# Empirical studies of the effect of leverage industry characteristics

Wei Li, Su-Sheng Wang
Shenzhen Graduate School
Harbin Institute of Technology
Shenzhen University Town in Shenzhen City
The People's Republic Of Chinese,0086-518055
liwei7311@gmail.com, wangsusheng@hotmail.com

*Abstract:* - The policy implication of itself is the noise of the stock market trading behavior. Good policy to price fluctuations than bad policy is called leverage effect, while the industry characteristics interval by the leverage effect. Based on the CSI 300 Sector Index, ARMA-GARCH model analysis of the CSI representative industries index volatility, the empirical results indicate that the GARCH (1,1) model can explain the fluctuations in the industry there are persistent, gathering; through TARCH (1,1) and EGARCH (1,1) models examined the impact of fluctuations in the various sectors of the leverage effect and information asymmetry, results show that the reverse impact than the same amount of positive impact to be various industries generate greater volatility.

*Key-Words:* -CSI 300 Sector Index; volatility; leverage effect

## 1 Introduction

Fluctuations on financial time series clustering and random perturbations are accompanied by more substantial fluctuations in the small amplitude fluctuations associated with smaller amplitude fluctuations. Early volatility model requires random disturbance with variance can not explain this phenomenon, Engle (1982)[1] proposed the ARCH model, Bollerslev (1986) [2]to promote the formation of GARCH model. Since the ARCH and GARCH model, the impact of the variance on the different directions symmetrically to react [3], because only the square of the impact conditional variance mapped to the information contained in the result on a change in price of symbols to be lost.

Black (1976) noted that the negative impact on the positive impact than the same degree of volatility is higher, the first time he uses the term "leverage effect" to describe this phenomenon, referring to the stock price movements and volatility negatively correlated with the same intensity bad news than good news led to greater market volatility.

Many scholars the help of the GJR-GARCH EGARCH and TARCH models useful exploration of the leverage effect of the stock market in China, but their conclusions are not consistent, and can not help but doubt: they come to different conclusions, whether it is due to the sample selection of different draw one-sided conclusions In other words, when the sample is not at the same time, the conclusion is different, so that a market research and come to very different conclusions, this will certainly portfolio securities pricing certain impact, risk management, and make positions exposed to unnecessary risks. Partial Knowledge and Full Knowledge learning scenario are relevant to the modeling of financial time series and how they can be used to assess the robustness of a modeling system for financial time series[3].

This paper will overcome these shortcomings, innovative representative CSI 300 Sector Index, either to judge whether the market has the existence of the leverage effect of this noise characteristics, they can go to look for different characteristics in the industry when, whether the leverage effect is a distinction there? This article is specific extensions to the representative industries, such as industrial, financial, real estate, medical and health industries, through specific study of various industry in Shanghai and Shenzhen index fluctuations, and learn more about the changes in the characteristics of different industries volatility. Different industries due to the different characteristics of each of the degree of fluctuation caused by external factors also differ on the degree of sensitivity of the information is not the same[4], so the difference in the industry is industry leveraged the difference between noise traders. Therefore, to select six representative industries in the CSI 300 Sector Index as the sample, the use of so the difference in the industry is industry leveraged the difference between noise traders. Therefore, to select six representative industries in the CSI 300 Sector Index as the sample, the use of ARMA-GARCH TARCH EGARCH model by industry specific analysis and draw the relevant conclusions.

