Price Linkage of Chinese Pilot Carbon Emission Trading Markets:

Empirical Study Based on Guangzhou and Shenzhen

Li Hongyan

Abstract

The historical high speed of economic growth has caused so much negative effects, one of which is the increasing global carbon emission. To deal with this crisis, governments and international organizations have adopted several measures. Definitely, carbon emission trading scheme is the most adopted because of its high efficient, transparent abatement cost and low intervention to market. In this paper, we focus on the Chinese carbon emission trading market which is still under construction and investigate the price linkages of these pilot markets (Shenzhen and Guangzhou as examples) to find the potential arbitrage chances and evidences for unified price setting. Even though Shenzhen carbon emission trading market has the most influence on other markets, we cannot find significant results by our GARCH-in-Mean VAR for the daily settlement price, which is consistent with the result for daily average price and the GARCH-BEKK model. Therefore, we find no evidence for price linkage between Shenzhen and Guangzhou carbon emission trading markets for arbitrage or price setting.

Keywords: Carbon Emission Trading, Price Linkage, Structural GARCH-in-Mean VAR

Classification Code: L16 Q54

1. Introduction
Recently, the historical high speed of economic growth also brings about a large amount of carbon emission, which has already attracted global attention. Carbon emission trading scheme is the most adopted measure with the highest market efficiency and lowest abatement cost. China, as the largest development country, attempts to establish its own carbon emission trading market and so far seven pilot markets has been set before the national unified market is established. Accompanied with this phenomenon is abundant potential arbitrage chances to make profits. For instance, predict the price trend of one market relying on the data of another or shift among different markets. Therefore, investigate the price linkage among different carbon emission trading markets may provide us evidence for arbitrage. Meanwhile, the price linkages among different carbon emission trading market are also beneficial for the price setting of the unified market. As for the seven pilot markets, Shenzhen is the largest, most complete and most influential one and Guangzhou shares the most major price determinants with Shenzhen. Hence, in this paper, we use the data of Guangzhou and Shenzhen carbon emission trading markets to investigate the price linkage between them, especially the influence of Shenzhen market to that of Guangzhou (based on their market power).

The volume of carbon emissions is large whether for the whole world or China since the economic boom has induced historical high carbon emissions during the past few years. According to World Bank, the global carbon emission was 9.386 billion metric tons in 1960 whereas that in 2013 is 35.849 billion metric tons ("World Bank," 2017). As for China, the carbon emission has risen from 0.781 billion metric tons in 1960 to 10.249 billion metric tons in 2013 ("World Bank," 2017). Therefore, the severe condition of carbon emission has aroused worldwide attention and effective measures have been taken to solve this problem. In 1997, Kyoto Protocol was signed and it marked the first time that carbon emissions were subject to specific laws. In 2009, Copenhagen Conference was held in Denmark, during which the nations around the whole world have made their carbon emission reduction promises. The Chinese government promised that by 2020 carbon emissions per unit of GDP would decrease by 40% to 45% compared to that of 2005. According to the 12th Five-Year Plan of Chinese government, the total carbon emissions per unit of GDP in 2015 will be 17% less than in 2010 (Qi, Hu, & Zheng, 2012). To achieve its goal, the Chinese government has taken a series of administrative measures, like environmental tax. These measures have worked but not so efficient because these administrative

**Table 1 Price Determinants of Carbon Emission Trading**
<table>
<thead>
<tr>
<th>Authors</th>
<th>Factors</th>
<th>Markets</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Ellerman, Marcantonini, &amp; Zaklan, 2016)</td>
<td>Price of the EU market</td>
<td>European Union and Australia</td>
</tr>
<tr>
<td>(Chen, Huidong, &amp; Wang, 2013)</td>
<td>Macroeconomic factors; Energy market factors</td>
<td>European Union</td>
</tr>
<tr>
<td>(Convery &amp; Redmond, 2007)</td>
<td>Weather; Fuel prices; Economic growth</td>
<td>European Union</td>
</tr>
<tr>
<td>(Schultz &amp; Swieringa, 2014)</td>
<td>Transaction costs</td>
<td>European Union</td>
</tr>
<tr>
<td>(Neuhoff)</td>
<td>Government Regulation</td>
<td>European Union</td>
</tr>
<tr>
<td>(Guo, 2015)</td>
<td>Future price of the EU market; Stock index; Oil and gas index; Exchange rate</td>
<td>Shenzhen, China</td>
</tr>
<tr>
<td>(Zhou &amp; Xu, 2016)</td>
<td>Industrial growth; Weather conditions</td>
<td>Shenzhen, China</td>
</tr>
</tbody>
</table>

measures cause deadweight loss and reduce market efficiency.

