The Oil Price-Macroeconomy Relationship: Relevance and Stability

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Abstract

We will test the effect that different oil price transformations have on output in a linear regression and vector autoregressive model. Several tests are employed to analyse the significance between the transformations and output and the stability of the models. We find evidence that transformations which are based on a volatility-scaling have the strongest link with the output and are the most stable. Furthermore, our results provide evidence for an asymmetric oil-output relation and show a strong breakdown in this relation after 1973.

Contents

1 Acknowledgements

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2 Introduction

This paper contributes to the large body of literature that has been constructed on the topic of oil prices and its macroeconomic influences. Starting with one of the pioneers, Hamilton(1983) has analysed the effect that many U.S. recessions seem to have been preceded by an oil price increase. Both a strong link between oil prices and output as well as a breakdown in this link around the first OPEC crisis of 1973 are well documented. Numerous explanations have been given that contribute to this weakened relation between oil and output.

We will focus on one of the approaches that is taken in order to explain the breakdown of the relation between oil prices and the output growth of the U.S. In this approach researchers focus on finding oil price transformations that do not lose their connection with the output growth as much. Examples of such transformations are series that use a volatility measure or series that compare the current oil price value with its maximum over the previous four quarters.

We will contribute in several ways. First, we will construct new oil price transformations. Second, the relations between these transformations and the output growth are analysed and compared with one another. Third, we will test the different relations for the existence of an unknown structural break by means of a Quandt-Andrews test. This contrasts with the common method of testing for a known structural break with a Chow test. Fourth, the effects of oil price shocks on output in a multivariate framework are analysed based on generalized impulse response functions instead of the regular impulse response functions. In this manner the results are invariable to the specific variable ordering. Finally, we test the relation between oil and output both in a direct way by ignoring other macroeconomic variables and in a multivariate framework which does include other macroeconomic measures.

This work is relevant due to numerous reasons. In the first place is the relation between oil prices and output growth important for many parties: companies, investors, and governments for example. Second, by analysing what happens with the characteristics between oil prices and the output growth when a different transformation is used, we can learn more about what aspects of the oil price are relevant for output and which are not. This could be valuable information for policymakers. Finally, the results might indicate possible interesting future research approaches that could be taken.

In Mork(1989) for example evidence is found for a breakdown between oil price movements and output growth. However, this breakdown is no longer present when oil price increases are used as the oil price input instead of the regular oil price movements. This is known in the literature as an asymmetric effect: oil price increases appear to have more relevance for macroeconomic variables, in particular output, than decreases.

The goal of this paper is to analyse what the effects are on the link between oil prices and the GNP growth when we use different oil price transformations. In particular we will pay attention to the statistical relevance of these relations and second of all to the stability of the relations.

We will both use existing oil price transformations as well as new oil price transformations in our research. The existing transformations are the oil price increases and decreases. The net oil price increase by Hamilton(1996) and a measure as constructed by Lee, Ni and Ratti(1995) which divides the oil price growth by the conditional volatility of the oil price. In that manner oil price shocks during a calm period get a larger weight than shocks that occur in a highly volatile period.

The two new measures are a series that, unlike the net oil price increase, does not compare the current value with a previous maximum but with the value of a moving average. Finally we will combine the net oil price increase of Hamilton and the series by Lee, Ni and Ratti by dividing the net oil price increase by the conditional volatility.

The link between these oil price transformations and output growth will be analysed within two different frameworks. First we will use a linear regression framework in which output growth is regressed on its own lags and lags of the oil price transformations. Second, more macroeconomic variables are included in order to make the model and hence the results more realistic. This second analysis is conducted with a vector autoregressive model. The included macroeconomic variables have been suggested by Sims(1980b) as a concise approximation of macroeconmic reality. Since his publication most of the literature investigating relations between oil prices and the macroeconomy have been using this framework and his suggested variables. We will use the same six variables and add one oil price variable.

In both these frameworks we will first analyse the nature of the relation between regular oil price movements and output growth. After those results are established we can compare them with the effects that the usage of different oil price transformations has.

The aspects of the transformations that we are most interested in are the relevance of the transformation for the output growth and the stability of the estimated model. The relevance will be investigated by applying Granger causality tests. Stability is investigated by analysing whether an unknown structural break is present in the model. As opposed to the general practice in the literature, will we not use the Chow test for the existence of a known structural break but will we use the Quandt-Andrews test for the presence of an unknown structural break.

The analyses in both sections indicate a negative relation between oil prices and the GNP growth. However, output reacts relatively slow on oil price shocks; the effects are strongest after three to four quarters. Second we find evidence for a breakdown in the relation between oil prices and the output after 1973. The different oil price transformations are less affected but nevertheless also show a breakdown. Furthermore evidence is found for an unknown structural break when the oil price movement are used or the net oil price increase in the regression model. Among all the oil price transformations, the series that consistently showed the highest significance towards output and was the least receptive for structural breaks, were the two transformations that are using a volatility scaling. This indicates that the oil price volatility is important in the link of oil prices to the macroeconmy.

Finally we think that improvements in the research between oil prices and output can be made by using MIDAS regressions, Ghysels et. al(2002). With this method it becomes possible to use the high frequency oil price data in combination with the low frequency macroeconomic data. Hence we do not have to discard information during the data processing. This could result in additional insights.

The paper is organized as follows. In section 2 an overview of the main topics covered in the literature is provided. It serves to place this research into its proper context and to familiarize the reader with the most important research angels and applied methodology. Section 3 contains a preliminary empirical analysis of the relation between oil prices and output. Section 4 introduces the different oil price transformations. After this introduction all the transformations are compared with one another in a linear regression framework. In particular the relevance and stability of the different models will be researched. Section 5 compares the performances of the different transformations within the context of a vector autoregressive model. Section 6 concludes.

3 Literature overview

The past decades a large body of research has been developed by academics on the role and significance of crude oil prices in the macroeconomy. Quite often, the academic world has renewed its interest in this theme after episodes that were characterized by abrupt and large movements in the price of crude oil: Tatom(1988) for example performed his research on the asymmetric responses of macroeconomic aggregates on oil price changes after a period known for the largest oil price decrease in world history.

The aim of this section is to introduce the academic framework as it has been established in our field of research in order to place this research into its proper context. First, some of the main findings that were established are discussed. Both the theoretical aspects as well as the performed empirical research aimed at validating those claims will be covered in detail. Second, some frequently used methodological procedures in this field of research will be addressed.

3.1 Results from the literature

As a starting point the *relation between oil price increases and U.S. recessions* is mentioned. A pioneer who addressed this issue empirically was Hamilton(1983). His research is based on the phenomenon that dramatic oil price increases are often followed by a U.S. recession several quarters later, when considering the period 1948-1972. In his paper three hypotheses trying to explain this observation are subjected to testing.

In the first hypothesis this correlation is considered to be a rare historical coincidence. In the second hypothesis the correlation is explained as the result of a third, endogenous variable, such as output, prices or the money supply, responsible for both the oil price increase *and* the U.S. recession. The final hypothesis is based on the existence of a causal, exogenous relationship between oil price increases and U.S. recessions.

After the rejection of the first two hypotheses at conventional significance levels, evidence is provided in favour of the last hypothesis. This suggests that the timing and magnitude of the U.S. recessions in the 1948-1972 period could have been different in the absence of the oil price increases. Support for this causality however, does not provide evidence for the statement that oil price increases are either a necessary or a sufficient condition for U.S. recessions.

An other question that is interesting within this context was proposed by Leduc and Sill(2004). They ask whether the recession following oil price shocks is directly related to the oil price shocks themselves or is in fact caused by the monetary policy measures that are taken in response to these shocks. In their work they calculate that the monetary measures taken after an oil price shock account for 40 percent to the drop in output that follows a rise in oil prices.

A second important issue in the literature is the *stability* of the oil price-macroeconomy relationships. Once a significant relationship has been found, its structure or significance often seems to display a high sensitivity to the sample period that is used in the estimation process. The discovery of relations that are severely different, when compared over two specific sample periods, could help us in pointing out the factors that are crucial in the macroeconomic framework for determining the behaviour of the oil price-macroeconomy interactions. Factors that could be influential are the creation of the OPEC, a change in exchange rate regime, changes related to fiscal or monetary policy or distortions of international relations. Furthermore relevant macroeconomic elasticities could alter or the expectations of agents, e.g Kilian(2006).

A paper that subjects the established Granger Causal relations in Hamilton's 1983 paper to stability tests is Hooker(1996). Strong empirical evidence is found that these relationships have severely weakened after 1973. This decline in relevance of crude oil prices in the macroeconomy is attributed to important, long-term changes in the economy: In 1973 the productivity started to slowdown, a floating exchange rate was introduced and the U.S. entered a period characterized by unusual low interest rates. Furthermore, oil prices were determined under a different institutional regime before 1973 than after 1973. The domestic supply in the period before 1973 was controlled by the Texas Railroad Company (TRC) which resulted in a unique, discrete price pattern during this period. An extensive treatment of this regime and the shift towards the current, more volatile and reactive market, is provided in Hamilton(2011).

The next topic of interest which is commonly discussed in the relevant literature is that of *symmetry*: To what extent are the effects of oil price declines the reverse of the effects of oil price increases? Interest in this topic of symmetry was renewed after one of the largest price declines in history of crude petroleum between the end of 1985 and the middle of 1986.[1] This drop, frequently referred to as the *1980's oil glut*, was a result of a crude oil surplus. This surplus was related to the falling demand that followed the Energy Crisis of the 1970's. Triggered by this event Tatom(1988) investigated the symme-

[1] In November 1985 the price of a barrel of West Texas Intermediate(WTI) peaked at almost \$31. By July 1986 it has dropped to \$11.58 per barrel: A total decline of more than 60%.

try question extensively. He has augmented the Andersen-Jordan(1968) GNP equations in order to account for the effects of oil price changes. Within that framework numerous tests have been performed in order to measure the degree of asymmetry in the effects that oil prices have on the macroeconomy. Regardless of the theoretical framework constructed in the early sections in favour of asymmetry, the presence of significant asymmetry is rejected by all tests. However, these results have been challenged by several researchers:

For example Mork(1989) provides an empirical justification for the existence of asymmetric effects. The six-variable system as introduced by Sims(1980b) to concisely approximate the macroeconomic reality is augmented with measures that differentiate between the effects of oil price increases and oil price decreases. In this model statistical evidence is found that oil price increases have a large , negative effect on real GNP, whereas the data does not identify any significant effects of oil price declines, suggesting a form of asymmetry.

However, in Hooker(1996) no evidence is found in favour of the asymmetry hypothesis. In order to account for potential asymmetric reactions, several transformations of oil price measures are constructed. When the results of Granger Causality tests and structural break tests with these transformations are analysed, no significant asymmetric affects can be established.

In Ferderer(1996) empirical support is provided that favours the asymmetry hypothesis. First, he constructs a new measure for the volatility of oil prices that is based on daily observations. Then, it is demonstrated that increases in this volatility measure are significantly related to a reduction in output. As opposed to the oil price increases which are found to be statistically unrelated to an output decrease.

Finally Hamilton(2003) finds strong support for the existence of a nonlinear, asymmetric relation between oil prices and output. He argues that linear approximations that are established between oil prices and the output are often wrongly classified as unstable. The instability is caused by the fact that the relation is actually not linear. Such a relation might seem to be unstable while the actual true underlying nonlinear relation is stable.

A problem however, with choosing an appropriate nonlinear specification is that one can choose from a large spectrum of specifications. This implies that it becomes difficult to properly distinguish between a nonlinear relation that is actual significant and a relation that seems to be significant due to the effects of data mining.

However, by using the methodology as constructed in Hamilton(2001), those issues can be resolved. In that manner a proper statistical test is performed which investigates the null hypothesis of linearity against a wide range of alternative nonlinear specifications. By using this approach in Hamilton(2003), sufficient evidence is found in favour of a nonlinear relation between oil prices and output. In particular it is found that oil price increases are more relevant for output than oil price decreases and that oil price increases are less important when they correct earlier decreases than when they do not seem to correct previous movements.

Furthermore, relating to this asymmetry question, is the topic of *specification* or *representation*. The crucial point here is whether oil price changes themselves are in fact sufficiently capturing the essence of the oil price-macroeconomic relationships. Perhaps more informative are transformations of the oil price changes. If this is the case a different representation of oil prices in the form of a transformation would be more appropriate in research and should gain more attention for policymakers than the commonly used price changes.

An example of choosing a different representation in order to capture more relevant information is given in Ferderer(1996). The oil price changes seem to fail in Granger Causing macroeconomic aggregates whereas a transformation representing the volatility, does significantly Granger Cause these aggregates. Hence, it appears that the conventional oil change representation is less capable then a volatility measure of capturing the true oil price-macroeconomic interactions.

Similarly, in Hamilton(1996) it is argued that the conventional log differences in oil prices do not contain the relevant information needed for capturing the real interactions between oil prices and the macroeconomy. In the first place a measure called the *net oil price increase* is constructed. Next, results of a structural break in 1973 by using conventional oil change measures are contrasted with the results of using the net oil price increase in the test. The main conclusion arising from this comparison is that a structural break is not present in the coefficients of the transformed measure as opposed to a significant change in the coefficients of the conventional measure. Furthermore, Granger Causality is shown to hold between the net oil price increase and macroeconomic aggregates during 1948-1994 whereas the null of no Granger Causality was easily accepted when using the regular oil change measure. Both results raise doubts about the validity of using oil price differences when attempting to describe the real dynamics between oil prices and the macroeconomy.

An other theme that frequently appears in the relevant literature is that of the *decomposition* of the price of crude oil into distinct components, each of which preferably has a clear economic interpretation. The reason for an interest in this theme is that a common approach among macroeconomists consists of evaluating the effects of a change in the price of oil on macroeconomic aggregates, Kilian(2006). However, a major drawback of this approach is that the price of oil is varied by the researcher *ceteris paribus*. Bernanke(2004) has argued that, while this theoretical simplification is applied for convenience, it does result in a large degree of freedom that is lost: oil price fluctuations do not happen in isolation but instead are usually influenced by the behaviour of macroeconomic aggregates themselves. Furthermore, lower or higher oil prices in turn might be driving forces for these macroeconomic aggregates. The crucial point addressed here is that cause and effect are no longer properly defined in this approach that attempts to relate oil prices to the macroeconomy. An implication is that, without knowing the exact cause of an oil price change, it will be difficult to predict the macroeconmic consequences of such a change. However, by decomposing the price of oil into components, these issues can be resolved.

In Kilian(2006) the price of crude oil is structurally decomposed into four components by using a vector autoregressive model. The first two components are related to the supply side of the market: A measure of supply shocks that are caused by political events in the OPEC countries as developed in Kilian(2005) and the other supply shocks as measured by the percent change in global crude oil production. The remaining two components are related to the demand side: A measure for an aggregate demand shock in commodities which is based on the dry cargo single voyage rates due to the established positive correlation between these rates and global economic activity, see Tinbergen(1959). The last component consists of demand shocks that are specific to the crude oil market.

Several interesting conclusions are made: First, the effect of political oil supply shocks on the real price of oil appears to be negligible. Both types of demand shocks seem to be far more relevant in the determination of the price of crude oil than these political oil supply shocks. The aggregate demand shock seems to be mainly responsible for long-lasting swings in the price whereas demand shocks specific to the crude oil market cause short term and more extreme effects on the price. Furthermore, the relative contribution of the four structural shocks on the real price of oil is shown to be specific to oil price shocks: this composition is often substantially different when compared over several periods of oil price shocks. [2]

A concern for policymakers was to understand what the contributing factors were of the rapid oil price increase during the 2003-2008 period. Speculative trading in commodities markets was often mentioned as one of the determining factors. In Kilian(2010) the validity of this presumption is investigated by explicitly modelling speculative demand shocks and, together with

[2]For example important differences in these contributions can be observed when comparing the Iranian Revolution of 1978/1979 with the Iran-Iraq War of 1980-1988

flow demand and flow supply shocks, analysing the effects of these shocks on the price of oil within a VAR-model. The speculative demand shock is estimated by considering the above-ground oil inventories. The intuition here is that speculative traders with their forward looking behaviour will, in anticipation of of an expected oil shortage, buy and store crude oil now, hoping to sell it with a profit later. This investor's behaviour is therefore reflected in the oil inventories.

The hypothesis that speculative behaviour by commodity traders was the main factor in the 2003-2008 oil price increase, is rejected however. Instead, aggregate demand shocks, driven by the global business cycle, appear to be the determining cause for the increase. This result implies that stricter regulations in the commodity markets would not have helped in preventing the oil price increase and is therefore crucial for those who are responsible for the financial regulatory framework.

3.2 Methodology

In this section some commonly applied methodological procedures in the oil price-macroeconomic field are covered. The first method that we discuss is the usage of vector autoregressive (VAR) models.

As previously mentioned, both Killian(2006, 2010) and Bernanke(2004), have reasoned that a frequent problem in macroeconomic research is the properly defining and separating of cause and effect. A second issue inherent to macroeconomic research is the frequent habit of imposing many, rather arbitrary restrictions, on a model, see e.g. Sims(1980b). A method for circumventing both issues is by specifying a model in which all variables are treated as *endogenous*. Such a treatment is realized by defining a VAR-model: every single variable is defined as a function on lags of itself and on lags of all the other variables included in the model specification. Essentially a VAR-model is a generalization of the univariate autoregressive(AR) model.

The information that is captured by a VAR-model can be presented in several manners. Rarely are all the individual parameter estimates with their standard errors reported, since this is both rather cumbersome and usually not particular informative. A method that is frequently used for presenting VAR-results are the Impulse Response Functions (IRF's). These show how a variable responds to a shock of an other variable in a VAR-model. This provides researchers with a clear interpretation of the effects of a shock on the other variables, after a VAR-model has been specified. This is necessary because this information can not be easily obtained from just the parameter estimates of the model due the underlying complicated dependence structured as is captured by the covariance matrix.

The second point that we will discuss is the concept of Granger causality. In many papers in the relevant literature this method is used. Granger has introduced the concept in Granger(1969) while discussing the difficulties that can be encountered when trying to decide the direction of causality that exists between two variables. One reason is that a correlation does not automatically imply a properly defined causal relationship between variables. In fact, many spurious and meaningless correlations can be found in economics and other sciences.

Two types of Granger causality tests exist. The *bivariate* Granger causality test addresses the question of whether x causes y by analysing how much of the behaviour of y can be explained by its past values. Next, it is tested how much adding lags of x adds to this overall explanation. Hence, the regression being used is: $y_t = \alpha_0 + \alpha_1 y_{t-1} + ... + \alpha_l y_{t-l} + \beta_1 x_{t-1} + ... + \beta_l x_{t-l} + \varepsilon_t$, where l is the number of lags that is considered. The null hypothesis is that of no Granger causality and is defined by $H_0 : \beta_1 = ... = \beta_l = 0$. This hypothesis is subjected to a Wald F-test for the joint significance of the parameter coefficients. When the null hypothesis is rejected, is it said that x Granger Causes y, which is denoted by $x \rightarrow y$.

A disadvantage of bivariate Granger causality tests is that $x \rightarrow y$ does not imply that y is the result of x. Granger causality in fact only measures the information content but does not by itself indicates causality in the normal sense of the word.

The concept of a bivariate Granger causality test can be extended to a multivariate framework, resulting in a *multivariate* Granger causality test. Hence this type of test is usually performed in the context of a vector autoregressive model. It tests whether a group of variables jointly has a significant effect on an other variable. Therefore it is commonly used in case macroeconmic variables are used together in a VAR-model in order to asses whether some variables are relevant for others, in Granger causality terms.

Both the bivariate Granger Causality tests and the multivariate Granger causality tests are often encountered in the relevant literature. Due to its clear interpretation and ease of use, the tests are commonly utilized for quantifying the oil price-macroeconomic structures. Advantageous to this testing procedure - thereby explaining its immense popularity - is its flexible nature: Tests can be performed on different lag lengths, different sample periods and on transformations of variables. In this manner specific questions can be addressed with the Granger Causality tests in the oil price-macroeconomic framework.

Important in the context of this research is the methodology commonly applied to test models for a *structural break*. In an econometric context, a structural change is a statement about model parameters. When one or more estimated parameters in a model change at a specific breakdate, a structural break has appeared at that time. Information about structural breaks is important due to several reasons. In the first place are many methods in time series analysis dependent on the assumption of stationarity, i.e. that model parameters do not change over time. In the second place can knowledge about a structural break within a certain model, be interpreted and give us valuable information.

Two common methods exist for testing a model for the existence of a structural break. The oldest test was suggested by Chow(1960). His method consists of splitting the sample into two subsamples. Then, the parameters are estimated in both samples and tested for equality by using the F-statistic.

The major drawback of this approach however is that the breakpoint needs to be specified at the beginning of the testing procedure. This implies that either an arbitrary date is picked or or a date is picked based on some characteristic of the data. Maybe the biggest issue in using this test might be the fact that its outcomes can be highly sensitive to the breakpoint that is chosen. Therefore, the likelihood of contradicting conclusions from researchers using the same data, increases, see Hansen(2001).

In much of the relevant oil price-macroeconomic literature the Chow test is used. Hooker(1996) establishes relationships that link GDP and the unemployment rate to the oil price. He then tests the model parameters belonging to the oil price coefficients for the existence of a structural break by Chow's test in 1973:III. In this manner he want to analyse whether the effect of oil prices on these macroeconomic variables has changed over time. His choice for a breakpoint at this time is bases on empirical evidence that many long-term macroeconomic changes have occurred at that time. Similarly in Hamilton(1996), the Chow test is used for the stability of a model for output growth. In these papers and others, the date that is used in the breakpoint test is set by the researcher a priori and is hence usually based on economic or political circumstances.

However, the question arises what to do when we do not know a possible point for a breakpoint. In that instance a test for an unknown breakdate needs to be performed: the Quandt-Andrews test for an unknown structural break. In essence this test performs the Chow test sequentially over all possible breakdates. The Quandt-Andrews test statistic then is the maximum of all these Chow tests.

