ORIGINAL ARTICLE

Navigating uncertainty: exploring electricity demand dynamics in Swedish industrial sectors amid global shocks and instability

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Abstract This study aims to provide insights into the factors shaping electricity demand in Swedish industrial sectors using the nonlinear version of the autoregressive distributed lag model (NARDL). This approach captures the complex short- and long-run relationships between uncertainty and electric power use in Swedish industrial sectors. The results reveal sector-specific responses to uncertainties and asymmetries in electricity use patterns. By examining the entire industrial sector in Sweden, this approach uncovers underlying issues and hidden patterns, while also providing insights into the functioning and behaviour of industrial systems. The rapid electrification and new green industrialisation initiatives in Sweden, coupled with the integration of a circular economy, underscore the importance of understanding the dynamics of electricity use in the face of uncertain shocks. This knowledge is vital for ensuring, amongst other things, grid stability, mitigating the need for costly peaking capacity, and identifying potential challenges in the interconnection of energy and material circular flows.

Introduction

Recent disruptions in the international energy sector, attributed to factors such as war and the COVID-19 pandemic, have led to an energy crisis in Europe (IEA, 2022) This crisis posed a significant risk to economic activities, affecting both energy utilisation and manufacturing (Overland et al., 2019). To mitigate uncertainties in the energy transition, restructuring of systems is necessary to withstand global shocks (Sovacool & Brown, 2010). This may involve diversifying energy sources, encouraging industrial synergies, and adopting sustainable technologies (Creutzig et al., 2018). Electrification plays a central role in this sustainable transformation. Electric power generated by low carbon emission technologies and biogenic energy sources will play a vital role, enabling the transition to a modern industrialised economy (IEA, 2022, 2023b; Tutak & Brodny, 2022; Van Nuffel et al., 2018). The projected rise in global electricity use is expected to more than double between 2021 and 2050. By 2050, electric power could make

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up to 50% of total final energy utilisation, amounting to as much as 45 trillion kWh (IEA, 2021). Additionally, transitioning to a net-zero emissions system will likely depend on abundant and affordable renewable and biogenic power sources. Managing variations between power production and end use is also important, especially with growing interdependencies between energy systems and other sectors (Amin & Wollenberg, 2005; Rinaldi et al., 2001). The growing interconnectedness among societal, and industrial sectors comes from extensive electrification and, development of circular practices focused on energy and resource efficiency (Geissdoerfer et al., 2017; Prieto-Sandoval et al., 2018). For example through industrial symbiosis (Chertow, 2000), energy system integration (Davis et al., 2018; Ilo & Schultis, 2022), sector coupling (Brown et al., 2018), the use of Power-to-X technologies (Daiyan et al., 2020; Gong et al., 2021), and developing smart energy systems (Lund et al., 2017; Lund & Mathiesen, 2009).

After a period of modest increases in electricity demand (IEA, 2022), electricity use is now projected to sharply rise. This raises question regarding the risk of competition for electricity among energy-intensive industries and concerns about the affordability of clean electricity (Frick et al., 2019; IEA, 2023a). A notable example is Sweden, which is expected to experience a significant surge in electricity use by mid-century, reversing its earlier decline (Swedish Energy Agency, 2022). Widespread electrification and the emergence of new green industries are driving the increase in demand. In particular, activities such as data centres, electric vehicles, battery factories, and fossil-free steelmaking in the country's northern regions significantly contribute to this rise (Swedish Energy Agency, 2023). As of 2021, renewable energy made up 63% of Sweden's total energy output (Swedish Energy Agency, 2022). In 2022, six major industrial sectors in Sweden accounted for about 72% of the country's industrial electricity use, totalling around 35 TWh. These sectors, listed from highest to lowest electricity use, are paper products, basic metals manufacturing, chemical and petrochemical, mineral products, pulp industry, and food and beverage (Statistics Sweden, 2022c). Competition for renewable electricity may constrain further sustainable investments (Lechtenböhmer et al., 2016). This could also affect the development of sustainable solutions like sector coupling, energy system integration,

and the utilisation of excess green electricity in storage and Power-to-X technologies (e.g. through energy storage and Power-to-X technologies).

Before a fully established renewable energy system is in place, the combined development of complex energy systems and energy-intensive activities like new green manufacturing poses risks, such as cascading failures and electricity shortages (Liebensteiner & Wrienz, 2020; Rinaldi et al., 2001). In a highly interdependent energy and industrial system, a major obstacle for developing and operating an efficient and affordable electricity system is the lack of a comprehensive understanding of energy utilisation patterns and the ramifications of system wide disturbances (Panteli & Mancarella, 2015; Thollander & Ottosson, 2008; Trianni et al., 2016). Additionally, the incorporation of circular economy practices will further increase the complexity in these systems. Therefore, it is critical to understand the dynamics and interactions of highly interconnected systems. An initial step could involve examining how electricity use in specific industrial sectors responds to various uncertainties.

While there is extensive research on demand-side management (Palensky & Dietrich, 2011), and load management approaches (Guelpa & Verda, 2021; Siano, 2014; Wang et al., 2017), the effects of global uncertainty on local industries are less studied. There is also ample literature concerning the technical aspects of power grid uncertainties and optimisation (Zheng et al., 2014), stemming from for example intermittent power generation (Weitemeyer et al., 2015). Some studies focus on short-term household electricity use predictions (Taieb et al., 2016), while others strive to forecast electricity supply in energy markets considering weather variables (Trespalacios et al., 2020).

Research on the long-term relationship between global uncertainty and electricity use in the industrial sector seems limited. It is unfortunate that research on this topic is limited, as incorporating uncertainty variables as predictors has shown that they can enhance the accuracy of electricity demand predictions (e.g. Rakpho & Yamaka, 2021). Understanding industry-specific electricity use patterns could be critical for optimising industrial operations, and efficient energy resource utilisation. For instance, the knowledge could be applied in the design of flexible electricity utilisation markets (capacity remuneration mechanisms) during

periods of peak load demand or in situations of limited grid capacity (Bublitz et al., 2019). The literature on uncertainty and electricity use primarily centres around the relationship between energy and economic growth (e.g. Alola & Yildirim, 2019; Erzurumlu & Gozgor, 2022; Marques et al., 2019; Sohail et al., 2022), or energy use and industrial production (e.g. Boyd & Pang, 2000; Rahman et al., 2017). However, when it comes to the relationship between uncertainty and electricity demand across various economic sectors the understanding remains incomplete.

In times where global shocks have revealed vulnerabilities in existing energy systems, it is essential to examine the effects of how uncertainties impact industrial sectors. It is in light of this situation, that this study, focuses on the dynamics of electricity utilisation in Swedish industry. The results provide a novel perspective on how uncertainty affects electricity consumption in specific industrial sectors. Where the results enable leveraging diverse uncertainty measures and insightfully assess both short and long-term dynamics, offering a comparative understanding of reactions.

Aim and scope

Specifically, the study aims to analyse electric power utilisation dynamics by examine the short- and long-term impact of systemic shocks arising from domestic (Swedish news based economic policy) and global (global news based economic policy) uncertainty. By taking a systems perspective, the analysis emphasises understanding the complex interactions and interdependencies within the system. Furthermore, the study introduces a novel feature by incorporating electricity market uncertainty in the analysis and in order to thoroughly capture complex short- and long-run relationships, the analysis applies the nonlinear (asymmetric) version of the autoregressive distributed lag model (NARDL). To the authors knowledge, there is no previous study that provides this level of comprehensible and deep insight into nonlinear industry sector specific electricity utilisation dynamics with an emphasis on uncertainty impacts. By considering the whole Swedish industrial sector, this approach helps to identify underlying issues, and hidden patterns, and provide insights into the functioning and behaviour of the system. The results, using three different types of uncertainty measures, reveals that there are indeed sector specific responses to uncertainties and asymmetries in electricity utilisation patterns. The conclusions drawn from this study are significant not only in terms of the energy systems, but also in relation to research exploring global value chains and production networks (Coe et al., 2008), as well as investigations into the sustainable transitions and global regimes (Fuenfschilling & Binz, 2018).

Materials and method

Figure 1 outlines the key steps in applying the NARDL model in this study. It begins by examining data trends and detecting changes using the Bai-Perron test (Bai & Perron, 2003). Data stability is then
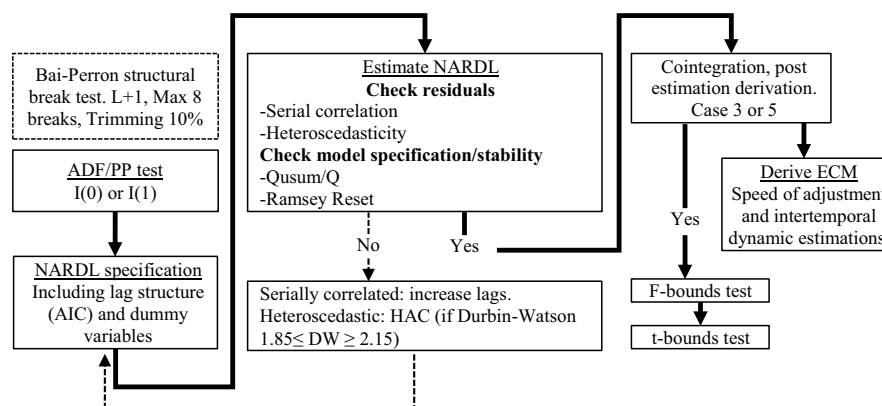
Fig. 1 Step by step procedure of the NARDL estimations. Note: Case 3: the model includes an intercept without any deterministic trend in the cointegrating equation. Case 5: the cointegrating equation contains both an intercept and a deterministic trend, indicating the series has a trend component

analysed using the Augmented Dickey-Fuller (ADF), and the Phillips-Perron (PP) tests. Next, the model's structure and variables are defined, model parameters are calculated and checked for coherence, and residuals are examined. The study then validated the long-term relationships between the variables through *F*- and *T*-bound tests, and concludes by identifying error correction mechanisms and short-term dynamics.

