Reducing China's Carbon Emissions

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Background

It is widely acknowledged that the accelerating global warming is mainly caused by anthropogenic activities and in particular, economic growth is the main driving force. Having witnessed rapid economic growth for more than thirty years, China has become the largest emitter of carbon dioxide since 2013 and the country faces increasing pressure from the global community to abate carbon emissions. As the world's largest developing country, China always argues for its right of carbon emissions during industrialization and is concerned about the negative effects carbon emission reduction brings about, even if its annual emission now is larger than the sum of the EU and US. Hence, it is worthwhile to examine to what extent economic growth influences China's carbon emissions, and whether the potential costs outweigh benefits from abatement, and how China can abate carbon emissions cost-effectively.

Impact of GDP Growth on Carbon Emissions

Although economic growth is the main driven factor of the increase of carbon emissions, bivariate analyses are too simplistic to yield robust policy recommendations due to the presence of variable biases (Mezghani & Haddad, 2017). To deal with this issue, this research will use Vector autoregression (VAR) model to examine the electricity consumption-economic growth nexus. The VAR model treats all variables as endogenous ones in a system, which means the introduction of lagged variables (Magazzino, 2016). To select variables, this research will first use variables based on the IPAT model. According to Xu and Lin (2015), the IPAT identity (P = A * T) is often used as a basis for investigating the role of economic activity in CO2 emissions while the STIRPAT model allows the endogenous variable change proportionally. From their research, three variables (population, GDP and emissions) are selected on the basis of the exogenous variables and endogenous variables (Shahbaz et al., 2014).

Carbon Reduction on Economic Growth by Governmental Policies

3. Cointegration test. If the variables are not integrated of the same order, Toda's and Yamamoto's approach (TV procedure) will be used. If all the variables share the same order of integration, the Johansen and Juselius cointegration test (10 test) could be employed to find the long-run relationship between carbon emissions and other variables. Autoregressive Distributed Lag (ARDL) Model can have different number of lag terms without the requirement of symmetry lag lengths like other cointegration estimation methods, while VEC (Vector Error Correction) model needs optimal lag to be selected based on VAR lag order selection criteria (Asumadu-Sarkodie & Owusu, 2016).
4. The Generalized Impulse response. It overcomes the orthogonality problem in traditional out-of-sample Granger causality tests, which shows how a variable in general respond to a shock of other variables while holding all other shocks equal to zero.
5. Variance decomposition shows the percent of the variation in one variable that is explained by the shock from another variable. Finally, this research will test the predictive ability of VAR model in comparison with mean, RW, AR, ARIMA and Exponential Smoothing (Magazzino, 2015).

Carbon Reduction by Sustainable Energy Development

This research will use Multi-criteria Decision Making (MCDM) and Confirmatory Factorial Analysis (CFA) to assess the social, political, environmental and economic costs and benefits of different types of energy (Hadian et al. 2013; Hadian et al. 2011). According to Kumar’s et al. (2015) research, a typical MPT model follows 4 steps:
1. Initialization. A logarithmic transformation may be applied to the data set to smooth the volatility effects. Future data are projected by ARCH, Exponential Smoothing or ARIMA, from which variance and covariance are acquired.
2. Fitness Function. This research will use MVC function to determine the optimal weights of the optimal risky portfolio and the optimal allocation between the non-risky and the risky assets. This research will obtain the parameters to solve the CVaR model and determine the optimal risky portfolio for the CVaR model.
3. When considering China's obligation of carbon reduction committed recently, the efficient frontier and optimum portfolio could change. At this stage, down-side risk or semi-variance portfolio needs may help realize the target where the Lower Partial Moment (LPM) needs to be considered (Gökçe & Atmaca, 2017).
4. This research will rerun the CGE model associated with different scenarios when energy consumption is treated as an exogenous variable and its value is set to the conclusion by Modern Portfolio Theory. The ultimate goal of this research is to design an optimal energy structure associated with proper governmental policies that can not only help meet carbon obligation but also have the largest economic, social and environmental benefits.

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