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Technology Exports and Electricity Use in Turkey: Nonlinear Frequency Evidence

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Abstract:

This paper investigates the nexus between medium- and high-technology exports and electricity consumption from 2016M1 to 2025M05 in Turkey. Nonlinear features in the data lead the use of a Smooth Transition Regression model that shows entrepreneurial expansion which intensifies electricity demand, while technology exports further increase electricity consumption in the nonlinear regime. Foreign direct investment is observed to reduce energy demand in the high entrepreneurship regime. Both Bootstrap Toda–Yamamoto and Fourier Cumulative Frequency causality tests indicate unidirectional causality from technology exports to electricity use. Moreover, Wavelet Transform Coherence analysis confirms time-varying and frequency-dependent properties based on strong medium-term interactions. Overall, findings imply that augmentation of high-technology share in export basket should consider the energy-intensity of the production.

Keywords: Technology exports, Electricity consumption, Smooth transition regression, Frequency domain causality, Wavelet coherence

JEL classification: C82, E32, N7, Q43

1. Introduction

High-technology production is a process of generating goods and services that is grounded in advanced scientific and technical knowledge, resulting in products with high value-added characteristics (Loschky, 2010). In comparison with traditional manufacturing, such production involves higher fixed costs for initial units but considerably lower marginal costs for subsequent units. Software products are a case in point that once the first unit is produced, additional copies can be realized at minimal cost. This feature reflects the transformative nature of today's technologies, which is driven by automation and digitalization that characterize the knowledge economy.

However, this transformation also prompts important questions. A central issue is whether the expansion of high-technology production necessarily entails higher energy consumption. Meanwhile, advanced technologies often substitute for resource-intensive processes. Their production and diffusion may also increase demand for energy inputs, which create a trade-off between efficiency gains and energy dependence.

High-technology industries usually lean less on material resources and direct labour, but their expansion is closely linked with export performance (Liu et al., 2019). As the production and export of high-technology goods increase, so does the demand for energy required to power machinery, equipment, and logistics as well(Sadorsky, 2012). Since energy is a fundamental input in manufacturing (Can et al., 2021), the level of industrialization of a country determines the intensity of its energy usage (Dinh et al., 2021). Consequently, spikes in exports often necessitate a higher supply of energy so that energy-constrained countries resort to additional imports to meet production demands (Shakeel and Salam, 2020).

The literature underlines different mechanisms linking technology and energy demand to each other. Takase and Murota (2004) emphasize the substitution and income effects of information and communication technologies (ICTs). The substitution effect signifies energy savings through efficiency improvements, while the income effect corresponds to an increase in energy demand through households and transportation leaning on ICT-led growth. Therefore, the net effect of technology on energy usage depends on the balance of these forces (Kouton, 2019). Regarding developed economies, high technology production is usually supported by renewable energy adoption, whereas developing economies remain dependent on heavy industries that are highly energy-intensive and less environmentally regulated. This upholds fossil fuel reliance and results in higher carbon emissions (Shahbaz et al., 2014; Dinh et al., 2021).

Within this framework, the relationship between high-technology exports and energy consumption is particularly crucial for emerging economies like Turkey. This nexus is vital for policy, as it shapes not only industrial upgrading and innovation but also sustainability and energy development strategies.

This study contributes to the literature in three directions. First, it interrogates the nonlinear and frequency-dependent dynamics between electricity consumption and medium- and high-tech exports by moving beyond standard linear approaches. Second, it exerts advanced econometric methods as Smooth Transition Regression (STR), Bootstrap Toda–Yamamoto causality, Fourier-based causality tests, and Wavelet Coherence analysis to capture both short and long-run linkages. Third, it provides novel empirical evidence for Turkey, which is a country balancing rapid industrialization, energy dependency, and drives on technological upgrading.

The remainder of the paper is organized as follows. Section 2 reviews the stylized facts about energy and high-tech exportation in Turkey. Section 3 provides a brief literature review. Section 4 outlines the empirical methodology. Section 5 describes the data and variables. Section 6 presents the empirical findings. While Section 7 provides a complementary panel data analysis for international comparison, Section 8 concludes by underlining the main policy implications derived from findings.

2. Energy and High-Tech Exportation in Turkey: Stylized Facts

Turkey's energy structure is heavily dependent on fossil fuel imports. Net energy imports cover approximately 74% of the consumption (Republic of Türkiye Ministry of Foreign Affairs, 2024). So, the economy becomes highly vulnerable to external prices and supply shocks due to over reliance particularly on oil, coal, and natural gases. Moreover, fossil fuels accounted for 80.2% of Turkey's total energy consumption in 2024 (Ember; Energy Institute, 2025). Such dependence not only enhances exposure to global energy market fluctuations, but also imposes structural vulnerabilities into production costs, trade balances, and industrial competitiveness.

Table 1: High Technology Exports (% of Manufactured Exports)

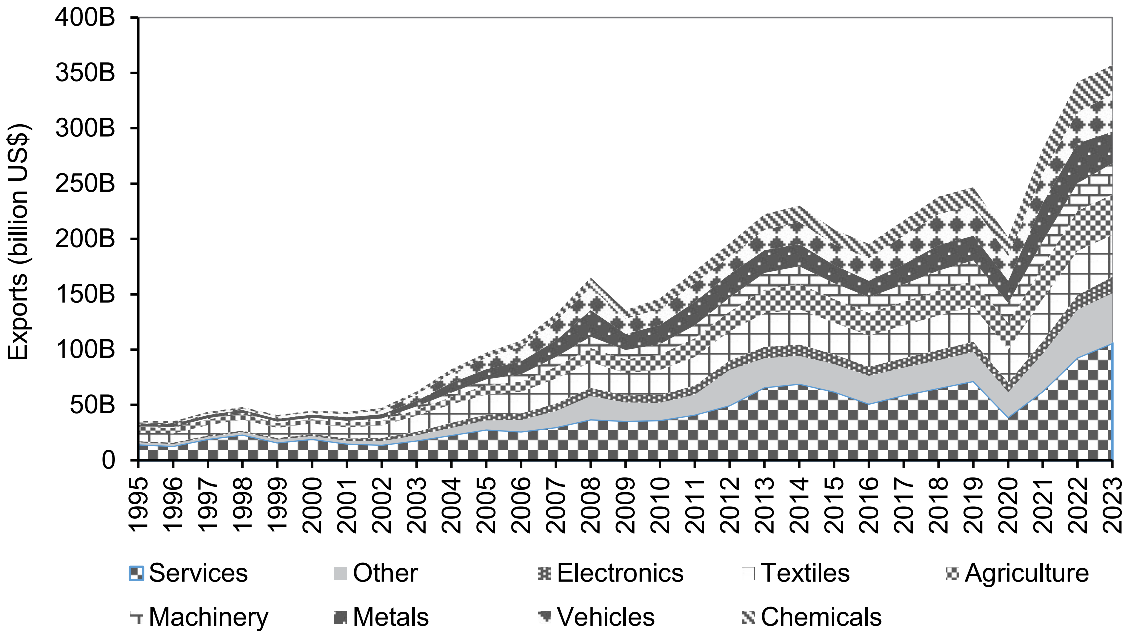
Country	2018	2019	2020	2021	2022	2023
EU	15.74	16.33	16.26	16.31	19.13	19.18
MENA	4.04	4.18	7.25	7.16	6.82	9.30
Low income	2.89	5.63	1.98	2.06	2.43	1.66
Lower middle income	18.61	19.22	20.98	19.08	20.59	15.74
Upper middle income	24.05	23.69	25.25	23.68	22.70	22.08
High income	19.69	19.94	20.93	21.03	23.21	23.45
Turkey	2.67	3.03	3.15	3.28	3.66	4.52

Source: The World Bank, 2025

Table 1 displays the share of high-technology exports across different income groups and regions. It is evident that Turkey maintains a relatively weak position in high-tech exports compared to global benchmarks. For instance, the EU average surpassed 19% in 2023, whereas Turkey's ratio was only 4.52%. While Table 1 reports data up to 2023, The World Bank (2025) data indicates that Turkey's share increased to 5.14% in 2024. It is seen that rate is markedly below the levels observed in upper middle-income economies.

These findings align with Kharas and Kohli's (2011: 53) argument that middle-income countries must reorient their manufacturing structures toward more capital and skill-intensive activities, while also complying with global consumer preferences to achieve higher value-added production. The relatively small share of high-tech exports underscores the structural challenges moving up the global value chain in Turkey's case.

Figure 1: Export Structure of Turkey by Technological Intensity



Source: Growth Lab at Harvard University, 2024

Figure 1 demonstrates the technological intensity of Turkey's exportation sectors. While traditional manufacturing sectors such as textiles, motor vehicles, and basic metals dominate the export basket, high-tech industries have yet to achieve a competitive scale. This asymmetry indicates that energy-intensive, low-to-medium technology sectors still dominate the structure of exports.

These stylized facts accentuate two crucial points. First, Turkey's energy demand is structurally dependent on fossil fuels that leads to higher sensitivity to external energy markets. Second, the low share of high-tech exports denotes a limited ability to offset energy dependency through technology-driven productivity gains. Together, these dynamics outline the nexus between energy consumption and high-tech exports in the Turkish framework.

3. Literature Review

Sun and Anwar (2015) argue that technological development reduces transportation and communication costs, thereby fostering international trade. Similarly, Agarwal (1992: 274) emphasizes the shift of world economies from quantity to quality-driven structures, underlining the role of knowledge-based production and technological progress in shaping export performance. In line with this, Aboal et al. (2016) investigate whether the technological content of exports contributes to economic development. Their analysis highlights the importance of knowledge intensity and production diversity, suggesting that countries must enhance the value-added and technological sophistication of their exports to converge with the development paths of advanced economies.

