Do Oil Prices Signal Shifts in Consumer’s Sentiment?

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Abstract

The present thesis deals with the relationship between oil prices and consumer's sentiment. In the framework of the discussion, an extensive literature review is being presented, elaborating the factors that seem to cause fluctuations in the oil prices and also clarifies the impact of that causal movement on the macro and micro-economy. Furthermore, seasonality adjustment along with the ADF, ADF-GLS and KPSS unit root tests have been adopted, in order to construct a simple bivariate model and test for causality. Using the Granger causality test, we concluded that there is a causal relationship between these two variables, in the time domain. Finally, by incorporating causality tests also in the frequency domain, proposed by the Breitung and Candelon (2006) and Lemmens et al. (2008), we obtained a broader and more cognitive aspect of that causal relationship, both in the short and long-run.
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1. Introduction

The relationship between oil prices and consumption is still a noteworthy matter of discussion and research in the academic scene. The way of one variable causing the other and to what extent, was always a beckon and a tool for the policy makers, to further understand and analyze the existing relationship and hence take the appropriate measures. For that reason, University of Michigan formed the Consumer Sentiment Index (CSI), in order to demonstrate the response that an individual might have, after the presence of a specific event. Such an event could be the employment conditions, a terrorist attack or the fluctuations in commodity prices, factors that can determine CSI’s direction. According to the index, upbeat responses make the CS curve to follow an upward trend, while on the other hand negative responses can make CS to follow a downward trend. So, commodity prices could have a negative or a positive impact on consumers’ sentiment and hence on consumption. To understand further the above relationship, let’s take a look at the energy commodity prices. In particular, high energy prices and more specifically crude oil prices, have contributed to rising food prices, because energy accounts for over one third of the costs of grain production. Between January 2002 and August 2008, the nominal oil price rose from 19.7$ to 133.4$ a barrel. Additionally, increasing oil prices may have an impact on aggregate demand. This operates via a number of channels, such as the reduction of discretionary income, increased precautionary savings and operating cost effects, whereby consumers are deterred from purchasing energy-intensive goods, and reallocation effects. Given this effect that oil prices have upon consumer’s habits, it is also expected to influence consumer’s sentiment.

Purpose of this study, is to investigate the possible channels of linkage between crude oil prices and consumers’ sentiment over the last 40 years for the US economy. For this purpose we are going to use the WTI oil price index along with the consumer sentiment index. The graphical representation of the relationship between these two variables is depicted as follows.

Figure 1. WTI oil prices along with CSI
As we can observe from the above figure, there seems to be a causal relationship between these two variables. That relationship is more obvious in years 1981 and 2008, when WTI oil prices started significantly to rise and almost simultaneously CS started to follow the same trend, in the opposite direction.

So, in order to obtain a more cognitive aspect of the possible causal relationship between WTI oil prices and Consumer Sentiment, we are planning to use a bivariate vector autoregressive (VAR) model and implement the Granger causality test, suggested by Granger (1969). That particular test procedure is based on a set of linear hypotheses, which demonstrate cointegration relationships. To get a deeper knowledge though regarding the WTI and CS causal relationship, we are also going to apply causality tests in the frequency domain, proposed by Breitung and Candelon (2006) and Lemmens et al. (2008). These tests allow new insights, due to the fact that they performed for certain frequencies. Therefore, it is possible to understand whether the assessed causal relationship or the corresponding predictive power spreads at low frequencies (long-run relationship), business cycle or high frequencies (short-run relationship).

The rest of the paper is organized as follows. Chapter 2 briefly reviews the literature, which examines the factors that seem to trigger oil prices and consumers’ sentiment and finally the relationship that oil prices have both with macro- and microeconomy. Chapter 3 is devoted to the methodological framework that is going to be implemented. In Chapter 4 we illustrate the data sources and apply the econometric analysis. Finally, Chapter 5 presents a discussion regarding our empirical findings, along with the derived conclusions.
2. Literature Review

Studies have shown that consumer’s sentiment could be affected mainly by inflation and employment conditions. However, consumers seem to be impacted by geopolitical events such as wars and terrorist attacks but also by the fluctuation in commodity prices. On the other hand, energy prices and especially crude oil prices are a key determinant of an economy, since it accounts more than the half of the costs of grain production. Therefore, increasing oil prices may have an impact on aggregate demand. In the following pages, a detailed literature review is going to be presented by introducing and analyzing the main factors that seem to contribute to a shift in consumer's sentiment and make oil prices to fluctuate over time.

2.1. Consumer's sentiment and consumer's sentiment index (CSI)

Consumer's sentiment is an economic indicator which measures the degree of optimism or pessimism that consumers feel about the overall state of the economy and their personal financial situation. In particular, it shows how confident people feel about the stability of their incomes, factor that seems to affect their economic decisions, such as spending activity. The result of that activity echoes to the general economy, determining the shape of it.

