# INDIVIDUALISM AS A DRIVER OF OVERCONFIDENCE, AND ITS EFFECT ON INDUSTRY LEVEL RETURNS AND VOLATILITY ACROSS MULTIPLE COUNTRIES

CHAD HORNE
Supervisor: YUDHVIR SEETHARAM

A research report submitted to the School of Economic and Business Sciences, Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment (50%) of the requirements for degree of Master of Commerce in Finance.

Date of submission:
March 2016

# DECLARATION

I, Chad Horne, declare that this research report is my own unaided work. It is submitted in partial fulfilment of the requirements for the degree of Master of Commerce in Finance at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at this or any other university.

Signed:________________________________ Date: ______________________________

# ACKNOWLEDGEMENTS

To my sponsors, Stewart and Candy Horne, for allowing me to pursue my dreams through tireless endeavours.

To my coach, Yudhvir Seetharam, for pushing me to my full potential, for being patient when I showed a lack of dedication and for continuing to train me despite this.

To my partner, Lina Hahnle, without whose constant support and drive I would never have made it this far.

And to my supporters, the very few of them who have cheered me on to the end.

Thank you all. This is the culmination of all of our efforts.

The race is finally over.

**TABLE OF CONTENTS**

## LIST OF FIGURES

## LIST OF TABLES

# ABSTRACT

This study attempts to determine the possible effects of individualism on industry volatility. The implications of this for behavioural finance are extensive, showing firstly that different industries react differently to behavioural biases and secondly that overconfidence is a possible driver of the positive effect of individualism on industry volatility. The country selection process was relatively objective, taking two countries with high individualism indexes and two with low indexes and including one with a medium index value. The result was a sample of the United States of America, the United Kingdom, South Africa, China and Taiwan. The industry selection process was more subjective. Industries were selected which should have a higher propensity to behavioural biases with lower book to market ratios (software and computer services industry and pharmaceutical and biotechnology industry) and other industries which should not be as strongly affected by behavioural biases (banks, mining, oil and gas producers, and mobile telecommunications industries). In order to correct for ARCH effects the series' were modelled using a GARCH (1, 1) model. The resulting residuals, which showed no autocorrelation, were then used to conduct panel data regressions on each of the industries. The results confirmed that individualism had a positive effect on volatility in the industries which were expected (software and computer services and pharmaceuticals and biotechnology industries). However, it was also determined that the banks industry was significantly affected by individualism, an effect which it was hypothesised, was due to the individualism of employees as opposed to investors.

# 1. INTRODUCTION

The Efficient Markets Hypothesis (EMH) has been under intense scrutiny since first being described by Fama (1965). The cornerstone of the EMH is the assumption that investors act in a perfectly rational, utility maximising manner. In recent years, the EMH has been under attack from the study of Behavioural Finance (BF), which provides a holistic theory of market behaviour by removing the assumption that market participants act in a perfectly rational, utility maximising way. The much-debated area of BF is the result of the reconciliation of psychology to the field of finance, which attempts to fill the gaps left by the Efficient Markets Hypothesis.

According to the EMH, any excess volatility of returns should be due to a measurable excess in the risk of the discounted value of the future cash flows of the asset (Bulkley and Tonks, 1992). However, volatility over and above what is implied by risk metrics has often been identified in security returns. Many explanations have been developed to explain this phenomenon; however none have been conclusively agreed upon (Shiller, 2003). Most of the explanations are attributed to behavioural biases of investors since non-behavioural risk metrics cannot fully account for the anomalies. Two of the several behavioural biases found empirically to have an effect on volatility are investor overconfidence and the self-attribution bias (Gervais and Odean, 2001; Daniel Hirshleifer and Subrahmanyam, 1998).

Investor overconfidence is defined as the phenomenon of investors overweighting the accuracy of their analysis, while the self-attribution bias is the idea that investors attribute successful outcomes to their ability and failures to external factors (Bem, 1965). If one considers overconfident investors to be noise traders as is suggested in Shefrin and Statman (1994) – a parallel which is possible when considering the definition of noise traders as investors trading on poor or no information by De Long (2005) or that noise traders do not have rational reasons to trade by Tetlock (2006); and also the similarities in the results attributed to noise traders and overconfident investors including increased volatility and volume (Ramiah , Xu and Moosa, 2015) – research on the effect of noise traders on volatility can then be applied here. The existence of noise traders (as a separate class of investor to informed investors) was proven by Goetzmann and Massa (1999). Noise traders have been found to affect volatility in numerous studies, despite the fact that the lasting volatility effects of noise traders is a direct contravention of the EMH since these effects should be offset by rational arbitrageurs. As noise traders force market prices away from fundamental prices, arbitrageurs take advantage of the discrepancy, forcing prices back to fundamental values.

Mathematically, volatility is a measure of the variation in trading prices over a given period of time and is captured by the standard deviation of the change in prices over time. It represents the risk of investing in the security as well as the inherent risk of the company itself (Butler and Pinkerton, 2007). The latter being due to the fact that future cashflows for the company are uncertain. However, volatility can also show an uncertainty in the pricing of an asset. If uncertainty is present among investors, prices will change more frequently. As an example, given two investors interested in the same security, neither of which has perfect knowledge of what the fundamental value of the security is: investor 1 may consider the current price of the security to be too high and therefore sell his investment in the security, driving the price down. At the new lower price however, investor 2 considers the security to be undervalued and therefore invests more. This drives the price back up. This results in higher standard deviations of price changes assuming a normal distribution. Therefore in industries or securities where less information is required in order to make an informed investment decision, share value is easier to determine and therefore discrepancies between share price and share value are easier to exploit. In those cases it makes sense that noise traders (overconfident investors or investors suffering from the self-attribution bias) would have a reduced effect on volatility since it will be easier for rational investors to arbitrage away any discrepancies. This concept is also discussed in Scheinkman and Xiong (2003) who develop a continuous-time equilibrium model in which increases in volatility are caused by discrepancies in valuations caused by overconfidence

The existence of investor overconfidence and the self-attribution bias has also been shown to have a positive effect on momentum profits (Daniel, Hirshleifer and Subrahmanyam, 1998). The momentum effect states that securities which have performed well in the recent past will continue to perform well into the near future (Chui, Titman and Wei, 2010). Overconfidence and the self-attribution bias propagate the momentum effect by causing public information supporting the private analysis of an investor to be seen as confirmation of his abilities. This increases his confidence and causes him to trade more, forcing the security price in the same direction. Due to the self-attribution bias, public information *not* supporting initial private analysis has very little effect on the confidence of the investor (Daniel, Hirshleifer and Subrahmanyam, (1998)).

It is interesting to note that overconfidence and the self-attribution bias may be nested within a different behavioural bias – one which is related to culture (Yates, Lee and Shinotsuka, 1996). The study of individualism shows that people from different cultures have different loci of responsibility, whether for the self or the community. This cultural bias may have a strong impact on overconfidence and as a result on volatility (leading to momentum). People brought up in individualistic cultures are taught that they are in some way superior to their neighbours while those brought up in collectivistic cultures are taught that everyone has faults. When reduced to its simplest form this is a question of Nature versus Nurture: one of the oldest questions in the field of psychology.

The application of psychological methods to the field of finance is an attempt to describe how and why investors stray from utility maximisation and was first propagated through the Prospect Theory of Kahneman and Tversky (1979), which showed that people are risk seeking in the plane of losses and risk averse in the plane of gains. In other words, they found that when individuals are faced with a loss, they would prefer to take on a larger loss with a lower probability than a smaller loss with a higher probability. However, when faced with a gain individuals were more likely to choose a smaller gain with more certainty than a larger gain with less certainty. The *expected* gain/loss was not necessarily taken into consideration. This collaboration between academics in the fields of finance and psychology was the first of its kind and the first to demonstrate a deviation from perfectly rational investor behaviour. BF has received considerable attention in recent years; however it has yet to result in a hypothesis that could be a reliable substitute for the EMH. New methods and schools of thought are constantly being introduced to BF in an attempt to create a sound basis for the substitution of the EMH, including the Adaptive Markets Hypothesis of Lo (2004), which takes the basis of the EMH and amends behavioural factors to it.

Since the development of Prospect Theory several other areas of psychology have been applied to the field of Finance with differing levels of success. One of these areas is that of cultural psychology and, in particular, the idea of individualism. The primary premise of individualism is that cultures can be divided into those which are more individualistic and those which are more collectivistic, the differentiation being that those which are more individualistic contain people who consider themselves to be independent from the crowd while people in collectivistic cultures view themselves as part of a whole, creating an “interdependent self-construct” (Chu, Titman and Wei, 2010). The field of individualism in general was revolutionised by Hofstede (1980) who conducted a survey study of IBM employees across 40 countries and constructed an individualism index from the results. The aim of Hofstede (1980)’s analysis was to measure the cultural diversity of countries using 5 different indices, namely: individualism, masculinity, power distance, uncertainty avoidance, and long term orientation. These results were later extended and conformed to 51 countries in total in Hofstede (2001). Hofstede (1980, 2001)’s results have formed the basis for studies across several different areas of research, which document behavioural differences between countries, including the field of Finance.

Individualism was originally introduced as a behavioural trait of a population. In the remainder of the current paper it is applied to a subset of a population, being investors/traders. A strong link has also been shown to exist between individualism and overconfidence, as well as the self-attribution bias. According to Markus and Kitayama (1991) people in individualistic societies focus more on their own attributes and they, along with Heine, Lehman, Markus and Kitayama (1999) show that more individualistic cultures believe that their abilities are above average while less individualistic cultures do not. In this way it can be said that the individualism effect is a result of overconfident investors relying less on fundamental valuations.

Chu, Titman and Wei (2010) consider the effects of individualism on equity market volatility, finding a statistically significant relationship. It is suggested that this relationship is caused by the effect of individualism on the performance of momentum strategies through similar investor behaviour; specifically overconfidence and the self-attribution bias. A relationship between individualism and volatility could therefore indicate the existence of overconfidence and (or) the self-attribution bias in an industry on which individualism has a significant effect. This study attempts to extend this line of thought by determining whether certain industries are more susceptible to the effects of individualism across countries in order to determine whether the effects of individualism which have been found to be prominent between countries have differing effects on industries *within* countries. This could lead to the conclusion that fundamental valuations are more important in certain industries than in others due to the fact that the effects of these behavioural biases have differing effects. Results such as these will inform which industries are most affected by behavioural biases. One could also determine the overall effects of individualism on a given market through the industrial composition of the market.

Using the results obtained by Hofstede (2001) as a starting point, daily international financial data at the industry level will be tested to determine which, if any, industries are most affected by individualism and which are least affected. The data set would have to include complete international daily security prices over a lengthy period of time, which would allow for the calculation of returns and volatility. It would also have to include industry classification data and Hofstede (2001)'s individualism index. Several measures which could affect industry volatility will be included to capture potential exogenous variables such as exchange rate volatility or systematic volatility. Several statistical methodologies would have to be used to determine the appropriateness of the data leading to a regression analysis.

The present study introduces a GARCH process, which it has been found, is far more accurate in modelling and predicting volatility than a random walk model (a model which assumes no autocorrelation) according to Jones (2011). ARCH (AutoRegressive Conditional Heteroschedasticity) models assume volatility clustering (periods of high volatility and periods of low volatility) which is conditional on previous periods' error terms. An extension of the

ARCH model to the Generalised ARCH (GARCH) model allows for a more parsimonious specification by including past (conditional) volatility values. This is required when the volatility is conditional on both past volatility and error terms, demonstrating an AutoReggressive Moving Average (ARMA) process.

ARCH/GARCH effects have been found in many series' of financial returns and the existence of volatility clustering is an accepted characteristic of financial markets (Lux and Marchesi, 2000). In order to determine the appropriateness of data for use in an ARCH/GARCH process, several tests must be run on the data. These include, but are not limited to, tests for stationarity of the series, whether the series is independently and identically distributed, and tests for the existence of ARCH/GARCH effects.

While analysis on the effects of individualism has been undertaken using regression analysis on entire markets, this is the first attempt to carry out the analysis at the industry level, meaning a significant contribution can be made to the areas of individualism as well as behavioural finance. This is also to the writer's knowledge the first attempt at applying an ARCH/GARCH framework to the problem. Determining whether there is a difference in the way which industries react to individualism extends the current research with regards to market efficiency and overconfidence. This study attempts to solidify some aspects of BF through the hypothesis that some industries are more severely impacted by the effects of individualism, the assumption that individualism causes overconfidence, and therefore, the concept that the valuations of some industries rely more heavily on fundamental value than others. In so doing, this study shall attempt to show that the EMH is subjective at best.

## 1.1 RESEARCH OBJECTIVE AND HYPOTHESES

The aim of the current study is to determine the effect of overconfidence through the cultural preconception of individualism on industries of differing levels of fundamental asset to security value (book to market) ratios and in turn the susceptibility of different industries to pricing uncertainty due to behavioural biases is uncovered.

### 1.1.1 PRIMARY HYPOTHESIS

*Hypothesis 1:* Individualism has diverse effects on industry trade volume and return volatility.

> *Hypothesis 1.1:* Individualism has a larger effect on industries which are seen to have lower book to market value ratios.
>
> *Hypothesis 1.2:* Individualism has a smaller effect on industries which are seen to have higher book to market value ratios.

### 1.1.2 SECONDARY HYPOTHESIS

*Hypothesis 2:* The effect of individualism on industry volume and volatility is transferred via investor overconfidence.

> *Hypothesis 2.1:* Industries with lower fundamental asset to market value ratios are more susceptible to the effects of overconfidence.
>
> *Hypothesis 2.2:* Industries with higher fundamental asset to market value ratios are less susceptible to the effects of overconfidence.

The study continues with an analysis of the literature relating to 7 different areas which are relevant to the study in Chapter 2. After the literature review the theoretical framework of the methodologies used are discussed in Chapter 3 before the data and methodology are defined in Chapter 4. Chapter 5 contains a discussion of the results and Chapter 6 concludes. References and appendices are found after the conclusion.

# 2. LITERATURE REVIEW

The current study gains insight from literature from several different and diverse areas of research. In the literature review Efficient Markets Hypothesis is discussed before moving on to Behavioural Finance and evidence for momentum strategies. The primary independent variable, individualism, is considered as well as its relationship with overconfidence. The relationship between overconfidence and excess volatility is analysed and finally industry specific volatility literature is reviewed.

## 2.1 EFFICIENT MARKET HYPOTHESIS

The Efficient Market Hypothesis (EMH) is the culmination of centuries of development in return distributions and was first described and formulated by Fama (1970). The Random Walk Theory is one of the developing principles behind the EMH and was first introduced to the field of finance by Regnault (1863). Regnault, a broker by trade, used a form of binomial distribution to show that the probability of price increases or decreases were equal, effectively proving that price movements were random. Interestingly, he attributed the Random Walk hypothesis to the lack of information as well as different interpretations of information among investors, possibly also pre-empting the EMH (Jovanovic & Le Gall, 2001). The Random Walk Theory, when applied to share prices, asserts that security price changes are independently distributed and do not follow any specific path. This leads to the assertion that one cannot consistently achieve returns in excess of average market returns on a risk-adjusted basis, since predicting share prices or share price patterns should be impossible. Fama (1970)’s definition stated that market prices reflect all possible information. However, he characterised this by formulating three levels of efficiency: weak form efficiency allows for market prices to reflect only historical market information; semi-strong form efficiency states that prices reflect both historical prices and all publicly available information; and strong form efficiency is achieved only when all publicly and privately held information is reflected in market prices. Fama (1970) made three assumptions in the development of the hypothesis, namely that there are no transaction costs, there is costless information and there is investor agreement with regards to the information received. Even without these assumptions markets should maintain a high-level of efficiency. Fama (1970) gives the example that as long as investment decisions are made while considering all available information, even large transactions costs will not necessarily inhibit prices from reflecting all available information. Likewise, if a sufficient number of investors have access to all available information markets should tend to efficiency.

Volumes of research have found evidence in favour of the Efficient Markets Hypothesis in its three separate forms, to be discussed below. Tests of the weak form of efficiency are generally supported in empirical studies. These show that investment strategies based on past prices alone cannot earn returns higher than the market or that markets follow a random walk. Roll (1978) finds the Treasury Bill market to be weak form efficient and Alexander (1961, 1964) finds that *Y%* filter trading rules (buying the top Y% of performing stocks while selling the bottom Y% over a given period of time) do not outperform buy-and-hold strategies (buying shares based on fundamental analysis and holding them for a given period of time) when transaction costs are included. In a South African context Smith, Jefferis and Ryoo (2002) find that the JSE follows a random walk while Jefferis and Smith (2005) use a GARCH model to show that the JSE has shown weak form efficiency over a period of 11 years at the end of the 20th and beginning of the 21st century. In direct contravention of the weak form of efficiency however, is the existence and *persistence* of noise traders. As mentioned earlier, this appears frequently in empirical work, which will be discussed in Section 1.1.6.

The semi-strong form of market efficiency states that prices reflect all publicly available information. When analysing stock splits, Fama, Fisher, Jensen and Roll (1969) find evidence of this. They consider that excessively high rates of returns prior to stock splits are due to increases in expected earnings and dividends and as information is disseminated, these expectations are accepted as true, driving returns even higher. This indicates an integration of public information among investors. Ball and Brown (1968) also support semi-strong form efficiency when looking at earnings announcements. Ball and Brown (1968) create expected firm income measures by analysing firm incomes in the past. They then create the unexpected change in income by subtracting the actual income from the expected income and find that returns for firms where the unexpected change in income is negative are lower than would otherwise be expected. This is another example of public information being incorporated into share prices. In an analysis of the adjustment of market prices to earnings and dividend announcements on the Malaysian Stock Exchange Ahmed, Hussin and Ying (2010) find significant evidence of prices adjusting to the new information with dividend announcements having a stronger effect than earnings announcements. Increases in both earnings and dividends resulted in higher abnormal returns, while decreases result in lower abnormal returns. However, in tests of earning announcements on the Indian Stock Market, Mallikarjunappa and Dsouza (2013) find that prices are slow in adjusting and reflect inefficiency. It is noted by Mallikarjunappa and Dsouza (2013) that it would be possible to earn abnormal returns up to 30 days after earnings announcements are made, indicating that this information is not entirely incorporated in share prices for a lengthy period after the announcement is made – a definite breach of market efficiency. In a study of the efficiency of futures prices in the Hog Futures Market, Leuthold and Hartman (1979) also find against the semi-strong form of market efficiency. Econometric models designed to predict future hog prices by incorporating all publicly available information often are more accurate in predicting hog prices than the futures market itself, suggesting market inefficiency.

Strong form efficiency, which states that all information, private and public, is reflected in security prices, is not as well supported. Scholes (1969) shows that corporate insiders have monopolistic access to information about their firms and Niederhoffer and Osborne (1966) show that they can use this information to generate profits, directly contravening the strong form of market efficiency. Specifically, Niederhoffer and Osborne (1966) find that the chances of an advance after a decline is three times higher than a second decline, and that subsequent to two consecutive moves in the same direction, the chances of a third move in the same direction are almost twice as high compared to the same move after two moves in different directions. Kara and Denning (1998) find that US markets are not strong form efficient by using a log-linear regression of abnormal returns. The analysis was done on known trades based on insider information and Kara and Denning (1998) prove that insiders were able to earn profit from these trades. Jensen (1968) however, finds that mutual funds are not able to achieve risk adjusted returns over and above the market when accounting for transaction fees, supporting market efficiency. The basis of this analysis is the definition of mutual fund managers as owners of insider information. If mutual funds cannot capitalise on their insider information, this indicates that security prices have already accounted for this information, showing efficiency in the market.

## 2.2 BEHAVIOURAL FINANCE

The assumption by the EMH of investor agreement is further predicated on the assumption of rational, utility maximising market participants. The claim of BF is that market participants are affected by biases, which force them away from utility maximisation in their investment decisions. The current study falls within the realm of BF since it describes the inclusion of behavioural biases in investment decisions.

Kahneman and Tversky (1979) were among the first to disagree with the view of utilitarian, risk averse investors. Their development of Prospect Theory was based on survey results and has formed the basis of behavioural finance. They found that investors overweight events which they consider to be certain relative to outcomes which are merely probable (the certainty effect), and are risk averse in the plane of gains while being risk seeking in the plane of losses (the reflection effect). Barberis, Huang and Santos (2001) show that models based on Prospect Theory better explain factors such as high volatility of returns and equity risk premia. The model developed by Barberis, Huang and Santos (2001) is based on prior investment outcomes, stating that investors become less risk averse after a large investment return. The investor then implements decreased discount rates in calculating discounted cashflows, pushing the price up higher. An opposite effect occurs for negative returns.

Other evidence in support for BF includes Coval and Shumway (2005) who find that investors who make losses in the morning show higher risk-taking activity in the afternoon and Baker and Wurgler (2007) who show that sentiment affects markets as a whole.

Lo (2004) introduced a middle ground to EMH vs. BF. The Adaptive Markets Hypothesis states that markets exhibit changing levels of efficiency. Lo (2004) considers that investor behaviour evolves over time by natural selection. The work of Simon (1955) on bounded rationality – the concept that investors are only rational up to a certain point due to the computational complexity of being perfectly rational – and satisficing, as opposed to optimizing, investor behaviour, is a strong influence on the work of Lo (2004). The hypothesis of Adaptive Markets assumes that individuals use heuristics to adapt satisfactorily to an environment, however if that environment were then to change, those adaptations would be conceived as behavioural biases if they were not suited to the new environment.

## 2.3 MOMENTUM STRATEGIES

A momentum strategy involves buying past winners and selling past losers under the hypothesis that securities which have increased in price in the near past will continue to increase in price in the near future and securities which have decreased in price in the near past will continue to decrease in price in the near future. The existence and success of momentum strategies is an anomaly since it indicates that security prices do not follow a random walk but are rather serially correlated.

De Bondt and Thaler (1985) uncover weak form market inefficiencies on the New York Stock Exchange (NYSE) by proving that share price momentum can predict reversals after a three year period. They show that if a share has been increasing in price over the past three years it will decrease in price over the next three years. They consider this to be an overreaction by investors to positive price movements and a subsequent correction.

Jegadeesh and Titman (1993) show that over a three to twelve month period significant returns can be made by investing in a relative strength momentum strategy on the NYSE and American Stock Exchange (AMEX). However, after twelve months significant reversals meant large losses for those maintaining the strategy. Hsieh and Hodnett (2011) find similar results on the JSE suggesting that the phenomenon is internationally relevant. Hsieh and Hodnett (2011) also note that contrarian investing (using an investment strategy which contradicts momentum strategies) may be a safe haven during market turmoil due to its low correlation with the market during those periods.

The existence of momentum profits has also been found to be related to overconfidence and the self-attribution bias. Daniel, Hirshleifer and Subrahmanyam (1998) theorise that overconfident investors overweight any private information they receive, causing market overreactions which are corrected over time with the introduction of new public information. However, if the new public information confirms the earlier private information, self-attribution bias will cause these investors to become more confident and leads to a further overreaction. This continued overreaction is the cause of momentum profits according to Daniel, Hirshleifer and Subrahmanyam (1998).

More specifically, Chui, Titman and Wei (2010) show that the link between overconfidence and momentum profits is driven by individualism. Chui, Titman and Wei (2010) find a 0.6% difference in average monthly momentum profits – as measured on a zero-cost momentum portfolio – between countries with individualism indexes in the top and bottom 30%, with those in the top 30% showing the higher profits.

## 2.4 INDIVIDUALISM

The study of independence forms one of two key areas in cultural psychology research. The area was first developed by Hofstede (1980) where a survey was given to IBM employees in 40 different countries and an independence index was created. The study was later extended to 50 countries in Hofstede (2001). This independence index has been used in several studies since.

Franke, Hofstede and Bond (1991) conduct an analysis of the effect of all of the Hofstede (1980) cultural variables on economic growth in 18 – 20 countries. The results show that individualism has a negative effect on economic growth over the sample period, and Franke, Hofstede and Bond (1991) conclude that individualism is a liability in a context where cohesion drives economic growth.

Markus and Kitayama (1991) note that Western cultures are representative of an independent self-construal, while Eastern cultures are more interdependent. They define independent people as follows:

> "…behavior is organized and made meaningful primarily by reference to one's own internal repertoire of thoughts, feelings, and action, rather than by reference to the thoughts, feelings, and actions of others" (p. 226).

Interdependence they define as:

> "…seeing oneself as part of an encompassing social relationship and recognizing that one's behaviour is determined, contingent on, and, to a large extent, organized by what the actor perceives to be the thoughts, feelings, and actions of others in the relationship" (p. 227).

Weber, Shenkar and Raveh (1996) also consider the effect of several of Hofstede (1980)'s cultural indices on the result of merger and acquisition deals. They find that cultural differences between merging/acquiring companies predict stress, poor attitudes towards the merger/acquisition or cooperation better than corporate culture differentials. This is further proof that business decisions are severely affected by national culture.

Kachelmeier and Shehata (1997) conducted a series of trials with participants managing fictional books and tested under what circumstances audits were requested from the parties given that audit requests cost "money". The results showed that while in a setting of high anonymity all "countries" tested were more demanding of audits, but in a setting of low anonymity countries with less individualism were less likely to request audits. This indicates that individuals in collectivistic cultures are more likely to trust their peers in an open environment.

Yang (1981) finds evidence of collectivism in China, even in the more modern segments of the population. Church et al. (2006) find that American and Anglo-Australian people are individualistic in nature while Chinese, Malaysian and Japanese people are collectivistic.

## 2.5 INDIVIDUALISM AND OVERCONFIDENCE

It has been hypothesised by many that individualistic cultures are more prone to overconfidence and self-attribution bias than are collectivistic cultures. This is mostly attributed to different loci of control: people of individualistic cultures focus on themselves while those in collectivistic cultures focus on their peers.

According to Heine et al. (1999), this effect is attributable to the upbringing of the youth. They note that in individualistic cultures (most notably North America) children are encouraged to think that they are special and capable of anything, while those in collectivistic cultures (most notably Japan) are made to focus more on their inadequacies and weaknesses in order to correct these aspects. This self-critical perspective of the Japanese is also found by Doi (1973) to name just one. According to Biais, Hilton, Mazurier and Pouget (2005), self-monitoring like this should cause a decrease in the prevalence of overconfidence.

In a study of negotiators from the United States of America and Japan, Gelfand, Higgins, Nishii, Raver and Dominguez (2002) find that Americans are more self-serving (prone to self-attribution bias) than their Japanese counterparts. This conclusion held across four different methodologies conducted by Gelfand et al (2002).

In a multi-cultural study of the United States of America and several Eastern countries, Lee et al. (1995) find that the US has the strongest form of peer-comparison overconfidence, which is what causes investors to be overly optimistic of the accuracy of their decisions according to Van den Steen (2004). Yates, Lee and Shinotsuka (1996) also find that individualism is clearly related to peer-comparison overconfidence.

Chui, Titman and Wei (2010) also show very high correlations between individualism and trading volume and volatility, which as can be seen below is an indication of overconfident investors. Chui, Titman and Wei (2010) find relatively small but highly significant relationship between individualism and trading volume and volatility when using panel data regression of 41 countries.

## 2.6 OVERCONFIDENCE AND EXCESS VOLATILITY

The existence of excess volatility has long plagued the study of efficient markets. Market prices should, in an efficient market, represent the sum of all discounted cashflows expected to accrue to the asset holder. If this is the case, then it is noted by Shiller (2003) that the maximum possible variance of the forecast (market prices) cannot exceed the variance of the variable being forecasted (future cashflows). However, this is consistently found to be the reality (Shiller, 1981; LeRoy and Porter, 1981; West, 1988). Since overconfident investors can be described as noise traders (Shefrin and Statman, 1994), the research done thereupon also applies here. It has been argued by a few (Grossman and Stiglitz, 1980; Black, 1986) that markets cannot be truly efficient without the existence of noise traders. Inefficiencies must exist in the market in order for informed investors to have a reason to uncover them. The investigations which informed investors do in search of these inefficiencies are what drive prices to equilibrium.

Based on the above it can be seen that the mere existence of noise traders leading to excess volatility is almost expected by the EMH. However, given that these noise traders should be arbitraged out of the market, the *persistence* of excess volatility caused by noise traders contradicts the EMH. Friedman (1953) and Figlewski (1979) both agree that these irrational investors should disappear from the market in the long run due to the depletion of their capital. Friedman (1953) creates a model which caters for the distribution of wealth amongst individuals and results in irrational investors being marginalised. Figlewski (1979) considers bettors of horse racers and finds that the information disseminated by handicappers is completely internalised by rational bettors but not by irrational bettors. Many people argue that noise traders are simply replaced by other noise traders. However, in an attempt to explain excess volatility during trading hours, French and Roll (1986) prove that 4% to 12% of daily variance is caused by mispricing.

De Long, Schleifer, Summers and Waldmann (1991) create a model which allows for the persistence of noise traders by proving that they can earn higher returns than rational investors. It is agreed that due to the fact that noise traders are on average more bullish and trade more, they take on more risk. Higher risk obviously results in higher *expected* returns but generally in long run ruin. De Long et al. (1991) show that it is possible for noise traders to earn higher returns than rational investors and survive - and even dominate - the market. They state that because noise traders take on more risk, they are rewarded with higher returns, however because noise traders trade on false or bad information, they will on average buy high and sell low (De Long et al., 1991). The result is that individual noise traders should end up bankrupt with a high probability or very wealthy with a low probability. On a collective basis however, it is possible that they can come to dominate the market. Miller (1977) argued that the smart money (money controlled by well-informed, rational investors), on identifying a price discrepancy, may short themselves completely out of the position, leaving only noise traders to set the price. This would result in inefficient markets with no rational investors.

Several studies have been conducted on the direct relationship between overconfidence, self-attribution bias and excess trading volatility. Gervais and Odean (2001) consider that over-confidence is a result of the self-attribution bias since traders attribute success to their own ability and failures to external forces. This results in investors becoming overconfident in their abilities.

Odean (1998) notes that overconfidence in different market players has different effects on the market. Of most interest is the finding that volatility is increased by overconfident traders and trading volume is increased by overconfident price takers, insiders or market makers. Since individualism increases overconfidence in an entire population, one would expect the effect to resolve as an increase in both volume and volatility.

Scheinkman and Xiong (2003) create a model which shows that overconfidence causes disparities in agents' opinions of asset fundamentals, resulting in excess volatility. In the same vein, it is found by Van den Steen (2004) that industries, in which there is disagreement with regards to the effectiveness of alternative strategies or technologies, are also prone to over optimism.

Finally, in a study of 41 countries using Hofstede's Individualism index Chu, Titman and Wei (2010) find a significant effect of individualism on both trading volume and volatility, which they posit could relate to the success of momentum strategies in more individualistic countries. This result is the basis for the current study, which takes a more in depth view of the effects of individualism on markets.