However, as opposed to the known distribution of the Chow-statistic, does the Quandt-Andrews test statistic not follow a regular distribution. Instead, it was not until the early 1990's in which Andrews(1993) and Andrews and Ploberger(1994) provided tables with the critical values of this distribution. Later, Hansen(2001) has developed a method for approaching the p-values that belong to this distribution. The critical values belonging to the Quandt-Andrews statistic are larger than those belonging to the Chow statistic. Therefore it might be possible that one finds evidence for a structural break at a user-specified point but fails to find enough statistical evidence to reject the null of no structural break with an unknown date.

Finally, we mention here the fact that there has been a clear separation in the research field of the oil price-macroecononmy relationship: on the one hand a large theoretical basis has been constructed and on the other hand much empirical research has been performed. Theoretical frameworks have been developed for example by Bruno(1982), Bruno and Sachs(1982) and Harkness(1982) in which the dynamics between oil price movements and the macroeconomy are analysed based solely on theoretical economic arguments. However, these theoretical papers commonly did not use empirical support for validating made claims as discussed in Burbidge and Harrison(1984). The work done in these and comparable papers tends to be based on simulation methods that are restrictive in nature. Hence, they prefer to conduct their research based on the VAR-methodology as introduced by Sims(1980b) and further developed by Doan and Litterman(1981).

The research conducted in this paper builds on the insights and methods of the literature. We will for example extend Sims original six-variable model by an oil price variable and conduct causality tests. Contributions are made to the literature by conducting tests for the presence of an unknown structural break instead of the Chow test for a known break. Furthermore new transformations are constructed and tested. Finally the improved generalized impulse response functions will be implemented for analysing the effects of oil price shocks on the output growth.

4 The oil price measures

In the relevant literature, no real consensus exists on which oil price measure to use. Most authors seem to utilise the producer price index for crude oil, e.g. Hamilton(1983) and Hooker(1996). Some authors argue that the composite refiner's acquisition costs for crude petroleum give a more realistic image of the real oil price behaviour. Finally, researchers occasionally prefer to construct their own measures because they argue that it enhances the level of realism of the series, e.g. in Mork(1989). In order to be in line with most of the literature, we will use the producer price index for crude as the oil price measure in this paper.

In this section we will shortly discuss the most common oil price indices for completeness and a general understanding. After this, some preliminary analyses are conducted on the different oil price measures and on the relation between oil prices and the aggregate output movements.

4.1 West Texas Intermediate(WTI)

WTI is an important, closely watched benchmark in the oil industry and the financial world. It is a light and sweet crude oil [3] traded in the U.S. domestic spot market at Cushing, Oklahoma. WTI is traded on the Chicago Mercantile Exchange(CME) where it serves as the underlying commodity on the crude oil futures contracts. From the Federal Reserve Economic Data database(FRED) at the St. Louis Federal Reserve Bank we obtained monthly data starting at January 1946. WTI data with a daily frequency was obtained from the U.S. Energy Information Administration(EIA), starting at January 2nd 1986.

4.2 U.S. refiner acquisition cost(RAC) for crude oil

This oil price measure is occasionally used in research relating oil prices to the macroeconomy. The main motivation for utilizing this series specifically is the fact that the price of crude oil was established in a different regulatory environment in the period 1948-1972, Hamilton(1983). In this period the Texas Railroad Commission (TRC)and comparable state regulatory agencies would forecast the demand for crude oil for the next month. Based on these estimates the allowable production levels for wells in the different states to meet this demand were determined. One important consequence of this system was that many cyclically endogenous components of crude oil demand

[3] Light refers to the low density of the oil, which is measured by the API gravity. Sweet refers to the fact that WTI is low in sulphur levels.

did manifest themselves as regulatory shifts in quantities and not in prices. After 1972 the oil market started to deregulate. Nowadays the petroleum market is mostly determined by global demand and supply forces. Due to this high level of regulation in earlier times, many researchers believe that the RAC serves as a better proxy for the price of crude oil than this controlled price. Three types of RAC are recorded by the EIA: the domestic, imported and composite Refiner Acquisition Cost for crude oil. The domestic RAC is defined as the price of crude oil produced in the U.S. or from its outer continental shelf. [4] The imported RAC is the price of oil produced outside the U.S. and transported to the U.S. The measure most often utilized is the composite RAC, which is calculated as the weighted average of the domestic and imported RAC. All three RAC series are available at a monthly frequency starting at January 1974.

4.3 Producer Price Index(PPI) for crude oil

A Producer Price Index[5] is a weighted index of prices as measured on the producer level. The Bureau of Labor Statistics releases every month several PPI's. The PPI for crude oil is available from January 1947 onwards. Most of the research in the oil price-macroeconomy literature uses this measure as the preferred way to represent oil prices. Therefore we have also decided to apply this series in our research as the oil price representative.

4.4 Analyses and comparisons of oil price measures

This section serves as a first and general discussion on the characteristics of oil price movements throughout time. Such a discussion is a logical first step in acquiring a basic, yet important knowledge about oil price movements. In this section we will take a closer look at the individual features of the different oil price measures. Furthermore, similarities and differences between these measures will be discussed.

First we want to mention the fact that most macroeconomic data is usually available at a quarterly frequency, such as the Gross National Product. Therefore relations between oil prices and macroeconomic variables are often investigated by first transforming the high frequency oil price data to the

[4]The precise definition can be found in 43 U.S.C. 1331.

[5]Until 1978 the PPI was named the Wholesale Price Index. The change in name did not include a change in the index methodology, and the continuity of the price index data was unaffected. The name change reflects only the theoretical model of the output price index that underlies the PPI.

lower frequency of the macroeconomic variables used. In this process of converting high frequency data to low frequency data, a lot of potentially useful information might be lost, which in turn might lead to a different estimated relation between oil and GNP than when such a conversion would not have been applied.

An alternative approach has been developed by Ghysels et al.(2002). They introduce MIxed DAta Sampling (MIDAS) regressions that allow left-hand and right-hand variables of time series regressions to be used at different frequencies, hence not discarding information by the process of lowering the frequency of the data. Instead the lower frequency data is modelled. The MIDAS regressions are a relatively new development and therefore some issues are still present and need to be resolved, see e.g. Ghysels et al.(2007). However it is evident that they provide benefits in the fields of finance and macroeconomics in particular. This because financial data nowadays commonly has a high frequency, even tick-data, but many relevant macroeconomic numbers are only published several times per year.

In our research we have converted the monthly oil price data to quarterly data by using the average aggregation method. However, for future research it might be valuable to repeat the experiments by using the MIDAS regressions on daily oil price data and on quarterly macroeconomic data. The higher frequency of the oil price data might provide additional insights.

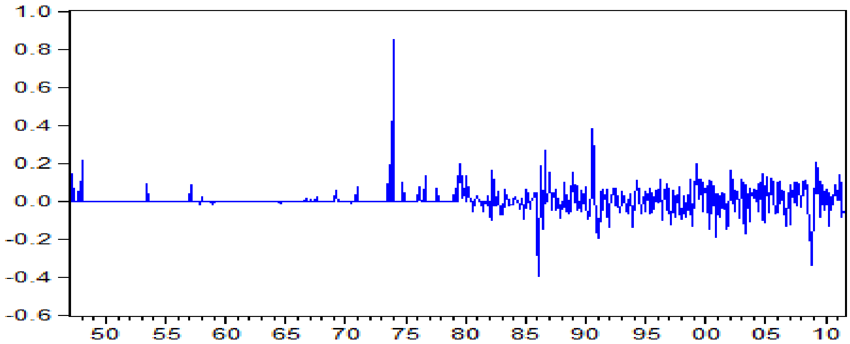
We will now provide a visual representation of the three oil price measures. The transformation of oil prices that is usually focused on within the literature is that of the first log differences.[6] Such a transformation represents the continuous growth rate of oil prices and removes the non-stationary behaviour of the time series. This transformation is commonly applied in macroeconomic research, mostly because of the problems that arise when using non-stationary time series, which are often encountered in macroeconomic data, such as GDP and price indices. Nevertheless, some researchers have argued within the oil price-macroeconomy literature that it is actually the level of the oil prices that is relevant for influencing the macroeconomy instead of price changes. For example, Carruth, Hooker and Oswald(1995) have constructed theoretical models that imply that it is in fact the level and not the change in firm's prices that is relevant for producers. The graphs of the log differences of the WTI, PPI and the composite RAC series are shown in figures (1) to (3) respectively. [7]

Next to these three graphs, tables (1), (2) and (3) contain summary

[6]If we represent the time series by $X(t)$, the first log difference is defined as: $\log[X(t)] - \log[X(t-1)]$.

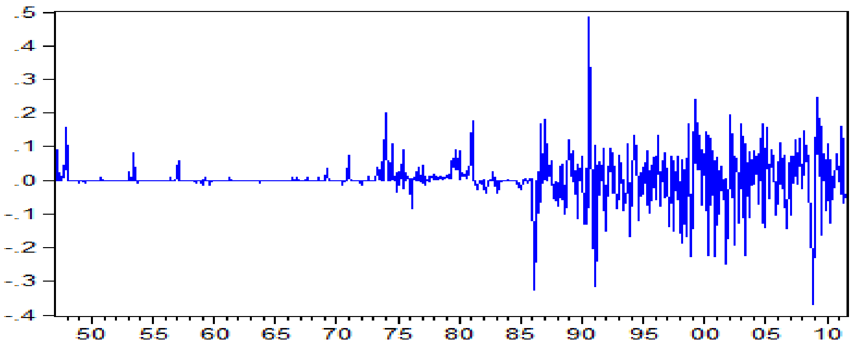
[7]As indicated before, does the composite RAC start later than the two other series.

Figure 1: West Texas Intermediate



Note: Plot of the monthly log differences of WTI over the period 1947:2 - 2011:6

Figure 2: Producer price index for crude oil

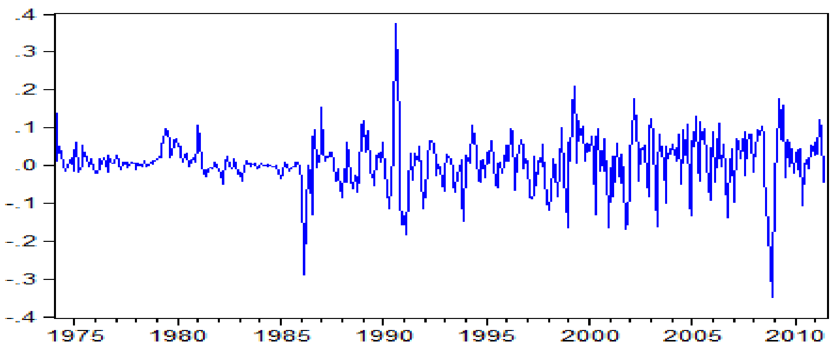


Note: Plot of the monthly log differences of the PPI over the period 1947:2 - 2011:6

statistics for all three series. These provided summary statistics are given in percentage terms, i.e. by multiplying the log difference series by hundred. Since the RAC series originates in 1974, we have also split our sample at 1974:1/1974:2. In that way it becomes possible to compare the three series in a consistent way with one another. Furthermore, the summary statistics might change over time, which could also cause potential oil price-macroeconomy relationships to alter at that point.[8] In this part, we refer to the sample 1947:2-2011:6 as the full sample period, the sample 1974:2-2011:6

[8]As has been discussed in the literature, often oil price-macroeconmic models are tested for having structural breaks. Some authors, like Hooker(1996), have established structural breaks around 1973. Therefore we might expect to observe rather different values for summary statistics in the pre- and post-1974 period.

Figure 3: Composite refiner acquisition costs for crude oil



Note: Plot of the monthly log differences of the RAC over the period 1974:2 - 2011:6

is called the post-1974 sample period and the sample 1947:2-1974:1 is referred to as the pre-1974 sample period.

Table 1: Summary statistics

	Mean	Std. Dev.	Max	Min	Skew.	Kurt.
$100 \times \Delta \log(WTI)$	.528	6.761	85.259	-39.601	2.274	39.310
$100 \times \Delta \log(PPI)$	.472	6.835	48.501	-36.743	-.416	11.478

Note: Summary statistics for the first (monthly) log differences of WTI and PPI over the full sample period 1947:2 - 2011:6

Table 2: Summary statistics

	Mean	Std. Dev.	Max	Min	Skew.	Kurt.
$100 \times \Delta \log(WTI)$	.502	7.719	37.706	-39.601	-0.413	7.176
$100 \times \Delta \log(PPI)$	.5442	8.836	48.501	-36.743	-.399	7.022
$100 \times \Delta \log(RAC)$	.584	6.978	37.473	-34.764	-.682	8.616

Note: Summary statistics for the first (monthly) log differences of WTI, PPI and RAC over the period 1974:2 - 2011:6

Table 3: Summary statistics

	Mean	Std. Dev.	Max	Min	Skew.	Kurt.
$100 \times \Delta \log(WTI)$	.565	5.158	85.259	-2.307	14.200	227.462
$100 \times \Delta \log(PPI)$	.3712	1.833	19.976	-1.482	6.854	61.033

Note: Summary statistics for the first (monthly) log differences of WTI and PPI over the period 1947:2 - 1974:1

In the full sample period the behaviour of the WTI and PPI series is quite similar in terms of their means and standard deviations. They both have a small, positive mean which indicates a tendency of oil prices to rise over time in the long run. In order to test to what extent this long run increase is related to the U.S. inflation, the same calculations were also run with the *real price of crude oil* by using the log differences of WTI and PPI that were adjusted for inflation with the CPI functioning as the deflator. In that case, the means of the WTI and PPI series are .23 and .17 respectively, indicating that the long run oil price increases are only partially explained by inflationary effects. The mean values in all three tables are similar in magnitude, and hence do not suggest the existence of structurally different behaviour in the pre- and post-1974 period in terms of mean values.

The results demonstrate a rather large volatility of oil price movements. For example, the S&P 500 index, commonly used as a major benchmark for the volatile stock market, exhibits a much lower volatility than these oil price measures, except for the PPI in the pre-1974 period: The standard deviation of the S&P 500 series takes on a value of 3.621. In contrast with the results found in terms of mean values between the pre- and post-1974 period, are there clear differences present in the volatility levels between the two periods. It appears that the volatility is higher in the post-1974 period than in the pre-1974 period. This is also evident from figures (1) to (3). A possible explanation for this phenomenon would be the different institutional regime under which oil prices were established that was prevalent in the mid 70's and early 80's, see Hooker(1996).

The statistical significance of the difference in volatility between the pre-1974 and post-1974 period can be addressed by means of an F-test. We will test $H_0 : \sigma^2_{\text{pre74}} = \sigma^2_{\text{post74}}$ versus the alternative $H_1 : \sigma^2_{\text{pre74}} < \sigma^2_{\text{post74}}$. For WTI we find an F-value of $F(448, 323) = 2.24$ and for the PPI we find $F(448, 323) = 23.24$. They have corresponding p-values of .00 and .00 respectively. Hence we have strong statistical evidence that the volatility of the oil prices is higher after 1974 than before 1974.

In terms of the extreme values of the series, a few observations can be made. The maximum value of the WTI series of 85 percent in the pre-1974 period is almost twice as large as the maximum values of the other series in all the sample periods. This enormous increase occurred in January 1974: Since August 1973 the price of a barrel of WTI was set at \$4.31 and it remained constant until the Texas Railroad Company decided to increase the price in January 1974 to \$10.11 per barrel. As stated, the other maximum values are remarkably lower. For example, the maximum value of the PPI was 49, which occurred in August 1990. At that same date the WTI series exhibited its second largest price increase in history. It is remarkable that the price increase of the PPI at January 1974 was only 20 percent compared to the value of 85 percent.

With regards to the minimum values we observe a phenomenon that might be related to the observed volatility difference between the two sample periods. The minimum values in the pre-1974 period are much smaller in absolute terms than in the post-1974 period. Furthermore, it appears from figures (1) to (3) that oil price decreases were a lot less common before 1974 than after 1974. This has for example also been noticed by Hamilton(1996). Over the entire sample period, the largest decrease of the WTI series happened in February 1986, corresponding to the oil glut. The minimum of both the PPI and the RAC happened in December 2008.

Large differences appear in the skewness in the pre- and post-1974 period. In the pre-1974 period the skewness takes on relatively large, positive values. Whereas all three oil price measures have a small, negative skewness in the period after 1974. This is related to the observation that oil price decreases were smaller and less common in the period before 1974 than after 1974: oil price increases were more common and larger in magnitude in the pre-1974 period than the decreases which results in a positively skewed distribution. Due to much larger and more common oil price decreases after 1974, the distribution has changed from positively skewed to a distribution that is slightly negatively skewed.

Finally, the kurtosis over all three sample periods and for all time series is large, indicating leptokurtic distributions. However, a large difference in the magnitude of the kurtosis in the pre- and post-1974 period is present: The magnitude decreases largely in the sample after 1974. Most likely again the changing institutional regime could be responsible for this decrease in kurtosis. Because oil prices were only changed occasionally on instigation of institutions such as the Texas RailRoad Company, this would result in a distribution with a higher peak around the mean value than a normal distribution which also implies the corresponding fatter tales. This would explain the high leptokurtic behaviour of the oil price movements in this period. In the period after 1974 the oil market was heavily deregulated, implying that oil prices were more determined by market forces, which most likely results in a less leptokurtic distribution, see Kilian(2006).

Based on figures (1) to (3), we do not expect the summary statistics in the post-1974 period to be stable over time. Especially after the mid 1980s all three the series seem to display a lot more volatility. We will split the post-1974 sample at 1985:12/1986:1. The reason for a split at this specific point is based on the fact that in the first quarter of 1986 a major oil market collapse occurred, see Mork(1989). Also, in Hamilton(1996) it is argued that oil prices seem to behave differently after 1986 than before. One interesting feature he mentions is that many oil price increases that occurred between 1986 and 1996 seems to be corrections of even larger decreases, which is based upon the analysis of his net oil price increase series. An interesting suggestion made in this paper is that the impact of oil price increases is linked to this correction phenomenon: oil price increases that correct previous decreases have less impact than stand-alone increases.

Table (4) displays the summary statistics of the oil price series in the period 1974:2 to 1985:12. In table (5) these statistics are shown for the post-1986 period, i.e. for 1986:1 to 2011:6.

Table 4: Summary statistics

	Mean	Std. Dev.	Max	Min	Skew.	Kurt.
$100 \times \Delta\log(WTI)$	.693	4.337	19.753	-12.369	1.183	7.599
$100 \times \Delta\log(PPI)$	.877	3.003	17.867	-8.423	2.299	12.570
$100 \times \Delta\log(RAC)$	.892	2.739	13.871	-4.878	1.684	7.468

Note: Summary statistics for the first (monthly) log differences of WTI, PPI and RAC over the period 1974:2 - 1985:12

Table 5: Summary statistics

	Mean	Std. Dev.	Max	Min	Skew.	Kurt.
$100 \times \Delta\log(WTI)$	.413	8.873	37.706	-39.601	-.441	5.817
$100 \times \Delta\log(PPI)$	.389	10.507	48.501	-36.743	-.333	5.100
$100 \times \Delta\log(RAC)$	.440	8.244	37.473	-34.764	-.590	6.413

Note: Summary statistics for the first (monthly) log differences of WTI, PPI and RAC over the period 1986:1 - 2011:6

The mean growth rates of all three oil price series is almost twice as large in the pre-1986 period than in the post-1986 period. [9] Furthermore, this growth rate around 8% is also highly unusual when compared with the mean growth values over the entire sample period as shown in table (1), which are close to 5%.

However, we have to properly test whether the mean values in the pre-1986 are significantly smaller than in the post-1986 period. We compare the mean values in both periods by means of a two-sample t-test. Hence we will test the null hypothesis $H_0 : \mu_{\text{pre86}} = \mu_{\text{post86}}$ against the alternative $H_1 : \mu_{\text{pre86}} > \mu_{\text{post86}}$.

This problem is the Behrens-Fisher problem since we are concerned with comparing the mean values between two normally distributed samples but the variances of these two samples are not assumed to be equal.

The t-statistic is calculated as described in equation (3.1). In which $\bar{x_1}$ and $\bar{x_2}$ denote the sample means in the pre-86 and post-86 sample respectively. Similarly s_1^2 and s_2^2 denote the sample variances among the two samples and n_1 and n_2 denote the two sample sizes. The correct number of degrees of freedom is calculated with Satterthwaite's approximation which is shown in eqution (3.2). The degrees of freedom is rounded down to the nearest integer.

$$t = (\bar{x_1} - \bar{x_2}) / \sqrt{\frac{s_1^2}{n_2} + \frac{2_2^2}{n_2}} \tag{4.1}$$

$$df = \frac{(s_1^2/n_1 + s_2^2/n_2)^2}{\frac{(s_1^2/n_1)^2}{n_1-1} + \frac{(s_2^2/n_2)^2}{n_2-1}} \tag{4.2}$$

We find the following test results. $t_{WTI}(446) = .45$ with $p_{WTI} = .33$, $t_{PPI}(395) = .75$ with $p_{PPI} = .23$ and $t_{RAC}(416) = .86$ with $p_{RAC} = .19$. Hence, we have not sufficient statistical evidence in order to conclude that the mean of the oil prices in the pre-1986 sample is larger than in the post-1986 period.

In the second place a strong difference in volatility is observed between the pre- and post-1986 period. The volatility in the pre-1986 period is rather low, especially when compared to the full sample values. However, the values for standard deviation more than double in the period after 1986. This can also be easily seen from figures (1) to (3), where the graphs clearly display more erratic behaviour after 1986 than before.

[9] In Hansen(2001) is discussed how a common view is that the labor productivity in the U.S. experiences a slowdown around 1973. This might be related to the relative high oil price growth as found in this 1974-1985 period.

We will formally test whether the volatility in the post-1986 period is statistically higher than in the pre-1986 period. The test statistic used is an F-statistic with degrees of freedom equal to $(n_1 - 1)$ and $(n_2 - 1)$. We obtain the following results for the test of $H_0 : \sigma^2_{pre86} = \sigma^2_{post86}$ versus $H_1 : \sigma^2_{pre86} < \sigma^2_{post86}$: $F_{WTI}(305, 142) = 4.19$ with $p_{WTI} = .00$. $F_{PPI}(305, 142) = 12.24$ with $p_{PPI} = .00$. $F_{RAC}(305, 142) = 9.05$ with $p_{RAC} = .00$. Hence we have strong evidence to reject the null of an equal variance in the oil price movements in the pre-1986 and post-1986 periods.

