Energy Demand Estimation and Forecasting in Qatar[1]

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Overview

The economic theory provides a rationale for linking the energy demand to a number of variables that might affect it. Starting from that, the empirical analyses specify a number of alternative specifications of the energy demands. For instance, Zarnikau (2003) suggests three possible forms. First, a linear specification involving the levels of the variables, where the energy demand is a linear function of production factors or of other elements affecting demand. The second form is still a linear specification, but where the log-levels of the variables replace the levels. These two forms are coherent with production (or consumption) functions being additive or multiplicative, respectively, in the underlying factors. The third case focuses on the share equations, most common in a production-based framework, where the share cost of energy, over the total cost of production, depends on the production factors in a linear fashion.

Methods

We will use the Auto Regressive Distribute Lag (ARDL) specification, which might be written as follows

$$y_t = \alpha + \sum_{i=1}^{p} \gamma_i \, y_{t-i} + \sum_{j=1}^{q} \beta_j' X_{t-j} + \varepsilon_t. \qquad (1)$$

The ARDL model might be estimated again by least squares methods. Notably, this specification allows computing short-run elasticities, the β_j' parameters, as well as long-run elasticities, which can be obtained by standardizing the coefficients by the autoregressive polynomial, i.e. $1 - \sum_{i=1}^{p} \gamma_i$.
A further advantage of the ARDL specifications comes from their coherence with the existence of a long-run equilibrium relation across the modelled variables. In fact, if we assume that the variables of interest are possibly cointegrated (and are thus non-stationary in their levels) and also characterized by short-term dynamic, we might recast the ARDL model into the so-called Error Correction Model representation (ECM) for the series first difference (denote by Δ)

$$\Delta y_t = \alpha + \omega(y_{t-1} - \delta' X_{t-1}) + \sum_{i=1}^{p} \gamma_i \, \Delta y_{t-i} + \sum_{j=1}^{q} \beta_j' \Delta X_{t-j} + \varepsilon_t. \qquad (2)$$

where $\omega(y_{t-1} - \delta' X_{t-1})$ is the error correction term, ω is the adjustment coefficient, $y_{t-1} - \delta' X_{t-1}$ is the cointegration residual. Such a specification is more appropriate for simulation and forecasting purposes, as it accounts for both the long-run equilibrium relation, i.e. the proper static energy demand, as well as for short term dynamic in the energy demand, which might be affected by shocks both on the energy demand as well as on the covariates. In fact, for scenario analyses, we might design scenarios on the covariates, account for them into the dynamic adjustment approach of the energy demand and simulate, single paths of the energy demand or simulate accounting for the uncertainty in the energy demand, i.e. the shocks ε_t. The estimation approach of such a model might follow the bounds testing approach to cointegration of Pesaran and Shin (1999) and Pesaran et al. (2001).
Despite its appealing form, the ECM representation of the ARDL model is appropriate when only a single cointegration relation exist across the modelled variables. A more general structure is that associated with Vector Error Correction Model (VECM) where the dynamic of a set of variables is jointly estimated. In that case, we can specify the model as follows

$$\begin{bmatrix} \Delta y_t \\ \Delta X_t \end{bmatrix} = \alpha\beta' \begin{bmatrix} y_{t-1} \\ X_{t-1} \end{bmatrix} + \sum_{j=1}^{p} \Phi_j \begin{bmatrix} \Delta y_{t-j} \\ \Delta X_{t-j} \end{bmatrix} + \varepsilon_t \qquad (3)$$

where there might exist more than a single cointegration relation. If we have *k* cointegration relation among the set of *m* variables (the energy demand and the covariates), the matrix β' contains *k* vectors of cointegration coefficients and the matrix α contains the *m* equations adjustment coefficients to the *k* cointegration equations. Note that we can

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expand the model in (5) by introducing an intercept, other deterministic variables as well as other exogenous covariates. The estimation and testing for cointegration might follow the approaches proposed by Johansen (1988, 1991, 1992, 1994 and 1995).