Carbon emission trading scheme is a burgeoning and efficient method of carbon emission reduction. The widely accepted concepted is that carbon emission trading is a special scheme in tons of carbon dioxide (tCO₂e) and it puts carbon emissions and fossil fuel consumption under effective government regulation (Cheng, Lin, & Lewis, 2008). According to former studies, the price of carbon emission trading is majorly determined by the following factors: market fundamentals, regulatory factors, climate and prices of carbon emission trading on other markets. Table 1 lists the relevant factors that have been proved.

Ever since the first carbon emission trading market of established by Netherlands and World Bank in 2002, the carbon emission trading scheme has aroused global attention. The European Union (EU) market is the most famous one. In terms of market power, the EU market has the most significant influence on others like the United States (US) market, the Japanese market (Ellerman, Buchner, & Carraro, 2010). When compared with other carbon emission reduction measures (like subsidies), it is the most effective one (Woerdman & Couwenberg, 2009). We can also find evidence from the studies on
other markets. The cap-and-trading scheme of the US market gradually reduces the permits in the long run (Bryce, 2013). Holmes also studied the method of distributing the carbon emission trading permits among different sectors based on the data of US (Holmes & Friedman, 2000). As for the New Zealand market, the carbon emission trading is more efficient when compared with carbon tax (Sung, 2011). We can also find evidence in the studies for the Australian market (Chen et al., 2013; Jotzo & Betz, 2009).

Chinese carbon emission trading market is being established and massive potential profitable opportunities are emerging, which is our initial motivation for this paper. In December 2011, seven pilot markets (Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangzhou and Shenzhen) were announced and in November 2016, it was announced that the national market will be established at the end of 2017. The target companies, organizations and individuals that meet the standard of carbon emission trading can be involved in the trade. The majority of the target companies on the pilot markets is restricted to the political district or in the provinces (cities) that signed contract with the pilot cities. For instance, the carbon emission trading of Inner Mongolia Wind Power can be traded in Shenzhen and Guangzhou market advocates trans-provincial trading. Meanwhile, as for individuals or organizations, they could be a member of any pilot market and get involved in the trading. In Guangzhou and Shenzhen, even foreign investment is allowed. All regulations and phenomenon make the Chinese carbon emission trading market be increasingly refined and acceptable. The gushed capital improves the enthusiasm of market participants and increases potential profitable opportunities, which contribute to our curiosity for price linkages among carbon emission trading markets.

During the period when the pilot markets are being operated, the difference and potential linkage of carbon emission trading prices on different markets interest us. Figure 1 shows the daily average price of carbon emission trading on the seven markets and we can read the following information from this figure. Firstly, the prices on different markets are significantly different. The question is that when the national market is setting, the government will rely on which one to set the unified price. Lack of specific policies, whether a company can set subsidiaries in different pilot cities to try to get the lowest cost carbon emission trading. Secondly, even though the prices fluctuate in different ways, there still exists potential linkages. The carbon emission trading price is majorly determined by the factors that we discussed; therefore, prices on different markets may have some inside linkages since some factors are the same.

Figure 1 Price of Carbon Emission Trading on Seven Pilot Markets
Thirdly, government policies cause shocks to these market. Hence, we show special interest in the study of price linkages among different carbon emission trading pilot markets.

We investigate the potential price linkage by using Shenzhen and Guangzhou as example. Firstly, Shenzhen carbon emission trading market is the first and most complete one. It has signed contract with other cities or provinces to help them for carbon emission trading. Therefore, we assume that the fluctuation of carbon emission price in Shenzhen would have influence on others. Secondly, the carbon emission trading price is majorly determined by the factors we discussed before. Guangzhou shares the most factors with Shenzhen, like government policies, weather, rainfall and other common factors. They are special cases among the pilot markets since for other provinces, they only have one market. Thirdly, both are located in Pearl River Delta economic circle where the economy is the most developed and the capital can flow most liberally. It guarantees the market efficiency of the pilot markets and the activity of the participates.

