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Is temperature-index derivative suitable for China?

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HIGHLIGHTS

- We explored whether temperature derivatives traded on CME are suitable to China.
- Cluster analysis in form of model parameters from the AR-EGARCH model is used to classify temperature data.
- Asymmetry of the volatility of the temperature is confirmed according to the AR-EGARCH model.
- HDD and CAT in Europe and CAT* in Japan can be used directly in Nanjing of China.

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ABSTRACT

In this paper, we assessed the suitability of temperature derivatives for China through modeling. We assumed that if the physical dynamics of temperature of some cities are identical, then the same types of temperature derivatives can be used in these cities. Nearly twenty years temperature data of forty-seven cities with traded temperature derivatives on the Chicago Mercantile Exchange Group (CME) and seven Chinese cities were collected and analyzed in a two-step approach. Firstly, the AR-EGARCH model capturing the shock asymmetry of the volatility of temperature is used to simulate the dynamics of temperature of the cities. Secondly, the temperature of the cities are classified through cluster analysis based on model parameters from the AR-EGARCH model. The results showed that the fitting effect of the AR-EGARCH model is very good, and only a few cities did not display the shock asymmetry. The model for Nanjing fitted well into one of the categories of the cities in the CME; but the other six Chinese cities belong to new categories, which are different from the cities in the CME. We concluded that HDD and CAT in Europe and CAT* in Japan can be used directly in Nanjing, but the existing temperature derivatives in CME were unsuitable for the other six Chinese cities. Recommendations for the establishment of weather derivatives market in China have been proposed.

1. Introduction

In recent decades, extreme weather has occurred frequently across the world, which seriously impedes the development of world economies. Countries are therefore actively taking measures to deal with climate changes for sustainability. One of the financial instruments used to hedge weather risk is weather derivative [1–3]. In 1997, the United States launched the first weather derivative. In 1999, weather derivatives were traded formally on the Chicago Mercantile

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Exchange Group (CME). Later, many countries such as Britain, France, Germany, Japan and many others also joined in. However, until date, China has no weather derivatives. Although there are some weather insurance products and related instruments of weather risk management in China, the weather derivatives market remains unexploited.

In general, weather risk is divided into catastrophic weather events and non-catastrophic weather events [4]. For catastrophic weather events, which cover rare weather events such as extreme cold or heat, hurricanes and floods, the solutions in China are usually availability of government bailout, social contributions and weather insurance products. In contrast, weather derivatives are designed to cover non-catastrophic weather events. Rainy or dry and warm or cold periods, which are expected to occur frequently, can reduce the economic revenue of a sector by affecting the volume of sales. Weather derivatives are mainly used to avoid the volume risk of weather. The weather changes in China are quite different in different regions so that non-catastrophic weather events frequently occur. However, there are no management tools for volume risk of weather events for the various economic sectors. Therefore, it is necessary for China to introduce weather derivatives. However, the introduction of weather derivatives into China requires an assessment of its suitability. Studies on weather derivatives related to climate conditions in China have not been fully developed [5,6], especially on the types of weather derivatives suitable for China.

While the direct adoption of mature weather derivatives in CME may be the most convenient way for China, an initial assessment of its suitability for China through Modelling techniques would provide practical indications of its feasibility. Most weather derivatives contracts are traded in the CME. According to CME, there are many types of weather derivatives including but not limited to temperature derivatives, hurricane derivatives, frost derivatives, and snowfall derivatives among others. Weather derivatives have a strong regional feature and its applicability could be context specific [7,8]. For example, weather derivatives in a city may not be suitable for other cities. Therefore, the purpose of this paper is to study whether the existing temperature derivatives on the CME can be used in China.

This paper is based on one key assumption. For the convenience of the research, we assumed that when temperatures in two cities have the same dynamic evolution, the two cities can use the same types of temperature derivatives. Cluster analysis was used to classify the temperature data of all the cities, which have weather derivatives on the CME, and seven cities in China. Consequently, we identified and grouped similar class members of the temperature data; and determined whether the seven Chinese cities should introduce temperature derivatives and if so, the types of temperature derivatives. Given that ordinary cluster analysis is only suitable for static data, and temperature data is a time series dynamic data, which has high dimensional feature, we used cluster analysis based on the AR-EGARCH model to classify the temperature data. At first, we used the AR-EGARCH model to fit the temperature data, and then classify the temperature data based on the model parameters through cluster analysis. The AR-EGARCH model used to model the dynamics of temperature is an improvement of the AR-GARCH model proposed by Campbell and Diebold [9]. Compared with the GARCH model, EGARCH model can capture the asymmetry of the volatility of time series. Studies show that many financial time series have the asymmetry of the volatility [10,11]. That is, the impact of good news and bad news on the volatility is not the same. The temperature fluctuation also has the asymmetry [12,13], consequently extreme cold and heat have different impact on the volatility of temperature.

The organization of this paper is as follows. In Section 2, we reviewed the related literature on weather derivatives; in Section 3, we introduce the data and methodology used in this paper. Section 4 is the data analysis and results, and Section 5 outlines our conclusions and recommendations.

2. Literature review

Pricing of weather derivatives is a task. In contrast to other assets, the underlying asset of weather derivatives is not tradable, and the corresponding market is relatively illiquid. So, the traditional non-arbitrage pricing theory (such as Black–Scholes pricing model) cannot be applied directly [14,15]. Almost all weather derivatives are based on temperature indices [16]. As a result, many pricing methods of temperature derivatives have been proposed in literature.

