4. A TIME-VARYING VAR INVESTIGATION OF THE RELATIONSHIP AMONG ELECTRICITY, FOSSIL FUEL PRICES AND EXCHANGE RATE IN TURKEY

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Abstract

This paper investigates the time-varying relationship among electricity, fossil fuel prices and exchange rate in Turkey based on quarterly data for the period 1988Q1 and 2016Q1. The time-varying responses imply that the impact of fossil fuel prices and exchange rate on the electricity prices differs substantially over time. Electricity prices are significantly affected by the change in exchange rate and natural gas and coal prices, though the explanatory power of oil prices in general is found to be minimal and insignificant. The results also indicate that electricity prices have been largely dominated by the fluctuations in the natural gas prices due to the increasing share of natural gas in production of electricity.

Keywords: electricity price, fossil fuel prices, exchange rate, TVP- VAR model, Turkey

JEL Classification: Q40, Q41

1. Introduction

Since the mid-1980s, several countries have started to restructure their electricity industries to increase productivity in all segments from generation to distribution. Chile is the first country implementing the major market reforms in 1987. UK presents another successful story for the reorganization and liberalization of the electricity market launched in 1989. The competition in the US wholesale electricity market has accelerated with the amendment of the Energy Policy Act in 1992, although no significant progress has been observed in the retail market since opening of Texas market in 2002. The reasons for the restructuring vary across the countries, but they are mainly aimed to promote competitiveness of the market to attract new investments and to increase efficiency to reduce costs at every level of the supply chain. [2]

As a consequence of the increasing competition, it can be argued that market prices of electricity are largely determined by the cost of fuels used for generation. In line with this

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[2] For a detailed information about the electricity market reforms undertaken by different countries see Newbery (2006) and Sioshansi and Pfaffenberger (2006).

view, recent empirical studies focused on the electricity markets in the US and the UK, have attempted to uncover the possible long-run relationship among electricity and fuel prices. For instance, Asche *et al*. (2006) analyze the relationship among natural gas, crude oil and electricity prices in the UK for the period from January 1995 to June 1998. The results favor the long-run relationship among the prices during the period of deregulation of the UK natural gas market. Mohammadi (2009) analyzes the dynamics among electricity prices and three fossil fuel prices, *i.e.* coal, natural gas and crude oil, using the annual US data for 1960-2007. The results only corroborate the presence of a long-run relationship between electricity and coal prices. Two-way long-run causality between electricity and coal prices is also reported. Mjelde and Bessler (2009) investigate the relationship between electricity spot market prices and natural gas, uranium, coil and oil prices using weekly prices covering the period from June 2001 to April 2008. The results support the long run relationship between the electricity and fuel prices.

Bencivenga and Sargenti (2010) analyze the relationship among crude oil, natural gas and electricity prices in US and in European commodity markets by employing daily data over the period October 2001 – March 2009. One cointegrating relationship among the three commodity price series is found based on the application of Johansen cointegration test. Error correction model estimates also suggest that the integration among the commodity markets is higher in the US as compared to Europe. Nakajima and Hamori (2013) investigate the relationship among wholesale electricity prices, natural gas, and crude oil prices in the US based on VAR estimates. The results based on the daily data for the period of January 3rd, 2005 – December 31st, 2009, imply that natural gas prices cause the electricity prices, whereas no causality in variance among the variables is reported.

Munoz and Dickey (2009) investigates the relationships among Spanish electricity prices, US dollar/Euro (USD/Euro) exchange rate and crude oil prices by using daily data during the period 2005–2007. The results indicate the presence of long-run relationship, electricity prices and exchange rate are also affected by oil prices in the short run. The results also support the existence of causality running in the direction from exchange rate and oil prices to electricity prices. Moutinho *et al*. (2011) also analyze the relationship among electricity and fossil fuel prices, *i.e.* oil, coal and natural gas, for Spain by using daily data covering the period of January 2002 to December 2005. Although they find an integration between the electricity and fuel prices, the price of electricity is largely explained by the fluctuations in the natural gas prices.

Ferkingstad *et al.* (2011) investigate the long run relationship among electricity and fuel prices with weekly data on Nordic and German electricity prices, and oil, gas and coal prices covering the period from 2002 to 2008. The results do not indicate the existence of long-run relationship between electricity coal and oil prices. However, they find the evidence for causality running from gas prices to electricity prices in both Nordic and German electricity markets. Dias and Ramos (2014) conduct a joint analysis of natural gas, crude oil and electricity prices of the US regions using Markov regime switching models covering period from January 1999 to December 2011. They find that electricity price returns show synchronization with the U.S. wholesale market prices, whereas natural gas price returns seem to be associated with the fluctuations in electricity prices only in the low volatility regime.

Despite a plethora of studies analyzing Turkish electricity market investigating the relationship between electricity consumption and GDP growth (*e.g.*, Altinay and Karagol, 2005; Soytas and Sari, 2009; Acaravci, 2010) or the determinants of electricity demand (*e.g.*, Halicioglu, 2007 and Arisoy and Ozturk, 2014), we found only one study, *i.e.* Gök *et al*.

(2016), analyzing the relationship among electricity and fossil fuel prices based on quarterly data covering the period from 1988 to 2013. The conventional cointegration test shows the presence of a long-run relationship among the variables, while no evidence on the asymmetric is obtained. Subsample VAR estimation also imply that the effects of natural gas prices has increased markedly with the enaction of the electricity market law in 2001.

