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Air Pollution Uncertainty Modelling based on urban API: a case of Beijing, China

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ABSTRACT

This paper models the uncertainty of Beijing API by introducing the econometric models widely used in financial econometrics in this field. In particular, this research focuses on three aspects: comparing the estimation and forecast performance of GARCH, GJR-GARCH, EGARCH and GARCH-M models; examining the seasonal dust effect of data, and detecting the existence of asymmetry in the data. With model diagnostic criteria, EGARCH outperforms other models, while out-of-data static forecasting performance does not.

1. Introduction

Air pollution is a critical problem in China. According to the World Bank, 16 of the worlds is 20 cities with the worst air are in China. According to Chinese government sources, about a fifth of urban Chinese breathe heavily polluted air. Air pollution problems in cities and their immediate vicinities have been and will continue to be one of the environmental concerns in the next decade in China (Chak K. Chan, Xiaohong Yao, 2008).

The air pollution index (API), a referential parameter describing air pollution levels, provides information to enhance public awareness of air pollution. API reporting in China requires one to convert monitored daily average air quality data into integer values, and then to report them to the public. In China, Shanghai was the first to report APIs dating back to June, 1997. Before June, 2000, three major pollutants, including total suspended particulates (TSPs), sulfur dioxide (SO2) and nitrogen oxides (NOx), were selected for API reporting. After June 2000, as required by the State Environment Protection Agency of China, these pollutants were switched to respirable

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particulate matter (PM10), SO2 and nitrogen dioxide (NO2; Kai *et al.*, 2008).

API forecasting is important since information can be released to the public so they can decide upon and adjust their activity in the next day. Much research on API forecasting has been published. The most widely used models in this field of study are artificial neutral network based models (Uwe *et al.*, 2006, 2003). Some scholars have tried the linear multiple partial correlation statistical method (Euro Cogliani, 2001). Other researchers use time series models. Xie and Wei used the auto-Regressive moving average (ARMA) method to forecast the API time series in different seasonal specifications and found that the ARMA model can provide reliable, satisfactory predictions for the problem (Xie and Wei, 2006).

Volatility modeling is important in controlling and forecasting uncertainty in API alerts. But because API is affected by a series of factors like energy use (Kimmel, 2002), transportation (Xie, 2006), topographic features (Chu *et al.* 2008), wind speed and temperature (Euro Cogliani, 2001), pressure (Chen *et al.* 2008, Jiang *et al.* 2004), much of the uncertainty may arise from the data used, which again may be based upon sub-data from the observation stations, simple parameterized representation of atmospheric processes, and so on. There may also be omitted or ignored factors in the modeling, either because they are not recognized as significant or because of incomplete knowledge. So it is not only complex, but also inaccurate to address the uncertainty of the API of a whole city via so many sub-data. Urban API is integrated from the sub-data of many observation stations. It is helpful since it can monitor the air quality affecting larger numbers of people, and become comparable between different cities. By examining the best way to modelg the uncertainty in API of a larger area, Beijing, this study contributes to the practical area ofn improving the accuracy API forecasting and air pollution alerts.

Instrumental in most of volatility studies has been the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models which are widely used in finance. Although volatility clustering had been documented earlier, it was not until Engle (1982) and the advent of the ARCH and GARCH (Bollerslev, 1986) models that financial econometricians started to seriously model this phenomenon. It then became a popular tool for volatility modeling and forecasting. However, despite the success of the GARCH model, it has been criticized for failing to capture asymmetric volatility. This limitation has been overcome by introducing more flexible volatility treatments and accommodating the asymmetric responses of volatility to positive and negative shocks. This more recent class of asymmetric GARCH models includes the Exponential GARCH (EGARCH) of Nelson (1991) and the 1993 threshold GARCH by Glosten, Jagannathan, and Runkle (GJR-GARCH; Hung and Jui, 2010).

Since daily API data have the same volatility clustering feature as financial data, GARCH type models have advantages in this field of research. McAleer et al. argue that, for a wide range of financial and other data series, time-varying conditional variances can be explained empirically through the autoregressive conditional heteroskedasticity (ARCH) model proposed by Engle. But to the best of our knowledge, it has not been used in the study of urban API. Our contribution in this paper is to complement the previous API researches with the application of new econometric models. First, we examine and compare the predictive ability of different GARCH models with various volatility specifications in API; second, we examine the seasonal effect of Beijing API, comparing the API with and without dust storms.