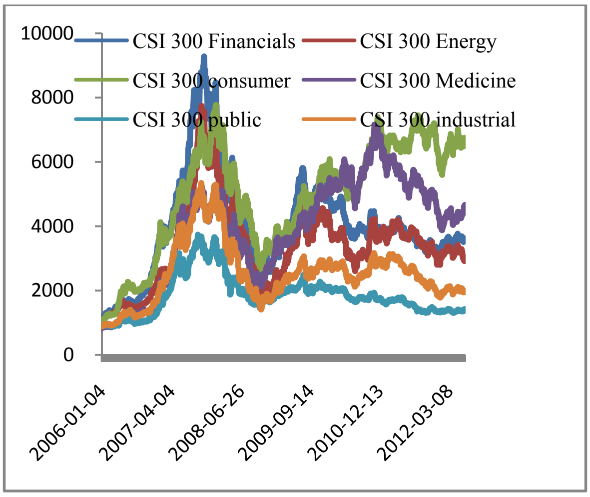
## 2 Data Selection And Descriptive Analysis

### 2.1 The data selected

CSI 300 Sector Index constituent stocks of the CSI 300 Index by industry standards to classify all stocks into their respective industries to form the corresponding industry index constituent stocks, reflecting the overall performance of the company's stock in different industries, to provide investors with market analysis tools. Samples of each industry, the paper selects six industry-CSI 300 Index and the CSI 300 Index to observe the samples, the time span of the data from January 2006 to June 2012, excluding holidays and individual transaction data capacity of 1570, a total of 9420 data from the Wind database.

Chart 2.1 CSI 300 Sector Index time series (January 2006, June 2012)

**Chart 2.1 CSI 300 Sector Index time series (January 2006, June 2012)**



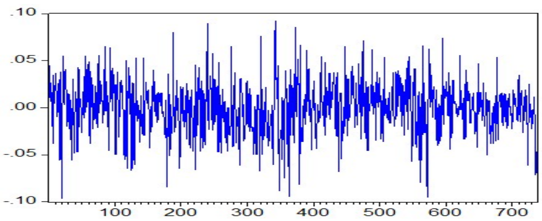

CSI 300 Sector Index sequence diagram (Chart 2.1), can be seen in China due to the impact of the financial crisis in 2007 to 2008 have greater volatility, the average rose a drop of about 2-3 times since 2009, China's economy is a full recovery, the industry also began to recover development, various industries index presents a gentle upward trend. Different industries fluctuations show different amplitude fluctuations of different sizes is also proved that the differences in the level of risk in the inter-industry, as shown here, changes in the financial and real estate industry index steepest utilities index has been in a more gradual change[5].

Look at the index of price changes from the industry, not stationary time series, in order to study the industry index smooth day closing price of the CSI 300 Sector Index based on the closing price index of minus two days logarithmic order differential to calculate the daily return rate in the industry index, calculated as Rt = log (Pt)-log (Pt-1), where Rt day t Sector Index yield, of Pt t-day industry index closing price.

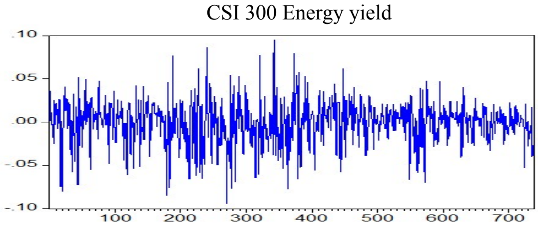
### 2.2 The descriptive statistics of the industry index

As can be seen from Figure 2: (1) during the observation period, the yield of various industries index at zero at the upper and lower frequent fluctuations, no significant change in trend, shows the time series of smooth; (2) fluctuations in various industries index yield have a significant cluster characteristics - larger fluctuations followed by large fluctuations, or small fluctuations within a certain period of time, in another period of time, which show that a common financial time series data the characteristics - fluctuations in the gathering, also can be inferred conditional heteroskedasticity serial correlation may exist;(3) yield fluctuations can again see the defensive sectors such as utilities and medical and health industry volatility and other industry small compared to the financial and real estate industry and the energy industry more susceptible to the environmental impact of the international market, and therefore more volatile。 Descriptive statistics in Chart 2.1 show: (1) the CSI industry index CSI 300 Index, financial, real estate, energy sector yields the standard deviation is