The actuarial method and the historical burn analysis (HBA) proposed earlier derive the price of derivatives by calculating the average (discounted) payoff of the historical performance of a temperature derivative. The actuarial method and the historical burn analysis are not based on the dynamics of the temperature itself [17]. Another method called "Index Modelling" [18,19], can model directly the temperature index, such as HDD, CDD, and CAT, to derive the pricing of derivatives. However, the shortcoming of Index Modelling is that different indices need different models. Therefore, Daily Modelling is proposed, which can model directly the daily temperature for pricing derivatives, no matter what kind of index [20]. Ahčan [21] held that under the assumption that market price of risk is zero; Daily Modelling can get the no-arbitrage pricing model of derivatives.

There are two methods proposed for modeling daily temperature: one assumes a continuous process of the temperature; another, a discrete process [22]. The continuous process uses a diffusion stochastic differential equation, such as a mean-reverting form, as used by Alaton et al. [23], Benth [24], Benth and Saltyte-Benth [25,26], Benth et al. [27,28], Zapranis and Alexandridis [29–31]. However, when one estimates the model parameters, the temperature has to be discretized. Moreno [32] thought a discrete process should be more reasonable, because temperature does not change continuously, as we know.

For a discrete process, many researchers make use of a general autoregressive moving average framework (e.g. GARCH). For example, Tol [33] used the GARCH model to capture the systematic variation of the volatility of temperature from the

Table 1
Cities which introduced temperature derivatives in CME.

Country/Region	United States		Europe	Canada	Australia	Japan
City	24 Cities- Atlanta Baltimore Boston Chicago Cincinnati Colorado Springs Dallas Des Moines Detroit Houston Jacksonville Kansas City	Las Vegas Little Rock Los Angeles Minneapolis New York Philadelphia Portland Raleigh Sacramento Salt Lake City Tucson Washington D.C.	11 Cities- Amsterdam Barcelona Berlin Essen London Madrid Oslo Paris Prague Rome Stockholm	6 Cities- Calgary Edmonton Montreal Toronto Vancouver Winnipeg	3 Cities- Brisbane Melbourne Sydney	3 Cites- Hiroshima Osaka Tokyo

Table 2
Temperature derivatives in CME.

City locations	Index used-winter	Index used-summer	Time frames for contracts
United States	HDD	CDD	Weekly,Monthly,Seasonal Srip:October through April for Winter, April through October for Summer
Europe	HDD	CAT	Monthly, Seasonal Strip:Same as U.S. contracts
Canada	HDD	CAT,CDD	Monthly, Seasonal Strip:Same as U.S. contracts
Australia	HDD	CDD	Monthly, Seasonal Strip:Same as U.S. contracts
Japan	CAT*	CAT*	Monthly, Seasonal Srip:October through April for Winter, April through October for Summer

Note: this form is from www.cmegroup.com/weather.

Netherlands. Franses et al. [12] proposed a non-linear GARCH model for the weekly temperature from the Netherlands. Taylor and Buizza [34,35] expanded the works of Tol [33] and Franses et al. [12] and used a low-order Fourier series to model the seasonality of temperature.

Cao and Wei [36] also built their unique framework, which is different from the stochastic differential equation. However, their model probably cannot forecast for long time periods. Campbell and Diebold [9] expanded the model of Cao and Wei [36]. They use a low-order Fourier series with autoregressive lags to model the seasonal mean and the conditional variance. However, the model needs large datasets for parameters estimation to reveal a long memory in dynamics of the temperature because the maximum number of lags in the model could be as high as 25. Bellini [37] think large datasets probably deteriorate the quality of the time trend. Similarly, Caporin & Preś [38] used an ARFIMA-GARCH model to measure the long memory of the temperature. They observed that fitting ARFIMA model needs a lot of time.

Svec and Stevenson [39] compared various models in modeling and forecasting Daily Average Temperature. These models are the modification of the AR-GARCH model proposed by Campbell and Diebold [9]. The results show that the modified models are better than the original model. In this paper, we also expanded the study of Campbell and Diebold [9]. However, differently with the above-modified models, we have incorporated a parameter, which captures the asymmetry of the volatility of the temperature into the original model.

3. Data and methodology

3.1. Data

Data for the study was collected from all temperature derivatives and temperature data of the corresponding forty-seven cities in CME. According to CME and [8], we tidy up the cities, which introduced temperature derivatives in CME. Table 1 shows the forty-seven cities with traded temperature derivatives in CME and Table 2 shows the types of temperature derivatives that every city used.

Temperature derivatives for winter (from October to April) and summer (from April to October) in the U.S. and Australia are all based on the Heating Degree Day (HDD) index and the Cooling Degree Day (CDD) index. In Europe, there are HDD and the Cumulative Average Temperatures (CAT); in Canada, there are HDD, CDD and CAT; and in Japan, there is CAT*. Both CAT and CAT* belong to the cumulative average temperature derivatives, but with different daily average temperature. There are two kinds of daily average temperatures defined by CME. The first is the arithmetic average of daily maximum temperature and minimum temperature (DAT_1). The second is the arithmetic average of hourly temperature accumulated over a 24-h period (DAT_2). CAT index uses the first definition, while CAT* uses the second.

Based on our main assumption, we purposively selected seven cities in China with different socio-economic and geographical characteristics. These are Harbin, Beijing, Jinan, Shanghai, Nanjing, Shenzhen and Sanya. To some extent, the development of these cities is more easily affected by temperature changes. The seven cities are all located in the

East of China, but distributed from north to south so that the sample data between different cities are heterogeneous, which is good for classification. Every city has its own characteristics. Harbin is an important central city located in the Northeast part of China. Harbin is also a famous tourist city, and International Ice and Snow Cultural Festival is held there every year. Beijing is the capital of China. Jinan is the capital of Shandong province, China. Shandong province is a big agricultural province, whose GDP is the third in China. Temperature changes have an important influence on Agricultural. Shanghai is the center of economy and finance of China. Nanjing is the capital of Jiangsu province, China. Jiangsu province is one of the economically developed provinces in China. Shenzhen as an economic center is the window of opening up of China. Sanya is a coastal and tourist city.

