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Stock Return Predictability

&

Output, Export and Import

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Executive Summary

This master's thesis investigates the ability of output, export and import to predict the stock return over long horizons and it aims to estimate this predictability both in- and out-of-sample.

Theoretically, the current thesis is founded on the works of Fama & French (1988) and Rangvid (2006). The theoretical idea behind stock return predictability using financial or macroeconomic ratios is that if the stock price is high relative to a given level of output, the investors are willing to pay a high price for the stocks because they expect one of two things to happen in the future, when ruling out bubbles. Either the output will be high due to good economic performing in terms of production or the stock returns rates will be low due to lower required rates of return. The effect will be the same for export, whereas high import compared with stock prices will predict low future import growth or low stock returns.

The stock return predictability is investigated by regressing the price-output, price-export or price-import ratios, respectively on the quarterly stock returns summed over 4, 12 or 20 quarters.
The countries investigated in the thesis are Denmark, The Netherlands, France and United Kingdom. These countries represent two small and to large countries, since the stock returns in the small countries may be assumed to be more influenced by the export and import due to the fact that their economies can be seen as more open.

The in-sample regression for the period 1970-1999 shows high predictability power, since the R2-values are high and the coefficients are very significant using heteroscedasticity and autocorrelation corrected standard errors. All countries and ratios have similar predictive power, except that prediction for The Netherlands seems to perform slightly inferior to the prediction for the other countries. The robustness tests reveal that the results are robust for Denmark and not for United Kingdom.

The out-of-sample testing from 2000-2010 reveals that the predictability of the stock return by the ratios is inferior to the stock return predictability by the random walk; hence the results cannot be used by the real time investors.

1 Introduction

Since Fama & French[1] and Campbell & Shiller[2] in 1988 first shook the otherwise firm perception of the efficient market and its random walk with two articles showing stock return predictability using the dividend yield and the dividend-price ratio, the financial literature has been debating the subject. Several researchers have since shown strong evidence for the stock return predictability over long horizons and several other researchers have found equally strong evidence supporting that stocks are not predictable. The first works of Fama & French and Campbell & Shiller have been criticised in later studies showing that the standard errors and squared R-values are not robust and bias due to overlapping observations and small sample size[3]. However, some later studies have shown that the dividend yield does forecast stock returns, and they have additionally added several other ratios, which were also shown to forecast stock returns. These ratios can be divided into two groups, financial ratios, which among others include the interest rate, the earning and the book-to-market, and macroeconomic ratios including cay[4] and output. The statistical tests have greatly been improved using e.g. autocorrelation corrected standard errors, implied squared R-values and bootstrapping. In general most studies have shown some stock return predictability over long horizons when looking at in-sample testing. The conclusion is different for out-of-sample test, where some tests have shown in-sample predictability but no out-of-sample predictability[5].

The predictability of stock returns is of interest both from a purely theoretical point of view and from a more practical point of view. Theoretically, stock predictability is a showdown with the classical perception of the random walk and it marks a new era with a less rigid definition of the efficient market. Practically, the predictability can be used by investors and help them chose the right portfolio at different times. It may possibly help investors to time the market and give them a higher return on the same risk. In this context, the out-of-sample testing is very important in the sense that it represents the investors' ability to use the predictability information on real time data.

This thesis will investigate the ability of the macroeconomic ratios; price-output, price-export and price-import to forecast the stock return in Denmark, the Netherlands, France and United

[1] Fama and French, 1988
[2] Campbell and Shiller, 1988b
[3] Goyal and Welch, 2003 and Ang and Bekaert, 2006
[4] consumption, asset holdings and current labour income
[5] Goyal and Welch, 2004

Kingdom both in- and out-of-sample. The price-export and price-import ratios are expected to have more pronounced effect on Denmark and The Netherlands, since they are small countries with more open economies and therefore a larger fraction of their economy is affected by the export and import.

2 Problem statement, scope and method

2.1 Problem statement

The purpose of this paper is to make a model, which can forecast stock returns on market portfolios over long horizons using the output-price ratio, the export-price ratio and the import-price ratio for the Danish, the Dutch, the French and the UK market, and test the potential practical value of the model for the real time investor.

The following questions will be investigated:

- What is the current research status on the subject area?
- How are the models estimated, and what are the estimates?
- How well do the models perform in- and out-of-sample predicting stock returns?

2.2 Scope

This thesis will focus on the forecast of stock returns on portfolios from Denmark, The Netherlands, France and United Kingdom. It will not look into other countries stock markets due to time and size restrictions. The countries are chosen for their location and individual qualities, which will be discussed in the data section. The time series used in the current thesis ranges from the 1st quarter (1Q) in 1970 to the 2nd quarter (2Q) in 2010. The last ten years, that is from 1Q 2000 to 2Q 2010, will be used for out-of-sample testing. This leaves 30 years of data to be used in the regression, which is necessary, due to the fact that the data points in the regression range over 5 years at the most.

This thesis will focus on return and exclude excess return. The return will be in real terms and deflated with the inflation, which will make it an approximation of the excess return, in that the risk-free rate of interest mainly consists of inflation risk. The risk-free is per definition risk free, which means that it is not subject to default risk, and the rate used is most commonly a government secured bond interest rate, such as the T-bill in USA. The risk for this interest rate is therefore only the inflation risk[6]. For this reason one can state that the real

[6] Brealey et al., 2006, page 639

return is an approximation of the excess return[7]. The excess return would be interesting to investigate, but is excluded due to time and size constrains.

The current thesis will use ordinary least squares (OLS) regressions and will therefore exclude vector autoregression (VAR). Additionally, this thesis will only look at time series and hence it will exclude cross-sectional data. Moreover, in-sample and out-of-sample testing will be done, but the current thesis exclude bootstrapping and will therefore not be using the McCracken[8] MSE-F statistic to formally test the out-of-sample predictions and will additionally not be using the implied squared R-value, which is more correct when the data is overlapping, as it is the case for the regressions in this study[10]. Lastly, the exclusion of bootstrapping also excludes an approach for testing which takes data mining into account[11]. However, the out-of-sample testing is often used to guard against data mining.

2.3 Method

The current thesis will do both in-sample and out-of-sample testing with time series. In the in-sample testing, the following tests will be performed: test for normal distribution of the residuals, test the presents of heteroscedasticity and autocorrelation, and test for the stationarity in the time series. If the time series are in fact nonstationary, test for cointegration in the parameters is performed. The tests used for this will be respectively: the Jarque-Bera (JB) test, White's heteroscedasticity test, the Breusch-Godfrey test (BG- or LM-test), the Dickey-Fuller (DF) test, the Augmented Dickey-Fuller (ADF) test and the Engle-Granger (EG) test. Additionally, graph will be used to support the conclusions of these tests. In the out-of-sample testing, the aggregated residuals from the out-of-sample tests will be compared with the aggregated residuals from a random walk test, and graphs showing the difference between the two groups of residuals over the out-of-sample period will be investigated in order to evaluate the forecast ability of the regressions.

Furthermore, descriptive statistics will be used to overview the data sample.

[7] Rangvid, 2006
[8] McCracken, 2007
[10] The implied squared R-value is used in Rangvid, 2006.
[11] The approach is used in Rapach et al., 2005

3 Theory

3.1 Previous Research

3.1.1 The breakthrough in the late 1980's

Before the late 1980' the general opinion in finance was dominated by the theory that the stock marked was efficient and followed a random walk[12]. On the basis of previous research, stock returns were seen as unpredictable and the price of stocks represented and contained most or all of the available information about fundamental values of the stock. Since all the information about the fundamental value of the stock was already included in the price, the best guess for the future stock price was expected to be the current price, which meant that the stock prices followed a random walk. Unexpected information could give rise to changes in the price, but these changes were seen as random noise and the expected price change was therefore zero. It was seen as impossible to obtain long term excess return on stocks on the basis of old information.

> *"If the market is efficient, then it should not be possible to profit by trading on the information contained in the asset's price history; hence the conditional expectation of future price changes, conditional on the price history, cannot be either positive or negative (if shortsales are feasible) and therefore must be zero."*[13]

If one could seen a pattern in the return on the basis of old information, others would see the same, and the opportunity would be exploited so fast that one would not be able to earn long term excess return. Additionally, the search for information was seen as highly competitive and there are no quick and easy excess returns to be gained. The only way to increase the return was to increase the risk of the investment.

In the late 1980´s the general opinion about the predictability of stock prices changed, and predicting stock market returns using aggregated financial variables has been a financial discipline during the last two decades[14]. Stock prices were seen as predictable over long horizons and unpredictable over short periods[15]. The long term stock prices were expected to

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[12] Cochrane, 2005, page 389f
[13] Campbell et al., 1997, page 30f
[14] Goyal and Welch (2003) and Fama and French (1988) both state that the discipline actually dates back all the way to 1920, with the first being Dow (1920).
[15] Cochrane, 2005, page 390f

be related to business cycles and this was not seen as a contradiction to the efficient marked theory.

> *"However, one of the central tenets of modern financial economics is the necessity of some trade-off between risk and expected return, and although the martingale hypothesis[16] places a restriction on expected returns, it does not account for risk in any way. In particular, if an asset's expected price change is positive, it may be the reward necessary to attract investors to hold the asset and bear the associate risks. Therefore, despite the intuitive appeal that the fair-game interpretation might have, it has been shown that the martingale property is neither a necessary nor a sufficient condition for rationally determined asset prices."[17]*

The real breakthrough came in the late 1980´s with the article by Fama and French[18] and the articles by Campbell and Shiller[19] all in 1988. These articles showed the relationship between the aggregated dividend-price ratio or the dividend yield[20] and the aggregated long-term stock return.

Since this breakthrough the concept of the efficient market has and still is interpreted more loosely and the predictability is seen as reflection of the agent's attitude towards risk. If the economy in general is down, the agents are less willing to invest in risky assets. Therefore, they require a higher future return and the price of the risky assets today will be lower. Lo and MacKinlay[21] published in 1988 an article, where they tested whether the prices on the stock market followed a random walk. This was rejected, and they stated that this rejection of a random walk does not mean a rejection of the efficient market theory and that the prices still can be based on fundamental values.

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[16] The martingale hypothesis is the theory that changes in stock prices are random noise and expected price changes are zero: $E[P_{t+1} - P_t | P_t, P_{t-1}, \ldots] = 0$. Campbell et al., 1997, page 30

[17] Campbell et al., 1997, page 31

[18] Fama and French, 1988

[19] Campbell and Shiller, 1988a and Campbell and Shiller, 1988b

[20] The price-dividend ratio is given by the dividend divided by the price or the difference between the log dividend and the log price (Goyal and Welch, 2004) and the dividend yield is given by the dividend divided by the lagged price or the difference between the log dividend and the lagged log price (Goyal and Welch, 2004)

[21] Lo and MacKinlay, 1988

3.1.2 The support of the idea of stock return predictability

In the end of the 1980's and through out the 1990's, many articles were written on the subject of stock predictability and various financial variables and ratios were used to investigate this. The two most debated ratios for forecasting stock returns were the dividend yield ratio and the price-earning ratio, where especially the dividend yield has been tested in many later articles. As previously stated the breakthrough came largely with the articles by Fama and French and by Campbell and Shiller, which are describe below.

Fama and French[22] showed that the dividend yield[23] could explain the stock return over long periods by regression analysis of the return of both the equal-weighted and value-weighted NYSE portfolio on the dividend yield. They tested on both nominal and real returns and showed that the dividend yield explained more than 20% of the variance in the return for 3 and 4 years using data from the subsample of 1957-1986 and 1941-1986.

Campbell and Shiller[24] came to a similar conclusion using a vector autoregression (VAR) model, with which they showed that stock returns were forecastable by the dividend-price ratio. They used both a real Cowles/S&P index and the real value-weighted NYSE portfolio. Their theory took basis in the definition of stock returns given by the discounted future expected dividends. They derived at a model, which they call the "Dividend-Ratio Model" of the "Dynamic Gordon Model"[25] after the famous original Gordon model[26]. This model is the theoretical foundation of the present study and will be discussed in greater details later. Campbell and Shiller extended their work in their second article of 1988[27]where they showed that stock returns could be forecasted with earnings and dividend. This was done by regression analysis of the real and excess stock return on different explanatory variables such as the dividend-price ratio, the lagged dividend growth and an earning-price ratio and by making a VAR model. The data used was the Cowles/S&P index.

Among the other financial ratios used for forecasting stock returns and prices was the term structure of interest rates, which was tested by Campbell[28] using data from 1959 to 1983. Another financial ratio used for predicting stock returns was the dividend-earnings ratio

[22] Fama and French, 1988
[23] They also test the price-dividend ratio
[24] Campbell and Shiller, 1988b
[25] Campbell and Shiller, 1988b
[26] Ross et al., 2006, page 237
[27] Campbell and Shiller, 1988a
[28] Campbell, 1987

investigated by Lamont[29]. He showed that the dividend-earnings ratio or payout ratio predicted the return through the predicting abilities of both dividend and earnings. Additionally, Hodrick[30] tested the one-month Treasury-bill return relatively to its previous 12-month moving average, and showed that this ratio had predictive power for the time period of 1952-1987. Moreover, he showed that the dividend-price ratio, the term premium and the default premium had strong predictive power in the same time period. Lastly, the book-to-market ratio has been investigated for its power to predict stock return. Kothari and Shanken[31] showed that this ratio did forecast one-year returns for the period from 1926-1991, and Pontiff and Schall[32] found that the book-to-market ratio predicted return, however, best before the 1960.

In 1989 Fama and French[33] stated that expected excess return on both stocks and bonds moved with the same business-condition variables, which were the dividend yield, the default premium[34] and the term premium. They concluded that the movements in return were due to general business conditions which were linked to the business cycle. They stated that when business conditions are poor and income is low, the agents require a high return on investments for them to substitute from consumption to investment. This is in line with the statement of Campbell[35].

3.1.3 The critic of stock return predictability – theoretically and methodologically

Generally, a series of studies showed that a number of different financial variables and ratios could be used to predict stock returns for data samples before 1990's. However, in the 1990's a number of articles were published showing that some of the financial ratios did not predict stock return as well as the previous tests had shown. When out-of-sample tests were done using data from the 1990's, the ratios did not predict better than the random walk and there was a general problem with weak out-of-sample testing. This was a period of very high dividend-price ratios and very low price-earnings ratios in the USA, and in out-of-sample

[29] Lamont, 1998
[30] Hodrick, 1992
[31] Kothari and Shanken, 1997
[32] Pontiff and Schall, 1998
[33] Fama and French, 1989
[34] The definition of the default premium and the term premium as in Fama and French, 1989, page 24. The default premium is given by the difference between the yield on a market portfolio of corporate bonds and the yield on Aaa bonds and the term premium is given by the difference between the Aaa yield and the one-month bill rate.
[35] Campbell et al., 1997

testing the ratios failed to predict the stock returns. With the ratios being high and low as they were, one would expect the stock returns to be low or even negative, and this was not at all the case until much later. Moreover, researcher found that the previous tests had several statistical problems and were therefore suspected not to be valid.

Already in 1993, Goetzmann and Jorion[36] showed through the use of bootstrapping, that the dividend yield did not forecast stock returns, since R^2 and the standard errors were misleading. This was caused by the bias from overlapping data in the regression analysis and the fact that the dividend yield as the independent variable was correlated with the lagged stock return as the dependent variable. During the same year, Nelson and Kim[37] showed that the predictive regressions suffered from two types of small sample biases, which both made the null hypotheses of no predictions, get rejected to often. They argued that firstly, if the independent variable was endogenous, then the coefficient estimate would be bias. Secondly, the standard errors were bias when the observations were overlapping, and this caused the estimated standard errors to be smaller than the true standard errors. Additionally, Kirby[38] argued that small sample size and overlapping observations made the estimated R^2-values larger than the true R^2-values and this along with regression being long-horizon could produce misleadingly high t-values and therefore lead to a false conclusion of predictability where there was actually none. Ang and Bekaert[39] found that when including the data from 1990's, the dividend yield did not predict excess stock return over long horizons, and even when the standard errors were corrected with Newey-West[40] or with Hansen-Hodrick[41], they lead to an over-rejection of the null hypothesis of no predictability. Lastly, Goyal and Welch[42] showed in 2003 by using graphs that the dividend ratios (dividend yield and dividend-price) did not predict excess stock return out-of-sample. In 2004 they tested the predictability of several financial variables and cay[43], and they showed that even though these variables had good predictive powers in-sample, most of them were outperformed by the prevailing mean of the excess stock return in the out-of-sample test.

[36] Goetzmann and Jorion, 1993
[37] Nelson and Kim, 1993
[38] Kirby, 1997
[39] Ang and Bekaert, 2006
[40] Newey and West, 1987
[41] Hansen-Hodrick, 1980, seen in Ang and Bekaert, 2006
[42] Goyal, 2003 and Goyal, 2004
[43] Cay will be discussed later in this section

3.1.4 The reactions to the criticism

There were two different responses to the criticism of the predictability of the stock return. On one hand researchers tried to find different and new variables to study in the regression analysis, variables which were different in that they were macroeconomic variables. On the other hand some researchers defended the financial variables using new R^2 values and t-statistics, which will be discussed in the next section.

Cay was the first and the most famous of the macroeconomic variables which were found to predict excess stock return as published by Lettau and Ludvigson[44]. Cay is a variable composed of consumption, asset holdings and current labour income[45]. As with all macroeconomic variables, the economic explanation for cay is founded in the business cycle. Investors prefer a flat consumption path and therefore, when excess return is expected to increase, investors will increase their consumption compared to asset holdings and current labour income in order to smooth out the consumption path, and this will increase cay. Therefore, the underlying assumption was that a high cay would predict high excess return. In 2005 Lettau and Ludvigson[46] showed that cay still predicted excess stock return but that this was not the case for cdy[47]. Moreover, Julliard[48] showed that labour income alone had high power to predict future stock return and excess stock return. In line with the research of Lettau and Ludvigson, Menzly, Santos and Veronesi[49] showed that time-varying risk preferences created a positive relation between dividend yield and expected stock returns. However, the time-varying expected dividend growth created a negative relation between them, when they were in equilibrium. These offsetting effects eliminated the ability of the dividend yield to forecast future dividend growth and reduced the ability to forecast stock returns. They suggested that one should divide the price/dividend ratio with a price/consumption ratio, which would be a control for changes in risk preferences. This would enable one to forecast the dividend growth using the dividend to consumption ratio, and additionally, they suggested that the stock return could be forecasted with these ratios. The study of Menzly, Santos and Veronesi can be seen in connection with the work of Lettau and Ludvigson[50] in that they found that dividend forecasts covary with changes in forecasts of excess stock returns. The

[44] Lettau and Ludvigson, 2001

[45] Cay is given by $cay_t = c_t - wa_t - (1-w)y_t$, where c is consumption, a is asset holdings, y is current labour income all at time t and w is the average share of asset holdings in total wealth

[46] Lettau and Ludvigson, 2005

[47] Cdy is consumption, dividend from asset wealth, and dividend from human wealth or current labour income

[48] Julliard, 2004

[49] Menzly et al., 2004

[50] Lettau and Ludvigson, 2005

positive correlation between the fluctuations in expected stock returns and expected dividend growth have offsetting effects on the dividend-price ratio. On this background they used the cdy to forecast the dividend growth and the stock return.

In 2006 Rangvid[51] showed that a price-to-GDP ratio or the price-output ratio[52] predicted stock return and excess stock return in-sample and predicted stock return out-of-sample for periods longer than 2 years. This was a better result than the dividend-price and the price-earning ratio for the data sample from the standard and Poor Composite Stock Price index from 1929-2003. Another test of the output as a predictor for stock return was made by Cooper and Priestley[53], who used the output gap to predict the stock return both in- and out-of-sample. Additionally, they showed that the output gap could predict excess stock return in 7 other countries including U.K, France and Germany.

Lastly, consumption have been investigated for having predictive power. Engsted, Hyde and Møller[54] showed that the surplus consumption ratio[55] alone but especially together with the dividend-price ratio could predict stock returns for most of the investigated countries including US, U.K, France and Sweden. Santos and Veronesi[56] showed that labour income-consumption ratio could forecast long horizon stock returns. Moreover, Møller and Rangvid[57] investigated the predictive power of the real consumption of the fourth quarter and they found that the growth rate of consumption in the fourth quarter could predict excess stock return both in- and out-of-sample for the US.

3.1.5 The current scientific status

Within the last 10 years the researchers have more or less been divided into two groups. One group that, as previously mentioned, defends the idea that it is possible to predict stock returns using the financial ratios and another group that evaluates many of the ratios at the time and concludes, that most of them do not predict stock returns.

Among the researchers, who defend the idea of prediction by use of financial ratios, Campbell and Shiller wrote two papers in 1998 and 2001[58]. In the paper from 1998, they showed that

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[51] Rangvid, 2006

[52] The test in this paper will be in line with this studie, in that it also will test the price-to-GDP ratio

[53] Cooper and Priestley, 2009

[54] Engsted et al., 2010

[55] This is defined in Campbell and Cochrane, 1999, as $surplus\ consumption\ ratio\ S_t \equiv (C_t - X_t)/C_t$, where C is the consumption and X is the habit.

[56] Santos and Veronesi, 2006

[57] Møller and Rangvid, 2010

[58] Campbell and Shiller, 1998 and Campbell and Shiller, 2001

dividend-price ratio still predicted stock returns for several countries including the Netherlands, UK and USA. In the 2001 paper, Campbell and Shiller did an investigation into the price-earning ratio and the dividend-price ratio mainly for USA, but also to some extent for twelve other countries. They showed that both ratios did predict the stock returns for USA, and that the results were not as strong for the other twelve countries. As mentioned earlier, the dividend-price ratio was very low in the 1990's and the price-earning ratio was very high, and Campbell and Shiller found it reasonable to suggest that the stock prices would not drift to far from the fundamental values (dividend and earnings), and the balance would therefore be restored with the stock prices falling and bringing the ratios back to their normal levels. Cochrane[59] also defended the ability of the dividend-price ratio to forecast stock returns, both theoretically and empirically. He found that the dividend-price ratio was not able to forecast the dividend, and he argued that the only way the dividend-price ratio could fluctuate, was if the price was then able to be forecasted. This will be explained in more details in the theory section. Additionally, Cochrane found strong evidence to support return forecasts over long horizons.

Several researchers have shown that the dividend-price ratio could forecast the stock returns if some of the assumptions were changed. Lettau and Niewerburgh[60] found that the poor out-of-sample performance of the ratios could be due to the fact that one of the assumptions of the model was that the economy had a fixed steady mean. They showed that if one adjusted for structural breaks, the in-sample test of predictability was significant. However, in practice it may be very difficult to utilize this in out-of-sample testing, since it may be hard not only to estimate when the structural break will occur, but also what level the values will be after the break. Paye and Timmermann[61] showed these structural breaks for many countries and found that the stock returns were less predictable after the last structural break. McMillan[62] investigated the dividend yield in a scenario, where this was a non-linear process. He stated that the dividend yield in the late 1990s appeared to be not stationary, which would indicate a breakdown of the relationship between the dividend and the price. This relationship could be maintained, if one allowed for a non-linear dividend yield, and McMillan showed that this non-linear dividend yield gave better predictions of future stock returns in out-of-sample testing than the random walk. Lastly, Lacerda and Santa-Clara[63] argued that variations in the

[59] Cochrane, 2008
[60] Lettau and Niewerburgh, 2008
[61] Paye and Timmermann, 2006
[62] McMillan, 2009
[63] Lacerda and Santa-Clara, 2010

dividend-price ratio could be caused by two things; changes in expected stock returns and changes in the investors' predictions of future cash-flow, the future dividend growth. If the model for predicting future stock returns was adjusted for changes in the future dividend growth, then Lacerda and Santa-Clara found strong evidence for stock return predictability using the dividend-price ratio both in- and out-of-sample.

Some researchers have tested many variables over the same time and for different countries. Goyal and Welch[64] tested in two articles a variety of different ratios for forecasting stock returns[65] and showed in both articles that most of the ratios performed poorly both in- and out-of-sample, and they seemed to be unstable and of no use to real investors having access only to real-time available information. Additionally, they did not agree with the theoretical foundation presented by Cochrane[66], which stated that in the absence of predictability of dividend growth by the dividend yield, the dividend yield must predict stock returns. Goyal and Welch[68] argued that the dividend-price ratio predicted either the stock return, the dividend growth or the next period dividend-price ratio, and they further argued that in resent years the predictability have mostly been in predicting the future dividend-price ratio. When they found weakening evidence both theoretically and empirically, they concluded that the financial and some of the macroeconomic ratios did not in fact forecast stock returns. Moreover, Rangvid, Schmeling and Schrimpf[69] showed that for small and medium-sized countries, the predictability for dividend growth was stronger than for stock return using the dividend yield. Other researchers testing several ratios were more positive regarding the forecasting ability. Lewellen[70] tested the dividend yield, the book-to-market and the earnings-price ratio and found that these ratios did predict stock returns, if they were corrected for small-sample biases. Additionally, Rapach, Wohar and Rangvid[71] tested several mostly macroeconomic variables[72] for a number of countries and found that the interest rate and the inflation rate performed well for most countries, and that the rest of the ratios had limited ability to forecast

[64] Goyal and Welch, 2004 and Welch and Goyal, 2008

[65] The ratios are for both articles: Dividend-Price Ratio, Dividend Yield, Earning Price, Dividend Payout Ratio, Book to Market, Net Issues, T-Bill Rate, ,Long Term Rate, Term Spread, Default Spread, Inflation and Consumption-Wealth- Income
Extra ratios for the 2008 articles are: Stock Variance, Pct Equity issuing, Long Term Return, Default Return Spread and Investment Capital Ratio

[66] Cochrane, 2008

[68] Goyal and Welch, 2003

[69] Rangvid et al., 2010

[70] Lewellen, 2004

[71] Rapach et al., 2005

[72] The ratios are: Relative money market rate, Relative Treasury bill rate, Relative government bond yield, Term spread, Inflation rate, Industrial production growth, Narrow money growth, Broad money growth and Change in unemployment rate

stock returns in most countries. One year after this article, Rapach and Wohar[73] again tested several ratios[74] on the USA market. They found that some of the variables did predict stock returns, whereas others did not. They also showed that the variables with good performance in-sample almost always had good performance out-of-sample. They used a bootstrap procedure in order to account for data mining, and they still found evidence for stock return predictability. Data mining is especially a problem when using American data, in that so many variables have been tested on these data over so many time periods and sub-periods. Out-of-sample testing is generally used as a way to avoid data mining, but the research of Rapach and Wohar ruled out data mining for the variables with predictive power in both the out-of-sample testing and the bootstrap procedure. Lastly, in line with the problems with data mining, Guo[75] tested cay and showed that it had poor predictive performance using real-time data in out-of-sample testing. He suggested that one explanation for this poor performance could be data mining.

[73] Rapach and Wohar, 2006
[74] The ratios are: Dividend-price ratio, log-level Payout ratio, log-level Equity share, Price-earnings ratio, log-level Term spread, Book-to-market ratio, log-level Default spread, Fed q and log-level Short-term interest rate
[75] Gou, 2009

3.2 Theory and the theoretical model

3.2.1 Theory

Most of the theory in the topic of stock returns forecasts using financial and macroeconomic ratios have been on the dividend-price ratio and the dividend yield, since these ratios were first used and are the most investigated ratios. However, the theory on the predictive power of these ratios can relatively easy be translated into other ratios.

When the stock price is high relative to the dividend, thereby leading to a high price-dividend ratio $\left(P_t / D_t \right)$, the investors are expecting one of three things to happen[76]:

1. The dividend will rise in the future. The investors will pay more for the stock compared with the fundamental value of the current dividend, if they expect the dividend to increase in the future.
2. The returns will be low in the future. The future cash-flows are discounted with a lower rate than usual, and this gives rise to higher stock prices. If the investors for instance have the perception that the risk level will be lower in the future, they will demand a lower return and they will be willing to pay more for the stock. On the other hand, if they expect an increases risk, they will demand higher returns and will be willing to pay less for the stocks.
3. Lastly, the investors can expect the stock price to rise forever, even if dividends never follow, and this would constitute a bubble. If the investors expect always to be able to sell the stocks for a higher price, even if the fundamental values of the stock do not change, the investors will pay more for the stock today.

The three different possibilities can be seen using the definition or identity of the stock prices.

The definition of the return on a stock is given by[77]: $R_{t+1} = \dfrac{P_{t+1} + D_{t+1}}{P_t} - 1$

Where R_{t+1} is the return on the stock held from time t to time t+1. Moreover, P_t is the price of the stock at the end of time t and D_{t+1} is the dividend on the stock at the end of time t+1, which is the dividend one would claim, if one holds the stock from time t to time t+1.

[76] Cochrane, 2005, page 396
[77] Campbell et al., 1997, p 254

The current stock price is therefore given by: $P_t = E_t \left[\frac{P_{t+1} + D_{t+1}}{R_{t+1} + 1} \right]$

E is the expected discounted income from owning the stock.

From the formulas above, one can se that, the variables influencing the current stock price are the future dividend, stock price and stock return. A high expected future dividend or a low expected future return will both be able to explain a high stock price today. So will an infinite increased stock price. However, this model has the assumption of no bubbles and this will be explained in the theoretical model section. Using the same line of argument, if the current stock price is low, the investors expect the dividend to decrease or the return to be high. Some researchers have shown, that most of the volatility in the stock price can be explained by the expected stock return[78]. Cochrane has shown that if the dividend yield does not predict dividend growth, it has to predict stock returns, since it can only move if it predicts either of these or if there are bubbles, and he argues that the dividend yield in fact does not predict dividend growth and therefore it must predict stock return[79]. On the other hand, some researchers have shown, that the dividend yield does predict dividend growth, and thereby making the argument for stock return predictability by Cochrane less strong. Ang[80] shows that the dividend yield predicts dividend growth stronger than stock returns on one year horizons. Ribeiro[81] has shown that most of the variation in the dividend yield comes from expected stock returns; however, some of the variation comes from the changes in the dividend growth. Lastly, Rangvid, Schmeling and Schrimpf[82] argued that the dividend growth predictability is stronger than the expected stock return predictability using the dividend yield for small and medium size countries. It seems that the debate on predictability of the dividend growth is going back and forth, and for this reason one cannot be absolutely sure of the expected stock return predictability only by looking at the absence of the dividend growth predictability.
A different component to the theory of the predictability of the expected stock return is the mean reversion of the dividend-price ratio. If one sees the dividend-price ratio[83] in a historical setting, it is clear that it fluctuates around a mean and that it does not move permanently outside its extremes. This stability in the dividend-price ratio indicates that it is mean-

[78] This is shown by the researchers in favour of the stock predictability theory, as they show that the dividend-price ratio or the dividend yield predicts stock returns. The statement comes from Cochrane, 2005, page 397
[79] Cochrane, 2008 and Cochrane, 2005, page 396
[80] Ang, 2002
[81] Ribeiro, 2002
[82] Rangvid et al., 2010
[83] The American dividend-price ratio seen in Campbell and Shiller, 2001

reverting and that it will move in a direction to restore the ratio to its normal level if it is at one of the extremes. This means that either the numerator or the denominator or both must be predictable. During the 1990's the dividend-price ratio was at an extreme low level and some researcher[84] argued that this was due to structural breaks. The speculations of the causes of the model breakdown and the structural breaks involved mainly the patterns in dividend payments and the repurchase of stocks. Campbell and Shiller[85] stated that a shift from dividend payment to stock repurchase can be the reason for the very low dividend-price ratio or maybe its permanent change. The change from dividend to repurchase decreases current dividend and thereby increases future dividend growth. This can permanently increase the stock price and lower the ratio. In line of this argument Fama and French[86] showed in 2001 that the number of companies paying out dividend decreased a great deal from 1978 to 1999. However, DeAngelo, DeAngelo and Skinner[87] showed that even though the number of companies paying dividend decreased during the period, the amount of dividend paid increased. The latter observation questions whether or not the low dividend-ratio in the 1990's was caused by the change in dividend payment and stock repurchase. Another problem with the dividend-price ratio is that the dividend on occasion does not reflect the value of the firm. Miller and Modigliani[88] showed that the amount of dividend paid by the company does not have to reflect the true performance or value of the company, and this makes the dividend policy "irrelevant" for the value of the company and it is therefore problematic to use the dividend-price ratio to forecast stock returns, which should reflect the true value of the company.

The theory of stock return predictability by ratios can also be used for the price-earning ratio $\left({P_t}/{E_t} \right)$. If the stock price today is high in relation to the earnings (the price-earning ratio is high), the investors are expecting that either the earnings are going to increase or the expected stock returns are going to be low. If the investors expect an increase in future earnings, they will be willing to pay more for the stocks today and this gives rise to the high price compared with current earning. Additionally, if the investors expect future stock returns to be low, they discount future cash-flows with a lower rate of interest and thereby get a higher current stock price, as was the case for the dividend-price ratio. The main concern with

[84] Lettau and Nieuwerburgh, 2008, Paye and Timmermann, 2006 and McMillan, 2009
[85] Campbell and Shiller, 2001
[86] Fama and French, 2001
[87] DeAngelo et al., 2004
[88] Miller and Modigliani, 1961

using the price-earning ratio to forecast stock return is that information on the earnings is from the income statement and therefore subject to accounting principals. This can give rise to the fact that earnings do not always reflect the value of the company, and the price-earning ration may therefore not be so efficient in forecasting the stock return. Firstly, one of the accounting problems in relation to the earnings is how the executive bonuses are treated in the financial reports. Hall and Murphy[89] showed the way stock options are treated differently in the accounts and argued that this will make the earnings noisy in relation to the true value of the company. Secondly, the problem with earnings in forecasting stock return is the increased investment in intangibles. Hall[90] argued that the increased investment in intangibles could explain the high price-earning ratio in the 1990's[91] and that this would be in line with rational valuations in the sense that the stocks did in fact earn cash-flows for the shareholders in the same period. Campbell and Shiller[92] on the other hand state that the problem with increased investments in intangibles is that the earnings suffer a downward bias due to the accounting principles of the intangibles, principles which prescribe that value of the intangibles are to be deducted from the earning at current expense. They argued that the high price-earning ratio in the 1990's could not be explained by the investments in intangibles. Concerning the low dividend-price ratio and the high price-earning ratio in the 1990's, some researches argued that these extremes were caused by unusually high stock prices. Campbell and Shiller[93] argued that one of the reasons for the high stock prices were that the baby-boom generation, which came to dominate the financial markets in the 1990's. They were and are less risk adverse and therefore willing to pay higher prices on stocks. This means that the ratios might remain at their extremes for the duration of this generation. In line of this, Lettau, Ludvigson and Wachter[94] argued that the increased stock prices could be due to a decrease in macroeconomic risk or decreased volatility of the aggregated economy. They argued that the volatility of the aggregated economy and the volatility of the stock market are correlated, and a low volatility of the aggregated economy would suggest a low volatility of the stock market. This would mean that the investors would accept lower returns and the stock prices would increase.

The ratios used to forecast stock returns also include macroeconomic variables, such as cay and the price-output ratio. These ratios are able to predict stock return, due to the fact that

[89] Hall and Murphy, 2003
[90] Hall, 2001
[91] The high price-earning ratio in the 1990's can be seen in Campbell and Shiller, 2001
[92] Campbell and Shiller, 2001
[93] Campbell and Shiller, 2001
[94] Lettau et al., 2008

they are linked to the general state of the economy and the stock market is affected in the long run by the general economic state, the stock return vary with the business cycle[95]. Cay works in the macroeconomic setting as follow. The ratio cay is given by the equation:

$cay = c_t - \hat{\beta}_a a_t - \hat{\beta}_y y_t$, therefore if cay is high, that is if consumption is high compared to asset wealth and labour income, then it must be because the investors expect high future stock returns. The investors want to have a flat consumption path and therefore aim to smooth out the temporary variation in the asset wealth coming from time movements in expected stock return. If the stock return is expected to be higher in the future, the investors will increase the consumption today and making cay increase by doing so. The same follows, if the stock return is expected to be low in the future, the investors will decrease the consumption today in order to smooth out the consumption path, and thereby decrease cay[96].

The three ratios which will be investigated in the current thesis are all macroeconomic ratios, and one of them is the price-output ratio $\left(P_t / Y_t \right)$. If the stock price is high compared to the output today (the price-output ratio is high), it must be because the investors expect the output (in terms of production) to increase in the future or because they expect the stock returns to be low in the future[97]. If the investors expect higher output in the future, then they are expecting a better economy and they will be less risk adverse and therefore be willing to pay more for the stocks today. If the investors expect low stock returns in the future, they will pay more for the stocks today for the same reasons as described in connection to the dividend-price ratio.

The national accounting identity states that the Gross Domestic Product (GDP) in an open economy is given by the following equation[98]:

$$GDP = C + I + G + X - Z$$

Where C is consumption, I is investment, G is government spending, X is export and Z is import. From this it can be seen, that the GDP partly comes from the import and the export of the country. The hypothesis of the current thesis is, that export and import are sufficiently important for small countries, that these alone will be able to forecast stock returns. Whereas, for large countries the import and export will not have sufficiently power to be able to forecast stock returns. In line with the theory on the dividend-price ratio and the price-output ratio, one can make ratios using the export and import, the price-export ratio $\left(P_t / X_t \right)$ and the

---

[95] Lettau and Ludvigson, 2001
[96] Lettau and Ludvigson, 2001
[97] Rangvid, 2006
[98] Froyen, 2005

price-import ratio $\left({P_t}/{Z_t} \right)$. Consider for example if the price is high compared to the export; a high price-export ratio. This means that the investors expect either the export to increase in the future or the stock returns to be low in the future, which will explain the high stock price today. If the export is expected to increase in the future, this can be seen as a sign of higher national production and positive trade balance, and this is sign of an increased economic activity. This will make the investors less risk adverse and thereby accept higher stock prices today. On the other hand, if the price is high compared to the import (a high price-import ratio), this means that the investors expect either the import to decrease in the future or the stock returns to be low in the future, which will explain the high stock price today. A low expected future stock return will mean a high stock price today no matter what the ratio is composed of other than stock price. The investors react differently to the changes in import. If the import is expected to decrease in future, the investor can take this as a sign of good competitiveness compared with the countries which the home country trades with. This will be a good sign for the future economy and the investors will be less risk adverse and be willing to pay higher stock prices today. The effect of the price-export ratio and price-import ratio will be most pronounced for small countries, due to the fact that the import and export constitutes a larger faction of the total economy for these countries than it does for the large countries.

3.2.2 The theoretical model

The basis for the models investigated in the current thesis is models based on the discounted-cash-flow or present-value model. From the definition of the return on a stock, one can derive the price-dividend (P/D) -model and from this the price-output (P/Y) -model and the price-export (P/X) - and price-import (P/Z) -model.

The definition of the return on a stock is given by[99]: $R_{t+1} = \dfrac{P_{t+1} + D_{t+1}}{P_t} - 1$

[99] Campbell et al., 1997, p 254

As before, R_{t+1} is the return on the stock held from time t to time t+1. P_t is the price of the stock at time t and D_{t+1} is the dividend on the stock at time t+1, which is the dividend one would claim, if one holds the stock from time t to time t+1.

The price of the stock at time t is given by: $P_t = E_t\left[\frac{P_{t+1} + D_{t+1}}{R_{t+1} + 1}\right]$, which is the expected, E, discounted income from owning the stock.

Solving forward to include more periods within the time horizon K, the equation for the price of the stock is[100]: $P_t = E_t\left[\prod_{j=1}^{K}(1 + R_{t+j})^{-1}\right]P_{t+K} + E_t\sum_{i=1}^{K}\left[\prod_{j=1}^{i}(1 + R_{t+j})^{-1}\right]D_{t+i}$

The first term in the equation above is the discounted value of the stock price at time t+K. If one rules out rational bubbles, the first term can be excluded when the horizon K moves toward infinity. $\lim_{K\to\infty} E_t\left[\prod_{j=1}^{K}(1 + R_{t+j})^{-1}\right]P_{t+K} = 0$

There are several theoretical and empirical reasons for ruling out bubbles[101]. Firstly, negative bubbles can never occur on assets with limited liability. Secondly, a bubble can never form within the asset pricing model, and it must therefore have existed since the start of the asset trading. This is due to the fact that a bubble can only have the value zero if it's expected future value is also zero, given the definition of bubbles seen below. Since a bubble can never be negative, the only way a bubble can take the value zero is if all future expectations of this bubble is zero[102].

$$P_t = P_{Dt} + B_t \qquad B_t = E_t\left[\frac{B_{t+1}}{1 + R}\right]$$

The term P_{Dt} is called the fundamental value and the term B_t is called a rational bubble. The rational is used because the term B_t in the first equation is consistent with constant expected return and rational expectations.

[100] This is equation number (7.1.5) in Campbell et al., 1997, only here the return is not constant over time.
[101] Campbell et al., 1997, pp 259
[102] Diba and Grossman, 1988, seen in Campbell et al., 1997

A third reason why bubbles can be ruled out is that bubbles cannot exist if the asset have an upper limit, such as high-price substitution or company intervention by issuing new stocks as a response to high prices.

The rational stock price for today with the assumption of no rational bubbles is:

$$P_t = E_t \sum_{i=1}^{\infty} \left[\prod_{j=1}^{i} (1 + R_{t+j})^{-1} \right] D_{t+i} \tag{3.2.1}$$

Dividing by the dividend today results in a P/D-model for the stock returns.

$$\frac{P_t}{D_t} = E_t \sum_{i=1}^{\infty} \left[\prod_{j=1}^{i} (1 + R_{t+j})^{-1} \right] \frac{D_{t+i}}{D_t}$$

This shows that the P/D-ratio depends on the expected future stock returns and the future growth rates of the dividend. However, this relationship is not linear and is therefore difficult to test using regressions.

A very famous special case for this relationship is worth mentioning. It is based on the Gordon growth model. Here the return is constant over time and so is the growth of the dividend. If the return of the stock is constant over time, the equation can be reduced to $P_t = E_t \left[\sum_{i=1}^{\infty} \left(\frac{1}{1+R} \right)^i D_{t+i} \right]$.

Additionally, if one assumes that the dividend growth rate, G, is constant over time and that G is smaller than R, as assumed in the Gordon growth model, the equation[103] is reduces to

$P_t = \frac{E_t(D_{t+1})}{R-G} = \frac{(1+G)D_t}{R-G}$, where $E_t(D_{t+i}) = (1+G)E_t(D_{t+i-1}) = (1+G)^i D_t$

Therefore the P/D-model is $\frac{P_t}{D_t} = \frac{1+G}{R-G}$

This model is mostly of theoretical interest, since the assumptions of constant return and constant dividend growth are unrealistic to be true in the real world. Moreover, the assumption that the returns being constant is a contradiction to underlying hypothesis of the current thesis, namely that stock returns are predictable and therefore cannot be constant.

[103] Gordon, 1962, seen in Campbell et al., 1997, p 256, equation (7.1.8) and (7.1.9)

For the purpose of testing the theory of predictability in stock returns the assumption of constant stock returns and also the assumption of constant dividend growth will not be used.

Going back to the definition of stock returns and taking the logarithm gives the following equations:

$$
\begin{aligned}
r_{t+1} &= \log\left(\frac{P_{t+1}+D_{t+1}}{P_t}\right) \\
&= \log(P_{t+1}+D_{t+1}) - \log(P_t) \\
&= \log\left(P_{t+1}\left[\frac{P_{t+1}+D_{t+1}}{P_{t+1}}\right]\right) - \log(P_t) \\
&= p_{t+1} - p_t + \log(1+\exp[d_{t+1}-p_{t+1}])
\end{aligned}
\qquad (3.2.2)
$$

Where $r_{t+1} = (1+R_{t+1})$. Using the returns as logarithms makes the return continuously compounding rather than periodically compounding, which is often used in financial literature. Both Fama and French[104] and Rangvid[105] used continuously compounding returns in their articles and the current thesis builds on their work. Moreover, continuously compounding returns have the advantage that it transforms the model into a log model with the positive effect, that it can normalize otherwise not normally distributed date samples. This will be discussed in more details in section 6 under the normality assumption. An additional advantage of using a log linear approach is that it is in line with the empirically plausible assumption that stock returns and dividends follow a log linear process[106]. In the following the small letters are use for the logarithm of the variable so that $p_t = \log(P_t)$ and $d_{t+1} = \log(D_{t+1})$. In general, the small letters are used this way except for the returns, which are given by the equation above.

Equation (3.2.2) is as equation (3.2.1) not linear and must therefore be made linear in order to be tested. Campbell and Shiller[107] use a log linear approach in the form of a first-order Taylor approximation.

[104] Fama and French, 1988
[105] Rangvid, 2006
[106] Campbell et al., 1997, p 261
[107] Campbell and Shiller, 1988b

Taking the first-order Taylor approximation to $\log(1+\exp(x))$ in equation (3.2.2) gives the following results as the first-order Taylor approximation is given by $f(x) \approx f(\bar{x}) + f'(\bar{x})(x-\bar{x})$:

Using $\log(1+\exp(x))$ as $f(x)$:

$$
\begin{aligned}
&f(x) = \log(1+\exp(x)) \\
&x = (d_{t+1} - p_{t+1}) \\
&f'(\bar{x}) = \frac{\exp\left(\overline{d-p}\right)}{1+\exp\left(\overline{d-p}\right)} = 1 - \frac{1}{1+\exp\left(\overline{d-p}\right)} = 1-\rho
\end{aligned}
$$

Where $\rho = \frac{1}{1+\exp\left(\overline{d-p}\right)}$ and $\left(\overline{d-p}\right)$ is the average log dividend-price ratio.

Together this makes the first-order Taylor approximation as follow:

$$f\left(d_{t+1} - p_{t+1}\right) = \log\left(1+\exp\left(\overline{d-p}\right)\right) + (1-\rho)\left(\left(d_{t+1} - p_{t+1}\right) - \left(\overline{d-p}\right)\right)$$

The Taylor approximation is inserted into equation (3.2.2) and this is rearranged as follow[108]:

$$
\begin{aligned}
r_{t+1} &= p_{t+1} - p_t + \log\left(1+\exp\left(\overline{d-p}\right)\right) + (1-\rho)\left(\left(d_{t+1} - p_{t+1}\right) - \left(\overline{d-p}\right)\right) \\
&= p_{t+1} - p_t + \log\left(1+\exp\left(\overline{d-p}\right)\right) + (1-\rho)\left(d_{t+1} - p_{t+1}\right) - (1-\rho)\left(\overline{d-p}\right) \\
&= p_{t+1} - p_t + \log\left(1+\exp\left(\overline{d-p}\right)\right) + (1-\rho)d_{t+1} - p_{t+1} + \rho p_{t+1} - (1-\rho)\left(\overline{d-p}\right) \\
&= \log\left(1+\exp\left(\overline{d-p}\right)\right) - (1-\rho)\left(\overline{d-p}\right) + \rho p_{t+1} + (1-\rho)d_{t+1} - p_t \\
&= k + \rho p_{t+1} + (1-\rho)d_{t+1} - p_t \qquad (3.2.3)
\end{aligned}
$$

[108] Campbell et al., 1997, p 261, equation (7.1.19)

$$Where\, k = \log\left(1+\exp\left(\overline{d-p}\right)\right) - (1-\rho)\left(\overline{d-p}\right)$$

$$\Updownarrow$$

$$\begin{aligned} -k &= -\log\left(1+\exp\left(\overline{d-p}\right)\right) + (1-\rho)\left(\overline{d-p}\right) \\ &= \log(1) - \log\left(1+\exp\left(\overline{d-p}\right)\right) + (1-\rho)\left(\overline{d-p}\right) \\ &= \log\left(\frac{1}{1+\exp\left(\overline{d-p}\right)}\right) + (1-\rho)\left(\overline{d-p}\right) \\ &= \log(\rho) + (1-\rho)\left(\overline{d-p}\right) \end{aligned}$$

$$\Updownarrow$$

$$\begin{aligned} k &= -\log(\rho) - (1-\rho)\left(\overline{d-p}\right) \\ &= -\log(\rho) - (1-\rho)\log\left(\exp\left(\overline{d-p}\right)\right) \\ &= -\log(\rho) - (1-\rho)\log\left(\frac{1}{\rho} - 1\right) \end{aligned}$$

The Taylor approximation replaces the log sum of the dividend and the stock price $\log(1+\exp(x))$ in equation (3.2.2) with a weighted average of the log dividend and the log stock price in equation (3.2.3) Empirically[109], the average log dividend-price ratio have been approximately 4% annually, which makes ρ about 0.96. With ρ close to one and (1- ρ) close to zero, the changes in stock prices have more effect on return than the changes in dividend.

Isolating the stock price of today on the left side in (3.2.3) gives the following equation:

$$p_t = k + (1-\rho)d_{t+1} - r_{t+1} + \rho p_{t+1} \tag{3.2.4}$$

Solving forward first two periods and then to period K-1:

$$\begin{aligned} p_t &= k + (1-\rho)d_{t+1} - r_{t+1} + \rho\left(k + (1-\rho)d_{t+2} - r_{t+2} + \rho p_{t+2}\right) \\ &= (1+\rho)k + (1-\rho)\left(d_{t+1} + \rho d_{t+2}\right) - \left(r_{t+1} + \rho r_{t+2}\right) + \rho^2 p_{t+2} \end{aligned}$$

$$p_t = \sum_{i=0}^{K-1}\left[\rho^i\left(k + (1-\rho)d_{t+1+i} - r_{t+1+i}\right)\right] + \rho^K p_{t+K} \tag{3.2.5}$$

Next using the previous assumption of no bubbles and letting K approaching infinity,

$$K \to \infty:\ \lim_{K\to\infty} \rho^K p_{t+K} = 0$$

[109] Campbell et al., 1997, p 261

Moreover, using the equation for infinite geometrical progressions[110]

$q^0 + q^1 + \cdots + q^n = \sum_{n=0}^{\infty} q^n = \frac{1}{1-q}$ equation (3.2.5) becomes[111]:

$$\begin{aligned} p_t &= \sum_{i=0}^{\infty} \left[\rho^i \left(k + (1-\rho)d_{t+1+i} - r_{t+1+i}\right)\right] \\ &= \frac{k}{1-\rho} + (1-\rho)\sum_{i=0}^{\infty}\left[\rho^i d_{t+1+i}\right] - \sum_{i=0}^{\infty}\left[\rho^i r_{t+1+i}\right] \end{aligned} \tag{3.2.6}$$

Equation (3.2.6) is a dynamic accounting identity[112], it is made from a definition, which has been made linear by approximation and then solved forward. In order to obtain a model, one has to make specific assumptions about the expected values of the dividend $E_t[d_{t+1+i}]$ and return $E_t[r_{t+1+i}]$ at time t+1+i. By taking the conditional expectation on both sides of equation (3.2.6) it will make the present value model (the PV-model). Since $E_t(p_t) = p_t$ this becomes[113]: $p_t = \frac{k}{1-\rho} + (1-\rho)\sum_{i=0}^{\infty}\left[\rho^i E_t(d_{t+1+i})\right] - \sum_{i=0}^{\infty}\left[\rho^i E_t(r_{t+1+i})\right]$ (3.2.7)

This model is in line with the previously explained theory, that states that the price of the stock today is given by the expected future dividend and the expected future stock returns. One can se that, if the price is high it must be because the investors expect the dividend, (d_{t+1+i}), to be high in the future, or they expect the stock return, (r_{t+1+i}), to be low in the future.

By deducting the dividend today, d_t, on both sides, the model becomes:

$$d_t - p_t = -\frac{k}{1-\rho} + \sum_{i=0}^{\infty} \rho^i E_t[r_{t+1+i}] - \left((1-\rho)\sum_{i=0}^{\infty} \rho^i E_t[d_{t+1+i}] - d_t\right)$$

---

[110] Calculus, p 783
[111] Campbell et al., 1997, p 262, equation (7.1.21)
[112] Campbell et al., 1997, p 263
[113] Campbell et al., 1997, p 263, equation (7.1.22)

Rearranging[114]

$$
\begin{aligned}
d_t - p_t &= -\frac{k}{1-\rho} + \sum_{i=0}^{\infty} \rho^i E_t[r_{t+1+i}] - (1-\rho)\left(\sum_{i=0}^{\infty} \rho^i E_t[d_{t+1+i} - d_t]\right) \\
&= -\frac{k}{1-\rho} + \sum_{i=0}^{\infty} \rho^i E_t[r_{t+1+i}] - (1-\rho)\left(\sum_{i=0}^{\infty} \rho^i \sum_{j=0}^{i} E_t[\Delta d_{t+1+j}]\right) \\
&= -\frac{k}{1-\rho} + \sum_{i=0}^{\infty} \rho^i E_t[r_{t+1+i}] - (1-\rho)\left(\sum_{j=0}^{\infty} \sum_{i=j}^{\infty} \rho^i E_t[\Delta d_{t+1+j}]\right) \\
&= -\frac{k}{1-\rho} + \sum_{i=0}^{\infty} \rho^i E_t[r_{t+1+i}] - (1-\rho)\left(\sum_{j=0}^{\infty} \rho^j \sum_{i=0}^{\infty} \rho^i E_t[\Delta d_{t+1+j}]\right) \\
&= -\frac{k}{1-\rho} + \sum_{i=0}^{\infty} \rho^i E_t[r_{t+1+i}] - \sum_{j=0}^{\infty} \rho^j E_t[\Delta d_{t+1+j}]
\end{aligned}
$$

The equation can be reduced to[115]

$$
d_t - p_t = -\frac{k}{1-\rho} + E_t\left[\sum_{i=0}^{\infty} \rho^i (r_{t+1+i} - \Delta d_{t+1+i})\right] \tag{3.2.8}
$$

This is known as the “Dividend-Ratio Model” of the “Dynamic Gordon Model”[116]. It says that the movements in the dividend-price ratio must be caused by the investors expecting changes in the stock return or the dividend and the ratio must therefore be able to forecast either one of them or both.

Rearranging (3.2.8) and making it a price-dividend model gives the following:

$$
p_t - d_t = \frac{k}{1-\rho} + E_t\left[\sum_{i=0}^{\infty} \rho^i (\Delta d_{t+1+i} - r_{t+1+i})\right]
$$

Rangvid[117] argues that one can pose the assumption that the dividend can be replaced with the output in that the dividend comes from output in the economy. This can be done using the following equation, $d_t = y_t + \mu_t$, where the dividend is equal to the output plus an zero mean stationary disturbance term, μ_t

The new price-output ratio model then becomes:

$$
p_t - y_t = \frac{k}{1-\rho} + E_t\left[\sum_{i=0}^{\infty} \rho^i (\Delta y_{t+1+i} - r_{t+1+i})\right] + \mu_t \tag{3.2.9}
$$

---

[114] Lecture note “Present Value (PV) Modeller” for the course ”Empirisk Finansiering” fall 2002 by Lund.
[115] Campbell et al., 1997, p 264, equation (7.1.24)
[116] Campbell and Shiller, 1988b
[117] Rangvid, 2006

This model states that the movement in the price-output ratio must be caused by movements in the expected future output growth or stock return. Furthermore, the model states that the price-output ratio must forecast either the future expected growth in output or the expected future stock return or both. However, this argument is not as strong for this model as it is for the dividend-price model, because this model has imposed another assumption, which is that the dividend can be substituted by output in the model. If this assumption does not hold perfectly, the movements in the price-output ratio can be caused by other thing, which are captured by the model. Additionally, the model shows that if the price is high compared to the output, the investors expect the future output growth to be high or the future stock return to be low, which is in line with the statements in the theory section.

As previously discussed, the output is partly made up by the export and import, and one can therefore assume that these variables can replace the output in the model. This will provide the opportunity to test for the effects of the export and import on the stock return.

The substitution of the output to export is similar to the substitution between dividend and output, in that both move in the same direction. The price-export model therefore becomes:

$$p_t - x_t = \frac{k}{1-\rho} + E_t\left[\sum_{i=0}^{\infty}\rho^i\left(\Delta x_{t+1+i} - r_{t+1+i}\right)\right] + \mu_t \tag{3.2.10}$$

As the previous model, this model states that the movement in the price-export ratio must be caused by movements in the expected future export growth or stock return. Furthermore, the model stipulates that if the price is high compared to the export, the investors expect the future export growth to be high or the future stock return to be low. This is also in accordance with the theory described in the theory section.

The substitution between the output and the import is a little more difficult, due to the fact that the movement is in opposite direction. An increase in the output is a sign of good economic growth, whereas an increase in import can be a sign of lower ability to compete with other countries and these two signs have opposite effects on the investors perception of risk and therefore on the stock price today. This corresponds with the accounting identity, where the two variables have different signs. Due to these different signs, the replacement of the output with the import will be done in equation (3.2.7), in order to se a more detail process.

$$p_t = \frac{k}{1-\rho} + (1-\rho)\sum_{i=0}^{\infty}\left[\rho^i E_t(-z_{t+1+i})\right] - \sum_{i=0}^{\infty}\left[\rho^i E_t(r_{t+1+i})\right]$$

By deducting the import today, z_t, on both sides, the model becomes:

$$z_t - p_t = -\frac{k}{1-\rho} + \sum_{i=0}^{\infty}\rho^i E_t[r_{t+1+i}] - \left((1-\rho)\sum_{i=0}^{\infty}\rho^i E_t[-z_{t+1+i}] - z_t\right)$$

Rearranging

$$\begin{aligned} z_t - p_t &= -\frac{k}{1-\rho} + \sum_{i=0}^{\infty}\rho^i E_t[r_{t+1+i}] - (1-\rho)\left(\sum_{i=0}^{\infty}\rho^i E_t[-z_{t+1+i} - z_t]\right) \\ &= -\frac{k}{1-\rho} + \sum_{i=0}^{\infty}\rho^i E_t[r_{t+1+i}] - (1-\rho)\left(\sum_{i=0}^{\infty}\rho^i \sum_{j=0}^{i} E_t[-\Delta z_{t+1+j}]\right) \\ &= -\frac{k}{1-\rho} + \sum_{i=0}^{\infty}\rho^i E_t[r_{t+1+i}] + \sum_{j=0}^{\infty}\rho^j E_t[\Delta z_{t+1+j}] \end{aligned}$$

The formula can be reduced to

$$z_t - p_t = -\frac{k}{1-\rho} + E_t\left[\sum_{i=0}^{\infty}\rho^i (r_{t+1+i} + \Delta z_{t+1+i})\right]$$

Rearranging and making it the price-import model and adding the zero mean stationary disturbance term, μ_t, gives the following:

$$p_t - z_t = \frac{k}{1-\rho} + E_t\left[\sum_{i=0}^{\infty}\rho^i (-\Delta z_{t+1+i} - r_{t+1+i})\right] + \mu_t \qquad (3.2.11)$$

As the other models, this model states that the movement in the price-import ratio must be caused by movements in the expected future import growth or stock return. However, it also states that if the price is high compared with the import, the investors expect the future import growth to be low or the future stock return to be low. A decrease in either one of the variables will lead to an increase in the stock price today and this is different from the other models, but in line with the theory.

3.3 The statistical model

Fama and French[118] used the following regression to test for stock predictability using the dividend yield and the dividend-price ratio: $r(t,t+T) = a + bY(t) + e(t,t+T)$, where $r(t,t+T)$ is the portfolio return on the stock portfolio from time t to time t+T, $Y(t)$ is the dividend yield or the dividend-price ratio at time t, and $e(t,t+T)$ is the stochastic error term of the regression. The same regression form was used by Rangvid[119], as he used the following model: $x_{t,t+K} = \kappa + \alpha z_t + \varepsilon_t$, where $x_{t,t+K}$ like $r(t,t+T)$ in the Fama-French regression is the return on the stock portfolio from time t to t+K, κ is a constant, z_t is the ratio at time t, in the article by Rangvid z_t is the price-dividend, the price-earnings or the price-output ratio, and lastly, ε_t is the stochastic error term of the regression.

The regression which will be used in the current thesis takes the same form and can be written as:

$$x_{t,t+K} = \beta_1 + \beta_2 w_t + \mu_t$$

Where $x_{t,t+K}$ is the variable being investigated, and in the current thesis this will be the stock return on the market portfolio, which will be denoted as $r_{t,t+K}$. In this t is time and K is the amount of periods investigated.

β_1 and β_2 are the regression parameter.

w_t is the investigated ratio at time t, in the current thesis the ratios are the price-output, py_t, the price-export, px_t, or the price-import ratio, pz_t.

μ_t is the stochastic error term of the regression.

As K increases and the predictability of stock return over longer horizons is investigated, the $r_{t,t+K}$ will include data from several quarters, and this will cause an overlapping of the observations. This will very like cause autocorrelation and thereby make the estimates biased. This will be discussed in more details in the autocorrelation section.

[118] Fama and French, 1988
[119] Rangvid, 2006

The three models, which will be investigated, can be written as follow.

The price-output: $$r_{t,t+K} = \beta_1 + \beta_2 py_t + \mu_t \qquad (3.3.1)$$

The price-export: $$r_{t,t+K} = \beta_1 + \beta_2 px_t + \mu_t \qquad (3.3.2)$$

The price-import: $$r_{t,t+K} = \beta_1 + \beta_2 pz_t + \mu_t \qquad (3.3.3)$$

4 Data

The data used in the different regressions all comes from Thomson Reuters DataStream[120], which is a very large source of financial data, and the Thomson Reuters name guaranties the accuracy of the data, especially when using data from western countries, where Thomson Reuters DataStream can be expected to collect data from very reliable sources such as government institutions and stock exchanges, and in fact Thomson Reuters DataStream has collected all the data used in the current thesis from the OECD and the MSCI, which also are trustworthy sources[121].

Four countries have been chosen for investigation, two which can be categorized as small countries and two large countries. The first small country is Denmark, which have special interest in that the author of the current thesis is Danish and the thesis is written at Copenhagen Business School in Denmark. The other small country is The Netherlands, and this is chosen due to its size and the fact that it is a country in the Western Europe. The choice was made only to use countries in the Western Europe because the study takes the origin in Denmark, due to the special interest in this country. There are a large differences between the Asian market and the Danish market, making comparison between countries difficult to interpret. Moreover, the American market has been the foundation of many of the studies in the stock predictability field and the data from this particular country can be seen as more exposed to data mining and over fitting, which can also been seen as part of the literature in the field[122]. On the other hand, a Nordic or Scandinavian country was perceived as to close a fit for Denmark and The Netherlands was chosen as a country, which Denmark is often compared to. The first large country is the UK, which is chosen for the size, the location and its reputation for having a very liquid and open stock market. Lastly, the other large country is France, which is chosen for its size and location. Germany may have been the more obvious choice, due to the fact that it is more a part for the Northern Europe than France. However, Germany was before 1989 divided into East and West Germany and this can pose a problem for the data sample, and give rise to structural breaks at the time of the reunion. The large countries around the Mediterranean Sea was not chosen due to the differences between them and Denmark for instance in regards to corruption and general way of life, which might be

[120] Thomson Reuters DataStream
[121] The descriptions of all the data from Thomson Reuters Datastream are in appendix A
[122] Clark, 2004 and Rapach and Wohar, 2006 among others

reflected in the data. Therefore, France was chosen as the middle way and the best possible choice for a second large country.

4.1 The return

For the portfolio returns and the stock prices, the Morgan Stanley Capital International (MSCI) index from the respective countries is used. The choice of this index for the return of the portfolios and the stock prices was made due to the fact that the MSCI indices are very close to the market portfolio for the respective countries in that they include all listed companies[123]. The data is free float adjusted, which means that in calculating the index, only the equity which is expected to be tradeable is used, and the weight of the company in the index are calculated on basis of the tradeable equity rather than on the basis of the total equity.

For the return on the portfolios, the MSCI total return index (MSCI(RI)) is used. This index includes the reinvested dividend and it represents the amount the investor would be able to earn on the portfolio if holding it from time t to time t+1. The index is, like the MCSI price index (MSCI(PI)), an accumulated index, which means that the value increase or decrease is added to the index at the end of each period, and the word return in the name of the MSCI(RI) index does not relate to the calculation of return, but it relates to the reinvestment of the dividend and the fact that the index represents all the possible gain from holding the portfolio. The return used as the dependent variable is calculated as continuously compounding return. This is done because of the theoretical reason, that the stock return is almost continuously compounding, in that it is produced by trade though out the day and the MSCI(RI) index is a daily index, however used here on a quarterly basis. This is possible because the index is accumulated and the index on a quarter basis represents the increase or decrease during the quarter even if it does not include the changes during the quarters. Another reason for using the continuously compounding return is that it has a normalizing effect on the residuals of the regression, due to the fact that it makes the regression log linear. The regression is log linear rather than a semilog model (log-lin model) because it is founded in the theoretical model and the logarithm is taken on both sides of the model. Furthermore, the log linear model have the advantage that it makes the slope coefficient β_2 an elasticity measure[124], and it can there be

[123] MSCI
[124] Gujarati, 2003

compared across different currencies, as will be the case in the current thesis. Additionally, it makes sense to use a continuously compounding ratio when using the continuously compounding return for the purpose of continuity in the data. Lastly, the use of a log linear model using the continuously compounding return and ratio is in line with most research within the area.[125]

Moreover, the return of the stock index will be the real return. That is; it will be deflated with the Consumer Price Inflation (CPI) index[126]. This is in line the work of some researchers[127] and not in line with the work of others[128]. The real return of the stock index reflects what the investor could earn from holding the index from period t to period t+K in real terms. One can argue that the investor reacts to the real return rather than the nominal return because the real return represents the investor's possible consumption, which is the parameter he or she is interest in. Furthermore, one can argue that the investor is able to see the difference between the nominal and real return and incorporate the inflation into the decision-making process and therefore make decisions on the basis of the real return, and this will in turn be the right variable to use in the investigation. As previously discussed in relation to cay, the investor is interest in the consumption path and the real return is better as the representative for the consumption than the nominal return. As with cay the variables in the current thesis are founded in the business cycle, and the importance of the consumption in this context makes for the choice of the real return in the current thesis.

The formula for calculating the real return on the MSCI index is as following[129]:

$$r_t = \log\left(1 + \frac{MSCI(RI)_t - MSCI(RI)_{t-1}}{MSCI(RI)_{t-1}}\right) - \log\left(1 + \frac{CPI_t - CPI_{t-1}}{CPI_{t-1}}\right) = \log\left(\frac{MSCI(RI)_t}{MSCI(RI)_{t-1}}\right) - \log\left(\frac{CPI_t}{CPI_{t-1}}\right)$$

When the returns over several quarters are used, the returns of the single quarters are added, so that the return is given by: $r_{t,t+K} = \sum_{t=1}^{K} r_{t,t+K}$ The return on the portfolio when buying it at time t is the sum of the returns at time t+K.

This means that for period one using four quarters, the return will be: $r_{1,t+4} = r_2 + r_3 + r_4 + r_5$.

Here the return on the portfolio when buying it at time t=1 and holding it for four quarters is the sum of the return at time t=2, 3, 4, 5.

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[125] Fama and French 1988, Rangvid 2006, Rapach 2005 et al., and Rapach and Wohar 2006 to name some.
[126] This is the inflation index used in Rapach et al., 2005
[127] Lettau and Ludvigson, 2001, Rapach et al., 2005 and Rapach and Wohar, 2006
[128] Rangvid, 2006, uses the nominal return and the excess return, which he argues is approximately the real excess return.
[129] The formula for continuously compounding returns can be seen in Brooks, 2002, page 7

4.2 The ratios

All the ratios are calculated on the basis of the MSCI stock price index (MSCI(PI)) and a macroeconomic component, the output, the export or the import.

The MSCI(PI) index is used as the stock price; the price of the portfolio. MSCI(PI) index does not include the dividend, and is the pure price changes of the stock index. As the MSCI(RI) index, the MSCI(PI) index is free float adjusted and a daily index. This index is used on a quarter basis for the reasons as the MSCI(RI) index. As discussed in the previous section 4.1, the price and the macroeconomic components are continuously compounding. For the sake of continuity in the data, the ratios are in real terms and the inflation is deducted at the price level and level of the output, export and import, rather than at the ratio level. This is done in order to be able to use the right correction for inflation for the different variables. The MSCI(PI) is as the MSCI(RI) deflated by the CPI, and this is done for the purpose of continuity in the data. The macroeconomic variables are collected from DataStream in real terms and are therefore deflated with their respective appropriate inflation deflators.

The stock price is calculated as following: $p_t = \log\left(MSCI(PI)_t\right) - \log\left(CPI_t\right)$

The ratios are given by: $$\begin{aligned} py_t &= p_t - y_{t-1} \\ px_t &= p_t - x_{t-1} \\ pz_t &= p_t - z_{t-1} \end{aligned}$$

Where the macroeconomic variables are given by: $$\begin{aligned} y_{t-1} &= \log\left(Y_{t-1}\right) \\ x_{t-1} &= \log\left(X_{t-1}\right) \\ z_{t-1} &= \log\left(Z_{t-1}\right) \end{aligned}$$

The stock prices are scaled with the macroeconomic variables from the previous quarter. This is the convention in the literature[130], and is done because the investor does not know the size of the macroeconomic variable before next quarter, due to the fact that these variables first have to be published. Therefore, the response from changes in these variables is delayed by a quarter compared with the response from changes in the stock prices.

[130] Rangvid. 2006

4.3 The size of the data sample

The data sample starts in Q1 1970 and ends in Q2 2010. The data from Q1 2000 to Q2 2010 will be used for out-of-sample testing. This leaves the data sample from Q1 1970 to Q4 1999, all together 120 observations for in-sample-testing. However, some of these observations are used in the calculations of the return and the ratios. The ratios use time t and t-1, which means that the first t will be at Q2 1970, leaving 119 observations for in-sample testing. The return is calculated by summing the returns of several quarters, and the amount of periods K must therefore be deducted in the end of the data sample. For four quarters the last time t used in the in-sample testing is Q4 1998, because $r_{Q4-1998,t+4}$ is calculated as $r_{Q4-1998,t+4} = r_{Q1-1999} + r_{Q2-1999} + r_{Q3-1999} + r_{Q4-1999}$. This leaves the amount of observations for in-sample test, R, as a function of the total amount of observations excluding the one Q1 1970 observation, T, and the amount of periods, K. The amount of observations for in-sample testing is given by $R = (\mathrm{T} - K)$. Therefore, the number of observations for in-sample testing for four quarters is 119-4=115.

5 Summary statistics and unit root testing

The summary statistics will include the average and the standard deviation of the ratios and the different returns over 4, 12 and 20 quarters. Furthermore, it will include the correlation between the variables as an indicator of their relationship with each other. Moreover, this section will include the unit root testing of the variables and lastly any corrections needed as a consequence of the findings.

5.1 Denmark

Table 5.1 shows that the real annual return for holding the MSCI stock portfolio in Denmark is 7.3% calculated as the sum of the quarterly returns, as shown in section 4.1. The real return for a 3 year period is 21.6% and the 5 year return is 39.0%. The fact that quarterly returns cannot just be multiplied by the number of quarters is due to the method of calculation of the returns over the different periods. The sum of the quarterly returns is taken before the average is calculated and therefore very high returns will impact the sum longer for the longer periods and therefore also impact the average more. The same is true for very low returns, but from the numbers it can be seen, that the impact of the high returns over the long period has been stronger than over the short periods. The standard deviation of the returns increases more from 4 quarters to 12 quarters than it does between 12 and 20 quarters. The standard deviation for the 12 and 20 quarter returns are very similar, which can be due to the flattening effect of summing over both 12 and 20 quarters. When summing over many observations such as 20 and then just changing one observation at the time, the effect on the variation will be less profound since 19 of the 20 observations are the same from one period to the next. In contrast the one new observation will potentially have more impact on the total variation if the number of summing observations is only 4. On the other hand, one would expect the variation to increase with the horizon as the average returns increase.

Additionally, it can be seen from table 5.1 that the py-ratio is larger than the px- and pz-ratios in absolute terms. This is due to the fact that the GDP is larger than the export and import, and this should always be the case. Generally, it can be seen that the px and pz- ratios are almost at the same level and have similar standard deviations, whereas the py-ratio have a higher standard deviation. This is due to the higher value of the py-ratio. Furthermore, the ratios are less volatile than the returns, when accounting for the respected values.

From the correlations, one can see that the ratios are quite correlated, but the px- and pz-ratios are extremely correlated with a coefficient of 0.97. The high correlations between the ratios can also be seen in figure 5.1.1, where the ratios do move very similar. The correlation between the px- and pz-ratios are very high because the export and import often move together, whereas the GDP also depends on consumption, investments, and government spendings, which do not vary as much with the export and import as they do with each other. The correlation between the returns is highest between the periods closed to each other, but generally not very high. This can be seen in figure 5.1.2, where the different returns seem to move somewhat differently. Lastly, the correlations between the ratios and the returns increase with time, in that the 20 quarter returns have higher correlations with the ratios than the 4 quarter returns. This is what would be expected since the predictability is expected to increase over longer periods.

Table 5.1

Denmark	py	px	pz	4 Quarterly returns	12 Quarterly returns	20 Quarterly returns
Average	-4,608	-3,481	-3,400	0,073	0,216	0,390
Standard Deviation	0,495	0,320	0,301	0,264	0,387	0,404
Correlations						
py	1					
px	0,69	1				
pz	0,76	0,97	1			
4 Quarterly returns	0,27	0,37	0,44	1		
12 Quarterly returns	0,41	0,50	0,58	0,50	1	
20 Quarterly returns	0,52	0,57	0,67	0,28	0,62	1
Unit root test						
DF tau	-0,77	-2,11	-2,24	-3,85	-2,40	-2,16
p-value (DF)	0,825	0,240	0,193	0,003	0,142	0,220
ADF tau, 1 lag	-1,47	-2,95	-3,14	-6,14	-3,59	-3,23
p-value (ADF 1 lag)	0,547	0,042	0,026	<,0001	0,007	0,021
ADF tau, 2 lag	-1,62	-3,20	-3,39	-7,71	-3,93	-3,68
p-value (ADF 2 lag)	0,469	0,022	0,013	<,0001	0,002	0,006

From the figure 5.1.1 below, where the ratios are plotted against the time, it seems that the ratios move somewhat smoothly, indicating that they may have a unit root. The px- and pz-ratios are stable at the same level though out the period, whereas the py-ratio increases over the period. It is possible that the py-ratio has a structural break around 1997, as the line seems to be at a generally higher level after 1997 than before. This will be investigated further in the section with robustness tests. For testing the stationarity of the time series the Dickey-Fuller and the Augmented Dickey-Fuller test for a random walk with drift will be used, since it allows for the time series to have a mean different from zero, when they are stationary, which seems to be the case. The test of stationarity in the variables can be seen in the bottom of table 5.1. The idea behind the Dickey-Fuller test for a random walk without drift is that if ρ in the equation $A_t = \rho A_{t-1} + u_t$ is 1, Y_t is nonstationary[131], whereas if ρ is less than one in absolute terms, when A_t is stationary[132]. If A_{t-1} is subtracted on both sides and rearranged, the equation is as follow

$$A_t - A_{t-1} = \rho A_{t-1} - A_{t-1} + u_t$$

$$A_t - A_{t-1} = (\rho - 1)A_{t-1} + u_t \qquad \text{Where } \delta = (\rho - 1)$$

$$\Delta A_t = \delta A_{t-1} + u_t$$

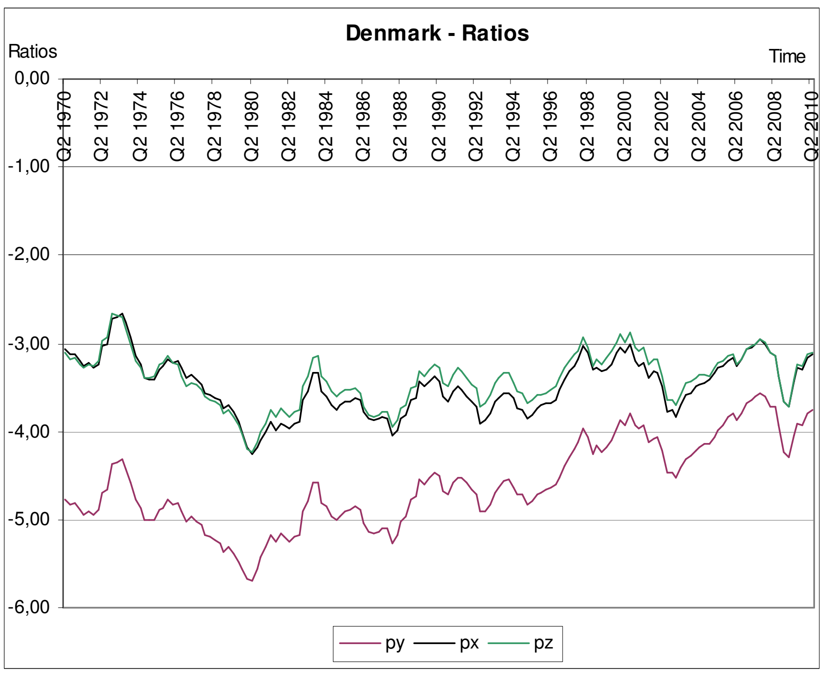
For the Dickey-Fuller test for a random walk with drift, the equation to be tested will be the following, taken into account the drift[133]: $\Delta A_t = \beta_1 + \delta A_{t-1} + u_t$

The Dickey-Fuller test runs this equation under the null hypothesis that $\delta = 0$, and therefore that $\rho = 1$, which is that the time series are nonstationary[134]. The test statistics of this is the τ (tau) statistic and can be seen in the first line of the unit root test in table 5.1. The critical value for this test is -1.95 at the 5% significance level, and it can be seen that for the ratios, especially the py-ratio, the δ is far from being significantly different from zero and the time series have a unit root. For the py-ratio, the Augmented Dickey-Fuller test also concludes that the time series has a unit root. However, the Augmented Dickey-Fuller test with one lag rejects the null hypothesis of a unit root for the px- and pz-ratios. The Dickey-Fuller test assumes that the error term u_t is uncorrelated. If this is not the case, one can use the Augmented Dickey-Fuller test, which includes the lagged value of the dependent variable and one should include enough lags so that the error term is no longer correlated. Therefore, the Dickey-Fuller equation $\Delta A_t = \beta_1 + \delta A_{t-1} + u_t$ is tested for autocorrelation using the Breusch-Godfrey (LM) test[135] and the AR(1) scheme has a value of 22.6 which is highly significant[136]. Therefore, the error term of the Dickey-Fuller equation is correlated and the Augmented Dickey-Fuller should be used[137]. This has the following equation for the random walk with

[131] A will represent an undefined time series
[132] Gujarati, 2003, page 802
[133] Gujarati, 2003, page 815
[134] Gujarati, 2003, page 814
[135] This test will be discussed further in the autocorrelation section
[136] All tests can be found in appendix B
[137] The right test for stationarity is marked in the table

drift[138]: $\Delta A_t = \beta_1 + \delta A_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta A_{t-i} + \mu_t$. One should estimate this equation with one lag and test for correlation in the error term. If correlation is present, one should add another lag and the procedure should be repeated. Lastly, from figure 5.1.2 it can be seen that the Autocorrelation Coefficient between the lags for the py-ratio, the ACF, is high up to the lags of 12 or 13, which is a strong indicator of the time series being nonstationary. The Partial Correlation, the PACF, is very high in lag one and just over the level of significance in lag two, which again is a sign of a unit root[139]. The implications of the unit root in the py-ratio and the correction will be discussed in section 5.5 about estimated ratios.

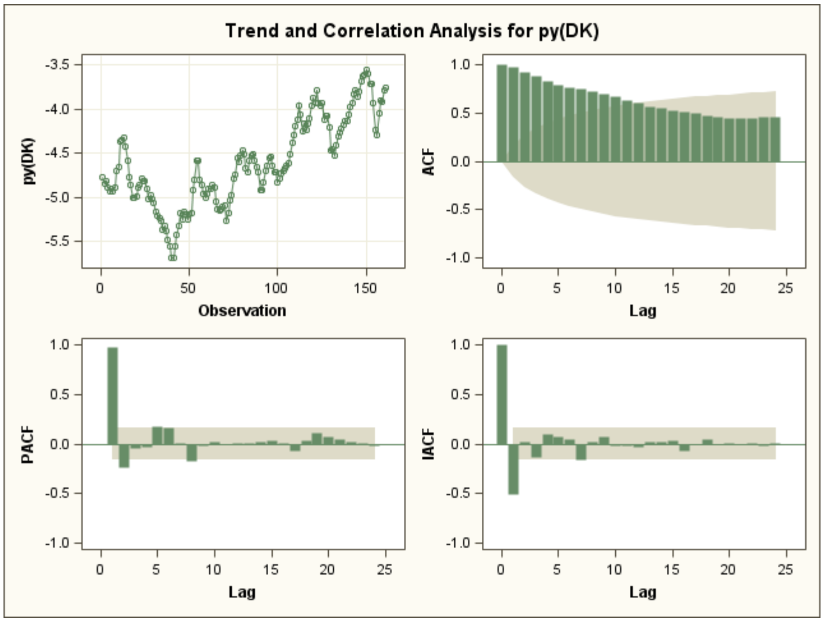
Figure 5.1.1



[138] Gujarati, 2003, page 817

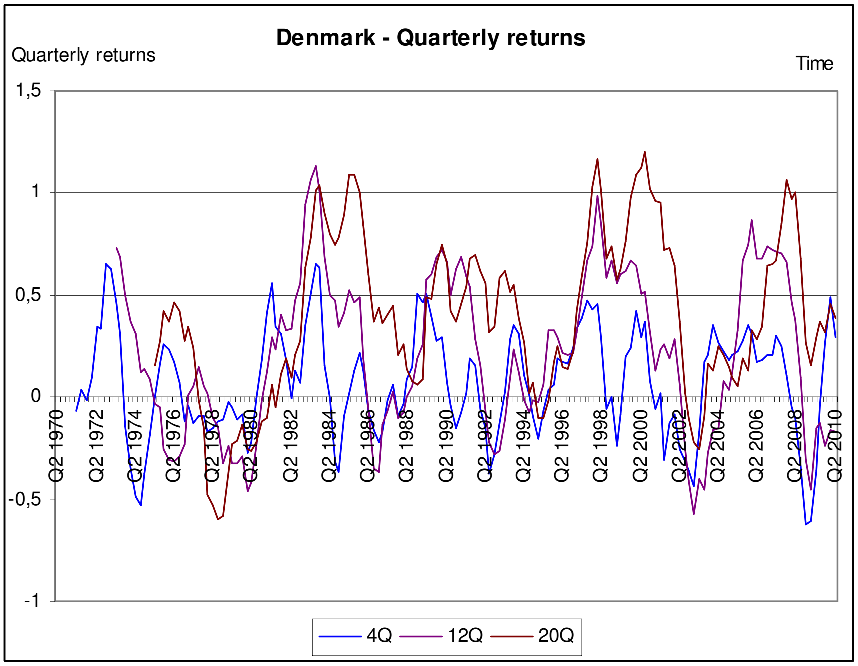
[139] The figures for the other ratios can be seen in appendix B

Figure 5.1.2



From the figure 5.1.3 below, where the returns are plotted against the time, it can be seen that the returns are fluctuating and seem stationary. The unit root test of the returns can be found in table 5.1, and δ is significantly different from zero at a 1% level for the 4 quarter return and it can therefore be concluded that this time series is stationary. However, δ is not significantly different from zero at a 10% level for the 12 quarter return and the 20 quarter return using the normal Dickey-Fuller test for a random walk with drift. The AR(1) scheme for the Dickey-Fuller test for 12 quarter return is 26.1, which again is highly significant, and therefore one should use the Augmented Dickey-Fuller test. When testing for autocorrelation in the Augmented Dickey-Fuller test with one lag the AR(1) scheme is 4.06, which is significantly different from zero at a 5% level, hence one should use the Augmented Dickey-Fuller test with two lags, and on the basis of this it can be concluded that the 12 quarter return is stationary. For the 20 quarter return the Augmented Dickey-Fuller test with two lags should be used and it can be concluded that this is also stationary.

Figure 5.1.3



5.2 The Netherlands

The table 5.2 below shows that the 4 quarter return is 6.8%, the 12 quarter return is 21.7% and the 20 quarter return is 41.2%. The standard deviations for the returns are increasing over the number of periods, and it can be seen that the flattening effect is less profound here than for Denmark, i.e. the difference between the standard deviation of the 12 quarter return and the 20 quarter return is larger for The Netherlands than for Denmark. Regarding the ratios, the tendencies are the same for The Netherlands as they were for Denmark in the sense that the py-ratio has a higher average and a higher standard deviation than the two other ratios. Moreover, the pattern of the correlation is also the same as for Denmark. Here the ratios are much correlated, the 12 quarter return has a high correlation with the other returns, but the 4 quarter return and the 20 quarter return is not as correlated, and the correlations of the returns with the ratios increase with the increase in the horizon of the returns.

Table 5.2

The Netherlands	py	px	pz	4 Quarterly returns	12 Quarterly returns	20 Quarterly returns
Average	-4,219	-3,509	-3,452	0,068	0,217	0,412
Standard Deviation	0,503	0,368	0,371	0,227	0,413	0,509
			Correlations			
py	1					
px	0,78	1				
pz	0,84	0,99	1			
4 Quarterly returns	0,18	0,31	0,33	1		
12 Quarterly returns	0,33	0,57	0,56	0,61	1	
20 Quarterly returns	0,39	0,68	0,66	0,37	0,79	1
			Unit root test			
DF tau	-1,31	-2,17	-1,97	-3,78	-1,85	-1,96
p-value (DF)	0,623	0,217	0,298	0,004	0,357	0,303
ADF tau, 1 lag	-1,52	-2,52	-2,26	-5,08	-2,37	-2,41
p-value (ADF 1 lag)	0,523	0,114	0,188	<,0001	0,151	0,140

In line with the ratios in Denmark, the ratios in The Netherlands are moving smoothly indicating that they may have a unit root[140]. When testing for this using the Dickey-Fuller test in table 5.2, it can be seen that the tau is very low in absolute terms for the py-ratio and one can therefore not reject the null hypothesis of non-stationarity in the time series and must therefore conclude that the ratio have a unit root. The px- and pz-ratios produces insignificant tau –values, which indicates unit root. However, where the py-ratio is very insignificant (significant at a 62% level), the px- and pz-ratios are only slightly insignificant (significant at about a 20% level). Hence, one might argue, that these ratios could be used, if when making conclusions regarding the results of these regressions, one would take into account the problems with unit roots.

The 4 quarter return for The Netherlands is stationary at a 1% level, when testing for a unit root using the Dickey-Fuller, whereas the 12 and 20 quarter returns only are borderline stationary at about a 15% level when testing for unit root using the Augmented Dickey-Fuller with one lag, which can be seen in table 5.2[141].

[140] The figure showing the ratios and the returns against time can be found in appendix B for The Netherlands, France and United Kingdom

[141] Again the autocorrelation tests can be seen in appendix B

5.3 France

In table 5.3 below, one can see that the 4 quarter return is 5.4%, the 12 quarter return is 16.9% and the 20 quarter return is 32.4%. The standard deviations for the returns are increasing over the number of periods and the standard deviation of the 12 quarter return and the 20 quarter return is close with a pattern more similar to the one in Denmark than in the Netherlands. The average and the standard deviation of the ratios have the same patterns as the ratios of both The Netherlands and Denmark. Lastly, the pattern is also repeated for the correlation between the variables.

Table 5.3

France	py	px	pz	4 Quarterly returns	12 Quarterly returns	20 Quarterly returns
Average	-5,173	-3,504	-3,533	0,054	0,169	0,324
Standard Deviation	0,510	0,399	0,392	0,247	0,417	0,485
Correlations						
py	1					
px	0,77	1				
pz	0,81	0,99	1			
4 Quarterly returns	0,19	0,25	0,31	1		
12 Quarterly returns	0,33	0,44	0,50	0,54	1	
20 Quarterly returns	0,41	0,57	0,59	0,30	0,72	1
Unit root test						
DF tau	-1,52	-2,71	-2,59	-4,19	-2,12	-2,11
p-value (DF)	0,522	0,076	0,098	0,001	0,238	0,241
ADF tau, 1 lag	-1,67	-2,85	-2,74	-5,04	-2,47	-2,40
p-value (ADF 1 lag)	0,447	0,054	0,071	<,0001	0,124	0,143

In table 5.3 the unit root test for the ratios show that py-ratio has a unit root, since the null hypothesis of non-stationarity cannot be rejected. However, the px- and pz-ratios are stationary at a 10% level.

In table 5.3 it can be seen that the French 4 quarter return is stationary at a 1% level, and the 12 and 20quarter return are as for The Netherlands borderline stationary at about a 14% level, when testing using the Augmented Dickey-Fuller test with one lag. This test is used, since when testing for autocorrelation, one find that some correlation may be present since the p-values of AR(1) are 0.053 for both. One cannot reject the null hypothesis of no autocorrelation at a 5% level and the case can be seen as borderline[142].

[142] The autocorrelation tests can be seen in appendix B

5.4 United Kingdom

Table 5.4 shows that the average return for 4 quarters is 5.5%, for 12 quarters is 15.9% and for 20 quarters is 31.8%. The standard deviations for the returns increase with the number of periods and the pattern for the United Kingdom market is similar to the one from The Netherlands.

The average and the standard deviation of the ratios have the same patterns as for the other markets except for the fact that the standard deviation of the py-ratio is almost the same as for the other ratios and must be considered low. The only thing standing out in regards to the correlations when comparing with the other countries is that the correlation between the 4 quarter return and the 20 quarter return is quite low, only 0.22.

Table 5.4

UK	py	px	pz	4 Quarterly returns	12 Quarterly returns	20 Quarterly returns
Average	-4,524	-2,869	-2,847	0,055	0,159	0,318
Standard Deviation	0,344	0,333	0,334	0,217	0,368	0,405
Correlations						
py	1					
px	0,76	1				
pz	0,59	0,95	1			
4 Quarterly returns	0,29	0,32	0,37	1		
12 Quarterly returns	0,45	0,53	0,57	0,58	1	
20 Quarterly returns	0,46	0,62	0,60	0,22	0,69	1
Unit root test						
DF tau	-1,96	-2,46	-2,44	-4,52	-2,35	-2,29
p-value (DF)	0,304	0,127	0,134	0,000	0,157	0,176
ADF tau, 1 lag	-2,21	-2,85	-2,78	-5,52	-2,93	-2,52
p-value (ADF 1 lag)	0,202	0,055	0,064	<,0001	0,044	0,112

As for the other countries the ratios show some signs of unit roots. When testing for unit roots using the Dickey-Fuller test in table 5.4, it is clear that the py-ratio has a unit root, which is the case for all the countries. As was the case for Denmark, the Dickey-Fuller test show signs of a unit root for the px- and pz-ratio, though only borderline at a 10% level. It is therefore necessary to test for autocorrelation to see if the Augmented Dickey-Fuller test would be right to use in this case. In the case of the pz-ratio, there autocorrelation is present, and one should test using the Augmented Dickey-Fuller test with one lag. The pz-ratio is now stationary at a 10% level and borderline at a 5% level, and the px-ratio, which have no autocorrelation is borderline stationary at a 10% level.

When testing the returns for unit root in table 5.4, it can be seen that the 4 quarter return is stationary at a 1% level using the Dickey-Fuller test and the 12 quarter return is stationary at a 5% level using the Augmented Dickey-Fuller test with one lag. The 20 quarter return time series is borderline stationary at a 10% level, as was the case for France and the Netherlands[143].

From the data and the discussion above, it can be concluded that the py-ratios for all the countries have severe problems with unit roots, and some measures will be taken in relation to this problem in section 5.5 below. The px-ratios are stationary at a 10% level or less for Denmark and France and borderline stationary at the same level for United Kingdom. Only for The Netherlands is time series not strictly stationary. However, the unit root is not as severe as for the py-ratios, and for the sake of consistency, the px-ratios will be used in the further estimation and testing for all four countries. The pz-ratios are stationary at a 10% level or less for all countries except The Netherlands. Again the ratios will be used for estimation and testing for all four countries. Lastly, the 4 quarter returns are stationary at a 1% level for all countries, and the 12 and 20 quarter returns are stationary for Denmark at the same level. Additionally, the 12 quarter returns are stationary for United Kingdom at a 5% level and borderline stationary for The Netherlands and France. The 20 quarter returns are borderline stationary for The Netherlands, France and United Kingdom, where the unit root is less serious in the case of United Kingdom, where the p-value is 11.2%. Since, all the tests for stationarity in the returns reveals p-values of 15% or less, it can be concluded that these time series are stationary or borderline, hence they will be used as they are in the further estimation and testing.

[143] The autocorrelation tests can be seen in appendix B

5.5 Estimated ratios

It can be seen from the previous sections, that especially the py-ratios have some severe problems with unit roots. Dealing with non-stationary time series can cause some serious problems, such as spurious regressions. In the case of spurious or nonsense regressions, two variables without any connection to each other can give very high R^2-values when regressed on one another[144]. Therefore, when dealing with time series with unit roots, one cannot trust the R^2-values. Moreover, t-test and the F-test in regressions with non-stationary time series cannot be trusted either, since they do not follow the t-distribution and the F-distribution[145]. When working with time series, one of the assumptions is that the variables are stationary[146], and if this is not the case, one cannot trust the results.

A variable is stationary if a shock gradually will die out, whereas it is non-stationary if a shock is persistent over infinite time. For an AR(1) without drift, the variable x is stationary if ϕ is less than 1 and non-stationary[147] if ϕ is 1 in the following equation[148] $A_t = \phi A_{t-1} + \mu_t$.
The ratios in the previous sections are a combination of the stock price and either the output, the export or the import. These time series alone are know to have a very strong unit root, especially the stock price is often said to follow a random walk[149], and as stated in the theory section the efficient market theory is build on the foundation that the stock prices follow a random walk. The output, export and import are macroeconomics variables, which are also famous for following random walks with drifts, and the best estimate of the value of the variable tomorrow is the value today.
When making a linear combination of two non-stationary variables, one can hope that these two variables are cointegrated and that the combination will be stationary. Many variables, which are non-stationary, move together over time because they may be influenced by an underlying market force. In the case of stock prices and output, export or import this underlying market force is most likely to be the economics cycle of the country and it is plausible that combination of two of the variables could make a stationary third variable, a ratio, and these ratios would work as an error correction mechanism. This is the case for the

[144] Brooks 2002, page 367
[145] Brooks 2002, page 368
[146] Gujarati, 2003, page 792
[147] The variable is also non-stationary if ϕ is more than 1, but in this case a shock will become more influential as time goes and this is not a typical phenomenon for economic and financial time series
[148] Brooks, 2002, page 370
[149] Gujarati, 2003, page 798

ratios studied by Rangvid[150], who showed that the py- and pe-ratios are stationary. However, the py-ratios in the current thesis are not stationary and this may have three possible causes. Firstly, the linear combination between the two original variables is limited to a combination with a slope of 1 and no constant. Secondly, the problem can be that the stock price and the output alone are not cointegrated. This can be due to structural breaks or that the ratio they form moves over time. Lastly, it may be that another variable is necessary in order to make the relationship stationary.