Our study is innovating and meaningful. Instead of discussing the price determinants, we straightly investigate the price linkage between different markets to find evidence for unified price setting and potential arbitrage chances. Meanwhile, we adopt dynamic time series model to solve this problem rather than listing theories evidences. Furthermore, our study can provide useful information for the government (price setting) as well as the individuals (profit making).

The contents of this papers are as follows. In Section 1, we list the basic information about carbon emission trading and explain why we focus on the price linkage in Guangzhou and Shenzhen carbon emission trading market. In Section 2, we display the basic properties of our sample and make preparation for the time series regression.

Table 2 Unit Root and Stationarity Tests
In Section 3, we explain the basic formula of the GARCH-in-Mean VAR model and we show the results in Section 4. We also make some improvement of our study by using alternative data (daily average price) and alternative model (GARCH-BEKK) in Section 5 and draw our conclusion in Section 6.

2. Data

We use the daily settlement price of carbon emission trading for both Shenzhen and Guangzhou market during the period of March 11 2014 to April 11 2017. The data is obtained from Wind database and Tanjiaoyi website with some mathematical computation\(^1\) and we have 750 observations of the daily settlement price of carbon emission trading eventually. The daily settlement prices for Shenzhen and Guangzhou are shown as SZSP and GZSP respectively and the measure is yuan per ton of carbon emission. In this section, we display the basic statistical information of the two series to make preparation for time series analysis.

We find that both the first-difference form of SZSP and GZSP (DSZSP and DGZSP, respectively) are stationary. In this paper, we examine the stationarity of the two series based on the augmented Dickey-Fuller (ADF) unit root test (Dickey & Fuller, 1981) and the KPSS test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992). The null hypothesis of the ADF and the KPSS test is that the variable has a unit root, which means that the variable is not stationary. For SZSP and GZSP, the null hypothesis cannot be reject at 5% level so we transform them for the first-difference. Table 2 displays the ADF test (level, trend and none) and KPSS test (level and trend) results of the two series. The ADF statistics of the two series are smaller than the 5% critical

![Table 3 Serial Correlation Test](image)

\(^1\) The data on Wind database have too much missing values and the daily price for Shenzhen market on Tanjiaoyi is not directly displayed. We fulfill the missing values based on the following rules:
(1) Missing value for Guangzhou market is straightly copied;
(2) Missing value for daily settlement price of Shenzhen (SZSP) is obtained by \(SZSP_t = \sum_{t=2013}^{y-1} SZSP_{t} \times Q_{it} \) and the daily average price (SZAP) is calculated by \(SZAP_t = \sum_{t=2013}^{y} SZAP_{t} \times Q_{it} \)
(3) There are more missing values of daily average price on both sources, so we use daily settlement price.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Q (2)</th>
<th>Q (4)</th>
<th>ARCH (1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DGZSP</td>
<td>114.580 (0.000)</td>
<td>114.580 (0.000)</td>
<td>-0.041 (0.070)</td>
</tr>
<tr>
<td>DSZSP</td>
<td>275.999 (0.000)</td>
<td>275.999 (0.000)</td>
<td>-0.045 (0.058)</td>
</tr>
</tbody>
</table>

value and the null hypothesis of the KPSS tests are rejected at 5% level. Hence, we conclude that the first-difference of carbon emission trading price in both Shenzhen and Guangzhou markets are stationary.

Neither of first difference form of daily settlement price in Shenzhen and Guangzhou has serial correlation. We test the serial correlation of DGZSP and DSZSP by performing the Ljung-Box Q test. The Ljung-Box test tests whether any group of autocorrelations of time series is different from zero (Ljung & Box, 1978). For the null hypothesis, the Q-statistic is asymptotically distributed as $\chi^2(36)$ and the Q test results are shown in Table 3. The results show that the series are not autocorrelated. In addition, we also performed the Engel autoregressive conditional heteroskedasticity (ARCH) $\chi^2$ test which is distributed as $\chi^2(1)$ on the null hypothesis of no ARCH (Robert F. Engle, 1982). The results provide strong evidence of conditional heteroskedasticity for both series.

3. Structural GARCH-in-Mean VAR

The empirical work is based on the bivariate structural vector autoregression model which is modified to accommodate GARCH-in-Mean errors. The model was firstly developed to study inflation uncertainty (J. Elder, 2004; J. R. Elder, 1995) and was also used for the research of the oil price uncertainty (J. Elder & Serletis, 2011). In this paper, we use this model to investigate the relationship of carbon emission trading prices of different markets.

