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A study of the real-time impact of economic policies on financial market liquidity based on time series analysis methods

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ABSTRACT
Since the financial crisis, the economies of all countries have been affected by the recession triggered by global events, and the uncertainty brought by the changes in economic policies has also become a risky shock, and the uncertainty of economic policies has been climbing worldwide. This paper firstly briefly analyzes the mechanism of economic policy and financial market, in order to comprehensively study the changes of market economic liquidity, this paper starts from the return of the market economy, and adopts the symbolic time series analysis method to analyze the prediction of the financial market by taking the stock market as an example. Then construct the regression model, and then study the impact of economic policy uncertainty on market liquidity. The regression coefficient of economic policy uncertainty is 0.064, which is significant at 1% level. Secondly, when GDP growth rate and inflation level are added as control variables, the regression coefficient of economic policy uncertainty obtained is 0.108, which is still significant at 1% level, implying that a rise in economic policy uncertainty brings about a decline in market liquidity. This study provides an effective analytical tool for the impact of economic policies on market liquidity. It also provides a basis for the government to improve market liquidity and enhance market vitality.

Keywords: regression model, signed time series, policy uncertainty, market liquidity

1. Introduction

China's economy is at a critical stage where the growth rate shifting period, the structural adjustment pain period and the digestion period of the previous stimulus policies are superimposed, and at the same time, it is facing the challenges of complex and changing domestic and international situations. Under such circumstances, it is inevitable that the implementation or adjustment of macro policies by the government will cause economic uncertainty [1]. The increase in economic policy uncertainty makes economic agents less active in participating in economic activities, which has an unavoidable

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negative impact on macroeconomic growth and financial market liquidity [2-4]. In addition, the stage of economic growth decline is often accompanied by higher economic policy uncertainty, forming a liquidity spiral, which in turn may cause liquidity depletion in the financial market or even trigger a financial crisis [5-7]. Economic policy uncertainty not only affects the investment and consumption behavior of enterprises and residents, but also has an impact on the macroeconomy as well as the healthy development of the capital market [8-9]. Currently, China's financial market system is still unsound, and frequent adjustments in economic policies will have a greater impact on the operating characteristics of the stock market, such as returns and volatility, and may lead to an increase in financing costs, and stock market participants will no longer carry out or postpone stock transactions, thus inhibiting the liquidity of the stock market [10-14]. Similarly, investors will assess the investment environment of the financial market based on the operating status of the macroeconomic environment, and when the economic policy is favorable, investors are more willing to participate in stock trading, and more funds flow to the stock market, which in turn increases the liquidity of the stock market [15-19]. In this context, it is particularly important to focus on the linkage between economic policy uncertainty and financial market liquidity.

This study establishes a regression model based on the analysis of the mechanism of the role of economic policy and the market, and takes economic policy uncertainty as the explanatory variable of the study, which is expressed by the economic policy uncertainty index, which is based on the text mining technique and is obtained after standardization. Subsequently, the research on the impact of economic policy uncertainty on financial market liquidity was launched. The study also proposes a method for market economic forecasting based on the symbolic time series analysis method. The stock market is then used as an example for its direction to study the feasibility of the market economy forecasting method in this paper, so as to provide a reliable analysis method for coping with the prevalent changes in the financial market.

2. Forecasting and the role of policy in the market economy

2.1. Mechanisms of Economic Policies and Markets

The interaction between economic policy and the macroeconomic environment has attracted the attention of a large number of scholars. In order to better understand the impact of economic policies on the market economy, researchers have actively explored the effects of policy uncertainty shocks transmitted to the macroeconomy. In this study develops its research on financial market liquidity on the basis of existing theories of economic policy uncertainty.

The study of policy uncertainty acting on markets has a long history. Most of the literature focuses on the impact of economic policy uncertainty on market volatility, and market returns. It has been found that market participants provide liquidity to the market, which depends on their ability to finance under different economic policies. At the same time, higher economic policy uncertainty increases the cost of financing, making investment costly. Therefore, economic policy uncertainty may have an impact on market liquidity through investment and financing channels, on the basis of which this paper deepens the study of the impact of policy uncertainty on market liquidity and examines the real-time implications of this impact.