The tests for unit roots in the new variables are different from the tests for unit roots in the ratios. This is because the variables tested have been estimated and are the residuals from a regression. Therefore, one cannot use the Dickey-Fuller test and critical values, and the correct test is the Engle-Granger (EG) for zero lags and the Augmented Engle-Granger (AEG) for one or more lags. The test procedure is the same as for the Dickey-Fuller and the Augmented Dickey-Fuller test. Using the Danish RESpy variable, which comes from a regression of the p and y, to explain the test as follows: First one must run the following regression $\Delta RESp\hat{y}_t = RESp\hat{y}_{t-1}$ and the tau-value (the t-value) from this must be tested against the Engle-Granger critical values[151], where one should use the critical values for N=2, because of the estimation regression where the residuals RESpy come from has two variables, p and y. Additionally, one should use the values for no trend, because the test is for a random walk without drift. This includes a constant, since the initial regression producing the residuals has an intercept. If tau is lower than the critical value in absolute terms, one can not reject the null hypothesis of non-stationarity, and if tau is higher than the critical value in absolute terms, one can conclude that the variable is stationary. If the variable has a unit root, it should be tested for autocorrelation, and if this is present, the Augmented Engle-Granger test with one lag should be use. If there is still autocorrelation present two lags should be used and so on.

The stock price and output for Denmark will be used to investigate these three possible causes, namely the estimation of price and output, the estimation with a structural break dummy or time trend and the estimation of the price, output and a third variable.

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[150] Rangvid, 2006
[151] Engle and Granger, 1991
[153] Paye and Timmermann, 2006

The first possibility is that by estimating the relationship between the price and output, the residuals will be stationary. When estimating the following equation $p_t = \beta_1 + \beta_2 y_{t-1} + \nu_t$, it was found to be stationary at a 10% level and borderline stationary at a 5% level. From this it can be seen that the price and output is cointegrated, though not in a combination where the slope, β_2, is restricted to be one 1 and the constant, β_1, is restricted to be zero.

When looking at figure 5.1.1, it can be seen that the series may have a structural break around 1997, and one could try to run the following regression $p_t = \beta_1 + \beta_2 y_{t-1} + \beta_3 D_t + \nu_t$, where D_t is the dummy taking the value zero before 1Q 1997 and the value one after. This regression did give relatively stationary residuals, when testing it using the Engle-Granger test. However, finding the cut point is an arbitrary decision in this case, and a serious problem with occurring breaks is that these breaks can only be detected using hindsight[153]. Hence the finding of the current thesis would be very difficult to use in real life. Moreover, different countries will have breaks at different times, which will again limit the use of the results. However, the result from the regression using the dummy gave relatively stationary residuals and it will be used for robustness test later[154].

The time variation factor can be include in the ratios by estimating the following regression $p_t = \beta_1 + \beta_2 y_{t-1} + \beta_3 t + \nu_t$, where t is the time trend. The residuals from this regression were not stationary, if anything only borderline, again using the Engle-Granger test.

The last possible correction method for the unit roots in the ratios is to include an extra variable when estimating the ratios[155]. The variable chosen for this estimation if the risk-free interest rate, since it will give the estimated ratios new information, and not be a variable which could substitute another variable. The interest rate used is in real terms, which is the nominal interest rate deflated by the changes in the CPI. Moreover, the interest rate is continuously compounding and calculated as follow $i_t = \log(1+i_t) - \log\left(1 + \frac{CPI_t - CPI_{t-1}}{CPI_{t-1}}\right)$

When estimating the equation $p_t = \beta_1 + \beta_2 y_{t-1} + \beta_3 i_t + \nu_t$, where i_t is the risk-free interest rate, the residuals were relatively stationary.

[154] The results for the unit root tests for the dummy, RESpyD, the time trend, RESpyt, and the interest rate, RESpyi, can be seen in appendix F

[155] The discussion of which variable to use and the specifics regarding the data of the risk-free interest rate can be seen in appendix F. This is due to the page limitations of the current thesis.

Since all the estimated ratios were relatively stationary or borderline stationary, the estimated py ratio, RESpy, is closest to the original ratio in the theory and will therefore be used in the further investigation. The other three ratios, the dummy ratio, RESpyD, the time trend ratio, RESpyt and the interest rate ratio, RESpyi, will be used for robustness tests.
The descriptive statistics and results from the unit root test for the RESpy ratio can be seen in table 5.5 below. The residuals from the regression for each country should have an average of zero given the Ordinary Least Squares[158], and this is therefore given in the table.

The new regression for the four countries, which will be investigated is as follow

The RESpy: $r_{t,t+K} = \beta_1 + \beta_2 RESpy_t + \mu_t$ (5.5.1)

Table 5.5

Denmark	RESpy	**France**	RESpy
Standard Deviation	0,32	Standard Deviation	0,43
Correlation		Correlation	
RESpy	1	RESpy	1
px	0,97	px	0,98
pz	0,96	pz	0,99
4 Quarterly returns	0,42	4 Quarterly returns	0,22
12 Quarterly returns	0,56	12 Quarterly returns	0,40
20 Quarterly returns	0,61	20 Quarterly returns	0,49
Unit root test		Unit root test	
EG tau, lag 0	-2.29	EG tau, lag 0	-2.52
EG tau, lag 1	-3.10	EG tau, lag 1	-2.65
The Netherlands	RESpy	**United Kingdom**	RESpy
Standard Deviation	0,37	Standard Deviation	0,31
Correlation		Correlation	
RESpy	1	RESpy	1
px	0,99	px	0,96
pz	0,97	pz	0,88
4 Quarterly returns	0,30	4 Quarterly returns	-0,03
12 Quarterly returns	0,55	12 Quarterly returns	0,34
20 Quarterly returns	0,67	20 Quarterly returns	0,50
Unit root test		Unit root test	
EG tau, lag 0	-2.40	EG tau, lag 0	-2.40
EG tau, lag 1	-2.69	EG tau, lag 1	-2.70

The critical values for the Engle-Granger test is for 1% -3.9001, for 5% -3.3377 and for 10% -3.0462

From table 5.5 it can be seen that the new variable, RESpy, for the countries are much correlated with the old ratios. This is due to the fact that the both the old ratios and the

[158] Gujarati, 2003, page 45

estimated ratio contains much of the same information. Additionally, it can be seen that the new variables follow the same pattern as the ratios in the sense that they are more correlated with the return over longer horizons than over shorter. The appropriate tau-values in table 5.5 are marked[159]. Moreover, in comparison with the old py-ratios it can be seen, that the standard deviation for the RESpy are slightly lower.

It can be seen in figure 5.5, that RESpy for all the countries seem to be fluctuating reasonably much and this could indicate that the estimated ratios are stationary. The Engle-Granger test in table 5.5 reveals that only the RESpy for Denmark is stationary at a 10% level and borderline stationary at a 5% level. RESpy for the other countries are strictly speaking not stationary with test value below 3 in nominal terms. However, the new estimated ratios seem to be at least as stationary as the old ratios for the output, which can be seen by comparing the two types of ratios. When looking at the PACF for the estimated ratios[160], it can be seen that they are only significantly high in the first lag. This graphical overview shows that the unit roots in the estimated ratios for The Netherlands, France and United Kingdom may not be as severe as the Engle-Granger tests indicate, and the decision to use these ratios in the further investigation should be founded in both the statistical tests and graphical analyses. The criticism made against the Dickey-Fuller test and thereby also the Engle-Granger test is that these tests have low power, if the process is borderline stationary[161]. The test will not be able to reject the null hypothesis of non-stationarity if the stationarity is borderline significant due to lack of information such as sample size. Using the AR(1) without drift in the beginning of this section, the problem for the Engle-Granger test is when it has to decide whether the $\phi = 1$ or $\phi = 0.95$ in equation $A_t = \phi A_{t-1} + \mu_t$.

Lastly, it is sometimes practiced in the literature to assume stationarity and not test for this[162] or to test for stationarity in the variables and then use the variables even though the tests show signs of unit roots[163]. In line with this practice, the estimated ratios for The Netherlands, France and United Kingdom will be used despite the signs of unit roots, because the unit roots do not seem to be very severe and the assessment in this situation is that the conclusions in relation to stock returns predictability will still be useful, even if one cannot make very strong conclusions.

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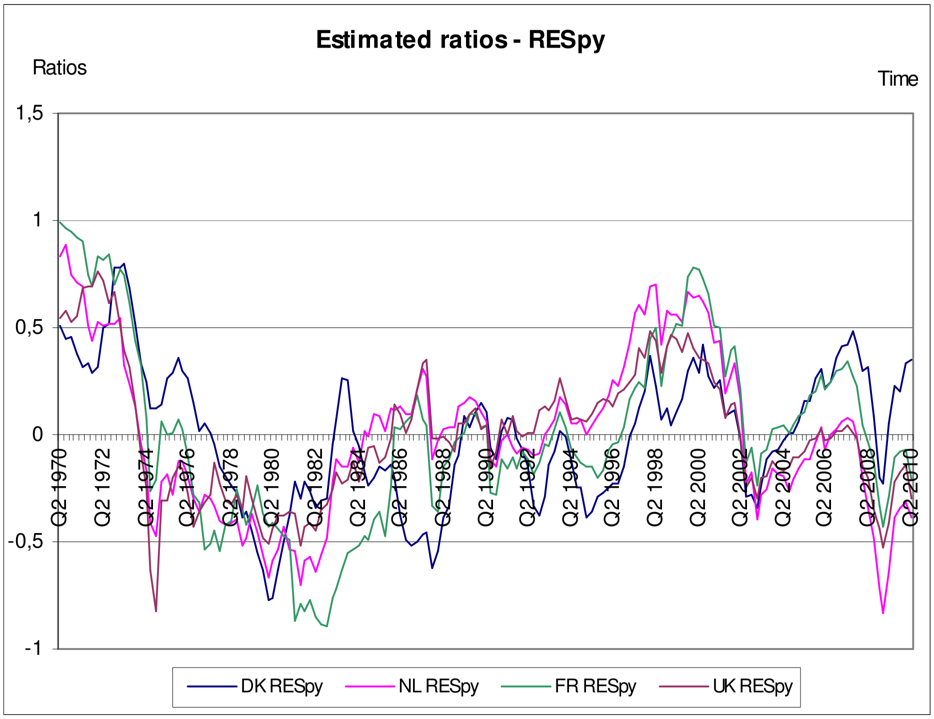
[159] The tests for autocorrelation can be found in appendix C
[160] They can be found in appendix C.
[161] Brooks, 2002, page 381f
[162] Goyal and Welch, 2004 and Rapach et al., 2005
[163] Rangvid, 2006

Figure 5.5.1


Estimated ratios - RESpy
Ratios
Time
1,5
1
0,5
0
-0,5
-1
Q2 1970
Q2 1972
Q2 1974
Q2 1976
Q2 1978
Q2 1980
Q2 1982
Q2 1984
Q2 1986
Q2 1988
Q2 1990
Q2 1992
Q2 1994
Q2 1996
Q2 1998
Q2 2000
Q2 2002
Q2 2004
Q2 2006
Q2 2008
Q2 2010
DK RESpy
NL RESpy
FR RESpy
UK RESpy

6 Results from in-sample testing

When doing regression analysis, working with time series and using the Ordinary Least Squares (OLS) method, one should be aware of the underlying assumptions for the model and test, if necessary, that the model and data satisfy these assumptions. Ten assumptions are made in the use of the Gaussian classical linear regression model (CLRM)[164], and when the model follows these assumptions it provides estimates which are BLUE, that is they have minimum variance for class of unbiased linear estimates[165].
The assumptions are as follow[166]:

1. The model is linear in the parameters
2. The A is nonstochastic and its value is fixed in repeated sampling
3. The mean value of the disturbance μ_i is zero
4. The model has homoscedasticity or equal variance of μ_i
5. The model has no autocorrelation between the disturbances
6. The covariance between μ_i and A_i is zero
7. The number of observations is greater than the number of parameters
8. There is variability in the A values
9. The regression is correctly specified
10. There is no perfect multicollinearity

In order to use the t, F and χ^2 statistics, an additional assumption, the normality assumption, is necessary. This makes the CLRM into the classical normal linear regression model (CNLRM)[167].

11. The disturbance μ_i is normally and independently distributed $\mu_i \sim NID(0, \sigma^2)$

Assumptions 1, 3 and 9 have to do with the setup of the model being tested. They state, that the model must have the right functional form and include all relevant variables, and omitted variables must not influence the disturbance systematically. The model used in the current thesis is founded in the theory of stock predictability and one can therefore assumed that it is specified correctly. Assumptions 2, 6, 7 and 8 are related to the data, and in the current thesis

[164] Gujarati, 2003, page 66
[165] This is the Gauss-Markov Theorem. Gujarati, 2003, page 79
[166] The assumptions can be seen in Gujarati, 2003, page 66-75
[167] Gujarati, 2003, page 108f

it can be seen that the estimated ratios used as A are nonstochastic and have variability. Moreover, there are more observations in the data sample than parameters to be estimated, and assumption 6 is automatically fulfilled, if A is nonstochastic and assumption 3 holds[168]. Lastly, assumption 10 is only relevant when testing models with two or more explanatory variables, which is not the case in the current thesis.

By the method of exclusion, it can be seen that the assumptions which need to be tested for in the current thesis are assumptions 4, 5 and 11. These assumptions and their tests will be discussed in the following

Assumption 11. The disturbance μ_i is normally and independently distributed

It is very common for financial data not to be normally distributed. This is among other reasons due to the limited liability of for instance stocks. An investor is only liable for the invested amount, which limits the downside of the investment. On the other hand there is no limit on the upside of the investment, and this will often make the distribution skewed. This skewness is fundamentally due to the fact that the financial time series are not linear[169] and when trying to regress them in a linear model, the residuals become skewed. This can be corrected by chancing the model into a log-linear model, and thereby making the residuals normally distributed because the model is correctly fitted.

Another reason for the residuals not being normally distributed is the fact that many financial series have a leptokurtic distribution[170] with a higher kurtosis than the kurtosis for the normal distribution which is 3. This distribution often arises from the presents of outliers in the data sample, and can be corrected using dummy variables. However, the use of dummy variables to remove outliers can be seen as a way to artificially improve the model and there is no final solution for the problems caused by outliers.

The normal distribution of the residuals will be graphically visualised using histograms and probability plots and it will be statistically tested using the Jarque-Bera (JB) test of normality, which tests the skewness and kurtosis of the distribution against the skewness and kurtosis of the normal distribution, which is $S = 0$ and $K = 3$.

[168] Gujarati, 2003, page 72
[169] Brooks, 2002, page 437
[170] Brooks, 2002, page 179ff

Assumption 4. The model has homoscedasticity or equal variance of μi

There are two types of heteroscedasticity. The first type is that the variance of the residuals changes over time, it increases or decreases over the time period. This variance is referred to as heteroscedasticity. This type of heteroscedasticity can come from a number of reasons including outliers, skewness in the distribution of one or more explanatory variables and an incorrectly specified model[171]. It will be graphically illustrated by plotting the residuals against the estimated dependent variable and it will be tested statistically by White's General Heteroscedasticity test[172].

The second type is that the volatility is clustering, meaning that high volatility is often followed by high volatility and low volatility is often followed by low volatility. This type of volatility clustering is very normal for financial data, especially for stock returns[173]. This is known as autoregressive conditional heteroscedasticity or ARCH. It will be graphically shown using squared residuals plotted against the lagged squared residuals, and it will be statistically testes using the Engle ARCH test.

In the presence of heteroscedasticity the estimated values are still correct and unbiased, linear and asymptotically normally distributed, but they are no longer the minimum variance for class of unbiased linear estimates and therefore they are not BLUE. Consequently, they cannot be testing using normal statistical tests such as t, F and χ^2 statistics, since the standard errors cannot be trusted[174].

Assumption 5. The model has no autocorrelation between the disturbances

Autocorrelation is present if the error terms are correlated over time. If this is the case, the estimates are still unbiased, linear and asymptotically normally distributed, but as for the case of heteroscedasticity, they are not BLUE and the t, F and χ^2 statistics are not valid[175].

There are several reasons for the presence of autocorrelation. Firstly, many economic series follow a business cycle, which makes them interdependent, and these time series are therefore subject to inertia. Secondly, nonstationary time series will often exhibit autocorrelation. Lastly, data manipulation can cause autocorrelation. If the data used in the regression are

[171] Gujarati, 2003, page 390f
[172] The test value for White's test will not be the one given by SAS, since it to frequently accept the null hypothesis of homoscedasticity, and therefore does not give the true picture of the degree of heteroscedasticity in the regression.
[173] Brooks, 2002, page 445f
[174] Gujarati, 2003, page 394
[175] Gujarati, 2003, page 442ff

quarterly but derived from monthly data by averaging the monthly data, this smoothening process will cause a systematic pattern in the disturbance and thereby autocorrelation.
In the current thesis the data is being manipulated, in the sense that the data used are quarterly and the prediction horizon is as high as 5 years or 20 quarters. This will cause autocorrelation due to the overlapping of the data.
The problem of the overlapping data can be shown from an example using one year and the output:
The first dataset for the one year regression with RESpy would be RESpy at time 1 and the stock return from holding the portfolio from time 1 and four periods ahead, four quarters in a year. The second dataset for the one year regression would be RESpy at time 2 and the stock return from holding the portfolio from time 2 and four periods and so on.

$$r_{1,1+4} = \beta_1 + \beta_2 RESpy_1 + \mu_1$$
$$r_{2,2+4} = \beta_1 + \beta_2 RESpy_2 + \mu_2$$
$$r_{3,3+4} = \beta_1 + \beta_2 RESpy_3 + \mu_3$$
$$r_{4,4+4} = \beta_1 + \beta_2 RESpy_4 + \mu_4$$

Where

$$r_{1,1+4} = r_2 + r_3 + r_4 + r_5$$
$$r_{1,2+4} = r_3 + r_4 + r_5 + r_6$$
$$r_{1,3+4} = r_4 + r_5 + r_6 + r_7$$
$$r_{1,4+4} = r_5 + r_6 + r_7 + r_8$$

It can be seen that the first dataset includes stock return data from time 2 to 5, the second dataset includes return data from time 3 to 6, the third dataset includes return data from time 4 to 7 and the fourth dataset includes return data from time 5 to 8. From this one can see that there is a great deal of overlapping in the datasets and this will only be worse for longer horizons. The error terms will be correlated over 4, 12 and 20 periods depending on the forecasting horizon.
The presence of autocorrelation will be graphically illustrated by plotting the studentized residuals against the lagged studentized residuals and against the time. It will be tested statistically by the Breusch-Godfrey (LM) test.

6.1 Denmark

On the basis of the 4 quarter returns and output regression for Denmark, the tests and results will be discussed in details, and all regression results and the rest results for Denmark are shown in table 6.1, including results for 12 an 20 quarter returns and output and all the results for export and import.

Table 6.1

Denmark	Output - RESpy			Export - px			Import - pz		
Horizon K quarters	4	12	20	4	12	20	4	12	20
β_1 Intercept	0,064	0,178	0,299	-1,140	-2,592	-2,889	-1,102	-2,790	-3,166
Standard errors	0,022	0,027	0,025	0,236	0,295	0,285	0,251	0,309	0,295
p-value	0,005	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
β_2 Coefficient	-0,302	-0,754	-0,925	-0,344	-0,790	-0,913	-0,341	-0,865	-1,008
Standard errors	0,066	0,079	0,072	0,066	0,082	0,080	0,072	0,088	0,084
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
HAC standard errors	0,122	0,187	0,146	0,109	0,188	0,132	0,120	0,152	0,119
p-value	0,015	0,000	0,000	0,002	0,000	0,000	0,005	0,000	0,000
R-square	0,156	0,465	0,629	0,193	0,468	0,574	0,165	0,478	0,596
Jarque-Bera test	5,234	9,780	5,515	6,270	6,059	2,879	4,798	3,003	4,213
p-value	0,073	0,008	0,063	0,044	0,048	0,237	0,091	0,223	0,122
White's R-square	0,024	0,045	0,022	0,023	0,045	0,015	0,015	0,036	0,071
White's test value	2,703	4,762	2,208	2,611	4,783	1,436	1,668	3,863	7,009
ARCH test, 1, order	55,383	48,381	50,666	56,417	44,090	32,301	54,969	50,852	58,021
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Breusch-Godfrey (LM) test, AR(1)	83,403	83,414	82,025	82,834	83,617	69,704	84,541	85,234	85,061
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000

The regression results come from running the equations (5.5.1) for output, (3.3.2) for export and (3.3.3) for import.

The intercept β_1 has no theoretical meaning, and is only shown here for the purpose of showing all the results from the regression analyses, since they will be used for out-of-sample testing[176].

The coefficient β_2 is negative for the output, as would be expected from the theory. RESpyi is given by $RESpyi_t = p_t - \beta_1 - \beta_2 y_{t-1}$, and therefore essentially has the same structure as the other ratios. The coefficient β_2 is negative for the export and import. This is also according to the theory, which was explained in section 3. The increase in the β_2 coefficient over the horizon is due to the fact that the returns are summing over 4, 12 and 20 quarter, meaning that the 4 quarter regression estimates the one year return and the 20 quarter return estimate the

[176] The intercept is not always show by researchers. Rangvid, 2006, does not show the intercept in his article.

five year return. It would be reasonable to expect a higher return on an investment, when holding it five years rather than one year.
The β_2 coefficient for RESpy and 4 quarters is -0.302, and from table 5.5 it can be seen that the standard deviation for RESpy is 0.32. This implies that a one standard deviation increase in RESpy will result in a 9.67 percentage point decrease in the expected one year return. As an example, in 1Q 1999 the RESpy was 0.0409 and the expected one year return was 0.0513 or 5.13%. If RESpy increased one standard deviation in 2Q 1999 to 0.3609 the expected one year return would decrease and be -0.0454 or -4.54%. The percentage point change is 0.0513 – (-0.0454) = 0.0967 or 9.67.

The R^2 is 0.156 and RESpyi captures 15.6% of the variation in the stock return over 4 quarters, which is quit high for studies regarding stock predictability. Some researchers have stated that the OLS R^2-value cannot be trusted due to overlapping observations[177] and small sample bias[178]. For this reason, some researchers use an implied R^2-value, which was developed by Hodrick[179]. However, the current thesis excludes bootstrapping and other simulations and in order to produce the implied R^2 simulations are necessary. Moreover, the standard OLS R^2 has been used by researchers after the discovery of the problem with its accuracy[180]. In table 6.1, it can be seen that the R^2-value increases with the estimation horizon. This is to be expected, since the increasing effect over the horizon comes from the underlying fact that the stock return is predicted by a persistent slow moving variable such as the GDP[181]. If the stock return variation is slightly predictable on a daily basis by a slow moving variable, then this predictability will be added over longer horizons. As Cochrane states:

> *"For example, you can predict that the temperature in Chicago will rise about 1/3 degree per day in the springtime. This forecast explains very little of the day-to-day variation in temperature, but tracks almost all of the rise in temperature from January to July. Thus, R^2 rises with horizon."* [182]

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[177] Goetzmann and Jorion, 1993 and Kirby, 1997
[178] Kirby, 1997
[179] Hodrick, 1992, used this implied R^2 value. As did Rangvid, 2006
[180] The standard OLS R^2 value or adjusted R^2 value was used by Goyal and Welch, 2004, Rapach et al., 2005 and Cochrane, 2008
[181] Lecture note "Forudsigelse af afkast" for the course "Empirisk Finansiering" fall 2008 by Rangvid. It is added as Appendix G
[182] Cochrane, 2005, page 393f

From this it can be seen that the regressions will capture more and more of the variation in the stock return as the predictability horizons increase, since RESpy is slow moving. The same effect is present for the export and import regressions, where the px- and pz- ratios capture 19.3% and 16.5% respectively of the 4 quarter returns. For the 12 quarter returns, all the ratios capture more than 45% and for the 20 quarter returns, the R^2-values are more than 0.57.

To test for normality in the disturbance the histogram and probability plot for the 4 quarter return and RESpy for Denmark can be seen below in figure 6.1.1 and 6.1.2. The residuals in the histogram seem to follow the normal distribution, even though they may be slightly skewed to the left. From the probability plot, it can be seen that the residuals are centred alone the probability line quit nicely, and this is a strong indication for normality in the residuals.

Figure 6.1.1

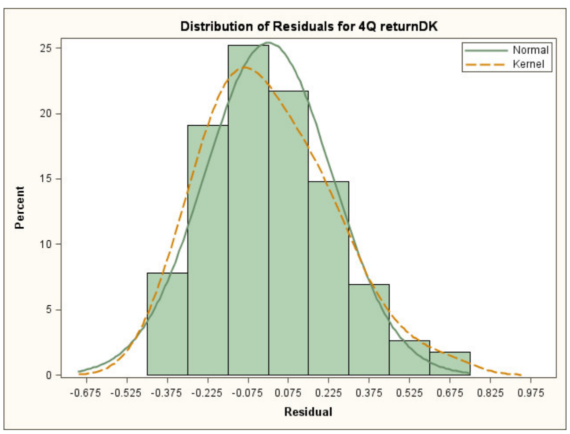
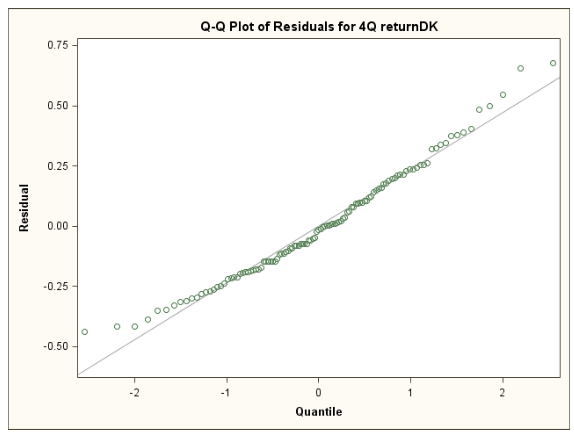


Figure 6.1.2



The Jarque-Bera (JB) test of normality is used to statistically test for normality in the residuals. This test is based on the skewness and kurtosis of the OLS residuals. The test statistic is given by the following: $JB = n\left[\frac{S^2}{6} + \frac{(k-3)^2}{24}\right]$

The null hypothesis of the JB test is that the residuals are normally distributed and the test asymptotically follows a χ^2 distribution with 2 df[183]. Therefore, the test requires large sample sizes to be valid, and a sample size of 100 or more can in this context be categorized as large. However, if the sample size is large, the JB test will reject the null hypothesis of normality even when the data just slightly differs from the normal distribution. In the case of large sample sizes, the normality in the residuals is not very important since a violation of the

[183] Gujarati, 2003, page 148

normality assumption is relatively inconsequential due to the central limit theorem[184]. Consequently, if the JB test borderline rejects the null hypothesis of normally distributed residuals, it will not have severe consequences on the further testing of the regression using the t, F and χ^2 statistics, which assume normal distribution. From table 6.1 it can be seen that the JB test in the case of 4 quarter returns and output for Denmark rejects the null hypothesis and hence one can conclude, that the residuals are not normally distributed. This is also the case for both the 12 and 20 quarter returns and output regressions. When testing for normality in the residuals for the export and import, the JB test also rejects the null hypothesis for the 4 and 12 quarter returns and export at a 5% level and for the 4 quarter returns and import at a 10% level. These rejections for normality is due to a slight skewness in the residuals, which can be seen from the histograms above and in appendix D, and this should not affect the normally distributed tests severely due to the large sample size, hence the regressions will still be used for testing. The 20 quarter returns for export and the 12 and 20 quarter returns for import have normally distributed residuals.

The graphical heteroscedasticity tests can be seen in figure 6.1.3 and 6.1.4, where figure 6.1.3 shows normal heteroscedasticity and figure 6.1.4 shows ARCH and volatility clustering. From figure 6.1.3 there are no signs of heteroscedasticity since the residuals are nicely spread and do not seem that have a clear pattern.

Figure 6.1.3

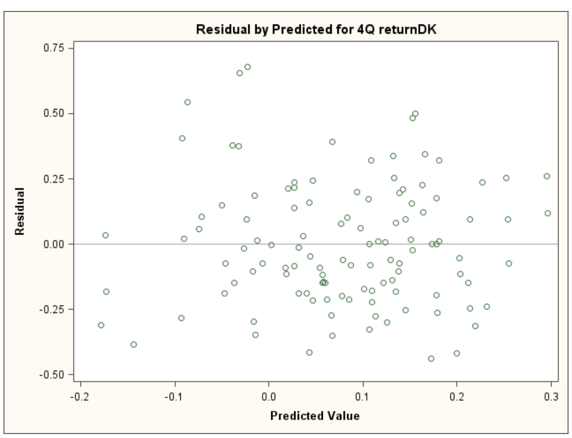
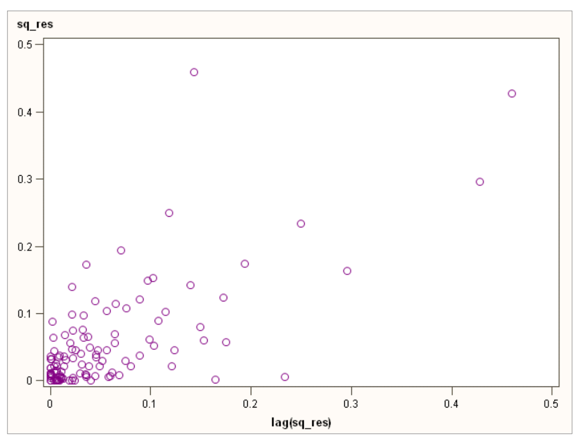


Figure 6.1.4



184 Brooks, 2002, page 182

The normal type of heteroscedasticity is in table 6.1 tested using White's General Heteroscedasticity test, which have the following procedure[185]. When the residuals are obtained from the regression, the following auxiliary regression is run

$\hat{\mu}_i^2 = \alpha_1 + \alpha_2 RESpy_i + \alpha_3 RESpy_i^2 + \varepsilon_i$

The test statistic for the White's test is given by the R^2 from the auxiliary regression multiplied by the number of observation, n. This asymptotically follows a χ^2 distribution with degrees of freedom equal to the number of regressors, excluding the constant, in the auxiliary regression, which in this case is 2 df. The null hypothesis for White's test is no heteroscedasticity or homoscedasticity, and if the test statistic is higher than the critical value given by the χ^2 distribution, the conclusion will be that there are heteroscedasticity in the residuals. From table 6.1 it can be seen that the test statistic does not exceed the critical chi-square value of 5.99 for the 5% level, hence one can conclude that there is no heteroscedasticity in the residuals. This is the case for all the Danish regressions.

The graphical test of ARCH can be seen in figure 6.1.4, and residuals here seem to form a pattern, which indicates that ARCH is present. The statistical ARCH test is as follow. The residuals from the regression are obtained, and the following auxiliary regression[186] is run for an ARCH(p), p being the number of autoregressive terms in the auxiliary regression, that is the number of periods the ARCH effect is expected to be present in the residuals.

$\hat{\mu}_t^2 = \gamma_0 + \gamma_1 \hat{\mu}_{t-1}^2 + \gamma_2 \hat{\mu}_{t-2}^2 + \cdots + \gamma_p \hat{\mu}_{t-p}^2 + \varepsilon_t$, where $\hat{\mu}$ is the estimated residuals and ε_t is the error term. From this regression the R^2 is obtained and multiplied with the number of observations and this is the test statistic. It follows a χ^2 distribution with df being the number of autoregressive terms in the auxiliary regression, p, and the null hypothesis is that all γ's are zero, hence there is no ARCH[187]. If the test statistic is higher than the critical χ^2 value, it can be concluded that ARCH is present. From table 6.1 ARCH(1) is shown and it is clear to see, that ARCH(1) is present in the residuals in all the regressions. In appendix D ARCH(2) to ARCH(12) can be seen, and they are very significantly different from zero. Hence, it can be concluded that the data is very plagued by ARCH heteroscedasticity, even though one cannot conclude if the effect comes from the ARCH(1) effect or a higher level ARCH.

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[185] Gujarati, 2003, page 413
[186] Brooks, 2002, page 448f
[187] Gujarati, 2003, page 859

The graphical test for autocorrelation can be seen in figure 6.1.5 and 6.1.6, which both show very strong signs of a pattern, indicating the presence of autocorrelation in the disturbance, which is to be expected.

Figure 6.1.5

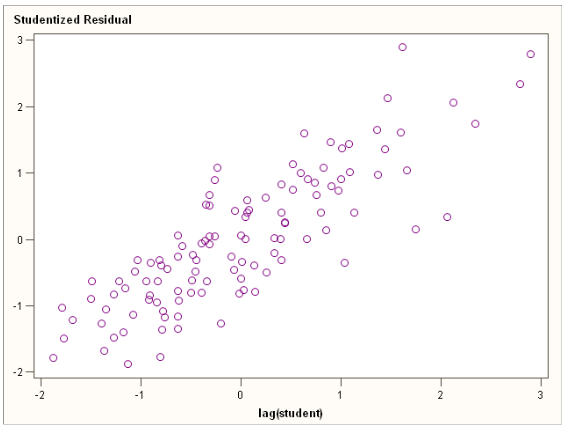
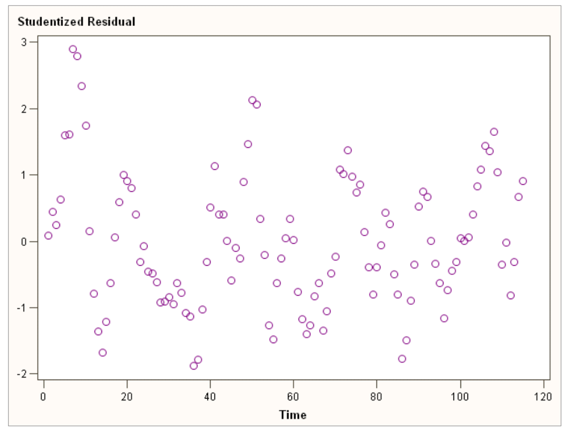


Figure 6.1.6



The autocorrelation is tested by the Breusch-Godfrey (LM) test. The idea behind this test is that the disturbance μ_t follows a pth-order autoregressive, AR(p), scheme given by $\mu_t = \rho_1\mu_{t-1} + \rho_2\mu_{t-2} + \cdots + \rho_p\mu_{t-p} + \varepsilon_t$, where ε_t is the white noise error term. Given no autocorrelation, all the $\rho's$ are insignificantly different from zero.

When testing using the LM test, one follows this procedure[188]. When the residuals are obtained from the regression, the following auxiliary regression is run

$$\hat{\mu}_t = \alpha_1 + \alpha_2 RESpyi_t + \hat{\rho}_1\hat{\mu}_{t-1} + \hat{\rho}_2\hat{\mu}_{t-2} + \cdots + \hat{\rho}_p\hat{\mu}_{t-p} + \varepsilon_t$$

The test statistic for the LM test is given by the R^2 from the auxiliary regression multiplied by the number of observation minus the order of autoregressive scheme, n-p. This asymptotically follows a χ^2 distribution with degrees of freedom equal to the order of autoregressive scheme, $(n-p)R^2 \sim \chi^2_p$. The null hypothesis for LM test is that there is no autocorrelation, and if the test statistic is higher than the critical value given by the χ^2 distribution, the conclusion will be that residuals are autocorrelated. From table 6.1 it can be seen that the test statistics for all the regressions are very high compared with the critical 5%-value, which is 3.84 for the

[188] Gujarati, 2003, page 473

AR(1) scheme[189]. Hence the conclusion of this test is that the residuals are highly autocorrelated, which again was the expectation.

The Durbin-Watson d test will not be used, despite its recognition, since it assumes that the disturbance μ_t is generated by a 1st-order autoregressive, AR(1), scheme $\mu_t = \rho\mu_{t-1} + \varepsilon_t$.[190] However, it is unlikely that the error term is generated by a scheme this low, due to the overlapping data. Additionally, the Durbin-Watson d is affected by ARCH in the regression, and one cannot trust a significant d-value in the presence of ARCH, which is the case for these data[191].

It can be seen from the previous discussion, that the regressions are plagued with autoregressive conditional heteroscedasticity and autocorrelation. Therefore, estimates are still unbiased but the standard errors cannot be trusted in the sense that they are not BLUE. Hence, the statistical tests, t, F and χ^2 statistics, using these standard errors are not valid. This is a serious problem for the in-sample testing of the models and a correction is necessary. One of the most frequently used methods to correct for the autocorrelation caused by overlapping data is by estimating the standard error by the Newey-West Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors[192]. One of the benefits of this method is that it corrects both the autocorrelation and the heteroscedasticity, and therefore the data do not need to be corrected by other means, such as being estimated by the generalized least-square (GLS) method or being corrected by the White's heteroscedasticity-consistent standard error[193]. Even though the Newey-West HAC have been criticized for having large size distortions, which leads to an over-rejection of the null hypothesis of stock predictability[194], it is still a very used way to correct for autocorrelation due to overlapping observations in articles regarding stock predictability, even in very recent studies[195].

The general idea behind the HAC is to correct the covariance matrix, which estimates the standard errors of the OLS. The normal covariance matrix has the following formula

[189] The results from the AR(2), AR(3) and AR(4) schemes can be seen in appendix D, and are all significant at a 1% level.
[190] Gujarati, 2003, page 467
[191] The Durbin-Watson d statistics can be found in appendix D, and are for all regression in all countries below the lower bound, and if this statistic could be trusted, the conclusion would be strong positive autocorrelation.
[192] Newey and West, 1987
[193] HAC is in fact an extension of White's heteroscedasticity-consistent standard error
[194] Ang, 2002
[195] This method is use by numerous researchers such as Boucher 2006, Cooper and Priestley2009, Engsted et al. 2010, Julliard 2004, Lacerda and Santa-Clara 2010, Lettau and Ludvigson 2001, Menzly et al. 2004, Møller and Rangvid 2010, Rangvid 2006 and Rangvid et al. 2010, to name some of the most important and resent.

$\text{cov}(\hat{\beta}) = \left(\sum_{t=1}^{T} x_t x_t'\right)^{-1} \text{cov}\left(\sum_{t=1}^{T} x_t \varepsilon_t\right)\left(\sum_{t=1}^{T} x_t x_t'\right)^{-1} = \left(\sum_{t=1}^{T} x_t x_t'\right)^{-1} \Omega_T \left(\sum_{t=1}^{T} x_t x_t'\right)^{-1}$, where Ω_T is defined as $\Omega_T = \text{cov}\left(\sum_{t=1}^{T} x_t \varepsilon_t\right)$, x is a $K \times 1$ vector of the explanatory variable and ε_t is the error term[196]. The difference between the normal covariance matrix and the HAC covariance matrix is the Ω_T. In the HAC covariance matrix this is given by $\Omega_T = S_0 + \sum_{j=1}^{L} w_j \left(S_j + S_j'\right)$, where L is the number of lags and w is the weighs. S is defined as $S = \sum_{t=j+1}^{T} \varepsilon_t \varepsilon_{t-j} x_t x_{t-j}'$.

White's heteroscedasticity-consistent standard error is given by this covariance matrix with zero lags, that is $\Omega_T = S_0 = \sum_{t=1}^{T} \varepsilon_t^2 x_t x_t'$. When the number of autocorrelation lags is know, as is the case in the current thesis, it is recommended to chose L as the number of lags, here the number of overlapping data, which is 4, 12 and 20. These lags could be weighted equally, however, in finite sample there is a possibility that this will give negative variances. Therefore, it is suggested that the weights, w, should be given by the following formula[197] $w_j = 1 - \frac{j}{L+1}$, where L again is the number of lags. The HAC standard errors in the current thesis are calculated in SAS using the code provided by Lund[198].

It can be seen from table 6.1 that even with the HAC standard errors, the estimates are very significant at less than 2%.

The conclusion for the in-sample testing for Denmark is that the output, export and import do present strong power to predict stock returns in sample, since they have very high R^2-values and very significant β_2 coefficients. It is difficult to say, which variable has the highest predictive power, since all perform well.

[196] Lund, 2006
[197] Feldhütter, 2008
[198] Lund, 2006

6.2 The Netherlands

In table 6.2 the results from the regressions for The Netherlands are given. It can be seen, that all the β_2 coefficients are negative, as was expected. The R^2-values are much lower than the value for Denmark, but they follow the same pattern, since they increase with the estimation horizon. The output seems to have the highest in-sample predictability, capturing 51% of the stock return over 20 quarters, whereas the import just captures less than 3% of variation in the 4 quarter stock returns. Moreover, the output is the only variable to have significant β_2 coefficients at a 5% level for all horizons using HAC standard errors. Export is significant at a 10% level or less and import is only significant for the 20 quarter return. The table reveals that all the regressions have normally distributed residuals. When testing for autocorrelation, it can be seen that all regressions have very strongly autocorrelated residuals, and in regards to heteroscedasticity, all regressions have ARCH and the output-20 quarter returns and the import-12 quarter returns have signs of normal heteroscedasticity, as they reject or borderline reject the null hypothesis for the White's test, where the critical chi-square value for the 5% level is 5.99. Lastly, the data from The Netherlands have some problems with unit root and one should therefore be careful in concluding on the basis of the regression results. This again reduces the trust in the in-sample predictability of the stock returns in The Netherlands, and one must conclude that the in-sample testing of the predictive power over stock returns for The Netherlands is not very strong for import and generally inferior to predictive power for the Danish market.

Table 6.2

The Netherlands	Output - RESpy			Export - px			Import - pz		
Horizon K quarters	4	12	20	4	12	20	4	12	20
β_1 Intercept	0,102	0,297	0,497	-0,363	-1,540	-2,519	-0,207	-1,019	-2,026
Standard errors	0,017	0,029	0,032	0,170	0,330	0,376	0,167	0,347	0,413
p-value	0,000	0,000	0,000	0,035	0,000	0,000	0,219	0,004	0,000
β_2 Coefficient	-0,153	-0,559	-0,898	-0,132	-0,523	-0,858	-0,089	-0,381	-0,727
Standard errors	0,046	0,083	0,089	0,048	0,093	0,105	0,048	0,098	0,116
p-value	0,001	0,000	0,000	0,007	0,000	0,000	0,067	0,000	0,000
HAC standard errors	0,078	0,217	0,165	0,078	0,248	0,230	0,078	0,286	0,306
p-value	0,053	0,012	0,000	0,095	0,037	0,000	0,258	0,186	0,020
R-square	0,090	0,299	0,510	0,063	0,233	0,408	0,029	0,125	0,287
Jarque-Bera test	1,352	3,091	1,253	2,910	2,705	1,611	3,651	2,070	2,884
p-value	0,509	0,213	0,535	0,233	0,259	0,447	0,161	0,355	0,237
White's R-square	0,016	0,007	0,060	0,009	0,022	0,038	0,007	0,079	0,042
White's test value	1,829	0,738	5,980	1,081	2,311	3,722	0,759	8,496	4,168
ARCH test, 1. order	61,030	71,642	78,528	63,519	70,901	78,648	63,734	74,110	76,415
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Breusch-Godfrey (LM) test, AR(1)	76,532	95,852	91,466	77,039	96,535	92,745	76,587	96,997	92,649
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000

6.3 France

The in-sample results for France can be seen in table 6.3. As for Denmark and The Netherlands, all the β_2 coefficients are negative and the R^2-values are high, as was the case for Denmark. Again all ratios have high in-sample predictability power capturing more than 60% of the variation in the stock returns over 20 quarters. Moreover, all 4 quarter returns have significant β_2 coefficients at a 5% level and the β_2 coefficients for 12 and 20 quarter returns are significant at a 1% level using HAC standard errors.

The table reveals that all 12 and 20 quarter return regressions have normally distributed residuals, whereas the 4 quarter regressions are rejected in the JB-test, and in line with the results for Denmark and The Netherlands, all the French regressions suffer strongly from ARCH and autocorrelation.

The conclusion for the in-sample testing for France is that all variables present strong predicting powers for stock returns in sample, since they have very high R^2-values and very significant β_2 coefficients.

Table 6.3

France	Output - RESpy			Export - px			Import - pz		
Horizon K quarters	4	12	20	4	12	20	4	12	20
β_1 Intercept	0,064	0,161	0,272	-0,647	-1,843	-2,721	-0,581	-1,835	-2,782
Standard errors	0,021	0,029	0,028	0,168	0,227	0,213	0,181	0,258	0,256
p-value	0,003	0,000	0,000	0,000	0,000	0,000	0,002	0,000	0,000
β_2 Coefficient	-0,182	-0,563	-0,855	-0,204	-0,579	-0,866	-0,184	-0,570	-0,871
Standard errors	0,046	0,063	0,058	0,047	0,063	0,059	0,050	0,071	0,070
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
HAC standard errors	0,079	0,117	0,091	0,082	0,118	0,100	0,082	0,130	0,135
p-value	0,023	0,000	0,000	0,014	0,000	0,000	0,027	0,000	0,000
R-square	0,121	0,432	0,688	0,144	0,444	0,687	0,106	0,379	0,612
Jarque-Bera test	5,522	1,173	2,394	5,508	0,286	0,398	6,333	0,676	1,048
p-value	0,063	0,556	0,302	0,064	0,867	0,819	0,042	0,713	0,592
White's R-square	0,034	0,003	0,020	0,027	0,001	0,031	0,026	0,009	0,026
White's test value	3,853	0,332	1,960	3,071	0,064	3,079	2,956	0,931	2,525
ARCH test, 1. order	30,766	63,079	64,760	30,598	59,932	64,904	34,192	63,515	67,775
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Breusch-Godfrey (LM) test, AR(1)	69,479	83,653	81,114	69,360	83,249	81,775	70,915	86,207	84,902
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000

6.4 United Kingdom

Table 6.4 shows the in-sample results for United Kingdom. As for other countries, all the β_2 coefficients are negative and the R^2-values are very high, even compared to Denmark and France. Moreover, all 12 and 20 quarter regressions have significant β_2 coefficients at a 1% level and the β_2 coefficients for 4 quarter regressions are significant at a 5% level using HAC standard errors.

In line with the results for all the other countries, the regressions for United Kingdom are plagued by ARCH and autocorrelation. However, contrary to the results for the other countries, the JB test for normally distributed residuals is strongly rejected for the 4 quarter regressions, which is due to outliers in the data for United Kingdom. Figure 6.4.1 shows the outliers for the export and 4 quarter regression, and it is clear, that there are some serious outliers. Figure 6.4.2, which is the histogram for the same regression, reveals that the outliers strongly contribute to the rejection of the JB test, since they elongate the tails of the distribution. The 4 quarter return for United Kingdom is plotted against time in figure 6.4.3, and from this it can be seen that the one year returns in end of 1974 are extremely low, which is due to several quarters of very low returns[199]. United Kingdom was in 1974 facing a bear market[200], which may have been caused by the collapse of the Bretton Woods system in 1971 or the 1973 oil crisis. As previously discussed, the correction of outliers by dummies can be seen as a way to artificially improve the model, and therefore this has not be done in the present study. The number of data for the 4 quarter returns is 115, which is fairly high, and the conclusions based on quite significant values will very likely be correct, since the violation of the normality assumption for large sample sizes is relatively inconsequential due to the central limit theorem. Another reason for not removing the outliers with dummy variables is due to the fact that the market made up for the very low returns in 1974 by having an extremely high return in the 1st quarter of 1975. These fluctuations were not part of a global financial crisis and can be seen as just being a severe bear market, which is part of the stock market, and therefore carries important information. Moreover, the normality of the residuals for the 12 and 20 quarter regressions are not affected due to the smoothing effect of the returns in these regressions. The 4 quarter return and export will be tested using the subsample from 1Q 1976 to 4Q 1999 in the section on robustness tests, which will remove the outliers.

[199] The quarterly returns can be seen in appendix D, under export and 4 quarter return
[200] BBC News, 06.05.2003 and Telegraph.co.uk, 27.07.2002

The conclusion for the in-sample testing for United Kingdom is that all variables present very strong predicting powers for stock returns in sample, since they have very high R^2-values and very significant β_2 coefficients, and none seem better than the others.

Table 6.4

United Kingdom	Output - RESpy			Export - px			Import - pz		
Horizon K quarters	4	12	20	4	12	20	4	12	20
β_1 Intercept	0,078	0,197	0,358	-0,664	-2,038	-2,258	-0,733	-2,321	-2,569
Standard errors	0,020	0,027	0,026	0,157	0,199	0,190	0,168	0,198	0,182
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
β_2 Coefficient	-0,236	-0,814	-0,996	-0,262	-0,793	-0,931	-0,294	-0,916	-1,069
Standard errors	0,060	0,082	0,079	0,055	0,069	0,066	0,061	0,071	0,065
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
HAC standard errors	0,112	0,230	0,195	0,120	0,178	0,152	0,139	0,152	0,122
p-value	0,038	0,001	0,000	0,031	0,000	0,000	0,036	0,000	0,000
R-square	0,120	0,482	0,620	0,167	0,554	0,672	0,173	0,613	0,734
Jarque-Bera test	179,443	1,504	2,884	153,696	3,133	1,921	161,963	0,045	0,826
p-value	0,000	0,471	0,237	0,000	0,209	0,383	0,000	0,978	0,662
White's R-square	0,022	0,153	0,009	0,046	0,102	0,040	0,056	0,113	0,154
White's test value	2,507	16,339	0,921	5,290	10,893	3,990	6,475	12,112	15,197
ARCH test, 1. order	51,403	40,396	65,583	48,335	34,502	61,836	49,127	27,395	51,815
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Breusch-Godfrey (LM) test, AR(1)	69,338	87,053	87,774	67,946	82,951	84,790	68,725	78,271	81,422
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000

Figure 6.4.1

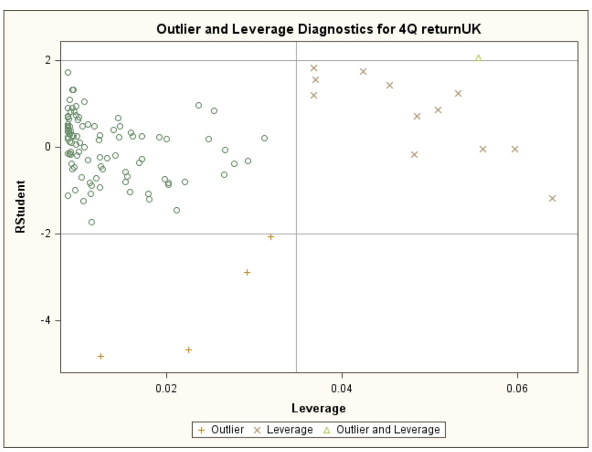


Figure 6.4.2

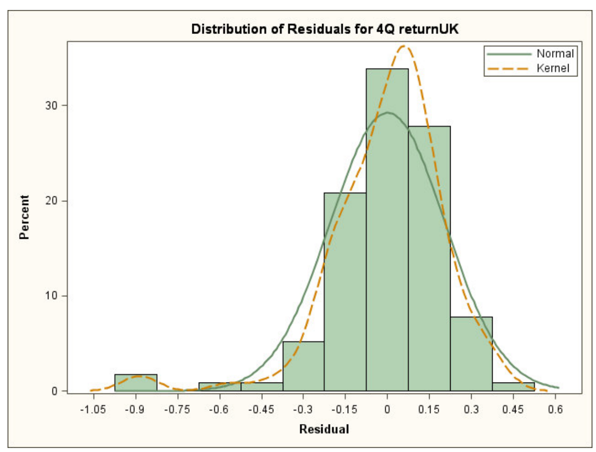
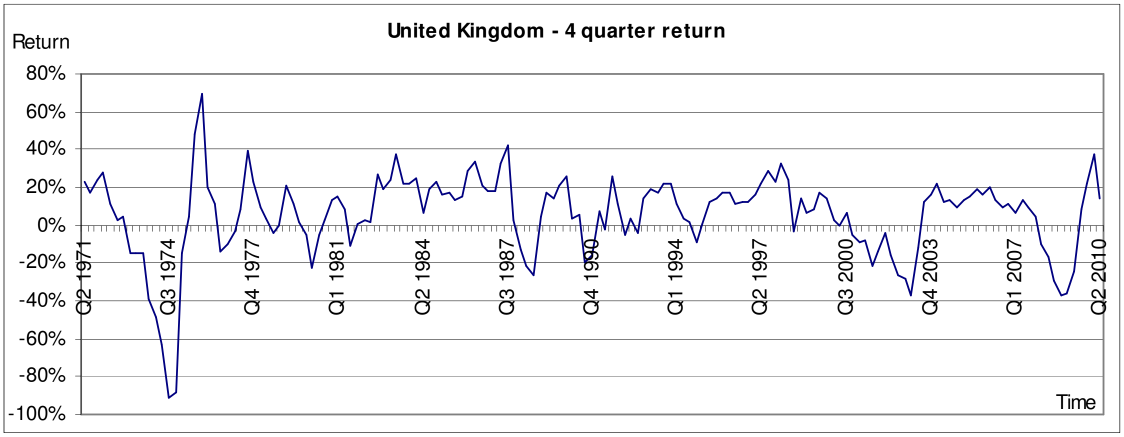


Figure 6.4.3


United Kingdom - 4 quarter return
Return
80%
60%
40%
20%
0%
-20%
-40%
-60%
-80%
-100%
Q2 1971
Q3 1974
Q4 1977
Q1 1981
Q2 1984
Q3 1987
Q4 1990
Q1 1994
Q2 1997
Q3 2000
Q4 2003
Q1 2007
Q2 2010
Time

7 Forecasting and out-of-sample testing

Out-of-sample testing can be used to see if the real time investor could benefit from the in-sample results. Moreover, some researchers[201] have said that out-of-sample testing can protect against data mining and overfitting, whereas others[202] have stated that this is not the case, since data mining can be done for both in- and out-of-sample testing.

The procedure for out-of-sample[203] testing in the current thesis will be founded in the procedure used by Rapach, Wohar and Rangvid[204]. The procedure will be explained using the 4 quarter return and export regression for Denmark as an example.

7.1 Denmark

When the regression is estimated using the in-sample data, the first forecast of the 4 quarter return is calculated using the following formula $\hat{r}_{t,t+4} = \hat{\beta}_1 + \hat{\beta}_2 px_t + \hat{\mu}_t$, where the coefficients are the estimates from the in-sample regression. The forecast error for the estimated model, E^M, is given by the difference between the forecast return and the actual observed return, $E^M = r_{t,t+4} - \hat{r}_{t,t+4}$, where $r_{t,t+4}$ is the observed 4 quarter stock return and $\hat{r}_{t,t+4}$ is the forecasted 4 quarter stock return. The alternative model used in the current thesis is the random walk model from the efficient theory[205], which was discussed in the theory section. This states that the best estimate for the stock return tomorrow is the stock return today. Therefore, the forecast error for the random walk model, E^{RW}, is given by $E^{RW} = r_{t,t+4} - r_{t-1,t+4-1}$. When generating the next forecast error, the regression is estimated using the in-sample data plus the first observation in the out-of-sample data, since the investor is expected to have this data available for forecasting the second observation. When the forecast of the second observation is obtained, the forecast error is calculated using the second observed stock return in the out-of-sample data. This means that in order to get the forecast error for 2Q 2000, one must estimate the regression using the in-sample data and the 1Q 2000 observation. The forecast error is calculated using the estimated 2Q 2000 stock return and the

[201] Clark, 2004
[202] Campbell and Thompson, 2005
[203] The calculations for the out-of-sample testing can be found in the excel sheets on the CD
[204] Rapach et al., 2005. The Theil's U could have been used as in Rangvid, 2006. This is not included, since it essentially gives the same results and conclusions as the MSE-F, and it can be seen in appendix E
[205] This is the alternative model used by Rangvid, 2006

observed 2Q 2000 stock return. This process is continued for the entire out-of-sample period. The forecast error for the random walk is also calculated for the out-of-sample period. When the forecast errors for both the model and the random walk is obtained, the Mean Squared Error, MSE^M, for the estimated model is calculated using the following formula[206]

$MSE = (T - R - K)^{-1} \sum_{t=R}^{T-K} \left(E_{t+1}^{M}\right)^2$, where T is the number of observations in the total data sample, both in- and out-of-sample, R is the number of observations in-sample, K as before is the estimation horizon, here 4 and t is the time. This is the mean of the squared forecast errors, since $(T - R - K)$ gives the number of out-of-sample observations. The MSE^{RW} for the random walk is calculated in the same way. When evaluating the estimated model out-of-sample against the random walk, the MSE's are compared. The model with the lowest MSE has performed best in forecasting the stock return over the out-of-sample period. McCracken[207] suggests a test value, which is founded in the MSE and can be tested using a distribution derived from a bootstrapping procedure. The current thesis excludes the use of bootstrapping, and the test will therefore not be performed. However, the size and sign of the test value holds information about the relative performance of the estimated model and the alternative model. The test value is give by[208] $MSE - F = (T - R - K) \cdot \frac{MSE^{RW} - MSE^{M}}{MSE^{M}}$. If MSE-F is positive, this means that the estimated model has performed better than the alternative model during the out-of-sample period. However, if MSE-F is negative, the alternative model has performed best during the period. The size of the test value determines how must one model has outperformed the other.

[206] Rapach et al, 2005
[207] McCracken, 2004, seen in Rapach et al., 2005
[208] Rapach et al., 2005

Table 7.1

Out-of-sample testing										
		Output - RESpy			Export - px			Import - pz		
	Horizon K quarters	4	12	20	4	12	20	4	12	20
Denmark	MSE Estimated model	0,0645	0,0928	0,0801	0,0653	0,1052	0,0896	0,0646	0,1103	0,1134
	MSE Random walk	0,0269	0,0260	0,0281	0,0269	0,0260	0,0281	0,0269	0,0260	0,0281
	MSE-F	-0,0139	-0,0171	-0,0155	-0,0140	-0,0179	-0,0163	-0,0139	-0,0182	-0,0179
The Netherlands	MSE Estimated model	0,0839	0,1761	0,1857	0,0840	0,1791	0,1822	0,0847	0,1833	0,1877
	MSE Random walk	0,0282	0,0281	0,0345	0,0282	0,0281	0,0345	0,0282	0,0281	0,0345
	MSE-F	-0,0158	-0,0200	-0,0194	-0,0158	-0,0201	-0,0193	-0,0159	-0,0202	-0,0194
France	MSE Estimated model	0,0653	0,1417	0,1248	0,0660	0,1354	0,1190	0,0675	0,1503	0,1324
	MSE Random walk	0,0246	0,0289	0,0296	0,0246	0,0289	0,0296	0,0246	0,0289	0,0296
	MSE-F	-0,0148	-0,0189	-0,0182	-0,0149	-0,0187	-0,0179	-0,0151	-0,0192	-0,0185
United Kingdom	MSE Estimated model	0,0321	0,0602	0,0631	0,0372	0,0893	0,0912	0,0453	0,1466	0,1612
	MSE Random walk	0,0126	0,0132	0,0152	0,0126	0,0132	0,0152	0,0126	0,0132	0,0152
	MSE-F	-0,0144	-0,0186	-0,0181	-0,0157	-0,0203	-0,0198	-0,0172	-0,0217	-0,0216

Table 7.1 shows the MSE for the estimated models and the random walk, and the test statistic MSE-F for all the countries. It is clear, that the forecasts for all regressions are out-performed by the random walk in predicting the stock return during the out-of-sample period, since all MSE^Ms are higher than the MSE^{RW}s, which give rise to the negative MSE-Fs. From the MSE-F, it can be seen that the output regressions generally perform best and the import regressions perform worst for Denmark.

Goyal and Welch[209] suggest, that the performance of the out-of-sample testing can be shown graphically by plotting the cumulative difference in the squared errors of the model versus the alternative, i.e. the following $\left(E_{t+1}^{RW}\right)^2 - \left(E_{t+1}^{M}\right)^2$ is plotted against time. When the estimated model outperforms the random walk, the line will be upward sloping, and when the random walk outperforms the estimated model, the line will be downward sloping. This gives a very clear view of the relative performance of the two models over the out-of-sample period.

Figure 7.1.1 shows the predictability of the 4 quarter return, and from this it is clear, that during most quarters the random walk outperforms the estimated model. However, the estimated model does outperform the random walk during short periods, such as from the late 2000 to the middle of 2001, and in 2003 and 2009.

[209] Goyal and Welch, 2004

Figure 7.1.1

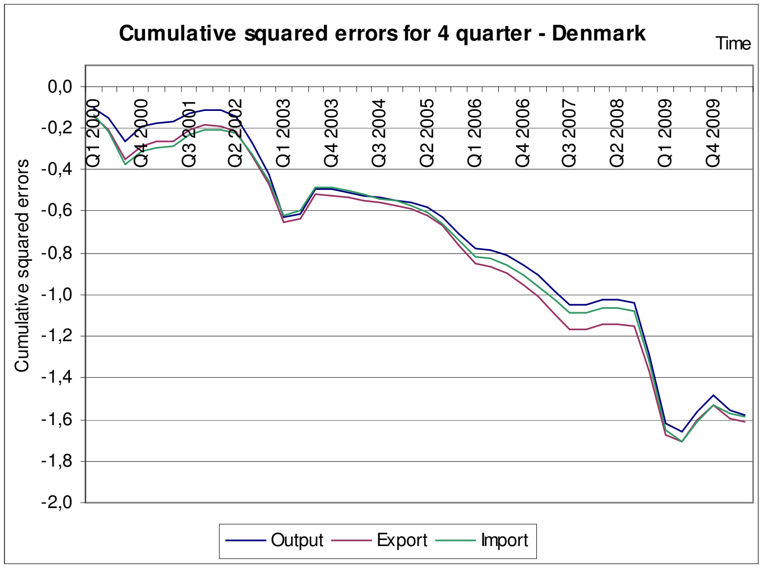


Figure 7.1.2 shows the predictability over 12 quarters, and for this prediction period, the two models perform relatively equal between the beginning of 2001 and the end of 2005, and again between the beginning of 2008 to the end of the sample period. However, the random walk greatly outperforms the estimated models in 2006 and 2007, and the estimated models never really forecast stock returns better than the random walk. Additionally, it is clear to see that the output regression performs better than the other regressions.

Figure 7.1.2

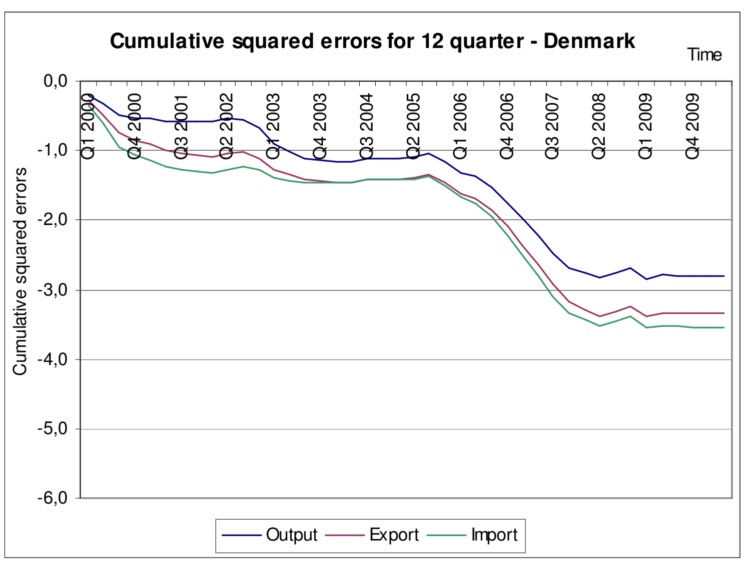
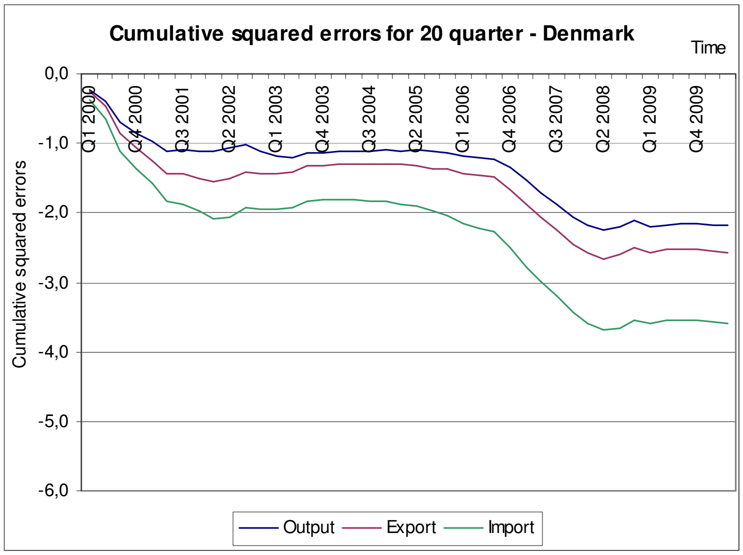


Figure 7.1.3 gives the predictability over 20 quarters. For this prediction period, the estimated models are outperformed in the beginning of the period and during 2006 and 2007, which is the same pattern as for the 12 quarter return. The import model seems to perform relatively more poorly compared with the other models.

Figure 7.1.3



7.2 The Netherlands

Table 7.1 above shows the out-of-sample performance for The Netherlands. As for Denmark, all the MSE^{M}s are higher than the MSE^{RW}s, and the estimated models are outperformed by the random walk. From the MSE-F, the three ratios seem to perform equally bad. However, when looking at the graphs for the cumulative difference in the squared errors in appendix E, it can be seen that import performs the worst of the ratios over longer periods. In line with the Danish pattern, the estimated models perform relatively well over long parts of the out-of-sample period, and really bad during short periods. The two worst periods for predicting stock returns using the ratios in The Netherlands are in 2003 and again in 2008-2009. However, ratios seem to fail to predict the 20 quarter return over the whole sample period, relative to the random walk.

7.3 France

Table 7.1 shows the out-of-sample performance for France. Again all the MSE^{M}s are higher than the MSE^{RW}s, and the estimated models are outperformed by the random walk. From the MSE-F, it can be seen that import performs the worst and export performs the best over longer prediction periods, 12 and 20 quarters. This is supported by the graphs for the cumulative difference in the squared errors in appendix E. It can be seen that the ratios predict the 20 quarter return relatively well compared to the random walk for most of the out-of-sample period, expect for the first two years. For predicting the 12 quarter return, the ratios fail to predict returns over the whole sample period. The pattern for the 4 quarter return is like the one seen for The Netherlands.

7.4 United Kingdom

Table 7.1 shows the out-of-sample performance for United Kingdom. As for the other countries, all the MSE^{M}s are higher than the MSE^{RW}s. The MSE-F reveals that the import does predict stock returns very poorly, especially over longer periods, whereas the output is relatively good compared to the other countries except Denmark. From the graphs in appendix E, it can be seen that the predictability for 4 quarter return follows the same pattern as for The Netherlands and France. For the 12 and 20 quarter return, the estimated models are greatly outperformed by the random walk at the end of the sample period from 2008 to 2010.

Generally, it can be concluded that the models perform poorly out-of-sample compared with the random walk, and that the output- and export-model outperform the import-model. Additionally, the best results of predictability are for Denmark, which has lower MSE-F values than the other countries and cumulated differences in the squared errors do not reach as high negative levels for Denmark, as they do for the other countries.

8 Robustness

All the robustness tests can be seen in table 8.

Table 8

Robustness tests								
	Denmark							United Kingdom
	Test of estimated ratios			Test of subsamples			Test of one year data points	Test of outlier's effect
Horizon 4 quarters	RESpyD	RESpyt	RESpyi	1970-1989	1990-2010	2000-2010	1970-2010, px	1976-1999, px
EG tau, lag 0	-2,69	-2,34	-3,24					
EG tau, lag 1	-3,46	-3,09	-2,97					
DF tau, px							-2,68	
p-value							0,086	
DF tau, 4 quarter return							-6,51	
p-value							0,000	
β_1 Intercept	0,077	0,063	0,069	-1,138	-1,438	-2,105	-1,037	-0,316
Standard errors	0,022	0,022	0,022	0,271	0,352	0,548	0,389	0,176
p-value	0,001	0,005	0,002	0,000	0,000	0,000	0,011	0,076
β_2 Coefficient	-0,391	-0,316	-0,356	-0,343	-0,439	-0,650	-0,320	-0,147
Standard errors	0,078	0,067	0,077	0,076	0,102	0,165	0,112	0,060
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,007	0,017
HAC standard errors	0,135	0,121	0,134	0,125	0,148	0,189		0,098
p-value	0,004	0,010	0,009	0,008	0,004	0,001		0,137
R-square	0,180	0,166	0,158	0,217	0,188	0,280	0,178	0,062
Jarque-Bera test	3,409	5,873	2,975	6,580	2,714	2,857	1,654	1,702
p-value	0,182	0,053	0,226	0,037	0,257	0,240	0,437	0,427
White's R-square	0,001	0,022	0,007	0,026	0,103	0,113	0,060	0,035
White's test value	0,161	2,553	0,794	3,025	11,891	12,949	2,396	3,220
ARCH test, 1, order	55,186	56,286	52,184	37,790	27,203	13,398	0,827	7,833
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,363	0,005
Breusch-Godfrey (LM) test, AR(1)	85,036	83,520	81,994	55,342	61,379	32,812	0,198	33,959
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,656	0,000

The critical values for the Engle-Granger test is at 1% -4.2981, at 5% -3.7429 and at 10% -3.4518

Test of estimated ratios

The estimated ratios are tested to see, if the choice of ratios were very significant. When testing for unit roots, the Engle-Granger critical values should be used for N=3, since there are three variable in the estimated regression[210]. It can be seen that RESpyD is stationary, and the other two estimated ratios only are borderline.

When comparing these ratios to RESpy, it can be seen that the coefficients are at the same level and slightly more significant using HAC for these ratios. Moreover, the R^2 are also slightly higher for RESpyD and RESpyt. The residuals are normally distributed for RESpyD and RESpyi, whereas RESpyt rejects the JB-test as was the case for RESpy.

[210] It is not clear, which N should be used for RESpyD, since one of the variables is a dummy

When comparing these ratios to the one used in the investigation, it can be seen that the results are almost the same. RESpyD does slightly better, however it is uncertain if this would be the case for the 12 and 20 quarter return regressions.

Test of subsamples

The subsample robustness tests are performed to see if the results are consistent over different sub time periods. The coefficient increases for the subsample 1990-2010 and 2000-2010, whereas the 1970-1989 gives almost the same results as the original regression from 1970-2000. It can be seen in table 8.2, that the effect is strongest between 2000 and 2010, which could explain the difficulties for the models to forecast out-of-sample for this period. When comparing the 2000-2010 period to the 1970-2000 period, it seems that there has been a structural break. It has been shown, that the predictable component in the stock return diminishes for many countries after the most recent break[211], and this could be the case to in the current thesis. However, the results seem to be consistent within the in-sample period, and the investigation of structural breaks is outside the scope of the current thesis.

Test of one year data points

The test of one year data point is made to see the results without the influence of overlapping data. The px-ratio and the 4 quarter return is calculated as described earlier. However, only the second quarter data is used, that is 2Q 1970 – 2Q 2009, thereby eliminating the overlapping data. The data points are given by the following

$$
\begin{gathered}
\left(r_{3Q1970} + r_{4Q1970} + r_{1Q1971} + r_{2Q1971}\right) = \beta_1 + \beta_2 px_{2Q1970} + \mu \\
\left(r_{3Q1971} + r_{4Q1971} + r_{1Q1972} + r_{2Q1972}\right) = \beta_1 + \beta_2 px_{2Q1971} + \mu \\
\vdots \\
\left(r_{3Q2009} + r_{4Q2009} + r_{1Q2010} + r_{2Q2010}\right) = \beta_1 + \beta_2 px_{2Q2009} + \mu
\end{gathered}
$$

From this it can be seen that no observation is used twice, but this leaves only 40 observations, and it is therefore impossible to do this for the 12 and 20 quarter returns. Table 8.3 reveals that the time series from this test are stationary and the regression has no autocorrelation or heteroscedasticity, hence HAC standard errors should not be used. Additionally, it can be seen that it has a high R^2-value and significant coefficients, which are very similar to the coefficient of the normal 4 quarter return and export regression. The conclusion of this test is that the results can be trusted despite the overlapping observations.

[211] Paye and Timmermann, 2006

Test of outlier's effect

The test for United Kingdom for the subsample 1976-1999 is done in the effort to remove the outliers, which caused the 4 quarter regression to be rejected in the JB-test. When removing the first 6 years of data, the residuals become normally distributed. However, the R^2-value decreases considerably and the β^2 coefficient is no longer significant at a 10% level. This shows that the results of the 4 quarter return and export regression is not consistent over different subsamples and that a large fraction of the predictable component is in the first 6 years, maybe even in the outliers. It is likely that the results would be the same for output and import. However, it is difficult to say how the results would be for the 12 and 20 quarter returns, and since those regressions have normally distributed residuals over the entire data sample, they will not be tested for the subsample.

9 Analysis

The in-sample results showed that the stock return is predictable over longer period from one year to five years. It is hard to see on the basis of the R^2-value, on which horizon the results are strongest, since the R^2-value always will increase with the horizon. However, the 12 and 20 quarter regression have slightly more significant coefficients, and may therefore be a little better at predicting the stock return.
Additionally, it can be seen that the level of stock return predictability is approximately the same for Denmark, France and United Kingdom in regards to the R^2-values, whereas the predictability is lower for The Netherlands, where especially the 4 quarter regressions have quit low R^2-values. It is hard to determine the reason for these results. The px- and pz-ratios for The Netherlands were more nonstationary than for the other countries, which all had stationary or borderline stationary px- and pz-ratios. However, the level of stationarity for RESpy was the same for The Netherlands as for United Kingdom, and the reason for the slightly inferior results for The Netherlands may be due to some unknown underlying economical factors.
Import seems to have the lowest predictive power in The Netherlands and France and have the highest in United Kingdom; whereas it cannot be determined which ratio has the highest predictive power in Denmark. This shows that the ratios are equally good at predicting stock returns in-sample, and depending on the country, one can chose to use either one of them.

The results for out-of-sample testing reveals that all the regression failed to forecast the stock return better than the random walk, and especially the regressions for The Netherland and United Kingdom forecasted the stock return poorly compared to the random walk. Denmark had the best forecasting results, however, still not superior to the alternative model. The import performed worst for all countries, whereas it is hard to determine whether output or export performed best. These results indicate that the results cannot be used by the real time investors to forecast stock returns and make portfolio decisions. There can be several reasons for the poor out-of-sample results. Campbell and Thompson[212] argue that two possible reasons are plain bad luck or structural breaks. It seems reasonable to argue that the very bad forecasts in the late 2000's may be due to the financial crisis, which no model could be expected to forecast. Moreover, several countries seem to have structural breaks in the

[212] Campbell and Thompson, 2005

1990's[213], which also could explain the lack of out-of-sample predictability, since if there is a break in the late 1990's, the regression only has little information after the break, and essentially the pre-break regression is forecasting the after-break period. Lastly, Inoue and Kilian[214] argue that the in-sample results can still be trusted despite bad out-of-sample results and the combination of good in-sample results and poor out-of-sample results are common[215]. From the results it can be seen that the export and import of the small countries, Denmark and The Netherlands, do not have higher predictive power than they have for the large countries, France and United Kingdom, and one can conclude that these ratios do not hold higher predictive power in more open economies.

The py-ratio has previously been investigated by Rangvid[216], and the result from the current thesis is much in line with the results reported by Rangvid, with the only important difference that the py-ratio provides significant out-of-sample results for the 4 and 6 years. However, the article does not give the out-of-sample results for other countries than USA; hence it is hard to know if the positive results are special to this country.

Further investigation into this topic could be interesting and one could investigate the ratios used in the current thesis for more countries. Furthermore, it could be interesting to do the same investigation in 20-30 years or more, since new data would be available and the estimation and testing could be done after the financial crisis and the possible structural breaks. Moreover, it is likely that more variables will be investigated in the future and this would also be interesting, though one should be aware of the data mining problem, which can arise from testing many variables on the same data, as has been done for the USA data. Lastly, it would be interesting to investigate the ratios ability to predict the output, export and import changes.

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[213] Paye and Timmermann, 2006
[214] Inoue and Kilian, 2004
[215] Goyal and Welch, 2004 and Gou, 2009
[216] Rangvid, 2006

10 Conclusion

During the last two decades, the stock return predictability has been debated in academic circles and numerous articles have been written on the subject. Before this time the market was believed to be efficient and impossible to forecast using previous stock returns. After the breakthrough in the late 1980´s with the article by Fama & French and Campbell & Shiller, who predicted stock returns using the price-dividend ratio, the concept of the efficient market was and still is interpreted more loosely and the predictability is seen as reflection of the agent's attitude towards risk. The ideas of stock return predictability was supported by several researchers in the following years and more financial variables were tested for their ability to forecast stock returns. However, in the 1990's some researches came forward with both theoretical and statistical criticism and stated that the financial ratios did not predict stock returns as well as previously claimed if they were corrected for small sample biases and overlapping observations. There were two types of the reactions to the criticism. On one hand researchers tried to find different and new macroeconomic variables to study in the regression analysis and variables such as cay and price-output were introduced. On the other hand some researchers defended the financial variables using new R^2-values and t-statistics. Within the last 10 years the researchers have more or less been divided into two groups. One group that defends the idea that it is possible to predict stock returns using the financial or macroeconomic ratios and another group that evaluates many of the ratios and concludes, that most of them do not predict stock returns.

The general ides behind the stock predictability with the py-ratio is that, if the price is high compared to the output, investors will expect one of two things in the future. Either the output will increase or the stock return will be low in future. If the investors expect higher output in the future, then they are expecting a better economy and they will be less risk adverse and therefore be willing to pay more for the stocks today. On the other hand, the high stock price can be a sign of the fact that the investors are expecting the risk level be lower in the future, therefore they will demand a lower return, discount cash-flows with a low rate of interest and be willing to pay more for the stock. The same effects are present for the price-export and the price-import ratios. The current thesis has investigated the ratios ability to predict future stock returns.

The inspection of the data found that the px- and pz-ratios were relatively stationary, which was also the case for the stock returns. However, the py-ratios had severe unit roots, hence their cointegrations were estimated and the residuals from this estimation were relatively stationary. The models used for testing were given by: $r_{t,t+K} = \beta_1 + \beta_2 RESpy_t + \mu_t$, $r_{t,t+K} = \beta_1 + \beta_2 px_t + \mu_t$ and $r_{t,t+K} = \beta_1 + \beta_2 pz_t + \mu_t$.

All in-sample tests revealed high R^2-values and significant β_2 coefficients. All the regressions were plagued by ARCH and autocorrelation due to overlapping observations and this was corrected in the standard errors by HAC, which all gave significant β_2 coefficients. Only the results for The Netherlands were slightly inferior to the other countries and all ratios performed equally well.

When testing the predictability of the stock returns using the ratios out-of-sample, they were found not to be able to perform better than the random walk. The results for the pz-ratio were inferior to the other ratios. The problems with out-of-sample testing are very common in the research of stock return predictability and may be due to factors such as bad luck or structural breaks.

From the robustness test, it could be seen that the results for Denmark were very robust, except for the out-of-sample period, since it seemed that there may have been a structural break in the late 1990's or in the 2000's. The Danish data was robust over the in-sample period, for different estimated ratios and when removing the influence of overlapping observation. On the other hand, the 4 quarter and px regression for United Kingdom were not robust, when removing the first 6 years of data and thereby the outliers. This result cannot necessarily be transferred to the 12 and 20 quarter regression.

The overall conclusion of the results in the current thesis is that all in-sample regression had strong predictability power. It is possible to make strong conclusion for Denmark and France, and slightly weaker conclusion for United Kingdom, due to the poor robustness test results, and The Netherlands, due to the unit roots in the ratios. The conclusion for the out-of-sample testing is that none of the ratios were able to forecast the stock returns better than the random walk.

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Appendix A - Data description

Denmark

GDP

Classification level 1	National Accounts
Classification level 2	GDP by Expenditure
Name	GDP (REAL) (AR)
DS Mnemonic	DKOCFGDPD
Start Date	Q1 1970
End Date	Q4 2011
Market	Denmark
Source	OECD Economic Outlook, Copyright OECD
Frequency	Quarterly
Unit	Danish Krone
Scale	Millions
Base Period	(2000 CHND PRC)
Adjustment	Constant prices,seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Jun 15 2010
Expanded Name	GDP (REAL) (AR)

Export

Classification level 1	External Sector
Classification level 2	Imports & Exports
Name	EXPORTS OF GOODS & SERVICES (REAL) (AR)
DS Mnemonic	DKOCFEGSD
Start Date	Q1 1970
End Date	Q4 2011
Market	Denmark
Source	OECD Economic Outlook, Copyright OECD
Frequency	Quarterly
Unit	Danish Krone
Scale	Millions
Base Period	(2000 CHND PRC)
Adjustment	Constant prices,seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Jun 15 2010
Expanded Name	EXPORTS OF GOODS & SERVICES (REAL) (AR)

Import

Classification level 1	External Sector
Classification level 2	Imports & Exports
Name	IMPORTS OF GOODS & SERVICES (REAL) (AR)
DS Mnemonic	DKOCFIGSD
Start Date	Q1 1970
End Date	Q4 2011
Market	Denmark
Source	OECD Economic Outlook, Copyright OECD
Frequency	Quarterly
Unit	Danish Krone
Scale	Millions
Base Period	2000
Adjustment	Constant prices,seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Jun 15 2010
Expanded Name	IMPORTS OF GOODS & SERVICES (REAL) (AR)

CPI

Classification level 1	Prices Consumer Sector
Classification level 2	Consumer Prices/Inflation
Name	CPI
DS Mnemonic	DKOCP009F
Start Date	Jan 1967
End Date	Jun 2010
Market	Denmark
Source	Main Economic Indicators, Copyright OECD
Frequency	Monthly
Unit	Index
Scale	
Base Period	2005
Adjustment	Price index,not seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Aug 6 2010
Expanded Name	Index publication base

MSCI

Name	MSCI DENMARK
DS Mnemonic	MSDNMKL
Market	Denmark
Base Date	Dec 31 1969
Currency	Danish Krone
Expanded Name	MSCI Denmark
Datatypes	MSRI-1269 MSPE-1269 MSDY-1269 MSEG- MSET-1202 MSFE-1202 more
Source	MSCI
Status	Active
Type	Standard Country
IBES Aggregate	@:DKMSCIP

Interest rate

Classification level 1	Money & Finance
Classification level 2	Interest Rates
Name	DISCOUNT RATE (EP)
DS Mnemonic	DKQ60...
Start Date	Q1 1957
End Date	Q2 2010
Market	Denmark
Source	IMF INTERNATIONAL FINANCIAL STATISTICS
Frequency	Quarterly
Unit	Percentage
Scale	
Base Period	
Adjustment	
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	End of Period
Last Updated	Jul 30 2010
Expanded Name	DISCOUNT RATE (EP)
Ecowin Code	ifs:s12860000zfq

The Netherlands

GDP

Classification level 1	National Accounts
Classification level 2	GDP by Expenditure
Name	GDP (REAL) (AR)
DS Mnemonic	NLOCFGDPD
Start Date	Q1 1970
End Date	Q4 2011
Market	Netherlands
Source	OECD Economic Outlook, Copyright OECD
Frequency	Quarterly
Unit	Euro
Scale	Millions
Base Period	(2000 CHND PRC)
Adjustment	Constant prices,seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Jun 15 2010
Expanded Name	GDP (REAL) (AR)

Export

Classification level 1	External Sector
Classification level 2	Imports & Exports
Name	EXPORTS OF GOODS & SERVICES (REAL) (AR)
DS Mnemonic	NLOCFEGSD
Start Date	Q1 1970
End Date	Q4 2011
Market	Netherlands
Source	OECD Economic Outlook, Copyright OECD
Frequency	Quarterly
Unit	Euro
Scale	Millions
Base Period	(2000 CHND PRC)
Adjustment	Constant prices,seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Jun 15 2010
Expanded Name	EXPORTS OF GOODS & SERVICES (REAL) (AR)

Import

Classification level 1	External Sector
Classification level 2	Imports & Exports
Name	IMPORTS OF GOODS & SERVICES (REAL) (AR)
DS Mnemonic	NLOCFIGSD
Start Date	Q1 1970
End Date	Q4 2011
Market	Netherlands
Source	OECD Economic Outlook, Copyright OECD
Frequency	Quarterly
Unit	Euro
Scale	Millions
Base Period	(2000 CHND PRC)
Adjustment	Constant prices,seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Jun 15 2010
Expanded Name	IMPORTS OF GOODS & SERVICES (REAL) (AR)

CPI

Classification level 1	Prices Consumer Sector
Classification level 2	Consumer Prices/Inflation
Name	CPI
DS Mnemonic	NLOCP009F
Start Date	Apr 1960
End Date	Jul 2010
Market	Netherlands
Source	Main Economic Indicators, Copyright OECD
Frequency	Monthly
Unit	Index
Scale	
Base Period	(2005=100)
Adjustment	Price index,not seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Aug 6 2010
Expanded Name	NLD CPI ALL ITEMS / Index publication base

MSCI

Name	MSCI NETHERLANDS
DS Mnemonic	MSNETHL
Market	Netherlands
Base Date	Dec 31 1969
Currency	Euro
Expanded Name	MSCI Netherlands
Datatypes	MSRI-1269 MSPE-1269 MSDY-1269 MSEG- MSET-1202 MSFE-1202 more
Source	MSCI
Status	Active
Type	Standard Country
IBES Aggregate	@:NLMSCIP

Interest rate

Classification level 1	Money & Finance
Classification level 2	Interest Rates
Name	DISCOUNT RATE (EP)
DS Mnemonic	NLQ60...
Start Date	Q1 1957
End Date	Q4 1993
Market	Netherlands
Source	IMF INTERNATIONAL FINANCIAL STATISTICS
Frequency	Quarterly
Unit	Percentage
Scale	
Base Period	
Adjustment	
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	End of Period
Last Updated	Nov 7 2008
Expanded Name	DISCOUNT RATE (EP)
Ecowin Code	ifs:s13860000zfq

France

GDP

Classification level 1	National Accounts
Classification level 2	GDP by Expenditure
Name	GDP (REAL) (AR)
DS Mnemonic	FROCFGDPD
Start Date	Q1 1970
End Date	Q4 2011
Market	France
Source	OECD Economic Outlook, Copyright OECD
Frequency	Quarterly
Unit	Euro
Scale	Millions
Base Period	(2000 CHND PRC)
Adjustment	Constant prices,seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Jun 15 2010
Expanded Name	GDP (REAL) (AR)

Export

Classification level 1	External Sector
Classification level 2	Imports & Exports
Name	EXPORTS OF GOODS & SERVICES (REAL) (AR)
DS Mnemonic	FROCFEGSD
Start Date	Q1 1970
End Date	Q4 2011
Market	France
Source	OECD Economic Outlook, Copyright OECD
Frequency	Quarterly
Unit	Euro
Scale	Millions
Base Period	(2000 CHND PRC)
Adjustment	Constant prices,seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Jun 15 2010
Expanded Name	EXPORTS OF GOODS & SERVICES (REAL) (AR)

Import

Classification level 1	External Sector
Classification level 2	Imports & Exports
Name	IMPORTS OF GOODS & SERVICES (REAL) (AR)
DS Mnemonic	FROCFIGSD
Start Date	Q1 1970
End Date	Q4 2011
Market	France
Source	OECD Economic Outlook, Copyright OECD
Frequency	Quarterly
Unit	Euro
Scale	Millions
Base Period	(2000 CHND PRC)
Adjustment	Constant prices,seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Jun 15 2010
Expanded Name	IMPORTS OF GOODS & SERVICES (REAL) (AR)

CPI

Classification level 1	Prices Consumer Sector
Classification level 2	Consumer Prices/Inflation
Name	CPI
DS Mnemonic	FROCP009F
Start Date	Jan 1960
End Date	Jun 2010
Market	France
Source	Main Economic Indicators, Copyright OECD
Frequency	Monthly
Unit	Index
Scale	
Base Period	2005
Adjustment	Price index,not seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Aug 6 2010
Expanded Name	Index publication base

MSCI

Name	MSCI FRANCE
DS Mnemonic	MSFRNCL
Market	France
Base Date	Dec 31 1969
Currency	Euro
Expanded Name	MSCI France
Datatypes	MSRI-1269 MSPE-0971 MSDY-1269 MSEG- MSET-1202 MSFE-1202 more
Source	MSCI
Status	Active
Type	Standard Country
IBES Aggregate	@:FRMSCIP

Interest rate

Classification level 1	Money & Finance
Classification level 2	Interest Rates
Name	TREASURY BILL RATE
DS Mnemonic	FRQ60C..
Start Date	Q1 1970
End Date	Q2 2010
Market	France
Source	IMF INTERNATIONAL FINANCIAL STATISTICS
Frequency	Quarterly
Unit	Percentage
Scale	
Base Period	
Adjustment	
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Jul 30 2010
Expanded Name	TREASURY BILL RATE
Ecowin Code	ifs:s13260c00zfq

UK

GDP

Classification level 1	National Accounts
Classification level 2	GDP by Expenditure
	Other National Accounts
Name	GDP (REAL) (AR)
DS Mnemonic	UKOCFGDPD
Start Date	Q1 1970
End Date	Q4 2011
Market	United Kingdom
Source	OECD Economic Outlook, Copyright OECD
Frequency	Quarterly
Unit	UK Sterling Pound
Scale	Millions
Base Period	(2005 CHND PRC)
Adjustment	Constant prices,seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	National Sources
Conversion Method	Average
Last Updated	Jun 15 2010
Expanded Name	GDP (REAL) (AR)

Export

Classification level 1	National Accounts
Classification level 2	GDP by Expenditure
	Other National Accounts
Name	EXPORTS OF GOODS & SERVICES (REAL) (AR)
DS Mnemonic	UKOCFEGSD
Start Date	Q1 1970
End Date	Q4 2011
Market	United Kingdom
Source	OECD Economic Outlook, Copyright OECD
Frequency	Quarterly
Unit	UK Sterling Pound
Scale	Millions
Base Period	(2005 CHND PRC)
Adjustment	Constant prices,seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	National Sources
Conversion Method	Average
Last Updated	Jun 15 2010
Expanded Name	EXPORTS OF GOODS & SERVICES (REAL) (AR)

Import

Classification level 1	National Accounts
Classification level 2	GDP by Expenditure
	Other National Accounts
Name	IMPORTS OF GOODS & SERVICES (REAL) (AR)
DS Mnemonic	UKOCFIGSD
Start Date	Q1 1970
End Date	Q4 2011
Market	United Kingdom
Source	OECD Economic Outlook, Copyright OECD
Frequency	Quarterly
Unit	UK Sterling Pound
Scale	Millions
Base Period	(2005 CHND PRC)
Adjustment	Constant prices,seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	National Sources
Conversion Method	Average
Last Updated	Jun 15 2010
Expanded Name	IMPORTS OF GOODS & SERVICES (REAL) (AR)

CPI

Classification level 1	Prices
	Consumer Sector
Classification level 2	Consumer Prices/Inflation
Name	CPI
DS Mnemonic	UKOCP009F
Start Date	Jan 1960
End Date	Jun 2010
Market	United Kingdom
Source	Main Economic Indicators, Copyright OECD
Frequency	Monthly
Unit	Index
Scale	
Base Period	(2005=100)
Adjustment	Price index,not seasonally adjusted
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Aug 6 2010
Expanded Name	Index publication base

MSCI

Name	MSCI UK
DS Mnemonic	MSUTDKL
Market	United Kingdom
Base Date	Dec 31 1969
Currency	United Kingdom Pound
Expanded Name	MSCI United Kingdom
Datatypes	MSRI-1269 MSPE-1269 MSDY-1269 MSEG- MSET-1202 MSFE-1202 more
Source	MSCI
Status	Active
Type	Standard Country
IBES Aggregate	@:UKMSCIP

Interest rate

Classification level 1	Money & Finance
Classification level 2	Interest Rates
Name	TREASURY BILL RATE
DS Mnemonic	UKQ60C..
Start Date	Q1 1957
End Date	Q2 2010
Market	United Kingdom
Source	IMF INTERNATIONAL FINANCIAL STATISTICS
Frequency	Quarterly
Unit	Percentage
Scale	
Base Period	
Adjustment	
Key Indicator	No
Forecast	Historical Series
Status	Active
Dataset	International Sources
Conversion Method	Average
Last Updated	Aug 31 2010
Expanded Name	TREASURY BILL RATE
Ecowin Code	ifs:s11260c00zfq

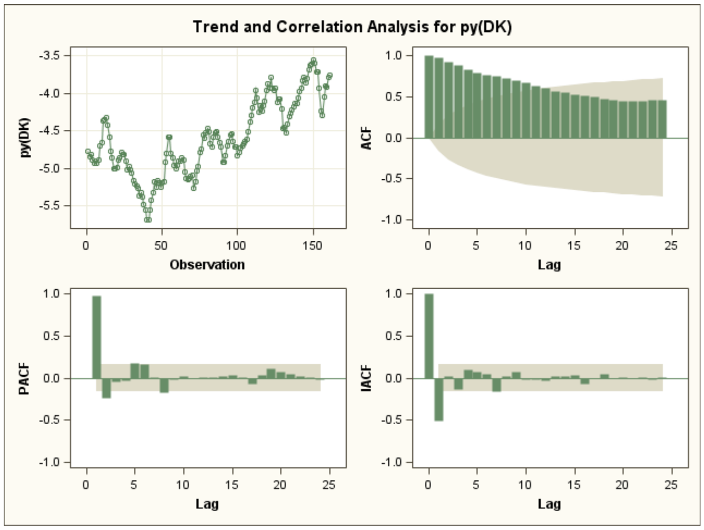
Appendix B - Unit root tests for ratios and returns

Denmark

py(DK)