Data

This analysis uses monthly time series data from January 2009 to September 2022, measuring electricity utilisation quantities (in GWh) for 14 SNI 2007 (NACE Rev. 2) industrial sectors in Sweden.[1] The analysis includes the explanatory variables of Swedish economic policy uncertainty (SWEEPU) developed by Armelius et al. (2017), global economic policy uncertainty (GEPU)[2] developed by Davis (2016), and electricity market uncertainty (conditional variance in electricity spot prices).

To reduce the variation of the series, minimise the impact of outliers, and make the data more linear, all variables were transformed to natural logarithms before testing and estimation (Box & Cox, 1964). A comprehensive description of the time series data can be found in Table 1 and the data series are presented in Figs. 2, 3, and 4 in the Appendix.

Additionally, to enable accurate comparisons over time and to uncover underlying trends and shifts, the electricity data was seasonally adjusted using Census X-13 ARIMA-SEATS (Findley et al., 1998). Moreover, the analysis incorporates control variables for industrial production[3] (IPI), and electricity market spot price[4] (SP) to ensure robust results (see Figure 4 in the Appendix). The GEPU and SWEEPU measures captures the level of uncertainty in Sweden and on the global level. The indices are derived from the frequency of newspaper articles that contain keywords related to economy, policy, and uncertainty. A higher EPU index value indicates greater uncertainty. Electricity market uncertainty

is generated by estimating a GARCH(1,1) model of Nord Pool system spot prices.

Pre-estimation tests

The descriptive statistics, Tables 5 and 6 in the Appendix, show the Jarque-Bera normality test, which indicates that most of the dependent variables have nonlinear features. To examine these nonlinear aspects in more detail, a BDS test was performed (Brock & Dechert, 1996). As demonstrated in Table 7 in the Appendix, the BDS test confirms the presence of nonlinearity in the series, thereby justifying the application of a nonlinear estimation method.

The order of integration of the variables are presented in Table 1. Both ADF and PP test shows that the dependent and explanatory variables exhibit mixed order of integration up to I(1), but not I(2), and are thus appropriate for NARDL (for detailed results see Table 8 in the Appendix). Additionally, to test the stationarity of the data for possible nonlinearities, the study also applied the Kapetanios-Shin-Snell (KSS) test for nonlinear unit root (Kapetanios et al., 2003). The results of the KSS test, which are shown in Table 1 with the symbol $\mathbb{N}\ell$, indicate that there are nonlinear unit root processes in 7 out of the 18 variables that are used as dependent and independent factors in the analysis. The full details of these results can be found in Table 9 in the Appendix.

The Bai-Perron break test identified structural breaks, and dummy variables were included in the models accordingly. Tables 8, 9, and 10 in the Appendix provide further details about the pre-estimation test results.

The general ARDL model

The general ARDL model is given by Eq. (1). For more details, please see Pesaran and Shin (1997) and Pesaran et al. (2001).

$$y_t = a_0 + a_1 t + \sum_{i=1}^{P} \psi_i y_{t-i} + \sum_{j=1}^{k} \sum_{l_j=0}^{q_j} \beta_{j,l_j} x_{j,t-l_j} + \epsilon_j \quad (1)$$

In Eq. (1), y_t is the dependent variable (e.g. monthly electric power use in industrial sectors) and x_j represents the explanatory variables (e.g. uncertainty measures) in the ARDL($p, q_1..., q_k$) model where k indicates number of independent variables (three in this study excluding control variables). Additionally, a_0 is the constant term and ϵ_j represents the usual innovations, and $a_1, \psi_i, \beta_{j,l_j}$ are the coefficients related to the

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[1] https://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START__EN__EN0108__EN0108A/ElForbr07M/
[2] https://www.policyuncertainty.com/global_monthly.html
[3] https://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START__NV__NV0402__NV0402A/IPI2010KedjM/
[4] https://www.nordpoolgroup.com/en/Market-data1/#/nordic/table

Table 1 Data description

Variable	Abbreviation	SNI2007	Details	Order of integration
Total industry	TOT	B+C	Mining, quarrying, and manufacturing. (SNI 05-33)	I(1)$^{\mathbb{N}\ell}$
Mining and quarrying	MQ	05–09	(05) Mining of coal and lignite, (06) Extraction of crude petroleum and natural gas, (07) Mining of metal ores, (08) Other mining and quarrying, (09) Mining support service activities.	I(0)
Food, beverage, and tobacco products	FBT	10–12	(10) Manufacture of food products, (11) Manufacture of beverages, (12) Manufacture of tobacco products	I(1)
Textile, clothing, leather, and leather products	TCLL	13–15	(13) Manufacture of textiles, (14) Manufacture of wearing apparel, (15) Manufacture of leather and related products.	I(1)
Wood, cork, straw, and plaiting	WCSP	16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	I(1)$^{\mathbb{N}\ell}$
Pulp industry	PULP	17.11	Manufacture of pulp	I(1)
Paper and paperboard industry	PAPER	17.12	Manufacture of paper and paperboard.	I(1)$^{\mathbb{N}\ell}$
Chemical, petroleum, and pharmaceutical products	CPP	19–21	(19) Manufacture of coke and refined petroleum products, (20) Manufacture of chemicals and chemical products, (21) Manufacture of basic pharmaceutical products and pharmaceutical preparations.	I(1)$^{\mathbb{N}\ell}$
Rubber and plastic products	RP	22	Manufacture of rubber and plastic products	I(1)$^{\mathbb{N}\ell}$
Other non-metallic mineral products	ONM	23	Manufacture of other non-metallic mineral products	I(1)
Basic metals	BM	24	Manufacture of basic metals	I(0)$^{\mathbb{N}\ell}$
Fabricated metal goods	FMG	25	Manufacture of fabricated metal products, except machinery and equipment	I(0)$^{\mathbb{N}\ell}$
Computer, electronic and optics products	CEOM	26–28	(26) Manufacture of computer, electronic and optical products, (27) Manufacture of electrical equipment, (28) Manufacture of machinery and equipment.	I(1)
Transport products	TRAN	29–30	(29) Manufacture of motor vehicles, trailers, and semi-trailers, (30) Manufacture of other transport equipment.	I(0)
Other manufacturing, installations, and repair industries	OMR	31–33	(31) Manufacture of furniture, (32) Other manufacturing, (33) Repair and installation of machinery and equipment	I(1)
Swedish economic policy uncertainty	SWEEPU	-	Swedish news based economic policy uncertainty index	I(0)
Global economic policy uncertainty	GEPU	-	News based economic policy uncertainty index	I(0)
Electricity market volatility	EMUNC	-	The conditional variance Nord Pool system spot price (GARCH 1, 1).	I(1)
Electricity spot price	SP	Control variable	Nord Pool system spot price	I(1)

Note: Data ranges from January 2009 to September 2022 and contains n = 165 observations and the order of integration indicated by I(0) and I(1). $\mathbb{N}\ell$ indicates nonlinear unit root process in variables according to KSS test. Industrial sectors are grouped according to the Swedish standard for industrial classification (SNI 2007). Industrial classification applies to both electricity utilisation and industrial production data. Electricity utilisation and industrial production data collected from Statistics Sweden (SCB), Swedish and global EPU uncertainty collected at www.policyuncertainty.com. Electricity prices collected at Nord Pool. Sector-specific industrial production index (IPI) is included as a control variable for sector-specific activity

linear estimations. Furthermore, Eq. (2) is the practical formulation for the intertemporal dynamic estimations.

$$y_t = a_0 + a_1 t + \sum_{i=1}^{p} b_{0,i} y_{t-i} + \sum_{j=1}^{k} b_j x_{j,t} + \sum_{j=1}^{k} \sum_{l_j=1}^{q_j-1} c_{j,l_j} \Delta x_{j,t-l_j} + \epsilon_t \qquad (2)$$

Equation (3) represents the post-regression derivation of the long-run relationships,

$$y_t = a_0 + a_1 t + \sum_{j=1}^{k} \theta_j(1) x_{j,t} + \sum_{j=1}^{k} \widetilde{\theta}_j(L) \Delta x_{j,t} + \xi_t \qquad (3)$$