Nelson (1987) emphasizes the tacit nature of technological knowledge, which makes imitation and the application of new techniques particularly difficult for firms in less developed countries. Archibugi and Pietrobelli (2003: 863) further note that the acquisition of a new technique does not automatically guarantee production efficiency; rather, it becomes usable only after repeated trials and a process of learning by doing (Nelson, 1987: 88). On the other hand, Arora and Siddiqui (2020: 9) argue that a firm's participation in the global value chain, by engaging in different stages of production, enhances productivity and generates technology spillovers for the host country. Through these connections, firms gain access to know-how, ideas, and investment, linking high value-added tasks with foreign technologies. This, in turn, strengthens export competitiveness and ultimately enhances technological capacity and economic development.

According to Schumpeter (1942/2003), entrepreneurship is a vital determinant of economic development through its role in facilitating credit creation. However, credit demand does not immediately generate purchasing power; it materializes in later stages of production, through product sales and the repayment of borrowings. Wang and Shao (2023) highlight the role of entrepreneurship in shaping the impact of digitalization on energy conservation, emphasizing the crucial contribution of the Internet and Industry

4.0 technologies. Similarly, Sadegh-Vaziri (2013) argues that technology acts as a key driver of domestic production, competition, trade, and living standards. Yet, economic development is also driven by the demand for technology, which in turn increases energy consumption. According to Wang and Shao (2023), this adverse impact on energy stems from infrastructure limitations and the high costs of new digital equipment.

Liu et al. (2021) argue that quality-based production and technological innovations aligned with contemporary environmental needs contribute to the reduction of fossil fuel-oriented energy consumption. Similarly, An et al. (2020) highlight the necessity of technological progress and industrial upgrading as crucial mechanisms to reduce fossil fuel-dependent electricity consumption without undermining economic development.

Liu et al. (2021) further investigate the nonlinear relationship between energy consumption, technological innovation, supply chain management, and entrepreneurial performance across 115 manufacturing firms in China over the period 2010–2019, applying Hansen's (1999) threshold methodology. Their findings indicate an inverse S-shaped nonlinear relationship between enterprise performance and energy consumption, and technological innovation exhibiting a significant threshold effect in this dynamic. Specifically, the influence of energy consumption on enterprise performance intensifies above a certain level of technological innovation, while energy consumption itself also exerts a threshold effect towards the impact of technological innovation on enterprise performance.

Sun and Anwar (2015) examine the relationship between electricity consumption, industrial production, and entrepreneurship in Singapore using an ARDL model and the Granger causality test with monthly data covering 1983–2014. Bounds testing confirms the presence of cointegration among the variables, and the results indicate that entrepreneurship Granger-causes electricity consumption.

Wang and Shao (2023) analyse the link between the digital economy and energy efficiency in China, employing system GMM and threshold models separately. According to the GMM results, an increase in digitalization has a significant positive impact on energy efficiency. Moreover, the threshold model results reveal that the positive impact of the digital economy on energy efficiency is particularly pronounced at higher levels of entrepreneurial innovation.

Dinh et al. (2021) examine the impact of the share of medium- and high-tech exports on the share of renewable energy in nine ASEAN countries using panel data covering 1994–2015. They employ the Driscoll-Kraay (1998) fixed effects method by including inflation, employment, population growth, and GDP per capita as control variables. The findings indicate that the share of medium- and high-tech exports has a U-shaped effect on renewable energy. The effect is negative at lower levels of development but becomes positive once economic development surpasses a certain threshold.

Meanwhile, Sharma et al. (2021) analyse the effect of export diversification and technological innovation on renewable energy consumption in BRICS countries using a CS-ARDL model for the period 1990–2018. Their results suggest that exports of new products decrease renewable energy consumption, while exports of traditional products increase renewable energy use in the long run. These findings imply that BRICS countries face trade-off between promoting new product exports and supporting renewable energy consumption. Nevertheless, Berke et al. (2025) investigate the impact of export diversification on carbon emissions in Turkey using nonlinear ARDL model over the period 1995–2018. Findings signify that negative shocks in export increase carbon emissions whilst positive shocks decrease it.

Xue et al. (2022) examine the nexus between energy consumption and digital economy in 30 Chinese cities using panel data covering 2011–2018. Their spatial regression results reveal that the digital economy increases the overall scale of energy consumption whilst, it simultaneously optimizes the structure of energy consumption in favour of clean energy. The findings suggest that the digital economy provides a new pathway for reducing energy waste. Accordingly, enterprises are encouraged to focus on technological innovation and digital transformation.

Similarly, Fang et al. (2022) emphasize the need for an entrepreneurial class to develop, advance, and promote Internet and network-based technologies, since regional entrepreneurship levels directly affect innovation efficiency. They employ a panel threshold model for 30 Chinese provinces over the period 2006–2018. It is obtained that both Internet penetration and entrepreneurship exert a significant positive impact on green innovation efficiency. Moreover, entrepreneurship demonstrates a two-threshold regime effect in this relationship, which becomes more prominent beyond certain threshold levels.

4. Empirical Methodology

The nonlinear time series models were studied by Tong (1978, 1980), and it was further developed in Tong and Lim (1980) with the introduction of threshold autoregressive models. Tsay (1989) proposed a systematic procedure for threshold estimation and model construction as well. Furthermore, Hansen (2000) offered a more robust approach to empirical applications by introducing a parsimonious estimation strategy for nonparametric functions in nonlinear threshold models.

Teräsvirta (1994) unified the autoregressive and exponential autoregressive approaches into a single context, which is denoted as the Smooth Transition Autoregressive (STAR) model. The specification of a STAR model begins with the procedure of nonlinearity tests (Escribano and Jordà, 1999: 289). According to Teräsvirta (1994: 208) the STAR model provides the appropriate nonlinear specification, if linearity is rejected. The logic behind the nonlinearity test is rooted in the dynamics of business cycles due to the different adjustment processes of the upward and downward phases. Such asymmetries cannot be adequately captured by linear models (Rothman, 1991: 291). Instead of this, transitions between contraction and expansion can occur in a smooth rather than acute pattern (Teräsvirta and Anderson, 1992: 121). Consequently, the STAR models are especially beneficial for analysing nonlinear nexuses, which allow parameters to switch smoothly over time (Zeng et al., 2018: 1205). According to Teräsvirta and Anderson (1992), a p-order STAR model is expressed in Equation 1.

$$y_t = \pi_{10} + \pi_1^{'} w_t + \left(\pi_{20} + \pi_2^{'} w_t\right) F\left(y_{t-d}\right) + u_t \tag{1}$$

F states the transition function, which takes values range between zero and one. The error term u_t is assumed to be distributed normally and independently. Vectors are defined as $\pi_j = (\pi_{jt}, ..., \pi_{jp})'$, $w_t = (y_{t-1}, ..., y_{t-p})'$. The STAR model uses two types of transition functions, which are expressed in Equation 2 and 3.

$$F(y_{t-d}) = \left(1 + \exp\left[-\gamma\left(y_{t-d} - c\right)\right]\right)^{-1}, \ \gamma > 0 \tag{2}$$

$$F(y_{t-d}) = \left(1 - \exp\left(-\gamma\left(y_{t-d} - c\right)^2\right)\right), \ \gamma > 0 \tag{3}$$

Equation 2 denotes the logistic form of the STAR model. Equation 3 expresses the exponential form of the STAR model. Here, c represents the threshold value, while γ controls the smoothness of the transition between regimes.

Eitrheim and Teräsvirta (1996) propound three key diagnostic tests to ensure the consistency and adequacy of the STAR models. The first is the LM test for autocorrelation, which assesses the absence of serial dependence of error terms and ensures the validity of parameter estimates. The second test examines additive nonlinearity that verifies whether the chosen specification sufficiently captures the nonlinear dynamics in the data. The third test is related with parameter stability, which detects potential misspecification in the autoregressive structure by measuring structural breaks and instabilities in parameters. These diagnostics provide an extensive frame for validating the robustness and reliability of the STAR models.

$$y_t = \beta_0 + \beta_1^{'} w_t + \sum_{j=1}^{p} \beta_{2j} y_{t-j} y_{t-d} + \sum_{j=1}^{p} \beta_{3j} y_{t-j} y_{t-d}^{2} + \sum_{j=1}^{p} \beta_{4j} y_{t-j} y_{t-d}^{3} + v_t \quad (4)$$

Equation 4 represents the third-order Taylor expansion of the STAR model. Linearity is tested under the null hypothesis $H_0 : \beta_{2j} = \beta_{3j} = \beta_{4j} = 0$, against the alternative nonlinear STAR. A series of nested hypotheses are expressed from Equations 5 to 7 for the choice between the LSTAR and the ESTAR forms.

$$H_{04} : \beta_{4j} = 0, \; j = 1, \ldots, p \quad (5)$$

$$H_{03} : \beta_{3j} = 0 \middle| \beta_{4j} = 0, \; j = 1, \ldots, p \quad (6)$$

$$H_{02} : \beta_{2j} = 0 \middle| \beta_{3j} = \beta_{4j} = 0, \; j = 1, \ldots, p \quad (7)$$

The selection criteria are determined as follows: If H_{04} is rejected then, the appropriate specification is the logistic LSTAR model. If H_{04} is accepted but H_{03} is rejected, ESTAR form is chosen. If H_{04} and H_{03} are accepted and H_{02} is rejected, the specification is again supported by the LSTAR model (Teräsvirta and Anderson, 1992: 122; Khadaroo, 2003: 770).

$$y_t = \beta'_0 w_t + (\theta'_0 w_t) F_1 (y_{t-d}; y_1, c) + \beta'_1 \overline{w}_t y_{t-e} + \beta'_2 \overline{w}_t y^2_{t-e} + \beta'_3 \overline{w}_t y^3_{t-e} + r_t \quad (8)$$

Equation 8 expresses the third-order Taylor approximation of the additive STAR model (Eitrheim and Teräsvirta, 1996: 64–65). This specification is designed to test for the existence of remaining nonlinearity. The entity of additive nonlinearity would correspond to a potential misspecification in the nonlinear structure. The null hypothesis assumes no additional nonlinearity, $H_0'' : \beta_1 = \beta_2 = \beta_3 = 0$ is tested against the alternative of nonlinear components remain extra (Dijk et al., 2002: 14).

$$y_t = \pi(t) \tilde{w}_t + \theta(t) \overline{w}_t F(y_{t-d}; \gamma_1, c) + u_t \quad (9)$$

Equation 9 describes the STAR model with smoothly changing parameters over time (Eitrheim and Teräsvirta, 1996: 67). While the standard STAR perspective assumes constant parameters, the functions of $\tilde{\pi}$, and $\overline{\theta}$ are allowed to change over time. The null hypothesis is that parameters remain stable in this case. $H_0 : H_j (t, \gamma_1, c_1) \equiv 0$ is tested against the alternative of parameter instability by using the LM test.