Michigan's University Consumer Sentiment Index (CSI), is one of the most widely followed measures that assess U.S. consumer confidence. It begun in 1940 as an annual survey, in 1952 became quarterly and finally in 1978 a monthly survey. Michigan's University CSI is based on 500 phone interviews conducted throughout a month and comprises of five questions, two of which project the present situation of a household economy and the remaining three, presents the future expectations. The two questions regarding the present conditions, ask the respondents if it is the right time for them to purchase major household items and whether the current situation is financially better or worse than a year ago. On the other hand the three questions concerning the expectations, are asking if the respondents think that the business conditions and a country's economy will become better or not in the following months and if in a year will be better off financially. Many states that one of the drawbacks that Michigan's survey has, is due to the fact that is based mainly on the personal financial situation of a household and is not closely tied to labor market. As CSI is being used now for several decades, there are still many questions that researchers try to answer, which are going to present in the following pages.
The factors that could trigger consumer's sentiment have long been discussed and analyzed through the years, but nobody seems to have found the exact reasons that lead the consumer, to take its final decision. Researchers still try to find how and in what extend CSI is a tool for the forecasters to predict the evolution of the economic activity. In the literature there seems to be two main groups. The first believes that indexes are of minor value (see Fuhrer, 1993; Garner, 1991; Hymans, 1970), while the second group believes that sentiment indexes are useful because they improve forecasts of consumption during exceptional periods, where wars or monetary shocks have been observed. The second opinion is the one that prevails (see Garner, 1991; Matsusaka and Sbordone, 1995; Carrol et al., 1994, Fuhrer, 1993; Bram and Ludvigson, 1998), but due to the complexity of the mind and the fact that fluctuations in CSI's forecasting power occur from time to time (see Fuhrer, 1993; Golinelli and Parigi, 2004), it makes it difficult for the researchers to come to a consensus. So, the question rises is how exactly could the Consumer's Sentiment Indexes (CSI), predict personal consumption?

As Campbell and Mankiw posit, in an economy there are two types of consumers. The first called the "life-cyclers", who plan and try to keep their consumption and saving levels approximately the same, over their entire lifetimes and on the other hand the second one, who follow a "rule of thumb" and set consumption equal to income. In an economy where these two types of consumers exist, sentiment might be a good indicator that can be used for the forecast of household spending. In a research made by Carroll, Fuhrer and Wilcox (1994) is mentioned that, when the signals of the economy are positive, life cyclers' optimism boosts consumer sentiment. On average, this optimism will be vindicated and income will rise. When it does, rule of thumbers' income will increase too (Carroll et al., 1994). In order to test this hypothesis Carroll, Fuhrer and Wilcox (1994) estimate consumption regressions in which household spending depends on lagged sentiment as well as on expected change in income. They actually found that lagged sentiment remains significant in the consumption equation, suggesting that it is a direct determinant of household spending. On the other hand lies an opposite belief, that sentiment simply foreshadows the overall state of the economy without being an independent driving factor in the economy. A good interpretation could be the one that, when consumers are optimistic about general economy, their interview responses are optimistic as well and that, on average, can cause an increase on spending.
Consumer's sentiment indexes reflect people's expectations about both non-economic and economic factors in the future and that makes it difficult for them to have a good explanatory power in forecasting consumption. Fan and Wong (1998), studied the relationship between consumer’s sentiment and household spending for the city of Hong-Kong, from 1985 to 1996. The results of this study indicate a negative correlation, despite the rapid economic growth, which has significantly increased people's income. To meet Hong-Kong growth, the immigration of workers was more than mandatory. So it did, more and more unskilled workers from mainland China came in the city of Hong-Kong to meet the demand. Workers of minimal education and minimum job qualifications were trying to compete for low-end jobs, which actually cause a decrease in wages. Hence, because the unskilled workers became a majority in Hong-Kong, it is very possible the most of the telephone interviews made during that period, reflects the pessimism that these workers felt about their economic future. Although income is one of the main factors that can determine consumers’ sentiment, it is obvious that there is something bigger behind consumer's sentiment and spending relationship.

Katona’s (1975) entrepreneurial research gave an insight into psychology and how this can determine and influence consumer's sentiment. He said that in ordinary times, the importance of CSI in explaining economic activity can be offset by other indicators, while it may become significant in the presence of unusual events or periods characterized by shocks that are possible to change in a way consumer's behavior.

![Figure 2. Impact of short-term events on consumer sentiment in the USA](image-url)
As showed through figure 2, consumer's sentiment does being influenced by extraordinary events in the short-term, but that seems not to influence its long-term attitude except from 02/2006 and on, where financial crisis initiated. To state Katona's (1975) opinion about the influential behavior of psychology in consumer's sentiment, Throop (1992) built a model describing USA's economy during ordinary times that seems to collapse during the Gulf War. In line with Throop, Garner (2002) found that the 1987 crash in the US stock market impacted consumer's sentiment by making it move independently from current economic conditions. The question rising here is, in what way consumers are getting informed about these changes that seems to affect their sentiment?