In this framework, the main objective of the paper is to contribute to the literature by expanding the analysis on the relationship among the electricity and fuel prices in Turkey with a time-varying parameter VAR (TVP-VAR) model. A time-varying analysis of the relationship among the electricity and fuel prices is important for two reasons. First, the liberalization of the electricity market has started with the amendment of the electricity market law no. 4628 in 2001. [3] Based on this law, the Energy Market Regulatory Authority (EMRA) was established to carry out autonomous regulation and supervision of the energy markets operating in a competitive environment. Since then, the structure of the electricity market has changed markedly. The distribution companies operating in 21 different regions are all privatized. The liberalization of the market increased the share of private power generation companies against state-owned company EUAS (Electricity Generation Company). In 2004, private companies produce only 18.23 percent of total generation. However, their share is increased over time due to the new energy investments and privatization of the existing power plants. Hence, by the year 2015, more than half of the electricity supply, *i.e.* 55.83%, has been produced in the plants operated by the 668 different private generation companies (EMRA, 2016). Second, along with the increasing share of private companies, fuel mix utilized in the electricity generation has evolved substantially over time. In 1990, the total electricity generation was 57543 GWh and mainly based on hydropower and coal, with 23148 GWh (40.2%) and 20181 GWh (35.1%), respectively. At that time, natural gas and oil products accounted only for 17.7%, and 6.9%, respectively, of the production of electric power. The importance of natural gas against coal, hydropower and other renewables increased remarkably over time, and natural gas has become the most utilized energy source, with 46216 GWh (37%) in 2000. By the year 2015, the amount of electricity generated from natural gas has reached 120438 GWh, corresponding to 48.1% of the total electricity supply. The figures presented above indicate that Turkey is heavily dependent on fossil fuels in the electricity production, in particular on natural gas imported from abroad. Therefore, hikes in the international energy prices may trigger increases in the domestic price of electricity through rising the cost of generation. Changing the nature of fuel mix in the electricity generation may also imply that linear methdologies may not be able to capture the underlying relationship among electricity and fossil fuel prices.

The paper is organized as follows. The data utilized in the estimates are introduced in the next section. Section three explains the structure of the estimated TVP-VAR model. Empirical evidences are reported in section four. Finally, section five includes concluding remarks and policy proposals.

2. Data

This paper uses quarterly data covering the 1988Q1-2016Q1 period to examine the effects of fossil fuel prices on the electricity prices. The vector of endogenous variables Y_t employed in the VAR is given by:

[3] *For more information regarding the recent developments in Turkish electricity market, see Erdogdu (2007, 2010) and Oğuz et al. (2014).*

$$Y_t{}' = [Er_t\ Poil_t\ Png_t\ Pcoal_t\ Pe_t] \quad (1)$$

Where: Pe_t represents the residential price of electricity. The prices of fossil fuels, high sulphur fuel oil $Poil_t$, natural gas Png_t and steam coal $Pcoal_t$ are obtained from the database of International Energy Agency (https://www.iea.org/data-and-statistics). All prices are defined as national currency Tonne of Oil Equivalent, net calorific value (*toe NCV)*. In addition to fuel prices, Er_t US/TL nominal exchange rate collected from the database of Central Bank of Republic of Turkey is added to the vector of endogenous variables to measure the effects of exchange rate fluctuations on the electricity prices.[4]

Table 1

Lee and Strazicich Unit Root Test with Two Structural Breaks

	Model A (Crash Model)				*Model C (Trend Shift Model)*					
	LM-Stat	Lag	Breaking Time		LM-Stat	Lag	Breaking Time			
			D_{1t}	D_{2t}			D_{1t}	D_{2t}	DT_{1t}	DT_{2t}
Er_t	-1.206	5	1994:01	2004:01 (ns)	-4.980	0	1993:04	2002:02	1993:04	2002:02
ΔEr_t	-9.430*	0	1998:01	2001:04	-	0	1993:04	2002:03	1993:04	2002:03
$Poil_t$	-1.300	5	1994:02 (ns)	2001:04	-3.777	1	1993:04 (ns)	2004:01 (ns)	1993:04	2004:01
$\Delta Poil_t$	-10.123*	0	1993:04 (ns)	2013:03 (ns)	-10.253*	0	1993:03	2008:04 (ns)	1993:03	2008:04
Png_t	-1.809	5	1992:01 (ns)	1994:01	-4.268	1	1993:02 (ns)	2003:01	1993:02 (ns)	2003:01
ΔPng_t	-8.213*	0	1994:03 (ns)	2001:02 (ns)	-8.618*	0	1992:02 (ns)	2009:01	1992:02 (ns)	2009:01
$Pcoal_t$	-1.812	6	1992:01 (ns)	2001:04	-3.660	6	1993:04 (ns)	2002:02 (ns)	1993:04	2002:02
$\Delta Pcoal_t$	-4.824*	1	1990:04	2002:04	-9.943*	0	1990:03 (ns)	2005:01 (ns)	1990:03	2005:01
Pe_t	-1.567	2	1991:03	1994:01	-4.037	2	1991:03	2001:02 (ns)	1991:03	2001:02

Note: * implies that the computed statistic is significant at least at 5 percent. Number of appropriate lags in the unit root test is selected through general to specific method. Critical values of the test are collected from Lee and Strazicich (2003). (ns) shows insignificant breakpoints, and the other breakpoints are significant at least at 10 percent significance level.