4.1 Unit Root Methodology

Dickey and Fuller (1979: 427) integrate the concept of a unit root within an autoregressive frame as stated in Equation 10. The null hypothesis $H_0 : \rho = 1$ indicates the existence of a unit root, whereas the alternative reflects stationarity in this specification.

$$y_t = \rho y_{t-1} + \varepsilon_t , \quad t = 1, 2, ..., T, \quad \varepsilon_t \sim iid\ N(0, \sigma_\varepsilon^2) \tag{10}$$

The Augmented Dickey–Fuller (ADF) regression includes lagged differences of the dependent variable to take higher-order serial correlation into consideration as shown in Equation 11.

$$\Delta y_t = \beta y_{t-1} + \sum_{j=1}^{\rho} \delta_j y_{t-j} + \varepsilon_t \tag{11}$$

Im et al. (2014: 321–322) put forward the Residual Augmented Least Squares (RALS) approach, which increases the power of unit root test under non-normal error distributions on this basis. This extension is described in Equation 12, where v_t denotes non-normal errors and $\widehat{w}_t$ represents residual functions that is derived from the Dickey–Fuller regression. The parameter $\hat{\rho}^2 = \hat{\rho}_A^2 / \hat{\sigma}^2$ determines the distribution of the test statistic, which $\hat{\sigma}^2$ is attained from the ADF regression and $\hat{\rho}_A^2$ from the RALS regression.

$$\Delta y_t = \alpha_1 + \alpha_{2t} + \beta y_{t-1} + \sum_{j=1}^{\rho} \delta_j \Delta y_{t-j} + \hat{w}_t^{'} \gamma + v_t \tag{12}$$

Enders and Lee (2012) incorporate a Fourier approximation into the ADF framework to capture nonlinear dynamics. So, frequency parameter k enables to model smooth structural breaks endogenously in Equation 13. Null hypothesis $H_0 : \rho = 0$ corresponds to a linear unit root, while the alternative supports a nonlinear stationary process.

$$\Delta y_t = \rho y_{t-1} + c_1 + c_{2t} + c_3 \sin\left(2\pi kt / T\right) + c_4 \cos\left(2\pi kt / T\right) + \varepsilon_t \tag{13}$$

Finally, Kılıç (2011) extends unit root test through an ESTAR-based nonlinear framework in Equation 14. The transition variable $z_t = y_{t-d}$ drives nonlinear adjustments in this approach. The null hypothesis of $H_0 : \phi = 1$ implies a linear unit root, whereas the alternative supports nonlinear stationarity within the ESTAR process.

$$\Delta y_t = \sum_{i=1}^{\rho} \delta_i \Delta y_{t-i} + \phi y_{t-1} (1 - \exp\left(-\gamma z_t\right)^2)) + u_t \tag{14}$$

4.2 Causality and Wavelet Coherence Methodology

This study employs three complementary econometric techniques to provide a robust analysis of the dynamic relationship between electricity consumption and medium- and high-tech exportation in Turkey: i) Bootstrap Toda–Yamamoto (BTY) causality test, ii) Fourier Cumulative Frequency Toda–Yamamoto (FTY) causality test, and iii) Wavelet Transform Coherence (WTC) analysis. While the Bootstrap Toda–Yamamoto test provides robust causality inference in a linear VAR framework by correcting small-sample distortions, the Fourier Cumulative Frequency approach captures frequency-dependent causalities, and the Wavelet Coherence analysis allows for exploring time-frequency localized nonlinear interactions.

The Bootstrap Toda–Yamamoto (BTY) causality test is developed by Hacker and Hatemi-J (2006). It extends the classical Toda–Yamamoto (1995) approach by including bootstrap simulations into small sample properties. The estimation of a $VAR(p+d_{max})$ model is stated in Equation 15.

$$Y_t = \alpha + \sum_{i=1}^{\rho+d_{max}} \Phi_i Y_{t-i} + \varepsilon_t \tag{15}$$

where ρ is the optimal lag length, d_{max} is the maximum order of integration among variables, and Y_t is the vector of variables. The BTY test exercises bootstrap critical values to the Wald statistics, which ensures more accurate statistical inference in finite samples.

Despite the BTY enables robust causality test, its ability to capture frequency dependent causal relationships is limited. This study further employs the Fourier Cumulative Frequency Toda–Yamamoto (FTY) test, which is proposed by Nazlıoğlu et al. (2016). The FTY is particularly effective in distinguishing between short- and long-run causality based on frequency distribution.

$$C_{x\to y}(w) = \frac{1}{\pi}\int_0^w f_{x\to y}(\lambda)d\lambda \tag{16}$$

The model for FTY is expressed in Equation 16, where $f_{x\to y}(\lambda)$ implies the causality measure at local frequency. λ, and w subtend to the target frequency in cumulative causality measurement. Fourier approximation is used to model potential smooth structural shifts by assessing causality across different ranges of horizons in the data.

This paper further employs the WTC method to capture the time-varying character of the nexus between electricity consumption and medium- and high-tech exports. The methodology of Torrence and Compo (1998), Torrence and Webster (1999), and Grinsted et al. (2004) is pursued for the WTC method in the study. The WTC permits the decomposition of time series into the time-frequency domain by identifying both the direction and strength of the relationships at different time periods. The continuous wavelet transforms of a time series $x(t)$ is defined with a mother wavelet (ψ) in Equation 17.

$$W_x\left(s,\tau\right)=\int_{-\infty}^{\infty}x\left(t\right)\frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right)dt \tag{17}$$

where s is the scale related to frequency, $1/\sqrt{s}$ is the normalization factor for the transformation of wavelet, and τ denotes frequency related time position. The wavelet transform provides both time and frequency localization in this form. The WTC between two series $x(t)$ and $y(t)$ is stated in Equation 18.

$$R^2\left(s,\tau\right)=\frac{\left|S\left(s^{-1}W_{xy}\left(s,\tau\right)\right)\right|^2}{S(s^{-1}\left|W_x\left(s,\tau\right)\right|^2\times S\left(s^{-1}\left|W_y\left(s,\tau\right)\right|^2\right)} \tag{18}$$

where S is a smoothing operator, and W_{xy} is the cross-wavelet transform. R^2 (s,t) is analogous to a squared correlation coefficient for each frequency and moment in time. It measures the strength of time-frequency co-movement, and its values lie between 0 and 1 from no dependence to perfect dependence (Crowley, 2007; Rua, 2010).

5. Data and Variables

This study employs monthly data spanning from January 2016 to May 2025. All dataset is arranged from the Turkish Statistical Institute (TurkStat), and the Central Bank of the Republic of Türkiye- Electronic Data Delivery System (CBRT-EVDS). The next flux present variables and their definitions, whereas all data sources and related transformations are detailly explained in Appendix C.

Medium- and High-Technology Exports (TECHX) is an aggregated data, which is constructed as a sum of sectors of medium- and high-tech components. It is arranged from TurkStat ISIC Rev. 4. classification. TECHX is generated as the total of sections C20, C21, and from C26 to C30 leaning on the Eurostat (2022) NACE REV.2.2 medium- and high-tech manufacturing taxonomy, which is implementing methodological consistency with international standards. Sectoral compositions are presented in Appendix A. Electricity Consumption (ELEC) is defined as the total electricity consumption measured in MWh as a proxy of energy demand.

Entrepreneurship (ENTREP) is measured as the net difference between the number of newly established and liquidated firms, which captures the dynamics of entrepreneurial activities. This variable is specified as the threshold variable to probe whether the effect of technology exports on electricity demand exhibits regime-dependent dynamics. The standardized transformation of transition variable is documented in Appendix C. Foreign Direct Investment (FDI) is described as inward FDI inflows that corresponds to the external capital component of economic development. Employment (EMP) refers to total employment levels, which is used as a control to account for labour market dynamics.

All series are seasonally adjusted with the U.S. Census Bureau's X-13 ARIMA-SEATS procedure. Then, series are corollary transformed into logarithmic first differences to eliminate non-stationarity, and permit for comparability across variables. Overall, the dataset is structured for the examination of the nonlinear regime-dependent relationship between medium- and high-tech exports and electricity consumption by controlling for entrepreneurship dynamics, capital inflows, and labour market conditions.