The structure of this paper is as follows: in section two, three GARCH family models used in this paper are discussed; in section three, data description is provided followed by an empirical application in section four and conclusion in section five.

2. Model

Volatility models have been very popular in empirical research in Finance and Econometrics since the early 1990s. The models are based on influential papers by Engle (1982) and Bollerslev (1986). All volatility models start off with a 'mean equation', which is commonly a standard ARIMA or regression model. Then involve adding a 'variance equation' to the original mean equation and which in turn models the conditional variance.
An ARIMA (p, d, q) is expressed as:

$$\left(1-\sum_{i}^{p}\theta_i L^i\right)(1-L)^d y_t = \left(1+\sum_{i}^{q}\Phi_i L^i\right)\varepsilon_t \quad (1)$$

Where p, d, and q are integers greater than or equal to zero and refer to the order of the autoregressive, integrated, and moving average parts of the model respectively. When one of the terms is zero, it is usual to drop AR, I or MA.

In this paper, volatility models to be estimated are associated with a stationary AR (1) conditional means given by:

$$Y_t = \mu + \theta Y_{t-1} + \varepsilon_t \quad |\theta| < 1$$

Or a MA (1) conditional means given by:

$$Y_t = \mu + \Phi\varepsilon_{t-1} + \varepsilon_t \quad |\Phi| < 1$$

Or a ARMA (1,1) conditional means given by:

$$Y_t = \mu + \theta Y_{t-1} + \Phi\varepsilon_{t-1} + \varepsilon_t \quad (4)$$

Where, Y_t is Air Pollution Index, ε_t is shock to API.

(1) GARCH

Generalised autoregressive conditional heterocedasticity (GARCH) model was developed by Bollerslev (1986). It is rare for the order (p, q) of a GARCH model to be high; indeed the literature suggests that the parsimonious GARCH (1,1) is often adequate for capturing volatility in financial data. In this empirical application, (p, q) tends to be (1, 1). The conditional variance is modeled as:

$$\varepsilon_t = \eta_t\sqrt{h_t}$$
$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \quad (5)$$

Where h_t is conditional volatility, conditional on the information of period t-1; η_t is standardized shock to API. ω >0, $\alpha \geq 0$, $\beta \geq 0$ are sufficient to ensure that the conditional variance h_t>0; Using results from Ling and Li and Ling and McAleer, the necessary and sufficient condition for the existence of the second moment of ε_t for GARCH (1,1) is $\alpha + \beta < 1$.

GARCH model is lack of asymmetric and leverage. It presumes that the impacts of positive and negative shocks are the same or isymmetric'. This is because the conditional variance in these equations depends on the magnitude of the lagged residuals, not their sign. In order to accommodate the differential impacts on the conditional variance between positive and negative shocks, Glosten, Jagannathan and Runkle (1992) proposed the following specification for h_t.

(2) GJR-GARCH

The threshold GARCH (TGARCH) (Glosten, Jaganathan, & Runkle, 1993) is a simple extension of the GARCH scheme with extra term (s) added to account for possible asymmetries:

$$\varepsilon_t = \eta_t\sqrt{h_t}$$
$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma I(\varepsilon_{t-1}) + \beta h_{t-1} \quad (6)$$

Where ω >0, $\alpha \geq$ 0, $\alpha + \gamma \geq 1$ and $\beta \geq$ 0 are sufficient conditions to ensure that the conditional variance h_t>0. $I(\varepsilon_{t-1})$ is an indicator function, taking the values of 1 if ε_{t-1} <0 (good news in this study) and 0 if ε_{t-1}>0. The impact of bad news and good news on the conditional variance in this model is different, if $\gamma > 0$, the positive innovations have a higher impact than negative ones. The GJR is asymmetric as long as γ is significant different from zero.

Regularity condition for the existence of the second moment of GJR model is $\left(\alpha + \beta + \frac{\gamma}{2}\right) < 1$.