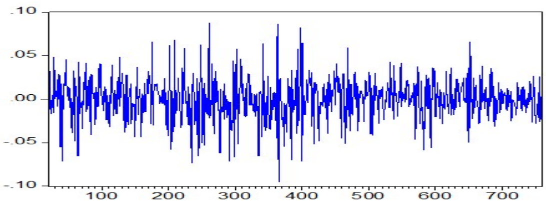
**Chart 2.2 CSI 300 Sector Index rate of return time sequence diagram**



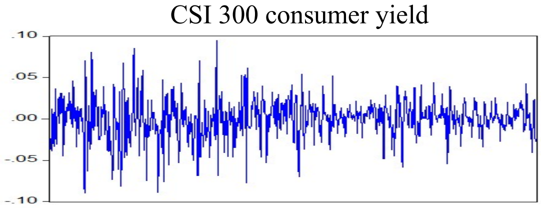
CSI 300 Energy yield



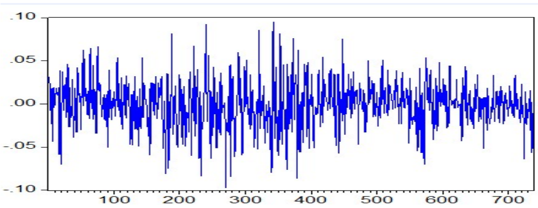
CSI 300 industrial yield



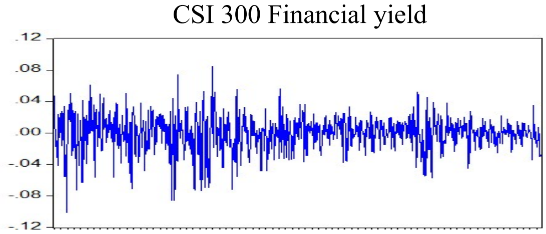
CSI 300 consumer yield



CSI 300 Medicine yield



CSI 300 Financial yield



CSI 300 public yield

greater than the yield of the stock market (in the CSI 300 Index based), the standard deviation, Further show that these two sectors relative to the market in terms of volatility, risk, utilities, pharmaceutical, consumer industries yields the standard deviation is less than the standard deviation of the rate of return of the stock market or their little difference, indicating its relative markets still relatively stable, with less risk. (2) Each of the index yield skew the coefficient (-0.102864-0.578800) is less than 0, indicating that their distribution is skewed left, showing the non-symmetry, while its kurtosis the coefficient (3.660562-4.670431) were greater than 3 , and then presents the "fat tail" characteristic that their distribution. (3) JB statistic larger than the statistical probability is close to zero, then reject the null hypothesis (the distribution is a normal distribution), that the sequence of these yield not follow a normal distribution.

**Table 2.1 Descriptive statistics of the index return seriesseries**

| Index | Mean | Standard deviation | Skew | Kurtosis | J-B Statistics | J-B statistical probability |
|---|---|---|---|---|---|---|
| CSI 300 | -0.000 | 0.024408 | -0.215 | 4.055106 | 38.33831 | 0.000000 |
| CSI 300 Energy | -9.48e-05 | 0.028858 | -0.102 | 3.660562 | 14.69906 | 0.000643 |
| CSI 300 industrial | -0.0004 | 0.025541 | -0.396 | 4.196880 | 63.32834 | 0.000000 |
| CSI 300 consumer | 0.0002 | 0.023629 | -0.153 | 4.353352 | 59.15178 | 0.000000 |
| CSI 300 Medicine | 0.0003 | 0.024649 | -0.312 | 4.670431 | 79.68637 | 0.000000 |
| CSI 300 Financials | -0.0002 | 0.027708 | -0.118 | 3.953118 | 29.63343 | 0.000000 |
| CSI 300 public | -0.0005 | 0.023127 | -0.578 | 4.586140 | 118.4076 | 0.000000 |

These indices yield sequence showing the characteristics of the "fat tail" the industry index yield fluctuations varies over time change, sometimes stable, sometimes fierce, and high or low phenomenon often continue for some time, this volatility gathering in the yield distribution is usually a "fat tail" characteristic. GARCH class model can well capture yield characteristics, to better reflect the volatility of the stock market.