Table 2: Descriptive Statistics of Variables

	D(LELEC)	D(LTECHX)	D(LENTREP)	D(LFDI)	D(LEMP)
Mean	0.002	0.008	0.003	−0.002	0.002
Maximum	0.101	0.391	0.996	1.796	0.049
Minimum	−0.145	−0.417	−1.020	−1.675	−0.052
Std. Dev.	0.039	0.121	0.245	0.668	0.014
Skewness	−0.677	−0.353	−0.003	0.019	−0.005
Kurtosis	5.552	5.035	7.626	3.119	6.618

Source: Author's own calculations

The descriptive statistic of each variable is reported in Table 2. Findings demonstrate that all series render high kurtosis values, which point significant deviations from the normal distribution. Particularly, entrepreneurship (D(LENTREP)) and employment (D(LEMP)) display the highest leptokurtic behaviour, followed by electricity consumption (D(LELEC)) and technology export (D(LTECHX)). This indicates the presence of fat tails and potential extreme observations. The skewness coefficients also show slight departures from symmetry, though none are excessively large. Another noteworthy finding is the relatively high volatility of foreign direct investment (D(LFDI)), as reflected by its large standard deviation compared to the other variables. These statistical properties collectively point to possible nonlinear dependence structures in the data. Therefore, the linearity of the series is further investigated using the McLeod and Li (1983) test to provide a more reliable model specification.

6. Empirical Findings

Linearity properties of the variables were assessed with the McLeod-Li test, applied to the squared residuals. Results are reported in Table 3.

Table 3: Linearity Test

D(LELEC)	D(LTECHX)	D(LENTREP)	D(LFDI)	D(LEMP)
149.318***	161.522***	141.775***	160.764***	126.346***

Notes: *** indicates significance at 0.01 level. Maximum lag is determined as 13. Robustness check is also done up to maximum 20 lag.

Source: Author's own calculations

The null hypothesis of linearity was rejected for all variables at conventional significance levels, indicating the presence of nonlinear dependence in the data. This outcome indicates that purely linear specification may be inadequate and supports the adoption of nonlinear modelling approaches in the subsequent analysis.

Table 4: Findings of Unit Root

			Demeaned		
	D(LELEC)	**D(LTECHX)**	**D(LENTREP)**	**D(LFDI)**	**D(LEMP)**
ADF	−6.315***	−17.620***	−15.726***	−11.648***	−10.997***
RALS-ADF	−6.973***	−24.748***	−21.978***	−12.102***	−13.461***
Fourier ADF	−6.789***	−17.898***	−8.628***	−8.609***	−11.240***
Kılıç (2011)	−2.885**	−3.347***	−3.108***	−3.540***	−2.459**
		Detrended			
ADF	−6.285***	−17.539***	−15.665***	−11.593***	−10.956***
RALS-ADF	−6.951***	−24.623***	−21.935***	−12.045***	−13.362***
Fourier ADF	−6.764***	−17.812***	−7.141***	−8.578***	−11.354***
Kılıç (2011)	−2.884**	−3.346***	−3.556***	−3.614***	−2.493*

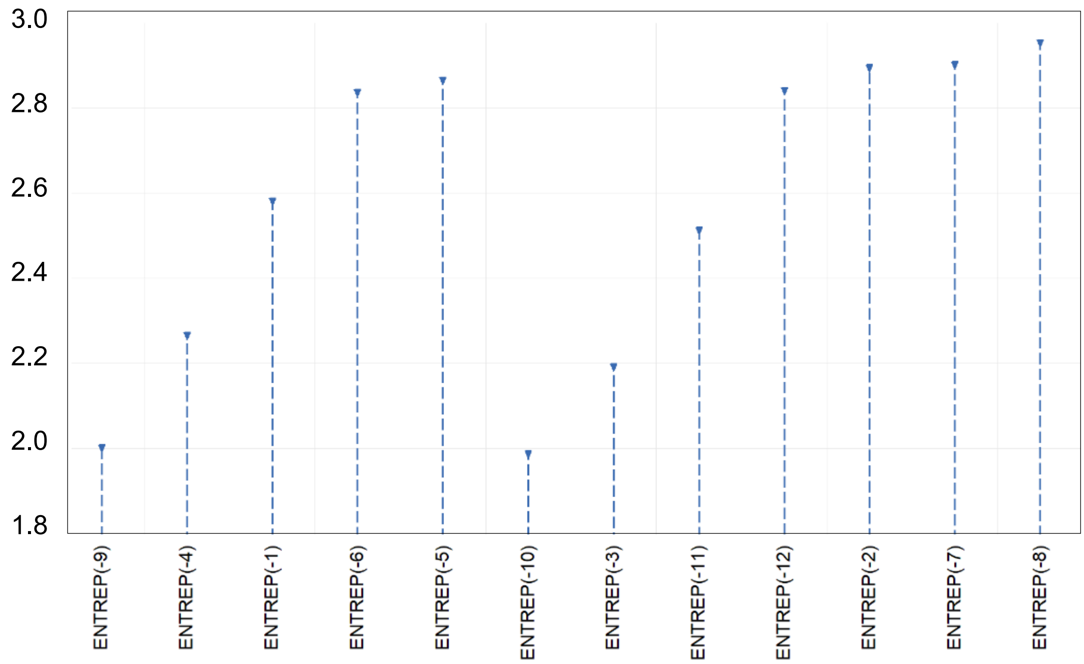
Notes: *, **, *** indicates significance at 0.10, 0.05, and 0.01 levels, respectively. Schwarz criterion is used for all test statistics up to maximum 13 lags.

Source: Author's own calculations

Findings of unit root are displayed in Table 4. All the null hypotheses of a unit root presence were rejected leaning on ADF test. All variables were achieved stationary at their logarithmic first difference level. RALS-ADF test was employed as a more powerful test for non-normal error distribution, which ensures akin findings. Fourier ADF investigates the existence of a unit root based on frequency components of smooth structural breaks. All the null hypotheses of existence of unit root were rejected with Fourier ADF as well. Kılıç (2011) introduces an ESTAR form unit root test. The null hypothesis of unit root presence was tested against alternative hypothesis of nonlinear stationarity. All variables were found stationary at 10% significance level. Fourier ADF accounts for smooth structural breaks in the frequency domain, whereas the nonlinear test of Kılıç (2011) explicitly considers nonlinear adjustment dynamics, both of which confirm the robustness of the unit root rejection. Since ADF, RALS-ADF and Fourier ADF tests evaluate the same unit-root null hypothesis under different assumptions, it is adopted a conservative joint decision rule to avoid size distortions from multiple testing. Specifically, stationarity is concluded only when consistent rejection occurs across procedures; otherwise, the series is treated as non-stationary. This ensures robust pre-testing and eliminates the risk of false significance due to multiple comparisons.

6.1 Findings of Smooth Transition Regression

Figure 2: Lag Length of Threshold Variable



Source: Author's own calculations

Figure 2 illustrates the lag length determination for the threshold variable D(LENTREP). Although the 10th lag of the transition variable produced a marginally lower sum of squared residuals (SSR), the specification with the 9th lag was ultimately preferred. This choice is supported by the coefficient consistency, and more theoretically coherent transition dynamics in the 9th lag model.

It was examined alternative transition variable lags around the optimal indication (i.e., lags 8 and 10 instead of 9). These alternative specifications created substantially different nonlinear dynamics and weakened the significance of transition effects. This reflects that transition variable is highly time-specific in the STR model. Therefore, the selection of 9 lag is the most appropriate specification for the transition variable. It enables both statistically significant parameters and coherent economic interpretation for the model. A robustness comparison is presented for the transition delays (8, 9, and 10) in Appendix D.

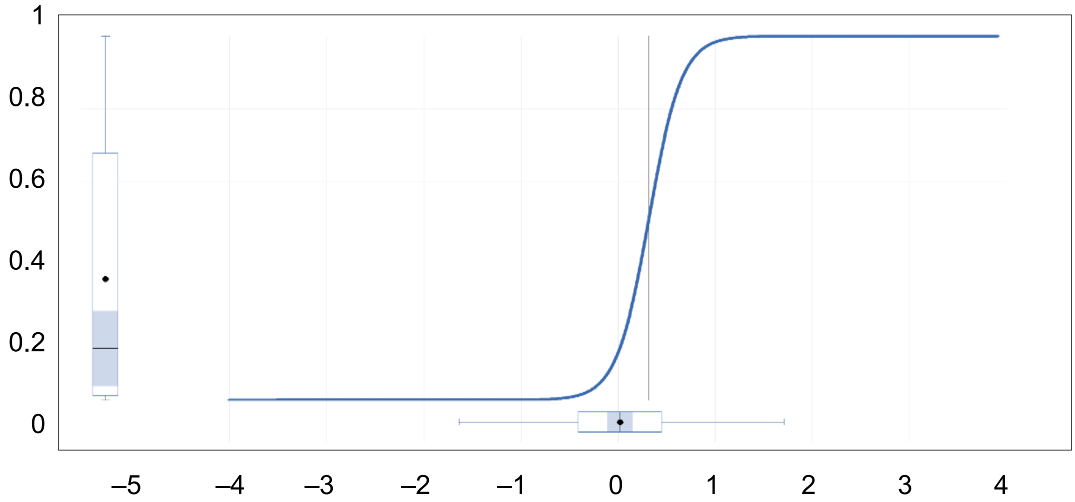
Table 5: Threshold, Slope and Summary Statistics of Threshold Weights

Lag Values	Coefficient	Std. Error
γ	5.960	4.437
c	0.318**	0.151
Mean	0.332	
Median	0.142	
Maximum	1.000	
Minimum	0.000	
Std Dev.	0.376	
Skewness	0.785	
Kurtosis	1.964	
Observations	103	

Note: ** indicates significance at 0.05 level.
Source: Author's own calculations

Table 5 presents the summary statistics of threshold weight. Both skewness and kurtosis are within the acceptable range, whereas threshold location parameter (c) reflects statistically significant findings. While the slope parameter (γ) is not statistically significant, this does not undermine the validity of the STR model, since the threshold effect is significant and the nonlinear component yields meaningful results. In fact, STR models do not require (γ) to be significant as stated by Teräsvirta (1994) and Dijk et al. (2002); rather, the essential point is whether the threshold effect exists, which is clearly confirmed in our case.