A lot of effort went into getting data of each city for nearly twenty years except Vancouver. For Vancouver, just four years data are collected, but it is enough for estimating EGARCH model. Data interval and volume are shown in Table 3 and the 29th February of the leap year is removed from the sample. Although the data span of each city is different, it does not affect the classified results because our classification is based on the model parameters, rather than the data itself. This is the advantage of clustering in the form of model parameters, and it has enough robustness. For United States, Europe, Canada, and Australia, we collected DAT_1, for Japan, DAT_2; and for the seven Chinese cities, DAT_1 and DAT_2. It amounts to sixty-one sets of time series data. All the data for the study were sourced from the CME's Website: www.cmegroup.com/weather and the NOAA's Website: www.noaa.gov.

Fig. 1 shows the original DAT_1 distribution (°F) of selected cities from 1 January 2014 to 31 December 2015. The temperature distribution of these cities has obvious seasonal variation. The variation of temperature in summer (peak) is larger than that in winter (valley) in Bankstown, Melbourne and Amsterdam. That is, the volatility of temperature in summer is greater than that in winter. On the other hand, the variation of temperature in winter (valley) is larger than that in summer (peak) in Tucson, Shenzhen, and Sanya. That is, the volatility of temperature in winter is greater than that in summer. It seems to imply that the variability of temperature is asymmetric.

3.2. The AR-EGARCH model

Franses et al. [12] avers that four characteristics of the temperature must be taken into account when constructing the dynamic model of the temperature: (a) the seasonality of temperature itself; (b) the seasonality of the volatility; (c) the aggregation of the volatility; and (d) the asymmetry of the volatility. Campbell and Diebold [9] proposed the AR-GARCH model, which can reflect the first three characteristics of temperature changes but cannot catch the asymmetry of the volatility. Therefore, we used the EGARCH model to replace GARCH model in AR-GARCH model. Cui et al. [40] used AR-EGARCH model to study the temperature from individual cities in China and their result shows that AR-EGARCH model can catch the asymmetry of the volatility of temperature, and the effectiveness of fitting and prediction with the AR-EGARCH model is better than that of the AR-GARCH model.

AR-EGARCH model is as follows:

$$T_t = Trend_t + Seasonal_t + \sum_{l=1}^{L} \rho_{t-l} T_{t-l} + \sigma_t \varepsilon_t \tag{1}$$

$$\ln \sigma_t^2 = \alpha_0 + \sum_{q=1}^{Q} \left(\lambda_{c,q} \cos\left(2\pi q \tfrac{d(t)}{365}\right) + \lambda_{s,q} \sin\left(2\pi q \tfrac{d(t)}{365}\right)\right) + \sum_{i=1}^{I} \left(\alpha_i \frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) + \sum_{j=1}^{J} \beta_j \ln \sigma_{t-j}^2 \tag{2}$$

where,

$$Trend_t = \sum_{r=0}^{R} \phi_r t^r,\ \varepsilon_t \underset{i.i.d}{\sim} N(0, 1)$$

$$Seasonal_t = \sum_{p=1}^{P} \left(\delta_{c,p} \cos\left(2\pi p \tfrac{d(t)}{365}\right) + \delta_{s,p} \sin\left(2\pi p \tfrac{d(t)}{365}\right)\right)$$

T_t is a temperature variable. ϕ_r, $\delta_{c,p}$, $\delta_{s,p}$, ρ_{t-l}, $\lambda_{c,q}$, $\lambda_{s,q}$, α_i, β_j and γ_i are parameters. $d(t)$ (t=1, ..., 365) is a repeated periodic function, excluding 29th February in leap year.

Eq. (1) is the conditional mean equation. $Trend_t$ is a time trend, reflecting the impact of global warming on temperature. $Seasonal_t$ is a Fourier series used to describe the seasonality of temperature itself. $\sum_{l=1}^{L} \rho_{t-l} T_{t-l}$ shows the auto-regressive characteristic of temperature. That is the temperature over the past few days will have an impact on the temperature today.

Eq. (2) is the conditional variance equation. There is still a Fourier series used to describe the seasonality of the volatility. γ_i is a parameter of the asymmetric effect. If $\varepsilon_{t-i} > 0$, the total effect of ε_{t-i} is $(\alpha_i + \gamma_i)|\varepsilon_{t-i}|$. If $\varepsilon_{t-i} < 0$, the total effect of ε_{t-i} is $(\alpha_i - \gamma_i)|\varepsilon_{t-i}|$. Different symbol of γ_i reflects the asymmetric effects of positive and negative information. For example, in a financial market, bad (negative) information usually brings greater impact on the volatility, so γ_i is negative.

Table 3
Data interval and volume of cities.

