Analyzing Energy Consumption and GDP Nexus Using Maximum Entropy Bootstrap: The Case of Turkey

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Abstract

We employ a maximum entropy bootstrap based framework to analyze the energy consumption and real GDP nexus between 1950 and 2006 in Turkey. Our approach provides more accurate inference in comparison to conventional hypothesis tests based on asymptotic theory. It also avoids preliminary testing and shape-destroying transformations such as differencing and detrending. The bivariate analysis as well as a multivariate framework controlling for exchange rate and oil prices show no evidence of a causal relation. Our results are robust to both the number of lags and the time period chosen. We also perform a cointegration analysis of the data and point out a common misunderstanding in the literature regarding the concept of causation. Keywords: Energy consumption, income, causality, meboot, bootstrap, Turkey. *JEL* Codes: Q43, C12.

1 Introduction

Studying the causal relationship between energy consumption (EC) and income is of course nothing new. Since the initial work of Kraft and Kraft (1978), different authors studied this

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topic and reported contradicting results for different countries as well as for different time periods within the same country.[1]

Turkey alone has been a subject of at least ten articles published in the recent years. Soytas and Sari (2003) used a vector error correction model (VECM) and found that causality runs from EC to GDP for the 1960-1995 period in Turkey. Altinay and Karagol (2004), employing the Hsiao's version of Granger method for the 1950-2000 period, found no evidence of causality between EC and GDP. For the same time period, Altinay and Karagol (2005) used a VAR model along with standard Granger tests and found causality running from electricity consumption to GDP. Jobert and Karanfil (2007) focused on the 1960-2003 period and, based on a cointegration and Granger causality analysis, concluded that no causal relationship exists between GNP and EC in the long run. Halicioglu (2007) employed a VECM approach for the 1968-2005 period and found causality running from GNP to electricity consumption in the long run. Lise and Montfort (2007) undertook an error correction model (ECM) approach for the 1970-2003 period and concluded that causality runs from GDP to EC. Narayan and Prasad (2008) used a basic parametric IID bootstrap approach for studying the OECD countries and found for Turkey no evidence of any causal relationship between GDP and EC between 1960 and 2002. Karanfil (2008), using data for the 1970-2005 period, also concluded that EC and GDP are neutral to each other. Erdal et al. (2008) employed a pair-wise Granger causality analysis for the 1970-2006 period and found bi-directional causality between EC and GNP. Recently, Halicioglu (2009) used an autoregressive distributed lag (ARDL) approach for the 1960-2005 period and found no causal relationship between EC and GNP in Turkey.

Understanding the nature of a possible causal nexus between EC and income has important implications for energy policy in Turkey. Over the last 30 years, Turkey regularly achieved high growth rates while her energy consumption more than tripled during the same period (World Energy Council, Turkish National Committee 2008). In May 2009, Turkey also ratified the Kyoto Protocol to the United Nations Framework Convention on Climate Change (UNFCCC)

[1] See Ozturk (2010) for a review.

and accepted a commitment to plan and reduce greenhouse gas (GHG) emissions starting with 2012. Consequently, if the so-called "growth hypothesis" that EC results in more output is true, energy conservation policies can be detrimental to future economic growth in Turkey. However, if there is a unidirectional causality running from economic growth to EC ("conservation hypothesis"), it may be possible to implement energy conservation policies and cut GHG emissions with little or no adverse effects on output. In fact, a possible negative causality running from output to EC can even result in energy conservation policies increasing the real GDP. On the other hand, neither energy conservation nor expansion policies will have any affect on economic growth if the "neutrality hypothesis" holds, which means that a causal relationship does not exist between EC and GDP.

Despite the potentially crucial policy implications, the inconsistency of the existing findings on the energy-income relationship currently makes it impossible to suggest a reliable policy direction for Turkey. The conflicting results are perhaps not surprising given the evolutionary nature of time series data along with the limited number of available observations. Together, these seem to create empirical results with a high sensitivity to the time period considered as well as the econometric methodology used. In response to the growing number of controversial results, Karanfil (2009) and Ozturk (2010) argued that future research on this subject should focus on state of the art econometric techniques rather than employing the usual methods for different countries and different intervals of time. We second this proposition and bring into play the maximum entropy bootstrap (meboot) technique. Simulation based hypothesis testing is long known to yield in small samples substantially more accurate results in comparison to conventional inferences based on asymptotic theory. In the energy economics literature, however, bootstrapping has been rarely employed, partly because of the absence of a bootstrap technique useful for strongly dependent time series data.[2] The recently developed meboot data generation process (DGP) is specifically designed to fill this gap. It can be employed in all forms of structural breaks and nonstationarity without transforming the data and allows hy-

[2] To our knowledge, the only studies investigating the EC - GDP nexus based on a bootstrap methodology are Narayan and Prasad (2008) and Balcilar et al. (forthcoming).

pothesis testing that is not only accurate, but also robust in the sense of avoiding specification errors. Our objective is to employ this advanced technique to provide conclusive evidence regarding short run precedence also known as Granger causality between energy consumption and GDP in Turkey.