## 2.7 INDUSTRY VOLATILITY

Cambell, Lettau, Malkiel and Xu (2001) find that there are vast differences in volatility between industries and find high correlations between industry and firm level volatility. Larger industries are found to have lower average volatilities. This is due to the fact that larger industries are made up of more established firms which have less volatility. Of 49 industries, 14 are found to have significantly positive volatility trends and seven have significantly negative volatility trends, indicating the vast differences in volatility properties between industries.

Ben Sita (2013) shows that volatility has a spill over effect between industries and that some industries lead this effect while others follow. Specifically, Ben Sita (2013) shows that the financial and manufacturing industries lead volatility of other industries, reasons for this are not given. However, they show that this effect contains a feedback mechanism and the relationships are far more complex than a simple linear progression. They also find that these spill over effects exhibit a time-varying pattern and did not follow a trend following the market crash of 1987.

Mazzucato (2002) finds that industry volatility peaks during times of technological innovation within an industry and thus concludes that industry specific volatility is due to a life cycle effect. When the revenue of an industry is derived more from new technologies which investors have little experience in valuing, the value of that industry is more difficult to determine, resulting in more volatility. Hou (2007) claims the volatility differences are due to differing levels of asymmetric information between industries. Industries for which there are large amounts of information asymmetry result in less efficient markets for that industry and a higher likelihood of excess volatility.

## 2.8 SUMMARY

It can be seen that the EMH has a strong theoretical background and while it does not perfectly fit observations, the simplicity of the theory makes it difficult to abandon without severe deviations from expectations. The field of BF has grown substantially in recent years, and while some aspects of financial markets are better explained by BF, there is yet to be an agreed, all-encompassing theory to replace the EMH.

Psychological biases of market participants are not a new concept, but the inclusion of individualism as a cultural bias in financial literature is. Individualism defines the manner in which a person may relate to other persons within an environment and can affect decisions made. Individualism can also cause overconfidence in a culture, which in turn can result in excess market volatility.

While differential industry specific volatility has been studied extensively from a non-behavioural perspective, little work has been conducted on behavioural factors affecting it. One of the behavioural factors considered here is the effect of individualism through overconfidence – however, the results could be extended to infer that behavioural factors have different levels of impact on different industries.

# 3. THEORETICAL MOTIVATIONS FOR THE EMPIRICAL FRAMEWORK

ARCH/GARCH effects present in the time-series volatility data are removed by implementing a simple GARCH process, the residuals of which are then used in tests of the hypotheses using panel data regression. Several statistical tests are used to determine the appropriate models as well as the appropriateness of the data for the given methodology. Both GARCH models and panel regressions are standard statistical tests which are used in the field of finance regularly.

## 3.1 LINEAR REGRESSION

The generalised specification of a multiple linear regression is given here:

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_q x_q + \varepsilon_t, \tag{1}$$

where $y$ is the dependent variable; $\alpha$ is the equation intercept, which is fixed in time; $\beta_i$ is the coefficient of the regressor, $x_i$, which in turn is the value of an independent variable (variable $i$) upon which $y$ is being modeled; and $\varepsilon_t$ is the error term which captures any noise causing the relationship of $y$ and $x_i$ to deviate from a linear equation. The error term is also variable through time and therefore creates a data series itself that represents how the relationship has deviated from linearity through time. $\beta_i$ measures the strength of the effect that the independent variable $x_i$ has on the dependent variable $y$.

Chu, Titman and Wei (2010) model the following specification of the above equation:

$$\begin{aligned} LnV_{jt} = \beta_0 + \beta_1 Indv_j + \beta_2 Insider_j + \beta_3 Credit_{jt} + \beta_4 Gwvol88_j + \beta_5 Fxvol_{jt} \\ + \beta_6 Open_{jt} + \beta_7 Debt_{jt} + \beta_8 MCap_{jt} + \varepsilon_{jt}, \end{aligned} \tag{2}$$

including variables for Individualism ($Indv$), prevalence of insider trading ($Insider$), the ratio of total private credit to GDP ($Credit$), the volatility of real GDP growth between 1988 and 2003 ($Gwvol88$), exchange rate volatility ($Fxvol$), openness of the capital market ($Open$), the country's debt ratio ($Debt$), and the market capitalisation ($MCap$) where the subscripts $j$ and $t$ represent the country and time respectively. In this case, the dependent variable, $LnV_{jt}$, is the natural log of the volatility of the market. While these variables are important in the study of individualism on an entire market, when considering industries within a market, many of these effects will be irrelevant.

## 3.2 PANEL DATA REGRESSION

Panel data is described as having both cross-sectional and time-series components. In mathematical terms the data takes the form:

$$X_{it}, i = 1, \dots, N; t = 1, \dots, T, \tag{3}$$

where $X$ is a specific observation, $i$ is a cross-sectional unit (test subject) and $t$ is a unit of time. In other words, panel data occurs when observations are taken from multiple subjects at multiple points in time. Due to the inclusion of multiple cross-sections, the specification for a panel data regression has a double subscript. A generalised equation is given by:

$$y_{it} = \alpha + \beta_k x_{itk} + u_{it}, \tag{4}$$

where again $i$ is a cross-sectional unit, $t$ is a unit in time, $y$ is the dependent variable for cross-section $i$ and time $t$, $\beta$ is the coefficient of the variable, which is represented by $k$, $x_{itk}$ is the value of the variable represented by $k$ in the cross-section $i$ and time $t$ and $u_{it}$ captures the disturbances (Baltagi, 2005). It should be noted that $u_{it}$ contains both a cross-sectional specific, time-invariant disturbance, as well as cross-sectional and time-variant disturbance and can be modelled as such, giving:

$$u_{it} = \mu_i + v_{it}, \tag{5}$$

where $\mu_i$ is the individual specific variance and $v_{it}$ is the cross-sectional and time-variant disturbance.

Panel data regression has been used frequently in the areas of finance and investment, going back as far as Kuh (1959) who states that analytical advantages can be achieved by modelling both time series and cross-sectional estimates simultaneously.

### 3.2.1 FIXED EFFECTS VERSUS RANDOM EFFECTS

The Fixed Effects model of panel data regression is particularly useful when focusing on a specific set of cross-sections. The model assumes that $\mu_i$ is a static value to be modelled, while $v_{it}$ is stochastic being independently and identically distributed (Baltagi, 2005). Furthermore $x_{it}$ is assumed to be independent of $v_{it}$ for all values of $i$ and $t$.

The Random Effects model assumes that both $\mu_i$ and $v_{it}$ are stochastic in nature and are both independently and identically distributed. In this case both $\mu_i$ and $v_{it}$ are independent of each other and both are independent of $x_{it}$. The Random Effects model is generally used when drawing individuals randomly from a population (Baltagi, 2005).

## 3.3 ARCH/GARCH MODELS

It is possible that the data series being modelled displays volatility clustering (periods of higher or lower volatility) and in fact this is quite common in financial data series. Since deviations from linearity are captured by the error term in the model specification this would cause error terms in the model to be quantifiably larger or smaller based on the value of the error term from the previous period. In order to account for this ARCH, models contain the previous $n$ values of the error term where $n$ is the calculated number of lags of the error term needed in order to fully capture the moving average nature of the error variance.

ARCH models were first explained by Engle (1982) and have been found to be very powerful in predicting and explaining innovations in time series' such as financial data. Engle (1982) suggested many reasons for the need of ARCH models, including the observation by McNees (1979) that the difficulty in accurately portraying randomness changes through time. Engle (1982) also notes that when the mean is modelled using a standard regression, the variance is automatically assumed to be constant.

ARCH models have been found to be very effective in modelling several economic phenomena such as inflation. Engle (1982) applies a GARCH model to inflation in Britain. Results showed highly significant ARCH effects and the applied ARCH model was found to be far more accurate in predicting inflationary dynamics than an unrestricted regression. Engle (1983) makes the point that the majority of the welfare loss related to inflation is due to the lack of predictability of inflation. He goes on to apply an ARCH model to US inflation time series data, finding greater predictability than moving variances, rolling regressions and other measures. ARCH models were even able to predict inflation in the high inflation volatility period during the seventies.

Engle, Lilien and Robins (1987) extend the ARCH specification of Engle (1982) by allowing the mean of the model to be determined by the conditional volatility as opposed to the conditional volatility only affecting future conditional volatility. The extension – called the ARCH-in-Mean (ARCH-M) – is applied to interest rate data and is found to predict the term structure of interest rates with great accuracy.

Domowitz and Hakkio (1985) apply an ARCH model to the market forecast errors of several currencies in an attempt to identify risk premia. They find ARCH effects in some but not all of the currencies and the results indicate the existence of a risk premium for the United Kingdom and Japan but not Germany, France or Switzerland. An ARMA model including ARCH errors is specified by Weiss (1984) in tests of 16 different economic time series'. In some, but not all, of these series' the conditional variance of the errors was well explained using ARCH effects, indicating that the series variance was influenced by past variance. However, Weiss (1984) notes that the ARCH model on occasion acts as an alternative to log transformations of the data.

A GARCH model introduces a lag of the error variance itself to the specification of the error variance. This is appropriate when the error variance follows an autoregressive process as well as a moving average process. The GARCH model was introduced by Bollerslev (1986) in an attempt to create a more flexible ARCH model. As Bollerslev (1986) notes, the ARCH model typically imposes a fixed lag structure in order to avoid problems with negative variance parameter estimates. By allowing a lagged conditional variance parameter in the specification of the conditional variance, Bollerslev (1986) asserts that a longer memory is allowed and the lag structure becomes more flexible.

## 3.4 SUMMARY

The methodologies used are common among the study of financial time-series as well as volatility modelling: ARCH/GARCH models being used extensively in volatility modelling to account for volatility clustering and panel regression models being used to determine both cross-sectional and time-series effects simultaneously. However there are several minor deviations from these standard procedures which have to be considered. To that end, the data will have to be tested to determine the correct specification of each methodology to use.

# 4. DATA AND METHODOLOGY

The data and methodology approach was separated into five different steps, which included data analysis, data collection, pre-processing and model estimation. The data analysis phase involved determining which countries and industries should be included in the analysis by considering the available data. Once the applicable sample was decided on the process of collecting the data was undertaken as described in the data collection section. Pre-processing, which involved cleaning the data as well as forming portfolios, was conducted once the data was available. Model estimation is the application of the models against the data and is split further into GARCH model estimation and panel data regression model estimation due to the use of both models in the statistical analysis.

## 4.1 DATA PRE-ANALYSIS

The sample period ranged from January 1995 to December 2015, spanning a total of 21 years. However, there were cases where an industry had not existed in a country for the entire period, in which case the sample was simply reduced for that series. In determining which countries should be included the independent variable – the Hofstede (2001) Individualism Index – was examined. It was decided that two countries with a high individualism index and two with a low individualism index should be included. A fifth country with an index value between the other two groups (between 55 and 65), was also included. This results in a data set of five countries including the United States of America (high), the United Kingdom (high), China (low), Taiwan (low) and South Africa (middle). The individualism indexes in order of highest to lowest, as well as the market used to represent the country, are given in table 1 below.

*Table 1 - Country, Representative Market and Individualism index in descending order of individualism*

| **Country** | **Market** | **Index Value** |
|---|---|---:|
| The United States of America | New York Stock Exchange | 91 |
| The United Kingdom | London Stock Exchange | 89 |
| The Republic of South Africa | Johannesburg Securities Exchange | 65 |
| China | Shanghai Stock Exchange | 20 |
| Taiwan | Taiwan Stock Exchange | 17 |

Industry selection was slightly more difficult in that it was a more subjective decision. The selected industries should represent areas which could hypothetically be more affected by behavioural biases and those which could be less affected. It was assumed that industries with less physical assets and more intangible assets would be more affected by behavioural biases since the valuation of such a company is more subjective. To that end, the pharmaceuticals and biotechnology industry was included since companies in this industry have large numbers of patents and other intellectual property which is a large source of income for the company. The same can be said for the software and computer services industry. Industries with more easily valuable assets should be less affected by behavioural biases such as banks, mining and oil & gas producers' industries, since a large portion of their assets are valued on easily accessible markets. However, since the assets in question have volatility in and of themselves, industry level volatility will have to be corrected for the volatility of the underlying assets. Lastly the mobile telecommunications industry is included since the companies in this industry have large amounts of tangible assets, which, while less easy to value, are also less volatile in value. The difference between the three types of industries can be seen in figures 1-3 below which plot volatility – not returns – on the Y-axis.[1]

---

[1] The total industry volatility (across all countries) for the figures which follow was calculated by creating a total industry (across all 5 countries) portfolio with the use of a market weighted share price for each industry and calculating the monthly standard deviation.

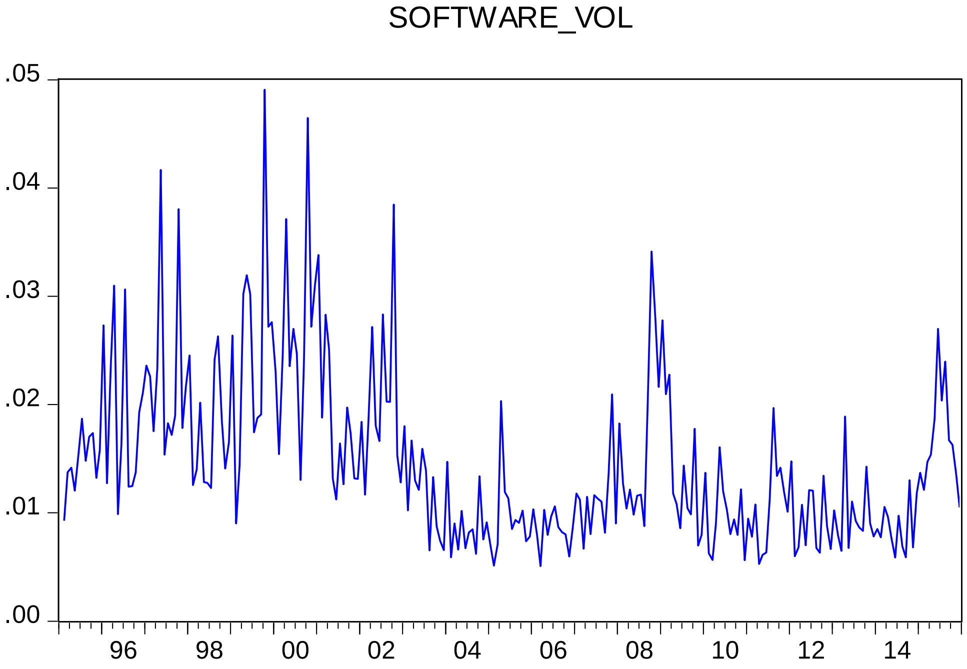


*Figure 1-Volatility of the Software and Computer Services industry across all 5 countries between 1995 and 2015*

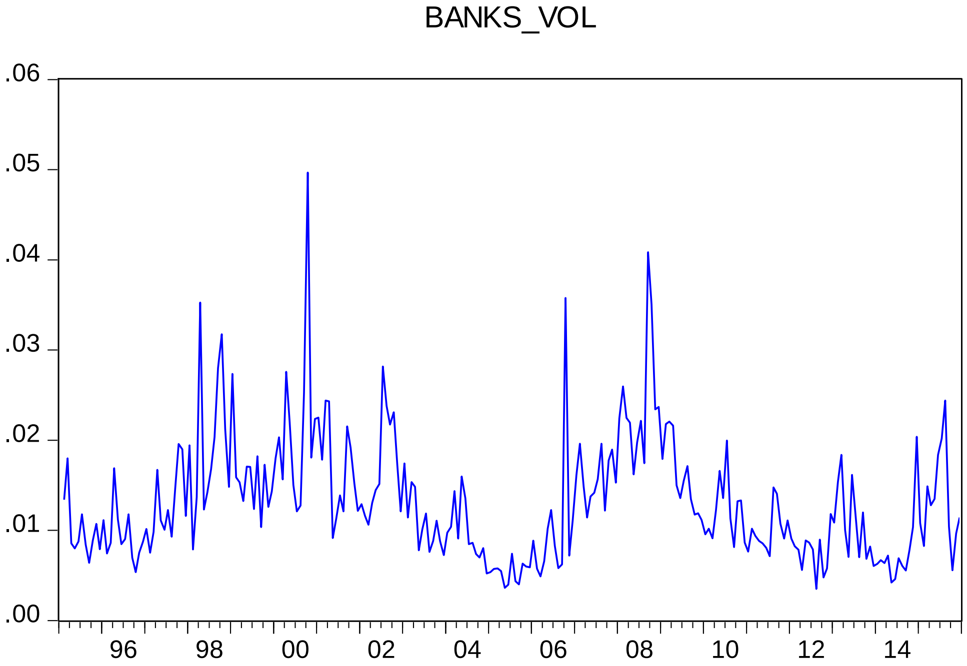


*Figure 2-Volatility of the Banks industry across all 5 countries between 1995 and 2015*

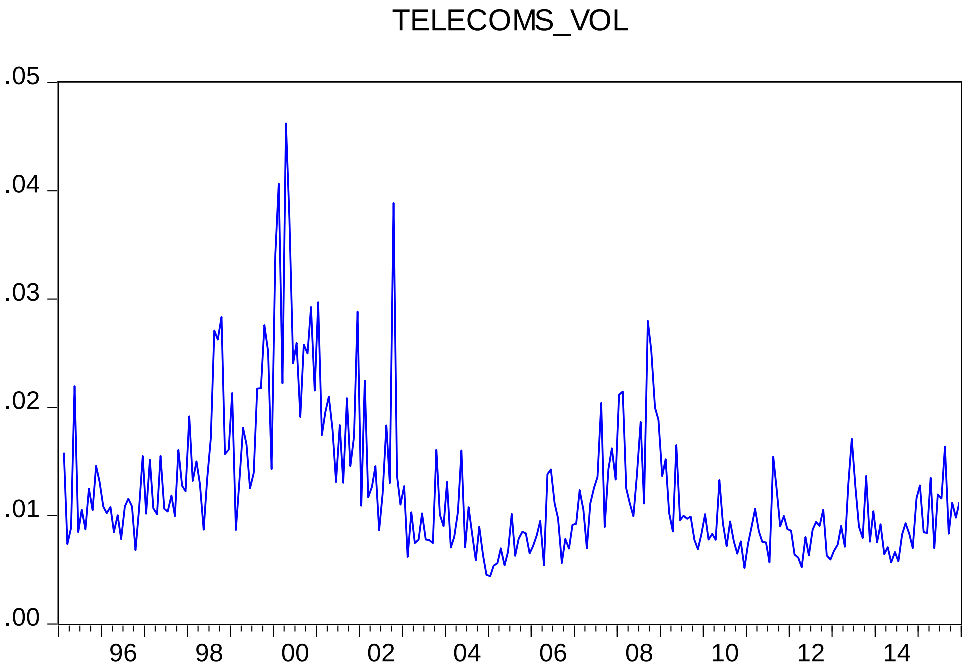


*Figure 3-Volatility of the Mobile Telecommunications industry across all 5 countries between 1995 and 2015*

The sample period was selected to limit the effect of any tumultuous market periods which may affect industries differently. For instance, the software and computer services industry is expected to be more volatile during the Dotcom bubble of 2000 while the banks industry should be more volatile during the 2007 Financial Crisis. This is evident in figures 4 and 5 below.

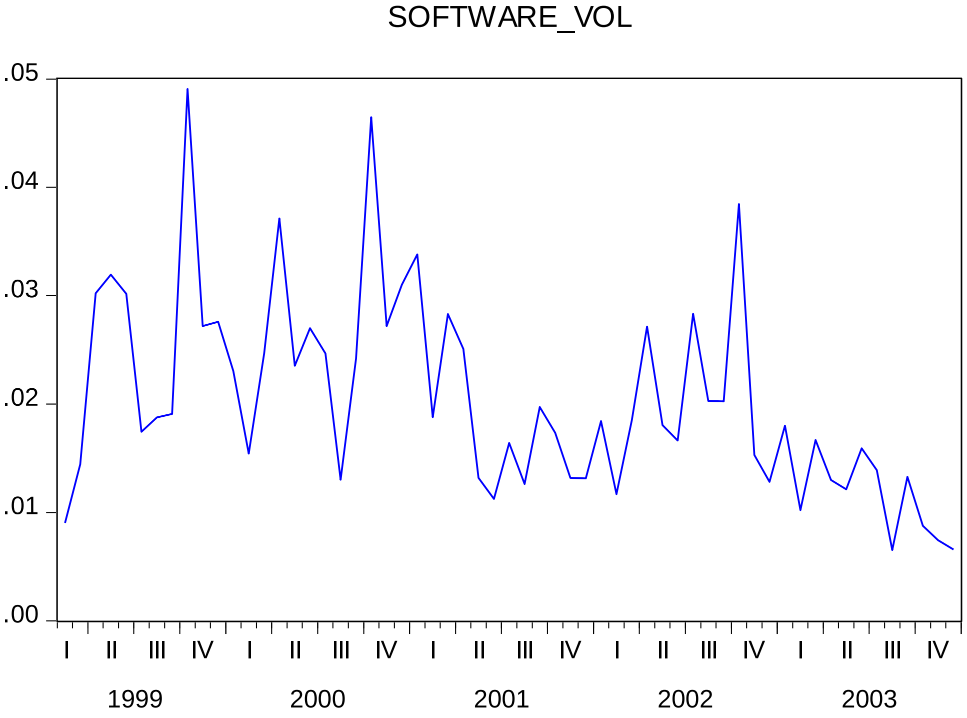


*Figure 4 - Volatility of the Software and Computer Services industry over the period 1999 - 2003 indicating the Dotcom Bubble*

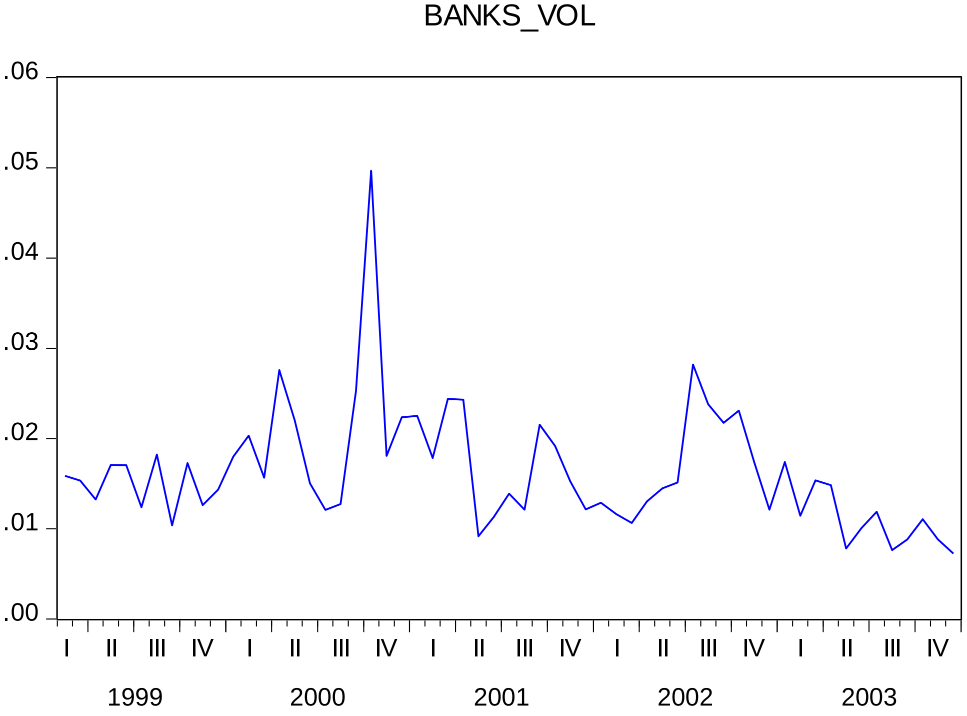


*Figure 5-Volatility of the Banks industry over the period 1999 - 2003 indicating the Dotcom Bubble*

It can plainly be seen that the software and computer services industry was more volatile over the period. When looking at the same two industries over the period 2007 – 2010, one can also clearly note that the banks industry is more volatile (note that the scales are different).

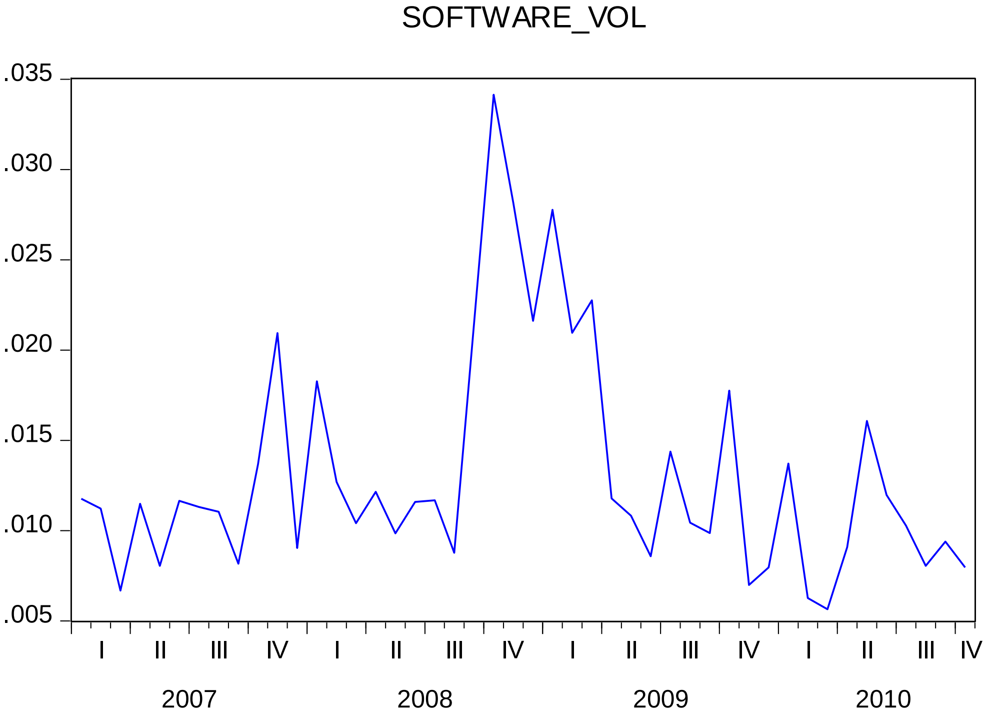


*Figure 6-Volatility of the Software and Computer Services industry over the period 2007 - 2010 indicating the Subprime Mortgage Crisis*

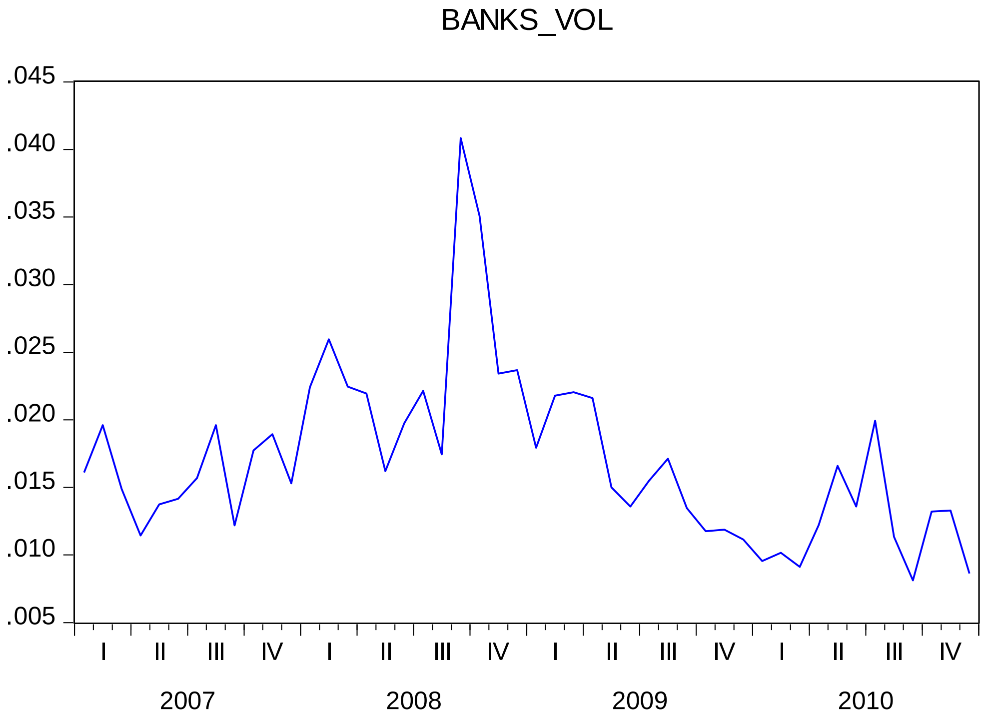


*Figure 7-Volatility of the Banks industry over the period 2007 - 2010 indicating the Subprime Mortgage Crisis*

Other variables to be included in the regression analysis are global volatility, volatility of spot gold prices and spot oil prices in order to account for volatility occurring due to factors other than individualism.

## 4.2 DATA COLLECTION

This section focuses on the sourcing of the data which is partially specified above. The first obstacle in collecting the correct data was determining the most accurate manner of representing an industry. At first industry index returns were collected, however some of the markets did not maintain industry indexes and of those that did there were on occasion entire industries missing. Further, none of the markets maintained a market cap for industry indexes since it is merely an index. It was then decided that to accurately represent an industry it would be required to determine the securities which make up the industry and then to collect the required data for each of these securities and aggregate them to the industry level. To that end the EQS function of Bloomberg Terminal was used to determine which shares were allocated to each of the six industries in each of the five markets. This analysis was done by using the ICB industry classification for each of the companies. The result was a total of 2000 securities for which the information was collected.

The information which was required included the closing share price at a daily frequency, the market capitalisation on a daily basis and the daily trade volume – dividend information was not included. Once the required data was collected the market industry portfolios could be created. Firstly, each of the shares was conformed to a single date set. This was generally different between each market due to the existence of differing exchange holidays and trading rules. However, within a market it was required that all securities conform to a single date set. This was achieved by removing dates where data was missing or inserting data where required. Inserted data was either an extension of the data from previous trade dates or future trade dates and never included share prices. For example, where a market capitalisation or trading volume was missing for a share the market capitalisation or trading volume from the previous day (or following day depending on data availability) was inserted. However, where a shares price was missing for several shares, then that date would be excluded from the set. Since the market capitalisation was used merely for industry portfolio construction, minor differences between the data and reality had little consequence.