Region	Cities name	Date interval	Data volume
U.S. (24 cities)	Atlanta	01/01/1997–27/09/2016	7210
	Baltimore	01/01/1997–31/05/2016	7091
	Boston	01/01/1997–31/05/2016	7091
	Chicago	01/01/1997–27/09/2016	7210
	Cincinnati	01/01/1997–27/09/2016	7210
	Colorado Springs	01/05/2008–31/05/2016	2953
	Dallas	01/01/1997–27/09/2016	7210
	Des Moines	01/01/1997–31/05/2016	7091
	Detroit	01/01/1997–31/05/2016	7091
	Houston	01/01/1997–31/05/2016	7091
	Jacksonville	01/05/2008–31/05/2016	2953
	Kansas City	01/01/1997–31/05/2016	7091
	Las Vegas	01/05/2008–27/09/2016	3075
	Little Rock	01/05/2008–31/05/2016	2953
	Los Angeles	01/05/2008–31/05/2016	2953
	Minneapolis	01/01/1997–27/09/2016	7210
	New York	01/01/1997–27/09/2016	7210
	Philadelphia	01/01/1997–31/05/2016	7091
	Portland	01/01/1997–31/05/2016	7091
	Raleigh	01/05/2008–31/05/2016	2951
	Sacramento	01/01/1997–27/09/2016	7210
	Salt Lake City	01/01/1997–31/05/2016	7091
	Tucson	01/01/1997–31/05/2016	7091
	Washington D.C.	01/05/2008–31/05/2016	2953
EUROPE (11 cities)	Amsterdam	14/09/2006–27/09/2016	3670
	Barcelona	16/11/2006–30/04/2016	3457
	Berlin	16/11/2006–30/04/2016	3457
	Essen	16/11/2006–30/04/2016	3457
	London	10/09/2006–27/09/2016	3670
	Madrid	16/11/2006–30/04/2016	3457
	Oslo	01/05/2008–30/04/2016	2917
	Paris	16/11/2006–30/04/2016	3457
	Prague	01/01/2010–30/04/2016	2310
	Rome	16/11/2006–30/04/2016	3457
	Stockholm	16/11/2006–30/04/2016	3457
CANADA (6 cities)	Calgary	20/06/2001–27/09/2016	5579
	Edmonton	01/01/1997–27/09/2016	7210
	Montreal	01/01/1997–27/09/2016	7210
	Toronto	11/01/1997–20/05/2015	6404
	Vancouver	01/01/1997–27/09/2016	7210
	Winnipeg	01/01/1997–27/09/2016	7210
AUSTRALIA (3 cities)	Bankstown	01/01/2009–09/27/2016	2827
	Melbourne	01/01/2009–09/27/2016	2827
	Sydney	01/01/2009–09/27/2016	2827
JAPAN (3 cities)	Hiroshima	01/01/1997–27/09/2016	7210
	Osaka	01/01/1997–27/09/2016	7210
	Tokyo	01/01/1997–27/09/2016	7210
CHINA (7 cities $\times$ 2)	Beijing	04/01/1998–31/12/2015	6573
	Beijing2	04/01/1998–31/12/2015	6573
	Harbin	01/01/1997–27/09/2016	7210
	Harbin2	01/01/1997–27/09/2016	7210
	Jinan	01/01/1997–27/09/2016	7210
	Jinan2	01/01/1997–27/09/2016	7210
	Nanjing	08/01/1998–31/12/2015	6569
	Nanjing2	01/01/1997–27/09/2016	7210
	Shanghai	01/01/2003–31/12/2015	4748
	Shanghai2	01/01/2003–31/12/2015	4748
	Shenzhen	01/01/1997–27/09/2016	7210
	Shenzhen2	01/01/1997–27/09/2016	7210
	Sanya	01/01/1997–27/09/2016	7210
	Sanya2	01/01/1997–27/09/2016	7210

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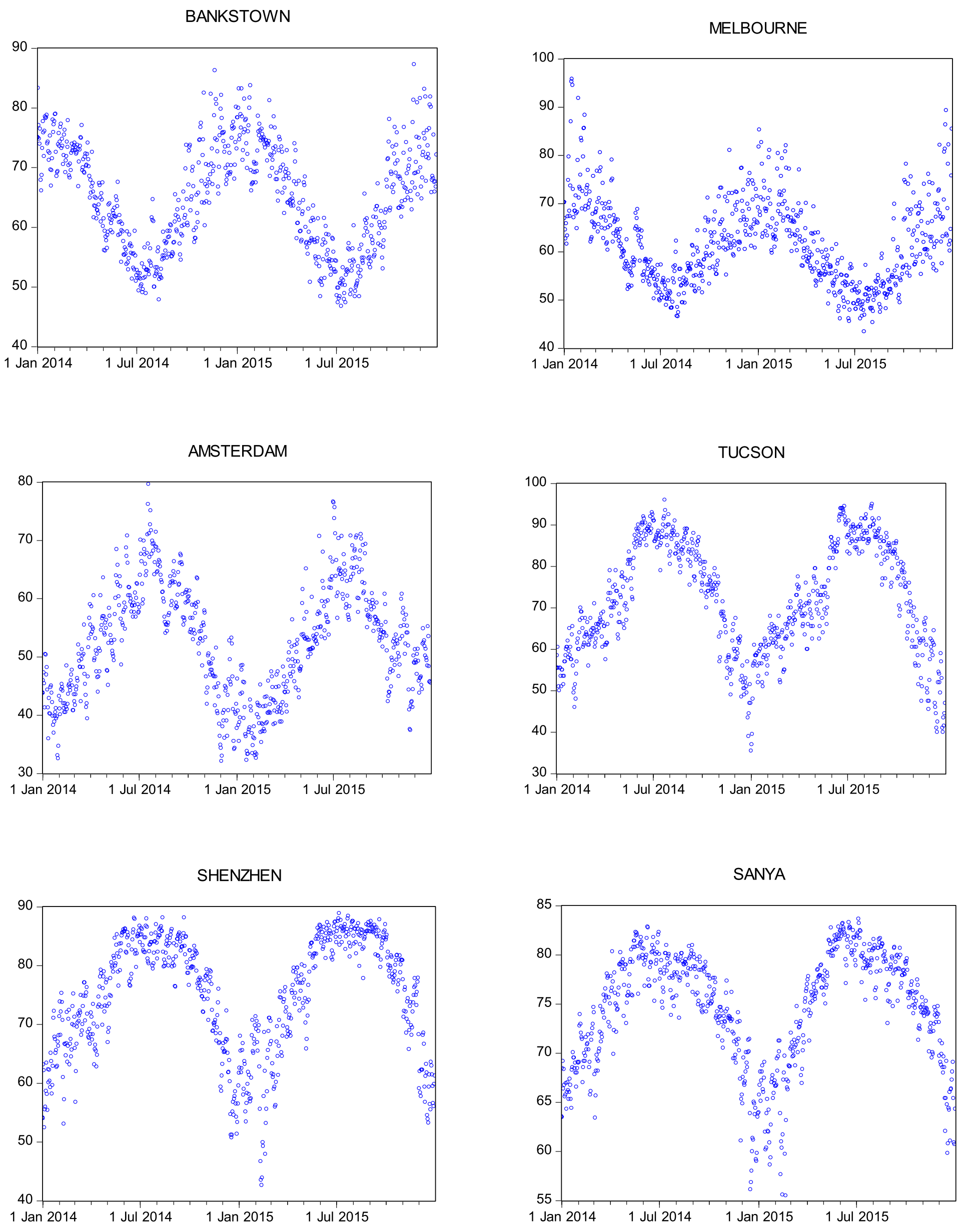