When the conditional shock (η_t) follow a symmetric distribution, the expected short run persistence is ($\alpha + \gamma/2$) , and the contribution of shocks to expected long run persistence is $\left(\alpha + \beta + \frac{\gamma}{2}\right)$.

(3) EGARCH

The EGARCH (p, q) model of Nelson (1991) can also accommodate asymmetry and specifies the conditional variance in a different way:

$$\varepsilon_t = \eta_t \sqrt{h_t}$$

$$\log h_t = \omega + \alpha \varepsilon_{t-1} + \gamma \varepsilon_{t-1} \quad \beta \log h_{t-1} \qquad (7)$$

EGARCH models the logarithm of conditional volatility, thereby removing the need for constraints on the parameters to ensure a positive conditional variance (Long more& Robinson, 2004). $|\varepsilon_{t-1}|$ and ε_{t-1} capture the size and sign effects of standardized shocks respectively. The presence of leverage effects can be tested by the hypothesis that γ <0 and $\gamma < \alpha < -\gamma$. The model permits asymmetries via γ and if γ < 0, negative shocks lead to an increase in volatility. Good news generate less volatility than bad news. The model is asymmetric as long as $\gamma \neq 0$.

EGARCH is asymmetric, can capture leverage, but it does not have statistical properties because we cannot differentiate $|\varepsilon_{t-1}|$.

(4) GARCH in Mean

The ARCH and GARCH framework was further extended to ARCH and GARCH in mean (ARCH-M and GARCH-M) by Engle, Lillen and Robins (1987). The GARCH-M model adds a heteroskedasticity term into the mean equation. It has the specification:

$$Y_t = \mu + \theta Y_{t-1} + \lambda h_t + \varepsilon_t \quad |\theta| < 1$$

$$\varepsilon_t = \eta_t \sqrt{h_t}$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (8)$$

The only difference of GJR in Mean (GJR-M) and EGARCH in Mean (EGARCH-M) with GARCH-M is that they have different variance equations:

$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma I(\varepsilon_{t-1}) + \beta h_{t-1}$ for GJR-GARCH-M (9)

and

$\log h_t = \omega + \alpha \varepsilon_{t-1} + \gamma \varepsilon_{t-1} \quad \beta \log h_{t-1}$ for EGARCH-M (10)

(5) Models with dummy

To examine the seasonal dust effect, we set a dummy variable D to equal zero when t is the non dust-storm season and 1 when t is the dust-storm season. Specifically, to consider the seasonal dust effect, we also employ all four above mentioned models; the only difference is that we put an additional intercept term D with d as coefficient in all four variance equations.

