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A Wavelet Transform Algorithm-Based Economic Cycle Fluctuation Analysis and Financial Risk Management Model under the Trend of Digital Intelligence Finance

Feifei Sun[1,*]
[1] School of Digital Commerce, Changzhou Vocational Institute of Industry Technology, Changzhou, Jiangsu, 213164, China
Corresponding authors: (e-mail: lec1811507@163.com).

Abstract Economic cyclical fluctuation is an economic phenomenon that is bound to appear in the market economic environment, and it is an objective law that must be followed in the process of macroeconomic operation. The study selected China's economic development from 2000 to 2023 as the research object, from an empirical point of view, the use of wavelet analysis to study the economic trend of per capita GDP in 30 provinces in China and the overall domestic economic cycle fluctuations. At the same time, the effectiveness of Var model in financial risk management is examined. The research data show that most provinces and cities have a total of three troughs between 2000 and 2023, but the overall trend is upward, in terms of the number of troughs, the provinces and cities in the country have at least 11 troughs, and the largest number of provinces and cities even have 15, and the economic cycle fluctuations between 2000 and 2005 are more stable, with a clear upward trend. The Var model performs well that has better management significance for financial risk.

Index Terms wavelet analysis, economic cycle, Var model, financial risk management

I. Introduction

Dependent on the industrial revolution, the world's economies have a common phenomenon in the process of continuous development, that is, the economy of each country is not static, all show the phenomenon of cyclical fluctuations in the economy [1], [2]. Specifically, the economy has a cyclical regularity and fluctuations. Cyclical regularity refers to the economic cycle regularity phenomenon of recovery, expansion, recession and contraction in every cycle, which is repetitive and reproducible [3]. And fluctuation specificity refers to the specific to each cycle, have its own has its own time point, such as cycle duration period is not exactly the same, fluctuation amplitude, peaks and valleys appeared time point is not exactly the same, etc. [4]. Macroeconomics has two main research directions, one is the economic growth theory that mainly examines the long-term trend of the economy, and the other is the economic cycle theory that studies the short-term fluctuations of the economy [5], [6]. Many scholars have gradually enriched this field of macroeconomics in the process of continuously studying the phenomenon of economic cycle fluctuations in countries around the world, and at the same time, they have constructed many analytical models used to study the short-term fluctuations of a country's economy and financial risks, which have provided policymakers with a lot of valuable suggestions [7]-[10].

The economic cycle analysis model based on intelligent algorithms can accurately judge the actual situation of the current digital-intelligent financial development [11]. On the one hand, it helps to predict the future fluctuation trend of the financial cycle, the macroeconomic development trend and the change trend of the financial cycle's impact on the future macroeconomy, so as to provide a basis for the government to formulate the financial and macroeconomic regulation policies in a forward-looking manner [12]-[14]. On the other hand, it also helps to understand more deeply and comprehensively the mechanism of the financial cycle's impact on the macroeconomy, as well as the role of macroeconomic policy channels [15], [16]. At the same time, in order to better fulfill the tasks of financial services for the real economy, preventing and controlling financial risks, and deepening financial reform, the financial risk management model proposed in the context of economic cycle fluctuation prediction can also provide a scientific basis for the innovation of financial policy adjustment [17]-[20].

The study uses empirical analysis methods, based on wavelet analysis theory to decompose the per capita GDP growth rate of 30 provinces in China from 2000 to 2023 into trend components and cyclical components, and compares the long-term growth and cyclical fluctuation trends of provinces and cities based on the decomposed trend components, in order to find out the convergence and divergence between them. Finally, the GARCH model and historical simulation method are utilized to measure Var risk, and a new loss function evaluation index is introduced because the loss function will be very small in the case of relatively conservative prediction results in the traditional evaluation index, which cannot reflect the actual value of risk.

II. Economic cycle fluctuation analysis based on wavelet transform algorithms

II. A. Wavelet transform methods

Wavelet analysis has its origins in Fourier analysis, which consists of the Fourier series together with the Fourier transform. In this section, we will mainly concentrate on Fourier analysis and wavelet theory.

II. A. 1) Fourier analysis

The theory of Fourier series is the expansion of functions in the trigonometric function system, reducing the data to the study of simple trigonometric functions [21]. Fourier series are used to analyze the distribution of functions that are periodic, generally often assuming that the period is 2π, then there are:

$$f(x)=\sum_{k=-\infty}^{\infty} c_k e^{ikx} \tag{1}$$

$$c_k=\frac{1}{2\pi}\int_0^{2\pi} f(x)e^{-ikx}dx \tag{2}$$

The Fourier transform is defined in equations (3) and (4):

$$F(\omega)=\int_{-\infty}^{\infty} f(x)e^{i\omega x}dx \tag{3}$$

$$f(x)=\frac{1}{2\pi}\int_{-\infty}^{\infty} F(\omega)e^{-i\omega x}d\omega \tag{4}$$