Fig. 1. DAT_1 of six cities.

If Eq. (2) is as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{q=1}^{Q} \left(\lambda_{c,q} \cos\left(2\pi q \tfrac{d(t)}{365}\right) + \lambda_{s,q} \sin\left(2\pi q \tfrac{d(t)}{365}\right)\right) + \sum_{i=1}^{I} \alpha_i \varepsilon_{t-j}^2 + \sum_{j=1}^{J} \beta_j \sigma_{t-j}^2,$$

it is AR-GARCH model by Campbell and Diebold [9], which cannot obviously catch the asymmetry of the volatility.

3.3. Cluster analysis

There are many clustering measures. Traditional clustering measures are mainly for static data, but temperature time series varies with time, which belongs to dynamic data. It is therefore very complex to cluster them. In recent years, many clustering measures for time series have come up, and can be divided into three types: clustering in the forms of raw data, extracted feature, or model parameters [41]. Clustering in the forms of raw data is to cluster directly high dimensional

Table 4
Iteration history.

Iteration	Change in cluster centers				
	1	2	3	4	5
1	3.6421	4.6007	4.5653	0.7958	3.3928
2	0.0000	0.2229	0.2484	0.0000	0.0000
3	0.0000	0.2115	0.2912	0.0000	0.0000
4	0.0000	0.0000	0.0000	0.0000	0.0000

time series. Thus, time and space complexity of the algorithm are increased. Clustering in the form of extracted feature and model parameters is to transform time series into static eigenvalues and model parameters, then use clustering measures for static data to indirectly cluster the time series. Especially clustering in the form of model parameters considers that similar time series should produce similar models, so the purpose of time series clustering can be achieved by comparing the similarity between the models.

In this paper, clustering in the form of model parameters is used to classify temperature time series data of different cities. There are two issues in this processing. One is to construct a proper model for temperature time series (see 3.2). Another is to use static clustering measure to classify the temperature data of different cities according to the model parameters. There are three classical static clustering measures: two-step clustering, system clustering and K-mean clustering. K-mean clustering is a widely classical clustering measure [42], which has the advantages of simple algorithm and fast speed; hence, we choose the K-mean clustering method in this study.

4. Results

4.1. Parameters estimation of AR-EGARCH model

According to the AR-EGARCH model, we considered repeated attempts, and set $R = 1$, $L = 3$, $P = Q = 2$, $I = J = 1$ so that R^2, F statistic, *AIC* and *SC* criteria can reach optimum state. Q-statistics with twelve lags by Box–Pierce test show that standardized residuals squared have no significant autocorrelation, except for Atlanta, Baltimore and Chicago.

The data for the study showed that twenty-eight cities had no significant time trend under 5% significance level in the mean Equation (1). It implies that people have taken effective measures to alleviate the phenomenon in the last twenty years, although there is plenty of evidence to suggest that the rapid development of human society has brought about global warming in recent decades. Parameters of Fourier series in the mean Equation (1) and the variance Equation (2) are also significant under 5% significance level, indicating that there is a significant seasonality under 1% significance level in both temperature itself and its volatility.

From the sixty-one sets of data, the asymmetry coefficients γ_i of only seven sets did not pass the 5% significance level. They involve these cities: Colorado, Las Vegas, Winnipeg, Edmonton, Barcelona, Madrid and Rome. In the remaining fifty-four sets of data whose asymmetry coefficients γ_i pass the significance test, there are six sets with negative γ_i. The cities involved are Tucson, Beijing, Shenzhen, and Sanya. In these four cities, the impact of temperature drop on the volatility is stronger than temperature rise. These results perhaps explain the phenomenon in Fig. 1; where the temperature volatility of Tucson, Shenzhen and Sanya in winter is higher than in summer. It means the temperature more easily falls significantly when the cold air strikes in winter, while a sharp drop in temperature will have a bigger impact on the volatility. Therefore, in the form of expression, temperature fluctuation in winter will be more obvious than in summer. For the cities with the positive γ_i, temperature fluctuation changing is opposite.

4.2. K-mean clustering

First, a classification of the forty-seven sets of data involving forty-seven cities, which have temperature derivatives in CME, was carried out. Before doing that, the initial classified number and the initial cluster centers were determined. After repeated attempts, the initial classified number was set to five. The initial cluster centers are determined by the software according to the characteristics of the input data. In this way, one can avoid the subjective factors. One can see the change history of the cluster center of each category in the iterative process from Table 4. After four iterations, the algorithm converges. It means the initial cluster centers determined by the software are effective. Euclidean distances between five new cluster centers and their corresponding initial cluster centers are respectively 3.6421, 4.6007, 4.5653, 0.7958, and 3.3928 after the first iteration. In the following three iterations, Euclidean distances between cluster centers gradually decrease, and are zero in the last iteration.