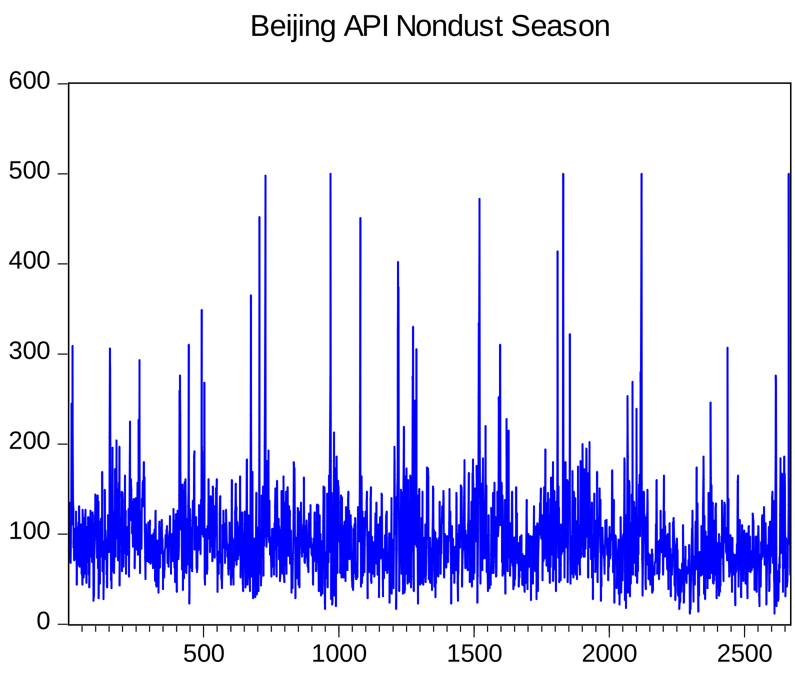
3. Data description

The data for this study consis of the daily average Air Pollution Index (API) of Beijing during the period from June 5th, 2000 to June 4th, 2010, which constitutes a total of 3652 observations. The data employed was retrieved from the database of the Ministry of Environmental Protection of the People is Republic of China (http://www.zhb.gov.cn//) (MEPPRC). The APIs are released to the public freely by MEPPRC, which were reported by the Environment Protection Bureau of each city. According to the Beijing Environment Protection Bureau, the daily average API of Beijing is integrated from the daily average index of 28 observation stations.

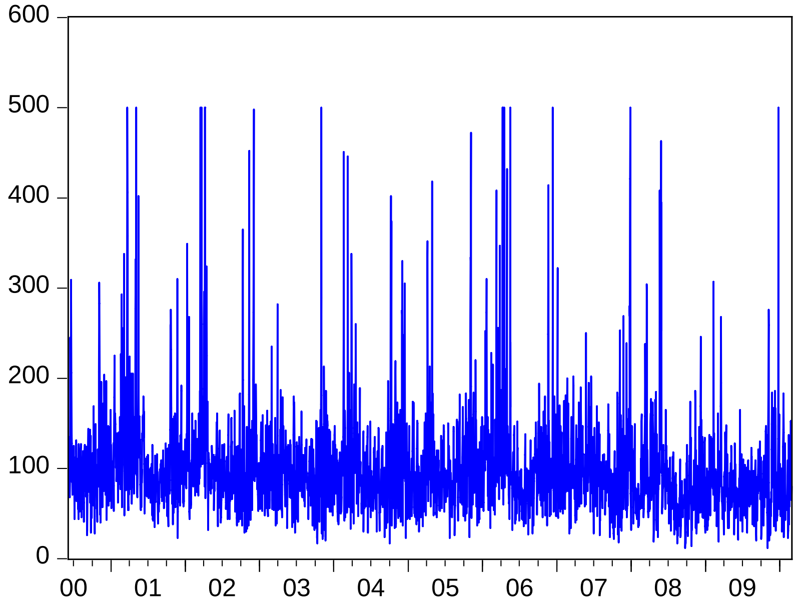
A total 3287 observation were used to estimate the models, while the forecasting performance of various volatility models for the last 365 days (from June 5th, 2009 to June 4th, 2010) of the data set is the focus of our out-of-sample evaluation and comparison.

According to previous research, the API is closely related with dust storms (Pisoni 2009, Zhang et al. 2010).To examine whether there are different features of API in the dust storm season and non dust storm season, we disaggregated the data into two segments: dust-storm season and non dust-storm season, then examined three series of API: complete API data, which start from, June 5th, 2000 to June, 4th, 2009; API in non dust-storm season, which consist of daily API from, June 5th, 2000 to June 4th 2009, but exclude the dust-storm season, say , from March 1st, to May 31st each year; and API in dust-storm season, which consists of daily API form March 1st to May31st during the period from 2001 to 2009. The three series are examined and illustrated in figure 1.