A third important difference in the behaviour of the time series when we compare both periods with each other is in terms of the skewness. In the pre-1986 period all three the oil price measures have a slightly positive skewness. In the post-1986 period this skewness becomes slightly negative. This phenomenon is most likely due to the fact that oil price decreases seem to be a lot more common after 1986 than before.

Finally, the value of the kurtosis decreases on average a little bit when we go from the pre-1986 period to the post-1986 period. Implying that extreme outcomes from the mean decrease in likelihood.

In conclusion we have clearly observed a change in the behaviour of oil prices over time. The price movements are more erratic and extreme after 1974 than before 1974. Also, the volatility of oil prices is significantly higher after the oil market collapse of 1986 than before. As stated at the beginning of this section, will we use the PPI for crude oil as our measure for oil prices. So far, we have seen that alternative oil price measures seem to behave in a comparable way. In order to analyse this observation more in depth, we will conduct correlation analyses in the next part.

Tables (6) and (7) display the correlation between the PPI, WTI and RAC series in the full sample as well as in the post-1974 sample. The correlation between PPI and WTI takes on a rather large value of 0.75 over the full sample period. However, this correlation increases to 0.81 when we consider only data after 1974 as can be seen from table 5. This gives rise to questioning to what extent the correlation between the different oil price measures is time-varying. Furthermore the correlation between PPI and RAC and between WTI and RAC has a very high correlation of 0.90 and 0.88 respectively.

Table 6: Correlations

	$\Delta\log(PPI)$	$\Delta\log(WTI)$
$\Delta\log(PPI)$	1	0.7543
$\Delta\log(WTI)$		1

Note: Correlations between the first log differences of the PPI and WTI as measured over the period 1947:2 - 2011:6

Table 7: Correlations

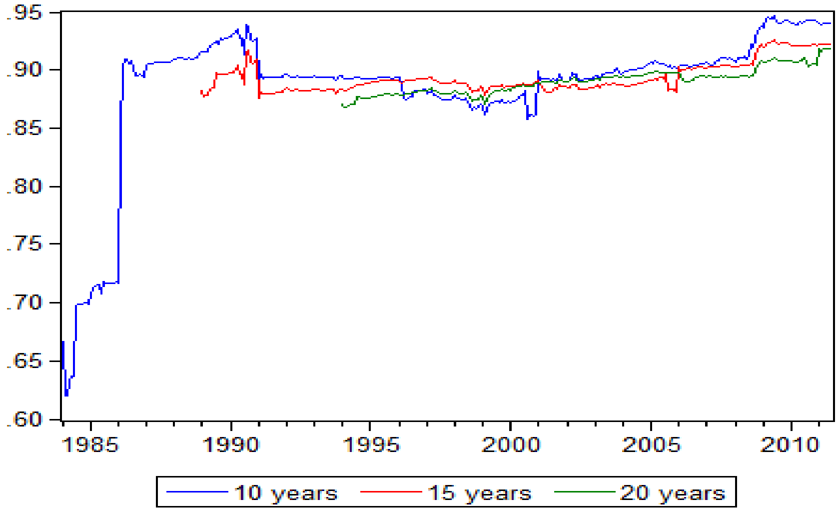
	$\Delta\log(PPI)$	$\Delta\log(WTI)$	$\Delta\log(RAC)$
$\Delta\log(PPI)$	1	0.8132	0.9010
$\Delta\log(WTI)$		1	0.8840
$\Delta\log(RAC)$			1

Note: Correlations between the first log differences of the PPI, WTI and RAC as measured over the period 1974:2 - 2011:6

In order to test the time-varying behaviour of the correlation between the different oil price measure pairs, we have calculated several moving correlations. Figures (4), (5) and (6) each show the moving correlation with a size of 120, 180 and 240 months between the three different pairs. A first important observation is that in the period 1990-2011 the correlation between all three pairs is rather high and seems to steadily increase to values that exceed 90%. This might imply that the characteristics of the three series converge towards each other, making it more appropriate to use them for similar research purposes.

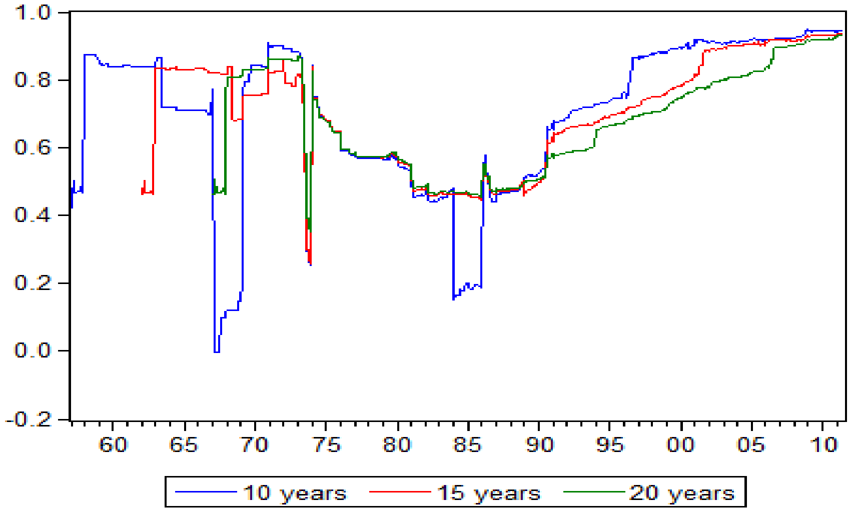
In contrast, the correlation between the different pairs does not behave as regular in the period before 1990. The correlation between PPI and WTI is high in the 50s but drops almost to zero in the early 60s. After this it quickly recovers to high correlation levels but from the mid 70s onwards the value decreases again to low levels, even to negative when the 60 month correlation is considered, to then adjust, starting in the mid 80s, again to high values of correlation. For the other two correlation pairs we only have moving correlations that start in 1979 due to the shorter sample of the RAC. These two pairs show a very similar pattern in the time variation of the correlation: Both have low values between 1980-1985 after which they rise to high values in the early 90s. From that point onwards the aforementioned steady increase occurs.

Figure 4: Moving correlation



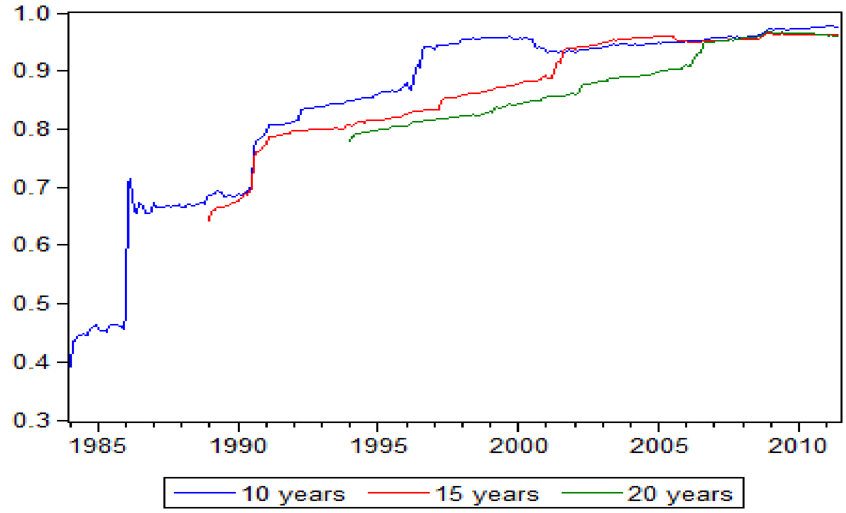
Note: Moving correlation between the PPI and the RAC for a window of 10,15 and 20 years. The period displayed is 1984:1 - 2011:6.

Figure 5: Moving correlation



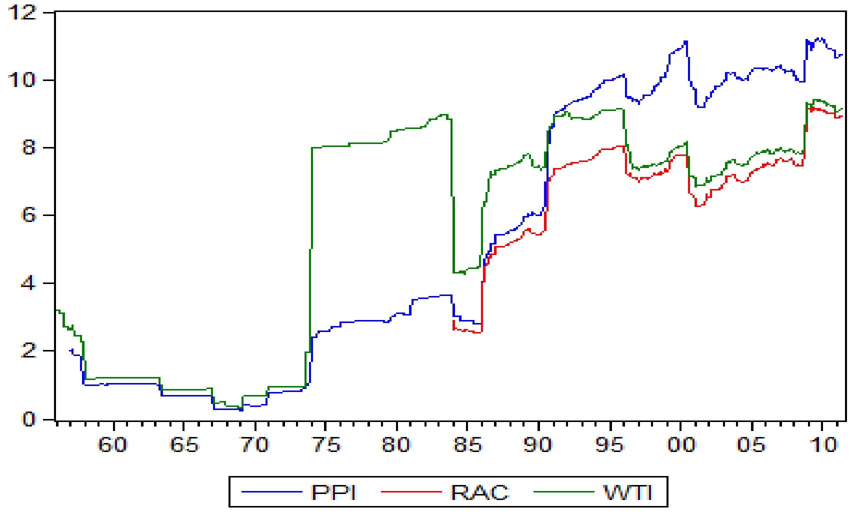
Note: Moving correlation between the PPI and WTI for a window of 10,15 and 20 years. The period displayed is 1957:1 - 2011:6.

Figure 6: Moving correlation



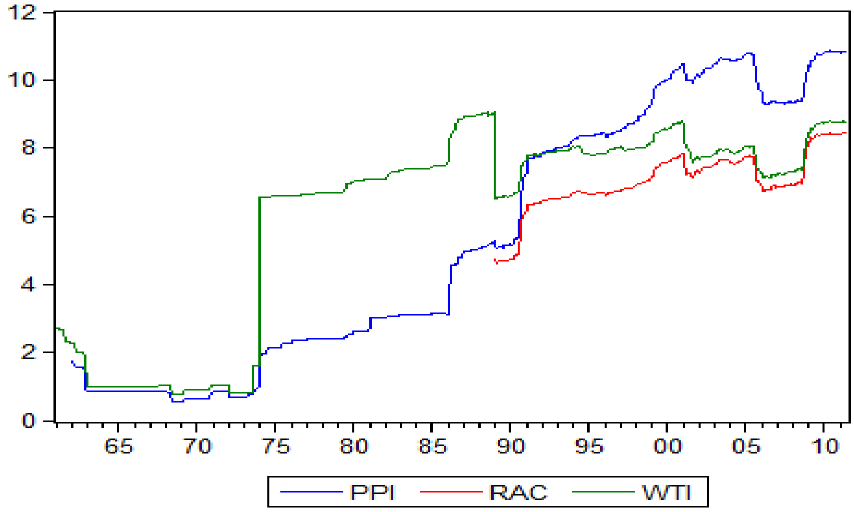
Note: Moving correlation between WTI and the RAC for a window of 10,15 and 20 years. The period displayed is 1984:1 - 2011:6.

Figure 7: Moving volatility



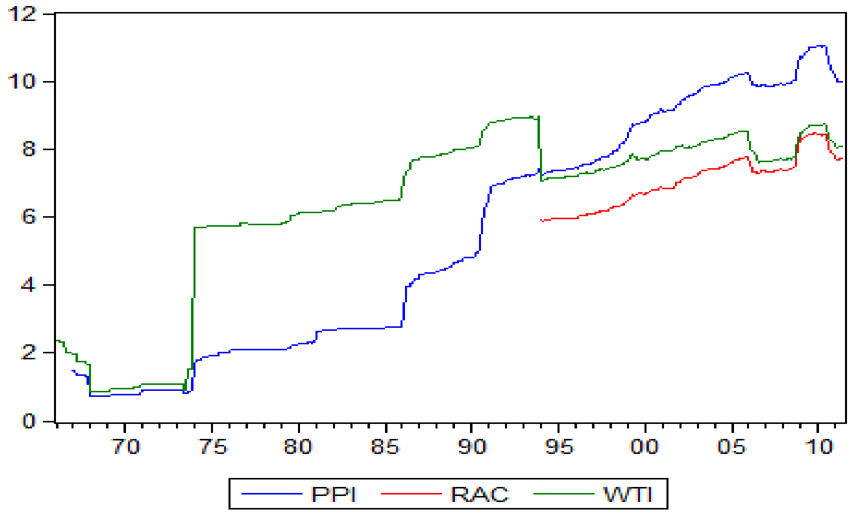
Note: Moving volatility of the PPI, RAC and WTI for a window of 10 years. The period displayed is 1956:1 - 2011:6.

Figure 8: Moving volatility



Note: Moving volatility of the PPI, RAC and WTI for a window of 15 years. The period displayed is 1961:1 - 2011:6.

Figure 9: Moving volatility



Note: Moving volatility of the PPI, RAC and WTI for a window of 20 years. The period displayed is 1966:1 - 2011:6.

Similarly, the time-varying behaviour of the volatility of the different oil price series is analysed by means of moving volatility functions. In figures (7) to (9) these moving volatilities are displayed for all three oil price series for a period of 120, 180 and 240 months as the window size. Again, the volatility is represented in percentage terms for the different series.

Several observations can be made from these graphs. In the first place do all four graphs confirm that the volatility of the oil price was remarkably low until 1973/1974. In the second place it can be seen that this oil price shock of 1973 had a more profound effect on the volatility of WTI than on the PPI. In the third place we see that the volatilities of the different oil price series from the late eighties onwards move closely together. This indicates that a higher level of freedom in the markets results in a convergence of behaviour of different oil prices measures. Finally, an overall upward moving trend in the volatility of the oil price can be detected. Whether we consider a moving volatility with a short window or one with a longer window. In fact, the average volatility in each decade is larger than that value for the previous decade.

5 The oil-output relation

Among the most important macroeconomic variables are aggregate output measures such as the Gross Domestic Product(GDP) and the Gross National Product(GNP).[10] Due to the value that is attributed to these output measures, we have chosen in this paper to focus on the link that exists between the oil price and the aggregate output. While the main focus of this paper is to investigate the effects of several oil price transformations in relation to the output growth, we will use some preliminary analyses between the oil price and the GNP in this section in order to obtain some potential insights.

This section covers the following. In the first place are the historical correlations between oil price changes and leaded output growth values discussed. Second, a downside correlation analysis will be performed. Third, results for the benchmark regression will be presented. Fourth, different oil price transformations will be introduced and finally we will analyse the usage of all these different transformations within the context of the regression framework.

5.1 Correlation analysis

As a starting point the historical correlations between the aggregate output and the oil price movements will be presented. Several authors have argued that the effects of oil price movements require some time to be fully absorbed, e.g. Hamilton(1983). Therefore, correlations between oil price movements and leaded values for the Real GNP are also included.

Tables (8) displays the correlations between the log difference of the oil price measures and the values for Real GNP growth. In order to account for a lagged response of the aggregate output to oil price shocks, we have included leaded values for the output growth up to twelve periods, i.e. three years. The corresponding p-values are displayed in brackets under the correlation coefficients. The sample period over which these historical correlations have been calculated is the full sample of 1947:II-2008:I.[11]

Table (8) has a characteristic pattern. The correlation takes on a slightly negative, statistically insignificant value between the non-leaded output series and the oil price measures. From 1 up to 4 leads, we observe a decrease in the correlation coefficients and at the same time does the significance of these

[10] The difference between these measures is that GDP is a measure for the total output generated within a country's borders. GNP measures the total output generated by all the enterprises of a country, regardless of their locations.

[11] The total data available covered the period 1947:II - 2011:I. But due to the included leads, is shortened by twelve quarters.

Table 8: Correlations

x	0	1	2	3	4	5	6	7	8	9	10	11	12
$\Delta\log(WTI)$	-0.08	-0.12	-0.15	-0.16	-0.19	-0.06	-0.03	-0.11	0.08	-0.03	-0.07	-0.06	-0.00
	(.234)	(.071)	(.016*)	(.013*)	(.002**)	(.311)	(.586)	(.097)	(.189)	(.597)	(.278)	(.363)	.997)
$\Delta\log(PPI)$	-0.04	-0.08	-0.06	-0.16	-0.17	-0.11	-0.11	-0.11	0.05	-0.01	-0.03	-0.01	0.05
	(.538)	(.205)	(.330)	(.010**)	(.006**)	(.091)	(.077)	(.087)	(.474)	(.846)	(.693)	(.903)	(.400)

Note: Correlations between the oil price growth at time t, o_t, and the GNP growth shifted x periods forward, y_{t+x}. The values are determined over the period 1947:II-2008:I. Standard errors are displayed in brackets below the correlation coefficients

* significant at 5% level

** significant at 1% level

Table 9: Asymmetric correlation analysis

x	0	1	2	3	4	5	6	7	8	9	10	11	12
$\Delta\log(WTI^+)$	-0.19	-0.14	-0.28	-0.22	-0.25	-0.13	0.03	-0.13	0.07	-0.08	-0.06	0.08	0.04
	(.06)	.1623	(.004**)	(.026*)	(.010**)	(.207)	(.805)	(.198)	(.525)	(.418)	(.553)	(.431)	.681)
$\Delta\log(PPI^+)$	-0.13	-0.18	-0.16	-0.16	-0.13	-0.08	0.01	-0.10	0.01	0.00	-0.08	0.01	0.05
	(.166)	(.054)	(.087)	(.074)	(.145)	(.416)	(.939)	(.300)	(.928)	(.878)	(.399)	(.927)	.624)

Note: Correlations between the pairs of oil price increases at time t, o_t^+ and the corresponding GNP growth shifted x periods forward, y_{t+x}. The values are determined over the period 1947:II-2008:I. Standard errors are displayed in brackets below the correlation coefficients

* significant at 5% level

** significant at 1% level

Table 10: Asymmetric correlation analysis

x	0	1	2	3	4	5	6	7	8	9	10	11	12
$\Delta\log(WTI^-)$	.39	.14	.13	.05	0.03	-0.05	-0.10	-0.13	0.05	0.02	0.13	0.04	0.02
	(.002**)	(.286)	(.304)	(.694)	(.793)	(.697)	(.442)	(.307)	(.701)	(.870)	(.344)	(.742)	(.893)
$\Delta\log(PPI^-)$	.11	.04	.18	.09	0.15	0.17	-0.02	-0.00	0.17	0.13	0.08	-0.07	-0.02
	(.404)	(.785)	(.154)	(.506)	(.257)	(.195)	(.843)	(.973)	(.175)	(.325)	(.528)	(.599)	(.883)

Note: Correlations between the pairs of oil price decreases at time t, o_t^- and the corresponding GNP growth shifted x periods forward, y_{t+x}. The values are determined over the period 1947:II-2008:I. Standard errors are displayed in brackets below the correlation coefficients

* significant at 5% level

** significant at 1% level

coefficients increase. Both for the PPI as WTI the minimum correlation with the highest significance is obtained when GNP growth is leaded by 4 quarters. From 5 leads onwards, the magnitude of the correlation coefficients gets smaller again. Furthermore, none of them is significant at the 95% confidence level. Only a few coefficients are found to be significant at the 90% level.

These results might indicate a tendency of aggregate output growth to have a lagged response to oil price shocks that lasts approximately three to four quarters. We will address this question more extensively later on by means of a regression framework and a VAR-model.

5.1.1 Downside correlation analysis

In recent work the topic of asymmetric correlations has been investigated in the field of equity research. In particular the recent credit crisis has shown that correlations between different financial instruments might be dependent on the economic climate. In fact it has been established that the correlation between different assets and asset classes increases in bear markets. This can have serious implications for hedging, since it often results in firms wrongly assuming that they are properly hedged, while in fact they are under hedged. For example, Ang and Chen(2002) showed that correlations between U.S. stocks and aggregate U.S. markets are much greater in case of downside moves than for upside moves. [12]

To our knowledge, an analysis to a possible asymmetric effect in correlations between the oil price and aggregate output has not yet been performed within the context of oil price-macroeconomic research. Therefore such an analysis will be conducted in this subsection.

The same principle as before is applied: Correlations are investigated between the oil price movements and different leaded values for GNP growth. However this time we have split the oil price changes in two different subseries, namely the increases and decreases in order to analyse the possibility of an asymmetric correlation structure. Effectively, the correlation between oil price increases and the corresponding GNP values is computed in this manner and the same principle is applied to the decreases.

The results of these *conditional* correlations can be found in tables (9) and (10). In the rows with $\Delta\log(WTI^{+})$ and $\Delta\log(PPI^{+})$ the correlations belonging to the oil price increases are displayed and similarly in the rows with $\Delta\log(WTI^{-})$ and $\Delta\log(PPI^{-})$ this is shown for the decreases.

[12] In fact they have found that correlations that are conditioned on the downside differ by 11.6% from conditional correlations as implied by a normal distribution.

The results from tables (9) and (10) indicate that oil price increases are significantly correlated with output changes for the first four leaded values of GNP. From five leads onwards this significance is no longer present. Overall this might indicate that oil price increases have a significant but delayed effect on output growth. This effect seems to be the largest around three to four quarters, based on the values of the coefficients and their corresponding p-values. This is the same conclusion that was drawn from the initial correlation analysis in the first part of this section.

The image for the correlation between oil price decreases and GNP is rather different. First of all, most of the correlation coefficients are positive instead of negative, indicating that oil price decreases might have a positive effect on output. However, none of these coefficients is significant at the conventional significance levels. [13]

The results from this downside correlation analysis indicate asymmetric features of the oil price-output interactions. Oil price movements are significantly negatively correlated with output growth. The strength and significance of this correlation is found to be greatest around three to four leaded values of GNP. However, oil price decreases do not seem to be significantly correlated to output movements at all and hence this shows an asymmetric bias in the effect of oil price decreases. vs. increases as measured by their correlation.

[13]The only exception to this is the correlation coefficient between $\Delta \log(WTI^{-})$ and the non-leaded value of $\Delta \log(GNP)$.

