Academic Journal of Economic Studies
Vol. 3, No. 1, March 2017, pp. 88–96
ISSN 2393-4913, ISSN On-line 2457-5836

Energy Use and Growth of Manufacturing Sector: Evidence from Turkey

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Abstract *This study investigates the relationship between Energy use and the growth of the Turkish Manufacturing Sector, using Vector Error Correction and Granger causality, between 1960 and 2015. The research found a long-run association among these variables. However, while the VEC granger causality test result suggests no causality running, either direction, from predetermined Energy Use to Growth in Manufacturing Sector, the Variance decomposition and impulse response tests suggested a positive causality, running from contemporaneous values Energy Use to current and future values of Growth in the Manufacturing Sector of Turkey. It is recommended that more investments be made in the energy sector to help sustain the current performance in the manufacturing sector.*

Key words Energy use, manufacturing sector, cointegration, vector error correction and Granger causality

JEL Codes: Q42, Q43, P28

1. Introduction and literature review

The manufacturing sector is one of the primary drivers of sustainable growth in today's modern economies. It is one of the biggest growth determining sectors of most advanced economies. This position is evident in the share of the manufacturing sector in the output of most industrialized countries today. And among the growing economies of the world, the manufacturing sector is gradually expanding in its growth determining capacity. According to Ademola (2012), apart from laying solid foundation for the economy, the manufacturing sector also serves as import substituting industry, providing ready market for intermediate goods. This position has come to be accepted in literature of development economics. Today, the works of Leeson (2013), Kirner and Som (2015), Jaswal et al (2015), Ceylan and Ozturk (2004), have loudly resounded this age-long position.

However, despite the enormous benefits associated with this sector, it is equally important to note, at this point, that this sector risks having optimal performances without steady supply of energy. The manufacturing sector depends heavily on energy to power industrial production equipment (Mukherjee, 2007; Soytas and Sari, 2007). This explains why most huge investments in the energy sector are continually being made by the most industrial countries of the world, to ensure the sustainable supply of energy for industrial and residential consumption. This should be a strategy template for other emerging economies, like Turkey, desirous of reaping the full benefits of a well-developed manufacturing sector.

Turkey, like other emerging economies, has continually initiated and implemented policies directed at enhancing the role of the manufacturing sector in her economic growth. Today, she has a strong developing manufacturing sector, with output growth rate of about 4% in the first quarter of 2013 (World Bank, 2017). Interestingly, when compared with the most industrialized countries in the west, her energy use capacity has been low. If her current advancements in the manufacturing sector must be sustained, efforts should be made to equally enhance her energy use in the sector. In view of the well documented reliance of the manufacturing sector on adequate energy supply, it becomes imperative to evaluate the contribution of the energy sector to the Value Added in the manufacturing sector of Turkey. It is against this backdrop that this research sought to investigate the relationship between energy use and the Value Added of the manufacturing sector in Turkey. The idea is to reveal the contribution of the energy sector to the growth of the Turkish economy via its contribution to the manufacturing sector.

The relationship between energy use and the performance of the manufacturing sector, for selected countries, enjoys some contributions in the literature. Mongia and Sathaye (1998) had presented this discussion within the context of the Indian economy. Their methodological approach involved a growth accounting approach, which was used to decompose growth of output in terms of growth of inputs and a residual. The residual is attributed to growth in productivity of input factors. Their finding is that energy is an important input for output especially for the Indian economy. This analysis is similar to the conclusion of the study Dagher and Yacoubian (2012) who evaluated the causal relationship between energy consumption and economic growth in Lebanon, between 1980 and 2009. Their approach was a bivariate framework, which was evaluated using granger causality technique. They concluded that there is a bidirectional causality running between energy consumption and economic growth. This result is significant considering the positive relationship between the manufacturing sector and growth of economies.

This study applied the Vector Error Correction Model (VECM) to establish the relationship between the Growth of Manufacturing Sector of Turkey and her Energy Use following the establishment of cointegrating relationship between them. In addition, the direction of relationship was also evaluated using the granger causality test. Our finding is that there exist a long-run relationship between energy use and growth of the manufacturing sector in Turkey. Though granger causality test indicate the absence of granger causality running either direction between energy use and the growth of the energy sector in Turkey, thereby implying lagged values of both variables do not hold enough information to predict current and future of each other, the variance decomposition test reviews a significant contemporaneous relationship running from energy use to growth of Turkish manufacturing sector with the period under review.