2 Methodology and the results

When the sample size is relatively small, the traditional hypothesis tests and confidence intervals based on asymptotic theory can yield seriously misleading results. As an example, MacKinnon (2002) discusses how an asymptotic J test at the 5% level can reject a true null hypothesis more than 80% of the time for sample sizes as large as 50. The significance of such over-rejection from the perspective of causality testing is, of course, the risk of wrongly finding a statistically significant relationship due to rejecting the true null of no causality. Fortunately, the tremendous increase in the power and capacity of modern computers has allowed applied economists to overcome size distortion problems by using simulation based bootstrap distributions for statistical inference. Bootstrapping essentially involves using a parametric method or resampling to calculate a large number of simulated values of an observed test statistic and construct a simulated empirical distribution function. For example, in the case of basic parametric IID bootstrap (Efron 1982), inference regarding a parameter of interest is made after residuals from the fitted model are randomly resampled a large number of times to create simulated error vectors, which are subsequently plugged into the original model for regression and the computation of confidence limits for the required test statistic. This approach permits substantially more accurate hypothesis testing,[3] however, it cannot always be relied to perform better under certain conditions such as serial correlation. This particular problem historically limited the use of the conventional IID bootstrap methods in time series econometrics, at least to some extent. In the last several years, however, various authors proposed advanced bootstrap DGP

[3]Davidson and MacKinnon (1999) show that the size distortion of a bootstrap test will in many cases be an order of magnitude smaller than that of the corresponding asymptotic test.

alternatives suitable for time series data.[4]

Introduced by Vinod (2004), meboot is a bootstrap DGP specifically designed for use with strongly time-dependent nonstationary data. Unlike some of the alternative bootstrap DGPs such as the various types of block bootstrap, meboot does not reorder the original data and therefore can avoid distorting the dependence and heterogeneity of information. Instead, it employs a seven step algorithm that creates replicates retaining the basic shape and dependence structure of the autocorrelation function and the partial autocorrelation function of the original data. The process satisfies the ergodic theorem as well as the central limit theorem. As a result, running a unit root test on a replicate, for example, will give p-values converging to that of the original series as the sample size increases. Creating a large number of such replicates allows constructing numerical sampling distributions for many pivotal statistics without having to know their possibly multimodal and nonnormal functional forms. The practical advantage of this procedure from the perspective of applied economists is that it renders redundant all shape-destroying transformations such as differencing, detrending, or spectral decomposition. It also allows more flexible and reliable empirical analysis because it offers a simplified approach that can be used in all forms of nonstationarity including near unit roots or long memory, which are often difficult to distinguish with confidence in small samples. For detailed information on the meboot technique, the reader is referred to Vinod (2008) and Vinod and de Lacalle (2009).

2.1 Bivariate analysis

Because meboot makes it possible to work with multiple time series without first making them stationary, simpler model specifications are allowed. As a result, we first investigate the bivariate causal relationship between real GDP and energy consumption by using the system

$$y_t = c_1 + \sum_{i=1}^{m} \alpha_{1i}\, e_{t-i} + \sum_{j=1}^{n} \beta_{1j}\, y_{t-j} + u_{1t}, \tag{1}$$

[4] To obtain more information regarding the use of bootstrap methods in econometrics, see for example Vinod (1993) or MacKinnon (2002). For a discussion of the various bootstrap DGPs, see MacKinnon (2007).

$$e_t = c_2 + \sum_{i=1}^{m} \alpha_{2i}\, e_{t-i} + \sum_{j=1}^{n} \beta_{2j}\, y_{t-j} + u_{2t} \tag{2}$$

where u_i $(i = 1, 2)$ is the residual term, c_i $(i = 1, 2)$ is the constant term, y is the log of real GDP, and e is the log of energy consumption. The real GDP in 1987 thousand Turkish Liras is obtained from Turkish Statistical Institute (2009). The data for total primary energy consumption, measured in kilotonne of oil equivalent, comes from World Energy Council, Turkish National Committee (1978, 2008). The reason for transforming the variables to natural logarithms is to remain consistent with the earlier studies. The data, which is annual, cover the sample period from 1950 to 2006. A plot of the two series is provided in Figure 1.

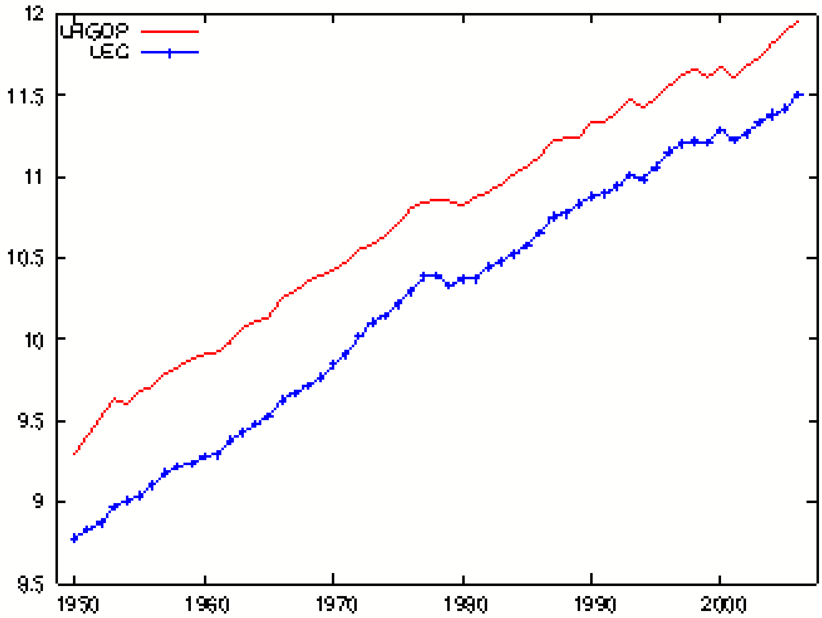

Figure 1: Plot of the log of real GDP and the log of EC.