where $i=\sqrt{(-1)}$. The existence of the Fourier transform of a singular function can be obtained by introducing the notion of a generalized function or distribution. For a constant function in the time domain, it will behave as a shock function in the frequency domain, which will have a good localization property in the frequency domain. From equation (3), in order to obtain $F(\omega)$, it is necessary to have all the information about the past and future of $f(x)$, and the variation of the localized values of $f(x)$ in the time domain will spread to the whole frequency domain, i.e., the information in any finite region of $F(\omega)$ will not be sufficient to determine $f(x)$ in any small region. In the time domain Haar $(Haar)$ bases are a set of orthogonal bases with optimal time-domain resolution, which are fully localized in the time domain but relatively poorly localized in the frequency domain, due to the lack of regularity of the Haar system together with the lack of vibrationality. For this reason, the researcher wishes to find Hilbert $(Hilbert)$ bases that are simultaneously good with respect to both spatial variables (or time variables and frequency domain variables). On this basis, the short-time Fourier transform can be used if $W\in L^2(R)$ chooses W with its Fourier transform $\hat{W}$ satisfying the condition $tW(t)\in L^2(R), \omega\hat{W}(\omega)\in L^2(R)$ as a window function. We will refer to the Fourier transform that introduces the window function in Eq. (5) as the STFT:

$$(\tilde{g}_b f)(\omega)=\int_{-\infty}^{\infty}(e^{-j\omega t}f(t))\overline{W((t-b))}dt \tag{5}$$

If the window function W is chosen to be a Gaussian function, then it is the Gabor transform. The disadvantage of the STFT is that the size and shape of the analysis window is fixed. The frequency is inversely proportional to the period, so if it is necessary to reflect the high-frequency components of the data, a narrower time window is needed; while if it is necessary to reflect the low-frequency components of the signal, a wider time window is needed.

II. A. 2) Basic wavelet transform equations

Wavelet transform, as an analytical tool that can automatically adjust the size of the analysis time window along with the change of frequency, has been widely used in signal processing, finance, economics and many other fields since the mid-1980s, and it has been gradually emphasized by econometricians as an emerging analytical method [22].

Wavelet transform is the use of a set of band-pass filters for adaptive filtering of selected variables, i.e., suitable scale parameters and translation parameters can be properly selected. Typically, it is possible to choose higher frequency resolution and lower time resolution in the low frequency part and higher time resolution and lower frequency resolution in the high frequency part, so the wavelet transform is able to accurately characterize the variables in the time and frequency domains. The specific model characteristics are as follows:

If the function $g(t)$ is satisfied:

$$\int_{-\infty}^{\infty} g(t)dt = 0, \int_R |\psi(\theta)|^2 / |\theta| d\theta < \infty \tag{6}$$

The function $g(t)$ is called the wavelet parent function or wavelet basis function, and $\psi(\theta)$ is the Fourier transform of $g(t)$, i.e., $\psi(\theta) = \int_{-\infty}^{\infty} g(t)e^{-j2\pi wt}dt$. The wavelet function $g(t)$ can be obtained by applying translational and telescopic transformations to the wavelet basis function $g(t)$. The wavelet function in the continuous case is $g_{a,b}(t) = a^{-1/2}[g[(t-b)/a]$, where a is referred to as the scale parameter and $a > 0$, and b is referred to as the translation parameter. The process of expanding a function $f(t)$ defined on any $L^2(R)$ space in a wavelet basis, i.e., transforming the original function into wavelet coefficients, is called the wavelet transform of the function $f(t)$, and is expressed as:

$$WT_f(a,b) = < f, g_{a,b} > = a^{-1/2} \int_R f(t) g[(t-b)/a]dt \tag{7}$$

where: $WT_f(a,b)$ is the wavelet transform coefficient.

If the wavelet function satisfies the following conditions:

$$C_\varphi = \int_R |\psi(\theta)|^2 / |\theta| d\theta < \infty \tag{8}$$

Then there exists an inverse transformation of the wavelet transform and the inverse transformation is:

$$f(t) = (\int_0^\infty \frac{|\psi(\theta)|}{a} d\theta)^{-1} \int_0^\infty \frac{da}{a^2} \int_{-\infty}^\infty a^{-1/2} WT_j(a,b) g[(t-b)/a]db \tag{9}$$

Real macroeconomic data series are usually discrete data, and if the scale parameter $a(a > 0)$ and the translation parameter b under continuous variation are taken at discrete points, then the discrete wavelet transform can be obtained. A common method is to discretize the scale parameter according to a power series, i.e., take $a_m = a_0^m$ (m is an integer, in general $a_0 = 2$), and take the value of b uniformly and cover the whole time axis, then the wavelet mother function is:

$$g_{m,n}(t) = 2^{-m/2} g(2^{-m} t - n) \tag{10}$$

The wavelet transform coefficients are:

$$WT_f(m,n) = < f, g_{m,n} > = 2^{-m/2} \int_R f(t) g(2^{-m} t - n)dt \tag{11}$$

Although the wavelet transform and Fourier transform are both integral transforms, the wavelet transform can examine both the information contained in the time window and the information contained in the frequency window under the action of the scale parameter $a(a > 0)$ and the translation parameter b. When a is extremely small, the time window observation range is very small, it can be considered that the observation is done with high-frequency wavelet in the frequency domain; when a is extremely large, the time window observation range is very large, which is equivalent to analyzing with low-frequency wavelet in the frequency domain. In this way the original sequence $f(t)$ is partitioned into different levels of frequency bands after wavelet transform.

II. A. 3) Selection of wavelet functions

There are many kinds of wavelet functions, and different wavelet functions apply to different signal characteristics, so choosing the correct wavelet function to process the signal is the key to wavelet analysis. For how to select the wavelet function to effectively analyze the signal, there is no perfect guidance theory, mainly through experience to determine. The wavelet functions that are more frequently used in current research mainly include Haar wavelet, dbN family of wavelets, symN family of wavelets, coif wavelet, biox wavelet, Morlet wavelet, etc. The following is a summary of the different kinds of wavelet functions used in wavelet analysis. The following are the different kinds of wavelet functions

(1) Orthogonality. Better orthogonality eliminates signal redundancy and maintains the irrelevance of wavelet coefficients, thus improving the noise removal performance; and since the signal denoising process requires the original signal to be decomposed at multiple levels, orthogonality is also necessary for the fast realization of discrete wavelet variations.