2. Methodology of research

2.1. Data

This study uses annual data on Energy Use per capita (EU) and Total Value added in the Manufacturing Sector, a proxy for growth in the manufacturing sector (GMS), for Turkey between the period of 1960 and 2015. Energy use, measured in kg of oil equivalent per capita, comprises energy from combustible renewables and waste - solid biomass and animal products, gas and liquid from biomass, and industrial and municipal waste. And GMS, measured in current US dollars, is the net output of the sector after adding up all outputs and subtracting intermediate inputs. The data were retrieved from World Bank Development Index (WDI) database. EU and GMS were transformed into their logarithms and labelled LNEU and LNGMS respectively.

2.2. Technique of analysis

The main technique of analysis in this study is the Vector Error Correction Model (VECM). The system of equations in the VECM is given as:

$$\Delta LNGMS_t = \pi + \sum_{i=1}^{p} \alpha_2 \Delta LNEU_{t-i} + \sum_{i=1}^{p} \beta_2 \Delta LNGMS_{t-i} + \psi_2 EC2_{t-i} + e_{2t}. \tag{1}$$

$$\Delta LNEU_t = \pi + \sum_{i=1}^{p} \alpha_2 \Delta LNGMS_{t-i} + \sum_{i=1}^{p} \beta_2 \Delta LNEU_{t-i} + \psi_2 EC2_{t-i} + e_{2t}. \tag{2}$$

Where ΔLNGMS and $\Delta LNEU_t$ are first differences of LNGMS and LNEU, respectively, θ and π are intercepts, α, β and Ψ are parameters to be estimated, ΨEC is the error correction term, and e_t is the error term.
The estimation of VECM is predicated on the establishment of a cointegration or long-run relationship among variables that are not stationary but integrated of order 1. We applied the Johanson-Juselius (1990) Maximum Likelihood technique of cointegration for multivariate models in evaluating the presence of cointegration between LNEU and LNGMS. This test involves the estimation of the equation one (3) below:

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + \Pi X_{t-K} + u_t. \tag{3}$$

Here, ΔX_t is the vector of variables in first difference, πX_{t-k} is the error correction term and u_t is the error term. And π can be factored into two separate matrices A and B such that $\Pi = AB'$ B' and A are the vector of cointegrating parameters and vector of error correction coefficients, measuring the speed of adjustment, respectively.
However, as a precondition for conducting a cointegration, the unit root properties of the variables were established by the application of Augmented Dickey Fuller (ADF); outlined by Dickey and Fuller (1981), Phillips Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for unit root. The general ADF equation, presented in equation 2 below, is estimated with a trend and intercept.

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \in_t. \tag{4}$$

Where ΔY_t is the first difference of any time series variable, ϵ_t represents white noise error term. The ADF comprises two hypotheses. Here, the null hypothesis is 'unit root' (non-stationary) against the alternative of stationary. The current study also employs an alternative test for unit root propounded by Phillip and Perron (1988).The test is a semi-parametric test and has same hypotheses to the ADF. However, the study for confirmatory results of stationarity properties of the series uses

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the KPSS test. The impulse response functions and variance decomposition function of the established relationship were also estimated and evaluated. The idea was to evaluate the impact of shock, on each of the variables, resulting from variations in the other variable across different time horizons. Next, the stability condition of the estimated model was evaluated by an estimation and evaluation of the serial correlation status of the residuals using the VEC Residual Serial Correlation Tests.

3. Empirical Findings

Table 1 below presents the summary of the descriptive statistics of the variables under consideration. The table shows that both variables are negatively skewed as well as normally distributed given by the Jarque-Bera probability.