We define vector $y_t$ as the varaible of interest which includes the first-difference form of daily settlement price in Shenzhen and Guangzhou markets. Then we assume that the system is a linear combination of $y_t$ plus a term which stands for the conditional variance (J. Elder & Serletis, 2011). That is

$$ B y_t = C + \sum_{i=1}^{N} \Gamma^i y_{t-i} + \Lambda \sqrt{H_t} + e_t $$ (1)

where

$$ B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}, \quad y_t = \begin{bmatrix} DGZSP_t \\ DSZSP_t \end{bmatrix} $$

where

$$ \Gamma^i = \begin{bmatrix} \gamma_{11}^i & \gamma_{12}^i \\ \gamma_{21}^i & \gamma_{22}^i \end{bmatrix}, \quad H_t = \begin{bmatrix} h_{ss,t} & h_{gs,t} \\ h_{sg,t} & h_{gg,t} \end{bmatrix}. $$

and $\sqrt{H_t}$ is the conditional standard deviation and it can influence conditional mean; $\Lambda$ is the parameter of the lagged $H_t$; $e_t$ is the disturbant term that is assumed uncorrelated and it can be expressed as $e_t = [e_{gt}, e_{st}]$.

We also specify the conditional covariance matrix $H_t$ by equation (2)

$$\text{diag}(H_t) = C^\nu + \sum_{i=1}^N F_i \text{diag}(e_{t-i}e_{t-i}') + \sum_{j=1}^M G_j \text{diag}(H_{t-j}) \tag{2}$$

where $\text{diag}$ is the operator extracts the diagonal from a square matrix. We impose additional restriction to the conditional variance of $y_t$ that it only depends on its own past squared errors and past conditional variance; therefore, parameter $F_i$ and $G_j$ are also diagonal matrices. Since we have specific research target on how the lagged volatility on one variable might interact with the conditional variance of another, we could set $M = N = 1$ for the estimation of the variance function given by equation (2). The dynamic system is also identified by the following assumptions. The elements of coefficient matrix $B$ for equation (1) are unity, so $B$ is lower triangular. The disturbances of the system are uncorrelated, which indicates that the $H_t$, the conditional covariance matrix, is diagonal.

The bivariate GARCH-in-Mean VAR model is given by equation (1) and (2) and the parameters are estimated by full information maximum likelihood (FIML) (J. Elder, 2004). In this way, we could avoid Pagan’s problems (Pagan, 1984) associated with the estimation of variance function parameters separates for the conditional mean parameters. The estimation procedure is to maximize the logged form likelihood $\sum_{t=1}^T l_t$ where $l_t$ can be expressed as

$$l_t = -\frac{n}{2} \ln(2\pi) + \frac{1}{2} \ln|B|^2 - \frac{1}{2} \ln|H_t| - \frac{1}{2} (e_t' H_t^{-1} e_t) \tag{3}$$

with respect to the parameters of the system $B$, $C$, $\Gamma$, $\Lambda$, $C^\nu$, $F$ and $G$.

In equation (3), we set the pre-sample values of the conditional variance matrix $H_0$ to their unconditional expectation and conditions on the pre-sample values of $y_t$. To ensure that $H_t$ is positively defined, we assume that $C^\nu$ is positive, $F$ and $G$ are nonnegative and the eigenvalues of matrix $(F + G)$ are smaller than one in modulus as described in (Robert F Engle & Kroner, 2015). Provided that the standard conditions are satisfied, full information maximum likelihood estimates are asymptotically normal and efficient with asymptotic covariance matrix given by the inverse of Fisher’s information matrix.
Impulse response functions are calculated in Elder’s method and they are generated from the maximum likelihood estimates (MLEs) (J. Elder, 2003). The confidence intervals (Hamilton, 1994) are based on the randomly distributed parameters drawn from the samples of the MLEs and are simulated by 1,000 impulse responses. Meanwhile, the covariance matrices of the MLEs is a derivation of the Fisher’s information matrix.

4. Empirical Evidence

We use the first-difference form of daily settlement prices of carbon emission trading of both Guangzhou and Shenzhen trading markets during the period of March 11, 2014 to April 11, 2017 for the estimation of bivariate GARCH-in-Mean VAR. The selection of lags of our model is based on the Schwarz information criterion (SIC), which indicates that less than four lags is enough to summarize the dynamics of our system (Schwarz, 1978). Therefore, we estimate the bivariate GARCH-in-Mean VAR with four lags by using the first-difference of carbon emission trading price in Shenzhen and Guangzhou markets.