5.2 Regression framework

5.2.1 Introduction

As has been stated in the introduction, one of the main goals of this paper is to investigate the effects of using different oil price transformations in explaining the output growth. In order to compare the results of the different transformations consistently with each other, we need a framework in which all transformations are compared. In this paper two models are used for this purpose. First we use a linear regression framework for the interactions between oil price transformation and output growth. Second, this approach is extended by adding relevant macroeconomic variables, in order to analyse these effects within a VAR-framework.

In the linear regression framework we will first establish *benchmark* results. These are the results that we obtain when we use the first log differences, i.e. the continuous growth rate, as the relevant oil price transformation. Next, we will compare the results as obtained by different oil price transformations with those of the benchmark. In particular we will pay attention to what effects the transformations have on the relevance and stability of the relations. Since finding an oil price transformations that is highly relevant for the output growth *and* is stable over time, implies that such a transformation captures those aspects of the oil price that are crucial and and stay crucial over time for the output.

This section is organized as follows. First we will introduce the regression that will serve as our benchmark for comparing purposes. Second, the different oil price transformations will be introduced. Third, the transformations are analysed and compared with the benchmark results. The last part concludes.

The benchmark regression regresses GNP growth, y_t, against four lags of itself and four lags of the oil price movements, as measured by the PPI for crude oil, o_t. Both variables are entered in log differences in order to represent the continuous growth rate. Finally, ε_t represents the error term of the regression. Equation (5.1) below displays this benchmark regression.

$$y_t = c + \alpha_1 y_{t-1} + ... + \alpha_4 y_{t-4} + \beta_1 o_{t-1} + ... + \beta_4 o_{t-4} + \varepsilon_t \qquad (5.1)$$

When the residuals are heteroskedastic then the OLS method for calculating the covariance matrix of the estimated coefficients: $VAR[\bar{\beta}^{OLS}]$ is no longer correct. Therefore, even though $\bar{\beta}^{OLS}$ is still an unbiased estimator, interval estimation and hypothesis testing is no longer reliable because the standard errors are not properly calculated. A proper method for calculating the standard errors in case of heteroskedasticity is by using White's standard errors, as was first described by White(1980).

Formally the residuals of the regression have been tested for heteroskedasticity by using White's heteroskedasticity test. This test statistic is calculated by regressing the squared residuals on the four lags of the output growth and on the four lags of the oil price movements. The test statistic is then the product of the number of observations and the R-squared of that regression, which follows a χ^2-distribution. We have not found sufficient evidence in favour of heteroskedasticity in the residuals of the regression.

Furthermore, we have tested whether the residuals exhibit signs of serial correlation. We have formally tested the residuals for the presence of autocorrelation up to twelve lags by means of the Ljung-Box Q-statistic. For none of these lag orders have we found sufficient evidence in favour of autocorrelation.

5.2.2 Results for the benchmark regression

The output of the benchmark regression is displayed in table (11). The table shows the estimated coefficients of the lagged variables. The corresponding standard errors are displayed in brackets below the coefficient estimates. Furthermore, the value and the corresponding p-values of exclusion F-tests for the joint significance of the parameters is shown. The regression is run over the full sample period which contains data from 1947:II to 2011:I. [14]

From table (11) we see that all the four coefficients belonging to the oil price, o_{t-1} to o_{t-4}, have a negative value. However, based on their corresponding standard errors, none of them is considered to be individually significant at the 95% confidence level. It is clear though that o_{t-3} and o_{t-4} carry the highest relevance respectively in the benchmark, with individual p-values of .09 and .22 respectively.

Table 11: Benchmark regression results

	Lag Coefficients				Exclusion Tests	
Variable	1	2	3	4	F(4,243)	p-Value
y_t	.3181	.1625	-.0898	-.0823	11.397	.0000
	(.064)	(.066)	(.066)	(.063)		
o_t	-.0053	-.0027	-.0093	-.0067	1.8866	.1134
	(.005)	(.006)	(.006)	(.005)		

Note: Estimation results for regression (5.1). The coefficient estimates are shown with their belonging standard errors below them in brackets. For The relevance of the GNP growth coefficients and the oil price coefficients the F-test value and corresponding p-value are shown.

The Wald-F exclusion test indicates that the four oil price coefficients o_{t-1} to o_{t-4} jointly are not different from zero when compared against the 5% level. However, they are borderline significant at the less strict, 10% level.

When the effects of using different oil price transformations are researched, we will conduct a more extensive treatment on Granger causality and investigate how it develops over time. Especially since much of the literature suggests a decrease in the link between the oil price movements and macroeconomic variables, which can be observed by means of the Granger causality.

Furthermore, the R-squared of the regression is .1926 and the adjusted R-squared is .1660. These values indicate how well the variance of the re-

[14] Due to the use of four lags, does the regression start four quarters later, at 1948:II.

gressand is explained by the model and is commonly used as the measure for the goodness of fit. Like the Granger causality analysis, it provides a good tool for comparing regressions using different oil price transformations among each other and with the benchmark regression. The higher the values are, the better the model is in explaining the variance of the output growth and hence, the better a transformation captures the essence of the oil price for the output growth.

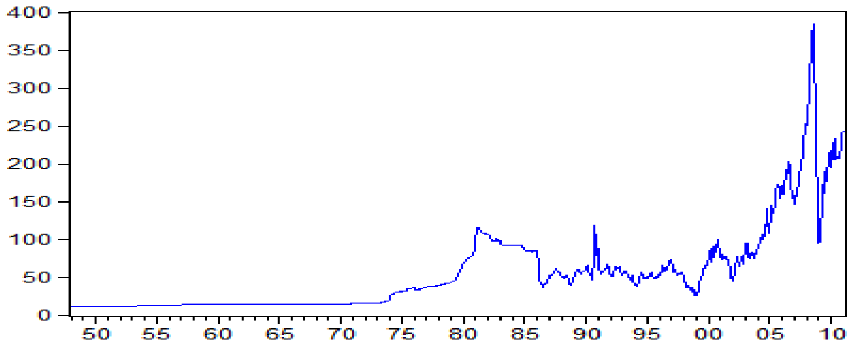
Summarizing we can say that we find some relatively weak evidence for a negative relationship between oil price movements and GNP growth. The estimated coefficients belonging to the oil price measures do suggest that around three to four quarters after an oil price shock the effects are most severe to the output, based on the most negative value for the estimated coefficients that is found around these lags. However, at the conventional significance levels oil prices are not found to Granger cause output, indicating indeed that the found negative relationship is rather weak.

In the rest of this paper we will try to construct transformations of the oil price that have a more causal relationship with respect to output. Furthermore we hope to increase the overall fit of the regressions and to generate relations that are less unstable than the benchmark.

5.3 Introducing the transformations

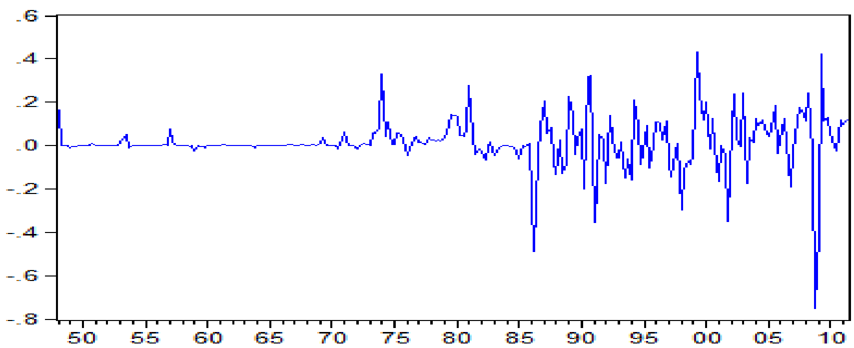
In this section the different transformations for which the performance is investigated within the regression framework are introduced. In order to facilitate the comparisons and discussions we begin by plotting the benchmark oil price series. Hence, in figure (10) the producer price index for crude petroleum is plotted, O_t and figure (11) shows the transformation that is used as the benchmark: i.e. the first log differences of the PPI, denoted by o_t.

Figure 10: Producer price index for crude oil: O_t



Note: Plot with the values of the producer price index for crude oil, denoted by O_t.

Figure 11: Log differences producer price index for crude oil: o_t



Note: Plot with the values of the first log differences of the producer price index for crude oil, denoted by o_t.

Several sources in the literature mention that oil price increases carry significantly more relevance for the output movements than oil price decreases, e.g. Mork(1989) and Hamilton(2003). This observation suggest an intuitive method for transforming the series o_t in order to test the validity of these statements.

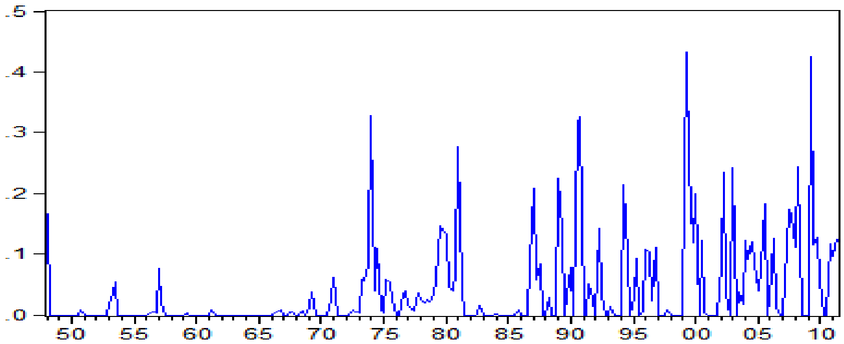
The o_t series is separated in two distinct new series. The first series represents the oil price increases, o_t^+, and the second series the oil price decreases, o_t^-. The construction of these two series is shown in equation (5.2) and (5.3).

$$o_t^+ = \begin{cases} 0 & \text{if } o_t \leq 0 \\ o_t & \text{if } o_t > 0 \end{cases} \tag{5.2}$$

$$o_t^- = \begin{cases} o_t & \text{if } o_t < 0 \\ 0 & \text{if } o_t \geq 0 \end{cases} \tag{5.3}$$

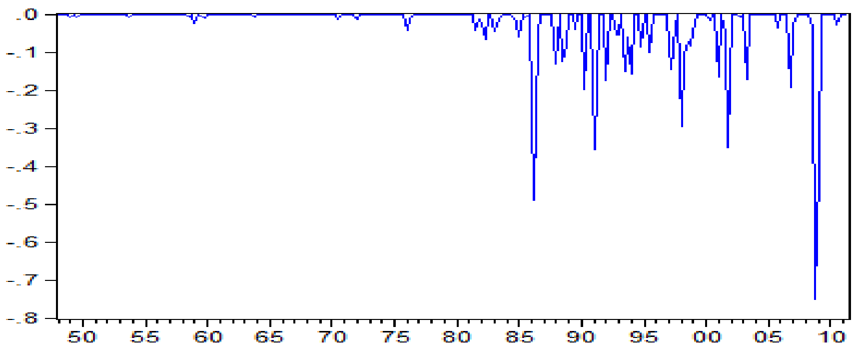
In figures (12) and (13) the oil price increase and decrease series are displayed respectively. By comparing the two series, two important points stand out. In the first place it is obvious that oil price movements were considerably larger after 1973 than before. In the second place we see that *only* the size of oil price *increases* jumped suddenly after 1973; such an increase in magnitude appeared approximately thirteen years later for the oil price *decreases*, in 1986 during the oil glut.

Figure 12: Oil price increases



Note: The o_t^+ series; which is zero in case of an oil price decrease and equals the continuous growth rate in case of an increase.

Figure 13: Oil price decreases



Note: The o_t^- series; which is zero in case of an oil price increase and equals the continuous growth rate in case of a decrease.

Furthermore, Hamilton (1996) has noted that many oil price increases that happened in the post-1986 period were simply corrections of larger price decreases. Whereas using o_t^+ as the relevant oil price transformation works reasonably well before 1986 as suggested by Mork(1989), Hamilton has argued that because of this change in oil price behaviour around 1986, this transformation is no longer an adequate representation.

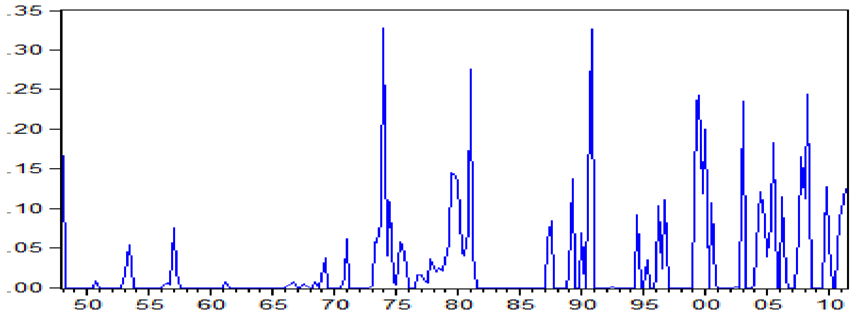
This was his motivation to construct an improved oil price transformation over Mork's o_t^+. In this new measure it is argued that the effect that an oil price increase has on the output depends on the maximum value of the oil price during the entire previous year, instead of just the previous quarter. The reason is that oil price increases probably will have a smaller effect when they correct previous decreases than when they are in fact fundamental increases.

Hamilton's(1996) measure is exactly constructed based upon this belief. His transformation is called the *net oil price increase($NOPI_t$)*. It is constructed by comparing the current value for O_t with its maximum value during the last four quarters. When the difference is positive, the $NOPI_t$ is equal to the growth rate between O_t and this previous maximum. A difference that is negative implies a value for the net oil price increase of zero. The $NOPI_t$ calculation is shown in equation (5.4) and the corresponding series is displayed in figure (14).

$$NOPI_t = \max(0, \log(O_t) - \log(\max(O_{t-1}, O_{t-2}, O_{t-3}, O_{t-4}))) \qquad (5.4)$$

The next transformation that is used in this paper, has not yet been

Figure 14: $NOPI_t$



Note: Plot of the net oil price increases ($NOPI_t$), following the methodology of Hamilton(1996).

analysed within the existing literature. It is based upon the idea that not only the quarter-to-quarter changes are relevant for the output, but also the *level* of values that the oil price takes. For example, car owners are often concerned with the price level of gasoline rather than just the growth rate.

We will conduct a method for determining relevant oil price thresholds, based upon an idea of technical trading in financial markets. One of the most implemented versions of technical trading rules compares the movements of moving averages with different window lengths, e.g. Brock et al.(1992). When the shorter moving average exceeds the value of the longer moving average, the trader takes a long position because of an expected upward price trend and vice versa.

We think that the net oil price increase as suggested by Hamilton might by a relative strong measure since it discards many increases that do not follow its criterion. Therefore we are interested to analyse how well this measure that is based upon moving averages performs, especially when compared with the $NOPI_t$. However, it is important to mention that in theory an unlimited universe consists of oil price transformations that are based on all sorts of comparisons in which also the window size can be varied. Just as in technical trading it might be possible, purely by large numbers, that apparently a very stable and relevant oil price transformations for the output growth is discovered. A research based on many of these series that are arbitrarily constructed might be valuable if one can account properly for these effects of data mining.

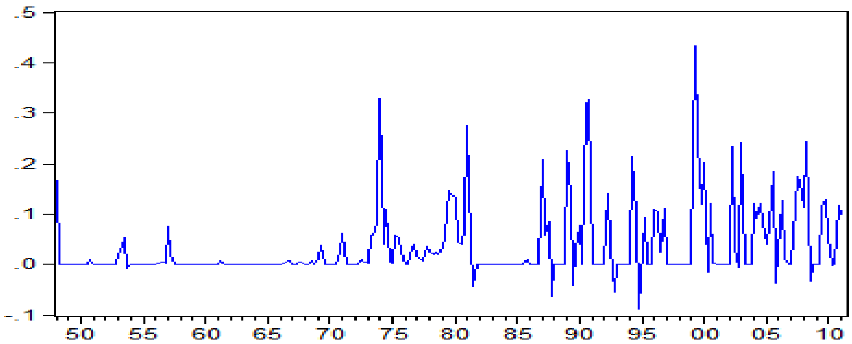
For the construction of the new oil price transformation, we first compute a moving average oil price series O_t^{ma} with a window of four quarters, see equation (5.5). Next, we compare the current value of the oil price, O_t, with the value of this moving average, O_t^{ma}. When the value of O_t exceeds that of the moving average, the new series, denoted by o_t^* takes on the growth rate between O_{t-1} and O_t, i.e. o_t, else it takes on a zero value, see equation (5.6)

$$O_t^{ma} = \frac{O_{t-1} + O_{t-2} + O_{t-3} + O_{t-4}}{4} \tag{5.5}$$

$$o_t^* = \begin{cases} o_t & \text{if } O_t^{ma} \leq O_t \\ 0 & \text{if } O_t^{ma} > O_t \end{cases} \tag{5.6}$$

Figure (15) shows this newly constructed transformation, o_t^*. As opposed to o_t^+ and $NOPI_t$, does this series not consist of solely non-negative values. Negative values are present in o_t^* when the last quarter-to-quarter change was negative but still the value of the current oil price exceeded the value of the moving average, for example because the first two observations used for calculating the moving average were very small. It might be possible that the fact that this series does not completely exclude negative values, provides us with better results than the oil price increases or the net oil price increases. This will be investigated in the next subsection, used for comparing the results of using all these different transformations in the regressions.

Figure 15: o_t^*-series



Note: Plot of the series that is based upon a comparison with the current price of oil with a moving average value.

The next transformation has been suggested by Lee, Ni and Ratti(1995). According to their paper, positive oil price shocks tend to have a larger effect on GNP if they occur in a period that is characterised by calm oil prices compared to a period in which oil prices exhibit a large volatility. Reasons for this could be that oil price shocks in volatile periods can more often be classified as correcting, and hence have less influence. Second, when oil prices have a tendency to move heavily all the time, the effect of a large shock will be most likely less than when those shocks are quite rare; in that case the shocks will be taken more seriously due to their unexpectedness by the the economy.

Lee, Ni and Ratti(1995) construct their new transformation by first modelling the conditional variance, h_t of the oil price with a GARCH(1,1)-process. This conditional variance is calculated for the series consisting of the first log differences of the oil price, o_t. This implies that we consider both the oil price increases as well as the decreases for the conditional variance calculations. Equations (5.7) and (5.8) show how the conditional variance of the oil price movements has been calculated.

$$e_t = \sqrt{h_t}\nu_t \quad \nu_t \sim N(0,1) \tag{5.7}$$

$$h_t = \omega + \alpha e_{t-1}^2 + \beta h_{t-1} \tag{5.8}$$

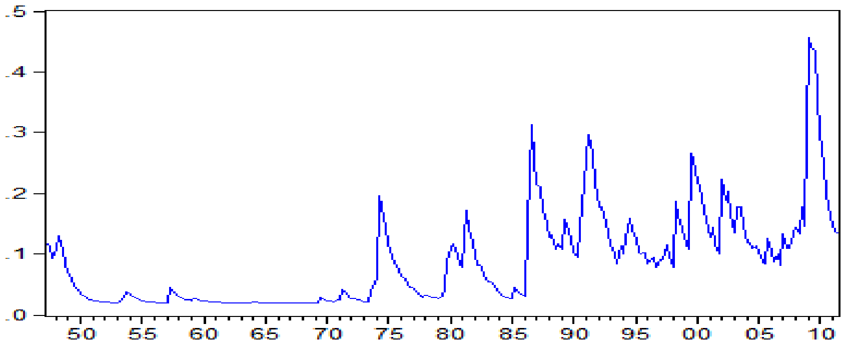
As Mork(1989) and Hamilton(1996), the authors argue the higher relevance of the price increases over the price decreases. Then, in order to construct the new measure which is denoted by o_t^{++}, the positive oil price shocks are divided by the conditional standard deviation $\sqrt{h_t}$ and the oil price decreases again get assigned a zero value. The result of this transformation is that the positive oil price movements o_t^{+}, are now scaled by the level of volatility as determined by a GARCH(1,1)-model. Equation (5.9) displays the exact construction of o_t^{++}.

$$o_t^{++} = \begin{cases} 0 & \text{if } o_t \leq 0 \\ o_t/\sqrt{h_t} & \text{if } o_t > 0 \end{cases} \tag{5.9}$$

In figure (16) the conditional standard deviation, $\sqrt{h_t}$, as determined by a GARCH(1,1) is shown. It shows clearly an increase in volatility after 1973 and again after 1986. Furthermore, historically high values for the volatility are seen after 2005 due to extreme price movements.

The next figure, (17), shows the series o_t^{+} and o_t^{++}. By comparing these two graphs the effect of the volatility-scaling becomes clear. The few positive oil shocks during the fifties are now comparable in size to the shocks after the mid-seventies, when the volatility suddenly increased. Furthermore, the shocks after 1986 are down weighted more heavily than the shocks during the seventies and early eighties. This results in smaller volatility-adjusted shocks after 1986 than during the mid-seventies and early eighties. Hence, after correcting for the volatility, the shock of 1973 belonging to the OPEC crisis, was the most severe.

