[*Title: disentangle the interactions between global and regional seasonality of crude oil consumption: some empirical findings*]

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Overview

This paper contributes to the stochastic modelling of commodity inventory literature by consistently modelling the potential seasonality of primary energy demand and supply across OECD and emerging countries with empirically observed properties. We use a comprehensive crude oil dataset which includes major regions over a 30-year period to investigate the trend and stochastic characteristics of variation in energy supply and demand on quarterly. This has extremely important implications for global energy markets design and coordination as well as optimisation of investment in long term energy supply infrastructures. In this paper, seasonality is modelled as the variation of quarterly crude oil consumption around a long-term trend. Across these regions, these seasonal patterns vary according to climate differences, intra-year variation in agricultural activity, income seasonality and other *idiosyncratic* factors. If quarterly seasonality can be modelled as a predictable, recurring pattern over for each year, it is possible to use this information to make forecasts that apply to upcoming trends in crude oil demand. Capturing seasonality of oil imports is important for both importing and exporting countries, for reasons pertaining to inventory control and production planning respectively.

Methods

Time-series econometric techniques are used for modelling seasonal patterns around a long-term trend. Our approach is based on classic demand theory: we assume that quantity crude oil demanded in each country depends on a reference crude oil price, income, price of substitute fuels and seasonal components. On the energy market, understanding the seasonality of energy prices behaviour has important implications, for instance: The difference between fuels (e.g. gas, heating oil, diesel) prices in winter and in summer can lead to an arbitrage between buying gas in winter or buying it in summer and store it. In other words, the winter/summer gas price difference is an estimator of a "good" storage price (Muzereau and Han, 2012). It must be noted that if the seasonality is unstable, classical methods such as Filtration, Regression and Bayesian method will not work, as they assume that trend and seasonal components are smooth and slowly changing, and cannot be used to detect change and breakdates wavelets decomposition method can be used for better data understanding and seasonality identification. We applied discrete wavelet transform (DWT) method to identify the global and regional seasonality and the underlying characteristics. DWT is a technique for decomposing a time-domain signal into a coarse approximation and detailed information by convoluting the given signal with filters(or wavelets) of different scales and frequencies.
The quarterly crude oil consumption of all the regions in the world is imported from the International Energy Agency's oil database, covering the period 1984-2013. In our analysis the world is divided into 11 subzones: North America (NA), Central and South America (SCA), Europe (former USSR excluded) which is divided in Western Europe (WE) and Eastern Europe (EE), former USSR, OECD Asia-Pacific, Middle-East(ME) and North Africa (NA), Sub-Saharan Africa(SSA), China, India, other Asia, and ROW.

Results

Our analysis showed all regions exhibited seasonal pattern in oil consumption to different extent, this seasonal behaviour is usually smoothed out when yearly series or multi-year series are applied, or more specifically in most macroeconomic models forecast in which time step is normally set to one year. Preliminary results indicate:

1. Seasonality of oil consumption is indeed identified in all the regions though to different extent, which can be interpreted as the variation in seasonal mean value in each region throughout the period. Further, the deviation from the series mean may coevolve in the same direction or in opposite way across regions at a given season, which in turn may either enhance or cancel out the global seasonality depending on the magnitude of the underlying interactions.
2. The degree of seasonality is heterogeneous across different regions in that some regions are characterised by more pronounced seasonal patterns as compared with others. This suggests the seasonality of oil consumption may be endogenously related to a country's energy supply resources.

3. seasonal variation is the more significant in large oil consumption and production regions and countries than other regions. For instance, it is observed that the seasonal variation in NA and China , JKAZ and MENA and Eurasia (large oil producers) are significantly larger than other regions. The quarterly seasonality in large oil consumption regions exhibits positive correlation with that of the world, suggesting oil markets are more integrated at the regional level.
4. Some regions show monotonous upwards or downwards trend for all seasons, whereas others are characterised by cyclical oscillatory behaviour. General patterns observed suggested the global oil demand seasonality has been essentially driven by the growth in new industrializing countries.

Conclusions

Our modelling results demonstrated that seasonal variation is the more significant in large oil consumption and production regions and countries than other regions. For instance, it is observed that the seasonal variation in NA and China (the first and second largest oil consumers in the world), JKAZ and ME and Eurasia (large oil producers) are significantly larger than other regions. Also some regional correlation patterns may also be identified from the chart, suggesting oil markets are more integrated at the regional level. For instance, India, China, JKAZ and Asia Pacific showed similar interseasonal variation in that Q1 is the most variable seasons (largest interquartile range and difference between Min and Max seasonal values) ,whereas oil demand in SA, NA, ME, Eurasia and Europe as well as the world aggregate are most variable in Q3, where the holidays effects could be one of the key determinants (January/February are usually holiday seasons in Asian countries whereas July/August are more the longest holiday season for most western countries).

However, further improvements will have to be made before reaching definitive conclusions. First, it will be necessary to re-consider the advantages and disadvantages of the ADL and global VAR methodologies and choose the most appropriate. Second, it has to be ensured that the long- and short-term characteristics of income are properly modelled. Third, the authors are trying to gather a more complete or comprehensive dataset of price of substitutes (natural gas and coal) across counties. A final section of the paper might include forecasts in which seasonal components are applied.

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