Dickey-Fuller test and Augmented Dickey-Fuller test

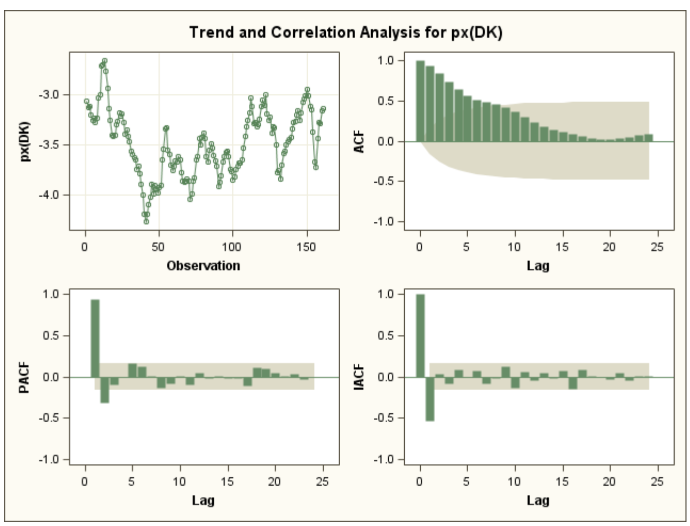
Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-0.2402	0.6273	-0.86	0.3428		
	1	-0.3000	0.6136	-0.77	0.3839		
	2	-0.3038	0.6128	-0.72	0.4043		
	3	-0.3120	0.6109	-0.79	0.3723		
	4	-0.2761	0.6191	-0.87	0.3380		
	5	-0.2438	0.6264	-0.86	0.3441		
Single Mean	0	-2.0383	0.7722	-0.77	0.8246	0.60	0.9214
	1	-5.6028	0.3750	-1.47	0.5465	1.27	0.7466
	2	-6.9231	0.2745	-1.62	0.4687	1.47	0.6956
	3	-6.1640	0.3289	-1.51	0.5288	1.34	0.7291
	4	-3.6829	0.5715	-1.12	0.7073	0.92	0.8369
	5	-2.7977	0.6787	-0.95	0.7710	0.74	0.8820
Trend	0	-9.4808	0.4612	-2.33	0.4173	3.13	0.5522
	1	-18.3933	0.0860	-3.07	0.1174	4.88	0.2020
	2	-24.3432	0.0232	-3.41	0.0534	6.00	0.0677
	3	-23.3686	0.0289	-3.20	0.0877	5.27	0.1233
	4	-16.0416	0.1394	-2.66	0.2539	3.71	0.4360
	5	-14.1856	0.2007	-2.52	0.3184	3.39	0.4999


Trend and Correlation Analysis for py(DK)
py(DK)
Observation
ACF
Lag
PACF
Lag
IACF
Lag

px(DK)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-0.0494	0.6705	-0.13	0.6368		
	1	-0.1489	0.6480	-0.28	0.5832		
	2	-0.1536	0.6469	-0.28	0.5852		
	3	-0.1539	0.6468	-0.30	0.5761		
	4	-0.0949	0.6602	-0.23	0.6023		
	5	-0.0427	0.6720	-0.12	0.6419		
Single Mean	0	-8.4953	0.1873	-2.11	0.2400	2.23	0.5021
	1	-17.8981	0.0169	-2.95	0.0421	4.36	0.0664
	2	-22.5130	0.0050	-3.20	0.0218	5.14	0.0346
	3	-20.7929	0.0079	-2.96	0.0417	4.37	0.0656
	4	-14.0280	0.0464	-2.43	0.1361	2.94	0.3204
	5	-11.4492	0.0896	-2.22	0.2008	2.46	0.4440
Trend	0	-8.8657	0.5070	-2.20	0.4855	2.97	0.5839
	1	-18.2076	0.0895	-3.01	0.1317	4.76	0.2261
	2	-22.8820	0.0323	-3.28	0.0740	5.60	0.0887
	3	-21.1844	0.0470	-3.03	0.1279	4.78	0.2214
	4	-14.4796	0.1897	-2.51	0.3230	3.38	0.5019
	5	-12.0088	0.3006	-2.32	0.4186	2.99	0.5791



Test for number of lags

Augmented Dickey-Fuller test, 0 lags $\quad delta(pxDK) = b_1 + b_2pxDK_{t-1}$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	-0.1854	0.0879	-2.11	0.0366
lag(pxDK)	1	-0.0531	0.0251	-2.11	0.0363

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	22.6108	<.0001
AR(2)	24.0015	<.0001
AR(3)	24.0751	<.0001
AR(4)	27.8294	<.0001

Augmented Dickey-Fuller test, 1 lags $\quad delta(pxDK_t) = b_1 + b_2pxDK_{t-1}+b_3delta(pxDK_{t-1})$

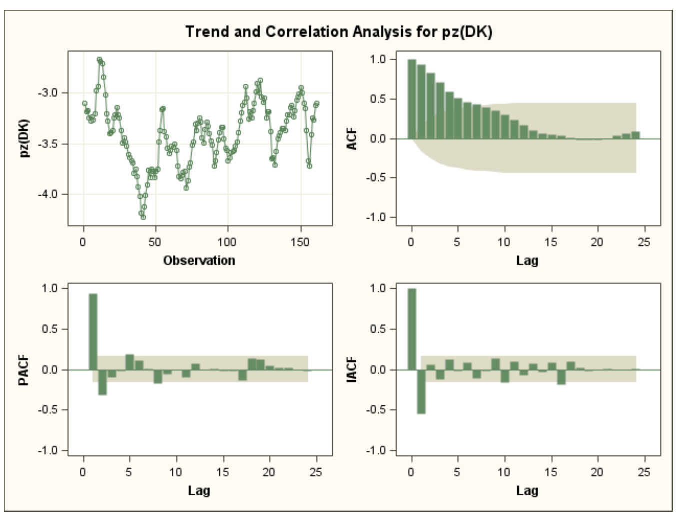
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	-0.2454	0.0835	-2.94	0.0038
lag(pxDK)	1	-0.0704	0.0239	-2.95	0.0036
lag(delta(pxDK))	1	0.3742	0.0740	5.05	<.0001

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	1.4609	0.2268
AR(2)	1.5858	0.4525
AR(3)	5.9825	0.1125
AR(4)	6.9451	0.1388

pz(DK)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-0.0770	0.6643	-0.20	0.6144		
	1	-0.1807	0.6408	-0.33	0.5643		
	2	-0.1831	0.6402	-0.32	0.5682		
	3	-0.1860	0.6395	-0.35	0.5581		
	4	-0.1090	0.6570	-0.26	0.5910		
	5	-0.0585	0.6684	-0.16	0.6282		
Single Mean	0	-9.8638	0.1336	-2.24	0.1928	2.51	0.4313
	1	-20.4881	0.0086	-3.14	0.0260	4.93	0.0408
	2	-25.8757	0.0021	-3.39	0.0129	5.75	0.0182
	3	-25.7085	0.0022	-3.23	0.0203	5.22	0.0320
	4	-16.2048	0.0263	-2.57	0.1008	3.31	0.2264
	5	-13.5736	0.0521	-2.36	0.1558	2.78	0.3631
Trend	0	-10.8122	0.3707	-2.42	0.3673	3.24	0.5300
	1	-21.7052	0.0420	-3.28	0.0729	5.50	0.0940
	2	-27.6329	0.0108	-3.56	0.0366	6.47	0.0463
	3	-27.6582	0.0107	-3.40	0.0558	5.87	0.0750
	4	-17.8364	0.0965	-2.75	0.2198	3.89	0.3999
	5	-15.3645	0.1594	-2.56	0.3007	3.42	0.4939



Test for number of lags

Augmented Dickey-Fuller test, 0 lags $\quad$ $delta(pzDK) = b_1 + b_2 pzDK_{t-1}$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	-0.2097	0.0940	-2.23	0.0271
lag(pzDK)	1	-0.0616	0.0275	-2.24	0.0265

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	20.7631	<.0001
AR(2)	22.2819	<.0001
AR(3)	22.2877	<.0001
AR(4)	27.1282	<.0001

Augmented Dickey-Fuller test, 1 lags $\quad$ $delta(pzDK_t) = b_1 + b_2 pzDK_{t-1} + b_3 delta(pzDK_{t-1})$

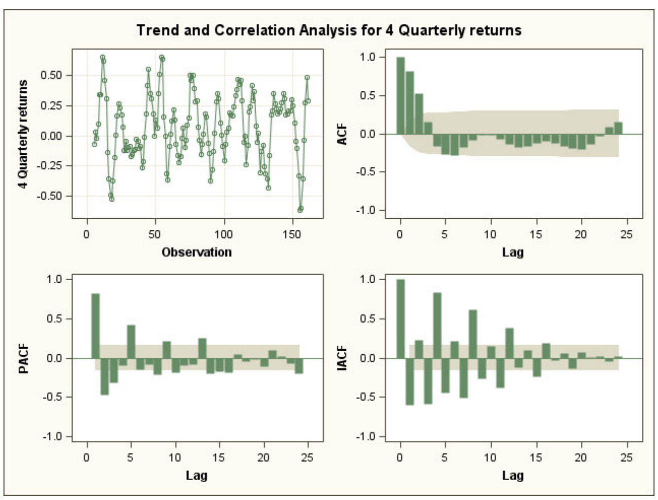
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	-0.2806	0.0899	-3.12	0.0021
lag(pzDK)	1	-0.0826	0.0263	-3.14	0.0020
lag(delta(pzDK)	1	0.3591	0.0746	4.81	<.0001

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	1.5246	0.2169
AR(2)	1.5263	0.4662
AR(3)	6.7603	0.0799
AR(4)	6.7827	0.1478

4 quarter return(DK)

Dickey-Fuller test and Augmented Dickey-Fuller test

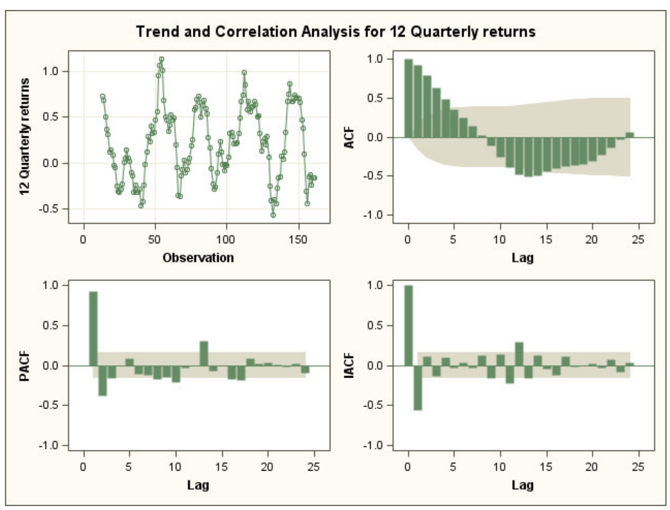
Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-25.3578	0.0002	-3.66	0.0003		
	1	-71.0839	<.0001	-5.87	<.0001		
	2	-170.048	0.0001	-7.23	<.0001		
	3	-234.001	0.0001	-6.64	<.0001		
	4	-33.2711	<.0001	-3.53	0.0005		
	5	-45.6932	<.0001	-3.74	0.0002		
Single Mean	0	-27.5940	0.0014	-3.85	0.0031	7.43	0.0010
	1	-77.9469	0.0012	-6.14	<.0001	18.88	0.0010
	2	-208.246	0.0001	-7.71	<.0001	29.75	0.0010
	3	-388.680	0.0001	-7.22	<.0001	26.06	0.0010
	4	-41.6415	0.0012	-3.76	0.0042	7.09	0.0010
	5	-63.8244	0.0012	-4.03	0.0017	8.17	0.0010
Trend	0	-27.6031	0.0108	-3.84	0.0170	7.37	0.0225
	1	-77.9292	0.0005	-6.12	<.0001	18.76	0.0010
	2	-208.272	0.0001	-7.69	<.0001	29.55	0.0010
	3	-388.615	0.0001	-7.19	<.0001	25.88	0.0010
	4	-41.6870	0.0005	-3.74	0.0223	7.01	0.0315
	5	-64.1090	0.0005	-4.03	0.0099	8.10	0.0077



12 quarter return(DK)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-9.2276	0.0337	-2.35	0.0187		
	1	-20.0128	0.0014	-3.26	0.0013		
	2	-25.4653	0.0002	-3.44	0.0007		
	3	-23.6559	0.0004	-3.19	0.0016		
	4	-16.6782	0.0038	-2.67	0.0077		
	5	-19.6321	0.0015	-2.73	0.0065		
Single Mean	0	-10.8652	0.1035	-2.40	0.1423	3.02	0.3008
	1	-25.9119	0.0020	-3.59	0.0072	6.48	0.0018
	2	-36.1900	0.0012	-3.93	0.0024	7.75	0.0010
	3	-35.8251	0.0012	-3.69	0.0053	6.82	0.0010
	4	-25.2474	0.0024	-3.05	0.0328	4.70	0.0480
	5	-34.8457	0.0012	-3.27	0.0183	5.36	0.0277
Trend	0	-11.0842	0.3527	-2.43	0.3629	2.96	0.5863
	1	-26.4663	0.0139	-3.62	0.0318	6.54	0.0445
	2	-37.0803	0.0010	-3.95	0.0124	7.81	0.0136
	3	-36.9457	0.0010	-3.70	0.0251	6.88	0.0352
	4	-26.2647	0.0145	-3.07	0.1171	4.73	0.2315
	5	-36.6796	0.0011	-3.27	0.0754	5.41	0.0992



Test for number of lags

Augmented Dickey-Fuller test, 0 lags   delta(12QDK) = $b_1 + b_2 12QDK_{t-1}$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.009973	0.0135	0.74	0.4627
lag(12QDK)	1	-0.0734	0.0305	-2.40	0.0175

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	26.1166	<.0001
AR(2)	29.5711	<.0001
AR(3)	29.5731	<.0001
AR(4)	31.6022	<.0001

Augmented Dickey-Fuller test, 1 lags delta($12QDK_t$) = $b_1 + b_2 12QDK_{t-1} + b_3$delta($12QDK_{t-1}$)

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0187	0.0125	1.50	0.1353
lag(12QDK)	1	-0.1023	0.0285	-3.59	0.0005
lag(delta(12QDK))	1	0.4194	0.0754	5.56	<.0001

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	4.0637	0.0438
AR(2)	4.0678	0.1308
AR(3)	7.2569	0.0641
AR(4)	8.1757	0.0854

Augmented Dickey-Fuller test, 1 lags $delta(12QDK_t) = b_1 + b_2 12QDK_{t-1} + b_3 delta(12QDK_{t-1}) + b_4 delta(12QDK_{t-2})$

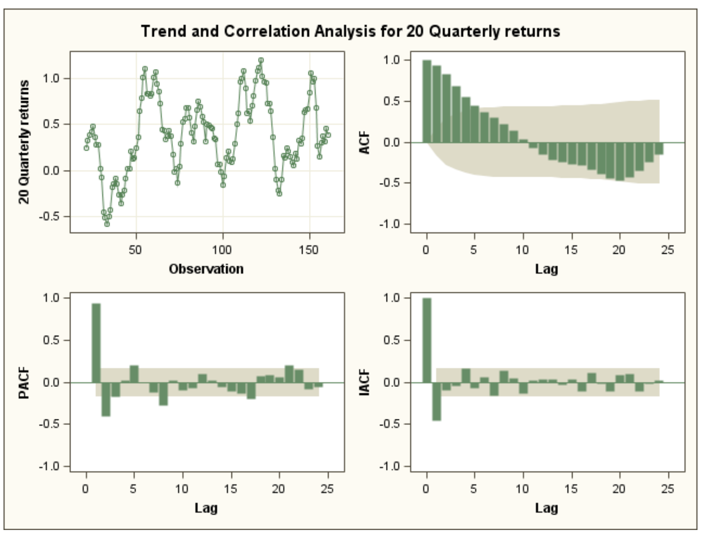
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0233	0.0125	1.86	0.0651
lag(12QDK)	1	-0.1166	0.0296	-3.93	0.0001
lag(delta(12QDK))	1	0.3634	0.0793	4.58	<.0001
2lag(delta(12QDK))	1	0.1663	0.0825	2.01	0.0458

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	0.0081	0.9285
AR(2)	1.6586	0.4364
AR(3)	1.8053	0.6138
AR(4)	6.5945	0.1589

20 quarter return(DK)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-4.6892	0.1350	-1.51	0.1216		
	1	-10.8640	0.0207	-2.31	0.0204		
	2	-14.3570	0.0075	-2.59	0.0097		
	3	-12.1380	0.0142	-2.33	0.0194		
	4	-7.1431	0.0633	-1.81	0.0677		
	5	-6.5638	0.0756	-1.68	0.0873		
Single Mean	0	-9.1350	0.1590	-2.16	0.2199	2.35	0.4729
	1	-21.2972	0.0067	-3.23	0.0206	5.21	0.0323
	2	-30.9860	0.0012	-3.68	0.0055	6.77	0.0010
	3	-28.6703	0.0012	-3.38	0.0135	5.71	0.0191
	4	-16.8897	0.0215	-2.61	0.0937	3.41	0.2028
	5	-17.1252	0.0201	-2.55	0.1071	3.24	0.2446
Trend	0	-9.7650	0.4390	-2.21	0.4791	2.46	0.6870
	1	-23.3544	0.0282	-3.36	0.0610	5.65	0.0864
	2	-35.1796	0.0016	-3.88	0.0155	7.52	0.0194
	3	-33.4330	0.0025	-3.59	0.0348	6.43	0.0476
	4	-19.9605	0.0600	-2.79	0.2038	3.89	0.4000
	5	-20.2746	0.0559	-2.68	0.2466	3.60	0.4581



Test for number of lags

Augmented Dickey-Fuller test, 0 lags delta(20QDK) = $b_1 + b_2 20QDK_{t-1}$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0259	0.0168	1.54	0.1255
lag(20QDK)	1	-0.0653	0.0301	-2.16	0.0321

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	23.1203	<.0001
AR(2)	26.6852	<.0001
AR(3)	26.7768	<.0001
AR(4)	31.4907	<.0001

Augmented Dickey-Fuller test, 1 lags delta($20QDK_t$) = $b_1 + b_2 20QDK_{t-1} + b_3$delta($20QDK_{t-1}$)

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0345	0.0156	2.22	0.0284
lag(20QDK)	1	-0.0910	0.0282	-3.23	0.0016
lag(delta(20QDK))	1	0.4061	0.0783	5.19	<.0001

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	4.2606	0.0390
AR(2)	4.3735	0.1123
AR(3)	8.8396	0.0315
AR(4)	9.2852	0.0544

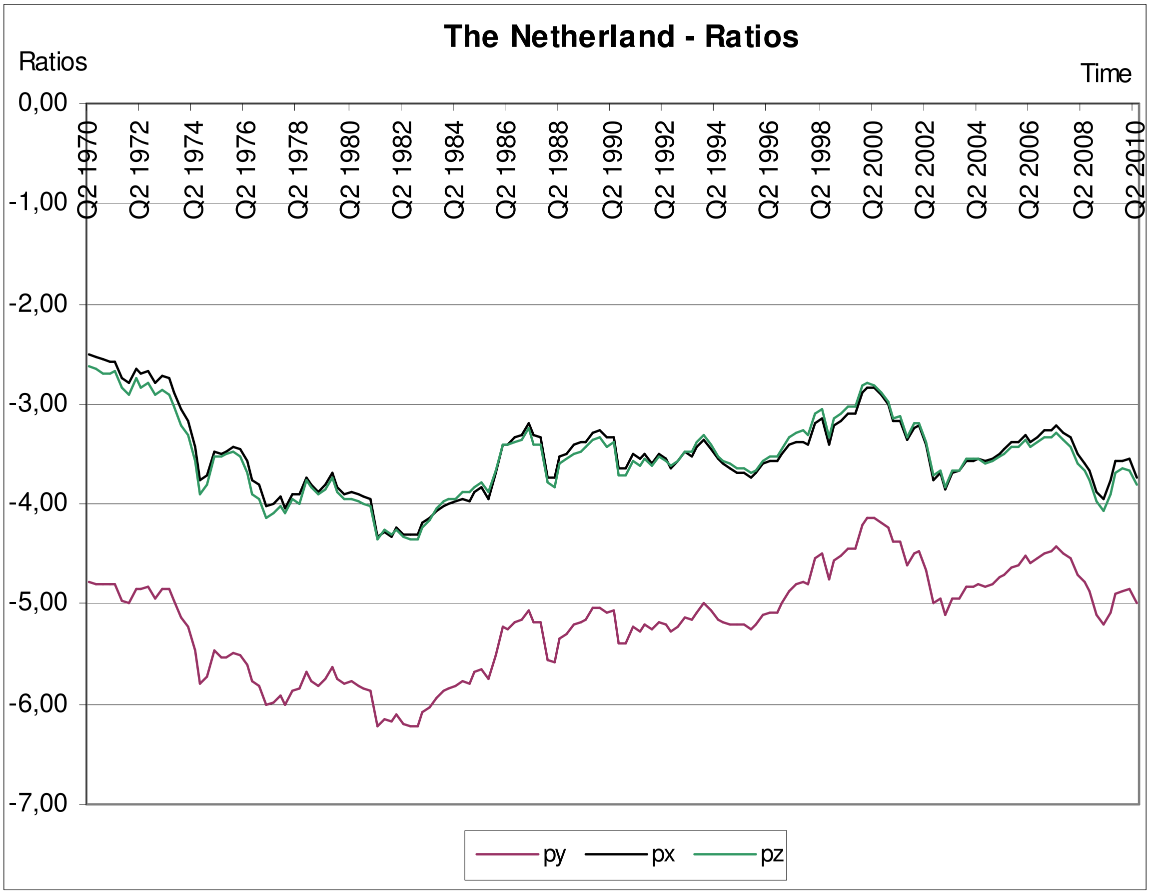
Augmented Dickey-Fuller test, 1 lags delta($20QDK_t$) = b_1 + $b_2 20QDK_{t-1}$+$b_3$delta($20QDK_{t-1}$) +$b_4$delta($20QDK_{t-2}$)

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0403	0.0158	2.56	0.0117
lag(20QDK)	1	-0.1067	0.0290	-3.68	0.0003
lag(delta(20QDK))	1	0.3494	0.0824	4.24	<.0001
2lag(delta(20QDK))	1	0.1752	0.0854	2.05	0.0423

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	0.1186	0.7306
AR(2)	5.6988	0.0579
AR(3)	5.7000	0.1272
AR(4)	6.9735	0.1373

The Netherlands

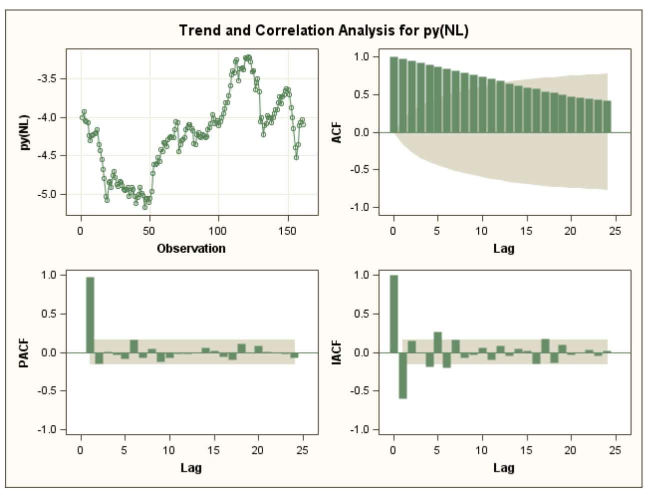
Ratios



py(NL)

Dickey-Fuller test and Augmented Dickey-Fuller test

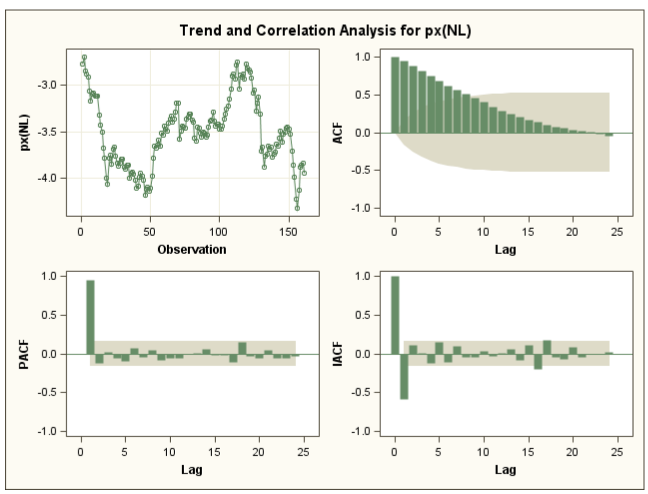
Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-0.0260	0.6759	-0.08	0.6536		
	1	-0.0160	0.6781	-0.05	0.6667		
	2	-0.0505	0.6703	-0.14	0.6331		
	3	-0.0525	0.6698	-0.15	0.6324		
	4	-0.0739	0.6649	-0.19	0.6175		
	5	-0.0772	0.6642	-0.24	0.6004		
Single Mean	0	-3.4027	0.6048	-1.31	0.6226	0.87	0.8498
	1	-4.5173	0.4790	-1.52	0.5228	1.16	0.7751
	2	-4.4969	0.4811	-1.47	0.5446	1.09	0.7937
	3	-4.8206	0.4479	-1.51	0.5268	1.14	0.7804
	4	-5.9179	0.3484	-1.64	0.4590	1.35	0.7274
	5	-4.0814	0.5260	-1.36	0.6014	0.93	0.8345
Trend	0	-7.5110	0.6145	-2.18	0.4996	2.46	0.6850
	1	-10.2989	0.4038	-2.55	0.3039	3.38	0.5028
	2	-10.0661	0.4194	-2.36	0.3969	2.84	0.6094
	3	-11.3367	0.3386	-2.46	0.3466	3.08	0.5622
	4	-14.9758	0.1722	-2.72	0.2312	3.74	0.4305
	5	-9.8540	0.4343	-2.07	0.5573	2.15	0.7485



px(NL)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	0.2466	0.7406	0.66	0.8571		
	1	0.2518	0.7419	0.60	0.8447		
	2	0.2164	0.7331	0.52	0.8280		
	3	0.2060	0.7305	0.48	0.8175		
	4	0.1848	0.7253	0.41	0.8011		
	5	0.1990	0.7288	0.52	0.8279		
Single Mean	0	-7.7375	0.2254	-2.17	0.2169	2.76	0.3669
	1	-10.3767	0.1175	-2.52	0.1138	3.54	0.1678
	2	-9.6043	0.1424	-2.27	0.1820	2.87	0.3384
	3	-10.8610	0.1040	-2.35	0.1566	3.03	0.2981
	4	-12.4867	0.0689	-2.43	0.1351	3.17	0.2631
	5	-8.6073	0.1820	-1.93	0.3192	2.11	0.5328
Trend	0	-7.8833	0.5843	-2.20	0.4846	2.50	0.6775
	1	-10.6238	0.3826	-2.56	0.2970	3.39	0.4997
	2	-9.8442	0.4352	-2.31	0.4234	2.71	0.6355
	3	-11.1909	0.3472	-2.40	0.3755	2.92	0.5941
	4	-12.9834	0.2518	-2.49	0.3323	3.12	0.5540
	5	-8.9489	0.5003	-1.95	0.6214	1.91	0.7958



Test for number of lags

Augmented Dickey-Fuller test, 0 lags   delta(pxNL) = $b_1 + b_2 pxNL_{t-1}$

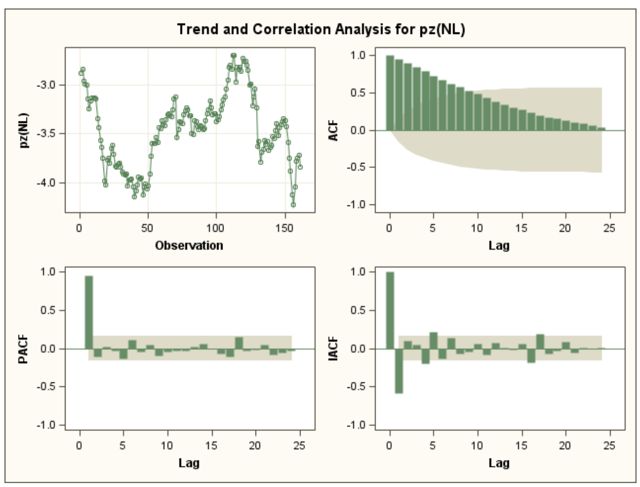
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	-0.1769	0.0785	-2.25	0.0256
lag(pxNL)	1	-0.0484	0.0223	-2.17	0.0313

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	2.6433	0.1040
AR(2)	2.6435	0.2667
AR(3)	3.1608	0.3675
AR(4)	3.8359	0.4287

pz(NL)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	0.1991	0.7288	0.53	0.8283		
	1	0.1946	0.7277	0.45	0.8110		
	2	0.1659	0.7207	0.40	0.7979		
	3	0.1608	0.7195	0.39	0.7942		
	4	0.1377	0.7139	0.31	0.7729		
	5	0.1619	0.7197	0.44	0.8075		
Single Mean	0	-6.9460	0.2731	-1.97	0.2976	2.23	0.5033
	1	-9.2856	0.1541	-2.26	0.1876	2.79	0.3600
	2	-8.5045	0.1868	-2.06	0.2607	2.32	0.4805
	3	-8.9388	0.1678	-2.07	0.2566	2.33	0.4778
	4	-11.2541	0.0942	-2.26	0.1869	2.69	0.3841
	5	-7.0182	0.2681	-1.71	0.4263	1.64	0.6520
Trend	0	-7.3918	0.6243	-2.06	0.5651	2.15	0.7478
	1	-9.9554	0.4277	-2.36	0.3976	2.83	0.6126
	2	-9.1048	0.4888	-2.14	0.5184	2.30	0.7178
	3	-9.6718	0.4473	-2.16	0.5075	2.34	0.7098
	4	-12.4386	0.2783	-2.38	0.3903	2.83	0.6122
	5	-7.6097	0.6062	-1.74	0.7284	1.53	0.8726



Test for number of lags

Augmented Dickey-Fuller test, 0 lags delta(pzNL) = $b_1 + b_2 pzNL_{t-1}$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	-0.1558	0.0763	-2.04	0.0427
lag(pzNL)	1	-0.0434	0.0220	-1.97	0.0501

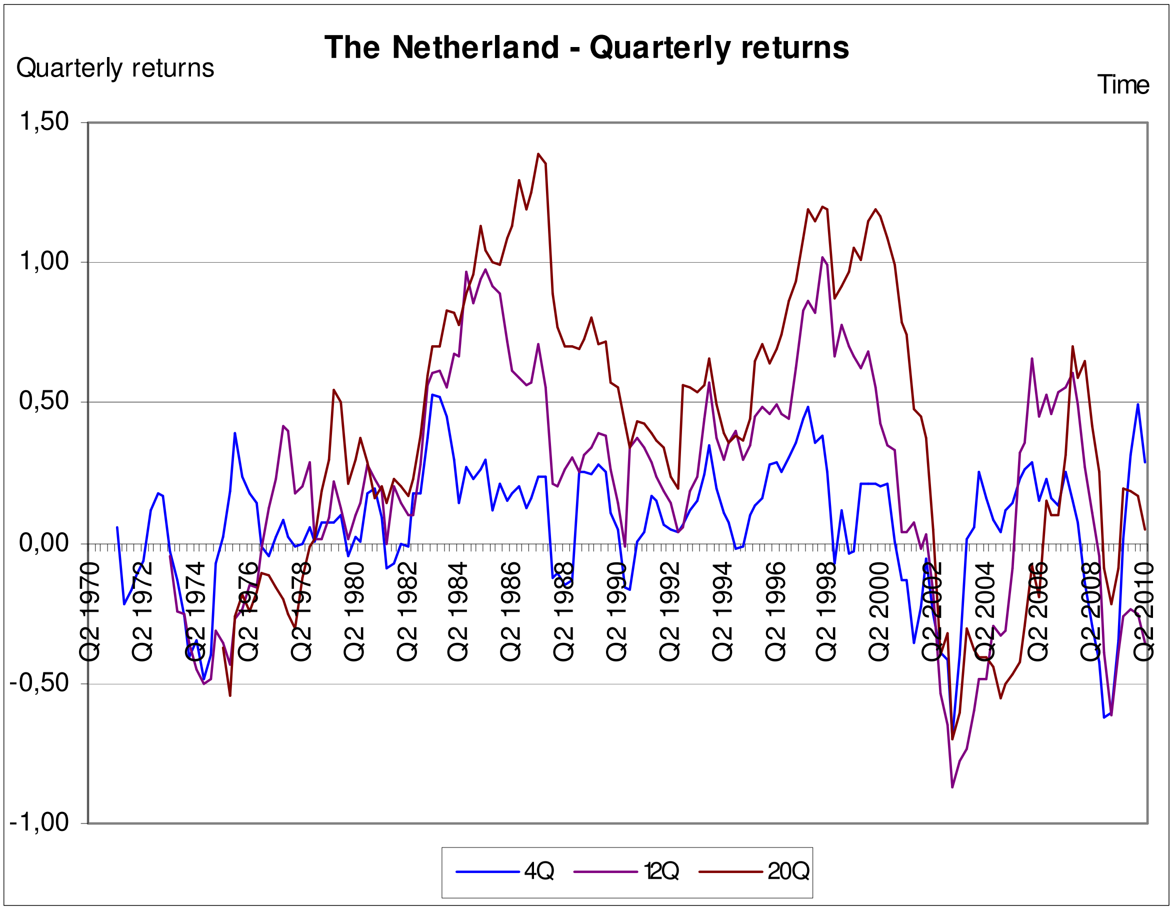
Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	3.1767	0.0747
AR(2)	3.2075	0.2011
AR(3)	3.3024	0.3473
AR(4)	4.8661	0.3013

Augmented Dickey-Fuller test, 1 lags delta($pzNL_t$) = $b_1 + b_2 pzNL_{t-1} + b_3$delta($pzNL_{t-1}$)

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	-0.1785	0.0770	-2.32	0.0218
lag(pzNL)	1	-0.0501	0.0222	-2.26	0.0255
lag(delta(pzNL))	1	0.1427	0.0790	1.81	0.0728

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	0.2498	0.6172
AR(2)	0.6110	0.7368
AR(3)	0.7257	0.8671
AR(4)	3.4663	0.4830

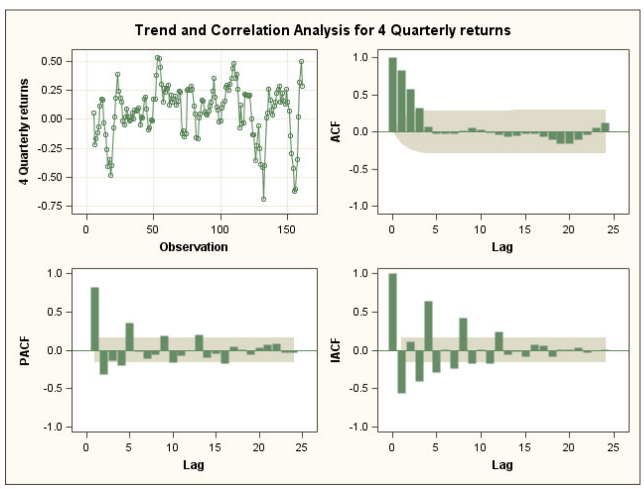
Returns


The Netherland - Quarterly returns
Quarterly returns
Time
1,50
1,00
0,50
0,00
-0,50
-1,00
Q2 1970
Q2 1972
Q2 1974
Q2 1976
Q2 1978
Q2 1980
Q2 1982
Q2 1984
Q2 1986
Q2 1988
Q2 1990
Q2 1992
Q2 1994
Q2 1996
Q2 1998
Q2 2000
Q2 2002
Q2 2004
Q2 2006
Q2 2008
Q2 2010
4Q
12Q
20Q

4 quarter return(NL)

Dickey-Fuller test and Augmented Dickey-Fuller test

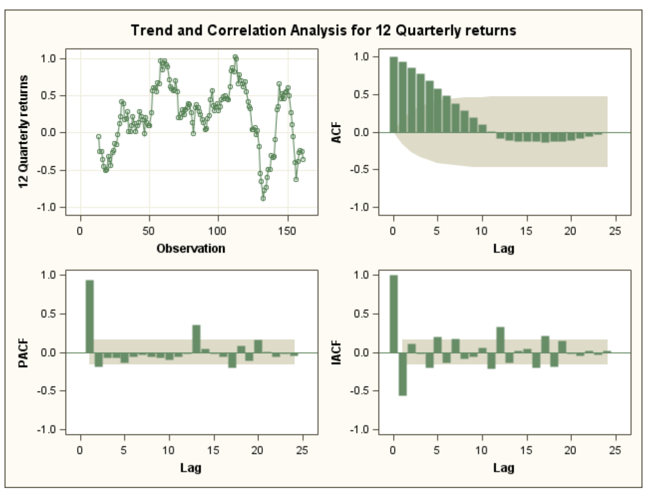
Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-24.5022	0.0003	-3.58	0.0004		
	1	-45.9388	<.0001	-4.75	<.0001		
	2	-63.9781	<.0001	-5.03	<.0001		
	3	-118.497	0.0001	-5.61	<.0001		
	4	-29.6572	<.0001	-3.31	0.0011		
	5	-26.2738	0.0001	-3.04	0.0026		
Single Mean	0	-26.9288	0.0016	-3.78	0.0039	7.15	0.0010
	1	-51.6915	0.0012	-5.08	<.0001	12.92	0.0010
	2	-75.0303	0.0012	-5.41	<.0001	14.67	0.0010
	3	-160.355	0.0001	-6.13	<.0001	18.78	0.0010
	4	-37.5251	0.0012	-3.61	0.0067	6.51	0.0012
	5	-34.4831	0.0012	-3.32	0.0159	5.51	0.0237
Trend	0	-26.9150	0.0127	-3.76	0.0211	7.11	0.0289
	1	-51.8316	0.0005	-5.07	0.0003	12.85	0.0010
	2	-75.3494	0.0005	-5.40	<.0001	14.60	0.0010
	3	-161.487	0.0001	-6.12	<.0001	18.70	0.0010
	4	-37.7237	0.0009	-3.61	0.0323	6.54	0.0446
	5	-34.5490	0.0020	-3.32	0.0674	5.53	0.0925



12 quarter return(NL)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-6.1054	0.0873	-1.72	0.0814		
	1	-9.1137	0.0349	-2.10	0.0346		
	2	-10.1767	0.0254	-2.17	0.0292		
	3	-11.0211	0.0198	-2.23	0.0253		
	4	-13.5037	0.0096	-2.42	0.0156		
	5	-12.8348	0.0117	-2.31	0.0207		
Single Mean	0	-7.4598	0.2406	-1.85	0.3568	1.72	0.6319
	1	-11.8669	0.0803	-2.37	0.1511	2.82	0.3531
	2	-13.6227	0.0512	-2.47	0.1250	3.05	0.2932
	3	-15.5626	0.0308	-2.60	0.0953	3.38	0.2089
	4	-20.6360	0.0080	-2.90	0.0478	4.22	0.0752
	5	-21.1518	0.0070	-2.83	0.0569	4.01	0.0880
Trend	0	-7.4895	0.6155	-1.85	0.6746	2.10	0.7574
	1	-11.8164	0.3102	-2.38	0.3894	3.31	0.5152
	2	-13.4789	0.2286	-2.47	0.3399	3.52	0.4744
	3	-15.2522	0.1620	-2.61	0.2769	3.98	0.3824
	4	-19.8799	0.0617	-2.91	0.1614	4.90	0.1988
	5	-19.9340	0.0609	-2.84	0.1866	4.81	0.2170



Test for number of lags

Augmented Dickey-Fuller test, 0 lags delta(12QNL) = $b_1 + b_2 12QNL_{t-1}$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.009011	0.0127	0.71	0.4799
lag(12QNL)	1	-0.0504	0.0273	-1.85	0.0669

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	5.7984	0.0160
AR(2)	6.3697	0.0414
AR(3)	6.6765	0.0830
AR(4)	8.0802	0.0887

Augmented Dickey-Fuller test, 1 lags delta($12QNL_t$) = $b_1 + b_2 12QNL_{t-1} + b_3$delta($12QNL_{t-1}$)

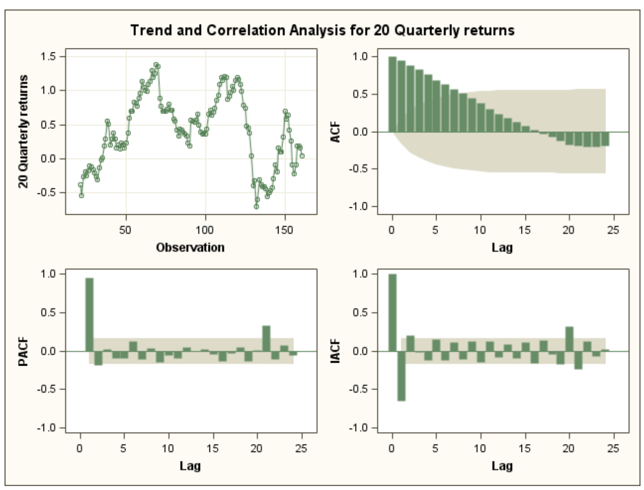
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0138	0.0126	1.10	0.2726
lag(12QNL)	1	-0.0645	0.0272	-2.37	0.0190
lag(delta(12QNL))	1	0.2014	0.0815	2.47	0.0146

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	0.4760	0.4902
AR(2)	0.4794	0.7869
AR(3)	0.5211	0.9142
AR(4)	1.9859	0.7383

20 quarter return(NL)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-3.4990	0.1973	-1.36	0.1615		
	1	-5.0514	0.1206	-1.64	0.0945		
	2	-5.0861	0.1193	-1.57	0.1090		
	3	-5.9721	0.0908	-1.67	0.0893		
	4	-6.4368	0.0786	-1.71	0.0821		
	5	-4.2154	0.1566	-1.39	0.1540		
Single Mean	0	-6.5043	0.3026	-1.96	0.3027	1.96	0.5720
	1	-9.6636	0.1394	-2.41	0.1401	2.96	0.3172
	2	-9.3902	0.1492	-2.17	0.2164	2.37	0.4671
	3	-11.2797	0.0928	-2.30	0.1725	2.65	0.3946
	4	-13.0597	0.0588	-2.43	0.1352	2.96	0.3164
	5	-8.7630	0.1741	-1.98	0.2945	1.97	0.5698
Trend	0	-6.7452	0.6767	-2.04	0.5760	2.79	0.6205
	1	-9.9224	0.4280	-2.51	0.3229	3.92	0.3933
	2	-9.6090	0.4499	-2.26	0.4535	2.95	0.5877
	3	-11.4723	0.3285	-2.39	0.3833	3.19	0.5399
	4	-13.1669	0.2412	-2.53	0.3133	3.60	0.4586
	5	-8.9594	0.4976	-2.11	0.5378	2.82	0.6146



Test for number of lags

Augmented Dickey-Fuller test, 0 lags delta(Q20NL) = $b_1 + b_2 20QNL_{t-1}$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0223	0.0155	1.43	0.1537
lag(20QNL)	1	-0.0465	0.0237	-1.96	0.0517

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	4.3714	0.0365
AR(2)	4.7158	0.0946
AR(3)	5.9301	0.1151
AR(4)	6.2161	0.1836

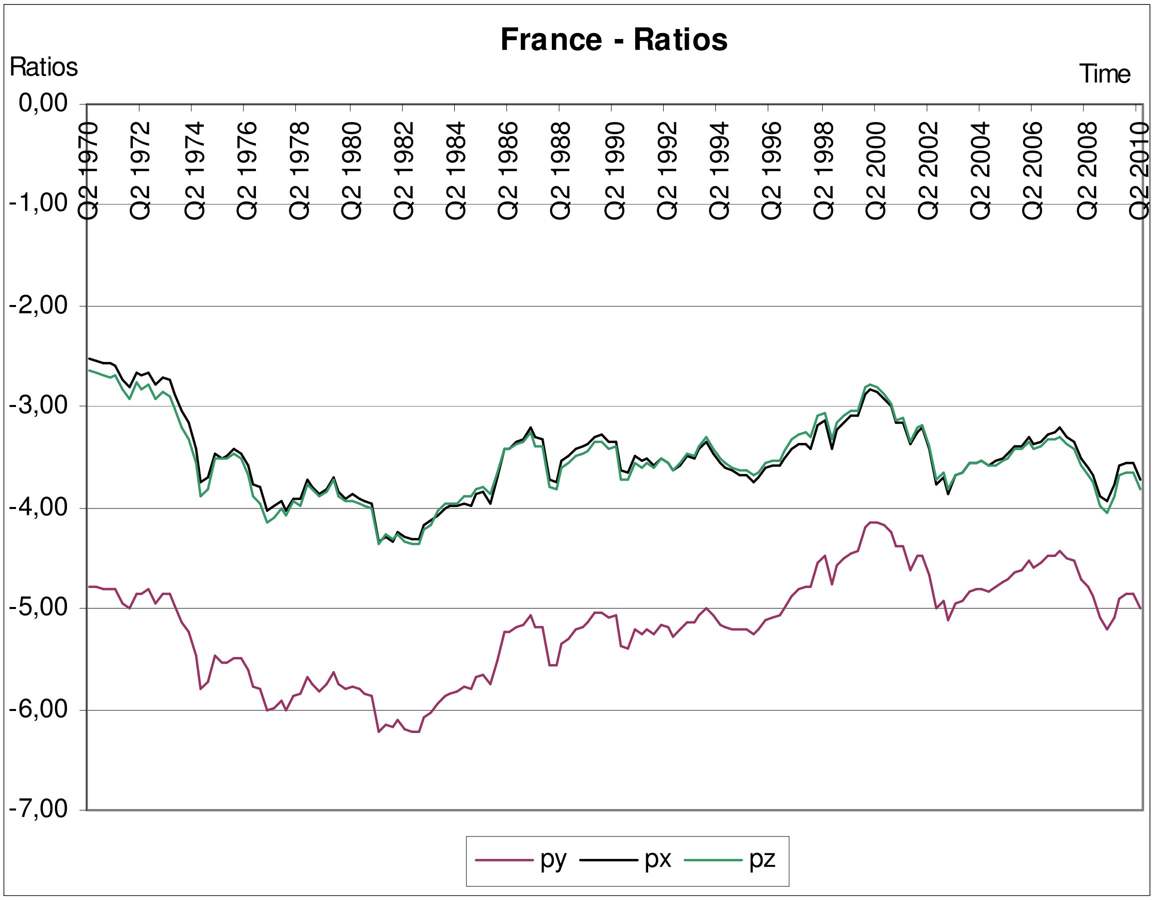
Augmented Dickey-Fuller test, 1 lags delta($Q20NL_t$) = $b_1 + b_2 20QNL_{t-1} + b_3$delta($20QNL_{t-1}$)

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0275	0.0155	1.78	0.0773
lag(20QNL)	1	-0.0570	0.0236	-2.41	0.0172
lag(delta(20QNL))	1	0.1807	0.0832	2.17	0.0317

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	0.3564	0.5505
AR(2)	2.2600	0.3230
AR(3)	4.0322	0.2580
AR(4)	5.3693	0.2515

France

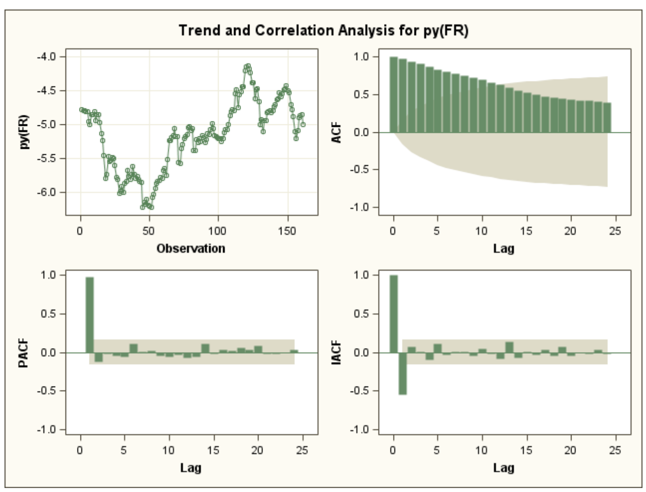
Ratios



py(FR)

Dickey-Fuller test and Augmented Dickey-Fuller test

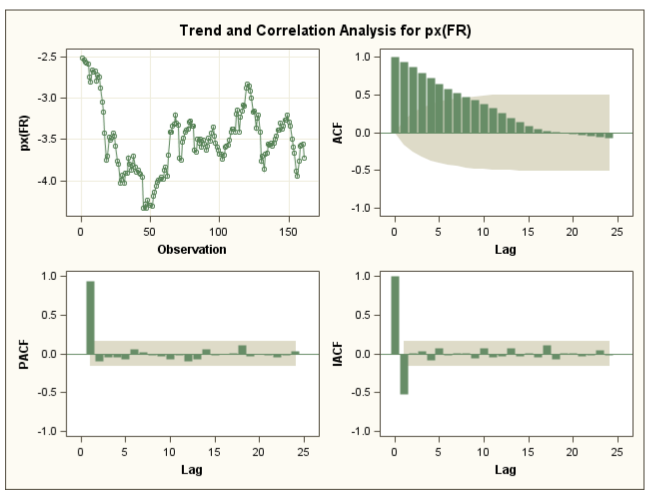
Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-0.0011	0.6815	-0.00	0.6805		
	1	-0.0086	0.6798	-0.03	0.6728		
	2	-0.0094	0.6796	-0.03	0.6719		
	3	-0.0137	0.6786	-0.04	0.6678		
	4	-0.0218	0.6768	-0.06	0.6608		
	5	-0.0338	0.6740	-0.11	0.6450		
Single Mean	0	-4.3626	0.4954	-1.52	0.5217	1.17	0.7738
	1	-5.4046	0.3926	-1.67	0.4465	1.40	0.7146
	2	-5.5257	0.3817	-1.66	0.4475	1.39	0.7156
	3	-6.0428	0.3384	-1.71	0.4225	1.48	0.6948
	4	-7.0511	0.2661	-1.82	0.3719	1.65	0.6494
	5	-5.5470	0.3798	-1.58	0.4897	1.25	0.7518
Trend	0	-8.6744	0.5217	-2.44	0.3598	3.20	0.5384
	1	-10.5917	0.3846	-2.60	0.2803	3.56	0.4657
	2	-11.2384	0.3445	-2.65	0.2593	3.69	0.4404
	3	-12.6435	0.2682	-2.75	0.2198	3.93	0.3914
	4	-15.4005	0.1584	-2.93	0.1551	4.45	0.2879
	5	-12.6195	0.2692	-2.56	0.3002	3.36	0.5070



px(FR)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	0.2160	0.7330	0.51	0.8244		
	1	0.1927	0.7273	0.40	0.7991		
	2	0.1891	0.7264	0.40	0.7968		
	3	0.1844	0.7252	0.38	0.7938		
	4	0.1759	0.7231	0.36	0.7862		
	5	0.1744	0.7227	0.39	0.7960		
Single Mean	0	-9.9392	0.1311	-2.71	0.0757	4.00	0.0882
	1	-12.1781	0.0747	-2.85	0.0542	4.33	0.0683
	2	-13.0440	0.0598	-2.90	0.0483	4.46	0.0604
	3	-14.0459	0.0462	-2.94	0.0432	4.58	0.0529
	4	-16.1308	0.0268	-3.07	0.0316	4.93	0.0407
	5	-13.2644	0.0564	-2.70	0.0772	3.86	0.0967
Trend	0	-9.8655	0.4339	-2.68	0.2455	4.01	0.3750
	1	-12.0920	0.2965	-2.84	0.1843	4.34	0.3095
	2	-12.9490	0.2536	-2.91	0.1633	4.53	0.2730
	3	-13.9438	0.2104	-2.97	0.1439	4.71	0.2365
	4	-16.0301	0.1397	-3.12	0.1065	5.14	0.1500
	5	-13.3464	0.2353	-2.76	0.2141	4.02	0.3740



Test for number of lags

Augmented Dickey-Fuller test, 0 lags delta(pxFR) = $b_1 + b_2 pxFR_{t-1}$

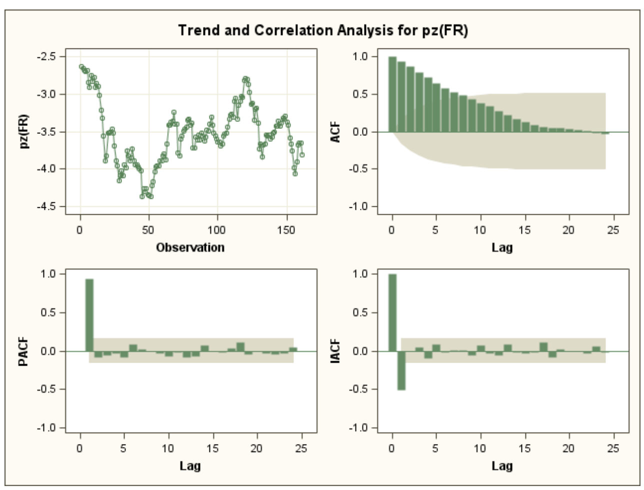
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	-0.2252	0.0810	-2.78	0.0061
lag(pxFR)	1	-0.0621	0.0230	-2.71	0.0076

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	2.5990	0.1069
AR(2)	2.6601	0.2645
AR(3)	2.7186	0.4371
AR(4)	3.0337	0.5522

pz(FR)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	0.2115	0.7319	0.50	0.8214		
	1	0.1906	0.7267	0.40	0.7991		
	2	0.1782	0.7237	0.37	0.7893		
	3	0.1795	0.7240	0.37	0.7911		
	4	0.1805	0.7242	0.37	0.7898		
	5	0.1849	0.7253	0.43	0.8063		
Single Mean	0	-9.8204	0.1350	-2.59	0.0980	3.66	0.1375
	1	-11.9202	0.0797	-2.74	0.0707	4.00	0.0887
	2	-13.2249	0.0571	-2.80	0.0615	4.14	0.0801
	3	-13.9814	0.0470	-2.83	0.0569	4.23	0.0743
	4	-16.0241	0.0275	-2.97	0.0405	4.64	0.0497
	5	-12.3519	0.0713	-2.53	0.1094	3.45	0.1908
Trend	0	-9.9646	0.4271	-2.62	0.2721	3.70	0.4389
	1	-12.0928	0.2965	-2.78	0.2073	4.06	0.3668
	2	-13.4401	0.2315	-2.85	0.1809	4.24	0.3304
	3	-14.2753	0.1974	-2.91	0.1632	4.40	0.2974
	4	-16.4850	0.1274	-3.08	0.1153	4.93	0.1911
	5	-12.9320	0.2541	-2.65	0.2598	3.63	0.4519



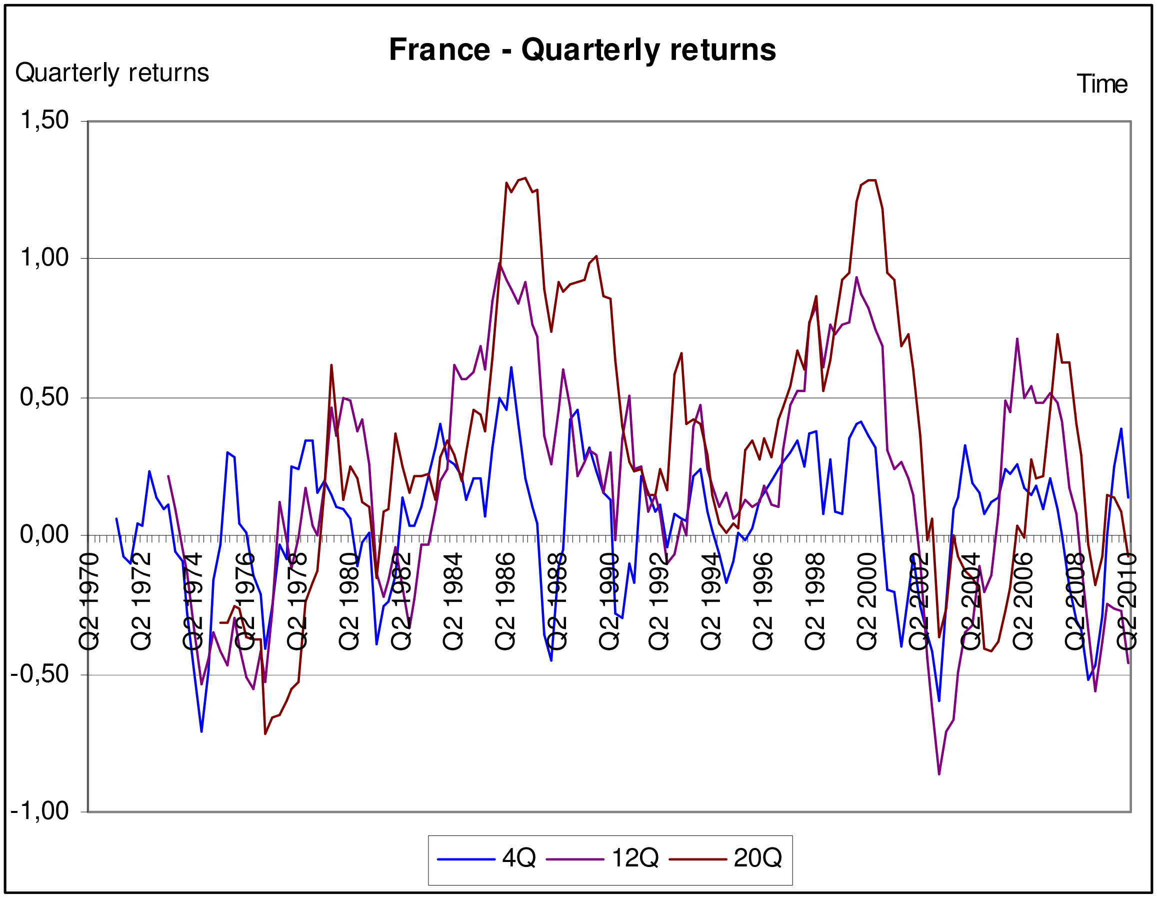
Test for number of lags

Augmented Dickey-Fuller test, 0 lags delta(pzFR) = $b_1 + b_2 pzFR_{t-1}$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	-0.2241	0.0843	-2.66	0.0086
lag(pzFR)	1	-0.0614	0.0237	-2.59	0.0106

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	2.1400	0.1435
AR(2)	2.5555	0.2787
AR(3)	2.5642	0.4638
AR(4)	2.7642	0.5980

Returns

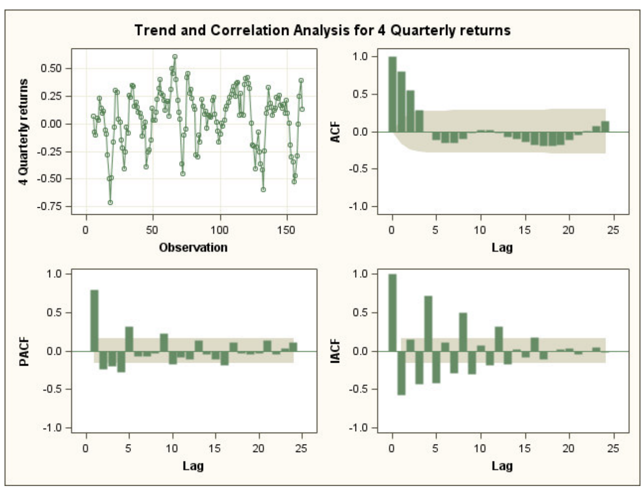


France - Quarterly returns
Quarterly returns
Time
1,50
1,00
0,50
0,00
-0,50
-1,00
Q2 1970
Q2 1972
Q2 1974
Q2 1976
Q2 1978
Q2 1980
Q2 1982
Q2 1984
Q2 1986
Q2 1988
Q2 1990
Q2 1992
Q2 1994
Q2 1996
Q2 1998
Q2 2000
Q2 2002
Q2 2004
Q2 2006
Q2 2008
Q2 2010
4Q
12Q
20Q

4 quarter return(FR)

Dickey-Fuller test and Augmented Dickey-Fuller test

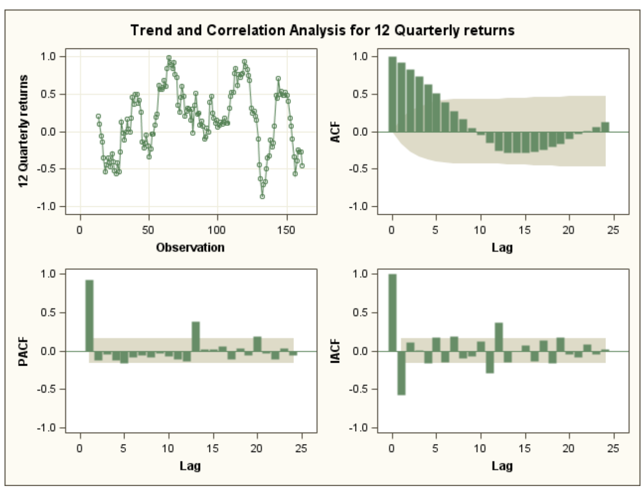
Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-30.4343	<.0001	-4.08	<.0001		
	1	-48.6958	<.0001	-4.89	<.0001		
	2	-76.7224	<.0001	-5.46	<.0001		
	3	-207.044	0.0001	-6.50	<.0001		
	4	-47.8355	<.0001	-3.95	0.0001		
	5	-55.2247	<.0001	-3.92	0.0001		
Single Mean	0	-31.9281	0.0012	-4.19	0.0010	8.76	0.0010
	1	-51.7352	0.0012	-5.04	<.0001	12.69	0.0010
	2	-83.8168	0.0012	-5.66	<.0001	16.04	0.0010
	3	-257.560	0.0001	-6.78	<.0001	22.99	0.0010
	4	-55.4792	0.0012	-4.12	0.0013	8.48	0.0010
	5	-67.0647	0.0012	-4.08	0.0014	8.35	0.0010
Trend	0	-31.9966	0.0037	-4.18	0.0060	8.74	0.0010
	1	-51.7550	0.0005	-5.02	0.0003	12.60	0.0010
	2	-83.8307	0.0005	-5.64	<.0001	15.93	0.0010
	3	-258.176	0.0001	-6.76	<.0001	22.87	0.0010
	4	-55.5403	0.0005	-4.10	0.0078	8.42	0.0012
	5	-67.6475	0.0005	-4.07	0.0085	8.30	0.0036



12 quarter return(FR)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-8.9502	0.0366	-2.09	0.0354		
	1	-12.0816	0.0146	-2.38	0.0172		
	2	-12.3500	0.0135	-2.35	0.0189		
	3	-16.0888	0.0046	-2.59	0.0097		
	4	-20.9180	0.0010	-2.86	0.0045		
	5	-22.6029	0.0006	-2.90	0.0040		
Single Mean	0	-9.8444	0.1337	-2.12	0.2380	2.30	0.4843
	1	-13.7901	0.0490	-2.47	0.1240	3.09	0.2823
	2	-14.5353	0.0403	-2.48	0.1230	3.09	0.2837
	3	-19.7886	0.0101	-2.79	0.0623	3.91	0.0941
	4	-27.9765	0.0012	-3.18	0.0232	5.07	0.0365
	5	-33.3053	0.0012	-3.32	0.0162	5.50	0.0240
Trend	0	-9.6913	0.4451	-2.06	0.5610	2.27	0.7238
	1	-13.5673	0.2249	-2.41	0.3716	3.08	0.5612
	2	-14.1497	0.2011	-2.40	0.3801	3.13	0.5512
	3	-19.2215	0.0712	-2.70	0.2378	3.95	0.3882
	4	-26.7708	0.0128	-3.07	0.1187	5.16	0.1457
	5	-31.0457	0.0046	-3.16	0.0963	5.65	0.0864



Test for number of lags

Augmented Dickey-Fuller test, 0 lags delta(12QFR) = $b_1 + b_2 12QFR_{t-1}$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.007011	0.0141	0.50	0.6196
lag(12QFR)	1	-0.0665	0.0314	-2.12	0.0359

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	3.7353	0.0533
AR(2)	3.8466	0.1461
AR(3)	6.3686	0.0950
AR(4)	8.8921	0.0639

Augmented Dickey-Fuller test, 1 lags delta($12QFR_t$) = $b_1 + b_2 12QFR_{t-1} + b_3$delta($12QFR_{t-1}$)

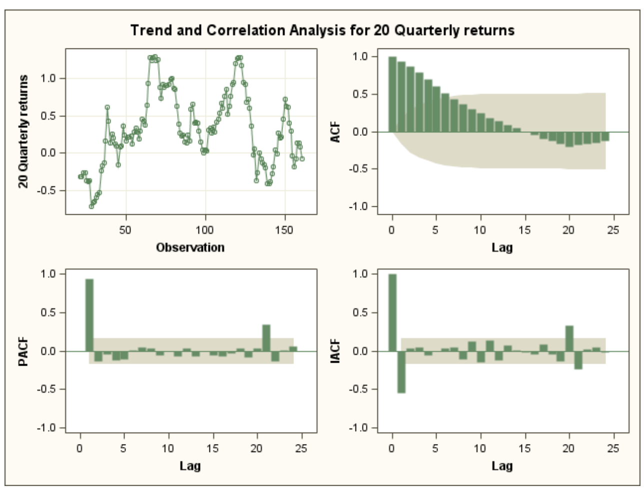
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0104	0.0141	0.74	0.4626
lag(12QFR)	1	-0.0788	0.0318	-2.47	0.0145
lag(delta(12QFR))	1	0.1603	0.0830	1.93	0.0554

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	0.3718	0.5421
AR(2)	2.4842	0.2888
AR(3)	2.8691	0.4123
AR(4)	5.2294	0.2646

20 quarter return(FR)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-5.3853	0.1088	-1.67	0.0892		
	1	-7.2691	0.0609	-1.91	0.0537		
	2	-7.8518	0.0510	-1.94	0.0499		
	3	-9.9949	0.0267	-2.14	0.0318		
	4	-11.1848	0.0188	-2.22	0.0260		
	5	-9.9393	0.0271	-2.06	0.0378		
Single Mean	0	-8.1781	0.2015	-2.11	0.2405	2.24	0.5009
	1	-11.1719	0.0954	-2.40	0.1432	2.89	0.3350
	2	-12.3421	0.0708	-2.44	0.1322	2.98	0.3103
	3	-16.3590	0.0247	-2.70	0.0763	3.66	0.1393
	4	-19.8999	0.0096	-2.90	0.0487	4.20	0.0761
	5	-18.8892	0.0126	-2.75	0.0680	3.80	0.1027
Trend	0	-7.7777	0.5914	-1.98	0.6088	2.42	0.6936
	1	-10.7490	0.3725	-2.29	0.4384	2.99	0.5798
	2	-11.8937	0.3049	-2.34	0.4112	3.06	0.5659
	3	-15.8354	0.1433	-2.61	0.2787	3.70	0.4389
	4	-19.0508	0.0731	-2.78	0.2063	4.26	0.3264
	5	-17.7451	0.0965	-2.62	0.2709	3.90	0.3971



Test for number of lags

Augmented Dickey-Fuller test, 0 lags delta(Q20FR) = $b_1 + b_2 20QFR_{t-1}$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0208	0.0162	1.29	0.1998
lag(20QFR)	1	-0.0584	0.0277	-2.11	0.0366

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	3.7374	0.0532
AR(2)	4.1505	0.1255
AR(3)	6.3492	0.0958
AR(4)	6.8023	0.1467

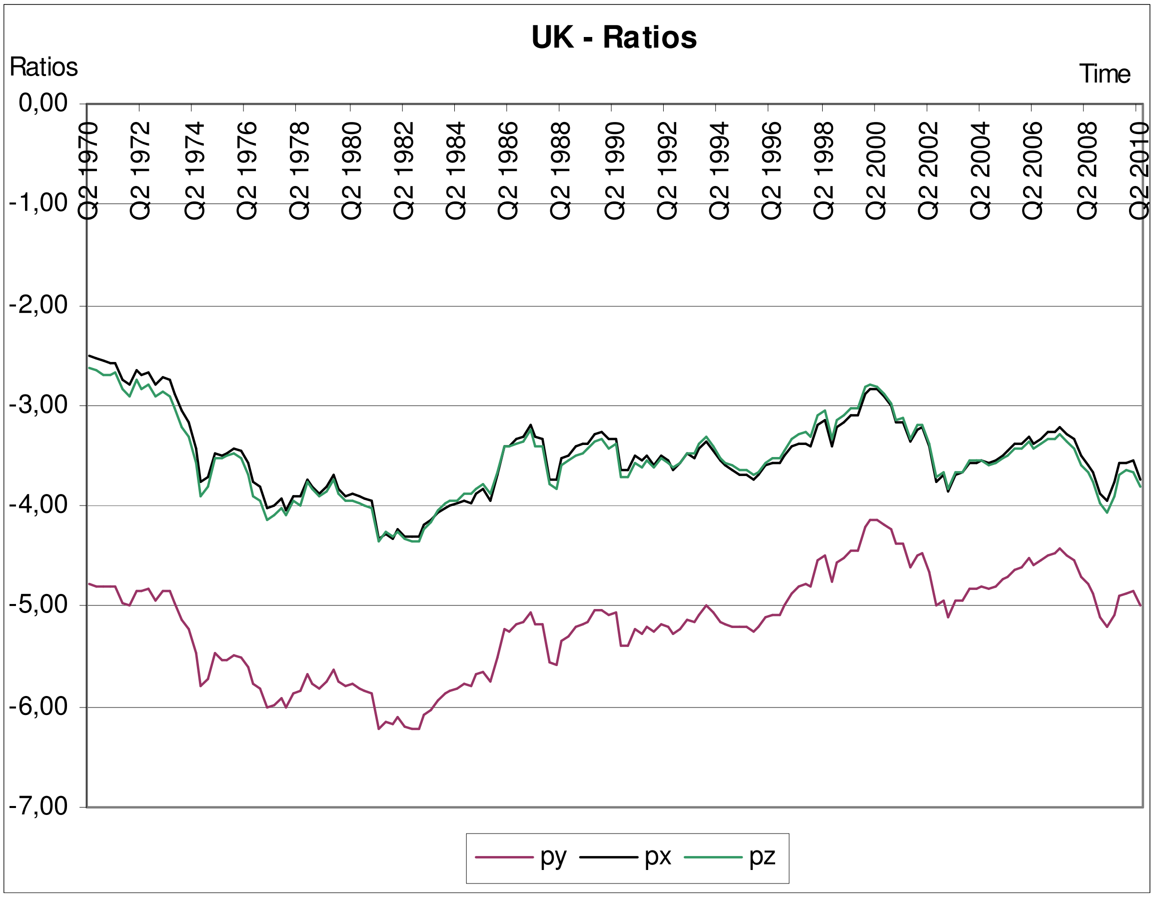
Augmented Dickey-Fuller test, 1 lags delta($20QFR_t$) = $b_1 + b_2 20QFR_{t-1} + b_3$delta($20QFR_{t-1}$)

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0235	0.0162	1.45	0.1502
lag(20QFR)	1	-0.0672	0.0280	-2.40	0.0177
lag(delta(20QFR))	1	0.1641	0.0845	1.94	0.0542

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	0.4216	0.5161
AR(2)	1.6385	0.4408
AR(3)	2.2671	0.5188
AR(4)	3.1968	0.5255

United Kingdom

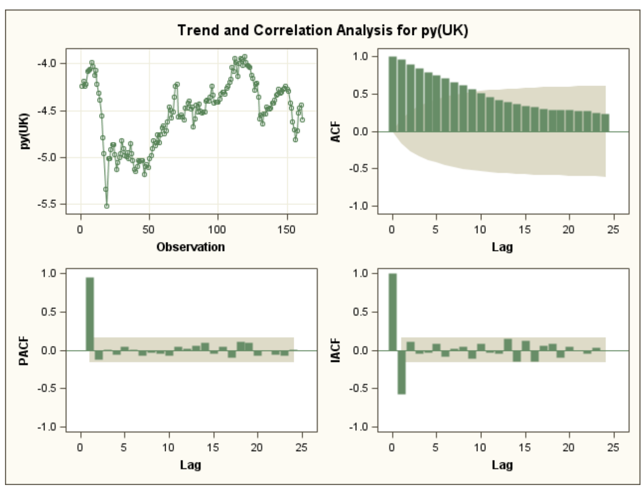
Ratios



py(UK)

Dickey-Fuller test and Augmented Dickey-Fuller test

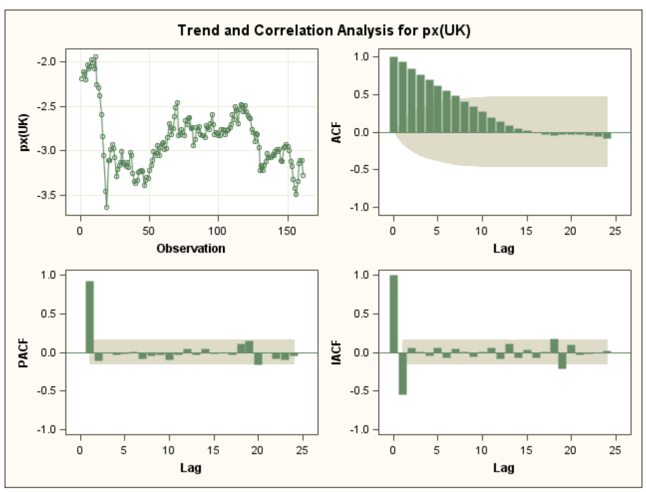
Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	0.0373	0.6904	0.13	0.7231		
	1	0.0437	0.6918	0.14	0.7251		
	2	0.0338	0.6895	0.11	0.7168		
	3	0.0400	0.6909	0.13	0.7221		
	4	0.0766	0.6994	0.28	0.7651		
	5	0.0808	0.7004	0.30	0.7723		
Single Mean	0	-7.2636	0.2529	-1.96	0.3041	1.96	0.5713
	1	-9.4604	0.1476	-2.21	0.2018	2.50	0.4339
	2	-9.0853	0.1619	-2.12	0.2373	2.28	0.4895
	3	-10.0685	0.1268	-2.20	0.2073	2.46	0.4438
	4	-8.7588	0.1754	-2.10	0.2465	2.29	0.4874
	5	-8.5113	0.1863	-2.05	0.2662	2.20	0.5104
Trend	0	-9.4850	0.4609	-2.31	0.4243	2.71	0.6353
	1	-12.5647	0.2723	-2.63	0.2658	3.52	0.4747
	2	-12.2813	0.2865	-2.53	0.3146	3.23	0.5329
	3	-14.1401	0.2026	-2.68	0.2479	3.62	0.4531
	4	-13.4628	0.2303	-2.72	0.2306	3.81	0.4152
	5	-13.9481	0.2100	-2.74	0.2222	3.88	0.4017



px(UK)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	0.2351	0.7378	0.49	0.8191		
	1	0.2419	0.7394	0.45	0.8110		
	2	0.2390	0.7387	0.47	0.8144		
	3	0.2231	0.7347	0.43	0.8059		
	4	0.3003	0.7542	0.68	0.8609		
	5	0.3017	0.7545	0.72	0.8693		
Single Mean	0	-10.2592	0.1210	-2.46	0.1266	3.34	0.2203
	1	-13.6975	0.0506	-2.85	0.0545	4.36	0.0663
	2	-13.4759	0.0535	-2.76	0.0667	4.12	0.0812
	3	-14.3798	0.0423	-2.75	0.0685	4.05	0.0852
	4	-13.4479	0.0539	-2.84	0.0557	4.52	0.0566
	5	-12.7431	0.0645	-2.70	0.0761	4.17	0.0782
Trend	0	-10.4589	0.3933	-2.44	0.3576	3.04	0.5707
	1	-13.9206	0.2115	-2.81	0.1947	4.05	0.3688
	2	-13.6658	0.2219	-2.73	0.2273	3.80	0.4181
	3	-14.6195	0.1847	-2.73	0.2280	3.77	0.4234
	4	-13.3215	0.2365	-2.76	0.2127	4.01	0.3766
	5	-12.5876	0.2707	-2.64	0.2640	3.64	0.4500



Test for number of lags

Augmented Dickey-Fuller test, 0 lags $delta(pxUK) = b_1 + b_2 pxUK_{t-1}$

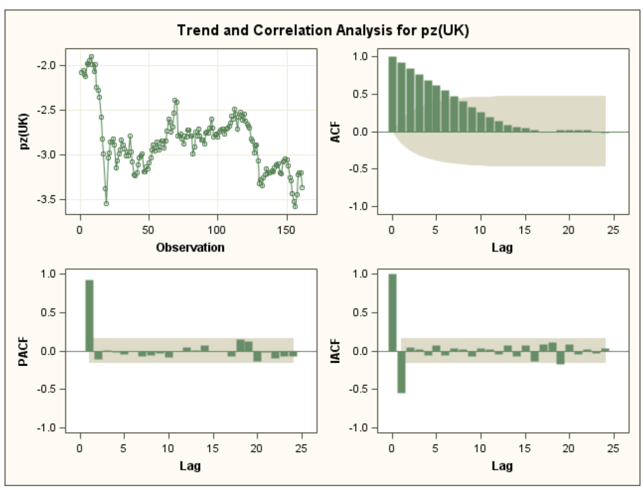
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	-0.1906	0.0751	-2.54	0.0122
lag(pxUK)	1	-0.0641	0.0260	-2.46	0.0149

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	2.3519	0.1251
AR(2)	2.4193	0.2983
AR(3)	2.5450	0.4672
AR(4)	5.0692	0.2803

pz(UK)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	0.3126	0.7574	0.65	0.8551		
	1	0.2929	0.7523	0.53	0.8289		
	2	0.2939	0.7526	0.57	0.8381		
	3	0.2988	0.7538	0.60	0.8447		
	4	0.3631	0.7703	0.83	0.8894		
	5	0.3709	0.7722	0.91	0.9020		
Single Mean	0	-9.9023	0.1323	-2.44	0.1335	3.42	0.1997
	1	-13.5851	0.0521	-2.78	0.0637	4.24	0.0738
	2	-12.6469	0.0662	-2.63	0.0902	3.83	0.0986
	3	-12.8347	0.0631	-2.61	0.0931	3.81	0.0997
	4	-12.4682	0.0693	-2.73	0.0708	4.39	0.0643
	5	-11.8168	0.0817	-2.63	0.0893	4.18	0.0773
Trend	0	-11.7425	0.3156	-2.57	0.2940	3.36	0.5068
	1	-16.4152	0.1295	-2.97	0.1443	4.45	0.2880
	2	-15.3767	0.1593	-2.80	0.1998	3.96	0.3870
	3	-15.6271	0.1515	-2.77	0.2113	3.87	0.4032
	4	-14.5118	0.1885	-2.78	0.2053	4.01	0.3758
	5	-13.6514	0.2222	-2.67	0.2517	3.68	0.4415



Test for number of lags

Augmented Dickey-Fuller test, 0 lags $delta(pzUK) = b_1 + b_2 pzUK_{t-1}$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	-0.1840	0.0727	-2.53	0.0124
lag(pzUK)	1	-0.0619	0.0254	-2.44	0.0160

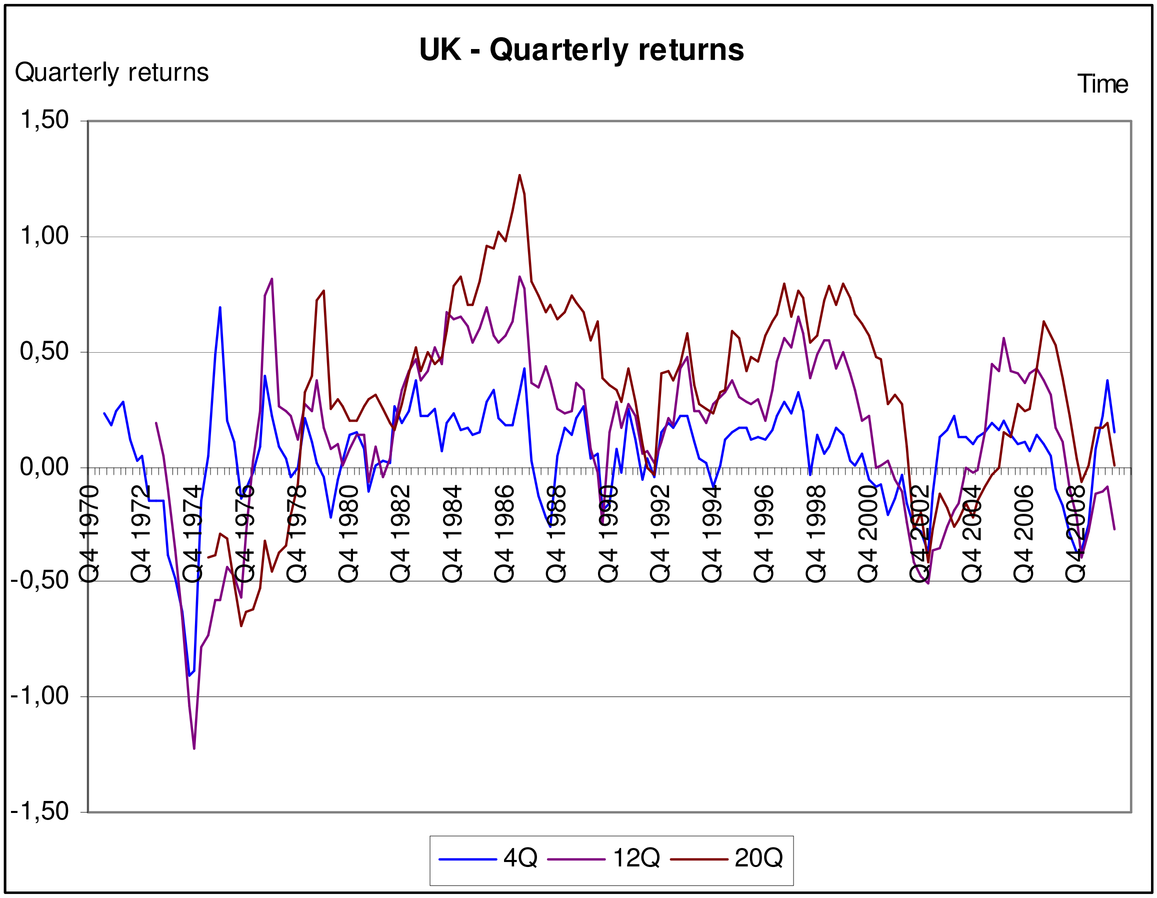
Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	3.9240	0.0476
AR(2)	4.2812	0.1176
AR(3)	4.3272	0.2282
AR(4)	6.3038	0.1776

Augmented Dickey-Fuller test, 1 lags $delta(pzUK_t) = b_1 + b_2\ pzUK_{t-1} + b_3 delta(pzUK_{t-1})$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	-0.2116	0.0739	-2.86	0.0048
lag(pzUK)	1	-0.0718	0.0258	-2.78	0.0061
lag(delta(pzUK))	1	0.1598	0.0786	2.03	0.0438

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	0.2124	0.6449
AR(2)	0.3119	0.8556
AR(3)	0.3540	0.9496
AR(4)	2.0874	0.7197

Returns

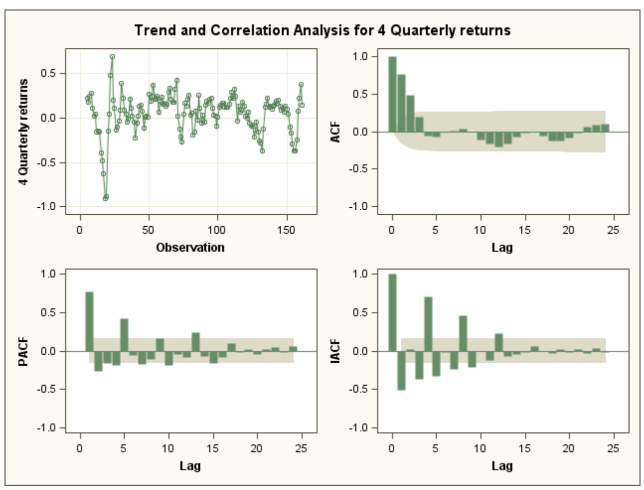


UK - Quarterly returns
Quarterly returns
Time
1,50
1,00
0,50
0,00
-0,50
-1,00
-1,50
Q4 1970
Q4 1972
Q4 1974
Q4 1976
Q4 1978
Q4 1980
Q4 1982
Q4 1984
Q4 1986
Q4 1988
Q4 1990
Q4 1992
Q4 1994
Q4 1996
Q4 1998
Q4 2000
Q4 2002
Q4 2004
Q4 2006
Q4 2008
4Q
12Q
20Q

4 quarter return(UK)

Dickey-Fuller test and Augmented Dickey-Fuller test

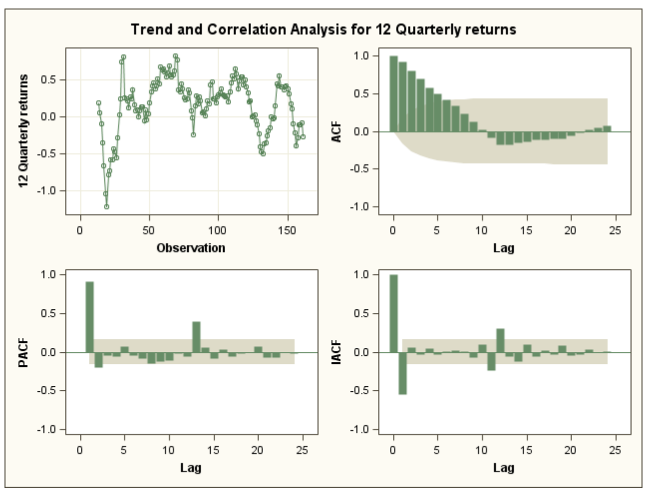
Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-34.2489	<.0001	-4.39	<.0001		
	1	-57.7284	<.0001	-5.34	<.0001		
	2	-84.8645	<.0001	-5.73	<.0001		
	3	-156.225	0.0001	-6.19	<.0001		
	4	-30.3058	<.0001	-3.39	0.0008		
	5	-32.9170	<.0001	-3.33	0.0010		
Single Mean	0	-36.3279	0.0012	-4.52	0.0003	10.22	0.0010
	1	-62.2842	0.0012	-5.52	<.0001	15.24	0.0010
	2	-95.0117	0.0012	-5.96	<.0001	17.77	0.0010
	3	-196.974	0.0001	-6.49	<.0001	21.08	0.0010
	4	-34.9216	0.0012	-3.53	0.0084	6.26	0.0068
	5	-39.6213	0.0012	-3.50	0.0092	6.15	0.0093
Trend	0	-36.3780	0.0013	-4.51	0.0020	10.22	0.0010
	1	-62.2762	0.0005	-5.51	<.0001	15.18	0.0010
	2	-94.9203	0.0005	-5.95	<.0001	17.72	0.0010
	3	-196.569	0.0001	-6.48	<.0001	21.06	0.0010
	4	-35.0418	0.0017	-3.53	0.0399	6.23	0.0558
	5	-39.7627	0.0005	-3.49	0.0436	6.11	0.0621



12 quarter return(UK)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-10.0670	0.0262	-2.26	0.0233		
	1	-15.5076	0.0054	-2.74	0.0065		
	2	-15.8483	0.0049	-2.69	0.0074		
	3	-16.8130	0.0037	-2.73	0.0066		
	4	-12.5282	0.0128	-2.41	0.0159		
	5	-12.9583	0.0113	-2.64	0.0085		
Single Mean	0	-11.4800	0.0887	-2.35	0.1565	2.81	0.3559
	1	-18.4563	0.0144	-2.93	0.0442	4.32	0.0690
	2	-19.5579	0.0107	-2.93	0.0446	4.30	0.0702
	3	-22.0349	0.0056	-3.07	0.0312	4.72	0.0473
	4	-17.3805	0.0190	-2.81	0.0592	3.97	0.0902
	5	-19.9314	0.0097	-3.27	0.0184	5.42	0.0259
Trend	0	-11.4096	0.3334	-2.32	0.4210	2.76	0.6257
	1	-18.3226	0.0864	-2.89	0.1701	4.29	0.3198
	2	-19.2789	0.0704	-2.87	0.1769	4.30	0.3173
	3	-21.3689	0.0445	-2.97	0.1435	4.82	0.2145
	4	-16.2538	0.1324	-2.66	0.2530	4.36	0.3065
	5	-17.8308	0.0955	-3.06	0.1199	6.34	0.0501



Test for number of lags

Augmented Dickey-Fuller test, 0 lags delta(12QUK) = $b_1 + b_2 12QUK_{t-1}$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.009442	0.0132	0.72	0.4755
lag(12QUK)	1	-0.0776	0.0329	-2.35	0.0199

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	7.8083	0.0052
AR(2)	7.9391	0.0189
AR(3)	8.3652	0.0390
AR(4)	9.7139	0.0455

Augmented Dickey-Fuller test, 1 lags delta($12QUK_t$) = $b_1 + b_2 12QUK_{t-1} + b_3$delta($12QUK_{t-1}$)

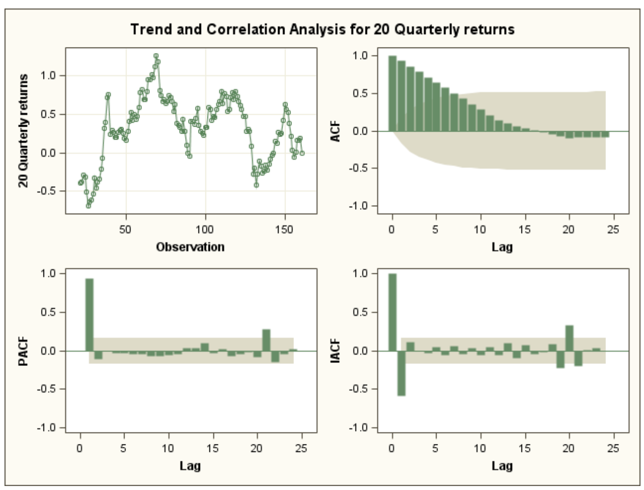
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0139	0.0130	1.07	0.2861
lag(12QUK)	1	-0.0965	0.0329	-2.93	0.0039
lag(delta(12QUK))	1	0.2313	0.0815	2.84	0.0052

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	0.4005	0.5268
AR(2)	2.1290	0.3449
AR(3)	2.1290	0.5461
AR(4)	4.8503	0.3030

20 quarter return(UK)

Dickey-Fuller test and Augmented Dickey-Fuller test

Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-4.9646	0.1239	-1.63	0.0968		
	1	-6.3724	0.0803	-1.81	0.0664		
	2	-6.1848	0.0850	-1.74	0.0771		
	3	-6.2004	0.0846	-1.73	0.0797		
	4	-5.6521	0.1001	-1.69	0.0861		
	5	-5.7044	0.0985	-1.75	0.0762		
Single Mean	0	-8.8429	0.1710	-2.29	0.1756	2.66	0.3931
	1	-11.4532	0.0889	-2.52	0.1123	3.20	0.2545
	2	-11.3802	0.0905	-2.42	0.1384	2.94	0.3226
	3	-12.0186	0.0769	-2.45	0.1291	3.03	0.2994
	4	-12.1662	0.0740	-2.58	0.1001	3.38	0.2106
	5	-13.6245	0.0507	-2.84	0.0557	4.14	0.0802
Trend	0	-8.5801	0.5274	-2.22	0.4750	3.12	0.5541
	1	-11.1233	0.3493	-2.46	0.3456	3.59	0.4605
	2	-11.0264	0.3551	-2.37	0.3932	3.28	0.5211
	3	-11.5692	0.3229	-2.41	0.3722	3.45	0.4888
	4	-11.4852	0.3276	-2.53	0.3110	4.18	0.3429
	5	-12.5705	0.2693	-2.82	0.1937	5.39	0.0998



Test for number of lags

Augmented Dickey-Fuller test, 0 lags delta(20QUK) = $b_1 + b_2 20QUK_{t-1}$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0230	0.0142	1.62	0.1076
lag(20QUK)	1	-0.0632	0.0276	-2.29	0.0234

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	2.7863	0.0951
AR(2)	2.8032	0.2462
AR(3)	2.8111	0.4217
AR(4)	3.4733	0.4820

Augmented Dickey-Fuller test, 1 lags delta($20QUK_t$) = $b_1 + b_2 20QUK_{t-1} + b_3$delta($20QUK_{t-1}$)

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	0.0252	0.0144	1.75	0.0822
lag(20QUK)	1	-0.0707	0.0280	-2.52	0.0128
lag(delta(20QUK))	1	0.1422	0.0846	1.68	0.0952

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	0.0057	0.9398
AR(2)	0.0274	0.9864
AR(3)	0.1011	0.9917
AR(4)	0.7574	0.9441

Appendix C - Estimated ratios with interest rate

Denmark

RESpy

$$p_t = \beta_0 + \beta_1 y_{t-1} + \hat{\mu}_t$$

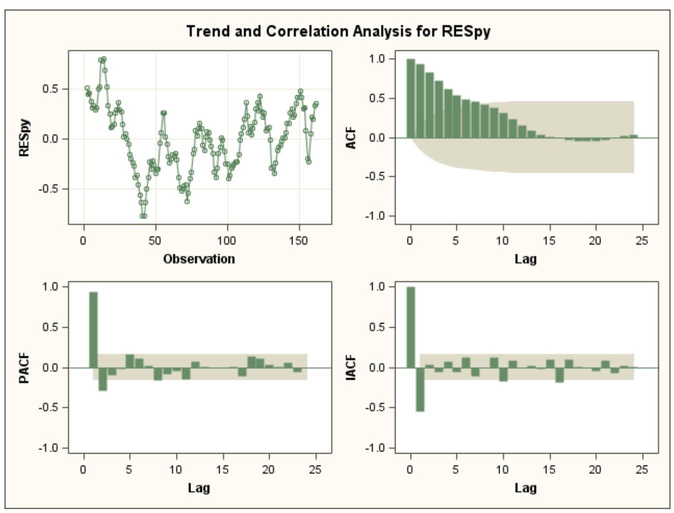
Number of Observations Read	162
Number of Observations Used	161
Number of Observations with Missing Values	1

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	61.97079	61.97079	615.68	<.0001
Error	159	16.00415	0.10066		
Corrected Total	160	77.97494			

Root MSE	0.31726	**R-Square**	0.7948
Dependent Mean	2.30117	**Adj R-Sq**	0.7935
Coeff Var	13.78696		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-15.45390	0.71600	-21.58	<.0001
lag(yDK)	1	2.56990	0.10357	24.81	<.0001

Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-9.4767	0.0314	-2.29	0.0217		
	1	-19.1333	0.0018	-3.10	0.0021		
	2	-23.5519	0.0004	-3.33	0.0010		
	3	-22.7345	0.0005	-3.12	0.0020		
	4	-15.2119	0.0059	-2.56	0.0105		
	5	-12.6625	0.0124	-2.37	0.0177		
Single Mean	0	-9.4807	0.1469	-2.28	0.1784	2.61	0.4046
	1	-19.1395	0.0122	-3.09	0.0295	4.78	0.0454
	2	-23.5669	0.0038	-3.32	0.0158	5.51	0.0236
	3	-22.7522	0.0047	-3.11	0.0278	4.85	0.0433
	4	-15.2362	0.0339	-2.56	0.1041	3.27	0.2368
	5	-12.6992	0.0653	-2.37	0.1523	2.81	0.3541
Trend	0	-9.4871	0.4608	-2.29	0.4379	3.28	0.5227
	1	-19.0187	0.0754	-3.09	0.1118	5.07	0.1649
	2	-23.3469	0.0291	-3.33	0.0659	5.84	0.0763
	3	-22.5178	0.0350	-3.12	0.1045	5.14	0.1502
	4	-15.1507	0.1664	-2.58	0.2912	3.64	0.4497
	5	-12.7083	0.2648	-2.40	0.3760	3.29	0.5192



Test for number of lags

Augmented Engle-Granger test, 0 lags   delta($RESpyDK_t$) = b_1 RESpyDK $_{t-1}$

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	21.3507	<.0001
AR(2)	22.4164	<.0001
AR(3)	22.4205	<.0001
AR(4)	26.6570	<.0001

Augmented Engle-Granger test, 1 lags $\quad$ delta($RESpyDK_t$) = b_1 $RESpyDK_{t-1}$ + b_2 delta($RESpyDK_{t-1}$)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	1.1613	0.2812
AR(2)	1.1672	0.5579
AR(3)	6.0057	0.1113
AR(4)	7.5059	0.1114

The Netherlands

RESpy

$$p_t = \beta_0 + \beta_1 y_{t-1} + \hat{\mu}_t$$

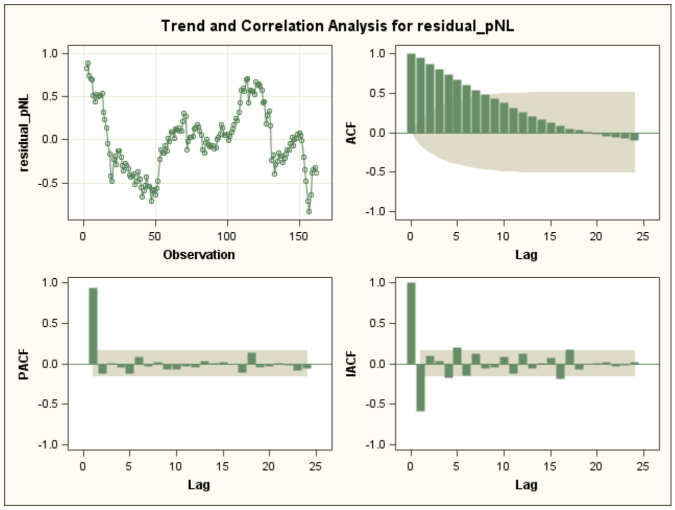
Number of Observations Read	162
Number of Observations Used	161
Number of Observations with Missing Values	1

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	63.03656	63.03656	449.03	<.0001
Error	159	22.32095	0.14038		
Corrected Total	160	85.35750			

Root MSE	0.37468	R-Square	0.7385
Dependent Mean	1.50121	Adj R-Sq	0.7369
Coeff Var	24.95842		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-10.84882	0.58356	-18.59	<.0001
lag(yNL)	1	2.15909	0.10189	21.19	<.0001

Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-8.5619	0.0413	-2.40	0.0165		
	1	-11.2321	0.0187	-2.69	0.0073		
	2	-10.7659	0.0214	-2.47	0.0135		
	3	-11.6331	0.0167	-2.50	0.0125		
	4	-14.4196	0.0075	-2.68	0.0077		
	5	-10.1157	0.0259	-2.13	0.0321		
Single Mean	0	-8.5410	0.1852	-2.39	0.1467	3.27	0.2374
	1	-11.1770	0.0962	-2.69	0.0778	4.00	0.0884
	2	-10.7017	0.1083	-2.47	0.1237	3.35	0.2180
	3	-11.5339	0.0878	-2.51	0.1154	3.41	0.2008
	4	-14.2127	0.0442	-2.68	0.0797	3.82	0.0995
	5	-9.9441	0.1307	-2.14	0.2301	2.52	0.4277
Trend	0	-8.5604	0.5305	-2.39	0.3840	3.03	0.5730
	1	-11.2246	0.3454	-2.71	0.2354	3.84	0.4092
	2	-10.7781	0.3727	-2.49	0.3304	3.20	0.5381
	3	-11.6617	0.3199	-2.54	0.3090	3.30	0.5171
	4	-14.4659	0.1902	-2.73	0.2267	3.80	0.4183
	5	-10.1880	0.4108	-2.17	0.5034	2.36	0.7054



Test for number of lags

Augmented Engle-Granger test, 0 lags   delta($RESpyNL_t$) = b_1 $RESpyNL_{t-1}$

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	2.8194	0.0931
AR(2)	2.8740	0.2376
AR(3)	3.0676	0.3813
AR(4)	4.4168	0.3525

Augmented Engle-Granger test, 1 lags   delta($RESpyNL_t$) = b_1 $RESpyNL_{t-1}$+ $b_2$delta($RESpyNL_{t-1}$)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	0.0547	0.8150
AR(2)	0.5942	0.7430
AR(3)	0.8017	0.8490
AR(4)	3.1214	0.5377

France

RESpy

$$p_t = \beta_0 + \beta_1 y_{t-1} + \hat{\mu}_t$$

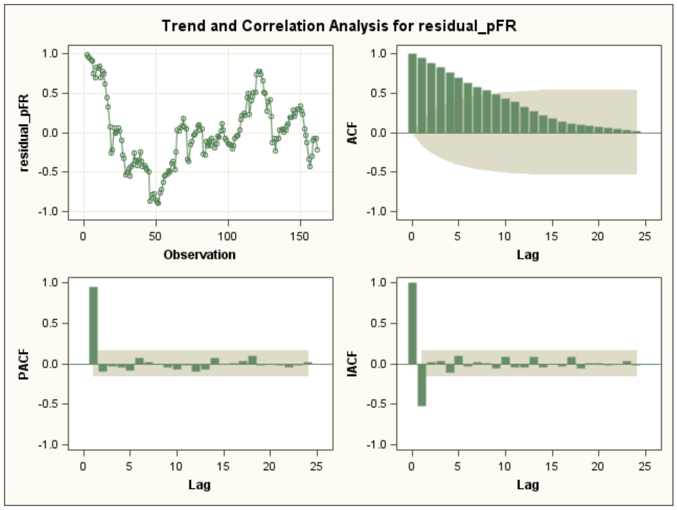
Number of Observations Read	162
Number of Observations Used	161
Number of Observations with Missing Values	1

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	47.34029	47.34029	259.88	<.0001
Error	159	28.96405	0.18216		
Corrected Total	160	76.30433			

Root MSE	0.42681	**R-Square**	0.6204
Dependent Mean	1.84666	**Adj R-Sq**	0.6180
Coeff Var	23.11232		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-12.64548	0.89961	-14.06	<.0001
lag(yFR)	1	2.06463	0.12807	16.12	<.0001

Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-8.5947	0.0409	-2.52	0.0119		
	1	-10.5068	0.0231	-2.65	0.0083		
	2	-10.9363	0.0204	-2.66	0.0081		
	3	-12.0288	0.0149	-2.70	0.0071		
	4	-14.2511	0.0078	-2.83	0.0049		
	5	-11.3850	0.0179	-2.45	0.0141		
Single Mean	0	-8.5859	0.1832	-2.51	0.1145	3.50	0.1793
	1	-10.4883	0.1143	-2.65	0.0855	3.78	0.1078
	2	-10.9138	0.1027	-2.66	0.0829	3.81	0.0998
	3	-11.9941	0.0782	-2.72	0.0732	3.94	0.0921
	4	-14.1701	0.0447	-2.85	0.0540	4.27	0.0719
	5	-11.3398	0.0922	-2.48	0.1225	3.27	0.2366
Trend	0	-8.8549	0.5078	-2.59	0.2870	3.78	0.4226
	1	-10.7941	0.3717	-2.74	0.2234	4.06	0.3650
	2	-11.2826	0.3418	-2.78	0.2081	4.18	0.3423
	3	-12.4388	0.2784	-2.86	0.1800	4.37	0.3032
	4	-14.7579	0.1797	-3.01	0.1315	4.81	0.2156
	5	-12.0587	0.2979	-2.65	0.2599	3.69	0.4390



Test for number of lags

Augmented Engle-Granger test, 0 lags delta(RESpyFR$_t$) = b_1 RESpyFR $_{t-1}$

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	2.7134	0.0995
AR(2)	2.7324	0.2551
AR(3)	3.0523	0.3836
AR(4)	4.0135	0.4042

Augmented Engle-Granger test, 1 lags delta(RESpyFR$_t$) = b_1 RESpyFR $_{t-1}$+ $b_2$delta(RESpyFR $_{t-1}$)

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	0.0520	0.8196
AR(2)	0.4637	0.7931
AR(3)	0.4792	0.9234
AR(4)	1.9728	0.7408

United Kingdom

RESpy

$$p_t = \beta_0 + \beta_1 y_{t-1} + \hat{\mu}_t$$

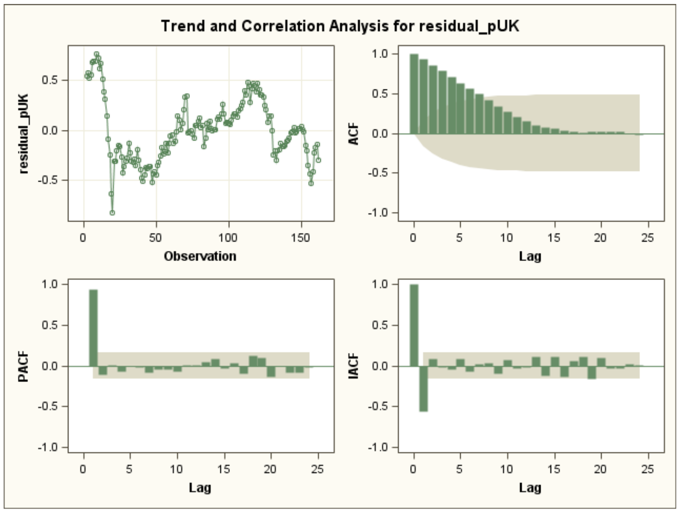
Number of Observations Read	162
Number of Observations Used	161
Number of Observations with Missing Values	1

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	29.49828	29.49828	308.97	<.0001
Error	159	15.18028	0.09547		
Corrected Total	160	44.67856			

Root MSE	0.30899	**R-Square**	0.6602
Dependent Mean	2.21680	**Adj R-Sq**	0.6581
Coeff Var	13.93845		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-8.28016	0.59768	-13.85	<.0001
lag(yUK)	1	1.55713	0.08859	17.58	<.0001

Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-9.9850	0.0270	-2.40	0.0163		
	1	-13.1347	0.0108	-2.70	0.0071		
	2	-12.6373	0.0125	-2.57	0.0103		
	3	-14.6805	0.0069	-2.72	0.0068		
	4	-13.6611	0.0093	-2.72	0.0068		
	5	-14.0721	0.0083	-2.71	0.0070		
Single Mean	0	-9.9686	0.1301	-2.39	0.1455	3.08	0.2864
	1	-13.1000	0.0590	-2.70	0.0767	3.85	0.0978
	2	-12.5958	0.0671	-2.57	0.1019	3.49	0.1820
	3	-14.6046	0.0399	-2.72	0.0733	3.89	0.0950
	4	-13.5399	0.0526	-2.73	0.0722	4.06	0.0850
	5	-13.8771	0.0482	-2.72	0.0735	4.06	0.0848
Trend	0	-9.9571	0.4276	-2.38	0.3871	2.89	0.5998
	1	-13.0898	0.2472	-2.69	0.2409	3.68	0.4416
	2	-12.6009	0.2704	-2.57	0.2957	3.34	0.5106
	3	-14.6308	0.1843	-2.73	0.2279	3.77	0.4246
	4	-13.6684	0.2215	-2.76	0.2156	3.94	0.3894
	5	-14.1505	0.2020	-2.77	0.2098	3.99	0.3797



Test for number of lags

Augmented Engle-Granger test, 0 lags delta($RESpyUK_t$) = b_1 $RESpyUK_{t-1}$

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	2.8309	0.0925
AR(2)	2.8655	0.2386
AR(3)	3.3327	0.3431
AR(4)	4.8158	0.3067

Augmented Engle-Granger test, 1 lags delta($RESpyUK_t$) = b_1 $RESpyUK_{t-1}$+ $b_2$delta($RESpyUK_{t-1}$)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	0.0441	0.8337
AR(2)	0.1029	0.9498
AR(3)	0.6334	0.8888
AR(4)	1.8771	0.7583

Appendix D - Results from in-sample testing

Denmark

Output

4Q

$$r_{t,t+4} = \beta_1 + \beta_2 RESpy_t + \varepsilon_t$$

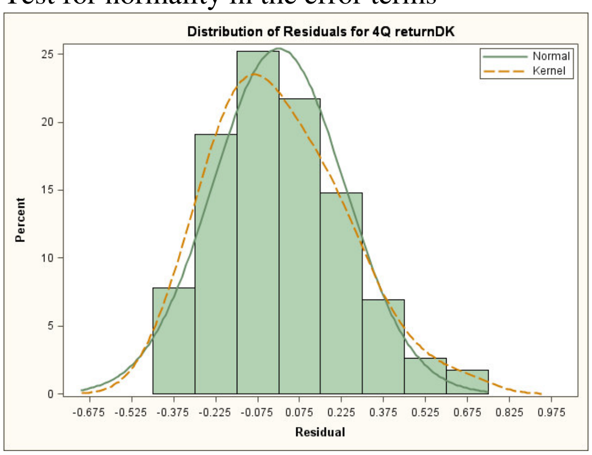
Number of Observations Read	115
Number of Observations Used	115

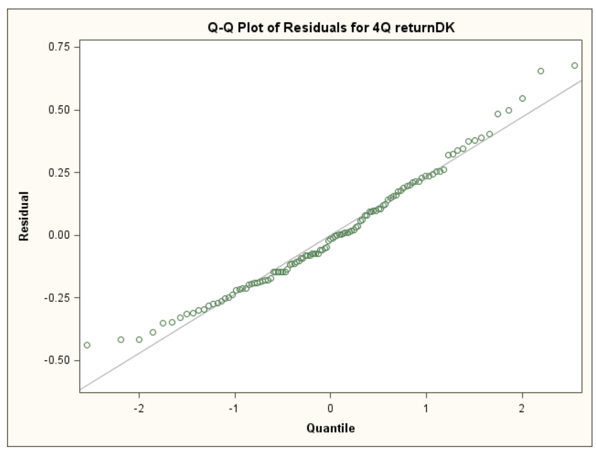
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	1.16327	1.16327	20.81	<.0001
Error	113	6.31651	0.05590		
Corrected Total	114	7.47977			

Root MSE	0.23643	**R-Square**	0.1555
Dependent Mean	0.08004	**Adj R-Sq**	0.1480
Coeff Var	295.38851		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.06362	0.02234	2.85	0.0052
RESpy4QDK	1	-0.30211	0.06623	-4.56	<.0001

Test for normality in the error terms

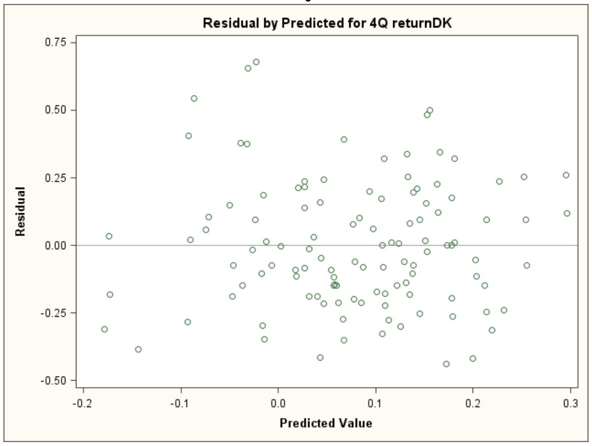


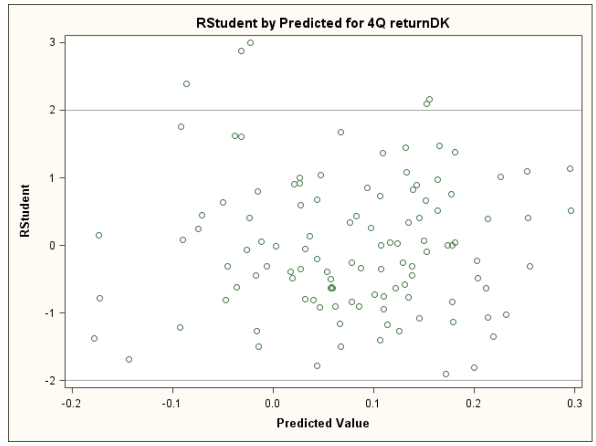


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	5.2339	0.0730	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.01609	0.00804	1.35	0.2646
Error	112	0.66963	0.00598		
Corrected Total	114	0.68572			

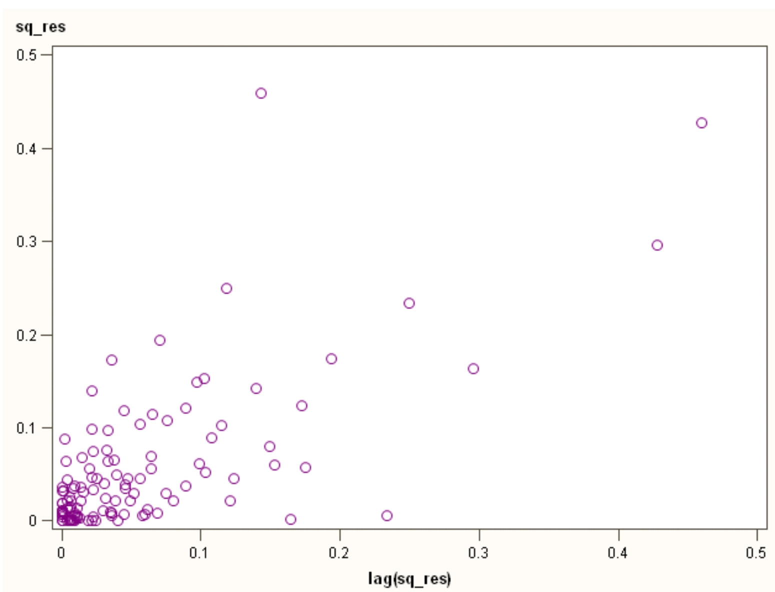
Root MSE	0.07732	**R-Square**	0.0235
Dependent Mean	0.05493	**Adj R-Sq**	0.0060
Coeff Var	140.77638		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.05259	0.00924	5.69	<.0001
RESpy4QDK	1	0.03182	0.02166	1.47	0.1447
sq_RESpy	1	0.03576	0.04969	0.72	0.4733

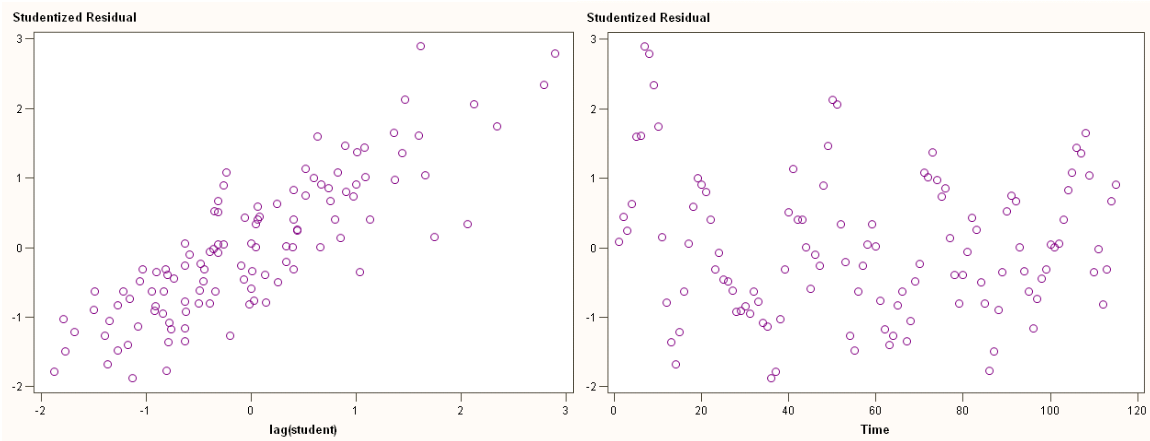
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_4Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	56.3672	<.0001	55.3825	<.0001
2	66.9076	<.0001	62.4579	<.0001
3	67.0459	<.0001	62.4581	<.0001
4	67.2822	<.0001	62.7185	<.0001
5	67.4388	<.0001	62.7816	<.0001
6	67.9552	<.0001	63.4823	<.0001
7	68.6713	<.0001	63.4883	<.0001
8	69.6760	<.0001	63.7897	<.0001
9	70.6537	<.0001	63.9148	<.0001
10	71.5794	<.0001	64.1494	<.0001
11	72.3506	<.0001	64.1744	<.0001
12	72.3513	<.0001	64.6306	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	83.4028	<.0001
AR(2)	88.6066	<.0001
AR(3)	91.2040	<.0001
AR(4)	91.4051	<.0001

Durbin-Watson d test

Durbin-Watson D	0.320
Number of Observations	115
1st Order Autocorrelation	0.837

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.063625	0.0408	1.56	0.1215
b1	-0.30211	0.1218	-2.48	0.0146

12Q

$$r_{t,t+12} = \beta_1 + \beta_2 RESpy_t + \varepsilon_t$$

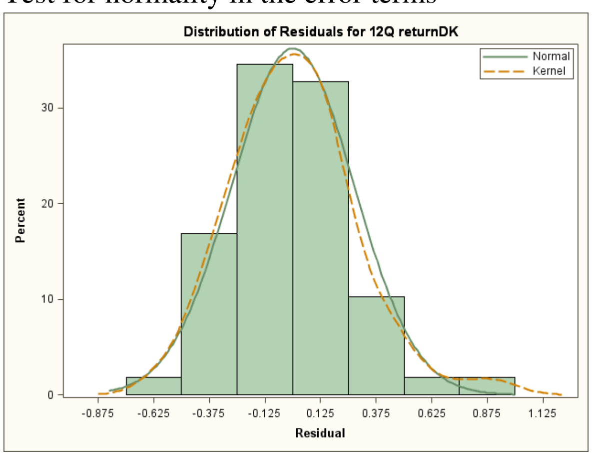
Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

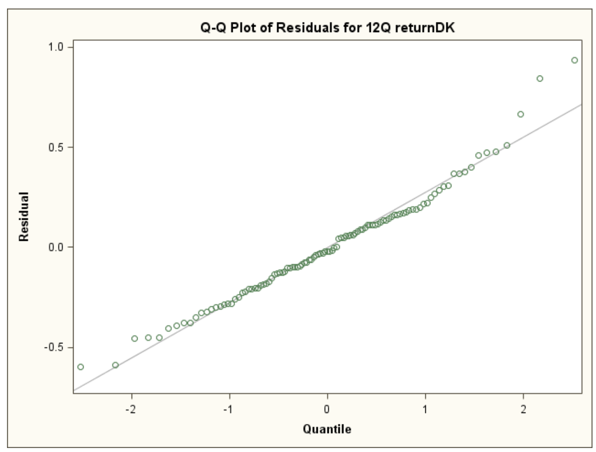
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	6.99163	6.99163	91.26	<.0001
Error	105	8.04465	0.07662		
Corrected Total	106	15.03628			

Root MSE	0.27680	**R-Square**	0.4650
Dependent Mean	0.23012	**Adj R-Sq**	0.4599
Coeff Var	120.28217		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.17802	0.02731	6.52	<.0001
RESpy12QDK	1	-0.75367	0.07890	-9.55	<.0001

Test for normality in the error terms

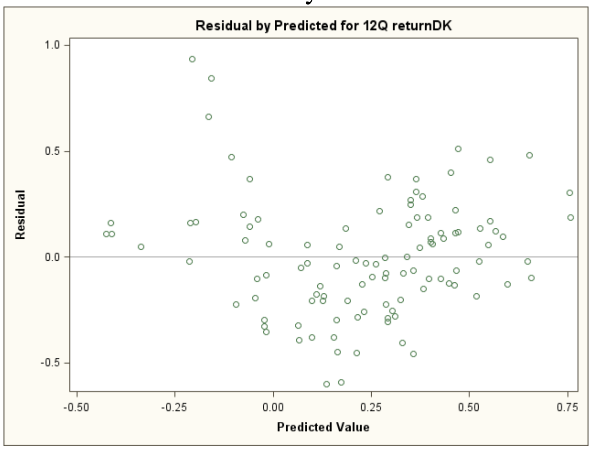


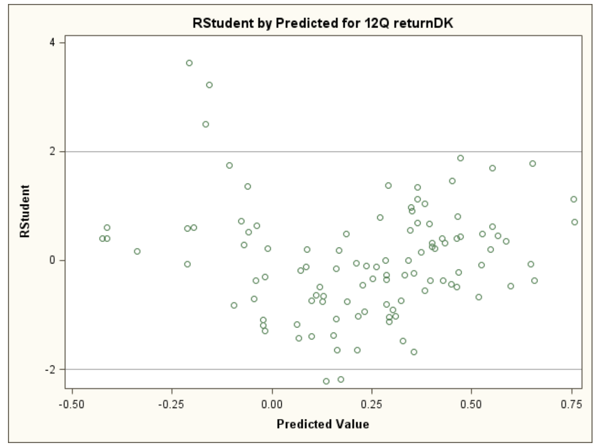


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	9.7800	0.0075	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.07951	0.03975	2.42	0.0936
Error	104	1.70608	0.01640		
Corrected Total	106	1.78559			

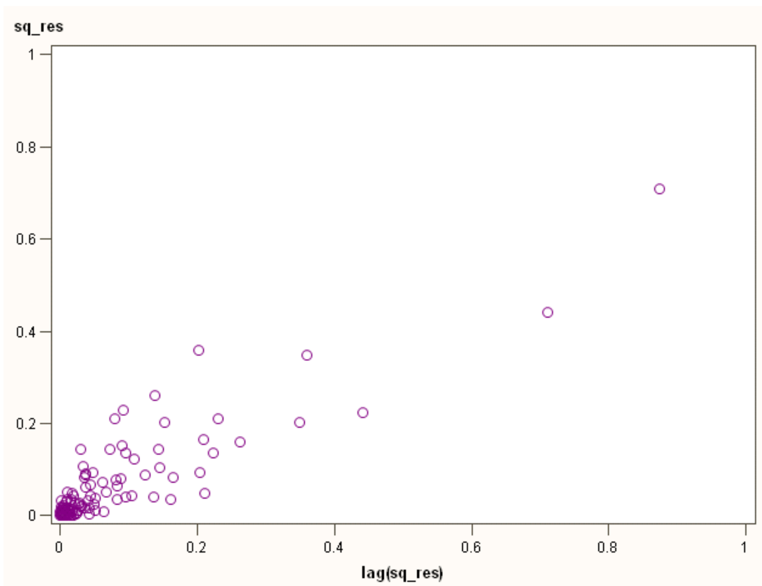
Root MSE	0.12808	**R-Square**	0.0445
Dependent Mean	0.07518	**Adj R-Sq**	0.0262
Coeff Var	170.35707		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.07887	0.01616	4.88	<.0001
RESpy12QDK	1	0.07991	0.03652	2.19	0.0309
sq_RESpy	1	0.01533	0.08356	0.18	0.8548

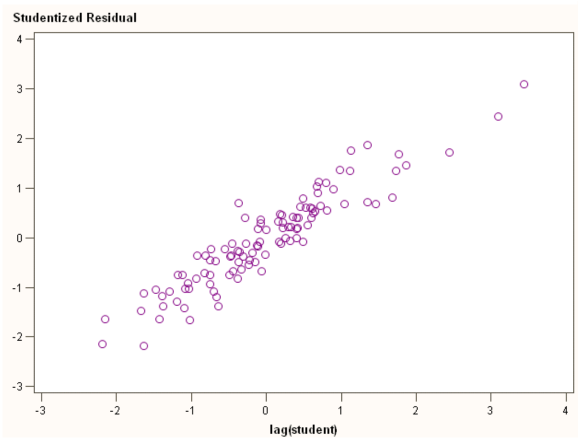
Autoregressive conditional heteroscedasticity (ARCH)

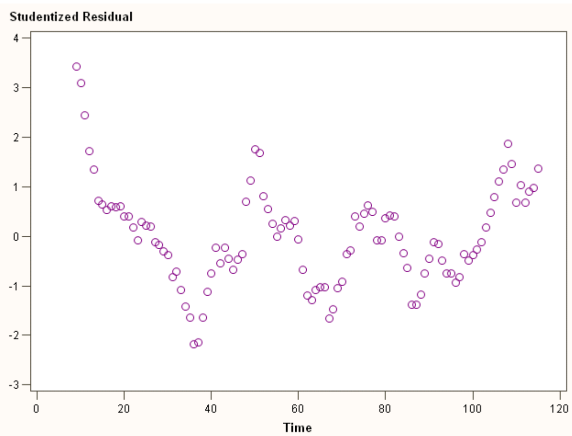
Dependent Variable	residual_12Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	54.8720	<.0001	48.3806	<.0001
2	70.9496	<.0001	51.9003	<.0001
3	73.4406	<.0001	52.1057	<.0001
4	73.4642	<.0001	52.2532	<.0001
5	73.9060	<.0001	52.5177	<.0001
6	74.7284	<.0001	52.5672	<.0001
7	75.9438	<.0001	52.9308	<.0001
8	77.3645	<.0001	53.0819	<.0001
9	78.9681	<.0001	53.4571	<.0001
10	80.6211	<.0001	53.7188	<.0001
11	81.8150	<.0001	53.8215	<.0001
12	82.3790	<.0001	53.9311	<.0001



Test for autocorrelation in the error terms





LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	83.4137	<.0001
AR(2)	84.3059	<.0001
AR(3)	84.4956	<.0001
AR(4)	84.5219	<.0001

Durbin-Watson d test

Durbin-Watson D	0.127
Number of Observations	107
1st Order Autocorrelation	0.873

The regression with Newey-West HAC standard errors, 12 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.178017	0.0725	2.45	0.0158
b1	-0.75367	0.1865	-4.04	0.0001

20Q

$$r_{t,t+20} = \beta_1 + \beta_2 RESpy_t + \varepsilon_t$$

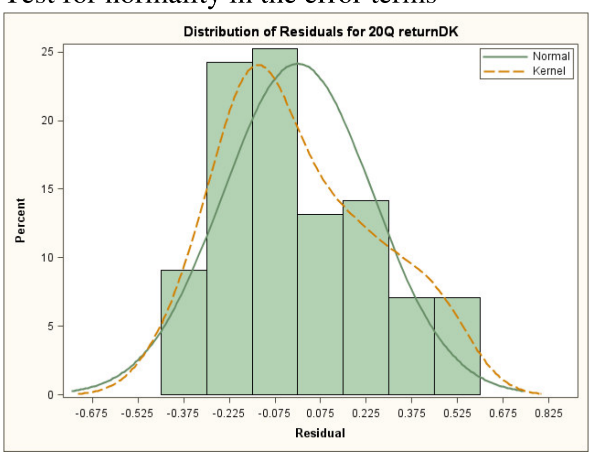
Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

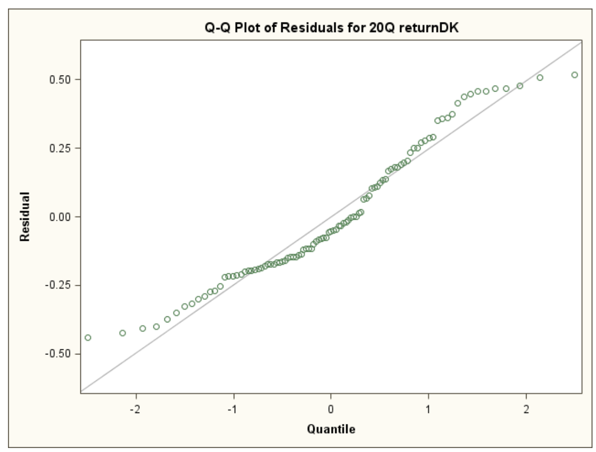
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	10.19331	10.19331	164.42	<.0001
Error	97	6.01358	0.06200		
Corrected Total	98	16.20689			

Root MSE	0.24899	**R-Square**	0.6289
Dependent Mean	0.34750	**Adj R-Sq**	0.6251
Coeff Var	71.65166		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.29861	0.02531	11.80	<.0001
RESpy20QDK	1	-0.92488	0.07213	-12.82	<.0001

Test for normality in the error terms

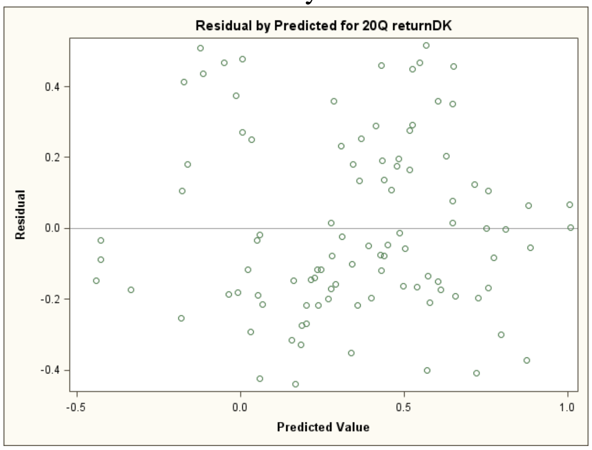


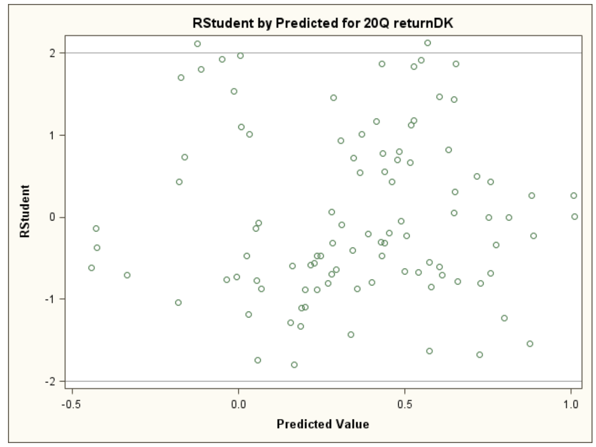


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	5.5152	0.0634	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.01041	0.00521	1.09	0.3389
Error	96	0.45661	0.00476		
Corrected Total	98	0.46702			

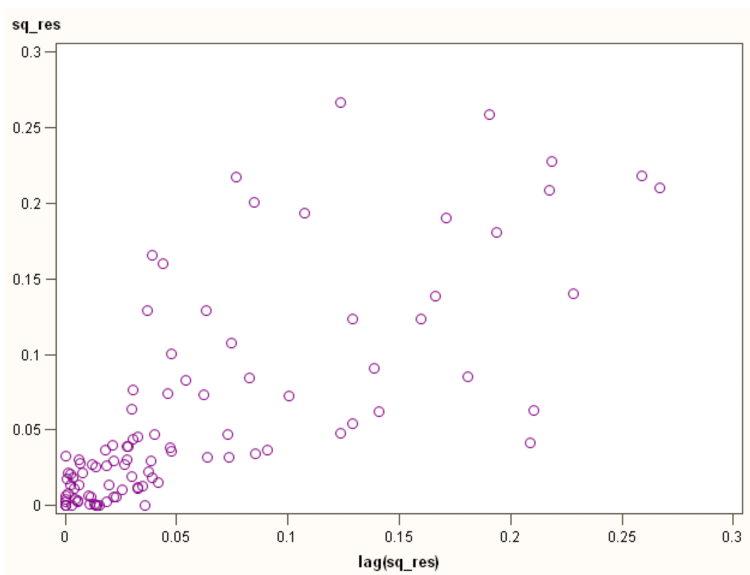
Root MSE	0.06897	**R-Square**	0.0223
Dependent Mean	0.06074	**Adj R-Sq**	0.0019
Coeff Var	113.53744		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.06711	0.00897	7.48	<.0001
RESpy20QDK	1	0.02348	0.01998	1.18	0.2428
sq_RESpy	1	-0.04161	0.04526	-0.92	0.3602

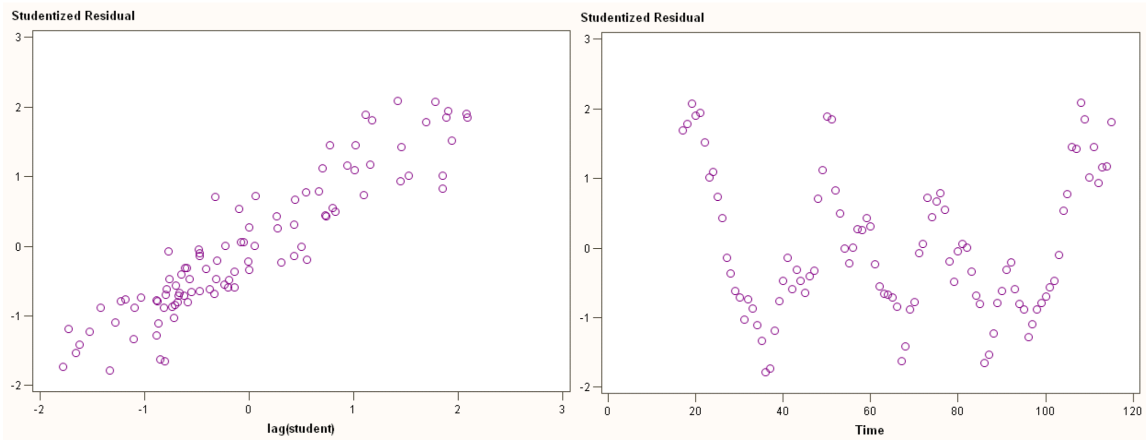
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_20Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	52.4596	<.0001	50.6659	<.0001
2	71.9580	<.0001	53.1599	<.0001
3	75.2059	<.0001	54.5157	<.0001
4	75.2177	<.0001	54.8906	<.0001
5	76.4094	<.0001	54.8906	<.0001
6	77.9350	<.0001	54.9494	<.0001
7	79.5087	<.0001	54.9507	<.0001
8	82.0082	<.0001	56.0516	<.0001
9	83.5468	<.0001	56.0519	<.0001
10	84.7870	<.0001	56.5359	<.0001
11	85.1795	<.0001	56.5524	<.0001
12	85.2391	<.0001	56.6535	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	82.0247	<.0001
AR(2)	83.1549	<.0001
AR(3)	84.0889	<.0001
AR(4)	84.0995	<.0001

Durbin-Watson d test

Durbin-Watson D	0.149
Number of Observations	99
1st Order Autocorrelation	0.895

The regression with Newey-West HAC standard errors, 20 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.29861	0.0566	5.28	<.0001
b1	-0.92488	0.1457	-6.35	<.0001

Export

4Q

$$r_{t,t+4} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

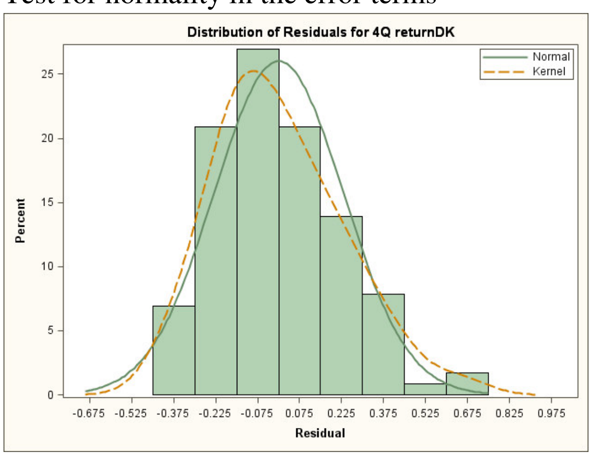
Number of Observations Read	115
Number of Observations Used	115

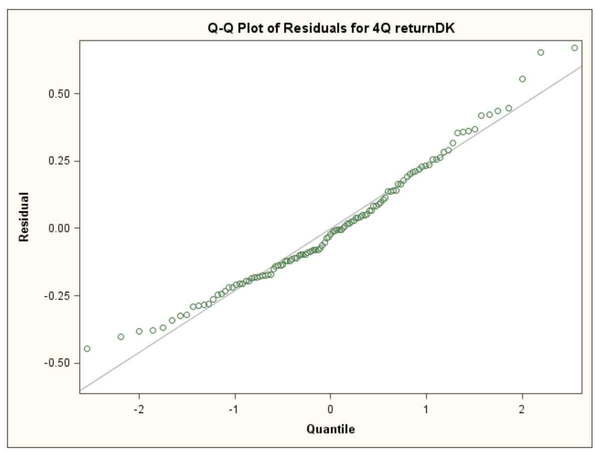
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	1.44457	1.44457	27.05	<.0001
Error	113	6.03520	0.05341		
Corrected Total	114	7.47977			

Root MSE	0.23110	**R-Square**	0.1931
Dependent Mean	0.08004	**Adj R-Sq**	0.1860
Coeff Var	288.73608		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-1.13968	0.23552	-4.84	<.0001
px4QDK	1	-0.34374	0.06610	-5.20	<.0001

Test for normality in the error terms

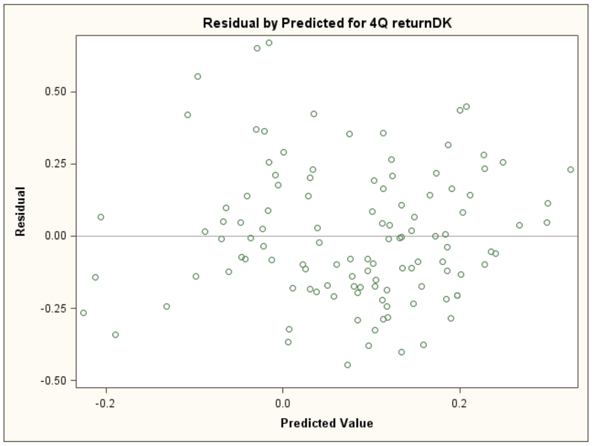


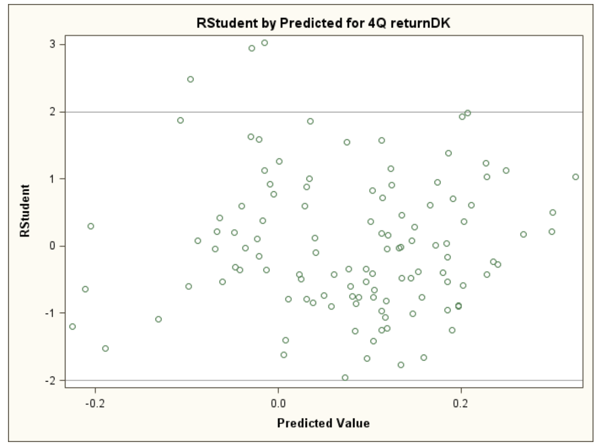


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	6.2700	0.0435	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.01481	0.00741	1.30	0.2767
Error	112	0.63831	0.00570		
Corrected Total	114	0.65312			

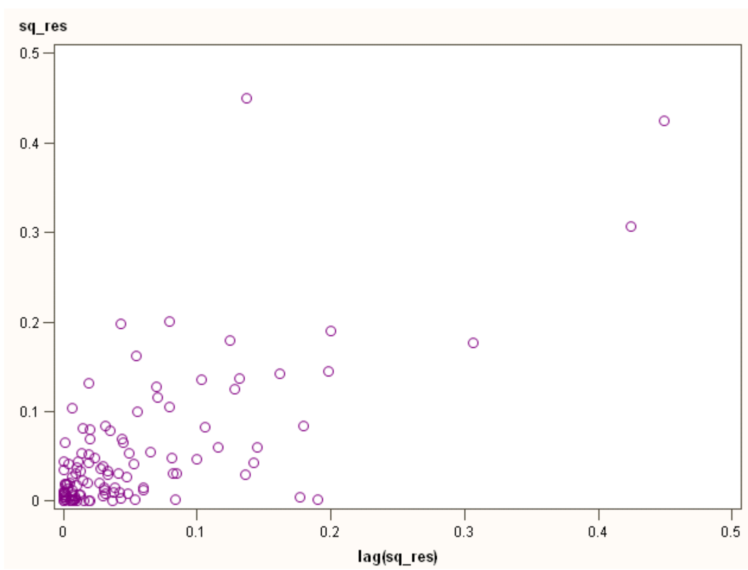
Root MSE	0.07549	**R-Square**	0.0227
Dependent Mean	0.05248	**Adj R-Sq**	0.0052
Coeff Var	143.85047		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.05666	0.59643	-0.10	0.9245
px4QDK	1	-0.09910	0.34385	-0.29	0.7737
sq_px	1	-0.01910	0.04932	-0.39	0.6993

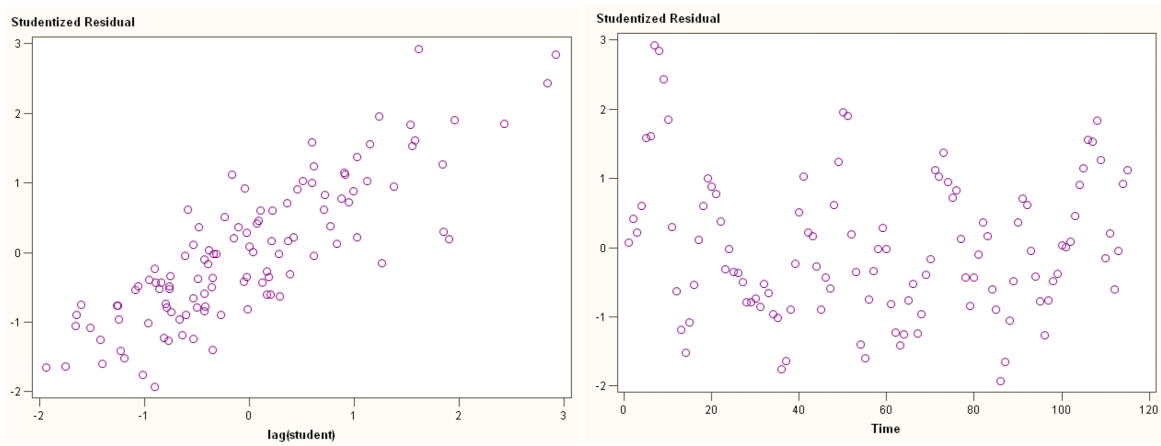
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_4Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	57.4344	<.0001	56.4173	<.0001
2	68.9456	<.0001	63.3050	<.0001
3	69.1491	<.0001	63.3240	<.0001
4	69.6012	<.0001	63.4194	<.0001
5	70.2873	<.0001	63.5242	<.0001
6	71.7468	<.0001	64.2489	<.0001
7	73.1513	<.0001	64.2489	<.0001
8	74.1689	<.0001	64.3625	<.0001
9	74.6766	<.0001	64.4783	<.0001
10	74.9940	<.0001	64.6490	<.0001
11	75.3820	<.0001	64.7531	<.0001
12	75.3856	<.0001	64.9872	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	82.8343	<.0001
AR(2)	88.1253	<.0001
AR(3)	90.6637	<.0001
AR(4)	90.7972	<.0001

Durbin-Watson d test

Durbin-Watson D	0.321
Number of Observations	115
1st Order Autocorrelation	0.834

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-1.13968	0.3972	-2.87	0.0049
b1	-0.34374	0.1085	-3.17	0.0020

12Q

$$r_{t,t+12} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

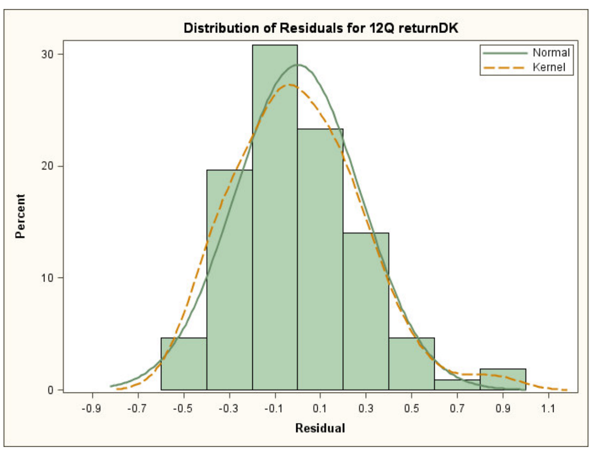
Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

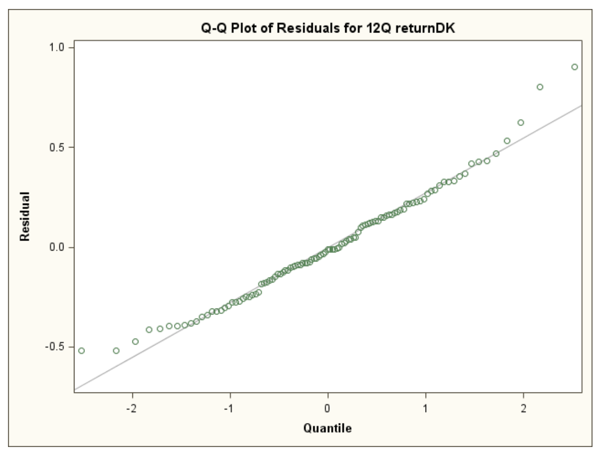
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	7.03633	7.03633	92.35	<.0001
Error	105	7.99994	0.07619		
Corrected Total	106	15.03628			

Root MSE	0.27603	**R-Square**	0.4680
Dependent Mean	0.23012	**Adj R-Sq**	0.4629
Coeff Var	119.94750		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-2.59236	0.29491	-8.79	<.0001
px12QDK	1	-0.79019	0.08223	-9.61	<.0001

Test for normality in the error terms

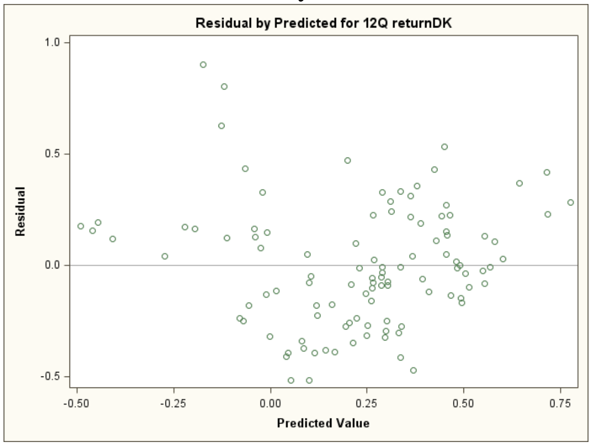


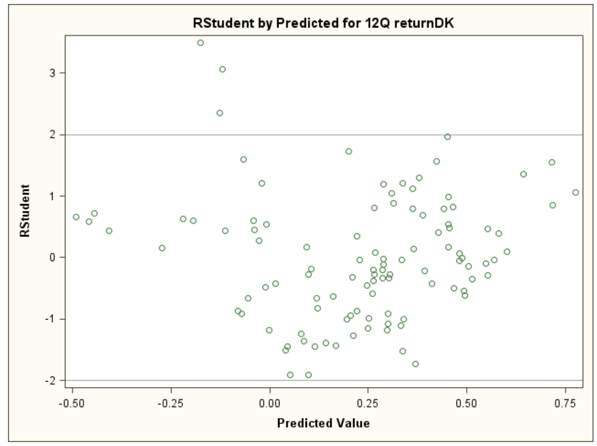


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	6.0589	0.0483	Pr > ChiSq

Test for heteroscedasticity in the error terms





White’s heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	0.06577	0.03288	2.43	0.0927
Error	104	1.40508	0.01351		
Corrected Total	106	1.47084			

Root MSE	0.11623	**R-Square**	0.0447
Dependent Mean	0.07477	**Adj R-Sq**	0.0263
Coeff Var	155.46409		

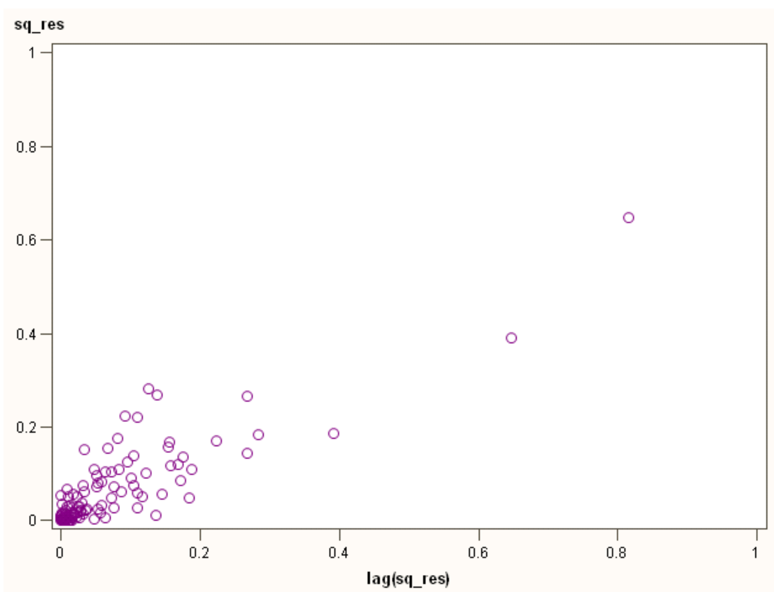
Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-0.12112	0.92612	-0.13	0.8962
px12QDK	1	-0.19367	0.53409	-0.36	0.7176
sq_px	1	-0.03855	0.07665	-0.50	0.6161

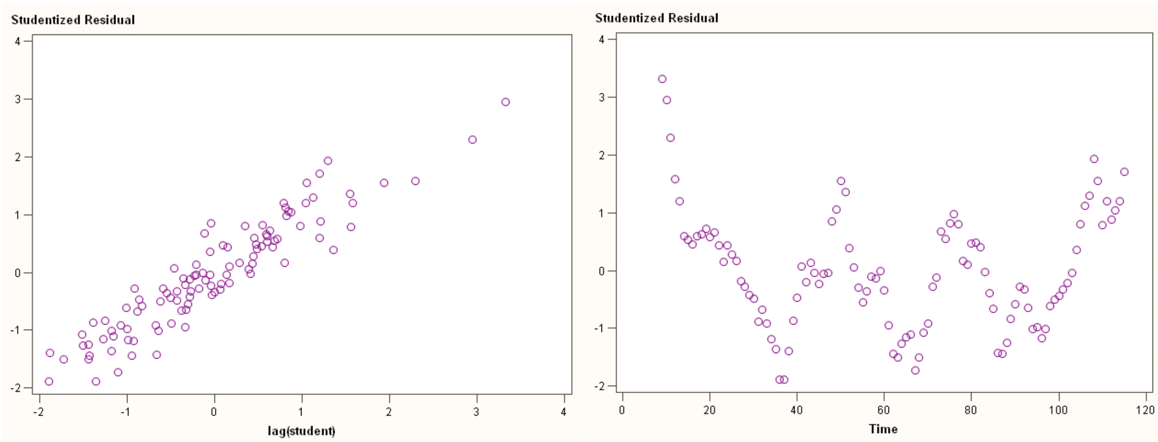
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_12Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	50.2829	<.0001	44.0903	<.0001
2	63.0791	<.0001	47.6747	<.0001
3	64.4654	<.0001	47.9522	<.0001
4	64.4814	<.0001	48.1322	<.0001
5	65.1166	<.0001	48.3864	<.0001
6	65.7787	<.0001	48.4213	<.0001
7	66.6116	<.0001	48.7744	<.0001
8	67.8184	<.0001	49.0721	<.0001
9	69.1040	<.0001	49.4206	<.0001
10	70.2388	<.0001	49.6756	<.0001
11	70.9494	<.0001	49.8649	<.0001
12	71.1856	<.0001	49.9956	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	83.6173	<.0001
AR(2)	84.5744	<.0001
AR(3)	84.7805	<.0001
AR(4)	84.7890	<.0001

Durbin-Watson d test

Durbin-Watson D	0.128
Number of Observations	107
1st Order Autocorrelation	0.871

The regression with Newey-West HAC standard errors, 12 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-2.59236	0.7025	-3.69	0.0004
b1	-0.79019	0.1880	-4.20	<.0001

20Q

$$r_{t,t+20} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

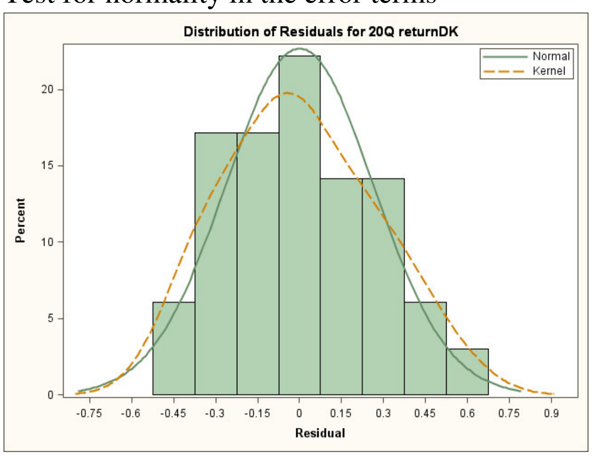
Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

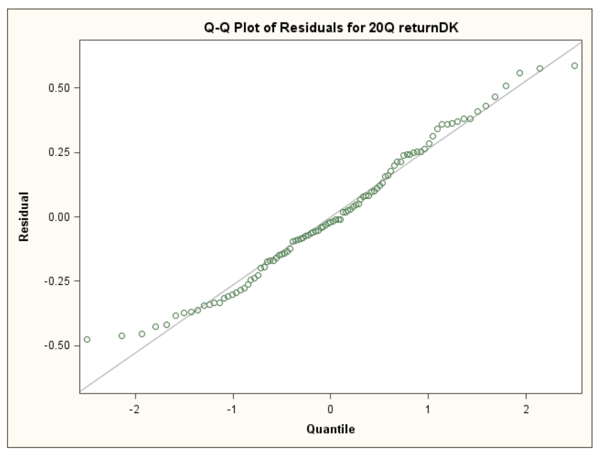
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	9.20216	9.20216	130.83	<.0001
Error	97	6.82249	0.07033		
Corrected Total	98	16.02465			

Root MSE	0.26521	**R-Square**	0.5743
Dependent Mean	0.36150	**Adj R-Sq**	0.5699
Coeff Var	73.36360		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-2.88910	0.28543	-10.12	<.0001
px20QDK	1	-0.91281	0.07980	-11.44	<.0001

Test for normality in the error terms

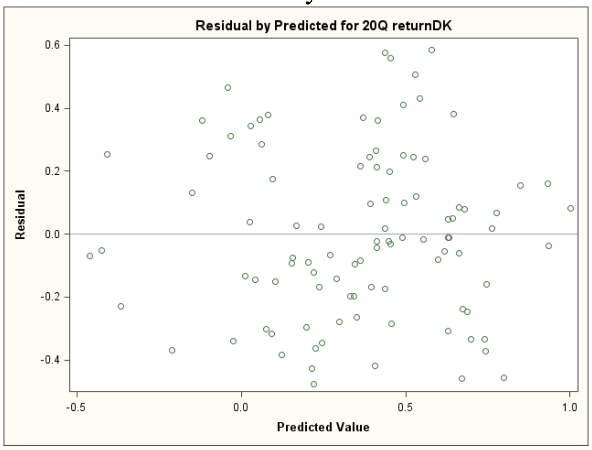


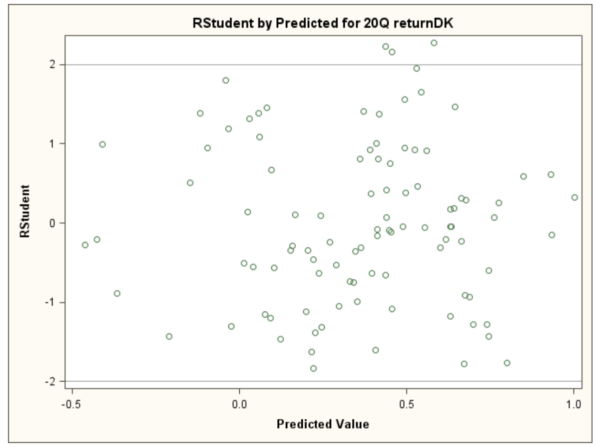


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	2.8791	0.2370	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.00891	0.00446	0.71	0.4957
Error	96	0.60522	0.00630		
Corrected Total	98	0.61414			

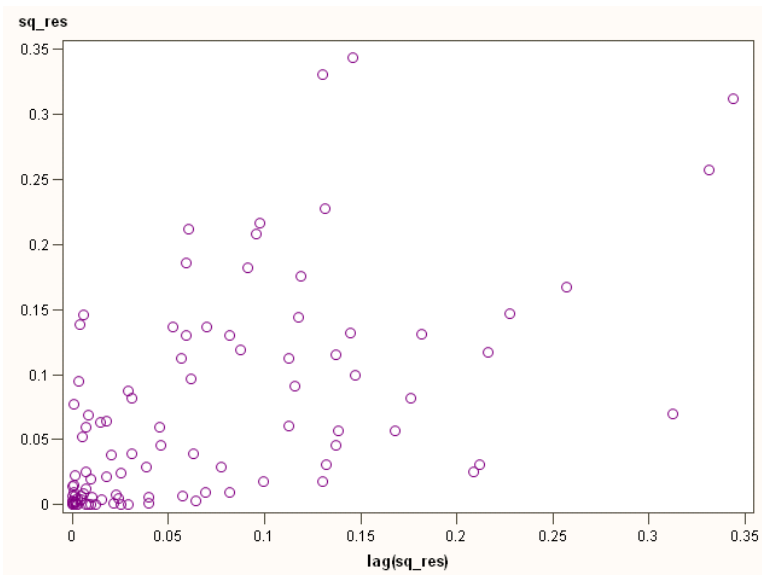
Root MSE	0.07940	**R-Square**	0.0145
Dependent Mean	0.06891	**Adj R-Sq**	-0.0060
Coeff Var	115.21627		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.62880	0.63838	-0.98	0.3271
px20QDK	1	-0.41328	0.36815	-1.12	0.2644
sq_px	1	-0.06050	0.05281	-1.15	0.2548

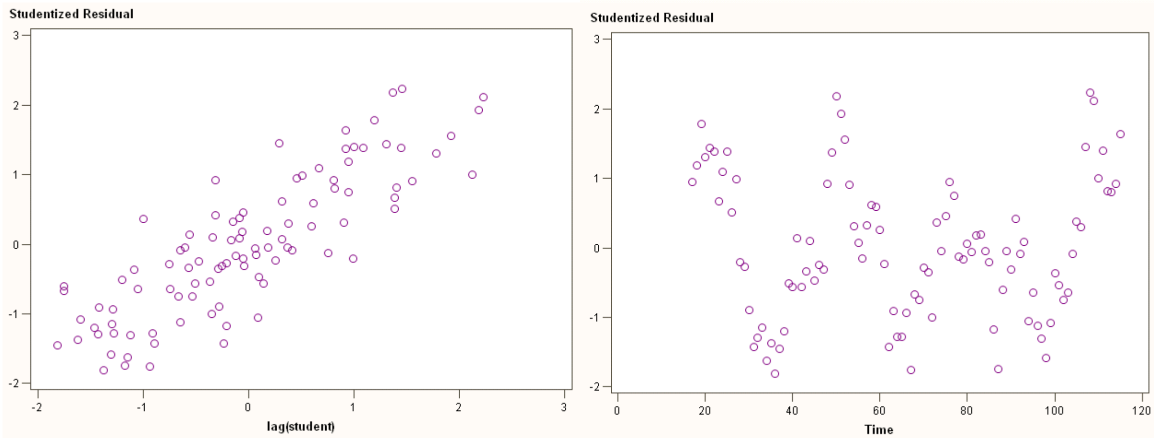
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_20Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	32.6866	<.0001	32.3006	<.0001
2	39.8478	<.0001	33.0429	<.0001
3	39.9483	<.0001	34.5498	<.0001
4	41.4545	<.0001	35.2270	<.0001
5	44.2654	<.0001	35.2696	<.0001
6	47.5021	<.0001	35.7609	<.0001
7	51.2458	<.0001	35.9671	<.0001
8	57.0847	<.0001	37.8299	<.0001
9	59.4566	<.0001	37.8379	<.0001
10	59.4587	<.0001	38.2748	<.0001
11	60.5838	<.0001	38.2889	<.0001
12	63.5184	<.0001	38.2891	0.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	69.7042	<.0001
AR(2)	69.7446	<.0001
AR(3)	71.0869	<.0001
AR(4)	71.1959	<.0001

Durbin-Watson d test

Durbin-Watson D	0.309
Number of Observations	99
1st Order Autocorrelation	0.827

The regression with Newey-West HAC standard errors, 20 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-2.8891	0.4795	-6.03	<.0001
b1	-0.91281	0.1319	-6.92	<.0001

Import

4Q

$$r_{t,t+4} = \beta_1 + \beta_2 pz_t + \varepsilon_t$$

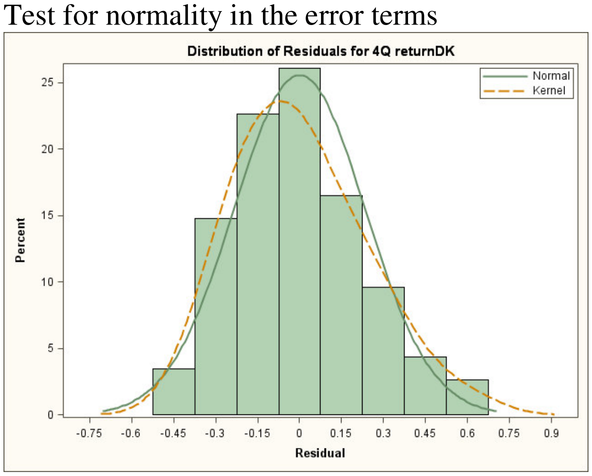
Number of Observations Read	115
Number of Observations Used	115

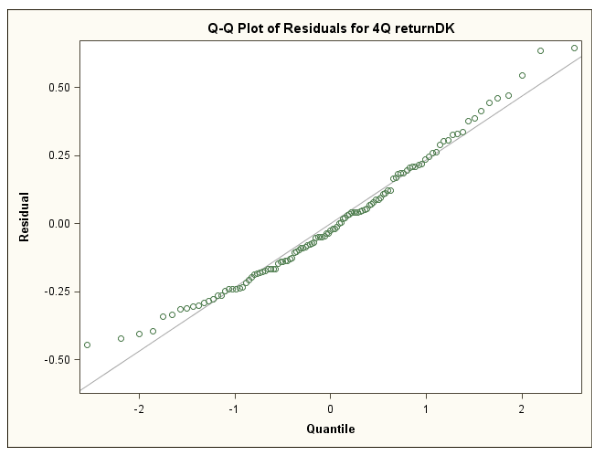
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	1.23297	1.23297	22.30	<.0001
Error	113	6.24681	0.05528		
Corrected Total	114	7.47977			

Root MSE	0.23512	**R-Square**	0.1648
Dependent Mean	0.08004	**Adj R-Sq**	0.1574
Coeff Var	293.75427		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-1.10182	0.25121	-4.39	<.0001
pz4QDK	1	-0.34100	0.07220	-4.72	<.0001

Test for normality in the error terms

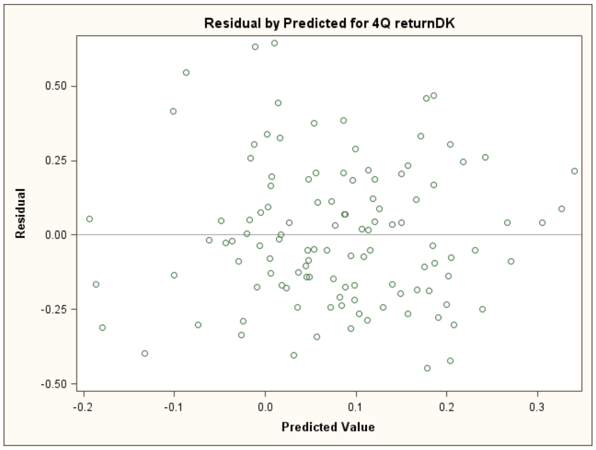


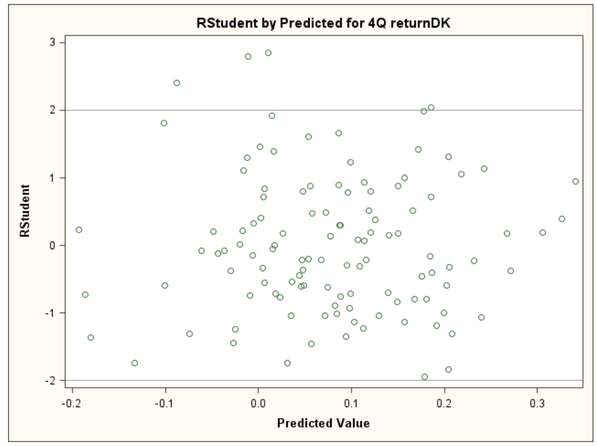


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	4.7976	0.0908	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	0.00918	0.00459	0.83	0.4401
Error	112	0.62150	0.00555		
Corrected Total	114	0.63068			

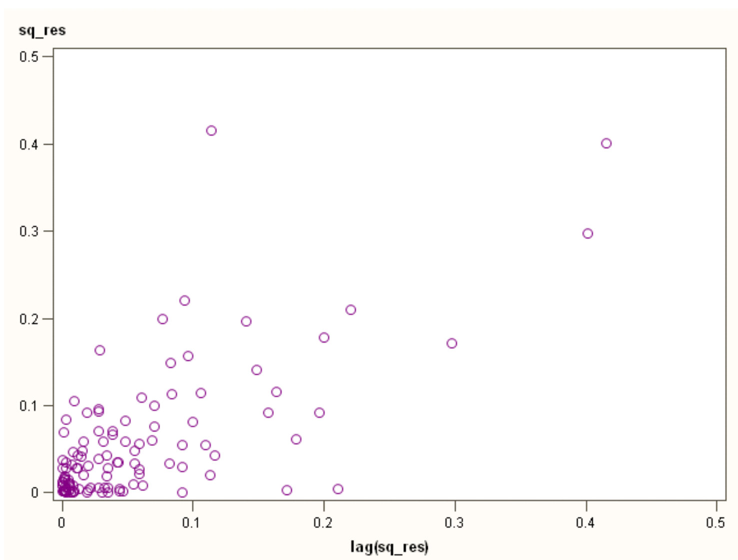
Root MSE	0.07449	**R-Square**	0.0145
Dependent Mean	0.05432	**Adj R-Sq**	-0.0030
Coeff Var	137.13628		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.36597	0.61349	0.60	0.5520
pz4QDK	1	0.15302	0.35597	0.43	0.6681
sq_pz	1	0.01807	0.05146	0.35	0.7262

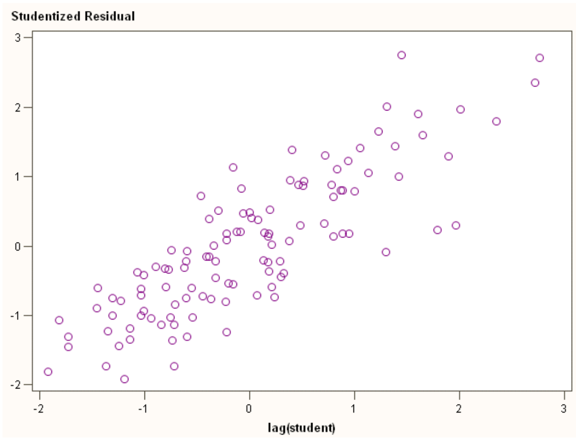
Autoregressive conditional heteroscedasticity (ARCH)

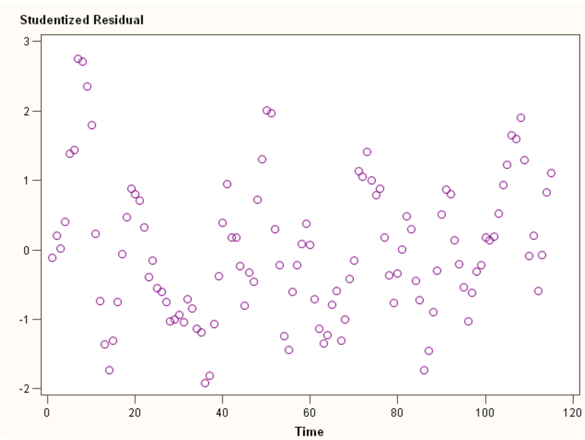
Dependent Variable	residual_4Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	55.9108	<.0001	54.9692	<.0001
2	65.3571	<.0001	62.9477	<.0001
3	65.3756	<.0001	62.9486	<.0001
4	65.9385	<.0001	63.1372	<.0001
5	66.3487	<.0001	63.2087	<.0001
6	67.1064	<.0001	63.8010	<.0001
7	68.1033	<.0001	63.8268	<.0001
8	69.3520	<.0001	64.0303	<.0001
9	70.6243	<.0001	64.2954	<.0001
10	72.1324	<.0001	64.6831	<.0001
11	73.6445	<.0001	64.7206	<.0001
12	73.8470	<.0001	64.9279	<.0001



Test for autocorrelation in the error terms





LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	84.5411	<.0001
AR(2)	89.2436	<.0001
AR(3)	91.6125	<.0001
AR(4)	91.6968	<.0001

Durbin-Watson d test

Durbin-Watson D	0.314
Number of Observations	115
1st Order Autocorrelation	0.838

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-1.10182	0.4234	-2.60	0.0105
b1	-0.341	0.1200	-2.84	0.0053

12Q

$$r_{t,t+12} = \beta_1 + \beta_2 pz_t + \varepsilon_t$$

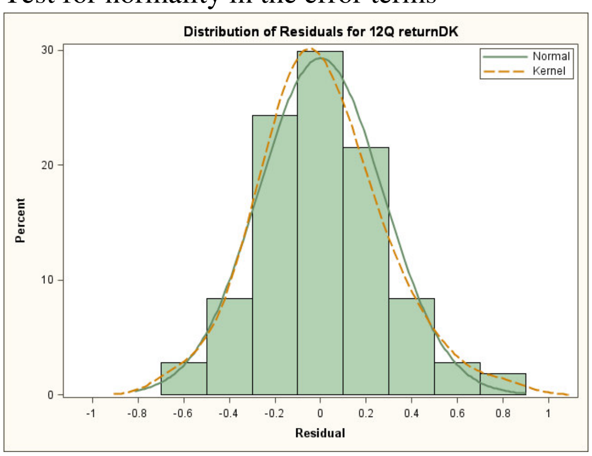
Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

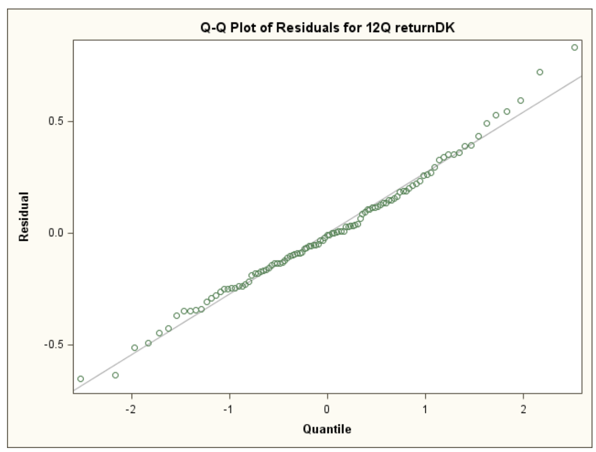
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	7.18060	7.18060	95.98	<.0001
Error	105	7.85567	0.07482		
Corrected Total	106	15.03628			

Root MSE	0.27352	**R-Square**	0.4776
Dependent Mean	0.23012	**Adj R-Sq**	0.4726
Coeff Var	118.86100		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-2.79010	0.30942	-9.02	<.0001
pz12QDK	1	-0.86528	0.08832	-9.80	<.0001

Test for normality in the error terms

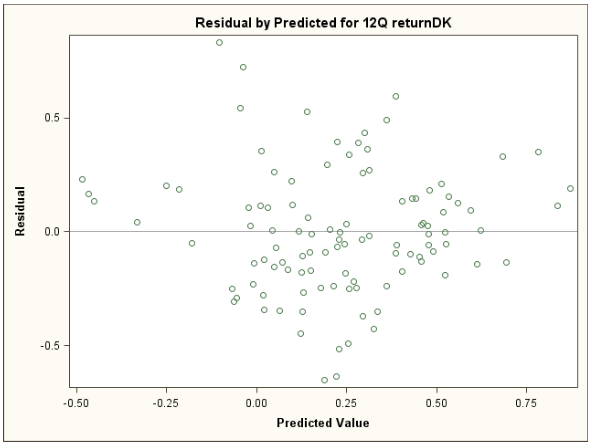


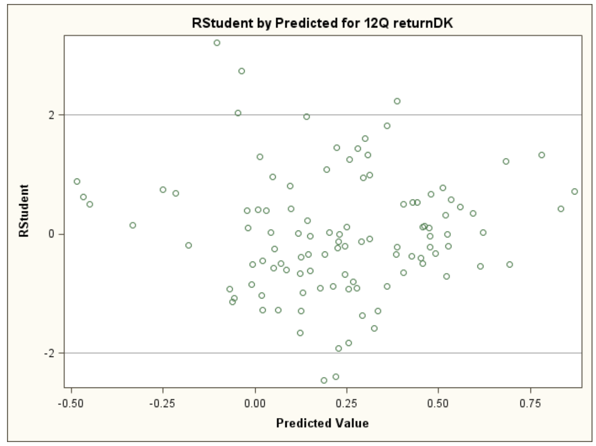


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	3.0034	0.2228	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.05091	0.02545	1.95	0.1476
Error	104	1.35815	0.01306		
Corrected Total	106	1.40906			

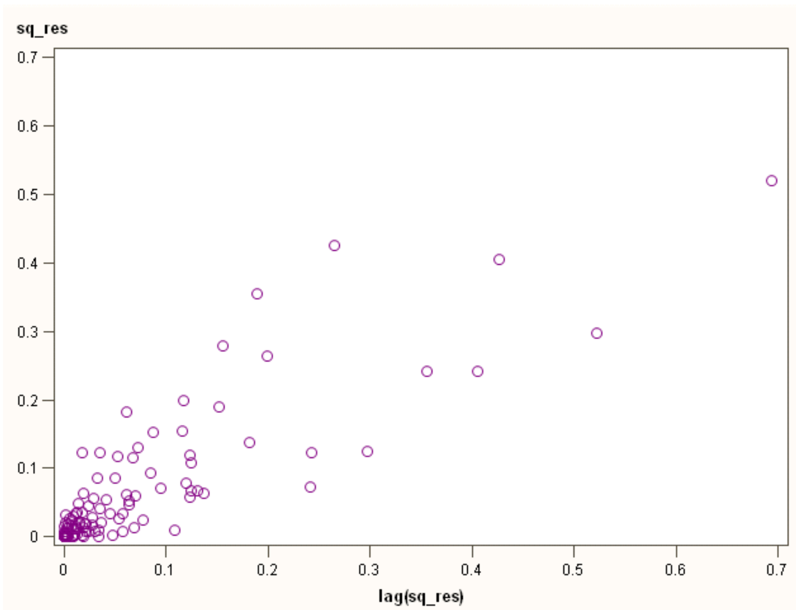
Root MSE	0.11428	**R-Square**	0.0361
Dependent Mean	0.07342	**Adj R-Sq**	0.0176
Coeff Var	155.65295		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.99304	0.95544	-1.04	0.3011
pz12QDK	1	-0.67754	0.55307	-1.23	0.2233
sq_pz	1	-0.10580	0.07981	-1.33	0.1879

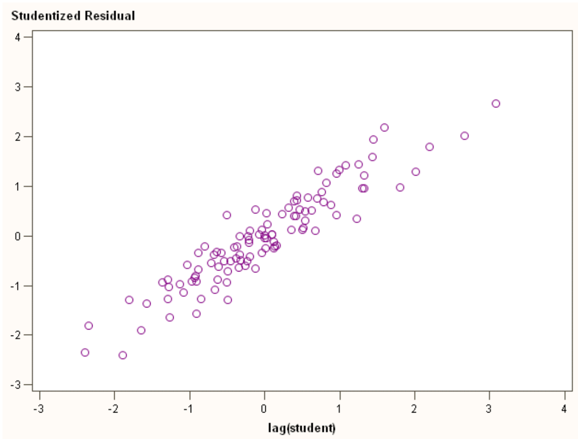
Autoregressive conditional heteroscedasticity (ARCH)

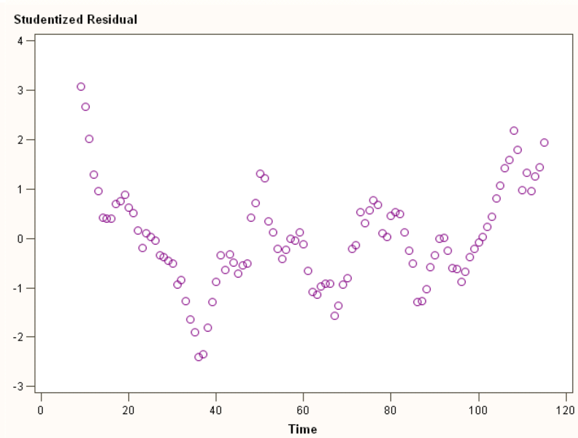
Dependent Variable	residual_12Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	55.8394	<.0001	50.8517	<.0001
2	74.5496	<.0001	53.5959	<.0001
3	78.5564	<.0001	53.7616	<.0001
4	78.9175	<.0001	53.8333	<.0001
5	78.9703	<.0001	53.9030	<.0001
6	79.1112	<.0001	53.9034	<.0001
7	79.4280	<.0001	53.9727	<.0001
8	80.1261	<.0001	54.0562	<.0001
9	81.0635	<.0001	54.2908	<.0001
10	82.4215	<.0001	54.5352	<.0001
11	84.1768	<.0001	54.7991	<.0001
12	85.8266	<.0001	54.8854	<.0001



Test for autocorrelation in the error terms





LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	85.2337	<.0001
AR(2)	85.9892	<.0001
AR(3)	86.1646	<.0001
AR(4)	86.2467	<.0001

Durbin-Watson d test

Durbin-Watson D	0.126
Number of Observations	107
1st Order Autocorrelation	0.875

The regression with Newey-West HAC standard errors, 12 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-2.7901	0.5600	-4.98	<.0001
b1	-0.86528	0.1515	-5.71	<.0001

20Q

$$r_{t,t+20} = \beta_1 + \beta_2 pz_t + \varepsilon_t$$

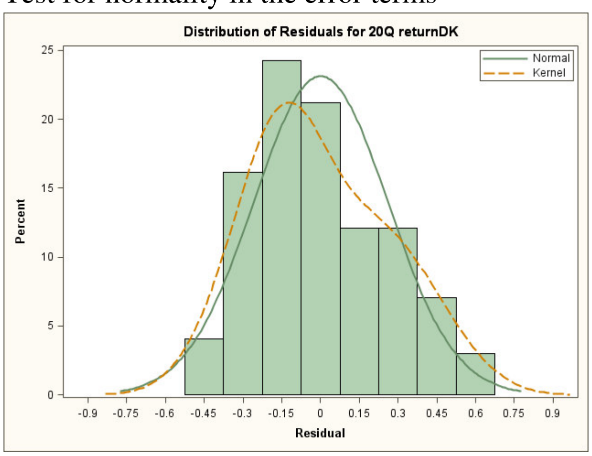
Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

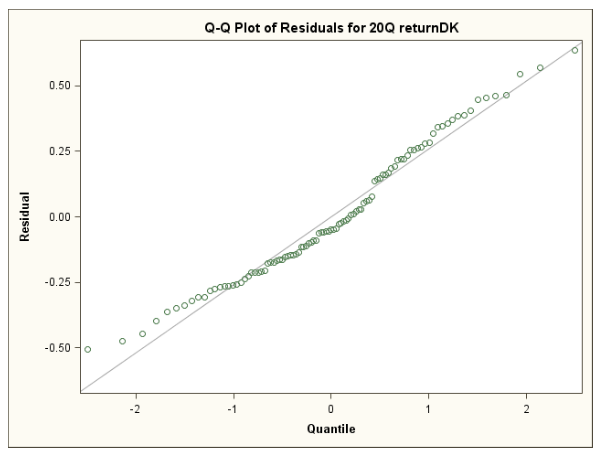
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	9.65142	9.65142	142.81	<.0001
Error	97	6.55547	0.06758		
Corrected Total	98	16.20689			

Root MSE	0.25997	**R-Square**	0.5955
Dependent Mean	0.34750	**Adj R-Sq**	0.5913
Coeff Var	74.81036		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-3.16580	0.29515	-10.73	<.0001
pz20QDK	1	-1.00804	0.08435	-11.95	<.0001

Test for normality in the error terms

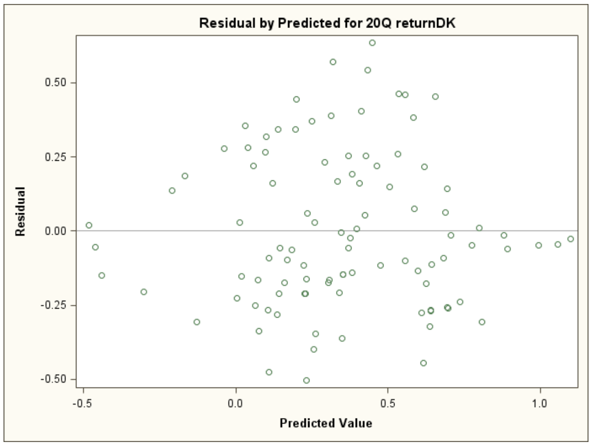


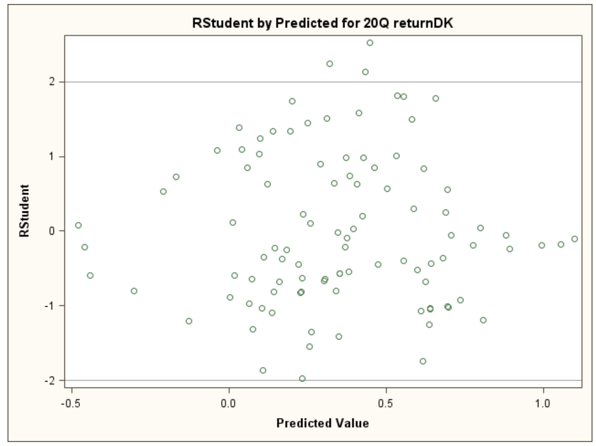


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	4.2126	0.1217	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.04245	0.02122	3.66	0.0295
Error	96	0.55741	0.00581		
Corrected Total	98	0.59985			

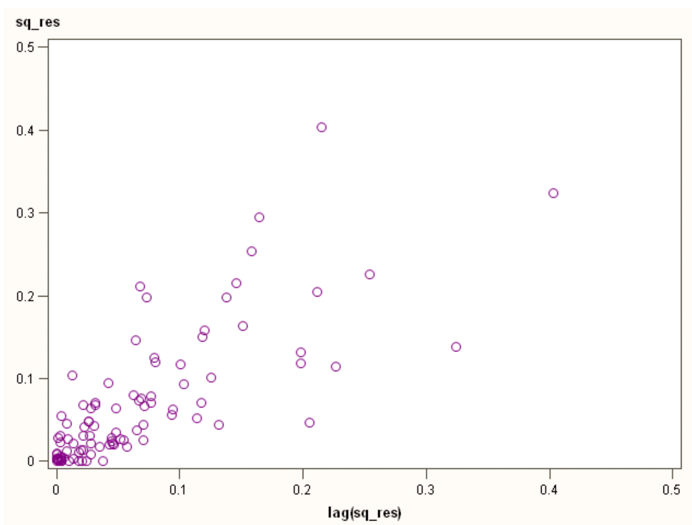
Root MSE	0.07620	**R-Square**	0.0708
Dependent Mean	0.06622	**Adj R-Sq**	0.0514
Coeff Var	115.07509		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-1.64474	0.64512	-2.55	0.0124
pz20QDK	1	-1.00159	0.37348	-2.68	0.0086
sq_pz	1	-0.14538	0.05387	-2.70	0.0082

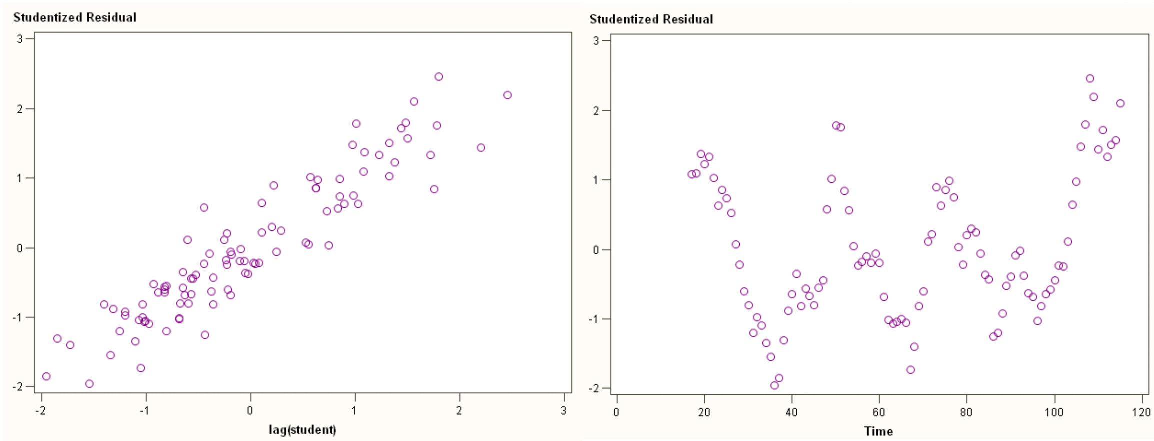
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_20Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	55.1303	<.0001	58.0211	<.0001
2	77.6341	<.0001	60.4553	<.0001
3	85.0439	<.0001	60.4557	<.0001
4	87.0748	<.0001	60.4607	<.0001
5	87.5996	<.0001	60.8214	<.0001
6	88.1188	<.0001	60.8514	<.0001
7	88.1204	<.0001	60.8655	<.0001
8	89.1414	<.0001	60.9892	<.0001
9	90.8136	<.0001	60.9902	<.0001
10	92.7470	<.0001	61.0318	<.0001
11	93.6480	<.0001	61.2972	<.0001
12	93.7213	<.0001	61.3846	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	85.0613	<.0001
AR(2)	86.3947	<.0001
AR(3)	86.9151	<.0001
AR(4)	86.9281	<.0001

Durbin-Watson d test

Durbin-Watson D	0.132
Number of Observations	99
1st Order Autocorrelation	0.906

The regression with Newey-West HAC standard errors, 20 lags

Nonlinear GMM Parameter Estimates				
Parameter	Estimate	Approx Std Err	t Value	Approx Pr > |t|
b0	-3.1658	0.4320	-7.33	<.0001
b1	-1.00804	0.1187	-8.49	<.0001

The Netherlands

Output

4Q

$$r_{t,t+4} = \beta_1 + \beta_2 RESpy_t + \varepsilon_t$$

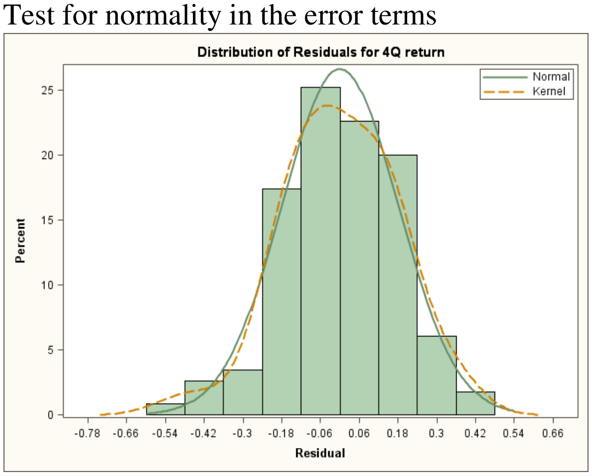
Number of Observations Read	115
Number of Observations Used	115

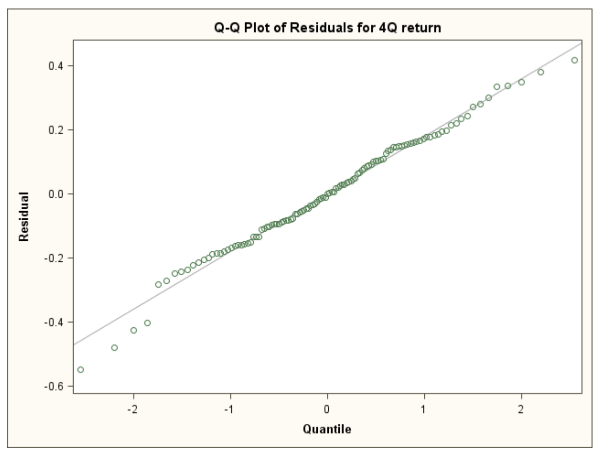
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.36549	0.36549	11.21	0.0011
Error	113	3.68525	0.03261		
Corrected Total	114	4.05074			

Root MSE	0.18059	**R-Square**	0.0902
Dependent Mean	0.10107	**Adj R-Sq**	0.0822
Coeff Var	178.68278		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.10185	0.01684	6.05	<.0001
RESpy4QNL	1	-0.15304	0.04571	-3.35	0.0011