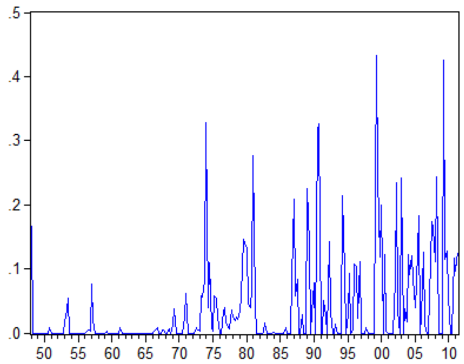
Figure 16: Conditional volatility



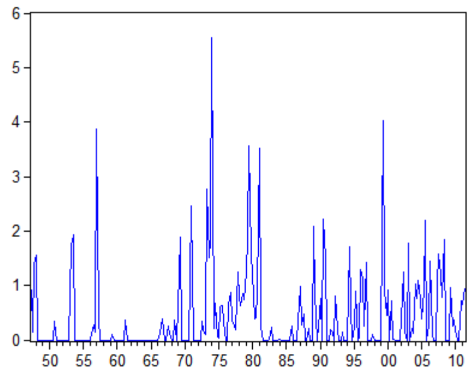
Note: the conditional volatility of the oil price series as determined by a GARCH(1,1)-model: $\sqrt{h_t}$

Figure 17: o_t^+- and o_t^{++}-series

(a) o_t^+



(b) o_t^{++}

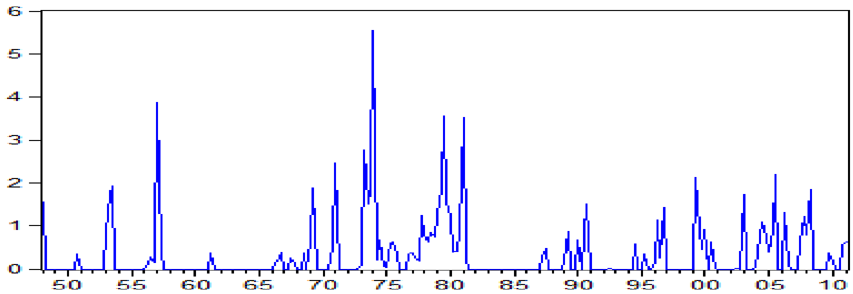


Note: Comparison of the oil price increase series and the oil price increases divided by the conditional volatility.

Finally, we have constructed a new series, called o_t^{**}, that uses Hamilton's $NOPI_t$ transformation and adjust this series for the volatility as has been done in the o_t++-series. Hence the new series is generated by taking the original $NOPI_t$-values and dividing them by $\sqrt{h_t}$, the same conditional variance as used before, see equation (5.10). Compared to o_t^{++}, this series is more conservative since it contains more zeros due to its derivation from the net oil price increase. Furthermore it has similar characteristics as the volatility adjusted series by Ni, Lee and Ratti: the oil price shocks of the fifties are blown up, the shocks of the seventies ware classified to be the most severe and the shocks after the mid-eighties are made smaller due to the largest oil price volatility during that period.

$$o_t^{**} = \frac{NOPI_t}{\sqrt{h_t}} \tag{5.10}$$

Figure 18: o_t^{**} - series



Note: Oil price transformation that is based upon the quotient of the net oil price increase and the conditional volatility.

5.4 Comparison of the transformations

The previous section has introduced the different transformations that are used in this paper. In this section we will analyse the effects of using the different oil price transformations with the benchmark and among each other. In particular, the consequences that the different representations might have on the relevance and stability with respect to output growth are addressed.

5.4.1 Granger causality results

First, the relevance of the oil price transformation on the output growth is investigated. This link is tested by means of bivariate Granger causality tests. In the initial discussion of the benchmark in section 4.2, it was shown that over the full sample of 1947:II to 2011:I, the four o_t coefficients did not jointly Granger cause GNP growth.

Virtually every paper in the literature in which these tests are conducted, does so on only a few different samples, e.g. Mork(1989). However, we argue that both the high sensitivity of the test outcomes to the sample chosen, as well as the fact that most of the established relations exhibit signs of one or more structural breaks, does not provide a solid foundation of conducting the research in such manners, see also Hansen(2001). Moreover, it is due to this sensitivity, possible for the researcher to try fixing a window that empirical proves best his hypothesis.

In our view, a better method for analysing the fluctuations in Granger causality, is by sequentially conducting Granger causality tests with a fixed, moving window. In this manner we simultaneously address the stability of the relationship implicitly and we circumvent the subjectivity of the window size by plotting a range of Granger causality values. Several window lengths have been tested and we have chosen for a window of twenty years. The shorter, ten and fifteen windows were too unstable and volatile for observing clear patterns and changes in the significance. On the other hand, the longer windows restricted the effective data we could show too much.

The bivariate Granger causality test values are computed as the Wald F-test when the four oil transformation coefficients are restricted to be zero. Hence, first the parameters are estimated in the unrestricted model and then they are estimated in the restricted model by setting the oil price transformation coefficients equal to zero.[15] The F-statistic is calculated by comparing the sums of squared residuals of the restricted model with those of the unrestricted model. The used formula is shown in equation (5.11).

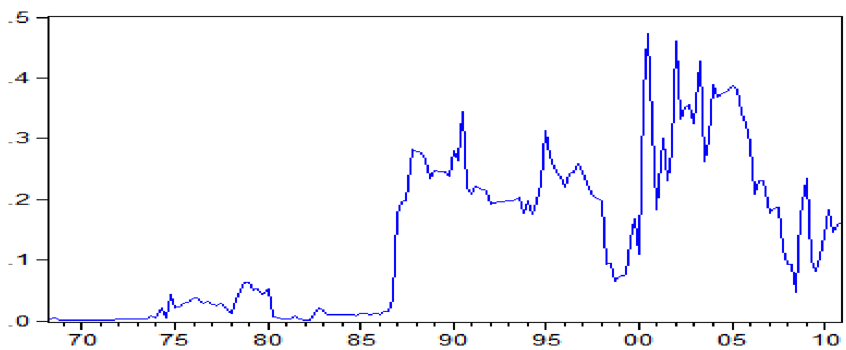
[15]This is implemented by setting the columns in the matrix of regressors, X belonging to the oil price coefficients equal to zero.

$$F(n, T-k) = \frac{(SSR_{restricted} - SSR_{unrestricted)})/n}{SSR_{unrestricted}/(T-k)} \tag{5.11}$$

The correct F-statistic has n and $T-K$ degrees of freedom; n being the number of imposed restrictions[16], T being the number of observations and k indicating the number of regressors, the constant included[17].

Figure (19) shows the development of the Granger causality test for the four coefficients of the producer price index for crude oil in the benchmark, o_t. The y-axis contains the corresponding p-values of the F-test values and the x-axis corresponds to the endpoint of a twenty year interval, e.g. the point 1990:I shows the Granger p-value for the regression over the interval 1970:II-1990:I.

Figure 19: Granger causality test results



Note: p-values of the test that the four oil lags, o_{t-1} to o_{t-4} Granger cause GNP growth, y_t. The Granger causality test is performed sequentially over a 20 year moving window.

The graph clearly confirms some of the established results from the literature. In the intervals from [1949-1969[to [1966-1986] do the four o_t coefficients mostly Granger cause output growth, y_t, at the 5% level.[18]

However, after this period the significance of the link between oil prices and output growth decreases remarkably. The p-values corresponding to the interval-endpoints between 1986 and 2011, fluctuate between .1 and .5.

However, the first OPEC crisis of 1973 does not seem to have a very strong effect initially on the Granger causality between oil and output. The

[16] $n = 4$ in this case.

[17] $k = 9$ in this case.

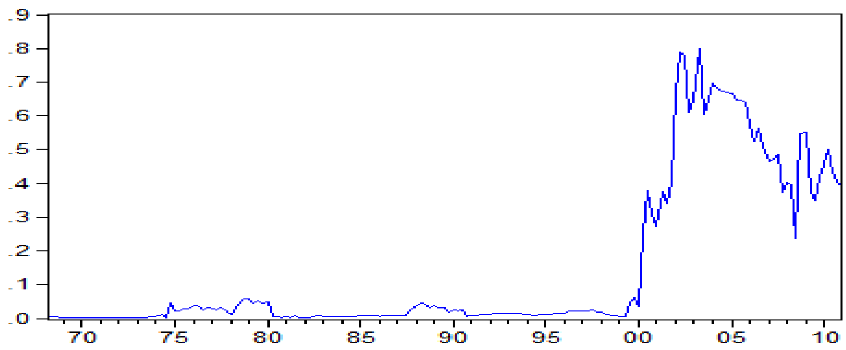
[18] The only exceptions to this occur when the endpoint of the interval lies between the mid-seventies and early eighties. Albeit that significance was still present at the less strict 90% level.

large jump in the graph in 1986 on the other hand, indicates that the oil glut and the associated price drop at that time might have causes a serious decrease in the link between oil and output.

With the following transformations we hope to obtain Granger causality values that have a higher significance and maintain this significance longer, preferably over the entire period. In that instance we would have a stable and significant oil price transformation in terms of Granger causality, hence indicating that it contains more relevant aspects for the aggregate output development than the oil price growth on its own.

Therefore, the first oil price transformation that we have used to test the Granger causality on, is the oil price increase series, o_t^+. Based on the many results in the literature we would expect to observe an improvement in Granger causality when compared to the causality analysis of the benchmark transformation, o_t. The results of the test on the regression using o_t^+ are shown in figure (20).

Figure 20: Granger causality test results



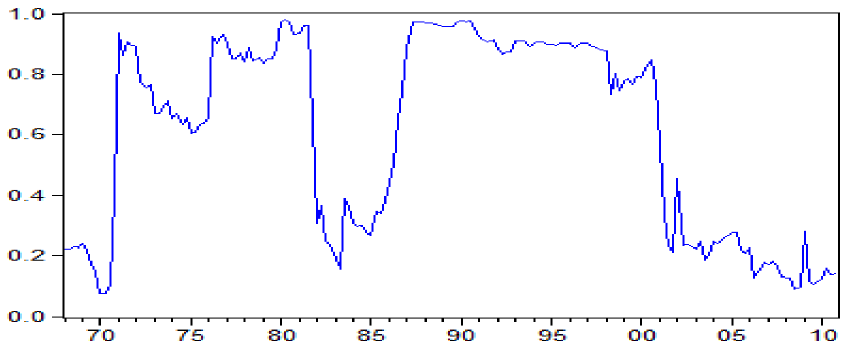
Note: p-values belonging to the Granger null hypothesis $H_0 : o_t^+ \nrightarrow y_t$. The Granger tests are sequentially performed over a 20 year moving window.

Confirming our beliefs, this transformation indicates large improvements over the benchmark in terms of relevance. A significant Granger causality remains present between o_t^+ and y_t until 2000:II enters the interval. At that moment in time an oil price increase of almost 20% from 1999:IV to 2000:I is changed in a decrease of 1.5% from 2000:I to 2000:II. The behaviour of the oil price after 2000 removes the existing Granger causality as found in the period before 2000. Moreover, we have also seen this sharp decline in Granger causality in the benchmark regression is shown in figure (19) after 2000.[19]

[19]It is also possible that around 1980 some characteristic behaviour *left* the moving

Next, for completeness, we have conducted the Granger causality analyses based on the oil price decrease, o_t^-, series. These results are shown in figure (21). As expected, we never obtain p-values below the conventional level of .05[20]. One notable aspect from this figure is the asymmetric behaviour of the causality after 2000 if compared with the previous transformation, o_t^+. Whereas that series rapidly lost its Granger significance do the negative oil price coefficients seem to achieve a stronger link with output growth after 2000. These two results combined might be interpreted as an indication that the economy seems to suddenly react more heavily on oil price decreases and less on oil price increases in the new millennium.

Figure 21: Granger causality test results



Note: p-values belonging to the Granger null hypothesis $H_0 : o_t^- \nrightarrow y_t$. The Granger tests are sequentially performed over a 20 year moving window.

Furthermore, it would be interesting to see whether superior results in terms of Granger causality could be achieved when both four o_t^+ and o_t^- coefficients are included in the regression. This suggested regression is shown in equation (5.12).

$$y_t = c+\beta_1 o_{t-1}^+ + ... + \beta_4 o_{t-4}^+ + \gamma_1 o_{t-1}^- + ... + \gamma_4 o_{t-4}^- + \delta_1 y_{t-1} + ... + \delta_4 y_{t-4} + \varepsilon_t \quad (5.12)$$

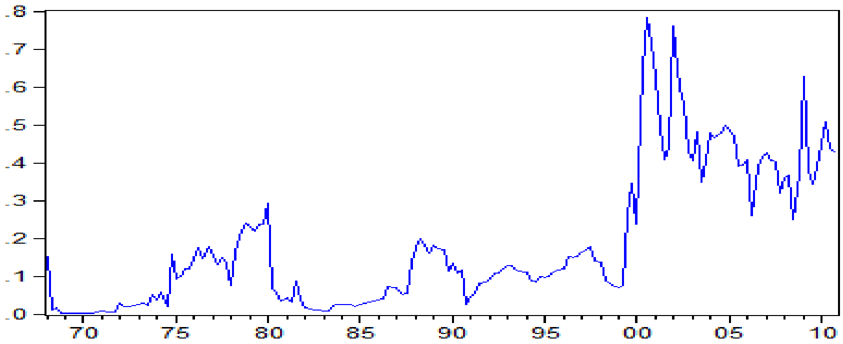
In order to test whether the usage of both transformations in one regression yields an improvement in terms of Granger causality, we test the mutual relevance of all eight coefficients. The results are shown in figure (22).

The figure indicates that no improvements are obtained over solely using o_t^+, when both transformations are used in one regression. The fact that oil

window, causing the strength of the causality to decrease.

[20] Only in a few cases do we obtain a significance at the 10% level

Figure 22: Granger causality test results

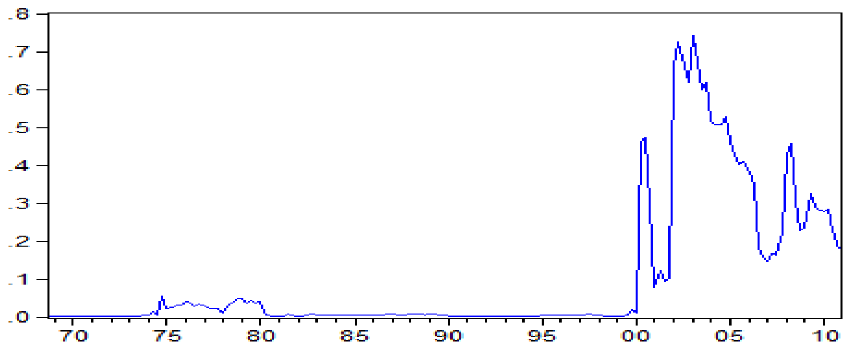


Note: p-values belonging to the Granger null hypothesis $H_0 : o_t^- \& o_t^+ \nrightarrow y_t$. The Granger tests are sequentially performed over a 20 year moving window.

price decreases seemed to improve after 2000 apparently does not help in achieving better results in the combined regression after 2000.

The next transformation tested with the moving Granger causalities is the Hamilton's $NOPI_t$. In figure (23) the results are shown.

Figure 23: Granger causality test results



Note: p-values belonging to the Granger null hypothesis $H_0 : NOPI_t \nrightarrow y_t$. The Granger tests are sequentially performed over a 20 year moving window.

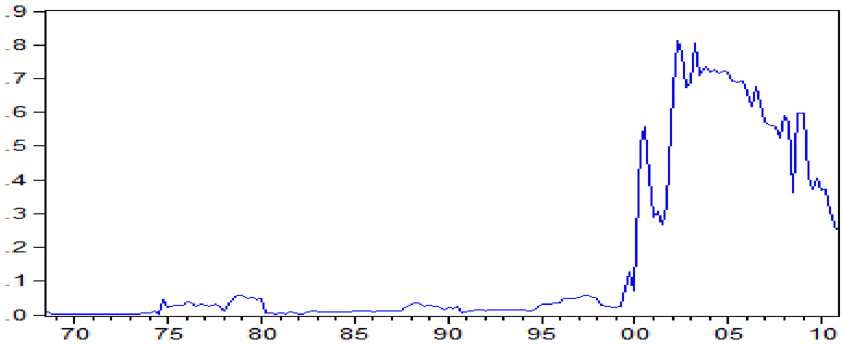
The results from using the net oil price increase are comparable to using solely the oil price increases. However, in the pre-2000 period, the p-values belonging to the $NOPI_t$ series seem to be structurally lower than those of the oil price increase series. Albeit the differences are rather small. The trend that the net oil price increases perform well until 2000 enters the window is comparable to the oil price increases only though.

The next figure, number(24), shows the Granger causality sequence when using o_t^* as the relevant oil price transformation. Again, its general pattern is similar to that of the o_t^+ and $NOPI_t$ series. However, it seems to perform marginally worse than those two transformations.

Next, the Granger causality of the volatility-scaled series by Ni, Lee and Ratti, o_t^{++}, is determined. This sequence is shown in figure (25). By comparing the p-values belonging to this series with the other transformation we have the best performing series in terms of Granger causality so far: those p-values tend to lie structurally below those of the other transformations. Apparently the scaling approach enhances the relevance that these coefficients have on the output growth. Unfortunately though, also for this transformation the strong link between o_t^{++} and y_t disappears after 2000.

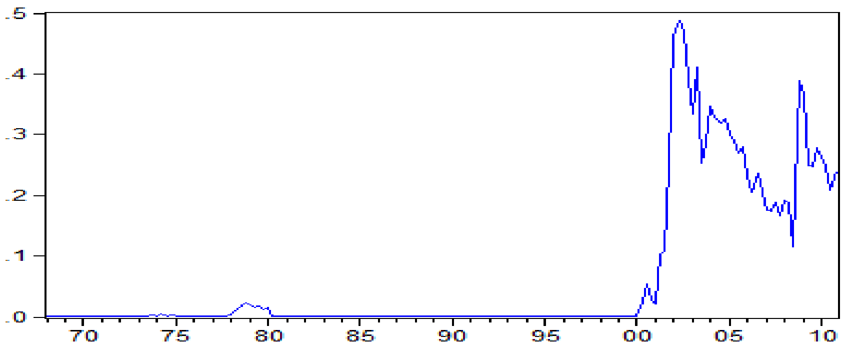
Next, the sequence of Granger causality p-values belonging to the quotient of the net oil price increase and its conditional standard deviation, o_t^{**} is shown in figure (26). Despite a combination of two sensible ideas, does this series not outperform the original series o_t^{++} by Ni, Lee and Ratti in a structural manner. However, together with o_t^{++} this series outperforms

Figure 24: Granger causality test results



Note: p-values belonging to the Granger null hypothesis $H_0 : o_t^* \nrightarrow y_t$. The Granger tests are sequentially performed over a 20 year moving window.

Figure 25: Granger causality test results



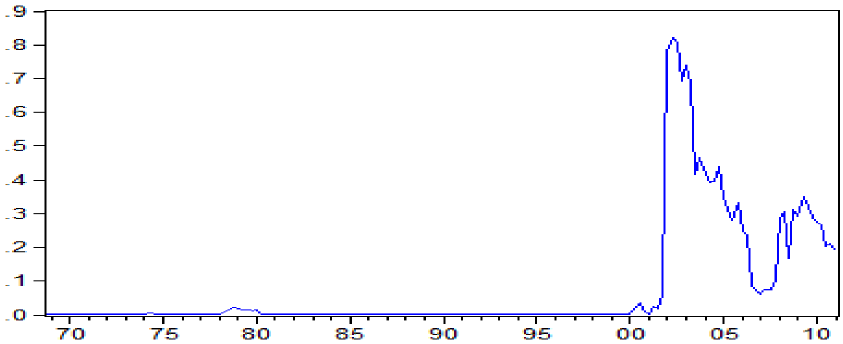
Note: p-values belonging to the Granger null hypothesis $H_0 : o_t^{++} \nrightarrow y_t$. The Granger tests are sequentially performed over a 20 year moving window.

structurally the benchmark and the other transformations.

Finally, for comparison purposes, in figure 27 and 28, the Granger causalities for all different oil price transformations have been plotted together. [21] Figure (27) shows the Granger causality results of the post-2000 period. In this period the transformations o_t^{++} and o_t^{**} structurally indicate the strongest link in Granger causality terms when compared with the other oil price transformations. One of these two transformations almost always takes on the smallest p-values among all transformations.

[21] All but the o_t^- series due to its obvious under performance compared to the other transformations.

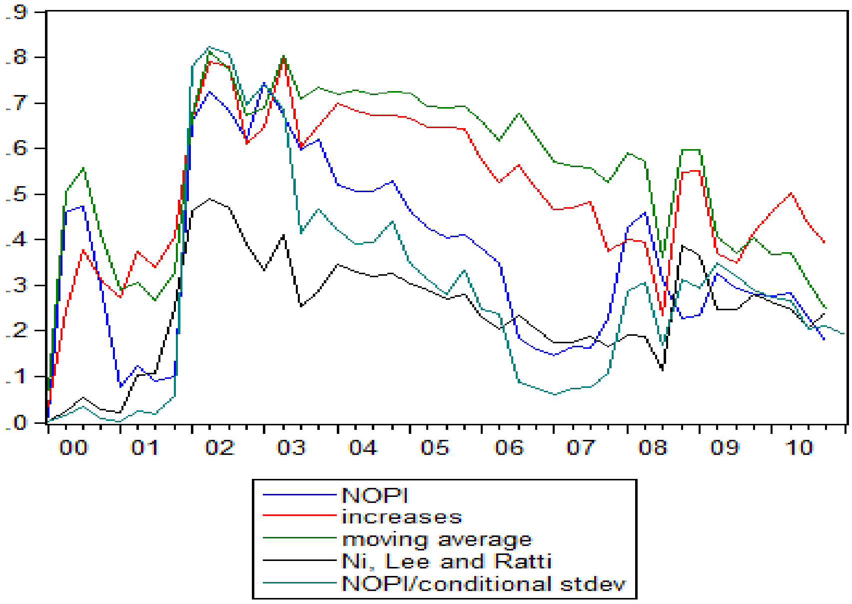
Figure 26: Granger causality test results



Note: p-values belonging to the Granger null hypothesis $H_0 : o_t^{**} \nrightarrow y_t$. The Granger tests are sequentially performed over a 20 year moving window.

The relevance of the net oil price increase for the GNP growth seems to be structurally lower than these two transformations. An even lower link between the transformations and the output growth is present when the oil price increases or the series that is based upon a moving average are used. Finally, the link between regular oil price movements and output seems to be the lowest among all these. Similar results are obtained when we consider the pre-2000 period, which is shown in figure (28). The main difference here is that overall the Granger causality is stronger in the pre-2000 interval than in the post-2000 interval.