Katona (1975) indicated the importance of mass media information and communication processes to explain the relative stability of consumer sentiment (see also Zullow, 1981). Each one of us has different educational background and possesses information that no one can tell that are going to be utilized in a similar way. The affect that information could have on an individual, determines the path one choose to follow with the consequences of that decision burdens himself, the general economy and vice versa. Coppejans et al. (2006) posed the power that policy announcements may have on individual's beliefs, about future prices. According to their findings, positive or negative policy announcements could change permanently the individual's beliefs, making him to either start or not purchasing certain goods. On the other hand, announcements could have modest effects on consumption, if an individual starts to believe that the measures have taken are temporary or are not going to be implemented.

Furthermore, as Katona (1975) states through his pioneering work, consumer's spending depends on the capacity and willingness to consume. As far as the psychological theory is concerned, willingness to consume cannot be explained only by the reaction of consumers to economic variables. In this view, a decrease in sentiment can cause a decline in consumption that cannot be predicted by economic variables, such as income or GDP. Even if consumers' financial situation remains stable, an uncertainty concerning the future can lead to a decline in consumption, as a rise in the uncertainty reduces the tendency to consume. Coppejans et al. (2006), by studying cigarette consumption on different US regimes using a Garch model, found that in areas with high price volatility the consumption of cigarettes was lower than that of regimes with lower price volatility. So, uncertainty seems to be a key determinant of consumption, since it shifts in consumer's sentiment, leading him eventually to its final decision to either purchase or not.
2.2. Factors that affect oil prices

Every commodity price fluctuates over time and that movement is due to some factors that can be predictive or not. As world's energy depends, almost exclusively, on oil production and supply, energy commodities such as oil, seem to be very volatile in changes. The factors that cause these changes are going to be analyzed from hereafter.

An important factor that can move oil prices upwards or downwards is the amount of oil reserves exist, which can determine the supply and demand of that good. The organization of the petroleum exporting countries (OPEC) is accounted for the production and supply of the 40%, of the world's oil. Although the non-OPEC suppliers are 50% larger than OPEC, they are incapable of controlling the price of oil due to the lack of sufficient reserves.

![Proven Reserves](image)

Figure 3. World proved oil reserves by country

At that point the role of inventories must be distinguished. When consumption exceeds supply, inventories can store the excess capacity and sell it when the markets allow it. On the other hand when consumption exceeds demand, then incremental demand has to be met, driving at the same time oil prices to a new level. But it is not only the amount of the existed reserves and the inventories. There are numerous other reasons that can determine the price of oil and that reasons could be physical ones, such as the geological formation in which oil can be found, the location of the reserves and finally, the extraction costs.
Climate is one of the driving factors which can influence oil prices. Seasonal changes in weather have an impact on the demand for oil. During the winter, where the days are cooler, more heating oil is consumed. On the other hand warmer days, induce people to use more gasoline because they get off from their houses more often, driving their vehicles. To measure the demand for energy needed to either cool or heat a building, we use the cooling degree days (CDD) and heating degree days (HDD). It is a measurement relative to a base temperature, above which a building needs no heating or cooling.

In his research, Considine (1999) tries to investigate the possible linkage between gasoline and jet oil with cooling and heating degree-days. The result shows that, the demand for gasoline and jet oil is not sensitive to temperature changes, while the same does not apply to the electricity consumption. When temperature rises and climate becomes warmer, more and more people make use of air conditioning systems to maintain the indoor temperature. The use of that auxiliary equipment requires electricity and hence greater consumption of fossil fuels used to generate that power.

In addition as climate getting warmer, may also cause a reduction in the efficiency of power production, of nuclear and many other fossil fuel power plants, due to the fact that these plants use water in order to maintain their temperature. Linnerud et al. (2011) states that as climate gets warmer, power plants will lose of its thermal efficiency and more frequent shutdowns are going to be happened. As colder the water is, the efficiency of generator is stabilized at high levels, meaning that less fuel is utilized as an input. According to Linnerud et al. (2011) findings, if the earth's temperature rises by 2 degrees and due to the efficiency loss that is going to be occurred, 30 TWh of power per year will get lost and that amount of power loss, have somehow to be replaced.

Climatologists generally agree that world's climate changes, as time goes by and for some of them there is evidence that, from 1960 and on, climate does getting warmer. Smith and Livezey (1999) argue that there is been an increase of one-half of one degree, in average annual temperature in the lower 48 states of the U.S.A, since 1960. On the other hand, Balling states that there is no significant change in temperature, since 1932. As we mentioned before, oil consumption is quite sensitive to temperature, primarily because it cause changes in electricity demand and hence to the consumption of certain fossil fuels. U.S. Energy Information Administration (EIA), through its annual energy review presents the total energy consumption of the states and also presents the types of fuels used to generate the needed power.
According to figure 4, from 1950 to the beginning of 1970, oil consumption kept rising steadily and that probably is due to immigration of workers, from all around the world, to the big cities of USA. The highest oil consumption is been located around 2007. After that point started to decline, probably because of the economic crisis and the impact that this crisis had on world's markets. One more think that we can observe from figure 4 is the fact that, although petroleum is the prevailing fuel, natural gas, nuclear and other renewables started to step forward in that consumption race, showing that world's consumption trends begin somehow to change and probably that happens due to environmental or other policies started to implemented.