Test for normality in the error terms

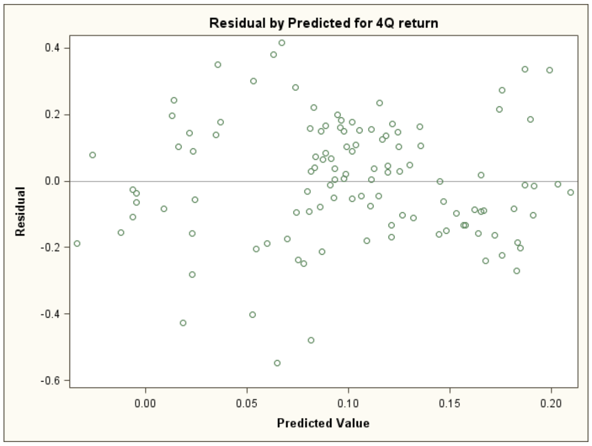


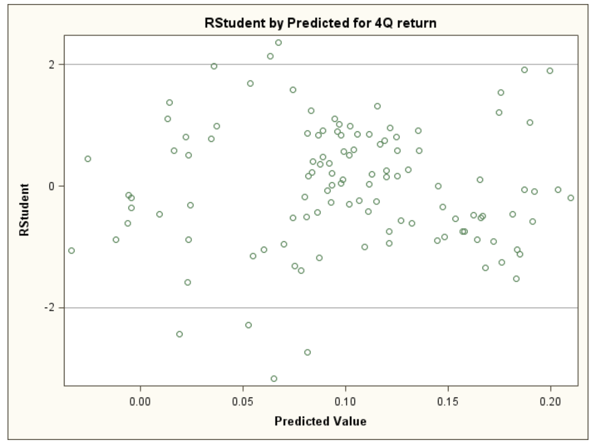


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	1.3515	0.5088	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.00420	0.00210	0.90	0.4076
Error	112	0.26026	0.00232		
Corrected Total	114	0.26447			

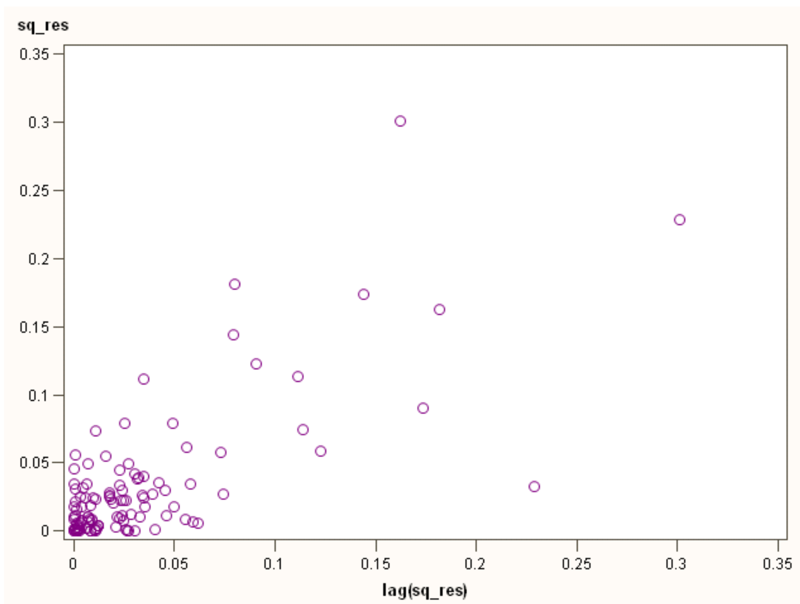
Root MSE	0.04821	**R-Square**	0.0159
Dependent Mean	0.03205	**Adj R-Sq**	-0.0017
Coeff Var	150.42771		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.03229	0.00582	5.54	<.0001
RESpy4QNL	1	0.01661	0.01248	1.33	0.1858
sq_RESpy	1	-0.00243	0.02738	-0.09	0.9294

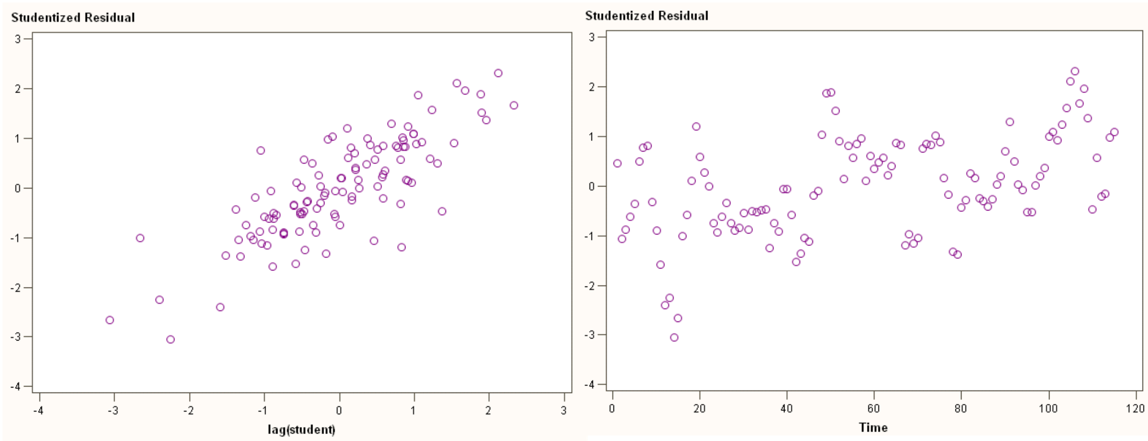
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_4Q return
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	62.3315	<.0001	61.0298	<.0001
2	83.2722	<.0001	64.0543	<.0001
3	87.2273	<.0001	64.2112	<.0001
4	87.2404	<.0001	64.4550	<.0001
5	87.5546	<.0001	64.6535	<.0001
6	88.7048	<.0001	65.1285	<.0001
7	90.0346	<.0001	65.1644	<.0001
8	92.1272	<.0001	65.6698	<.0001
9	94.5513	<.0001	65.6860	<.0001
10	97.3118	<.0001	65.9832	<.0001
11	99.4663	<.0001	66.0223	<.0001
12	100.0848	<.0001	66.0237	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	76.5323	<.0001
AR(2)	77.3409	<.0001
AR(3)	77.8446	<.0001
AR(4)	79.5704	<.0001

Durbin-Watson d test

Durbin-Watson D	0.376
Number of Observations	115
1st Order Autocorrelation	0.806

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.101845	0.0305	3.34	0.0011
b1	-0.15304	0.0782	-1.96	0.0527

12Q

$$r_{t,t+12} = \beta_1 + \beta_2 RESpy_t + \varepsilon_t$$

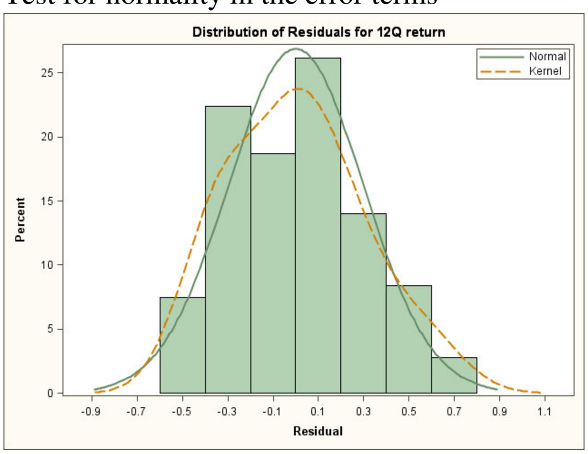
Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

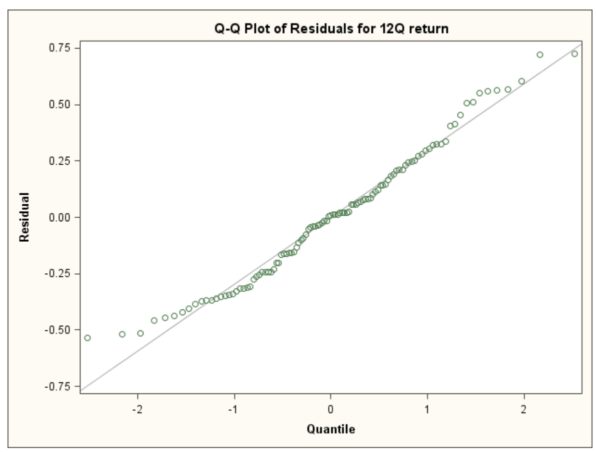
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	3.98198	3.98198	44.77	<.0001
Error	105	9.33980	0.08895		
Corrected Total	106	13.32178			

Root MSE	0.29825	**R-Square**	0.2989
Dependent Mean	0.31767	**Adj R-Sq**	0.2922
Coeff Var	93.88626		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.29683	0.02900	10.24	<.0001
RESpy12QNL	1	-0.55851	0.08347	-6.69	<.0001

Test for normality in the error terms

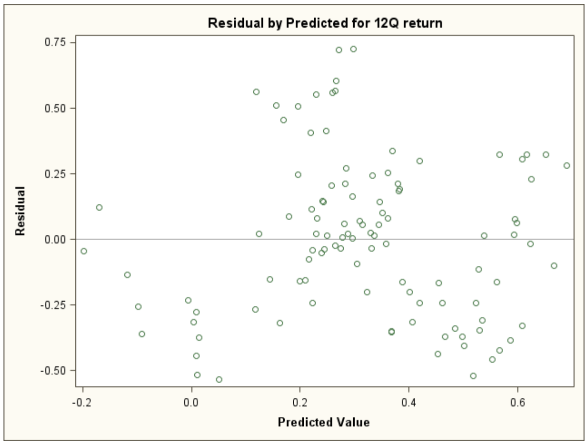


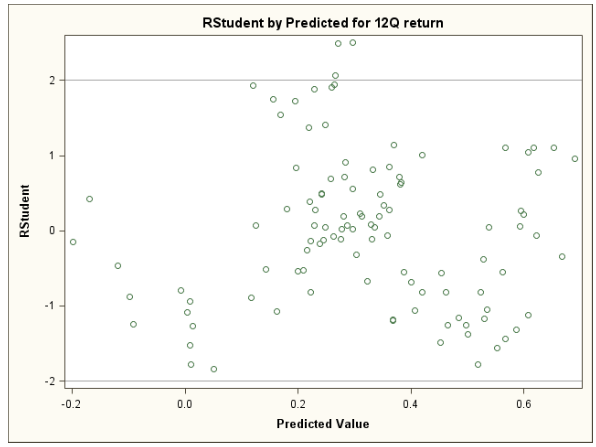


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	3.0913	0.2132	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.00857	0.00428	0.36	0.6967
Error	104	1.22857	0.01181		
Corrected Total	106	1.23714			

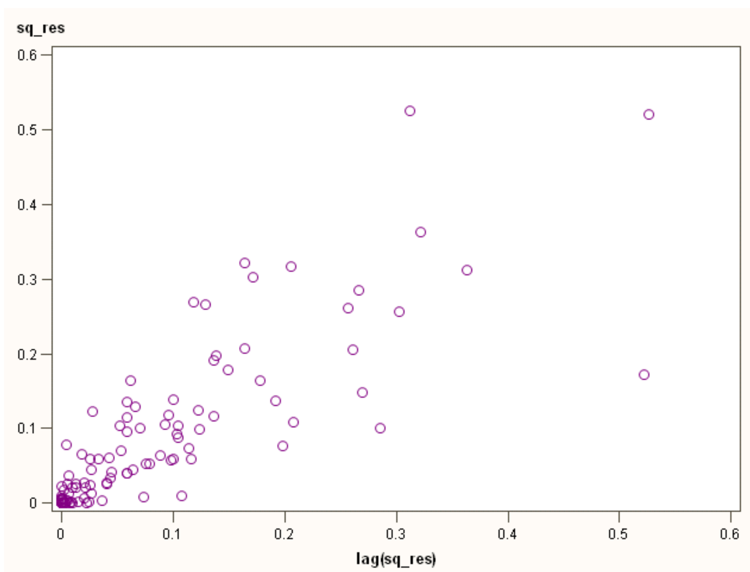
Root MSE	0.10869	**R-Square**	0.0069
Dependent Mean	0.08729	**Adj R-Sq**	-0.0122
Coeff Var	124.51723		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.09156	0.01322	6.93	<.0001
RESpy12QNL	1	0.02324	0.03049	0.76	0.4478
sq_RESpy	1	-0.02817	0.06516	-0.43	0.6664

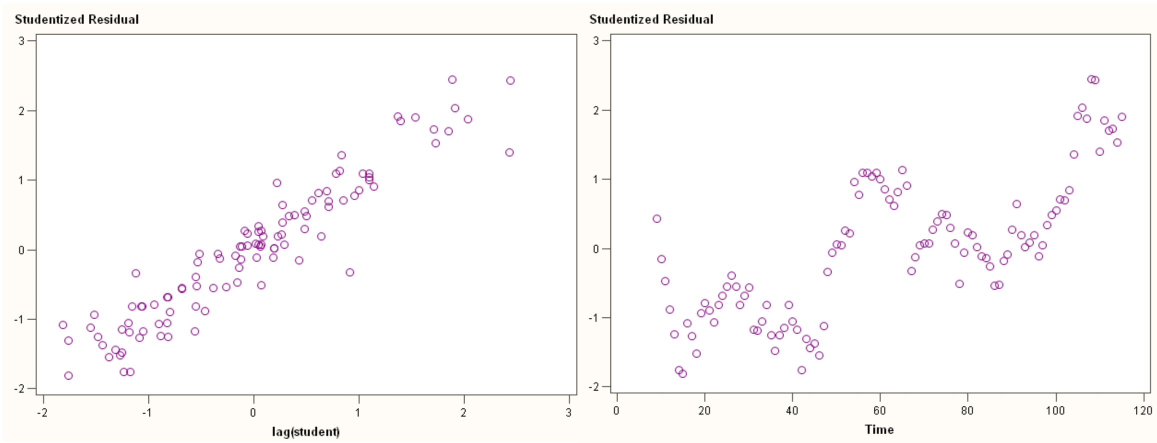
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_12Q return
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	70.0307	<.0001	71.6422	<.0001
2	118.9486	<.0001	71.7707	<.0001
3	158.4951	<.0001	72.8299	<.0001
4	185.6552	<.0001	73.1613	<.0001
5	198.1432	<.0001	74.5449	<.0001
6	207.2212	<.0001	74.7939	<.0001
7	212.2808	<.0001	74.8834	<.0001
8	213.7177	<.0001	74.8974	<.0001
9	214.3591	<.0001	75.0488	<.0001
10	214.4909	<.0001	75.2052	<.0001
11	214.6661	<.0001	76.1491	<.0001
12	215.4810	<.0001	76.2704	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	95.8516	<.0001
AR(2)	95.8525	<.0001
AR(3)	96.1048	<.0001
AR(4)	96.1082	<.0001

Durbin-Watson d test

Durbin-Watson D	0.108
Number of Observations	107
1st Order Autocorrelation	0.928

The regression with Newey-West HAC standard errors, 12 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.29683	0.0883	3.36	0.0011
b1	-0.55851	0.2174	-2.57	0.0116

20Q

$$r_{t,t+20} = \beta_1 + \beta_2 RESpy_t + \varepsilon_t$$

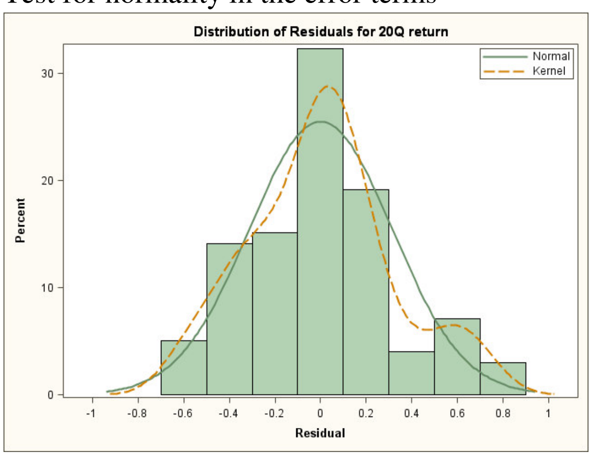
Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

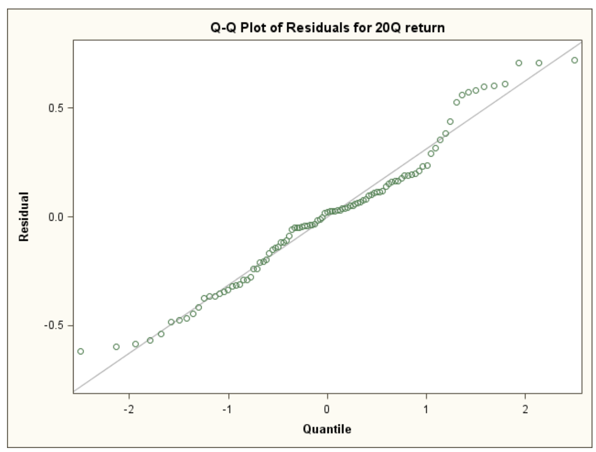
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	9.98117	9.98117	100.95	<.0001
Error	97	9.59045	0.09887		
Corrected Total	98	19.57162			

Root MSE	0.31444	**R-Square**	0.5100
Dependent Mean	0.54394	**Adj R-Sq**	0.5049
Coeff Var	57.80741		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.49652	0.03195	15.54	<.0001
RESpy20QNL	1	-0.89844	0.08942	-10.05	<.0001

Test for normality in the error terms

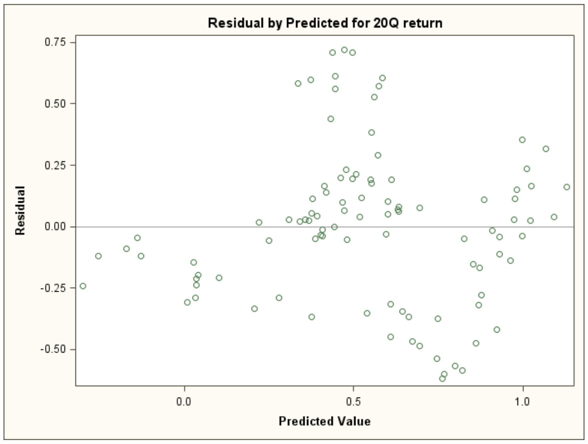


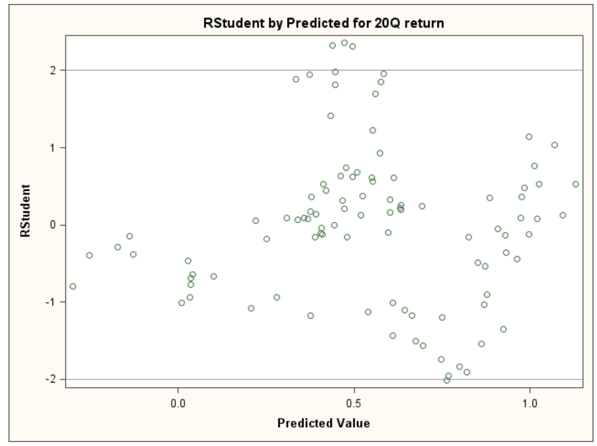


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	1.2530	0.5345	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.10486	0.05243	3.08	0.0504
Error	96	1.63221	0.01700		
Corrected Total	98	1.73707			

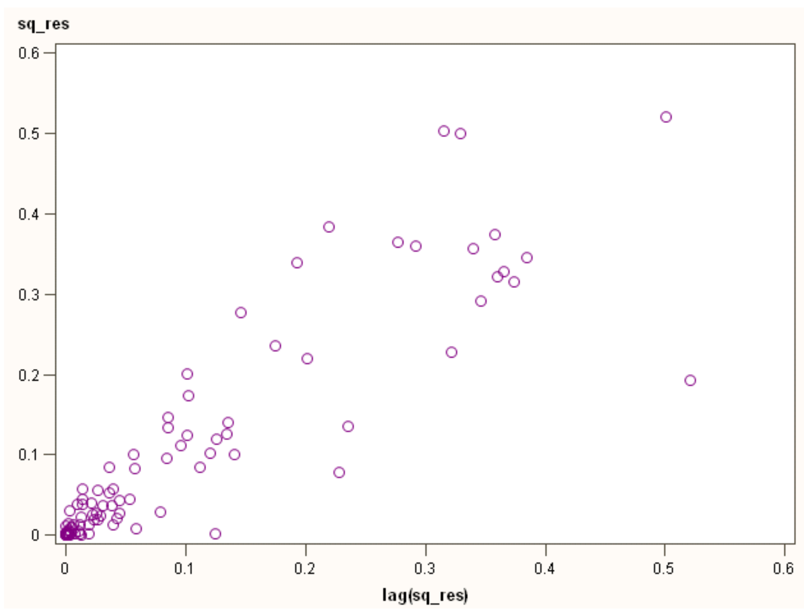
Root MSE	0.13039	**R-Square**	0.0604
Dependent Mean	0.09687	**Adj R-Sq**	0.0408
Coeff Var	134.60106		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.12019	0.01679	7.16	<.0001
RESpy20QNL	1	-0.01697	0.03724	-0.46	0.6496
sq_RESpy	1	-0.18962	0.07936	-2.39	0.0188

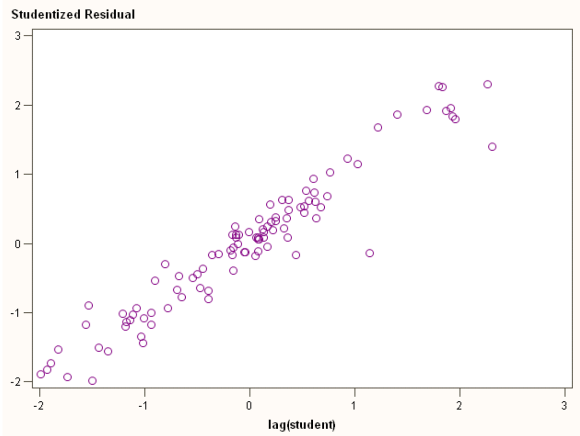
Autoregressive conditional heteroscedasticity (ARCH)

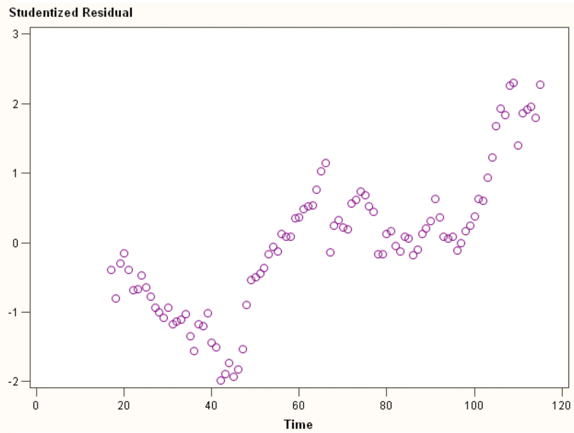
Dependent Variable	residual_20Q return
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	72.7215	<.0001	78.5277	<.0001
2	131.8422	<.0001	78.6706	<.0001
3	178.8669	<.0001	78.8014	<.0001
4	212.7660	<.0001	79.0632	<.0001
5	233.7446	<.0001	79.6194	<.0001
6	251.2760	<.0001	80.2782	<.0001
7	261.2534	<.0001	80.4087	<.0001
8	265.0456	<.0001	80.6378	<.0001
9	266.8666	<.0001	80.7555	<.0001
10	267.1650	<.0001	81.0429	<.0001
11	267.2219	<.0001	81.5656	<.0001
12	267.8715	<.0001	81.6616	<.0001



Test for autocorrelation in the error terms





LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	91.4656	<.0001
AR(2)	91.4925	<.0001
AR(3)	91.6939	<.0001
AR(4)	91.6941	<.0001

Durbin-Watson d test

Durbin-Watson D	0.077
Number of Observations	99
1st Order Autocorrelation	0.934

The regression with Newey-West HAC standard errors, 20 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.496518	0.1126	4.41	<.0001
b1	-0.89844	0.1652	-5.44	<.0001

Export

4Q

$$r_{t,t+4} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

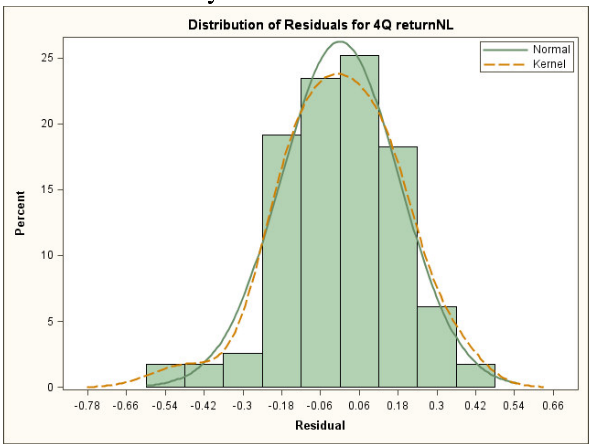
Number of Observations Read	115
Number of Observations Used	115

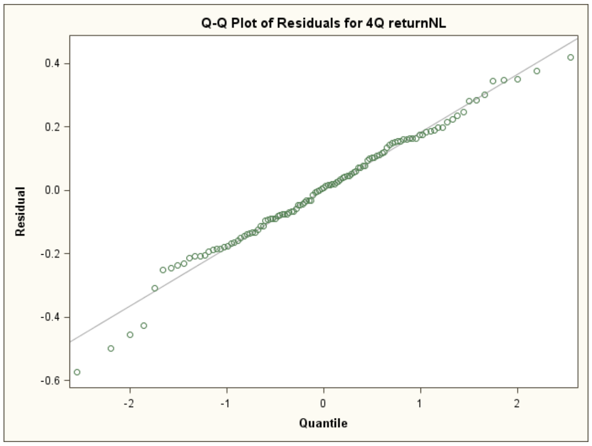
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.25384	0.25384	7.55	0.0070
Error	113	3.79690	0.03360		
Corrected Total	114	4.05074			

Root MSE	0.18331	**R-Square**	0.0627
Dependent Mean	0.10107	**Adj R-Sq**	0.0544
Coeff Var	181.36925		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.36256	0.16955	-2.14	0.0346
px4QNL	1	-0.13219	0.04810	-2.75	0.0070

Test for normality in the error terms

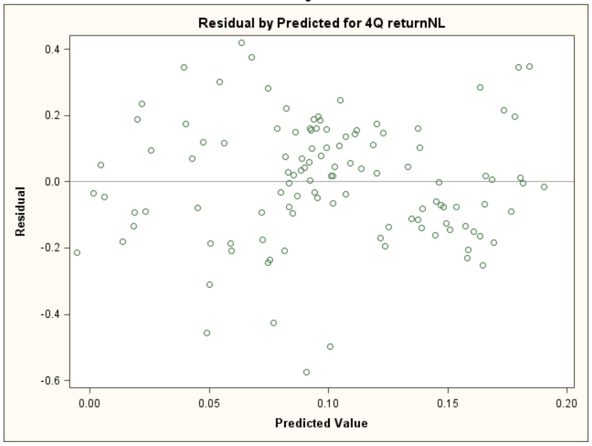


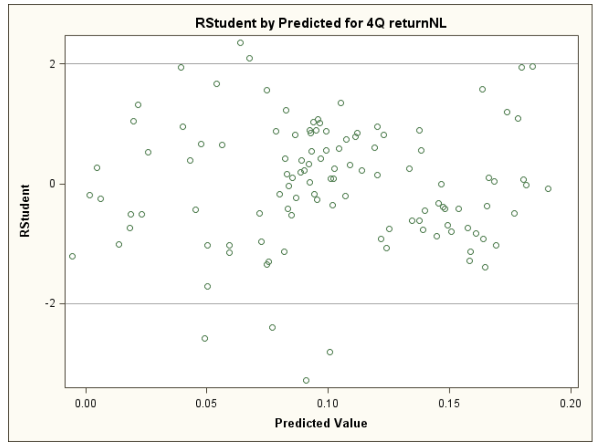


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	2.9099	0.2334	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.00290	0.00145	0.53	0.5880
Error	112	0.30451	0.00272		
Corrected Total	114	0.30741			

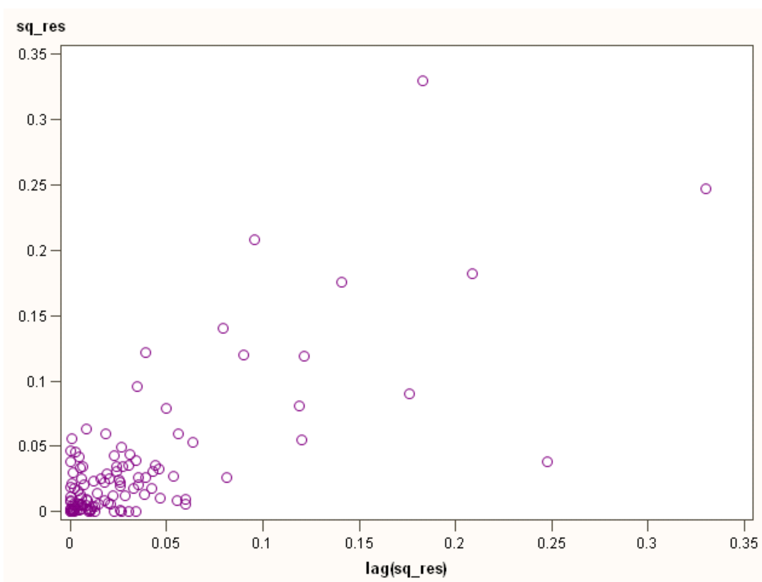
Root MSE	0.05214	**R-Square**	0.0094
Dependent Mean	0.03302	**Adj R-Sq**	-0.0083
Coeff Var	157.92793		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.02380	0.39520	-0.06	0.9521
px4QNL	1	-0.04712	0.22808	-0.21	0.8367
sq_px	1	-0.00873	0.03269	-0.27	0.7900

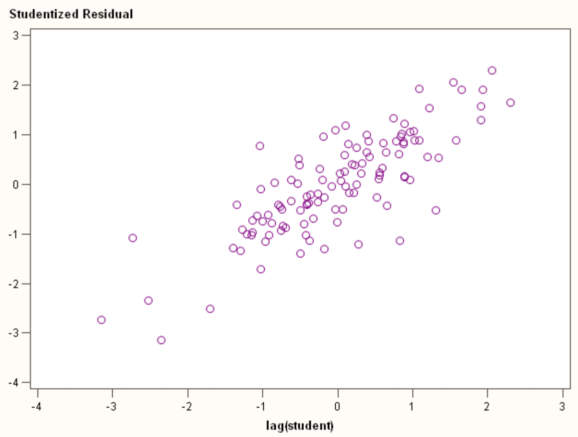
Autoregressive conditional heteroscedasticity (ARCH)

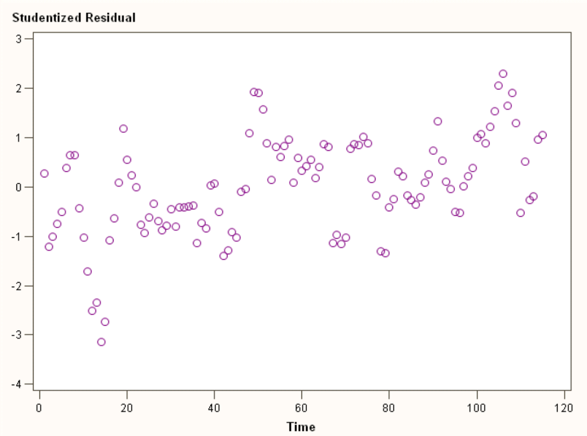
Dependent Variable	residual_4Q returnNL
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	64.8418	<.0001	63.5192	<.0001
2	88.5094	<.0001	66.4620	<.0001
3	93.5112	<.0001	66.7082	<.0001
4	93.5659	<.0001	66.9953	<.0001
5	93.9090	<.0001	67.1817	<.0001
6	95.4063	<.0001	67.7271	<.0001
7	97.1379	<.0001	67.7911	<.0001
8	99.2309	<.0001	68.0853	<.0001
9	101.1582	<.0001	68.1128	<.0001
10	103.0039	<.0001	68.3611	<.0001
11	104.4815	<.0001	68.3697	<.0001
12	104.8511	<.0001	68.3840	<.0001



Test for autocorrelation in the error terms





LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	77.0388	<.0001
AR(2)	78.0133	<.0001
AR(3)	78.4697	<.0001
AR(4)	80.0690	<.0001

Durbin-Watson d test

Durbin-Watson D	0.373
Number of Observations	115
1st Order Autocorrelation	0.808

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-0.36256	0.2812	-1.29	0.1999
b1	-0.13219	0.0784	-1.69	0.0946

12Q

$$r_{t,t+12} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

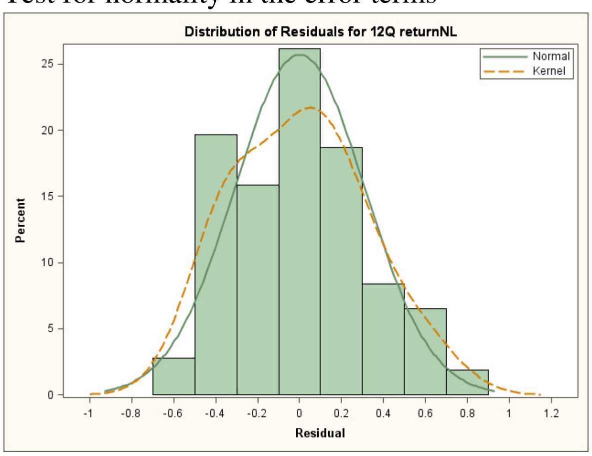
Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

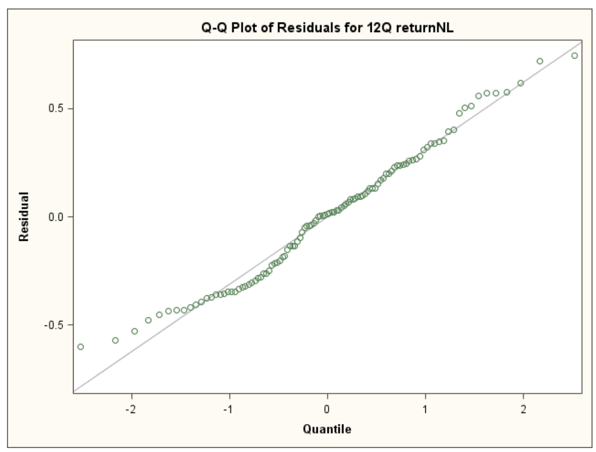
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	3.10307	3.10307	31.88	<.0001
Error	105	10.21871	0.09732		
Corrected Total	106	13.32178			

Root MSE	0.31196	**R-Square**	0.2329
Dependent Mean	0.31767	**Adj R-Sq**	0.2256
Coeff Var	98.20447		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-1.53969	0.33031	-4.66	<.0001
px12QNL	1	-0.52288	0.09260	-5.65	<.0001

Test for normality in the error terms

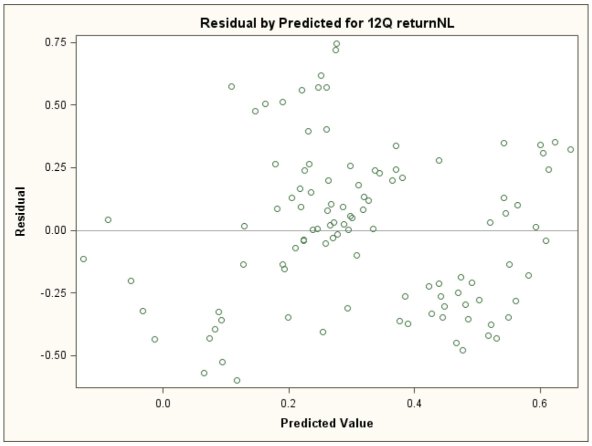


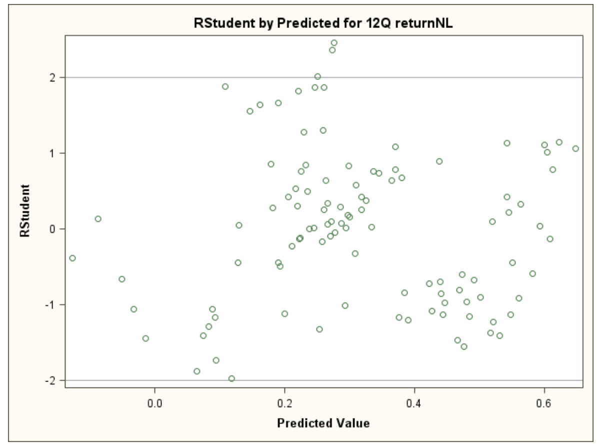


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	2.7045	0.2587	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.02932	0.01466	1.15	0.3208
Error	104	1.32635	0.01275		
Corrected Total	106	1.35567			

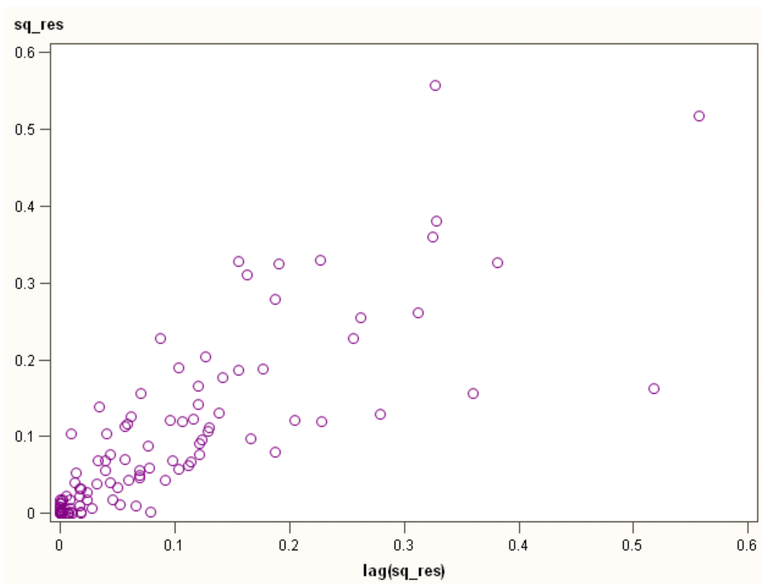
Root MSE	0.11293	**R-Square**	0.0216
Dependent Mean	0.09550	**Adj R-Sq**	0.0028
Coeff Var	118.24976		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.11590	1.01541	0.11	0.9093
px12QNL	1	-0.04028	0.57642	-0.07	0.9444
sq_px	1	-0.01285	0.08140	-0.16	0.8749

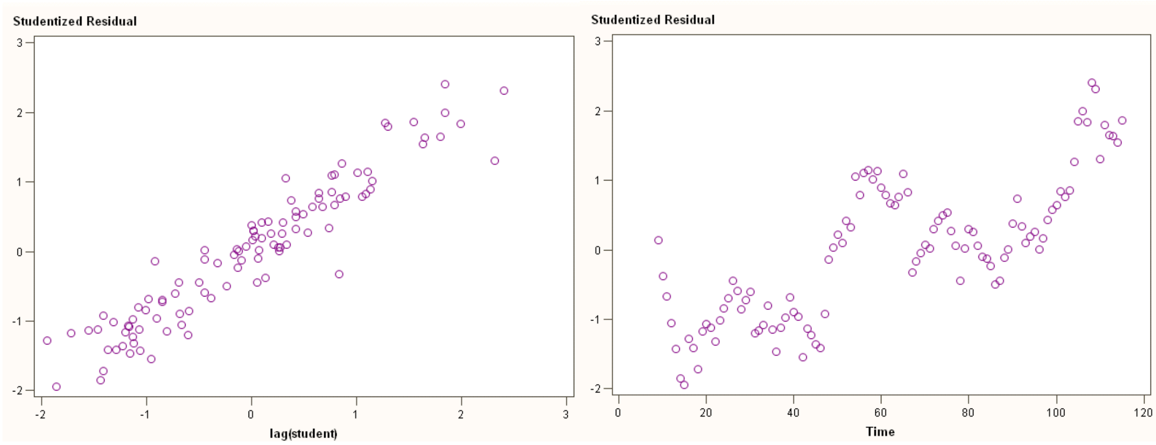
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_12Q returnNL
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	69.2416	<.0001	70.9013	<.0001
2	116.4576	<.0001	70.9868	<.0001
3	155.8360	<.0001	72.3836	<.0001
4	181.2498	<.0001	73.3232	<.0001
5	193.2542	<.0001	74.0129	<.0001
6	202.7246	<.0001	74.2075	<.0001
7	208.8823	<.0001	74.4998	<.0001
8	211.0001	<.0001	74.5001	<.0001
9	212.0945	<.0001	74.5205	<.0001
10	212.4638	<.0001	74.7877	<.0001
11	212.5026	<.0001	75.8159	<.0001
12	212.9085	<.0001	75.8668	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	96.5353	<.0001
AR(2)	96.5353	<.0001
AR(3)	96.7091	<.0001
AR(4)	96.7144	<.0001

Durbin-Watson d test

Durbin-Watson D	0.103
Number of Observations	107
1st Order Autocorrelation	0.932

The regression with Newey-West HAC standard errors, 12 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-1.53969	0.9022	-1.71	0.0909
b1	-0.52288	0.2481	-2.11	0.0374

20Q

$$r_{t,t+20} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

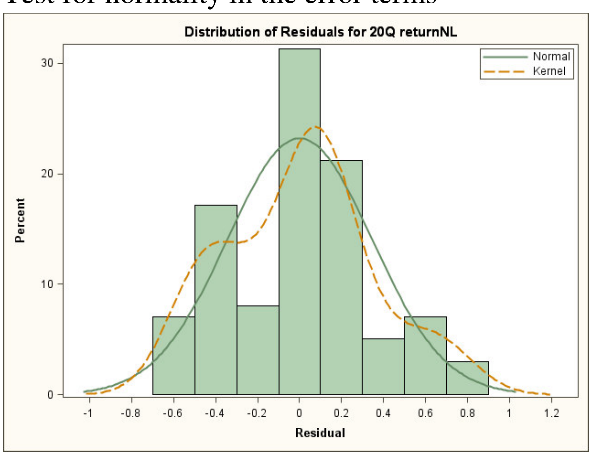
Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

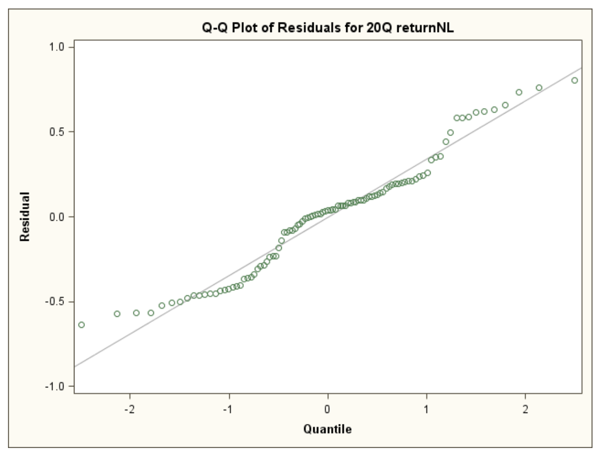
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	7.98170	7.98170	66.80	<.0001
Error	97	11.58992	0.11948		
Corrected Total	98	19.57162			

Root MSE	0.34566	**R-Square**	0.4078
Dependent Mean	0.54394	**Adj R-Sq**	0.4017
Coeff Var	63.54834		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-2.51859	0.37631	-6.69	<.0001
px20QNL	1	-0.85794	0.10497	-8.17	<.0001

Test for normality in the error terms

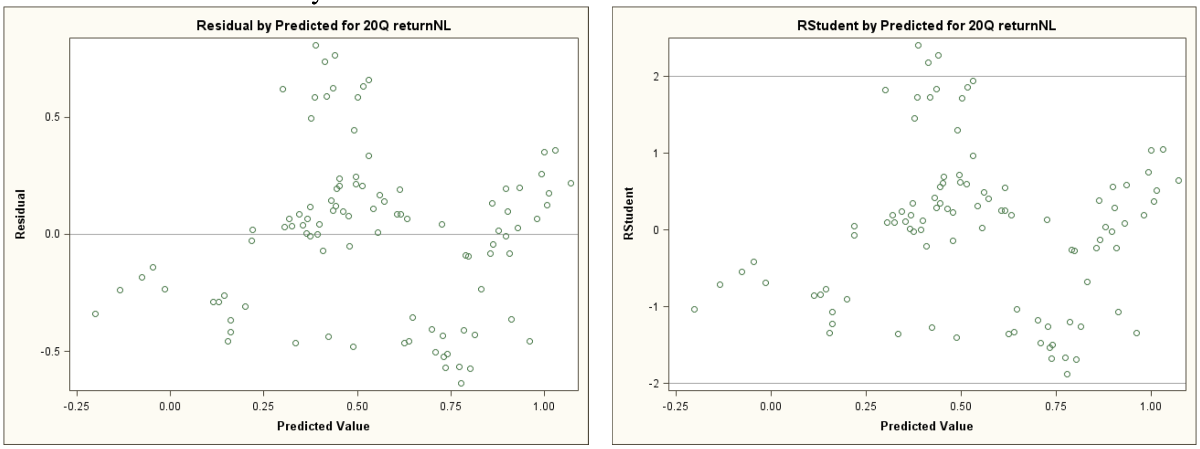




Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	1.6107	0.4469	Pr > ChiSq

Test for heteroscedasticity in the error terms



White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.07983	0.03991	1.88	0.1586
Error	96	2.04134	0.02126		
Corrected Total	98	2.12117			

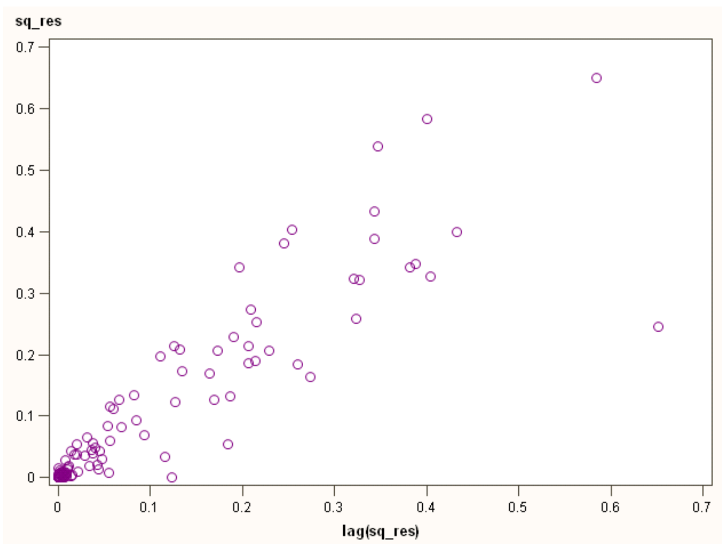
Root MSE	0.14582	**R-Square**	0.0376
Dependent Mean	0.11707	**Adj R-Sq**	0.0176
Coeff Var	124.55944		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-2.35433	1.32425	-1.78	0.0786
px20QNL	1	-1.42553	0.75244	-1.89	0.0612
sq_px	1	-0.20365	0.10633	-1.92	0.0584

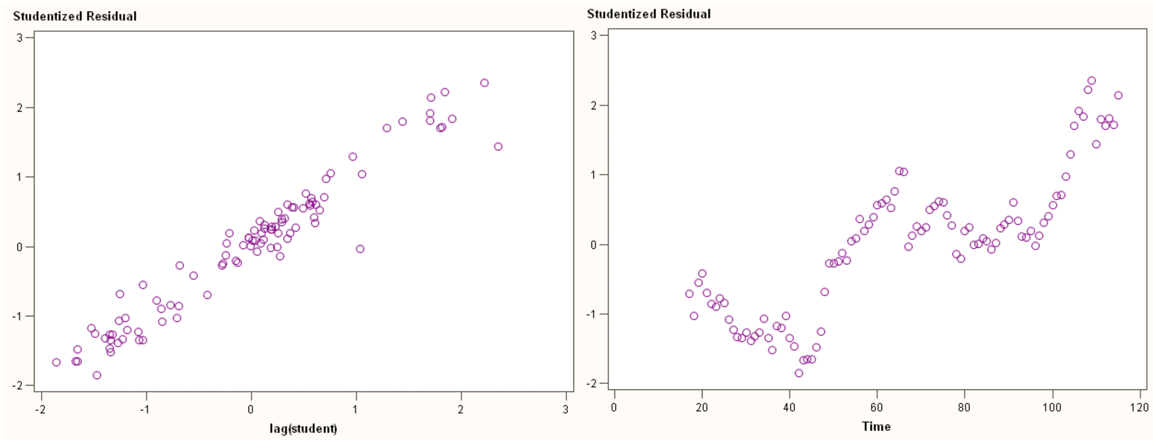
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_20Q returnNL
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	74.0570	<.0001	78.6482	<.0001
2	135.2187	<.0001	78.8244	<.0001
3	183.5819	<.0001	78.8303	<.0001
4	220.2616	<.0001	78.9174	<.0001
5	244.3598	<.0001	79.2822	<.0001
6	264.8675	<.0001	80.0372	<.0001
7	276.5767	<.0001	80.0584	<.0001
8	282.1549	<.0001	80.0598	<.0001
9	285.4301	<.0001	80.1161	<.0001
10	286.5569	<.0001	80.5955	<.0001
11	286.6794	<.0001	80.9436	<.0001
12	286.6919	<.0001	80.9881	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	92.7445	<.0001
AR(2)	92.7453	<.0001
AR(3)	92.9160	<.0001
AR(4)	92.9216	<.0001

Durbin-Watson d test

Durbin-Watson D	0.061
Number of Observations	99
1st Order Autocorrelation	0.944

The regression with Newey-West HAC standard errors, 20 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-2.51859	0.8427	-2.99	0.0035
b1	-0.85794	0.2301	-3.73	0.0003

Import

4Q

$$r_{t,t+4} = \beta_1 + \beta_2 pz_t + \varepsilon_t$$

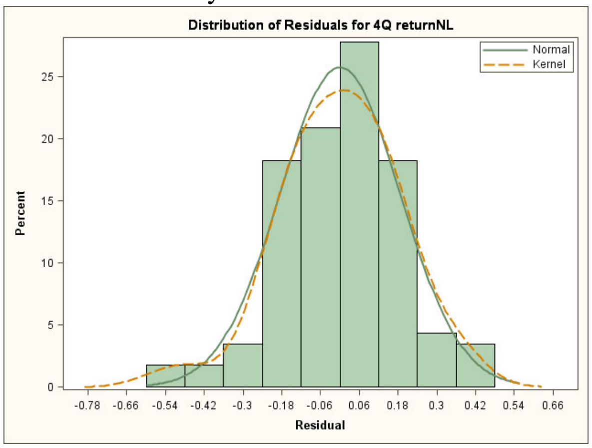
Number of Observations Read	115
Number of Observations Used	115

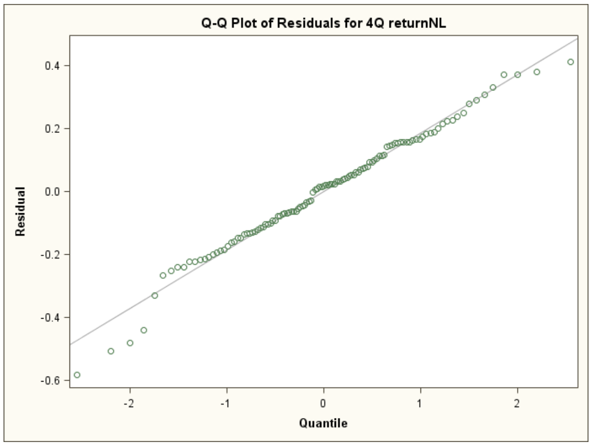
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.11925	0.11925	3.43	0.0667
Error	113	3.93149	0.03479		
Corrected Total	114	4.05074			

Root MSE	0.18653	**R-Square**	0.0294
Dependent Mean	0.10107	**Adj R-Sq**	0.0208
Coeff Var	184.55587		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.20667	0.16713	-1.24	0.2188
pz4QNL	1	-0.08885	0.04799	-1.85	0.0667

Test for normality in the error terms

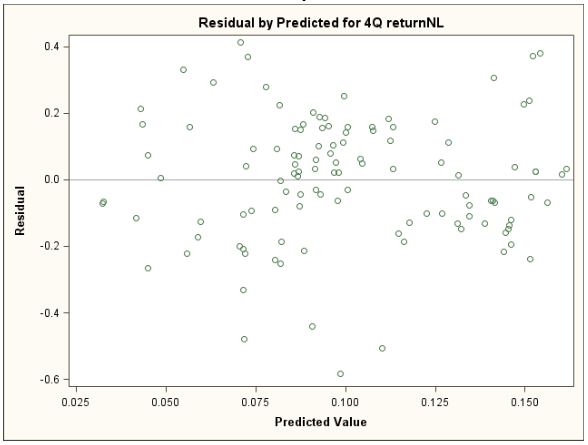


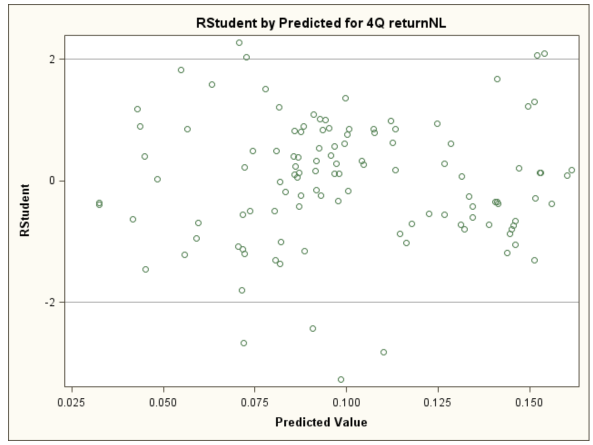


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	3.6513	0.1611	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.00223	0.00111	0.37	0.6904
Error	112	0.33547	0.00300		
Corrected Total	114	0.33770			

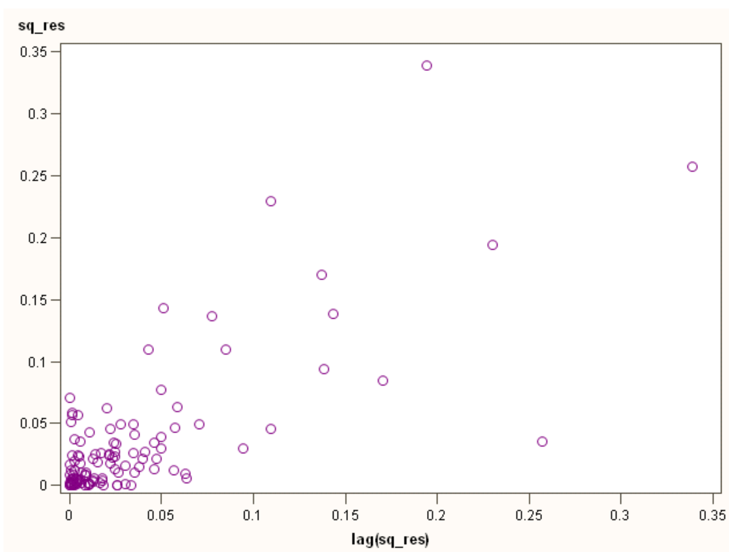
Root MSE	0.05473	**R-Square**	0.0066
Dependent Mean	0.03419	**Adj R-Sq**	-0.0111
Coeff Var	160.08858		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.00204	0.42440	0.00	0.9962
pz4QNL	1	-0.03076	0.24559	-0.13	0.9005
sq_pz	1	-0.00613	0.03526	-0.17	0.8622

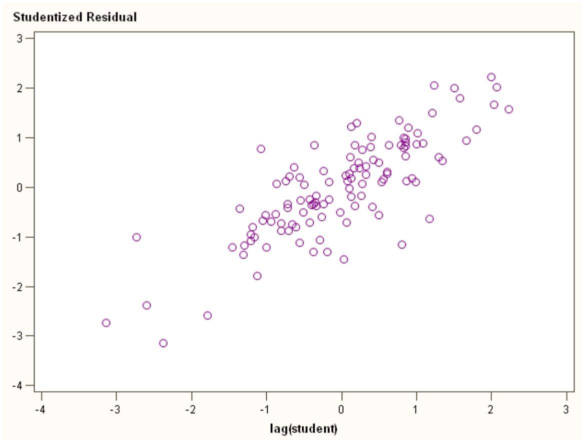
Autoregressive conditional heteroscedasticity (ARCH)

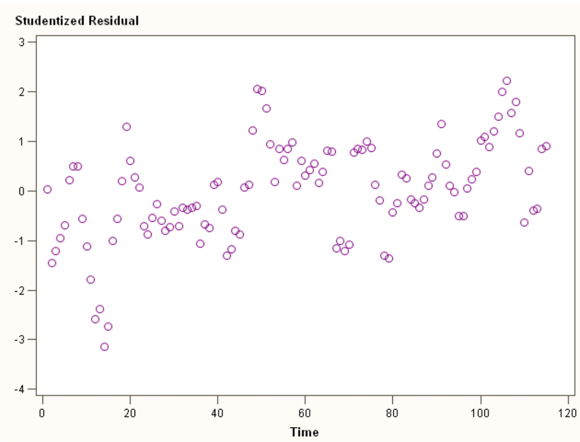
Dependent Variable	residual_4Q returnNL
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	65.0195	<.0001	63.7335	<.0001
2	89.0206	<.0001	66.7235	<.0001
3	94.1141	<.0001	66.9966	<.0001
4	94.1961	<.0001	67.2159	<.0001
5	94.4853	<.0001	67.3574	<.0001
6	96.0418	<.0001	68.0258	<.0001
7	97.6955	<.0001	68.1828	<.0001
8	99.4948	<.0001	68.4812	<.0001
9	100.8673	<.0001	68.5448	<.0001
10	101.8545	<.0001	68.7330	<.0001
11	102.7031	<.0001	68.7389	<.0001
12	102.8360	<.0001	68.7885	<.0001



Test for autocorrelation in the error terms





LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	76.5868	<.0001
AR(2)	77.6940	<.0001
AR(3)	78.1695	<.0001
AR(4)	80.0044	<.0001

Durbin-Watson d test

Durbin-Watson D	0.378
Number of Observations	115
1st Order Autocorrelation	0.808

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-0.20667	0.2766	-0.75	0.4566
b1	-0.08885	0.0781	-1.14	0.2579

12Q

$$r_{t,t+12} = \beta_1 + \beta_2 pz_t + \varepsilon_t$$

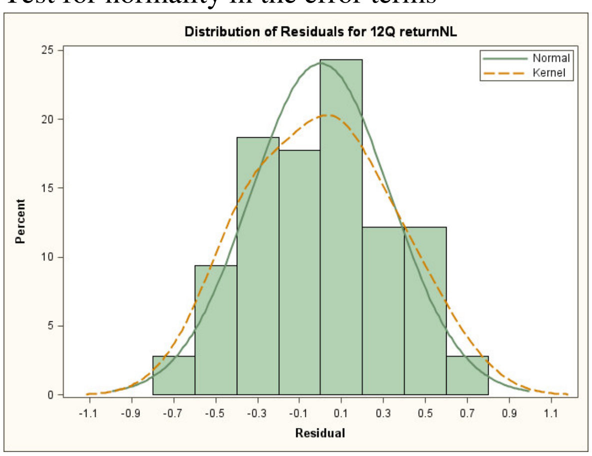
Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

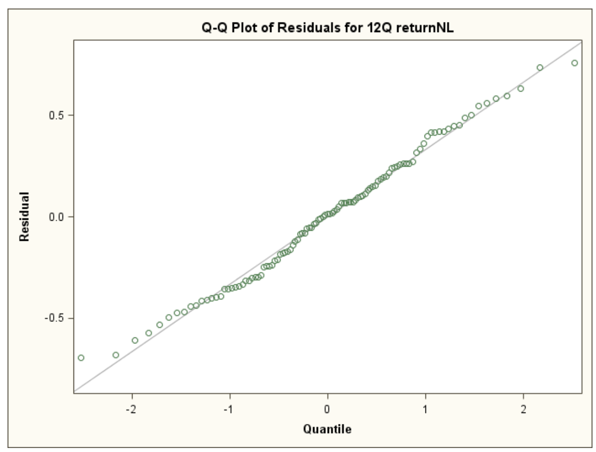
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	1.65874	1.65874	14.93	0.0002
Error	105	11.66304	0.11108		
Corrected Total	106	13.32178			

Root MSE	0.33328	**R-Square**	0.1245
Dependent Mean	0.31767	**Adj R-Sq**	0.1162
Coeff Var	104.91534		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-1.01908	0.34741	-2.93	0.0041
pz12QNL	1	-0.38062	0.09849	-3.86	0.0002

Test for normality in the error terms

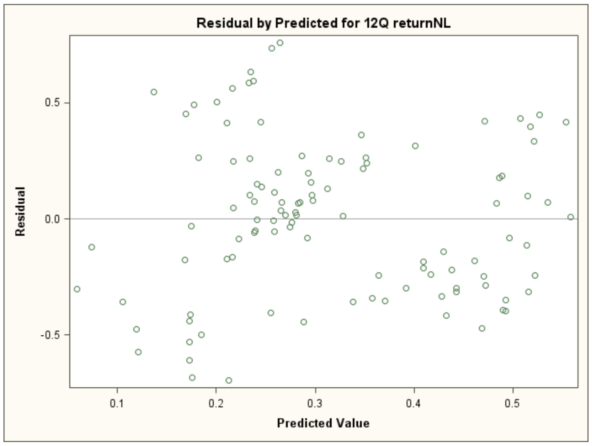


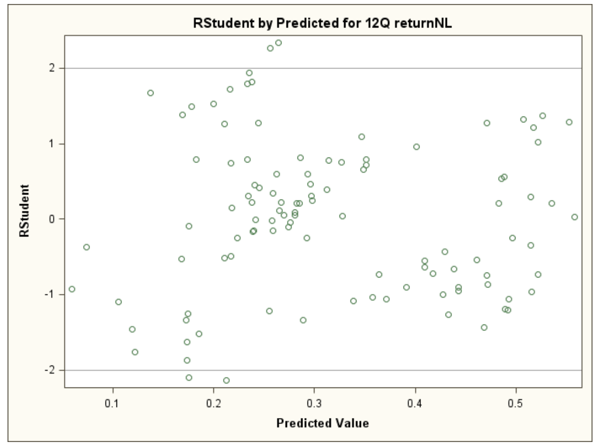


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	2.0703	0.3552	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.13681	0.06840	4.49	0.0135
Error	104	1.58557	0.01525		
Corrected Total	106	1.72238			

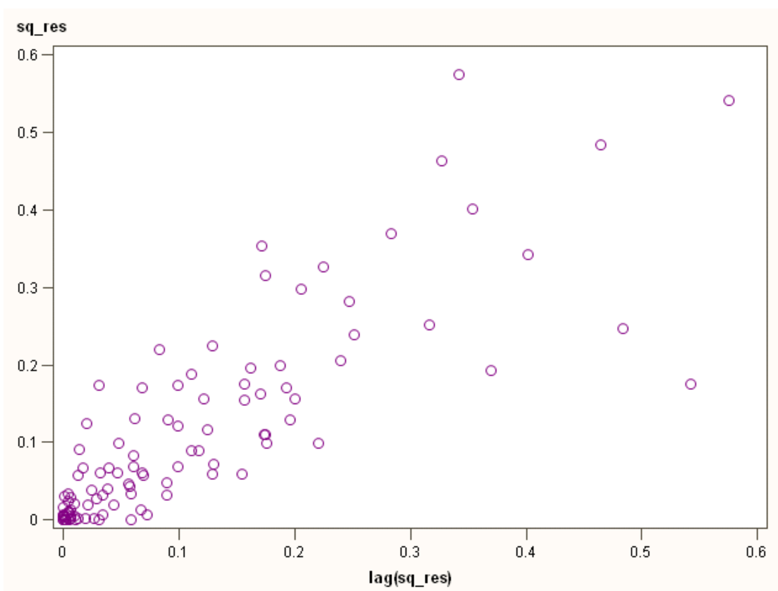
Root MSE	0.12347	**R-Square**	0.0794
Dependent Mean	0.10900	**Adj R-Sq**	0.0617
Coeff Var	113.27882		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	2.95976	1.43660	2.06	0.0419
pz12QNL	1	1.53000	0.81258	1.88	0.0625
sq_pz	1	0.20276	0.11414	1.78	0.0786

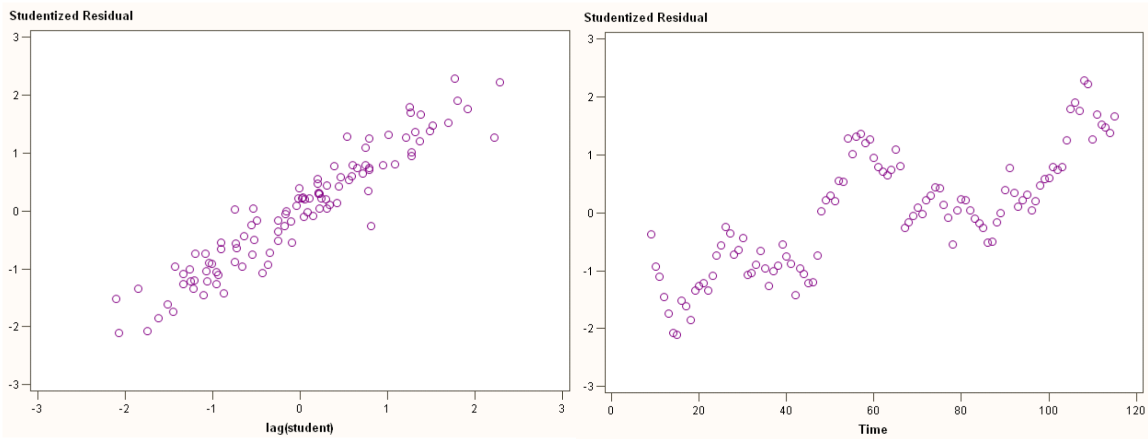
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_12Q returnNL
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	74.0352	<.0001	74.1100	<.0001
2	126.7636	<.0001	74.1290	<.0001
3	169.2302	<.0001	74.6712	<.0001
4	195.7754	<.0001	76.2242	<.0001
5	208.1921	<.0001	77.1340	<.0001
6	215.8328	<.0001	77.1448	<.0001
7	220.2313	<.0001	77.5450	<.0001
8	221.6297	<.0001	77.5458	<.0001
9	222.0390	<.0001	77.5781	<.0001
10	222.0823	<.0001	77.8666	<.0001
11	222.3102	<.0001	78.8919	<.0001
12	223.0219	<.0001	78.9042	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	96.9966	<.0001
AR(2)	97.0084	<.0001
AR(3)	97.1489	<.0001
AR(4)	97.1491	<.0001

Durbin-Watson d test

Durbin-Watson D	0.098
Number of Observations	107
1st Order Autocorrelation	0.938

The regression with Newey-West HAC standard errors, 12 lags

Nonlinear GMM Parameter Estimates				
Parameter	Estimate	Approx Std Err	t Value	Approx Pr > |t|
b0	-1.01908	1.0361	-0.98	0.3276
b1	-0.38062	0.2856	-1.33	0.1855

20Q

$$r_{t,t+20} = \beta_1 + \beta_2 pz_t + \varepsilon_t$$

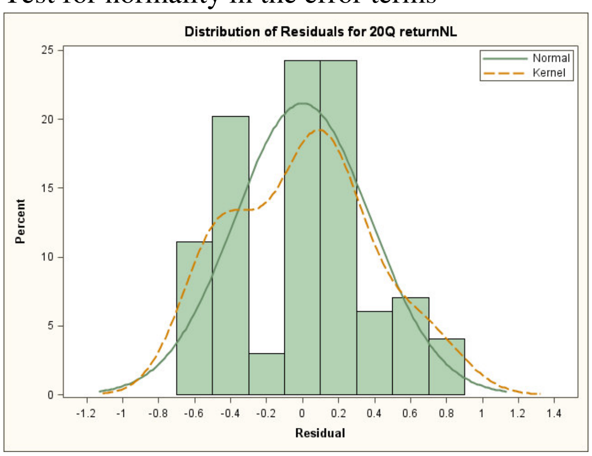
Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

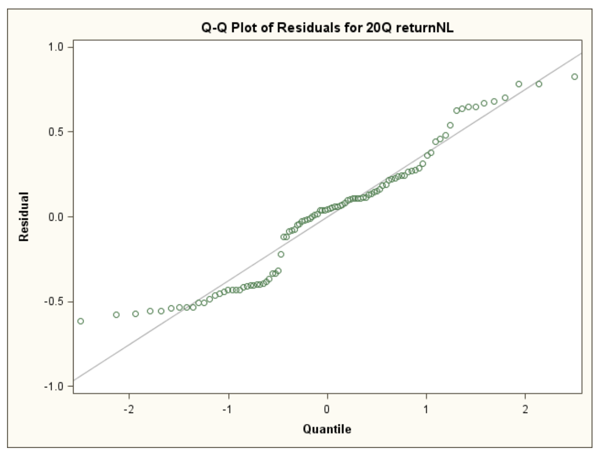
Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	5.62146	5.62146	39.09	<.0001
Error	97	13.95016	0.14382		
Corrected Total	98	19.57162			

Root MSE	0.37923	**R-Square**	0.2872
Dependent Mean	0.54394	**Adj R-Sq**	0.2799
Coeff Var	69.71938		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-2.02628	0.41286	-4.91	<.0001
pz20QNL	1	-0.72702	0.11629	-6.25	<.0001

Test for normality in the error terms

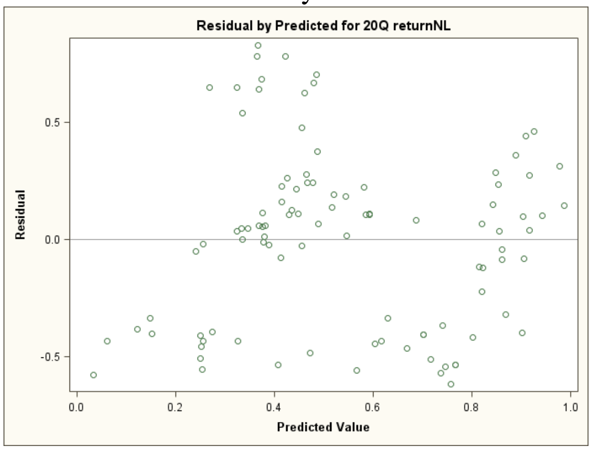


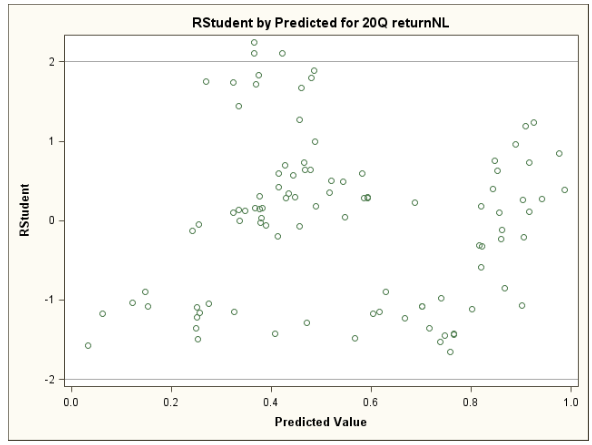


Jarque-Bera test

Miscellaneous Statistics			
Statistic	Value	Prob	Label
Normal Test	2.8837	0.2365	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.10536	0.05268	2.11	0.1266
Error	96	2.39518	0.02495		
Corrected Total	98	2.50054			

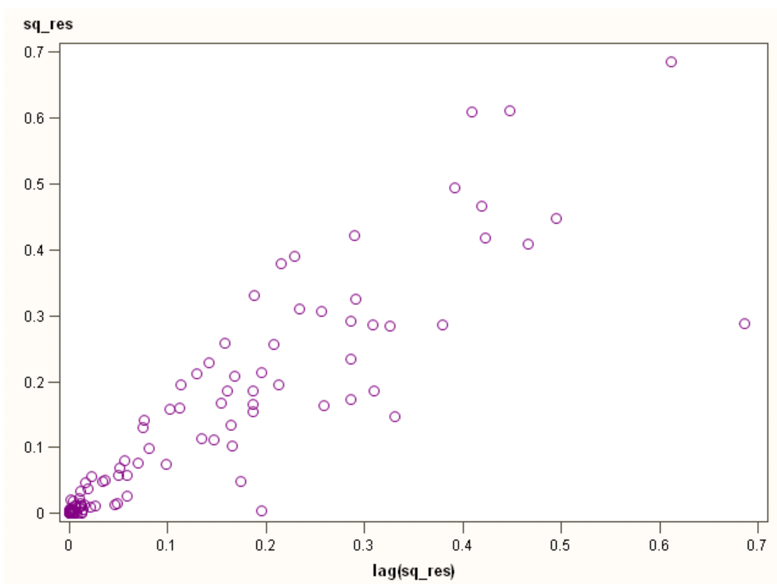
Root MSE	0.15795	**R-Square**	0.0421
Dependent Mean	0.14091	**Adj R-Sq**	0.0222
Coeff Var	112.09580		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.13917	1.88372	0.07	0.9413
pz20QNL	1	-0.10038	1.06384	-0.09	0.9250
sq_pz	1	-0.02801	0.14924	-0.19	0.8515

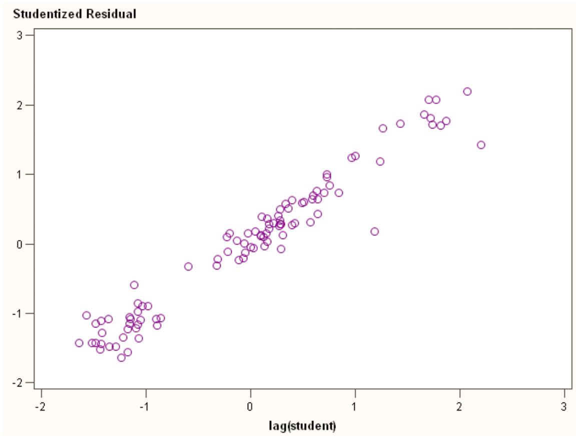
Autoregressive conditional heteroscedasticity (ARCH)

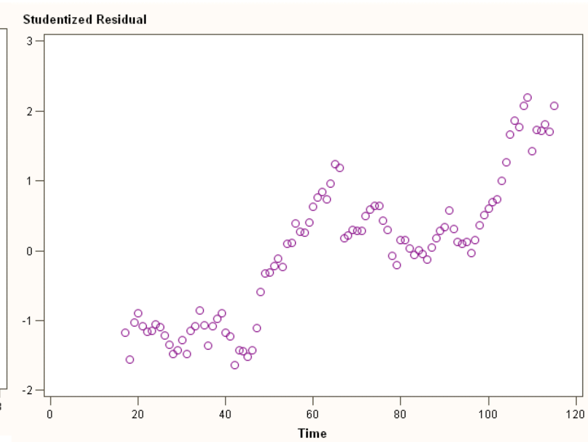
Dependent Variable	residual_20Q returnNL
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	72.7812	<.0001	76.4152	<.0001
2	131.3629	<.0001	76.4612	<.0001
3	178.2670	<.0001	76.7088	<.0001
4	214.5708	<.0001	76.7384	<.0001
5	239.3485	<.0001	77.0533	<.0001
6	260.1821	<.0001	77.3656	<.0001
7	272.3952	<.0001	77.3664	<.0001
8	279.0705	<.0001	77.4189	<.0001
9	283.5460	<.0001	77.5050	<.0001
10	285.4454	<.0001	77.8056	<.0001
11	285.8784	<.0001	78.1568	<.0001
12	285.9163	<.0001	78.3867	<.0001



Test for autocorrelation in the error terms





LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	92.6493	<.0001
AR(2)	92.6675	<.0001
AR(3)	92.8831	<.0001
AR(4)	92.9061	<.0001

Durbin-Watson d test

Durbin-Watson D	0.054
Number of Observations	99
1st Order Autocorrelation	0.945

The regression with Newey-West HAC standard errors, 20 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-2.02628	1.1324	-1.79	0.0767
b1	-0.72702	0.3063	-2.37	0.0196

France

Output

4Q

$$r_{t,t+4} = \beta_1 + \beta_2 RESpy_t + \varepsilon_t$$

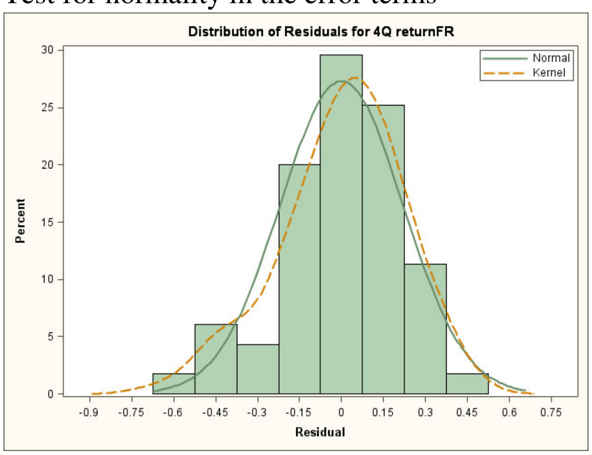
Number of Observations Read	115
Number of Observations Used	115

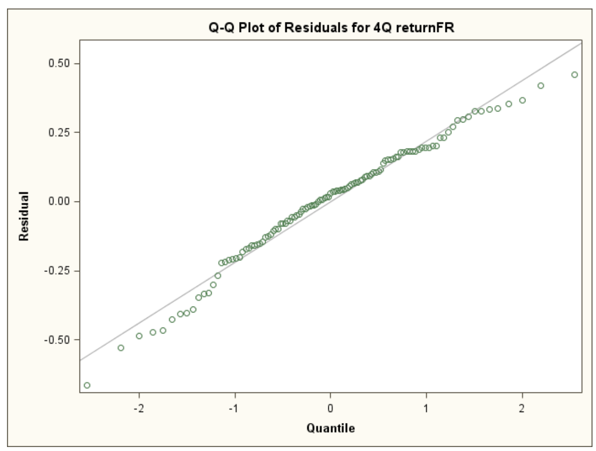
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.75261	0.75261	15.55	0.0001
Error	113	5.46935	0.04840		
Corrected Total	114	6.22196			

Root MSE	0.22000	**R-Square**	0.1210
Dependent Mean	0.07677	**Adj R-Sq**	0.1132
Coeff Var	286.55618		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.06386	0.02078	3.07	0.0026
RESpy4QFR	1	-0.18203	0.04616	-3.94	0.0001

Test for normality in the error terms

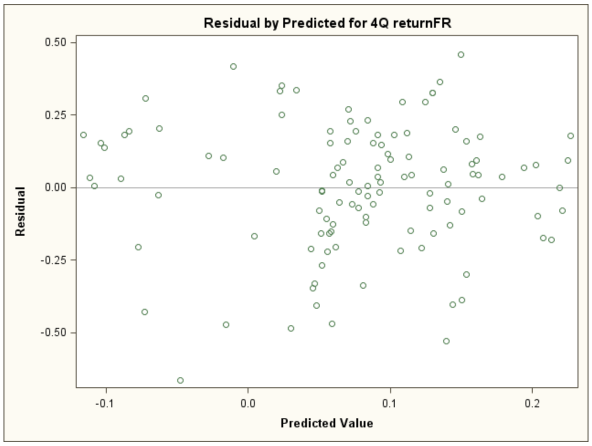


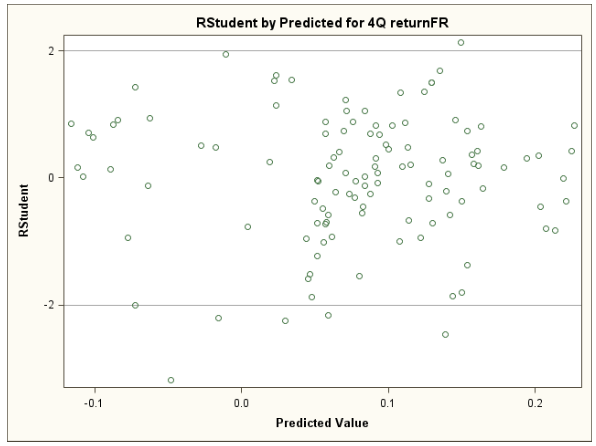


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	5.5217	0.0632	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.01880	0.00940	1.94	0.1482
Error	112	0.54208	0.00484		
Corrected Total	114	0.56088			

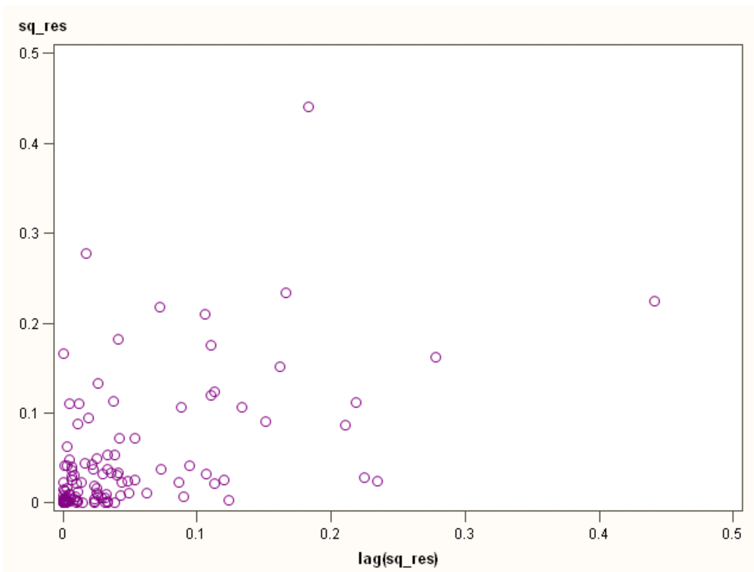
Root MSE	0.06957	**R-Square**	0.0335
Dependent Mean	0.04756	**Adj R-Sq**	0.0163
Coeff Var	146.28028		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.05438	0.00843	6.45	<.0001
RESpy4QFR	1	0.02780	0.01485	1.87	0.0639
sq_RESpy	1	-0.02396	0.02512	-0.95	0.3423

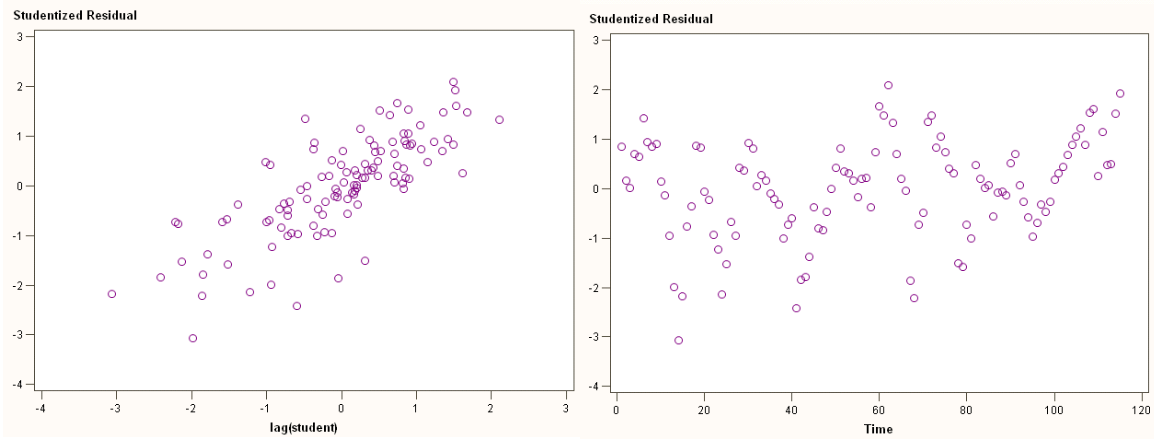
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_4Q returnFR
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	30.6147	<.0001	30.7662	<.0001
2	31.2814	<.0001	36.0812	<.0001
3	31.7463	<.0001	36.1262	<.0001
4	33.1154	<.0001	36.6147	<.0001
5	33.3368	<.0001	37.1552	<.0001
6	33.3478	<.0001	37.4465	<.0001
7	33.5445	<.0001	37.4481	<.0001
8	33.6804	<.0001	37.4520	<.0001
9	33.6841	0.0001	37.4742	<.0001
10	34.7154	0.0001	38.9250	<.0001
11	34.7809	0.0003	40.6052	<.0001
12	36.4327	0.0003	40.8788	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	69.4786	<.0001
AR(2)	70.2309	<.0001
AR(3)	71.1621	<.0001
AR(4)	75.7684	<.0001

Durbin-Watson d test

Durbin-Watson D	0.442
Number of Observations	115
1st Order Autocorrelation	0.760

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.063862	0.0371	1.72	0.0882
b1	-0.18203	0.0792	-2.30	0.0233

12Q

$$r_{t,t+12} = \beta_1 + \beta_2 RESpy_t + \varepsilon_t$$

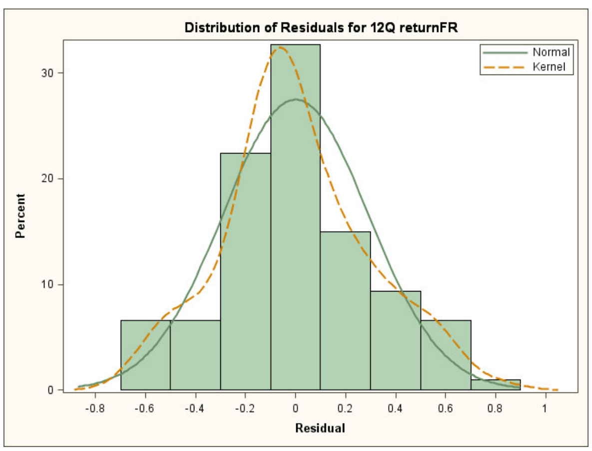
Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

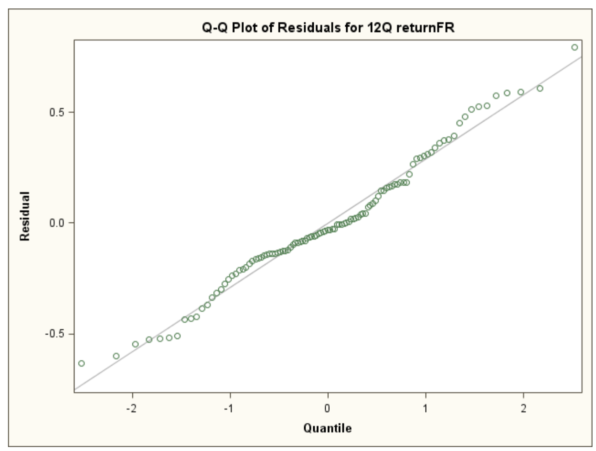
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	6.78274	6.78274	79.76	<.0001
Error	105	8.92941	0.08504		
Corrected Total	106	15.71215			

Root MSE	0.29162	**R-Square**	0.4317
Dependent Mean	0.21641	**Adj R-Sq**	0.4263
Coeff Var	134.75458		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.16064	0.02888	5.56	<.0001
RESpy12QFR	1	-0.56317	0.06306	-8.93	<.0001

Test for normality in the error terms

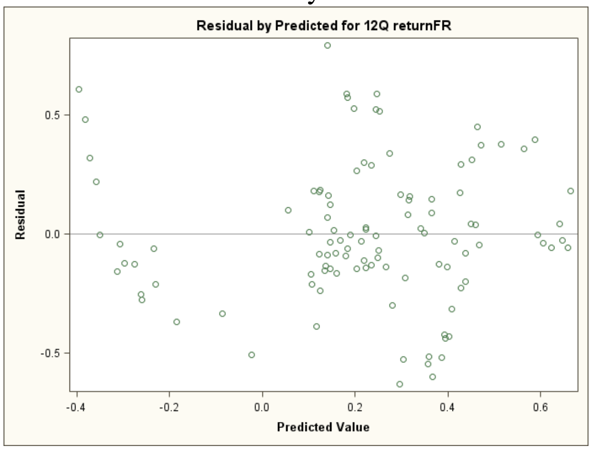


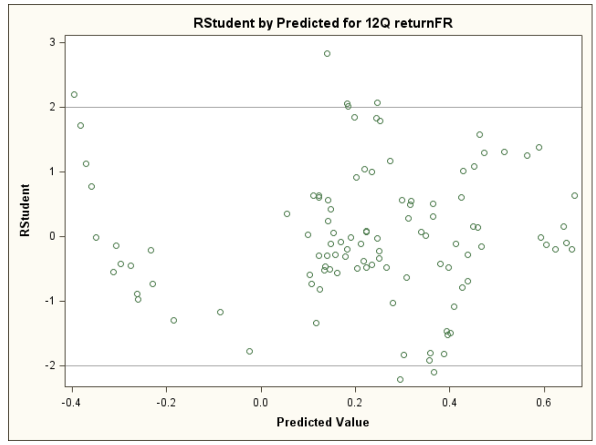


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	1.1729	0.5563	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	0.00461	0.00230	0.16	0.8499
Error	104	1.47161	0.01415		
Corrected Total	106	1.47622			

Root MSE	0.11895	**R-Square**	0.0031
Dependent Mean	0.08345	**Adj R-Sq**	-0.0160
Coeff Var	142.54132		

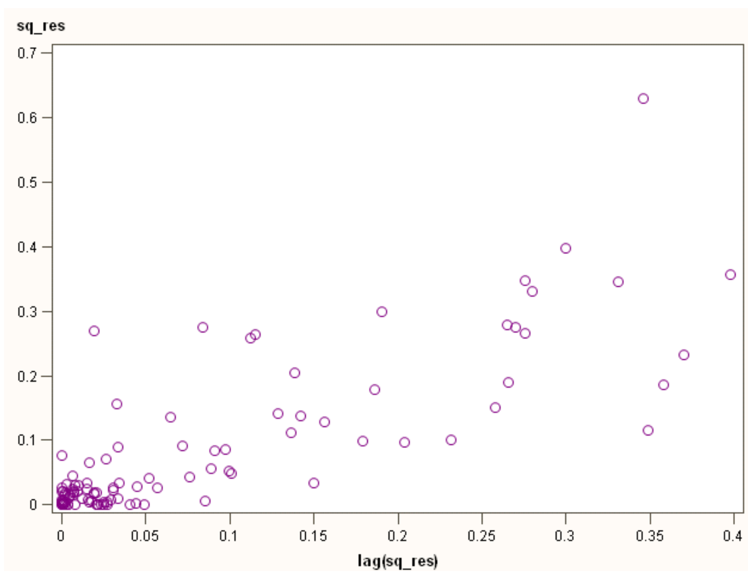
Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.08869	0.01524	5.82	<.0001
RESpy12QFR	1	0.01156	0.02631	0.44	0.6614
sq_RESpy	1	-0.01953	0.04354	-0.45	0.6547

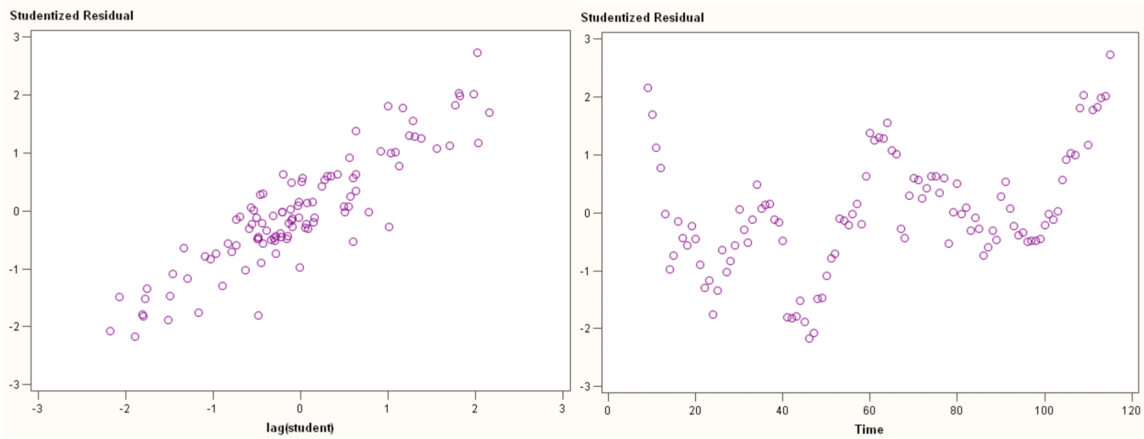
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_12Q returnFR
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	54.3847	<.0001	63.0785	<.0001
2	87.3117	<.0001	63.1340	<.0001
3	108.0202	<.0001	63.3918	<.0001
4	120.3108	<.0001	63.3957	<.0001
5	124.4159	<.0001	64.1606	<.0001
6	126.2457	<.0001	64.1712	<.0001
7	126.2986	<.0001	64.5197	<.0001
8	128.5569	<.0001	64.6927	<.0001
9	131.9032	<.0001	64.6949	<.0001
10	136.0360	<.0001	64.7057	<.0001
11	140.8048	<.0001	64.7350	<.0001
12	144.3383	<.0001	64.8604	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	83.6534	<.0001
AR(2)	83.6820	<.0001
AR(3)	83.9671	<.0001
AR(4)	84.2234	<.0001

Durbin-Watson d test

Durbin-Watson D	0.186
Number of Observations	107
1st Order Autocorrelation	0.851

The regression with Newey-West HAC standard errors, 12 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.160644	0.0713	2.25	0.0264
b1	-0.56317	0.1170	-4.81	<.0001

20Q

$$r_{t,t+20} = \beta_1 + \beta_2 RESpy_t + \varepsilon_t$$

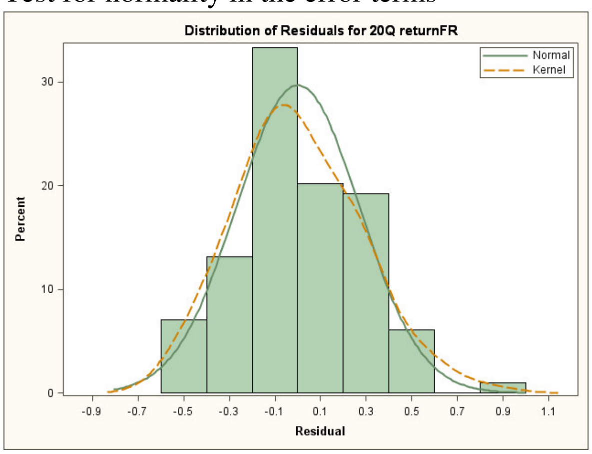
Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

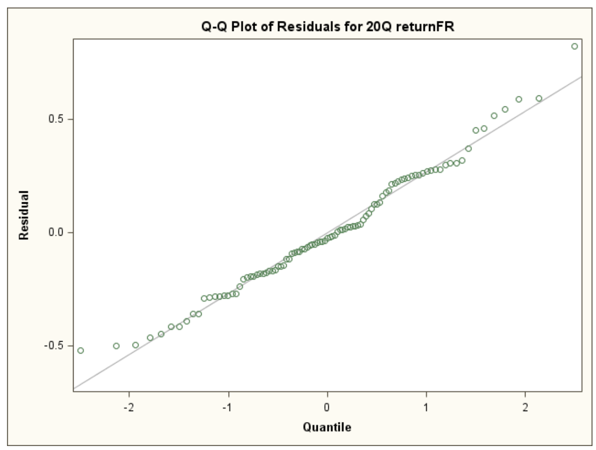
Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	15.59355	15.59355	213.74	<.0001
Error	97	7.07657	0.07295		
Corrected Total	98	22.67011			