3.1. Descriptive statistics

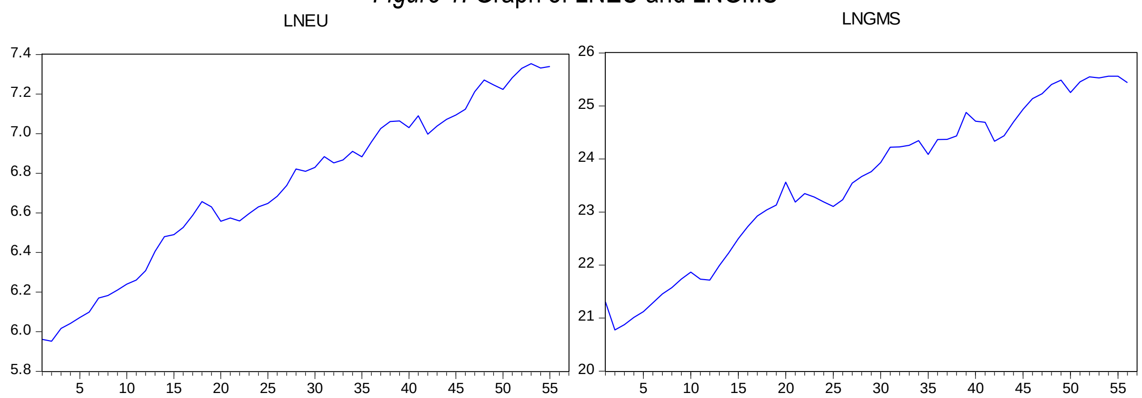
Table 1. Summary Statistics

	LNGMS	LNEU
Mean	23.52716	6.732583
Std. Dev.	1.457147	0.409953
Skewness	-0.325689	-0.2948
Kurtosis	1.929093	2.022569
Jarque-Bera	3.600517	2.986043
Probability	0.165256	0.224693
Sum	1293.994	370.2921
Sum Sq. Dev.	114.6569	9.075301
Observations	55	55

Source: Authors' Estimation

The graphs of LNEU and LNGMS are presented in the diagrams below. These graphs show steady increases in both EU and VAMS with the period under consideration.

Figure 1. Graph of LNEU and LNGMS



Source: Authors' Computation, 2017.

Table 2. Pearson Correlation Coefficient

	LNGMS	LNEU
LNGMS	1	

LNEU	0.990541	1
t-stat	52.55429	---
p-value	0.00000	---

Source: Authors' Computation, 2017.

Pearson correlation matrix is given above. The Pearson correlations depict the degree of relationship between two variables. This table shows the existence of significant positive correlation between manufactured value added and energy use, with a correlation coefficient of about 99%.

3.2. Unit root test

The result of the unit root tests is presented in table 3 and 4 below. This result shows that, under the ADF and PP tests, the null hypothesis of a unit root at levels is not rejected for both LNGMS and LNEU at 5% level of significance. We therefore state that both variables are not stationary at levels. This is because the p-values for both ADF and PP tests, at levels, are less than 5% for both variables. This is further confirmed by the KPSS test is table 5. Here, the test is conducted under the null hypothesis of no unit root. In this case, we reject the null hypothesis at 5% level of significance as the KPSS statistic is greater than its 5% critical value for both variables at levels.
The ADF, PP and KPSS all confirmed that both variables are integrated of order 1. While the null hypothesis of unit root is rejected at 5% for both variables at first difference under the ADF and PP approach, the null hypothesis of no unit root is not rejected, at 5% level of significance, for both LNGMS and LNEU by the KPSS approach at first difference.

Table 3. Unit root test results ADF

Variables	Level		First Difference	
	intercept	trend and intercept	Intercept	trend and intercept
LNGMS	0.867 [0.791]	-2.205 [0.477]	-8.360 [0.000][a]	-8.476[0.000][a]
LNEU	-1.358 [0.595]	- 2.312[0.4205]	-7.042 [0.000][a]	-7.176[0.000][a]

Note: [a] Signifies level of rejection at 1%, while [ ] gives corresponding probability value.

