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China's Greenhouse Gas emissions' dynamic effects in the process of its urbanization: A perspective from shocks decomposition under long-term constraints

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Abstract

This paper is about to quantify the effect of China's urbanization on greenhouse gas (GHG) emissions by separating the part driven by the economic growth from the whole effect. In order to be accurate to estimate unknown parameters, this paper follows the method of Blanchard & Quah (1989), in which identifying conditions are set by assuming some shocks have no long-term effect on corresponding explained variables. We conclude that 1) Urbanization shock has an inverted hump-shaped effect on GHG emissions, in other words, nowadays the process of China's urbanization has been accompanied with saving energy and reducing emissions; 2) The growth rate of GHG emissions, owning to the GDP shock, can be raised by almost 1.53% annually and the urbanization level approximately contributes to 18% of the change of CO2 emissions based on empirical results; 3) China's emission reductions, in the short run, are actualy in expense of decreasing economic growth and delaying the process of its urbanization.

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Keywords: China's urbanization; greenhouse gas emissions; Structural VAR; shocks decomposion

1. Introduction

Ever since Blanchard & Quah (B&Q) published a paper whose title was "the dynamic effects of aggregate demand and supply disturbances" in American Economic Review (AER), the thought of shocks decomposition have been extensively applied to analyze variables' dynamics. In essence, B&Q provided another method used for the identification of unknown parameters of Structural Vector Autoregression (SVAR). Just as VAR has its advantage in the analysis of dynamic characteristics, SVAR inherits this

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strength, and could accurately capture concrete features of each period. This paper is in an attempt to solve the dynamic change of China's GHG emissions using the SVAR model based on the B&Q method.

The latest multinational conference on climatic change, followed Kyoto Protocol, Bali Roadmap and Copenhagen Conference, has concluded in Cancun on December 10th, 2010. Though the Cancun conference has made some progress, the negative impact of climatic change has become an unavoidable issue in our daily life. Although now China has surpassed United States to become the top country in emissions of greenhouse gas, Chinese government has an active attitude toward carbon dioxide emissions. Since 2006, the Chinese government has been continually publishing several policy documents on climatic change. In 2007, NDRC announced Medium and Long Term Development plan for Renewable Energy Sources. Moreover, China invested 221 billion US dollars on developing renewable energy sources, which is almost twice as much as that of United States who's the second largest country in investing renewable energy sources (Robins et al. 2009)[1]. Huang Ming, the creator of the well-known Sun Valley and vice chairman of the international institute of solar energy, was invited to attend Copenhagen Climatic Change Conference as a civic delegate by several multinational environmental protection organizations. In 2009, China's government stated that, compared with the GHG emissions per unit of GDP in 2005, they would reduce it by 40% to 45% in 2020, which is an arduous task.

In this paper, three components of the growth rate of greenhouse gas emissions (RCO_2)[a] can be decomposed by structural disturbances, of which are GDP component (driven by the growth rate of per capital GDP), CITY component (driven by the process of China's urbanization), and CO_2 component (driven by itself). Thus the relative percentage of each component can be shown through SVAR model under long-term constraints of innovations. The rest of this paper is organized as follows. Section 2 is devoted to review relevant references maily about various decomposing techniques that are recently adopted. Data and model are discussed in section 3. Section 4 characterizes the dynamic effect of each component. And section 5 makes conculusions.

2. Literature review

The references searched are mainly focused on a growing number of decomposing techniques that are used to deal with GHG emissions' aggregate data, especially applied to analyze China's GHG emissions.

Kaya (1989) made an innovative research, decomposing greenhouse gas emissions into four factors: energy consumption amounts, energy intensity, per capita GDP and population [2]. After that many refrences are found to use adjusted Kaya identity to construct CO_2 emissions' model, such as Feng et al. (2008) and Lin et al. (2010) [3,4]. Sun (1998) accounted for energy use in China [5] and Zhang et al. (2009a, 2009b) used Sun's method to decompose China's energy-related CO_2 emissions [6,7].

At the same time, the index technique has formed a trend recently. Emmanouil et al. (2008) dealt with the decompositon with Arithmetic mean divisia index and Logarithmic mean divisia index techniques, and conclued that income effect played the biggest contributor to the rise in CO_2 emissions in Greece [8]. Wang et al. (2005), Liu et al. (2007), and Zha et al. (2010) took a similar approach to decompose China's CO_2 emissions [9-11].