Table 2 NARDL model specifications

Cointegration hypothesis (NARDL)	Selected model (AIC)	F-statistics (lag)
F(TOT|$SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$)	ARDL(6, 0, 1, 0, 3, 6, 3)	29.37(6)***
F(PAPER| $SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$)	ARDL(6, 0, 1, 0, 0, 6, 3)	46.22(6)***
F(BMP| $SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$)	ARDL(3, 4, 5, 0, 2, 4, 0)	28.38(5)***
F(CPP| $SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$)	ARDL(1, 5, 3, 0, 0, 0, 4)$.\mathscr{I}$	22.26(6)***
F(MQ| $SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$) $\ddot{\imath}$	ARDL(4, 9, 9, 9, 9, 9, 9)$\mathscr{H}.\mathscr{I}$	10.51(4,9)***
F(PULP| $SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$)	ARDL(3, 1, 0, 2, 0, 1, 1)	27.89(6)***
F(FBT| $SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$)	ARDL(4, 1, 1, 0, 0, 2, 1)	5.969(6)***
F(TRAN| $SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$)	ARDL(3, 6, 7, 0, 1, 7, 1)$.\mathscr{I}$	31.98(7)***
F(WCSP| $SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$)	ARDL(1, 1, 0, 0, 0, 0, 0)	21.11(6)***
F(CEOM| $SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$)	ARDL(7, 1, 0, 0, 2, 4, 5)	93.99(7)***
F(FMG| $SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$)	ARDL(1, 0, 1, 1, 2, 4, 1)	11.42(6)***
F(RP| $SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$)	ARDL(1, 0, 6, 0, 2, 1, 0)	9.77(6)***
F(ONM| $SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$)	ARDL(1, 0, 0, 0, 0, 0, 0)	9.68(6)***
F(OMR| $SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$)	ARDL(1, 0, 6, 0, 0, 0, 1)	40.50(6)***
F(TCLL| $SWEEPU^{\pm}$, $GEPU^{\pm}$, $EMUNC^{\pm}$)	ARDL(1, 0, 5, 0, 0, 0, 1)	33.57(6)***

Note: Models have been selected by AIC criteria iteratively (selected model). Model selection maximum lag order (lag). Model significance indicated by *(10%), **(5%), and ***(1%). $\mathscr{H}$ indicates that model has been estimated with fixed number of lags in order to ensure no serial correlations. $\mathscr{I}$ indicates selection of robust standard errors (HAC) based on model heteroscedasticity test and Durbin-Watson test statistics (DW between 1.85 and 2.15). $\ddot{\imath}$ Due to model instability MQ series was adjusted to include observations between January 2011 and September 2022

and Eq. (4) represents the conditional error correction form.

$$
\begin{aligned}
&= a_0 + a_1 t + \psi(L)y_{t-1} + \sum_{j=1}^{k} \beta_j(1)x_{j,t-1} \\
&\quad + \left(\hat{\psi}^*(L)\Delta y_{t-1} + \sum_{j=i}^{k} \tilde{\beta}_j(L)\Delta x_{j,t-1} \right) \\
&\quad + \sum_{j=1}^{k} \beta_j(L)\Delta x_{j,t} + \epsilon_t
\end{aligned}
\tag{4}
$$

This study uses a nonlinear version of the ARDL model, which can capture more complex and asymmetric patterns in the data. For more information on this method, please refer to Shin et al. (2014).

The approach studies how positive and negative values of the independent variables ($SWEEPU^{\mp}$, $GEPU^{\mp}$, $EMUNC^{\mp}$) can explain electricity utilisation in Swedish industrial sectors. Table 2 shows the model specifications, where the optimal lag length was selected based on the AIC criteria (Akaike, 1974), and the maximum order of lags were set to minimise loss of degrees of freedom (Halicioglu, 2009). In models with persistent autocorrelation,

increased lag order was used to obtain uncorrelated and unbiased model specifications.

In the NARDL model, the partial sum decompositions of the distributed lag model are defined in the following manner (using TOT and GEPU as an illustration): $GEPU_t = GEPU_0 + GEPU_t^+ + GEPU_t^-$ where $GEPU_0$ is the initial value, and $GEPU_t^+, GEPU_t^-$ are the partial sums of either positive or negative differences. Estimation is performed according to Eq. (5) where $GEPU_t$ is a $k \times 1$ vector of the explanatory (distributed lag) variables (besides GEPU also SWEEPU and EMUNC) and ϕ TOT is the lagged dependent variable, ϕ_j represent the autoregressive parameter, and θ_j^+, θ_j^- represent the asymmetric parameters of the distributed lag variables.

$$
\begin{aligned}
TOT_t &= \sum_{j=1}^{P} \phi_j TOT_{t-j} + \sum_{j=0}^{q_j} \theta_j^{+\prime} SWEEPU_{t-j}^+ \\
&\quad + \theta_j^{-\prime} SWEEPU_{t-j}^- + \varepsilon_j
\end{aligned}
\tag{5}
$$

Departing from Pesaran et al. (2001), Eq. (6) extends the equation, in order to deal with the possibility of non-zero contemporaneous relations between regressor and residuals; the following conditional error correction model (ECM) is obtained:

$$\Delta TOT_t = \rho \xi_{t-1} + \sum_{j=1}^{P-1} \gamma_j \Delta TOT_{t-j} + \sum_{j=0}^{q-1} \left(\pi_j^{+'} \Delta SWEEPU_{t-j}^+ + \pi_j^{-'} \Delta SWEEPU_{t-j}^- \right) + \varepsilon_t \qquad (6)$$

where $\xi_t = TOT - \beta^{+'} GEPU_t^+ - \beta^{-'} GEPU_t^-$ is the nonlinear error correction term.

Post-estimation tests

To validate the models, after the estimation, the Breusch-Godfrey test was applied for autocorrelation and the Breusch-Pagan-Godfrey test for constant variance. Model stability was assessed with CUSUM and CUSUMQ tests, as per Brown et al. (1975). Results are presented in Figure 5 in the Appendix. The Ramsey Reset test tested the models' functional forms. Diagnostic tests affirmed all models as valid and stable, with details in Table 3 and in the Appendix.

Results

The findings are ordered from the highest to lowest electricity users, highlighting major users (PAPER, BMP, CPP, MQ, PULP, FBT), representing over 72% of Swedish industrial sector electricity use in 2022 (Statistics Sweden, 2022a).

Long-run estimations

Considering the coefficients in Table 3, at a 5% significance level, the findings show a long-run relationship between electricity usage and uncertainty, contingent upon the source of uncertainty and the specific industrial sector. Electricity usage in the entire Swedish industrial sector, denoted as TOT, has a negative and asymmetric long-term relationship. This is characterised by a decline in electricity usage significant only for negative cumulative sums of global uncertainty and relates to a drop in global uncertainty, termed GEPU. Previous research has shown that in Sweden's industrial sectors, electricity demand is fairly inelastic, relying on factors such as electricity and fuel prices, wages, carbon taxes, and permit trading systems (Brännlund & Lundgren, 2007; Henriksson et al., 2014). Other studies on energy-intensive industries in the Nordic region have shown that energy price elasticities tend to be lower

Table 3 Estimated NARDL long-run relations

Variable	TOT	PAPER	BM	CPP	MQ	PULP	FBT	TRAN	WCS	CEOM	FMG	RP	ONM	OMR	TCLL
$SWEEPU^+$				-0.167***	0.227***				-0.034*	-0.049**	-0.075***	-0.041*'			
$SWEEPU^-$		-0.118***		-0.228***	0.175**										
$GEPU^+$				0.046**						0.044**	-0.033*				
$GEPU^-$	-0.067**							-0.063***	0.064***		-0.068***				
$EMUNC^+$								0.026***		0.033***	0.018***			0.022***	
$EMUNC^-$										-0.024**					
F-test	9.626***	11.376***	7.762***	14.071***	6.170***	12.052***	4.743**	13.123***	26.056***	16.764***	21.173***	19.103***	19.464***	21.261***	25.348***
t-test	-5.923***	-7.552***	-6.675***	-9.135***	-5.528***	-8.951***	-4.904**	-9.063***	-13.130***	-8.380***	-12.040***	-11.529***	-11.559***	-11.981***	-13.055***
RAMSEY stat	0.404	1.733*	0.914	0.388	0.037	0.762	1.986	4.872	1.239	0.015	1.151	0.787	0.186	1.766	0.995
QUSUM/Q	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
Ψ	0.106	0.935	0.552	0.022	0.692	0.184	0.571	0.916	0.251	0.186	0.388	0.230	0.333	0.733	0.240
Φ	1.230	1.202	0.993	1.756*	1.813*'	0.899	0.961	1.554*	0.923	1.396	0.835	1.190	0.912	1.232	0.849

Note: Ψ = Breusch-Godfrey serial correlation LM test, Φ = Breusch-Pagan-Godfrey heteroskedasticity test. The symbols *, **, and *** represent the 10%, 5%, and 1% significance level. Results for cusum test and cusum of squares test can be found in Figure 5 in the Appendix

for highly energy-dependent companies (Bjørner & Jensen, 2002).

The results for the paper industry sector, denoted as PAPER, show a notably significant and asymmetric long-term relationship with domestic uncertainty, denoted SWEEPU. This relationship is marked by reduced electricity usage, significant only for negative sums of domestic uncertainty. A possible explanation for this results is that many paper mills in Sweden rely on biomass for energy (Laurijssen et al., 2012), and Sweden constitute a major supplier of biomass on the global market (Kumar et al., 2021). The biomass market is affected by a range of uncertainty factors, including policies, regulations, feedstock availability, and geopolitical aspects (Scarlat et al., 2015; Thrän et al., 2010). An alternative consideration is that energy management programmes in Sweden may contribute to reductions in electricity use via R&D investment (Henriksson et al., 2012), where lower domestic uncertainties can be beneficial for investments (Baker et al., 2016). As a result, the negative association between electricity usage and negative domestic uncertainty values might arise from a substitution effect. For instance, the paper industry sector might be switching to or altering its use of bioenergy (Ådahl & Harvey, 2007), or adopting energy management practices and technologies (Joelsson & Gustavsson, 2008).

The chemical and petroleum sector, denoted as CPP, shows a negative relationship with domestic uncertainty fluctuations. However, it has a positive long-term relationship with increases in global uncertainty. This suggests a general sensitivity to domestic uncertainty, which includes factors like regulatory uncertainty (Hedeler et al., 2023; Holmberg & Persson, 2023), and energy efficiency measures (Johansson & Thollander, 2018). Regulations could, for instance, impact the manufacturing of plastic, which requires petrochemical input products (Kungliga Ingenjörsvetenskapsakademien, 2003).