(2) Support length. The support length can be understood as the size of the window opened during wavelet transform. The longer the support length is, the better the frequency domain characteristics are, and the more local information is included; the smaller the support length is, the better the local discriminative ability of the wavelet is, the finer the noise removal is, and the less local information is included.

(3) Vanishing moment. If $\int \psi(t)t^m dt = 0,(m = 0,1,\cdots,M-1)$ then the wavelet is said to have M order vanishing moment. The higher the order of the vanishing distance, the smoother the wavelet coefficients after wavelet transform processing. However, when there are more singularities in the signal, choosing too high a vanishing distance will increase the degree of signal reconstruction distortion.

(4) Symmetry. Wavelets with better symmetry will have less deviation after wavelet transform, which is conducive to the recovery and reconstruction of the signal after noise removal.

The results of the error comparison obtained after reconstruction by decomposition of three wavelet functions are shown in Table 1.

Table 1: Different wavelet base wavelet solution reconstruction error

Wavelet base	Wavelet base 1	Wavelet base 2	Wavelet base 3	Wavelet base 4	Wavelet base 5	Wavelet base 6
coif	2.531e-007	3.293e-006	1.505e-007	7.122e-003	1.541e-003	——
sym	2.493e-009	1.725e-007	2.131e-006	1.381e-007	4.727e-008	2.183e-007
db	2.493e-009	1.725e-007	2.131e-006	3.941e-007	6.215e-007	3.247e-007

Through comparison, it can be seen that symN system wavelet, dbN system wavelet for decomposition and reconstruction after the error is relatively small, especially syml, dbl wavelet. However, the wavelet function with lower vanishing distance is suitable for analyzing the sequence with strong singularity, as can be seen from the price curve of copper futures, the price sequence of copper futures is relatively smooth, and the singularity is not obvious, so the wavelet function with higher vanishing distance can be selected. From the error comparison analysis, it can be seen that sym5 and db5 are more suitable wavelet functions.

II. B.Wavelet analysis of provincial economic cycles

II. B. 1) Data description

The data indicator selected for this paper is the per capita GDP data of 30 provincial regions in the country for the years 2000-2023, which is assumed to be $Y_{i,t}$, where i stands for a certain inter-provincial region, and t stands for a specific year. At the same time, in order to compare the relevant results of each inter-provincial region with the national level, this paper also selects per capita GDP data at the national level for the years 2000-2023, which comes from the same sources as the aforementioned regions. In order to facilitate the calculation of the economic growth rate using the GDP per capita data, this paper applies the following transformation to $Y_{i,t}$:

$$g_{i,t} = LnY_{i,t} - LnY_{i,t-1} = Ln\frac{Y_{i,t}}{Y_{i,t-1}} = Ln(1+\frac{Y_{i,t}-Y_{i,t-1}}{Y_{i,t-1}}) \approx \frac{Y_{i,t}-Y_{i,t-1}}{Y_{i,t-1}} \tag{12}$$

From this, it is possible to calculate the economic growth rate for each region for the relevant year by taking the natural logarithm of GDP per capita $g_{i,t}$.

II. B. 2) Wavelet analysis results for long-term growth trends

In this paper, the per capita GDP data of each province and city in the relevant years are firstly selected, and then the data are transformed accordingly according to the formula, and then wavelet analysis is carried out by using matlab12 software. Before that, this paper needs to focus on solving two problems: one is the choice of wavelet basis function, and the other is the choice of decomposition layers. For the first problem, this paper in order to strive for accuracy and use the method of trial value, the principle of selecting the wavelet basis function to make a choice. Specifically described as follows: in order to be more representative, this paper selects the real per capita GDP growth rate data at the national level as the test data, and tests the wavelet basis function that comes with the matlab software according to the test, and then calculates the standard deviation of the high-frequency components obtained after decomposition of the wavelet basis function, and selects the Db2 wavelet basis function that has the smallest deviation.13 The relevant values of the test results are shown in Table 2.

Table 2: Standard deviation data for each wavelet base function (Unit:10-3)

Wavelet base function	Db1	Db2	Db3	Db4	Db5	Db6	Db7	Db8
Standard deviation	67	61.56	70.22	64.93	69.55	64.74	69.15	65.82
Wavelet base function	Db9	Db10	Coif5	Haar	Dmey	Sym4	Bior3.9	Rbio2.4
Standard deviation	67.12	64.97	67,47	68	67.41	69.39	67.55	70.31

Regarding the selection of decomposition layers, 3-layer wavelet decomposition is selected based on the criterion of 3-5 layers. Therefore, this paper first takes the national data as the test object and finds out the Db2 wavelet basis function and the 3-layer decomposition criterion as the wavelet decomposition criterion for other provinces in the country. According to the equation $A = A_3 + D_1 + D_2 + D_3 = A_3 + \sum_{i=1}^{3} D_i$, in this paper, we choose A_3 after the wavelet 3-layer decomposition to represent the long term growth trend component of the regions. $\sum_{i=1}^{3} D_i$ represents the cyclical fluctuation component of each region. The following section will summarize and comparatively analyze the characteristics of the long-term trend component and the short-term fluctuation component of the national and inter-provincial regions, respectively.