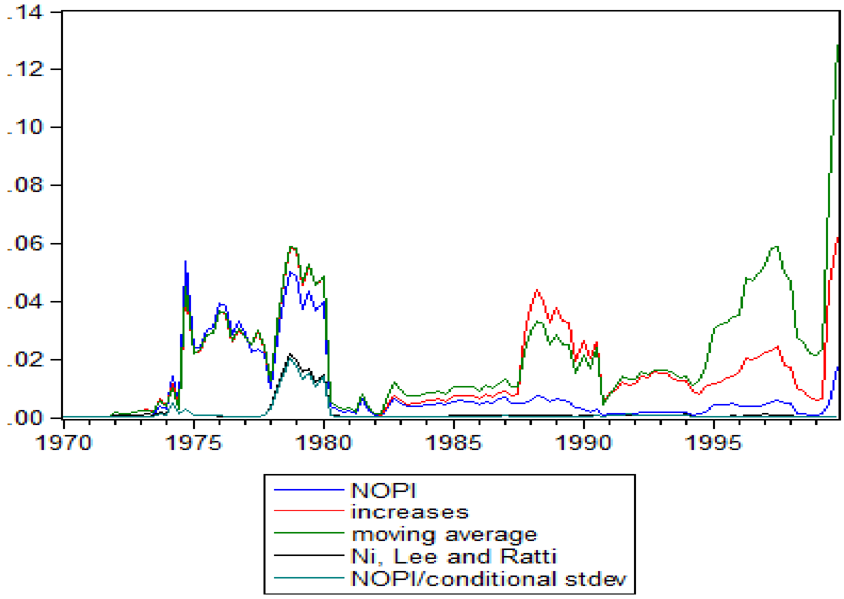
Figure 27: Granger causality test results



Note: Comparison of the Granger causality test results for the different oil price transformations.

We can conclude that oil price transformations that take into account the volatility level show the highest causality towards output growth when used within this regression framework. Furthermore, all the other transformations, except the oil price decreases, show a stronger link with the output than the regular oil price movements. This provides support for the asymmetry hypothesis: oil price increases seem to be more relevant for output growth than decreases. The fact that the two series that take the oil price volatility into account show the highest causality towards output, is an important indication. Apparently oil price shocks have a stronger effect in calm markets than in tumultuous markets on output growth. Finally, the causality disappears after 2000 for all transformations. This could be related to the continuing growth of the oil price since the new millennium. The historically high oil prices in real terms since 2000 could be related to the upcoming of the emerging markets

Figure 28: Granger causality test results



Note: Comparison of the Granger causality test results for the different oil price transformations.

5.4.2 Individual coefficients

Up to this point we have focused on the joint significance between the oil price transformation coefficients and the output growth. Now the attention will be directed towards the individual coefficients of those transformations. Investigating the movements and significance of the individual coefficients might provide additional information related to the significance and stability when different transformations are applied. Similar to the case in which the joint significance is addressed, a moving window of twenty years is used in the analysis in order to observe the behaviour of the individual coefficients over time.

we start by providing information on the individual coefficient values and relevance over time of the benchmark regression in the four panels as shown in figure (41) in appendix B. The two top panels, (a) and (b), display the coefficient values of o_{t-1} to o_{t-4}. In the two bottom panels, (c) and (d), information on the significance of the four oil transformation lags is provided by displaying their individual p-values.

A few elements stand out from these four graphs. First, all the coefficients belonging to the lags of o_t are negative most of the time, somehow indicating a negative link between oil price movements and output growth. Nevertheless, the values of these individual coefficients are rarely large enough to be statistically relevant at the regular significance levels.

Second, lags three and four seem to be more important for the output growth than the first two lags. This seems to be particularly true for those intervals with end dates before 1986.

Third, the behaviour of the coefficient of the first lag is noticeable. In 1973 we see a distinct sudden loss in significance of this coefficient. Furthermore, this coefficient has risen rapidly and steadily in value between 1968 and 1975.

Fourth, the coefficients of lags one and two seem to move opposite to each other in terms of relevance. Commonly, when one of them increases in relevance, the level of relevance of the other coefficient decreases and vice versa. This might indicate a shift in timing of the effect that oil price movements have on the aggregate output. In some periods an oil shock might be absorbed quicker by the economy than in other periods. The economic climate and variables that could be responsible for this, might be interesting material for a future research paper.

Figures(42) to (47) in appendix B, display information on the values and significance of the individual coefficients belonging to the different transformations. The coefficients corresponding to lags one and two of the transformations all seem to behave rather similar to each other and to the benchmark coefficients. They commonly are not individually significant and the coefficient of the first lag increases much in value in the first few years which results in a loss of significance. Finally, they all seem to move in opposite directions in terms of significance, as was noted in the benchmark case. The performance of the four coefficients of the o_t^- series is the worst among all the transformations and the benchmark.

The main difference among the different transformations in terms of the significance of the individual coefficients is found in lags three and four. These coefficients of the o_t^+, o_t^* and $NOPI_t$ transformations are more significant at these lags than at the benchmark lags. Among these, o_t^* performs the worst and is followed by o_t^+ and $NOPI_t$. The two best performing transformations when based upon the significance of the coefficients of the last two lags, are the two volatility-scaled series; o_t^{++} and o_t^{**}. Until 2000 enters the moving window, the significance of the coefficients belonging to lags three and four is comparable among these two transformations. After these intervals, the third lag is more important in the o_t^{++} transformation and the fourth lag carries a higher significance in lag four of the o_t^{**} transformation.

In conclusion we can tell that all transformations, the oil price decreases excluded, perform better in terms of individual coefficient significance than the four benchmark coefficients, o_t. Joint coefficient significance of the four lags seems to be mostly caused by the coefficients of lags three and four and not by those belonging to the first two lags, since the p-values of the last two lags are generally lower than those of the first two lags. This might be an indication of a delayed response of the output growth to oil price movements. Finally, the two transformations that utilize a volatility scaling, o_t^{++} and o_t^{**}, have the highest significance of their individual coefficients among all the other transformations and the benchmark. Again indicating that the volatility level of oil prices seems to be relevant for the link between oil prices and aggregate output growth.

5.4.3 R-squared

The next aspect that we will investigate for each transformation is the goodness of fit of the regression. As before, a moving window of twenty years is chosen. The goodness of fit at every window and for each transformation is determined with the adjusted R-squared.

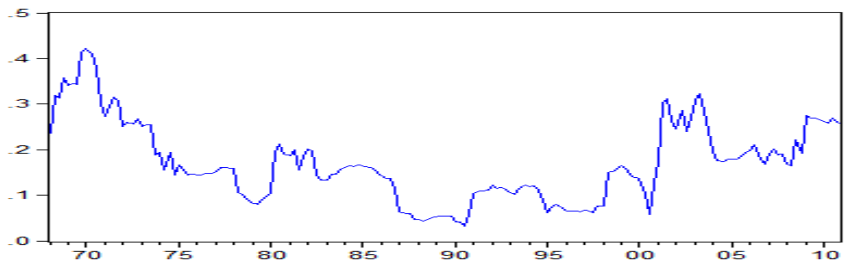
Whereas the regular R-squared improves with every explanatory term that is added to the model, does the adjusted R-squared only increase when the added term is a model improvement that is larger than expected by pure chance. Equation (5.13) shows how the adjusted R-squared is calculated. In this formula n indicates the sample size, p the number of regressors and R^2 is the unadjusted, regular R-squared. For completeness, equation (5.14) shows how to calculate the regular R-squared. The $SS_{residuals}$ refers to the sum of squared residuals and SS_{total} refers to the total sum of squares.

$$\bar{R}^2 = 1 - (1 - R^2)\frac{n-1}{n-p-1} \tag{5.13}$$

$$R^2 = 1 - \frac{SS_{residuals}}{SS_{total}} \tag{5.14}$$

Figure (29) shows the adjusted R-squared values for the benchmark regression. The graph indicate that the fit has been decreasing over time from a value that exceeded .40 for some time to values that lie approximately between .1 and .2. When the 2000s enter the interval, a slight structural improvement in terms of the adjusted R-squared is achieved.

Figure 29: Adjusted R^2

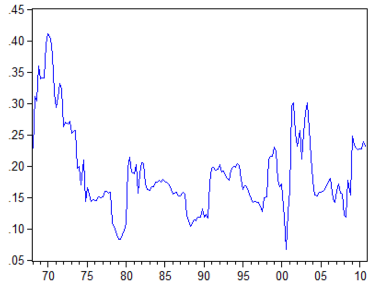


Note: Values of the adjusted R^2 of the benchmark regression. The values are calculated by using a moving window of twenty years.

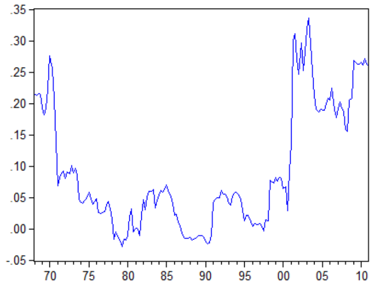
Figure (30) contains the sequences of adjusted R-squared values for all the used oil price transformations. All of them follow a trend over that is comparable to the benchmark regression.[22] However, some transformations seem to produce structurally higher values for the adjusted R-squared than other transformations.

Figure 30: Adjusted R^2

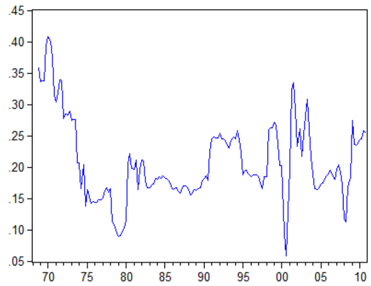
(a) o_t^+



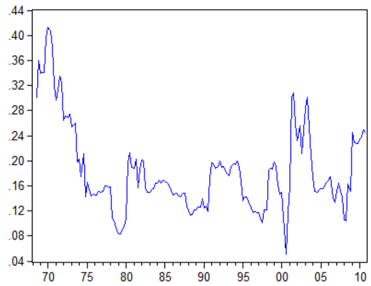
(b) o_t^-



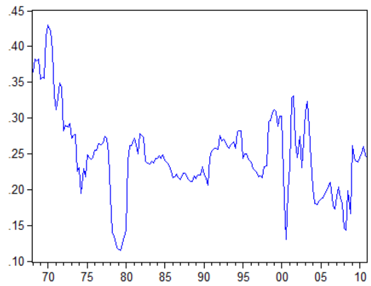
(c) $NOPI_t$



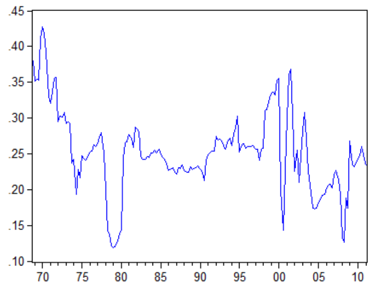
(d) o_t^*



(e) o_t^{++}



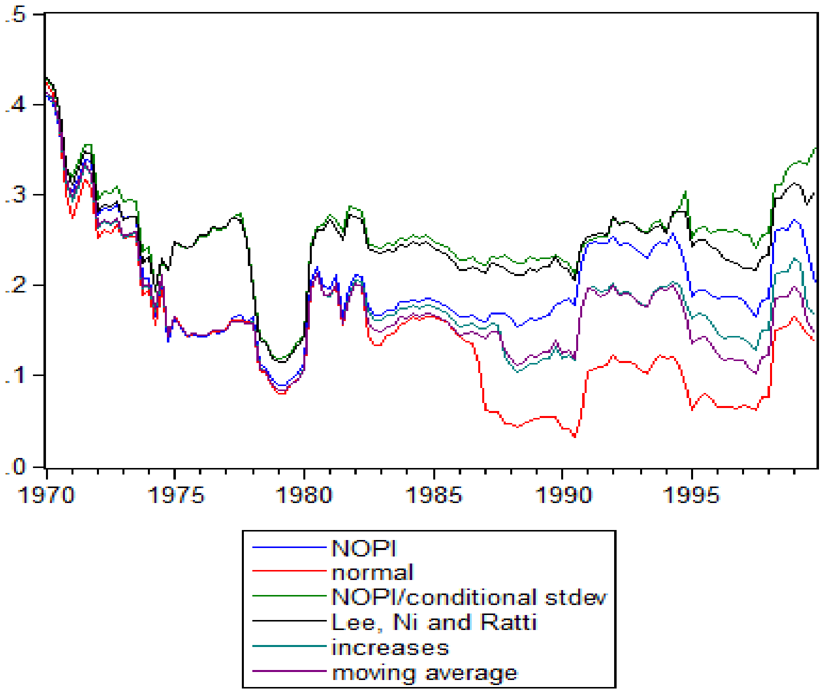
(f) o_t^{**}



Note: Sequences of the adjusted R^2 values for the regressions using different oil price transformations. All values are based on a 20-year moving window.

[22]Except for the o_t^- transformation which has been added for completeness.

Figure 31: Adjusted R^2



Note: Comparison of the adjusted R^2 values in the regressions using the different oil price transformations.

In order to see clearly that some transformations outperform others in terms of their model fit, we have plotted all oil price transformations[23] in figure (31). This graph convincingly demonstrates the out-performance of o_t^{++} and o_t^{**} in terms of their model fit. The next best performing transformation is Hamilton's net oil price increase. This series is followed by the oil price increase transformation and the one based on the moving average. Finally, the benchmark regression shows the lowest model fit overall.

Hence, we have again seen a weakening in the link between oil prices and output. This time because the model fit has structurally decreased over time. All tested transformations outperform the benchmark in terms of model fit, except the oil price decrease transformation. Finally, transformations that take into account the volatility level of the oil price, structurally outperform the other transformations when it comes to model fitting.

[23]Due to a clear under-performance the adjusted R-squared values for the oil price decrease transformation are not included.

5.4.4 Stability

Finally we will analyse how choosing a different oil price transformation influences the stability of the regression. The classical approach for testing stability is by means of the Chow test for parameter stability, see Chow(1969). It is commonly used in econometric research and hence has many variations for fitting in different situations. An extensive overview of adaptations and implementations is provided in Andrews and Fair(1988). However, the major problem of the Chow test approach is that the breakpoint of the test has to be selected by the researcher *a priori.* This implies that a breakdate is either solely based on the researcher's view or is based upon the characteristics of the data, Hansen(2001).

In either case issues arise. First, picking a subjective date can result in a false outcome in case no evidence is found for a break at that point while a break is actually present at an other point. Second, Chow test results are commonly highly sensitive to the chosen breakpoint. Therefore it is possible that researchers reach different conclusions based on equal models and data, which is not desirable.

Hence, the proper objective and scientific approach is to treat a breakpoint as unknown instead of defining it at the beginning. Quandt(1960) has proposed this approach and he defines the maximum value of the sequence with Chow values to be the proper statistic for this purpose. This maximum value is therefore known as Quandt's statistic.

The original Chow test statistic follows a known $F-$ or χ^2- distribution. Hence it is relatively straightforward to evaluate the test outcomes. However, Quandt's statistic does not follow a standard distribution. When Quandt proposed its use in 1960, all the critical values were unknown. The result was that the statistic had no practical value at that time. It took some time before the proper critical values were determined in Andrews(1993). Therefore the test statistic is now commonly referred to as the Quandt-Andrews test.

The Quandt-Andrews test is not performed over the entire sample because the test statistic becomes degenerate at both ends of the sample. Instead the parameter stability is investigated over a sample that symmetrically excludes a part on both sides of the sample. When the full sample is scaled to be uniform, i.e. $[0, 1]$, the sample from which parts are excluded is denoted as $[\pi_0, 1 - \pi_0]$. A common value for π_0 is .15. Therefore, the Quandt-Andrews results as reported in this section also exclude the first and last 15% of the sample.

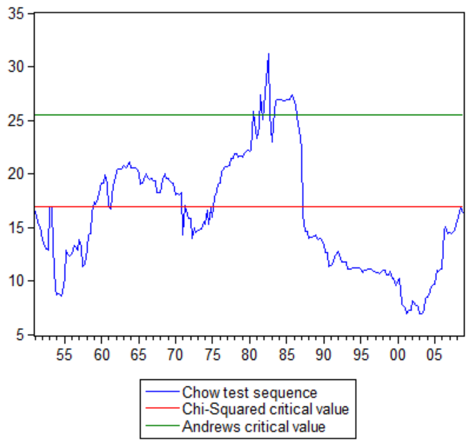
The critical values as provided in Andrews(1993) depend on both the interval parameter π_0 and on the number of regressors being tested for stability. For the regressions in this paper the 10%. 5% and 1% critical values are 23.15, 25.47 and 30.52 respectively. [24]

A proper method for calculating the p-values belonging to the Quandt-Andrews statistic was developed by Hansen(1997). With his method it is possible to asymptotically determine the proper p-values. This method with its proper interpretation and derivation can be found in Hansen(1997). In this work we will refer to these p-values.

[24]For comparison purposes, these three critical values for the regular χ^2- distribution are 14.68, 16.92 and 21.67 respectively. Note that the critical values for the Chow test and Quandt-Andrews test coincide when $\pi_0 = .50$ is chosen.

The Chow test sequence for parameter stability in all regressors for the benchmark regression is displayed in figure (32). For comparison purposes, the 5% significance level for both the χ^2- distribution and the Quandt-Andrews statistic are included. The maximum Chow value, i.e. the Qandt-Andrews test statistic, is 31.23 and its p-value is .0070. Hence strong evidence is found in favour of an unknown structural break in the estimated benchmark parameters.

Figure 32: Quandt-Andrews test results

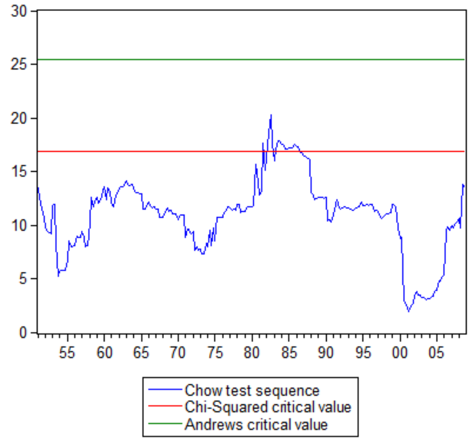


Note: Plot of the Chow test sequence for the benchmark regression with the 5% critical value that is used for the original Chow test and Andrews critical value. The latter is used for testing for an unknown structural break and is compared against the maximum value of the Chow test sequence.

The Quandt-Andrews test results when using the positive oil price transformation are shown in figure (33). We can see clearly that the 5% critical value for an unknown structural break is not exceeded. In fact, also the 10% critical value is not exceeded. Hence, the regression using the oil price increases as the oil price measure has no structural break at an unknown point. This indicates that the relation between oil price increases and output growth when modelled with a linear regression, is more stable than the relation between regular oil price movements and output growth. Finally, this graph illustrates that evidence in favour of a structural break would have been acquired in case a researcher would have picked a breakdate a priori somewhere in the early eighties.

The Quandt-Andrews test results for the regression that uses o_t^* as the oil price transformation are given in figure (34). Similar to the previous

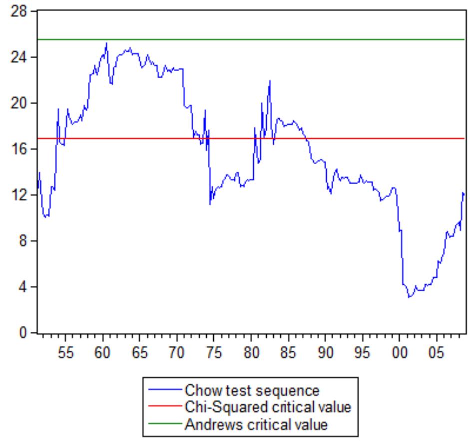
Figure 33: Quandt-Andrews test results



Note: Plot of the Chow test sequence for the regression using o_t^+ with the 5% critical value that is used for the original Chow test and Andrews critical value. The latter is used for testing for an unknown structural break and is compared against the maximum value of the Chow test sequence.

transformation, not enough empirical evidence is found in order to reject the null of parameter stability for an unknown breakpoint at the 5% level. At most we find borderline evidence for a break, with a test statistic of 25.17 and its corresponding p-value of .054. Hence, this relation is more stable than the benchmark regression but not as stable as the regression that uses the oil price increases.

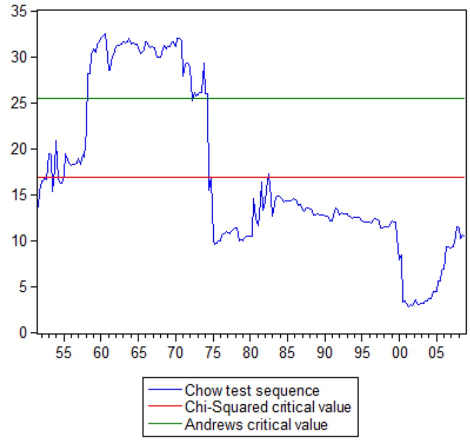
Figure 34: Quandt-Andrews test results



Note: Plot of the Chow test sequence for the regression using o_t^* with the 5% critical value that is used for the original Chow test and Andrews critical value. The latter is used for testing for an unknown structural break and is compared against the maximum value of the Chow test sequence.

The next transformation being tested for its existence of an unknown structural break is Hamilton's net oil price increase. Results are found in figure (35). In contrast with the previous two transformations, does the Quandt-Andrews test indicate sufficient empirical evidence for an unknown structural break. The test statistic is 35.5 with a corresponding $p = .004$.

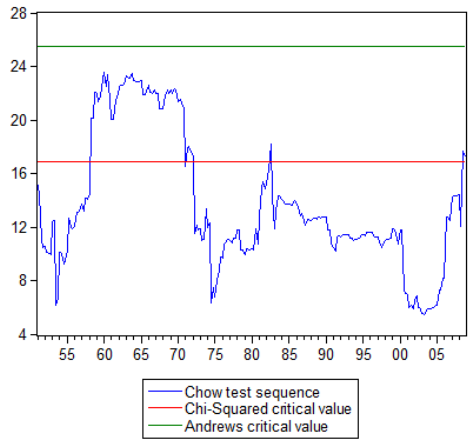
Figure 35: Quandt-Andrews test results



Note: Plot of the Chow test sequence for the regression using $NOPI_t$ with the 5% critical value that is used for the original Chow test and Andrews critical value. The latter is used for testing for an unknown structural break and is compared against the maximum value of the Chow test sequence.