To ensure that our model specification can capture the major features of our data, we calculate the Schwarz information criterion for both the bivariate GARCH-in-Mean VAR as well as the conventional homoscedastic VAR. The Schwarz criterion includes a substantive penalty for the additional parameters that is required to estimate the GARCH models. Hence, if there is any improvement in the Schwarz information criterion, our model will be proved as good estimation by solid evidence (J. Elder & Serletis, 2011). The SIC value for the structural GARCH-in-Mean VAR is 6377.889 whereas that of the conventional homoscedastic VAR is 7079.109. Hence, we can conclude that our GARCH-in-Mean VAR model is consistent with our data.

We estimate the parameters of both the mean function (shown as equation (2)) and the variance function (shown as equation (3)) and the results of the estimation are shown in Table 4. Panel A reports the parameters of the mean function whereas Panel B shows the coefficients of the variance function. The ARCH effect of price uncertainty in Shenzhen and the GARCH effect of price change in Guangzhou are statistically significant. In particular, the volatility process of daily settlement price for both Shenzhen and Guangzhou markets are shown as $0.601 + 0.158 = 0.758$ and

<table>
<thead>
<tr>
<th>Table 4 Coefficients estimated by GARCH-in-Mean VAR</th>
</tr>
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<tbody>
<tr>
<td>Coefficient</td>
</tr>
<tr>
<td>A. Mean Equation</td>
</tr>
</tbody>
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\[
\begin{array}{lrr}
  b & 0.011(0.233) & -0.015(0.173) \\
c_1 & -0.141(0.025) & -0.026(0.635) \\
\gamma^1_{11} & -0.054(0.272) & 0.058(0.324) \\
\gamma^1_{12} & 0.073(0.235) & 0.015(0.789) \\
\gamma^1_{21} & -0.096(0.097) & -0.040(0.486) \\
\gamma^1_{22} & -0.631(0.000) & -0.509(0.000) \\
\gamma^1_{31} & -0.201(0.000) & -0.351(0.000) \\
\gamma^1_{32} & -0.201(0.000) & -0.175(0.000) \\
\gamma^1_{41} & -0.110(0.000) & -0.138(0.000) \\
\gamma^1_{42} & 0.049(0.584) & -0.083(0.416) \\
\lambda_{11} & 0.000(0.000) & 0.000(0.000) \\
c_2 & 0.024(0.583) & -0.266(0.000) \\
\gamma^2_{11} & 0.037(0.331) & -0.017(0.632) \\
\gamma^2_{12} & -0.026(0.471) & -0.103(0.016) \\
\gamma^2_{21} & -0.024(0.439) & -0.054(0.138) \\
\gamma^2_{22} & -0.014(0.322) & -0.016(0.242) \\
\gamma^2_{31} & -0.019(0.028) & -0.003(0.836) \\
\gamma^2_{32} & 0.025(0.136) & -0.001(0.969) \\
\gamma^2_{41} & -0.019(0.029) & -0.008(0.486) \\
\gamma^2_{42} & 0.025(0.668) & -0.094(0.650) \\
\lambda_{21} & -0.019(0.209) & -0.001(0.997) \\
\end{array}
\]

B. Variance Equation

\[
\begin{array}{lrr}
c^1_v & 7.610(0.000) & 10.862(0.000) \\
f^1_{11} & 0.601(0.000) & 0.350(0.000) \\
g^1_{11} & 0.000(0.000) & 0.000(0.000) \\
c^2_v & 0.018(0.000) & 0.094(0.000) \\
f^2_{22} & 0.158(0.000) & 0.222(0.000) \\
g^2_{22} & 0.840(0.000) & 0.769(0.000) \\
\end{array}
\]

0.000 + 0.840 = 0.840, which are not persistent. Meanwhile, the coefficient for 
\( e_i(t-1)^2 \) and \( H_{ii}(t-1) \) (shown as \( f_{ii} \) and \( g_{ii} \)) are statistically significant.

We use this model to investigate the effect of price change of Shenzhen on that of Guangzhou carbon emission trading market. The coefficient \( \lambda_{21} \) is associated with what we interest and it is the parameter on the conditional standard deviation of the

**Figure 2 Impulse Responses of Price Change in Guangzhou**
price change of Guangzhou trading market in the equation of Shenzhen. According to the first column of Table 4, it is -0.019 with p-value of 0.209. Hence, although the coefficient shows shock of Shenzhen has negative effect on that of Guangzhou, it is not statistically significant.