Morever, data envelopment analysis (DEA) technique also can be used to decompose CO_2 emission change. Li (2010) allowed for cross-sectional analysis under flexible data requirements based on Shepherd output distance function and found that GDP scale effect accounted for the majorority of emisson increments [12]. Zhu et al. (2008) presented two studies on decomposing the CO_2 emissions for world regions and OECD countries and proposed a comparision between the DEA technique and other

[a] The abbreviation of RCO2 is introduced in section 3.

techniques [13]. Ratnakar (2010) also showed the variance analysis approach from the perspective of management accounting [14].

The techinque used in this paper is the Structural VAR under long-term constraints, which has an advantage of comprehensively showing the dynamics of time series varibles. Based on the historical data (1979-2009), the SVAR model can well separately decompose each component of the growth rate of China's annual GHG emissions.

3. Data and model

This paper is based on the analysis of China's data, which are followed:

The growth rate of per capita GDP (RGDP), defines the difference of logarithm of per capita GDP, the source of which is from the database of China Economic Information Network.

The growth rate of China's urbanization (RCITY), denotes the difference of logarithm of urbanization, using the ratio of the number of people living in urban area to that of people living in China as its agent variable. And the data comes from the database of China Economic Information Network.

The growth rate of CO_2 emissions (RCO_2), means to the difference of logarithm of CO_2 emissions, the source of which is from Carbon Dioxide Information Analysis Center (CDIAC). All these variables are annual data from 1979 to 2009. In order to guarantee their stationary, the following test is outlined in table1.

Table1. ADF test for variables's stationary.

variables	RGDP	RCITY	RCO_2
ADF test statistic	-3.58376	-3.90291	-3.1233
test critical value	-2.97626**	-3.67017***	-2.96777**
test form	(c,0,3)	(c,0,0)	(c,0,1)

Note: (1) In test form, c, t and k represent the corresponding intercept term, trend term and lag length based on SIC criterion; (2) ** means to reject the nonstationary hypothesis in 5% significant level, *** in 1% significant level respectively.[b]

Table 1 above shows that the three variables are stationary after the difference of logarithm of initial data. According to Wold decompositon theorem, stationary time series can be represented as :

$$X(t)=A(0)*e(t)+A(1)*e(t-1)+A(2)*e(t-2)\ +...=\sum A(i)*e(t-i) \qquad (1)$$

Where i=1,2,..., $\mathbf{X(t)}$=(RGDP(t), RCITY(t), RCO_2(t))', A(i)=(a_{11} a_{12} a_{13}, a_{21} a_{22} a_{23}, a_{31} a_{32} a_{33})'(i), $\mathbf{e(t)}$=(e_{GDP}(t), e_{CITY}(t), e_{CO2}(t))', var($\mathbf{e}$)=I, and $\mathbf{e}$ is the whole set of $\mathbf{e(t)}$. In order to get $\mathbf{e(t)}$, we first construct the vector autoregression (VAR) model, then transform to its vector moving average (VMA) model. The VMA form is as followed:

$$X(t)=v(t)+C(1)*v(t-1)+C(2)*v(t-2)+...\ =\sum C(i)*v(t-i) \qquad (2)$$

Where i=1,2,..., $\mathbf{v(t)}$=(v_{GaDP}(t), v_{CITY}(t), v_{CO2}(t))', var($\mathbf{v}$)=$\mathbf{\Omega}$, $\mathbf{v}$ is the set of $\mathbf{v}$(t).

Comparing equation (1) and (2) we see that $\mathbf{v}$, the vector of innovations, and $\mathbf{e}$, the vector of structural innovations, are related by $\mathbf{v=A(0)*e}$, and that $\mathbf{A(i)=C(i)*A(0)}$, for all i. Thus the information of $\mathbf{A(0)}$ allows one to recover $\mathbf{e}$ from $\mathbf{v}$, and similarly to obtain $\mathbf{A(i)}$ from $\mathbf{C(i)}$[c][15].