Figure 3: Graphical Illustration of Threshold Weight Function



Source: Author's own calculations

Figure 3 illustrates the transition function, which exhibits a smooth and gradual adjustment across regimes. Although the slope parameter (γ) is not statistically significant, this does not invalidate the presence of smooth transition behaviour. The threshold location parameter (c) is significant, and the nonlinear part of the model yields meaningful results, confirming that the regime change occurs in a gradual rather than abrupt manner. Hence, both statistical evidence and graphical representation support the presence of smooth transition dynamics in the model.

Table 6: Diagnostic Checks

Variables	Test Statistics	Probability
Jarque-Bera	4.372	0.112
LM (1)	0.707	0.402
LM (2)	2.278	0.108
LM (12)	1.414	0.177
Breusch-Pagan-Godfrey	0.264	0.900
White	1.606	0.110

Source: Author's own calculations

Table 6 presents the diagnostic check for the residuals of the model. According to the Jarque-Bera statistic, the residuals render normal distribution. The LM statistic verifies that there is no serious autocorrelation problem. The Breusch-Pagan-Godfrey and White tests confirm the absence of heteroskedasticity in variance of errors. Multicollinearity was assessed by using the Variance Inflation Factor (VIF), its value was found as 2.40. It is well below the traditional threshold value, which is 10. This validates the absence of multicollinearity in line with Filipescu et al. (2013) and Dinh et al. (2021).

Table 7: Linearity Tests

Hypotheses	F-Statistics	Probability
$H_{01}: \beta_1 = 0$	5.522	0.000
$H_{02}: \beta_1 = \beta_2 = 0$	3.260	0.001
$H_{03}: \beta_1 = \beta_2 = \beta_3 = 0$	2.360	0.007
$H_{04}: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$	2.270	0.006

Source: Author's own calculations

Table 7 notifies the findings of the linearity tests of the model depending on a fourth-order Taylor expansion. The null hypothesis of linearity presence is tested against the alternative of a nonlinear STAR model (Teräsvirta and Anderson, 1992: 122). All four hypotheses were rejected at conventional significance levels that verifies the nonlinearity of the model. Among these the rejection of H_{01} has the highest F-statistics. It corresponds that the logistic form is the most appropriate procedure for the model.

Table 8: Additive Non-Linearity Tests

Hypotheses	F-Statistics	Probability
$H_{01}: \beta_1 = 0$	**1.641**	**0.158**
$H_{02}: \beta_1 = \beta_2 = 0$	**1.936**	**0.052**
$H_{03}: \beta_1 = \beta_2 = \beta_3 = 0$	**1.649**	**0.081**
$H_{04}: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$	**1.239**	**0.250**

Source: Author's own calculations

Table 8 demonstrates findings of the additive nonlinearity tests leaning on a fourth-order Taylor approximation. Additive nonlinearity assays whether there exists remaining nonlinearity, or not (Eitrheim and Teräsvirta, 1996: 60). Findings imply that H_{02} and H_{03} are marginally significant at the 10% level, whereas most hypotheses fail to reject linearity. It indicates the presence of weak remaining nonlinearity. The encapsulated nonlinearity test was further applied for the robustness.

Table 9: Encapsulated Non-Linearity Tests

Hypotheses	F-Statistics	Probability
$H_{01}: \beta_1 = 0$	1.480	0.162
$H_{02}: \beta_1 = \beta_2 = 0$	1.370	0.167
$H_{03}: \beta_1 = \beta_2 = \beta_3 = 0$	0.953	0.545
$H_{04}: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$	0.802	0.756

Source: Author's own calculations

Findings for the remaining nonlinearity of encapsulated tests take place in Table 9. All hypotheses could not be rejected at the 10% significance level. This validates the non-existence of remaining nonlinearity in the model. This outcome reflects that the STR specification sufficiently captures the nonlinear dynamics of the series, and no further nonlinear adjustment is required for the model.

Table 10: Parameter Stability Tests

Hypotheses	F-Statistics	Probability
$H_{01}: \beta_1 = 0$	0.826	0.605
$H_{02}: \beta_1 = \beta_2 = 0$	0.635	0.873
$H_{03}: \beta_1 = \beta_2 = \beta_3 = 0$	0.793	0.753
$H_{04}: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$	0.989	0.509

Source: Author's own calculations

Table 10 reports the findings of the parameter stability test. The null hypothesis states constant parameters against the alternative of smoothly changing parameters over time (Dijk et al., 2002: 15). The findings confirm that all hypotheses fail to reject constant parameters over time. Parameters of the nonlinear STR model are not smoothly changing over the sample period. This outcome indicates that both parameter instability and remaining nonlinearity are not issues for this model specification.

Table 11: Parameter Estimates of Smooth Transition Regression

Linear Part		
Variables	**Coefficient**	**Std. Error**
Constant	−0.003	0.004
D(LELEC) (−1)	−0.351***	0.105
D(LTECHX)	0.071*	0.040
D(LFDI)	0.011**	0.005
D(LEMP)	0.087	0.254
Nonlinear Part		
Constant	0.016**	0.007
D(LELEC) (−1)	0.349*	0.209
D(LTECHX)	0.148**	0.071
D(LFDI)	−0.023**	0.011
D(LEMP)	0.500	0.505
R2	0.559	
Adjusted-R2	0.505	
F Statistics (Prob)	38.855 (0.000)	
Akaike Criterion	−4.500	
Schwarz Criterion	−4.193	
Durbin-Watson Stat.	2.116	

Note: *, **, *** indicates significance at 0.10, 0.05, and 0.01 levels, respectively.
Source: Author's own calculations

Table 11 reports the parameters of the nonlinear STR model. The Durbin–Watson statistic confirms the absence of autocorrelation. The model explains approximately 56% of the variation in electricity consumption. Even though the lagged value of electricity consumption is statistically significant in both the linear and nonlinear regimes, the direction of its impact changes from negative to positive in the nonlinear regime. A 10% increment in the lag value of electricity consumption raises current electricity consumption by 3.49% in the high-entrepreneurship regime, which implies the additional energy burden at higher levels of entrepreneurship.

The impact of medium- and high-tech exports (TECHX) is positive and statistically significant in both linear and nonlinear regimes, but a stronger effect is observed in the nonlinear regime. A 10% rise in TECHX increases ELEC by 0.71% in the low-entrepreneurship regime, while the same shock leads to a 1.48% increase in the high-entrepreneurship regime. This indicates that electricity burden of export growth nonlinearly strengthens as the entrepreneurial activity exceeds a certain threshold level. Foreign direct investment has a dual impact across regimes. While it has statistically significant and positive effect in the linear regime, its impact turns into negative in the nonlinear regime. A 10% increase in FDI reduces ELEC by 0.23% in the high-entrepreneurship regime. This implies that higher FDI inflows may help to offset energy consumption pressures during upward phases of business activity.

The TECHX variable affects ELEC twice as strongly in the nonlinear regime. This necessitates a review of the relative weights of medium- and high-tech products within the TECHX composition, which takes place in Appendix A. One of the energy-intensive medium technology products as motor vehicles (C29) and transport equipment (C30) dominate the TECHX structure. Both together have approximately over 44% average weight, which explains the stronger nonlinear energy burden. TECHX becomes sensitive to alternative classifications if the components of C29 and C30 are excluded from the variable.

C29 has the largest share among all components, whereas the joint contribution of electrical equipment (C27), machinery (C28), C29, and C30 exceeds 75% on average over the period. These are capital- and electricity-intensive sectors, which induce a structural explanation for the stronger elasticity of TECHX in the nonlinear regime of the STR model. On the other hand, chemicals (C20), pharmaceuticals (C21), and computer, electronic, and optical products (C26) have a small share in the composition of the variable despite their lower electricity intensities. Transportation and machinery related manufacturing activities are mainly the drivers of the higher energy concentration during the whole period.

Turkey has undergone crucial structural shifts in energy demand during the sample period. Although the Covid-19 shock temporarily reduced electricity consumption in 2020, energy demand recovered in the post-pandemic period. However, medium- and high-tech exports are still predominantly driven by capital- and electricity-intensive sectors that reflect evidence of nonlinear electricity intensity in the STR findings. The nexus between technology-driven industrial expansion and electricity demand is not affected by such temporary shocks in the STR model. When total electricity use temporarily declines in the crisis periods, the sectors driving TECHX continue to impose a non-proportional energy burden. This reinforces the continuity of the nonlinear pattern in the findings.

The STR was re-estimated by adding a Covid-19 dummy to ensure the structural stability of the model. The fundamental nonlinear effect of TECHX remains intact, which is demonstrated in Appendix B. TECHX continues to significantly increase ELEC especially in the upward phases of business activity. Although some parameters become less precise due to the volatility during pandemic period, the main nonlinear conclusion is qualitatively preserved. Covid-19 only creates a temporarily statistically significant and negative impact in the linear regime. The Covid-19 dummy implies that electricity consumption growth declined by about 1.5% in the linear regime, whereas it increased by around 3.2% in the nonlinear regime. These findings confirm the robustness of the nonlinear relationship to the pandemic-induced shock.

6.2 Findings of Bootstrap T&Y and Fourier T&Y Causalities

Table 12 presents the Granger causality findings between ELEC and TECHX by employing the Bootstrap T&Y and Fourier T&Y approaches. The Toda and Yamamoto (1995) approach allows testing Granger causality in levels without pre-differencing the data by adding extra lags in the VAR framework. Since the variables have $d_{max} = 1$, they are analyzed in logarithmic levels rather than logarithmic first differences to avoid information loss.