The mining and quarrying sector, denoted as MQ, has undergone extensive electrification of mining operations (Stenqvist & Nilsson, 2012). The findings show a positive long-term relationship between electricity use and domestic uncertainty. One possible reason for the growing dependence on electricity is the need to address various challenges related to sustainability, such as regulatory frameworks, local environmental impacts, renewable energy transition, greenhouse gas emissions, and socioeconomic

tensions (Olsson et al., 2019). These findings are consistent with previous research on electricity demand in the Swedish mining industry. For instance, Henriksson et al. (2014) determined that labour and oil serve as substitutes for electricity in mining processes and that capital investment and electricity demand are complements.

However, in this study, the results associate electricity use dynamics more directly to domestic uncertainty. This supports the notion that long-term domestic factors, like regulatory pressures and other factors reflected in the Swedish economic uncertainty index, influence electricity in the long term.

The findings regarding electricity usage in the transportation manufacturing sector, denoted as TRAN, indicate a negative long-term relationship with declines in global uncertainties. Specifically, only a decrease in GEPU results in reduced electricity usage. Additionally, there is a positive relationship with rising electricity market uncertainty, where only increases in EMUNC lead to rising electricity usage. The findings regarding TRAN and the effect from global uncertainty closely resembles that of the entire industry (TOT). These findings further affirm that the Swedish transport manufacturing sector, predominantly consisting of motor vehicle production, trailers, semi-trailers, and other transportation equipment, has a significant relationship to the global market, being the country's leading export sector (Statistics Sweden, 2021). Another possible explanation (e.g. expressed in financial statements) for the negative response to reductions in global uncertainty might be supply chains related. When global uncertainty declines, it may lead to shortages of transportation services for delivering input materials and components.

The results for the wood and wood product manufacturing industry, denoted as WCS, reveal a positive long-term relationship between global events and uncertainty. The Swedish wood product industry is a relatively under-researched area, particularly in terms of electricity demand dynamics. However, related studies show that the energy intensity in Swedish wood product industries is not as high as in other European countries (Locmelis et al., 2019). One possible reason for the sector electricity use being affected by global events is the significant increase in the export value of wood and wood products from Sweden in the last 10 years, which almost doubled (Statistics Sweden, 2022b).

The industries that involve manufacturing computers, electronics, electrical equipment, machinery, and optical products, denoted as CEOM, exhibit asymmetric relationships with domestic uncertainty and electricity market uncertainty. In these relationships, increases in uncertainty lead to reduced electricity use, while decreases in uncertainty result in the opposite effect.

The fabricated metal goods sector, denoted as FMG, displays a negative relationship with increases in domestic uncertainty and decreases in global uncertainty. This implies that increasing domestic uncertainty and decreasing global uncertainty leads to a reduction in electricity usage within this sector. However, electricity usage in sector displays a positive long-term relationship, where positive values of EMUNC results in increasing in electricity usage.

Industries such as other manufacturing, installations, and repair, denoted as OMR, exhibit a positive long-term relationship with positive values of EMUNC in terms of electricity usage. This means that increasing uncertainty leads to rising electricity use. Previous research indicates that Swedish industries also utilise electricity for support services, such as heating and ventilation, demonstrating that other energy sources could substitute, for example, heating (Henning & Trygg, 2008). This suggests that the potential for electricity conservation and switching to other energy carriers, which could in turn reduce electricity utilisation (Lundgren et al., 2016). However, there is a problem of generalising these results without available bottom-up energy end-use data (Andersson et al., 2018).

Short-run dynamics

Considering the coefficients, presented in Table 4, at 5% significance, there is evidence of diverse short-term relationships between electricity usage and uncertainty. These relationships depend on the source of uncertainty, the specific industrial branch, and time-related factors. The short-term dynamics for TOT, suggest that a decrease in global uncertainty in preceding months results in increased electricity usage. Conversely, a reduction in electricity market uncertainty in prior months results in a decrease in electricity usage. The error correction term is negative and significant, suggesting that total industrial electricity utilisation returns to normal in just under 2 months following a disturbance. In contrast to the

long-run dynamics that primarily exhibit a negative relationship, the short-run dynamics reveal that Swedish industrial electricity consumption is sensitive to both positive and negative electricity market uncertainty within a period of up to 5 months. This sensitivity may be attributed to the fact that electricity usage accounts for approximately one-third of the total energy consumption in the Swedish industry, which amounted to around 46 TWh in 2021 (Swedish Energy Agency, 2022).

The findings in Table 4 also show that the PAPER sector is relatively unaffected by global and domestic uncertainties in the short-term. However, changes in EMUNC impact the sector's electricity usage, which responds to both increases and decreases in uncertainty occurring in the preceding months. Notably, the reactions are stronger for negative values of electricity market uncertainty. The electricity use returns to normal levels in approximately 1 month after a disturbance.

The PULP sector seems to remain relatively unaffected by both global and domestic uncertainties. This aligns with past studies, showing that even though the Swedish pulp and paper sector demonstrates a relative indifference to short-term fluctuations in energy input costs, there are indications of considerable changes over the course of time (Henriksson & Lundmark, 2013). However, it is one of two sectors—the other being ORM, which encompasses other manufacturing, installations, and repair industries—that show sensitivity to uncertainty in the electricity market within a specific month of electricity utilisation. After an uncertainty shock, electricity use seems to return to normal levels in just under one month. The sensitivity to electricity market uncertainty may stem from the fact that the pulp sector, together with the paper and forestry sectors (SNI 17), used roughly 18 TWh in 2020, which was roughly 15% of Sweden's total electricity use that year. The sector is also highly dependent on bioenergy, which constitutes approximately 96% of total fuel consumption in the sector, and where 40% of electric power is generated within the industry (Svensk skogsindustri, 2022), and most of the biomass side streams are converted into energy (Lipiäinen et al., 2022). A reduction in electricity consumption amid declining electricity market uncertainty may suggest a substitution between bioenergy and electricity usage, as well as decisions to either supply the market or use it within the industry. Comparing the results from the paper industry with those from the pulp industry

Table 4 Estimated NARDL short-run relations

Variable	TOT	PAPER	BM	CPP	MQ	PULP	FBT	TRAN	WCS	CEOM	IFMG	RP	ONM	OMR	TCLL
C	3.446***	6.144***	2.030***	4.534***	4.969***	5.693***	3.351***	2.541***	4.519***	3.142***	3.381***	3.349***	3.419***	2.913***	1.816***
Trend	−0.001***	−0.003***	−0.002***	−0.0003**		0.003***	0.0001**	−0.009***	0.004***	−0.003***	NA	NA	NA	NA	NA
ΔY_{t-1}	−0.261***		−0.286***				−0.249**	−0.156**		−0.282***					
ΔY_{t-2}	−0.130*		−0.124*			−0.126*		−0.279***		−0.230***					
ΔY_{t-3}							0.132*								
ΔY_{t-5}	−0.162**														
$\Delta SWEEPU^{+}$		−0.208***					0.035**								
$\Delta SWEEPU^{+}_{t-1}$			−0.043*	0.103***	−0.191***			−0.095***							
$\Delta SWEEPU^{+}_{t-2}$			−0.058**	0.048**	−0.216***			−0.080***				−0.044*			
$\Delta SWEEPU^{+}_{t-3}$			−0.089***	0.081***	−0.108**							−0.047*			
$\Delta SWEEPU^{+}_{t-4}$				0.062***	−0.124***			−0.092***				−0.078***			
$\Delta SWEEPU^{+}_{t-5}$					−0.078**			−0.053*				−0.040*			
$\Delta SWEEPU^{+}_{t-6}$										0.118*					
$\Delta SWEEPU^{-}$							−0.039**								
$\Delta SWEEPU^{-}_{t-1}$			−0.062*	0.054*	−0.211***						0.111***			−0.068**	
$\Delta SWEEPU^{-}_{t-2}$				0.075**	−0.180***									−0.104***	
$\Delta SWEEPU^{-}_{t-3}$					−0.227***			−						−0.126***	
$\Delta SWEEPU^{-}_{t-4}$			−0.089***		−0.135**			−0.078**						−0.130***	−0.082**
$\Delta SWEEPU^{-}_{t-5}$					−0.133**			−0.083**							
$\Delta SWEEPU^{-}_{t-6}$					−0.111**			−0.053*							
$\Delta GEPU^{+}_{t-1}$	0.042***		0.079***			0.078***				0.036*		0.052**			
$\Delta GEPU^{+}_{t-7}$	0.026*														
$\Delta GEPU^{-}$					−0.084**					0.076***					
$\Delta EMUNC^{+}_{t-1}$			−0.018**				0.011**	−0.036***		−0.024***					
$\Delta EMUNC^{+}_{t-2}$			−0.014*					−0.032***		−0.014*					
$\Delta EMUNC^{+}_{t-3}$	−0.012**		−0.020**					−0.036***			−0.025***				
$\Delta EMUNC^{+}_{t-4}$								−0.017*							
$\Delta EMUNC^{+}_{t-5}$	−0.021***							−0.034***							
$\Delta EMUNC^{+}_{t-6}$		−0.036***						−0.019**							
$\Delta EMUNC^{-}_{t}$						−0.103***								−0.057**	

Table 4 (continued)

Variable	TOT	PAPER	BM	CPP	MQ	PULP	FBT	TRAN	WCS	CEOM	IFMG	RP	ONM	OMR	TCLL
$\Delta EMUNC_{t-1}^-$	−0.029**	−0.086***			−0.076***					0.062***					
$\Delta EMUNC_{t-2}^-$		−0.068***		−0.039**						0.053***					
$\Delta EMUNC_{t-3}^-$				−0.032*											
$\Delta EMUNC_{t-4}^-$										0.027*					
ECM_{t-1}	−0.534***	−0.892***	−0.469***	−0.707***	−1.170***	−0.987***	−0.730***	−0.755***	−1.035***	−0.834***	−0.899***	−0.908***	−0.905***	−0.859***	−1.025***

Note: The symbols *, **, and *** represent the 10%, 5%, and 1% significance level. Only coefficients with a minimum of 10% significance presented in table and trend included at 5% significance

sector, there are notable differences. An explanation for these variations could be that the production process in the paper industry is influenced by customer orders and relies heavily on storage. In contrast, pulp production is a continuous process with minimal need or desire for alterations in production. However, if electricity prices become too high, mechanical pulp industries may shut down either entirely or partially.