For that reason, each country's legislation is very important factor due to the fact that can determine, not only the environmental framework in which every participant must be committed to but also the prices of goods that are capable of driving the economy. In the United States for instance, almost every state and city has different price on oil and gas. That happens because of the taxation that accounts for approximately 12%, of the price an individual has to pay at the pump.
Beside the fact that oil reserves and climate can cause fluctuations on the oil prices, unforeseeable events, such as wars, terrorist attacks and hurricanes can also drive prices to a different new level. In 2005, because of the hurricane Katrina, the price of a barrel of oil increased by three dollars and the 19% of US oil production, hit as well. At that time, oil supply was disturbed immediately, but demand remained the same, inducing eventually prices to go up to 70$/bbl. One more event causing oil prices to increase happened in 2008, where concerns raised about the war in Iraq. Prices went up to 136$/bbl and that, according to many economists, happened because suppliers had no guarantee that the oil cargo will be actually delivered.

![Figure 5. Historical oil price fluctuations due to events happened](image)

The above figure depicts the fluctuations of the oil prices, from the late 1970s up to 2012. It is obvious that wars and other crisis could cause the price of oil to move upwards or downwards, depending on geopolitics and the nature of crisis itself. In the case of Iran-Iraq and the Persian Gulf wars, price followed an upward trend mainly due to the fact that, since 1990, Iraq and Kuwait accounted for almost 9% of world oil production. Especially as far as the Persian Gulf War is concerned the oil prices doubled within few months because there were concerns that the conflict might have an impact on Saudi Arabia too. On the other hand in the case of the East Asian crisis, from its initiation and on, oil prices kept declining.
In the July of 1997, South Korea, Thailand and other countries dealt some serious stresses on their financial systems, causing the dollar price of oil to fall below 12$/bbl by the end of 1998. In 2004 and 2005, due to the impressive global economic growth, world oil consumption grew 5mb/d\(^1\), inducing the steady increase of the prices over that period. The main factors that probably caused that rising in oil prices may be the impressive growing demand, the several of the oil fields that had already reached maturity and the oil peak hypothesis which seemed to be up to date.

Understanding what causes fluctuation in oil prices can be very confusing for people outside commodities market. Recession is a leading indicator that can affect oil prices, by decreasing the demand for certain goods. When a consumer, for instance, sees his wage cut off, one of the first things that will do is to minimize his expenses, which could be gasoline and furniture purchases. By decreasing spending, demand for oil and its products starts to decline too, as fewer goods getting delivered from the manufacturers to the consumers and hence oil prices are getting lower. One more factor that is related to the above mentioned and can cause the oil prices to decrease, is the exchange value of the dollar. The currency in which oil is being traded internationally, is dollar and how strong or weak dollar might be, could also have an impact on oil demand and hence to oil price.

How exactly oil prices affect macro economy and vice versa are subjects that we are going to analyze further, through the next sub-section.

2.3. Oil prices and macro-economy

Oil price changes, is a leading factor that can determine world's economy. An increase in oil prices could have a serious impact on world's economy and especially on oil-importing countries, such as Europe and United States. About 40% of the petroleum that United States consumed in 2012 relied on net import. As U.S. Energy Information Administration states, there is a decline of imported oil from 2005 and on, mainly because of the improvements made in efficiency and the changes in consumer behavior, but there is still more for the U.S. to do in order to minimize its risk exposure.

\(^1\) \text{md/d stands for million barrels per day}
Literature mentions about two level effects that taking place, almost spontaneously, during the interaction of oil prices with macro economy. The first level comprises the direct impact that oil price change might have directly on consumer prices and that occurs mainly due to the inflation. The second stage includes the indirect effects or the second round effects, on consumer prices. That effect occurs in cases where the cost of producing goods and services, using oil derivatives as an input, raises and due to that movement, changes in the retail prices seem to be observed. Another interpretation of the second round effects would be the one that, due to an increase in a price of a good, consumer may find hard to consume the same quantity and for that reason, it is possible to seek for a substitute. The above effects describe the general framework of the oil price-macro economy relationship. But how exactly oil prices interact with macro economy?