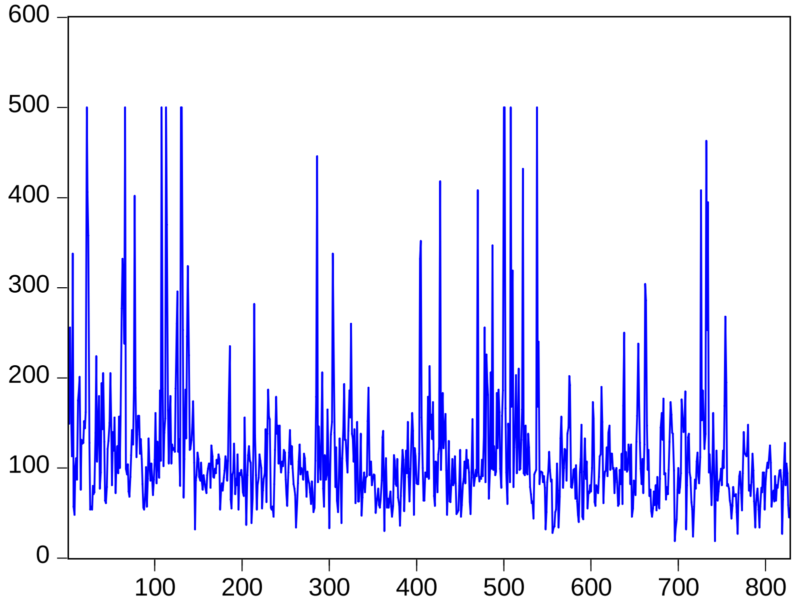
Figure 1: Daily average API of Beijing



Beijing API Complete



Beijing Dust Season API



As shown in Table 1, the API of Beijing in the dust-storm season exhibits the highest mean and variance, while the data in the non dust-storm season have the lowest. The complete data are affected accordingly. These indicate the importance of taking into consideration the seasonal dust effect when modeling the API of Beijing.

An initial assessment of the three series for unit root test for stationarity using the Phillips–Perron procedure, and ADF procedure rejects the null hypothesis that there is a unit root in the series at the 1% level of significance. From the figure 1 above, we fail to observe strong seasonality, positive or negative trends.

Table 1: Statistical descriptions of the three series

	Beijing API Complete	Beijing API Nondust	Beijing Dust-storm season API
Mean	100.7904	95.88685	116.5966
Median	91	89	97
Maximum	500	500	500
Minimum	12	12	19
Std. Dev.	56.84017	49.19411	74.31373
Skewness	3.166342	2.941982	2.870551
Kurtosis	18.85839	19.25981	13.34073
Jarque-Bera	42487.29	33251.57	4826.237
Probability	0	0	0
Sum	352464	255922	96542
Sum Sq. Dev.	11294895	6456722	4567133
Observations	3497	2669	828

4. Empirical Study

The ARMA (p,q)-GARCH (1,1), ARMA (p,q)-GJR-GARCH (1,1), ARMA (p, q)-EGARCH (1,1) and GARCH in mean models are used to estimate the conditional mean and volatility of Beijing daily average API between period June 5th, 2000 to June 4th, 2009. In our paper, only models which passed the residual non heteroskedasticity test with a statistical order of 10, and with all coefficients significant aere listed in Tables 2 3.

Table 2 presents the model estimates and diagnostic tests for Beijing API during the sample period. Table 3 is the out-of-sample forecasting evaluation of different models.

All the estimates in this paper are obtained using the EViews6.1 econometric software package. The error normal distribution assumption and Marquardt algorithm have been used in all cases.

As shown in Table 2, the parameters, μ, θ, Φ, ω, a, and β in the mean and conditional variance equations in panel A and B are all positive and found to be highly significant. ARCH effect tests of residuals did not reject the null hypothesis of no serial correlation in the squared standardized residuals at the 1% level, suggesting that the models listed capture the time varying volatility in the data very well. The symmetric GARCH component exhibits the existence of strong volatility persistence in the Beijing API, as the $a+\beta\approx 1$. Turning to the asymmetric effect, in panel A, the parameter γ of the conditional volatility equation in the GJR-GARCH model is negative and highly significant, implying that negative shocks (good news) exert smaller impacts on Beijing API volatility than positive shocks (bad news) of the same magnitude. Similarly, γ in EGARCH models in both panels are positive and highly significant, implying that positive shocks (bad news) exert bigger impacts on Beijing API. The parameter d in the four models AR (1) GARCH, ARMA (1,1)-EGARCH, MA (1)-EGARCH, AR (1)-TGARCH-M is positive and highly significant, indicating a strong seasonal effect, with higher volatility in the dust-storm season compared with the non dust-storm season.