To illustrate the effect of price uncertainty in Shenzhen on the dynamic response of the first-difference of price in Guangzhou to that of Shenzhen, we plot the impulse responses in Figure 1, which is simulated from the maximum likelihood estimates of the parameters. We use a shock of the magnitude to ensure the impulses comparable to those of standard homoscedastic VAR. Meanwhile, we simulate the response of Guangzhou to both a positive and negative shocks in Shenzhen to investigate whether the responses to positive and negative are symmetric or asymmetric.

The first one shows the response of Guangzhou to a positive shock in Shenzhen. The impulse response indicates that, if a positive shock is given to the first-difference of Shenzhen, Guangzhou market will response negatively, inducing a downward revision in the first-difference of price in Guangzhou trading market by approximately 3 basis point immediately. The dynamic effect of the positive shock to the price change in Shenzhen is also relatively persistent. The second figure displays the response when negative shock is given to Shenzhen. If a negative shock is given to Shenzhen, it will induce an upwards revision by about 3 basis point. Compare the two figures, both are significant since the one-standard error bands are not crossing the zero line.

Finally, a sense of the economic significance of the effect of price change in Shenzhen on that of Guangzhou can be assesses, to some extent, by examine the estimated effect of price change in Shenzhen on that of Guangzhou in the conditional standard deviation of the change of carbon emission trading in Shenzhen. Our estimates indicates that the median change in the conditional standard deviation is 1.56 percentage points and the standard deviation of the change in the price is -0.019. Therefore, the effect of a one-standard-deviation shock on Shenzhen carbon emission trading market in the daily settlement price is $-0.019 \times 1.56 = 2.96$ percentage
points.

5. Robustness

From the empirical results, we know that positive shock to Shenzhen will induce negative response of Guangzhou and this effect is not statistically significant according to the regression result and the impulse responses. Meanwhile, the impulse responses of both positive and negative shocks are asymmetric. In this part, we will discuss the robustness of our model with alternative measure of carbon emission trading price (daily average price) and alternative models.

5.1 Daily Average Prices

Although we select the daily data for almost three years, there are so much missing values from the database. In this section, we investigate the robustness of our results by using the daily average price obtained from Wind database. The SIC for GARCH-in-Mean VAR is 4976.499 whereas that for the conventional VAR is 5352.760, which means that our model fits the data well and captures more information than the conventional homoscedastic VAR. We show the estimation results in the last column of Table 4, in the same way which we display that for daily settlement price. The coefficients estimated for the mean function are shown in panel A and those estimated for the variance function are shown in panel B. Again, the GARCH in price change of Guandao market and the ARCH effect in the price change in Shenzhen market. The coefficient associated with the effect of price change is -0.009 with p-value of 0.000. The sign of the coefficient is negative which means that positive shock to carbon emission trading price change in Shenzhen trading market tend to decrease the price change in Shenzhen. The results are consistent with what we have when using daily settlement price.

5.2 GARCH-in-Mean BEKK Model

The empirical model is based on the GARCH-in-Mean model suggested by Engle (Robert F. Engle, Lilien, & Robins, 1987) and the Asymmetric-BEKK model (Grier, Henry, Olekalns, & Shields, 2004).

The mean function is VAR (4) where 4 is the lags and it can be expressed as

\[ y_t = \alpha + \sum_{i=1}^{n} \beta_i y_{t-i} + \psi \sqrt{H(t)} + e_t \]  \hspace{1cm} (4)

Table 5 Coefficients Estimates by BEKK GARCH
\[
\begin{array}{ccc}
(1,1) & 1.434(0.003) & 0.553(0.000) & 0.787(0.000) \\
(1,2) & 0.000(0.000) & -0.016(0.102) & 0.008(0.319) \\
(2,1) & -0.009(0.846) & -0.010(0.942) & 0.012(0.836) \\
(2,2) & 0.131(0.001) & 0.367(0.000) & 0.928(0.000) \\
\end{array}
\]

where \( \mathbf{y}_t \) is the \( 2 \times 1 \) vector and its elements \( y_{1t} \) and \( y_{2t} \) represent the first-difference form of carbon emission trading on both Shenzhen and Guangzhou trading markets; \( \alpha \) is also the \( 2 \times 1 \) vector and \( \beta \) is the coefficient vectors \( (2 \times 2) \) and \( \mathbf{e}_t \) is the shock that the market is given; \( \mathbf{e}_t | \Omega_{t-1} \sim N(0, H) \).

