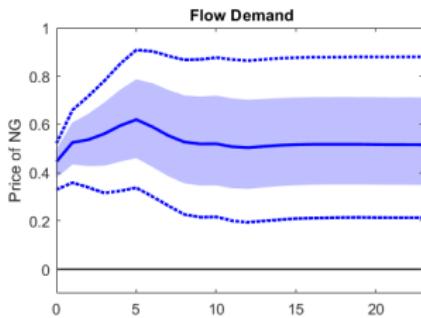


Results: (cumulative) IRF of two demands

- Precautionary demand anticipates disruptions on the cheap imports.



Results: (cumulative) IRF of two demands



Results: Forecast Error Variance Decomposition

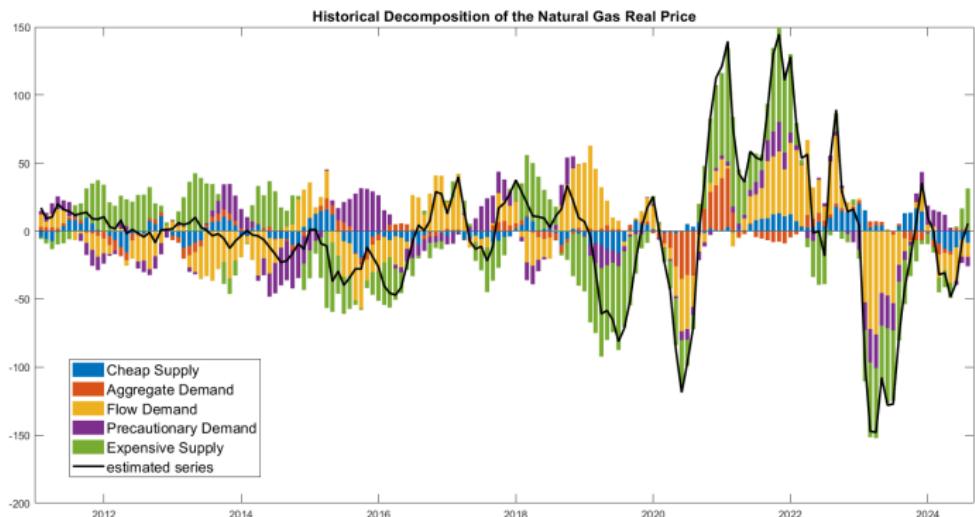
Table: Median FEVD of the Price (contribution of every shock in %)

	Cheap. Sup.	Aggr. Dem.	Flow Dem.	Prec. Dem.	Exp. Sup.
1 month	22.7	15.0	21.1	21.1	19.1
2 months	18.4	42.9	11.0	13.9	10.9
3 months	19.3	43.1	9.4	15.1	9.5
6 months	16.9	55.8	5.2	14.6	5.5
1 year	15.7	53.7	4.4	19.5	4.7
2 years	15.6	53.7	4.3	19.8	4.7

- Supply factors shape more than 40% of the price variance in the short-run.
- Aggregate demand explains alone most of the long run variance.

Results: Historical Decomposition of the Price

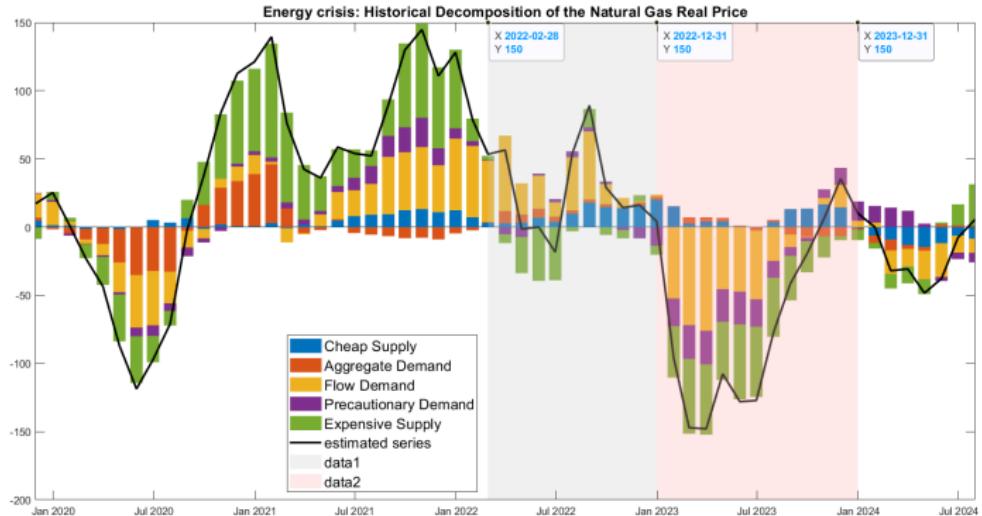
Historical Decomposition of the log-growth of the price