For the causality testing procedure, we employ the meboot algorithm to create a resample of $Q = 999$ series for y and e. As a whole, these series represent the "population" of the original data and are referred to as "ensemble" in the statistical literature. We take these replicates and run Q regressions for (1) and (2). The 999 coefficient estimates for each parameter are subsequently used to obtain the confidence intervals for α_{1i} and β_{2j}. In order to compute these intervals, we use the Highest Density Region (HDR) method discussed by Hyndman (1996).[5]

[5]The R package hdrcde (Hyndman 2010) was used.

The HDR offers an advanced and reliable approach especially when the sampling distribution is bimodal as was the case for some of our estimates. Finally, the null hypothesis that e does not cause y (y does not cause e) is rejected if zero is outside the $(1-\alpha)100\%$ confidence interval for α_{1i} (β_{2i}).

Reported in Column I of Table 1 are the causality test results along with the respective Schwarz Bayesian Criterion (SBC) values for different models that we consider for the standard bivariate case specified in Equations (1) and (2).[6] We choose lag lengths up to $i = j = 2$, resulting in a combination of four model specifications.[7] In all estimations, zero is found inside the 90% confidence intervals for the respective α_{1i} and β_{2j} parameters. As a result, we do not reject the null of no causality at the $\alpha = 0.1$ level.[8]

The large number of studies on the energy-income nexus show that causality results can vary just by changing the time period considered (Karanfil 2009; Ozturk 2010). Consequently, the lower parts of Table 1 present the results when the tests are repeated with the 1950-2000, 1960-2003, and 1970-2006 subperiods respectively. This is done in order to show that our findings do not change when different time intervals are taken into consideration. Indeed, while there is a general increase in the SBC values due to the decreased number of observations, the overall result of no causality does not change. Thus, we conclude that our results are robust to the number of lags as well as the time period chosen.[9]

For spurious regression problems with or without structural breaks, an extensive Monte Carlo simulation by Vinod (2010) shows that meboot confidence limits are superior to those obtained by OLS, OLS applied to differenced data, and the alternative block bootstrap procedure when the regression residuals are stationary. Consequently, we test for a unit root in the estimated residuals using the familiar KPSS and ADF tests. The results do not reject stationar-

[6]R version 2.11.1 and gretl version 1.9.0 were used. Our data and code are available upon request.

[7]We also tried larger number of lag combinations, which result in estimations with a higher Schwarz criterion. We do not report these results for brevity.

[8]When k hypothesis tests are performed at the same time, the well-known Bonferroni inequality requires setting $\alpha' = \alpha/k$. As a result, for models 3 and 4 where two lags of the independent variable are used, α' equals 0.05.

[9]Other alternatives namely 1965-1995, 1968-2005, and 1970-2003 were also examined but not reported in view of the similar findings. Of course, determining whether the results do not change in all subperiods requires a more extensive approach such as rolling window estimations.

ity and reject the unit root hypothesis for $\alpha = 0.1$, providing additional support for the accuracy of our estimations.[10]

2.2 Multivariate analysis

Most studies on the causal relationship between EC and GDP employ a bivariate framework, however, recent research such as Karanfil (2008) and Halicioglu (2009) consider other variables as well. Because a potential omitted variable bias can distort the results, we extend our analysis into a multivariate framework. The first variable that we introduce is the U.S. per barrel first purchase crude oil prices in chained (2000) U.S. dollars. This is a useful variable to include in a multivariate system because Turkey is an oil importing country and World oil prices can have an impact on both Turkish EC and real output. The second variable that we consider is the log of Turkish Lira-U.S. Dollar real exchange rate. Recommended also by Karanfil (2009) and Ozturk (2010), the exchange rate is important because it directly influences the domestic prices of internationally traded energy sources while also affecting production through its influence on exports.

With the inclusion of the new variables, our model specifications become

$$y_t = c_1 + \sum_{i=1}^{m} \alpha_{1i}\, e_{t-i} + \sum_{j=1}^{n} \beta_{1j}\, y_{t-j} \sum_{k=1}^{q} \gamma_{1k}\, p_{t-k} + \sum_{l=1}^{s} \lambda_{1l}\, r_{t-l} + v_{1t}, \tag{3}$$

$$e_t = c_2 + \sum_{i=1}^{m} \alpha_{2i}\, e_{t-i} + \sum_{j=1}^{n} \beta_{2j}\, y_{t-j} + \sum_{k=1}^{q} \gamma_{2k}\, p_{t-k} + \sum_{l=1}^{s} \lambda_{2l}\, r_{t-l} + v_{2t} \tag{4}$$

where p is the log U.S. real oil prices, and r is the log of Lira-Dollar real exchange rate. The first variable comes from U.S. Energy Information Administration (2009), while the second is computed by the author.[11] Figure 2 provides a plot of the additional series considered in the multivariate analysis.