Although previous research does not show any dominant theoretical mechanism, there are few state in which way may oil affect macro economy. One of those mechanisms is the inflation effect of oil price increases and the impact that this could have on macro economy, through the so-called real balance and the monetary policy channels. The real balance channel is the one that, an increase in oil prices will lead to inflation and that consequently will drive aggregate demand to a decline, due to the change of money's purchasing power. On the other hand, the monetary policy channel, through monetary authority's response to the oil prices movement, could exacerbate further or not the impact that the oil shock already had on the economy, either by tighten or loosen its policy. Barsky and Kilian (2002, 2004) argued that, monetary policy was responsible for the 1973-74 oil price increase that caused a subsequent decline in output too. Additionally, Askari and Krichene (2007) indicate monetary policy as a leading factor that has powerful effect on oil markets. More specifically through their results show that monetary policy variables, such as interest rates, can determine the course of the economy, due to its significant impact on oil demand.

Except from the real balance and the monetary policy channels, there is another mechanism that links oil to macro economy and that occurs in case we are viewing oil price, as an import price. When oil prices increase, there is an income transfer from the importing countries, such as the United States, to oil-exporting countries. The initial response of the economic agents, to this price increment, would be the reduction of spending, leading eventually to a decline on the aggregate demand (Mehra and Petersen, 2005).
As we previously mentioned, the first round effect that oil price has on macro economy entails the change on retail prices due to the inflation. Many where those who tried to find the possible linkage, between the oil prices and inflation and Hooker (2002) definitely, was among them. In his study, Hooker (2002) through statistical tests from 1962-1980 and 1981-2000, found that the linkage does exist and it is significant in the earlier period, but not in the later one. Jacquinot (2009) also stated through his assessment of the inflationary impact of oil shocks in the Euro Area, that changes in oil prices are of significant importance for the understanding of inflation on the short run, but it becomes more complex on the long run. Furthermore, Castillo et al. by analyzing the relationship between oil price volatility and average inflation concluded that, when oil volatility getting higher induces also higher levels of average inflation.

Although there is a proven relationship between oil prices and inflation, there is also a relationship between inflation, recession and interest rates that could make the impact that oil shocks have on macro economy, more severe. Inflation is the constant increase of prices of goods and services in an economy. In the face of inflation, banks trying to adjust the interest rates in order to increase the demand for money and hence spending. In case the banks could not be able to smoothly adjust the interest rates, relatively to the inflation rates, for a long period of time, recession follows since economy discourages spending and promotes saving. Hamilton (1983) by using data from 1950-1980, concluded that there is a relationship between the oil prices and recession and more specifically he stated that all U.S. recessions, caused by a rapid incline of oil prices. The same opinion with Hamilton share, Hoover and Perez (1994) and more recently Dhawan and Jeske (2006) who also state that, from 1973 and on, almost every incline of energy prices had been followed by a recession.

On the other hand there is a theory posing that, oil price shocks can lead to recessions also due to the uncertainty, which an increase in oil price can trigger. Pindyck and Rotemberg (1984) and Hamilton (1988, 1999) afterwards, suggested that uncertainty, can raise the cost of specific durable goods, reducing at the same time the demand for them and eventually leading the economy to a recession.
2.4. Oil prices and micro-economy

In the previous section, where we analyzed the relationship of the oil prices with macro economy, we mentioned that from 2005 and on there is a decline in net oil imports for the United States, fact that mainly attributes to the increased efficiency and change in consumer's behavior. But how exactly we, as individuals, switched to this new way of living?

Since oil is a dominant traded commodity, changes in its price could have significant effects for oil producing countries and also for countries that are highly dependent on oil. A possible way to get a better insight into the microeconomic impact of oil price fluctuations is to better focus on some economic principles, such as the elasticity and the supply and demand analysis of the oil and its derivatives. According to economic theory demand is derived from desire when three important factors meet each other and these are the strong desire, the necessary purchasing power and the power to take decision. This becomes quite obvious if we think the decisions we make in everyday life regarding the purchase of a good, such as bread, furniture, a car or a house. How big or small the purchasing power of an individual is, determines the result of his decision and in this situation is either to proceed and buy or retain his money.

According to economists, there is a strong relationship between price and demand of a good or service. When more and more people desire the purchase of a good and at the same time the supply remains constant, an increase in the price of this particular good occurs, making eventually its purchase harder and harder. That could happen only in the case we assume that all the other factors remain constant (ceteris paribus). If we make that assumption, then when the price of a product or service price goes up, the demand for that product or service would go down and vice versa. So, ceteris paribus assumption makes it easier to understand the relationship between two variables, such as oil price and consumer demand and also to forecast the result of that co-movement.

To make prediction in a real life situation though, is a little different due to the variety of the factors that also participate in that relationship and can determine the shape of it, such as consumer sentiment, expectations and uncertainty, that we also have to take into account. In general, as the cost of energy rises, consumer's budget getting squeezed and as a result the total consumption of energy reduced. On their study, Mehra and Petersen (2005) tried to investigate the relationship between personal consumption and oil prices in the United States. The results show a non-linear relationship, leading to the conclusion that an incline in oil prices has definitely a negative impact on personal consumption, but the opposite does not apply.
On the other hand, Bernanke (2006) stated that the recent decline occurred in energy prices, contributed to a higher consumer confidence and higher household purchasing power. But where exactly the truth lies? Maybe there is something else, a time-variable factor, which might be capable enough to determine the personal consumption.