Once the data was conformed industry portfolios were constructed by summing the market capitalisations of all the securities within the industry for a given date and then dividing the security specific market capitalisation of each security by this cumulative market capitalisation to give a portfolio weight to each security. The equation is given here:

$$W_x = {}^{MC_x}\!/_{MC_i}, \tag{6}$$

where $W_x$ is the portfolio weight of the specific security, $MC_x$ and $MC_i$ are the market capitalisation of the security and the portfolio respectively.

Once the portfolio weights were determined, the portfolio price could be calculated by summing the products of the individual security prices and weights as below.

$$P_i = \sum_{x=1}^{m} P_x . W_x, \tag{7}$$

where $P_i$ is the industry portfolio price, $P_x$ is the individual share price and $m$ is the number of shares in an industry.

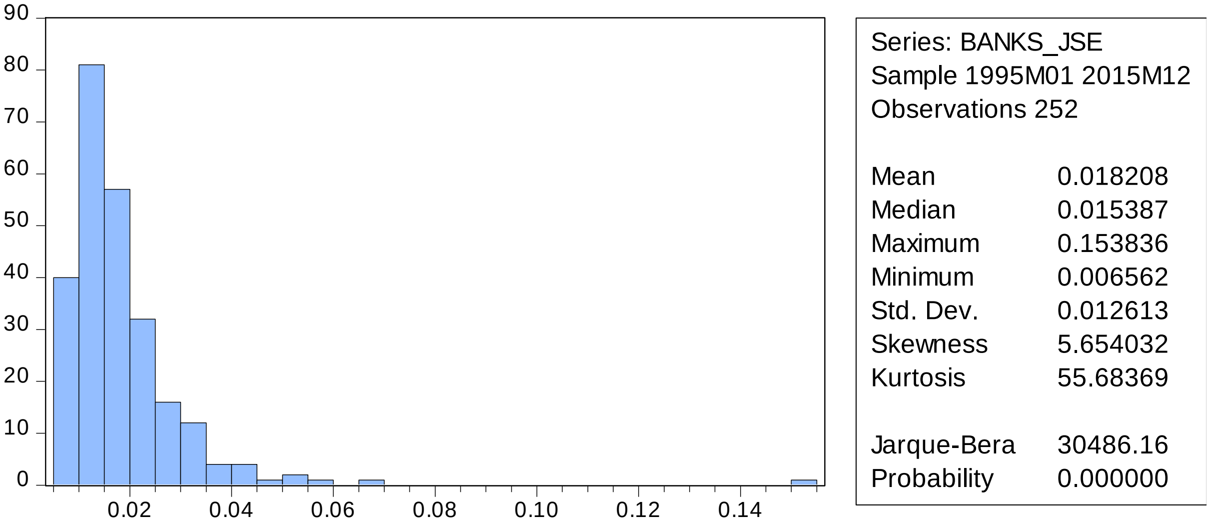
Industry trade volume was created simply by summing the trade volumes of each of the constituent shares. A monthly industry volatility was created by taking the standard deviation of all of the industry log returns (calculated as $\ln({}^{P_t}/_{P_{t-1}})$) for each calendar month during the period, resulting in 252 observations per market industry portfolio of which there were 29 (since there is no mining industry in Taiwan). This gives a total of 7308 observations across the entire sample for each of industry volatility, market capitalisation and trade volume. This industry volatility becomes the dependent variable of all of the specifications, which aligns with the specifications used by Chui, Titman and Wei (2010).

## 4.3 PRE-PROCESSING

Before statistical models could be applied to the data, the distributions of the data must be analysed and transformations applied where necessary. The distributional factors which are investigated include the normality, independence and stationarity of the volatility series. These tests need to be carried out on each of the 29 series; however, since the GARCH model will be run on the industries as a whole and not on individual series', several panel unit root tests will also be carried out to test for stationarity across the entire industry. The panel unit root tests include the Levin, Lin and Chu (2002) and the Breitung (2000) unit root tests which test for a common unit root across cross-sections and the Im, Pesaran and Shin (2003), Augmented Dickey-Fuller and Phillips-Perron tests which test for individual unit roots within cross-sections.

### 4.3.1 NORMALITY

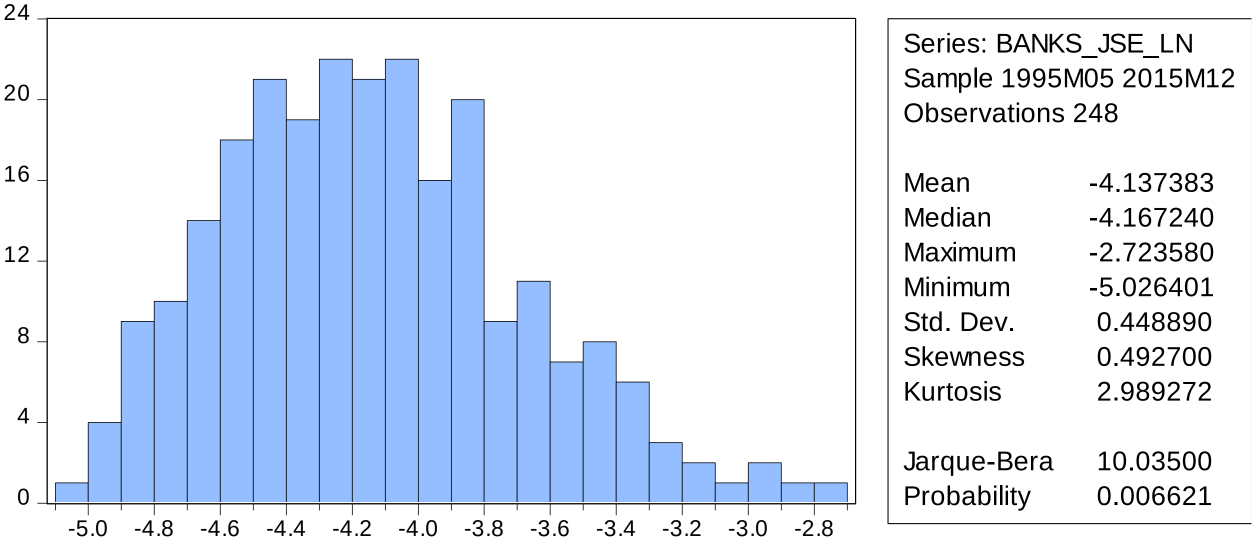
While GARCH modelling techniques can estimate a model using different distributions, in order to accurately apply a GARCH model to a data set the data set should be distributed similarly to the normal distribution. In order to determine the normality of the data set, a frequency distribution histogram is examined as well as descriptive statistics and the results of the Jarque-Bera test for normality. Below is a sample of the histogram and descriptive data analysis from the JSE banks industry.



```
Series: BANKS_JSE
Sample 1995M01 2015M12
Observations 252

Mean           0.018208
Median         0.015387
Maximum        0.153836
Minimum        0.006562
Std. Dev.      0.012613
Skewness       5.654032
Kurtosis       55.68369

Jarque-Bera    30486.16
Probability    0.000000
```

*Figure 8-Frequency Distribution Histogram and Descriptive Statistics of the Banks industry on the JSE*

As can be seen from figure 8 above, the volatility is far right skewed and the Jarque-Bera test for normality results in a value of 30486.16 and a p-value of 0, rejecting the null hypothesis that the series is normally distributed. In order to rectify the data, the same methodology of Christiansen, Schmeling and Schrimpf (2012) is applied, whereby a log transformation is used on the volatility data. The results as can be seen below, greatly improve the distribution of the data.



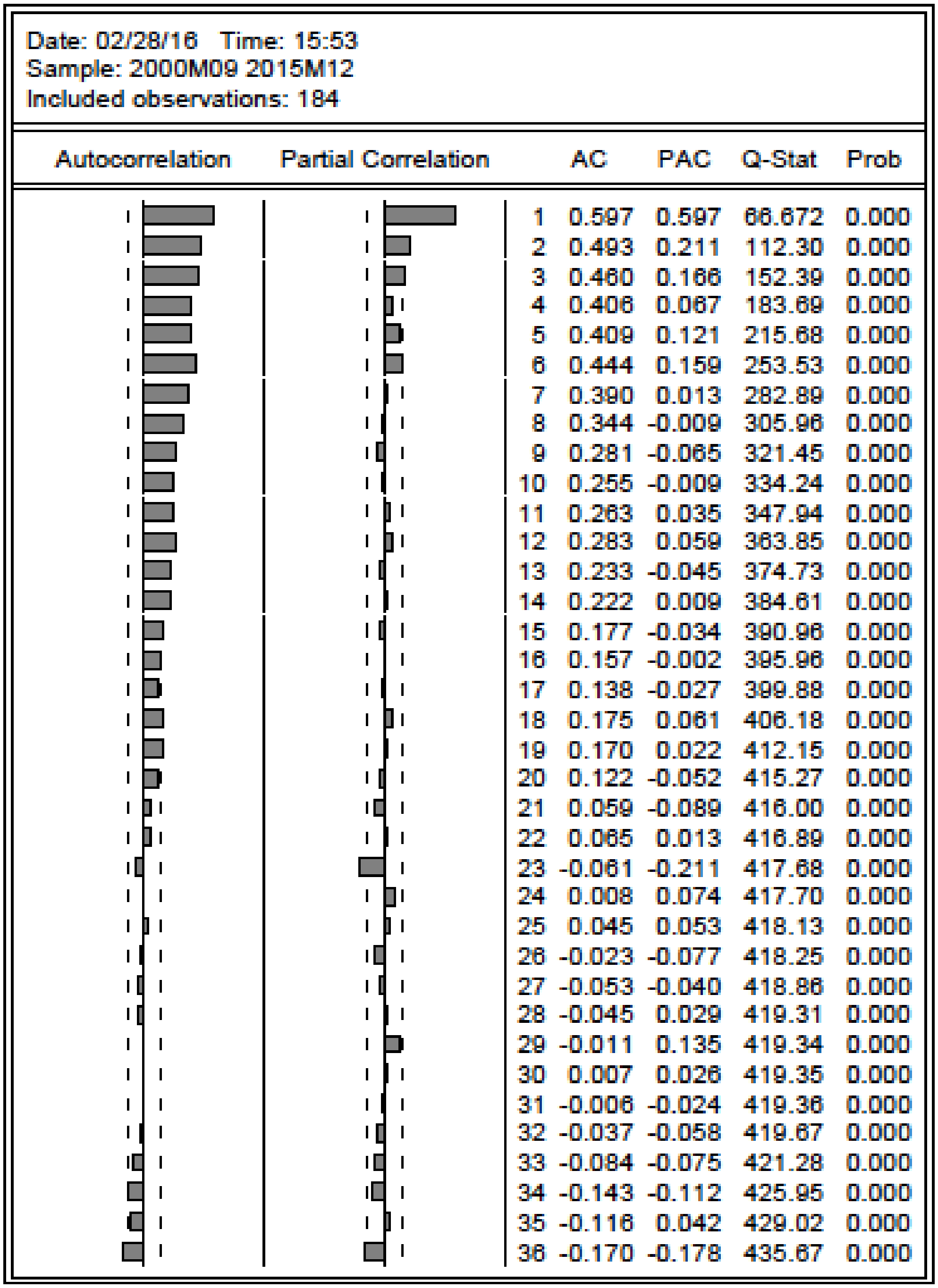
```
Series: BANKS_JSE_LN
Sample 1995M05 2015M12
Observations 248

Mean           -4.137383
Median         -4.167240
Maximum        -2.723580
Minimum        -5.026401
Std. Dev.       0.448890
Skewness        0.492700
Kurtosis        2.989272

Jarque-Bera     10.03500
Probability     0.006621
```

*Figure 9-Frequency Distribution Histogram and Descriptive Statistics of the Banks industry on the JSE after Log Transformation*

The p-value of the Jarque-Bera test is now 0.093035, which does still reject the null hypothesis of normality at the 10% level but cannot reject the null hypothesis of normality at the 1% or 5% levels.

### 4.3.2 INDEPENDENCE

In order to test for independence, the correlogram of each of the series' was examined. An independently distributed time series is one in which an observation of the time series is not related to any of the observations before. This should be indicated by little to no autocorrelation. As can be seen in figure 10 below the autocorrelation only dissipates between the 20th and 23rd lag. However, the partial correlation which controls for all values of the time series at shorter lags drops off after the 3rd lag. While these are not great results we cannot reject the idea of independence based on this.



```
Date: 02/28/16   Time: 15:53
Sample: 2000M09 2015M12
Included observations: 184

Autocorrelation   Partial Correlation       AC     PAC    Q-Stat   Prob

                                       1   0.597   0.597  66.672  0.000
                                       2   0.493   0.211  112.30  0.000
                                       3   0.460   0.166  152.39  0.000
                                       4   0.406   0.067  183.69  0.000
                                       5   0.409   0.121  215.68  0.000
                                       6   0.444   0.159  253.53  0.000
                                       7   0.390   0.013  282.89  0.000
                                       8   0.344  -0.009  305.96  0.000
                                       9   0.281  -0.065  321.45  0.000
                                      10   0.255  -0.009  334.24  0.000
                                      11   0.263   0.035  347.94  0.000
                                      12   0.283   0.059  363.85  0.000
                                      13   0.233  -0.045  374.73  0.000
                                      14   0.222   0.009  384.61  0.000
                                      15   0.177  -0.034  390.96  0.000
                                      16   0.157  -0.002  395.96  0.000
                                      17   0.138  -0.027  399.88  0.000
                                      18   0.175   0.061  406.18  0.000
                                      19   0.170   0.022  412.15  0.000
                                      20   0.122  -0.052  415.27  0.000
                                      21   0.059  -0.089  416.00  0.000
                                      22   0.065   0.013  416.89  0.000
                                      23  -0.061  -0.211  417.68  0.000
                                      24   0.008   0.074  417.70  0.000
                                      25   0.045   0.053  418.13  0.000
                                      26  -0.023  -0.077  418.25  0.000
                                      27  -0.053  -0.040  418.86  0.000
                                      28  -0.045   0.029  419.31  0.000
                                      29  -0.011   0.135  419.34  0.000
                                      30   0.007   0.026  419.35  0.000
                                      31  -0.006  -0.024  419.36  0.000
                                      32  -0.037  -0.058  419.67  0.000
                                      33  -0.084  -0.075  421.28  0.000
                                      34  -0.143  -0.112  425.95  0.000
                                      35  -0.116   0.042  429.02  0.000
                                      36  -0.170  -0.178  435.67  0.000
```

*Figure 10-Correlogram of the Log transformed volatility of the Banks industry on the JSE*

### 4.3.3 STATIONARITY

Stationarity refers to the premise that the mean, variance and autocorrelation structure do not change over time. A simple manner to determine this is by looking at a line graph of the time series and examining the mean and variance of the series, which is done below for the JSE banks industry. Tests for stationarity test either for a unit root in the data or for stationarity itself. Three stationarity tests including the Augmented Dickey-Fuller unit root test, the Phillips-Perron unit root test and the Kwiatkowski-Phillips-Schmidt-Shin stationarity test are employed.

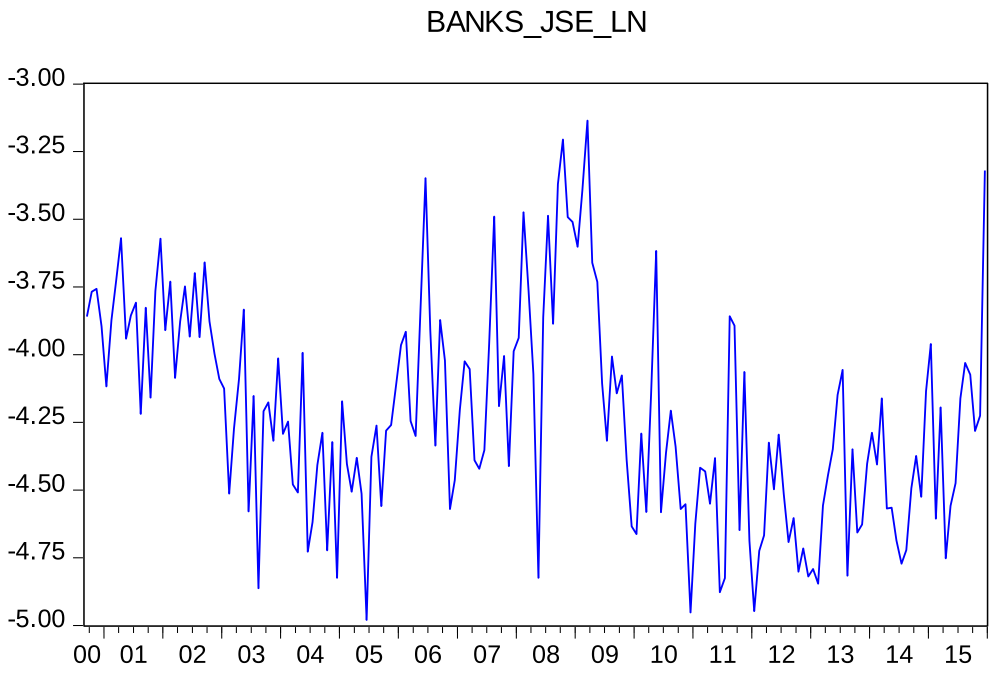


*Figure 11 - Line graph of the Log transformed volatility of the Banks industry on the JSE*

As can be seen from figure 11 above, both the mean and variance appear to change over time. However, it is still possible that the series is statistically stationary. In table 2 below are the formal stationarity test results, again for the JSE banks industry.

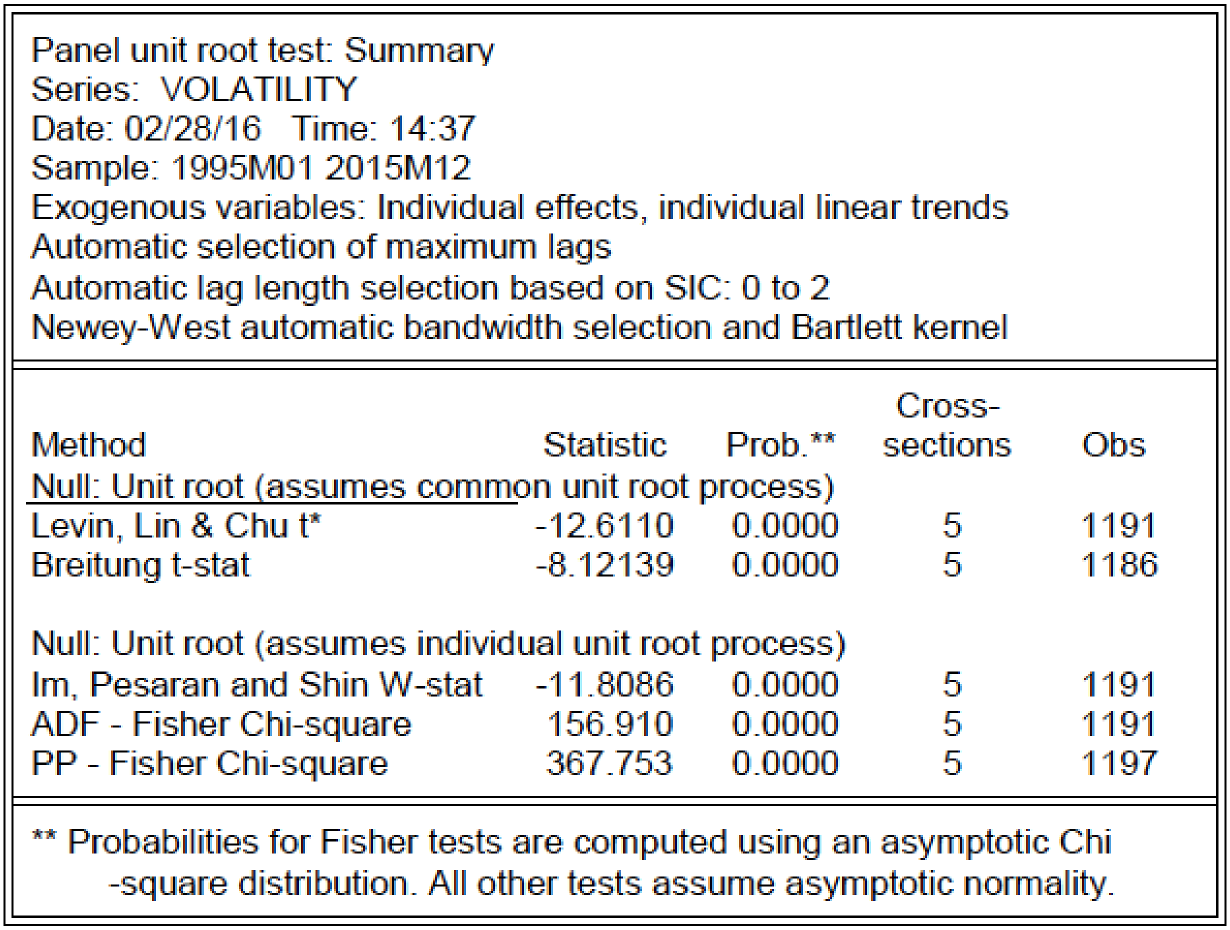
*Table 2-Unit root test results for the Banks industry of the JSE*

| **Test** | **Test Statistic** | **1% Critical Value** | **5% Critical Value** | **10% Critical Value** |
|---|---|---|---|---|
| ADF | -5.026986 | -4.008706 | -3.434433 | -3.141157 |
| PP | -7.318497 | -4.008706 | -3.434433 | -3.141157 |
| KPSS | 0.106217 | 0.216000 | 0.146000 | 0.119000 |

The null hypothesis of both the Augmented Dickey-Fuller and the Phillips-Perron tests is that the data series contains a unit root. As can be seen in both of the first two rows above, the null hypothesis can be rejected at the 1% level since the test statistics of both tests are larger than the 1% critical values, with p-values of 0.0003 and 0 for the Augmented Dickey-Fuller and the Phillips-Perron respectively. Thus it can be determined that the data series does not have a unit root. The Kwiatkowski-Phillips-Schmidt-Shin tests the null hypothesis that the series *is* stationary. Therefore if the Kwiatkowski-Phillips-Schmidt-Shin test statistic is larger than the asymptotic critical values calculated by the test then the null hypothesis of stationarity can be rejected and it can be concluded that the series is non-stationary. However, it can be seen in the above results that the Kwiatkowski-Phillips-Schmidt-Shin test statistic is below the asymptotic critical values at the 10%, 5% and 1% significance level and therefore the null hypothesis of stationarity cannot be rejected. It is found that many of the series’ are non-stationary; however since the series’ are modelled together, it is the stationarity of the industries as a whole – across the different markets – which is important.

Panel data was created by using the market as the cross-section indicator variable. A summary of unit root results was obtained from EViews 9, the null hypothesis of all tests being that a unit root exists in the data, either individually or commonly across cross-sections. An example of the results is included below.

*Table 3 - Summary of Panel Unit Root test results for the Banks industry*



```
Panel unit root test: Summary
Series:  VOLATILITY
Date: 02/28/16   Time: 14:37
Sample: 1995M01 2015M12
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 2
Newey-West automatic bandwidth selection and Bartlett kernel

                                                        Cross-
Method                              Statistic  Prob.**  sections   Obs
Null: Unit root (assumes common unit root process)
Levin, Lin & Chu t*                 -12.6110   0.0000      5       1191
Breitung t-stat                     -8.12139   0.0000      5       1186

Null: Unit root (assumes individual unit root process)
Im, Pesaran and Shin W-stat         -11.8086   0.0000      5       1191
ADF - Fisher Chi-square              156.910   0.0000      5       1191
PP - Fisher Chi-square               367.753   0.0000      5       1197

** Probabilities for Fisher tests are computed using an asymptotic Chi
    -square distribution. All other tests assume asymptotic normality.
```

Table 3 above illustrates that all p-values for tests of unit roots are essentially 0, allowing us to reject the null hypothesis that the series contains a unit root. According to these results, the data series' are stationary and therefore a GARCH model can be applied.

## 4.4 MODEL ESTIMATION

The data is modelled in 2 phases – GARCH model estimation and Linear Regression estimation. The purpose of the GARCH model is to remove conditional heteroscedasticity from the series'. The resulting residuals are then used as the dependent variable in the Linear Regression estimation. This should result in a more accurate description of the relationship between volatility and individualism since a large proportion of the time varying nature of volatility should be removed through the application of a GARCH model, aligning with the (time invariable) individualism index better.

The returns of each of the series are calculated as the natural logarithm of the current observation divided by the previous observation or, specified mathematically as:

$$\ln\left({}^{S_t}/{}_{S_{t-1}}\right), \tag{8}$$

where $S_t$ and $S_{t-1}$ are the share price at time $t$ and $t-1$ respectively. Volatility of industry returns are calculated as

$$\sigma_{jqm} = \frac{\sum_{t=1}^{k_m}(R_{jqt} - \overline{R_{jqm}})^2}{k_m}, \tag{9}$$

where $\sigma_{jqm}$ is the standard deviation of returns of industry $j$ in country $q$ in month $m$, $k_m$ is the number of days within month $m$, $R_{jqt}$ is the return for industry $j$ in country $q$ at time $t$ and $\overline{R_{jqm}}$, which represents the average return for industry $j$ in country $q$ in month $m$, is calculated as $\overline{R_{jqm}} = \frac{\sum_{t=1}^{k} R_{jqt}}{k}$.

### 4.4.1 GARCH MODEL ESTIMATION

A GARCH (1, 1) model is applied after consideration of the Akaike Information Criterion of several different specifications. The GARCH (1, 1) model is also widely considered to contain a sufficient number of lags of both the conditional variance and residuals for most time series data. The GARCH model specification is given below.

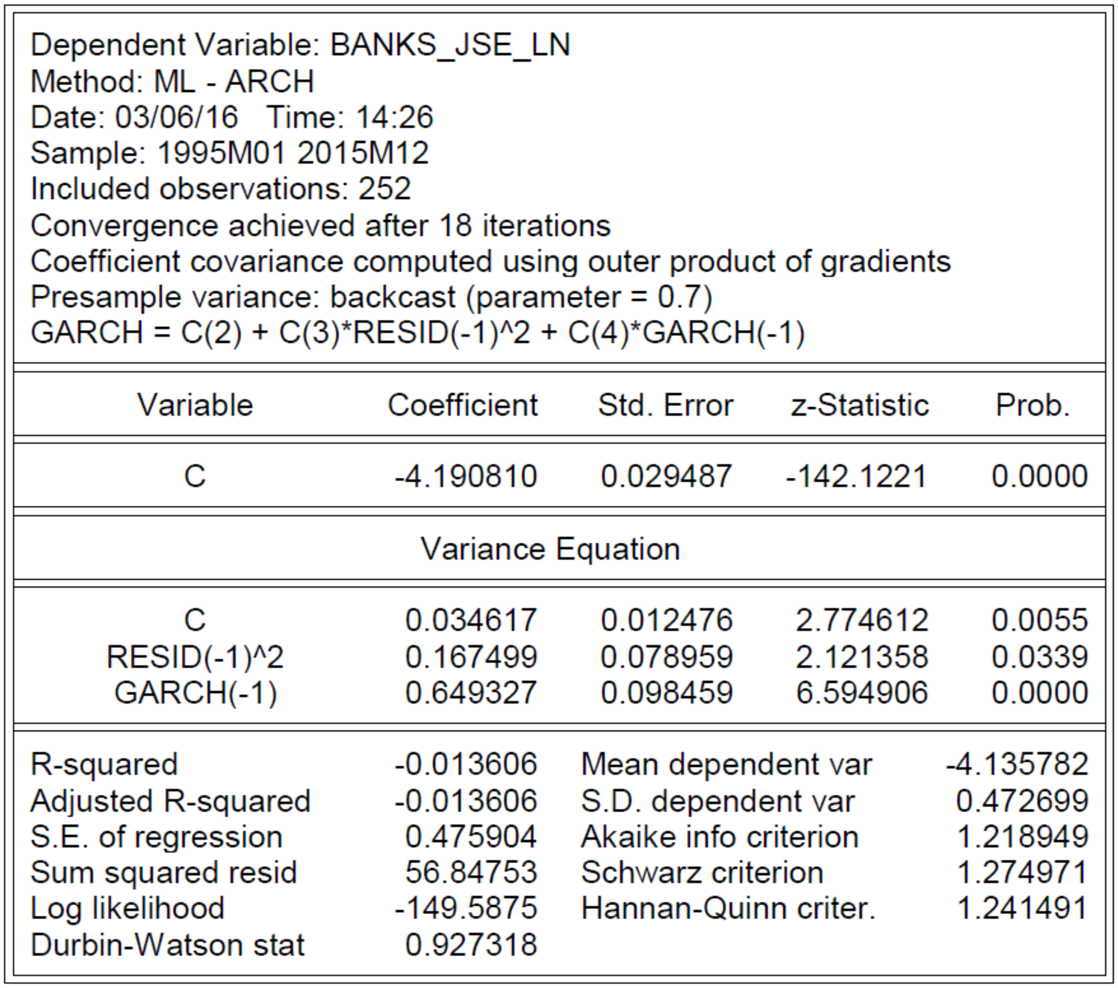
$$h_t = \alpha + \sum_{p=1}^{P} \gamma_p \varepsilon_{t-p}^2 + \sum_{q=1}^{Q} \lambda_q h_{t-q}, \tag{10}$$

where $\gamma_p$ is the regression coefficient of the squared lagged residual at time $t - p$ (in this case $p = 1$), $\lambda_q$ is the regression coefficient of the lagged conditional volatility at time $q$ (also $= 1$) and $h_t$ is the conditional variance of the error term, $\varepsilon$, and $\varepsilon_t$ is modeled as

$$\varepsilon_t = v_t \sqrt{h_t}, \tag{11}$$

where $v_t$ is white noise and the variance of such is equal to 1. This model is run on all volatility series' since they show signs of heteroscedasticity. Several of the other regressors – namely the volatility of the MSCI World Index, spot gold price and spot oil price – are also modelled using GARCH effects due to their frequency distributions. A Normal distribution is assumed for the GARCH model since almost all of the time series' examined earlier were considered to be normally distributed through statistical analysis. No other changes were made to the standard GARCH specification on EViews. An example of the output of one of the GARCH models is given below:

*Table 4 - GARCH Model results for the Banks industry of the JSE*



```
Dependent Variable: BANKS_JSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:26
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable          Coefficient    Std. Error    z-Statistic    Prob.

            C              -4.190810     0.029487      -142.1221     0.0000

                          Variance Equation

            C               0.034617     0.012476      2.774612      0.0055
       RESID(-1)^2          0.167499     0.078959      2.121358      0.0339
        GARCH(-1)           0.649327     0.098459      6.594906      0.0000

R-squared                  -0.013606    Mean dependent var        -4.135782
Adjusted R-squared         -0.013606    S.D. dependent var         0.472699
S.E. of regression          0.475904    Akaike info criterion      1.218949
Sum squared resid           56.84753    Schwarz criterion          1.274971
Log likelihood             -149.5875    Hannan-Quinn criter.       1.241491
Durbin-Watson stat          0.927318
```

As can be seen from table 4 the model itself is not particularly powerful, with a negative R-Squared. It should be taken into account that the R-Squared value is a test of the mean equation whereas a GARCH model is a specification of the conditional volatility; therefore the R-Squared is not particularly important in determining goodness of fit. However, the intercept variable and the lagged conditional variance variable are both statistically significant at the 1% level and the lagged squared residual variable is significant at the 5% level. In order to test the efficacy of the GARCH analysis in removing GARCH effects the squared residuals were examined, specifically the correlogram of the squared residuals. Upon examination, any autocorrelation had been removed from the series. These residuals were then used in the regression analysis.