Root MSE	0.27010	R-Square	0.6878
Dependent Mean	0.35684	Adj R-Sq	0.6846
Coeff Var	75.69240		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.27206	0.02776	9.80	<.0001
RESpy20QFR	1	-0.85482	0.05847	-14.62	<.0001

Test for normality in the error terms

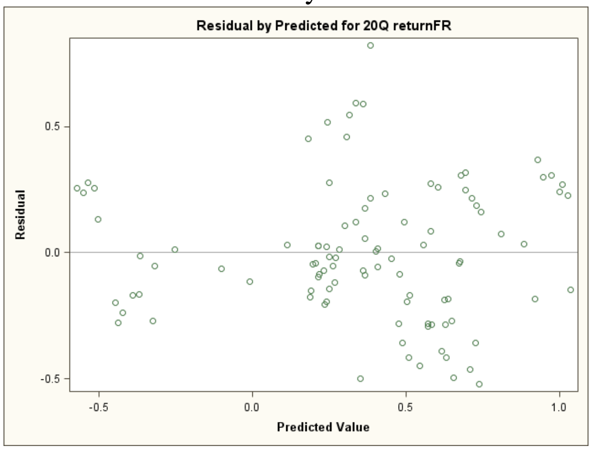


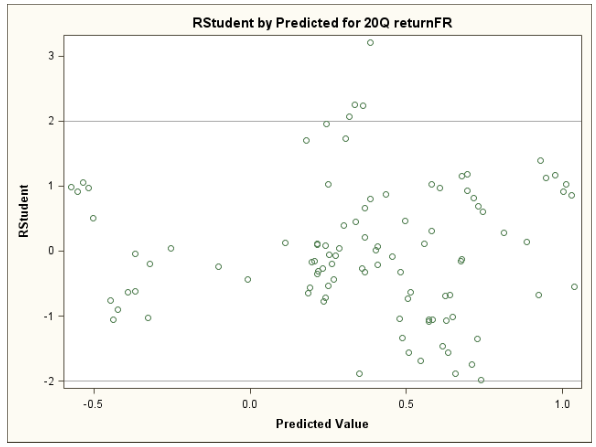


Jarque-Bera test

Miscellaneous Statistics			
Statistic	Value	Prob	Label
Normal Test	2.3940	0.3021	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.02034	0.01017	0.97	0.3823
Error	96	1.00544	0.01047		
Corrected Total	98	1.02578			

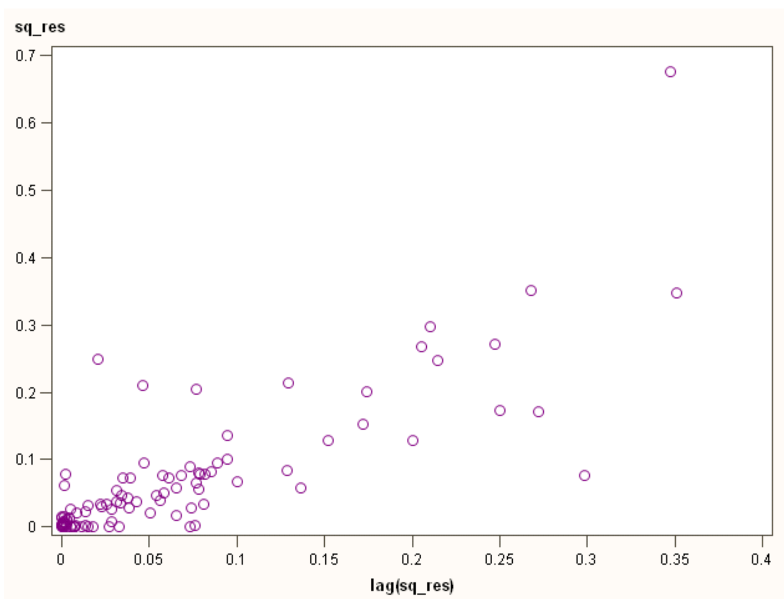
Root MSE	0.10234	**R-Square**	0.0198
Dependent Mean	0.07148	**Adj R-Sq**	-0.0006
Coeff Var	143.17110		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.07373	0.01392	5.30	<.0001
RESpy20QFR	1	-0.02562	0.02269	-1.13	0.2617
sq_RESpy	1	-0.02124	0.03832	-0.55	0.5807

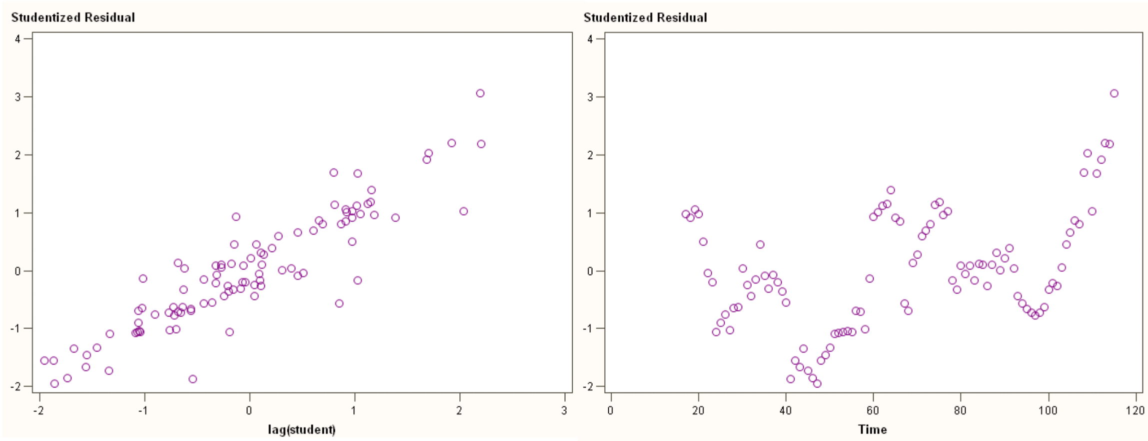
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_20Q returnFR
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	42.8513	<.0001	64.7595	<.0001
2	73.3864	<.0001	66.3699	<.0001
3	91.7245	<.0001	66.3878	<.0001
4	103.7328	<.0001	66.4129	<.0001
5	109.0026	<.0001	67.9199	<.0001
6	115.5579	<.0001	68.8291	<.0001
7	116.8139	<.0001	69.0636	<.0001
8	116.8553	<.0001	70.3571	<.0001
9	117.0447	<.0001	70.4197	<.0001
10	117.6546	<.0001	70.4332	<.0001
11	118.4961	<.0001	70.4353	<.0001
12	119.5623	<.0001	70.4405	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	81.1139	<.0001
AR(2)	81.1546	<.0001
AR(3)	81.1556	<.0001
AR(4)	81.4230	<.0001

Durbin-Watson d test

Durbin-Watson D	0.175
Number of Observations	99
1st Order Autocorrelation	0.860

The regression with Newey-West HAC standard errors, 20 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.272059	0.0704	3.86	0.0002
b1	-0.85482	0.0909	-9.40	<.0001

Export

4Q

$$r_{t,t+4} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

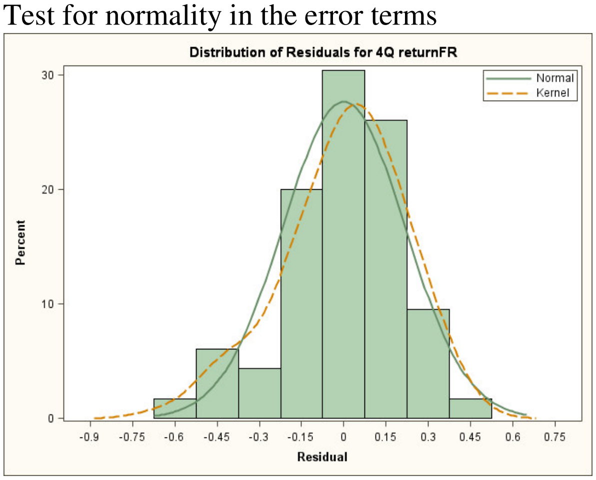
Number of Observations Read	115
Number of Observations Used	115

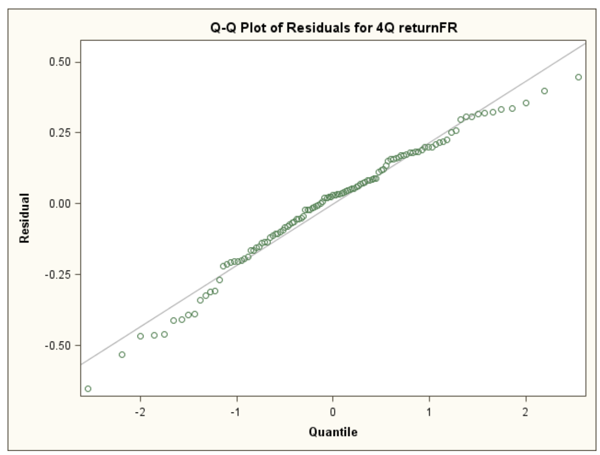
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.89300	0.89300	18.94	<.0001
Error	113	5.32895	0.04716		
Corrected Total	114	6.22196			

Root MSE	0.21716	**R-Square**	0.1435
Dependent Mean	0.07677	**Adj R-Sq**	0.1359
Coeff Var	282.85445		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.64744	0.16765	-3.86	0.0002
px4QFR	1	-0.20442	0.04698	-4.35	<.0001

Test for normality in the error terms

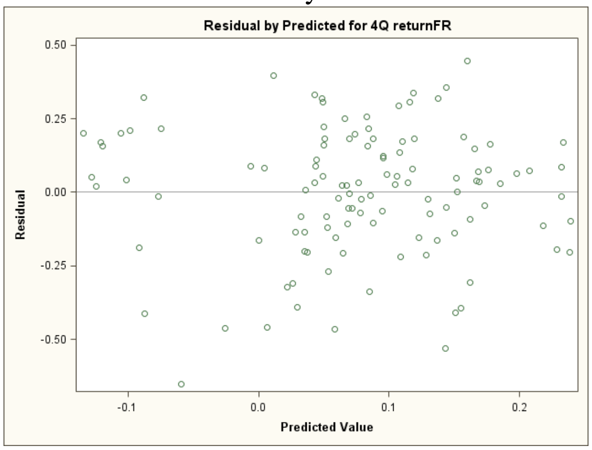


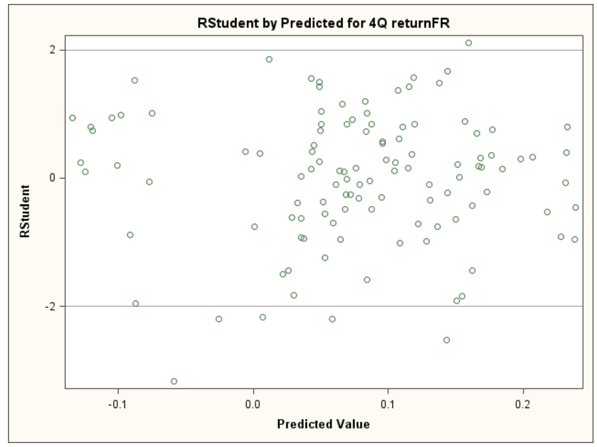


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	5.5077	0.0637	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.01393	0.00697	1.54	0.2196
Error	112	0.50773	0.00453		
Corrected Total	114	0.52167			

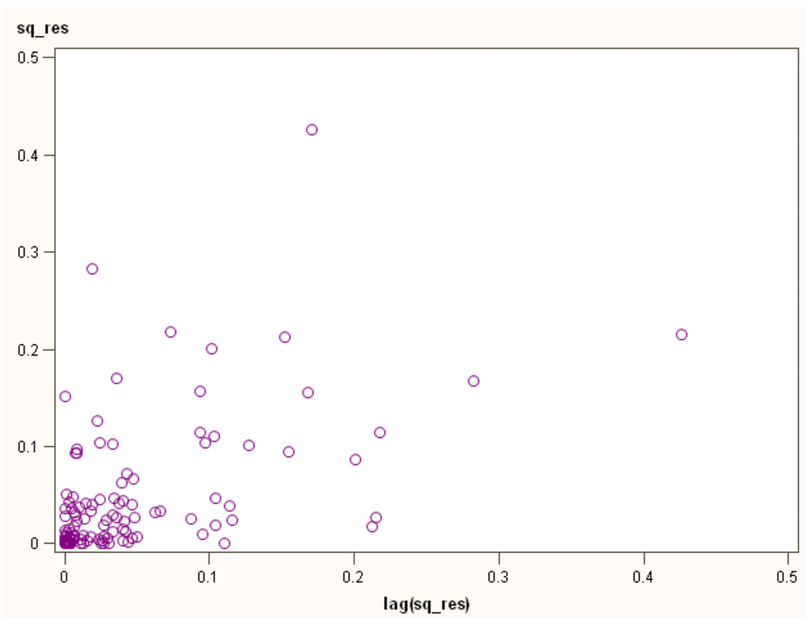
Root MSE	0.06733	**R-Square**	0.0267
Dependent Mean	0.04634	**Adj R-Sq**	0.0093
Coeff Var	145.29955		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.05714	0.29787	-0.19	0.8482
px4QFR	1	-0.08762	0.17467	-0.50	0.6169
sq_px	1	-0.01625	0.02539	-0.64	0.5235

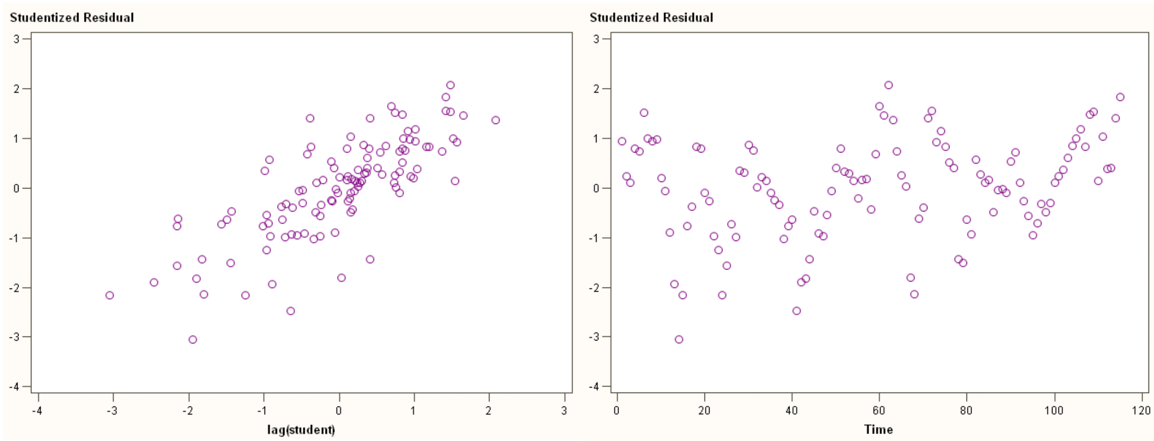
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_4Q returnFR
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	30.7061	<.0001	30.5976	<.0001
2	31.4821	<.0001	35.6275	<.0001
3	31.8351	<.0001	35.6802	<.0001
4	33.0295	<.0001	36.1584	<.0001
5	33.2014	<.0001	36.6759	<.0001
6	33.2272	<.0001	37.0653	<.0001
7	33.4643	<.0001	37.0657	<.0001
8	33.5783	<.0001	37.0708	<.0001
9	33.5783	0.0001	37.0911	<.0001
10	34.6424	0.0001	38.3654	<.0001
11	34.6724	0.0003	40.1864	<.0001
12	36.4424	0.0003	40.4206	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	69.3602	<.0001
AR(2)	70.0595	<.0001
AR(3)	70.8847	<.0001
AR(4)	75.5081	<.0001

Durbin-Watson d test

Durbin-Watson D	0.443
Number of Observations	115
1st Order Autocorrelation	0.760

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-0.64744	0.2991	-2.16	0.0325
b1	-0.20442	0.0822	-2.49	0.0144

12Q

$$r_{t,t+12} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

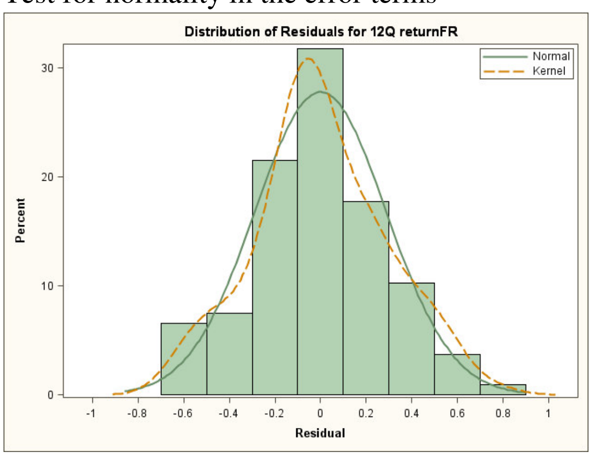
Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

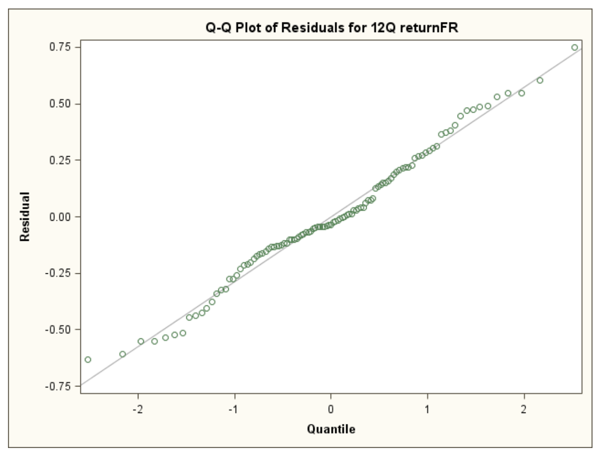
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	6.97907	6.97907	83.91	<.0001
Error	105	8.73308	0.08317		
Corrected Total	106	15.71215			

Root MSE	0.28840	**R-Square**	0.4442
Dependent Mean	0.21641	**Adj R-Sq**	0.4389
Coeff Var	133.26492		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-1.84346	0.22659	-8.14	<.0001
px12QFR	1	-0.57868	0.06317	-9.16	<.0001

Test for normality in the error terms

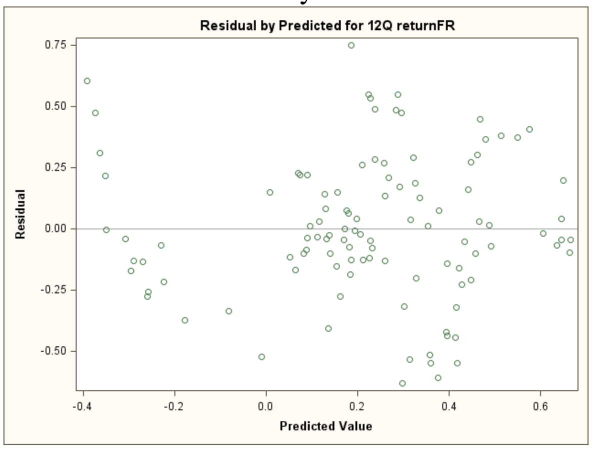


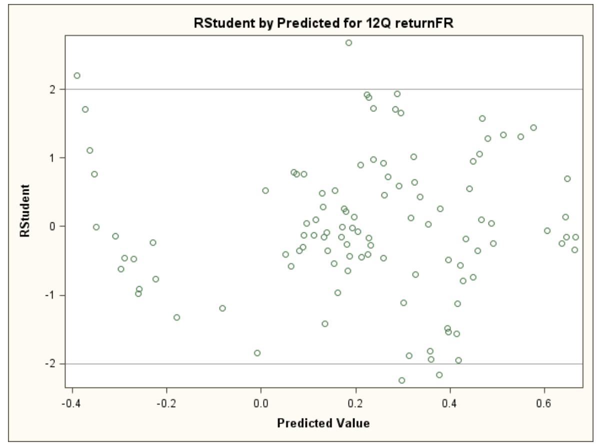


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	0.2857	0.8669	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.00077985	0.00038993	0.03	0.9698
Error	104	1.32057	0.01270		
Corrected Total	106	1.32135			

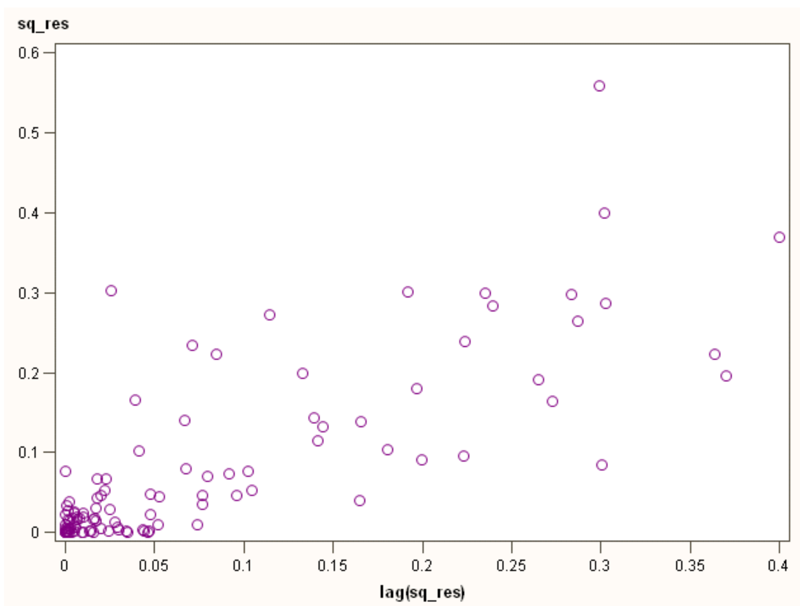
Root MSE	0.11268	**R-Square**	0.0006
Dependent Mean	0.08162	**Adj R-Sq**	-0.0186
Coeff Var	138.06388		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.02952	0.50573	-0.06	0.9536
px12QFR	1	-0.06202	0.29759	-0.21	0.8353
sq_px	1	-0.00852	0.04335	-0.20	0.8445

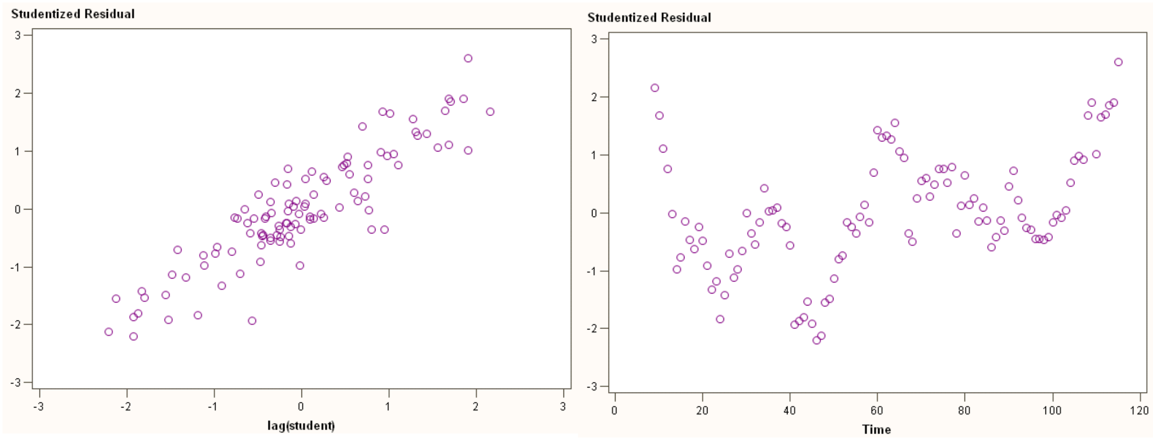
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_12Q returnFR
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	53.8004	<.0001	59.9319	<.0001
2	85.0367	<.0001	59.9472	<.0001
3	104.4557	<.0001	60.2047	<.0001
4	115.8369	<.0001	60.2114	<.0001
5	119.4075	<.0001	61.0555	<.0001
6	120.6305	<.0001	61.1380	<.0001
7	120.8974	<.0001	61.7447	<.0001
8	123.9335	<.0001	61.9254	<.0001
9	128.1989	<.0001	61.9257	<.0001
10	133.2344	<.0001	61.9318	<.0001
11	138.8868	<.0001	61.9515	<.0001
12	142.8759	<.0001	62.1059	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	83.2492	<.0001
AR(2)	83.2774	<.0001
AR(3)	83.6068	<.0001
AR(4)	83.8959	<.0001

Durbin-Watson d test

Durbin-Watson D	0.191
Number of Observations	107
1st Order Autocorrelation	0.852

The regression with Newey-West HAC standard errors, 12 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-1.84346	0.4072	-4.53	<.0001
b1	-0.57868	0.1183	-4.89	<.0001

20Q

$$r_{t,t+20} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

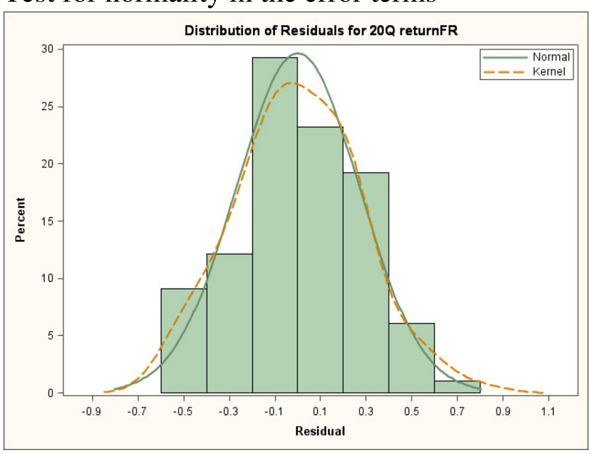
Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

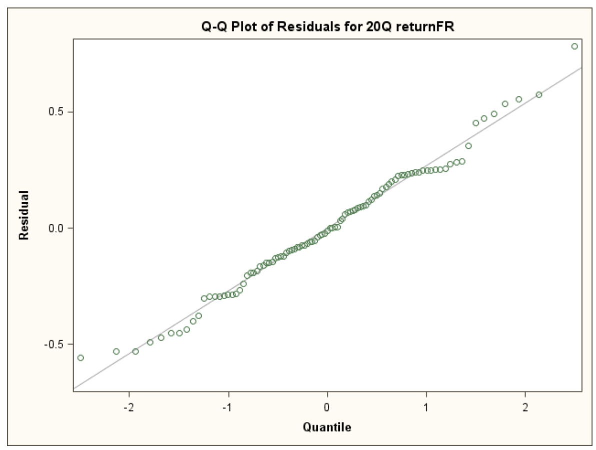
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	15.56759	15.56759	212.61	<.0001
Error	97	7.10253	0.07322		
Corrected Total	98	22.67011			

Root MSE	0.27060	**R-Square**	0.6867
Dependent Mean	0.35684	**Adj R-Sq**	0.6835
Coeff Var	75.83110		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-2.72119	0.21284	-12.79	<.0001
px20QFR	1	-0.86614	0.05940	-14.58	<.0001

Test for normality in the error terms

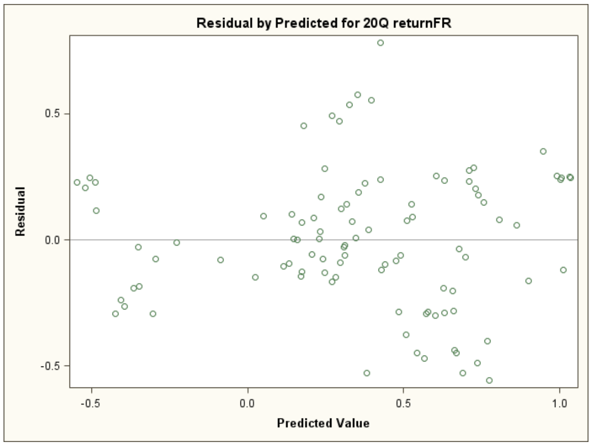


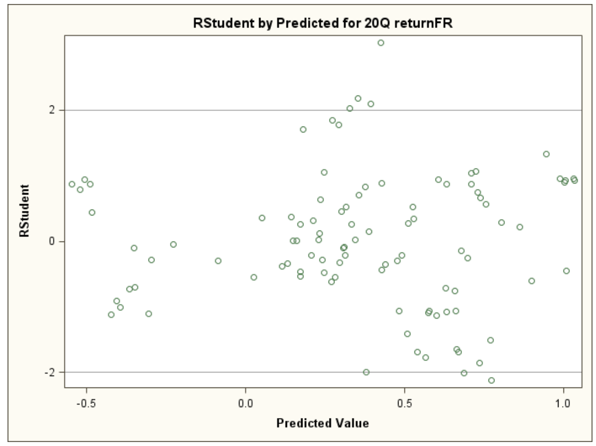


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	0.3983	0.8194	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	0.03072	0.01536	1.54	0.2200
Error	96	0.95852	0.00998		
Corrected Total	98	0.98924			

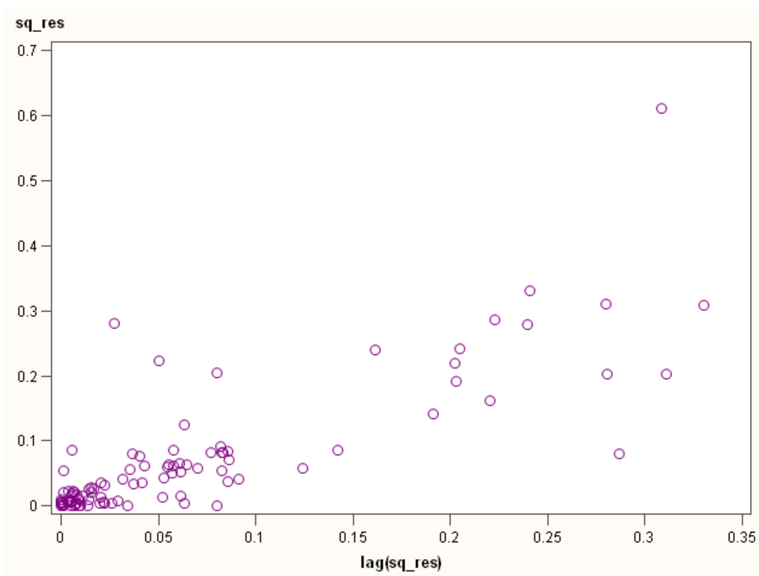
Root MSE	0.09992	**R-Square**	0.0311
Dependent Mean	0.07174	**Adj R-Sq**	0.0109
Coeff Var	139.27960		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-0.26985	0.45647	-0.59	0.5558
px20QFR	1	-0.16210	0.26884	-0.60	0.5480
sq_px	1	-0.01826	0.03914	-0.47	0.6419

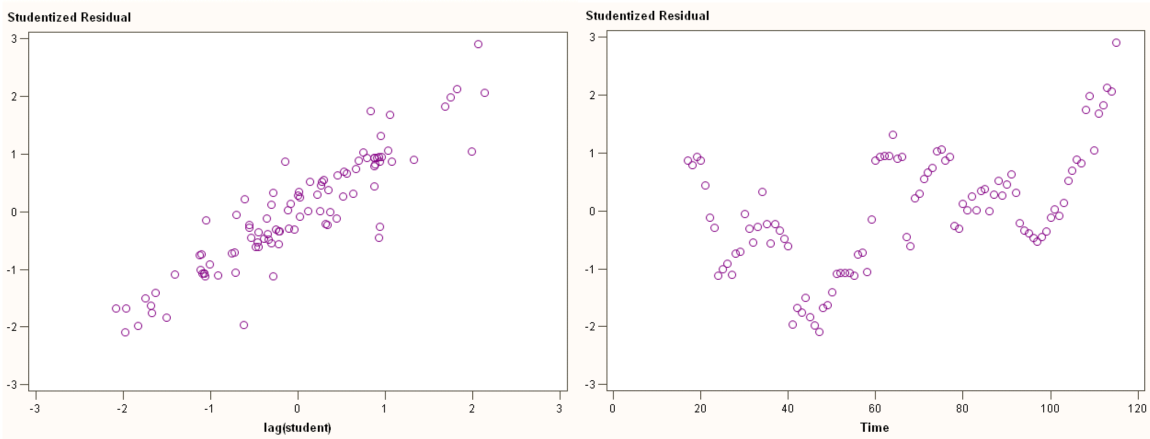
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_20Q returnFR
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	47.0337	<.0001	64.9040	<.0001
2	82.7148	<.0001	66.6019	<.0001
3	105.0359	<.0001	66.6062	<.0001
4	121.2381	<.0001	66.6552	<.0001
5	129.4762	<.0001	67.8190	<.0001
6	137.9751	<.0001	68.2098	<.0001
7	140.1594	<.0001	68.6261	<.0001
8	140.1694	<.0001	69.6640	<.0001
9	140.2701	<.0001	69.6665	<.0001
10	140.9560	<.0001	69.7331	<.0001
11	142.0036	<.0001	69.8070	<.0001
12	143.5515	<.0001	69.8258	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	81.7754	<.0001
AR(2)	81.7799	<.0001
AR(3)	81.8018	<.0001
AR(4)	81.9611	<.0001

Durbin-Watson d test

Durbin-Watson D	0.170
Number of Observations	99
1st Order Autocorrelation	0.868

The regression with Newey-West HAC standard errors, 20 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-2.72119	0.3194	-8.52	<.0001
b1	-0.86614	0.0996	-8.69	<.0001

Import

4Q

$$r_{t,t+4} = \beta_1 + \beta_2 pz_t + \varepsilon_t$$

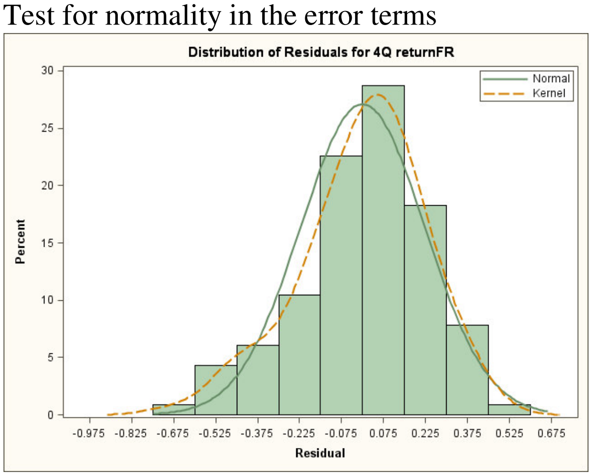
Number of Observations Read	115
Number of Observations Used	115

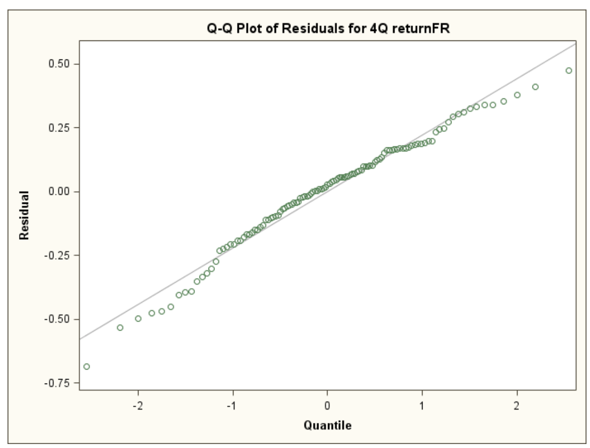
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.65939	0.65939	13.40	0.0004
Error	113	5.56257	0.04923		
Corrected Total	114	6.22196			

Root MSE	0.22187	**R-Square**	0.1060
Dependent Mean	0.07677	**Adj R-Sq**	0.0981
Coeff Var	288.98788		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.58132	0.18100	-3.21	0.0017
pz4QFR	1	-0.18409	0.05030	-3.66	0.0004

Test for normality in the error terms

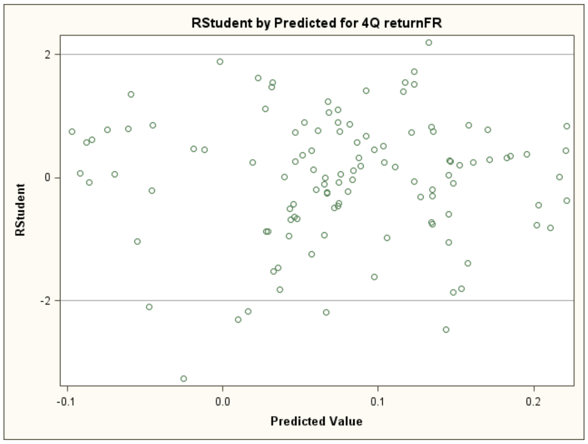


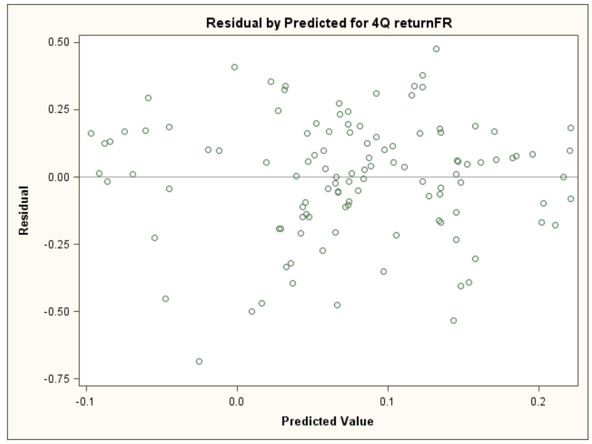


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	6.3327	0.0422	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.01568	0.00784	1.48	0.2321
Error	112	0.59361	0.00530		
Corrected Total	114	0.60930			

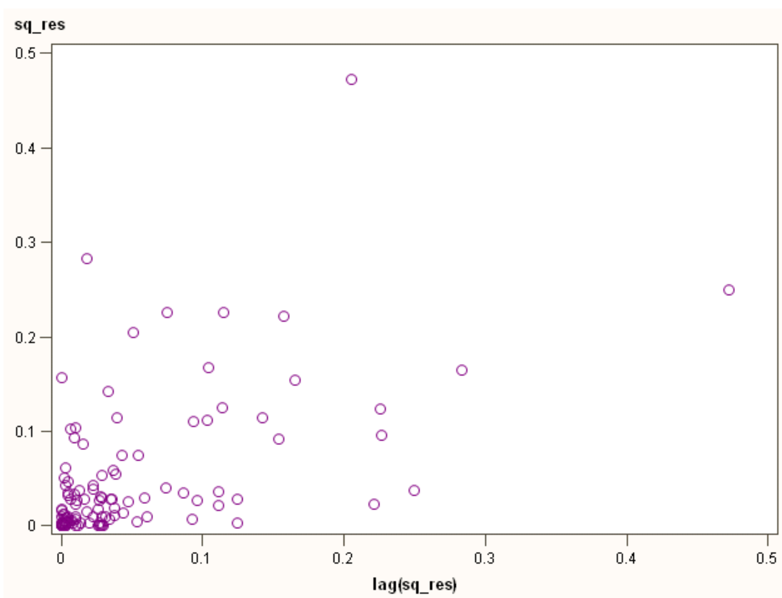
Root MSE	0.07280	**R-Square**	0.0257
Dependent Mean	0.04837	**Adj R-Sq**	0.0083
Coeff Var	150.50989		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.23583	0.38115	-0.62	0.5373
pz4QFR	1	-0.18930	0.21835	-0.87	0.3878
sq_pz	1	-0.03031	0.03103	-0.98	0.3308

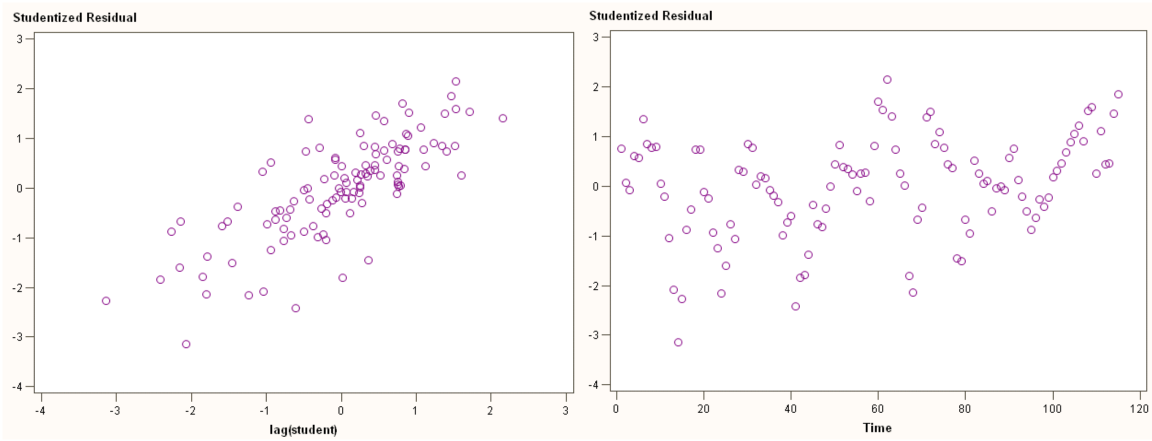
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_4Q returnFR
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	34.1624	<.0001	34.1917	<.0001
2	35.6043	<.0001	39.4418	<.0001
3	35.8808	<.0001	39.4716	<.0001
4	37.4906	<.0001	40.0896	<.0001
5	38.0418	<.0001	40.5377	<.0001
6	38.1827	<.0001	40.8679	<.0001
7	38.5479	<.0001	40.8707	<.0001
8	38.7222	<.0001	40.8825	<.0001
9	38.7228	<.0001	40.9466	<.0001
10	39.8113	<.0001	42.1418	<.0001
11	39.9258	<.0001	43.6587	<.0001
12	41.2084	<.0001	43.8911	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	70.9149	<.0001
AR(2)	71.5553	<.0001
AR(3)	72.3128	<.0001
AR(4)	76.4288	<.0001

Durbin-Watson d test

Durbin-Watson D	0.432
Number of Observations	115
1st Order Autocorrelation	0.767

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-0.58132	0.3015	-1.93	0.0564
b1	-0.18409	0.0821	-2.24	0.0268

12Q

$$r_{t,t+12} = \beta_1 + \beta_2 pz_t + \varepsilon_t$$

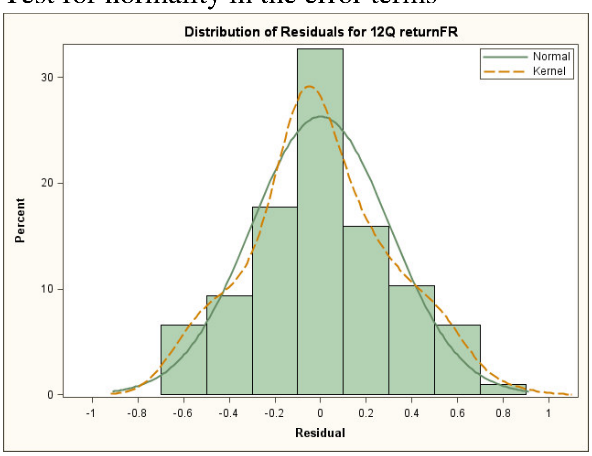
Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

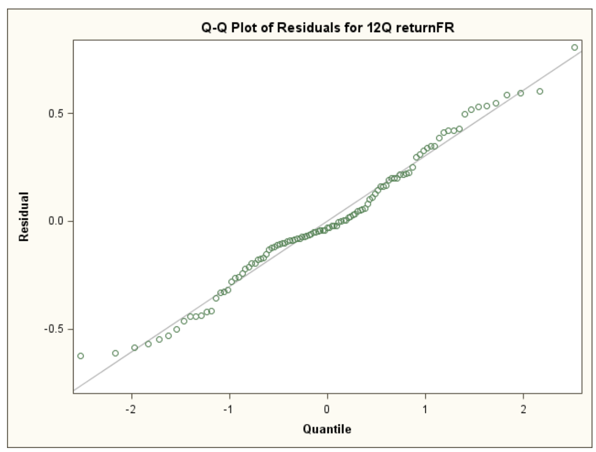
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	5.94696	5.94696	63.94	<.0001
Error	105	9.76519	0.09300		
Corrected Total	106	15.71215			

Root MSE	0.30496	**R-Square**	0.3785
Dependent Mean	0.21641	**Adj R-Sq**	0.3726
Coeff Var	140.91998		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-1.83496	0.25822	-7.11	<.0001
pz12QFR	1	-0.56967	0.07124	-8.00	<.0001

Test for normality in the error terms

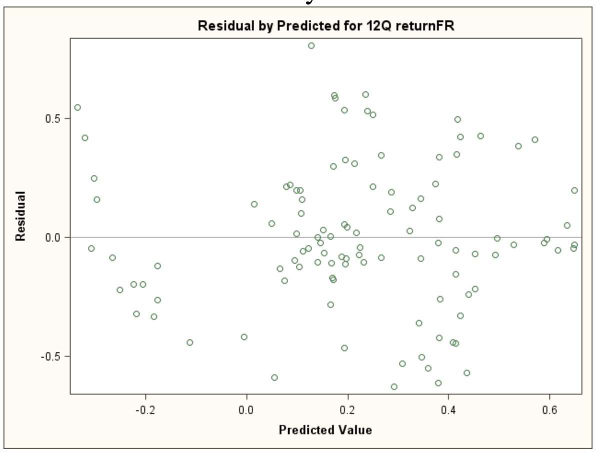


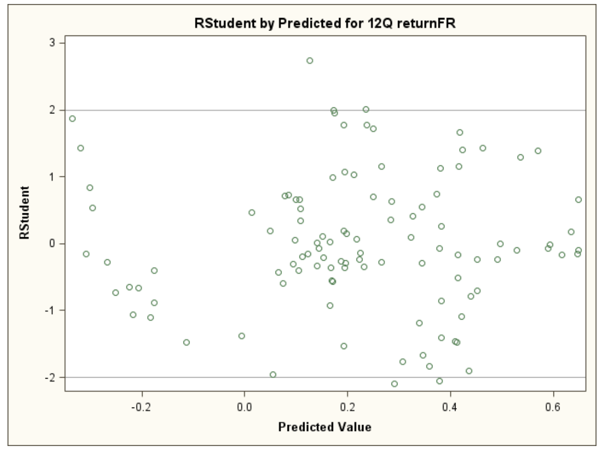


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	0.6762	0.7131	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	0.01370	0.00685	0.45	0.6364
Error	104	1.57004	0.01510		
Corrected Total	106	1.58374			

Root MSE	0.12287	**R-Square**	0.0087
Dependent Mean	0.09126	**Adj R-Sq**	-0.0104
Coeff Var	134.62976		

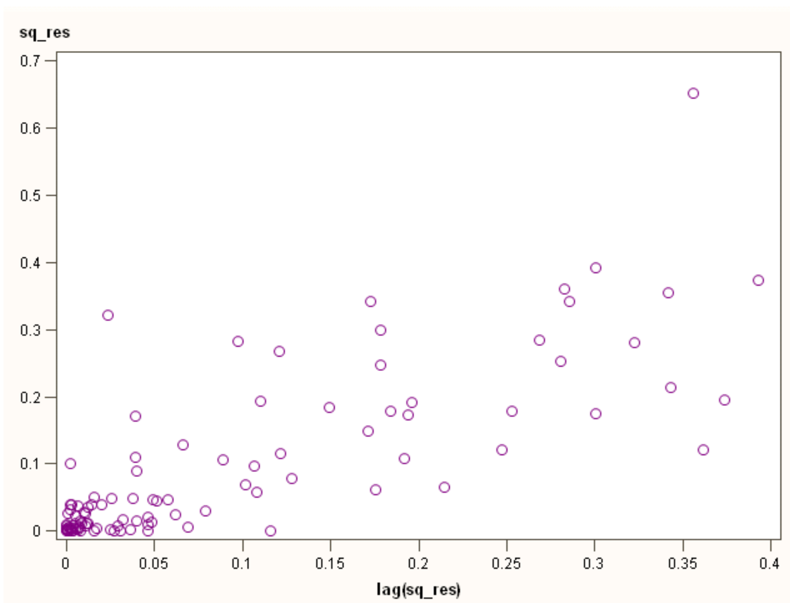
Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-0.51707	0.64703	-0.80	0.4260
pz12QFR	1	-0.35261	0.37123	-0.95	0.3444
sq_pz	1	-0.05034	0.05284	-0.95	0.3429

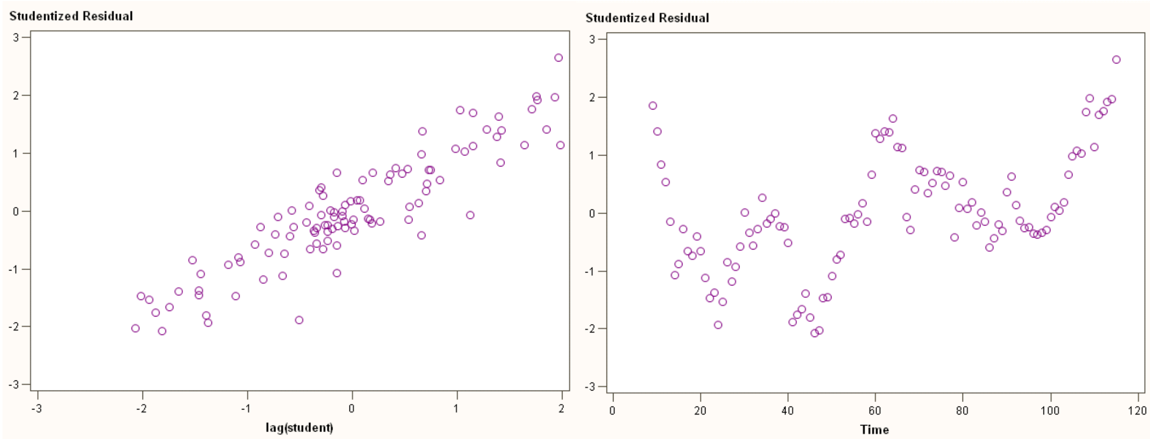
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_12Q returnFR
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	54.3874	<.0001	63.5145	<.0001
2	87.5838	<.0001	63.5952	<.0001
3	108.0106	<.0001	63.7508	<.0001
4	120.1682	<.0001	63.7508	<.0001
5	124.0259	<.0001	64.7757	<.0001
6	125.7435	<.0001	64.7759	<.0001
7	125.8538	<.0001	65.3417	<.0001
8	128.3278	<.0001	65.4184	<.0001
9	132.0807	<.0001	65.4193	<.0001
10	136.8397	<.0001	65.4262	<.0001
11	142.7421	<.0001	65.4774	<.0001
12	147.8388	<.0001	65.5033	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	86.2073	<.0001
AR(2)	86.2157	<.0001
AR(3)	86.5627	<.0001
AR(4)	86.7692	<.0001

Durbin-Watson d test

Durbin-Watson D	0.172
Number of Observations	107
1st Order Autocorrelation	0.865

The regression with Newey-West HAC standard errors, 12 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-1.83496	0.4575	-4.01	0.0001
b1	-0.56967	0.1296	-4.40	<.0001

20Q

$$r_{t,t+20} = \beta_1 + \beta_2 pz_t + \varepsilon_t$$

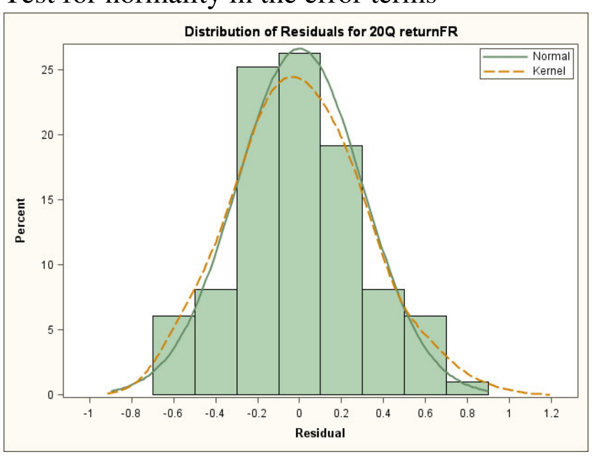
Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

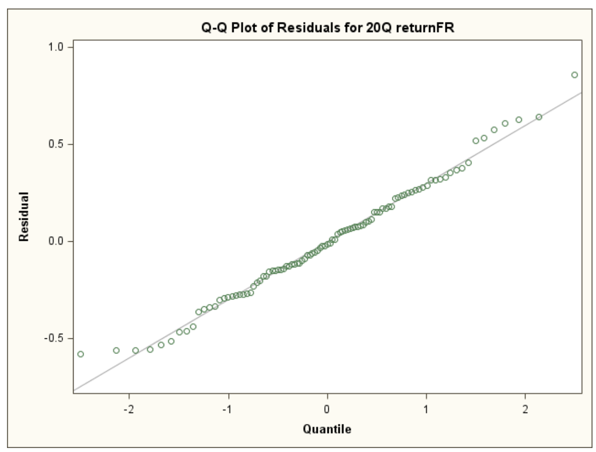
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	13.87503	13.87503	153.03	<.0001
Error	97	8.79508	0.09067		
Corrected Total	98	22.67011			

Root MSE	0.30112	**R-Square**	0.6120
Dependent Mean	0.35684	**Adj R-Sq**	0.6080
Coeff Var	84.38416		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-2.78207	0.25554	-10.89	<.0001
pz20QFR	1	-0.87136	0.07044	-12.37	<.0001

Test for normality in the error terms

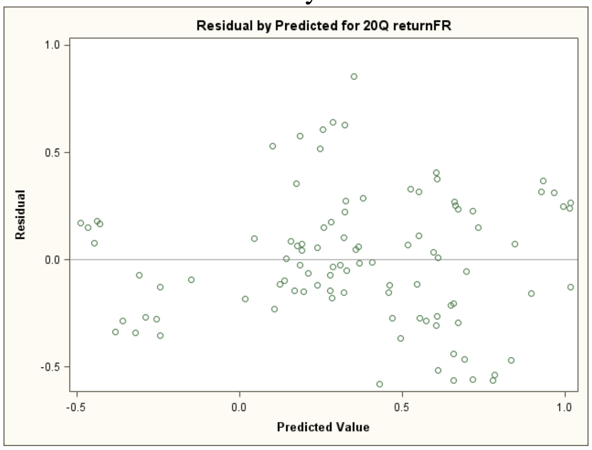


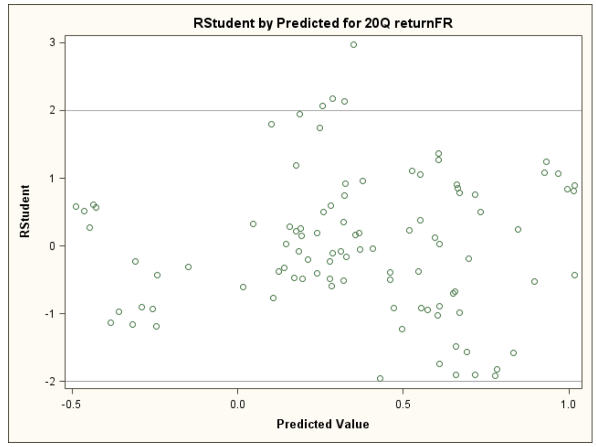


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	1.0479	0.5922	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.03759	0.01879	1.26	0.2892
Error	96	1.43544	0.01495		
Corrected Total	98	1.47302			

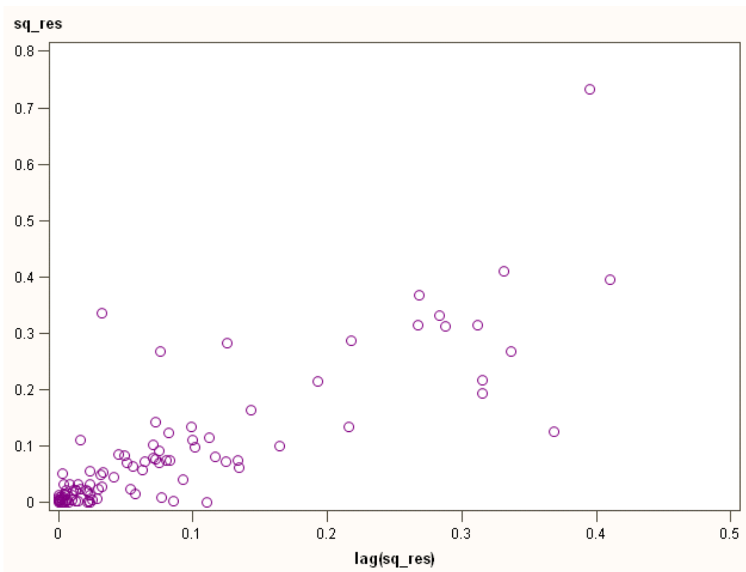
Root MSE	0.12228	**R-Square**	0.0255
Dependent Mean	0.08884	**Adj R-Sq**	0.0052
Coeff Var	137.64215		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.44206	0.65769	-0.67	0.5031
pz20QFR	1	-0.26213	0.37801	-0.69	0.4897
sq_pz	1	-0.03141	0.05382	-0.58	0.5609

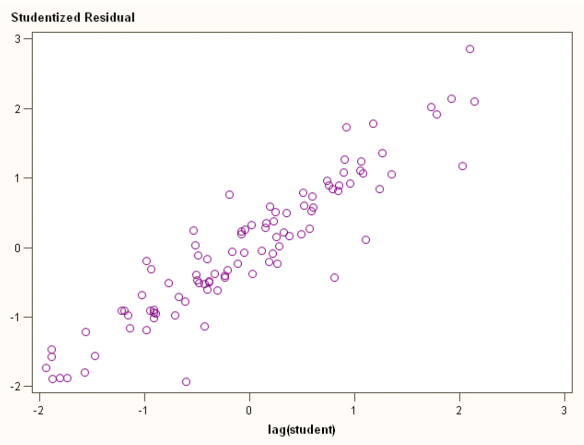
Autoregressive conditional heteroscedasticity (ARCH)

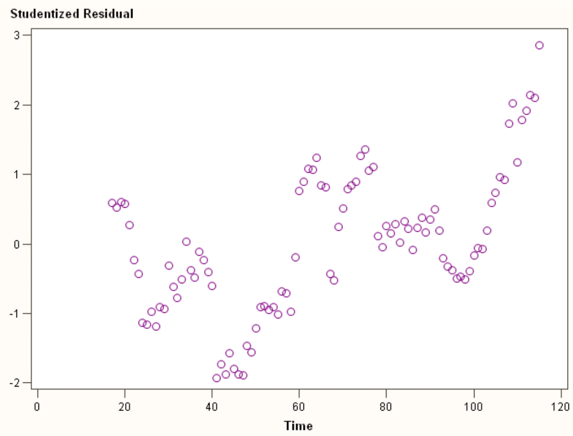
Dependent Variable	residual_20Q returnFR
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	49.7308	<.0001	67.7754	<.0001
2	86.9029	<.0001	69.1806	<.0001
3	109.9288	<.0001	69.2060	<.0001
4	124.5410	<.0001	69.2072	<.0001
5	130.4748	<.0001	70.6153	<.0001
6	135.8490	<.0001	71.1593	<.0001
7	136.5024	<.0001	71.3778	<.0001
8	136.6304	<.0001	71.6298	<.0001
9	137.1196	<.0001	71.6332	<.0001
10	138.3031	<.0001	71.6675	<.0001
11	139.7053	<.0001	71.7215	<.0001
12	141.2721	<.0001	71.7395	<.0001



Test for autocorrelation in the error terms





LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	84.9017	<.0001
AR(2)	84.9384	<.0001
AR(3)	84.9412	<.0001
AR(4)	85.0690	<.0001

Durbin-Watson d test

Durbin-Watson D	0.141
Number of Observations	99
1st Order Autocorrelation	0.886

The regression with Newey-West HAC standard errors, 20 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-2.78207	0.4581	-6.07	<.0001
b1	-0.87136	0.1345	-6.48	<.0001

United Kingdom

Output

4Q

$$r_{t,t+4} = \beta_1 + \beta_2 RESpy_t + \varepsilon_t$$

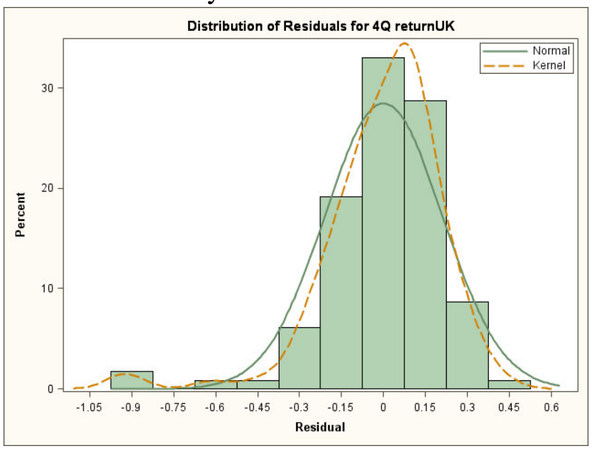
Number of Observations Read	115
Number of Observations Used	115

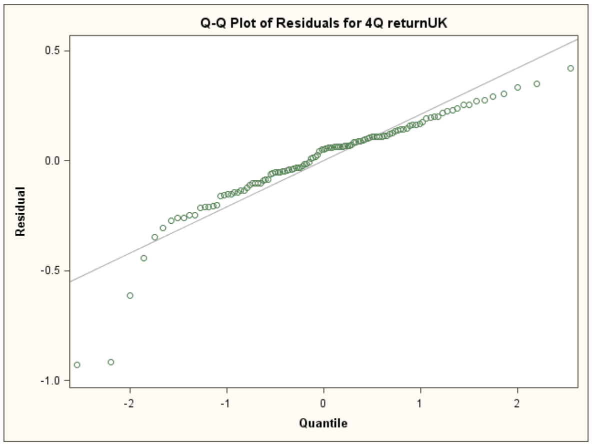
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.68410	0.68410	15.34	0.0002
Error	113	5.03834	0.04459		
Corrected Total	114	5.72244			

Root MSE	0.21116	**R-Square**	0.1195
Dependent Mean	0.07599	**Adj R-Sq**	0.1118
Coeff Var	277.88067		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.07780	0.01970	3.95	0.0001
RESpy4QUK	1	-0.23592	0.06023	-3.92	0.0002

Test for normality in the error terms

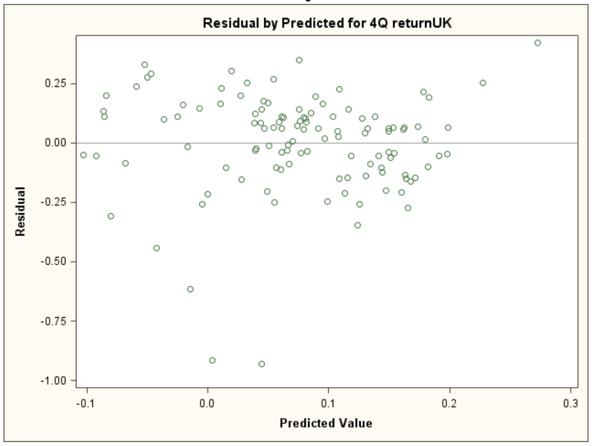


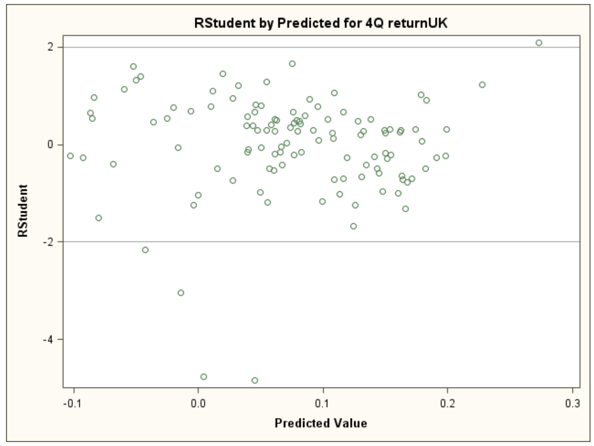


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	179.4426	<.0001	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.03455	0.01727	1.25	0.2912
Error	112	1.55071	0.01385		
Corrected Total	114	1.58525			

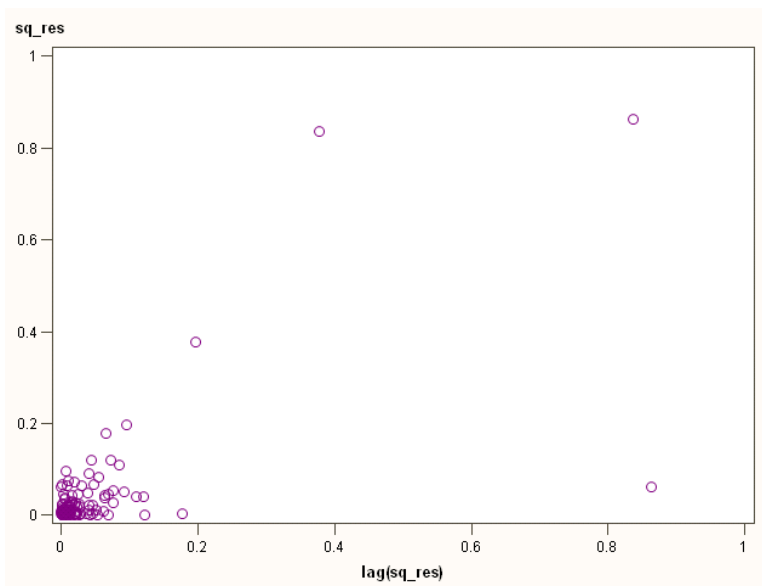
Root MSE	0.11767	**R-Square**	0.0218
Dependent Mean	0.04381	**Adj R-Sq**	0.0043
Coeff Var	268.57507		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.04128	0.01394	2.96	0.0037
RESpy4QUK	1	0.05014	0.03473	1.44	0.1516
sq_RESpy	1	0.02013	0.08099	0.25	0.8042

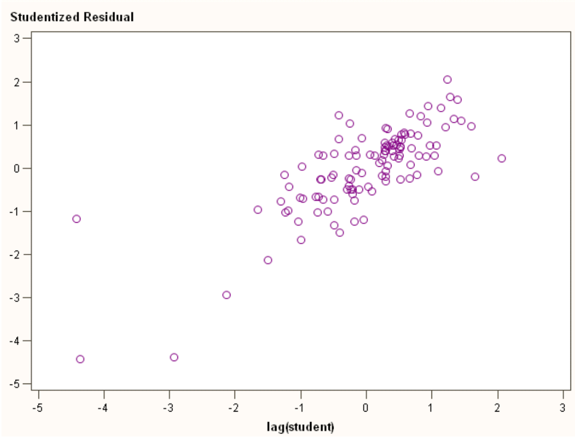
Autoregressive conditional heteroscedasticity (ARCH)

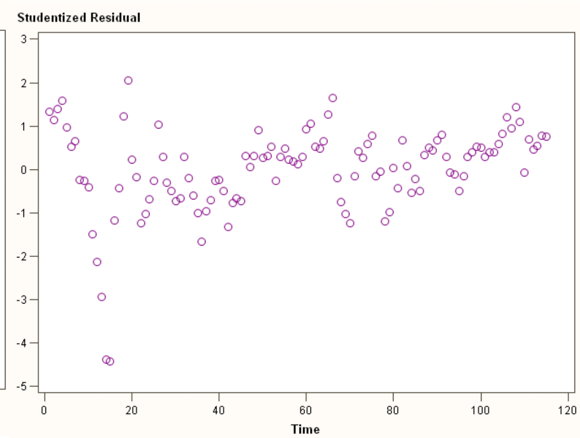
Dependent Variable	residual_4Q returnUK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	52.9480	<.0001	51.4034	<.0001
2	61.7206	<.0001	57.9418	<.0001
3	63.5828	<.0001	60.1600	<.0001
4	64.8705	<.0001	60.2155	<.0001
5	64.9323	<.0001	60.9164	<.0001
6	65.1165	<.0001	61.0461	<.0001
7	65.1470	<.0001	61.0834	<.0001
8	65.1561	<.0001	61.1397	<.0001
9	65.1769	<.0001	61.2443	<.0001
10	65.3178	<.0001	61.3036	<.0001
11	65.7469	<.0001	61.3036	<.0001
12	65.8762	<.0001	61.4288	<.0001



Test for autocorrelation in the error terms





LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	69.3381	<.0001
AR(2)	70.8813	<.0001
AR(3)	71.5106	<.0001
AR(4)	73.0297	<.0001

Durbin-Watson d test

Durbin-Watson D	0.448
Number of Observations	115
1st Order Autocorrelation	0.766

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.077796	0.0333	2.34	0.0211
b1	-0.23592	0.1122	-2.10	0.0377

12Q

$$r_{t,t+12} = \beta_1 + \beta_2 RESpy_t + \varepsilon_t$$

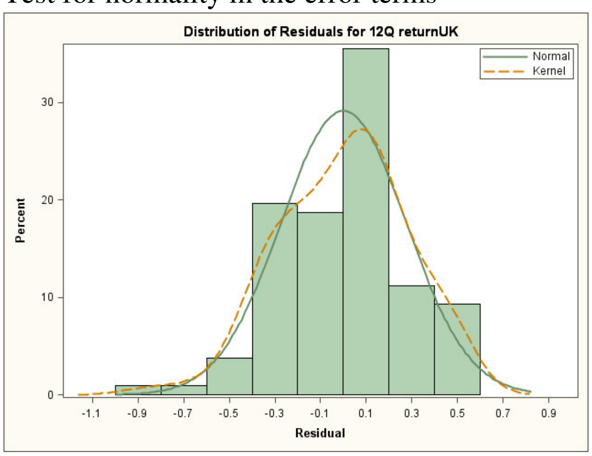
Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

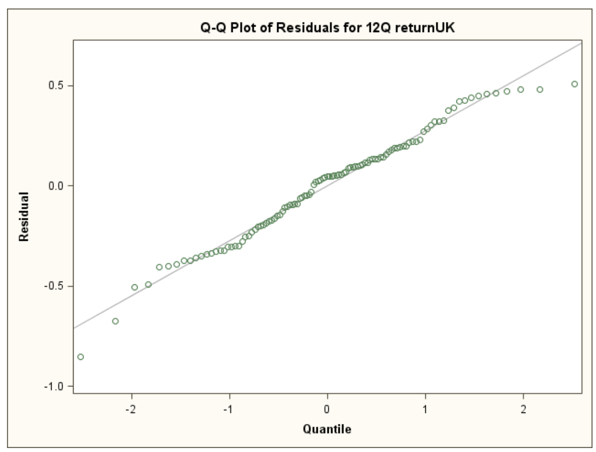
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	7.38777	7.38777	97.56	<.0001
Error	105	7.95148	0.07573		
Corrected Total	106	15.33925			

Root MSE	0.27519	**R-Square**	0.4816
Dependent Mean	0.21258	**Adj R-Sq**	0.4767
Coeff Var	129.45225		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.19719	0.02665	7.40	<.0001
RESpy12QUK	1	-0.81381	0.08239	-9.88	<.0001

Test for normality in the error terms

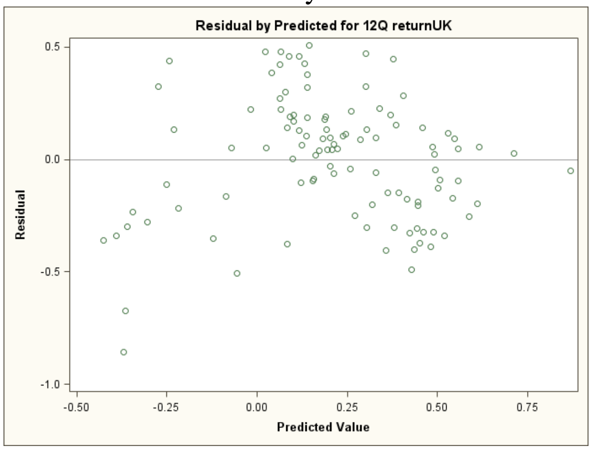


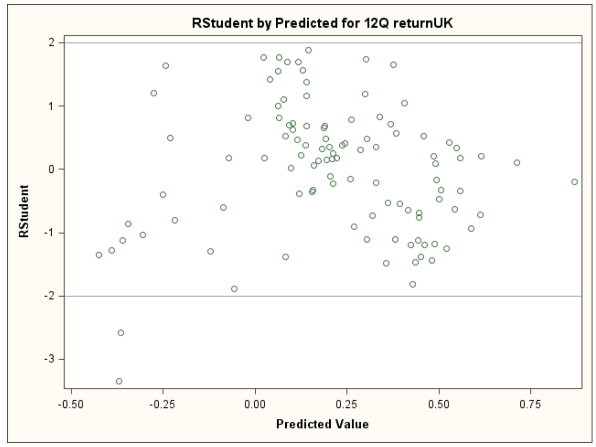


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	1.5041	0.4714	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.17015	0.08507	9.37	0.0002
Error	104	0.94385	0.00908		
Corrected Total	106	1.11400			

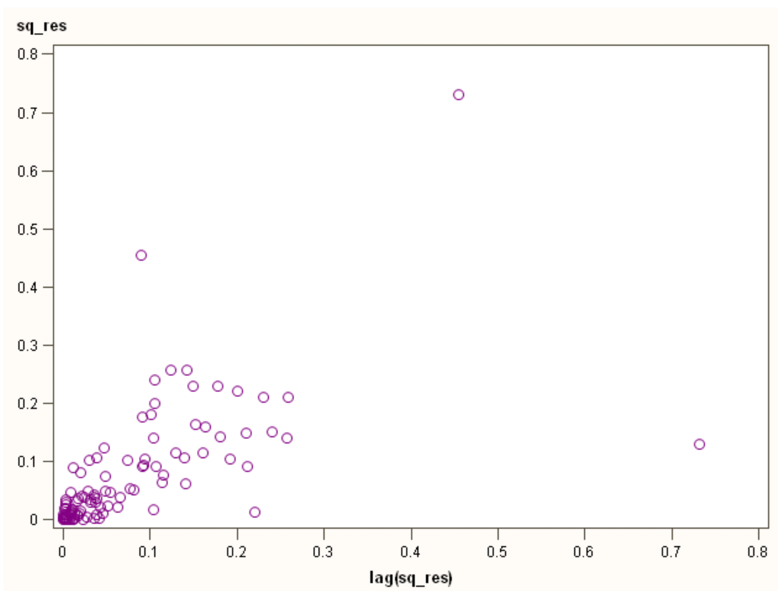
Root MSE	0.09527	**R-Square**	0.1527
Dependent Mean	0.07431	**Adj R-Sq**	0.1364
Coeff Var	128.19511		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.06271	0.01160	5.41	<.0001
RESpy12QUK	1	0.09622	0.02942	3.27	0.0015
sq_RESpy	1	0.12834	0.06588	1.95	0.0541

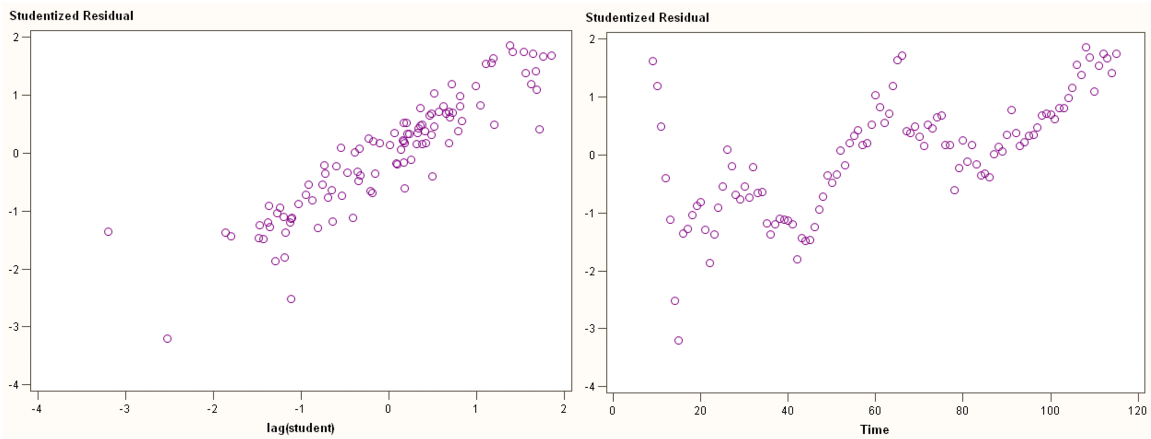
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_12Q returnUK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	41.8921	<.0001	40.3955	<.0001
2	50.7335	<.0001	42.1902	<.0001
3	53.8212	<.0001	43.1708	<.0001
4	56.1506	<.0001	43.3104	<.0001
5	60.2219	<.0001	44.3424	<.0001
6	67.0637	<.0001	44.5414	<.0001
7	73.7462	<.0001	44.5474	<.0001
8	76.7010	<.0001	44.5989	<.0001
9	76.9161	<.0001	45.7169	<.0001
10	77.5061	<.0001	46.6012	<.0001
11	79.1841	<.0001	47.2999	<.0001
12	80.6147	<.0001	47.5127	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	87.0533	<.0001
AR(2)	87.2757	<.0001
AR(3)	87.4161	<.0001
AR(4)	87.4477	<.0001

Durbin-Watson d test

Durbin-Watson D	0.172
Number of Observations	107
1st Order Autocorrelation	0.888

The regression with Newey-West HAC standard errors, 12 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.197185	0.0772	2.56	0.0120
b1	-0.81381	0.2298	-3.54	0.0006

20Q

$$r_{t,t+20} = \beta_1 + \beta_2 RESpy_t + \varepsilon_t$$

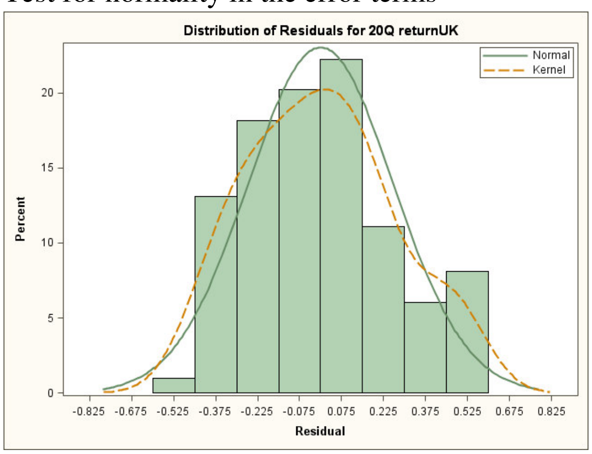
Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

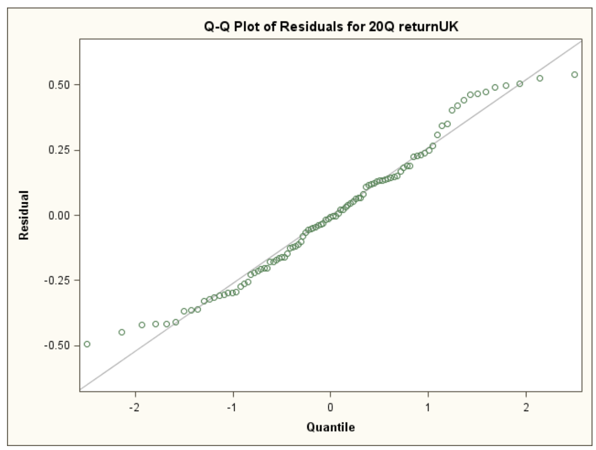
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	10.80414	10.80414	158.49	<.0001
Error	97	6.61250	0.06817		
Corrected Total	98	17.41663			

Root MSE	0.26109	**R-Square**	0.6203
Dependent Mean	0.39040	**Adj R-Sq**	0.6164
Coeff Var	66.87924		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.35823	0.02637	13.59	<.0001
RESpy20QUK	1	-0.99556	0.07908	-12.59	<.0001

Test for normality in the error terms

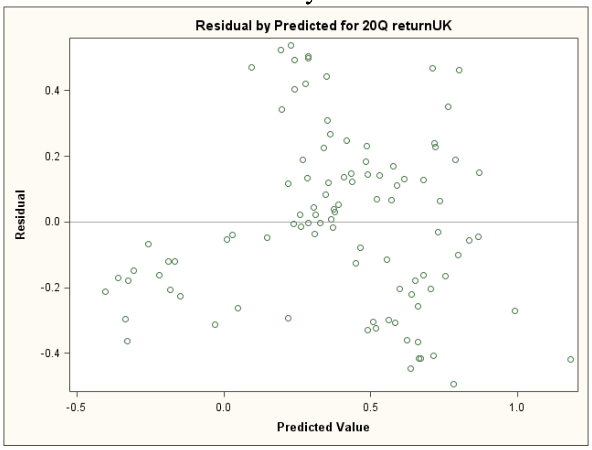


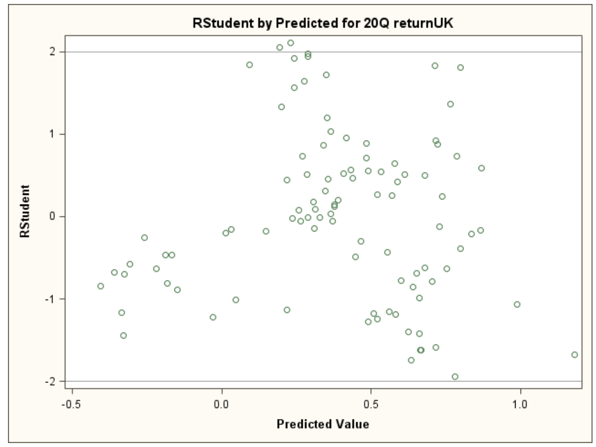


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	2.8835	0.2365	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.00547	0.00273	0.45	0.6373
Error	96	0.57989	0.00604		
Corrected Total	98	0.58536			

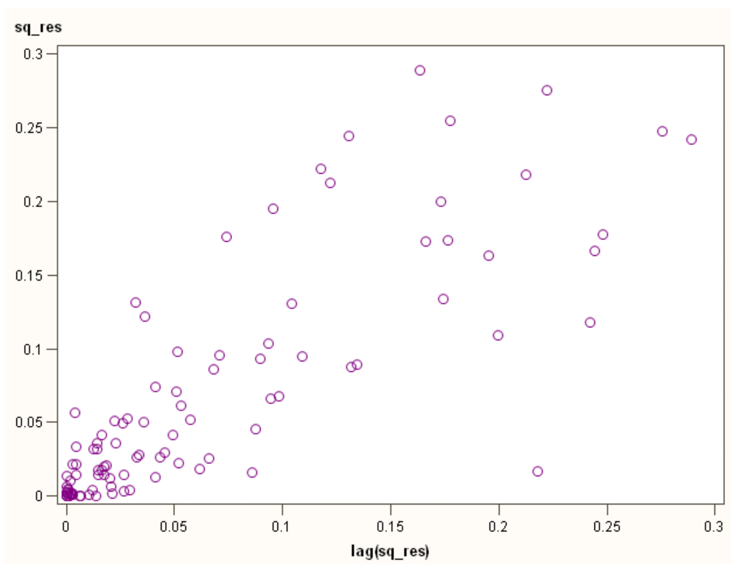
Root MSE	0.07772	**R-Square**	0.0093
Dependent Mean	0.06679	**Adj R-Sq**	-0.0113
Coeff Var	116.36122		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.06420	0.01008	6.37	<.0001
RESpy20QUK	1	-0.02327	0.02448	-0.95	0.3443
sq_RESpy	1	0.01660	0.05490	0.30	0.7630

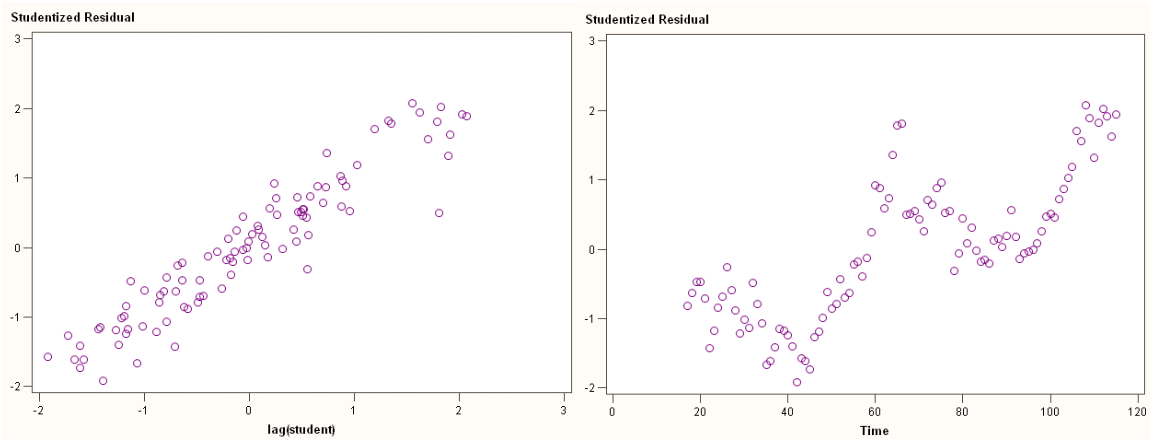
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_20Q returnUK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	63.5151	<.0001	65.5834	<.0001
2	103.8842	<.0001	65.5894	<.0001
3	132.3115	<.0001	66.5635	<.0001
4	151.5899	<.0001	66.6016	<.0001
5	166.3534	<.0001	66.8693	<.0001
6	180.1583	<.0001	66.8827	<.0001
7	188.1517	<.0001	66.9802	<.0001
8	190.6051	<.0001	67.2678	<.0001
9	191.3568	<.0001	67.2717	<.0001
10	191.4986	<.0001	68.7269	<.0001
11	192.1915	<.0001	68.8172	<.0001
12	193.4541	<.0001	69.0007	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	87.7739	<.0001
AR(2)	87.7750	<.0001
AR(3)	88.0608	<.0001
AR(4)	88.1678	<.0001

Durbin-Watson d test

Durbin-Watson D	0.109
Number of Observations	99
1st Order Autocorrelation	0.923

The regression with Newey-West HAC standard errors, 20 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.358229	0.0929	3.85	0.0002
b1	-0.99556	0.1949	-5.11	<.0001

Export

4Q

$$r_{t,t+4} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

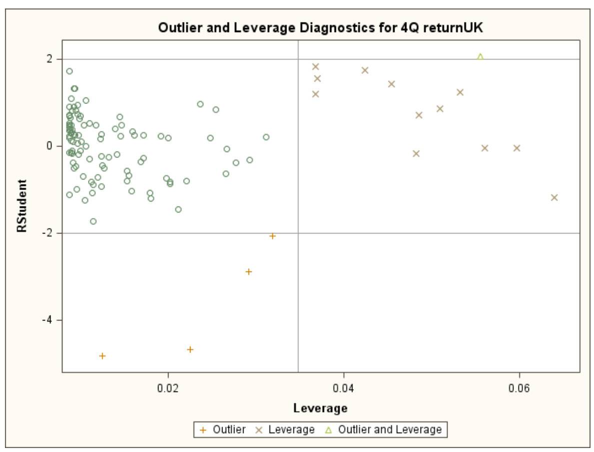
Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.95549	0.95549	22.65	<.0001
Error	113	4.76695	0.04219		
Corrected Total	114	5.72244			

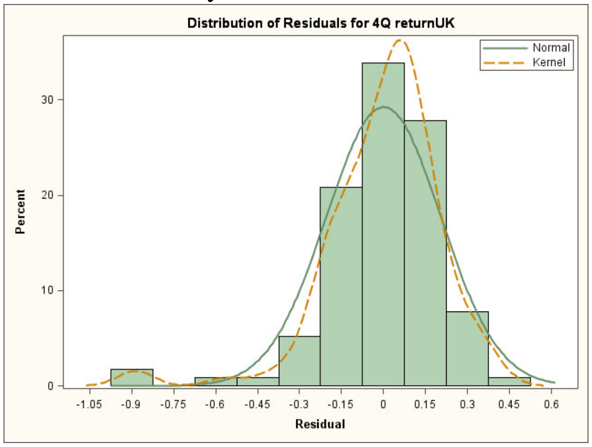
Root MSE	0.20539	**R-Square**	0.1670
Dependent Mean	0.07599	**Adj R-Sq**	0.1596
Coeff Var	270.29295		

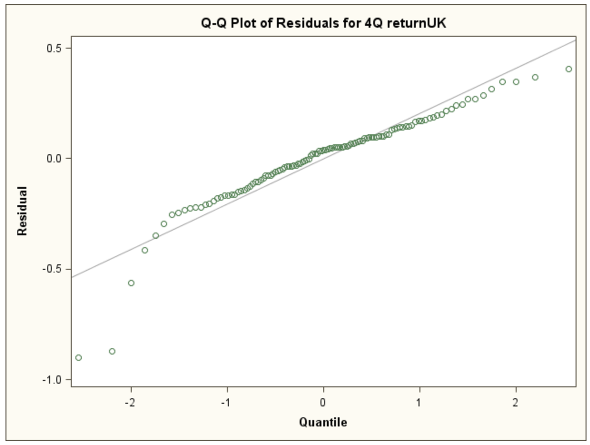
Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.66415	0.15669	-4.24	<.0001
px4QUK	1	-0.26198	0.05505	-4.76	<.0001

Outliers



Test for normality in the error terms

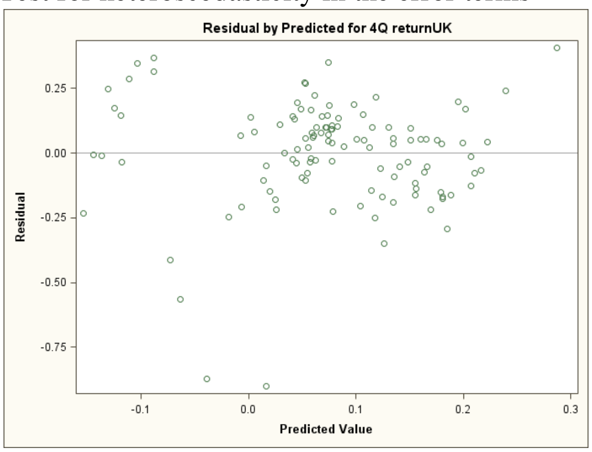


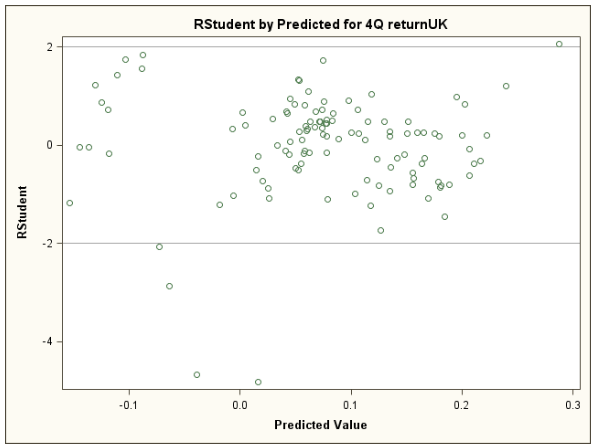


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	153.6961	<.0001	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.06205	0.03102	2.70	0.0716
Error	112	1.28713	0.01149		
Corrected Total	114	1.34918			

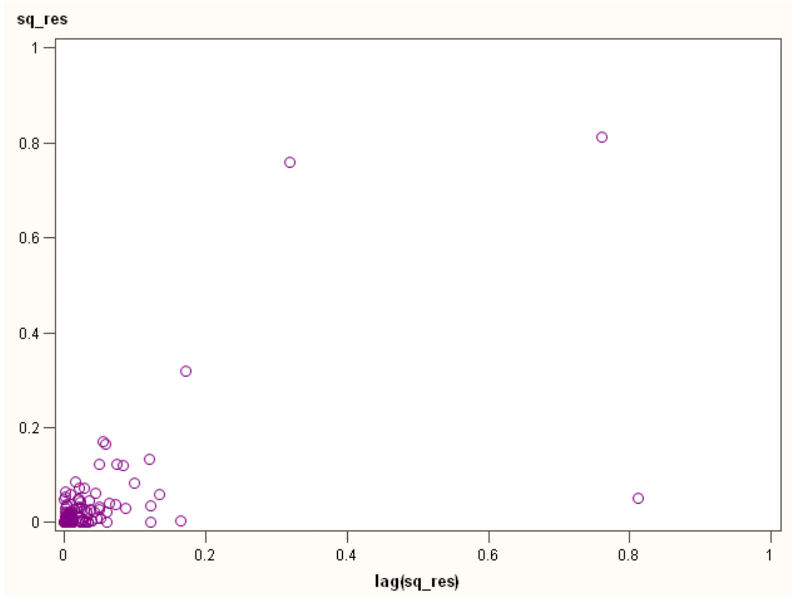
Root MSE	0.10720	**R-Square**	0.0460
Dependent Mean	0.04145	**Adj R-Sq**	0.0290
Coeff Var	258.61848		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.50129	0.44820	1.12	0.2658
px4QUK	1	0.27191	0.33004	0.82	0.4118
sq_px	1	0.03806	0.06025	0.63	0.5289

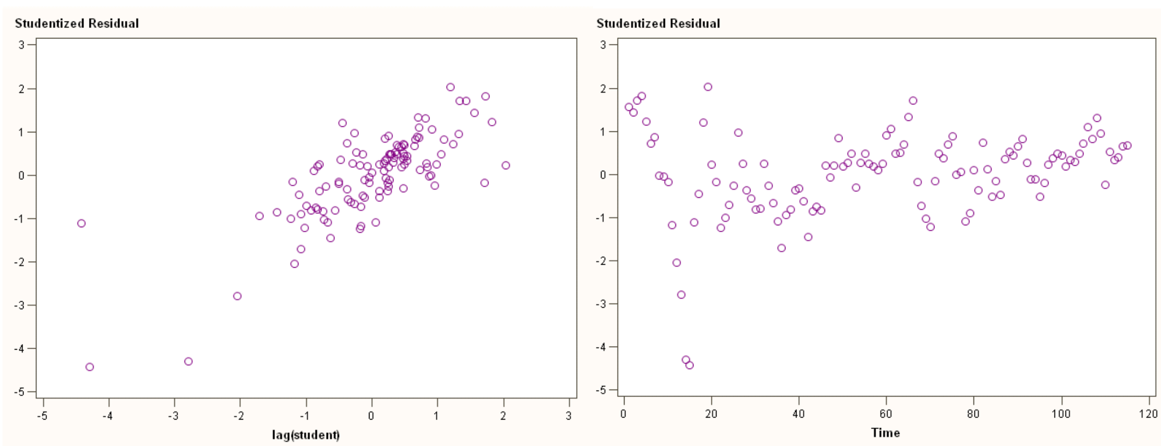
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_4Q returnUK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	49.9198	<.0001	48.3354	<.0001
2	57.1494	<.0001	54.5768	<.0001
3	58.3984	<.0001	56.2994	<.0001
4	59.2427	<.0001	56.3321	<.0001
5	59.2766	<.0001	56.8283	<.0001
6	59.4816	<.0001	56.8431	<.0001
7	59.4905	<.0001	57.0331	<.0001
8	59.5638	<.0001	57.0915	<.0001
9	59.7608	<.0001	57.2644	<.0001
10	60.4470	<.0001	57.4624	<.0001
11	61.8958	<.0001	57.4782	<.0001
12	62.6534	<.0001	57.5948	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	67.9461	<.0001
AR(2)	69.4102	<.0001
AR(3)	70.1608	<.0001
AR(4)	71.9287	<.0001