## 2.3 The stationary test

GARCH class models yield modeling, requirements of the yield of the sequence with smoothness, in order to test its smooth, and further through the ADF test to analyze the existence of

| Index | ADF statistic | Test probability | 1% threshold | 5% threshold | 10% threshold |
|---|---|---|---|---|---|
| CSI 300 | -25.585 | 0.0000 | -3.4008 | 2.8251 | -2.8802 |
| CSI 300 Energy | -25.704 | 0.0000 | -3.4008 | -2.5251 | -2.8802 |
| CSI 300 industrial | -25.709 | 0.0000 | -3.4900 | -2.8251 | -2.8802 |
| CSI 300 consumer | -26.935 | 0.0000 | -3.9008 | -2.8251 | -2.8802 |
| CSI 300 Medicine | -23.450 | 0.0000 | -3.4008 | -2.8251 | -2.5880 |
| CSI 300 Financials | -26.037 | 0.0000 | -3.4008 | -2.8251 | -2.580 |
| CSI 300 public | -25.859 | 0.0000 | -3.4900 | -2.8251 | -2.5802 |

unit root in each industry index return series. ADF test results (Table 2.2) show that the test statistics volume was significantly less than 1%, 5%, 10% threshold, and verify that the probabilities are close to 0, it may be inferred that these sequences does not exist a significant unit root, reject the null hypothesis (yield sequence unit root), indicates that the return series for stationary time series.

**Table 2.2 index return series unit root (ADF) stationarity test results**

| Index | ADF statistic | Test probability | 1% threshold | 5% threshold | 10% threshold |
|---|---|---|---|---|---|
| CSI 300 | -25.858 | 0.0000 | -3.4390 | 2.8652 | -2.5688 |
| CSI 300 Energy | -25.760 | 0.0000 | -3.4390 | -2.8652 | -2.5688 |
| CSI 300 industrial | -25.706 | 0.0000 | -3.4390 | -2.8651 | -2.5688 |
| CSI 300 consumer | -26.435 | 0.0000 | -3.4398 | -2.8651 | -2.5602 |
| CSI 300 Medicine | -23.184 | 0.0000 | -3.4390 | -2.865 | -2.5688 |
| CSI 300 Financials | -26.790 | 0.0000 | -3.4390 | -2.8652 | -2.5688 |
| CSI 300 public | -25.82 | 0.0000 | -3.4390 | -2.8652 | -2.568 |

# 3 Model And Empirical Analysis

Descriptive analysis of each industry index return series, these sequences are "fat tail" smooth sequence, these sequences to establish the ARMA model, GARCH model, TARCH model and the EGARCH model, further observation in various industries Index yield volatility characteristics [6][7].

## 3.1 ARMA model with ARCH test

Therefore, income lag of 12 ACF-PACF (autocorrelation - partial autocorrelation) test, carried out by the various industry index return series can be found in the sequence of the various yield auto correlogram and partial auto correlogram are tailing, The rate sequence ARMA (p, q) model, and after repeated screening, in addition to CSI 300 index is p = 2, q = 2 addition to other indices take p = 4, q = 4, ARMA (p, q) model estimation results are shown in Table 2.3.

**Table2.3 index return series, an ARMA (p, q) model estimation results**

| Index | Coefficient & t-Statistic | | | |
|---|---|---|---|---|
| | AR(2) | AR(4) | MA(2) | MA(4) |
| CSI 300 | | -0.662819 (-4.632297) | | 0.7570 (5.3326) |
| CSI 300 Energy | | 0.659566 (3.131738) | | -0.6012 (-2.854) |
| CSI 300 industrial | | -0.5933937 (-3.999272) | | 0.67326 (4.9250) |
| CSI 300 consumer | | 0.965189 (93.30461) | | -0.98512 (216.90) |
| CSI 300 Medicine | -0.616272 (-2.6426) | | 0.55612 (2.2579) | |
| CSI 300 Financials | | -0.734604 (-5.030799) | | 0.7809 (5.8438) |
| CSI 300 public | | -0.825478 (-13.66019) | | 0.86568 (16.423) |

Index rate of return of the various industries ARMA (p, q) model residual plots of observed volatility clustering phenomenon can be seen, description of the error term conditional heteroscedasticity may exist, and further through

ARCH-LM test sequence exists conditional heteroskedasticity in Table 3.1.