### 4.4.2 PANEL DATA REGRESSION

The residuals of the GARCH models were used in a panel data regression against several different independent variables which are discussed below. The data was organised into six different panel data sets, one for each industry, the cross-sectional variable being the market which the series represents. The data sets included the industry volatility residuals as the dependent variable, the individualism index for each country, the GARCH residuals of the MSCI World Index and the total market capitalisation of the market-industry series. Other regressors were also applied where necessary meaning that the specification was not the same for all series'. For example, the oil & gas producers sector was modelled against the spot oil price. The specifications are given below:

<u>Banks, Mobile Telecommunications, Pharmaceuticals & Biotechnology and Software & Computer Services:</u>

$$\sigma_{qmk} = c + Ind_q + MC_{qm} + \sigma_{wm} + \sigma_{qm-1k} + \varepsilon_m, \tag{12}$$

where $\sigma_{qmk}$ is the residual of the natural log of volatility of industry $k$ in country $q$ in month $m$, $Ind_q$ is country $q$'s individualism index, $MC_{qm}$ is the market capitalisation of country $q$ in month $m$, $\sigma_{wm}$ is the residual volatility of the MSCI World index in month $m$, $\sigma_{qm-1k}$ is the volatility of industry $k$ in country $q$ in the previous month $(m-1)$ and $\varepsilon_m$ is the error term for month $m$.

Oil & Gas Producers:

$$\sigma_{qmk} = c + Ind_q + MC_{qm} + \sigma_{wm} + \sigma_{om} + \sigma_{qm-1k} + \varepsilon_m \tag{13}$$

The specification for the oil & gas producers' industry is the same as the others except for the inclusion of $\sigma_{om}$, which represents the residual volatility of the spot oil price in month $m$. The volatility of the spot oil price is expected to have an effect on the volatility of oil & gas producers since that is the primary means of income for the majority of the constituent companies of the oil & gas producers industry.

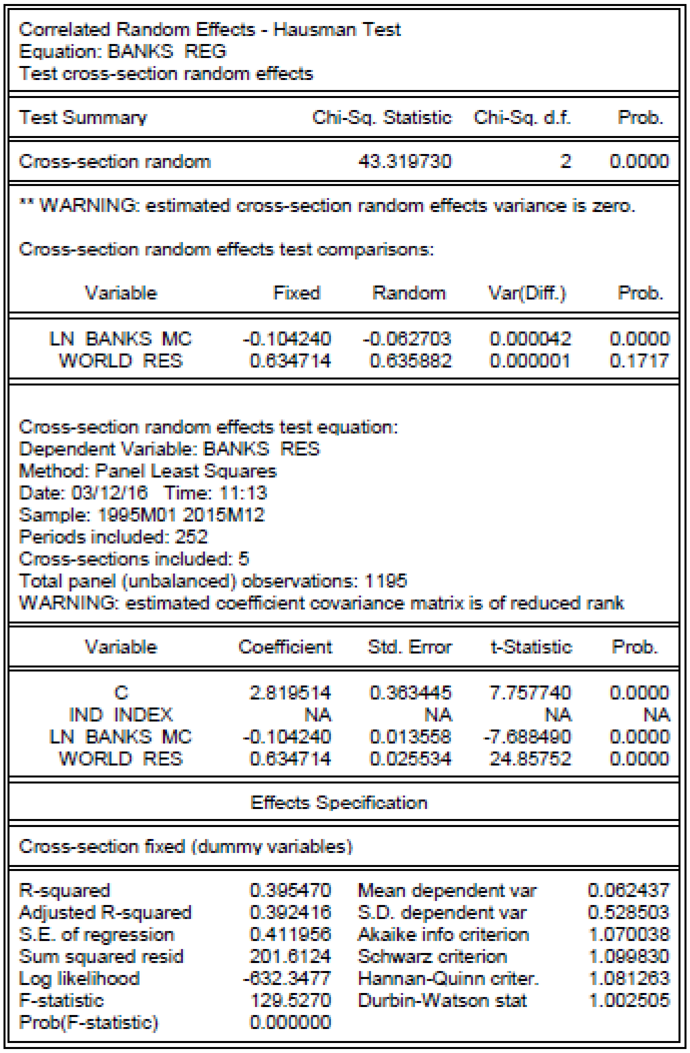
Mining:

$$\sigma_{qmk} = c + Ind_q + MC_{qm} + \sigma_{wm} + \sigma_{gm} + \sigma_{qm-1k} + \varepsilon_m \tag{14}$$

Again, the mining industry only includes the residual volatility of the spot gold price in month $m$ – represented by $\sigma_{gm}$ – as an extra independent variable. The volatility of the spot gold price is again included as it is expected to have a strong effect on the volatility of the mining industry as a whole.

A panel linear regression was used to estimate the different models, using the Least Squares methodology. A Fixed Effects model was initially specified in order to account for unobserved effects caused by variables which are correlated with the covariates. However, this specification resulted in a near singular matrix on all occasions, possibly due to the small number of covariates. A Random Effects model was also considered to account for possible exogenous variables which have no effect on the covariates, which is quite possible in this arena. In order to test if Random Effects models are appropriate, the Hausman Test is conducted on the model output. The Hausman test tests the null hypothesis that Random Effects are consistent with the data. If this is the case then Random Effects should be included in the model since they are consistent and efficient, whereas Fixed effects are inefficient. However, if the null hypothesis is rejected then Random Effects should not be applied to the data. In order to conduct the Hausman test the Random Effects model must first be estimated. Unfortunately, in order to use the Random Effects methodology, the number of cross-sections must be larger than the number of independent variables. This was not the case for the mining industry since there were only 4 cross-sections and 4 regressors. An example of the Hausman test results is given below.

*Table 5 - Hasuman Test results for the Banks panel Regression*



```
Correlated Random Effects - Hausman Test
Equation: BANKS  REG
Test cross-section random effects

Test Summary                   Chi-Sq. Statistic  Chi-Sq. d.f.     Prob.

Cross-section random                   43.319730             2    0.0000

** WARNING: estimated cross-section random effects variance is zero.

Cross-section random effects test comparisons:

        Variable            Fixed        Random     Var(Diff.)      Prob.

      LN  BANKS  MC      -0.104240    -0.062703     0.000042     0.0000
       WORLD  RES         0.634714     0.635882     0.000001     0.1717


Cross-section random effects test equation:
Dependent Variable: BANKS  RES
Method: Panel Least Squares
Date: 03/12/16   Time: 11:13
Sample: 1995M01 2015M12
Periods included: 252
Cross-sections included: 5
Total panel (unbalanced) observations: 1195
WARNING: estimated coefficient covariance matrix is of reduced rank

        Variable          Coefficient    Std. Error    t-Statistic     Prob.

            C              2.819514      0.363445      7.757740      0.0000
        IND  INDEX               NA            NA            NA          NA
      LN  BANKS  MC       -0.104240      0.013558     -7.688490      0.0000
       WORLD  RES          0.634714      0.025534      24.85752      0.0000

                              Effects Specification

Cross-section fixed (dummy variables)

R-squared                  0.395470    Mean dependent var        0.062437
Adjusted R-squared         0.392416    S.D. dependent var        0.528503
S.E. of regression         0.411956    Akaike info criterion     1.070038
Sum squared resid          201.6124    Schwarz criterion         1.099830
Log likelihood            -632.3477    Hannan-Quinn criter.      1.081263
F-statistic                129.5270    Durbin-Watson stat        1.002505
Prob(F-statistic)          0.000000
```

As can be seen from table 5 above the p-value of the Hausman test is equal to 0, allowing us to reject the null hypothesis of the consistency of Random Effects with the data. Fixed Effects were out of the question for this model due to the existence of a variable which does not vary over time – the Individualism Index – and a variable which does not vary between cross-sections – the residuals of the returns to the MSCI World Index. The Hofstede (2001) Individualism Index was only ever created once, resulting in a time-invariant variable. The reason for this is the intense effort that went into collecting and analysing the results of the surveys which were used to conduct the study and produce the index. Therefore, no effects are used when specifying the regression models.

In order to test that the regressors were correctly specified an analysis of the actual versus fitted residuals is undertaken. If regressors are correctly specified, the actual versus fitted residuals plot should be uniformly or linearly distributed. For example, if a regressor requires a square root transformation the residuals will display a cone shape. An example of the actual versus fitted residuals graph is given below. In this case the JSE market has been modelled alone to avoid contamination from the other market series'.

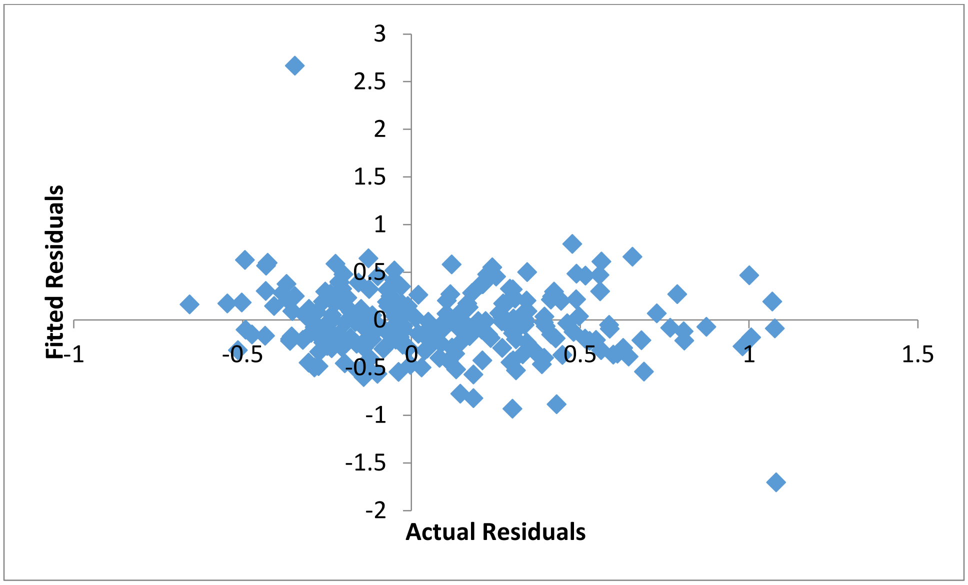
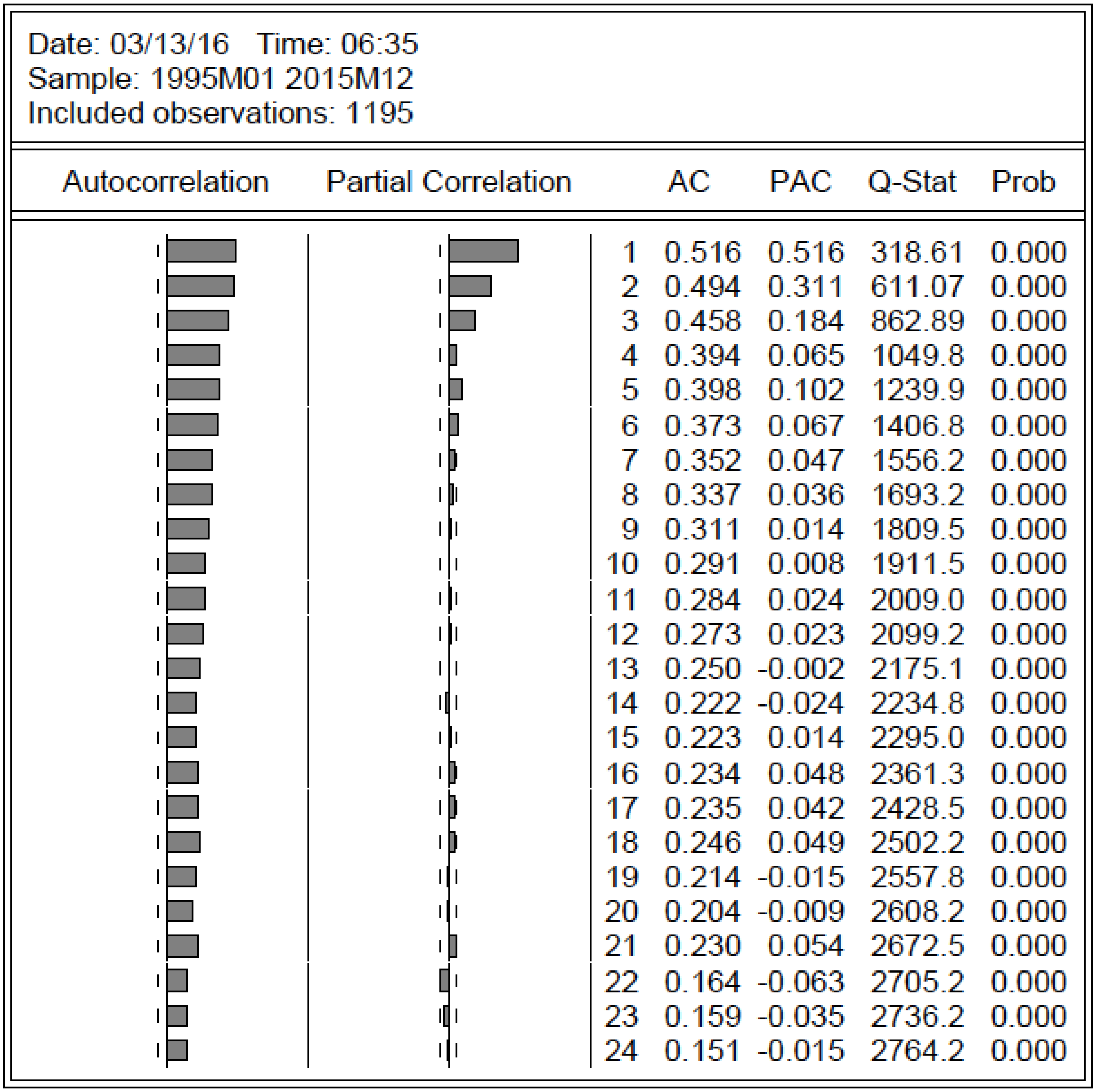


*Figure 12 - Actual verses Fitted Residuals plot for the Banks industry of the JSE*

As can be seen from the residual diagram, figure 12, above, the fitted residuals generally plot in a linear fashion against the actual residuals around the x-axis. The above graph does not tell us enough about the result to make any conclusions of the goodness of fit of the model.

A last test of goodness of fit is to test the correlogram of the residuals for autocorrelation. Below is an example of the correlogram of the residuals of the banks industry using Least Squares regression with no effects, weighting or coefficient covariance methods.

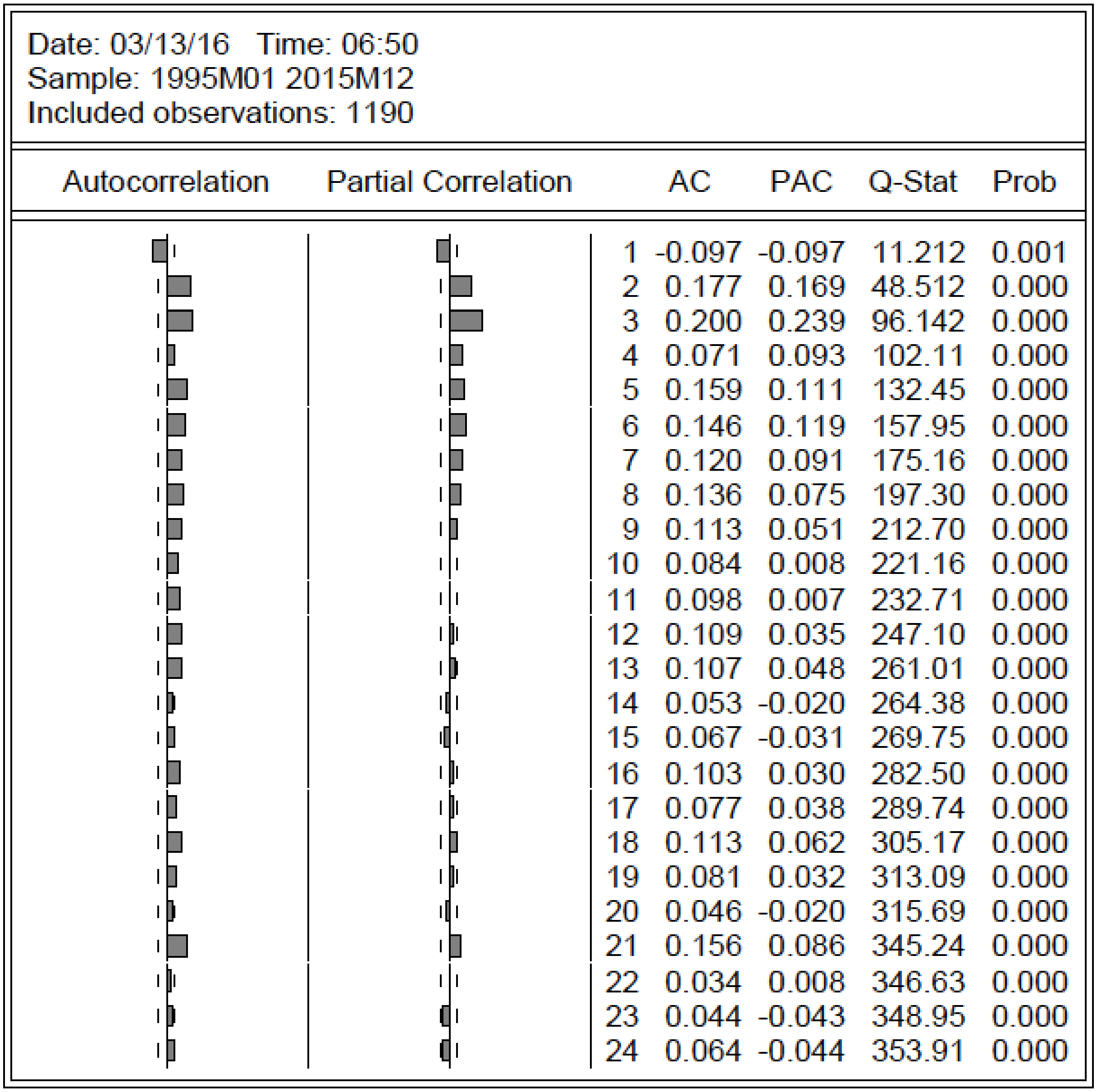


```
Date: 03/13/16   Time: 06:35
Sample: 1995M01 2015M12
Included observations: 1195

Autocorrelation   Partial Correlation        AC     PAC    Q-Stat   Prob

                                        1  0.516   0.516   318.61  0.000
                                        2  0.494   0.311   611.07  0.000
                                        3  0.458   0.184   862.89  0.000
                                        4  0.394   0.065   1049.8  0.000
                                        5  0.398   0.102   1239.9  0.000
                                        6  0.373   0.067   1406.8  0.000
                                        7  0.352   0.047   1556.2  0.000
                                        8  0.337   0.036   1693.2  0.000
                                        9  0.311   0.014   1809.5  0.000
                                       10  0.291   0.008   1911.5  0.000
                                       11  0.284   0.024   2009.0  0.000
                                       12  0.273   0.023   2099.2  0.000
                                       13  0.250  -0.002   2175.1  0.000
                                       14  0.222  -0.024   2234.8  0.000
                                       15  0.223   0.014   2295.0  0.000
                                       16  0.234   0.048   2361.3  0.000
                                       17  0.235   0.042   2428.5  0.000
                                       18  0.246   0.049   2502.2  0.000
                                       19  0.214  -0.015   2557.8  0.000
                                       20  0.204  -0.009   2608.2  0.000
                                       21  0.230   0.054   2672.5  0.000
                                       22  0.164  -0.063   2705.2  0.000
                                       23  0.159  -0.035   2736.2  0.000
                                       24  0.151  -0.015   2764.2  0.000
```

*Figure 13 - Correlogram of Residuals of Bank inudstry Panel Regression with no transformation*

As can be seen from figure 13 above, the residuals are highly correlated through time with a p-value for the Q-statistic being 0 for all lags. In an attempt to combat this both the White method and the Panel Corrected Standard Error methodologies were used, which both compute standard errors which are robust in the presence of within cross- section heteroscedasticity and serial correlation. Unfortunately, neither of these methodologies has any effect on the autocorrelation of the residuals.

Lastly a lagged dependent variable was introduced in a final attempt to mitigate autocorrelation of residuals. The results are given below.



Date: 03/13/16 Time: 06:50
Sample: 1995M01 2015M12
Included observations: 1190

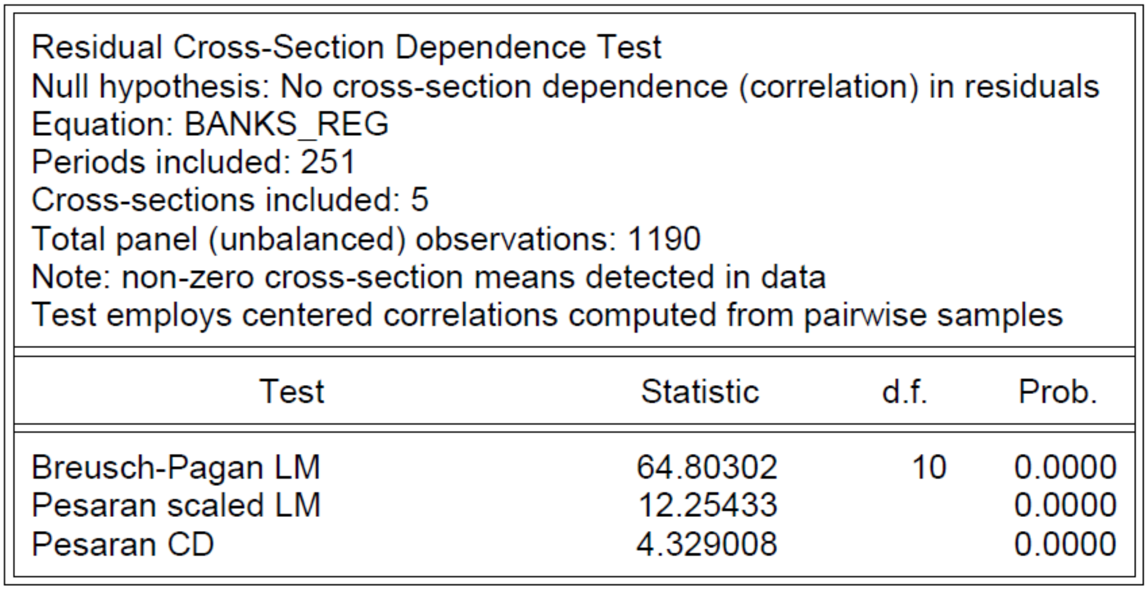
| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.097 | -0.097 | 11.212 | 0.001 |
| | | 2 | 0.177 | 0.169 | 48.512 | 0.000 |
| | | 3 | 0.200 | 0.239 | 96.142 | 0.000 |
| | | 4 | 0.071 | 0.093 | 102.11 | 0.000 |
| | | 5 | 0.159 | 0.111 | 132.45 | 0.000 |
| | | 6 | 0.146 | 0.119 | 157.95 | 0.000 |
| | | 7 | 0.120 | 0.091 | 175.16 | 0.000 |
| | | 8 | 0.136 | 0.075 | 197.30 | 0.000 |
| | | 9 | 0.113 | 0.051 | 212.70 | 0.000 |
| | | 10 | 0.084 | 0.008 | 221.16 | 0.000 |
| | | 11 | 0.098 | 0.007 | 232.71 | 0.000 |
| | | 12 | 0.109 | 0.035 | 247.10 | 0.000 |
| | | 13 | 0.107 | 0.048 | 261.01 | 0.000 |
| | | 14 | 0.053 | -0.020 | 264.38 | 0.000 |
| | | 15 | 0.067 | -0.031 | 269.75 | 0.000 |
| | | 16 | 0.103 | 0.030 | 282.50 | 0.000 |
| | | 17 | 0.077 | 0.038 | 289.74 | 0.000 |
| | | 18 | 0.113 | 0.062 | 305.17 | 0.000 |
| | | 19 | 0.081 | 0.032 | 313.09 | 0.000 |
| | | 20 | 0.046 | -0.020 | 315.69 | 0.000 |
| | | 21 | 0.156 | 0.086 | 345.24 | 0.000 |
| | | 22 | 0.034 | 0.008 | 346.63 | 0.000 |
| | | 23 | 0.044 | -0.043 | 348.95 | 0.000 |
| | | 24 | 0.064 | -0.044 | 353.91 | 0.000 |

*Figure 14 - Correlogram of Residuals of Bank industry Panel Regression with lagged dependent variable*

As can be seen from figure 14 above, the introduction of a lagged dependent variable has certainly improved the autocorrelation of the residuals when looking at the box diagram, however the p-value of the Q-statistic is still statistically significant at all lags.

Unfortunately, as can be seen from table 6 below, the analysis does suffer from cross-sectional dependence with p-values of 0 for the Breusch-Pagan LM, Pesaran scaled LM and Pesaran CD tests. This is to be expected since market volatility is not independent of the volatility of other markets. However, this may have negative impacts on the accuracy of the analysis.

*Table 6 - Residual Cross-Section Dependence test results for Banks industry Panel Regression*



Residual Cross-Section Dependence Test
Null hypothesis: No cross-section dependence (correlation) in residuals
Equation: BANKS_REG
Periods included: 251
Cross-sections included: 5
Total panel (unbalanced) observations: 1190
Note: non-zero cross-section means detected in data
Test employs centered correlations computed from pairwise samples

| Test | Statistic | d.f. | Prob. |
|---|---|---|---|
| Breusch-Pagan LM | 64.80302 | 10 | 0.0000 |
| Pesaran scaled LM | 12.25433 | | 0.0000 |
| Pesaran CD | 4.329008 | | 0.0000 |

# 5. RESULTS AND DISCUSSION

## 5.1 EMPIRICAL RESULTS

The results of the analysis are by no means uniform across industries, which was expected. However, this does not mean that the results were not surprising. A review of the statistical results is given here before the implications and possible explanations are considered in the discussion.

### 5.1.1 BANKS

The first observation to make regarding the results in table 7 below are with respect to the R-Squared and Adjusted R-Squared values. The R-Squared value gives the squared multiple correlation coefficient and represents the proportion of variation of the data that is explained through the regression equation. The Adjusted R-Squared value reflects the number of data points and variables in the equation in order to scale the R-Squared value. If an added variable does not contribute significantly to the model fit, the adjusted R-Squared may decrease while the R-Squared may increase. In this case, the R-Squared and Adjusted R-Squared are both above 0.54 or 54%. The similarity between the two shows that the equation does not include redundant variables. In general while this may seem low, it is a reasonable fit for a model of return volatility.

Each of the variables in the given equation are statistically significant at all levels of significance with p-values below 0.01 meaning that we can reject the null hypothesis that the coefficient is equal to 0 for all variables. The intercept is the least significant of the variables with a p-value of 0.0035 but has the largest coefficient. This indicates that the natural logarithm of the bank industry's standard volatility is 0.85 or that the bank industry's normal return standard deviation is 2.33 ($e^{0.85}$) when the effects of the other coefficients are negated.

Market capitalisation is the next weakest variable with a p-value of 0.0011 and interestingly has a *negative* coefficient of -0.034375. This signifies that the higher the market capitalisation, the lower the volatility for the banks industry. This is in line with the findings of Campbell, Lettau, Malkiel and Xu (2001) that show that larger industries have less volatility.

The lagged natural logarithm of the industry volatility variable is the most powerful with a t-statistic of 21.00381 and a relatively large coefficient of 0.488124 showing that the volatility of the previous month has a very high impact on the current period volatility. In fact if the natural logarithm of the previous month's volatility was 1 then the natural logarithm of the current month's volatility would be 0.488 higher than usual. Since both variables are log transformed the interpretability of the coefficients is slightly different to a regression with untransformed variables. In this case a 1% increase in the lagged banks industry volatility results in a 0.488% increase in the current banks volatility.

The MSCI World Index is also very powerful with a t-statistic of 14.56927 and a coefficient of 0.371184. The reason that the coefficient of this variable is not higher is probably due to the diversification effect of including many very different countries in the sample.

Lastly, the individualism index has a t-statistic of 4.272446 showing that it is highly statistically significant, however the coefficient is only 0.001505. The interpretation of this result is slightly different from the others since the individualism index is not log transformed. In this case the coefficient of 0.001505 indicates a 0.15% change in the dependent variable for a one-unit change in the individualism Index. This is both a statistically and economically significant result.

*Table 7 - Panel Regression results for Banks industry*

| **Variable** | **Coefficient** | **t-Statistic** | **p-Value** |
|---|---|---|---|
| Intercept*** | 0.845741 | 2.922999 | 0.0035 |
| Individualism Index*** | 0.001505 | 4.272446 | 0.0000 |
| Market Capitalisation*** | -0.034375 | -3.266716 | 0.0011 |
| MSCI World Index*** | 0.371184 | 14.56927 | 0.0000 |
| Lagged Dependent Variable*** | 0.488124 | 21.00381 | 0.0000 |
| R-Squared | 0.544414 | | |
| Adjusted R-Squared | 0.542876 | | |

* = significant at the 10% level, ** = significant at the 5% level and *** = significant at the 1% level

### 5.1.2 MINING

Except for the inclusion of the volatility of the gold price, the same model specification was given for the mining industry.

The results in table 8 are vastly different to that of the banks industry. The R-Squared and Adjusted R-Squared values are much lower, indicating that only 41% of the dependent variables volatility is explained by the regression line. This indicates that there are possible omitted variables. The power of the intercept is larger in this case with a coefficient of 1.073117 and a t-statistic of 4.645948.

The MSCI World Index is far less significant both statistically and economically with a t-statistic of 5.747927 and a coefficient of 0.179804, the introduction of the spot gold price as an independent variable possibly detracting from the power of the MSCI World Index. The volatility of the gold spot price achieved a t-statistic of 5.184368 and a coefficient of 0.169005 showing that a 1% change in the volatility of the gold price results in a 0.169% increase in the volatility of the mining industry.