Table 4. Unit root test results PP

Variables	Level		First Difference	
	intercept	trend and intercept	Intercept	trend and intercept
LNGMS	-0.865 [0.792]	-2.389 [0.381]	-8.360 [0.000][a]	-8.497[0.000][a]
LNEU	-1.432[0.559]	-2.368[0.391]	-7.039[0.000][a]	-7.206[0.000][a]

Note: [a] signifies level of rejection at 1% .while [ ] gives corresponding probability

Table 5. Unit root test results KPSS

Variables	Level		First Difference	
	intercept	trend and intercept	Intercept	trend and intercept
LNGMS	0.884 [0.739][a]	0.191 [0.216]	0.083 [0.739][a]	0.055[0.216]
LNEU	0.884[0.739] [a]	0.171[0.119]	0.149[0.739]	0.0394[0.216]

Note: [a] Signifies level of rejection at 1%, while [ ] gives corresponding probability.

Source: Authors' Computation, 2017.

3.3. Lag selection criteria

The optimum lag for the proposed VECM was determined by all three of AIC, SIC and HQ as presented in table 6 below. Interestingly, all three criteria unanimously selected 1 lag as the optimum l. For this reason, lag of 1 was applied in specifying the test for cointegration test and estimating the VECM presented in table 7 and 8 respectively, below.

Table 6. Lag Selection Criteria Test

Lag	AIC	SC	HQ
1	-4.589901*	-4.436939*	-4.531652*
2	-4.459045	-4.153121	-4.342547
3	-4.350254	-3.891368	-4.175508
4	-4.232946	-3.621099	-3.999951
5	-4.121834	-3.357025	-3.830591

Note: *Signifies selection of optimum lag length.

Source: Authors' Computation, 2017.

3.4. Cointegration test

Following the determination of the unit root properties of the variables, which were both confirmed to be integrated of order 1, next step was to determine whether both variables are cointegrated. The approach applied in this case is the Johanson cointegration test. The result of this test is presented in table 7 below. This result indicates the existence of one cointegrating equation as the null hypothesis of no cointegrating equation is rejected at 5% by both the Trace statistic and Max. Eigen-value. This implies that, though both variables are integrated of order I(1), their linear combination would be of order 1(0).

Table 7. Result of Johanson Cointegration Test

Hypothesized No. of CE(s)	Trace Statistic	Prob
r=0	21.57317	0.0054
r≤ 1	2.553529	0.1100

Hypothesized No. of CE(s)	Max-Eigen Statistic	Prob
r=0	19.01964	0.0082
r≤ 1	2.553529	0.1100

Source: Authors' estimation, 2017.

3.5. The Vector Error Correction Model

The established cointegrating relationship between LNEU and LNGMS means both the short-run and long-run dynamics of the relationship can be estimated by VECM. This result is presented in table 8 below.

Table 8. Result of Granger causality Test

Cointegrating Eq:	LNGMS (-1)
LNEU(-1)	-3.492853
	[-39.4200]
C	-0.003938
Error Correction:	**D(LNGMS)**
CointEq1	-0.556163
	[-4.38901]
D(LNGMS (-1))	0.042262
	[0.35087]
D(LNEU(-1))	-0.715864
	[-1.08735]
C	0.105407
	[4.18429]

Note: [ ] is the t-statistic.
Source: Authors' estimation, 2017.

The estimates of the cointegrating equation indicate a significant long-run relationship between LNGMS and LNEU in first lag. Here, the slope is 3.49 with a t-statistic of about 39.42 (the signs of the results have been changed). This means there is a positive long-run relationship between LNGMS and LNEU. In the lower part of the table, the error correction term, which indicates the speed of convergence to equilibrium, is -0.55, and it is statistically significant. The implication is that, if LNGMS deviates from the equilibrium for any reason, in the long-run, equilibrium will be restored at the speed of -0.55. However, the result of the short-run dynamics between LNGMS and LNEU is negative but statistically insignificant at first lag.

3.6. VEC Granger Causality Test

The VEC Granger causality test is usually conducted to determine the direction of relationship among variables. The result of the granger causality between LNGMS and LNEU is presented in table 9 below. This result suggests no granger causality running from LNEU to LNGMS. Here, we fail to reject the null hypothesis that 'LNEU does not Granger Cause LNGMS' at 5% level of significance. Similarly, LNGMS does not granger cause LNEU as we fail to reject the null hypothesis that 'LNGMS does not Granger Cause LNEU' at 5% level of significance. The implication is that past values of LNEU cannot be used to predict LNGMS.