The BM industry sector exhibits short-run asymmetric sensitivity to global and electricity market uncertainty, and for the basic metal industry an increase in electricity market uncertainty leads to a decrease in electricity use. When accounting for domestic uncertainty, changes up to 3 to 4 months prior, both positive and negative fluctuations, lead to a decrease in electricity consumption. The Swedish basic mental industry is the second largest industry when it comes to electricity utilisation, and in 2020 the total electricity use was just under 7 TWh (Statistics Sweden & Swedish energy agency, 2021). A decrease in global uncertainty in the immediate month prior yields an increase in electricity use. Conversely, an increase in electricity market uncertainty up to 3 months prior leads to a decrease in electricity use. The error correction term indicates that electricity use returns to normal just over two months after a disturbance.

In the short-term, the CPP industry sector respond to increasing domestic uncertainties from up to 4 months earlier, which results in a rise in electricity use. The electricity usage also show sensitivity to decreases in both domestic and electricity market uncertainty 2 months prior. The error correction term suggests that electricity usage returns to normal levels approximately one and a half months following a disturbance. Short-term electricity usage in the MQ sector seems to be consistently sensitive to both increases and decreases in domestic uncertainty up to 6 months prior. However, the error correction term provides inconclusive evidence regarding a return to normal electricity usage.

The FBT sector present a similar situation, exhibiting relative insensitivity to uncertainties. However, within the month of utilisation, this sector does show sensitivity to domestic uncertainty, resulting in decreased electricity usage. Conversely, decreases in electricity market uncertainty leads to increases in electricity usage. The error correction term is negative and significant, suggesting that sector electricity utilisation returns to normal in just over a month, following a disturbance.

Despite the food and beverage sector's considerable size and numerous companies in Sweden, with

a turnover of 200 billion SEK in 2021 (Livsmedels-företagen, 2021, 2023), electricity consumption in 2021 was merely 2.37 TWh (Statistics Sweden, 2023). Most of these companies are situated in the middle to southern part of Sweden, and are sensitive to short- and long-term electricity prices (County Administrative Board (Länsstyrelsen), 2022). This sensitivity could potentially reduce the resilience of domestic food and beverage production. Considering that roughly 70% of all food and beverage production in Sweden caters to the domestic market, it is reasonable to anticipate sensitivity to domestic uncertainty.

The TRAN industry sector is, in the short-term, influenced by both upward and downward shifts in domestic uncertainty values from up to 5 months earlier. Moreover, there is a negative and asymmetric short-term relationship between the sector and increasing electricity market uncertainty up to 6 months prior. The error correction term indicates that electricity usage returns to normal levels around one and a half months after a disturbance. Thus, in the short term, the transportation manufacturing sector is sensitive to increased electricity market uncertainty, resulting in reduced electricity utilisation. This sector is also among the most affected in Sweden by short term volatile electricity prices (Business Sweden, 2022), which are caused by the interconnected European energy system where a sudden rise in gas prices quickly translates into higher electricity costs (Newbery et al., 2018).

Sectors that have the lowest share of electricity use, such as WCS, CEOM, IFMG, RP, ONM, OMR, and TCLL, are typically not affected by short-run uncertainties. However, the OMR sector is different. In this sector, a reduction in domestic uncertainty directly results in decreased electricity use. Apart from the inconclusive data for WCS and TCLL, the error correction terms imply that sectors generally revert to their standard levels of electricity use within roughly 1 month.

At a global scale, high electricity prices are generally considered a viable long-term strategy for promoting energy management and electricity conservation. Nonetheless, in the short term, the effectiveness of these prices may be limited, as indicated by Kwon et al. (2016). Another factor to consider is that large and electricity-intensive industries frequently engage in long-term contracts that offer stable rates. However, these power contracts often necessitate that consumers commit to a predetermined amount of electricity use months in advance, at a time when future demand is not yet definitively known (Zhang et al., 2018).

Discussion

The industry sector responses to changes in uncertainty demonstrate consistency between short-term and long-term results. For example, a sector significantly affected by a specific type of uncertainty in the short term (Table 4) often experiences a similar effect in the long term (Table 3). The short-term results, as presented in Table 4, incorporate multiple lagged variables. This implies that past values have a notable impact on current values across several sectors. The "Trend" term is predominantly negative and significant for many of the sectors, signalling a consistent pattern of declining electricity use over time within industrial sectors.

However, there are some differences in the magnitude and direction of the coefficients across the industrial sectors, illustrating the varying nature of short-term and long-term reactions to changes in uncertainties. The sensitivity of different sectors to uncertainty varies between short-term and long-term periods. Some sectors show considerable changes in electricity use in the short term but not in the long term, or the other way around. The differences in the significance and size of the coefficients across sectors underline the unique impact that uncertainty has on electricity use in each sector.

The results for short-term dynamics and sector-specific behaviours confirm the potential for electricity-based industrial synergies. For instance, the dynamics of electricity usage could be leveraged for energy storage solutions, such as Power-to-X technology. However, these findings are based on aggregated sectors, underscoring the need for more detailed, localised evaluations to understand the impact of uncertainty on electricity use. For instance, identifying the most suitable geographic locations for these solutions could be important for ensuring optimal operational conditions.

When it comes to electricity uses in Swedish companies and industries, more recent studies reveal a rising awareness of energy efficiency among firms, even at top management levels. However, energy prices seem to be the primary influence on energy intensities (Dahlqvist & Söderholm, 2019). These findings show that, over time, high energy prices have triggered decision-making and energy practices. Notably, firms concerned with "hidden" costs like production disruptions tend to have higher energy intensity (Dahlqvist & Söderholm,

2019). Future research could focus on these local evaluations, potentially uncovering industry specific condition and regions where electricity-based industrial synergies could be most effectively implemented.

This study provides a broad and comprehensive analysis, offering valuable insights into the subject at hand. However, this wide-ranging approach has its drawbacks. Specifically, the expansive scope could potentially overlook subtle details that are specific to individual producers or actors. Thus, while the study serves as a useful general overview, there may be a need for additional research that focuses on the intricacies of individual manufacturing actors in order to achieve a more thorough understanding of sector-specific electricity use behaviour.

Future research should also aim to develop data collection based on SNI/NACE sector classifications at a more detailed 4-digit level. This approach could reveal more insights into the diverse characteristics and electricity usage patterns within each sector, thereby leading to a more accurate understanding of the dynamics. Furthermore, to gain deeper insights into the relationships between electricity use and uncertainty, future research should strive for collecting and incorporating hourly data. This would facilitate a more detailed analysis of short-term fluctuations and their corresponding impacts on electricity consumption. Other areas for future development pertain to the specific characteristics and inherent meanings of the uncertainty measures used in this study. The concept of electricity market uncertainty should evolve into a comprehensive uncertainty index, similar to country-specific economic policy uncertainty. This would better capture mechanisms associated with uncertainties tied specifically to energy or electricity. Such an approach could help reveal the ways in which uncertainty measures influence electricity utilization patterns across various industries and regions, furthering our understanding of heterogeneity within each industry sector.

Conclusion and policy implications

This study offers a novel perspective on electricity use in Swedish industrial sectors by relating it to uncertainty. The findings reveal long and short-term dynamic responses to uncertainty, shaping electricity utilisation across sectors. Results demonstrate sector-specific variations and asymmetries in electricity use patterns due to domestic, global, and energy market uncertainties.

Key findings include negative long-run relationships between electricity use and domestic uncertainty in the paper industry, positive relationships for the mining and quarrying sector with domestic uncertainty, and the transportation manufacturing sector with electricity market uncertainty. These results emphasise the impact of domestic and global uncertainties on electricity consumption across Swedish sectors and shed light on how industries responses to uncertainty.

Short-term relationships between electricity usage and uncertainty also exist, varying depending on the source of uncertainty, the specific industrial sector, and time-related factors. Industries also display different sensitivities to uncertainties. Error correction terms indicate that electricity usage typically returns to normal levels within 1 to 2 months after a disturbance. Sectors with the lowest electricity use are generally insensitive to uncertainties, except for a few that exhibit sensitivity to specific forms of uncertainty.