[10] The tests included a constant and a trend. Considering the sample size, 3 lags were used. The results were not sensitive to the choice of lags. We do not include these statistics for brevity.

[11] The formula used was $r = e\frac{CPI_{\text{US}}}{CPI}$ with 1987 as the base year. The data were obtained from State Planning Organization of Turkey (2007) and U.S. Bureau of Labor Statistics (2010).

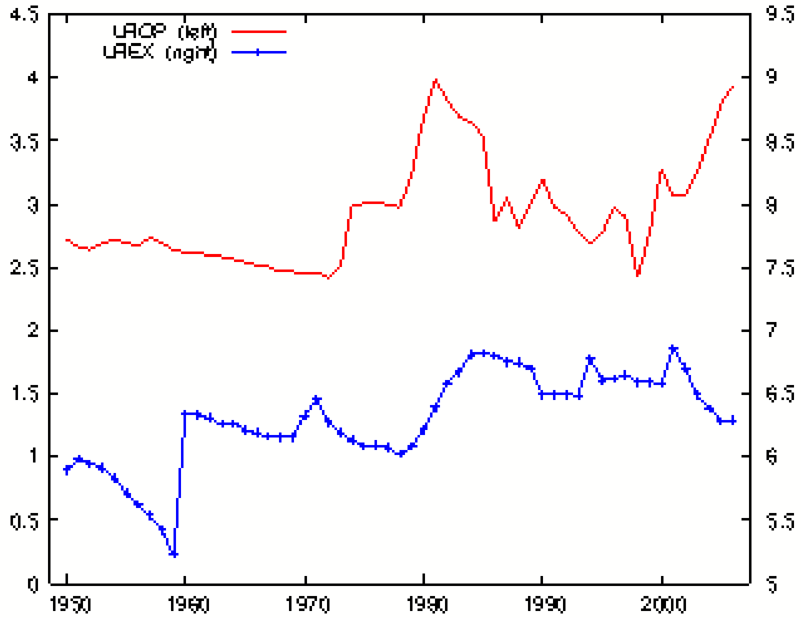

Figure 2: Plot of the log of real exchange rate and the log of U.S. real oil prices.

Column II of Table 1 shows the causality test results for the multivariate analysis. The choice of lags is made based on the SBC values, which remains similar to those from the bivariate analysis. Overall, after controlling for the exchange rate and oil prices, we once again obtain consistent results supporting the neutrality hypothesis between EC and GDP. These results are arguably more reliable since they take into account two variables important for explaining the relationship between EC and GDP in an open economy setting.

Finally, Figure 3 and Figure 4 respectively show the HDR intervals for the parameter estimates of log of EC and log of GDP for models 1 through 4 for the multivariate analysis. The three horizontal bars in each plot represent the probability coverage levels 90, 95, and 99 respectively. The plots show how the HDRs, which are narrower than the naive percentile intervals, cover zero for $\alpha = 0.1$ in all models.

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http://ideas.repec.org/a/eee/eneeco/v33y2011i3p453-460.html.

3 Cointegration Analysis

Testing for unit roots and cointegration is not germane to our study because, as discussed earlier, meboot can be seamlessly applied under all sorts of non-stationarity. Still, a formal investigation of the time series properties of the data can be useful to illustrate the advantages of our approach in the analysis of the causal relationship between macroeconomic variables.

Table 2 presents the results for the KPSS, ADF, Engle-Granger, and Johansen-Juselius tests for the different periods as well as for the bivariate and the multivariate cases for two different deterministic specifications namely a constant and a constant plus a linear trend.[12] The variation in the results is striking, which underlines the fact that formal tests are helpful only to some extent in reducing the ever-present uncertainty involved in the analysis of time series. What is more, it is possible still to obtain other sets of results by using a different lag order, by trying other deterministic terms, by choosing a different level of significance, or simply by employing other unit root and cointegration tests among the many available alternatives. Based on a subset of these findings, one can advocate the use of one or more of a variety of econometric models including VAR in levels, VAR in differences, error correction, or bounds testing among others. It is hardly surprising that the resulting analysis leads to the varying causality conclusions between EC and GDP that we observe in the literature.

The table clearly shows that errors are inevitable in the standard practice of testing for unit roots and cointegration. Our approach, on the other hand, avoids such preliminary analyses which can and do induce incorrect results into causality testing. Consequently, one main advantage of the meboot based framework is in the department of reliability in the sense of avoiding specification errors. However, it is important to note that our approach is strictly based on the concept of Granger causality, which is concerned with precedence and short run forecastability. This can be considered as a limitation with respect to the cointegration technique providing results for both short run and long run causality.

[12]The modern econometric literature offers many methods for testing for unit roots and cointegration, each with its own set of weaknesses. We choose these four because they are the most commonly used tests in the existing studies.

The general ambiguity in the results in Table 2 presents an opportunity to also point out a common misunderstanding in the literature that cointegration necessarily means causality. In many papers performing a cointegration analysis, one finds statements such as

> If cointegration exists between two variables in the long run, then, there must be either unidirectional or bi-directional Granger-causality between these variables.

or

> Cointegration implies that causality exists between the two series but it does not indicate the direction of the causal relationship.

or even

> The existence of cointegration rules out Granger non-causality.