So we can solve equation (1) as long as we know every factor of $\mathbf{A(0)}$. There are nine factors in $\mathbf{A(0)}$, six of which can be solved by $\mathbf{\Omega=A(0)*A(0)'}$. $\mathbf{\Omega}$ can be derived by the VAR model, three factors left unknown; given long-run constraints: $\sum a_{12}(i)=0$, $\sum a_{13}(i)=0$, $\sum a_{23}(i)=0$, we can solve all nine factors.

4. Empirical results

The dynamic effects of three shocks can be shown in three different forms. First, it shows the responses of RCO_2, and the effect will be diminished to 0 almost in 6th period.

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[b] Lin (2010) used ADF and PP test to demonstrate these variables' stationary in 1% significant level.

[c] If you want to get the detail, refer to the technical appendix of Blanchard & Quah (1989).

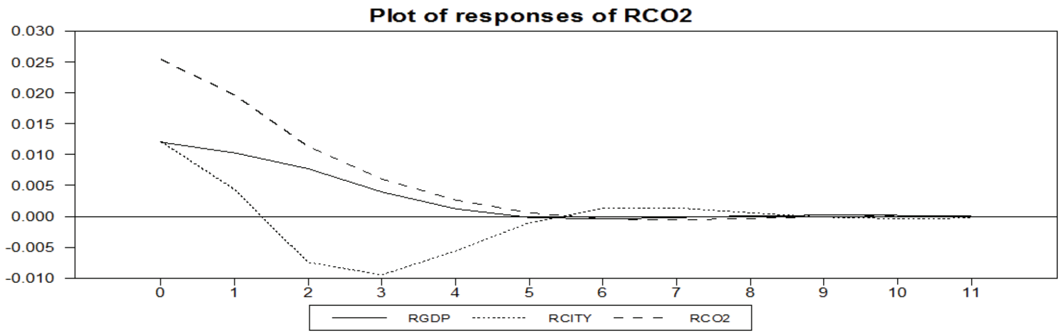


Fig. 1. impulse responses of RCO_2 to three shocks.

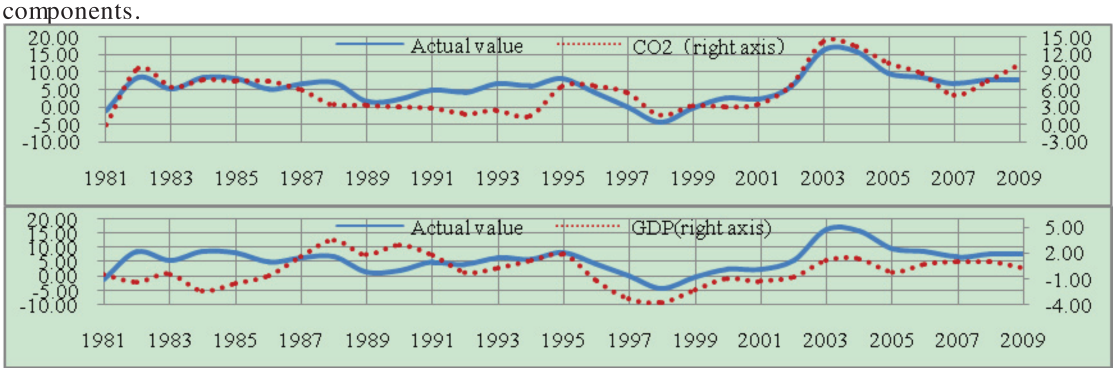
Based on figure 1, it is clear that GDP shock and CO_2 shock, both of which represent positive shocks, have a gradual decreasing impact on RCO_2, and that this impact is vanished to 0 almost in 5 years. But urbanization (RCITY) shock has an inverted hump-shaped effect on RCO_2. That the effect is positive in first period and negative from the second period to fifth period indeed shows that nowadays China's urbanization has been progressing under constraints of saving energy and reducing emissions and that the government macroeconomic policy, to some extent, has a leading effect on reducing CO_2 emissions. Then relative percentages of RCO_2's each component are below.