Consumer preferences may change in the future, causing elasticity estimation to change as well. Except from the changes that may occur on consumer preference though, rising fuel price also create incentives for consumers to purchase higher-efficiency residential or automotive energy systems. Edelstein and Kilian (2009) shed light on how fuel prices affect automobile consumption, in the United States. By analyzing and trying to explain consumers' response towards higher fuel prices, concluded that the overall demand for cars remained almost steady, however there is an increase in the demand for higher-efficiency small cars, rather than energy-inefficient large cars. Although this conclusion seems to get positive results for the U.S. economy, actually is not and that is because U.S. automobile industries, especially in the 1970s, tend to produce fuel-inefficient large cars, such as SUVs. To meet the demand, an increase of foreign automobiles occurred, inducing at the same time the domestic automobile consumption to a decline. Odusami (2010), by analyzing the impact that oil price changes could have on the consumption-wealth ratio for the U.S. households, concluded that it is smoother and more flexible, compared to the past 30 years. That occurs because nowadays, consumer has a wider range of alternatives available as far as the fuel consumption is concerned and that is attributed again to the change in consumer preferences and needs, which constantly seem to change as years go by.
3. Methodological Framework

To investigate the relationship between oil prices and consumer's sentiment, first we are going to test the time series for stationarity through the ADF, ADF-GLS and KPSS unit root tests and then a granger causality test is going to be implemented, in order to demonstrate the causality existence between the two variables. Finally and in addition to the granger causality test, two frequency domain causality tests proposed by Breitung and Candelon (2006) and Lemmens et.al.(2008) will be employed, to understand further the effects that this particular causal relationship has on the short and long run.

3.1. Stationarity

The process, in which the statistical parameters do not change over time, is called stationarity (Challis and Kitney, 1991). Stationarity is used in time series, where under certain procedures the non-stationary raw data transformed into stationary ones. An example could be the economic data often used, that contains non-stationary price levels. In literature, any time series can be stationary when properties such as mean and variance do not follow trends and stay constant over time. The most important of the properties though, is the auto-correlation function (acf) that depends solely on the lag and not on the time at which function was calculated. In general, any time series ($Y_t$) can be called as stationary when certain requirements are being met, regarding the statistical parameters:

Mean,

$$E(Y_t) = \mu$$  \hspace{1cm} (1.1)

Variance,

$$Var(Y_t) = E(Y_t - \mu)^2 = \sigma^2$$  \hspace{1cm} (1.2)

Auto-correlation,

$$Cov(Y_t, Y_{t+k}) = E[(Y_t - \mu)(Y_{t+k} - \mu)] = \gamma_k$$  \hspace{1cm} (1.3)

In the case where there is not a simultaneous satisfaction of the above three criteria, time series $Y_t$ is being characterized as not stationary. Additionally, any time series that has an upward or even a downward trend, or in the case where seasonality exists, are indicative factors showing that the time series are not stationary.
There are two levels of stationarity, the truly or strict stationarity and the second order or weak stationarity. In a strict stationarity all the higher-order moments, including mean and variance are constant over time. In particular, in a strictly stationary stochastic process the joint statistical distribution of $Y_{t_1+\pi}, \ldots, Y_{t+\pi}$ for all $t$ and $\pi$ is the same with the joint statistical distribution $Y_{t_1}, \ldots, Y_t$, meaning that all moments of all degrees are the same. Furthermore, is worth mentioning that because $(Y_{t_1}, Y_{t_1})$ is the same with $Y_{t_1+\pi}, \ldots, Y_{t+\pi}$, the joint statistical distribution is not being depended on the values of $t_1$ or $t$, but on the distance between $t_1$ and $t$. Strict stationarity processes are very hard to be seen in everyday life. On the other hand, the second order or the weak stationarity is more commonly used. In weak stationarity the statistical parameters, such as the mean and variance, do not depend on $t$ and the auto-correlation function can only depend on the lag $k$, as showed in the equation below.

$$\text{Cov}(Y_t, Y_{t+k}) = \gamma_k$$

(1.4)

So, the first step as far as the analysis of the time series is concerned, is to check whether our data are stationary. In literature, there are two general approaches that can indicate if the data samples that we use, are stationary or not and that approaches are the parametric and the non-parametric one. Parametric approaches usually used in the time domain frame, by making assumptions about the nature of the system or data. On the other hand, the non-parametric approaches used by researchers working in the frequency domain frame and unlike parametric, in non-parametric approaches no assumption can be made. The term "parametric" refers to certain tests, such as t-tests used to determine by hypothesis testing or assumption making, if the data set that we are using is normally distributed.

There are two options regarding stationarity testing. The first one is by drawing the graph of the data series, which is the easiest way to observe the existence of variations or fluctuations that indicate non-stationarity, such as the cyclical fluctuations, irregular variations and seasonality. The second option belongs to the parametric approaches and it is by applying unit root tests, a procedure that we are going to present in the upcoming pages.