Figure 1 shows the long-term trend of the national per capita GDP growth rate after wavelet decomposition, and the fluctuation of the GDP growth rate can be divided into 10 cycles according to the “valley-valley” method as shown in Figure 2, and the comparison of the two figures shows that most of the national economic cyclical fluctuations are still short-term fluctuations because Figure 1 shows that the long-term trend component of the domestic per capita GDP growth rate has only three waves. There are only three troughs in the long-term trend part, which are roughly in 2005, 2012, and 2023, and the troughs are rising sequentially, which indicates that China's economy is gradually strengthening its ability to withstand risks.

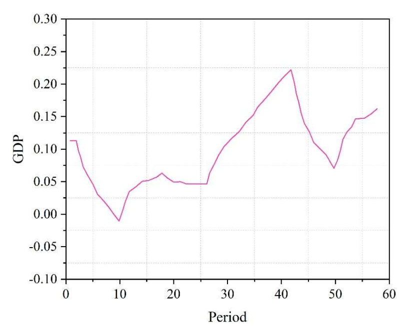

Figure 1: The long-term growth trend of GDP per person in the national level after the small wave

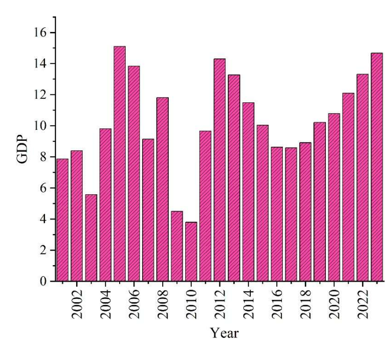

Figure 2: Long-term growth trend per capita GDP

II. B. 3) Results of wavelet analysis of short-term fluctuations

In this paper, we use Db2 wavelets to realize the decomposition of the actual per capita GDP growth rate data of provinces and cities in China, and obtain the potential per capita GDP growth rate data and the fluctuation data of per capita GDP growth rate of provinces and cities. The previous section focuses on the results related to the potential trend component, and the short-term fluctuation component of each province and city will be analyzed at the national level and inter-provincial level, respectively, in the next section.

Figure 3 shows the short-term volatility component of the national real GDP per capita data after wavelet decomposition. It is clear from the figure that the national economy suffered a sharp drop at one time, and the former drop was larger than the latter. Frequent fluctuations then began. Since then, although the short-term fluctuations have still continued, the domestic short-term economic fluctuations have been reduced in frequency and amplitude compared with those before the previous year, which fully verifies the far-reaching impact of the economic system reform on the Chinese economy.

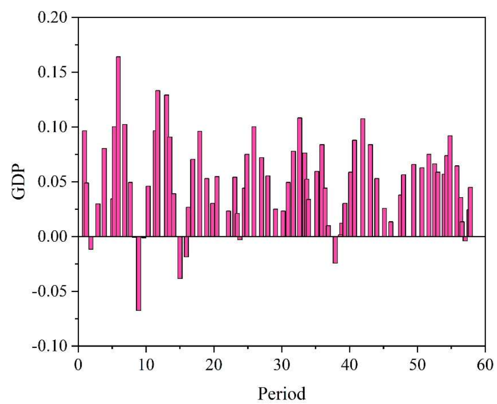

Figure 3: Short-term fluctuation trend after wavelet of per capita GDP data

The number of troughs in the GDP fluctuation trend of each province and city is shown in Table 3. In terms of the number of troughs occurring in the cyclical fluctuation trend of each province and city, all 30 provinces and cities in the country have at least 11 troughs, while a few provinces and cities even have 15 troughs. Statistics show that the number of troughs in eastern provinces and cities, such as Beijing, Shanghai and Tianjin, is significantly smaller than that in other provinces and cities across the country, while the number of troughs in western provinces and cities, such as Ningxia, Inner Mongolia, Qinghai, Tibet and Xinjiang, is significantly higher than that in other provinces and cities across the country. In addition, if we look at it from a regional perspective, the number of troughs in the eastern region is, on average, less than in the center, which in turn is less than in the west. This suggests that the frequency of economic cycle fluctuations is lower in the eastern region than in the other two regions, and that there is some variability in the short-term fluctuations of the economy among the eastern, central and western regions of China.

Table 3: The valley of the provinces

Provinces and cities	Beijing	Shanghai	Tianjin	Guangdong	Zhejiang	Jiangsu	Shandong	Liaoning	Hebei	Fujian
Number	11	12	11	13	12	14	12	14	12	13
Provinces and cities	Anhui	Jiangxi	Henan	Hunan	Hubei	Heilongjiang	Jilin	Shanxi	Guangxi	Gansu
Number	14	12	14	141	15	14	14	14	14	14
Provinces and cities	Yunnan	Chongqing	Sichuan	Ningxia	Xinjiang	Inner Mongolia	Tibet	Qinghai	Shaanxi	Guizhou
Number	15	13	12	15	15	15	15	15	14	14

II. C.Wavelet analysis of the country's overall economic cycle

Generally, economic cycle theory focuses on the fluctuation components between 1.5 and 8 years. The identification of the components of the cycle fluctuations in this period is also more practical and guiding significance for the analysis of the economic situation and the formulation of economic policies. Therefore, we firstly utilize Christiano-Fitzgerald band-pass filtering to isolate the 6-32 quarterly components of China's GDP growth rate, which serves as a basic indicator for China's economic cycle research. Figure 4 is a graph of the cyclical fluctuation components of China's GDP growth rate (6-32 quarters). The peaks and valleys of China's economic cycle fluctuations can be distinguished from the figure, and the specific peak and valley turning points are listed in Table 4.