**Table 3.1: Index yield sequences of ARCH-LM test results**

| Index | Coefficient & t-Statistic | | | |
|---|---|---|---|---|
| | AR(2) | AR(4) | MA(2) | MA(4) |
| CSI 300 | | -0.662819<br>(-4.6397) | | 0.728570<br>(5.543326) |
| CSI 300 Energy | | 0.659566<br>(3.1338) | | -0.602712<br>(-2.6154) |
| CSI 300 industrial | | -0.53937<br>(-3.9972) | | 0.673926<br>(4.925027) |
| CSI 300 consumer | | 0.965189<br>(93.361) | | -0.989512<br>(-216.95) |
| CSI 300 Medicine | -0.272<br>(-2.678) | | 0.556125<br>(2.257926) | |
| CSI 300 Financials | | -0.734604<br>(-5.099) | | 0.780949<br>(5.8858) |
| CSI 300 public | | -0.825478<br>(-13.019) | | 0.865681<br>(16.498) |

Each yield sequence F statistic and the LM statistic corresponding probability is less than 0.05, reject the null hypothesis (conditional heteroskedasticity sequence does not exist), that is, the presence of significant ARCH effects, the model error sequence exists autoregressive conditional heteroscedasticity, so you can build the GARCH model.

## 3.2 GARCH (1,1) model and test

ARCH-LM test by the industry index return series, found to exist on the assumption that residuals as white noise sequence, various industries index yield autocorrelation coefficients and partial correlation coefficients are relatively small, which may be subject to conditional heteroskedasticity impact, so we built these industry data GARCH class model to estimate and test. Found after screening GARCH (1,1) model can better reflect the continued stock market volatility.

**Table 3.2: Index return series GARCH (1,1) model estimation results**

| Index | w | a | β | a +β | Coefficient | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | AR(2) | AR(4) | MA(2) | MA(4) |
| CSI 300 | 8.75E-06<br>(2.727924) | 0.057868<br>(4.415863) | 0.927079<br>(59.40463) | 0.984947 | | -0.824374<br>(-11.01681) | | 0.860540<br>(12.84649) |
| CSI 300 Energy | 3.39E-05<br>(2.001038) | 0.049714<br>(2.895667) | 0.910023<br>(28.27519) | 0.959737 | | 0.733487<br>(4.905088) | | -0.684520<br>(-4.292219) |
| CSI 300 industrial | 9.67E-06<br>(3.487937) | 0.064880<br>(5.051899) | 0.919772<br>(67.81813) | 0.984652 | | -0.670180<br>(-4.433277) | | 0.719855<br>(5.096338) |
| CSI 300 consumer | 7.26E-06<br>(1.578373) | 0.066614<br>(5.092190) | 0.921923<br>(59.72841) | 0.988537 | | -0.971453<br>(-54.16016) | | 0.961375<br>(44.98667) |
| CSI 300 Medicine | 6.48E-06<br>(2.278683) | 0.065908<br>(4.620105) | 0.925835<br>(67.37957) | 0.991743 | -0.814280<br>(-7.193655) | | 0.815379<br>(7.119344) | |
| CSI 300 Financials | 7.99E-06<br>(2.028507) | 0.044355<br>(3.608325) | 0.945497<br>(63.22707) | 0.989852 | | -0.872292<br>(-17.34212) | | 0.903458<br>(21.66640) |
| CSI 300 public | 7.81E-06<br>(2.658810) | 0.103716<br>(5.772226) | 0.883481<br>(46.82702) | 0.987197 | | -0.659765<br>(-6.136639) | | 0.714956<br>(7.318650) |