Understanding the diverse short-term relationships between electricity usage and uncertainty across different industrial sectors can yield significant insights. These insights become especially valuable when trying to establish connections between specific industrial sectors, such as through the implementation of industrial symbiosis or sector coupling. Comprehending these relationships can help identify potential synergies or conflicts, enabling more effective and sustainable energy and material management. Moreover, it could contribute to the development of more resilient industrial systems, better prepared to navigate fluctuations in electricity usage amid uncertainty. Therefore, pinpointing sector-specific sensitivities to uncertainties allows policymakers and industry stakeholders to better anticipate and plan for variations in electricity demand. Furthermore, knowledge about electricity usage behaviour can aid in optimising operations for example when using excess electricity in power-to-X technologies. This can be achieved by adjusting conversion processes based on anticipated sector specific variations in electricity usage, thereby enhancing the stability of the grid and the overall efficiency of integrated energy systems.
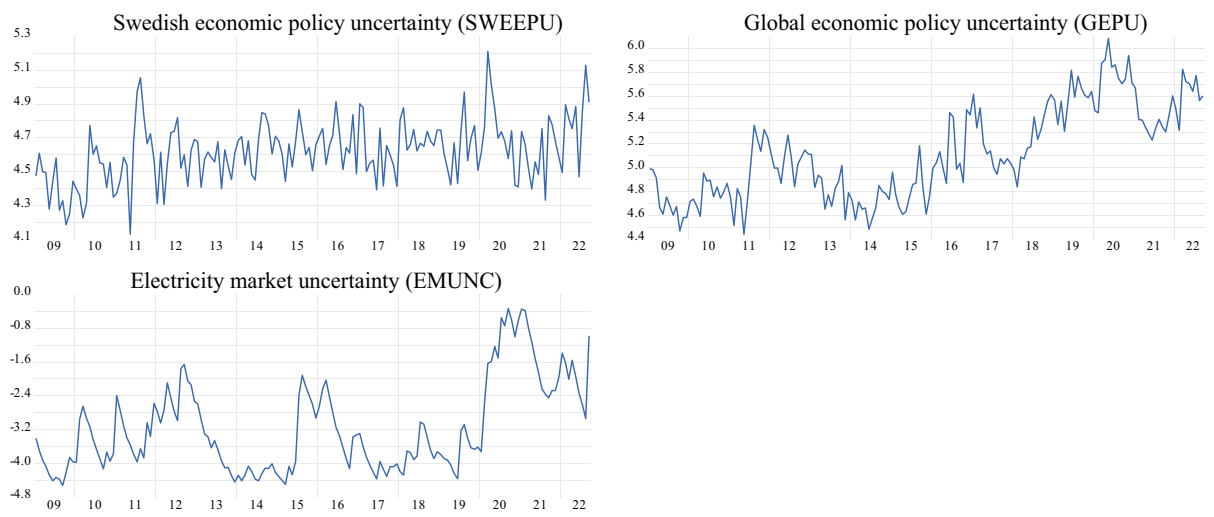
The practical implications suggest that, at the industry sector level, electricity use is responsive to
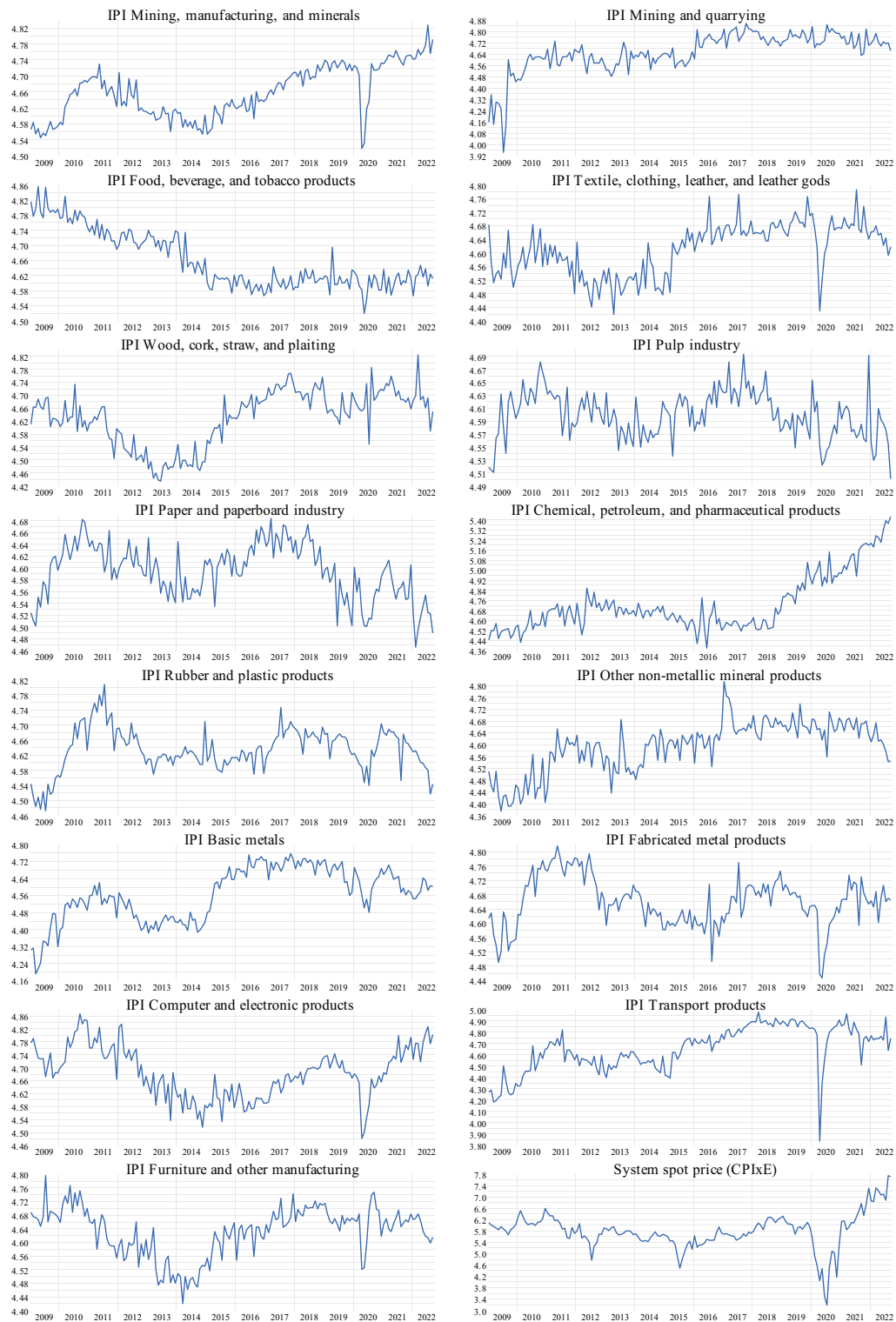
Appendix
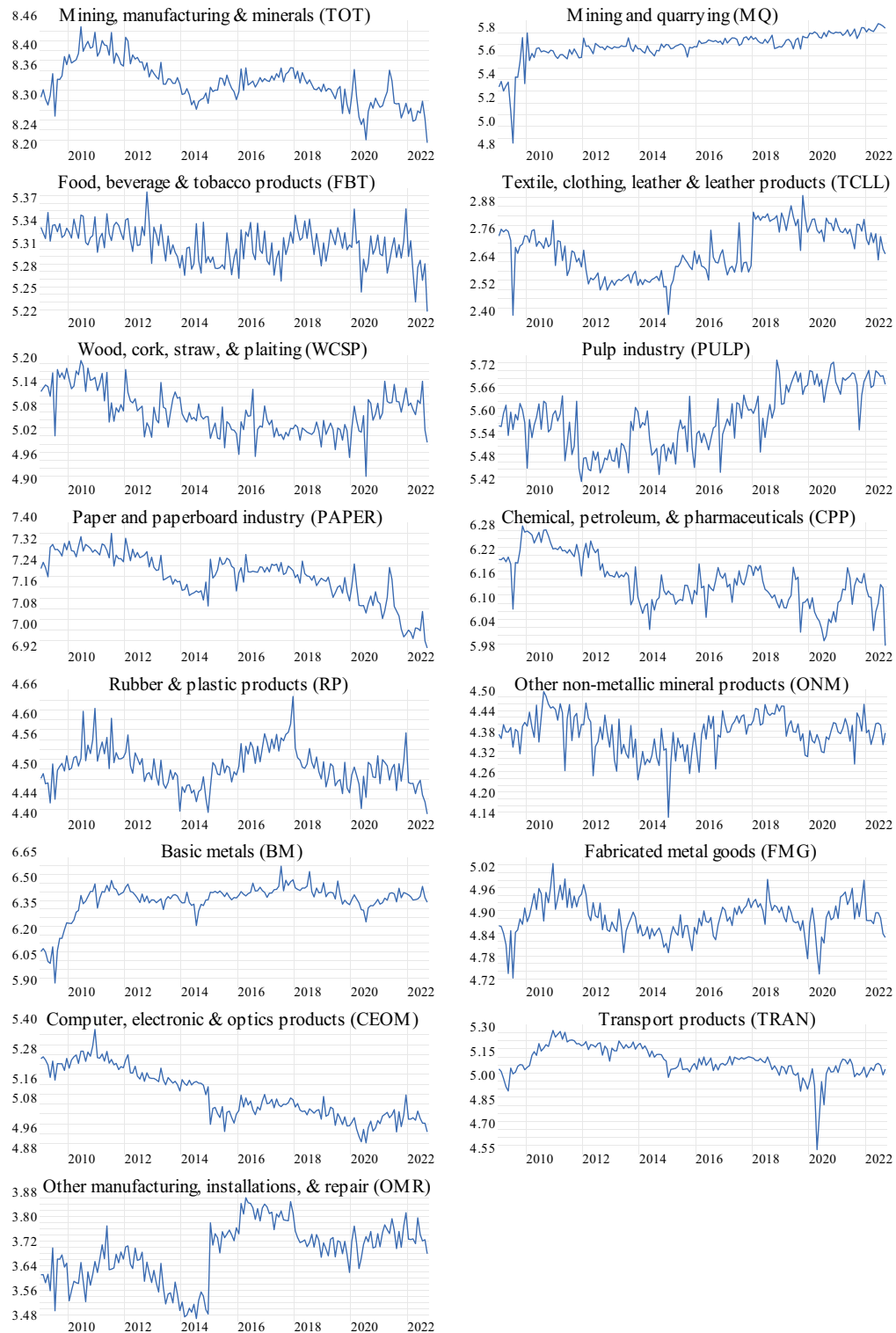
Fig. 2 Dependent variables