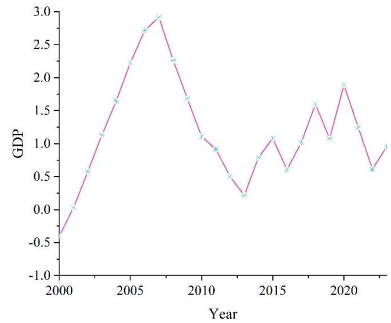

Figure 4: The cyclical composition of GDP growth rate

Table 4: A turning point in the economic cycle measured by the time dimension

Peak	In the third quarter of 2006	In the first quarter of 2015	The quarter of 2018	First quarter of 2022
Valley	In the fourth quarter of 2008	In the first quarter of 2013	The quarter of 2021	

Figure 5 is a contour plot of the wavelet coefficients of the cyclical fluctuation components of China's CDP growth rate. The horizontal coordinate of the graph is the time axis, and the vertical coordinate represents the length of the cycle. The contour rings of different shades in the graph represent the alternation of boom and bust periods of the economic cycle. The vertical scale corresponding to the center of the contour ring is the duration of the cycle, and the corresponding horizontal scale is the date of the peak or trough. As can be seen from the figure, from 2000 to 2023, China's economic cycle fluctuations in the long run are mainly characterized by five turning points: the peak at the end of 2001, which corresponds to a cycle of about four years; The trough at the end of 2005 corresponds to a cycle of about 5 years; the peak at the beginning of 2010 corresponds to a cycle of about 6 years; the trough at the end of 2015 corresponds to a cycle of about 5 years; and the peak at the end of 2020 corresponds to a cycle of about 4 years.

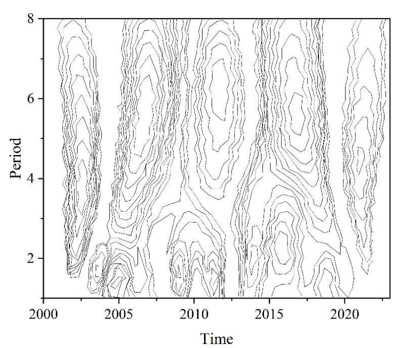

Figure 5: The wavelet coefficient contour map of the GDP growth cycle

It can also be seen in Figure 4 that the GDP growth rate, while showing small fluctuations in 2000-2005, was generally on an upward trend. This is shown in Figure 5 as a superposition of two different lengths of cycle fluctuations up and down. Therefore, the wavelet coefficient contour plot not only shows the time-frequency characteristics of the economic cycle at the same time, but also clearly portrays the superposition phenomenon of the long and short cycles of the economic cycle.

From the perspective of fluctuation characteristics, China's economic cycle fluctuations from 2000 to 2023 can be divided into three phases: the cycle fluctuations from 2000 to 2005 are relatively stable, and the economic performance is obviously rising; the cycle fluctuations from 2006 to 2020 are more violent, and the overall trend shows a trend of big ups and downs; the waveform of the cycle fluctuations in 2020 is simple and clear, and the overall amplitude is similar to that of the previous stage.

III. Financial risk management based on the VaR model

III. A. VaR Modeling and Calculation Methods

III. A. 1) VaR model

VaR is the maximum loss that can be suffered or potentially suffered at a given level of probability over a given period of time. It can also be viewed as an estimate of the maximum loss in market value that could occur before a given position is eliminated or revalued [23]. VaR can be expressed as:

$$P(\Delta P > VaR) = 1 - \alpha \tag{13}$$

Where ΔP is the loss of the security over the holding period and VaR is the value at risk at the confidence level α, the above equation can be equivalently expressed as:

$$P(\Delta P \le VaR) = \alpha \text{ or } F(VaR) = \alpha \tag{14}$$

F is a monotonically nondecreasing, right-continuous function, and to ensure the uniqueness of the VaR expression one can rewrite Eq. (13) as:

$$VaR = \min(F^{-1}(\alpha)) = \min(VaR, F(VaR) = \alpha) \tag{15}$$

From the definition, it is clear that the VaR concept is simple and easy to accept. It integrates different market factors, different financial instruments composed of a portfolio of securities into a single value, which is more active in investors and decision makers to grasp the understanding of risk.

III. A. 2) VaR calculation method based on distributional assumptions

By definition, three factors are needed to calculate VaR: holding period, confidence level, and loss distribution. The most critical of these is the loss distribution. Consider a portfolio of securities and assume that P_0 is the initial value of the portfolio, R is the return on investment during the holding period, μ,σ is the expected return and volatility of R, and R^* is the minimum return for a given level of confidence α during the holding period, then the value of VaR is:

$$\begin{aligned} VaR &= E(P) - P^* \\ &= E(P_0(1+R)) - P_0(1+R^*) \\ &= P_0 + P_0 E(R) - P_0(1+R^*) \\ &= P_0(\mu - R^*) \end{aligned} \tag{16}$$

Consider a stochastic process for the behavior of a portfolio's returns over a holding period, and assume that the probability density function of the returns is $f(p)$, so that for a certain confidence level α the minimum return on the portfolio is R^*, then we have $\alpha = \int_{R^*}^{\infty} f(p)dp$ regardless of whether the distribution is discrete or continuous, skewed or spiked, this expression is valid for any distribution.