The stability test results for the volatility adjusted oil price transformation as developed by Lee, Ni and Ratti are shown in figure (36). According to the test statistic of 23.6 we have no evidence in favour of a structural break.

Figure 36: Quandt-Andrews test results

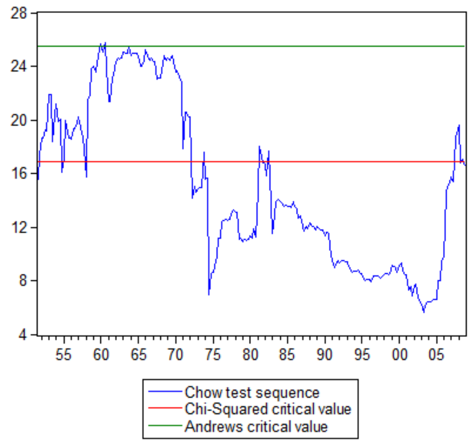


Note: Plot of the Chow test sequence for the regression using o_t^{++} with the 5% critical value that is used for the original Chow test and Andrews critical value. The latter is used for testing for an unknown structural break and is compared against the maximum value of the Chow test sequence.

Finally, the stability test results for the regression using o_t^{**} as the oil price measure are shown in figure (37). At the 5% level we have borderline evidence for this series for the existence of a break.

In conclusion these Quandt-Andrews tests shown overwhelming evidence for the presence of an unknown structural break in the model parameters of the benchmark regression. However, using any of the oil price transformations instead, results in stable model coefficients. The only exception is the net oil price increase, which does contain an unknown structural break.

Figure 37: Quandt-Andrews test results



Note: Plot of the Chow test sequence for the regression using o_t^{**} with the 5% critical value that is used for the original Chow test and Andrews critical value. The latter is used for testing for an unknown structural break and is compared against the maximum value of the Chow test sequence.

6 VAR-analysis

6.1 Introduction

In the previous section we have focused on the effects of the different oil price transformations within a linear regression framework. This implies that the link between oil and output growth was investigated in a rather direct way. However, we have ignored numerous variables which might play a crucial role in the actual interactions. This implies that some of the results as found in the previous section are caused by an omitted-variable bias. Therefore in this section other relevant macroeconomic variables will be included and used within a vector autoregression model.

This section is structured in the following way. We will start by providing a theoretical background for the VAR-models. Then we will discuss the implementation and the results. In particular we will focus on Granger causalities and on generalized impulse response functions.

The vector autoregression (VAR) model is the multivariate extension of the univariate autoregression (AR) models. Its usefulness arises from the fact that when we are dealing with macroeconomic variables, the value of one variable is often not only related to its predecessors in time but also on past values of other variables. Hence, when a dynamic interrelation is present between all these variables, VAR-models might be a good method for representing them, see Lütkepohl (2005).

One of the pioneers in applying a VAR-model for analysing macroeconomic phenomena was Sims in Sims(1980b). He disagreed with the common practice of macroeconomists to apply many a priori restrictions to the data. Instead, he analysed several common macroeconomic themes, such as the Philips curve, without using these theoretical perspectives. In his VAR-model he used six key macroeconomic variables. These variables often have been applied in the relevant literature and are henceforth also included in our research.

6.2 Theoretical background

6.2.1 Introduction

We will now provide some essential theoretical information on the VAR-models. A VAR-model of order p is a model in which every time series is regressed on its own p lags as well as on p lags of all the other time series that are included in the model. Mathematically, a VAR(p)-model with m regressors is defined by equation (6.1).

$$\mathbf{y_t} = \mathbf{c} + \mathbf{\Phi_1 y_{t-1}} + \ldots + \mathbf{\Phi_p y_{t-p}} + \varepsilon_\mathbf{t} \tag{6.1}$$

In this formulation $\mathbf{y_t} = (y_{1t}, ..., y_{mt})'$ is a $(m \times 1)$ vector with the values for the m jointly determined dependent variables. The vector $\mathbf{c} = (c_1, ..., c_m)'$ contains all the intercept terms. The matrices $\mathbf{\Phi_i}$, $\forall i = 1, ..., p$, are the $(m \times m)$ coefficient matrices. Finally, $\varepsilon_\mathbf{t}$ is the m-dimensional vector with error terms of the model. This vector is assumed to follow a white noise process. Furthermore, the covariance matrix is assumed to be nonsingular. [25]

Next to equation (6.1), an other representation exists of a VAR(p)-process. In this representation $\mathbf{y_t}$ is expressed in terms of its present and past error terms $\varepsilon_\mathbf{t}$ and its mean vector $\mathbf{c}$. By rewriting a VAR-model in this manner, impulse response functions can be deducted from it. It is also referred to as the Wold representation due to its origin in Wold(1954). It is displayed in equation (6.2)[26].

$$\mathbf{y_t} = \mathbf{c} + \sum_{j=0}^{\infty} \mathbf{A_j} \varepsilon_\mathbf{t-j} \tag{6.2}$$

In the Wold representation the $m \times m$ coefficient matrices $\mathbf{A_j}$ are obtained with a recursive relation as shown in (6.3). The recursion is initiated with $\mathbf{A_0} = \mathbf{I_m}$ and moreover $\mathbf{A_j} = \mathbf{0}$ when $j < 0$.

$$\mathbf{A_j} = \mathbf{\Phi_j A_{j-1}} + ... + \mathbf{\Phi_p A_{j-p}} \tag{6.3}$$

A crucial assumption that underlies VAR-models is the weak stationarity of the series $\mathbf{y_t} = (y_{1t}, ..., y_{mt})'$. This implies time-invariant behaviour of

[25] Nonsingularity of a square $(n \times n)$ matrix A implies that a square $(n \times n)$ matrix B exists such that $AB = BA = I_n$, in which I_n indicates the $(n \times n)$-identity matrix. Hence nonsingularity guarantees that the inverse matrix exists.

[26] We have to note that the moving average representation is only feasible under the stability assumption. Formally a VAR-process is stable if the reverse characteristic polynomial has no roots in and on the complex unit circle. An extensive treatment of this technicality is provided in Lütkephohl (2005).

the first and second moments of $\mathbf{y_t}$. An important result is that under weak stationarity the impulse response functions converge to zero as the time horizon increases. Empirically, we have to subject all the variables that are candidates for a VAR-analysis to tests for stationarity. In this paper this will be established by executing the Augmented Dickey-Fuller (ADF) test for the existence of a unit root.

When dealing with a stationary and stable VAR(p)-process of the form in equation (6.1), estimation is based on the method of multivariate least squares (LS), Lütkepohl (2005). When we are using an unrestricted VAR-model[27] it can be shown that multivariate LS estimation is equivalent to OLS estimation in each of the m equations in (6.1) separately. Similarly to OLS estimation, does multivariate LS estimation yield consistent estimators that adhere asymptotic normality. Furthermore, the OLS estimator is equal to the ML estimator in case the residuals in the VAR-model are normally distributed.

[27]This implies that all the individual equations in the model contain the same regressors.

6.2.2 Structural analyses

Since a VAR(p) model contains numerous parameters, it might be complicated to rightly interpret the complex interactions and feedback between the variables by looking at the values of all coefficient estimates. Therefore, many dynamic properties of a VAR-model are often summarized by using different types of *structural analysis.* In this research we will use two types of structural analysis: Granger causality and impulse response functions. Both of which are discussed in this part.

6.2.3 Granger causality

Granger has defined a concept of causality that is easy to handle within the framework of VAR-models and it therefore has gained popularity among researchers, see Granger (1969) and Lütkepohl (2005). The main idea is that an effect always follows the cause and not the other way around. Hence, when a variable x has an influence on a variable z, the variable x *should* help to improve the predictions on z. It is said that when a variable or a group of variables, x, helps sufficiently in the prediction of an other variable or group of variables, z, that x Granger causes z, which is usually denoted by $x \rightarrow z$.

This idea is formally implemented by using the mean squared error (MSE) of forecasts. Officially, x fails to Granger cause z, when the MSE of a forecast of z is not significantly different when this forecast is based solely on information of past values of z when compared to a forecast that is based on *both* past values of x as well as on past values of z. More precisely, x fails to Granger cause z when a forecast of z_{t+S} is not significantly better when based on $(x_t, x_{t-1}, ...)$ and $(z_t, z_{t-1}, ...)$, than when only based on $(z_t, z_{t-1}, ...)$.

In mathematical terms Granger causality is explained by equation (6.4). When this equation holds for at least one $h = 1, 2, ...$ then x Granger causes z. In here Ω_t represents the information set that contains all the relevant information that is available until period t. $z_t(h|\Omega_t)$ represents the h-step predictor of z_t which is based on all the information contained in Ω_t. Finally, $\Omega_t \backslash \{x_s | s \leq t\})$ is the set containing all relevant information for the prediction except information on the history of the process x_t. Hence (6.4) tells us that x Granger causes z when the MSE of an h-step predictor is significantly smaller when information is used about x than when this information is excluded. Derivations, characterizations and technicalities of Granger causality testing within a VAR-framework are provided in Lütkepohl (2005).

$$MSE_z(h|\Omega_t) < MSE_z(h|\Omega_t \backslash \{x_s | s \leq t\}) \tag{6.4}$$

6.2.4 Impulse response analysis

In empirical work a researcher is often interested in how one variable will respond to an impulse in an other variable when both of these variables are included in a multivariate system. For this purpose impulse response functions (IRF's) are used.

A reason why IRF's are particularly useful for analysing VAR-results is related to the complicated nature of VAR-models: in a VAR(p) model the higher order cross correlations between y_{it} and y_{jt} for $i \neq j$ is given by a complicated function of the model parameters. Therefore it is difficult to analyse the dynamic relationships between the different series by solely observing these coefficients. IRF's are commonly used instead.

In technical terms an IRF analyses what the effect is over time on a variable $y_{j,t+n}$ in case of the occurrence of an exogenous shock of a size δ on the i-th variable. Hence when $\varepsilon_{it} = \delta$ occurs. Furthermore, it is assumed that the other shocks are zero at the time of this shock, i.e. $\varepsilon_{jt} = 0 \; \forall j \neq i$. An other useful definition of an IRF is to view it as the difference between two conditional expectations, i.e. the difference when we do assume a shock in one of the variables at the initial state and when we do not assume this.

The Wold representation of a VAR-model is used in order to derive the IRF's. In fact the coefficient matrices of that representation give information on the effects of a unit shock in $\varepsilon_i t$ on the other variables. An extensive treatment of these derivations can be found in Lüthkepohl(2005).

However, assuming that a shock only appears in one variable at a time while it is zero for the other variables, might not be realistic. This is because the error terms among the different variables in the model most likely are not uncorrelated. This implies that a shock in one variable is likely to be accompanied simultaneously by shocks in other variables. Hence, in such a situation, we will obtain unrealistic results when we set the shocks of all variables to zero except for the shock of the variable that we want to investigate the responses of.

Usually this issue is resolved by using so-called orthogonalized shocks. In this method as first proposes by Sims(1980b), a Cholesky decomposition is applied on the covariance matrix Σ_ε:

$$LL' = \Sigma_\varepsilon \tag{6.5}$$

In here L is a $m \times m$ lower triangular matrix. The shock $\xi_t = L^{-1}\varepsilon_t$ is now orthogonalized since $E(\xi_t \xi_t') = I_m$. Hence these orthogonalized shocks are no longer correlated to one another, which enables us to conduct an impulse response analysis by using the moving average representation. In equation (6.6) it is shown how these IRF's are properly calculated. It shows the effect of a unit shock on the jth variable in the model n periods in the future, so at time $t+n$. The vector $\mathbf{e_j}$ is a $m \times 1$ vector with a one at the jth place and zero at the other positions. The matrix A_j comes from the moving average representation, (6.2), and L is the lower triangular matrix resulting from the Cholesky decomposition.

$$\Psi_j^o(n) = \mathbf{A_n L e_j}, \qquad n = 0, 1, 2, ... \tag{6.6}$$

Unfortunately, the use of the lower triangular matrix L implies that the IRF's are sensitive to the ordering of the variables in the model. In practice the use of the lower triangular matrix imposes a *recursive* or *causal* ordering on the variables in the system as is shown in (6.7).

$$y_1 \to y_2 \to ... \to y_m \tag{6.7}$$

The ordering in (6.7) implies that the instantaneous values of those variables to the left of an arrow affect the values to the right. However, this relation does not hold in the opposite direction. Stated differently, y_{st} does not have a contemporaneous effect on y_{kt} $\forall k < s$.

The problem with this ordering is that is cannot be determined by purely objective statistical methods. Instead, this ordering needs to be specified by the researcher a priori.[28] Commonly this ordering is chosen based on the specific context of the problem. Furthermore, results of IRF's from different orderings can be compared with one another in order to investigate the sensitivity of these responses to the specific variable ordering.

However, this problem of the ordering, can be resolved by using a Generalized impulse response analysis as proposed in Pesaran and Shin(1997). Their proposed alternative is that, instead of using orthogonalized shocks, an actual assumed distribution of the error terms ε_t is followed. When ε_t is assumed to follow a multivariate normal distribution, the scaled generalized impulse response functions are obtained by calculating (6.8). A full derivation of this generalized impulse response function is provided in Koop et al. (1996).

$$\Psi_j^g(n) = \sigma_{jj}^{-\frac{1}{2}} \mathbf{A_n} \mathbf{\Sigma}_\varepsilon \mathbf{e_j}, \qquad n = 0, 1, 2, ... \tag{6.8}$$

The advantage of this methodology over Sims original suggestion, is the invariance of the IRF's to the ordering of the model variables. Hence, researchers do no longer need to determine subjectively a proper ordering of the analyses.

[28]In fact there are $m!$ possible different recursive orderings.

Finally, we have to mention that in some instances the orthogonalized and generalized impulse response functions coincide with one another. They are equal in case the covariance matrix $\mathbf{\Sigma}_\varepsilon$ is diagonal and in case a shock is given to the first variable $j = 1$. Hence in those two cases $\psi_j^o(n) = \psi_j^g(n)$.

6.3 Implementation and results

The VAR-model as implemented in this paper will consist of the six variables as proposed by Sims(1980b) to represent the macroeconomic system. These variables are the GNP growth, GNP deflator inflation, the unemployment rate, wage inflation, import price inflation and the 3-month Treasury bill rate. This last variable replaces the money supply as measured by M1, which was part of the original six variables in Sims model. Sims himself has suggested to replace M1 by this rate which is explained in Sims(1980a). The seventh variable is the oil price transformation. The VAR-model is estimated based on a quarterly frequency over the period 1950:I - 2010:IV. Just as in the linear regression framework do we utilize four lags, hence yielding a 7-variable VAR(4)-model. We have executed lag exclusion tests that choose the appropriate number of lags based upon minimizing an information criterion. Both Schwarz and Akaike's information criterion choose models containing 3, 4 or 5 lags. However, the difference in the value of the information criterion between these three values is small. Hence, for consistency we will use a VAR(4)-model throughout this entire section. More information on the data is attached in appendix A. All the variables are entered in annual percentage terms.[29]

The augmented Dickey-Fuller test was performed on all these series in order to detect the presence of a unit root. Based upon these results all the variables have been entered in their first log differences in order to remove the non-stationarity. Only the unemployment rate and the Treasury Bill rate have been used in their original form because in these series the null of a unit root was already rejected without making a transformation. For informative purposes, the summary statistics of the six variables that are used in the VAR-model next to an oil price transformation, are given in table (12).

We have also tested if the four non-stationary variables, i.e. GNP, imports, the GNP deflator and the wage level might be cointegrated with one another. This implies that a stationary linear combination of these variables can be found. By using the Johansen cointegration test we find small support for the existence of one cointegration relation at the 5% level. However, we will not use this information since we follow the common method in the literature by using a VAR-model with stationary time series as input. We only vary the oil price measure as input.

[29]Hence the quarterly log differences are multiplied by 400 and the unemployment rate and the T-Bill rate by 100.

Table 12: Summary statistics

	Mean	Std. Dev.	Max	Min	Skew.	Kurt.
$\mathrm{unemployment_t}$	5.75	1.62	10.67	2.57	.68	3.36
$\mathrm{wage_t}$	1.61	2.89	11.76	-6.52	.49	4.29
$\mathrm{imports_t}$	9.16	17.66	97.02	-76.06	-.09	8.73
$\mathrm{inflation_t}$	3.36	2.49	14.45	-0.97	1.36	5.07
$\mathrm{tbill_t}$	4.70	2.91	15.05	0.06	0.95	4.26
$\mathrm{GNP_t}$	3.25	4.02	15.91	-11.40	-0.24	4.65

Note: Summary statistics for the time series as used in the VAR-model over the period 1950:I - 2010:IV

6.3.1 Granger causality results

Two types of structural analyses will be performed within the VAR-framework: Granger causality tests and an impulse response analysis. We will start by conducting Granger causality tests.

Table (13) displays the results from the Granger causality tests. Every row corresponds to a 7-variable VAR(4)-model that uses the oil price transformation as indicated in the left column. The values in the table hence show the results for the hypothesis $H_0 : x \nrightarrow y$, in which x represents the different oil price transformations and y represents the output growth. Hence we test whether a Granger causality exists between the mentioned oil price transformation and the output growth. The Granger causality tests yield a χ^2-value with four degrees of freedom.[30] The right column shows the p-value corresponding to this test statistic.

The values in the table show in the first place that oil price changes do not Granger cause GNP growth when used within this 7-variable VAR(4)-model over the period 1950:I-2010:IV. On the other hand, all the oil price transformations that are considered, at least Granger cause output growth at the 10% level. The only exception is the oil price decrease series which is highly insignificant.

Especially the transformations that use a volatility scaling, o_t^{++} and o_t^{**}, seem to have a strong link with the output growth. The other transformations do not show such high Granger causality as these two transformations but are nevertheless still significant at the 5% level. Therefore they seem to capture important aspects for the GNP growth that is missed when the regular oil price changes, o_t, are used as the appropriate oil price measure in this VAR-

[30]The degrees of freedom have to equal the number of restrictions.

Table 13: Granger causality test results

Excluded	$\chi^2(4)$	p-value
o_t	4.52	.34
o_t^+	14.59	.0056**
o_t^-	5.08	.2800
$NOPI_t$	17.57	.0015**
o_t^*	12.50	.0140*
o_t^{++}	35.10	.0000**
o_t^{**}	38.32	.0000**

Note: Granger causality tests are of the restriction that all lags of the oil price transformation coefficients are zero. The sample used is 1950:I-2010:IV.
* Significant at the 5% level.
** Significant at the 1% level.

model.

The fact that the volatility-scaled transformations show such high causality with the output growth might be an indication that the effect of oil price shocks on the macroeconomy is linked to the volatility of the oil price. When the oil prices have behaved rather calm, shocks can have a greater impact than when an equal shock would hit the oil price in a macroeconomic system that is characterized by highly volatile oil prices. This is exactly the reason why this series has been constructed in the first place by Lee, Ni and Rattti (1995) and it seems to perform well over this sample.

Hamilton(1983) and Hooker(1996) among others have shown, within the context of vector autoregressive models, that the link between oil prices and macroeconomic variables has weakened around 1973. This seems to be true in particular for the link between oil prices and the output growth and the link between oil prices and the unemployment rate.[31]

For comparison purposes we have split our sample at 1973:III/1973:IV as in Hooker(1996). By conducting Granger causality analyses on different sub-samples, we can obtain valuable information on the changing strength in the link between oil price movements and output growth. In table (14) the block Granger causality results over the sample period 1950:I-1973:III are shown.

[31]The existing relations between oil price movements and Sims other macroeconomic variables has not altered that much since 1973. This is due to the fact that no strong relation has been present between those variables to begin with.

Table 14: Granger causality results

Excluded	$\chi^2(4)$	p-value
o_t	18.41	.0010**
o_t^+	19.24	.0007**
o_t^-	2.85	.5832
$NOPI_t$	21.30	.0003**
o_t^*	19.16	.0007**
o_t^{++}	20.80	.0003**
o_t^{**}	22.61	.0002**

Note: Granger causality tests are of the restriction that all lags of the oil price transformation coefficients are zero. The sample used is 1950:I-1973:III.
* Significant at the 5% level.
** Significant at the 1% level.

The values in the table confirm the results from Hooker(1996) and Hamilton(1983): both the regular oil price movements, o_t, as well as all the different transformations, except for the oil price decreases, do Granger cause GNP growth at the 1% level. Furthermore the fact that the χ^2 test value that belongs to the regular oil price movement series lies very close to these χ^2 values of all the different oil price transformations, indicates that over this sample the regular oil prices seem to capture the relevant aspects of the oil for the output as well as this is captured by the different oil price transformations. Overall, we conclude that a very strong link is present between oil prices and the output in the pre-1973 period.

In order to be able to compare our results with with Hooker(1996), we also have performed the block Granger causality tests over the period 1973:IV-1994:II.[32] Those test results are shown in table (15).

From the χ^2 test statistics it is clear that neither o_t, nor any of the oil price transformations do Granger cause output growth at the conventional significance levels. The strongest link that is found is the one between the net oil price increase that is scaled for the volatility,o_t^{**}, which has a p-value of .1832, which is not significant or borderline significant.

These results are remarkable since it implies that the weakened relation between oil prices and the output in the period 1973:IV-1994:II can not be resolved by applying one of the suggested oil price transformations. Hence, not only do we observe a reduction in the relevance between oil prices and

[32]Hence we do not use the full post-1973 period: 1973:IV-2010:IV, because that data was not available at the publishing of Hooker(1996).

Table 15: Granger causality results

Excluded	$\chi^2(4)$	p-value
o_t	3.02	.5549
o_t^+	2.57	.6319
o_t^-	2.85	.5543
$NOPI_t$	21.30	.3047
o_t^*	19.16	.5351
o_t^{++}	20.80	.3133
o_t^{**}	22.61	.1832

Note: Granger causality tests are of the restriction that all lags of the oil price transformation coefficients are zero. The sample used is 1973:IV-1994:II.
* Significant at the 5% level.
** Significant at the 1% level.

output growth in the period 1973:IV-1994:II when compared to the period 1950:I-1973:III, but this reduction is also present in all the different oil price transformations that have been investigated. Therefore, the different aspects that these oil price transformations represent, do not seem to be sufficient for obtaining a significant link between oil and the output over this period.