Again the lagged natural logarithm of the volatility of the mining industry is the strongest predictor with a t-statistic of 19.10338 and a coefficient of 0.498169 signifying that almost 50% of the volatility of the mining industry in the current period is explainable from the previous period's volatility.

Market capitalisation has a relatively similar effect with a coefficient of -0.042197 and a t-statistic of -4.706227, therefore a 1% change in market capitalisation causes a -0.042% change in volatility – again in line with the results of Cambell, Lettau, Malkiel and Xu (2001). The biggest difference however, is the insignificance of the individualism index with a p-value of 0.4329; making it impossible to reject the null hypothesis that the effect of the individualism index is equal to 0.

*Table 8 - Panel Regression results for the Mining industry*

| **Variable** | **Coefficient** | **t-Statistic** | **p-Value** |
|---|---|---|---|
| Intercept*** | 1.073117 | 4.645948 | 0.0000 |
| Individualism Index | -0.000349 | -0.784561 | 0.4329 |
| Market Capitalisation*** | -0.042197 | -4.706227 | 0.0000 |
| Spot Gold*** | 0.169005 | 5.184368 | 0.0000 |
| MSCI World Index*** | 0.179804 | 5.747927 | 0.0000 |
| Lagged Dependent Variable*** | 0.498169 | 19.10338 | 0.0000 |
| R-Squared | 0.409612 | | |
| Adjusted R-Squared | 0.406655 | | |

* = significant at the 10% level, ** = significant at the 5% level and *** = significant at the 1% level

### 5.1.3 OIL & GAS PRODUCERS

For the oil & gas producers industry the gold spot price volatility was replaced with the oil spot price volatility. The specification besides this was the same as the other industries due to similar results of the tests conducted above.

The R-Squared and Adjusted R-Squared for the oil & gas producers' industry is very low with values of 0.369585 and 0.366210 respectively. These are low values and indicate that the model does not fit the data particularly well but again is still respectable for a series of this nature.

Both the intercept and market capitalisation are insignificant at the 1% and 5% levels of significance, showing vast differences in the structure of the volatility from the other industries tested so far. The market capitalisation result, with a coefficient of -0.009030, still conforms with the assumption that larger industries have less volatility. The intercept coefficient of 0.202057 indicates that the oil & gas producers industry has less intrinsic volatility than the others so far.

The volatility of the spot oil price is the next weakest variable with a p-value of 0.0029; however, this is statistically significant at all levels. The coefficient of 0.101423 indicates a weaker effect than that of the gold spot price on the mining industry. However, the MSCI World Index has a very similar effect to that of the mining industry with a t-statistic of 6.011385 and a coefficient of 0.179415.

The lagged natural logarithm of the oil & gas producers industry volatility is still the best predictor of current volatility with a t-statistic of 16.82534 and a coefficient of 0.466331 and the individualism index is again insignificant at all levels with a p-value of 0.2663.

*Table 9 - Panel Regression results for the Oil & Gas Producers industry*

| **Variable** | **Coefficient** | **t-Statistic** | **p-Value** |
|---|---|---|---|
| Intercept* | 0.202057 | 1.733483 | 0.0833 |
| Individualism Index | 0.000425 | 1.112266 | 0.2663 |
| Market Capitalisation* | -0.009030 | -1.926771 | 0.0543 |
| Spot Oil*** | 0.101423 | 2.987092 | 0.0029 |
| MSCI World Index*** | 0.179415 | 6.011385 | 0.0000 |
| Lagged Dependent Variable*** | 0.466331 | 16.82534 | 0.0000 |
| R-Squared | 0.369585 | | |
| Adjusted R-Squared | 0.366210 | | |

* = significant at the 10% level, ** = significant at the 5% level and *** = significant at the 1% level

### 5.1.4 PHARMACEUTICALS & BIOTECHNOLOGY

The specification for the pharmaceuticals & biotechnology industry was the same as that of the banks industry with no additional regressors.

The results for the pharmaceuticals and biotechnology industry are interesting and different from the results of the industries which came before. The R-Squared and Adjusted R-Squared are 0.461845 and 0.460106 respectively, indicating a relatively good fit of the model for a market volatility specification.

The intercept and market capitalisation variables are both significant only at the 10% level of significance, and both have the opposite sign to any of the results of the previous industries. The intercept with a coefficient of -0.246073 is not difficult to understand because when correcting for the log transformation the result becomes 0.358. However, this is the lowest value that has been recorded thus far and indicates that the pharmaceuticals & biotechnology industry has the lowest industry specific volatility. The market capitalisation coefficient of 0.009708, while small, is counterintuitive since this indicates that a 1% change in the market capitalisation would result in a 0.0097% *increase* in volatility.

Again the lagged pharmaceutical & biotechnology industry volatility is a strong predictor with a coefficient of 0.641355 and a t-statistic of 29.99894 and the MSCI World Index is also very strong with a coefficient of 0.122307 and a t-statistic of 5.076766.

The individualism index is significant at the 10% and 5% levels of significance with a p-value of 0.0495. The coefficient of 0.000695 indicates that a 1% change in the individualism index would result in a 0.0695% increase in volatility. While this effect is smaller than that of the effect on the banks industry, it points to a similar relationship.

*Table 10 - Panel Regression results for the Pharmaceuticals & Biotechnology industry*

| **Variable** | **Coefficient** | **t-Statistic** | **p-Value** |
|---|---|---|---|
| Intercept* | -0.246073 | -1.957287 | 0.0505 |
| Individualism Index** | 0.000695 | 1.966423 | 0.0495 |
| Market Capitalisation* | 0.009708 | 1.885517 | 0.0596 |
| MSCI World Index*** | 0.122307 | 5.076766 | 0.0000 |
| Lagged Dependent Variable*** | 0.641355 | 29.99894 | 0.0000 |
| R-Squared | 0.461845 | | |
| Adjusted R-Squared | 0.460106 | | |

* = significant at the 10% level, ** = significant at the 5% level and *** = significant at the 1% level

### 5.1.5 SOFTWARE & COMPUTER SERVICES

The software & computer services results are quite similar to that of the banks industry. The specifications are identical since no additional regressors were added to the equation.

Again the R-Squared and Adjusted R-Squared are 0.428847 and 0.426937 respectively reflecting an acceptable model fit. The results regarding the intercept and market capitalisation are more in line with expectations although are both insignificant at the 1% level of significance. The intercept with a coefficient of 0.317072 and a p-value of 0.0478 is quite high but still reasonable, while the market capitalisation with a p-value of 0.0217 and a coefficient of -0.015345 again aligns with the results of Cambell, Lettau, Malkiel and Xu (2001).

The MSCI World index and the lagged dependent variable also both follow expectations with t-statistics of 6.048918 and 26.47547 respectively and coefficients of 0.159329 and 0.597680 respectively.

The individualism index is again highly significant at all levels of significance with a p-value of 0.0061 and the coefficient of 0.001037 aligns with what has come to be expected. The coefficient implies that a 1% change in the individualism index would result in a 0.1037% increase in the volatility of the software & computer services industry.

*Table 11 -Panel Regression results for the Software & Computer Services industry*

| **Variable** | **Coefficient** | **t-Statistic** | **p-Value** |
|---|---|---|---|
| Intercept** | 0.317072 | 1.981502 | 0.0478 |
| Individualism Index*** | 0.001037 | 2.745182 | 0.0061 |
| Market Capitalisation** | -0.015345 | -2.298468 | 0.0217 |
| MSCI World Index*** | 0.159329 | 6.048918 | 0.0000 |
| Lagged Dependent Variable*** | 0.597680 | 26.47547 | 0.0000 |
| R-Squared | 0.428847 | | |
| Adjusted R-Squared | 0.426937 | | |

* = significant at the 10% level, ** = significant at the 5% level and *** = significant at the 1% level

### 5.1.6 MOBILE TELECOMMUNICATIONS

The mobile telecommunications industry was subject to the same model specification as that of the banks, pharmaceuticals & biotechnology and software & computer services industries with no additional regressors.

The mobile telecommunications industry produces results that are similar to that of mining and oil & gas producers industries with a significant intercept and market capitalisation variable (p-values of 0.0042 and 0.0025 respectively), the coefficients of which meet expectations as discussed this far. The R-Squared and Adjusted R-squared are slightly low with values of 0.379641 and 0.377527 respectively, but they are still reasonable.

The lagged mobile telecommunications industry volatility is significant at all levels (with a t-statistic of 19.83102) and has a reasonable coefficient of 0.484272. The MSCI World index is slightly more powerful with a t-statistic of 9.667549 and a coefficient of 0.239354, which may be due to the lack of an additional regressor as with the banks industry.

The individualism index is statistically insignificant at all levels with a p-value of 0.3436.

*Table 12 -Panel Regression results for the Mobile Telecommunications industry*

| **Variable** | **Coefficient** | **t-Statistic** | **p-Value** |
|---|---|---|---|
| Intercept*** | 0.542099 | 2.866768 | 0.0042 |
| Individualism Index | 0.000352 | 0.947543 | 0.3436 |
| Market Capitalisation*** | -0.022172 | -3.035804 | 0.0025 |
| MSCI World Index*** | 0.239354 | 9.667549 | 0.0000 |
| Lagged Dependent Variable*** | 0.484272 | 19.83102 | 0.0000 |
| R-Squared | 0.379641 | | |
| Adjusted R-Squared | 0.377527 | | |

* = significant at the 10% level, ** = significant at the 5% level and *** = significant at the 1% level

### 5.1.7 VOLUME

In order to test all of the hypotheses, similar tests had to be conducted on the volume of the representative industries traded on a daily basis. The volume data is also log transformed in an attempt to achieve normality. The results for each of the industries are given in table 13 below – the coefficients above and the p-values in brackets below.

The below results imply interesting results with the effects almost being opposite to those of the results of the tests conducted on the volatility of the industries, especially the results regarding the individualism index. However, it is quite possible that these models are misspecified considering that the R-Squared and Adjusted R-Squared of the models are suspiciously high, ranging from 0.81 to 0.88.

*Table 13 - Results of Panel Data Regression on trading volume*

| **Variable** | **Banks** | **Mining** | **Oil & Gas** | **Pharmaceuticals** | **Software** | **Telecoms** |
|---|---|---|---|---|---|---|
| Intercept | -0.5753<br>(0.3212) | 0.9264**<br>(0.0358) | 0.4111<br>(0.1354) | -3.2873***<br>(0.0000) | -0.6473**<br>(0.0432) | -1.7560***<br>(0.0007) |
| Individualism | -0.0006<br>(0.3992) | -0.0030***<br>(0.0010) | 0.0022**<br>(0.0174) | -0.0075***<br>(0.0000) | -0.0002<br>(0.7516) | 0.0016*<br>(0.0982) |
| Market Capitalisation | 0.1333***<br>(0.0000) | 0.0700***<br>(0.0002) | 0.0583***<br>(0.0000) | 0.3647***<br>(0.0000) | 0.1543***<br>(0.0000) | 0.1703***<br>(0.0000) |
| MSCI World Index | 0.1065**<br>(0.0185) | -0.0147<br>(0.7970) | -0.0111<br>(0.8715) | -0.0004<br>(0.9944) | -0.0333<br>(0.5073) | 0.0137<br>(0.8205) |
| Lagged Volume | 0.8374***<br>(0.0000) | 0.8556***<br>(0.0000) | 0.8831***<br>(0.0000) | 0.6729***<br>(0.0000) | 0.8134***<br>(0.0000) | 0.8408***<br>(0.0000) |
| Gold | - | 0.1109*<br>(0.0784) | - | - | - | - |
| Oil | - | - | 0.00003<br>(0.9997) | - | - | - |

* = significant at the 10% level, ** = significant at the 5% level and *** = significant at the 1% level

## 5.2 DISCUSSION

The primary objective of this study is to determine the relative effect of certain behavioural biases on the volatility of industries with differing structures and characteristics. The concept that some industries are easier to value, deriving more income from market-valued assets than others, is the cornerstone of the hypothesis. Those industries that draw income from assets which are difficult to value (patents, future earnings and growth, as well as others) are more vulnerable to behavioural biases in valuations.

Two hypotheses were described at the beginning of the current study, both of which will be discussed in this section with reference to the results in the previous section as well as the literature in Chapter 2. The hypotheses are discussed in reverse order due to the level of detail of each hypothesis – the secondary hypothesis being the most detailed with the primary hypothesis being the most abstract.

### 5.2.1 SECONDARY HYPOTHESIS

*Hypothesis 2* states that the effect of individualism on volatility is driven through overconfidence. A direct test of this hypothesis is difficult since no variable representing overconfidence is available. However, it is possible to account for the effects of overconfidence bias through the analysis of proxy variables and effects based on the work of other researchers.

Odean (1998) and Daniel, Hirshleifer and Subrahmanyam (1998) show that volatility is increased through overconfident traders. This implies that overconfidence should have a positive relationship with industry volatility. In the case of the banks, pharmaceuticals & biotechnology and software & computer services industries the individualism index is found to have a significant positive relationship with volatility which aligns with the expectations of Odean (1998) regarding the effect of overconfidence on volatility. Therefore this result supports the null hypothesis that the effect of individualism on industry volatility occurs through the mechanism of overconfidence.

Gervais and Odean (2001) prove that investor overconfidence leads to increased trading volume. The concept behind this states that if an investor is overconfident in his abilities he will place more money behind his abilities, expecting higher returns. This results in higher trade volumes.

The results of the current study don’t support those of Gervais and Odean (2001) since the effects of individualism are different on volatility and volume. The results show that for those industries where individualism is significant in predicting volatility, individualism is insignificant in predicting volume. And for those industries where individualism isn't significant in predicting volatility, it is significant in predicting volume. This contradicts the expectation that individualism should significantly affect both volatility and volume within an industry in order to show that the effect of individualism occurs through the existence of overconfidence in the market.

It should be noted quite strongly at this stage that the results regarding the effect of individualism on the trading volume of each of the industries seem to be counterintuitive when compared to those of previous literature (Odean, 1998; Daniel, Hirshleifer and Subrahmanyam, 1998; Gervais and Odean, 2001; Chu, Titman and Wei, 2010). With high R-Squared and Adjusted R-Squared values and counterintuitive results the validity of the analysis is sceptical at best. Further analysis should be conducted to investigate the relationship further.

### 5.2.2 PRIMARY HYPOTHESIS

The primary hypothesis of the current study states that Individualism has different effects on different industries and further; *Hypothesis 1.1* states that industries with lower fundamental asset to market value ratios – those industries which are more difficult to value fundamentally – are more affected by Individualism than those which are easier to value.

It should be noted first that due to the structuring of the data into a panel set where country, represented by the different equity markets, is the cross-sectional identifier, we are able to make specific conclusions on the effect of the variables between countries. The regression specifications test the effect of the different variables on a specific industry *across* countries. Therefore, any kind of significance of any of the variables shows that that variable can be used to predict volume and volatility even in different countries and therefore the effect is not independent of country.

In the current specifications, individualism is shown to be significant as a regressor of volatility in the banks, pharmaceuticals & biotechnology and software & computer services industries signifying that individualism can be used as a predictor of volatility for those industries within each of the separate countries. Because of this result we can infer that individualism has differing effects on different regions at least and quite possibly on each of the countries separately. This supports the findings of Chui, Titman and Wei (2010) who show that the effect of individualism is different for different countries.

The basis of *Hypothesis 1* comes from the model of Scheinkman and Xiong (2003), which shows that overconfidence causes disparities in the valuations of asset fundamentals, which in turn causes an increase in price volatility. This concept is then expanded on further by noting that asset fundamentals of certain industries are easier to measure than others, resulting in a reduced effect from overconfidence on the price volatility. A further link shows that individualism *causes* overconfidence (Biais et al., 2005; Gelfand et al., 2002; Yates, Lee & Shinotsuka, 1996). However, *Hypothesis 1* specifically considers the direct relationship between individualism and industry volatility and volume.

With regards to the industries themselves, it is expected that the pharmaceuticals & biotechnology and software & computer services industries should be strongly affected by behavioural biases, specifically individualism and overconfidence, due to the fact that a large proportion of the income earned by these companies is due to patents or proprietary information – assets which are very difficult to value. The mining and oil & gas industries are much easier to value since the products of the industries are valued almost constantly on an open exchange market. Banks should be similarly easy to value since the assets they maintain are generally exchange traded, deposits from customers or home loans which are easily valued using discounted cash flow methods. The mobile telecommunications industry maintains slightly less liquid – but no less difficult to value – infrastructure assets. These last four industries should have little or no impact from individualism or other behavioural biases.

The results almost perfectly align with expectations with respect to the effect of individualism on industry volatility. The effect of individualism is strong in both the pharmaceuticals & biotechnology and software & computer services industries. The effect is slightly stronger, both in terms of magnitude and significance in the software & computer services industry, possibly due to the fact that the pharmaceuticals & biotechnology industry may include some physical assets which are more easily valuable, while software & computer services is almost entirely service based.

The most unexpected result from the analysis is that of the banks industry. The individualism effect is strongest – again with respect to both magnitude and significance – on the banks industry. This is intriguing since the banks industry should be more uniformly valued as discussed before. However, it is quite possible that this relationship is not due to the overconfidence, or other behavioural biases of traders and investors in those regions, but rather due to the behaviour of employees.

The definition of individualism is the extent to which one considers oneself as a single unit, autonomous from others in the environment or as a part of a whole which makes up the environment. In a collectivistic culture it is very likely that employees of banks show more restraint in terms of risk taking activities since they are custodians of the money of their communal members. While in individualistic cultures bank employees may consider this fact less important and take on more risk. These excessive risk-taking activities would be reflected in bank security prices, causing more volatility in those cultures. The extreme example is that of the financial crisis of 2007/2008 which was precipitated in the United States of America – the most individualistic culture in the current study.

An alternate explanation is the consideration that the sample period includes the financial crisis of 2007/2008 and that the two individualistic cultures – the United States of America and the United Kingdom – were the most severely affected by the crisis, thus creating a spurious result. It follows that the volatility of the banks industry in both the United States and the United

Kingdom would be higher than in other countries over this period. However, given that the sample period stretches over 20 years and the financial crisis only occurred during a short part of this sample, this effect should be diluted. The fact that the p-value of the individualism index in the banks specification was so extremely significant indicates that this is most likely not the case.

On the other side of the spectrum, three of the four industries which we expected not to be affected by individualism did meet expectations. The effect of individualism on the mining industry was highly insignificant and even had a negative coefficient. This was the least powerful result in all of the analyses. The mining industry clearly shows serial autocorrelation in price volatility and subsumes both the gold price volatility as well as global systemic volatility. The industry also shows a high standard volatility with a large, significant intercept.

The effect of individualism on the mobile telecommunications industry was the next least powerful effect. The mobile telecommunications industry relies on its physical infrastructure to produce income. Again, autocorrelation is a large driver of volatility as well as systemic volatility. The intercept was lower for the mobile telecommunications industry, suggesting a lower average industry specific volatility.

The oil & gas producers industry also has an insignificant effect of individualism, but is largely affected by oil price volatility and global systemic volatility. Autocorrelation of volatility is also a powerful force, but with a very small and largely insignificant intercept, it seems the Oil & Gas Producers industry has a low industry specific volatility.

### 5.2.3 SUMMARY

The three hypotheses tested had varying levels of success. The *Tertiary Hypothesis* (that individualism had no differing effect on regions) was rejected, while *Hypothesis 3.1* was generally found to hold true, allowing the conclusion that individualism has different effects on different regions, specifically between Western and Eastern regions. The *Secondary Hypothesis* – that overconfidence is the driver of volatility increases in regions of high individualism – was also found to generally hold true in that individualism was linked to higher volatility, which aligns with previous research on overconfidence. However, the effect of individualism on trading volume was inconclusive and could not confirm the generally supported hypothesis that overconfidence causes increases in trading volume.

*Hypothesis 1*, which represented the primary objective of the study, was found to hold true, and the statement that individualism has different effects on different industries was accepted. Specifically, those industries which were identified as being susceptible to behavioural biases due to generally low book to market ratios were to found to be significantly affected by individualism, while those which were identified to be relatively immune had no such significant relationship. The obvious outlier was the banks industry, which was expected to not be affected by individualism due to the fact that most of a bank's assets are valued on open markets. However, an alternative explanation was given for the impact of individualism on banks: the concept of individualism drives employee behaviour, resulting in less risk taking activities in collectivistic countries and therefore less volatility in those countries.

# 6. CONCLUSION

Behavioural Finance has been gaining traction over the past few decades due to two key points: the existence of evidence to indicate that the EMH does not hold and the successful use of behavioural factors in describing market returns and volatility. The evidence is constantly growing with the number of explanatory factors increasing exponentially. However, no accepted methodology or defined set of variables has been found – one of the biggest criticisms of Behavioural Finance. The Efficient Markets Hypothesis has endured due to the sound structure of its development, the parsimonious nature of its specification and the lack of a fully specified alternative (the largest obstacle being the lack of suitable proxies for known behavioural biases). In the endeavour to replace the usable specification of the Efficient Markets Hypothesis with the more accurate specification of Behavioural Finance, this study analysed the differing effects of behavioural variables – specifically individualism – on industries.

The introduction of a GARCH specification in an attempt to remove volatility clustering and create a more time-invariant series was an extension of previous literature on the subject. The use of GARCH models in volatility modelling is however, present in past literature and has found much success in this arena. The resulting residual series' were modelled using a panel regression using the market (as a proxy of the country) as the cross-sectional identifier. A panel model was used in order to identify cross-country effects over time.

Variables considered included, the Individualism Index of Hofstede (2001), the variable of focus for the current study; the market capitalisation of the industry, the effect of which was suggested by Cambell, Lettau, Malkiel and Xu (2001); residual volatility of the MSCI World Index, which was an attempt to capture the effect of global volatility since the focus was on country specific volatility; a one period lag of the industry volatility to counteract the effect of autocorrelation (longer lag periods were also considered but made no meaningful difference to the results); and the residual volatility of the gold and oil spot prices were used in the models of the mining and oil & gas producers industries respectively in order to capture commodity price volatility in those industries. The same tests were conducted on the trading volume of the industries, however the results were deemed inconclusive.

The results of the tests were used to analyse three hypotheses. The third hypothesis being that the effect of individualism on industries was independent of country or region. It was concluded that the effect of individualism was at least dependent of region, given the results of the analyses conducted. It could not however be deduced that the effect of individualism was dependent of country since the tests were not conducted at a granular enough level.

The second hypothesis stated that the effect of individualism on industries was transferred via overconfidence. This hypothesis could be justified but not confirmed. While it was shown that the effect of individualism on industry volatility could be due to overconfidence, the results of the analysis done on industry trading volumes could not confirm the hypothesis.

The primary focus of the current study was the hypothesis that individualism has differing effects on different industries and the sub-hypotheses that the effect of individualism would be higher or lower based on the means from which the industry draws an income. The hypotheses stated that industries which have easily valuable assets should be less prone to the effects of behavioural biases and therefore individualism should have an insignificant effect and vice versa for those which have less easily valuable assets.

The results for the most part supported the hypotheses, with the pharmaceuticals & biotechnology and software & computer services industries (both industries which were considered to be difficult to value) had significant and strong relationships with individualism. The mobile telecommunications, oil & gas producers and mining industries (all of which are considered to be easier to value) had insignificant relationships with Individualism. However, the banks industries – which was considered relatively easy to value due to the assets in the industry being predominantly market valued, client deposits or easily valued loans – had a strong and positive relationship with individualism.

It is posited that this relationship does not stem from the trading activity of individualistic/collectivistic traders but rather from the actions of individualistic/collectivistic employees. Employees in individualistic cultures may in fact be creating more risk, and therefore volatility, for the banks of those cultures. While those employees of collectivistic cultures are more restrained, treating the money of their compatriots as if it were their own.

This most intriguing relationship (the effect of individualism on volatility through industry employees as opposed to investors) requires further investigation. The focus of the effect of cultural factors on security volatility has thus far been on the determination of prices by investors. However, there is no reason to assume that this effect does not rather act through other agents, namely industry employees or market makers. The relationship between individualism and volume/volatility as a whole also deserves further attention and any further investigation should take more variables – such as foreign exchange volatility, industry trading volume *as a regressor* and possibly an indicator of strike action (quite pertinent in a South African context at least) – into account as well as identifying different methods to model the relationship in order to avoid possible spurious results as those of the relationship between individualism and trading volume. A more in depth analysis should be made into the driving forces behind the relationship, specifically those forces of overconfidence and the self-attribution bias and whether these effects influence volatility through trading activity – as is predominantly assumed here – or whether the influence in fact occurs through strategic means as is explained by the example of the banks industry.

## 7. REFERENCES

Ahmed, A., Hussin, B., & Ying, T. (2010). Semi-Strong Form Efficiency: Market Reaction to Dividend and Earnings Announcements in Malaysian Stock Exchange. *IUP Journal of Applied Finance, 16*(5), 36-60.

Alexander, S. (1961). Price Movements in Speculative Markets: Trends or Random Walks. *Industrial Management Review, 2* (2), 7-26.

Alexander, S. (1964). Price Movements in Speculative Markets: Trends or Random Walks, No. 2. *Industrial Management Review, 5* (2), 25-46.

Baker, M., & Wurgler, J. (2007). Investor Sentiment in the Stock Market. *Journal of Economic Perspectives , 21* (2), 129-151.

Ball, R., & Brown, P. (1968). An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research , 6* (2), 159-178.

Baltagi, B. H. (2005). Econometric Analysis of Panel Data (3rd ed.). Chichester, England: John Wiley & Sons Ltd.

Barberis, N., Huang, M., & Santos, T. (2001). Prospect Theory and Asset Prices. *Quarterly Journal of Economics , 116* (1), 1-53.

Bem, D. (1965). An Experimental Analysis of Self-Persuasion. *Journal of Experimental Social Psychology, 1*(3), 199-218.

Ben Sita, B. (2013). Volatility Links Between US Industries. *Applied Financial Economics , 23* (15), 1273-1286.

Biais, B., Hilton, D., Mazurier, K., & Pouget, S. (2005). Judgemental Overconfidence, Self-Monitoring, and Trading Performance in an Experimental Financial Market. *Review of Economic Studies , 72* (2), 287-312.

Black, F. (1986). Noise. *The Journal of Finance, 41*(3), 529-543.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics, 31* (3), 307-327.

Bulkley, G., & Tonks, I. (1992). Trading Rules and Excess Volatility. *Journal of Financial and Quantitative Analysis , 27* (3), 365-382.

Butler, P. J., & Pinkerton, K. A. (2007). Company-Specific Risk: The Dow 30 v. Private Company USA. *The Value Examiner , 1* (1), 12-15.

Campbell, J., Lettau, M., Malkiel, B., & Xu, Y. (2001). Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk. *Journal of Finance, 56* (1), 1-43.

Christiansen, C., Schmeling, M., & Schrimpf, A. (2012). A Comprehensive Look at Financial Volatility Prediction by Economic Variables. *Journal of Applied Econometrics, 27*(6), 956-977.

Chu, A., Titman, S., & Wei, J. (2010). Individualism and Momentum Around the World. *The Journal of Finance , 65* (1), 361-392.

Church, A., Katigbak, M., Del Prado, A., Ortiz, F., Mastor, K., Harumi, Y., et al. (2006). Implicit Theories and Self-Perceptions of Traitedness Across Cultures. *Journal of Cross-Cultural Psychology , 37* (6), 694-716.

Coval, J., & Shumway, T. (2005). Do Behavioral Biases Affect Prices? *Journal of Finance , 60* (1), 1-34.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *The Journal of Finance, 53*(6), 1839-1885.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1991). The Survival of Noise Traders in Financial Markets. *Journal of Business, 64*(1), 1-19.

De Long, J. (2005). Financial Markets, Noise Traders, and Fundamental Risk: Background Memo. *University of California Berkeley and National Bureau of Economic Research Note*, 1-27.

DeBondt, W. F., & Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance, 40*(3), 793-805.

Doi, L. (1973). The Japanese Patterns of Communication and the Concept of Amae. *Quarterly Journal of Speech , 59* (2), 180-186.

Domowitz, I., & Hakkio, C. (1985). Conditional Variance and the Risk Premium in the Foreign Exchange Market. *Journal of International Economics, 19* (1), 47-66.

Engle, R. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica, 50* (4), 987-1007.

Engle, R. (1983). Estimates of the Variance of U.S. Inflation Based on the ARCH Model. *Journal of Money, Credit and Banking, 15* (3), 286-301.

Engle, R., Lilien, D., & Robins, R. (1987). Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model. *Econometrica, 55* (2), 391-407.

Fama, E. (1965). The Behavior of Stock Market Prices. *Journal of Business , 38* (1), 34-105.

Fama, E. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance , 25* (2), 383-417.

Fama, E., Fisher, L., Jensen, M., & Roll, R. (1969). The Adjustment of Stock Prices to New Information. *International Economic Review , 10* (1), 1-21.

Figlewski, S. (1979). Subjective Information and Market Efficiency in a Betting Market. *Journal of Political Economy, 87*(1), 75-88.

Franke, R. H., Hofstede, G., & Bond, M. H. (1991). Cultural Roots of Economic Performance: A Research Note. *Strategic Management Journal , 12* (Special Issue), 165-173.

French, K., & Roll, R. (1986). Stock Return Variances: The Arrival of Information and the Reaction of Traders. *Journal of Financial Economics, 17*(1), 5-26.

Friedman, M. (1953). Choice, Chance and the Personal Distribution of Income. *Journal of Political Economy, 61*(4), 277-290.

Gelfand, M., Higgins, M., Nishii, L., Raver, J., & Dominguez, A. (2002). Culture and Egocentric Perceptions of Fairness in Conflict and Negotiation. *Journal of Applied Psychology , 87* (5), 833-845.

Gervais, S., & Odean, T. (2001). Learning to Be Overconfident. *The Review of Financial Studies , 14* (1), 1-27.

Goetzmann, W., & Massa, M. (1999). Daily Momentum and Contrarian Behavior of Index Fund Investors. *Working Papers - Yale School of Management's International Center for Finance*, 1-49.

Grossman, S. J., & Stiglitz, J. E. (1980). On the Impossibility of Informationally Efficient Markets. *The American Economic Review, 70*(1), 393-408.

Heine, S., Lehman, D., Markus, H., & Kitayama, S. (1999). Is There a Universal Need for Positive Self-Regard? *Psychological Review , 106* (4), 766-794.

Hofstede, G. (1980). *Culture's Consequences: International Differences in Work Related Values* (1st ed.). Beverley Hills, California, USA: Sage Publications.

Hofstede, G. (2001). *Culture's Consequences: Comparing Values, Behaviors, Institutions and Organizations Across Nations* (2nd Edition ed.). Thousand Oaks, California, USA: Sage Publications.