Before the estimation of the model, we investigate integration properties of the variables. Dickey and Fuller (1981) ADF and Phillips and Perron (1988) PP, linear unit root tests imply that nominal exchange rate, electricity, coal, oil and natural gas prices are first difference stationary.[5] Lee and Strazicich (2003) unit root test is also employed to examine significance

[4] The data utilized in the empirical analysis are presented in Figure A4 in the appendix.

[5] The results of those tests are not reported in the paper but are available upon request from the author.

of the possible structural breaks. The test results accounting for two endogenous structural breaks presented in Table 1 support the conventional unit root tests suggesting that all variables are integrated of order one when the breaks are taken into consideration.

Endogenously estimated breaking dates indicate that the crises over the investigation period have important consequences on the energy prices. The estimated breaks for the fossil fuel prices are mostly significant and seem to be connected with the 1994 and 2001 crises and the timing of breaks are also found to be similar to that of exchange rate. This might be attributed to the fact that the rise in inflation and the depreciation of the domestic currency during the period of financial crises may eventually lead to a higher natural and coal prices in the electricity market. We found a significant structural break in the trend of the fuel oil and natural gas variables around the period of 2008 global financial crisis. Along with the financial crisis, the Gulf War in 1991 seems to generate a significant structural break in the electricity prices. Since all variables are I(1), they are used in the VAR model in their first-difference form.

3. The TVP-VAR Model

In this paper, the effects of fossil fuel prices on the electricity prices is examined with a time-varying VAR model proposed by Primiceri (2005). The model has a state-space specification and the signal equation is written as,

$$y_t = B_{0_t} + B_{1,t}y_{t-1} + \ldots + B_{p,t}y_{t-p} + u_t = X_t'\Theta_t + \varepsilon_t \quad (2)$$

In the above equation, $B_{0,t\ldots p,t}$ represent the vectors of time-varying coefficients redfined as a matrix form Θ_t. X_t is the matrix of containing intercepts and the lags of endogenous variables. In contrast with the linear VAR model, the distribution of error term u_t of TVP-VAR model is heteroscedastic with zero mean and a covariance matrix Ω_t. The variance-covariance matrix of error terms used to model the relationship among electricity and fossil fuel prices is decomposed as follows:[6]

$$\Omega_t = A_t^{-1}H_t(A_t^{-1})' \quad (3)$$

In the above equation H_t is a matrix including the stochastic volatilities on its diagonals and A_t is a lower triangular matrix including the coefficients illustrating the instantaneous relationship among the electricity and fossil fuel prices.

$$A_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 & 0 \\ \alpha_{51,t} & \alpha_{52,t} & \alpha_{53,t} & \alpha_{54,t} & 1 \end{bmatrix},\ H_t = \begin{bmatrix} h_{1,t} & 0 & 0 & 0 & 0 \\ 0 & h_{2,t} & 0 & 0 & 0 \\ 0 & 0 & h_{3,t} & 0 & 0 \\ 0 & 0 & 0 & h_{4,t} & 0 \\ 0 & 0 & 0 & 0 & h_{5,t} \end{bmatrix} \quad (4)$$

Time-varying parameters and stochastic volatilities are assumed to change in accordance with the following transition equations (Primiceri, 2005 and Nakajima *et al.*, 2011):

$$\Theta_t = \Theta_{t-1} + v_t \quad v_t \sim N(0, Q) \quad (5)$$

$$\alpha_t = \alpha_{t-1} + \zeta_t$$

$$\zeta_t \sim N(0, S) \quad (6)$$

[6] *In line with Primiceri (2005), Cholesky identification is used to identify shocks in the TVP-VAR model.*

$$ln\, h_{i,_t} = ln\, h_{i,_{t-1}} + \sigma_i \eta_{i,t}$$

$\eta_{i,t} \sim N(0,1)$ (7)

Time-varying parameters Θ_t and α_t follow random walk without drift process, as indicated by Eq. (5) and Eq. (6).[7] Conversely, following Primiceri (2005) the vector of stochastic volatilities h_t in Eq. (7) is assumed to follow independent geometric random walk. It is further assumed that the covariance among the error terms of the TVP-VAR equations are assumed to be zero. This allows the parameters of A_t matrix to evolve independently in each equation.[8]

Table 2

Nonlinearity Tests for the Linear VAR Residuals

	Equations									
	ΔEr_t		$\Delta Poil_t$		ΔPng_t		$\Delta Pcoal_t$		ΔPe_t	
	Bootstrap	Asymptotic	Bootstrap	Asymptotic	Bootstrap	Asymptotic	Bootstrap	Asymptotic	Bootstrap	Asymptotic
McLeod and Li										
Up to lag 2	0.041	0.058	0.028	0.030	0.047	0.053	0.005	0.002	0.000	0.000
Up to lag 4	0.026	0.034	0.092	0.118	0.121	0.147	0.008	0.006	0.000	0.000
Bicovariance										
Up to lag 9	0.001	0.001	0.031	0.043	0.000	0.000	0.001	0.000	0.000	0.000
Engle										
Up to lag 1	0.171	0.248	0.034	0.042	0.035	0.042	0.010	0.007	0.005	0.010
Up to lag 2	0.080	0.135	0.022	0.030	0.037	0.052	0.006	0.009	0.027	0.032
Up to lag 3	0.059	0.122	0.042	0.054	0.040	0.062	0.013	0.019	0.041	0.047
Up to lag 4	0.052	0.116	0.060	0.087	0.077	0.114	0.019	0.030	0.067	0.090
Tsay	0.007	0.010	0.064	0.082	0.038	0.037	0.065	0.063	0.124	0.141

Notes: [a] Only p-values are presented, the null hypothesis that the time series is a serially iid process.