So, in order to analyze and test data we apply stationary tests, such as the Augmented Dickey-Fuller (ADF) test, the Dickey-fuller GLS (DF-GLS) test and also Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root test. These tests are going to be further analyzed in the lines that follow.
3.2. Basic Unit Root Theory

With the term "unit root" we mean that any root of the polynomial function, \( f(x) = 1 - p_1x - p_2x^2 - \cdots - p_nx^n = 0 \), could be equal to one, meaning that moves in the unit cycle. In that case, any exogenous variation might have a constant impact on any of the endogenous macroeconomic variables, of the above polynomial function. That conclusion derived and can be fully understood, if we consider a first order autoregressive model AR(1):

\[
Y_t = \rho Y_{t-1} + u_t \quad (1.5)
\]

where \( \rho \) is the parameter to be estimated and \( u_t \) is assumed to be white noise, with mean equals to zero and constant variation. In the case where the parameter (\( \rho \)) of the autoregressive model AR(1), equals to one (\( \rho = 1 \)) and indicating at the same time a unit root existence, \( Y_t \) is a non-stationary series whose variance increases over time. When that occurs, the above equation (1.5) becomes:

\[
Y_t = Y_{t-1} + u_t \quad (1.6)
\]

The equation (1.6) is being called random walk and the time series we used, is characterized as non-stationary time series. In the case now, where the parameter (\( \rho \)) is smaller than one (\( \rho < 1 \)), \( Y_t \) is a trend-stationary time series.

As it is being obvious, unit root theory is a parametric approach based on hypothesis testing. ADF and ADF-GLS stationarity tests are based on the same hypothesis described above, while the KPSS test incorporates different hypothesis structure, fact that we are going to further analyze later.

3.3. Augmented Dickey-Fuller (ADF) test

Dickey and Fuller (1979) by using Monte Carlo simulations, found an asymmetric distribution that they used to test the basic unit root hypothesis of the parameter (\( \rho \)) of the autoregressive model AR(1), be equal to one (\( \rho = 1 \)). The basic Dickey-Fuller (DF) stationarity test, can be estimated from the following equations:

\[
Y_t = \rho Y_{t-1} + u_t \quad (1.7)
\]
so, after subtracting $Y_{t-1}$ from both sides of the equation:

$$Y_t - Y_{t-1} = \rho Y_{t-1} - Y_{t-1} + u_t$$

$$Y_t - Y_{t-1} = (\rho - 1)Y_{t-1} + u_t$$

$$\Delta Y_t = \delta Y_{t-1} + u_t$$ \hfill (1.8)

where $\delta = \rho - 1$. In the case where the equation (1.8) has a unit root ($\rho = 1$ or $\delta = 0$), we take the first difference of the variable that we use for testing. So, the null and the alternative hypotheses that we use in order to run the DF unit root test could be written as:

$$H_0: \delta = 0 \quad (Y_t, \text{is not stationary})$$

$$H_1: \delta < 0 \quad (Y_t, \text{is stationary})$$ \hfill (1.9)

In DF stationarity test, we can reject or fail to reject the null hypothesis ($H_0$), by comparing the t-student with a critical value. When t-student is smaller than the critical value ($t_{st} < t_{cr}$), then we reject the null hypothesis and the variable we use, is stationary. On the other hand, when t-student is larger than the critical value ($t_{st} > t_{cr}$), then we accept the alternative hypothesis or we fail to reject the null hypothesis and the variable we use, is not stationary.

In the case where larger and more complicated time series are used, the augmented Dickey-Fuller unit root test is applied. So, the new higher-order autoregressive model AR($p$) is written as:

$$\Delta Y_t = \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + \cdots + \beta_p \Delta Y_{t-p} + u_t$$ \hfill (1.10)

where $\beta$ is the coefficient presenting process root and $p$ is the lag order. To determine the existence of a unit root we have to examine the t-values on coefficients.

So, in order to test for stationarity we can compare again, as we do in a simple DF test, the t-student with the critical values. Therefore, if t-student is smaller than the critical value ($t_{st} < t_{cr}$), then we reject the null hypothesis (stationary variable) and in the case where t-student is larger than the critical value ($t_{st} > t_{cr}$), we fail to reject the null hypothesis (non-stationary variable). Furthermore, it is possible to conclude to the same result if we take into consideration the Schwartz, Akaike or the Hannan-Quinn information criterion.
3.4. Augmented Dickey-Fuller GLS (ADF-GLS) test