Hsieh, H.-H., & Hodnett, K. (2011). Tests of the Overreaction Hypothesis and the Timing of Mean Reversals on the JSE Securities Exchange (JSE): The Case of South Africa. *Journal of Applied Finance & Banking, 1*(1), 107-130.

Hou, K. (2007). Industry Information Diffusion and the Lead-lag Effect in Stock Returns. *Review of Financial Studies, 20* (4), 1113-1138.

Im, K. S., Pesaran, M. H. & Shin, Y. (2003) Testing for Unit Roots in Heterogeneous Panels. *Journal of Econometrics, 115* (1), 53-74.

Jefferis, K., & Smith, G. (2005). The Changing Efficiency of African Stock Markets. *South African Journal of Economics, 73*(1), 54-67.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance, 48*(1), 65-91.

Jensen, M. (1968). The Performance of Mutual Funds in the Period 1945-1964. *Journal of Finance , 23* (2), 389-416.

Jones, S. (2011). Volatility Forecasting for Mutual Fund Portfolios. *North American Journal of Finance and Banking Research, 5*(5), 13-22.

Jovanovic, F. & Le Gall, P. (2001). Does God Practice a Random Walk? The 'Financial Physics' of a Nineteenth-Century Forerunner, Jules Regnault. *The European Journal of the History of Economic Thought, 8*(3), 332-362.

Kachelmeier, S. J., & Shehata, M. (1997). Internal Auditing and Voluntary Cooperation in Firms: A Cross-Cultural Experiment. *The Accounting Review , 72* (3), 407-431.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision Under Risk. *Econometrica , 47* (2), 263-291.

Kara, A., & Denning, K. (1998). A Model and Empirical Test of the Strong Form Efficiency of US Capital Markets: More Evidence of Insider Trading Profitability. *Applied Financial Economics, 8*(3), 211-220.

Kuh, E. (1959). The Validity of Cross-Sectionally Estimated Behavior Equations in Time Series Applications. Econometrica, 27(2), 197-214.

Lee, J., Yates, J,, Shinotsuka, H., Singh, R., Onglatco, M., Yen, N., Gupta, M. & Bhatnagar, D. (1995). Cross National Differences in Overconfidence. *Asian Journal of Psychology, 1* (1), 63-69.

LeRoy, S. F., & Porter, R. D. (1981). The Present-Value Relation: Tests Based on Implied Variance Bounds. *Econometrica , 49* (3), 97-113.

Leuthold, R., & Hartmann, P. (1979). A Semi-Strong Form Evaluation of the Efficiency of the Hog Futures Market. *American Journal of Agricultural Economics, 61*(3), 482-489.

Lo, A. W. (2004). The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective. *Journal of Portfolio Management, 30*(5), 15-29.

Lux, T., & Marchesi, M. (2000). Volatility Clustering in Financial Markets: A Microsimulation of Interacting Agents. *International Journal of Theoretical and Applied Finance , 3* (4), 675-702.

Mallikarjunappa, T., & DSouza, J. (2013). A Study of Semi-Strong Form of Market Efficiency of Indian Stock Market. *Amity Global Business Review, 8*(1), 60-68.

Markus, H., & Kitayama, S. (1991). Culture and the Self: Implications for Cognition, Emotion and Motivation. *Psychological Review , 98* (2), 224-253.

Mazzucato, M. (2002). The PC Industry: New Economy or Early Life-Cycle? *Review of Economic Dynamics*, *5* (2), 318-346.

McNees, S. (1979). The Forecasting Record of the 1970's. *New England Economic Review*, *10* (5), 33-53.

Miller, E. M. (1977). Risk, Uncertainty, and Divergence of Opinion. *Journal of Finance, 32*(4), 1151-1168.

Niederhoffer, V., & Osborne, M. (1966). Market Making and Reversal on the Stock Exchange. *Journal of the American Statistical Association , 61* (316), 897-917.

Odean, T. (1998). Volume, Volatility, Price, and Profit When All Traders Are Above Average. *The Journal of Finance , 53* (6), 1887-1934.

Ramiah, V., Xu, X., & Moosa, I. A. (2015). Neoclassical Finance, Behavioral Finance, and Noise Traders: A Review and Assessment of the Literature. *International Review of Financial Analysis*, 41, 89-100.

Regnault, J. (1863). *Calcul des Chances et Philosophie de la Bourse* (1st ed.). Paris, France: Mallet-Bachelier.

Roll, R. (1978). Ambiguity When Performance is Measured by the Securities Market Line. *The Journal of Finance , 33* (4), 1051-1069.

Scheinkman, J., & Xiong, W. (2003). Overconfidence and Speculative Bubbles. *Journal of Political Economy , 111* (6), 1183-1220.

Scholes, M. (1969). A Test of the Competitive Hypothesis: the Market for New Issues and Secondary Offerings. PhD Thesis, Graduate School of Business, University of Chicago.

Shefrin, H., & Statman, M. (1994). Behavioral Capital Asset Pricing Theory. *Journal of Financial and Quantitative Analysis , 29* (3), 323-349.

Shiller, R. J. (1981). The Use of Volatility Measures in Assessing Market Efficiency. *Journal of Finance , 36* (2), 291-304.

Shiller, R. J. (2003). From Efficient Markets Theory to Behavioral Finance. *Journal of Economic Perspectives, 17*(1), 83-104.

Simon, H. (1955). A Behavioral Model of Rational Choice. *Quarterly Journal of Economics , 69* (1), 99-118.

Smith, G., Jefferis, K., & Ryoo, H.-J. (2002). African Stock Markets: Multiple Variance Ratio Tests of Random Walks. *Applied Financial Economics, 12*(7), 475-484.

Tetlock, P. C. (2006). Does Noise Trading Effect Securities Market Efficiency? *Working Paper, McCombs School of Business, University of Texas, Austin*, 1-43.

Van den Steen, E. (2004). Rational Overoptimism (and Other Biases). *The American Economic Review , 94* (4), 1141-1151.

Weber, Y., Shenkar, O., & Raveh, A. (1996). National and Corporate Cultural Fit in Mergers/Acquisitions: An Explanatory Study. Management Science , 42 (8), 1215-1227.

Weiss, A. (1984). ARMA Models with ARCH Errors. *Journal of Time Series Analysis, 5* (2), 129-143.

West, K. D. (1988). Dividend Innovations and Stock Price Volatility. *Econometrica , 56* (1), 36-71.

Yang, K. (1981). Social Orientation and Individual Modernity Among Chinese Students in Taiwan. *Journal of Social Psychology , 113* (2), 159-171.

Yates, J., Lee, J., & Shinotsuka, H. (1996). Beliefs About Overconfidence, Including its Cross-National Variation, *Organizational Behavior and Human Decision Processes, 65* (1), 138-147.

# 8. APPENDIX

## 8.1 LINE GRAPHS OF UNTRANSFORMED VOLATILITY

The below graphs represent the monthly volatility of each of the industries as a whole. As can be seen, the volatility is generally not normally distributed or stationary, showing signs of changing means. The graphs also definitely exhibit signs of volatility clustering.

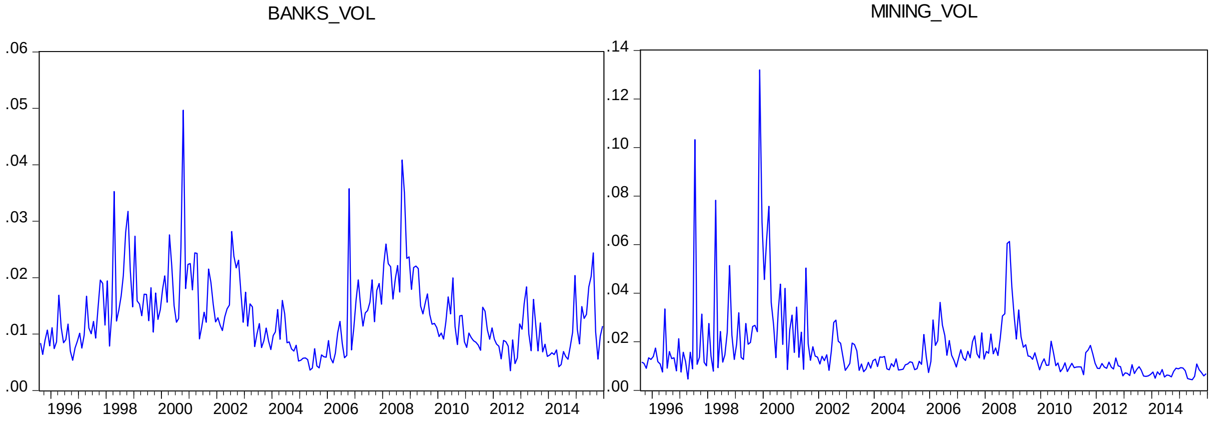


*Figure 15 - Volatility diagrams of the Banks and Mining industries*

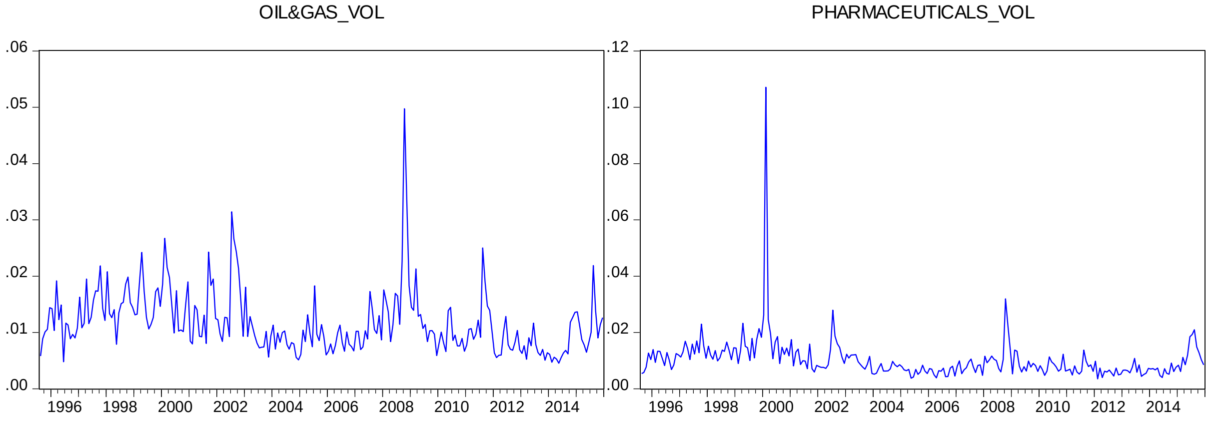


*Figure 16 - Volatility diagrams of the Oil & Gas Producers and Pharmaceuticals & Biotechnology industries*

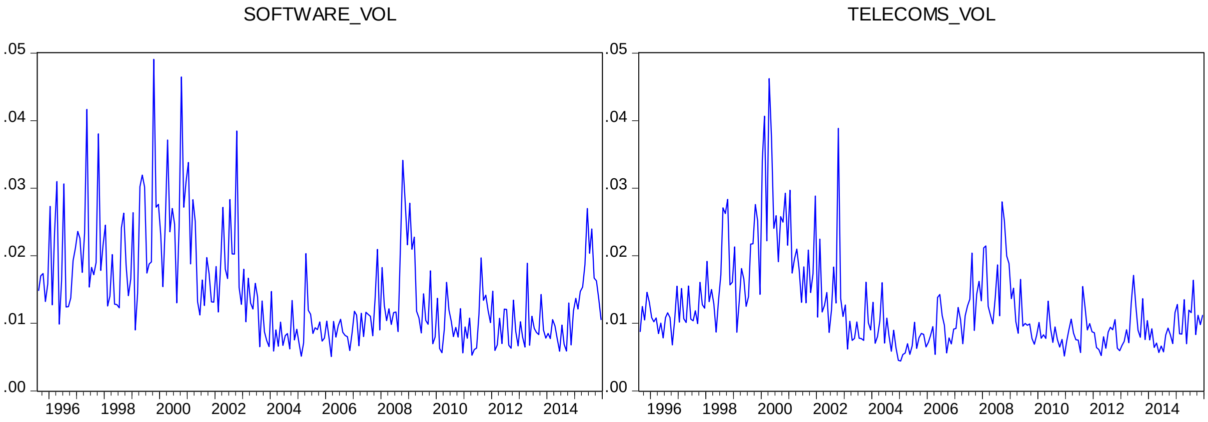


*Figure 17 - Volatility diagrams of the Software & Computer Services and Mobile Telecommunications industries*

## 8.2 LINE GRAPHS OF TRANSFORMED VOLATILITY

The graphs below have been log-transformed in order to induce normality in the volatility series'. While the movement around the means is more uniformly distributed, the means themselves seem to be changing over time, indicating non-stationarity. The results of stationarity tests however, indicate that the series' are stationary.

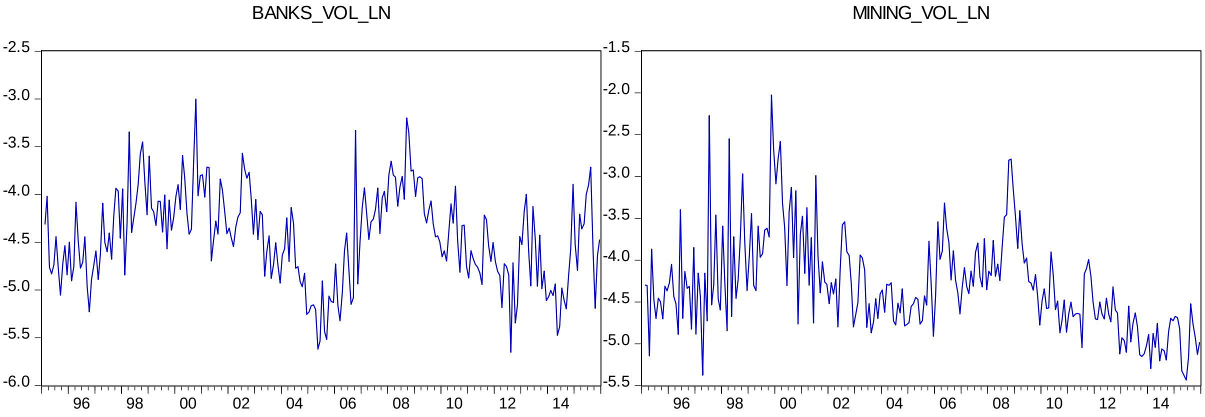


*Figure 18 - Volatility diagrams of the log-transformed volatility of the Banks and Mining industries*

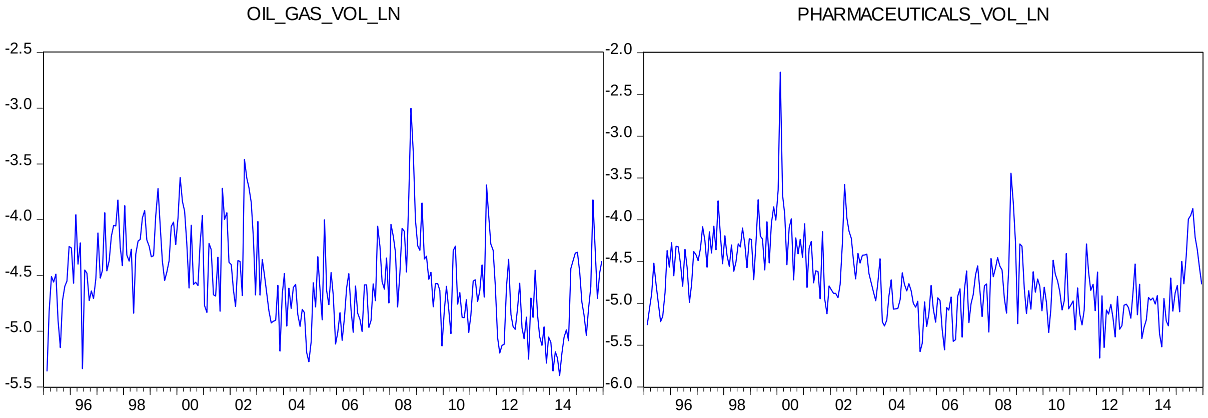


*Figure 19 - Volatility diagrams of the log-transformed volatility of the Oil & Gas Producers and Pharmaceuticals & Biotechnology industries*

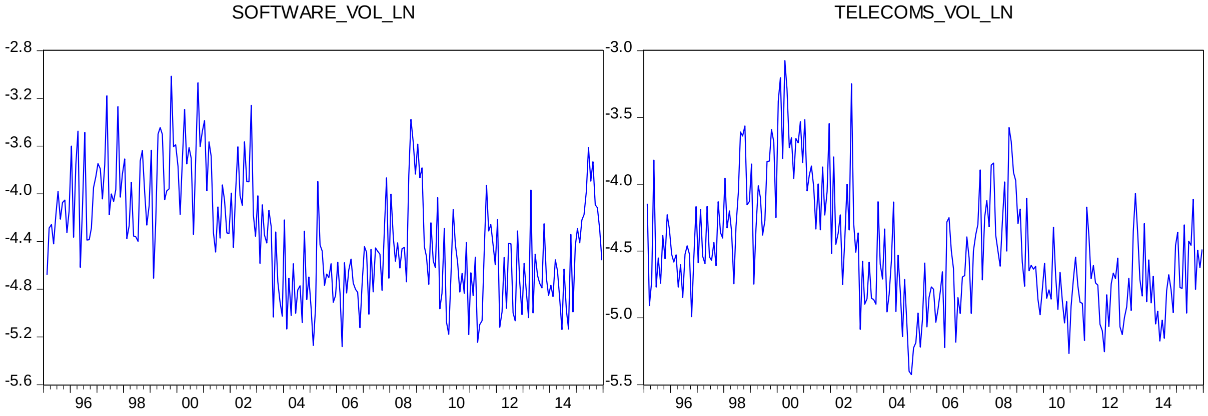
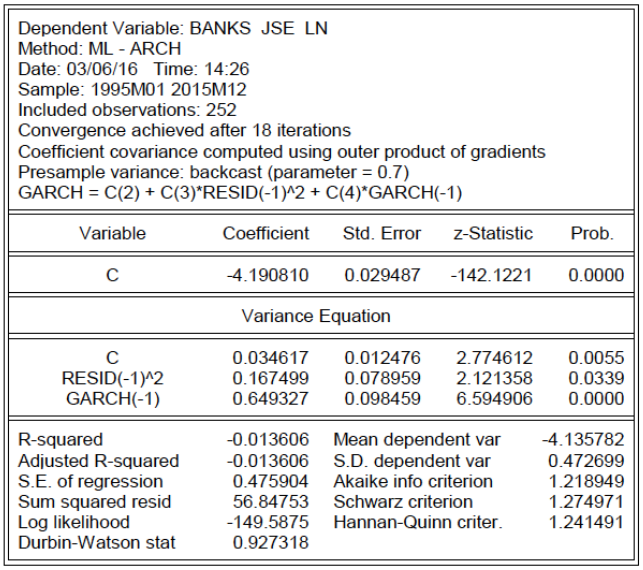


*Figure 20 - Volatility diagrams of the log-transformed volatility of the Software & Computer Services and Mobile Telecommunications industries*

## 8.3 GARCH MODEL RESULTS

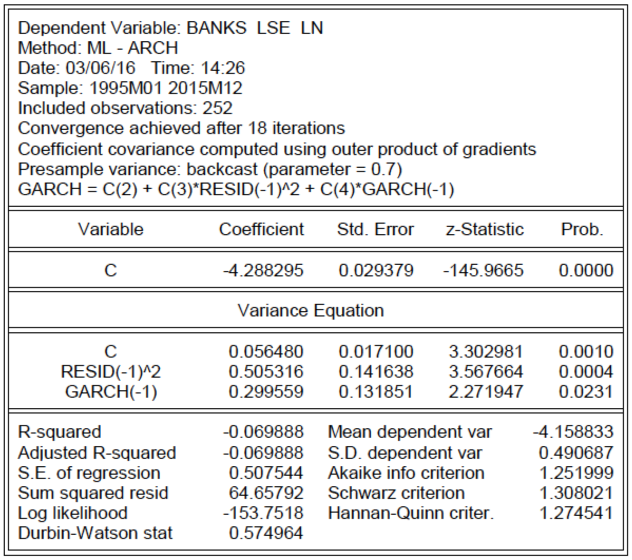
The results of the GARCH models given below forms part of the pre-processing of data in preparation for panel data regression. The GARCH models themselves have very low and sometimes negative R-Squared values, however as discussed earlier this does not necessarily mean that the models are misspecificed. The significance of most of the ARCH and GARCH variables indicate that the models are appropriate.

*Table 14 - GARCH model Results for the Banks industry of the JSE*



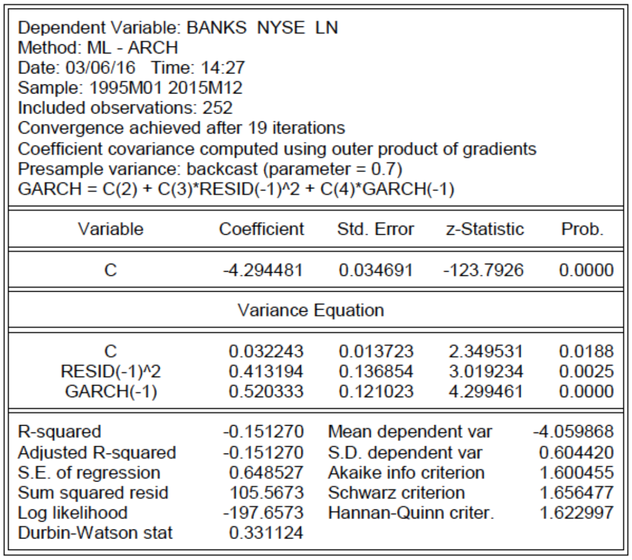
```
Dependent Variable: BANKS  JSE  LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:26
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable       Coefficient   Std. Error   z-Statistic    Prob.

           C            -4.190810    0.029487    -142.1221     0.0000

                           Variance Equation

           C             0.034617    0.012476     2.774612     0.0055
      RESID(-1)^2        0.167499    0.078959     2.121358     0.0339
       GARCH(-1)         0.649327    0.098459     6.594906     0.0000

R-squared               -0.013606   Mean dependent var    -4.135782
Adjusted R-squared      -0.013606   S.D. dependent var     0.472699
S.E. of regression       0.475904   Akaike info criterion  1.218949
Sum squared resid        56.84753   Schwarz criterion      1.274971
Log likelihood          -149.5875   Hannan-Quinn criter.   1.241491
Durbin-Watson stat       0.927318
```

*Table 15 - GARCH model Results for the Banks industry of the LSE*



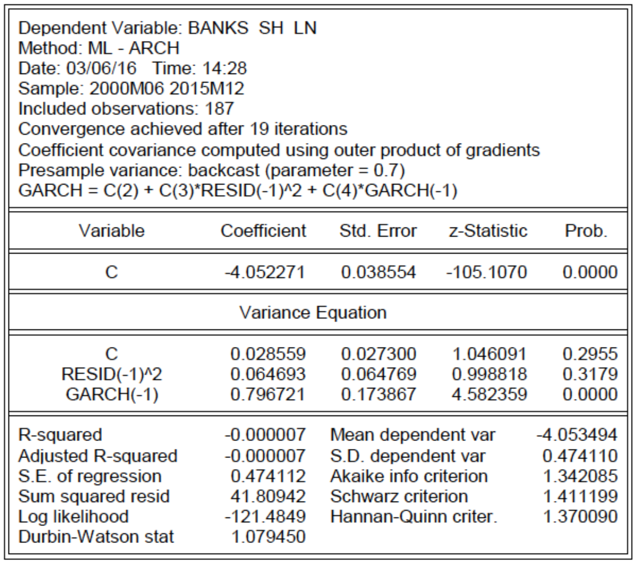
```
Dependent Variable: BANKS  LSE  LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:26
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable       Coefficient   Std. Error   z-Statistic    Prob.

           C            -4.288295    0.029379    -145.9665     0.0000

                           Variance Equation

           C             0.056480    0.017100     3.302981     0.0010
      RESID(-1)^2        0.505316    0.141638     3.567664     0.0004
       GARCH(-1)         0.299559    0.131851     2.271947     0.0231

R-squared               -0.069888   Mean dependent var    -4.158833
Adjusted R-squared      -0.069888   S.D. dependent var     0.490687
S.E. of regression       0.507544   Akaike info criterion  1.251999
Sum squared resid        64.65792   Schwarz criterion      1.308021
Log likelihood          -153.7518   Hannan-Quinn criter.   1.274541
Durbin-Watson stat       0.574964
```

*Table 16 - GARCH model Results for the Banks industry of the NYSE*



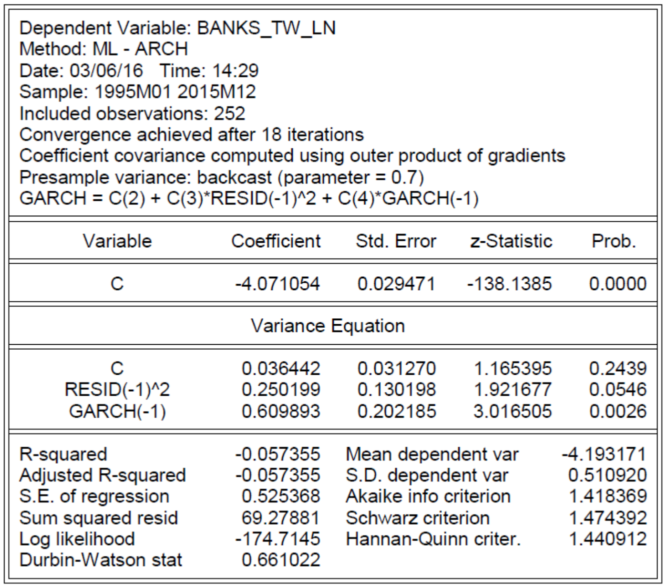
```
Dependent Variable: BANKS_NYSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:27
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable        Coefficient   Std. Error   z-Statistic    Prob.

           C             -4.294481    0.034691    -123.7926     0.0000

                            Variance Equation

           C              0.032243    0.013723     2.349531     0.0188
       RESID(-1)^2        0.413194    0.136854     3.019234     0.0025
        GARCH(-1)         0.520333    0.121023     4.299461     0.0000

R-squared                -0.151270   Mean dependent var     -4.059868
Adjusted R-squared       -0.151270   S.D. dependent var      0.604420
S.E. of regression        0.648527   Akaike info criterion   1.600455
Sum squared resid         105.5673   Schwarz criterion       1.656477
Log likelihood           -197.6573   Hannan-Quinn criter.    1.622997
Durbin-Watson stat        0.331124
```

*Table 17 - GARCH model Results for the Banks industry of Shanghai*



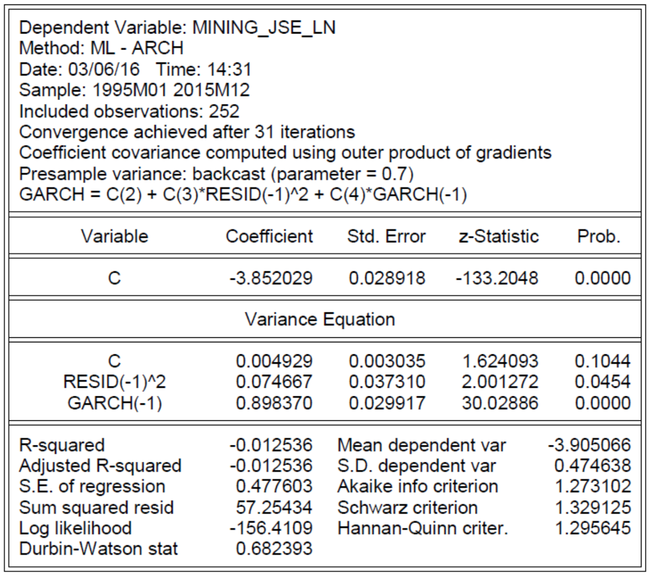
```
Dependent Variable: BANKS_SH_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:28
Sample: 2000M06 2015M12
Included observations: 187
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable        Coefficient   Std. Error   z-Statistic    Prob.

           C             -4.052271    0.038554    -105.1070     0.0000

                            Variance Equation

           C              0.028559    0.027300     1.046091     0.2955
       RESID(-1)^2        0.064693    0.064769     0.998818     0.3179
        GARCH(-1)         0.796721    0.173867     4.582359     0.0000

R-squared                -0.000007   Mean dependent var     -4.053494
Adjusted R-squared       -0.000007   S.D. dependent var      0.474110
S.E. of regression        0.474112   Akaike info criterion   1.342085
Sum squared resid         41.80942   Schwarz criterion       1.411199
Log likelihood           -121.4849   Hannan-Quinn criter.    1.370090
Durbin-Watson stat        1.079450
```

*Table 18 - GARCH model Results for the Banks industry of Taiwan*



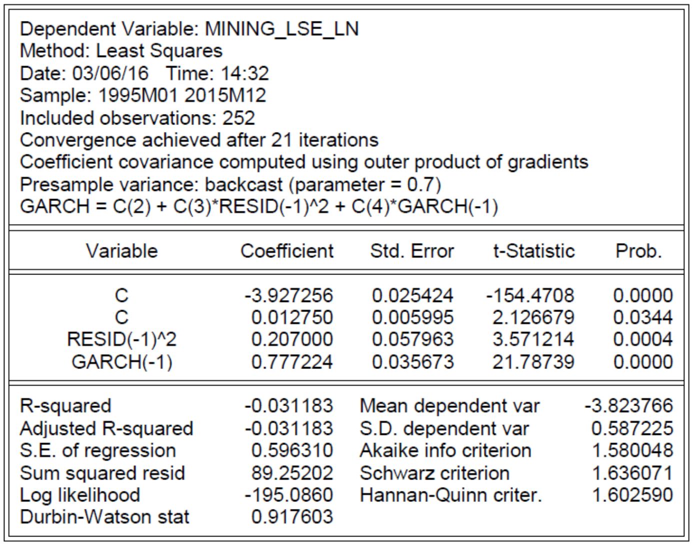
```
Dependent Variable: BANKS_TW_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:29
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

     Variable        Coefficient   Std. Error   z-Statistic    Prob.

        C            -4.071054     0.029471     -138.1385     0.0000

                         Variance Equation

        C             0.036442     0.031270     1.165395      0.2439
    RESID(-1)^2       0.250199     0.130198     1.921677      0.0546
     GARCH(-1)        0.609893     0.202185     3.016505      0.0026

R-squared            -0.057355    Mean dependent var     -4.193171
Adjusted R-squared   -0.057355    S.D. dependent var      0.510920
S.E. of regression    0.525368    Akaike info criterion   1.418369
Sum squared resid     69.27881    Schwarz criterion       1.474392
Log likelihood       -174.7145    Hannan-Quinn criter.    1.440912
Durbin-Watson stat    0.661022
```