[b] The nonlinearity test are conducted by using WINRATS 9.1 econometric software and the Nonlinear Toolkit Version 4.60 by Patterson and Ashley (2000).

4. Empirical Results

Before starting the TVP-VAR estimation, linearity of the VAR model is investigated. For this purpose, first a constant parameter version of the TVP-VAR model in (2) is estimated, and the residuals of each equation are obtained. Then the nonlinearity of the residuals is investigated by employing various statistical tests. The tests considered in this study include Tsay (1986), Engle (1982), Hinich (1996) bicovariance test and the McLeod and Li (1983) test.

Although those tests investigate the nonlinearity based on different specifications, their null hypotheses suggest that the time series are independently and identically distributed (iid). [9]

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[7] Since the random walk model is non-stationary, the stability constraint is imposed on the evolution of the time-varying parameters following Cogley and Sargent (2005).

[8] This simplification is needed to increase the efficiency of the MCMC estimation algorithm as indicated previously by Primiceri (2005).

[9] For a detailed methodological information about the tests see Patterson and Ashley (2000) and Panagiotidis and Pelloni (2007).

The results of nonlinearity tests are presented in Table 2, with both their asymptotic and bootstrapped p-values. The bicovariance test fully rejects the null hypothesis of linearity of the residuals for each equation at 5 percent level of significance, while Engle and McLeod and Li test rejects the null at some lags. It is also noteworthy that except for the Tsay's test the linearity hypothesis for the residual of the electricity price equation is rejected by all tests for at least at the 10 percent significance level. Hence, the findings in general favor the the evidence on nonlinearity in the residual generating mechanism and corroborate the use of TVP-VAR.

After checking for the nonlinearity, the TVP-VAR model including the electricity price, fossil fuel prices and exchange rate defined in the previous section is estimated through the Bayesian approach. The Markov chain Monte Carlo (MCMC) method is used to estimate time-varying parameters in terms of unobserved latent variables of the state-space model. In order to draw sample from the exact posterior density of the stochastic volatility, the multi-move sampler developed by Watanabe and Omori (2004) is utilized following Nakajima *et al*. (2011).[10] Using this sampling technique, 100.000 sample from the posterior distribution is drawn, the initial 10.000 draw is reserved for the convergence of the parameters. The posterior means, standard deviations and 95 percent confidence intervals of the selected parameters based on the MCMC estimation of the TVP-VAR model are reported in Table 3 along with their convergence diagnostics (CD) and the inefficiency factors. The CD test proposed by Geweke (1992) indicates that the null hypothesis of the convergence to the posterior distribution is not rejected for the parameters at the significance level of 5 percent. Low inefficiency factors also imply that the number of iterations is sufficient for the convergence of the parameters.[11]

Table 3

Estimation Results of Selected Parameters of theTVP-VAR Model

Parameter	Mean	Std. Dev.	95%L	95%U	CD	Inefficiency
$(\Sigma_\Theta)_1$	0.012	0.003	0.008	0.018	0.535	25.420
$(\Sigma_\Theta)_2$	0.013	0.004	0.008	0.022	0.293	26.190
$(\Sigma_\alpha)_1$	0.105	0.045	0.047	0.219	0.355	66.050
$(\Sigma_\alpha)_2$	0.085	0.034	0.042	0.171	0.588	46.430
$(\Sigma_h)_1$	0.427	0.104	0.249	0.645	0.665	83.910
$(\Sigma_h)_2$	0.330	0.145	0.116	0.665	0.664	79.270

Figure 1 plots the stochastic volatility of the shock of the variables, based on the posterior mean with their one standard deviation error bands. The results reveal the existence of three significant rises in the stochastic volatility of electricity prices during the Gulf War, 1994 financial crisis and 2008 global financial crisis. Spikes in the stochastic volatility of exchange rate and oil prices observed around the financial crisis is also noteworthy. Stochastic volatility of natural gas prices is not constant, but follows a relatively stable path as compared to the other variables. The changing pattern in the evolution of the stochastic volatility of the

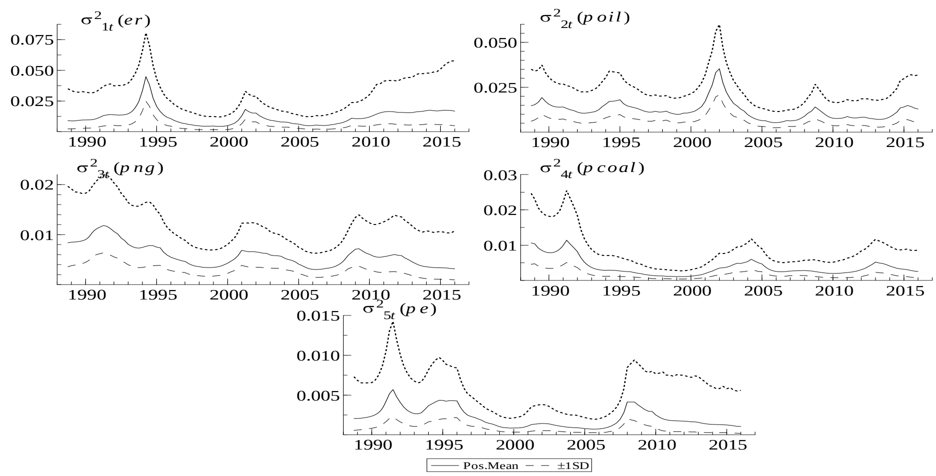
[10] *Number of lags in the VAR is selected according to Akaike Information Criterion. In the estimation, we use the same priors in Nakajima et al. (2011).*

[11] *The diagnostics tests analyzing convergence of the parameters are presented in Fig. A1 in Annexes. The results including the sample autocorrelation function, the sample paths and the posterior densities support the convergence parameters after the estimation.*

variables implies that constant parameter models may not be convenient for the estimation of the relationship among electricity and fossil fuel prices.