Table 12: Dynamics of Causality

LTECHX ¿LELEC

Test	Wald Stat.	Asymptotic p	Bootstrap p	Optimal lag	k	d_{max}
Bootstrap T&Y	8.773**	0.012	0.019	2	-	1
Fourier T&Y	11.321***	0.003	0.006	2	3	1
	7.458**	0.024	0.028	2	2	1
	6.297*	0.043	0.052	2	1	1

LELEC ¿ LTECHX

Test	Wald Stat.	Asymptotic p	Bootstrap p	Optimal lag	k	d_{max}
Bootstrap T&Y	1.211	0.546	0.540	2	-	1
Fourier T&Y	0.693	0.707	0.710	2	3	1
	1.029	0.598	0.600	2	2	1
	0.855	0.652	0.640	2	1	1

Notes: *, **, *** indicates significance 0.10, 0.05 and 0.01 levels, respectively. Schwarz criterion is used for all test statistics up to maximum 13 lags. Maximum frequency (k) is determined as 3 for Fourier T&Y. Bootstrap critical values are attained with 10.000 replications.

Source: Author's own calculations

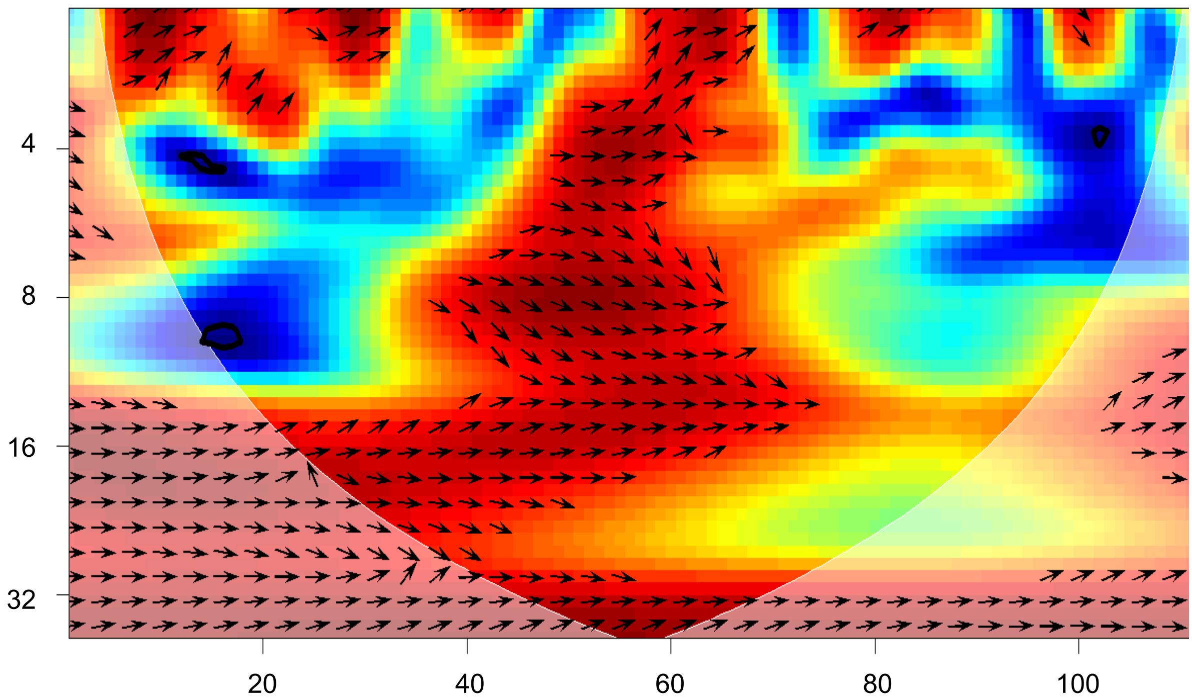
The Fourier T&Y causality test was performed by including three frequency components in level data. The analysis is restricted up to k ≤ 3 to avoid over-parameterization on the sample size (Nazlıoğlu et al., 2016). Even if maximum frequency is chosen as k=3, robustness check is also conducted for frequencies 2 and 1, which both yield similar findings. Low-frequency components correspond to permanent and long-term changes, while high-frequency reflect short-term fluctuations. Hence, the findings capture both short- and long-run dynamics of the causal nexus.

The results show that the Granger causality from TECHX to ELEC is statistically significant in all tests and variations, whilst reverse causality does not exist in any tests. On the other hand, the statistical significance of the findings gets stronger as the frequency increases for the causality from TECHX to ELEC in the Fourier T&Y tests. Besides lead-lag robustness check confirms one-way causality without feedback effect, which is reported in Appendix E. Moreover, a VAR-based Granger Causality test verifies this unidirectional causality with no feedback effect as an additional robustness check, which controls Global Brent Oil Price shocks as exogenous. This aims to consider the external shocks on this causality nexus, which is shown in Appendix F.

These findings imply a unidirectional causality running from TECHX to ELEC with a stronger impact in the short run. This promotes the view that energy demand is a derived factor in energy-intensive technology sectors. Overall, the evidence of the causality matches the STR findings. Technology exports are both statistically and economically significant in forming electricity demand. Energy capacity plans especially become crucial for the export-driven technology sectors during expansion periods of business activity.

6.3 Findings of Continuous Wavelet Coherent Analysis

Figure 4: Wavelet Coherence Analysis



Source: Author's own calculations

Figure 4 displays the continuous Wavelet Transform Coherence (WTC) analysis between TECHX and ELEC in Turkey. Time is represented on the horizontal axis of the graph. The vertical axis refers to the scale of months, which is inversely related to frequency.

The thick black arrow lines mark statistically significant regions at the 5% level. Red warm colours show high coherence, whereas cool blue colours denote lower coherence levels. The cone of influence (COI) indicates the area, which is not affected by edge effects. COI is represented by the semicircle in the figure. If the phase arrows point to the right, it means positive correlation and in-phase movement between the series. If phase arrows are prone upward, it implies that ELEC tends to lead TECHX. If arrows point downward, TECHX tends to lead ELEC.

The results mainly demonstrate persistent and statistically significant coherence in the medium-term of 8-16 months. The period is mostly visible during 2017-2020. This implies that TECHX and ELEC execute strong co-movement during the medium-term period. There is a positive correlation and in-phase movement during this period. Even though arrows are strongly downward, some arrows are slightly upward. Thus, TECHX predominantly tends to lead ELEC in the medium term. Meanwhile, similar findings are also visible with weaker evidence in the long-term of 16-32 months. This reflects that technology exports dominate as a driver of electricity demand both in medium- and long-term. In contrast, the interaction is weaker and more complex in the short-term of 0-8 months.

The WTC findings complement the causality results of bootstrap T&Y and Fourier T&Y approaches. Although causality results indicate strong impact in the short run, the WTC highlights strong interaction in the medium run. Overall, all findings confirm that the nexus between TECHX and ELEC is both time-varying and frequency-dependent.

7. A Discussion on International Comparison: A Complementary Panel Data Analysis

This part is designed to reveal whether similar dynamics exist for other countries in the world. Thus, panel data are constituted as a complementary framework for the causal linkage between electricity consumption and high technology exports based on the World Bank (2025) dataset. High-technology variable is intentionally preferred to proxy high value-added exports instead of medium- and high-tech exports as a comparison of previous findings from the aspect of Turkey. High-tech exports ratio of Turkey was previously discussed. Therefore, a weakened or non-linkage is expected due to low level of high-tech exports ratio. Data covers the yearly period of 2007–2023. Countries are chosen leaning on the availability of the values, and divided into three income groups as expressed in Appendix G.

Konya (2006: 979) introduces Seemingly Unrelated Regressions (SUR) model into panel data approach with bootstrap critical values oriented to Wald test for each cross-country. This test has many advantages in panel causality investigations. The unit root and cointegration tests are not required under bootstrap framework, while the SUR equations clear up the cross-sectional dependency by modelling cross-correlations of errors.

Findings of Bootstrap Panel Causality is reported in Appendix G. There exists positive and statistically significant bootstrap Granger causality running from high-tech exports to electricity consumption in Finland and Lithuania. Income effect corresponds for Finland and Lithuania, which larger exports of high-tech creates additional costs on energy demand. This can be due to household consumption and transportation activities, which can be interpreted within the previously discussed ICT-led growth mechanism. Meanwhile, there is negative and statistically significant causality running from high-tech exports to electricity consumption in Belgium, Costa Rica, and Iceland. These countries correspond to substitution effect with energy savings through efficiency obtainment in high-tech exports. On the other hand, there is positive and statistically significant causality running from electricity consumption to high-tech exports in Czechia, Luxembourg, and Slovenia. These countries are demand-oriented, which additional energy demand is linked with high-tech exports. Moreover, there exists no statistically significant causality in Turkey as expected. There can be claimed a positive causality running from high-tech exports to electricity consumption at around the 20% significance level. This suggests a weak and economically negligible linkage at conventional significance levels, indicating that high-tech exports alone are insufficient to generate a robust energy demand effect.

8. Conclusion

This study investigates the nexus between TECHX and ELEC through a variety of econometric techniques over the period 2016M01–2025M05 in Turkey. The STR model was adopted to capture regime-dependent effects relying on the distributional properties of the variables. The findings reveal that lag values of ELEC are statistically significant in both regimes, despite the sign of the impact turns from negative to positive in the nonlinear regime. Elasticities of parameters indicate that a 10% increase in lag value of ELEC reduces electricity demand by 3.51% in the low-entrepreneurship regime, whereas it increases electricity demand by 3.49% in the high-entrepreneurship regime. This highlights the need for policies that integrate entrepreneurship incentives with energy efficiency, especially to cope with strong energy reliance on technology industries during the upward phases of business activity.