GARCH (1.1) model for the industry index yield analysis, various index the ARCH items and the GARCH term coefficients are statistically significant, indicating that the conditional variance is not constant. Table 3.3 GARCH (1.1) model is derived from the ARCH-LM test F statistic is smaller and the corresponding test probability greater than 0.05, suggesting that the model

**Table 3.3 GARCH (1,1) model, ARCH effect test**

| Index | F-statistic | Probability | Index | F-statistic | Probability |
|---|---|---|---|---|---|
| CSI 300 | 0.076585 | 0.782061 | CSI 300 Medicine | 1.993203 | 0.158528 |
| CSI 300 Energy | 0.309502 | 0.578156 | CSI 300 Financials | 0.204438 | 0.651297 |
| CSI 300 industrial | 0.046979 | 0.828469 | CSI 300 public | 0.338102 | 0.561106 |
| CSI 300 consumer | 0.055276 | 0.814192 | | | |

eliminates the industry index yield ARCH effect, the model can intend aggregate data.

Reflect the impact of fluctuations in GARCH (1.1) model in a beta reflects the system's long-term memory, a + β reflects persistent fluctuations; various industries in Table 3.2 a + β 0.959737 to 0.991743, average close to 1, but less than 1, indicating that the various industries GARCH process is wide and smooth volatility presents gathering and persistent income fluctuations will eventually decay, but relatively slow rate of decay, and that the impact will last for a long time market risk, have an important role and impact on all future predictions[8].

## 3. 3 TARCH (1,1) and EGARCH (1,1) model and test

GARCH (1.1) model can better reflect the persistent volatility of various industries, but not a good description of the impact of various external factors impact on various industries, therefore to establish TARCH and EGARCH model to test the leverage effect of external factor sand asymmetric effects[9].

**Table 3.4 Index return series TARCH (1,1) model estimation results**

| Index | w | a | r | β | Coefficient | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | AR(2) | AR(4) | MA(2) | MA(4) |
| CSI 300 | 1.46E-05 (3.716842) | 0.000297 (0.018591) | 0.099077 (4.448316) | 0.919197 (48.23989) | | -0.765114 (-8.217153) | | 0.816177 (9.746531) |
| CSI 300 Energy | 5.15E-05 (2.609911) | 0.013354 (0.806238) | 0.089015 (2.947776) | 0.879798 (24.04289) | | 0.685409 (4.131213) | | -0.627405 (-3.541963) |
| CSI 300 industrial | 1.60E-05 (4.041206) | 0.018783 (1.070032) | 0.083902 (3.502136) | 0.907590 (54.08314) | | -0.635056 (-3.958389) | | 0.692569 (4.631628) |
| CSI 300 consumer | 1.91E-05 (2.753927) | 0.032425 (1.814166) | 0.081085 (2.681211) | 0.893277 (39.37670) | | -0.963990 (-48.06404) | | 0.953530 (41.14434) |
| CSI 300 Medicine | 1.08E-05 (2.909021) | 0.039221 (2.130263) | 0.053682 (2.155314) | 0.916680 (59.16188) | -0.817497 (-7.456537) | | 0.819206 (7.424402) | |
| CSI 300 Financials | 1.77E-05 (3.101075) | -0.001694 (-0.134547) | 0.089181 (4.054232) | 0.932491 (53.96225) | | -0.820373 (-14.87961) | | 0.860650 (18.60348) |
| CSI 300 public | 1.19E-05 (3.064467) | 0.074329 (2.547878) | 0.064018 (1.999103) | 0.868017 (37.19044) | | -0.535928 (-4.229835) | | 0.607941 (5.200875) |