Figure 1

Posterior Estimates for Stochastic Volatility of Structural Shock



The the time-varying cumulated responses of electricity prices are illusrated in the panel A of Figure 2 for the time horizons $t = 0, 1, 2, \ldots, 12$. The impluse response functions are calculated by fixing an initial shock size equal to the time-series average of stochastic volatility over the sample period (Nakajima, 2011).[12] In addition to three dimensional representation the accumulated responses at the latest horizon are also presented with their confidence intervals to evaluate their significance over the investigation period.[13]

Time-varying responses in general indicate that the the effects of shocks are positive and mainly die out within five quarters.[14] Exchange rate turns out to be the most influential variable. A positive shock to exchange rate initially results in a 2.71 percent instantaneous

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[12] *The responses based on the estimation of the corresponding linear VAR model are also presented in Figure A2.The linear responses are all found to be positive as expected but the magnitude of the responses varies across the different estimation subsamples. This also provides additional support for the time-varying relationship. Linear responses indicate that US nominal exchange rate is the most important variable. The magnitude of the exchange rate shocks has a declining pattern over time whereas natural gas price shocks are increasing impact on the electricity prices.*

[13] *Following Nakajima (2011) the standard error bands are calculated based on asymptotically Gaussian distribution of responses. To do this, first standard deviation of time-varying responses over the estimation sample is calculated. Then two standard error bands corresponding to around 95 percent confidence interval of the responses are calculated through the following formula:* $resp(i,j)_t \pm 2 \times S.E.[\ resp(i,j)_t]$ *where* $resp(i,j)_t$ *represents the time-varying response of variable i to the shock in the variable j.*

[14] *The non-accumulated time-varying responses of electricity prices are presented in Figure A3 (see Annexes).*

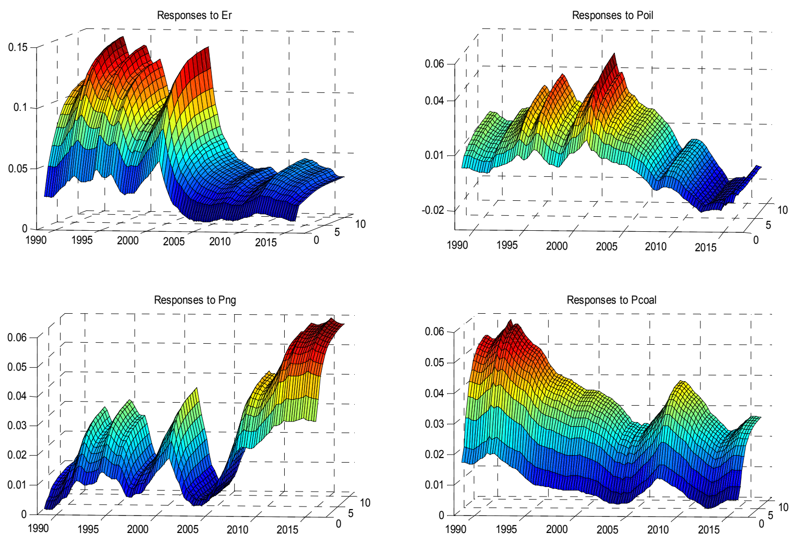
(h=0) increase in the electricity prices, at the end of the forecast horizon (h=12) the cumulated impact of exchange rate is realized as 11.33 percent. The instantaneous impact of exchange rate shocks is increased to 4.04 percent by the end of 1992 attributed to the possible impact of Gulf War. The highest instantaneous effect of exchange rate shocks on the electricity prices has been observed in the second quarter of 2001, with 5.7 percent. The cumulated impact of exchange rate on that time has also reached the maximum value, with 13.66 percent at h=12. By the end of the estimation period, the contemporaneous impact of the exchange rate shocks is declined gradually to 1.06 percent. It can be observed from Figure 2 that a positive exchange rate shock is associated with a 3.10 percent cumulated increase in the electricity prices in the first quarter of 2016.

The time-varying responses of electricity prices to the fossil fuel prices in general reveal the increasing importance of natural gas price shocks on the electricity prices, in particular for the period after the 2008 financial crisis. However, the natural gas prices shocks are found to be insignificant and lagging behind the impact of coal price shocks at the earlier periods. A positive shock to coal prices has led to a 5.29 percent increase in the electricity prices, whereas the same figure for the natural gas is obtained as less than one percent (0.93 percent). Coal shocks have reached the highest level at the earlier time of the estimation period, *i.e.* 5.78 percent by the second quarter of 1992, and show a gradually declining pattern up to 2006, and then increased to 3.81 percent in the second quarter of 2008 due to the possible impact of financial crisis. By the end of the investigation period, the accumulated impact of coal prices has been declined to 2.64 percent.