Liquidity is a tool for hedging and risk management, asset pricing, determination of the cost of capital and efficient capital allocation. Market liquidity refers to the extent to which a market allows assets to be bought and sold at stable, transparent prices. Market liquidity is one of the most controversial topics in the economics and finance literature. Market liquidity can be expressed in a number of ways; first, market liquidity is expressed as the ability of investors to trade in a sound stock market. Second, market liquidity indicates the volume of trading in the stock market. Third, stock market liquidity indicates whether the trading price is affected by the trading volume.

The mechanism of economic policy and financial markets is shown in Figure 1, where macroeconomic growth is closely related to financial market behavior, and investors pay close attention to changes in macroeconomic variables when trading. Macroeconomic indicators affect financial markets mainly through their impact on trading volume and investor expectations. Specifically, a positive macroeconomic environment positively affects market liquidity by decreasing the cost of financing and increasing the incentive for investors to trade, while an increase in economic output is a signal to investors that the macroeconomic environment is improving, and therefore, an increase in economic output increases market liquidity.

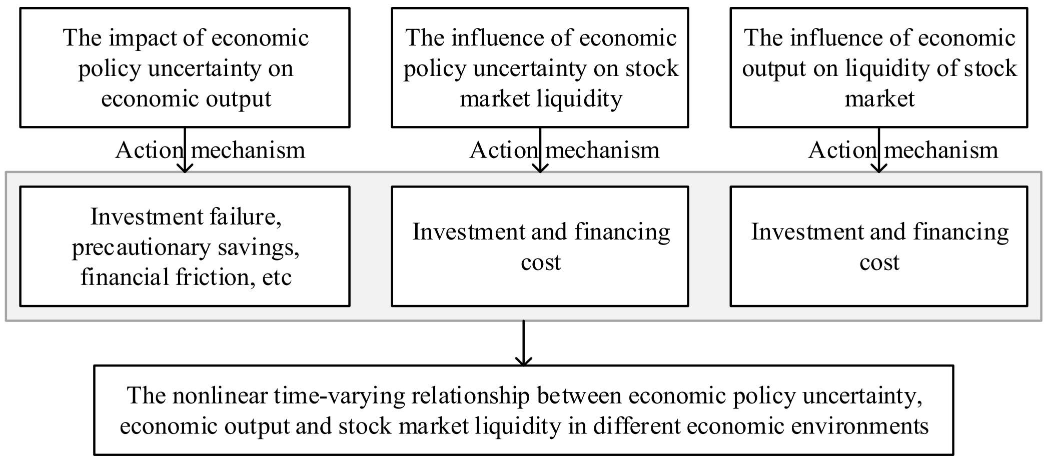

Fig. 1. The mechanism of economic policy and financial markets

2.2. Market liquidity forecasts based on time-series analysis

2.2.1. Symbolic Time Series Analysis Methods. Symbolic time series analysis (STSA) is a new method of data analysis based on the theory of nonlinear dynamics, developed by symbolic dynamics theory, chaotic time series analysis and information theory. In this paper, the symbolic time series analysis method is introduced into the study of financial markets to reflect the characteristics of return changes from a large-scale perspective and to realize the prediction of market level.

The so-called symbolization is to transform the real series into symbolic series. Unlike rough set and orbital symbolization which emphasize the division on the basis of understanding, symbolization does not start with much analysis of the system characteristics corresponding to the real series, but directly based on the numerical characteristics of the real series to make a coarse-grained processing of it, after obtaining the symbolic sequence. Then do all kinds of reasoning and calculation to understand the system characteristics, that is, “first divide, then calculate”. That is, according to a unified rule to divide the system into a large number of small particles, and then apply the symbolic dynamics method or statistical methods to reason out the implicit “pattern” of the system. The main task of symbolization is to retain as much valid information of the system as possible with the smallest set of symbols.

The general methods of symbolization fall into two main categories. First, the symbol division is made directly according to the numerical characteristics of the sequence without any preprocessing, which mainly includes static method, dynamic method and synthesis method, and we collectively refer to these three methods as the direct method. Second, the sequence is firstly transformed appropriately and then divided, mainly wavelet space method.