▶ Details

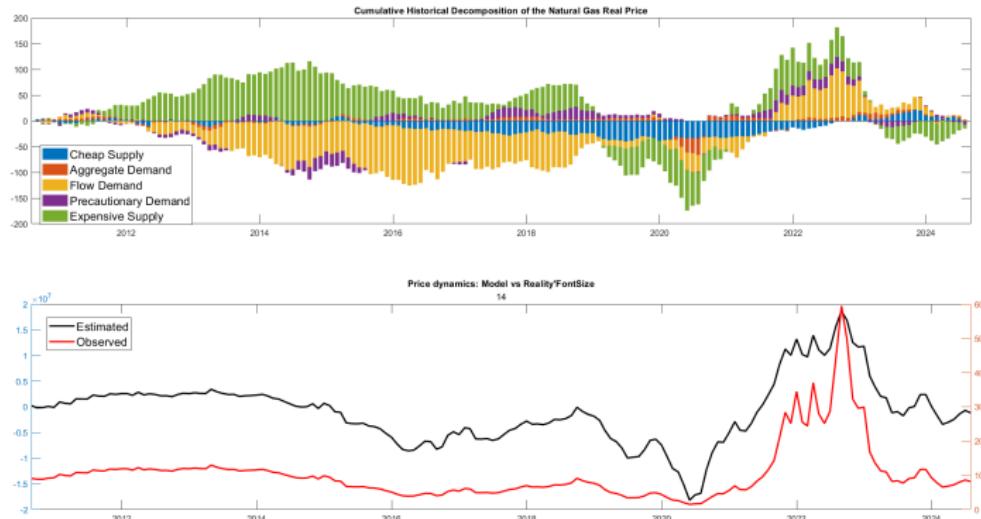
Results: Historical Decomposition of the Price

Historical Decomposition of the log-growth of the price



Results: Historical Decomposition of the Price

Cumulative Historical Decomposition of the log-growth of the price



Local Projections Specification (preliminar)

$$y_{t+h} = \alpha_h + \beta_h s_t + \tilde{\gamma}_h^\top \tilde{x}_t + \varepsilon_{t+h}, \quad h = 0, 1, \dots, H$$

Explanation:

- The equation is estimated separately for each horizon h (*Local Projection*, Jordà 2005).
- y_{t+h} : response variable (e.g. a sectoral price index) at horizon h .
- s_t : structural shock at time t .
- \tilde{x}_t : control vector including contemporaneous and lagged controls, lagged y , and lagged s .
- β_h : captures the impulse response of y_{t+h} to a unit innovation in s_t .

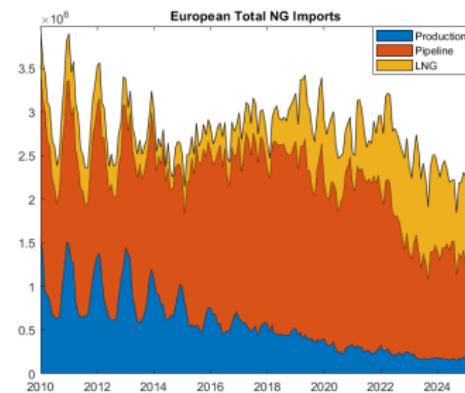
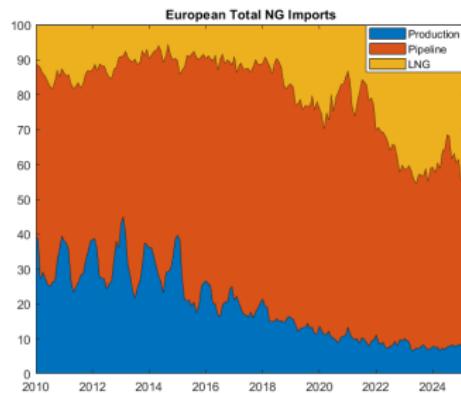
Conclusion