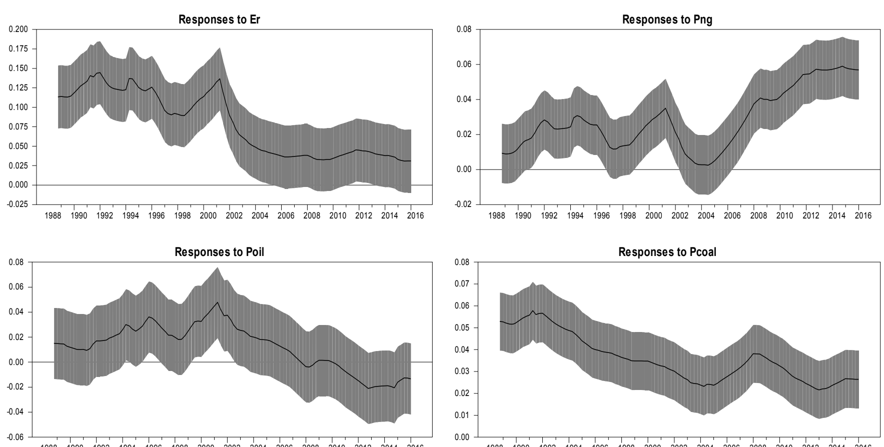
The responses of electricity prices to the natural gas price shocks are more volatile than to coal and oil price shocks. The natural gas price shocks, computed as less than one percent in the beginning, increased sharply to 2.83 percent in the second quarter of 1992 and, then declined below one percent in the first quarter of 1995. In the second quarter of 2001, the impact of natural gas prices has jumped to 3.50 percent and then declined again below one percent by the first quarter of 2003. Natural gas price shocks display a steadily increasing trend from the first quarter of 2006 (1.36 percent) to the end of the estimation period (5.69 percent). At the end of the estimation period, the impact of natural gas prices has surpassed the impact of exchange rate shocks, natural gas prices therefore become the highest impact variable on the electricity prices.

The impact of oil price shocks is found to be positive in the beginning, although the responses plotted with standard error bands suggest that oil price shocks are only significant during the period of 1994 and 2001 crises (see Panel b of Figure 2). The highest impact of oil price shocks is observed in the second quarter of 2001, with 4.77 percent, then the responses decline gradually below zero.

Figure 2
The Time-varying Accumulated Responses of Electricity Prices



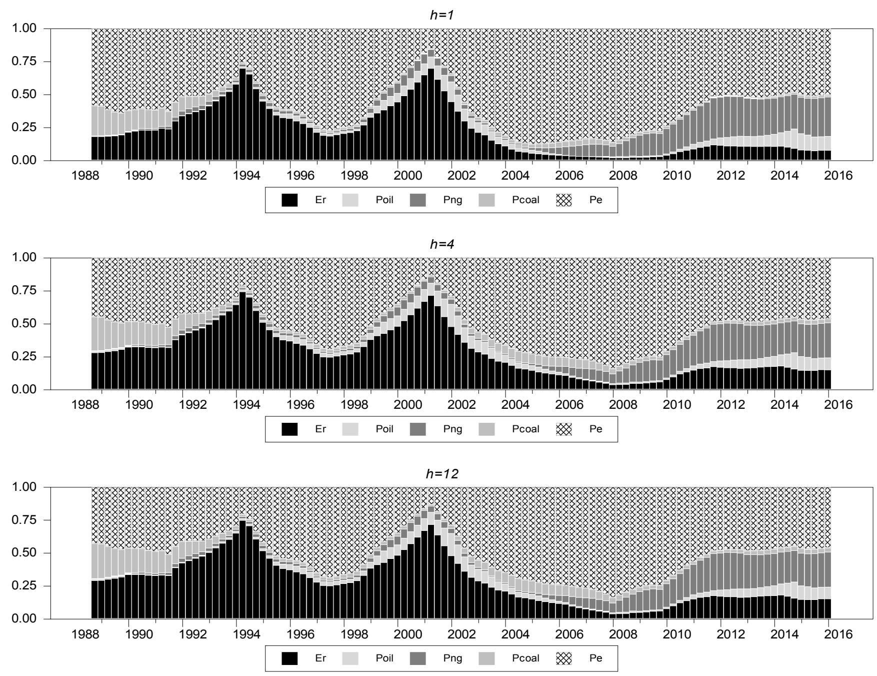
(a) Accumulated Responses of Electricity Prices



(b) Accumulated Responses of Electricity Prices at h=12 with ±2 Standard Error Bands

Figure 3

Time-varying Forecast Error Decompositions



Along with the impulse responses, time-varying forecast error decomposition analysis is also conducted to illustrate the importance of the fuel prices in the explanation of electricity prices over the investigation period. The variance decompositions for electricity prices at the 1, 4 and 12 quarter time horizons are presented in Figure 3. At the one-quarter forecast horizon h=1, total variation in the electricity prices are largely explained by their own shocks in the beginning of the investigation period (with 58.88 percent). This is followed by the coal prices with 22.78 percent and exchange rates with 17.78 percent. The contribution of natural gas and fuel oil prices on that time even falls below 1 percent. It is also noteworthy that the prediction power of exchange rate shocks surpasses the own shock of the electricity prices, especially during the 1994 and 2001 financial crises. Exchange rate shocks are able to explain around 57.56 percent around 1994 crisis and 64.59 percent around 2001 crisis of the variation in the electricity prices at the one-quarter forecast horizon h=1. Oil price shocks constantly account for less than 5 percent of the variation in the electricity prices over the investigation period. The contribution of natural gas price shocks which is below the 5 percent up to 2000, but has increased sharply and then exceeds the impact of coal price shocks (4.28 percent) by the end of 2007, by explaining 9.04 percent of the variation in the electricity prices after the own shocks of the electricity (84.06 percent of the variation is attributed to the own shock). After that time, the portion explained by natural gas prices has increased steadily, around 29.60 percent of the variation in the electricity prices can be attributable to natural gas by the end of the investigation period. The results of one-quarter forecast error decomposition are found to be similar with the variance decompositions at longer time horizons with few exceptions. The explanatory power of the own shock of electricity prices has declined as the forecast horizon is increased to 12-quarter ahead. Coal prices and exchange rate shocks together explain more on the own shocks of the electricity prices, with 55.51 percent in the earlier part of the investigation period. Similarly exchange rate shocks still explain the most part of the variation in the electricity prices during the crisis periods. By the end of the sample period most of the forecast error variance of the electricity prices has been accounted by the own shock (46.45 percent) followed by natural gas prices with 30.17 percent and exchange rates with 14.90 percent.