These statements[13] are perhaps due to taking too literally the Representation Theorem introduced by Engle and Granger (1987). Such proclamations can be easily challenged not only because of the aforementioned difficulty in determining for sure the true time series properties of the data, but also because there can always be extra variables, not included in the information set, altering causation conclusions between two series.

Granger (1988) himself notices the possibility of a jointly causal variable and states that

> If X and Y are a pair of continuous random variables, there potentially could exist a third variable Z such that the joint distribution of $X, Y, Z, \phi(x, y, z)$, has the property
>
> $$\phi(x, y, z) = \phi(x|z)\phi(y|z)\phi(z),$$
>
> so that $X|Z$ and $Y|Z$ are independent.

This means that even if X and Y are cointegrated, in reality they can be "independent" of each other. Without doubt, independent variables cannot have causal effects ever in reality.

[13] We decide not to give references because such statements are common and are not limited to the studies quoted from.

If cointegration relation shows otherwise, it is a spurious result due to omission of a jointly causal variable.[14] Taking this into account once again points out the importance of a multivariate approach in causality testing. It also suggests that some of the earlier studies conducting cointegration analysis and finding a causal relationship between EC and GDP may have been biased due to wrongly expecting that cointegration always requires causality in at least one direction. Because statistical independence is a stronger concept than causality, authors should exert caution regarding such expectations.

4 Conclusion

In the last ten years, Turkey has experienced significant development and has become the 16th largest economy in the world by purchasing power parity (International Monetary Fund 2010). Due to the growing population and ongoing industrialization, energy investments remain of crucial importance for the country. Turkey is also strategically located at the crossroads of the world's largest oil and natural gas routes, where a number of large multinational energy investment projects are being undertaken or planned at the moment. Furthermore, Turkey has recently ratified the Kyoto Protocol and, as an Annex I country, accepted to reduce GHG emissions starting with the protocol's second commitment period in 2012. These are the main reasons which make Turkey a source of interest in the energy economics literature and bring about a number of studies analyzing the causal relationship between its energy consumption and national income. However, after numerous articles published in the last decade, the findings are still indecisive, pointing out the need for investigating this issue using state of the art econometric techniques rather than employing the usual methods.

The recently introduced maximum entropy bootstrap DGP provides a flexible and powerful tool for doing statistical inference using time series data. It has the main advantage of yielding in small samples substantially more accurate results in comparison to conventional hypothesis

[14]This can also be thought of as a time series version of the well-known Yule-Simpson effect seen in cross sections.

tests based on asymptotic theory. Moreover, the technique can be used without performing shape-destroying transformations under all types of nonstationarity including structural breaks, near unit roots, and fractional integration. This in turn improves reliability in the sense of avoiding specification errors caused by preliminary testing.

Proposing a meboot based framework for causality analysis, we attempt to provide conclusive evidence regarding the causal relationship between energy consumption and income in Turkey. Our extensive testing reveals that a statistically significant relationship does not exist. In addition, we employ a multivariate framework that can help avoid a potential omitted variable bias and better explain the EC and GDP nexus in an open economy setting. Controlling for the real exchange rate and oil prices, the results once again indicate no causal relationship between EC and GDP in all considered cases. Our findings are robust to the time period chosen as well as the number of lags used in model specification. Finally, applying various stationarity and cointegration tests, we observe contradicting results that can explain some of the variation in causality conclusions that we observe in the literature.

Our findings provide strong evidence supporting the neutrality hypothesis for Turkey. Based on the robustness of the results, it is possible that some of the previous findings on this nexus can be caused by over-rejecting the null of no causality due to the severe size distortions typical for small sample statistical inference based on asymptotic theory.[15] Such size distortions can be orders of magnitude smaller when bootstrapping is used and the meboot DGP is suitable for performing such analysis using time series data. As a result, future research should focus on testing the validity of our diagnosis by extending this analysis to other countries. Potentially fruitful directions for future research also include considering other useful variables such as capital formation as well as carrying out a sectoral analysis using disaggregated data. Exploiting other new and innovative econometric tools should be encouraged as usual.

[15]This argument is further supported by the fact that two studies by Narayan and Prasad (2008) and Balcilar et al. (forthcoming), which employ a less sophisticated bootstrap methodology, also mostly report no causality.

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References

Altinay G, Karagol E. 2004. Structural Break, Unit Root, and the Causality Between Energy Consumption and GDP in Turkey. *Energy Economics*, **26**: 985–994.

Altinay G, Karagol E. 2005. Electricity Consumption and Economic Growth: Evidence from Turkey. *Energy Economics*, **27**: 849–856.

Balcilar M, Ozdemir ZA, Arslanturk Y. forthcoming. Economic Growth and Energy Consumption Causal Nexus Viewed Through a Bootstrap Rolling Window. *Energy Economics*.

Davidson R, MacKinnon JG. 1999. The Size Distortion of Bootstrap Tests. *Econometric Theory*, **15**: 361–376.

Efron B. 1982. *The Jackknife, the Bootstrap and Other Resampling Plans*. Society for Industrial and Applied Mathematics, Philadelphia.

Engle RF, Granger C. 1987. Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica*, **55**: 251–276.