Let the state of the system be represented by the sequence $\{x_t, t=1,\dots T\}$, then x_t represents the state of the system at the moment t, and T represents the total number of data in the sequence. Suppose that $\{x_t, t=1,\dots T\}$ corresponds to a sequence of symbols denoted by $\{s_t, t=1,\cdots T\}$. A brief description of each of these two methods is given below.

1) Static method:

$$s_t = \begin{cases} n-1, & x_t \geq a_{n-1} \\ \vdots & \vdots \\ 1, & a_2 > x_t \geq a_1 \\ 0 & a_1 > x_t \end{cases} \tag{1}$$

where $a_t(t = 1, 2, \cdots, n-1)$ is a set threshold for division. Symbols $0, 1, \ldots, n-1$ form a set $\{0, 1, \cdots, n-1\}$ called symbol set, the size of the symbol set can be adjusted arbitrarily, at this time the size of the symbol set is n. From this point of view, the static method can be increased by increasing the size of the symbol set n, to infinitely approximate the original sequence of real numbers, but in practice when the symbol set is too large, the symbol of the symbol processing of the significance of the loss of the most commonly used or the symbol set size of 2 taken in the formula, that is:

$$s_t = \begin{cases} 1, & x_t > a \\ 0, & otherwise \end{cases} \tag{2}$$

where a is a set threshold value, usually set to the expectation of x_t or some other value with a specific meaning.

The biggest inconvenience in using the static method is in determining a series of threshold values a, and there are usually two ways to do this, the equal-interval method and the equal-probability method. Equal interval method is to let the division of each interval is equal in size, the operation is relatively simple. Equal probability method is to let the number of data points falling into each interval is basically equal, that is, the probability of occurrence of different symbols is basically equal, which is conducive to retaining the effective information of the sequence, but the operation is relatively cumbersome. The method described above is also the traditional interval segmentation method.

2) First-order dynamic method:

$$s_t = \begin{cases} 1, & x_t > x_{t-1} \\ 0, & otherwise \end{cases} \tag{3}$$

For the dynamic method, the size of the symbol set can also be adjusted, which requires considering not only the first-order difference of the sequence, but also the second-order difference, or even the third-order and fourth-order, corresponding to the symbol set size of 2, 4, 8, and 16, respectively.Commonly used in general, only the first-order and second-order differences are considered, for example, the expression for the definition of $s_i(t = 1, 2, \cdots, T)$ in the second-order dynamic method is:

$$s_t = \begin{cases} 3, & x_t < x_{t-1}, \quad x_{t+1} + x_{t-1} < 2x_t \\ 2, & x_t < x_{t-1}, \quad x_{t+1} + x_{t-1} \geq 2x_t \\ 1, & x_t \geq x_{t-1}, \quad x_{t+1} + x_{t-1} < 2x_t \\ 0, & x_t \geq x_{t-1}, \quad x_{t+1} + x_{t-1} \geq 2x_t \end{cases} \tag{4}$$

However, the difference method has a disadvantage that it is not sensitive enough to the noise and cannot characterize the fine details of the state at each moment, i.e., sometimes the symbols obtained from a very large difference and a very small difference are not different, and cannot appropriately reflect the changes in the time series.

3) Synthesis method

Static method and dynamic notes have their own advantages and disadvantages, they can be combined to complement each other's strengths and weaknesses, that is, the so-called integrated method. For example, the sequence can be symbolized according to the formula, and then its corresponding fine combination, to get 00, 01, 10, 11 four elements, corresponding to the symbol 0, 1, 2, 3, then we get a symbol set size of 4 symbols of the sequence. It can be seen that the symbol set size of the synthesis method can only be 4, 6, 8 and other even numbers.

After generating a sequence of symbols, for each sequence of symbols, in order to calculate its statistics, a more convenient and intuitive numerical expression is to base n of the sequence is transformed into a decimal series of base 10, a process known as sequence coding. This process is called sequence coding. e.g., a sequence 010 with a base of 2 has a decimal sequence code of $2(0\times 2^0+1\times 2^1+0\times 2^2)$, and a sequence 110 with a base of 2 has a decimal sequence code of $6(0\times 2^0+1\times 2^1+1\times 2^2)$. It can be seen that when coding, it is necessary to first determine the size of the symbol set n, and the coding length of the symbol sequence L (i.e., the number of data points contained in each code).