5. Conclusions

This paper examined the relationship among electricity prices and the fossil fuel prices and exchange rate in Turkey. The possible time-varying dynamics among the variables has been investigated with the estimation of a TVP-VAR model by using quarterly data covering the period 1988 to 2016.

The results obtained from time-varying responses and forecast error decompositions indicate that the impact of fossil fuel prices and exchange rate on the electricity prices differs markedly over time. Exchange rate and natural gas and coal prices significantly explain changes in the electricity prices, whereas the contribution of oil prices remained relatively low and insignificant over the investigation period. Exchange rate turns out to be the most important variable, in particular during the crisis, this may be attributed to fact that depreciation of domestic currency may rise energy import costs. However, the time-varying impact of exchange rate shocks has declined remarkably due to the successful implementation of monetary policy based on inflation targeting with flexible exchange rate strategies. The results in general also reveal that electricity prices in Turkey have been recently to a large extent affected by the developments in the natural gas prices, due to the increasing share of natural gas in the generation of electricity. The evidences on the increasing importance of natural gas prices and low contribution of oil prices are consistent with the findings of Mohammadi (2009), Ferkingstad *et al*. (2011) Gök *et al*. (2016).

Our results have underlined the fact that the increasing share of natural gas in the electricity generation pose a potential threat on the sustainability of energy security in Turkey, since around 99 percent of the natural gas is imported from abroad (MENR, 2015). In this context, reducing the share of natural gas and diversification of importing countries may improve energy security in the electricity sector. Increasing the generation of electricity based on indigenous resources such as hard coal, lignite, hydro and also other renewable resources can be considered as a short-term solution. Although it requires qualified labor and high level of investment during the construction stage, nuclear power can be also considered as a potential alternative to reduce dependency on imported fossil fuels, due to its small share of fuel costs in the total generation cost. Hence, fossil fuel price changes and exchange rate fluctuations would have limited impact on the external balance and price level of the country after the completion of nuclear power plants to be built in Mersin Akkuyu and Sinop.

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Annexes

Figure A1

Sample Autocorrelation Functions, the Sample Paths and the Posterior Densities for Selected Parameters