- The role of natural gas **supply-side drivers** has been largely underestimated in previous studies.
- While **demand factors** remain crucial for the long run price formation, **supply** is nearly as influential in the short run.
- Greater LNG supply and reduced flow demand (driven by the EU's energy-saving measures) contributed to stabilizing prices by the end of 2022.
- Future research: complete the Local Projections step.

Thank you!

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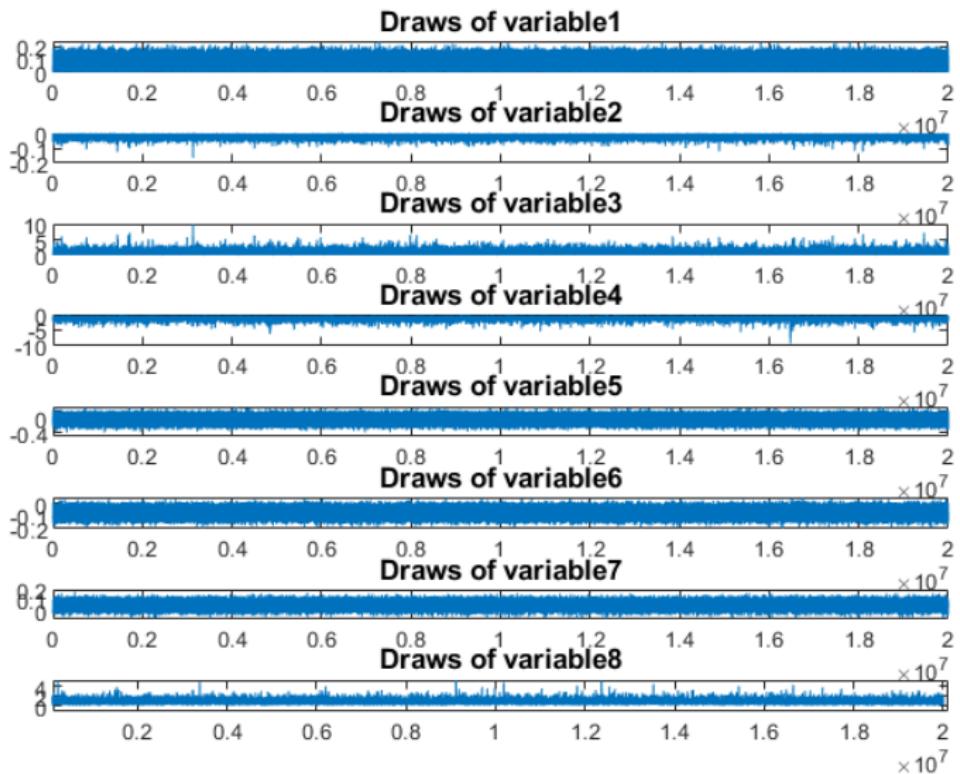
European NG Supply by source



▶ Back

Convergence of the MCMC

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Posterior formula (Theorem 1 BH15)

- Joint posterior decomposition:

$$p(\mathbf{A}, \mathbf{B}, \mathbf{D} \mid Y_T) = p(\mathbf{A} \mid Y_T) p(\mathbf{D} \mid \mathbf{A}, Y_T) p(\mathbf{B} \mid \mathbf{A}, \mathbf{D}, Y_T)$$

- Posterior of \mathbf{D} (diagonal covariance):

$$d_{ii}^{-1} \mid \mathbf{A}, Y_T \sim \Gamma(\kappa_i^*, \tau_i^*(\mathbf{A})), \quad \kappa_i^* = \kappa_i + \frac{T}{2}, \quad \tau_i^*(\mathbf{A}) = \tau_i + \xi_i^*(\mathbf{A})$$