Erdal G, Erdal H, EsengÃijn K. 2008. The Causality Between Energy Consumption and Economic Growth in Turkey. *Energy Policy*, **36**: 3838–3842.

Granger C. 1988. Some Recent Developments in a Concept of Causality. *Journal of Econometrics*, **39**: 199–211.

Halicioglu F. 2007. Residential Electricity Demand Dynamics in Turkey. *Energy Economics*, **29**: 199–210.

Halicioglu F. 2009. An Econometric Study of CO2 Emissions, Energy Consumption, Income and Foreign Trade in Turkey. *Energy Policy*, **37**: 1156–1164.

Hyndman RJ. 1996. Computing and Graphing Highest Density Regions. *American Statistician*, **50**: 120–126.

Hyndman RJ. 2010. Package 'hdrcde'. *R Package version 2.13*, URL http://cran.r-project.org/web/packages/hdrcde/index.html.

International Monetary Fund. 2010. *World Economic Outlook – April 2010*. Washington DC, URL www.imf.org/external/pubs/ft/weo/2010/01/pdf/text.pdf.

Jobert T, Karanfil F. 2007. Sectoral Energy Consumption by Source and Economic Growth in Turkey. *Energy Policy*, **35**: 5447–5456.

Karanfil F. 2008. Energy Consumption and Economic Growth Revisited: Does the Size of Unrecorded Economy Matter? *Energy Policy*, **36**: 3029–3035.

Karanfil F. 2009. How Many Times Again Will We Examine the Energy Income Nexus Using a Limited Range of Traditional Econometric Tools? *Energy Policy*, **37**: 1191–1194.

Kraft J, Kraft A. 1978. On the Relationship Between Energy and GNP. *Journal of Energy and Development*, **3**: 401–403.

Lise W, Montfort KV. 2007. Energy Consumption and GDP in Turkey: Is There A Co-Integration Relationship? *Energy Economics*, **29**: 1166–1178.

MacKinnon JG. 2002. Bootstrap Inference in Econometrics. *Canadian Journal of Economics*, **35**: 615–645.

MacKinnon JG. 2007. Bootstrap Hypothesis Testing. *QED Working Paper No. 1127*, URL http://ideas.repec.org/p/qed/wpaper/1127.html.

Narayan PK, Prasad A. 2008. Electricity Consumption–Real GDP Causality Nexus: Evidence from a Bootstrapped Causality Test for 30 OECD Countries. *Energy Policy*, **36**: 910–918.

Ozturk I. 2010. A Literature Survey on Energy–Growth Nexus. *Energy Policy*, **38**: 340–349.

Soytas U, Sari R. 2003. Energy Consumption and GDP: Causality Relationship in G-7 Countries and Emerging Markets. *Energy Economics*, **2003**: 33–37.

State Planning Organization of Turkey. 2007. *Economic and Social Indicators (1950-2006)*. Ankara, Turkey.

Turkish Statistical Institute. 2009. *Statistical Indicators 1923-2008*. Ankara, Turkey.

US Bureau of Labor Statistics. 2010. *Consumer Price Index*. Washington DC, URL ftp.bls.gov/pub/special.requests/cpi/cpiai.txt.

US Energy Information Administration. 2009. *Annual Energy Review 2008*. Washington DC, URL http://www.eia.gov/FTPROOT/multifuel/038408.pdf.

Vinod HD. 1993. Bootstrap Methods: Applications in Econometrics. In GS Maddala, CR Rao, HD Vinod (eds.), *Handbook of Statistics: Econometrics*, vol. 11, 629–661, North Holland, Elsevier, New York.

Vinod HD. 2004. Ranking Mutual Funds Using Unconventional Utility Theory and Stochastic Dominance. *Journal of Empirical Finance*, **11**: 353–377.

Vinod HD. 2008. *Hands-On Intermediate Econometrics Using R*. 1st edn., World ScientiïňĄc Publishing Ltd., Singapore.

Vinod HD. 2010. New Solution to Time Series Inference in Spurious Regression Problems. *SSRN Working Paper Series*, URL http://ssrn.com/paper=1560074.

Vinod HD, de Lacalle JL. 2009. Maximum Entropy Bootstrap for Time Series: The meboot R Package. *Journal of Statistical Software*, **29**: 1–19.

World Energy Council, Turkish National Committee. 1978. *Turkey, The Third General Energy Congress Statistics*. Ankara.

World Energy Council, Turkish National Committee. 2008. *2007-2008 Energy Report for Turkey (in Turkish)*. Ankara.