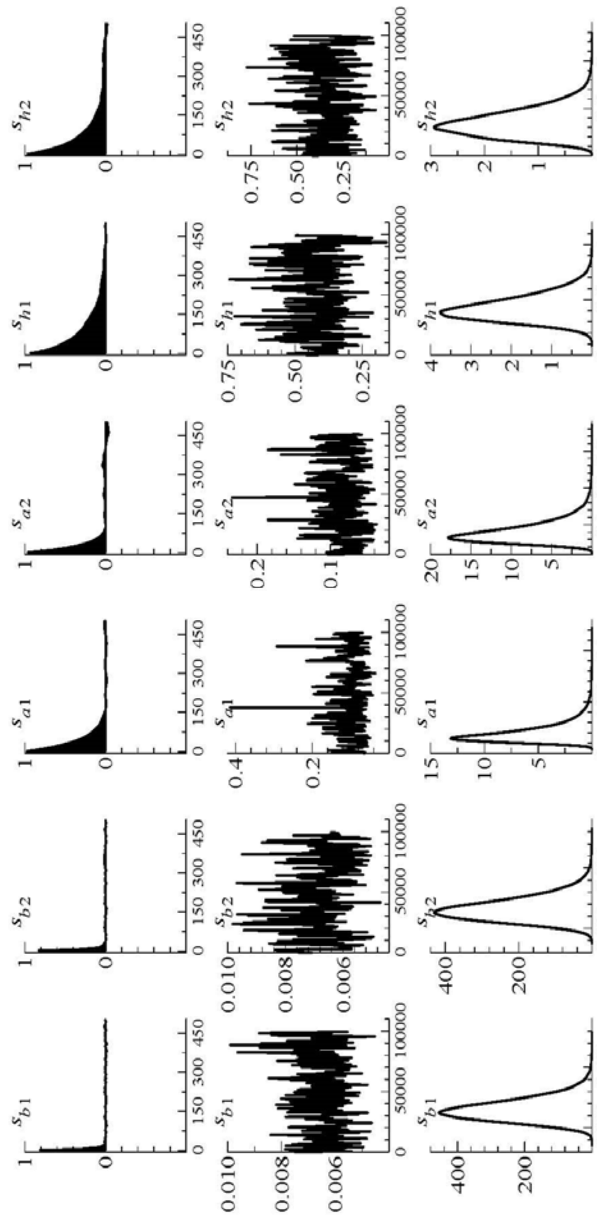

Figure A2

Linear Responses of Electricity Prices

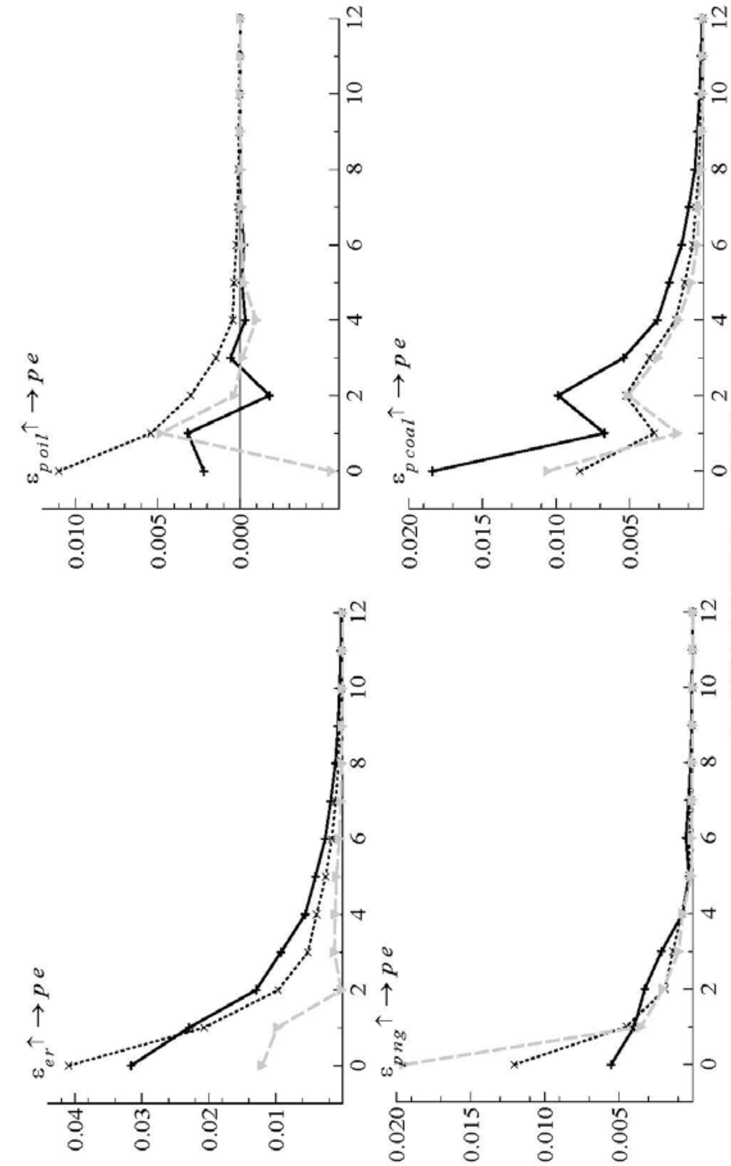

Figure A3

Time-varying Responses to Electricity Prices (Non-accumulated)

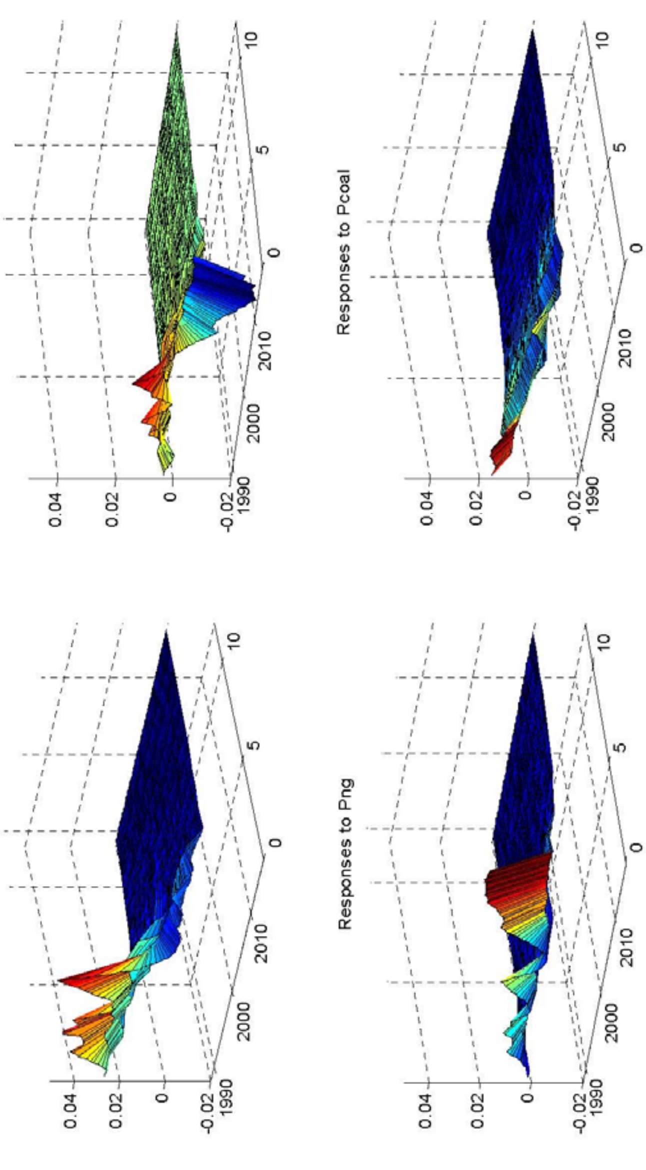

Figure A4

Data