For the standard normal distribution there is $\alpha = \int_{R^*}^{\infty} \phi(x)dx$ where $\phi(x)$ is the density function of the standard normal distribution. The following relationship exists between the normal distribution and the distribution of the standard normal:

$$-\alpha = \frac{-R^* - \mu}{\sigma}(\alpha > 0) \tag{17}$$

Since VaR measures the magnitude of the degree of loss, in general R^* is negative, which is obtained from equation (17):

$$R^* = -\alpha\sigma + \mu \tag{18}$$

Assuming that μ,σ is computed on a daily basis, the VaR for the holding period Δ under a normal distribution is:

$$VaR = P_0(\mu - R^*) = P_0 a\sigma\sqrt{\Delta t} \tag{19}$$

In VaR calculation, volatility modeling and valuation modeling are the core and difficult part of it. According to different volatility and valuation simulations constitute different methods of VaR calculation.

III. A. 3) VaR calculation based on volatility and valuation under simulation

(1) Historical simulation method. This method is based on histograms and simulates the future gains and losses of asset portfolios based on historical sample changes in market factors. It does not need to assume the statistical distribution of the market factors, and can better deal with non-linear and large fluctuations. The method is theoretically simple, easy to implement, and has a wide range of use.

(2) Monte Carlo method. The basic idea of this method is to repeatedly simulate the stochastic process of the price or return of the financial instrument we are interested in, and calculate the volatility, correlation coefficient, etc. of the estimated parameters based on historical data. Then construct a sample path of random variables, each set of random numbers will produce a set of hypothetical simulation of the final price of the portfolio, through a large number of simulations, the simulated distribution of the final value and the portfolio's “real” distribution is close enough to be used as an approximation of the true distribution, then we can calculate the VaR based on the approximation of the distribution. This method can better deal with the problems of non-linearity and non-normality.

(3) Parameter estimation method. The basic method of this estimation is to infer a probability distribution based on the data, and then make an inference on the risk measure based on the inferred distribution, and usually the estimation of VaR is carried out under the assumption of normality or the assumption of approximate normality. The parametric approach is more powerful than the nonparametric approach because it uses a pre-assumed distribution density function or additional information in the distribution function, which makes estimating the risk measure come easier.

III. B. Empirical analysis of the VaR model

III. B. 1) Parametric approach

NGARCH model. Due to the leverage effect, as negative stock returns imply that the decline in stock value makes the firm more leveraged and therefore riskier (assuming that the debt level remains constant). Asymmetric GARCH models (NGARCH) can portray the GARCH family of models with asymmetric volatility response to past positive and negative disturbances. Model Form:

$$R_t = \sigma_t z_t, \sigma_{t+1}^2 = \omega + \alpha(R_t - \theta\sigma_t)^2 + \beta\sigma_t^2 \tag{20}$$

III. B. 2) Model Run Flow

(1) Select the measurement target and calculate its logarithmic return.

(2) Normalize its model (GARCH or NGARCH) with parameter distributions (normal ort distribution).

(3) Apply great likelihood estimation method for iteration. Derive the model parameters.

(4) Apply the parameters to calculate $\sigma_{PF,t}$ and finally compute the computed Var.

III. B. 3) Non-parametric approach to linearly weighted historical simulations

In the sliding window, the weighting process is first carried out linearly and incrementally according to the time sequence of historical returns; the sequence obtained after weighting and the weights are sorted according to the sequence to obtain the corresponding empirical distribution; based on the obtained empirical distribution, the corresponding Var is calculated at a given level of significance.

Intercept the size of the sliding window, let it be d, let the weighting coefficient be θ, then the weighting coefficient (weight) of day i is:

$$w_i = \frac{1}{d} - \frac{\theta \bullet (d-1)}{2} + i \bullet \theta \tag{21}$$

Table 5: Optimal weighted parameter

Weighted parameter	Var mean	Actual failure frequency	LR statistics	Cost function	Loss function
10-6	-0.029	0.053	0.181	735.219	0.204
4×10-6	-0.029	0.056	0.194	745.176	0.206
5×10-6	-0.029	0.056	0.000	762.893	0.209
10-5	-0.029	0.056	Nan	765.543	0.211
4×10-5	-0.029	0.058	Nan	779.328	0.214
0.0001	-0.029	0.061	Nan	765.097	0.209

The problem can be transformed into finding the optimal parameters that make the failure frequency test or loss function test case optimal under different sliding window conditions.

Finding the optimal weighting parameter for a sliding window of 100 θ is shown in Table 5. It can be seen that the weighted history simulation after the parameter selection of 10-6 is closer to the ideal case.

Introducing a new loss function: the traditional loss function is small in the case that Var's forecasts are too conservative, but this is not a good representation that the confidence interval Var is in is the one or quartile that the investor wants.

Two ways to represent it:

$$C_{t+1} = \begin{cases} 1+(r_{t+1}, v_t)^2 + \beta \cdot relu(p^* - p) & r_{t+1} < v_t \\ 0 & r_{t+1} \geq v_t \end{cases} \tag{22}$$

Where β is the weighting factor, which is meant to be used to penalize the actual probability of failure being much smaller than the expected probability. p^* represents the expected failure frequency, which is the failure frequency.

$$p^* = 1 - \alpha \quad p = p(N/T) \quad relu(x) = \max(0, x) \tag{23}$$

It is also possible to adjust the additional terms to square form:

$$C_{t+1} = \begin{cases} 1+(r_{t+1}, v_t)^2 + \beta \cdot [relu(p^* - p)]^2 & r_{t+1} < v_t \\ 0 & r_{t+1} \geq v_t \end{cases} \tag{24}$$

The re-comparison of the loss function as well as its actual situation is shown in Tables 6 and 7. It can be found that tGarch is the smallest on the original defined loss function, but its failure frequency is only 0.01, which can be learned that the Var simulated by tGarch is too conservative and does not meet the requirement of 5% for actual risk management control. Different β will lead to different loss functions.