Table 5 shows the number of cases in each cluster. The first category consists of three members. The second category contains fifteen members; the third category contains twelve members; the fourth category contains three members; the fifth category contains fourteen members. The number of valid data is forty-seven; the number of missing data is zero.

Table 6 shows the cluster membership and the distance between the cluster members and their corresponding cluster centers. Compared with Table 7, it is found that the distance between each cluster member and the cluster center is less

Table 5
Number of cases in each cluster.

Cluster	1	2	3	4	5
Number of cases	3	15	12	3	14
Valid	47				
Missing	0				

Table 6
Cluster membership.

Member	Cluster	Distance	Member	Cluster	Distance	Member	Cluster	Distance
Altanta	3	2.3366	New York	3	1.5498	Prague	5	6.6988
Baltimore	3	3.9906	Philadelphia	1	5.2834	Rome	5	1.3515
Boston	3	1.6898	Portland	2	2.9611	Stockholm	5	1.2614
Chicago	2	1.2065	Raleigh	3	2.6868	Winnipeg	2	1.3935
Cincinnati	2	1.2099	Sacramento	2	2.9315	Vancouver	2	1.4012
Colorado	3	2.7461	Salt Lake City	2	1.4910	Toronto	2	1.2439
Dallas	3	1.1740	Tucson	3	3.1191	Montreal	2	1.4622
Des Moines	2	1.3845	Washington	3	1.4349	Edmonton	2	3.3928
Detroit	2	1.0319	Amsterdam	5	.7958	Calgary	1	1.1375
Houston	3	3.8297	Barcelona	5	1.7159	Sydney	4	1.6070
Jacksonville	3	4.1950	Berlin	5	1.2201	Brisbane	4	1.0992
Kansas City	2	1.6043	Essen	5	5.0033	Melbourne	4	1.7558
Las Vegas	2	2.7260	London	5	3.0209	Osaka	5	3.3535
Little Rock	3	1.1690	Madrid	5	2.2949	Tokyo	5	3.8746
Los Angeles	2	4.3761	Oslo	5	2.9412	Hiroshima	5	2.7112
Minneapolis	1	3.6421	Paris	5	4.2139			

Table 7
Distance of final cluster centers.

Cluster	1	2	3	4	5
1		9.6454	11.5422	12.9051	11.6848
2	9.6454		5.3267	15.1088	11.4582
3	11.5422	5.3267		12.0605	16.5488
4	12.9051	15.1088	12.0605		22.3322
5	11.6848	11.4582	16.5488	22.3322	

than the distance between the cluster centers, which shows that the clustering result is effective. The United States is divided into three categories: two cities belong to the first category; ten cities belong to the second category; and twelve cities belong to the third category. Canada is divided into two categories. Except for Calgary, which belongs to the first category, the other five cities belong to the second category. Three cities in Australia belong to the fourth category. All the cities in Europe and Asia belong to the fifth category.

In Table 7, the minimum distance of cluster centers is 5.3267, which is between the second category and the third category. This is reasonable because the cities of the second category and the third category are neighbors in the United States. The maximum distance of cluster centers is 22.3322, which is between the fourth category and the fifth category. The fourth category, Australia, is dominated by tropical deserts and grasslands climate. There are also subtropical monsoon humid climate and tropical rainforest climate in Australia. Therefore, there is a big difference with the fifth category, Europe and Japan, in their climate such that the distance of the cluster center is very big.

Finally, the validity of the whole model is further verified by ANOVA variance analysis. In Table 8, with the exception of ρ_{t-3} which did not pass the significance test and α_1 which passed the 10% significance test, the other parameters passed the 5% significance test.

Based on the classification of forty-seven cities in CME, fourteen sets of data from the other seven cities in China were added into the classification. The software was still used to determine the initial cluster centers. In determining the initial classified number, we started with five, and in turn, try six, seven … twelve to find the best-classified number. It turns out that the sixty-one sets of data can be divided into eleven categories, and still maintain the original classified relationship for forty-seven cities. As a result, the new fourteen sets of data belong to either the original categories of forty-seven cities or a new category.

Table 9 shows the iteration history. The algorithm converges after three iterations. After the first iteration, Euclidean distances between the new eleven cluster centers and the initial cluster centers are respectively 0.5067, 3.4490, 0.7958, 2.4459, 5.0002, 2.2893, 0.3103, 1.8531, 4.4226, 3.7763, and 4.5412. In the following two iterations, Euclidean distances rapidly reduce to zero, and cluster iteration is over.

One can see the number of cases in each cluster from Table 10. The first category, the second category, the fourth category, the sixth category, the seventh category and the tenth category include two cluster members respectively. The third category includes three cluster members. The fifth category includes four cluster members. The eighth category

Table 8
ANOVA variance analysis.