The general method of coding a symbol time series with symbol set size n, symbol sequence length L, and symbol sequence size N is summarized as taking the L data sequentially in order or coding each subsequence.

Once the symbol sequences are generated and coded, symbol statistics reflecting the probability of occurrence of different symbol sequences can be computed so that the pattern represented by a certain code word can be analyzed in the overall time series, which can reflect the changes in returns and their fluctuations.

The symbol tree is a function of the length of the symbol sequence L and is a graphical representation of the symbol statistics, which can be easily extracted after obtaining the symbol tree.

For a general symbol time series with symbol set size n and symbol sequence length L, it corresponds to a symbol tree with L levels and n sub-nodes under each node. At the bottom of the symbol tree, there are a total of n^L child nodes. In the symbol tree, the value in each node corresponds to the probability that the symbol sequence in that layer represents a pattern.

2.2.2. Forecast analysis of the financial market economy. In this chapter, the Shanghai Stock Exchange (SSE) Composite Index, abbreviated as SSE Composite Index and denoted as H, is selected, which also includes SSE Industrial Stock Index (H1), SSE Commercial Stock Index (H2), SSE Real Estate Stock Index (H3) and SSE Utilities Stock Index (H4). Meanwhile, the constituent index of the Shenzhen Stock Exchange, referred to as SZSE Composite Index, is selected and denoted as S. The daily closing price is used as the sample sequence, from which the two sequences represent the prices of the two market economies in China, respectively, where the entropy value of the return symbol sequence of SZSE Composite Index is greater than that of the return symbol sequence of the SSE Composite Index when L=4. It also shows that the stochasticity of the return series of SZSCI is stronger and the main change pattern is not as obvious as the main change pattern of the return series of SSE Composite Index. Then the histogram of symbol series is built, and the histogram of return symbol series is used in order to determine the main change pattern of return series. Both the SSE Composite Index and the SZSE Composite Index can take the change pattern corresponding to the word with a large relative frequency as the main change pattern, and the main change pattern of the index return sequence is shown in Table 1. The SZSE index is the words numbered 81, 38 and 63, and the corresponding decimal sequence codes are 80, 37 and 62, respectively. 38 and 63 have a relative frequency of 0.0191. 81 is 2222, which indicates that the change pattern is that the return of the SZSE index is high for four consecutive trading days, and the return fluctuates in the range of greater than 0.0087, and the relative frequency of the occurrence of this change pattern is 0.0201. The relative frequency of this change pattern is 0.0201.38 The number of characters is 1105, which indicates the change pattern is that the SZSE index has medium returns on the first, second and fourth trading days, with returns between -0.0058 and 0.0085, and low returns on the third trading day, with returns lower than -0.0056, and the relative frequency of this change pattern occurs is 0.0191. The number of characters is 2022.63 The number of characters is 2022, which indicates the change pattern is that the first, third and fourth trading days of the SZSE index are high return, with returns above 0.0085, while the second trading day is low return, with returns below -0.0054, and the relative frequency of occurrence of this change pattern is also 0.0191.

Most of the major change patterns of the six index return series are concentrated in the change patterns corresponding to words 1111, 2222 and 2022. Except for the SSE Composite Index and SSE Business Stocks Index, the major change patterns of the return series of the other four indices include the pattern corresponding to the word 2022. In addition, the main change patterns that occur most frequently in the return series of three indexes, SSE Industrial, Real Estate, and Utilities, are exactly the same, and they are all the change patterns corresponding to words 1111 and 2022. It can be seen that the main change patterns of these index return series have a high degree of consistency, and the change patterns represented by these three words are dominant in the analyzed index return series.