Table 2. variance decompositons for RC02.[d]

variables	period	Std Error	RGDP(%)	RCITY(%)	RCO_2(%)
RCO_2	1	0.030667	15.36	15.71	68.93
	2	0.038134	17.24	11.47	71.29
	3	0.041205	18.28	13.09	68.63
	6	0.043374	17.41	18.31	64.28

Table 2 shows that GHG self component has a vital effect on its variance decomposition, almost 65% in sixth period; the urbanization level shows an inverted U-shape, being stable to 18.31% at last; the growth rate of per capita GDP account for 17.41% in the sixth period. If the growth rate of per capita GDP keeps the level of 9%, then the growth rate, due to the increasing effect of GDP, will be raised by 1.53% annually. Thus China's government will be under more pressure in its process of urbanization and due to its rapid economic growth in the foreseeable time.

At last we can make a comparison of the historical data about RCO2 real value and its respective components.



[d] From the 6[th] period, the ratio of RGDP approximately has no change, so there is no deed to list all the lags' value and the same are with RCITY and RCO_2.

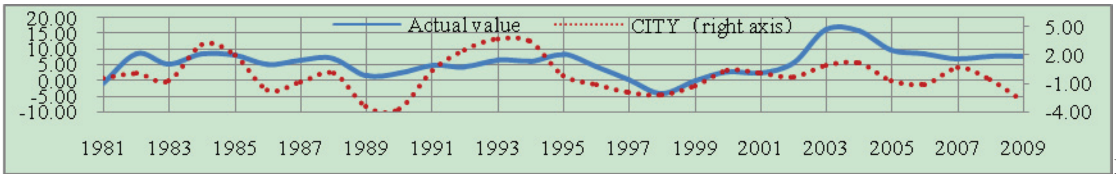


Fig. 2. The comparison of RCO_2 real value with CO_2 component, GDP component and CITY component, respectively.

By decomposing RCO_2, we can have three components: GDP component (driven by the growth rate of per capital GDP), CITY component (driven by the process of China's urbanization), and CO_2 component (driven by itself). Each single impact can be derived from equation (1), by setting the corresponding shock to be 1, the others 0. For examle, by setting GDP shock, CITY shock, and CO_2 shock to be 1, 0, 0 at each period, we can get GDP component at each year from 1979 to 2009. From graph 2, it is clear that CO_2 component, in some sense, better reflects real value's fluctuations.

From 1998 to 2003, RCO_2 is gradually stepping into a "rising path", with the climax being more than 15% in 2003. But in 1998, it is well known that China encountered Asian financial crisis and flood, both of which happened every 50 years, and that the whole market, is already under the negative expectation, so the central government activly release a series of efficient fiscal and monetary policies in order to boost the economy and change residents' long-term expectations. After 5 years, it is shown above that RCO_2 began to decline, which means that China has stepped out of the shadow of Asian financial crisis in the expense of higher growth rate of CO_2 emissions. Thus, RCO_2, to some extent, can be one of valuable indexes that reflect China's macroeconomic cycle.

Two periods, in the whole sample, apparently show the significant decreasing trend of RCO_2: 1995-1998 and 2003-2009. In the first period, CO_2 emissions (not the RCO_2), not just showing a down trend, enen are negatively increasing. That the red dotted line of CO_2 component is above the real line and the other two is under the real line, means that nowadays GDP component and CITY component have been cooperately lowing down the growth rate of GHG emissions, in other words, China's emissions reducing policy is in sacrifice of higher economic growth; in the seconod period, in the condition of stable GDP component and decling CITY component, CO_2 component represents a rising trend, otherwise the whole effect of RCO_2 would show a falling trend.

Based on the analysis above, it's clear that China's government has already determined to adopt an active policy to effectively mediate the atmospheric warming problem, even in expense of its decreasing economic growth and delaying the process of urbanization in the short run.

5. Conclusions

This paper is mainly about shocks decomposition of the growth rate of greenhouse gas emissions based on the B&Q method. It is conclued that 1) urbanization shock has an inverted hump-shaped effect on RCO_2, in other words, the process of China's urbanization is accompanied with saving energy and reducing emissions; 2) RCO_2, owning to the GDP shock, will be raised by 1.53% annually; 3) the urbanization level approximately contributes to 18% of the change of CO_2 emissions; 4) RCO_2, to some extent, can be one of valuable indexes that reflect China's macroeconomic cycle; 5) China's emission reducing policy, in the short run, is in expense of decreasing economic growth and delaying the process of urbanization.

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