The results of the diagnostic tests are reported in the lower parts of Tables 2. In general, the Log (L), AIC and SC values for the Beijing API are very close to each other under the different GARCH type models. In panel A, AR (1)-EGARCH model is slightly better than other models. In panel B, ARMA (1,1)-EGARCH outperforms other models. Even though GARCH parameters λ in mean equation is significant in both GARCH in mean models, they are not winners in terms of

Log (L), AIC and BC criterions, indicating considering the time varying conditional mean did not necessarily improve the estimation effects.

Table 2: Alternative model estimates

Panel A: Beijing API complete				
Parameters	AR (1)-GARCH	ARMA (1,1)-GJR	AR (1)-EGARCH	AR (1) GARCH-M
μ	89.62381***[1.732972]	102.9434*** [1.940284]	93.60075*** [0.011011]	86.55898*** [1.818188]
	0.571685*** [0.016972]	0.419339*** [0.018344]	0.561286*** [0.003529]	0.555780*** [0.018457]
θ		0.048909*** [0.005048]		
Φ	47.74526*** [3.491872]	828.5415*** [27.88218]	3.118119*** [0.010706]	44.65979***[3.534796]
	0.151421*** [0.005425]	0.250845*** [0.014663]	0.664823*** [0.011558]	0.143422***[0.005153]
ω	0.855344*** [0.002732]	0.598744*** [0.012438]	0.567177*** [0.001813]	0.862059***[0.002866]
α		-0.465034*** [0.018208]	0.026395*** [0.014814]	
β				0.214387*** [0.064160]
	-17020.34	-17037.58	-16798.52	-17013.02
γ	10.36235	10.37406	10.22795	10.35850
λ	10.37162	10.38705	10.23908	10.36963
Log (L)				
AIC				
SC				
Panel B: Beijing API Dust-storm season Effect				
Parameters	AR (1) GARCH	ARMA (1,1) EGARCH	MA (1) EGARCH	AR (1) TGARCH-M
μ	84.27316*** [1.228650]	96.50940***	90.59344***[0.945654]	89.11463*** [2.153406]
	0.514101*** [0.017521]	[1.639249]		0.478098*** [0.025031]
θ		0.549851*** [0.023444]	0.454085***[0.016464]	
Φ	422.5460*** [20.07806]	0.051837***	3.064264***[0.121002]	326.5947*** [16.41542]
	0.533013*** [0.019871]	[0.026013]	0.494104***[0.017196]	0.921949*** [0.049292]
ω	0.280536*** [0.012967]	2.443729*** [0.103295]	0.523754***[0.016937]	0.438086*** [0.012879]
α		0.173772***	0.336181***[0.022818]	-1.018548*** [0.048965]
	1728.135*** [59.89515]	[0.021130]	0.632187***[0.028828]	1143.711*** [45.74495]
β		0.630396***		0.336176*** [0.073343]
γ		[0.014998]		
d	-19462.37	0.523433***	-16728.02	-16670.48
λ	10.24651	[0.015601]	10.18255	10.15123
	10.25637	0.447940*** [0.024969]	10.19554	10.16608
Diagnostic				
Log (L)				
AIC		-16633.27		
SC		10.12859		
		10.14343		

*Notes: Standard errors for the estimators are included in parentheses. ***indicate significant at the 1% level. Log (L) is the logarithm maximum likelihood function value. AIC is the average Akaike information criterion. SC is the Schwarz is Bayesian Information Criterion.*

Table 3: Forecasting comparison

Panel A: Beijing API complete				
Forecast evaluation	AR (1) GARCH	ARMA (1,1) GJR	AR (1) EGARCH	AR (1) GARCH-M
RMSE	45.48273	45.59952	45.48113	46.07910
MAE	27.21879	29.07968	27.36118	27.69474
MAPE	40.62409	47.53355	41.67376	42.57467
TIC	0.238841	0.232276	0.236899	0.238182
BP	0.001121	0.042088	0.005284	0.009583
VP	0.206929	0.355866	0.217117	0.190030
CP	0.791949	0.602046	0.777599	0.800388
Panel B: Beijing API Dust-storm season Effect				
Forecast evaluation	AR (1) GARCH	ARMA (1,1) EGARCH	MA (1) EGARCH	AR (1) TGARCH-M
RMSE	44.99964	45.89406	45.68275	47.70428
MAE	26.95854	27.55905	28.11112	28.51678
MAPE	39.43186	42.19349	42.69992	45.05349
TIC	0.240208	0.237159	0.240223	0.241483
BP	0.000370	0.009488	0.004742	0.028827
VP	0.272077	0.185714	0.365482	0.140638
CP	0.727553	0.804798	0.629776	0.830535

Note: RMSE is Root Mean Squared Error, MAE is Mean Absolute Error, MAPE is Mean Abs. Percent Error, TOC is Theil Inequality Coefficient, BP is Bias Proportion, VP is Variance Proportion, CP is Covariance Proportion.