Table 1. The main change patterns of the exponential revenue sequence

Index	Sequence code	Relative frequency	Word	Major pattern
H	40	0.346	1111	The four consecutive days are medium returns, and the gains are fluctuating between -0.005 and 0.0066
	80	0.264	2222	Earnings for four consecutive days are high income, and the profit value is fluctuating at greater than 0.0066
S	80	0.0201	2222	Earnings for four consecutive days are high, and the gains are fluctuating in the range greater than 0.0085
	37	0.0191	1105	The first, second, and four trading days are in the middle of the income, and the gains value is between -0.0058 and 0.0085, the third trading day is low income, and the profit is less than -0.0056
	62	0.0191	2022	The first, third, and four trading days are high returns, the gains value is greater than 0.0066. the second trading day is low yield, and the profit is less than -0.0054
S1	40	0.213	1111	The earnings are medium income for four consecutive days, and the gains are fluctuating between -0.0055 and 0.0062
	65	0.210	2022	The first, third, and four trading days are high returns, the gains value is greater than 0.0062. the second trading day is low yield, and the profit is less than -0.0055
S2	80	0.208	2222	Earnings for four consecutive days are high income, and the profit value is fluctuating in the interval greater than 0.0064
	49	0.175	1211	The income of the first, third and fourth days of the day is medium income, and the profit value is between the -0.0054 and 0.0065, the second day of the second day is high, the profit value is greater than 0.0065
S3	40	0.214	1111	The earnings are medium income for four consecutive days, and the gains are fluctuating between -0.0073 and 0.0071
	62	0.0193	2022	The first, third and fourth days of the day are high returns, the gains are greater than 0.0071, the second trading day is low, and the gains are less than -0.0073
S4	40	0.0242	1111	The earnings are medium income for four consecutive days, and the gains are fluctuating between -0.0056 and 0.0063
	62	0.0193	2022	The first, third, and four trading days are high returns, the gains value is greater than 0.0063. the second trading day is low yield, and the profit is less than -0.0056

When analyzing a sequence of returns, since each word represents a pattern of return changes, the histogram of the sequence of return symbols can indicate the relative frequency with which each pattern of return changes occurs in the sequence of returns. When the sample size is large enough, the relative frequency indicated by the vertical coordinate of the symbol sequence histogram can also be approximated as the probability of occurrence of a word in the sequence. Let the word length L=4, the symbol set size n=3, and the symbols corresponding to the three value intervals are denoted by 0, 1, and 2, respectively, and according to the full probability formula there are:

$$P(b_4 \mid b_1 b_2 b_3) = \frac{P(b_1 b_2 b_3 b_4)}{P(b_1 b_2 b_3)} = \frac{P(b_1 b_2 b_3 b_4)}{P(b_1 b_2 b_3 0) + P(b_1 b_2 b_3 1) + P(b_1 b_2 b_3 2)} \tag{5}$$

For the dominant change pattern of each index return series given above, the probability that the return change of the current 3 trading days still meets the dominant change pattern on the next trading day when the change of the return of the current 3 trading days meets the dominant change pattern is given according to equation (19). The results of the market return prediction based on the change pattern of each index return series are shown in Table 2, for example, the change pattern corresponding to the word 1111 is the most dominant change pattern of the return series of the Shanghai Composite Index, which indicates that the 4 consecutive trading days are all medium returns, then the probability that the next trading day still meets medium returns can be predicted to be 0.56 when the current 3 trading days are all medium returns.As can be seen through the table, a certain return The probability of a certain pattern of return change is large, it does not mean that when it is known that the return changes in the previous 3 trading days conform to the pattern of change, the probability that the next trading day still conforms to the pattern of change is also large. For example, in the SZSE index return symbol sequence, the word 2222 has a higher probability of occurrence than 2022, but the P(2|222) of 0.40 is smaller than the P(2|202) of 0.53. In addition, the calculations based on $P(b_4 \mid b_1 b_2 b_3)$ are all greater than 0.4, which suggests that where the change in returns in the previous 3 trading days is known to conform to the main pattern of change, the probability that it still conforms to that pattern on the next trading day is greater than average (the probability corresponding to the average is about 33% due to the size of the symbol set, n=3).