TECHX exerts positive and statistically significant impact on ELEC in both regimes, although the effect is twice as strong in the nonlinear regime. The elasticities of parameters demonstrate that a 10% rise in TECHX raises ELEC by 1.48% in high-entrepreneurship regime, whereas it increases ELEC by 0.71% in low-entrepreneurship regime. This finding shows that the expansion of TECHX disproportionately raises energy demand. It further signifies the energy-intensive nature of export-oriented industries. This nonlinear energy burden indicates that the sustainability of technology-driven exports depends on improving electricity efficiency in transport- and machinery-related sectors. While such exports support entrepreneurship, they also pose concerns about the composition of the export basket. Capital- and energy-intensive sectors such as C27, C28, C29, and C30 constitute around 75% of the TECHX structure during this period. In contrast, less energy-intensive sectors such as C20, C21, and C26 have a much smaller share in the export basket. Therefore, policies should focus on the promotion of less energy-intensive sectors within the export structure. Moreover, integration of renewable energy and green technologies can alleviate the energy burden in heavy industries.

FDI has a negative and statistically significant impact on ELEC in the nonlinear regime. The elasticity of parameter displays that 10% upswings in FDI reduce ELEC by 0.23% in the high-entrepreneurship regime. This indicates that FDI inflows may alleviate energy pressures through technology transfer and efficiency improvements. It further underlines the strategic role of FDI not only as a source of capital but also as a channel to balance energy burden with cleaner production process.

The second part of the analysis employs Bootstrap T&Y and Fourier T&Y causality tests. Both tests indicate a unidirectional Granger causality running from TECHX to ELEC. Furthermore, robustness check was conducted with lead-lag and Brent oil included Granger causality tests to mitigate doubt about the reverse causality and consider the impacts of external shocks on the causality. These results reinforce the finding of a unidirectional influence spreading from TECHX to ELEC. This reflects the income effect of technology-intensive exports, which amplifies energy demand in the production structure. Finally, the WTC analysis was used to examine time-frequency localized dynamics. Findings show that the interaction appear more volatile and episodic in the short run. Strong and persistent coherence emerges predominantly from TECHX to ELEC in the medium run. A similar finding is also visible with weaker evidence in the long run. Our findings are consistent with the short-term findings of Sun and Anwar (2015) and partially like the U-shaped effect in the onward development stage, which is emphasized by Dinh et al. (2021). The study also provides complementary bootstrap panel causality results, which assist to place Turkey's findings with a broader international context without changing the core design of the research.

Overall, the evidence confirms that the nexus between TECHX and ELEC is nonlinear, time-varying, and frequency-dependent in Turkey. The STR model demonstrates that once entrepreneurial activity surpasses a certain threshold, the energy impact of technology exports intensifies, underscoring entrepreneurship's role as a regime-switching mechanism. Complementary causality tests consistently indicate unidirectional effects running from TECHX to ELEC, while the WTC highlights persistent medium-term linkages. These findings reveal that technology exports predominantly intensify electricity demand during short- and medium-term business expansions in the high-entrepreneurship regime. Nevertheless, technology exports remain one of the main drivers of economic development in Turkey. This indicates a double-edged-sword effect on the economy, where more technological progress on the one hand, but higher energy costs on the other. Therefore, Turkey should address energy vulnerabilities particularly in transport- and machinery-related industries to sustain technological upgrading and energy efficiency. Policy implications include fostering less energy-intensive sectors in export, especially which have characteristics "lighter in weight and heavier in value" as a tool to realize structural transformations in harmony with knowledge era. In accordance with this, strategically channelling FDI to balance energy burden is another recommended policy tool for more energy-efficient manufacturing. Moreover, renewable energy adoption and expanding high-tech production capacities are other recommended policies to support cleaner and more energy-efficient exportation.

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Appendix A:

Sectoral Composition of Medium- and High-Tech Exports- ISIC Rev.4 (Thousand US $)

Years	C20	C21	C26	C27	C28	C29	C30	Total
2016	6421114	974860	2678531	9473609	7510796	22769639	2539613	52368161
2017	7377428	1015575	2744168	10087861	8555803	27206771	3794634	60782241
2018	8768550	1315779	2798406	11108883	10333000	29836008	3084142	67244769
2019	9420531	1439833	2766560	11304696	11155544	28655915	3736709	68479789
2020	9699677	1832737	2364110	11291951	10599147	23696048	3330151	62813821
2021	13514202	1898827	2730892	14657111	13565421	26770696	4443498	77580645
2022	18400768	1915578	2969093	16063161	15804005	28047880	5226925	88427410
2023	16811891	2218160	3624876	16940447	18269451	32531637	6370761	96767224
2024	16864293	2284988	3432589	17961928	18473017	34483321	6443862	99943999
2025a	6968720	1094058	1251034	7612223	7427649	15483234	2834418	42671336
				Percentage of Total				
2016	12.26	1.86	5.11	18.09	14.34	43.48	4.85	100
2017	12.14	1.67	4.51	16.60	14.08	44.76	6.24	100
2018	13.04	1.96	4.16	16.52	15.37	44.37	4.59	100
2019	13.76	2.10	4.04	16.51	16.29	41.85	5.46	100
2020	15.44	2.92	3.76	17.98	16.87	37.72	5.30	100
2021	17.42	2.45	3.52	18.89	17.49	34.51	5.73	100
2022	20.81	2.17	3.36	18.17	17.87	31.72	5.91	100
2023	17.37	2.29	3.75	17.51	18.88	33.62	6.58	100
2024	16.87	2.29	3.43	17.97	18.48	34.50	6.45	100
2025	16.33	2.56	2.93	17.84	17.41	36.28	6.64	100

Notes: C20- Manufacture of chemicals and chemical products, C21- Manufacture of basic pharmaceutical products and pharmaceutical preparations, C26- Manufacture of computer electronic and optical products, C27- Manufacture of electrical equipment, C28- Manufacture of machinery and equipment n.e.c., C29- Manufacture of motor vehicles trailers and semi-trailers, C30- Manufacture of other transport equipment. a-2025 values are total sum up to May.

Source: TurkStat, 2025

Appendix B:

Parameter Estimates of STR Model with Covid 19 Dummy Variable

Variables	Linear Part		Nonlinear Part			
	Coef.	Std. Er.	Coef.	Std. Er.		
Constant	0.003	0.006	0.005	0.013	**R^2**	0.577
D(LELEC) (–1)	−0.346***	0.126	0.364	0.272	**Adjusted-R^2**	0.515
D(LTECHX)	0.050	0.053	0.208**	0.102	**F Statistics**	9.335
D(LFDI)	0.015**	0.006	−0.029**	0.014	**Akaike Criterion**	−4.504
D(LEMP)	0.197	0.506	0.130	0.697	**Schwarz Criterion**	−4.145
DUMMY	−0.015*	0.008	0.032*	0.017	**Durbin-Watson**	2.075

Notes: *, **, *** indicates significance at 0.10, 0.05, and 0.01 levels, respectively. DUMMY = 1 for 2020M12 onward, 0 otherwise.

Source: Author's own calculations

Appendix C:

Data Sources, Transformations, and Reproducibility Notes

C.1: Data Sources and Transformations

Variable	Description	Source	Series Code	Sea.Adj.	Transformation
ELEC	Electricity Consumption	CBRT	TP.ELEKTUKETİM.TKT1	X-13	Log-difference
TECHX	Medium- and High-Tech Export	TurkStat	Constructed by aggregating ISIC Rev.4 of C20, C21, and C26 to C30	X-13	Log-difference
FDI	Foreign Direct Investment Inflows	CBRT	TP.YD109	X-13	Log-difference
ENTREP	Entrepreneurship index (new firms – closed firms)	CBRT	TP.AC2.TOP.A and TP.KAP2.TOP.A	X-13	Log-difference
EMP	Total Employment	CBRT	TP.YISGUCU2.G3	X-13	Log-difference
OIL	Europe Brent Crude Oil Spot FOB Price	CBRT	TP.BRENTPETROL.EUBP	X-13	Logarithmic

Notes: All variables are monthly covering 2016M01–2025M05. All series are seasonally adjusted using X-13 ARIMA-SEATS. Stationarity achieved through first differences of logarithms. ENTREP is defined as newly established firms (TP.AC2.TOP.A) minus closed firms (TP.KAP2.TOP.A). The transition variable is constructed as the standardized log-difference of the entrepreneurship indicator with a delay of 9 periods. Transition variable = $\frac{\Delta \ln\,(ENTREP_{t-9})}{\sigma_{\Delta \ln\,(ENTREP_{t-9})}}$

C.2: Reproducibility Code Snippet

```
Seasonal Adjustment + Log Difference
x12(adj_elec) elec
genr dlelec = d(log(adj_elec))

x12(adj_techx) techx
genr dltechx = d(log(adj_techx))

x12(adj_fdi) fdi
genr dlfdi = d(log(adj_fdi))

x12(adj_emp) emp
genr dlempl = d(log(adj_emp))

x12(adj_entrep) entrep
genr dlentrep = d(log(adj_entrep))
genr z_dlentrep = dlentrep(-9)/ @stdev(dlentrep(-9))

STR Estimation
str dlelec c dlelec(-1) dltechx dlfdi dlempl
transition = z_dlentrep
type = logistic
```

Appendix D:

Transition Lag Robustness of The STR Model (Lags=8, 9, 10)

Transition Lag	Nonlinear TECHX Effect	AIC	SC	Interpretation
8	Negative-Significant (p = 0.014)	–4.308	–4.003	Wrong dynamics/ instability
9	Positive-Significant (p = 0.039)	–4.500	–4.193	Best fit/ valid nonlinearity
10	Not significant (p = 0.175)	–4.302	–3.993	Nonlinearity disappears

Source: Author’s own calculations

Appendix E:

Lead–Lag Granger Causality Results

			LTECHX ¿ LELEC			
Model	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
Chi-square	4.640**	4.476	8.859**	7.854*	7.794	7.155
p-value	0.031	0.107	0.031	0.097	0.168	0.307
			LELEC ¿ LTECHX			
Chi-square	1.974	0.582	3.379	4.510	4.573	4.364
p-value	0.160	0.748	0.337	0.341	0.470	0.628

Notes: **, * indicate significance at 0.05 and 0.10 levels, respectively.