*Table 19 - GARCH model Results for the Mining industry of the JSE*



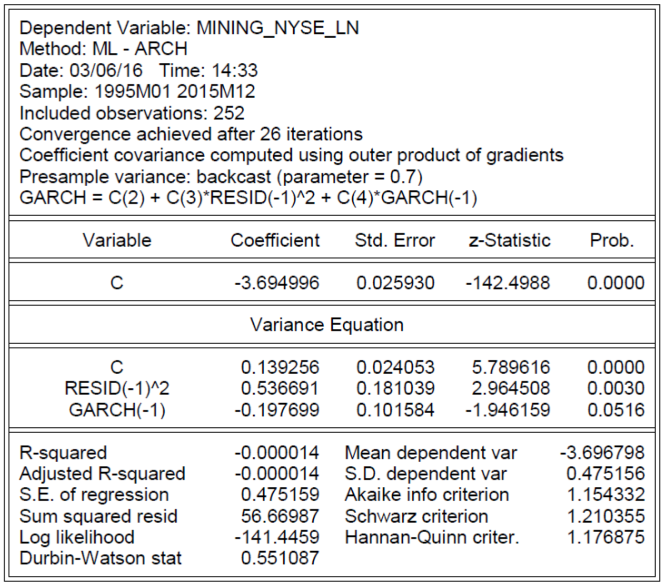
```
Dependent Variable: MINING_JSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:31
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 31 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

     Variable        Coefficient   Std. Error   z-Statistic    Prob.

        C            -3.852029     0.028918     -133.2048     0.0000

                         Variance Equation

        C             0.004929     0.003035     1.624093      0.1044
    RESID(-1)^2       0.074667     0.037310     2.001272      0.0454
     GARCH(-1)        0.898370     0.029917     30.02886      0.0000

R-squared            -0.012536    Mean dependent var     -3.905066
Adjusted R-squared   -0.012536    S.D. dependent var      0.474638
S.E. of regression    0.477603    Akaike info criterion   1.273102
Sum squared resid     57.25434    Schwarz criterion       1.329125
Log likelihood       -156.4109    Hannan-Quinn criter.    1.295645
Durbin-Watson stat    0.682393
```

*Table 20 - GARCH model Results for the Mining industry of the LSE*



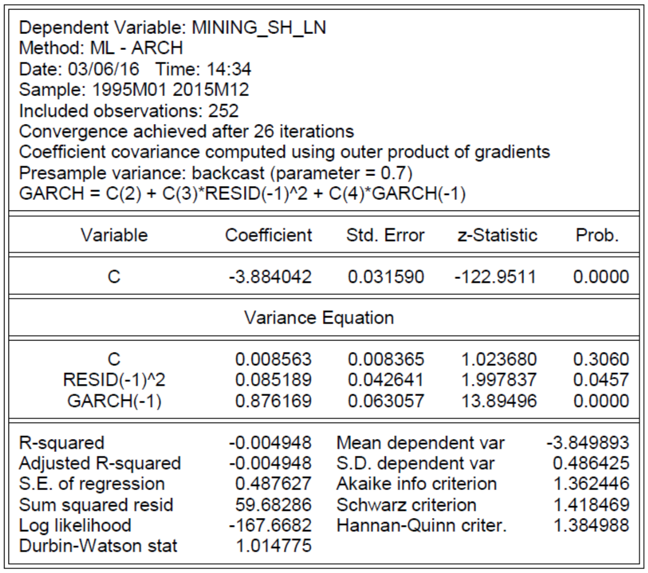
```
Dependent Variable: MINING_LSE_LN
Method: Least Squares
Date: 03/06/16   Time: 14:32
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 21 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable        Coefficient   Std. Error   t-Statistic     Prob.

            C            -3.927256    0.025424     -154.4708     0.0000
            C             0.012750    0.005995      2.126679     0.0344
        RESID(-1)^2       0.207000    0.057963      3.571214     0.0004
        GARCH(-1)         0.777224    0.035673      21.78739     0.0000

R-squared                -0.031183   Mean dependent var       -3.823766
Adjusted R-squared       -0.031183   S.D. dependent var        0.587225
S.E. of regression        0.596310   Akaike info criterion     1.580048
Sum squared resid         89.25202   Schwarz criterion         1.636071
Log likelihood           -195.0860   Hannan-Quinn criter.      1.602590
Durbin-Watson stat        0.917603
```

*Table 21 - GARCH model Results for the Mining industry of the NYSE*



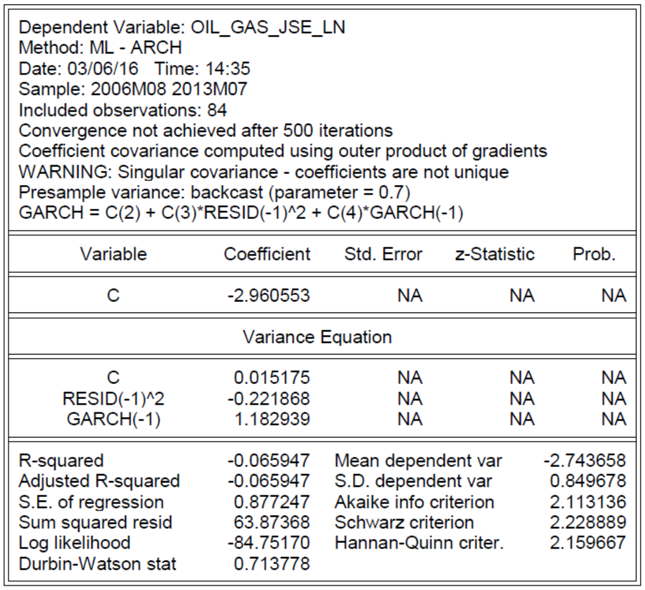
```
Dependent Variable: MINING_NYSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:33
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 26 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable        Coefficient   Std. Error   z-Statistic     Prob.

            C            -3.694996    0.025930     -142.4988     0.0000

                          Variance Equation

            C             0.139256    0.024053      5.789616     0.0000
        RESID(-1)^2       0.536691    0.181039      2.964508     0.0030
        GARCH(-1)        -0.197699    0.101584     -1.946159     0.0516

R-squared                -0.000014   Mean dependent var       -3.696798
Adjusted R-squared       -0.000014   S.D. dependent var        0.475156
S.E. of regression        0.475159   Akaike info criterion     1.154332
Sum squared resid         56.66987   Schwarz criterion         1.210355
Log likelihood           -141.4459   Hannan-Quinn criter.      1.176875
Durbin-Watson stat        0.551087
```

*Table 22 - GARCH model Results for the Mining industry of Shanghai*



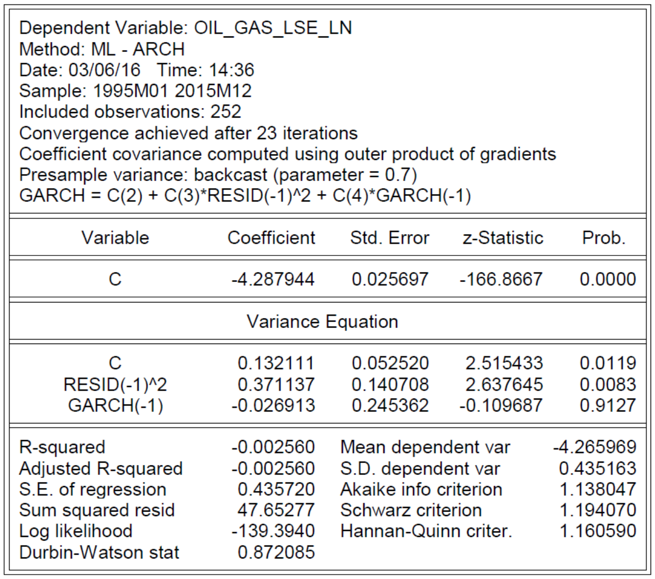
```
Dependent Variable: MINING_SH_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:34
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 26 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable        Coefficient   Std. Error   z-Statistic    Prob.

           C             -3.884042     0.031590    -122.9511     0.0000

                           Variance Equation

           C              0.008563     0.008365     1.023680     0.3060
       RESID(-1)^2        0.085189     0.042641     1.997837     0.0457
        GARCH(-1)         0.876169     0.063057     13.89496     0.0000

R-squared               -0.004948   Mean dependent var      -3.849893
Adjusted R-squared      -0.004948   S.D. dependent var       0.486425
S.E. of regression       0.487627   Akaike info criterion    1.362446
Sum squared resid        59.68286   Schwarz criterion        1.418469
Log likelihood          -167.6682   Hannan-Quinn criter.     1.384988
Durbin-Watson stat       1.014775
```

*Table 23 - GARCH model Results for the Oil & Gas Producers industry of the JSE*



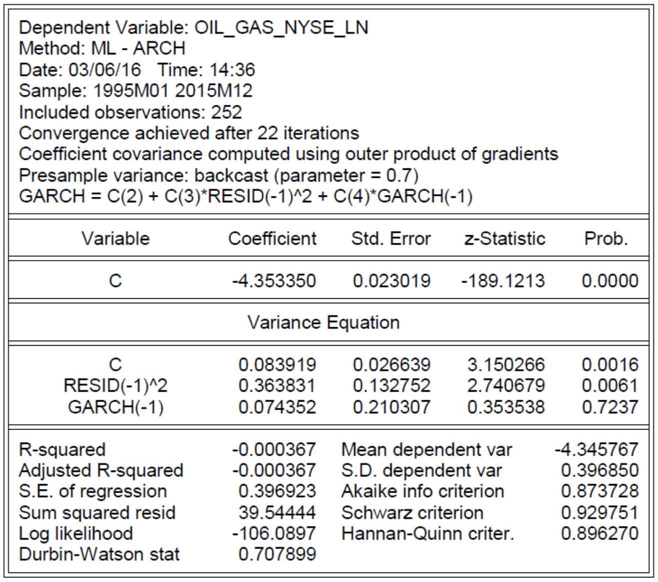
```
Dependent Variable: OIL_GAS_JSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:35
Sample: 2006M08 2013M07
Included observations: 84
Convergence not achieved after 500 iterations
Coefficient covariance computed using outer product of gradients
WARNING: Singular covariance - coefficients are not unique
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable        Coefficient   Std. Error   z-Statistic    Prob.

           C             -2.960553          NA           NA         NA

                           Variance Equation

           C              0.015175          NA           NA         NA
       RESID(-1)^2       -0.221868          NA           NA         NA
        GARCH(-1)         1.182939          NA           NA         NA

R-squared               -0.065947   Mean dependent var      -2.743658
Adjusted R-squared      -0.065947   S.D. dependent var       0.849678
S.E. of regression       0.877247   Akaike info criterion    2.113136
Sum squared resid        63.87368   Schwarz criterion        2.228889
Log likelihood          -84.75170   Hannan-Quinn criter.     2.159667
Durbin-Watson stat       0.713778
```

*Table 24 - GARCH model Results for the Oil & Gas Producers industry of the LSE*



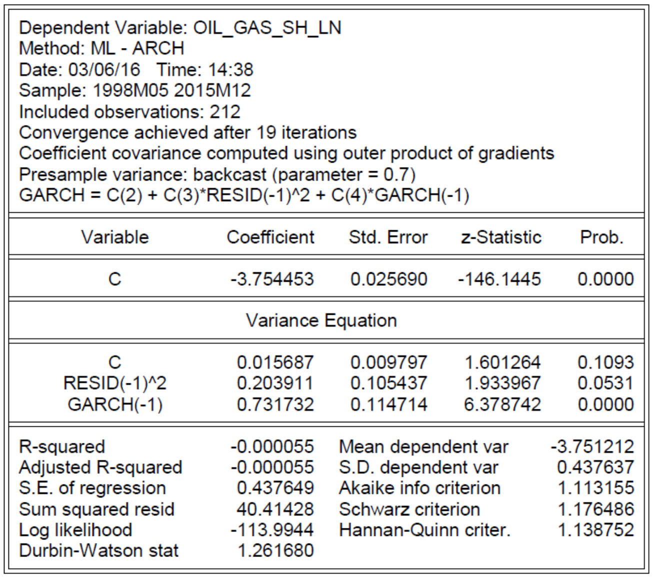
```
Dependent Variable: OIL_GAS_LSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:36
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable      Coefficient   Std. Error   z-Statistic    Prob.

           C           -4.287944    0.025697    -166.8667     0.0000

                           Variance Equation

           C            0.132111    0.052520     2.515433     0.0119
       RESID(-1)^2      0.371137    0.140708     2.637645     0.0083
        GARCH(-1)      -0.026913    0.245362    -0.109687     0.9127

R-squared              -0.002560   Mean dependent var    -4.265969
Adjusted R-squared     -0.002560   S.D. dependent var     0.435163
S.E. of regression      0.435720   Akaike info criterion  1.138047
Sum squared resid       47.65277   Schwarz criterion      1.194070
Log likelihood         -139.3940   Hannan-Quinn criter.   1.160590
Durbin-Watson stat      0.872085
```

*Table 25 - GARCH model Results for the Oil & Gas Producers industry of the NYSE*



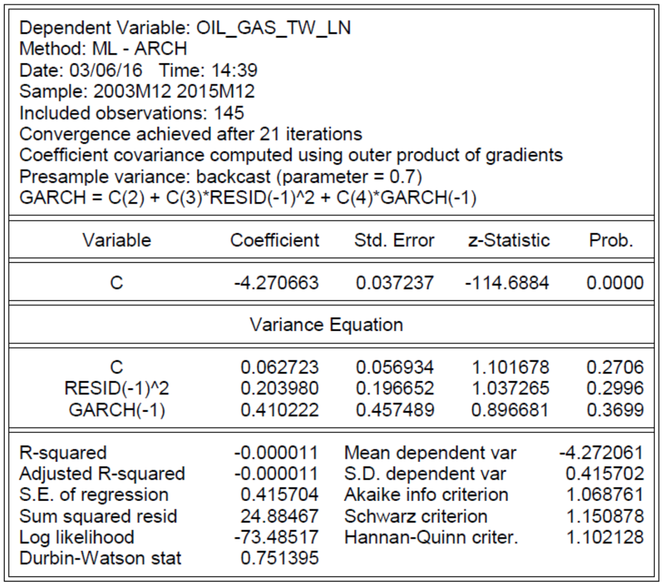
```
Dependent Variable: OIL_GAS_NYSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:36
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 22 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable      Coefficient   Std. Error   z-Statistic    Prob.

           C           -4.353350    0.023019    -189.1213     0.0000

                           Variance Equation

           C            0.083919    0.026639     3.150266     0.0016
       RESID(-1)^2      0.363831    0.132752     2.740679     0.0061
        GARCH(-1)       0.074352    0.210307     0.353538     0.7237

R-squared              -0.000367   Mean dependent var    -4.345767
Adjusted R-squared     -0.000367   S.D. dependent var     0.396850
S.E. of regression      0.396923   Akaike info criterion  0.873728
Sum squared resid       39.54444   Schwarz criterion      0.929751
Log likelihood         -106.0897   Hannan-Quinn criter.   0.896270
Durbin-Watson stat      0.707899
```

*Table 26 - GARCH model Results for the Oil & Gas Producers industry of Shanghai*



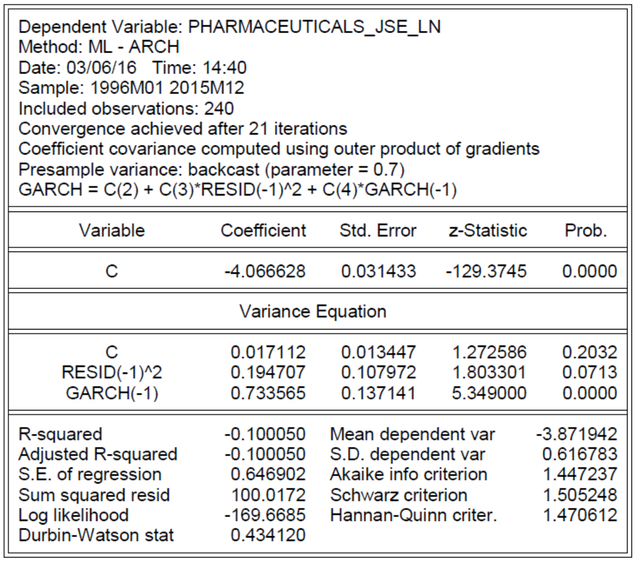
```
Dependent Variable: OIL_GAS_SH_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:38
Sample: 1998M05 2015M12
Included observations: 212
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

      Variable        Coefficient   Std. Error   z-Statistic    Prob.

         C             -3.754453    0.025690    -146.1445     0.0000

                         Variance Equation

         C              0.015687    0.009797     1.601264     0.1093
     RESID(-1)^2        0.203911    0.105437     1.933967     0.0531
      GARCH(-1)         0.731732    0.114714     6.378742     0.0000

R-squared             -0.000055   Mean dependent var     -3.751212
Adjusted R-squared    -0.000055   S.D. dependent var      0.437637
S.E. of regression     0.437649   Akaike info criterion   1.113155
Sum squared resid      40.41428   Schwarz criterion       1.176486
Log likelihood        -113.9944   Hannan-Quinn criter.    1.138752
Durbin-Watson stat     1.261680
```

*Table 27 - GARCH model Results for the Oil & Gas Producers industry of Taiwan*



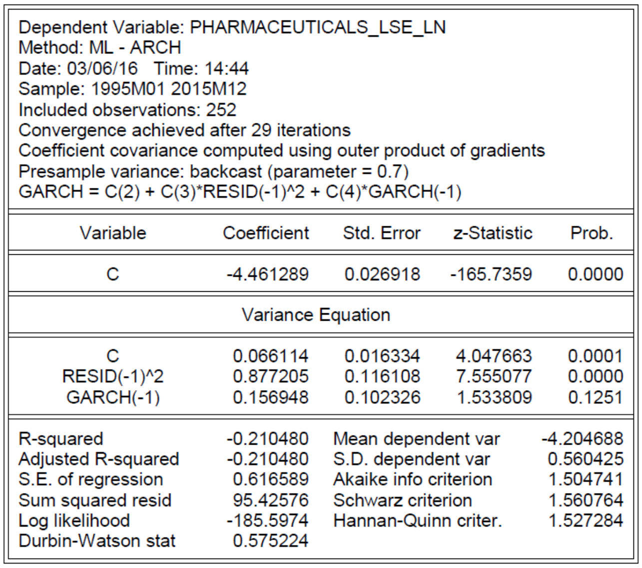
```
Dependent Variable: OIL_GAS_TW_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:39
Sample: 2003M12 2015M12
Included observations: 145
Convergence achieved after 21 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

      Variable        Coefficient   Std. Error   z-Statistic    Prob.

         C             -4.270663    0.037237    -114.6884     0.0000

                         Variance Equation

         C              0.062723    0.056934     1.101678     0.2706
     RESID(-1)^2        0.203980    0.196652     1.037265     0.2996
      GARCH(-1)         0.410222    0.457489     0.896681     0.3699

R-squared             -0.000011   Mean dependent var     -4.272061
Adjusted R-squared    -0.000011   S.D. dependent var      0.415702
S.E. of regression     0.415704   Akaike info criterion   1.068761
Sum squared resid      24.88467   Schwarz criterion       1.150878
Log likelihood        -73.48517   Hannan-Quinn criter.    1.102128
Durbin-Watson stat     0.751395
```

*Table 28 - GARCH model Results for the Pharmaceuticals & Biotechnology industry of the JSE*



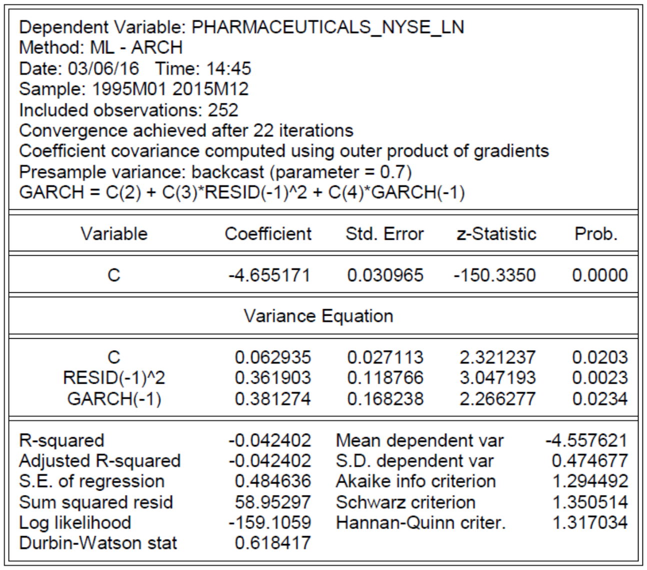
```
Dependent Variable: PHARMACEUTICALS_JSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:40
Sample: 1996M01 2015M12
Included observations: 240
Convergence achieved after 21 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

     Variable        Coefficient   Std. Error   z-Statistic    Prob.

        C             -4.066628    0.031433     -129.3745     0.0000

                          Variance Equation

        C              0.017112    0.013447      1.272586     0.2032
   RESID(-1)^2         0.194707    0.107972      1.803301     0.0713
    GARCH(-1)          0.733565    0.137141      5.349000     0.0000

R-squared             -0.100050   Mean dependent var     -3.871942
Adjusted R-squared    -0.100050   S.D. dependent var      0.616783
S.E. of regression     0.646902   Akaike info criterion   1.447237
Sum squared resid      100.0172   Schwarz criterion       1.505248
Log likelihood        -169.6685   Hannan-Quinn criter.    1.470612
Durbin-Watson stat     0.434120
```

*Table 29 - GARCH model Results for the Pharmaceuticals & Biotechnology industry of the LSE*



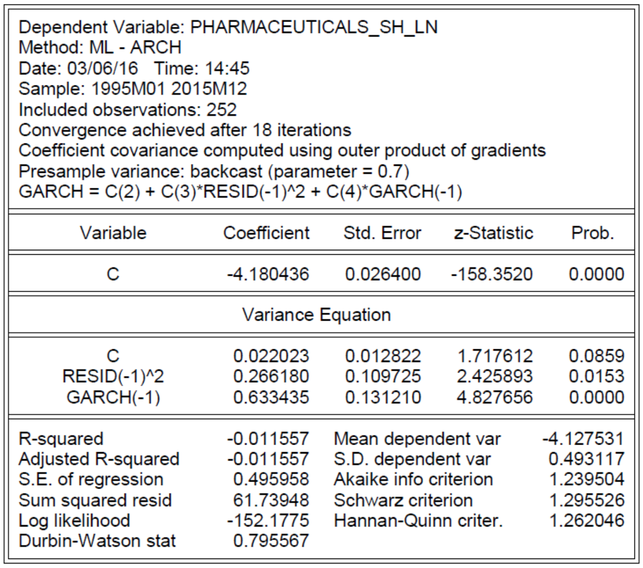
```
Dependent Variable: PHARMACEUTICALS_LSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:44
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 29 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

     Variable        Coefficient   Std. Error   z-Statistic    Prob.

        C             -4.461289    0.026918     -165.7359     0.0000

                          Variance Equation

        C              0.066114    0.016334      4.047663     0.0001
   RESID(-1)^2         0.877205    0.116108      7.555077     0.0000
    GARCH(-1)          0.156948    0.102326      1.533809     0.1251

R-squared             -0.210480   Mean dependent var     -4.204688
Adjusted R-squared    -0.210480   S.D. dependent var      0.560425
S.E. of regression     0.616589   Akaike info criterion   1.504741
Sum squared resid      95.42576   Schwarz criterion       1.560764
Log likelihood        -185.5974   Hannan-Quinn criter.    1.527284
Durbin-Watson stat     0.575224
```

*Table 30 - GARCH model Results for the Pharmaceuticals & Biotechnology industry of the NYSE*



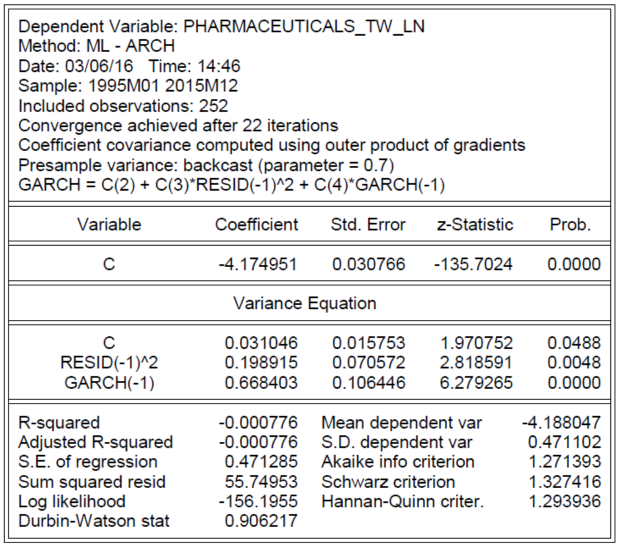
```
Dependent Variable: PHARMACEUTICALS_NYSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:45
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 22 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

      Variable        Coefficient   Std. Error   z-Statistic    Prob.

         C             -4.655171     0.030965    -150.3350     0.0000

                          Variance Equation

         C              0.062935     0.027113     2.321237     0.0203
     RESID(-1)^2        0.361903     0.118766     3.047193     0.0023
      GARCH(-1)         0.381274     0.168238     2.266277     0.0234

R-squared              -0.042402   Mean dependent var    -4.557621
Adjusted R-squared     -0.042402   S.D. dependent var     0.474677
S.E. of regression      0.484636   Akaike info criterion  1.294492
Sum squared resid       58.95297   Schwarz criterion      1.350514
Log likelihood         -159.1059   Hannan-Quinn criter.   1.317034
Durbin-Watson stat      0.618417
```

*Table 31 - GARCH model Results for the Pharmaceuticals & Biotechnology industry of Shanghai*



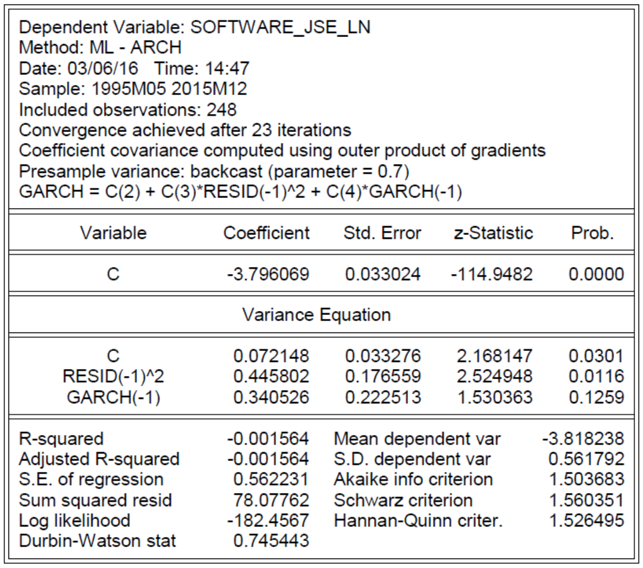
```
Dependent Variable: PHARMACEUTICALS_SH_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:45
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

      Variable        Coefficient   Std. Error   z-Statistic    Prob.

         C             -4.180436     0.026400    -158.3520     0.0000

                          Variance Equation

         C              0.022023     0.012822     1.717612     0.0859
     RESID(-1)^2        0.266180     0.109725     2.425893     0.0153
      GARCH(-1)         0.633435     0.131210     4.827656     0.0000

R-squared              -0.011557   Mean dependent var    -4.127531
Adjusted R-squared     -0.011557   S.D. dependent var     0.493117
S.E. of regression      0.495958   Akaike info criterion  1.239504
Sum squared resid       61.73948   Schwarz criterion      1.295526
Log likelihood         -152.1775   Hannan-Quinn criter.   1.262046
Durbin-Watson stat      0.795567
```

*Table 32 - GARCH model Results for the Pharmaceuticals & Biotechnology industry of Taiwan*



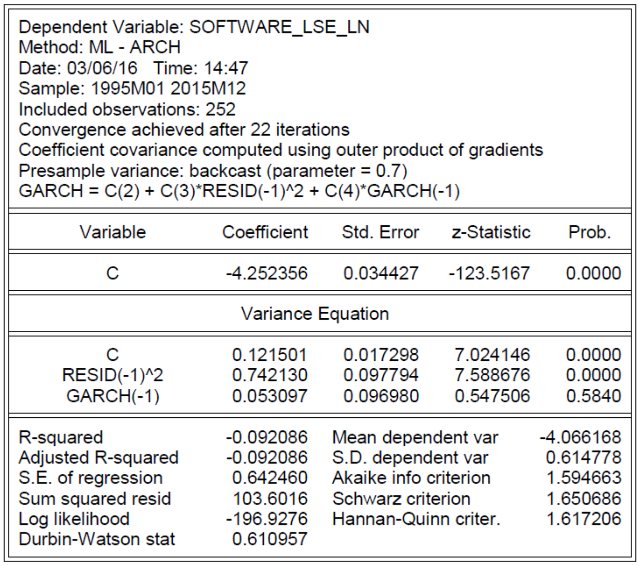
```
Dependent Variable: PHARMACEUTICALS_TW_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:46
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 22 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

     Variable       Coefficient    Std. Error   z-Statistic    Prob.

         C           -4.174951     0.030766     -135.7024     0.0000

                         Variance Equation

         C            0.031046     0.015753      1.970752     0.0488
     RESID(-1)^2      0.198915     0.070572      2.818591     0.0048
      GARCH(-1)       0.668403     0.106446      6.279265     0.0000

R-squared            -0.000776   Mean dependent var      -4.188047
Adjusted R-squared   -0.000776   S.D. dependent var       0.471102
S.E. of regression    0.471285   Akaike info criterion    1.271393
Sum squared resid     55.74953   Schwarz criterion        1.327416
Log likelihood       -156.1955   Hannan-Quinn criter.     1.293936
Durbin-Watson stat    0.906217
```

*Table 33 - GARCH model Results for the Software & Computer Services industry of the JSE*