Variable	Cluster		Error		F	Sig.
	Mean square	df	Mean square	df		
ϕ_0***	543.3433	4	3.9357	42	138.0565	0.0000
ϕ_1**	0.0000	4	0.0000	42	2.3534	0.0493
$\delta_{c,1}$***	121.7976	4	1.8456	42	65.9933	0.0000
$\delta_{s,1}$***	13.2299	4	1.0849	42	12.1946	0.0000
$\delta_{c,2}$**	0.0990	4	0.0426	42	2.3227	0.0323
$\delta_{s,2}$***	14.6085	4	0.8885	42	16.4409	0.0000
ρ_{t-1}***	3.3221	4	0.1738	42	19.1194	0.0000
ρ_{t-2}***	0.0607	4	0.0043	42	13.9783	0.0000
ρ_{t-3}	0.0037	4	0.0021	42	1.8116	0.1446
α_0**	1.9862	4	0.5797	42	3.4261	0.0164
α_1*	0.0130	4	0.0052	42	2.4886	0.0577
γ_1***	0.0292	4	0.0053	42	5.5321	0.0011
β_1**	0.0482	4	0.0716	42	0.6734	0.0142
$\lambda_{c,1}$***	0.1123	4	0.0172	42	6.5355	0.0003
$\lambda_{s,1}$***	0.0416	4	0.0080	42	5.2247	0.0017
$\lambda_{c,2}$**	0.0099	4	0.0030	42	3.2609	0.0204
$\lambda_{s,2}$***	0.0085	4	0.0013	42	6.5053	0.0004

Note:
F = Cluster mean square/Error mean square.
*10% significance level.
**5% significance level.
***1% significance level.

Table 9
Iteration history.

Iteration	Change in cluster centers										
	1	2	3	4	5	6	7	8	9	10	11
1	0.5067	3.4490	0.7958	2.4459	5.0002	2.2893	0.3103	1.8531	4.4226	3.7763	4.5412
2	0.0000	0.0000	0.0000	0.0000	1.9206	0.0000	0.0000	0.0000	0.0000	0.0000	0.7015
3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 10
Number of cases in each cluster.

Cluster	1	2	3	4	5	6	7	8	9	10	11
Number of cases	2	2	3	2	4	2	2	16	12	2	14
Valid	61										
Missing	0										

includes sixteen cluster members. In addition, the ninth category includes twelve cluster members. The eleventh category includes fourteen cluster members. The number of valid data is sixty-one; the number of missing data is 0.

Table 11 shows the category each city belongs to and the distance between cluster members and their corresponding cluster centers. Compared with Table 6, there are eleven categories in Table 11, and the classified result of the first forty-seven cities is nearly the same, except for Las Vegas, Los Angeles, and Portland. The result suggests the latter clustering is based on the previous clustering.

Because of the new numerical order, Table 12 shows the change of the first five numerical orders in Tables 6 and 11. The fifth category in Table 11 corresponds to the first category in Table 6. The ninth category in Table 11 corresponds to the second category in Table 6, and so on.

The United States is still divided into three categories: Three cities belong to the fifth category; seven cities belong to the ninth category; and fourteen cities belong to the eleventh category. In Canada, except for Calgary, which belongs to the fifth category, the other five cities belong to the ninth category. Three cities in Australia belong to the third category. All cities in Europe and Japan belong to the eighth category.

In the other fourteen sets of the Chinese data, only two sets of data in Nanjing, which include Nanjing (DAT_1) and Nanjing2 (DAT_2), belong to the eighth category, which is the same category as Europe and Japan, while the rest of six cities belong to the different categories with the forty-seven cities in CME. Beijing and Beijing2 belong to the second category. Harbin and Harbin2 belong to the seventh category; Jinan and Jinan2 belong to the first category; Shanghai and Shanghai2 belong to the sixth category; Shenzhen and Shenzhen2 belong to the fourth category; and Sanya and Sanya2 belong to the tenth category. There are HDD and CAT in Europe and CAT* in Japan, so the three temperature derivatives could be suitable for Nanjing, but not the other Chinese cities. CDD cannot be used directly in the seven Chinese cities.

Table 11
Cluster membership.

Member	Cluster	Distance	Member	Cluster	Distance	Member	Cluster	Distance
Altanta	11(3)	1.9647	Sacramento	9(2)	3.5920	Calgary	5(1)	1.2415
Baltimore	11(3)	3.8875	Salt Lake City	9(2)	1.3948	Sydney	3(4)	1.4945
Boston	11(3)	1.8200	Tucson	11(3)	2.7446	Brisbane	3(4)	1.2092
Chicago	9(2)	1.0070	Washington	11(3)	1.8311	Melbourne	3(4)	1.8531
Cincinnati	9(2)	1.5564	Amsterdam	8(5)	0.7958	Osaka	8(5)	3.2368
Colorado	11(3)	2.4792	Barcelona	8(5)	1.7159	Tokyo	8(5)	3.7510
Dallas	11(3)	1.0198	Berlin	8(5)	1.2201	Hiroshima	8(5)	2.6129
Des Moines	9(2)	0.9572	Essen	8(5)	4.4226	Nanjing	8	2.1141
Detroit	9(2)	0.9119	London	8(5)	3.4315	Nanjing2	8	2.0218
Houston	11(3)	4.2014	Madrid	8(5)	2.1196	Beijing	2	3.4490
Jacksonville	11(3)	4.5653	Oslo	8(5)	2.5065	Beijing2	2	3.4490
Kansas City	9(2)	1.8228	Paris	8(5)	3.7259	Harbin	7	0.3103
Las Vegas	11(2)	3.2296	Prague	8(5)	6.3847	Harbin2	7	0.3103
Little Rock	11(3)	0.7519	Rome	8(5)	1.5097	Jinan	1	0.5067
Los Angeles	5(2)	4.9345	Stockholm	8(5)	1.3505	Jinan2	1	0.5067
Minneapolis	5(1)	4.4954	Winnipeg	9(2)	1.4640	Shanghai	6	2.2893
New York	11(3)	1.3958	Vancouver	9(2)	1.5387	Shanghai2	6	2.2893
Philadelphia	5(1)	5.7617	Toronto	9(2)	1.4162	Shenzhen	4	2.4459
Portland	11(2)	3.2821	Montreal	9(2)	1.4884	Shenzhen2	4	2.4459
Raleigh	11(3)	3.1766	Edmonton	9(2)	3.5541	Sanya	10	3.7763
						Sanya2	10	3.7763

Note: the numbers in the brackets are the numerical orders of the previous clustering.