			Bivariate Case				Multivariate Case			
			Log of Real GDP		Log of EC		Log of Real GDP		Log of EC	
Model	Period	Lags	SBC	Causality	SBC	Causality	SBC	Causality	SBC	Causality
1	1950-2006	1, 1	-194,56	none	-207,92	none	-185.24	none	-199.08	none
2	1950-2006	2, 1	-186,27	none	-199,67	none	-177.29	none	-191.22	none
3	1950-2006	1, 2	-186,12	none	-199,62	none	-177.14	none	-191.21	none
4	1950-2006	2, 2	-182,47	none	-195,70	none	-173.35	none	-187.22	none
5	1950-2000	1, 1	-184,28	none	-190,22	none	-177.35	none	-180.44	none
6	1950-2000	2, 1	-175,58	none	-181,66	none	-170.20	none	-171.65	none
7	1950-2000	1, 2	-176,31	none	-181,99	none	-169.63	none	-171.63	none
8	1950-2000	2, 2	-173,14	none	-178,15	none	-166.36	none	-167.76	none
9	1960-2003	1, 1	-152,97	none	-156,01	none	-147.13	none	-147.51	none
10	1960-2003	2, 1	-149,73	none	-152,38	none	-144.04	none	-143.72	none
11	1960-2003	1, 2	-149,27	none	-152,24	none	-143.54	none	-143.72	none
12	1960-2003	2, 2	-147,75	none	-148,97	none	-140.43	none	-139.94	none
13	1970-2006	1, 1	-120,76	none	-128,97	none	-127.54	none	-135.27	none
14	1970-2006	2, 1	-117,37	none	-125,53	none	-124.05	none	-131.73	none
15	1970-2006	1, 2	-117,31	none	-125,36	none	-125.00	none	-132.00	none
16	1970-2006	2, 2	-115,18	none	-122,22	none	-124.97	none	-128.47	none

Note: Lags are for log of real GDP and log of EC respectively. The multivariate case includes the log of real exchange rate and its first lag as well as the real U.S. crude oil prices and its first lag in the specification.

Table 1: Causality Test Results Based on Maximum Entropy Bootstrap Inference

		1950-2006		1950-2000		1960-2003		1970-2006	
Test	Variable	constant	+trend	constant	+trend	constant	+trend	constant	+trend
KPSS	LEC	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
	LRGDP	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)	I(0)
	LROP	I(1)	I(0)	I(0)	I(0)	I(0)	I(1)	I(0)	I(0)
	LREX	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(0)	I(0)
ADF	LEC	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
	LRGDP	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
	LROP	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
	LREX	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(1)	I(1)
EG	bivariate	coint	coint	coint	coint	no coint	no coint	coint	no coint
	multivariate	no coint	no coint	coint	coint	no coint	no coint	no coint	no coint
JJ	bivariate	1	1	1	1	1	1	1	1
	multivariate	1	0	1	1	4	2	1	4

Note: For all tests, $\alpha = 0.05$. Lag order used in the stationarity tests and the cointegration tests is 3 and 1 respectively. Engel Granger procedure skips the initial unit root tests. JJ results show the number of cointegrating vectors based on the trace test.