The variance function can be expressed as

\[
H_t = C'C + B'H_{t-1}B + A'e_{t-1}e_{t-1}'A + D'e_{t-1}e_{t-1}'
\]

where \( C \) is the lower triangular matrix; \( B \) is the coefficient matrix of the GARCH, \( A \) is the coefficient matrix of ARCH and \( \mathbf{e}_t = \{0, \mathbf{e}_t\} \).

The likelihood is estimated by equation (3) shown in section 3. And the logged form likelihood is estimated by quadratic maximum likelihood estimates (QMLE) and results are shown in Table 5.

The ARCH effect as well as GARCH effect of Shenzhen carbon emission trading market to that of Guangzhou are negative which means that a positive shock to Shenzhen market would induce negative price change in Guangzhou. However, both the coefficients that we are interested are not statistically significant, which is in accordance with the empirical results.

5.3 Government Intervention

The carbon emission trading market of China is still under construction and it highly relies on the government regulations, which has already proved by others to have influence on the price of carbon emission trading. For instance, Eva Benz has proved that the decision of government about the allocation of certificates tend to induce downward trend of carbon emission trading price (Benz & Trück, 2009). By mathematical method, we cannot eliminate the influence of government interventions on price as well as its influence on market efficiency. Hence, the government regulation can be regarded as one of the source that depress the objectiveness of our model.

6. Conclusion
In this paper, we use the first-difference form of daily settlement price of carbon emission trading for both Shenzhen and Guangzhou markets to investigate the price linkage between these two markets. Our sample contains abundant observations and it comprises the data for more than three years, which means that it includes the basic market information during the period when both the two markets were being operated. Therefore, the regression based on this sample can illustrate enough information of the carbon emission trading. Meanwhile, the first-difference form of the two series are stationary and has no autocorrelation, which satisfies the basic standard for time series regressions. However, our sample is not so precise since we get the whole data set from both Wind and Tanjiaoyi website (both data sets of the two sources are not complete).

We use the bivariate structural vector autoregression model modified to accommodate the GARCH-in-Mean errors in this paper and we find that there is the price change in Shenzhen carbon emission trading market has no statistically significant influence on that of Guangzhou. By comparing the SIC value with the traditional VAR model, we find that this model captures more information of our sample. The regression results show that if a positive shock is given to Shenzhen it would induce negative response of Guangzhou but it is not significant (the same result can also be seen from the impulse responses figures). This phenomenon can be explained that these markets are separate and independent and external market information has slight influence on it. Hence, we could conclude that we cannot predict the price change of Guangzhou market by simply analysis the change in Shenzhen market and we cannot find arbitrage chances between these two markets as well.

As for the robustness, we do the regression of GARCH-in-Mean VAR based on the daily average price, use the GARCH-BEKK model and try to find the influence of government policies. Mentioned above, the major factor that influence the objectiveness of our paper is the data. As a result, we also use the daily average price to do the same regression and the result of it indicates the same features of that of the empirical part. We conclude that the results of the two regressions are persistent with that of the empirical evidence part and the government policy may also have influence.

Therefore, we can get the following conclusions from this paper. Firstly, this is no statistically significant price linkage of Shenzhen and Guangzhou carbon emission trading market even though Shenzhen is believed to have influence on other markets. It can be explained by the fact the carbon emission trading market is still not mature. It still has such problems like geographical restricts, low market activity. The
participates of carbon emission trading is not so active as those of stock markets; hence, the information associated with price cannot be displayed in the fluctuation of price. Secondly, participates cannot find potential arbitrage chances by just analysis price. The carbon emission trading price still be influenced by the factors like government regulations and the activity of market. Thirdly, simply analysis the price linkage among different market provide no information for unified price setting. If the government plan to set the unified price in the future, it is much practical to rely on the price determinants. Lastly, the robustness of our model is influenced by the imperfection of the sample and government regulations and we cannot conclude that when using the data of other markets, we can get the similar results. Maybe it is helpful to investigate the price linkage among all the seven pilot markets even though it will involve too much variables in the time series model.

References


Book Review.