Has been eliminated by ARCH Tests TARCH (1,1) model in Table 3.5, the ARCH effect, reflecting a better fit of the model of the basic characteristics of the industry index yield. In TARCH (1,1) model (see Table 3.4). impact factor of the good news for a, the influence coefficient Lee bad news for a + r when r = 0, the conditional variance reaction is symmetric shocks when r ≠ 0, the conditional variance reaction asymmetric shocks call this phenomenon as the leverage effect. In

**3.5 TARCH (1,1) model ARCH Tests**

| Index | F-statistic | Probability | Index | F-statistic | Probability |
|---|---|---|---|---|---|
| CSI 300 | 4.58E-05 | 0.994603 | CSI 300 Medicine | 1.31309 | 0.252295 |
| CSI 300 Energy | 0.00157 | 0.968408 | CSI 300 Financials | 0.56361 | 0.453050 |
| CSI 300 industrial | 0.01442 | 0.904422 | CSI 300 public | 0.02905 | 0.864710 |
| CSI 300 consumer | 0.26825 | 0.604668 | | | |

industry and CSI 300 Utilities index of a statistically significant, other index showed a statistically significant; addition of the industry index r and β are statistically significant [10].

It follows that: (1) the "good news" of the pharmaceutical industry to bring its stock price index 0.053682 times the impact, "Lee bad news to 0.092903 times the impact of its stock index, while utilities" good news "0.074329 times the impact to its stock price index, "Lee bad news to 0.138247 times the impact its stock price index, which indicates greater volatility Lee bad news than good news [11]. (2) the energy, industrial, and consumer industries leverage effect coefficient r is greater than 0, to prove the existence of the leverage effect, a greater than 0, but not significantly so visible that the negative impact of these three sectors have a significantly larger impact [12].(3) the financial and real estate industries r is greater than 0, there are also the leverage effect, but a less than 0 and not significant, when εt-i2 is large enough, the final results of the conditional heteroskedasticity may be negative, with conditions heteroscedasticity Hengda 0 contradictions, while following through EGARCH (1,1) model is better to solve this problem[13].

**Table 3.6 Index return series of the EGARCH (1,1) model estimation results**

| Index | w | a | r | β | Coefficient | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | AR(2) | AR(4) | MA(2) | MA(4) |
| CSI 300 | -0.424183 (-4.622754) | 0.125297 (3.893077) | -0.084056 (-4.965468) | 0.956845 (92.20628) | | -0.822893 (-12.23941) | | 0.863232 (14.56963) |
| CSI 300 Energy | -0.519134 (-3.034264) | 0.118876 (3.104430) | -0.067282 (-3.120202) | 0.940117 (42.42442) | | 0.693076 (4.195893) | | -0.633796 (-3.622916) |
| CSI 300 industrial | -0.427020 (-4.703979) | 0.137304 (4.802624) | -0.071418 (-4.112370) | 0.957168 (91.11059) | | -0.619631 (-3.733846) | | 0.680105 (4.387054) |
| CSI 300 consumer | -0.655826 (-4.013155) | 0.194979 (4.884955) | -0.081263 (-3.259184) | 0.933110 (46.80255) | | 0.944676 (58.48418) | | -0.974851 (-96.77745) |
| CSI 300 Medicine | -0.369127 (-4.411535) | 0.159956 (5.414174) | -0.055507 (-2.716968) | 0.966612 (94.90919) | -0.864108 (-9.134442) | | 0.880548 (9.990669) | |
| CSI 300 Financials | -0.234379 (-3.581152) | 0.081809 (3.242924) | -0.066650 (-4.223594) | 0.976388 (126.7720) | | -0.864162 (-18.62827) | | 0.897762 (23.18092) |
| CSI 300 public | -0.482839 (-4.264690) | 0.237005 (5.537544) | -0.061785 (-2.643176) | 0.961698 (78.99486) | | -0.412985 (-2.473448) | | 0.503324 (3.226135) |