Table 9. Granger causality Test

Dependent variable: D(LNGMS)		
Excluded	Chi-sq	Prob.
D(LNEU)	1.182333	0.2769
All	1.182333	0.2769

Dependent variable: D(LNEU)		
Excluded	Chi-sq	Prob.
D(LNGMS)	0.234653	0.6281
All	0.234653	0.6281

Source: Authors' estimation, 2017.

3.7. Variance decomposition analysis

Table 10 below presents the result of the variance decomposition tests on the variables. The lower component of the result shows the impact of own shock on fluctuations in LNEU is above 90% across the 10 time horizons, while a small amount, of less than 10%, is resulting from shocks to LNGMS for the same time horizons. This result is, however, different from the variance decomposition of LNGMS presented in the upper component of the table. This result shows that the impact of own shock to LNGMS is fallings sharply from 100% in the first time horizon to about 26.2 % in the 10th time horizon. The implication is that the share of the impact of shock to LNEU on fluctuations in LNGMS rose sharply from 0% to as high as about 74.8% across the time horizons. This is at variance with the result of the VEC granger causality discussed above. However, according to Chris (2002), variations between the result of the VEC granger causality and Variance Decomposition is usually due to the fact that; while VEC granger causality test focuses on the causality between contemporaneous and future values of an endogenous variable resulting from the predetermined values of an exogenous variable, Variance Decomposition measures the impact of a shock on the contemporaneous and future values of an endogenous variable, resulting from both the contemporaneous and future values of an exogenous variable.

Table 10. Result of the Variance Decomposition

V.D of LNGMS : Period	LNGMS	LNEU
1	100.0000	0.000000
2	93.28634	6.713663
3	73.95338	26.04662
4	56.97783	43.02217
5	45.70182	54.29818
6	38.38634	61.61366
7	33.42816	66.57184
8	29.88719	70.11281
9	27.24031	72.75969
10	25.18795	74.81205

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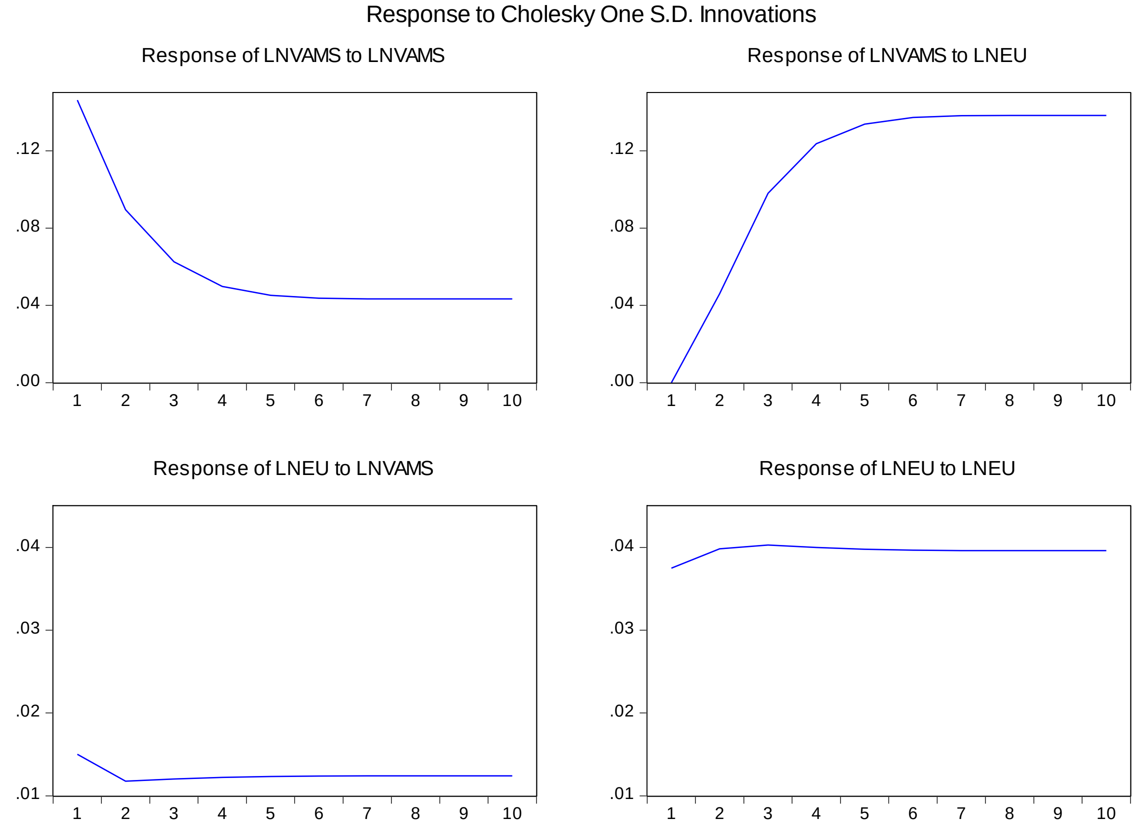
V.D of LNEU: Period	LNGMS	LNEU
1	13.82141	86.17859
2	10.84845	89.15155
3	9.927856	90.07214
4	9.571509	90.42849
5	9.409622	90.59038
6	9.320678	90.67932
7	9.263113	90.73689
8	9.221553	90.77845
9	9.189583	90.81042
10	9.164056	90.83594