Durbin-Watson d test

Durbin-Watson D	0.458
Number of Observations	115
1st Order Autocorrelation	0.759

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	Estimate	Approx Std Err	t Value	Approx Pr > |t|
b0	-0.66415	0.3601	-1.84	0.0677
b1	-0.26198	0.1201	-2.18	0.0313

12Q

$$r_{t,t+12} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

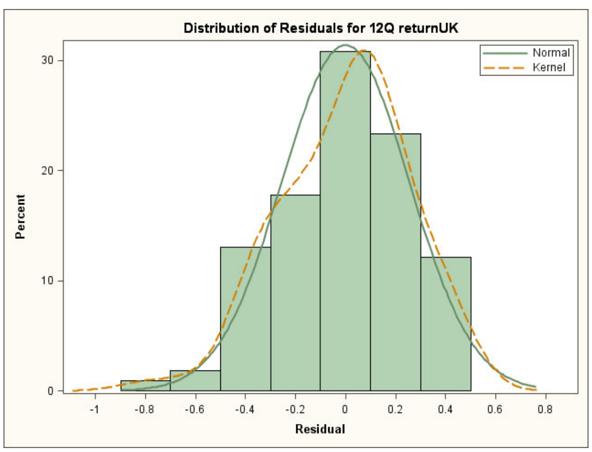
Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

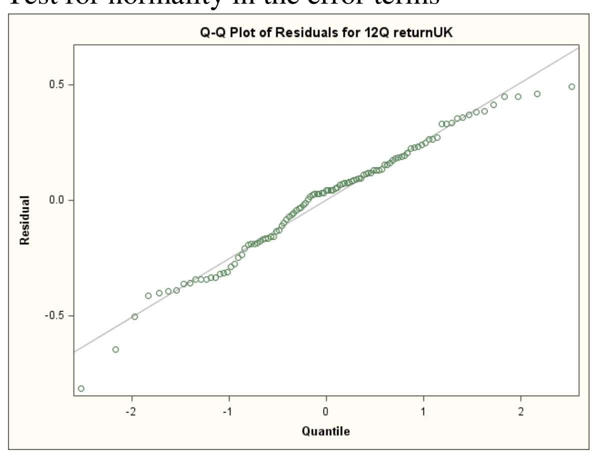
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	8.49285	8.49285	130.25	<.0001
Error	105	6.84640	0.06520		
Corrected Total	106	15.33925			

Root MSE	0.25535	**R-Square**	0.5537
Dependent Mean	0.21258	**Adj R-Sq**	0.5494
Coeff Var	120.12040		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-2.03833	0.19877	-10.25	<.0001
px12QUK	1	-0.79250	0.06944	-11.41	<.0001

Test for normality in the error terms

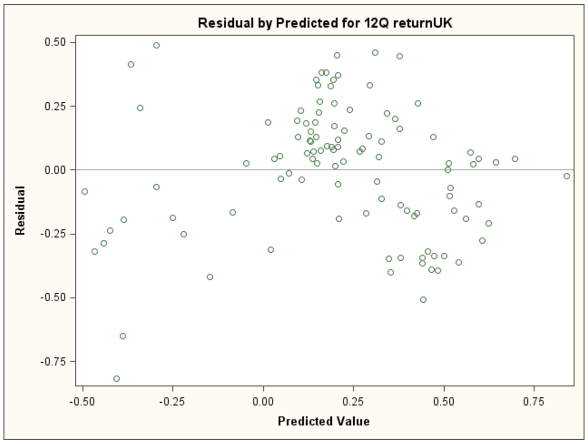


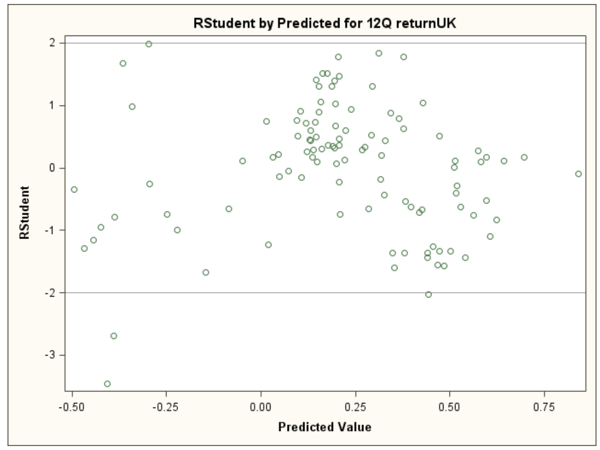


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	3.1330	0.2088	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.09182	0.04591	5.90	0.0038
Error	104	0.80981	0.00779		
Corrected Total	106	0.90163			

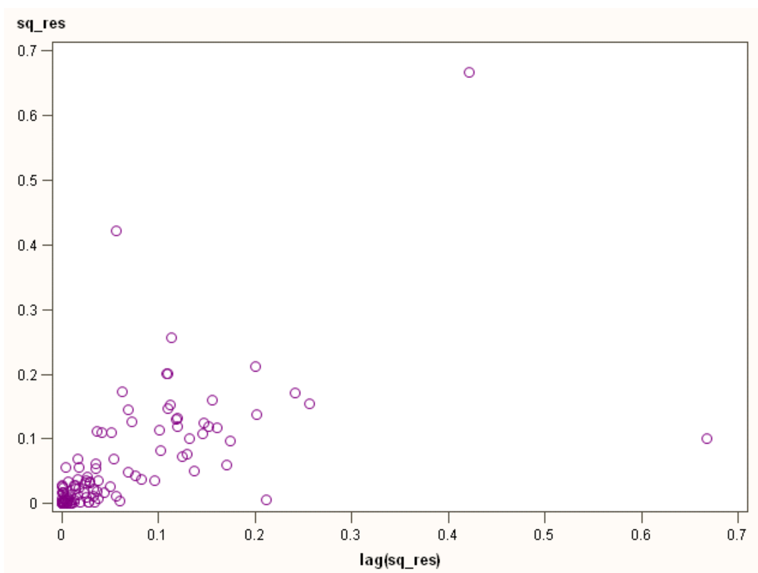
Root MSE	0.08824	**R-Square**	0.1018
Dependent Mean	0.06399	**Adj R-Sq**	0.0846
Coeff Var	137.91049		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.98228	0.37349	2.63	0.0098
px12QUK	1	0.61197	0.27604	2.22	0.0288
sq_px	1	0.10006	0.05052	1.98	0.0503

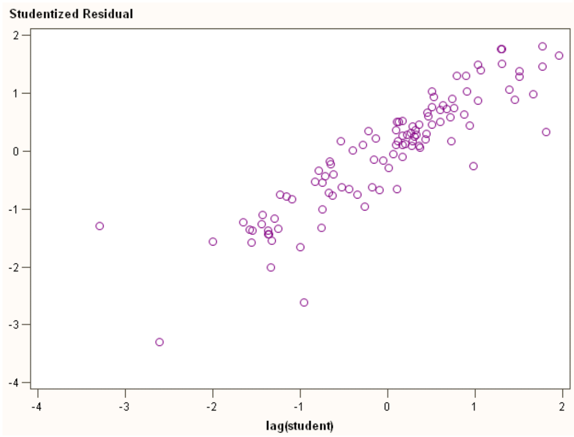
Autoregressive conditional heteroscedasticity (ARCH)

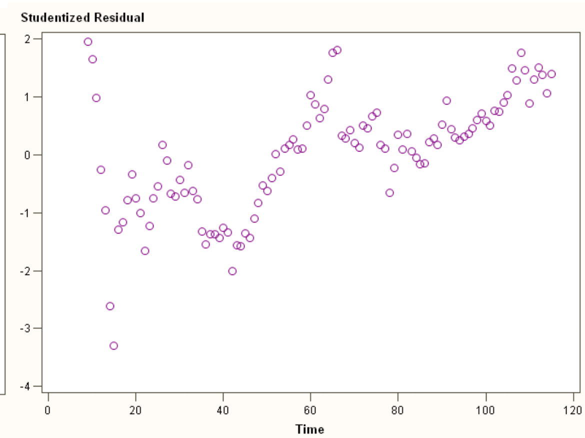
Dependent Variable	residual_12Q returnUK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	37.0650	<.0001	34.5017	<.0001
2	41.7314	<.0001	37.5833	<.0001
3	42.9497	<.0001	38.5485	<.0001
4	45.0101	<.0001	38.9200	<.0001
5	50.7518	<.0001	40.3904	<.0001
6	56.6894	<.0001	40.4330	<.0001
7	59.6659	<.0001	40.4954	<.0001
8	60.7241	<.0001	40.4961	<.0001
9	60.7563	<.0001	42.7496	<.0001
10	62.0187	<.0001	43.4659	<.0001
11	63.8838	<.0001	44.1580	<.0001
12	65.5039	<.0001	44.4336	<.0001



Test for autocorrelation in the error terms





LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	82.9506	<.0001
AR(2)	83.4192	<.0001
AR(3)	83.4606	<.0001
AR(4)	83.4879	<.0001

Durbin-Watson d test

Durbin-Watson D	0.204
Number of Observations	107
1st Order Autocorrelation	0.871

The regression with Newey-West HAC standard errors, 12 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-2.03833	0.5085	-4.01	0.0001
b1	-0.7925	0.1784	-4.44	<.0001

20Q

$$r_{t,t+20} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

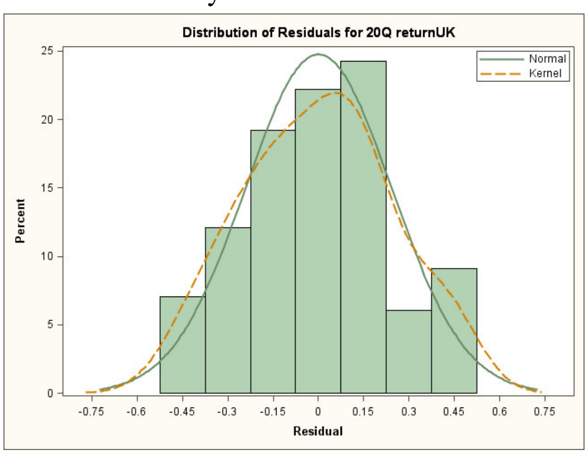
Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

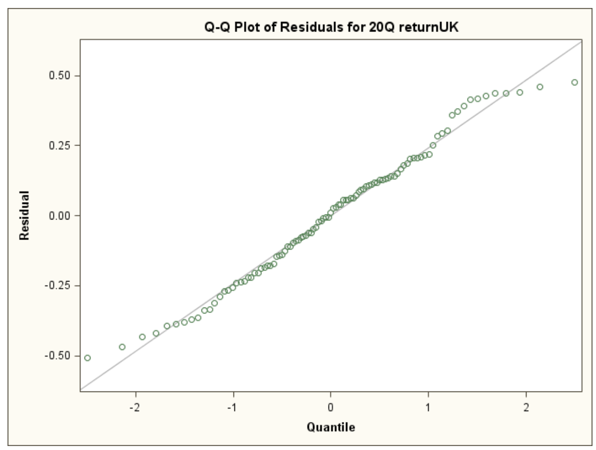
Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	11.69521	11.69521	198.28	<.0001
Error	97	5.72142	0.05898		
Corrected Total	98	17.41663			

Root MSE	0.24287	**R-Square**	0.6715
Dependent Mean	0.39040	**Adj R-Sq**	0.6681
Coeff Var	62.21005		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-2.25771	0.18964	-11.91	<.0001
px20QUK	1	-0.93100	0.06612	-14.08	<.0001

Test for normality in the error terms

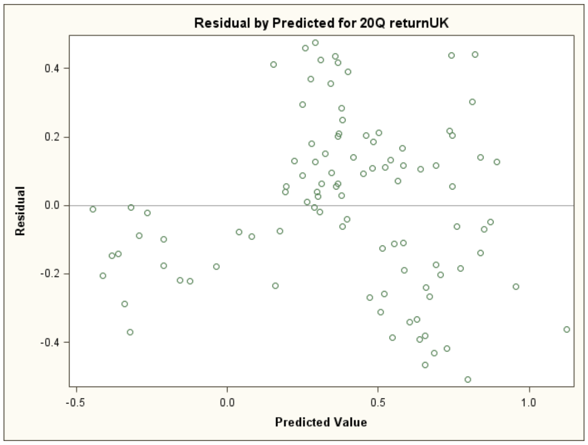


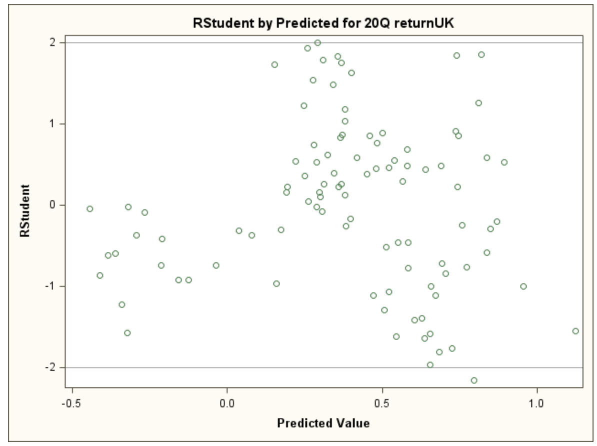


Jarque-Bera test

Miscellaneous Statistics			
Statistic	Value	Prob	Label
Normal Test	1.9212	0.3827	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.01759	0.00880	2.01	0.1391
Error	96	0.41933	0.00437		
Corrected Total	98	0.43692			

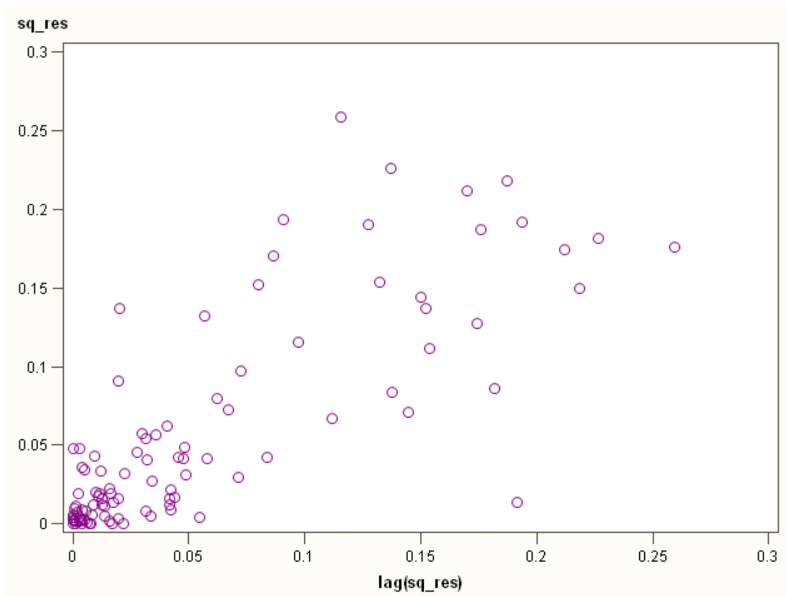
Root MSE	0.06609	**R-Square**	0.0403
Dependent Mean	0.05779	**Adj R-Sq**	0.0203
Coeff Var	114.35988		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.03081	0.28614	0.11	0.9145
px20QUK	1	0.02039	0.21211	0.10	0.9236
sq_px	1	0.01033	0.03886	0.27	0.7909

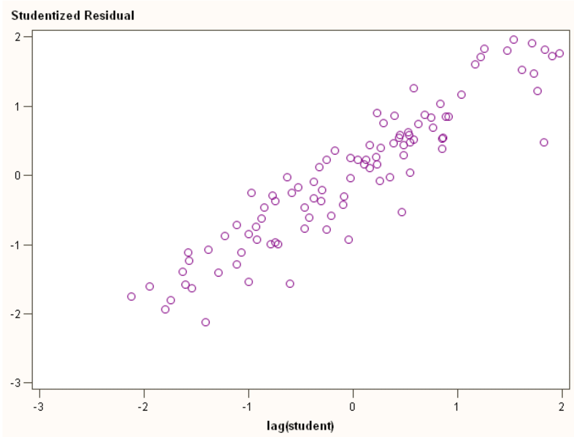
Autoregressive conditional heteroscedasticity (ARCH)

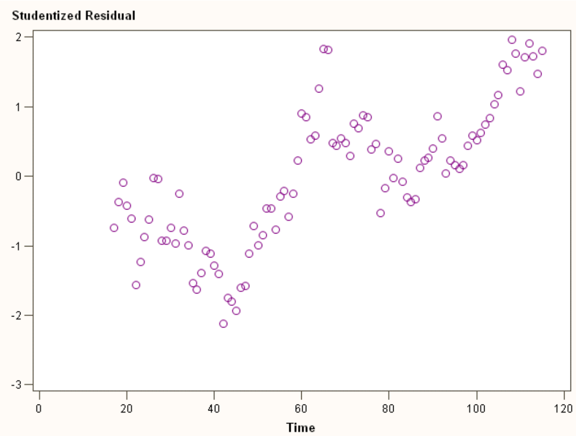
Dependent Variable	residual_20Q returnUK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	61.0586	<.0001	61.8364	<.0001
2	96.7236	<.0001	61.8933	<.0001
3	121.4629	<.0001	62.9160	<.0001
4	137.1208	<.0001	62.9211	<.0001
5	148.9831	<.0001	63.3389	<.0001
6	159.0964	<.0001	63.3961	<.0001
7	164.7104	<.0001	63.4084	<.0001
8	166.5137	<.0001	63.5823	<.0001
9	166.9475	<.0001	63.5942	<.0001
10	167.2639	<.0001	65.0322	<.0001
11	168.2173	<.0001	65.2899	<.0001
12	169.8972	<.0001	65.6611	<.0001



Test for autocorrelation in the error terms





LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	84.7896	<.0001
AR(2)	84.7899	<.0001
AR(3)	85.2314	<.0001
AR(4)	85.2829	<.0001

Durbin-Watson d test

Durbin-Watson D	0.142
Number of Observations	99
1st Order Autocorrelation	0.910

The regression with Newey-West HAC standard errors, 20 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-2.25771	0.4157	-5.43	<.0001
b1	-0.931	0.1524	-6.11	<.0001

Import

4Q

$$r_{t,t+4} = \beta_1 + \beta_2 pz_t + \varepsilon_t$$

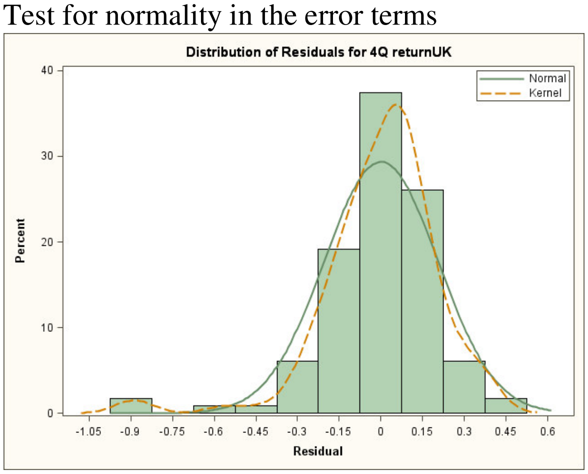
Number of Observations Read	115
Number of Observations Used	115

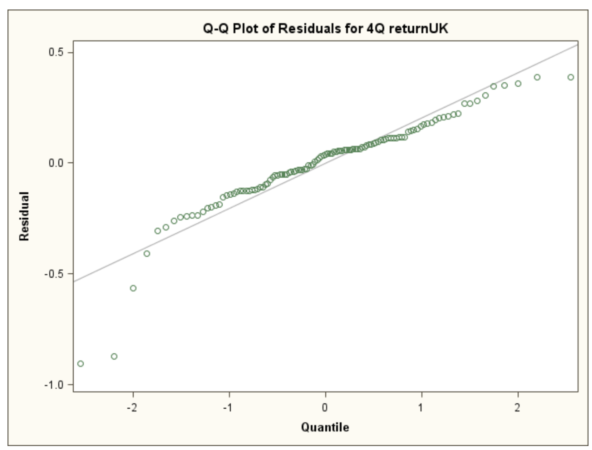
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.98766	0.98766	23.57	<.0001
Error	113	4.73478	0.04190		
Corrected Total	114	5.72244			

Root MSE	0.20470	**R-Square**	0.1726
Dependent Mean	0.07599	**Adj R-Sq**	0.1653
Coeff Var	269.37934		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.73295	0.16771	-4.37	<.0001
pz4QUK	1	-0.29375	0.06050	-4.86	<.0001

Test for normality in the error terms

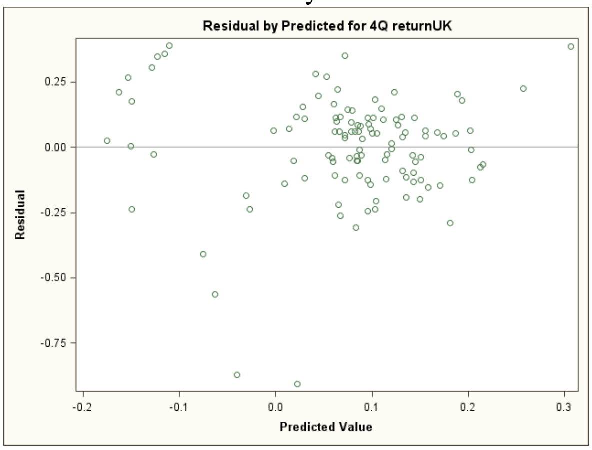


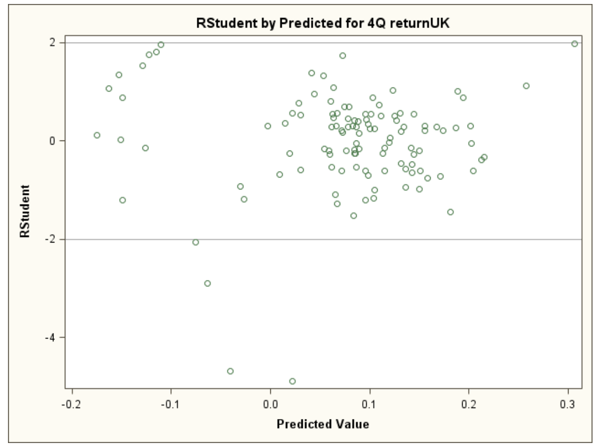


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	161.9627	<.0001	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.07711	0.03855	3.34	0.0389
Error	112	1.29227	0.01154		
Corrected Total	114	1.36938			

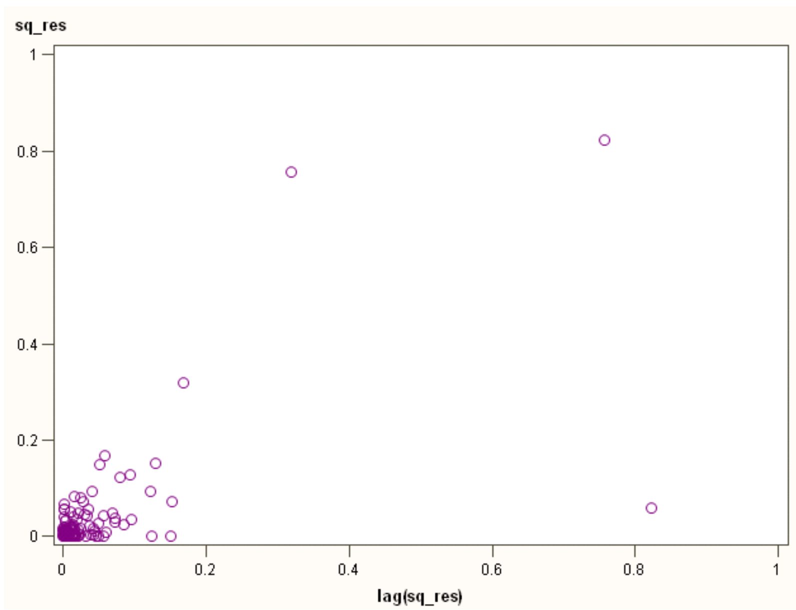
Root MSE	0.10742	**R-Square**	0.0563
Dependent Mean	0.04117	**Adj R-Sq**	0.0395
Coeff Var	260.89506		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.38877	0.46845	0.83	0.4084
pz4QUK	1	0.17731	0.35991	0.49	0.6232
sq_pz	1	0.01831	0.06861	0.27	0.7901

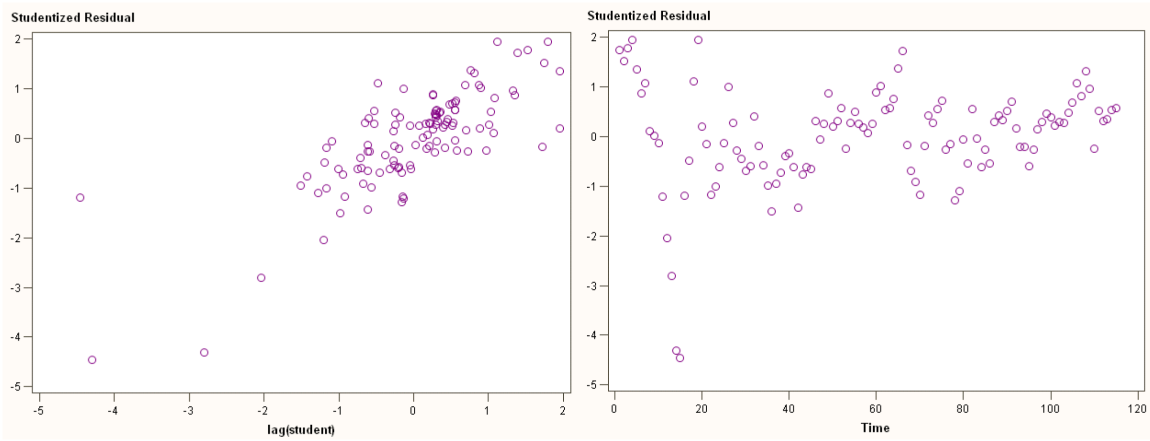
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_4Q returnUK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	50.8251	<.0001	49.1271	<.0001
2	58.7113	<.0001	55.2157	<.0001
3	60.0816	<.0001	56.7351	<.0001
4	60.7952	<.0001	56.7962	<.0001
5	60.8049	<.0001	57.2315	<.0001
6	61.0026	<.0001	57.2558	<.0001
7	61.0035	<.0001	57.4469	<.0001
8	61.1933	<.0001	57.4543	<.0001
9	61.5403	<.0001	57.5285	<.0001
10	62.6094	<.0001	57.9515	<.0001
11	64.7172	<.0001	57.9598	<.0001
12	65.9506	<.0001	58.0526	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	68.7245	<.0001
AR(2)	69.9626	<.0001
AR(3)	70.6005	<.0001
AR(4)	72.6906	<.0001

Durbin-Watson d test

Durbin-Watson D	0.446
Number of Observations	115
1st Order Autocorrelation	0.763

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-0.73295	0.4040	-1.81	0.0723
b1	-0.29375	0.1386	-2.12	0.0362

12Q

$$r_{t,t+12} = \beta_1 + \beta_2 pz_t + \varepsilon_t$$

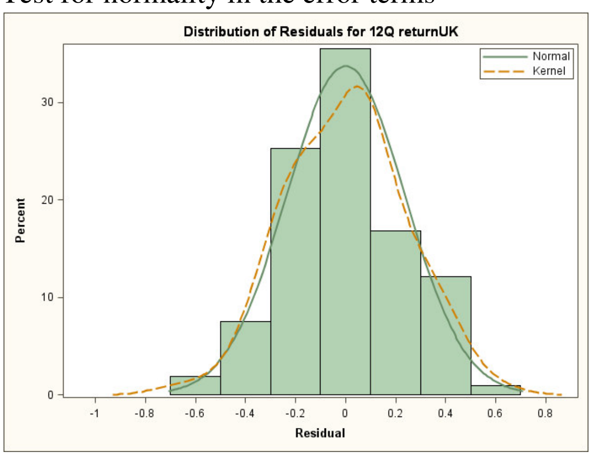
Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

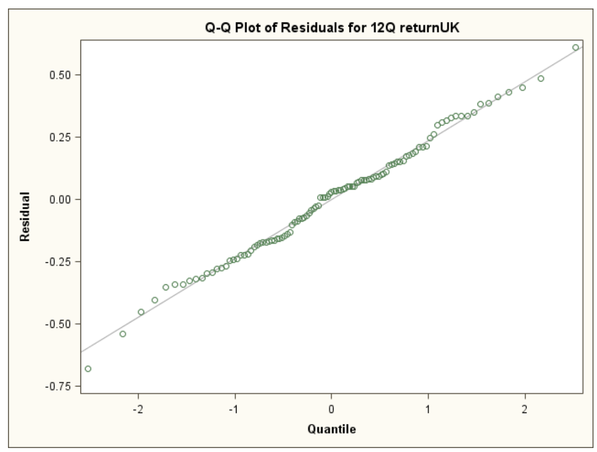
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	9.39918	9.39918	166.15	<.0001
Error	105	5.94007	0.05657		
Corrected Total	106	15.33925			

Root MSE	0.23785	**R-Square**	0.6128
Dependent Mean	0.21258	**Adj R-Sq**	0.6091
Coeff Var	111.88743		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-2.32078	0.19788	-11.73	<.0001
pz12QUK	1	-0.91609	0.07107	-12.89	<.0001

Test for normality in the error terms

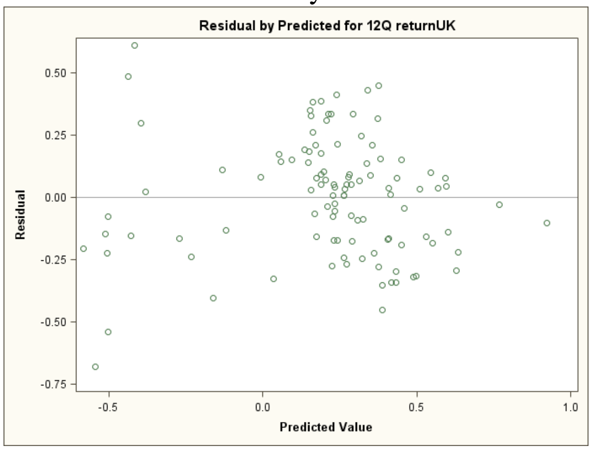


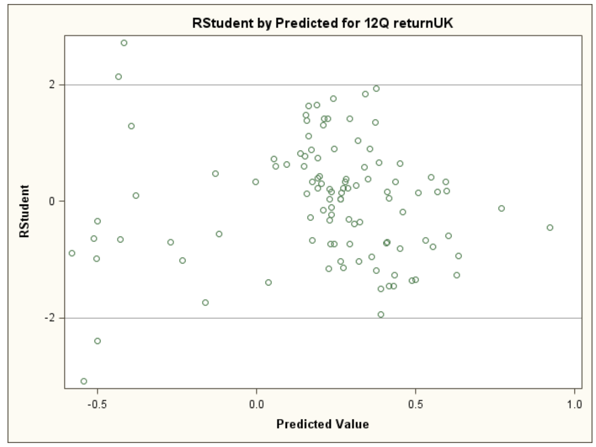


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	0.0451	0.9777	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	107
Number of Observations with Missing Values	8

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.07128	0.03564	6.64	0.0019
Error	104	0.55843	0.00537		
Corrected Total	106	0.62970			

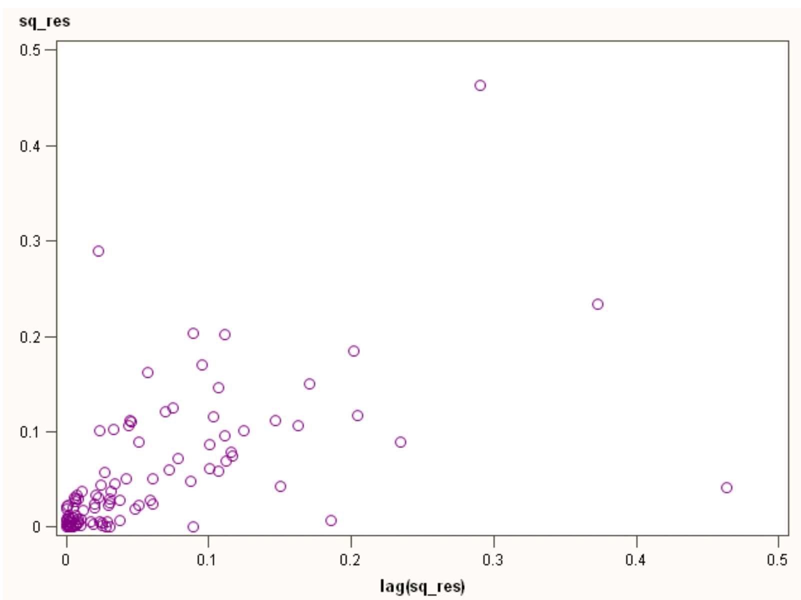
Root MSE	0.07328	**R-Square**	0.1132
Dependent Mean	0.05551	**Adj R-Sq**	0.0961
Coeff Var	131.99524		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.26381	0.09266	2.85	0.0053
12Q returnUK	1	-0.00520	0.03007	-0.17	0.8630
pz12QUK	1	0.07492	0.03519	2.13	0.0356

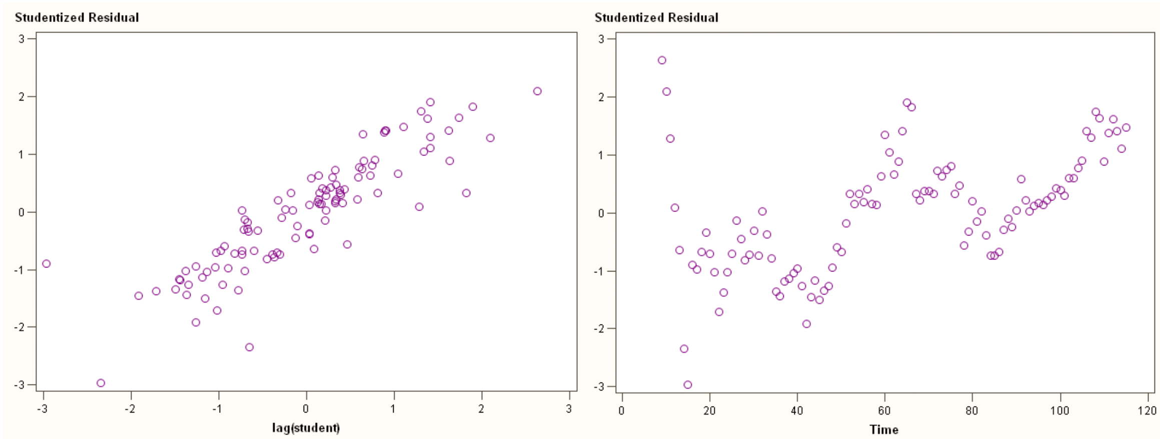
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_12Q returnUK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	31.3097	<.0001	27.3949	<.0001
2	33.2054	<.0001	31.5935	<.0001
3	33.6064	<.0001	32.5123	<.0001
4	36.1607	<.0001	33.3506	<.0001
5	47.1898	<.0001	36.8400	<.0001
6	57.4381	<.0001	36.8598	<.0001
7	59.1034	<.0001	37.5704	<.0001
8	59.6289	<.0001	37.9286	<.0001
9	59.7180	<.0001	41.9460	<.0001
10	60.8561	<.0001	43.1161	<.0001
11	62.1262	<.0001	44.2786	<.0001
12	62.5195	<.0001	44.2793	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	78.2711	<.0001
AR(2)	78.6860	<.0001
AR(3)	78.8130	<.0001
AR(4)	78.8187	<.0001

Durbin-Watson d test

Durbin-Watson D	0.226
Number of Observations	107
1st Order Autocorrelation	0.846

The regression with Newey-West HAC standard errors, 12 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-2.32078	0.4226	-5.49	<.0001
b1	-0.91609	0.1521	-6.02	<.0001

20Q

$$r_{t,t+20} = \beta_1 + \beta_2 pz_t + \varepsilon_t$$

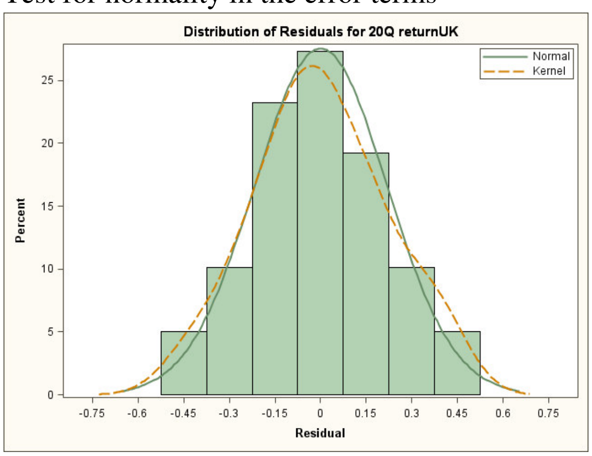
Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

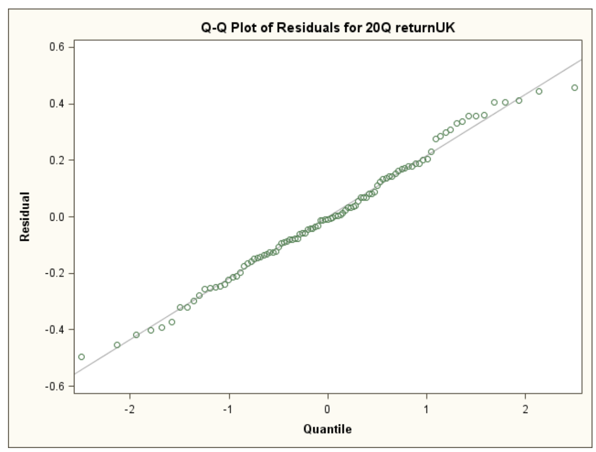
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	12.78477	12.78477	267.74	<.0001
Error	97	4.63186	0.04775		
Corrected Total	98	17.41663			

Root MSE	0.21852	**R-Square**	0.7341
Dependent Mean	0.39040	**Adj R-Sq**	0.7313
Coeff Var	55.97401		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-2.56946	0.18222	-14.10	<.0001
pz20QUK	1	-1.06926	0.06535	-16.36	<.0001

Test for normality in the error terms

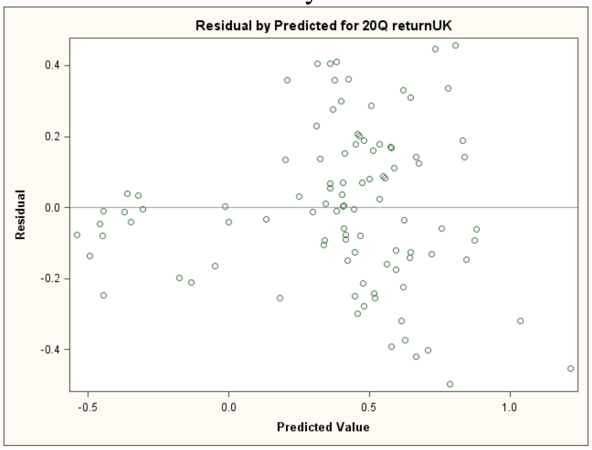


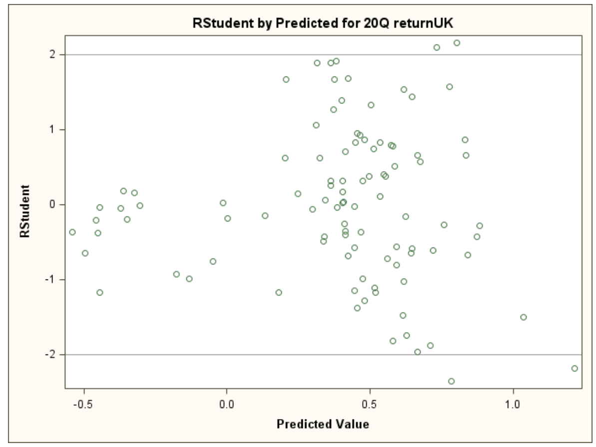


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	0.8259	0.6617	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	99
Number of Observations with Missing Values	16

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.05203	0.02602	8.71	0.0003
Error	96	0.28689	0.00299		
Corrected Total	98	0.33892			

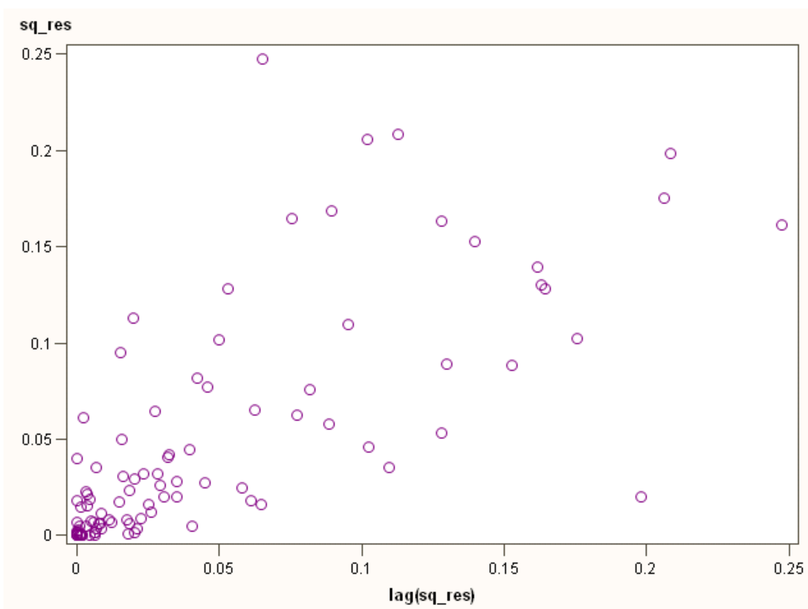
Root MSE	0.05467	**R-Square**	0.1535
Dependent Mean	0.04679	**Adj R-Sq**	0.1359
Coeff Var	116.84169		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.31633	0.24769	1.28	0.2046
pz20QUK	1	0.28336	0.19162	1.48	0.1425
sq_pz	1	0.06621	0.03666	1.81	0.0740

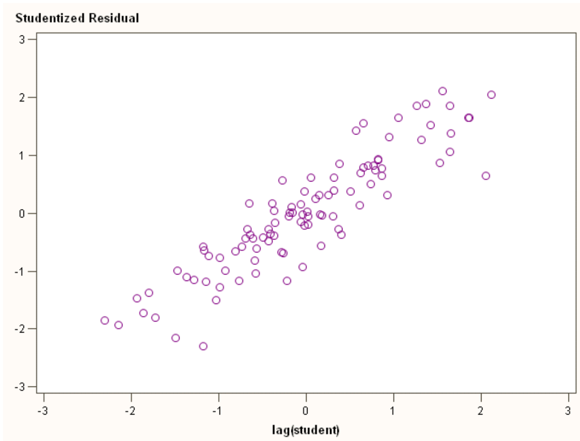
Autoregressive conditional heteroscedasticity (ARCH)

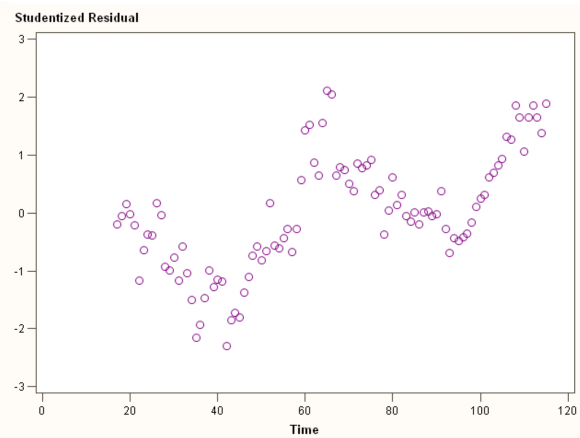
Dependent Variable	residual_20Q returnUK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	50.4730	<.0001	51.8149	<.0001
2	72.4544	<.0001	52.1908	<.0001
3	87.8182	<.0001	54.6990	<.0001
4	98.5151	<.0001	54.7049	<.0001
5	105.5406	<.0001	54.8083	<.0001
6	111.9481	<.0001	54.9002	<.0001
7	116.7263	<.0001	55.0006	<.0001
8	118.2129	<.0001	55.3781	<.0001
9	118.4300	<.0001	55.4607	<.0001
10	118.9102	<.0001	56.6876	<.0001
11	120.0309	<.0001	56.7728	<.0001
12	122.9482	<.0001	58.5578	<.0001



Test for autocorrelation in the error terms





LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	81.4222	<.0001
AR(2)	81.4223	<.0001
AR(3)	82.1883	<.0001
AR(4)	82.2177	<.0001

Durbin-Watson d test

Durbin-Watson D	0.183
Number of Observations	99
1st Order Autocorrelation	0.890

The regression with Newey-West HAC standard errors, 20 lags

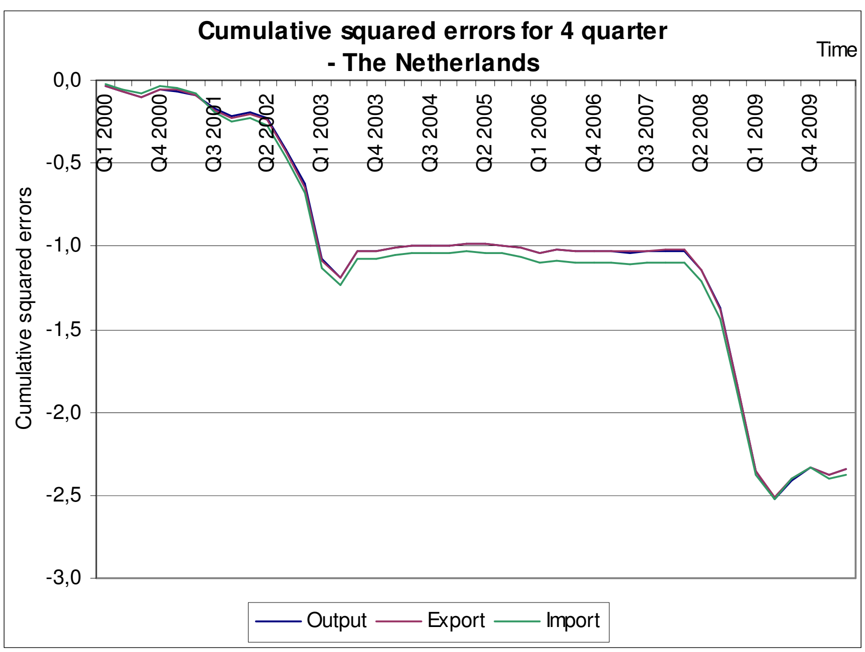
Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-2.56946	0.2940	-8.74	<.0001
b1	-1.06926	0.1224	-8.74	<.0001

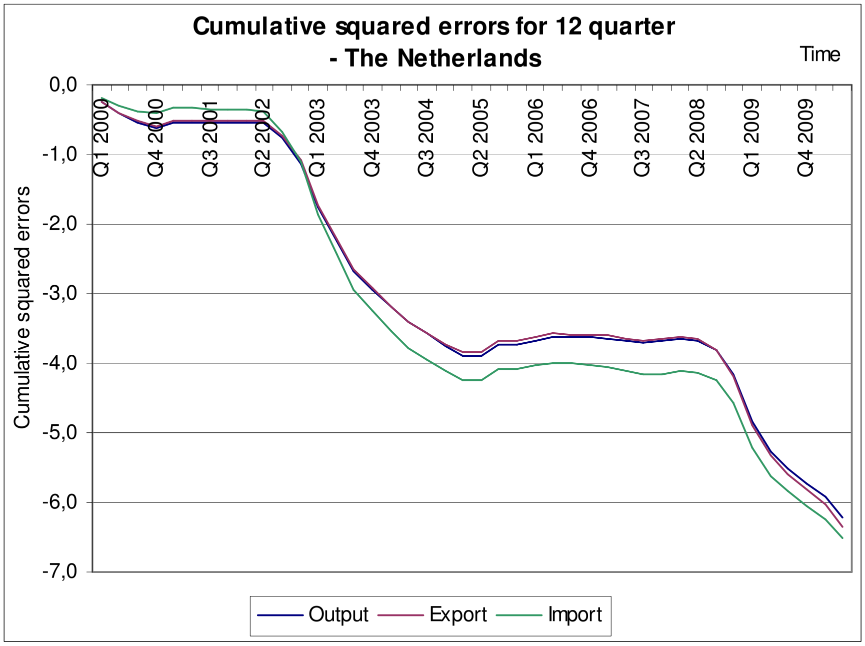
Appendix E – Out-of-sample testing

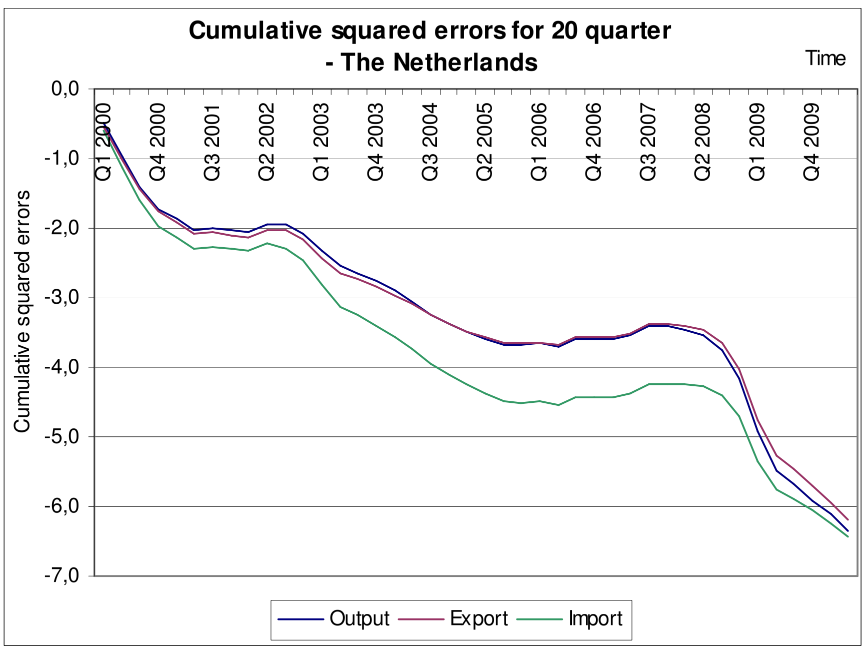
Theil's U

Out-of-sample testing - Theil's U									
	Output - RESpy			Export - px			Import - pz		
Horizon K quarters	4	12	20	4	12	20	4	12	20
Denmark	1,55	1,89	1,69	1,56	2,01	1,79	1,55	2,06	2,01
The Netherlands	1,73	2,50	2,32	1,73	2,52	2,30	1,73	2,55	2,33
France	1,63	2,21	2,05	1,64	2,16	2,01	1,66	2,28	2,12
United Kingdom	1,59	2,14	2,04	1,72	2,60	2,45	1,89	3,33	3,25

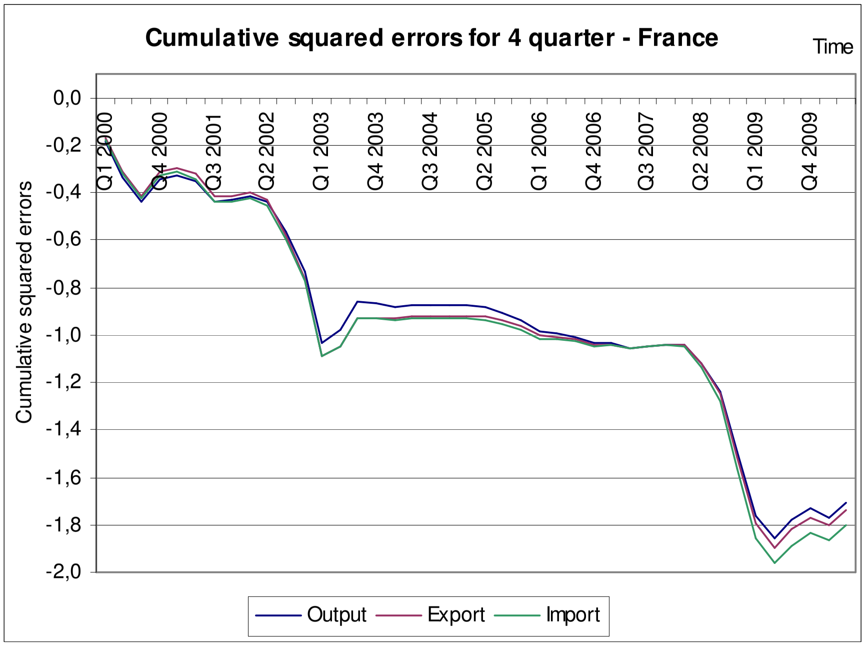
The Netherlands



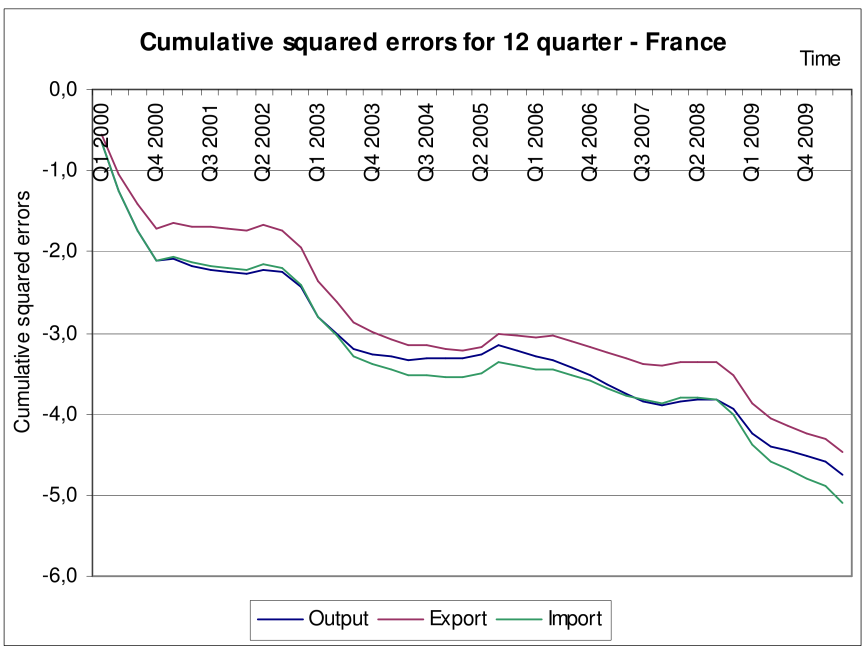

Cumulative squared errors for 12 quarter
- The Netherlands
Time
Cumulative squared errors
0,0
-1,0
-2,0
-3,0
-4,0
-5,0
-6,0
-7,0
Q1 2000
Q4 2000
Q3 2001
Q2 2002
Q1 2003
Q4 2003
Q3 2004
Q2 2005
Q1 2006
Q4 2006
Q3 2007
Q2 2008
Q1 2009
Q4 2009
Output
Export
Import


Cumulative squared errors for 20 quarter
- The Netherlands
Time
Cumulative squared errors
0,0
-1,0
-2,0
-3,0
-4,0
-5,0
-6,0
-7,0
Q1 2000
Q4 2000
Q3 2001
Q2 2002
Q1 2003
Q4 2003
Q3 2004
Q2 2005
Q1 2006
Q4 2006
Q3 2007
Q2 2008
Q1 2009
Q4 2009
Output
Export
Import

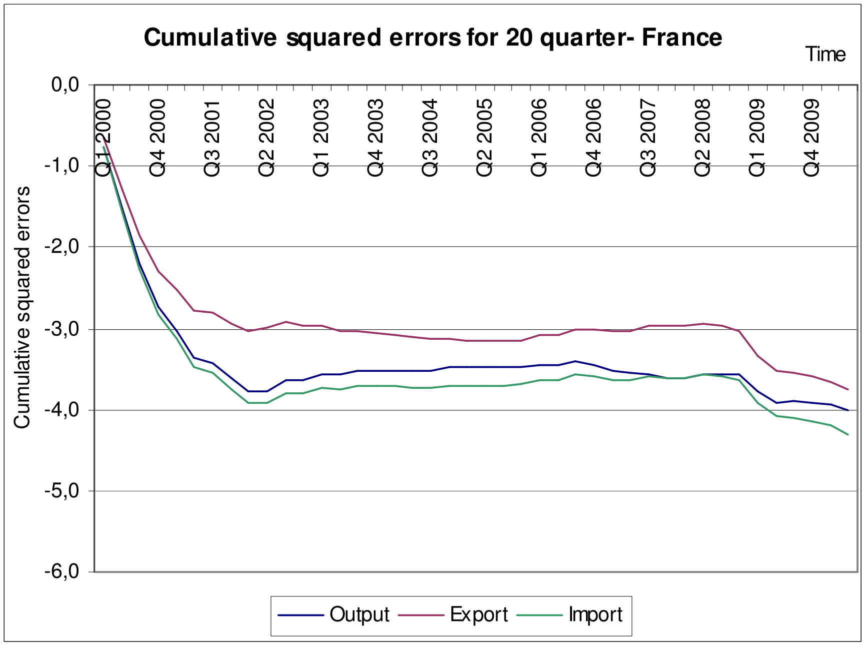
France



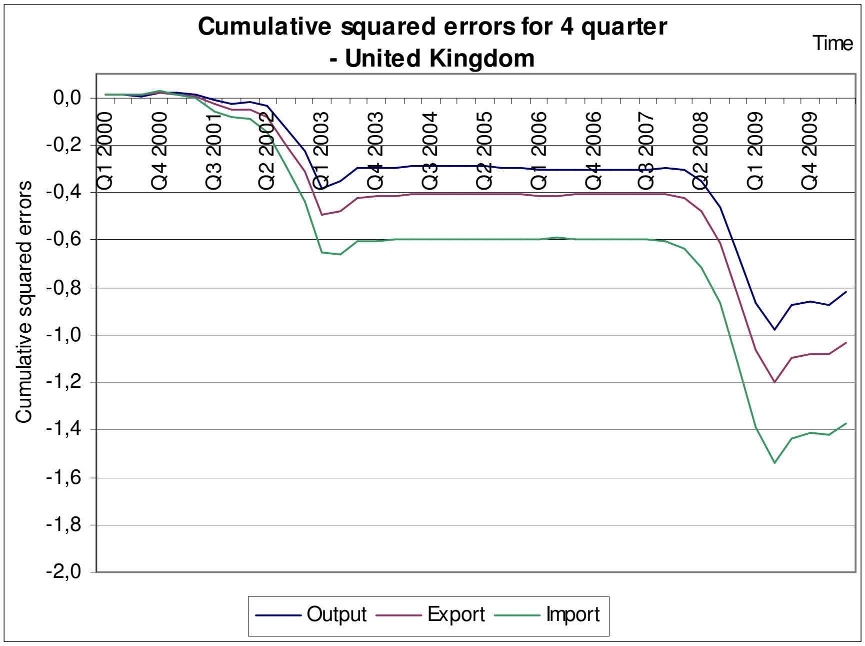
Cumulative squared errors for 4 quarter - France
Time
Cumulative squared errors
0,0
-0,2
-0,4
-0,6
-0,8
-1,0
-1,2
-1,4
-1,6
-1,8
-2,0
Q1 2000
Q4 2000
Q3 2001
Q2 2002
Q1 2003
Q4 2003
Q3 2004
Q2 2005
Q1 2006
Q4 2006
Q3 2007
Q2 2008
Q1 2009
Q4 2009
Output
Export
Import

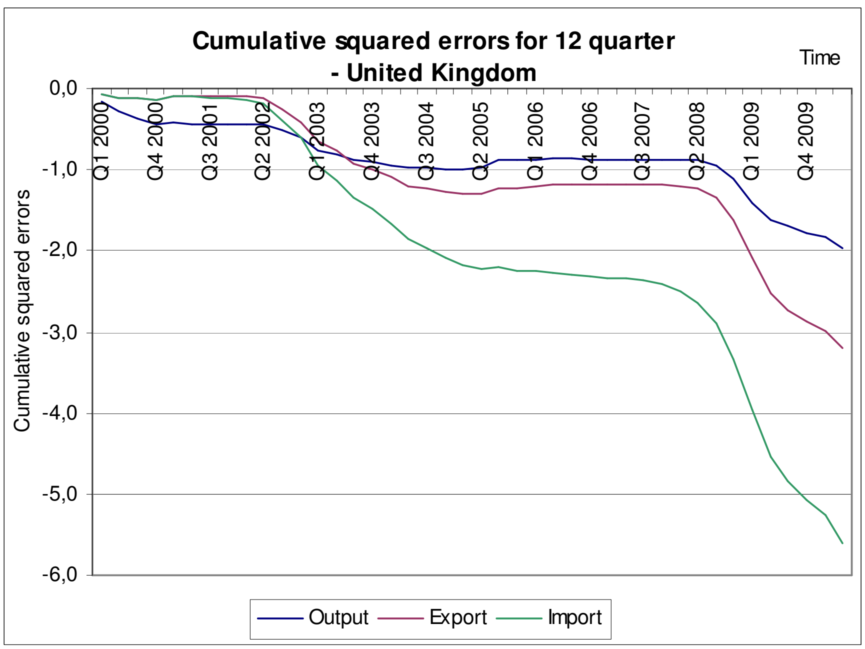


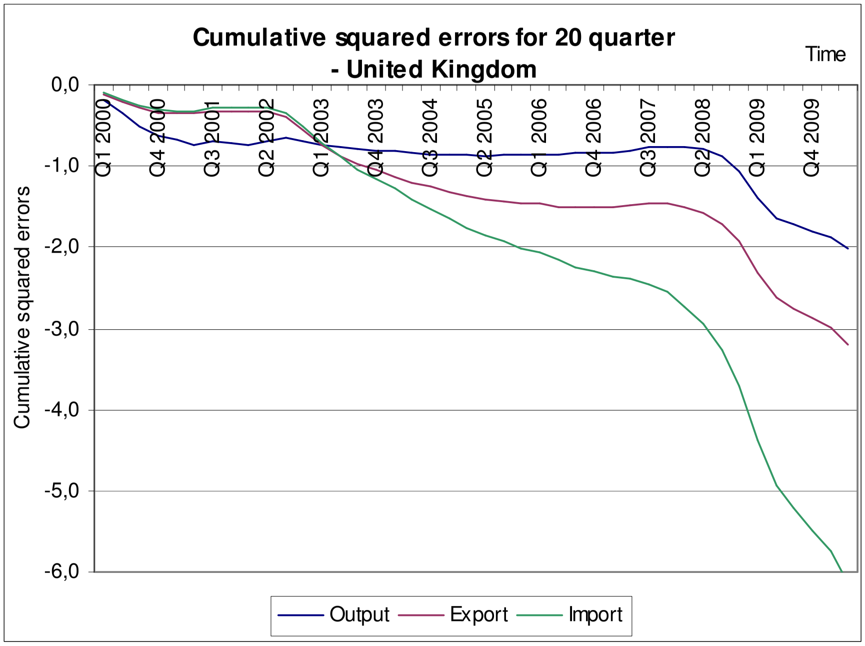
Cumulative squared errors for 12 quarter - France
Time
Cumulative squared errors
0,0
-1,0
-2,0
-3,0
-4,0
-5,0
-6,0
Q1 2000
Q4 2000
Q3 2001
Q2 2002
Q1 2003
Q4 2003
Q3 2004
Q2 2005
Q1 2006
Q4 2006
Q3 2007
Q2 2008
Q1 2009
Q4 2009
Output
Export
Import


Cumulative squared errors for 20 quarter- France
Time
Cumulative squared errors
0,0
-1,0
-2,0
-3,0
-4,0
-5,0
-6,0
Q1 2000
Q4 2000
Q3 2001
Q2 2002
Q1 2003
Q4 2003
Q3 2004
Q2 2005
Q1 2006
Q4 2006
Q3 2007
Q2 2008
Q1 2009
Q4 2009
Output
Export
Import

United Kingdom






Cumulative squared errors for 20 quarter
- United Kingdom
Time
Cumulative squared errors
0,0
-1,0
-2,0
-3,0
-4,0
-5,0
-6,0
Q1 2000
Q4 2000
Q3 2001
Q2 2002
Q1 2003
Q4 2003
Q3 2004
Q2 2005
Q1 2006
Q4 2006
Q3 2007
Q2 2008
Q1 2009
Q4 2009
Output
Export
Import

Appendix F – Robustness test

Denmark

RESpyD

$$p_t = \beta_1 + \beta_2 y_{t-1} + \beta_3 D_t + \nu_t$$

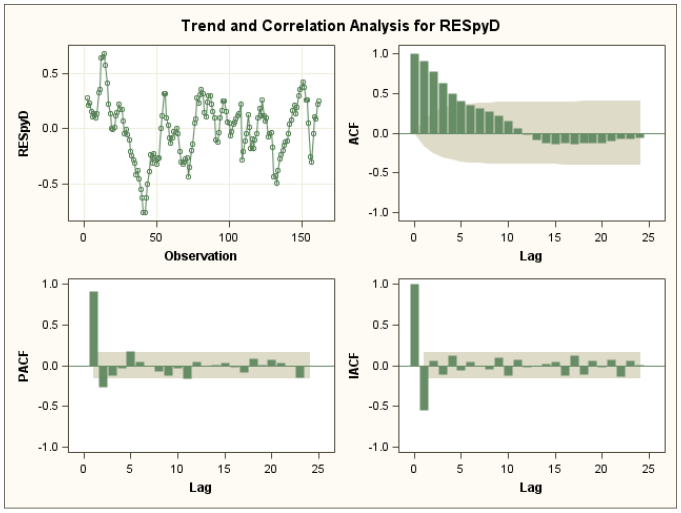
Number of Observations Read	162
Number of Observations Used	161
Number of Observations with Missing Values	1

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	66.69993	33.34997	467.34	<.0001
Error	158	11.27501	0.07136		
Corrected Total	160	77.97494			

Root MSE	0.26713	**R-Square**	0.8554
Dependent Mean	2.30117	**Adj R-Sq**	0.8536
Coeff Var	11.60863		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-8.55794	1.03972	-8.23	<.0001
lag(yDK)	1	1.54073	0.15358	10.03	<.0001
D	1	0.63930	0.07853	8.14	<.0001

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-13.8395	0.0089	-2.69	0.0073		
	1	-24.4969	0.0003	-3.46	0.0006		
	2	-32.6772	<.0001	-3.80	0.0002		
	3	-33.5767	<.0001	-3.65	0.0003		
	4	-21.3636	0.0009	-2.92	0.0038		
	5	-20.5713	0.0011	-2.80	0.0054		
Single Mean	0	-13.8406	0.0488	-2.68	0.0794	3.60	0.1532
	1	-24.4975	0.0030	-3.45	0.0108	5.96	0.0136
	2	-32.6825	0.0012	-3.79	0.0037	7.19	0.0010
	3	-33.5787	0.0012	-3.63	0.0062	6.60	0.0010
	4	-21.3673	0.0068	-2.91	0.0474	4.22	0.0749
	5	-20.5798	0.0083	-2.79	0.0624	3.89	0.0950
Trend	0	-13.8619	0.2139	-2.68	0.2449	3.83	0.4124
	1	-24.4613	0.0226	-3.45	0.0490	6.05	0.0652
	2	-32.5984	0.0032	-3.79	0.0196	7.30	0.0239
	3	-33.4846	0.0026	-3.63	0.0304	6.68	0.0405
	4	-21.3663	0.0451	-2.91	0.1630	4.32	0.3134
	5	-20.6581	0.0527	-2.80	0.1996	4.04	0.3708



Test for number of lags

Augmented Engle-Granger test, 0 lags delta($RESpyDDK_t$) = b_1 RESpyDDK $_{t-1}$

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	13.2244	0.0003
AR(2)	15.6284	0.0004
AR(3)	15.6776	0.0013
AR(4)	20.0725	0.0005

Augmented Engle-Granger test, 1 lags delta($RESpyDDK_t$) = b_1 RESpyDDK $_{t-1}$ + b_2 delta(RESpyDDK $_{t-1}$)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	2.4466	0.1178
AR(2)	2.4654	0.2915
AR(3)	7.2466	0.0644
AR(4)	7.2716	0.1222

$$r_{t,t+4} = \beta_1 + \beta_2 RESpyD_t + \varepsilon_t$$

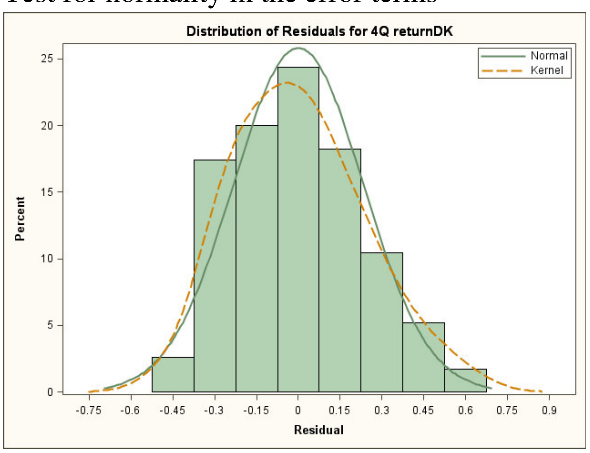
Number of Observations Read	115
Number of Observations Used	115

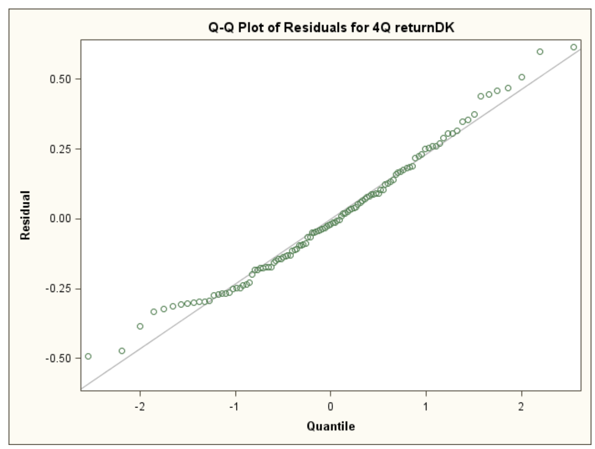
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	1.34945	1.34945	24.87	<.0001
Error	113	6.13032	0.05425		
Corrected Total	114	7.47977			

Root MSE	0.23292	**R-Square**	0.1804
Dependent Mean	0.08004	**Adj R-Sq**	0.1732
Coeff Var	291.00253		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.07740	0.02173	3.56	0.0005
RESpyD4QDK	1	-0.39110	0.07842	-4.99	<.0001

Test for normality in the error terms

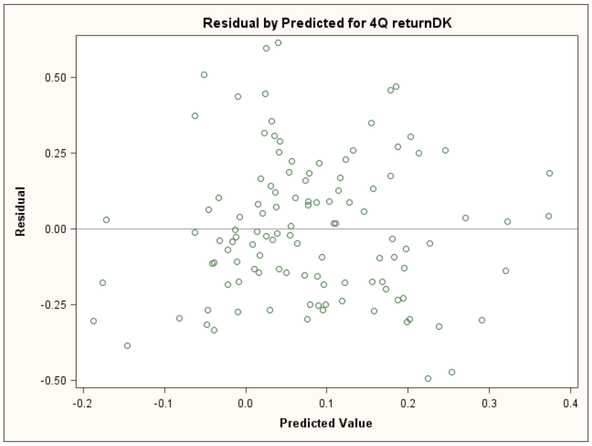


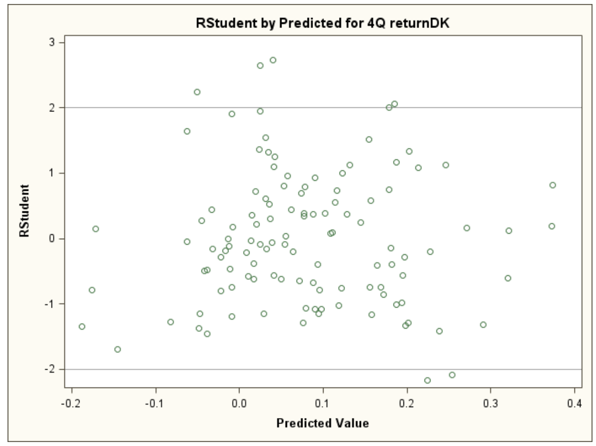


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	3.4089	0.1819	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.00080864	0.00040432	0.08	0.9243
Error	112	0.57476	0.00513		
Corrected Total	114	0.57556			

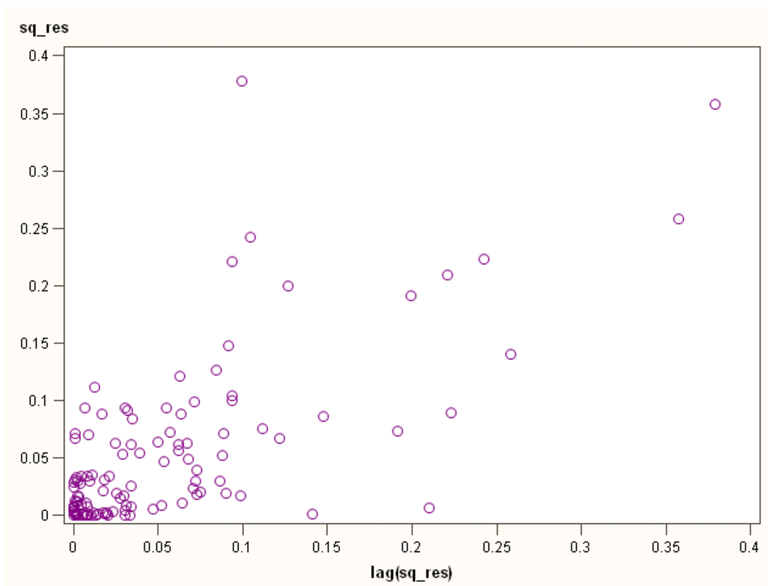
Root MSE	0.07164	**R-Square**	0.0014
Dependent Mean	0.05331	**Adj R-Sq**	-0.0164
Coeff Var	134.38393		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.05152	0.00806	6.39	<.0001
RESpyD4QDK	1	0.00198	0.02463	0.08	0.9360
sq_RESpyD	1	0.02346	0.05909	0.40	0.6922

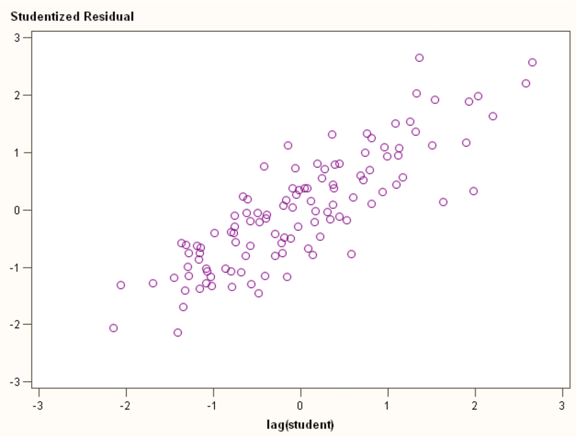
Autoregressive conditional heteroscedasticity (ARCH)

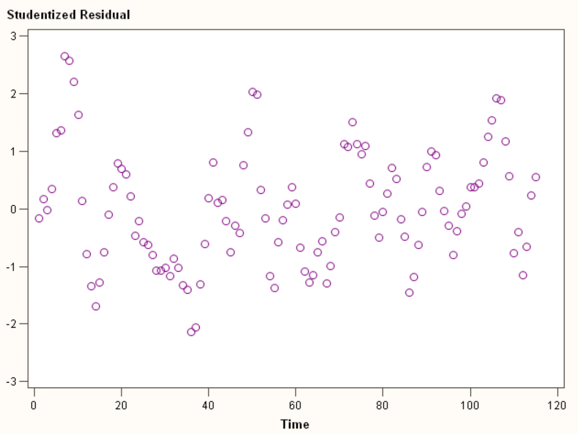
Dependent Variable	residual_4Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	55.9987	<.0001	55.1861	<.0001
2	65.2216	<.0001	63.4230	<.0001
3	65.2345	<.0001	63.4375	<.0001
4	65.7321	<.0001	63.6443	<.0001
5	66.0095	<.0001	63.6786	<.0001
6	66.7705	<.0001	64.6594	<.0001
7	68.5099	<.0001	64.7991	<.0001
8	71.1449	<.0001	64.9968	<.0001
9	74.0325	<.0001	65.4522	<.0001
10	77.3905	<.0001	66.1025	<.0001
11	80.3118	<.0001	66.1050	<.0001
12	80.9323	<.0001	66.2412	<.0001



Test for autocorrelation in the error terms





LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	85.0359	<.0001
AR(2)	90.0544	<.0001
AR(3)	93.0121	<.0001
AR(4)	93.0400	<.0001

Durbin-Watson d test

Durbin-Watson D	0.304
Number of Observations	115
1st Order Autocorrelation	0.847

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.07731	0.0388	1.99	0.0488
b1	-0.3918	0.1348	-2.91	0.0044

RESpyt

$$p_t = \beta_1 + \beta_2 y_{t-1} + \beta_3 t + \nu_t$$

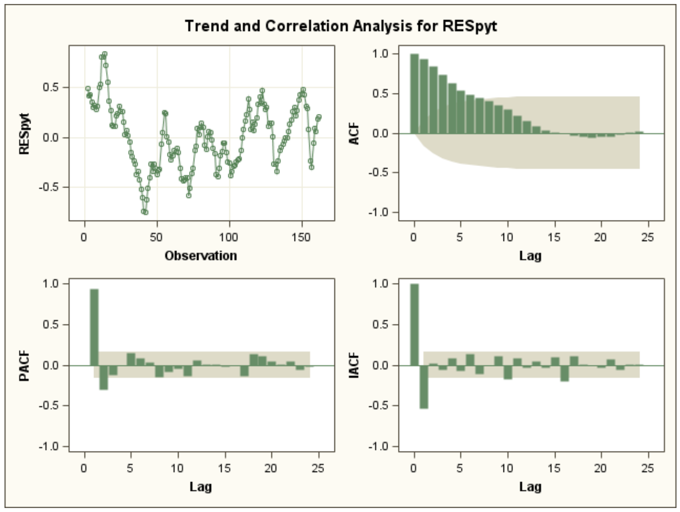
Number of Observations Read	162
Number of Observations Used	161
Number of Observations with Missing Values	1

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	62.19569	31.09784	311.39	<.0001
Error	158	15.77925	0.09987		
Corrected Total	160	77.97494			

Root MSE	0.31602	**R-Square**	0.7976
Dependent Mean	2.30117	**Adj R-Sq**	0.7951
Coeff Var	13.73301		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-6.59434	5.94679	-1.11	0.2692
lag(yDK)	1	1.20273	0.91689	1.31	0.1915
Time	1	0.00715	0.00476	1.50	0.1354

Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-9.5170	0.0310	-2.34	0.0192		
	1	-18.5924	0.0022	-3.09	0.0022		
	2	-24.3718	0.0003	-3.41	0.0008		
	3	-23.3689	0.0004	-3.20	0.0016		
	4	-15.9382	0.0048	-2.65	0.0083		
	5	-13.9136	0.0086	-2.48	0.0131		
Single Mean	0	-9.5209	0.1454	-2.33	0.1632	2.74	0.3720
	1	-18.5968	0.0140	-3.08	0.0302	4.76	0.0462
	2	-24.3772	0.0031	-3.40	0.0124	5.80	0.0171
	3	-23.3790	0.0040	-3.19	0.0226	5.09	0.0359
	4	-15.9552	0.0280	-2.64	0.0871	3.50	0.1802
	5	-13.9316	0.0475	-2.48	0.1219	3.10	0.2812
Trend	0	-9.4930	0.4603	-2.32	0.4181	3.15	0.5471
	1	-18.5008	0.0841	-3.08	0.1158	4.91	0.1953
	2	-24.2124	0.0239	-3.40	0.0547	5.99	0.0686
	3	-23.2277	0.0298	-3.19	0.0897	5.25	0.1271
	4	-15.9133	0.1430	-2.65	0.2581	3.70	0.4378
	5	-13.9736	0.2090	-2.51	0.3252	3.38	0.5028



Test for number of lags

Augmented Engle-Granger test, 0 lags   delta($RESpytDK_t$) = b_1 RESpytDK $_{t-1}$

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	20.7826	<.0001
AR(2)	22.8171	<.0001
AR(3)	22.8287	<.0001
AR(4)	26.6715	<.0001

Augmented Engle-Granger test, 1 lags   delta($RESpytDK_t$) = b_1 RESpytDK $_{t-1}$ + b_2 delta(RESpytDK $_{t-1}$)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	2.1831	0.1395
AR(2)	2.2091	0.3314
AR(3)	6.7658	0.0798
AR(4)	7.6616	0.1048

$$r_{t,t+4} = \beta_1 + \beta_2 RESpyt_t + \varepsilon_t$$

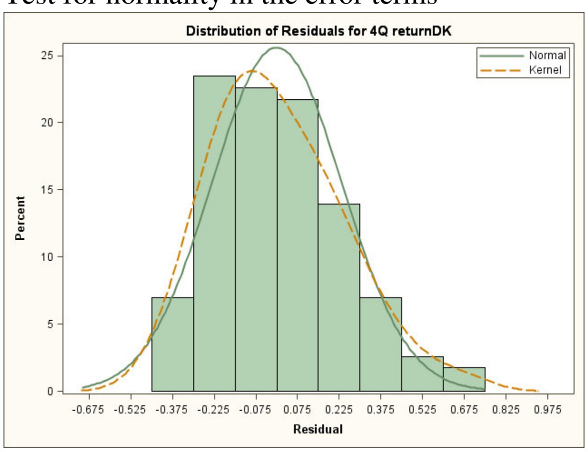
Number of Observations Read	115
Number of Observations Used	115

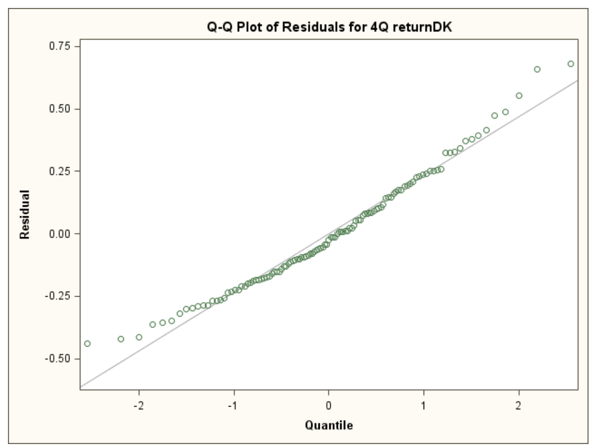
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	1.24255	1.24255	22.51	<.0001
Error	113	6.23722	0.05520		
Corrected Total	114	7.47977			

Root MSE	0.23494	**R-Square**	0.1661
Dependent Mean	0.08004	**Adj R-Sq**	0.1587
Coeff Var	293.52875		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.06344	0.02219	2.86	0.0051
RESpyt4QDK	1	-0.31617	0.06664	-4.74	<.0001

Test for normality in the error terms

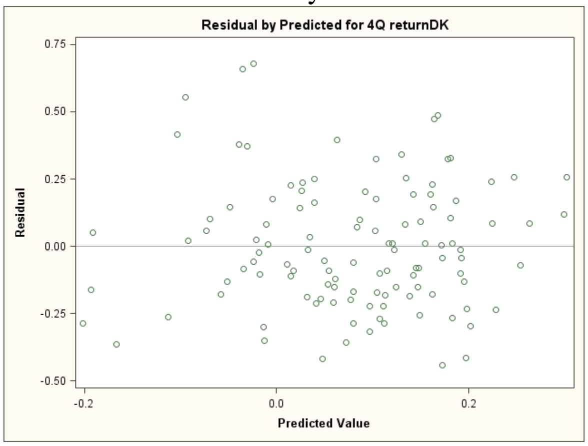


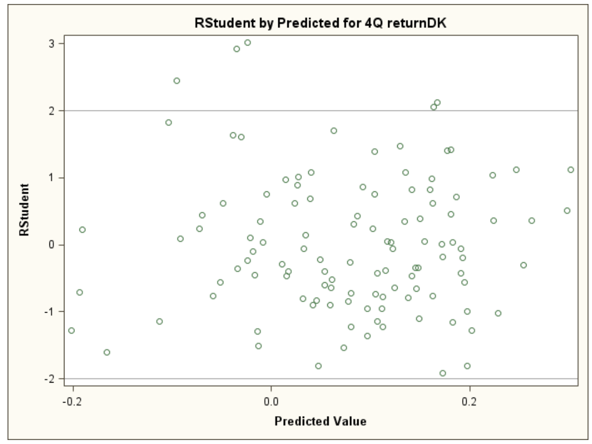


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	5.8727	0.0531	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.01526	0.00763	1.27	0.2839
Error	112	0.67123	0.00599		
Corrected Total	114	0.68649			

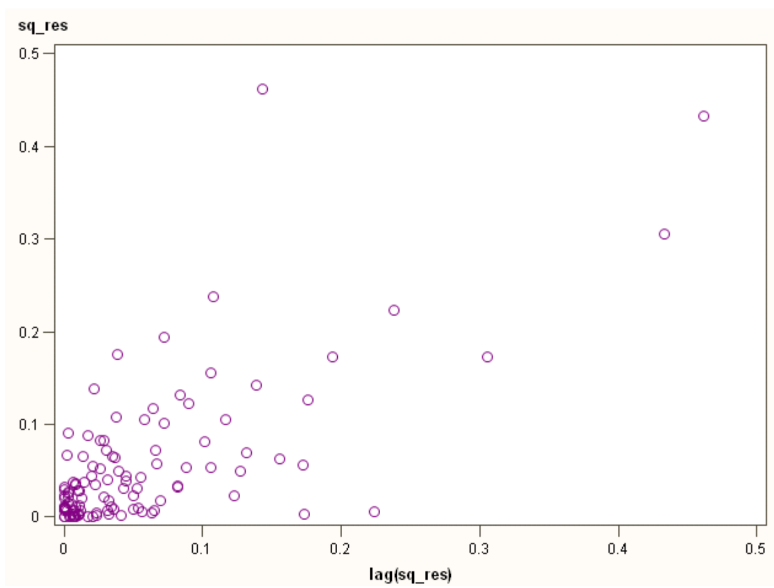
Root MSE	0.07742	**R-Square**	0.0222
Dependent Mean	0.05424	**Adj R-Sq**	0.0048
Coeff Var	142.73607		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.05367	0.00924	5.81	<.0001
RESpyt4QDK	1	0.03287	0.02208	1.49	0.1394
sq_RESpyt	1	0.02066	0.04990	0.41	0.6797

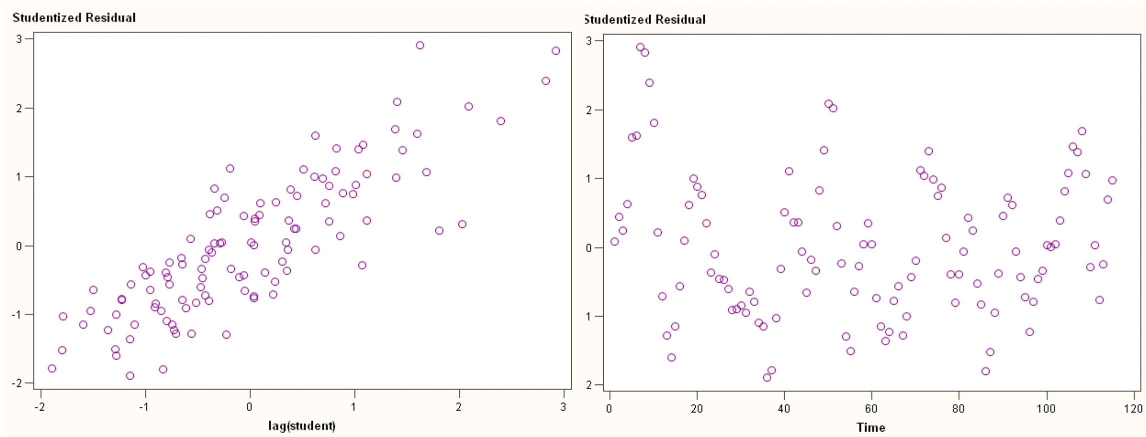
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_4Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	57.3111	<.0001	56.2861	<.0001
2	68.6789	<.0001	63.2131	<.0001
3	68.8860	<.0001	63.2202	<.0001
4	69.1944	<.0001	63.3941	<.0001
5	69.5641	<.0001	63.4819	<.0001
6	70.5582	<.0001	64.2706	<.0001
7	71.7135	<.0001	64.2724	<.0001
8	72.8919	<.0001	64.4914	<.0001
9	73.7521	<.0001	64.6041	<.0001
10	74.4339	<.0001	64.8188	<.0001
11	75.0369	<.0001	64.8591	<.0001
12	75.0369	<.0001	65.1991	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	83.5200	<.0001
AR(2)	88.7753	<.0001
AR(3)	91.2982	<.0001
AR(4)	91.4344	<.0001

Durbin-Watson d test

Durbin-Watson D	0.318
Number of Observations	115
1st Order Autocorrelation	0.837

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.063444	0.0406	1.56	0.1212
b1	-0.31617	0.1209	-2.62	0.0101

RESpyi

The discussion for choosing the risk-free interest rate as the extra variable:

As discussed in 3.2.2 "The theoretical model", the dividend can been seen as holding the same information as the output and including this could be seen as basically using the same variable twice. The same is the case for the earnings and the book-to-market ratio, which are also financial variables and contain the same information as the dividend. The interest rate is a macroeconomic variable and does not come from the same system of variables as the dividend, earning and the output[217]. The interest rate has been used in the past to forecast the stock return[218]. One could use a variable for the money market or another macroeconomic variable such as the unemployment rate or the industrial production growth. The information in the unemployment rate or the industrial production growth is very similar to the information in the output, export and import, and these are therefore not chosen. The information in the money market and the interest rate is also linked, since these two variables belong to the same system of variables along with the currency. The interest rate, more precisely the risk-free interest rate was chosen, because it can be seen as a foundation for the returns. This is the rate of return, the investor demands for holding the risk-free asset and including this will give information in regards to the investors risk aversion to the inflation risk, which as previously discussed is the main risk for the risk-free asset. By including the risk-free interest rate, the estimated ratios will have new information, but not a variable which could substitute another variable.

The data on the risk-free interest rate:

The risk-free interest rate used for Denmark and The Netherlands is the Discount Rate, which is the rate the national bank lens money to other financial institutions on a day-to-day basis. For France and United Kingdom the Treasury Bill Rate is used, which is the government backed short-term debt-obligation. Both of these interest rates are risk-free and the reason for the difference is lack of information. The Treasury Bill Rate is theoretically the right interest rate to use in this case because it is the risk-free interest rate faced by the normal investors. However, it does not go back to 1970 for Denmark and The Netherlands, and it is only available for France and United Kingdom for the studied time period.