Table 2: Summary of the Unit Root/Stationarity and Cointegraton Test Results

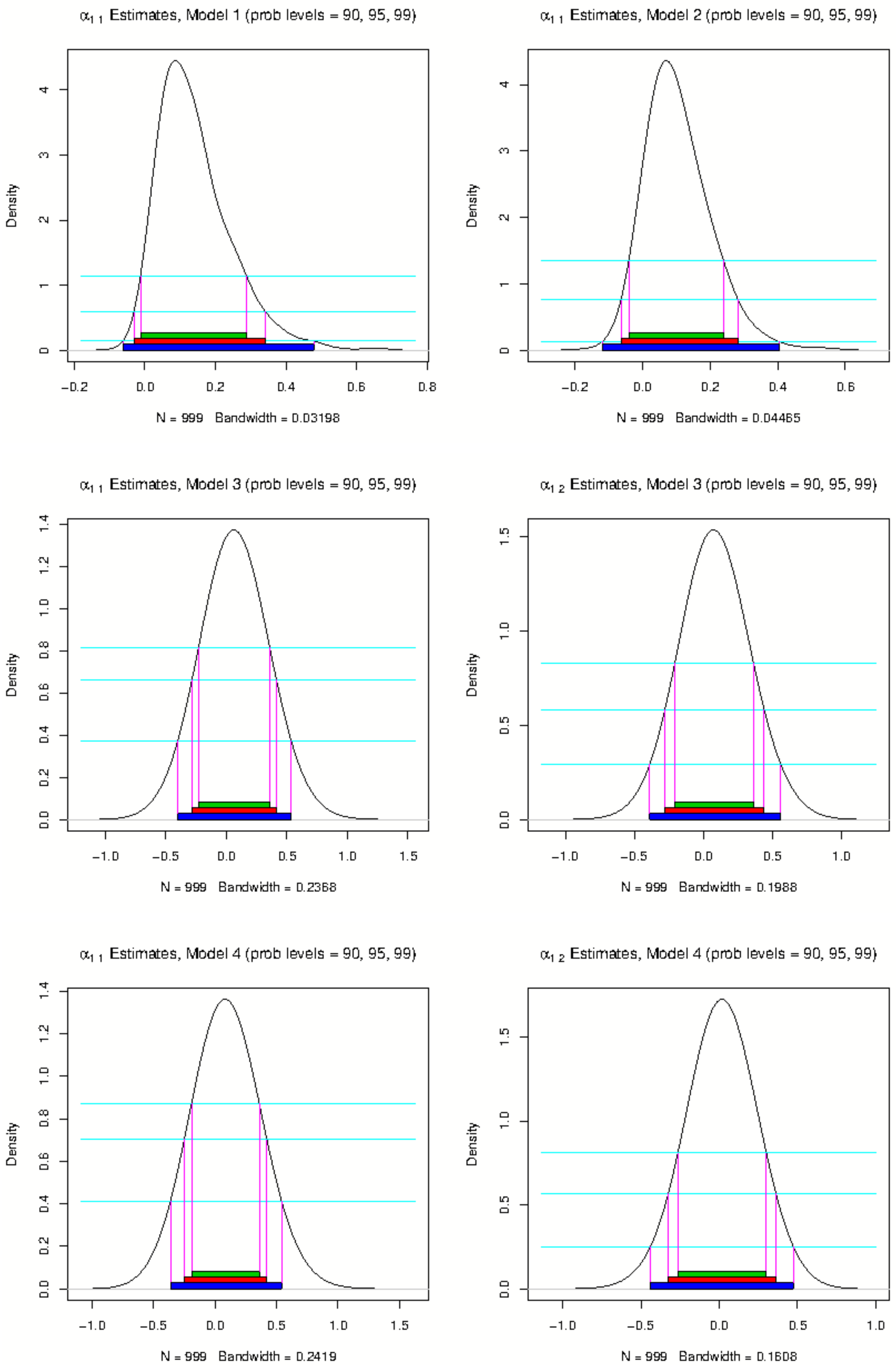

Figure 3: Highest density confidence regions for the estimates of log of energy consumption for the full sample multivariate case.

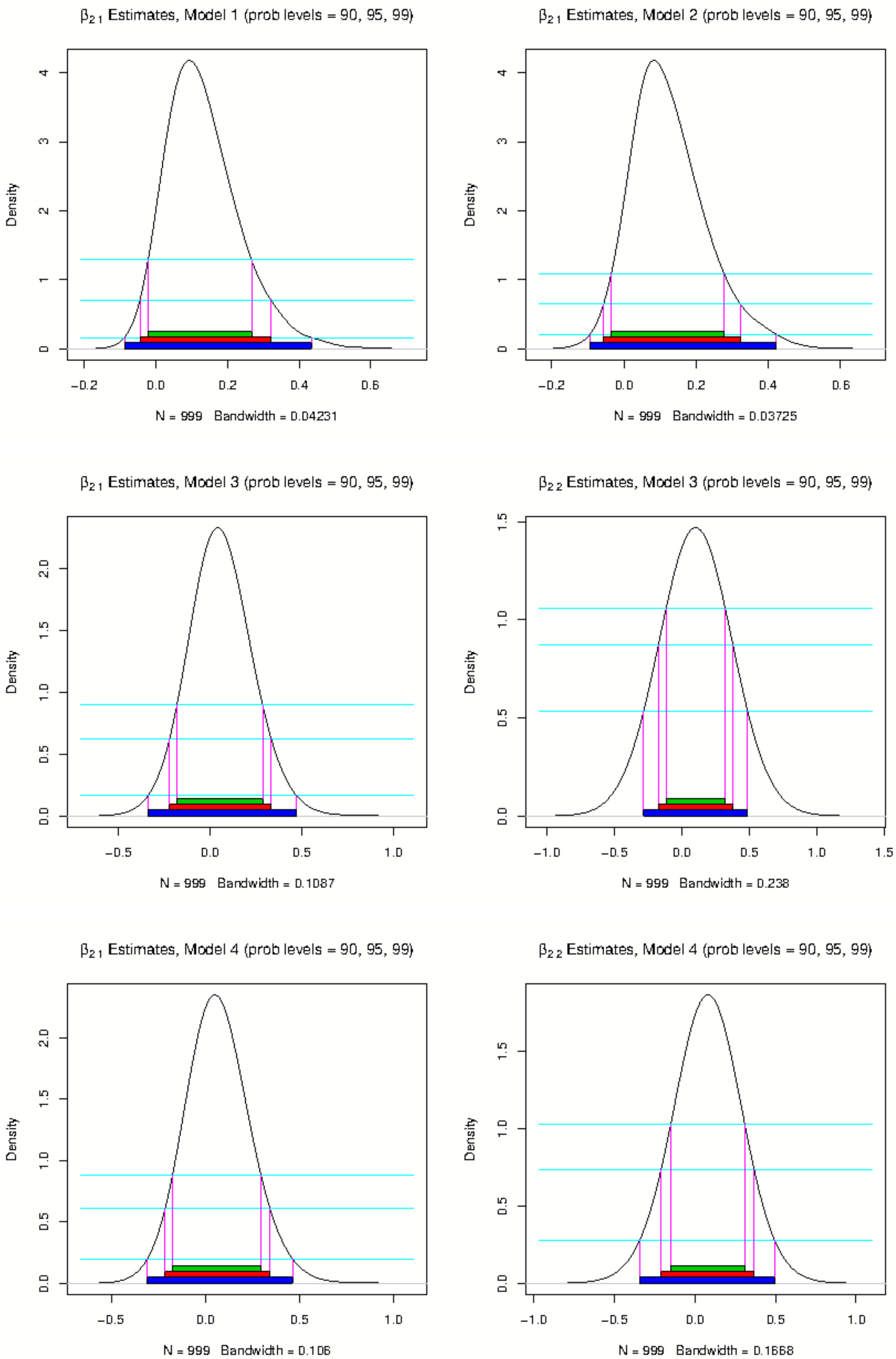

Figure 4: Highest density confidence regions for the estimates of log of real GDP for the full sample multivariate case.