Source: Authors' estimation, 2017.

3.8. Analysis of Impulse Response Function

The result of the impulse response functions are presented in figure 2 below. The first row shows the responses of LNGMS to shocks in LNEU, while the lower row presents the responses of LNEU to shocks in LNGMS. These results indicate a positive and non-converging impact to LNGMS, from shocks to the error of LNEU across the 10 point time horizon.

Figure 2. The Impulse Response Functions



Source: Authors' estimation, 2017.

3.9. Analysis VEC Residual Serial Correlation LM Test

The test of residual serial correlation is presented in table 11 below. This test is conducted under the null hypothesis of no serial correlation in residual of the estimated model. In this case, except for the 10^{th} lag, we failed to reject the null hypothesis, at 5% level of significance, and conclude that the residual of the VEC model are not serially correlated. This is an indication of the stability of the estimated model in explaining the estimated relationship.

Table 11. The Result of VEC Residual serial Correlation LM Test

Lags	LM-Stat	Prob
1	1.179074	0.8815
2	2.564439	0.6331
3	1.754087	0.7809
4	3.225522	0.5208
5	0.382593	0.9839
6	5.281721	0.2596
7	3.340759	0.5025
8	6.618780	0.1575
9	1.198501	0.8783
10	11.11192	0.0253

Source: Authors' Computation, 2017.

4. Conclusions

This study sets out to investigate the relationship between energy use and the performance of the manufacturing sector in Turkey. Specifically, the desire was to determine the influence of energy use and the value added in the manufacturing sector of Turkey using annual time series data between 1960 and 2015. An evaluation of the unit root properties of the variables indicated there were both integrated of order 1(1). Next, the variables were tested for cointegration using the Johanson cointegrtation technique, and one cointegration equation was found. This was necessary for the application of the Vector Error Correction Model (VECM) to capture both the short-run and long-run dynamics. Though the short-run relationship was found negative and insignificant, the long-run relation was positive and significant. The error correction term of about -0.55, which specifies the speed of adjustment to equilibrium, was found to be significant. The model was evaluated for stability using the LM serial correlation test for residuals and the result indicated the absence of serial correlation in the lags of the residual up to the ninth lag.

The test of granger causality indicted no directional causality running from energy use to the performance of the manufacturing sector. The implication is that past values of energy use is not a predictive factor of the performance of the manufacturing sector. This result, however, is not in line with the conclusions of other studies in literature that has established positive relationship between these variables for other economies. But in terms of the impact of contemporaneous values of energy use one current and future values of growth in the energy sector, the variance decomposition test reveals that shocks to energy have an increasing share of impact on the fluctuations in the growth of the manufacturing sector. However, shocks to the performance of the manufacturing sector had very low impact, mostly less than 0.5% across a 10^{th} time horizon, on the energy use in Turkey. It is therefore imperative that Turkey promote investments in the energy sector if they desire to sustain the current huge performances being witnessed in the manufacturing sector.

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