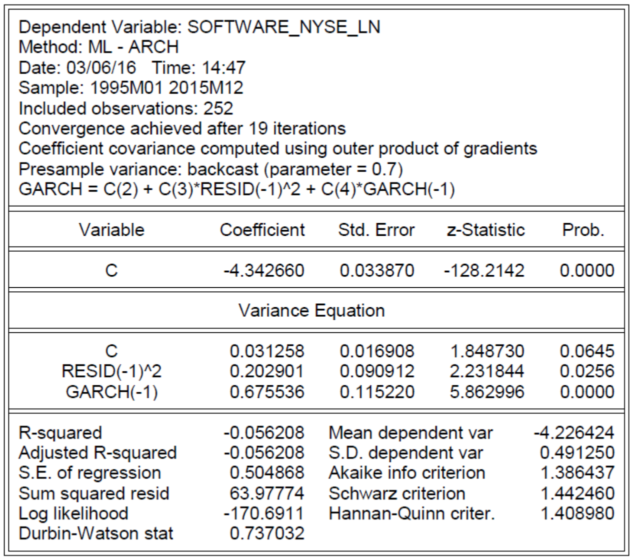
```
Dependent Variable: SOFTWARE_JSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:47
Sample: 1995M05 2015M12
Included observations: 248
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

     Variable       Coefficient    Std. Error   z-Statistic    Prob.

         C           -3.796069     0.033024     -114.9482     0.0000

                         Variance Equation

         C            0.072148     0.033276      2.168147     0.0301
     RESID(-1)^2      0.445802     0.176559      2.524948     0.0116
      GARCH(-1)       0.340526     0.222513      1.530363     0.1259

R-squared            -0.001564   Mean dependent var      -3.818238
Adjusted R-squared   -0.001564   S.D. dependent var       0.561792
S.E. of regression    0.562231   Akaike info criterion    1.503683
Sum squared resid     78.07762   Schwarz criterion        1.560351
Log likelihood       -182.4567   Hannan-Quinn criter.     1.526495
Durbin-Watson stat    0.745443
```

*Table 34 -GARCH model Results for the Software & Computer Services industry of the LSE*



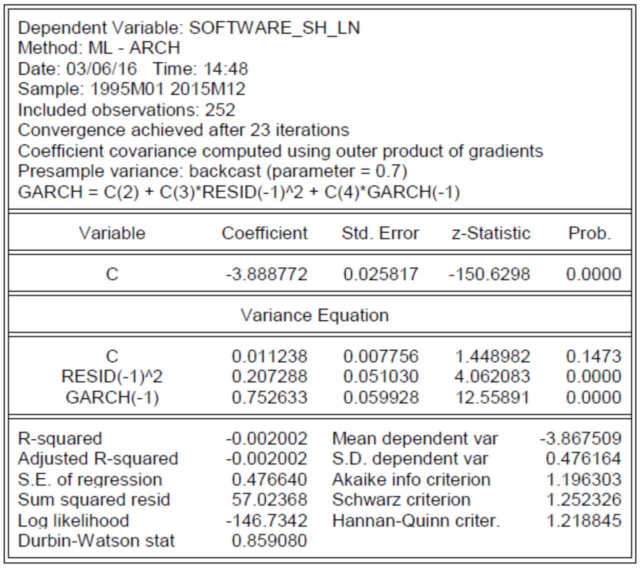
```
Dependent Variable: SOFTWARE_LSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:47
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 22 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable        Coefficient   Std. Error   z-Statistic     Prob.

           C             -4.252356     0.034427     -123.5167     0.0000

                             Variance Equation

           C              0.121501     0.017298      7.024146     0.0000
      RESID(-1)^2         0.742130     0.097794      7.588676     0.0000
       GARCH(-1)          0.053097     0.096980      0.547506     0.5840

R-squared               -0.092086    Mean dependent var      -4.066168
Adjusted R-squared      -0.092086    S.D. dependent var       0.614778
S.E. of regression       0.642460    Akaike info criterion    1.594663
Sum squared resid        103.6016    Schwarz criterion        1.650686
Log likelihood          -196.9276    Hannan-Quinn criter.     1.617206
Durbin-Watson stat       0.610957
```

*Table 35 - GARCH model Results for the Software & Computer Services industry of the NYSE*



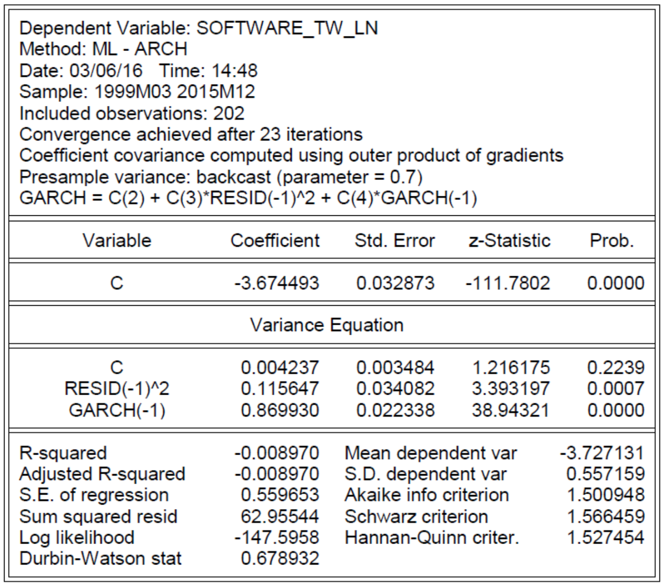
```
Dependent Variable: SOFTWARE_NYSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:47
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable        Coefficient   Std. Error   z-Statistic     Prob.

           C             -4.342660     0.033870     -128.2142     0.0000

                             Variance Equation

           C              0.031258     0.016908      1.848730     0.0645
      RESID(-1)^2         0.202901     0.090912      2.231844     0.0256
       GARCH(-1)          0.675536     0.115220      5.862996     0.0000

R-squared               -0.056208    Mean dependent var      -4.226424
Adjusted R-squared      -0.056208    S.D. dependent var       0.491250
S.E. of regression       0.504868    Akaike info criterion    1.386437
Sum squared resid        63.97774    Schwarz criterion        1.442460
Log likelihood          -170.6911    Hannan-Quinn criter.     1.408980
Durbin-Watson stat       0.737032
```

*Table 36 - GARCH model Results for the Software & Computer Services industry of Shanghai*



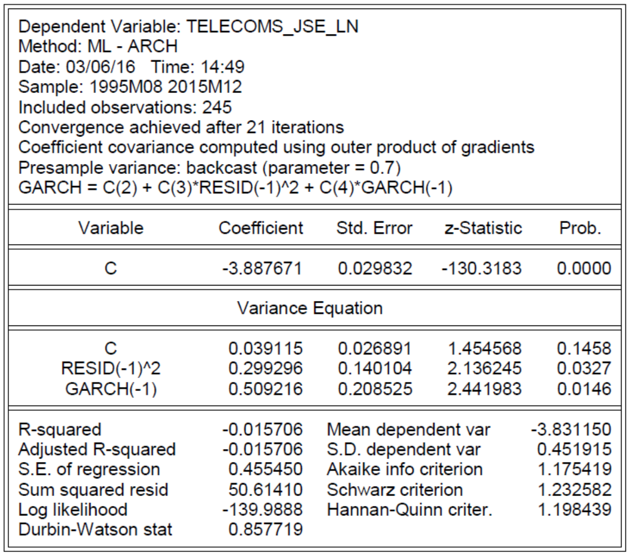
```
Dependent Variable: SOFTWARE_SH_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:48
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable        Coefficient   Std. Error   z-Statistic    Prob.

           C             -3.888772     0.025817    -150.6298     0.0000

                            Variance Equation

           C              0.011238     0.007756     1.448982     0.1473
       RESID(-1)^2        0.207288     0.051030     4.062083     0.0000
        GARCH(-1)         0.752633     0.059928     12.55891     0.0000

R-squared                -0.002002   Mean dependent var      -3.867509
Adjusted R-squared       -0.002002   S.D. dependent var       0.476164
S.E. of regression        0.476640   Akaike info criterion    1.196303
Sum squared resid         57.02368   Schwarz criterion        1.252326
Log likelihood           -146.7342   Hannan-Quinn criter.     1.218845
Durbin-Watson stat        0.859080
```

*Table 37 - GARCH model Results for the Software & Computer Services industry of Taiwan*



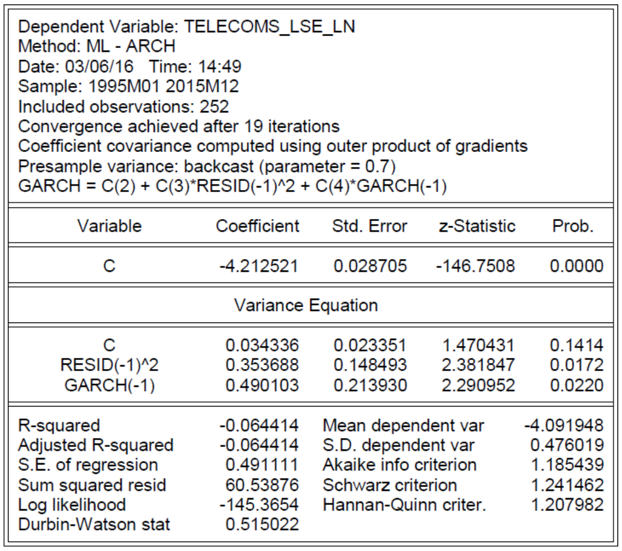
```
Dependent Variable: SOFTWARE_TW_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:48
Sample: 1999M03 2015M12
Included observations: 202
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable        Coefficient   Std. Error   z-Statistic    Prob.

           C             -3.674493     0.032873    -111.7802     0.0000

                            Variance Equation

           C              0.004237     0.003484     1.216175     0.2239
       RESID(-1)^2        0.115647     0.034082     3.393197     0.0007
        GARCH(-1)         0.869930     0.022338     38.94321     0.0000

R-squared                -0.008970   Mean dependent var      -3.727131
Adjusted R-squared       -0.008970   S.D. dependent var       0.557159
S.E. of regression        0.559653   Akaike info criterion    1.500948
Sum squared resid         62.95544   Schwarz criterion        1.566459
Log likelihood           -147.5958   Hannan-Quinn criter.     1.527454
Durbin-Watson stat        0.678932
```

*Table 38 - GARCH model Results for the Mobile Telecommunications industry of the JSE*



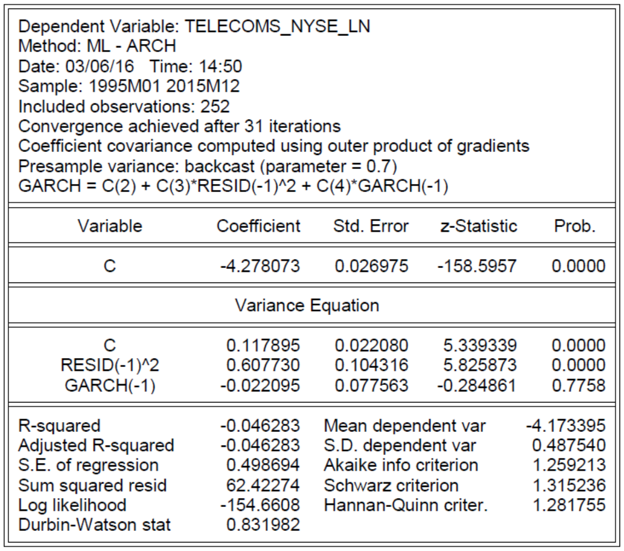
```
Dependent Variable: TELECOMS_JSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:49
Sample: 1995M08 2015M12
Included observations: 245
Convergence achieved after 21 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable          Coefficient    Std. Error    z-Statistic    Prob.

           C               -3.887671     0.029832      -130.3183     0.0000

                              Variance Equation

           C                0.039115     0.026891      1.454568      0.1458
       RESID(-1)^2          0.299296     0.140104      2.136245      0.0327
        GARCH(-1)           0.509216     0.208525      2.441983      0.0146

R-squared                -0.015706    Mean dependent var      -3.831150
Adjusted R-squared       -0.015706    S.D. dependent var       0.451915
S.E. of regression        0.455450    Akaike info criterion    1.175419
Sum squared resid         50.61410    Schwarz criterion        1.232582
Log likelihood           -139.9888    Hannan-Quinn criter.     1.198439
Durbin-Watson stat        0.857719
```

*Table 39 - GARCH model Results for the Mobile Telecommunications industry of the LSE*



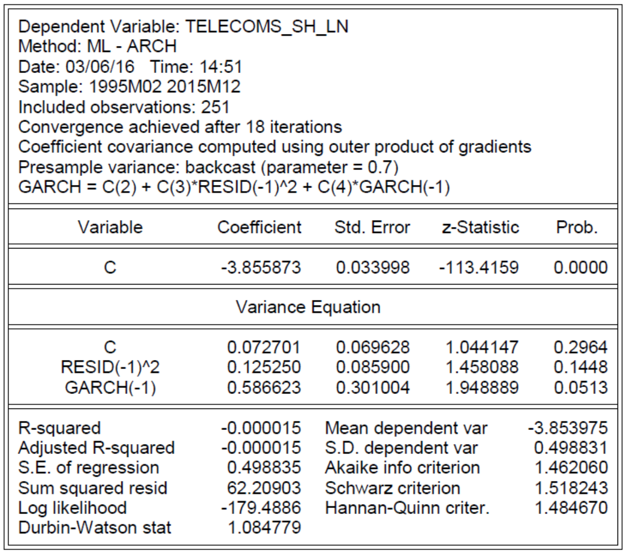
```
Dependent Variable: TELECOMS_LSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:49
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable          Coefficient    Std. Error    z-Statistic    Prob.

           C               -4.212521     0.028705      -146.7508     0.0000

                              Variance Equation

           C                0.034336     0.023351      1.470431      0.1414
       RESID(-1)^2          0.353688     0.148493      2.381847      0.0172
        GARCH(-1)           0.490103     0.213930      2.290952      0.0220

R-squared                -0.064414    Mean dependent var      -4.091948
Adjusted R-squared       -0.064414    S.D. dependent var       0.476019
S.E. of regression        0.491111    Akaike info criterion    1.185439
Sum squared resid         60.53876    Schwarz criterion        1.241462
Log likelihood           -145.3654    Hannan-Quinn criter.     1.207982
Durbin-Watson stat        0.515022
```

*Table 40 - GARCH model Results for the Mobile Telecommunications industry of the NYSE*



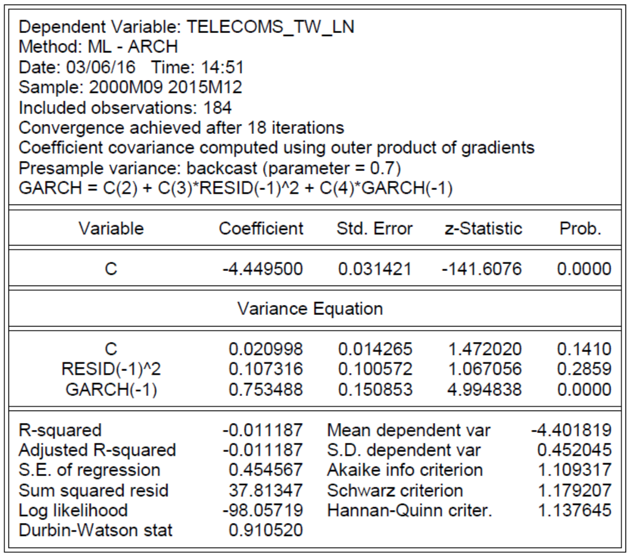
```
Dependent Variable: TELECOMS_NYSE_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:50
Sample: 1995M01 2015M12
Included observations: 252
Convergence achieved after 31 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable        Coefficient   Std. Error   z-Statistic   Prob.

           C            -4.278073     0.026975    -158.5957     0.0000

                           Variance Equation

           C             0.117895     0.022080     5.339339     0.0000
      RESID(-1)^2        0.607730     0.104316     5.825873     0.0000
       GARCH(-1)        -0.022095     0.077563    -0.284861     0.7758

R-squared              -0.046283    Mean dependent var     -4.173395
Adjusted R-squared     -0.046283    S.D. dependent var      0.487540
S.E. of regression      0.498694    Akaike info criterion   1.259213
Sum squared resid       62.42274    Schwarz criterion       1.315236
Log likelihood         -154.6608    Hannan-Quinn criter.    1.281755
Durbin-Watson stat      0.831982
```

*Table 41 - GARCH model Results for the Mobile Telecommunications industry of Shanghai*



```
Dependent Variable: TELECOMS_SH_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:51
Sample: 1995M02 2015M12
Included observations: 251
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable        Coefficient   Std. Error   z-Statistic   Prob.

           C            -3.855873     0.033998    -113.4159     0.0000

                           Variance Equation

           C             0.072701     0.069628     1.044147     0.2964
      RESID(-1)^2        0.125250     0.085900     1.458088     0.1448
       GARCH(-1)         0.586623     0.301004     1.948889     0.0513

R-squared              -0.000015    Mean dependent var     -3.853975
Adjusted R-squared     -0.000015    S.D. dependent var      0.498831
S.E. of regression      0.498835    Akaike info criterion   1.462060
Sum squared resid       62.20903    Schwarz criterion       1.518243
Log likelihood         -179.4886    Hannan-Quinn criter.    1.484670
Durbin-Watson stat      1.084779
```

*Table 42 - GARCH model Results for the Mobile Telecommunications industry of Taiwan*

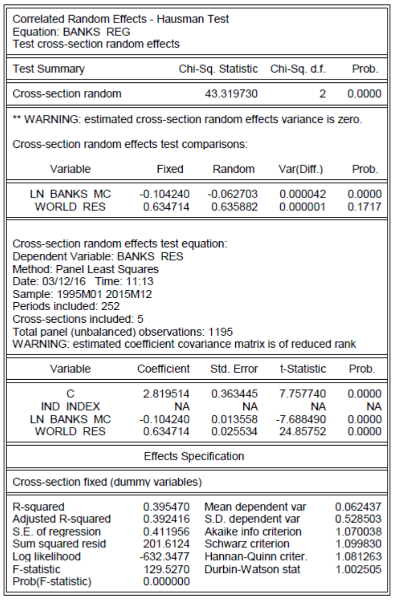


```
Dependent Variable: TELECOMS_TW_LN
Method: ML - ARCH
Date: 03/06/16   Time: 14:51
Sample: 2000M09 2015M12
Included observations: 184
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

        Variable        Coefficient   Std. Error   z-Statistic     Prob.

           C             -4.449500     0.031421    -141.6076      0.0000

                              Variance Equation

           C              0.020998     0.014265     1.472020      0.1410
       RESID(-1)^2        0.107316     0.100572     1.067056      0.2859
        GARCH(-1)         0.753488     0.150853     4.994838      0.0000

R-squared               -0.011187    Mean dependent var      -4.401819
Adjusted R-squared      -0.011187    S.D. dependent var       0.452045
S.E. of regression       0.454567    Akaike info criterion    1.109317
Sum squared resid        37.81347    Schwarz criterion        1.179207
Log likelihood          -98.05719    Hannan-Quinn criter.     1.137645
Durbin-Watson stat       0.910520
```

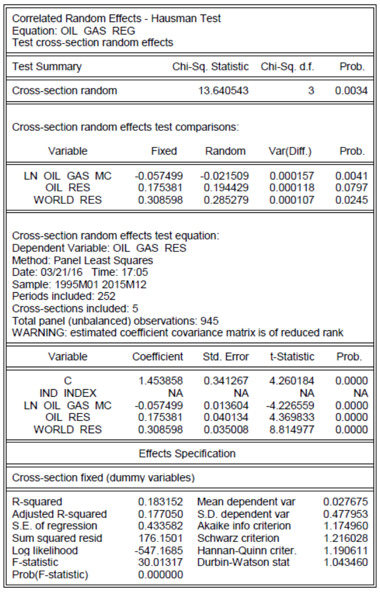
## 8.4 HAUSMAN TEST RESULTS

Hausman tests were conducted on each of the panel data regression specifications and the results below show unequivocally that random effects were not present in each of the panel data sets. As can be seen from the cross-section random test statistics and probabilities, the null hypothesis of the existence of random effects was rejected for each set.

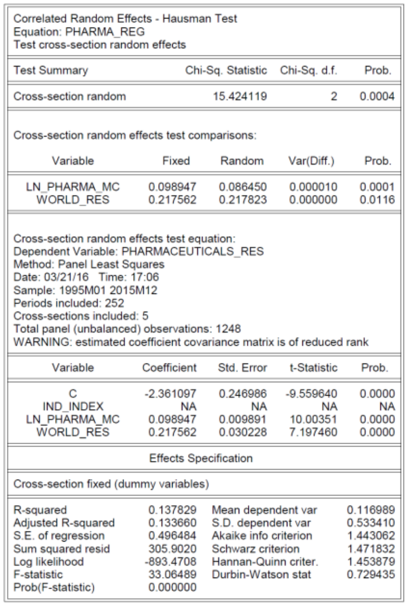
*Table 43 - Hausman test results for the Banks, Oil & Gas Producers and Pharmaceuticals & Biotechnology industries*



```
Correlated Random Effects - Hausman Test
Equation: BANKS  REG
Test cross-section random effects

Test Summary                 Chi-Sq. Statistic  Chi-Sq. d.f.    Prob.

Cross-section random                 43.319730             2   0.0000

** WARNING: estimated cross-section random effects variance is zero.

Cross-section random effects test comparisons:

     Variable            Fixed       Random    Var(Diff.)    Prob.

   LN  BANKS  MC     -0.104240    -0.062703     0.000042    0.0000
    WORLD  RES        0.634714     0.635882     0.000001    0.1717


Cross-section random effects test equation:
Dependent Variable: BANKS  RES
Method: Panel Least Squares
Date: 03/12/16   Time: 11:13
Sample: 1995M01 2015M12
Periods included: 252
Cross-sections included: 5
Total panel (unbalanced) observations: 1195
WARNING: estimated coefficient covariance matrix is of reduced rank

     Variable         Coefficient   Std. Error   t-Statistic    Prob.

        C              2.819514     0.363445     7.757740     0.0000
    IND  INDEX               NA           NA           NA         NA
   LN  BANKS  MC      -0.104240     0.013558    -7.688490     0.0000
    WORLD  RES         0.634714     0.025534     24.85752     0.0000

                          Effects Specification

Cross-section fixed (dummy variables)

R-squared              0.395470    Mean dependent var       0.062437
Adjusted R-squared     0.392416    S.D. dependent var       0.528503
S.E. of regression     0.411956    Akaike info criterion    1.070038
Sum squared resid      201.6124    Schwarz criterion        1.099830
Log likelihood        -632.3477    Hannan-Quinn criter.     1.081263
F-statistic            129.5270    Durbin-Watson stat       1.002505
Prob(F-statistic)      0.000000
```

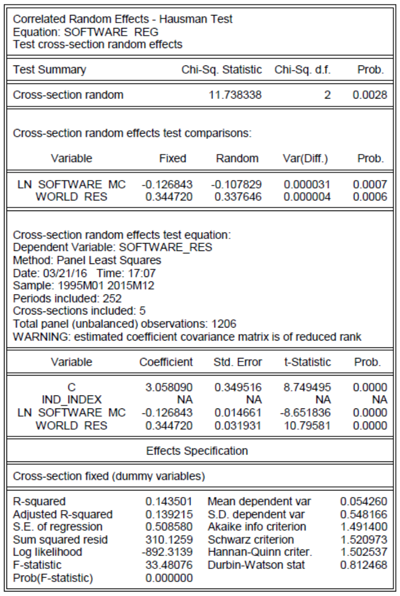


```
Correlated Random Effects - Hausman Test
Equation: OIL  GAS  REG
Test cross-section random effects

Test Summary                 Chi-Sq. Statistic  Chi-Sq. d.f.    Prob.

Cross-section random                 13.640543             3   0.0034


Cross-section random effects test comparisons:

     Variable            Fixed       Random    Var(Diff.)    Prob.

   LN  OIL  GAS  MC  -0.057499    -0.021509     0.000157    0.0041
      OIL  RES        0.175381     0.194429     0.000118    0.0797
    WORLD  RES        0.308598     0.285279     0.000107    0.0245


Cross-section random effects test equation:
Dependent Variable: OIL  GAS  RES
Method: Panel Least Squares
Date: 03/21/16   Time: 17:05
Sample: 1995M01 2015M12
Periods included: 252
Cross-sections included: 5
Total panel (unbalanced) observations: 945
WARNING: estimated coefficient covariance matrix is of reduced rank

     Variable         Coefficient   Std. Error   t-Statistic    Prob.

        C              1.453858     0.341267     4.260184     0.0000
    IND  INDEX               NA           NA           NA         NA
  LN  OIL  GAS  MC    -0.057499     0.013604    -4.226559     0.0000
      OIL  RES         0.175381     0.040134     4.369833     0.0000
    WORLD  RES         0.308598     0.035008     8.814977     0.0000

                          Effects Specification

Cross-section fixed (dummy variables)

R-squared              0.183152    Mean dependent var       0.027675
Adjusted R-squared     0.177050    S.D. dependent var       0.477953
S.E. of regression     0.433582    Akaike info criterion    1.174960
Sum squared resid      176.1501    Schwarz criterion        1.216028
Log likelihood        -547.1685    Hannan-Quinn criter.     1.190611
F-statistic            30.01317    Durbin-Watson stat       1.043460
Prob(F-statistic)      0.000000
```

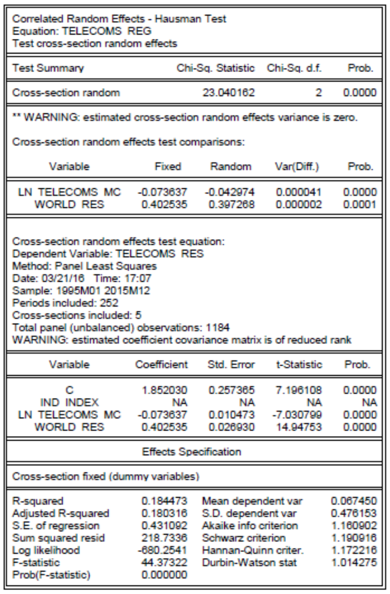


```
Correlated Random Effects - Hausman Test
Equation: PHARMA_REG
Test cross-section random effects

Test Summary                 Chi-Sq. Statistic  Chi-Sq. d.f.    Prob.

Cross-section random                 15.424119             2   0.0004


Cross-section random effects test comparisons:

     Variable            Fixed       Random    Var(Diff.)    Prob.

   LN_PHARMA_MC       0.098947     0.086450     0.000010    0.0001
     WORLD_RES        0.217562     0.217823     0.000000    0.0116


Cross-section random effects test equation:
Dependent Variable: PHARMACEUTICALS_RES
Method: Panel Least Squares
Date: 03/21/16   Time: 17:06
Sample: 1995M01 2015M12
Periods included: 252
Cross-sections included: 5
Total panel (unbalanced) observations: 1248
WARNING: estimated coefficient covariance matrix is of reduced rank

     Variable         Coefficient   Std. Error   t-Statistic    Prob.

        C             -2.361097     0.246986    -9.559640     0.0000
     IND_INDEX               NA           NA           NA         NA
   LN_PHARMA_MC        0.098947     0.009891     10.00351     0.0000
     WORLD_RES         0.217562     0.030228     7.197460     0.0000

                          Effects Specification

Cross-section fixed (dummy variables)

R-squared              0.137829    Mean dependent var       0.116989
Adjusted R-squared     0.133660    S.D. dependent var       0.533410
S.E. of regression     0.496484    Akaike info criterion    1.443062
Sum squared resid      305.9020    Schwarz criterion        1.471832
Log likelihood        -893.4708    Hannan-Quinn criter.     1.453879
F-statistic            33.06489    Durbin-Watson stat       0.729435
Prob(F-statistic)      0.000000
```

*Table 44 - Hausman test results for the Software & Computer Services and Mobile Telecommunications industries*



```
Correlated Random Effects - Hausman Test
Equation: SOFTWARE  REG
Test cross-section random effects

Test Summary                 Chi-Sq. Statistic  Chi-Sq. d.f.    Prob.

Cross-section random                 11.738338             2   0.0028


Cross-section random effects test comparisons:

     Variable            Fixed       Random    Var(Diff.)    Prob.

 LN  SOFTWARE  MC    -0.126843    -0.107829     0.000031    0.0007
    WORLD  RES        0.344720     0.337646     0.000004    0.0006


Cross-section random effects test equation:
Dependent Variable: SOFTWARE_RES
Method: Panel Least Squares
Date: 03/21/16   Time: 17:07
Sample: 1995M01 2015M12
Periods included: 252
Cross-sections included: 5
Total panel (unbalanced) observations: 1206
WARNING: estimated coefficient covariance matrix is of reduced rank

     Variable         Coefficient   Std. Error   t-Statistic    Prob.

        C              3.058090     0.349516     8.749495     0.0000
     IND_INDEX               NA           NA           NA         NA
 LN  SOFTWARE  MC     -0.126843     0.014661    -8.651836     0.0000
    WORLD  RES         0.344720     0.031931     10.79581     0.0000

                          Effects Specification

Cross-section fixed (dummy variables)

R-squared              0.143501    Mean dependent var       0.054260
Adjusted R-squared     0.139215    S.D. dependent var       0.548166
S.E. of regression     0.508580    Akaike info criterion    1.491400
Sum squared resid      310.1259    Schwarz criterion        1.520973
Log likelihood        -892.3139    Hannan-Quinn criter.     1.502537
F-statistic            33.48076    Durbin-Watson stat       0.812468
Prob(F-statistic)      0.000000
```



```
Correlated Random Effects - Hausman Test
Equation: TELECOMS  REG
Test cross-section random effects

Test Summary                 Chi-Sq. Statistic  Chi-Sq. d.f.    Prob.

Cross-section random                 23.040162             2   0.0000

** WARNING: estimated cross-section random effects variance is zero.

Cross-section random effects test comparisons:

     Variable            Fixed       Random    Var(Diff.)    Prob.

 LN  TELECOMS  MC    -0.073637    -0.042974     0.000041    0.0000
    WORLD  RES        0.402535     0.397268     0.000002    0.0001


Cross-section random effects test equation:
Dependent Variable: TELECOMS  RES
Method: Panel Least Squares
Date: 03/21/16   Time: 17:07
Sample: 1995M01 2015M12
Periods included: 252
Cross-sections included: 5
Total panel (unbalanced) observations: 1184
WARNING: estimated coefficient covariance matrix is of reduced rank

     Variable         Coefficient   Std. Error   t-Statistic    Prob.

        C              1.852030     0.257365     7.196108     0.0000
    IND  INDEX               NA           NA           NA         NA
 LN  TELECOMS  MC     -0.073637     0.010473    -7.030799     0.0000
    WORLD  RES         0.402535     0.026930     14.94753     0.0000

                          Effects Specification

Cross-section fixed (dummy variables)

R-squared              0.184473    Mean dependent var       0.067450
Adjusted R-squared     0.180316    S.D. dependent var       0.476153
S.E. of regression     0.431092    Akaike info criterion    1.160902
Sum squared resid      218.7336    Schwarz criterion        1.190916
Log likelihood        -680.2541    Hannan-Quinn criter.     1.172216
F-statistic            44.37322    Durbin-Watson stat       1.014275
Prob(F-statistic)      0.000000
```