However, our actual available sample is almost twenty years longer. Therefore in table (16) the results are shown over the period 1973:IV-2010:IV. These results contrast with the results that have been found over the period 1973:IV-1994:II. Because the link between the different oil price transformations and GNP growth seems to be stronger: In the benchmark case, o_t Granger causes output borderline (p-value =.07) Also, the net oil price increase and the net oil price increase divided by the conditional standard deviation are significant at the 5% and 1% level respectively. All the other transformations, the oil price decreases and increases excepted, can be considered to Granger cause output growth at the less restrictive 10% level.

The difference in the level of Granger causality between oil price transformations and GNP growth between the periods 1973:IV-1994:II and 1973:IV-2010:IV is remarkable. Therefore we suspect that the link between oil price transformations and output in the period 1994:II-2010:IV has to be rather strong in order to explain this difference. For this purpose table (17) displays these results for the period 1994:II-2010:IV. Indeed significant Granger causalities are observed between these oil price transformation and the output growth: the regular oil price movements, o_t, are significant at the 10% level, while all the oil price transformations, except for the decrease series,

Table 16: Granger causality results

Excluded	$\chi^2(4)$	p-value
o_t	8.87	.0700
o_t^+	5.39	.2492
o_t^-	7.59	.1078
$NOPI_t$	12.25	.0156*
o_t^*	8.62	.0714
o_t^{++}	8.93	.0627
o_t^{**}	13.55	.0088**

Note: Granger causality tests are of the restriction that all lags of the oil price transformation coefficients are zero. The sample used is 1973:IV-2010:IV.
* Significant at the 5% level.
** Significant at the 1% level.

are significant at either the 5% or 1% level. This seems to indicate that after 1994 the relation between oil and output has strengthened again. Next to that, the different oil price transformations all show a higher causality with the output than the regular oil price movements.

Table 17: Granger causality results

Excluded	$\chi^2(4)$	p-value
o_t	8.47	.08
o_t^+	10.30	.0356*
o_t^-	3.03	.55
$NOPI_t$	15.90	.0032**
o_t^*	14.84	.0050**
o_t^{++}	15.46	.0038**
o_t^{**}	12.43	.0145*

Note: Granger causality tests are of the restriction that all lags of the oil price transformation coefficients are zero. The sample used is 1994:II-2010:IV.
* Significant at the 5% level.
** Significant at the 1% level.

We can conclude that in this 7-variable VAR(4)-model a strong causality exists between oil prices and the output in the period before 1973. This holds for both the regular oil price movements as well as for all the different tested transformations. In the period from 1973 to 1994 no significant

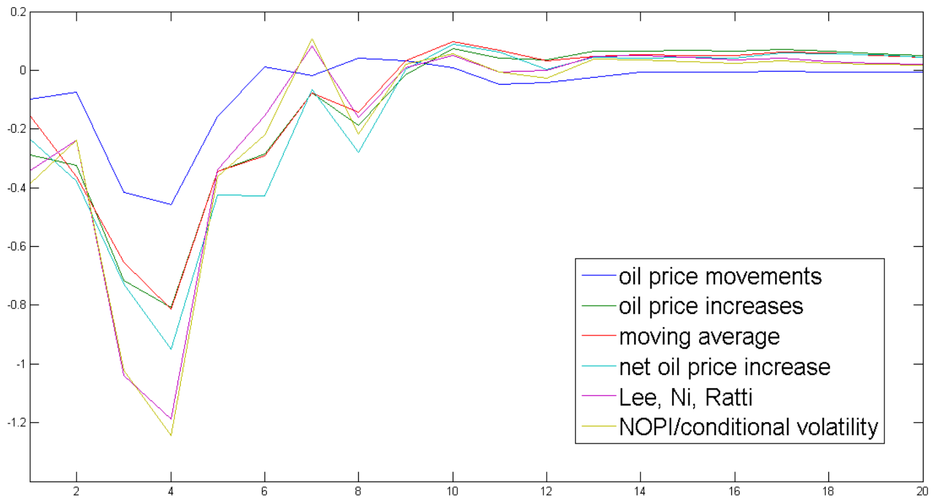
Granger causality can be established between any of the transformations and the output growth. Confirming the breakdown of this relation as shown in Hooker(1996) but more importantly, also showing that none of these transformations is capable of creating a significant relation with the output growth in this period. Finally, the link between oil prices and output seems to increase after 1994, although it does not reach the pre-1973 levels.

6.3.2 Impulse response analysis

We will now analyse the different oil price transformations within this VAR-framework based on an impulse response analysis. As discussed in the theoretical part, two types or impulse response functions exist: the orthogonalized impulse response functions and the improved generalized impulse functions. In this section we will use generalized impulse response functions due to the fact that they are invariant to the ordering of the variables in the VAR-model. [33]

The generalized impulse response functions, showing the effects of a standardized shock in an oil price transformation on output growth, as calculated over the full sample 1950:I-2010:IV, are shown in figure (38). The effects are shown up to 20 quarters, i.e. 5 years.

Figure 38: Impulse response analysis



Note: The generalized impulse response functions, indicating the effects of a shock in the indicated oil price transformation on the GNP growth up to 20 quarters. The sample period is 1950:I-2010:IV.

A shock in any of the oil price transformations has a comparable effect on output growth in terms of the global pattern that will be followed by the GNP growth. We see that a positive shock leads to a reduction of the output growth. It seems to take some time before the effects are fully noticeable.

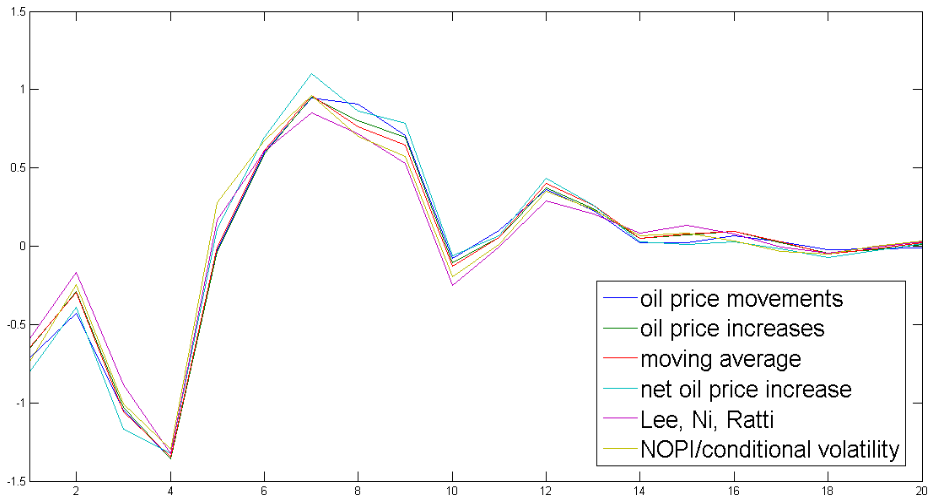
[33]Recall that a generalized impulse function is equal to the orthogonalized IRF in case the effect is investigated of a shock given to the first variable in the ordering.

After four periods the effect is the strongest. Ten quarters after the applied shock the effect on output growth has mostly worn out.

The direction in which the response functions of the different transformations move is similar. However, the size of the movements varies largely among these different impulse response functions. First, all the different oil price transformations have a stronger effect on output growth than a shock in the regular oil price series o_t. Second, the two volatility adjusted series, o_t^{++} and o_t^{**} have the most pronounced effect on output growth. They are followed by the net oil price increase. Finally, the oil price increases and the series that is based upon the moving average show a smaller effect than this net oil price increase. However, they still have a larger effect than the regular oil price series.

As in the previous part, we are interested in how the relations between the different oil price transformations and the output growth might have altered over time. In order to be consistent with the previous part on Granger causality analyses, we have used the same splitting of the sample size for the impulse response analyses. Therefore figure (39) shows the generalized impulse response functions over the period 1950:I-1973:III.

Figure 39: Impulse response analysis



Note: The generalized impulse response functions, indicating the effects of a shock in the indicated oil price transformation on the GNP growth up to 20 quarters. The sample period is 1950:I-1973:III.

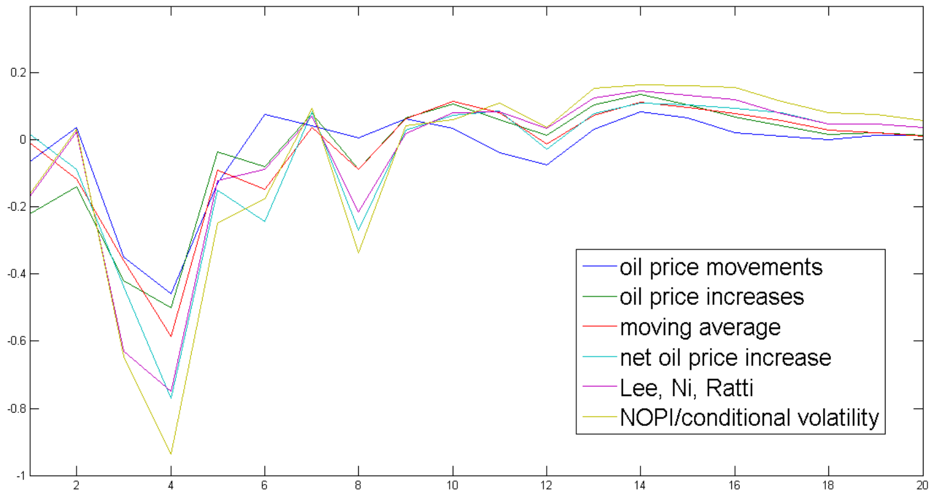
In contrast to the generalized impulse response functions as determined over the full sample 1950:I-2010:IV, are the impulse response functions in this sample belonging to the different oil price transformations very close to one another: all of them have a very strong negative impact on the GNP growth. Again, we see a delayed response in which the negative effect on output is the largest after four quarters, after which it slowly returns to normal values. Furthermore it is remarkable that the impulse responses are positive between 5 and 10 quarters. This could imply that markets initially negatively overreact to an oil price shock and that the positive response values are a correction of this.

The results confirm the results as obtained from the Granger causality analysis. In there we also saw a strong link between the different oil price transformations and the output growth and there was no difference in significance between all the different transformations. In here we can make it more specific and we can see the expected trajectory that the output growth will follow in response of a shock in one of the transformations and all these trajectories lie very close to one another. Hence they have a comparable magnitude and direction. Indicating that no improvements could be obtained by using a different oil price transformation in this period.

Finally the generalized impulse response functions are determined over the period 1973:IV-2010:IV. These are shown in figure (40).

Compared to the generalized impulse response functions over the period 1950:I-1973:III we see major differences. First the effects that a shock in one of the oil price transformations has on the GNP growth now varies widely among the transformations. The transformations that use a volatility scaling show the strongest effect on output. All the other transformations also show a stronger effect on GNP growth than a shock in the normal oil price series. In the second place do we again have some evidence for a breakdown in the link between oil prices and the output after 1973: the impact of the oil price shocks is remarkably lower than in the pre-1973 period.

Figure 40: Impulse response analysis



Note: The generalized impulse response functions, indicating the effects of a shock in the indicated oil price transformation on the GNP growth up to 20 quarters. The sample period is 1973:IV-2010:IV.

7 Conclusion

In this paper we have taken a closer look at the relation that exists between different oil price transformations and the output growth. In the linear regression framework all the oil price transformations, except for the price decreases, showed a stronger Granger causality towards output growth than the regular oil price movements. The strongest link was present between the series as constructed by Lee, Ni and Ratti and the series that divides the net oil price increase by the conditional volatility. However, in all transformations a decrease in Granger causality is seen from the 2000's onwards. We expect that the steady oil price increase from that moment onwards could be related to this. All transformations in the regression framework have been tested for the existence of an unknown structural break by means of the Quandt-Andrews test. Only when the regular oil price movements or when the net oil price is used, we find enough evidence for the existence of a structural beak. This shows that using one of the oil price transformations often results in more stable relations.

In the vector autoregressive model we clearly saw the breakdown at 1973. Before 1973 a shock in any of the oil price transformations had a very comparable effect on the output as based on the generalized impulse response functions. This was a strong negative effect with a delay of three to four quarters. However, after 1973 the direction and timing of the effects is still the same, namely negative and slightly delayed. However, the magnitude of the effect is a lot smaller. Furthermore, this time noticeable differences are present between the different oil price transformations. The transformations that use the volatility again show the strongest effect and the regular oil price movements the smallest effect. Hence the different transformations apparently do capture some important aspects that are relevant for the output that are missed when one just looks at the oil price movements.

In terms of Granger causality we find similar results. Before 1973 all transformations do strongly Granger cause output. After 1973 this link weakens but the transformations perform better than the regular oil price movements. However since 1994 we have indications that the link between oil and the output became stronger again.

In future research low frequency macroeconomic data could be combined with higher frequency oil price data. MIDAS regressions could be used for this. By not discarding information that is inherent to the process of transforming high frequency data to low frequency data, we could obtain additional insights.

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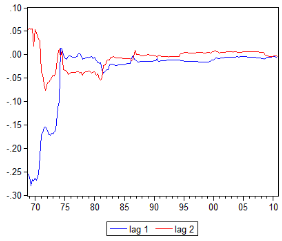
8 Appendix A - Data overview

Import prices: the import value of goods and services, from FRED and prepared by the U.S. bureau of economic analysis, entered in log-differences, seasonally adjusted.
Interest rate: As measured by the 3 month treasury bill rate in the secondary market, from FRED and prepared by the board of governors of the federal reserve system, entered in log-differences, average aggregation method
Price level: Given by the implicit price deflator of the Gross National Product, from FRED, entered in log-differences, seasonally adjusted.
Producer Price Index(PPI) for crude oil: Data from FRED, entered in log-differences, aggregated from monthly to quarterly using average aggregation.
Real GNP: From the Federal Reserve Economic Data database(FRED) at the St. Louis Federal reserve Bank noand prepared by the U.S. bureau of labor statistics, entered in log-differences, seasonally adjusted.
Refiner composite acquisition costs: from the U.S. Energy Information Administration(EIA), entered in log-differences, weighted average of the domestic and imported RAC, average aggregation method.
Unemployment rate: Rate for civilians of age 16 and older, from FRED and prepared by the U.S. bureau of labor statistics, for civilians age 16 and older, seasonally adjusted, aggregated using average aggregation.
Wages: The real compensation per hour for the nonfarm business sector, from FRED and prepared by the U.S. bureau of labor statistics, seasonally adjusted
West Texas Intermediate (WTI): Price of a barrel of crude WTI, data from FRED and prepared by Dow Jones & Company, entered in log-differences, aggregated from monthly to quarterly using average aggregation method.

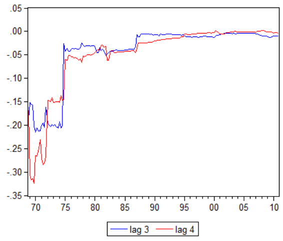
9 Appendix B - Individual coefficients

Figure 41: Information on the individual coefficients of o_t

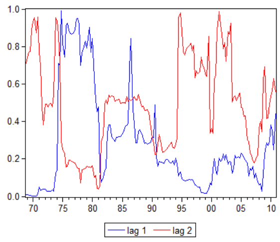
(a) coefficient values



(b) coefficient values



(c) p-values



(d) p-values

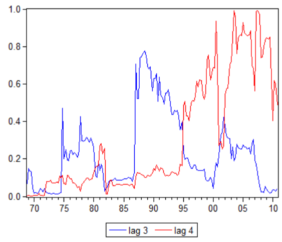
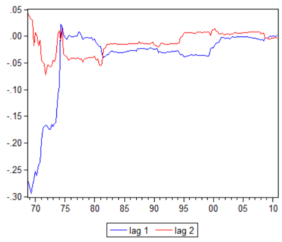
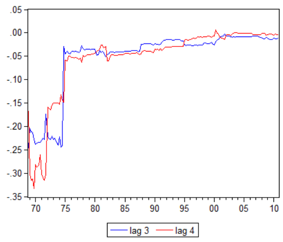


Figure 42: Information on the individual coefficients of o_t^+

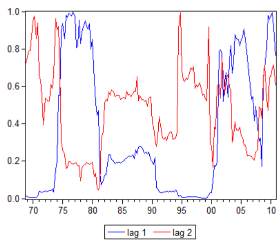
(a) coefficient values



(b) coefficient values



(c) p-values



(d) p-values

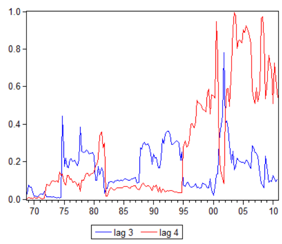
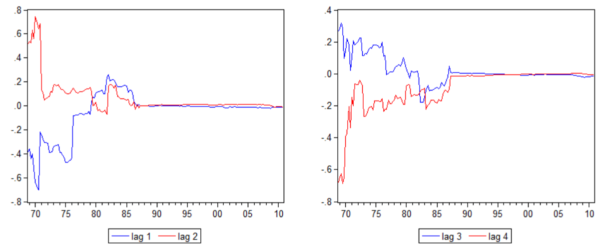


Figure 43: Information on the individual coefficients of o_t^-

(a) coefficient values (b) coefficient values



(c) p-values (d) p-values

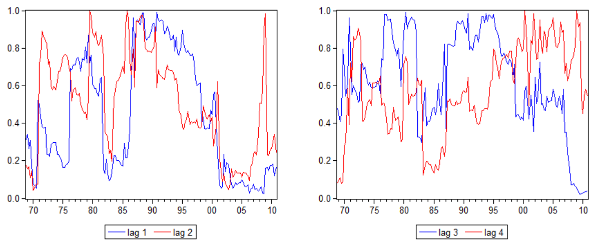
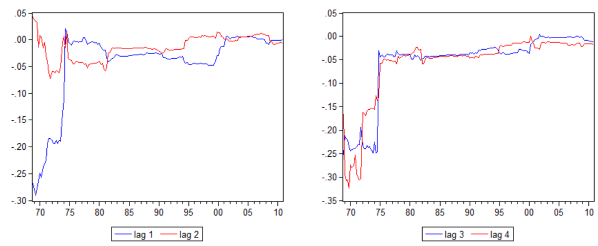


Figure 44: Information on the individual coefficients of $NOPI_t$

(a) coefficient values (b) coefficient values



(c) p-values (d) p-values

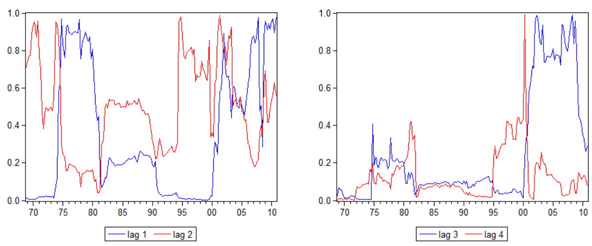
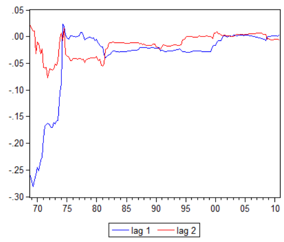
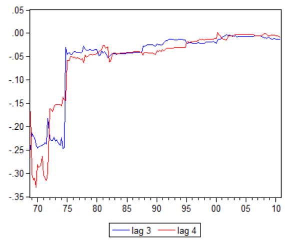


Figure 45: Information on the individual coefficients of o_t^*

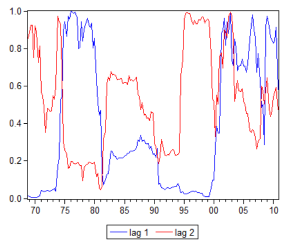
(a) coefficient values



(b) coefficient values



(c) p-values



(d) p-values

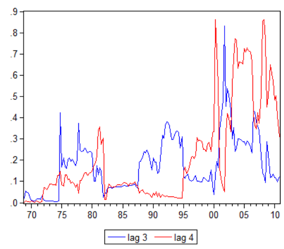
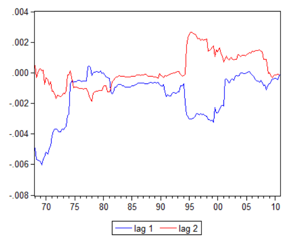
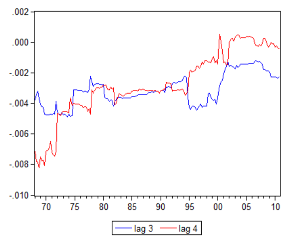


Figure 46: Information on the individual coefficients of o_t^{++}

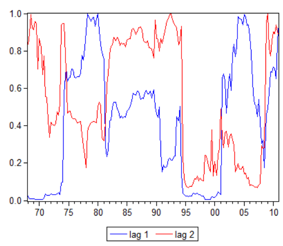
(a) coefficient values



(b) coefficient values



(c) p-values



(d) p-values

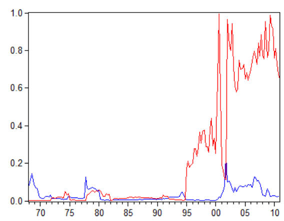
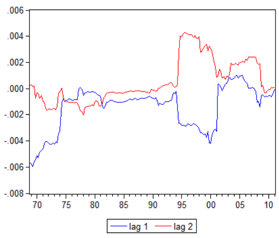
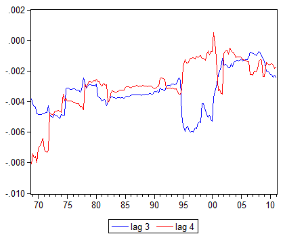


Figure 47: Information on the individual coefficients of o_t^{**}

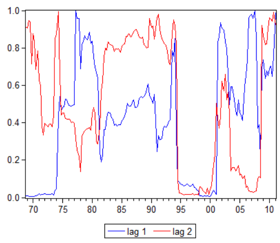
(a) coefficient values



(b) coefficient values



(c) p-values



(d) p-values