Moving back to the three approaches listed by Zarnikau (2003), we now briefly discuss the estimation of share equations. This approach focuses on the estimation of the share cost of various inputs with respect to the total cost of production for a specific good. We express energy demand as a function of energy prices, the appropriate price should be a weighted average of the prices of the underlying energy sources (electricity, gas, oil…etc.). The weights might be interpreted as share costs, and therefore the approaches for the estimation of share equations turn out to be relevant in this case, see Fuss (1986). Share equations are nothing more than linear equations for the share of the specific energy source on the total energy demand. However, the crucial aspect to be here considered is the presence of constraints: the shares must be positive and must sum up to one. However, various approaches have been proposed to introduce the appropriate constraints, see for instance the methods by Zellner (1962 and 1963). Further, we can take gasoline price as an indicator for energy price in the demand function.

We close this set of methodological approaches by taking into account the use of structural time series methods, see Harvey (1989). In this approach, the static energy demand of (1) is augmented by the presence of a stochastic trend

$$
\begin{aligned}
y_t &= \alpha + \mu_t + \beta' X_t + \varepsilon_t, \\
\mu_t &= \mu_{t-1} + \delta_{t-1} + \eta_t \\
\delta_t &= \delta_{t-1} + \zeta_t
\end{aligned}
\tag{4}
$$

where, usually, the shocks are uncorrelated, normally distributed and with an unknown variance. Such an approach might be extended with the presence of stochastic cyclical and seasonal components and could represent an alternative approach to classical time series methods.

Results

Building on an ARDL specification with a latent trend, Dilaver and Hunt (2011a) provide a scenario analysis for Turkey industrial energy demand and Dilaver and Hunt (2011b) analyze scenarios for residential electricity demand in Turkey. Both studies consider three scenarios, the reference one and two opposite cases representing an increase/decrease in the energy demand due to changes in the production levels, the energy efficiency and the prices. Jiang and Li (2012) provide three different scenarios for the evolution of China energy demand starting from a static long-run relation and using scenarios for the underlying factors. Li et al. (2010) analyze the evolution of energy demand and CO2 emissions in Shanghai under two alternative scenarios, one associated with energy conservation policies. Tajudeen (2015) performs a forecast and scenario analysis for aggregated energy demand. He consider three scenarios, the reference one and two alternatives with increases/decreases in the factors affecting energy demand. Zachariadis and Taibi (2015) provide a scenario analysis for Cyprus energy demand based on different projections of underlying macroeconomic factors as well as in terms of energy efficiency improvements.

Conclusions

We use the following variables in the estimation process and we will present the results in conference. 1- Per capita income in Qatar, gross value added by sector, inflation index or deflator of the GDP, GDP by sector or any form of decomposition of the GDP (in particular investment expenditures, gross fixed capital formation). 2- Price of electricity, gasoline, oil, natural gas in Qatar, ok but we also need information on the role of each energy source in electricity production. 3- Urbanization index in Qatar, as well as population growth, and the ratio of population living in urban areas and the population increase by separating urban/no urban. And, financial development index in Qatar, trades, tourism inflows. Energy efficiency index.

Selected references

- Adetutu, M.O., Glass, A.J., and Weyman-Jones, T.G., (2016). Decomposing energy demand across BRIIC countries, Energy Economics, 54, 396-404.
- Amusa, H., Amusa, K., and Mabugu, R., 2009, Aggregate demand for electricity in South Africa: An analysis using the bounds testing approach to cointegration, Energy Policy, 37, 4167-4175
- Apergis, N., and Payne, J.E., 2011, A dynamic panel study of economic development and the electricity consumption-growth nexus, Energy Economics, 33, 770-781.
- Arsenault, E., Bernard, J.T., Carr, C.W., and Genest-Laplant, E., 1995, A total energy demand model for Quebec, Energy Economics, 17(2), 163-171.
- Badr, E.A., and Nasr, G.E., 2001, On the relationship between electrical energy consumption and climate factors in Lebanon: co-integration and error-correction models, International Journal of Energy Research, 25, 1033-1042.