EGARCH (1,1) model (Table 3.6) are presented the index yield coefficient estimated in various industries are statistically significant, and the model elimination ARCH effects (Table 3.7). Various industries leverage effect coefficients are negative and statistically significant, suggesting that the various industries leverage, and the reverse shock will lead to a positive impact than the same amount of the next higher variance results in EGARCH (1,1) model has also been verified. The financial and real estate industry through the EGARCH (1,1) model better explain its asymmetric effect, "good news" to 0.015159 times the impact of its stock index to its share price, "Lee bad news the index 0.148459 times the impact, the obvious advantage of the impact of bad information than good information, and that the impact of this information asymmetry allows the volatility of the stock market fell reaction increased more rapidly than the market [14]. Base on the other empirical research, it is found that the results based on high-frequency data are slightly different from the results based on GARCH models. However, the method based on high frequency data is simpler and contains more information [15].

**Table 3.7 EGARCH (1,1) model, ARCH effect test**

| Index | F-statistic | Probability | Index | F-statistic | Probability |
|---|---|---|---|---|---|
| CSI 300 | 0.0891 | 0.76540 | CSI 300 Medicine | 0.724 | 0.394935 |
| CSI 300 Energy | 0.0199 | 0.88765 | CSI 300 Financials | 0.3013 | 0.583193 |
| CSI 300 industrial | 0.0858 | 0.76964 | CSI 300 public | 0.007 | 0.930682 |
| CSI 300 consumer | 0.7556 | 0.38499 | | | |

# 4 Conclusion

## 4.1 Descriptive statistical analysis

Smaller defensive sectors such as utilities and medical and health industry volatility compared with other industries, the standard deviation of the rate of return is less than the standard of China's stock market yield difference or not their difference, showed that its relative to the market is still relatively stable, with less risk. The standard deviation of the standard deviation of the financial and real estate industry and the energy industry yield greater than China's stock market rate of return (based on the CSI 300 Index), more susceptible to the environmental impact of the international market, so volatile. Each industry index yield "fat tail" distribution are presented and volatility clustering features smooth time series, and were significantly different from the normal distribution [16].

## 4.2 ARCH-LM test conclusions

By the ARCH-LM test: Industry indexes yield significant ARCH effect, the fluctuation rate exist autoregressive conditional heteroscedasticity, the current volatility influenced by the volatility, showed obvious thing denaturation and agglomeration. Index of yields of various industries through the establishment of the GARCH (1.1) model to get a better fit, the various index the ARCH items and the GARCH term coefficients are statistically significant, and the elimination of the ARCH effect. Industry a + β GARCH (1.1) model were less than 1 and is very close to 1, that various industries GARCH process is wide and smooth, the volatility of the industry presents clustering and persistent external shocks on the conditional variance persistence. With the expansion of the scale of the stock market and the market system is perfect, all industries are subject to market risk factors impact and affect their income situation is also changing, abnormal fluctuations in a short period of time to compare the yield impact difficult to eliminate[17].

## 4.3 Conclusions of the examination

TARCH (1.1) and EGARCH (1.1) model to illustrate the impact of various external factors impact on various industries, the performance for the leverage effect and asymmetric effect[17], and model eliminates the ARCH effect. Two models illustrate the significant leverage effect between industries, "Lee bad news," the shock of impact than the same amount of "good news" will produce stronger fluctuations. EGARCH (1.1) in the fitting Financials Index yield to overcome the TARCH model a negative and significant ground is not 0, the conditional heteroskedasticity negative phenomenon, also came to the same conclusion and other industries. Different visible by the industries affected by the impact of good and bad news of Lee, the leverage effect of the stock market as a whole Specifically, medicine, utility industry leverage effect is relatively small, the degree of asymmetry of information on the impact of smaller[12]. while consumer industries leverage effect is relatively large, the financial and energy industries leverage effect is located between them. It is widely accepted that financial time series in the international financial market share a common set of well-established stylized features. Both ARCH and GARCH models can explain volatility clustering phenomena with great success, and have been quite successful in modeling real data in various applications[18].

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