Fig. 3 Explanatory variables

Fig. 4 Control variables

Fig. 5 Stability diagnostics, cusum and cusum of squares tests. Note: Upper graphs: cusum test, lower graph cusum of squares

Table 5 Descriptive statistics dependent and explanatory variables

Variable name	Mean	Median	Max	Min	Std. Dev.	Skew	Kurt	J-B
Log level series								
EL Mining, manufacturing, and minerals	8.334	8.337	8.484	8.115	0.065	−0.536	3.68	11.07***
EL Mining and quarrying	5.682	5.694	5.932	4.828	0.141	−2.241	12.564	766.92***
EL Food, beverage, and tobacco products	5.313	5.318	5.451	5.187	0.052	−0.115	2.405	2.79
EL Textile, clothing, leather, leather gods	2.681	2.708	2.944	2.079	0.156	−0.721	3.93	20.22***
EL Wood, cork, straw, and plaiting	5.065	5.112	5.303	4.431	0.176	−2.009	6.782	209.31***
EL Pulp industry	5.593	5.598	5.775	5.389	0.089	0.007	2.252	3.84
EL Paper and paperboard industry	7.199	7.218	7.391	6.913	0.095	−0.652	3.137	11.81***
EL Chemical, petroleum, pharmaceutical	6.154	6.155	6.323	5.938	0.072	−0.155	2.962	0.67
EL Rubber and plastic products	4.497	4.533	4.663	4.043	0.129	−2.009	6.648	202.50***
EL Other non-metallic mineral products	4.389	4.407	4.564	4.111	0.095	−0.969	3.716	29.32***
EL Basic metals	6.398	6.43	6.581	5.609	0.135	−2.171	10.158	481.85***
EL Fabricated metal products	4.89	4.934	5.1	4.29	0.152	−2.039	7.049	227.11***
EL Computer and electronic products	5.111	5.118	5.389	4.585	0.152	−0.86	4.29	31.77***
EL Transport products	5.116	5.13	5.407	4.543	0.144	−1.233	5.215	75.57***
EL Furniture and other manufacturing	3.693	3.738	3.932	2.944	0.174	−2.008	8.299	303.86***
Swedish news based EPU index	4,619	4,616	5,21	4,13	0.182	0.141	3.405	1,67
Global economic policy uncertainty	5,116	5,044	6,08	4,442	0.387	0.366	2,116	9,06**
Electricity market volatility	−3.158	−3.437	−0.338	−4.515	1.063	0.879	2.905	21.30***
Log seasonally adjusted series								
EL Mining, manufacturing, and minerals	8.335	8.334	8.448	8.214	0.043	0.11	2.985	0.33
EL Mining and quarrying	5.685	5.695	5.876	4.859	0.127	−2.769	15.495	128.42***
EL Food, beverage, and tobacco products	5.315	5.317	5.385	5.227	0.024	−0.4	3.63	7.13**
EL Textile, clothing, leather, leather gods	2.687	2.69	2.928	2.408	0.105	−0.09	2.098	5.81*
EL Wood, cork, straw, and plaiting	5.078	5.069	5.208	4.92	0.054	0.259	2.699	2.47
EL Pulp industry	5.594	5.593	5.748	5.428	0.081	−0.033	1.968	7.34**
EL Paper and paperboard industry	7.199	7.216	7.361	6.934	0.089	−0.804	3.28	18.30***
EL Chemical, petroleum, pharmaceutical	6.155	6.151	6.292	5.995	0.063	0.062	2.553	1.48
EL Rubber and plastic products	4.504	4.505	4.647	4.41	0.04	0.449	3.794	9.87***
EL Other non-metallic mineral products	4.393	4.397	4.515	4.145	0.057	−0.757	4.277	26.96***
EL Basic metals	6.402	6.423	6.599	5.92	0.097	−2.281	9.463	430.31***
EL Fabricated metal products	4.9	4.9	5.044	4.742	0.048	−0.28	4.003	9.06**
EL Computer and electronic products	5.118	5.092	5.382	4.924	0.101	0.29	1.972	9.58***
EL Transport products	5.122	5.114	5.315	4.575	0.096	−1.36	9.234	318.03***
EL Furniture and other manufacturing	3.702	3.721	3.882	3.488	0.095	−0.382	2.434	6.20**

Note: Series are in log level, and log level seasonal adjusted by Census X-13, observations (n) = 165. J-B indicate the Jarque and Berea test for normality where the symbols *, **, and *** represent the 10%, 5%, and 1% significance level. Electricity data collected from Statistics Sweden, and uncertainty tracker indices collected from economic policy uncertainty

Table 6 Descriptive statistics control variables: Industrial production index and system spot price

Variable name	Mean	Median	Max	Min	Std. Dev.	Skew	Kurt	J-B
Log level series								
IPI Mining, manufacturing, and minerals	4.659	4.654	4.828	4.519	0.065	0.026	2.029	6.502**
IPI Mining and quarrying	4.656	4.673	4.856	3.945	0.141	−1.867	8.375	294.494***
IPI Food, beverage, and tobacco products	4.66	4.626	4.856	4.52	0.075	0.643	2.253	15.215***
IPI Textile, clothing, leather, leather gods	4.61	4.628	4.786	4.419	0.077	−0.33	2.351	5.886*
IPI Wood, cork, straw, and plaiting	4.63	4.649	4.824	4.434	0.086	−0.513	2.376	9.905***
IPI Pulp industry	4.599	4.604	4.693	4.501	0.037	−0.117	2.948	0.398
IPI Paper and paperboard industry	4.594	4.601	4.684	4.466	0.047	−0.348	2.493	5.095*
IPI Chemical, petroleum, pharmaceutical	4.729	4.666	5.425	4.38	0.224	1.221	3.784	45.198***
IPI Rubber and plastic products	4.634	4.632	4.807	4.473	0.057	−0.18	3.568	3.108
IPI Other non-metallic mineral products	4.594	4.616	4.814	4.374	0.086	−0.616	2.94	10.444***
IPI Basic metals	4.566	4.574	4.757	4.191	0.125	−0.526	2.632	8.525**
IPI Fabricated metal products	4.66	4.665	4.816	4.447	0.069	−0.28	3.207	2.449
IPI Computer and electronic products	4.684	4.684	4.867	4.482	0.079	−0.032	2.496	1.776
IPI Transport products	4.654	4.681	4.978	3.839	0.197	−0.792	3.764	21.272***
IPI Furniture and other manufacturing	4.631	4.652	4.797	4.42	0.072	−0.673	2.927	12.493***
Nord Pool system spot price	5.805	5.803	7.753	3.185	0.632	−0.445	6.338	82.061***

Note: Series are in log level seasonal adjusted from source, observations $n = 165$. J-B indicate the Jarque and Berea test for normality where the symbols *, **, and *** represent the 10%, 5%, and 1% significance level. Data collected from Statistics Sweden (SCB)

Table 7 BDS test for dependent variable normality

Variable name	m				
	2	3	4	5	6
Log seasonally adjusted series					
Mining, manufacturing, and minerals	19.292***	21.723***	24.081***	26.254***	28.955***
Mining and quarrying	16.833***	18.532***	20.190***	22.088***	24.775**
Food, beverage, and tobacco products	0.061	1.692	3.076**	4.248***	4.769***
Textile, clothing, leather, leather gods	29.210***	32.529***	34.842***	37.243***	40.052***
Wood, cork, straw, and plaiting	12.891***	14.705***	15.203***	16.074***	16.860***
Pulp industry	24.006***	25.611***	26.579***	27.872***	29.239***
Paper and paperboard industry	20.611***	21.893***	23.645***	25.551***	28.305***
Chemical, petroleum, pharmaceutical	23.839***	26.568***	28.501***	30.547***	33.129***
Rubber and plastic products	6.218***	7.484***	7.849***	8.387***	9.090***
Other non-metallic mineral products	5.095***	6.313***	7.052***	7.672***	7.730***
Basic metals	12.697***	13.038***	13.076***	13.288***	13.609***
Fabricated metal products	7.485***	8.966***	9.484***	9.812***	10.446***
Computer and electronic products	40.293***	45.548***	50.265***	56.170***	63.770***
Transport products	21.411***	23.968***	26.416***	29.250***	32.569***
Furniture and other manufacturing	25.001***	27.976***	30.096***	32.314***	35.184***

Note: BDS test for normality where fraction of pairs 0.7, $m = 6$, and bootstrap with 5000 repetitions is used as estimation method. The symbols *, **, and *** represent the rejection of the null-hypothesis at the 10%, 5%, and 1% significance level