- Posterior of \mathbf{B} (VAR coefficients):

$$b_i \mid \mathbf{A}, \mathbf{D}, Y_T \sim \mathcal{N}(m_i^*, d_{ii} M_i^*), \quad m_i^* = (\tilde{X}_i' \tilde{X}_i)^{-1} (\tilde{X}_i' \tilde{Y}_i), \quad M_i^* = (\tilde{X}_i' \tilde{X}_i)^{-1}$$

- Posterior of \mathbf{A} (structural matrix):

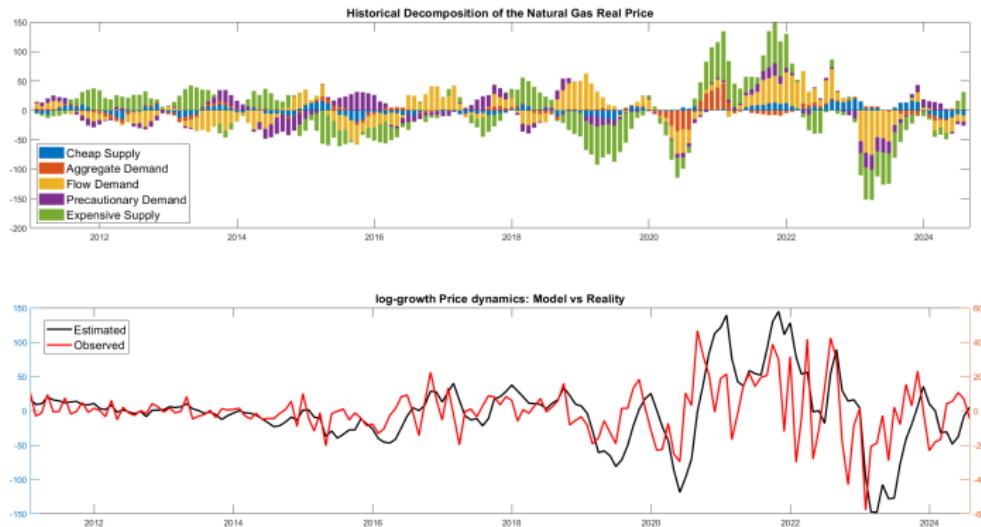
$$p(\mathbf{A} \mid \mathbf{Y}_T) = \frac{k_T p(\mathbf{A}) [\det(\mathbf{A} \hat{\Omega}_T \mathbf{A}')]^{T/2}}{\prod_{i=1}^n [(2\tau_i^*/T)^{\kappa_i^*}]} \prod_{i=1}^n \left\{ \frac{|\mathbf{M}_i^*|^{1/2}}{|\mathbf{M}_i|^{1/2}} \frac{\tau_i^{\kappa_i}}{\Gamma(\kappa_i)} \Gamma(\kappa_i^*) \right\}.$$

Table 1: Priors and posteriors distributions for parameters in **A**

	γ_{qp}	β_{qp}	α_{yp}	α_{qy}	α_{qp}	ψ_1	ψ_2	ψ_3
<i>Priors affecting contemporaneous coefficients A</i>								
Location	0.1	0.1	-0.05	0.7	-0.1 0.3	0	0	0
Scale	0.2	0.2	0.1	0.2	0.2	0.5	0.5	0.5
Degrees of freedom	3	3	3	3	3	3	3	3
Sign restriction	t^+	t^+	t^-	t^+	t^-	t	t	t
<i>Posterior affecting contemporaneous coefficients A</i>								
5%	0.033	0.339	-0.027	0.351	-2.566	-0.148	-0.112	0.010
50%	0.081	0.776	-0.007	0.881	-1.210	-0.036	-0.070	0.053
95%	0.131	1.474	-0.001	2.011	-0.654	0.075	-0.029	0.094
Mean	0.081	0.827	-0.010	0.993	-1.332	-0.036	-0.070	0.053

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European NG Supply by source



▶ Back