[217] Previously, the output has been substituting the dividend in the theoretical model under the assumption that the two variables essentially hold the same information

[218] Rapach et al., 2005, has used the interest rate in the relative treasury bill rate and the term spread

$$p_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 i_t + \hat{\mu}_t$$

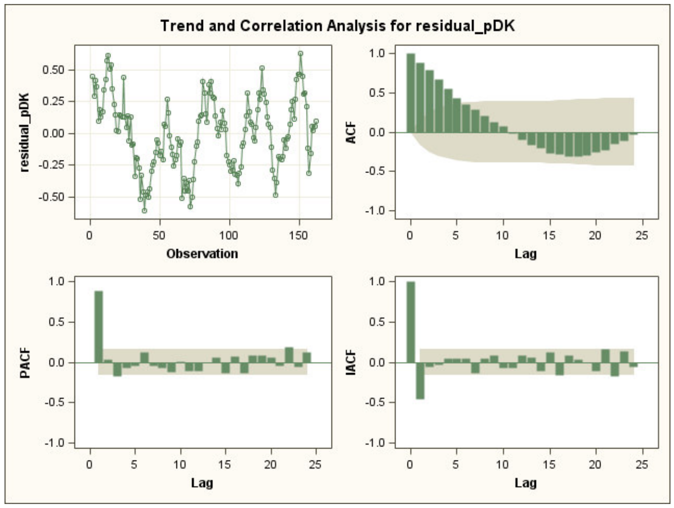
Number of Observations Read	163
Number of Observations Used	161
Number of Observations with Missing Values	2

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	65.22857	32.61428	404.28	<.0001
Error	158	12.74637	0.08067		
Corrected Total	160	77.97494			

Root MSE	0.28403	**R-Square**	0.8365
Dependent Mean	2.30117	**Adj R-Sq**	0.8345
Coeff Var	12.34286		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-11.13326	0.93443	-11.91	<.0001
lag(yDK)	1	2.00618	0.12832	15.63	<.0001
iDK	1	-8.62321	1.35698	-6.35	<.0001

Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-18.4865	0.0022	-3.24	0.0014		
	1	-17.2191	0.0033	-2.97	0.0032		
	2	-25.3444	0.0002	-3.50	0.0006		
	3	-29.2909	<.0001	-3.57	0.0004		
	4	-33.4363	<.0001	-3.52	0.0005		
	5	-23.6807	0.0004	-3.00	0.0029		
Single Mean	0	-18.4892	0.0145	-3.23	0.0205	5.23	0.0316
	1	-17.2231	0.0201	-2.97	0.0408	4.41	0.0636
	2	-25.3493	0.0024	-3.49	0.0096	6.11	0.0103
	3	-29.3015	0.0012	-3.57	0.0076	6.37	0.0044
	4	-33.4372	0.0012	-3.51	0.0090	6.17	0.0088
	5	-23.6819	0.0037	-3.00	0.0377	4.50	0.0578
Trend	0	-18.5209	0.0838	-3.23	0.0831	5.37	0.1033
	1	-17.2515	0.1091	-2.97	0.1449	4.50	0.2771
	2	-25.3696	0.0183	-3.50	0.0432	6.25	0.0545
	3	-29.3170	0.0072	-3.58	0.0350	6.53	0.0448
	4	-33.4938	0.0026	-3.52	0.0411	6.20	0.0572
	5	-23.8919	0.0256	-3.01	0.1316	4.60	0.2586



Test for number of lags

Augmented Engle-Granger test, 0 lags delta(RESpyiDK$_t$) = b$_1$ RESpyiDK$_{t-1}$

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
lag(RESpyi)	1	-0.1155	0.0357	-3.24	0.0015

Godfrey's Serial Correlation Test		
Alternative	LM	Pr > LM
AR(1)	0.0230	0.8794
AR(2)	4.3942	0.1111
AR(3)	4.9469	0.1757
AR(4)	6.3861	0.1721

$$r_{t,t+4} = \beta_1 + \beta_2 RESpyi_t + \varepsilon_t$$

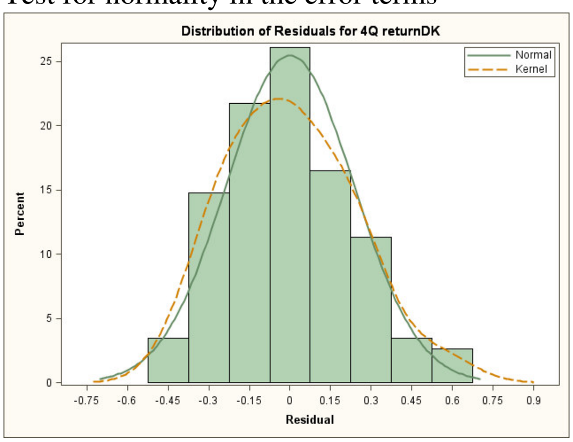
Number of Observations Read	115
Number of Observations Used	115

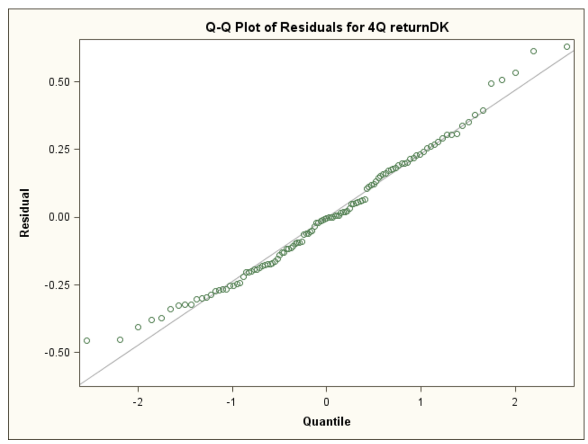
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	1.17942	1.17942	21.15	<.0001
Error	113	6.30035	0.05576		
Corrected Total	114	7.47977			

Root MSE	0.23613	**R-Square**	0.1577
Dependent Mean	0.08004	**Adj R-Sq**	0.1502
Coeff Var	295.01051		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.06934	0.02214	3.13	0.0022
RESpyi4QDK	1	-0.35559	0.07731	-4.60	<.0001

Test for normality in the error terms

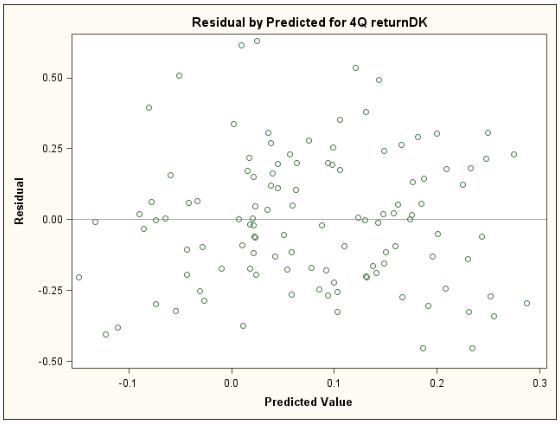


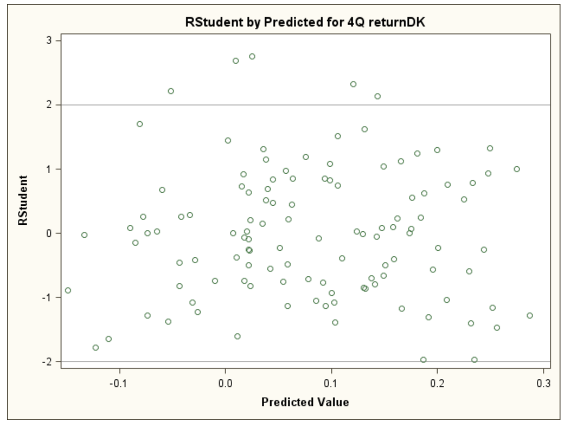


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	2.9746	0.2260	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	115
Number of Observations Used	115

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.00413	0.00206	0.39	0.6797
Error	112	0.59628	0.00532		
Corrected Total	114	0.60041			

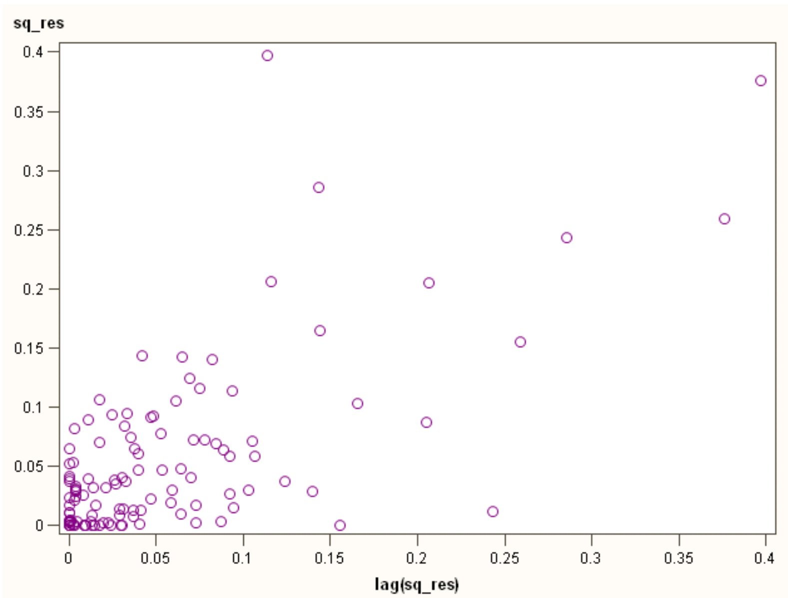
Root MSE	0.07297	**R-Square**	0.0069
Dependent Mean	0.05479	**Adj R-Sq**	-0.0109
Coeff Var	133.18360		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.04944	0.00913	5.42	<.0001
RESpyi4QDK	1	0.00113	0.02409	0.05	0.9628
sq_RESpyi	1	0.06562	0.07476	0.88	0.3820

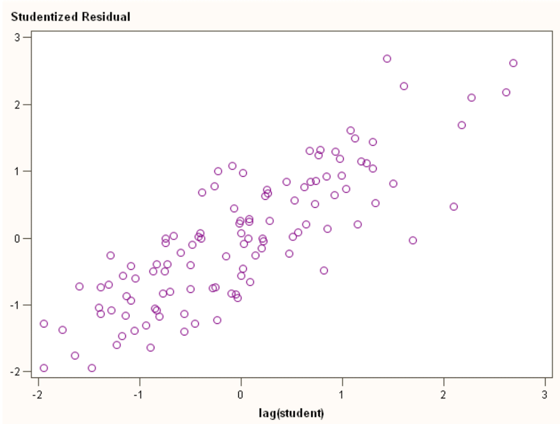
Autoregressive conditional heteroscedasticity (ARCH)

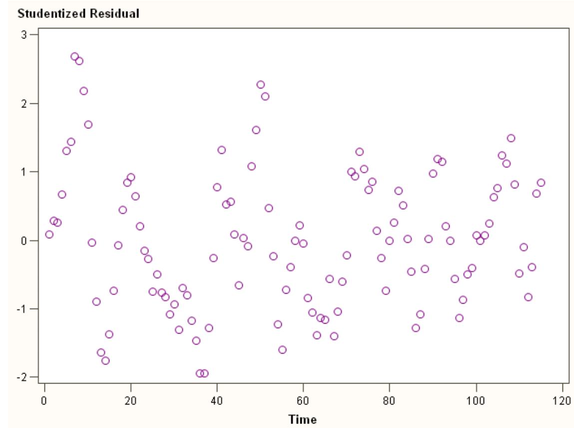
Dependent Variable	residual_4Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	53.0129	<.0001	52.1841	<.0001
2	60.7139	<.0001	59.9680	<.0001
3	60.7165	<.0001	60.0219	<.0001
4	60.7200	<.0001	61.2587	<.0001
5	60.9661	<.0001	61.3680	<.0001
6	61.0655	<.0001	61.6416	<.0001
7	61.3240	<.0001	62.1330	<.0001
8	62.5018	<.0001	62.1620	<.0001
9	64.3407	<.0001	62.7122	<.0001
10	65.8231	<.0001	62.8310	<.0001
11	67.3626	<.0001	63.1045	<.0001
12	67.3830	<.0001	64.6147	<.0001



Test for autocorrelation in the error terms





LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	81.9942	<.0001
AR(2)	87.5605	<.0001
AR(3)	91.2468	<.0001
AR(4)	91.3055	<.0001

Durbin-Watson d test

Durbin-Watson D	0.330
Number of Observations	115
1st Order Autocorrelation	0.832

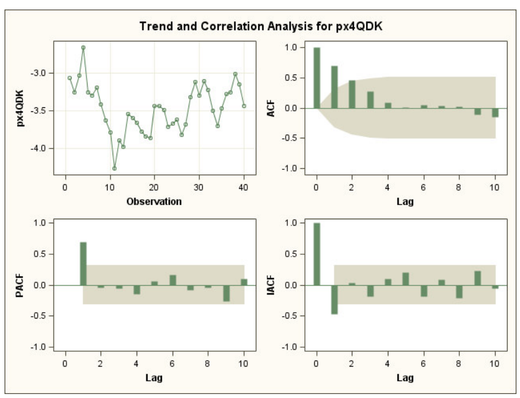
The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.069343	0.0385	1.80	0.0746
b1	-0.35559	0.1335	-2.66	0.0088

px and 4 quarter return, one year data

px

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	0.0093	0.6794	0.02	0.6841		
	1	-0.0271	0.6711	-0.07	0.6541		
	2	0.0262	0.6828	0.07	0.7008		
	3	0.1012	0.6996	0.32	0.7737		
	4	0.0112	0.6791	0.04	0.6892		
	5	0.0280	0.6827	0.13	0.7186		
Single Mean	0	-11.8211	0.0656	-2.68	0.0855	3.64	0.1734
	1	-12.6615	0.0509	-2.46	0.1321	3.04	0.3193
	2	-14.8048	0.0263	-2.51	0.1221	3.18	0.2864
	3	-26.1107	0.0005	-3.28	0.0228	5.58	0.0310
	4	-19.0321	0.0063	-2.28	0.1843	2.61	0.4241
	5	-11.3224	0.0727	-1.86	0.3464	1.76	0.6312
Trend	0	-11.9366	0.2600	-2.69	0.2471	3.76	0.4491
	1	-12.6743	0.2204	-2.46	0.3428	3.12	0.5701
	2	-14.2899	0.1511	-2.54	0.3091	3.60	0.4794
	3	-22.4812	0.0155	-3.56	0.0482	7.81	0.0249
	4	-17.8572	0.0588	-2.59	0.2878	3.82	0.4384
	5	-12.3095	0.2318	-2.45	0.3489	3.97	0.4097

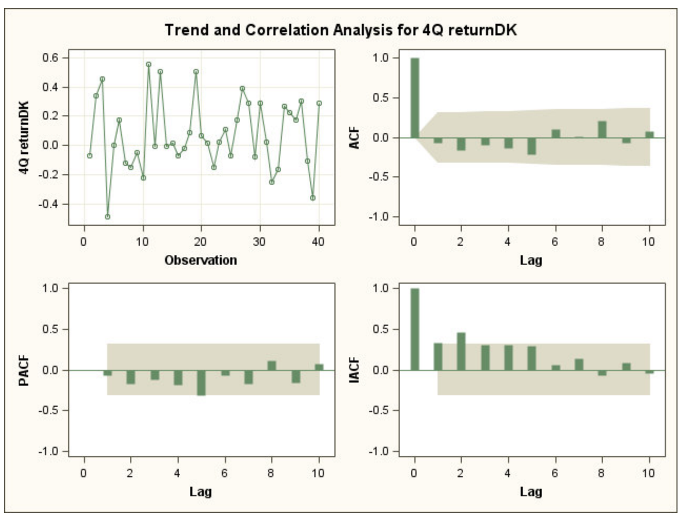


Test for number of lags: Augmented Engle-Granger test, 0 lags delta($pxDK_t$) = b_1 $pxDK_{t-1}$

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	0.1865	0.6659
AR(2)	0.2111	0.8998
AR(3)	0.2948	0.9610
AR(4)	0.7697	0.9425

4 quarter return

Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-38.4087	<.0001	-5.97	<.0001		
	1	-42.7199	<.0001	-4.54	<.0001		
	2	-44.2865	<.0001	-3.89	0.0003		
	3	-41.1949	<.0001	-2.97	0.0041		
	4	-112.674	0.0001	-2.91	0.0048		
	5	-22.8882	0.0002	-2.00	0.0452		
Single Mean	0	-41.9148	0.0003	-6.51	0.0002	21.25	0.0010
	1	-58.0764	0.0003	-5.15	0.0002	13.26	0.0010
	2	-96.5657	0.0002	-4.51	0.0009	10.27	0.0010
	3	1647.039	0.9999	-4.05	0.0031	8.21	0.0010
	4	45.0490	0.9999	-4.60	0.0007	10.58	0.0010
	5	39.9302	0.9999	-3.45	0.0156	5.95	0.0221
Trend	0	-41.9136	<.0001	-6.43	<.0001	20.65	0.0010
	1	-58.7511	<.0001	-5.10	0.0010	13.06	0.0010
	2	-112.228	0.0001	-4.62	0.0037	10.79	0.0010
	3	503.1535	0.9999	-4.04	0.0163	8.21	0.0185
	4	41.7188	0.9999	-4.64	0.0037	10.85	0.0010
	5	34.2039	0.9999	-3.62	0.0429	6.55	0.0579



$$r_{t,t+4} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

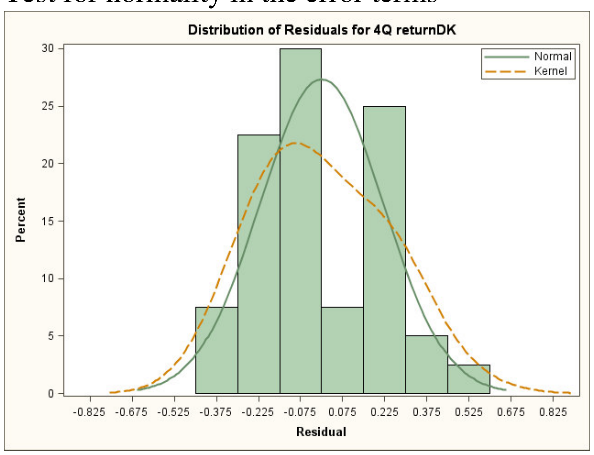
Number of Observations Read	40
Number of Observations Used	40

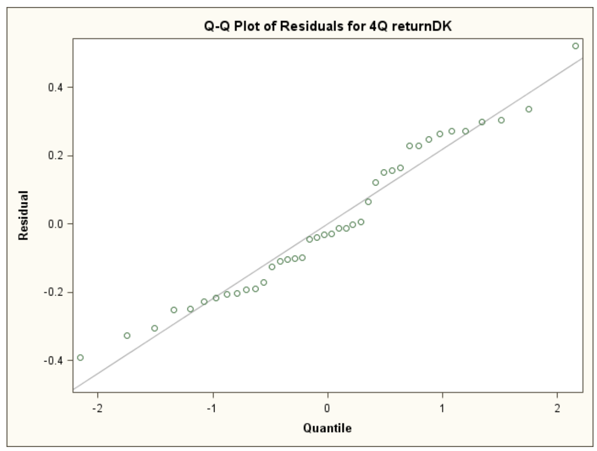
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.40448	0.40448	8.22	0.0067
Error	38	1.87019	0.04922		
Corrected Total	39	2.27467			

Root MSE	0.22185	**R-Square**	0.1778
Dependent Mean	0.07322	**Adj R-Sq**	0.1562
Coeff Var	302.97811		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-1.03681	0.38879	-2.67	0.0112
px4QDK	1	-0.32030	0.11173	-2.87	0.0067

Test for normality in the error terms

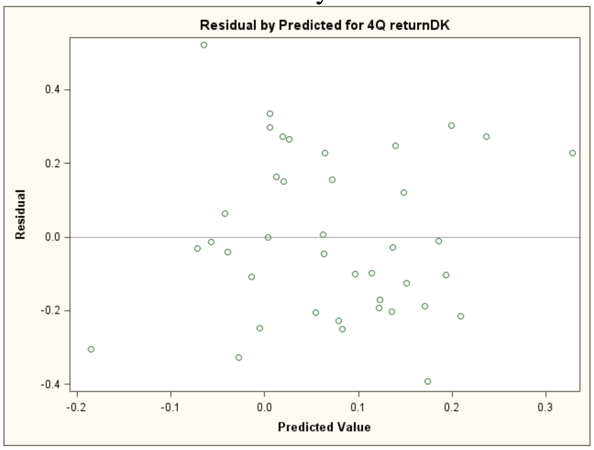


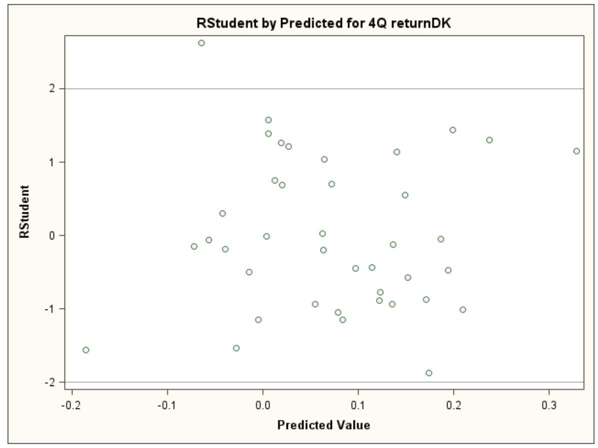


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	1.6544	0.4373	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	40
Number of Observations Used	40

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.00643	0.00321	1.18	0.3190
Error	37	0.10089	0.00273		
Corrected Total	39	0.10732			

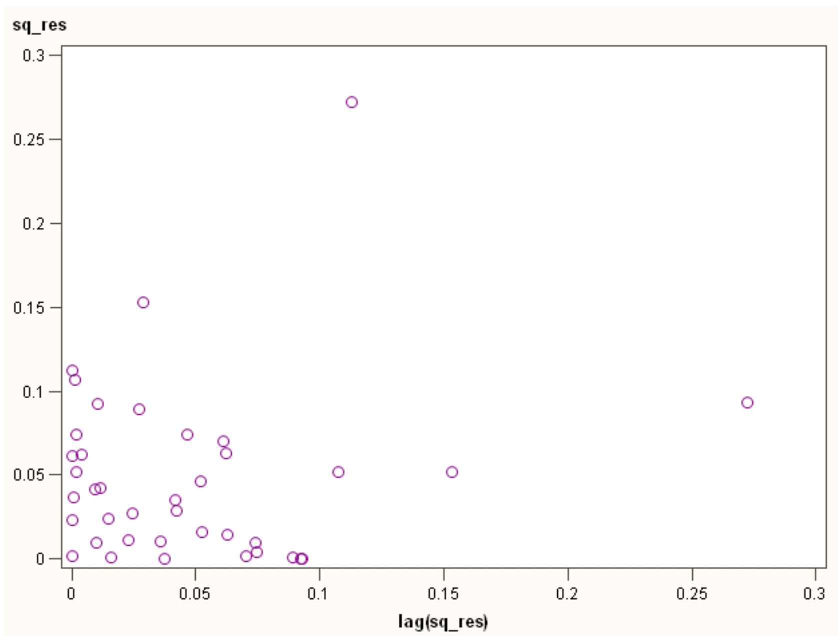
Root MSE	0.05222	**R-Square**	0.0599
Dependent Mean	0.04675	**Adj R-Sq**	0.0091
Coeff Var	111.68427		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	1.03323	0.70593	1.46	0.1517
px4QDK	1	0.55187	0.40779	1.35	0.1842
sq_px	1	0.07648	0.05866	1.30	0.2004

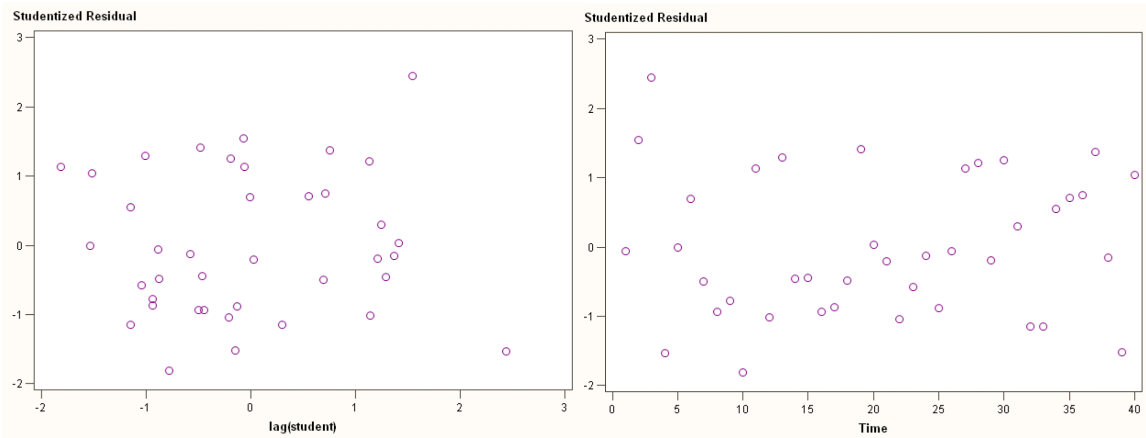
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_4Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	0.6717	0.4125	0.8267	0.3632
2	1.2666	0.5308	1.7174	0.4237
3	1.3353	0.7208	2.1242	0.5470
4	2.3861	0.6651	4.8215	0.3061
5	2.6226	0.7579	5.2315	0.3883
6	2.8442	0.8281	5.3361	0.5015
7	5.4351	0.6070	5.8027	0.5630
8	5.5775	0.6944	6.8484	0.5531
9	6.4735	0.6918	7.3600	0.5997
10	6.4808	0.7734	9.0533	0.5271
11	6.6058	0.8301	9.0729	0.6152
12	7.1342	0.8486	11.2842	0.5047



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	0.1980	0.6564
AR(2)	0.4412	0.8020
AR(3)	0.8339	0.8413
AR(4)	1.9339	0.7479

Durbin-Watson d test

Durbin-Watson D	1.868
Number of Observations	40
1st Order Autocorrelation	0.052

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-1.03681	0.2411	-4.30	0.0001
b1	-0.3203	0.0669	-4.78	<.0001

Subsample 1970-1989, px and 4 quarter return

$$r_{t,t+4} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

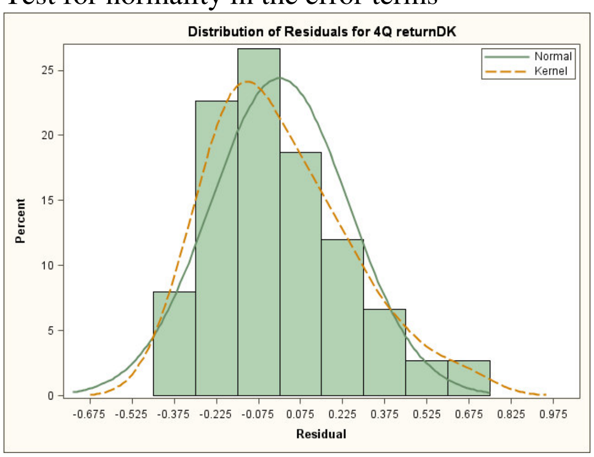
Number of Observations Read	75
Number of Observations Used	75

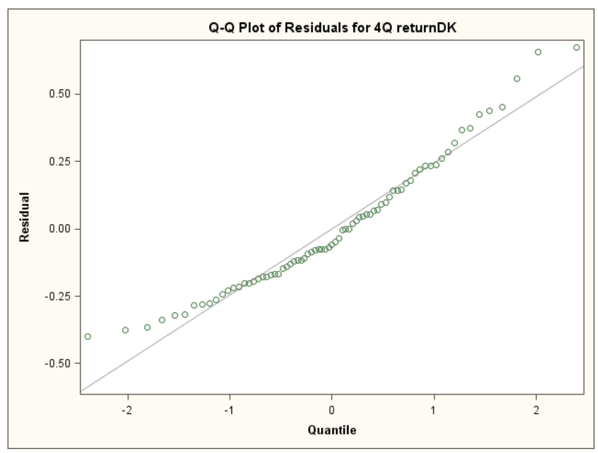
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	1.23398	1.23398	20.24	<.0001
Error	73	4.45152	0.06098		
Corrected Total	74	5.68550			

Root MSE	0.24694	**R-Square**	0.2170
Dependent Mean	0.07608	**Adj R-Sq**	0.2063
Coeff Var	324.56967		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-1.13813	0.27142	-4.19	<.0001
px4QDK	1	-0.34253	0.07614	-4.50	<.0001

Test for normality in the error terms

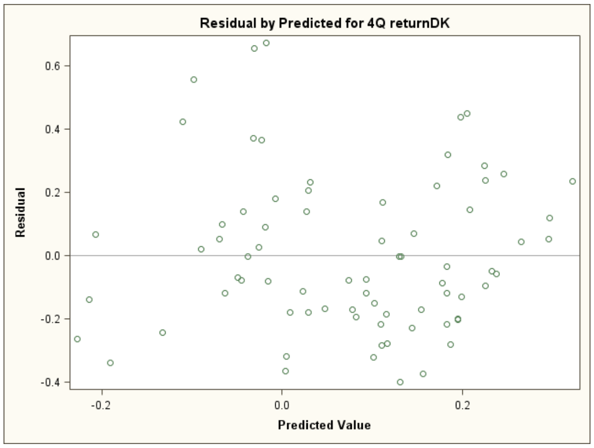


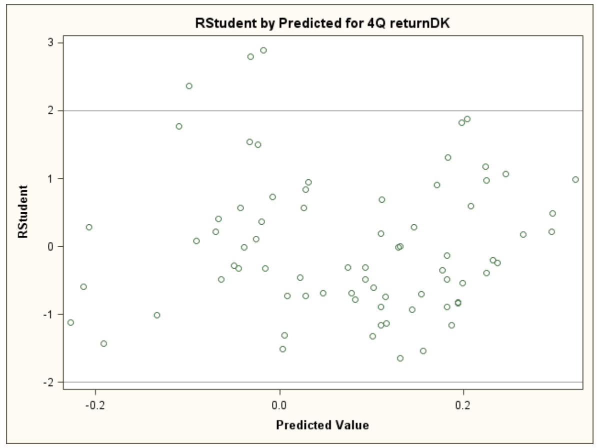


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	6.5796	0.0373	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	75
Number of Observations Used	75

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.01441	0.00721	0.97	0.3836
Error	72	0.53433	0.00742		
Corrected Total	74	0.54874			

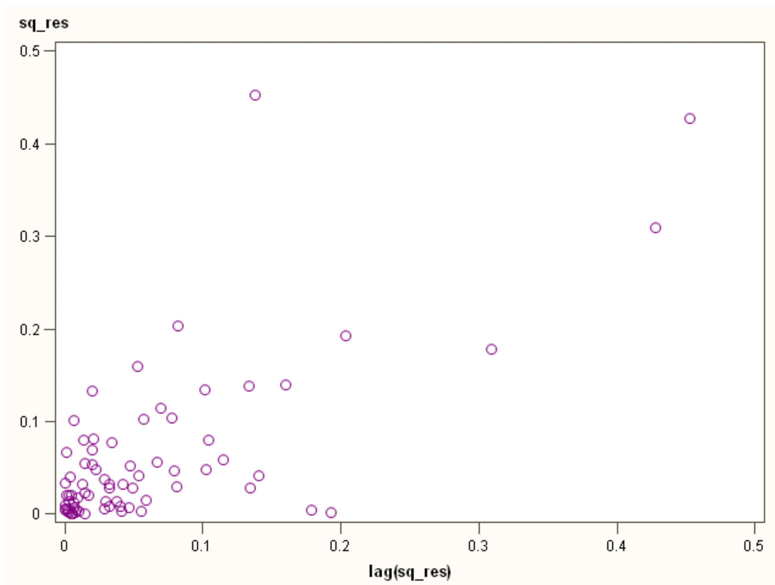
Root MSE	0.08615	**R-Square**	0.0263
Dependent Mean	0.05935	**Adj R-Sq**	-0.0008
Coeff Var	145.14152		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.13562	0.73569	-0.18	0.8543
px4QDK	1	-0.15085	0.42547	-0.35	0.7240
sq_px	1	-0.02674	0.06105	-0.44	0.6627

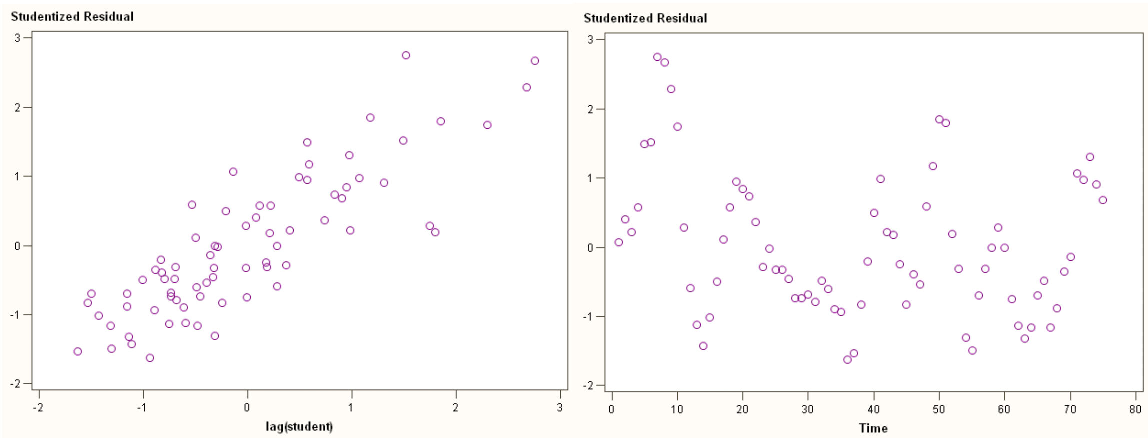
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_4Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	38.7996	<.0001	37.7896	<.0001
2	47.0842	<.0001	42.2694	<.0001
3	47.3528	<.0001	42.2703	<.0001
4	47.4467	<.0001	42.4635	<.0001
5	47.5698	<.0001	42.5347	<.0001
6	48.1870	<.0001	43.1695	<.0001
7	49.0172	<.0001	43.1712	<.0001
8	49.8743	<.0001	43.3411	<.0001
9	50.4522	<.0001	43.4234	<.0001
10	51.0589	<.0001	43.7124	<.0001
11	51.6815	<.0001	43.7155	<.0001
12	51.7401	<.0001	43.7856	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	55.3416	<.0001
AR(2)	58.9057	<.0001
AR(3)	60.8555	<.0001
AR(4)	60.9268	<.0001

Durbin-Watson d test

Durbin-Watson D	0.301
Number of Observations	75
1st Order Autocorrelation	0.846

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-1.13813	0.4606	-2.47	0.0158
b1	-0.34253	0.1246	-2.75	0.0075

Subsample 1990-2010, px and 4 quarter return

$$r_{t,t+4} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

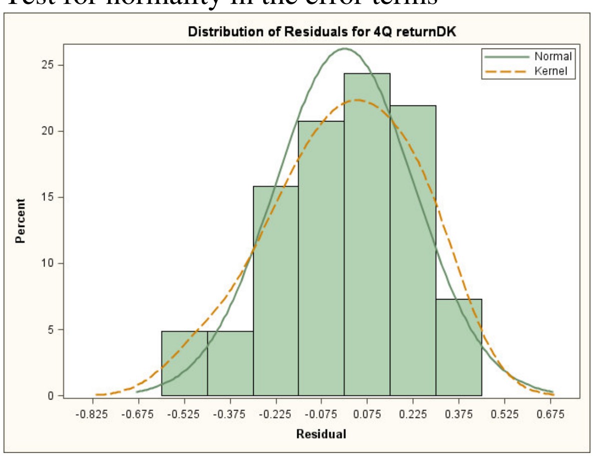
Number of Observations Read	82
Number of Observations Used	82

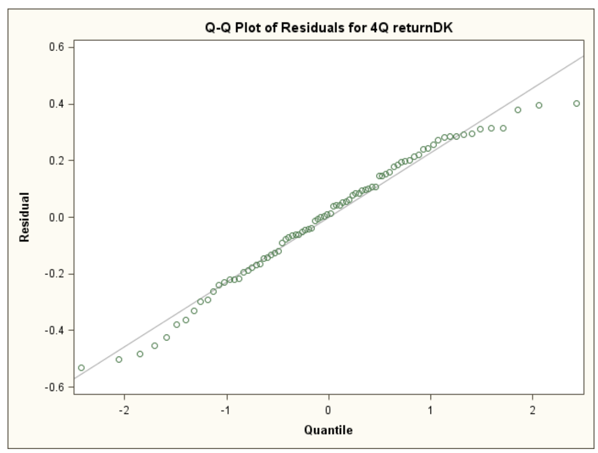
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.97213	0.97213	18.46	<.0001
Error	80	4.21324	0.05267		
Corrected Total	81	5.18537			

Root MSE	0.22949	**R-Square**	0.1875
Dependent Mean	0.06980	**Adj R-Sq**	0.1773
Coeff Var	328.77213		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-1.43838	0.35195	-4.09	0.0001
px4QDK	1	-0.43891	0.10216	-4.30	<.0001

Test for normality in the error terms

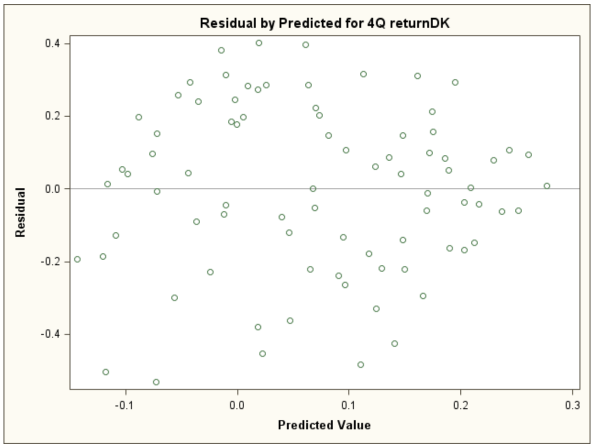


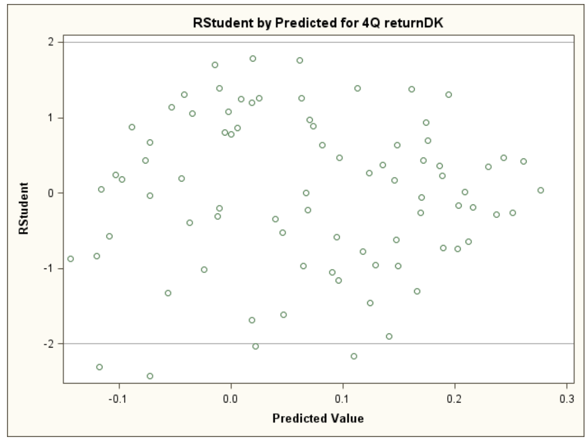


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	2.7141	0.2574	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	82
Number of Observations Used	82

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.03240	0.01620	4.56	0.0134
Error	79	0.28089	0.00356		
Corrected Total	81	0.31329			

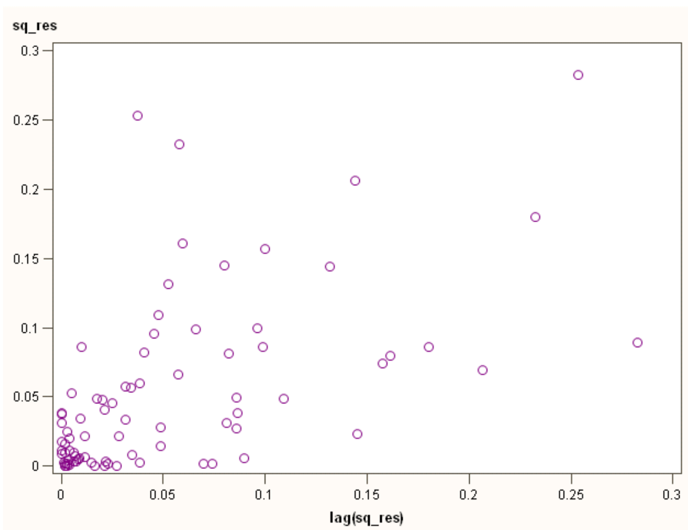
Root MSE	0.05963	**R-Square**	0.1034
Dependent Mean	0.05138	**Adj R-Sq**	0.0807
Coeff Var	116.05088		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-2.37744	1.28714	-1.85	0.0685
px4QDK	1	-1.48505	0.75386	-1.97	0.0524
sq_px	1	-0.22530	0.10994	-2.05	0.0438

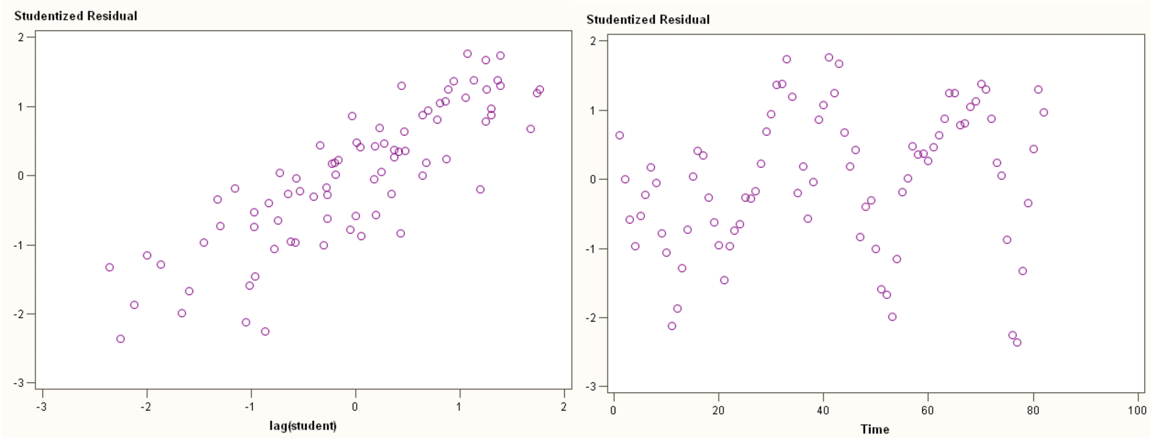
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_4Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	27.9619	<.0001	27.2026	<.0001
2	28.3353	<.0001	35.2983	<.0001
3	34.6738	<.0001	36.4918	<.0001
4	42.7522	<.0001	36.5370	<.0001
5	48.2029	<.0001	37.4065	<.0001
6	50.6903	<.0001	37.6625	<.0001
7	51.5523	<.0001	37.7201	<.0001
8	51.5905	<.0001	37.8560	<.0001
9	51.8860	<.0001	38.0858	<.0001
10	55.5187	<.0001	40.7605	<.0001
11	58.6808	<.0001	41.5652	<.0001
12	61.8626	<.0001	43.5712	<.0001



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	61.3786	<.0001
AR(2)	62.5935	<.0001
AR(3)	62.9596	<.0001
AR(4)	62.9841	<.0001

Durbin-Watson d test

Durbin-Watson D	0.306
Number of Observations	82
1st Order Autocorrelation	0.839

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-1.43838	0.5245	-2.74	0.0075
b1	-0.43891	0.1478	-2.97	0.0039

Subsample 2000-2010, px and 4 quarter return

$$r_{t,t+4} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

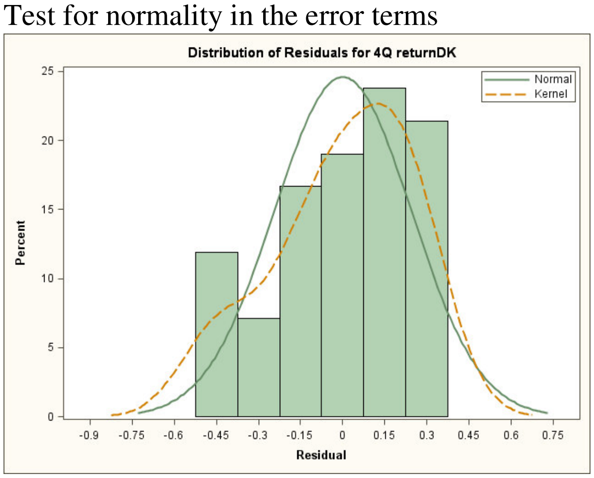
Number of Observations Read	42
Number of Observations Used	42

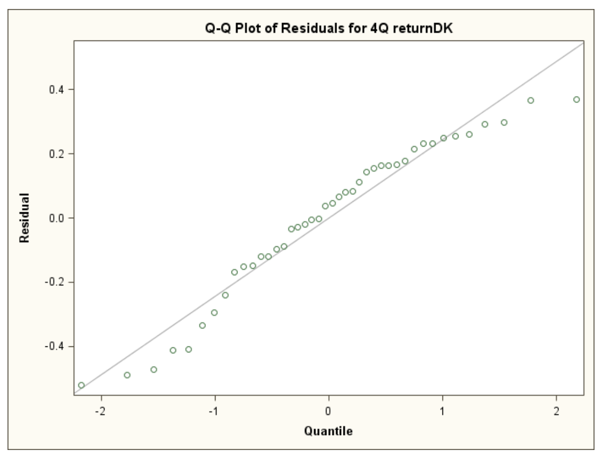
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.94445	0.94445	15.57	0.0003
Error	40	2.42568	0.06064		
Corrected Total	41	3.37013			

Root MSE	0.24626	**R-Square**	0.2802
Dependent Mean	0.05299	**Adj R-Sq**	0.2622
Coeff Var	464.76103		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-2.10532	0.54822	-3.84	0.0004
px4QDK	1	-0.64950	0.16458	-3.95	0.0003

Test for normality in the error terms

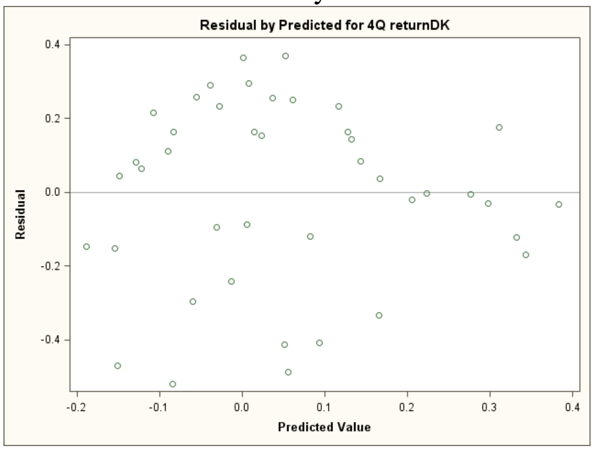


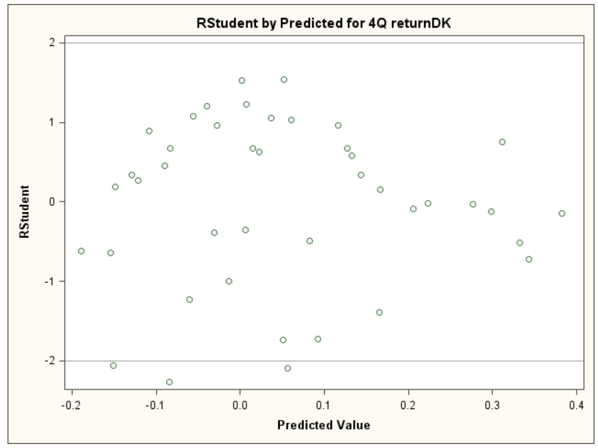


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	2.8566	0.2397	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	42
Number of Observations Used	42

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.02220	0.01110	2.47	0.0974
Error	39	0.17505	0.00449		
Corrected Total	41	0.19726			

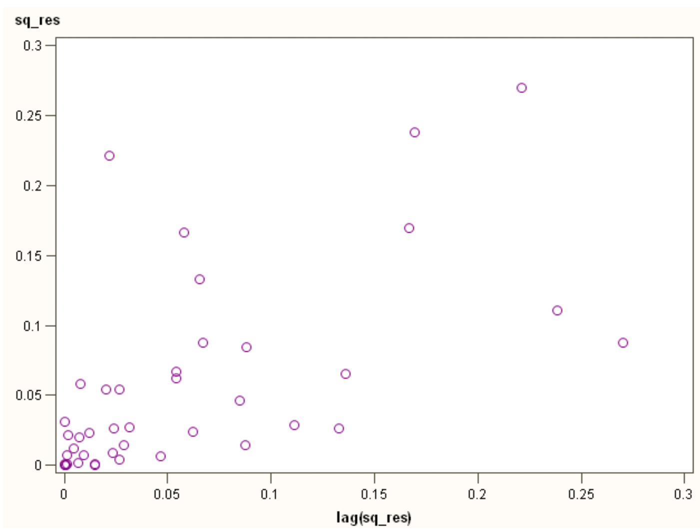
Root MSE	0.06700	**R-Square**	0.1126
Dependent Mean	0.05775	**Adj R-Sq**	0.0671
Coeff Var	116.00297		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-2.83878	2.07862	-1.37	0.1799
px4QDK	1	-1.79354	1.23362	-1.45	0.1540
sq_px	1	-0.27609	0.18236	-1.51	0.1381

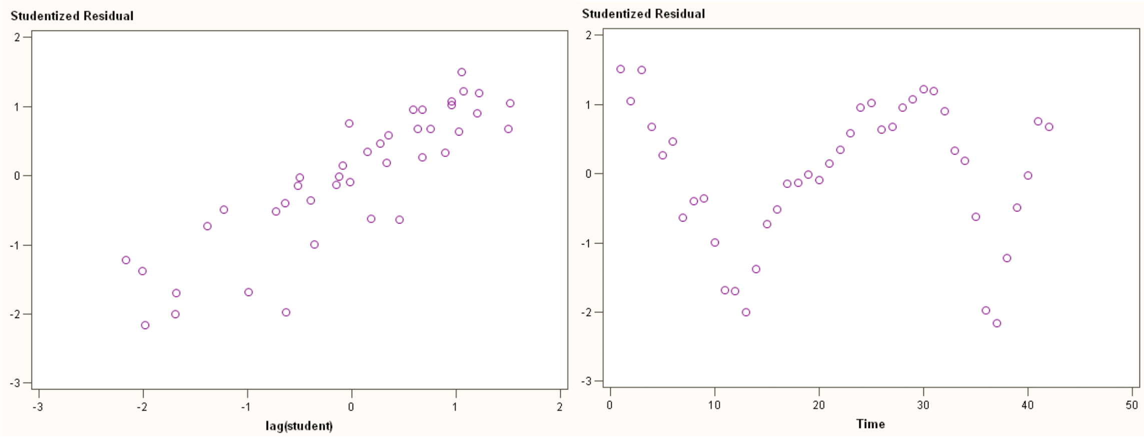
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_4Q returnDK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	**Q**	**Pr > Q**	**LM**	**Pr > LM**
1	15.7525	<.0001	13.3975	0.0003
2	16.2873	0.0003	17.0020	0.0002
3	18.9306	0.0003	18.4673	0.0004
4	23.5685	<.0001	18.4675	0.0010
5	26.2428	<.0001	18.6052	0.0023
6	27.2936	0.0001	19.1604	0.0039
7	27.9774	0.0002	19.5377	0.0067
8	28.6187	0.0004	19.5382	0.0122
9	29.1555	0.0006	19.5740	0.0207
10	29.1568	0.0012	19.7604	0.0316
11	29.3845	0.0020	20.0103	0.0452
12	30.4691	0.0024	20.0802	0.0656



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	32.8115	<.0001
AR(2)	32.8133	<.0001
AR(3)	32.8155	<.0001
AR(4)	32.9549	<.0001

Durbin-Watson d test

Durbin-Watson D	0.247
Number of Observations	42
1st Order Autocorrelation	0.843

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-2.10532	0.6545	-3.22	0.0026
b1	-0.6495	0.1887	-3.44	0.0014

United Kingdom

px and 4 quarter return, excluding outliers, subsample 1977-1999

$$r_{t,t+4} = \beta_1 + \beta_2 px_t + \varepsilon_t$$

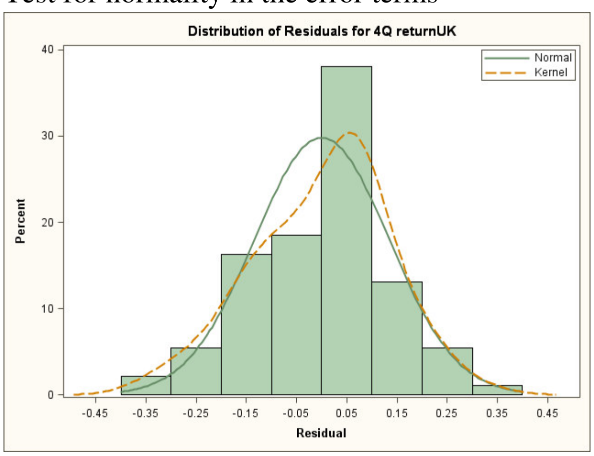
Number of Observations Read	92
Number of Observations Used	92

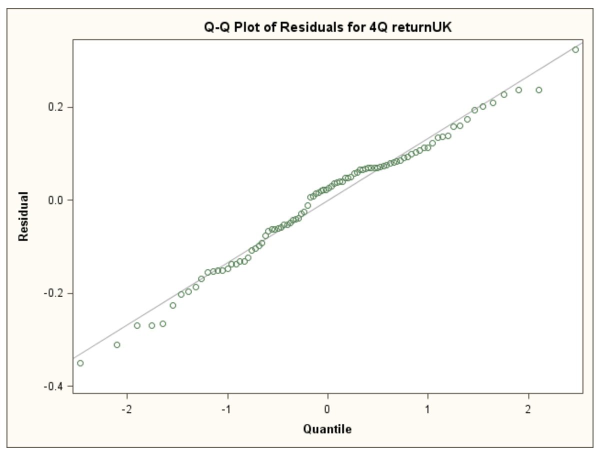
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.10705	0.10705	5.92	0.0170
Error	90	1.62851	0.01809		
Corrected Total	91	1.73557			

Root MSE	0.13452	**R-Square**	0.0617
Dependent Mean	0.11119	**Adj R-Sq**	0.0513
Coeff Var	120.97328		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.31631	0.17632	-1.79	0.0762
px4QUK	1	-0.14707	0.06047	-2.43	0.0170

Test for normality in the error terms

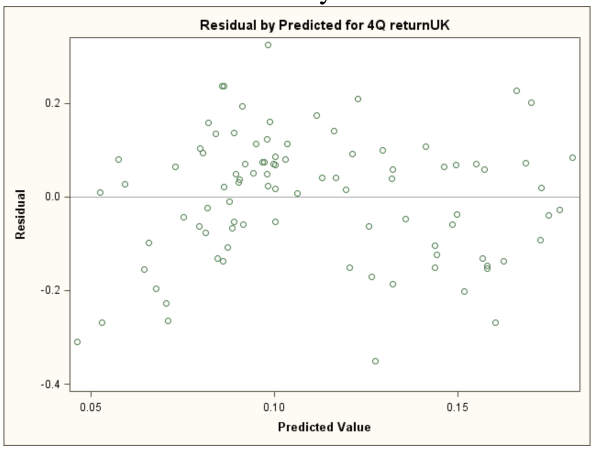


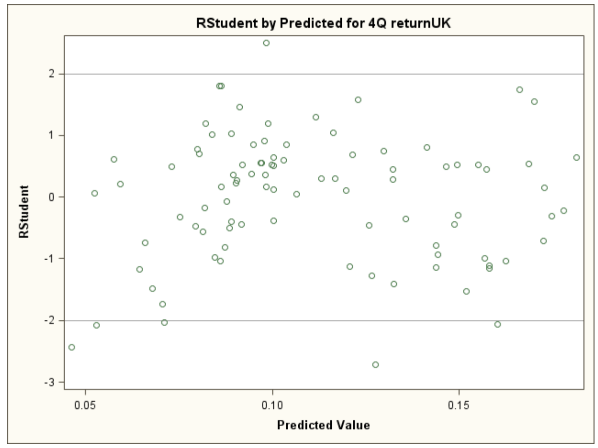


Jarque-Bera test

Miscellaneous Statistics			
Statistic	**Value**	**Prob**	**Label**
Normal Test	1.7022	0.4269	Pr > ChiSq

Test for heteroscedasticity in the error terms





White's heteroscedasticity test
Dependent variable: squared residuals

Number of Observations Read	92
Number of Observations Used	92

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.00187	0.00093421	1.61	0.2053
Error	89	0.05159	0.00057962		
Corrected Total	91	0.05345			

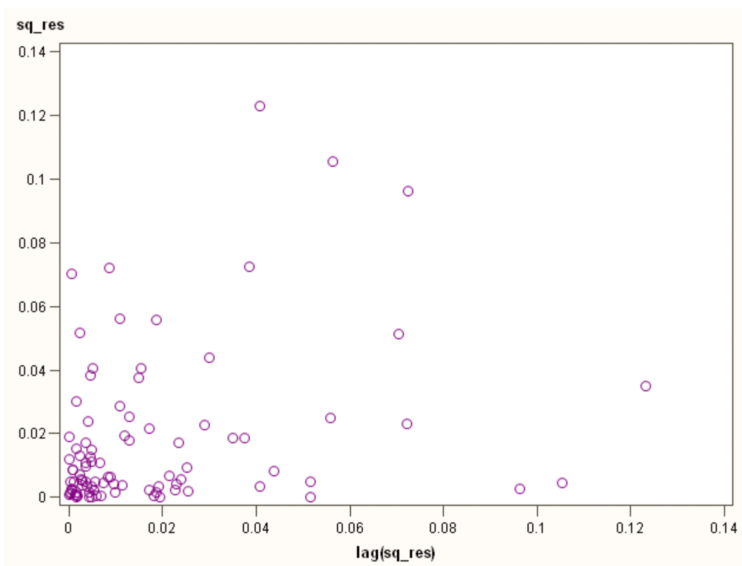
Root MSE	0.02408	**R-Square**	0.0350
Dependent Mean	0.01770	**Adj R-Sq**	0.0133
Coeff Var	136.00861		

Parameter Estimates					
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.69256	0.40791	1.70	0.0930
px4QUK	1	0.45223	0.27803	1.63	0.1074
sq_px	1	0.07523	0.04714	1.60	0.1141

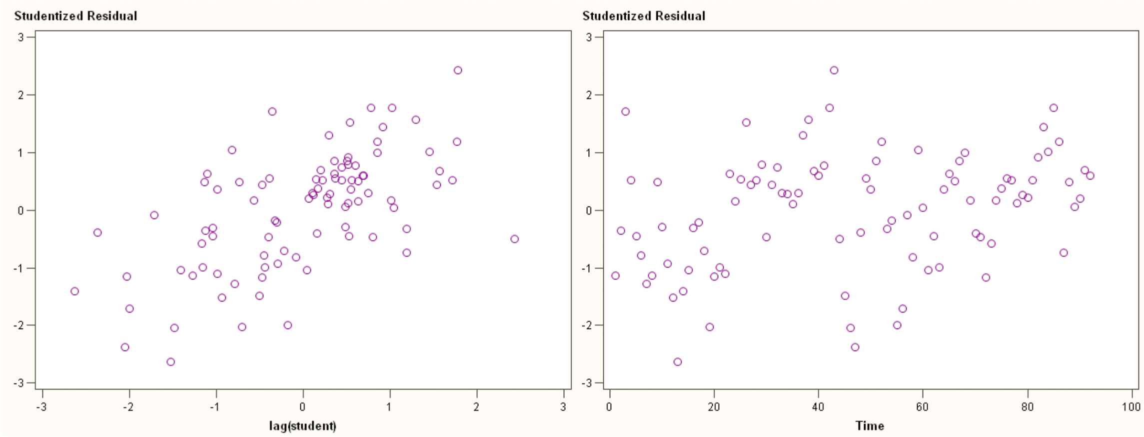
Autoregressive conditional heteroscedasticity (ARCH)

Dependent Variable	residual_4Q returnUK
	Residual

Q and LM Tests for ARCH Disturbances				
Order	Q	Pr > Q	LM	Pr > LM
1	8.2113	0.0042	7.8328	0.0051
2	8.2682	0.0160	8.9811	0.0112
3	8.3628	0.0391	8.9815	0.0295
4	9.6375	0.0470	10.4389	0.0336
5	10.1381	0.0714	10.4464	0.0635
6	10.5017	0.1051	10.7445	0.0966
7	11.1238	0.1333	11.8420	0.1059
8	11.1255	0.1947	12.0354	0.1496
9	12.4474	0.1892	12.8809	0.1681
10	12.4519	0.2560	13.6684	0.1887
11	14.7308	0.1952	14.3890	0.2122
12	14.8144	0.2517	15.7634	0.2023



Test for autocorrelation in the error terms



LM-test (The Breusch-Godfrey BG test)

Godfrey's Serial Correlation Test		
Alternative	**LM**	**Pr > LM**
AR(1)	33.9590	<.0001
AR(2)	34.4910	<.0001
AR(3)	34.5103	<.0001
AR(4)	37.4582	<.0001

Durbin-Watson d test

Durbin-Watson D	0.780
Number of Observations	92
1st Order Autocorrelation	0.601

The regression with Newey-West HAC standard errors, 4 lags

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	-0.31631	0.2849	-1.11	0.2698
b1	-0.14707	0.0979	-1.50	0.1366

Forudsigelse af afkast

Jesper Rangvid

Empirisk finansiering
Efteråret 2008

Vi vil se på, hvad vi kan sige om variation over tid i forventede afkast:

- Er det OK, at man kan forudsige afkast i et efficient marked?
- Hvorfor burde man forvente, at pris-dividende forholdet indeholder information om fremtidige afkast?
- Hvilke andre variable kunne forudsige afkast?
- Empiriske resultater

Én årsag til, at det er vigtigt at vide om afkast kan forudsiges

- Strategisk asset allocation: Løsninger til investeringsproblemer, hvor investeringshorisonten er længere end én periode.
  - I en én-periode model ligger investeringsmulighedsområdet fast.
  - I fler-periodes modeller kan inv. mulighedsområdet ændre sig over tid.
- Konsekvenser:
  - Løsningen for hvordan vi skal investere over tid er forskellig fra løsningen i et én-periodes set-up.
  - Løsningen vil bl.a. indeholde termer for, hvordan man kan håndtere, at der er forventede ændringer over tid i investeringsmulighedsområdet.
- Points: Variation i *forventede afkast* er <u>centralt</u> i strategisk asset allokering.

  *This (*inter-temporal shocks to investment opportunities og brugen af financial assets to hedge inter-temporal risks*) should be important in practice because there is a great deal of empirical evidence that investment opportunities – both interest rates and risk premia on bonds and stocks – vary through time.* (Campbell & Viceira, 2002).

”Teori”

Mormors fødselsdag for 40 år siden

Borddamen siger:

- ”Du som er så klog - og har så meget forstand på aktier – hvordan tror du, at aktiemarkedet udvikler sig over de næste par år”.
- Du siger (husk, vi er ”for 40 år siden”):
  - ”Det ved jeg intet om. Markederne er nemlig efficiente. Det betyder, at hvis nogle skulle forvente en positiv prisændring på et aktiv, investerer de i aktivet, og den forventede prisændring bliver drevet ned til nul”.
- Borddamen siger:
  - ”Det var dog et kedeligt svar. Hvad får du så alle dine penge for……”

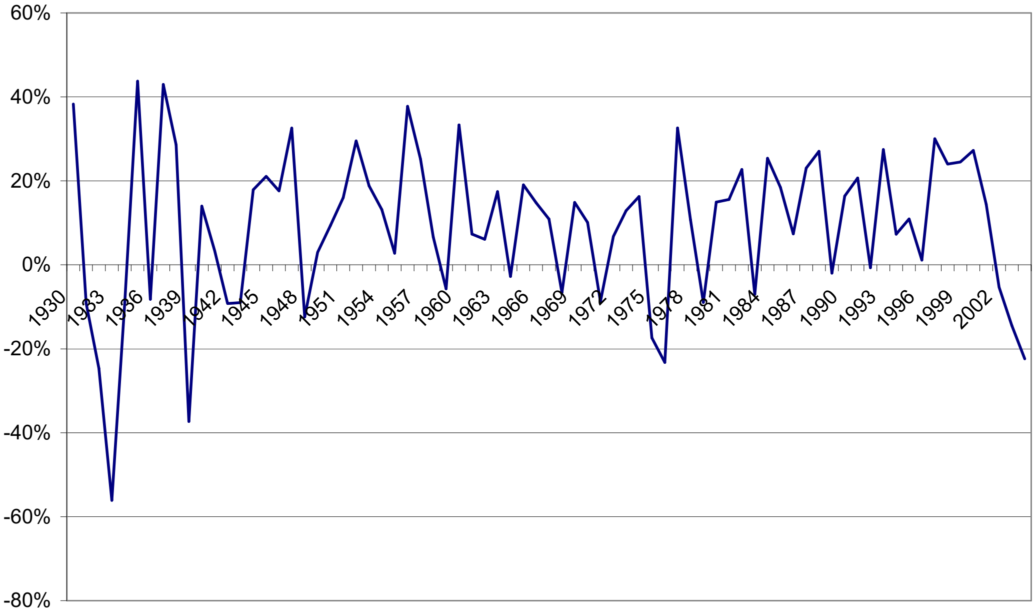
Traditionel forståelse af efficiente markeder

- Al information om et aktiv er indeholdt i dets pris.
  - Det bedste bud på prisen i morgen $E_t\ (P_{t+1})$ er prisen i dag P_t: $E_t(P_{t+1}) = P_t$
- Kun ny *uforventet* information kan få prisen til at ændre sig.
  - Ændringer i priserne er tilfældig ”støj” u_t: $P_{t+1} - P_t = u_t$
- Den forventede ændring i priserne er 0: $E_t(P_{t+1} - P_t) = 0$.

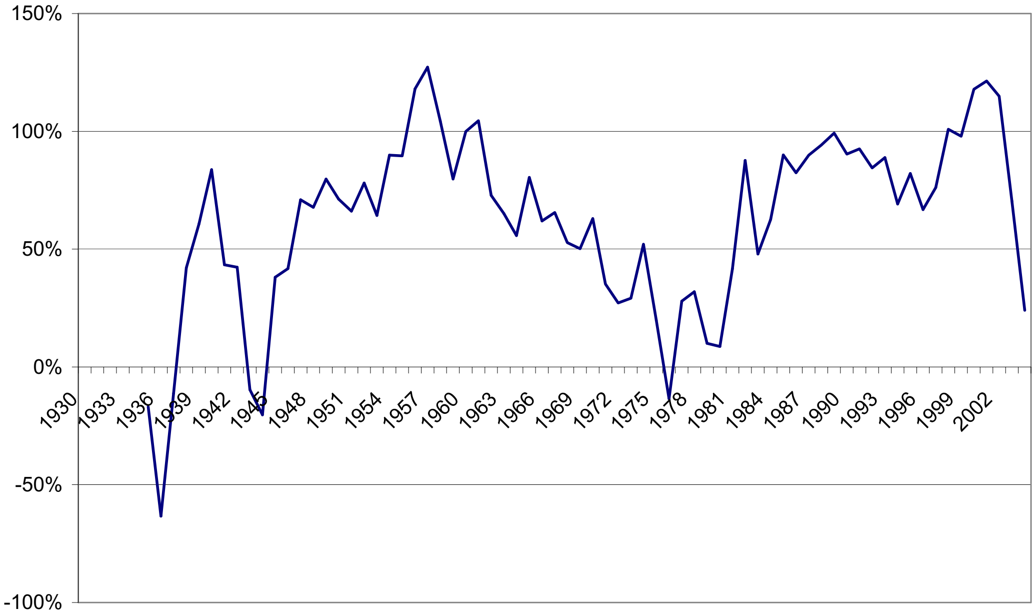
- Vi kan ikke sige noget om fremtidige prisændringer.
- Vi *må* ikke kunne sige noget om fremtidige prisændringer, hvis markederne er efficiente (sagde vi for 40 år siden).

Er det en god beskrivelse af ”virkeligheden”?

Årlige U.S. afkast: Ikke megen systematik



Afkast over 5 år: Klar systematik



Mormors fødselsdag "i dag"

Borddamen siger:

- "Du som er så klog - og har så meget forstand på aktier – hvordan tror du, at aktiemarkedet udvikler sig over de næste par år".
- Mit gæt er, at det ikke er usandsynligt, at den typiske finansieringsprofessor i dag ville sige noget á la følgende:

"Hvad er den nuværende aktiekurs i forhold til virksomhedernes indtjening/dividender?

60. Wow, det er højt. Så forventer jeg lave fremtidige afkast."

I dag

- Vi har lært, at afkastforudsigelighed ikke nødvendigvis medfører, at markederne er inefficiente.
  - Vi bruger en "bredere" fortolkning af efficiens begrebet.
- I dag defineres et efficient marked som et marked, hvor afkastene afspejler "agenternes" risikoindstilling overfor variation (over tid) i deres forbrug.
  - Hvad er så et inefficient marked? Lidt løst sagt: Hvis et givent forventet afkast ikke kan forklares (givet den tilgængelige informationsmængde) via risikoen på aktivet, vil vi sige, at markedet ikke er efficient.
- Og hvis forbruget så varierer over tid, så forventes afkastene også at gøre det.

Campbell, Lo, MacKinlay, side 31

"However, one of the central tenets of modern financial economics is the necessity of some trade-off between risk and expected return, and although the martingale hypothesis (at prisen i dag er det bedste bud på den forventede prisen i morgen) places a restriction on expected returns, it does not account for risk in any way.

In particular, if an asset's expected price change is positive, it may be the reward necessary to attract investors to hold the asset and bear the associate risks.

Therefore, despite the intuitive appeal that the fair-game interpretation might have, it has been shown that the martingale property is neither a necessary nor a sufficient condition for rationally determined asset prices."

Efficiente markeder. Intuition

- Forestil jer, at økonomien er dårlig: I er måske blevet fyret.

  $\Rightarrow$ I får mindre i løn. I har ikke så mange penge at forbruge for.
- I er ikke glade for at investere på det *risikofyldte* aktiemarked.
  - Prisen på aktier i dag skal være lav for, at I vil købe.
- For en given forventet pris i morgen, medfører dette et højt forventet afkast.

- Da vi jo kan sige noget om økonomien i dag (og har forventninger til økonomien i morgen) er det ikke umuligt, at vi kan sige noget om det forventede afkast.
- Og dette har intet med inefficiens at gøre. Det er ligevægtsbetragtninger over, hvordan investorer reagerer.

En vis grad af afkastforudsigelighed er OK

Humlen:

- De *risikojusterede* *diskonterede* afkast er stadig konstante!
- F.eks. har vi i en forbrugsbaseret asset-pricing model:

$$E_t\left(\beta\frac{u'(c_{t+1})}{u'(c_t)}(1+R_{t+1})\right)=1$$

  - Cochrane (2001, pp. 17): "Although expected *returns* can vary across time and assets, expected *discounted* returns should always be the same, 1".

Valuation ratios

Hvilke variable kan tænkes at forudsige afkast?

- Der er en *stor* akademisk litteratur, der undersøger/understøtter afkastforudsigelighed med:
  - Aktiekurser skaleret med dividender.
  - Aktiekurser skaleret med indtjening (earnings).

- Vi starter derfor ud med at se på, hvorfor pris-dividende forholdet spiller en central rolle her. Vi vil se på 3 udtryk for *pd*-forholdet:
  1. Det generelle ikke-lineære udtryk for *pd*-forholdet.
  2. Et specialtilfælde: Konstant afkast og dividendevækst.
  3. Approksimativt lineært *pd*-forhold.

Intuition: Pris-dividende forholdet som forudsiger af aktieafkast

- Definitionen af et aktieafkast:

$$1 + R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t}$$

- Vi har derved prisen på en aktie:

$$P_t = \left(1 + R_{t+1}\right)^{-1} P_{t+1} + \left(1 + R_{t+1}\right)^{-1} D_{t+1}$$

- Lead prisen én periode og plug ind:

$$P_t = \left(1 + R_{t+1}\right)^{-1}\left(1 + R_{t+2}\right)^{-1} P_{t+2} + \left(1 + R_{t+1}\right)^{-1}\left(1 + R_{t+2}\right)^{-1} D_{t+2} + \left(1 + R_{t+1}\right)^{-1} D_{t+1}$$

- Hvis også udtrykket for P_{t+3} plugges ind (med R^{-1} for $(1+R)^{-1}$):

$$P_t = \left(R_{t+1}^{-1}\right)\left(R_{t+2}^{-1}\right)\left(R_{t+3}^{-1}\right)P_{t+3} + \left(R_{t+1}^{-1}\right)\left(R_{t+2}^{-1}\right)\left(R_{t+3}^{-1}\right)D_{t+3} + \left(R_{t+1}^{-1}\right)\left(R_{t+2}^{-1}\right)D_{t+2} + \left(R_{t+1}^{-1}\right)D_{t+1}$$

- For en given horisont K har vi altså (efter vi har taget forventninger):

$$P_t = E_t\left[\prod_{j=1}^{K}(1 + R_{t+j})^{-1}\right]P_{t+K} + E_t\sum_{i=1}^{K}\left(\prod_{j=1}^{i}(1 + R_{t+j})^{-1}\right)D_{t+i}$$

Pris-dividende forholdet (II)

- Det første led er den tilbagediskonterede værdi af aktien efter K perioder:

$$P_t = E_t\left[\prod_{j=1}^{K}(1+R_{t+j})^{-1}\right]P_{t+K}$$

- Hvis aktien forventes *ikke* at vokse *for evigt* med en værdi, der er lig eller højere end de fremtidige afkast, dvs. at der ikke er bobler i aktiekurserne, så vil dette led være nul:

$$\lim_{K\to\infty} E_t\left[\prod_{j=1}^{K}(1+R_{t+j})^{-1}\right]P_{t+K} = 0$$

Pris-dividende forholdet (III)

- En rationel bestemt aktiekurs er derfor lig:

$$P_t = E_t\sum_{i=1}^{\infty}\left(\prod_{j=1}^{i}(1+R_{t+j})^{-1}\right)D_{t+i}$$

- Vi kan dividere denne igennem med dividenderne i dag, D_t, for at finde pris-dividende forholdet:

$$P_t / D_t = E_t\sum_{i=1}^{\infty}\left(\prod_{j=1}^{i}(1+R_{t+j})^{-1}\right)D_{t+i} / D_t$$

- Illustration: To perioder (med R^{-1} for $(1+R)^{-1}$):

$$P_t / D_t = \left(R_{t+1}^{-1}\right)\left(R_{t+2}^{-1}\right)\left(D_{t+2} / D_t\right) + \left(R_{t+1}^{-1}\right)\left(D_{t+1} / D_t\right)$$

$$P_t / D_t = \left(R_{t+1}^{-1}\right)\left(R_{t+2}^{-1}\right)\left(D_{t+2} / D_{t+1}\right)\left(D_{t+1} / D_t\right) + \left(R_{t+1}^{-1}\right)\left(D_{t+1} / D_t\right)$$

⇨ Pris-dividende forholdet i dag afhænger af forventninger til fremtidige dividendvækstrater og fremtidige afkast.

Et berømt/illustrativt specialtilfælde: Gordons vækstmodel. Konstante afkast og dividendevækstrater

- Antag at det forventede afkast er konstant:

$$E_t\,(1+R_{t+1}) = 1 + R.$$

- Antag også, at den forventede vækstrate i dividenderne er konstant (G):

$$E_t\,(D_{t+i}) = (1 + G)^i\, D_t.$$

- I dette tilfælde bliver prisen:

$$P_t = \left(\frac{1}{1+R}\right)D_{t+1} + \left(\frac{1}{1+R}\right)^2 D_{t+2} + \dots$$

$$P_t = \left(\frac{1}{1+R}\right)(1+G)D_t + \left(\frac{1}{1+R}\right)^2 (1+G)^2 D_t + \dots$$

$$P_t = \left[\left(\frac{1+G}{1+R}\right) + \left(\frac{1+G}{1+R}\right)^2 + \left(\frac{1+G}{1+R}\right)^3 + \dots\dots\right]D_t$$

Gordons vækstmodel

- En uendelig kvotientrække er:

$$q^0 + q^1 + q^2 + q^3 + \dots = \sum_{n=0}^{\infty} q^n = \frac{1}{1-q}$$

- Vi har derfor i vores tilfælde:

$$P_t = \left[1 + \left(\frac{1+G}{1+R}\right) + \left(\frac{1+G}{1+R}\right)^2 + \left(\frac{1+G}{1+R}\right)^3 + \dots\dots\right]D_t - D_t = \frac{1+R}{R-G}D_t - D_t$$

- Gordons vækstformel:

$$P_t = D_t\,(1 + G) / (R - G).$$

- Pris-dividende forholdet bliver:

$$P_t / D_t = (1 + G) / (R - G).$$

- Hvis P/D-forholdet svinger omkring 25, skal R – G (det ”vækstkorrigerede afkast”) være omkring 0.04. F.eks. R = 0.06 og G = 0.02.

Det generelle tilfælde: Tidsvarierende afkast og dividendevækst. Et approksimativt lineært *pd*-forhold

- Start med igen - fra definitionen af afkast - at finde

$$P_t / D_t = (1/(1+R_{t+1}))(1 + P_{t+1}/D_{t+1})(D_{t+1}/D_t)$$

- Tag logs

$$p_t - d_t = -r_{t+1} + \ln(1 + P_{t+1}/D_{t+1}) + \Delta d_{t+1}$$

- Husk: $$\frac{P_{t+1}}{D_{t+1}} = e^{\ln(P_{t+1}/D_{t+1})} = e^{p_{t+1}-d_{t+1}}$$
- Lav en Taylor-approksimation af denne ($\ln[1+e(p_{t+1} - d_{t+1})]$) omkring middelværdien af log(pris-dividende) forholdet.
- Substituer ind. Løs fremad. Find:

$$p_t - d_t = E_t \sum_{j=0}^{\infty} \rho^j \left(\Delta d_{t+1+j} - r_{t+1+j}\right)$$

Implikationer fra det lineære approksimative *pd*-forhold

1. Hvis $\Delta d_t = 0$ og $\Delta p_t > 0$, så <u>må</u> dette skyldes, at agenterne forventer, at fremtidige afkast går ned eller dividender går op.
   - Det kan ikke være anderledes!
   - Implikation af definitionen af afkast.

2. Hvis Δd_t og Δp_t svinger omkring forventede konstante værdier (måske svinger Δp_t omkring 6% om året og Δd_t omkring 2% om året), så vil venstresiden (p_t - d_t) også svinge omkring en nogenlunde konstant værdi.
   - p_t og d_t vil følge hinanden på ”lang sigt”.
   - Vi siger, at p_t og d_t er ”kointegreret”.

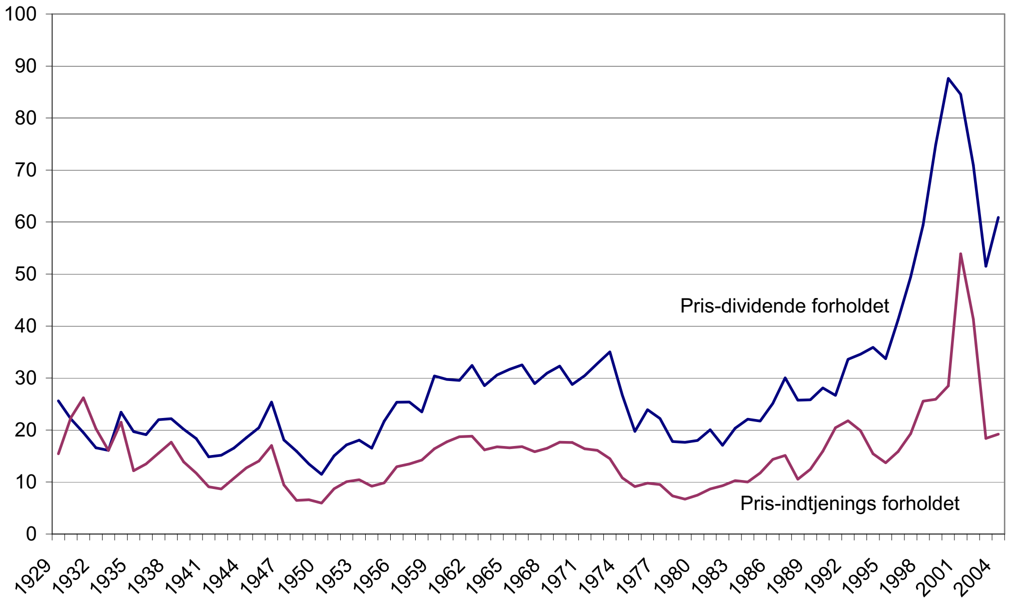
Empiriske implikationer

- Aktiepriser og dividender skal følge hinanden.
- Hvis aktiekursen er høj ift. dividender skal der være en tendens til, at aktiekurserne falder (evt. dividenderne stiger).
- Er det sådan ude i "det rigtige liv"?

- Indtil midt-1990'erne: stort set "ja".
- Efter midt-1990'erne: ikke klart.
  - I andre ord: Op gennem 1990'erne blev aktiekurserne ved med at stige og stige, også meget mere end dividender og indtjening:

    Markederne blev ligefrem kaldt "irrational exeburant"

P/D og P/E forholdet i USA



En mand tænkte: Kan vi ”redde” aktiekursforudsigelighed ved at skalere aktiepriser med andet end dividender?

- Hypotese: aktiekurser er på lang sigt bestemt af BNP.
- I så fald vil forholdet mellem aktiekurser og BNP fortælle os noget om, hvad vi tror om afkastene i den nærmeste fremtid.
- Hvis kurserne i dag er højere end BNP, forventer vi at kurserne kommer ned (afkast bliver lave).
- Hvis BNP er vokset meget, men kurserne ikke, så forventer vi, at kurserne stiger (afkast bliver høje).

Formelt

- Antag at væksten i dividender følger væksten i det der bliver produceret i økonomien (BNP; y):

$$d_t = y_t + v_t$$

- Der er teoretiske modeller, hvor det ligefrem er sådan, at dividender er lig det, der produceres i økonomien (Lucas, 1978):
dividender = output (= forbrug)

Et *py*-forhold

- Modellen bliver herved:

$$p_t - y_t = E_t \sum_{j=0}^{\infty} \rho^j \left(\Delta y_{t+1+j} - r_{t+1+j} \right)$$

- Samme implikationer som før:
  1. Hvis $\Delta y_t = 0$ og $\Delta p_t > 0$, så <u>må</u> dette skyldes, at agenterne forventer, at fremtidige afkast går ned eller BNP går op.
  2. Hvis Δy_t og Δp_t svinger omkring forventede konstante værdier, så vil venstresiden (p_t - y_t) også svinge omkring en nogenlunde konstant værdi.
     - p_t og y_t vil følge hinanden på ”lang sigt”.

Intuitivt: hvorfor kunne der måske være ekstra information i at skalere med BNP i stedet for d eller e?

- “Problemer” med dividender:
  - Miller & Modigliani (1961).
  - Aktietilbagekøb.
  - The disappearance of dividends: Fama & French (2001).
  - Empiriske undersøgelser viser, at *pd*-forholdet ikke virker så godt mere (Goyal & Welsh, 2003 + Ang & Bekaert, 2003 + …).

- “Problemer” med earnings:
  - Investeringer i intangibles; Hall (2001).
  - Ledelsesoptioner i regnskabet; Murphy & Hall (2003).
  - Goodwill og nedskrivninger.

Empiri

US årlige data: 1929 - 2004

- Y: BNP (fra FED's St- Louis data base)
- P: S & P aktiekursindex (fra Shiller's home page)
  - Værdien af S&P i januar.

$\Rightarrow$ $py = ln(P_t) - ln(Y_{t-1}) = p_t - y_{t-1}$:

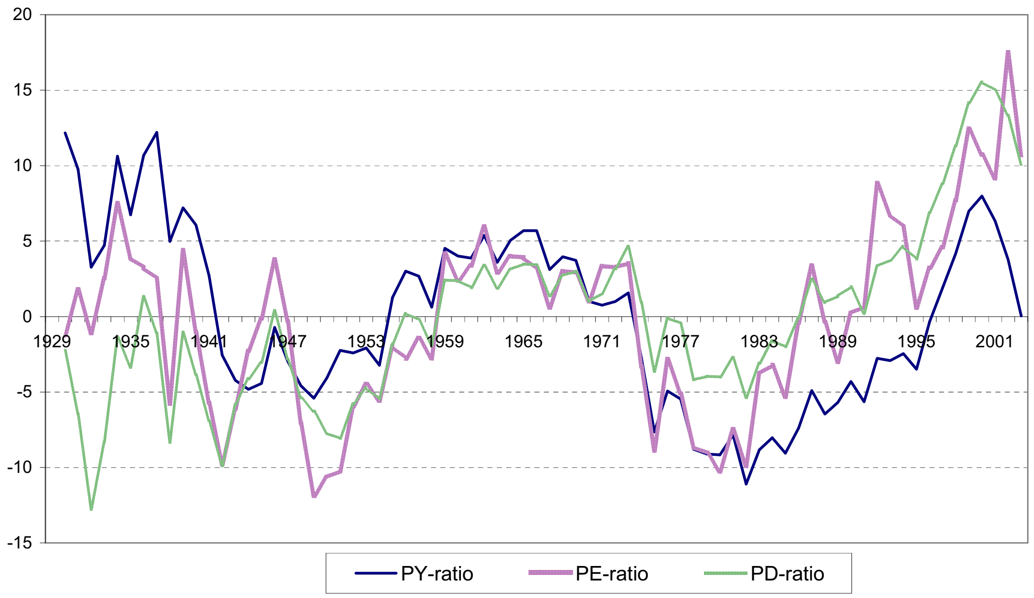
- Fra Shiller's home page, kan man også downloaded earnings (E; $e=ln(E)$) og dividender (D; $d=ln(D)$)
  - $\Rightarrow$ $pe = p_t - e_{t-1}$,
  - $\Rightarrow$ $pd = p_t - d_{t-1}$

Summary statistics

Summary statistics
U.S. data: 1929–2003

	py	*pe*	*pd*	*r*	*er*
Panel A: Means and standard deviations					
Mean	−2.46	2.67	3.27	11.48	6.78
Std.	0.43	0.41	0.44	19.57	19.80
Panel B: Correlations					
py	1.00				
pe	0.59	1.00			
pd	0.30	0.80	1.00		
r	−0.02	0.12	0.20	1.00	
er	0.11	0.16	0.26	0.97	1.00

Visualisering af forholdene (pd, pe, py)



Hvor stor en del af afkastvariationen kan vi fange?

- Dette kan undersøges ved at regressere afkast på laggede værdier af *pd*-, *pe*- og *py*-forholdet (som i øvelsen tidligere i dag), dvs. regressioner á la:

$$R_{t,t+K} = \kappa + \alpha z_t + \varepsilon_t$$

hvor z_t er en af variablene, der forventes at forudsige afkast (*pd*-, *pe*- eller *py*-forholdet).

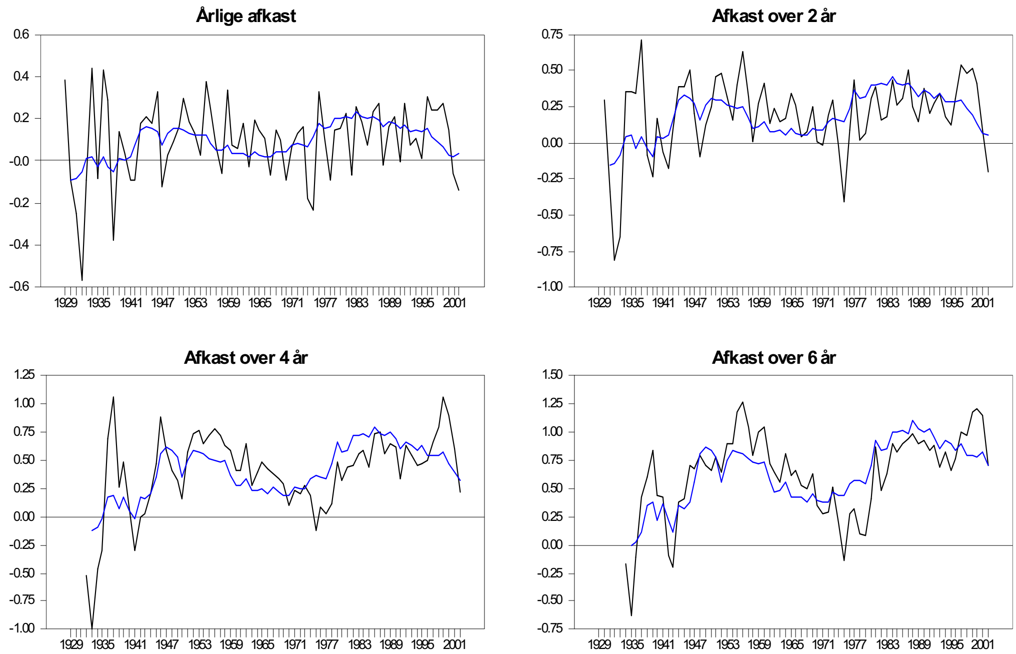
- $R_{t,t+K}$ er afkastet fra periode t til $t+K$ (dvs. kan være afkast over flere år).

Resultater. USA 1929-2004.

Horizon K:		1	2	3	4	5	6
Panel A: Stock return univariate regressions							
py	coef.	−0.17**	−0.32**	−0.37**	−0.44**	−0.51**	−0.56**
	t-stat.	(3.23)	(3.26)	(3.87)	(5.64)	(6.81)	(7.42)
	$\overline{R}^2$	**0.15**	**0.25**	**0.35**	**0.35**	**0.42**	**0.49**
pe		−0.11*	−0.17*	−0.17	−0.21	−0.27	−0.30
		(2.38)	(1.99)	(1.16)	(1.21)	(1.45)	(1.27)
		0.04	**0.04**	**0.02**	**0.03**	**0.06**	**0.07**
pd		−0.05	−0.11	−0.09	−0.12	−0.19	−0.17
		(0.77)	(0.95)	(0.54)	(0.64)	(0.94)	(0.67)
		0.00	**0.01**	**−0.00**	**0.00**	**0.02**	**0.01**
Panel B: Excess return univariate regressions							
py		−0.14*	−0.25*	−0.27*	−0.29*	−0.32*	−0.33*
		(2.26)	(2.18)	(2.14)	(2.38)	(2.43)	(2.21)
		0.08	**0.13**	**0.12**	**0.12**	**0.12**	**0.12**
pe		−0.09*	−0.15	−0.14	−0.16	−0.21	−0.23
		(1.89)	(1.44)	(0.79)	(0.79)	(0.91)	(0.82)
		0.02	**0.02**	**0.01**	**0.01**	**0.02**	**0.02**
pd		−0.06	−0.15	−0.16	−0.22	−0.34	−0.38
		(0.98)	(1.23)	(0.89)	(1.05)	(1.44)	(1.25)
		0.01	**0.03**	**0.02**	**0.03**	**0.08**	**0.08**

Graf over realiseret og forventet afkast

Sort linie: realiseret afkast. Blå linie: forudsagt afkast



Det ser ud som om, at man kan forudsige afkast over mange år bedre

- *T*-statistikker, R^2 stiger med horisonten.
- Ups: Dette skyldes faktisk alene det faktum, at årlige afkast forudsiges af en persistent (langsomt bevægende) variabel.
- Som Cochrane skriver s. 391:
  - ”You can predict that the temperature in Chicago will rise about 1/3 degree per day in the springtime. This forecast explains very little of the day-to-day variation in temperature, but tracks almost all of the rise in temperature from January to July. Thus, R^2 rises with horizon”.

Long-horizon forecasts (fortsat)

- Illustration:

$$R_{t,t+1} = \kappa + \alpha z_t + \varepsilon_{t+1}$$
$$z_{t+1} = \rho z_t + \upsilon_{t+1}$$

- For 2 års afkast:

$$\begin{aligned} R_{t,t+1} + R_{t+1,t+2} &= (\kappa + \alpha z_t + \varepsilon_{t+1}) + (\kappa + \alpha z_{t+1} + \varepsilon_{t+2}) \\ &= 2\kappa + \alpha(z_t + z_{t+1}) + \varepsilon_{t+1} + \varepsilon_{t+2} \\ &= 2\kappa + \alpha(1 + \rho)z_t + \varepsilon_{t+1} + \varepsilon_{t+2} + \alpha\upsilon_{t+1} \end{aligned}$$

- I vores tilfælde:
  - α = -0.17. ρ = 0.87.
  - Dvs. koefficienten i 2-års regressionen skulle være -0.3179 ≈ -0.32 – hvad den også er….
- Konklusion: Long-horizon tests viser tydeligt den *økonomiske* implikation (hvor meget batter det virkelig) af forudsigelighed. Men giver os ikke så meget *statistisk* ny information.

Sammenligning med den ”hotteste” predictor-variabel; *cay*-ratio

- Den ”smarteste/hotteste variable” derude for øjeblikket er (nej, ikke *py*-ratio….), men *cay*-forholdet.
- Denne er et forhold ml. forbrug, formue og indkomst.
- Idé: Hvis forbruget i dag er højt ift. indkomst og formue, må det skyldes, at det forventes, at afkastene fra aktiemarkedet er høje i fremtiden, eller at forbruget bliver lavt i fremtiden.
  - På denne måde indeholder *cay* information omkring det forventede fremtidige afkast fra aktiemarkedet.

cay

- Start med budgetbetingelsen for en forbruger:
  $$W_{t+1} = (1+R_{t,t+1})(W_t - C_t).$$
- Divider med W_t:
  $$W_{t+1} / W_t = (1+R_{t,t+1})(1 - C_t / W_t).$$
- Tag logs:
  $$\Delta w_t = r_{t,t+1} + \ln(1 - C_t / W_t)$$
  $$\Delta w_t = r_{t,t+1} + \ln(1 - e^{c_t - w_t})$$
- Denne er meget lig udtrykket vi havde fra *pd*-forholdet. Så vi kan bruge samme maskineri vi brugte der. Dvs. tage en første-ordens approksimation omkring middelværdien af C/W-forholdet og så løse fremad. Vi finder:
  $$c_t - w_t = E_t \sum_{j=0}^{\infty} \rho^j \left(r_{t+1+j} - \Delta c_{t+1+j} \right)$$

cay (II)

- I *cay* antages det, at formuen *w* både kommer fra den finansielle formue (*a*) og lønindkomst (*y*). Derved bliver den endelige ligning:

  $$c_t - \omega a_t - (1-\omega) y_t = E_t \sum_{j=0}^{\infty} \rho^j \left(\left[\omega r_{a,t+1+j} + (1-\omega) r_{h,t+1+j} \right] - \Delta c_{t+1+j} \right)$$

  hvor $r_{a,t,t+1}$ er afkastet fra de finansielle aktiver og $r_{h,t,t+1}$ er afkastet fra human kapitalen.
- Implikationer:
  - *c*, *a*, og *y* "følger hinanden på lang sigt".
  - Høj værdi af *cay* må skyldes forventninger om (*i*) højt afkast eller (*ii*) lavt fremtidigt forbrug.

Empiri

Regressions of long-horizon cumulative returns and excess returns on *py*, *pe*, *pd*, and $\widehat{cay}$, 1948–2003

Horizon K:		1	2	4	6
Stock returns					
py	coef.	−0.12**	−0.24**	−0.37**	−0.57**
	t-stat.	(3.03)	(3.52)	(4.38)	(4.28)
	$\bar{R}^2$	**0.08**	**0.17**	**0.26**	**0.39**
pe		−0.13**	−0.24**	−0.34**	−0.42*
		(2.88)	(3.30)	(2.90)	(1.97)
		0.13	**0.19**	**0.22**	**0.21**
pd		−0.13*	−0.24*	−0.36*	−0.54*
		(2.12)	(2.35)	(2.54)	(2.26)
		0.12	**0.18**	**0.20**	**0.26**
$\widehat{cay}$		5.43**	10.15**	12.92**	17.55**
		(4.72)	(7.06)	(4.73)	(5.72)
		0.26	**0.46**	**0.41**	**0.46**
Excess returns					
py		−0.09*	−0.17*	−0.26*	−0.43*
		(1.81)	(1.89)	(1.66)	(1.68)
		0.02	**0.06**	**0.07**	**0.09**
pe		−0.11*	−0.21*	−0.29	−0.39
		(2.26)	(2.15)	(1.53)	(1.30)
		0.07	**0.11**	**0.10**	**0.10**
pd		−0.13*	−0.25*	−0.39*	−0.69*
		(2.06)	(2.19)	(2.06)	(2.23)
		0.09	**0.15**	**0.17**	**0.25**
$\widehat{cay}$		6.32**	11.93**	15.84**	22.20**
		(4.79)	(7.39)	(6.56)	(6.64)
		0.29	**0.50**	**0.43**	**0.48**

Konklusion

- Afkast er – til en vis grad(!!!) – forudsigelige.
- Dette har ikke noget med inefficiente markeder at gøre.
  - Markeder kan fint være forudsigelige og efficiente.
- Der er megen debat om, hvilke variable, der "bedst" forudsiger aktiemarkedet.
- Også andre markeder (obligation/valuta) er (til en vis grad) forudsigelige.

<u>Overordnet:</u>

- Investeringsmulighedsområdet ændrer sig over tid på en forudsigelig måde.
- Der er dog samtidig rimelig stor usikkerhed forbundet med forudsigelser af ændringer i investeringsmulighedsområdet.