Table 8 Unit root tests dependent and explanatory variables

Variable name	ADF		PP	
	Level	FD	Level	FD
Log series				
EL Mining, manufacturing, and minerals	−0.779(13)	−3.849***(12)	−7.662***(2)	−73.298***(162)
EL Mining and quarrying	−2.554(12)	−5.848***(11)	−5.187***(0)	−28.390***(14)
EL Food, beverage, and tobacco products	−1.243(12)	−4.281***(13)	−8.907***(8)	−45.308***(29)
EL Textile, clothing, leather, leather gods	−1.196(13)	−3.289**(13)	−7.717***(2)	−52.137***(91)
EL Wood, cork, straw, and plaiting	−1.818(13)	−3.855***(13)	−8.691***(26)	−43.111***(33)
EL Pulp industry	−0.723(12)	−4.999***(11)	−6.899***(7)	−60.682***(71)
EL Paper and paperboard industry	0.414(12)	−4.240***(11)	−4.379***(6)	−41.930***(24)
EL Chemical, petroleum, pharmaceutical	−1.534(12)	−4.647***(11)	−5.864***(5)	−33.445***(11)
EL Rubber and plastic products	−1.593(13)	−3.148**(13)	−11.844***(28)	−51.006***(26)
EL Other non-metallic mineral products	−1.402(13)	−3.907***(13)	−9.212**(8)	−42.700***(30)
EL Basic metals	−4.610***(13)	−2.817*(12)	−6.483***(2)	−42.237***(89)
EL Fabricated metal products	−2.520(13)	−4.036***(12)	−9.250***(16)	−89.762***(47)
EL Computer and electronic products	−0.974(13)	−2.909**(13)	−6.569***(3)	−74.292***(85)
EL Transport products	−1.884(13)	−3.178**(13)	−7.634***(1)	−47.530***(54)
EL Furniture and other manufacturing	−1.985(13)	−3.264**(12)	−8.838***(1)	−66.747***(46)
Log seasonal adjusted series				
EL Mining, manufacturing, and minerals	−3.250*(8)	−5.428***(6)	−4.986***(5)	−23.757***(16)
EL Mining and quarrying	−4.549***(3)	−8.140***(4)	−7.055***(3)	−49.027***(71)
EL Food, beverage, and tobacco products	−2.875(6)	−9.171***(4)	−10.733***(6)	−86.754***(162)
EL Textile, clothing, leather, leather gods	−2.213(2)	−14.279***(1)	−4.159***(5)	−30.804***(25)
EL Wood, cork, straw, and plaiting	−2.024(5)	−8.363***(5)	−7.143***(8)	−45.133***(32)
EL Pulp industry	−3.194*(2)	−8.892***(4)	−7.049***(8)	−35.739***(18)
EL Paper and paperboard industry	−1.588(5)	−8.480***(4)	−5.293***(7)	−26.793***(16)
EL Chemical, petroleum, pharmaceutical	−3.084(3)	−9.610***(2)	−5.235***(5)	−21.158***(14)
EL Rubber and plastic products	−1.856(4)	−9.933***(3)	−7.134***(7)	−40.808***(52)
EL Other non-metallic mineral products	−1.952(6)	−8.567***(5)	−8.965***(7)	−90.906***(122)
EL Basic metals	−3.416**(2)	−12.801***(1)	−3.678***(4)	−21.261***(7)
EL Fabricated metal products	−3.251**(10)	−9.134***(4)	−6.250***(5)	−61.866***(162)
EL Computer and electronic products	−2.821(6)	−5.572***(5)	−6.559***(7)	−29.227***(16)
EL Transport products	−3.790**(3)	−8.278***(3)	−4.622***(4)	−19.890***(11)
EL Furniture and other manufacturing	−1.940(6)	−5.678***(5)	−3.273**(2)	−25.390***(30)
Swedish news based EPU index	−9.18***(0)	−7.141***(8)	−9.186***(0)	−71.930***(162)
Global economic policy uncertainty	−4.146***(1)	−10.325***(2)	−4.827***(5)	−19.3125***(13)
Electricity market uncertainty	−2.096(0)	−10.873***(0)	−2.227(1)	−10.604***(6)

Note: Augmented Dickey Fuller test, (lag) length is automatically decided based on AIC. maximum lags = 13. Philips-Perron test estimated with Bartlett kernel and automatic bandwidth selection by Newey-West. All series have been log-transformed. Power supply series have also been tested seasonally adjusted (the logarithm of seasonal adjusted series), where the symbols *, **, and *** represent the 10%, 5%, and 1% significance level

Table 9 Nonlinear unit root test

	Case 1	Case 2	Case 3
EL Mining, manufacturing, and minerals	−0.451(2)	−2.057(2)*	−3.670(2)**
EL Mining and quarrying	1.488(12)	0.332(12)	−1.237(12)
EL Food, beverage, and tobacco products	−0.604(2)	−1.445(2)	−2.403(2)*
EL Textile, clothing, leather, leather gods	0.145(6)	−1.351(6)	−1.657(6)
EL Wood, cork, straw, and plaiting	−0.401(6)	−3.507(2)***	−4.223(2)***
EL Pulp industry	0.253(2)	−1.147(2)	−3.310(2)*
EL Paper and paperboard industry	−0.884(1)	−0.199(1)	−3.620(1)**
EL Chemical, petroleum, pharmaceutical	−0.611(1)	−1.800(1)	−4.125(1)***
EL Rubber and plastic products	−0.335(2)	−3.611(2)***	−3.500(2)**
EL Other non-metallic mineral products	−0.146(2)	−1.656(2)	−1.656(2)
EL Basic metals	0.560(8)	−5.479(7)***	−5.823(7)***
EL Fabricated metal products	0.382(6)	−4.610(6)***	−4.606(6)***
EL Computer and electronic products	−1.457(2)	−1.597(2)	−2.161(2)
EL Transport products	−0.021(2)	−1.911(2)	−1.846(2)
EL Furniture and other manufacturing	0.349(6)	−2.610(6)	−2.724(6)
Swedish news based EPU index	0.285(4)	−1.428(4)	−1.623(4)
Global economic policy uncertainty	0.327(3)	−1.698(3)	−3.321(1)*
Electricity market uncertainty	−0.825(6)	−2.936(2)**	−2.952(2)
Critical values t_{NL}			
1%	−2.82	−3.48	−3.93
5%	−2.22	−2.93	−3.40
10%	−1.92	−2.66	−3.13

Note: Unit root, nonlinear STAR framework (KSS), t-statistics $H_0: \delta = 0$, $H_1: \delta > 0$ where the critical values of t_{NL} are presented at the end of the table. All series tested up to 20 lags using AIC criteria where the symbols *, **, and *** represent the 10%, 5%, and 1% significance level

various uncertainty measures. This implies that, for various reasons, industrial sectors display distinct impact patterns due to uncertainty. Consequently, linking different sectors through mechanisms such as energy system integration, sector coupling, or circular economy practices such as industrial symbiosis might either amplify or mitigate electricity use reactions to uncertain events. Therefore, when designing circular applications, it is essential to align with sectors that best fit the stability dynamics.

Limiting factors in this study include the preference for conducting a detailed investigation using at least daily data, and ideally hourly data for electricity use dynamics. Moreover, since sustainable solutions will primarily be implemented on a local scale through circularity, additional considerations must be taken into account concerning local conditions and industry-specific characteristics.

Table 10 Unit root tests control variables

Variable name	ADF		PP	
	Level	FD	Level	FD
Log series				
IPI Mining, manufacturing, and minerals	−2.929(1)	−17.723***(0)	−3.757**(4)	−20.949***(14)
IPI Mining and quarrying	−4.0338***(2)	−14.560***(1)	−6.049***(6)	−27.537***(15)
IPI Food, beverage, and tobacco products	−2.096(13)	−7.581***(7)	−6.291***(7)	−86.338***(101)
IPI Textile, clothing, leather, leather gods	−2.635*(2)	−13.283***(1)	−5.047***(7)	−30.763***(17)
IPI Wood, cork, straw, and plaiting	−1.457(3)	−10.602***(2)	−3.607***(8)	−27.165***(2)
IPI Pulp industry	−4.037***(2)	−8.875***(4)	−7.052***(6)	−25.688***(21)
IPI Paper and paperboard industry	−2.382(2)	−7.774***(4)	−4.209***(3)	−23.531***(20)
IPI Chemical, petroleum, pharmaceutical	0.360(3)	−14.015***(2)	−2.687(8)	−25.065***(3)
IPI Rubber and plastic products	−2.784*(1)	−12.675***(1)	−4.111***(7)	−21.514***(5)
IPI Other non-metallic mineral products	−2.316(2)	−15.747***(1)	−4.244***(8)	−22.256***(3)
IPI Basic metals	−2.423(1)	−16.912***(0)	−2.525(4)	−17.919***(8)
IPI Fabricated metal products	−2.701*(4)	−9.044***(3)	−4.044***(2)	−23.225***(24)
IPI Computer and electronic products	−2.028(2)	−12.711***(1)	−3.234**(3)	−22.731***(13)
IPI Transport products	−3.083**(2)	−10.035***(2)	−3.832***(2)	−25.228***(17)
IPI Furniture and other manufacturing	−1.822(4)	−9.312***(3)	−3.718***(2)	−25.552***(47)
Nord Pool system spot price	−2.516(5)	−5.238(5)***	−2.300(6)	−13.005(5)***

Note: Augmented Dickey Fuller test, (lag) length is automatically decided, based on AIC. maximum lags = 13. Philips-Perron test estimated with Bartlett kernel and automatic bandwidth selection by Newey-West. All series have been log-transformed. Power supply series have also been tested seasonally adjusted (the logarithm of seasonal adjusted series), where the symbols *, **, and *** represent the 10%, 5%, and 1% significance level

Declarations

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