Table 2. Market earnings forecast results

Index	Sequence code	Relative frequency	Word	$P(b_4 \mid b_1 b_2 b_3)$	
S	40	0.346	1111	P(1|111)	0.56
	80	0.264	2222	P(2|222)	0.53
H	80	0.0201	2222	P(2|222)	0.40
	37	0.0191	1105	P(1|110)	0.42
	62	0.0191	2022	P(2|202)	0.53
S1	40	0.213	1111	P(1|111)	0.45
	62	0.210	2022	P(2|202)	0.53
S2	80	0.208	2222	P(2|222)	0.44
	49	0.175	1211	P(1|121)	0.46
S3	40	0.214	1111	P(1|111)	0.44
	62	0.346	2022	P(2|202)	0.47
S4	40	0.264	1111	P(1|111)	0.47
	62	0.0201	2022	P(2|202)	0.47

3. A study of the impact of economic policies on financial market liquidity

3.1. Multivariate regression models

Assuming that there is a linear relationship between random variable Y and m independent variables $X_1, X_2, \cdots, X_m$, the regression analysis established at this point is known as multiple linear regression analysis. The expression for multiple linear regression is:

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_m X_m \tag{6}$$

where β_0 is the constant term and $\beta_1, \beta_2, \ldots, \beta_m$ is the unknown parameter, also known as the regression coefficient. If there are n observations $(y_i, x_{i1}, x_{i2}, \cdots, x_{im}), i = 1, 2, \cdots, n$, the multiple regression model for these n observations can be written in the following form:

$$\begin{cases} y_1 = \beta_0 + \beta_1 x_{11} + \cdots + \beta_{1m} x_{1m} + \varepsilon_1 \\ y_2 = \beta_0 + \beta_1 x_{21} + \cdots + \beta_{2m} x_{2m} + \varepsilon_2 \\ \quad \vdots \\ y_3 = \beta_0 + \beta_1 x_{n1} + \cdots + \beta_{nm} x_{nm} + \varepsilon_n \end{cases} \tag{7}$$

where $\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_n$ is the random error term, reflecting the effect of random factors on the dependent variable, and is the variability that cannot be represented by a linear relationship between the independent and dependent variables. Eq. can be rewritten into a matrix representation, i.e.:

$$Y = X\beta + \varepsilon \tag{8}$$

Among them:

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, X = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1m} \\ 1 & x_{21} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \cdots & x_{nm} \end{bmatrix}, \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_m \end{bmatrix}, \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \tag{9}$$

Usually regression analysis requires the assumption that the random error terms satisfy the Gauss-Markov condition, i.e., that the random error terms $\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_n$ are independent of each other, have equal and zero means and are chi-square. In addition, the random error terms can be assumed to follow a normal distribution with zero expectation.

As can be seen from the expression of multiple linear regression, one of the main tasks in the process of multiple linear regression modeling is to calculate the estimated value of the parameter vector β, and a common method of parameter estimation is the method of least squares. The basic principle of the least squares method is to find the least squares estimate $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1, \cdots, \hat{\beta}_m)'$ of the parameter β, which minimizes the sum of error squares $Q(\beta)$ of the model, i.e.:

$$Q(\beta) = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} \left[y_i - (\beta_0 + \beta_1 x_{i1} + \cdots + \beta_m x_{im}) \right] = (Y - X\beta)'(Y - X\beta) \tag{10}$$

Obtain the minimum value. where X, if $(XX)^{-1}$ exists, the least squares estimate of β is:

$$\hat{\beta} = (XX)^{-1} XY \tag{11}$$

The multivariate linear regression model developed after obtaining the estimates of the regression coefficients based on Eq:

$$Y = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \cdots + \hat{\beta}_m X_m \tag{12}$$

Multiple linear regression models using the least squares method usually require that the variables are independent of each other, and if there is multicollinearity between the independent variables, the stability and accuracy of the parameter estimates in the regression model will be reduced. Multicollinearity refers to the phenomenon of correlation between independent variables, which can be categorized into complete multicollinearity and approximate multicollinearity. When the correlation coefficient between the independent variables is 1, there is a complete linear relationship between the independent variables, i.e., for the independent variable $X_1, X_2, \ldots, X_m$, there is a set of incomplete zeros $c_0, c_1, \ldots, c_m$, which satisfies the following relation equation:

$$c_0 + c_1 X_1 + c_2 X_2 + \cdots + c_m X_m = 0 \tag{13}$$

Then full multicollinearity is said to exist between the independent variables. Full multicollinearity is an extreme state, in general, the correlation coefficient of the independent variables lies between 0 and 1, then it is said that there is approximate multicollinearity between the independent variables.