Table 6: The loss function compares the results

Method	Expected days of failure	Actual days of failure	Failure frequency	LR statistics	Cost function	Loss function
Garch normal	189.21	172	0.0453	2.159	614.537	0.169
tGarch	189.21	47	0.0124	164.896*	222.431	0.062
Weighted historical simulation	189.21	186	0.0509	0.0183	735.476	0.209

Table 7: Actual situation

p	The loss function of the garch normal state	tGarch loss function	Weighted historical simulation loss function
1000	0.168	0.073	0.205
10000	0.181	0.165	0.205
100000	0.302	1.077	0.205

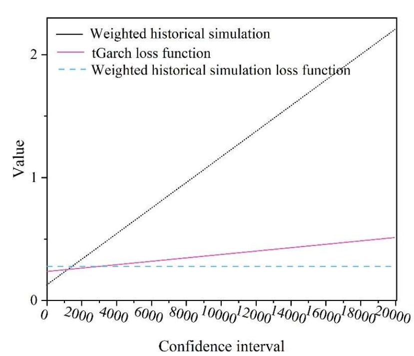

Figure 6: Linear relation

The linear relationship between the values of β and the three loss functions is shown in Figure 6.

If the investor focuses on whether the value of Var is close to the confidence interval α, i.e., focuses on the expected probability of failure itself ρ^*, the value of β can be larger; similarly, if the investor focuses on the extreme risk only, and does not pay attention to whether the value of Var is close to the confidence interval α, β can be a smaller value.

If the investor focuses on whether the value of Var is close to the confidence interval α, i.e., focuses on the expected probability of failure itself, we suggest that the value of β can be: $\beta = \frac{d}{n^*}$, where d is the total number of simulation days, and p^* is the expected probability of failure.

III. C. Strategic analysis of financial risk management

(1) Strengthen and improve the enterprise's information management system

Enterprises in the process of carrying out various business activities will produce a large amount of information, due to this part of the data and information is more complicated, through the artificial way to deal with the greater difficulty. Therefore, enterprises can make use of big data technology to process, not only can make the complex and diverse data and information more rational, but also can effectively screen out invalid information, prompting enterprise managers to obtain effective information, and as a reference basis for making business development decisions. In addition, the enterprise adopts big data technology for financial risk management, can also be integrated with various information in the operation and management, prompting the relevant personnel to better carry out the financial risk management work, which is conducive to improving the efficiency of the enterprise's financial risk management, to ensure the quality of financial risk management. Enterprises in the implementation of financial risk management during the application of big data technology, you can have a clear understanding of their own operating conditions, which will help to adjust the business strategy in a timely manner to reduce the financial risks arising in the process of operation.

(2) Strengthen the control of the enterprise network environment

With the continuous development of modern information technology, big data technology, as an important data analysis tool, is widely used in the financial industry. In the context of big data, enterprises should pay attention to the organization and analysis of all kinds of data and information. By analyzing and processing all kinds of information through big data technology, enterprises can significantly improve the utilization efficiency of data resources and operational efficiency, and promote the reduction of enterprise market riskiness. However, under the background of big data, the network environment is in the process of continuous change, resulting in the stability of enterprise data and information being significantly affected, thus increasing the risk of enterprise data storage. In order to protect the quality of financial risk management work, enterprises should also pay attention to the control of the network environment. Because the effect of network environment control has a positive impact on the solution of network security problems. Therefore, financial risk management personnel should also pay attention to enterprise information security management, constantly improve the information management system, improve network information confidentiality.

(3) Strengthen the construction of data and information sharing platforms

If the financial industry is to achieve sustainable development, it is necessary to strengthen the connection between the various departments of the enterprise to realize the data and information sharing, to avoid the situation of unequal information, thus affecting the balanced development of the enterprise. Therefore, in order to achieve financial risk management, the relevant departments should strengthen the construction of financial information data sharing platform, break the monopoly of industry information, and maximize the use of resources. In the creation of information sharing platform, each department of the enterprise should combine its own actual situation, from a variety of perspectives on the implementation of a comprehensive analysis of the data and information, through a comprehensive and in-depth understanding of the credit status of the customer and the potential risks, and to take measures to deal with them, reduce the risk of financial management of the enterprise.

(4) Enhance the level of data processing and automation

When enterprises carry out financial risk management, improving the automation level of data processing and analysis is the key to guaranteeing data safety and quality. Enterprises can use advanced data analysis and processing technologies such as artificial intelligence and machine learning methods to automate the identification and correction of errors in data information to ensure the accuracy of data information. Automated processing can improve the efficiency of data information processing. In addition, when enterprises take real-time monitoring of data information, they also need to take advantage of the automated monitoring system, which can not only avoid data information from being tampered with and leaked, but also discover potential data security problems in a timely manner. At the same time, enterprises in the processing of data information using automated data processing tools, can avoid damage to corporate data assets, can prevent errors due to human factors, to avoid more data security loopholes.