Source: Author's own calculations

Appendix F:

Brent Oil-controlled Causality Robustness Check

Model	**Chi-square**	**Degree of freedom**	**Asymptotic probability**
LTECHX ¿ LELEC	6.585*	3	0.086
LELEC ¿ LTECHX	3.239	3	0.356

Notes: * indicates significance at 0.10 level. Brent Oil Prices (LOIL) included as exogenous control.

Source: Author's own calculations

Appendix G:

Complementary Cross Country Evidence

G1: Bootstrap Panel Causality from LHTECH to LELECT

Countries	id	Coefficient	Wald	Critical Values		
				%10	%5	%1
Brazil	0	−0.071	66.214	44.396	72.020	167.805
Chile	0	−0.004	0.072	52.975	89.591	253.309
Costa Rica	0	−0.053	107.785**	56.456	89.167	218.811
Czechia	0	0.016	0.669	40.489	65.446	164.083
Estonia	0	0.087	4.106	38.231	63.194	159.786
Greece	0	−0.089	5.317	39.020	66.739	178.984
Hungary	0	−0.097	47.554	65.227	106.376	238.289
Latvia	0	0.077	14.930	35.683	55.725	128.980
Lithuania	0	0.251	53.869*	51.977	86.334	211.955
Poland	0	0.047	13.088	81.419	126.534	269.149
Portugal	0	0.008	0.940	43.662	70.324	170.392
Slovak Republic	0	0.023	1.596	25.371	39.347	90.242
Turkey	0	0.089	39.026	73.128	120.501	298.033
Canada	1	0.126	6.259	21.110	34.471	75.611
Finland	1	0.062	18.670*	15.419	23.794	52.476
France	1	−0.024	0.849	20.962	32.182	68.121
Germany	1	0.147	11.676	18.167	27.094	60.287
Israel	1	−0.039	6.480	12.880	20.037	49.112
Italy	1	−0.040	0.538	18.083	27.939	59.947
Korea, Rep.	1	0.024	0.181	15.701	24.669	55.197
New Zealand	1	−0.022	0.441	15.238	24.964	57.919
Slovenia	1	0.068	1.296	17.327	28.258	57.855
Spain	1	−0.028	1.975	19.347	30.731	72.551
United Kingdom	1	−0.101	5.197	25.253	39.014	80.274
Australia	2	−0.060	11.735	18.404	28.784	61.831
Austria	2	−0.005	0.016	20.517	31.670	67.251
Belgium	2	−0.113	74.275**	36.555	55.596	123.809
Denmark	2	0.084	11.015	24.493	38.392	85.275
Iceland	2	−0.081	38.541**	18.116	28.077	60.362
Ireland	2	0.029	1.418	23.597	38.752	96.974
Luxembourg	2	0.184	13.502	40.469	64.055	151.786
New Zealand	2	−0.016	0.127	30.589	46.454	102.674
Norway	2	−0.151	10.699	20.093	31.344	64.306
Sweden	2	0.126	11.325	25.653	38.179	83.253
Switzerland	2	0.011	2.943	19.525	29.864	67.109
United States	2	0.097	5.805	17.255	26.923	59.669

Notes: *, ** indicates significance at 0.10, and 0.05 levels, respectively. id represents country groups, 0 refers countries less than $30000 per capita income, 1 refers countries from $30000 to $55000 per capita income, and 2 refers countries have more than $55000 per capita income based on the World Bank (2025) GNI per capita values. Critical values are attained with 10000 replicates.

LHTECH is the logarithmic values of high- technology exports (% of manufactured exports).

LELECT is the logarithmic values of electric power consumption (kWh per capita), and variables are from the World Bank (2025).

Source: Author’s own calculations

G2: Bootstrap Panel Causality from LELECT to LHTECH

Countries	id	Coefficient	Wald	Critical Values		
				%10	%5	%1
Brazil	0	−0.188	0.371	44.478	67.941	151.551
Chile	0	1.760	11.091	18.810	28.716	66.077
Costa Rica	0	−0.560	0.158	32.202	49.193	105.998
Czechia	0	1.872	47.901*	30.862	49.543	103.314
Estonia	0	−0.880	5.296	48.412	75.679	180.961
Greece	0	−1.222	20.558	44.772	71.357	165.260
Hungary	0	0.323	1.891	36.111	55.113	128.638
Latvia	0	2.431	26.381	38.198	58.893	131.960
Lithuania	0	0.470	11.794	34.249	53.753	116.418
Poland	0	0.106	0.212	29.024	44.138	85.689
Portugal	0	2.634	5.524	47.437	76.145	179.525
Slovak Republic	0	−0.567	1.918	38.256	62.171	145.090
Turkey	0	0.568	5.423	38.576	58.930	129.564
Canada	1	0.454	4.993	12.497	19.003	38.720
Finland	1	0.520	2.429	17.255	26.094	54.314
France	1	0.572	9.014	19.187	28.764	58.343
Germany	1	0.075	0.377	20.351	29.917	59.406
Israel	1	0.323	0.266	22.030	34.283	78.270
Italy	1	−0.054	0.053	18.222	26.381	53.343
Korea, Rep.	1	0.073	0.290	15.031	23.493	51.533
New Zealand	1	−0.427	7.706	18.914	28.262	54.453
Slovenia	1	1.419	59.830**	21.860	35.267	81.588
Spain	1	−1.461	7.758	19.217	28.960	56.825
United Kingdom	1	−0.334	10.449	26.320	39.504	81.678
Australia	2	−0.860	5.538	56.535	86.460	185.945
Austria	2	0.939	7.023	39.066	62.268	141.940
Belgium	2	−0.331	0.094	24.514	36.767	73.626
Denmark	2	0.858	4.088	24.043	37.125	80.344
Iceland	2	0.408	1.932	32.899	56.824	161.601
Ireland	2	−0.199	0.088	40.039	60.462	126.086
Luxembourg	2	1.284	22.057*	17.175	26.898	57.139
New Zealand	2	−0.901	6.513	22.707	35.679	79.566
Norway	2	1.237	14.397	26.481	41.288	87.837
Sweden	2	0.495	14.986	31.528	46.880	92.022
Switzerland	2	1.587	7.218	41.415	59.785	124.376
United States	2	0.459	2.658	27.123	42.881	102.542

Notes: *, ** indicates significance at 0.10, and 0.05 levels, respectively. id represents country groups, 0 refers countries less than $30000 per capita income, 1 refers countries from $30000 to $55000 per capita income, and 2 refers countries have more than $55000 per capita income based on the World Bank (2025) GNI per capita values. Critical values are attained with 10000 replicates.

LHTECH is the logarithmic values of high- technology exports (% of manufactured exports).

LELECT is the logarithmic values of electric power consumption (kWh per capita), and variables are from the World Bank (2025).

Source: Author's own calculations

G3: Methodological Description of Bootstrap Panel Causality

$$lhtech_{1,t} = \alpha_{1,1} + \sum_{l=1}^{llhtech1} \beta_{1,1,l}\, lhtech_{1,t-1} + \sum_{l=1}^{llelect1} \theta_{1,1,l}\, lelect_{1,t-1} + \varepsilon_{1,1,t}$$

$$lhtech_{2,t} = \alpha_{1,2} + \sum_{l=1}^{llhtech1} \beta_{1,2,l}\, lhtech_{2,t-1} + \sum_{l=1}^{llelect1} \theta_{1,2,l}\, lelect_{2,t-1} + \varepsilon_{1,2,t}$$

$$\vdots$$

$$lhtech_{N,t} = \alpha_{1,N} + \sum_{l=1}^{llhtech1} \beta_{1,N,l}\, lhtech_{N,t-1} + \sum_{l=1}^{llelect1} \theta_{1,N,l}\, lelect_{N,t-1} + \varepsilon_{1,N,t}$$

$$and$$

$$lelect_{1,t} = \alpha_{2,1} + \sum_{l=1}^{llhtech2} \beta_{2,1,l}\, lhtech_{1,t-1} + \sum_{l=1}^{llelect2} \theta_{2,1,l}\, lelect_{1,t-1} + \varepsilon_{2,1,t}$$

$$lelect_{2,t} = \alpha_{2,2} + \sum_{l=1}^{llhtech2} \beta_{2,2,l}\, lhtech_{2,t-1} + \sum_{l=1}^{llelect2} \theta_{2,2,l}\, lelect_{2,t-1} + \varepsilon_{2,2,t}$$

$$\vdots$$

$$lelect_{N,t} = \alpha_{2,N} + \sum_{l=1}^{llhtech2} \beta_{2,N,l}\, lhtech_{N,t-1} + \sum_{l=1}^{llelect2} \theta_{2,N,l}\, lelect_{N,t-1} + \varepsilon_{2,N,t}$$

Equation 19 and Equation 20 demonstrate system of Seemingly Unrelated Regression (SUR) models. $\varepsilon_{1,1,t}$ and $\varepsilon_{2,1,t}$ are white noise error terms and both are in correlation for each cross country, but not among other countries. There exists unidirectional Granger causality running from LHTECH to LELECT, if all $\beta_{2,i}$, s are zero in Equation 20, but all $\theta_{1,i}$, s are not zero in Equation 19. Likewise, there exists unidirectional causality running from LELECT to LHTECH, if all $\beta_{2,i}$, s are not zero in Equation 20, but all $\theta_{1,i}$, s are zero in Equation 19 (Kónya, 2006: 981).