Table 12
Change of Tables 6 and 11 cluster.

Table 6	1	2	3	4	5
Table 11	5	9	11	3	8

Table 13
ANOVA variance analysis.

Variable	Cluster		Error		F	Sig.
	Mean square	df	Mean square	df		
ϕ_0***	1374.7126	10	4.3721	50	314.4297	0.0000
ϕ_1**	0.0000	10	0.0000	50	37.0070	0.0000
$\delta_{c,1}$***	1110.4773	10	1.5492	50	716.8029	0.0000
$\delta_{s,1}$***	78.4971	10	0.9691	50	81.0026	0.0000
$\delta_{c,2}$***	10.8445	10	0.0402	50	269.7731	0.0000
$\delta_{s,2}$***	6.0747	10	1.0716	50	5.6691	0.0000
ρ_{t-1}***	0.9668	10	0.2263	50	4.2715	0.0003
ρ_{t-2}***	0.0266	10	0.0050	50	5.3404	0.0000
ρ_{t-3}*	0.0028	10	0.0016	50	1.7555	0.0941
α_0***	6.5687	10	0.9563	50	6.8689	0.0000
α_1**	0.0107	10	0.0049	50	2.1568	0.0367
γ_1***	0.0338	10	0.0047	50	7.1565	0.0000
β_1**	0.1587	10	0.0734	50	2.1634	0.0361
$\lambda_{c,1}$***	0.0754	10	0.0167	50	4.5216	0.0001
$\lambda_{s,1}$***	0.0478	10	0.0074	50	6.4284	0.0000
$\lambda_{c,2}$**	0.0059	10	0.0026	50	2.3026	0.0259
$\lambda_{s,2}$***	0.0110	10	0.0014	50	7.7720	0.0000

Note:
F = Cluster mean square/Error mean square.
*10% significance level.
**5% significance level.
***1% significance level.

Finally, the validity of the whole model is further verified by ANOVA variance analysis (Table 13) where α_1 passed the 10% significance test, and the other parameters passed the 5% significance test.

5. Conclusion and recommendations

We used cluster analysis on temperature data to classify forty-seven cities in CME and seven cities in China. For temperature time series, cluster analysis in the form of model parameters was better. Thus, the AR-EGARCH model was applied to fit temperature data, and then cluster analysis. AR-EGARCH model is an extension of AR-GARCH model because

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it can factor in the asymmetry of the temperature fluctuation. The results show that asymmetry parameters γ_i of just seven sets in the sixty-one sets of temperature data are not significant, and the fitting effect is good. γ_i is positive in some cities and negative in other cities. It suggests that in some cities the heat wave had greater impact on temperature changes, while in other cities the strong cold air had greater impact.

Based on the results of the AR-EGARCH model, K-mean clustering measure was used to classify the temperature data of cities. A 2-step approach was used: first of all, temperature data of forty-seven cities with temperature derivatives in the CME are classified to get basic classified criteria. Secondly, the temperature data of the seven Chinese cities were added to the classified program based on the previous classified criteria. The results show that Harbin, Beijing, Jinan, Shanghai, Shenzhen and Sanya cannot directly use all the existing temperature derivatives in the CME, but Nanjing can directly use HDD, CAT and CAT*. We concluded that temperature-index derivatives from the CME are not necessarily suitable for the selected cities in China based on our assumptions and the model used. That notwithstanding, the relevance of weather derivative market to the economy of China cannot be underestimated.

The following recommendations are therefore put forward for the establishment of China's weather derivatives market:

(1) The introduction of weather derivatives into China is feasible

Weather derivatives market can attract social capital to participate in the dispersion of meteorological risk for enterprises closely related to climate. It is the most convenient way for China to directly introduce a mature weather derivative into its economy. However, weather derivatives have a strong regional characteristic, and products suitable for foreign cities are not surely suitable for China. In this paper, we proposed a method for the determination of the suitability of introducing weather derivatives into China. This research is a good proof. On the other hand, since the reform and opening up, the Chinese economy has developed rapidly, and financial markets continue to improve, and the Chinese market seems well prepared for the introduction of weather derivatives.

(2) Designing weather derivatives suitable for China's climate

Existing weather derivatives are not surely suitable for China, which requires designing new products to adapt to Chinese climate changes. The development of weather derivatives would not only enrich the types of investment for investors, but also help to promote Chinese financial engineering innovation, and train financial engineers. At the same time, it would also make it conducive for the Chinese financial industry to participate in the competition of the international financial market.

(3) Policy makers should introduce relevant policies and regulations

The establishment of a perfect market of weather derivatives is supported by a highly developed and multi-level capital market. At present, the scale of Chinese capital market is still not large enough, and the insurance market and the futures and options market are not developed completely. Some weather derivatives are designed on the basis of agricultural insurance and options. Therefore, the Chinese government should introduce relevant policies and regulations to promote the development and improvement of the insurance market, the futures and options market.

We conclude by stating that in this paper, we made a key assumption that when temperatures in two cities have the same dynamic evolution, the two cities can use the same types of temperature derivatives. From the perspective of risk management, when the risk source is homogeneous and its dynamic evolution is the same, perhaps it is possible to use the same types of risk management tools for hedging. This may seem more applicable to temperature risk because temperature is an objective phenomenon and does not change with human behavior and ideas. The question as to whether the temperature derivatives used in this study will be applicable to China still needs further probing through other modeling techniques and test. This notwithstanding, our study provides contributes need to solve the problem that lack of weather derivatives in China.

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