That is, for a number $c_0, c_1, \cdots, c_m$ that is not exactly zero, such that

$$c_0 + c_1 X_1 + c_2 X_2 + \cdots + c_m X_m \approx 0 \tag{14}$$

The harm of multicollinearity for least squares regression is specifically twofold:

1) If there is full multicollinearity between the independent variables, for the regression model, there is

$$c_0 + c_1 x_{i1} + c_2 x_{i2} + \cdots + c_m x_{im} = 0, i = 1, 2, \cdots, n \tag{15}$$

At this point due to

$$rank(X) < m + 1 \tag{16}$$

Then:

$$|x'x| = 0 \tag{17}$$

At this point $(XX)^{-1}$ does not exist, so it is not possible to derive an estimate of the regression coefficient using Eq.

2) If there is approximate multicollinearity between the independent variables, for the regression model though:

$$rank(X) = m + 1 \tag{18}$$

But:

$$|X'X| \approx 0 \tag{19}$$

This means that the diagonal element of $(XX)^{-1}$ will be larger, which makes the variance $Var(\hat{\beta}) = \sigma^2 (XX)^{-1}$ of $\hat{\beta}$ larger. This will lead to a decrease in the precision of the regression coefficient estimates, making it difficult to quantitatively analyze the degree of influence of the independent variable on the dependent variable through the regression coefficients. At the same time, the larger variance of the regression coefficient estimate will lead to a larger confidence interval of the regression coefficient, and the value of t in the significance test will decrease, which will easily lead to the difficulty of passing the significance test for the important independent variables, and ultimately affect the accuracy of the regression model.

3.2. *Analysis of the impact of economic policies on market liquidity*

This study first analyzes the effect of economic policy uncertainty on market liquidity and constructs a regression model. The impact of economic policy uncertainty index on market liquidity is studied.

The explanatory variable of this paper is economic policy uncertainty, and the economic policy uncertainty index used in the study, which is based on text mining technology, the index is obtained by screening the number of articles related to economic policy uncertainty through keyword search every month, dividing it by the total number of articles in the month, and then standardizing it. In this paper, the annual index is obtained after a simple arithmetic average of the monthly data from 2007 to 2019. The changes of the economic policy uncertainty index are shown in Figure 2, in which there was a wave peak of economic policy uncertainty in 2009 (380), which is consistent with the fact that the government adjusted its economic policy in response to the financial crisis in a smooth manner.Around 2013, because of the negative effect of the government's economic policy and the impact effect of the European debt crisis became apparent, the government's economic policy regulation faced the domestic and foreign double pressure, and the economic Around 2014-2017, economic policy uncertainty was again at a high level, peaking at more than 600, against the backdrop of China's structural transformation and upgrading of its economy, with high policy attention being paid to issues such as overcapacity. After a brief pullback, economic policy uncertainty climbed sharply to its highest level after 2018, hit by shocks including the US-China trade war and the New Crown epidemic, which made the domestic and international situation during this period grim and complex. Overall, the volatile changes in economic policy were consistent with the nodes of major political and economic events and their impacts.