Table 3 is the comparative evaluation of the predictive performance of the competing models. We present seven criteria which were provided by EVIEWS

6 measuring the accuracy of one step ahead out-of-sample forecasts. There is no universally preferred measure of estimation accuracy and forecasting experts often disagree over which measure should be used (Chu, 2009). The most widely used is the MAPE and RMSE. MAPE is the mean of the absolute percentage differences between the forecasts and the actual APIs measuring the magnitude of the error. While RMSE gives more weight to larger forecasting errors than the smaller ones, some researchers (Witt and Witt, 1991) suggest that an accuracy criterion specified in terms of squared errors is more appropriate that specified in terms of absolute errors. The bias proportion tells us how far the mean of the forecast is from the mean of the actual series. The variance proportion tells us how far the variation of the forecast is from the variation of the actual series. The covariance proportion measures the remaining unsystematic forecasting errors. In this research, considering that the health impact caused by heavy pollution (very high API) is serious, we rank the RMSE as the primary forecasting evaluation criteria, followed by MAPE and BP accordingly. Other criteria in both panels A and B, the forecasting performance of different models are very similar. In both panels A and B, the parsimonious model AR (1)-GARCH outperformed the others. This reveals that the best model chosen by Log (L) and AIC, BC criteria did not necessarily provide best the forecast. In this case of Beijing API, since the forecast performance difference between EGARCH model and the GARCH model is slightly, and since EGARCH can capture the leverage effect, we think the ARMA (1,1)-EGARCH model with a seasonal effect is the best tool for modeling and forecasting the Beijing API.

5. Conclusion

The Beijing daily Air pollution index series is characterized by stationary and volatility clustering. Another feature is that it is affected by the spring dust storm (Guo et al. 2004, Zheng et al. 2005, Han et al. 2007).

In this study, we introduce the GARCH type models which are widely used in finance studies into the Beijing daily API study. Specifically, we estimated GARCH, GJR-GARCH, EGARCH as well as GARCH in Mean models. The estimated models are compared in terms of the Log Likelihood ratio, AIC and SC criteria.

The estimation of the model indicates that GARCH type models can capture the conditional mean and conditional variance of the Beijing API very well.

In addition, the seasonal dust dummy parameter confirmed that both the conditional mean and conditional variance of the data were higher in the dust-storm season than that in other seasons. This result is compatible with other research in this field.

The existence of a leverage effect was confirmed by the asymmetric parameters in all the significant models we estimated. Both GJR-GARCH and EGARCH models reveal that bad news (higher API) causes higher volatility.

Even though the Log Likelihood ratio, AIC and SC criteria choose EGARCH model as the best, forecasting performance tells a different story. Parsimonious models give a better forecast.

The practical policy suggestions arising from this study fall into two categories. For the API forecasting agency, GARCH type models can be incorporated with meteorology method now in use so as to improve the forecasting. For the vulnerable population such as the old and medical patients, they should take actions to protect their health, especially during the dust storm season, since the mean, variance, and volatility are higher, and bad news exerts higher uncertainty.

The shortcomings of this study come mostly from three aspects. First, urban ambient air pollution comes from many sources of emission, but the pollution index employed in this study is non-disaggregated by particulate matter, carbon dioxide, nitrous oxide, etc. so that it is difficult to trace the source of the pollution to particular industries. This should be considered in future research. Second, the data we employed were integrated from the observations of 28 stations to form a daily average index, which left aside much information. Finally, the method we used omitted several potentially relevant exogenous variables. As these may improve the performance of the model, they need to be considered in future studies.

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