IV. Conclusion

In this paper, the per capita GDP of 30 provinces in China from 2000 to 2023 is used as the research data, Db2 wavelet is selected as the decomposition function of the region, and the long-term trend and short-term fluctuation of the 30 inter-provincial regions are analyzed by combining with the 3-layer decomposition layer criterion, and then finally the Var model is used to measure and analyze the risk. The results show that all provinces and cities show an upward trend among themselves, and most of them had a trough before 2005, after which they gradually improved, indicating that the long-term economic growth rate of China's provinces and cities has gradually improved. From the fluctuation characteristics of the overall economic cycle, it can be found that China's cycle fluctuation from 2000 to 2005 is relatively stable, and the economic performance is obviously rising; the cycle fluctuation from 2006 to 2020 is more violent, and the waveform of the cycle fluctuation in 2020 is simple and clear, with the overall amplitude similar to that of the previous period. the Var model performs excellently, the The weighted historical simulation process with a weighting parameter of 10-6 has an actual failure frequency of 0.05, and then a new loss function evaluation index is introduced, and it is found that the Garch family simulation fails to meet the requirement of 5% of the actual risk management control, while the weighted historical simulation method is able to maintain stability under different weighting coefficients β.

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References

[1] Lepeyko, T. (2020). On the waves of economic Fluctuations. Environmental Economics, 11(1), 65.
[2] Tyapkina, M., Mongush, Y., & Ilina, E. (2019, November). Cyclical fluctuations of the Russian economy. In IOP Conference Series: Materials Science and Engineering (Vol. 667, No. 1, p. 012105). IOP Publishing.
[3] De Giorgi, G., & Gambetti, L. (2017). Business cycle fluctuations and the distribution of consumption. Review of Economic Dynamics, 23, 19-41.
[4] Xiong, X. (2022). Analyzing the Influencing Factors of Economic Fluctuations in the Era of Big Data. Scientific Programming, 2022(1), 9374025.
[5] Gertler, M., & Klenow, P. J. (2019). Economic fluctuations and growth. NBER Reporter, (2), 1-13.
[6] Furlanetto, F., Ravazzolo, F., & Sarferaz, S. (2019). Identification of financial factors in economic fluctuations. The Economic Journal, 129(617), 311-337.
[7] Mazur, B. (2017). Probabilistic predictive analysis of business cycle fluctuations in Polish economy. Equilibrium. Quarterly Journal of Economics and Economic Policy, 12(3), 435-452.
[8] Begenau, J. (2020). Capital requirements, risk choice, and liquidity provision in a business-cycle model. Journal of Financial Economics, 136(2), 355-378.
[9] Bhandari, A., Evans, D., Golosov, M., & Sargent, T. J. (2021). Inequality, Business Cycles, and Monetary‐Fiscal Policy. Econometrica, 89(6), 2559-2599.
[10] Jawadi, F., Ameur, H. B., Bigou, S., & Flageollet, A. (2022). Does the real business cycle help forecast the financial cycle?. Computational Economics, 60(4), 1529-1546.
[11] Mandler, M., & Scharnagl, M. (2022). Financial cycles across G7 economies: A view from wavelet analysis. The Journal of Economic Asymmetries, 26, e00277.
[12] Si, D. K., Liu, X. H., & Kong, X. (2019). The comovement and causality between stock market cycle and business cycle in China: Evidence from a wavelet analysis. Economic Modelling, 83, 17-30.
[13] Adarov, A. (2021). Dynamic interactions between financial cycles, business cycles and macroeconomic imbalances: A panel VAR analysis. International Review of Economics & Finance, 74, 434-451.
[14] Lewin, P., & Cachanosky, N. (2016). A financial framework for understanding macroeconomic cycles: The structure of production is relevant. Journal of Financial Economic Policy, 8(2), 268-280.
[15] Deng, C., Zhao, X., & Xu, M. (2022). Financial cycle and the effect of monetary policy. Finance Research Letters, 47, 102570.
[16] Bauer, G., Pasricha, G., Sekkel, R., & Terajima, Y. (2018). The global financial cycle, monetary policies, and macroprudential regulations in small, open economies. Canadian Public Policy, 44(2), 81-99.
[17] Beutel, J., Emter, L., Metiu, N., Prieto, E., & Schüler, Y. (2025). The global financial cycle and macroeconomic tail risks. Journal of International Money and Finance, 103342.
[18] Atalay, E., Drautzburg, T., & Wang, Z. (2018). Accounting for the sources of macroeconomic tail risks. Economics Letters, 165, 65-69.

[19] Bidabad, B. (2019). Fluctuations and business cycles prevention by new financial instruments and banking structure reform. International journal of accounting & finance review, 4(1), 35-50.
[20] Zheng, C., Chen, S., & Dong, Z. (2021). Economic fluctuation, local government bond risk and risk-taking of city commercial banks. Sustainability, 13(17), 9871.
[21] H.De Sterck,S.Friedhoff,O. A.Krzysik & S. P.MacLachlan. (2024). Multigrid Reduction‐In‐Time Convergence for Advection Problems: A Fourier Analysis Perspective. Numerical Linear Algebra with Applications,32(1),e2593-e2593.
[22] Faezeh Amirteimoury,Farshid Keynia,Elaheh Amirteimoury,Gholamreza Memarzadeh & Hanieh Shabanian. (2025). A novel wind speed prediction model based on neural networks, wavelet transformation, mutual information, and coot optimization algorithm. Scientific Reports,15(1),10860-10860.
[23] Ruifeng Lyu. (2024). A Study on Innovative Teaching Strategies of English in Universities Based on VAR Model. Applied Mathematics and Nonlinear Sciences,9(1).