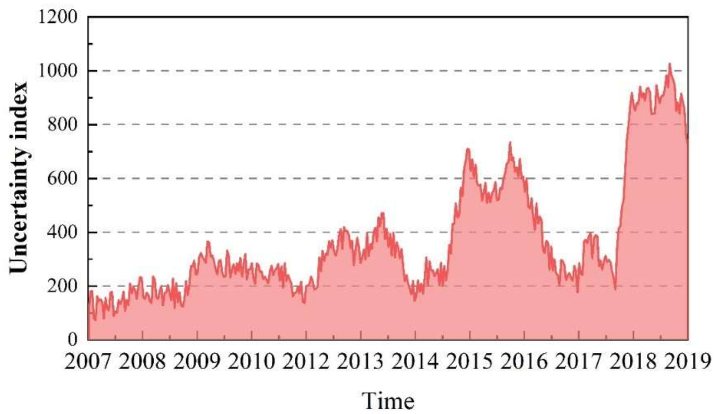

Fig. 2. Changes in economic policy instability

In this paper, we refer to the existing literature and select a series of control variables covering both the firm level and the macroeconomic level. At the firm level, the selected variables include firm size, financial leverage, return on equity (ROE), revenue level, market share (top1), investor share, share of shares outstanding, market price, and volatility of returns, Tobin's Q (Tobin Q). At the macroeconomic level, GDP growth rate (GDP) and inflation level (inflation) are selected as control variables.

In this paper, all A-share listed companies in China from 2008 to 2021 are taken as the research samples, and the data are obtained from the Cathay Pacific database. After screening the sample data, 20,485 sample observations are obtained. For the study of the relationship between the impact of economic policy uncertainty on market liquidity, the overall sample is first utilized for empirical analysis, and the results of the analysis of the impact of economic policy uncertainty on market liquidity are shown in Table 3. Firstly, adding the control variables at the firm level, the results are shown in column (1), the regression coefficient of economic policy uncertainty (EPU) is 0.064, which is significant at 1% level, indicating that uncertainty is positively correlated with illiquidity, and secondly, adding the control variables at the macro-market economic level on the basis of column (1), the results are shown in column (2), obtaining that the regression coefficient of economic policy uncertainty (EPU) is 0.108, which is still significant at 1% level, and the results are shown in Table 3. The regression coefficient is 0.108, which is still significant at the 1% level. In terms of the quantitative relationship, after adding all control variables, for every 1% increase in economic policy uncertainty, market liquidity decreases by 0.108%. The above indicates that a rise in economic policy uncertainty leads to a decline in market liquidity.

Table 3. Impact analysis of market liquidity

Variable	(1) ILLIQ	(2) ILLIQ
EPU	0.064***	0.108***
	(6.647)	(10.042)
Size	-0.826***	-0.786***
	(-38.391)	(-33.803)
lev	0.975***	0.915***
	(16.252)	(15.131)
ROE	0.0212	0.004

	(0.433)	(0.079)
rev	-0.026	-0.020
	(-1.285)	(-1.073)
top1	0.579***	0.563***
	(5.255)	(5.017)
institution	1.783***	1.735***
	(21.432)	(21.042)
share	-0.179***	-0.165***
	(-5.667)	(-4.738)
price	-0.540***	-0.533***
	(-30.402)	(-30.367)
volatility	8.813***	7.599***
	(15.505)	(12.915)
Tobin Q	-0.258***	-0.234***
	(-26.845)	(-26.289)
GDP	—	-5.577***
		(-12.148)
inflation	—	-1.832***
		(-11.355)
Constant term	-10.851***	-10.851***
	(37.355)	(29.123)

4. Conclusion

This paper examines the characteristics of financial market liquidity and discusses the impact of economic policy uncertainty on market liquidity. An analysis of the economic policy uncertainty index reveals that economic policy uncertainty peaked once in 2009 (380) and then ushered in sharp fluctuations around 2013. Around 2014-2017, economic policy uncertainty was back at a higher level, with a peak of more than 600. After a brief retracement, economic policy uncertainty dramatically after 2018 climbed to its highest level. Overall, changes in economic policy volatility are consistent with the nodes of major political and economic events and their impacts, and the economic policy uncertainty index can serve as a valid explanatory variable.

The regression coefficient of economic policy uncertainty on financial market liquidity is 0.064, and the regression coefficient of economic policy uncertainty obtained by adding the control variables at the macro-market economic level is 0.108, all of which are significant at at the 1% level. This indicates that uncertainty is positively related to illiquidity. Second, for every 1% rise in economic policy uncertainty, market liquidity falls by a corresponding 0.108%, proving that a rise in economic policy uncertainty leads to a fall in market liquidity.

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