Elliott, Rothenberg and Stock (1996) proposed a modified Dickey-Fuller test using a generalized least squares (GLS) method. In particular this test, in terms of small sample size and power, has the best overall performance and seems to dominate the ordinary DF-test. As with the simple DF-test, in ADF-GLS test we have again two possible hypotheses. Those hypotheses test, if the series regressed with or without a trend term. Under the first hypothesis we have to estimate the trend and intercept via GLS. By doing so, the new variables $\tilde{Y}_t, x_t, z_t$ are generated:

$$
\begin{align*}
\tilde{Y}_1 &= Y_1 \\
\tilde{Y}_t &= Y_t - a^* Y_{t-1}, \quad t = 2, \ldots, T \\
x_1 &= 1 \\
x_t &= 1 - a^*, \quad t = 2, \ldots, T \\
z_1 &= 1 \\
z_t &= 1 - a^*(t - 1)
\end{align*}
$$

where, $a^* = 1 - (13.5/T)$. Then an ordinary least squares (OLS) regression for the equation is estimated:

$$
\tilde{Y}_t = \varepsilon_0 x_t + \varepsilon_1 z_t + u_t \tag{1.11}
$$

so the OLS estimators $\hat{\varepsilon}_0, \hat{\varepsilon}_1$ are then used to remove the trend from $Y_t$:

$$
Y^* = Y_t - (\hat{\varepsilon}_0 + \hat{\varepsilon}_1 t) \tag{1.12}
$$

Finally, an augmented Dickey-Fuller test is being performed on the transformed variable by fitting the OLS regression:

$$
\Delta Y^*_t = \alpha + \beta Y^*_{t-1} + \sum_{j=1}^{k} \xi_j \Delta Y^*_{t-j} + u_t \tag{1.13}
$$

then we test the null hypothesis ($\beta = 0$) with the use of tabulated critical values.

To perform the second hypothesis (GLS runs without a trend term), we proceed in the same way as before but now we take $a^* = 1 - (7/T)$, we eliminate $z$ from the regression and compute $Y^* = Y_t - \varepsilon_0$. In order to determine the existence of a unit root we act in the same way as we mentioned previously about the simple DF or ADF stationarity tests. So, if t-student is smaller than the critical value ($t_{st} < t_{cr}$), then we reject the null hypothesis (stationary variable) and in the case where t-student is larger than the critical value ($t_{st} > t_{cr}$), we fail to reject the null hypothesis (non-stationary variable).
3.5. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test

Kwiatkowski, Phillips, Schmidt, and Shin (1992) introduced a test that differs from the other two unit root tests mentioned in the previous pages. In KPSS test time series $Y_t$, is assumed not to have a unit root ($Y_t$ is stationary) under the null hypothesis and not under the alternative one. This stationarity test is based on the residuals from the OLS regression of $Y_t$, on the exogenous variables $x_t$:

$$Y_t = x_t'\delta + u_t$$

(1.14)

the definition of the LM statistic used, is:

$$LM = \sum_t S(t)^2/(T^2 f_0)$$

(1.15)

where $f_0$, is a residual spectrum estimator at frequency zero and $S(t)$ is a cumulative residual function:

$$S(t) = \sum_{r=1}^t u_r$$

(1.16)

based on the residuals $u_r = y_t - x_t'\delta(0)$. It is worth mentioning that the estimator $\delta$, differs from the one that used in the GLS detrending test, since it is based on the original data that being involved on the regression and not on the quasi-differenced data.

In KPSS unit root test, in order to test a time series for stationarity, we test again the relation between the t-student and critical values, in a way opposite than we used during the ADF and ADF-GLS unit root tests. So, in KPSS if t-student is larger than the critical value ($t_{st} > t_{cr}$), then we reject the null hypothesis (stationary variable) and in the case where t-student is smaller than the critical value ($t_{st} < t_{cr}$), we fail to reject the null hypothesis, meaning that the time series used are non-stationary.

3.6. Granger Causality test

Granger (1969) based on a linear regression model, formed a statistical hypothesis concept of causality, through which he could determine the potential predictive power one time series might have on another. In particular his model states that, if the variable $X_t$ Granger-causes another variable $\Psi_t$, then the lag values of $X_t$ contains information that can predict future values of $\Psi_t$. 
In order to perform the Granger causality test we have to determine first, if the variables we are using are stationary or not. In the case where the time series is stationary, we are using the level values and on the other hand when the time series is non-stationary we take the first differences of the variables. To determine the optimal lag length to be included, we take into consideration information criteria, such as Schwarz information criterion or the Akaike information criterion.

So, in order to test the null hypothesis that variable $X_t$ does not Granger-cause variable $\Psi_t$, we perform a univariate auto regression, that includes also the optimal lagged values of the time series $X_t$:

$$\Psi_t = \alpha_0 + \alpha_1 \Psi_{t-1} + \alpha_2 \Psi_{t-2} + \cdots + \alpha_m \Psi_{t-m} + b_1 X_{t-1} + \cdots + b_n X_{t-n} + \varepsilon_t$$  \hspace{1cm} (1.17)

where $\alpha_0$ is a constant and $\varepsilon_t$ is the residual.

3.7. Breitung and Candelon Causality test

To investigate the relationship between oil prices and consumer's sentiment, we have to implement a frequency domain causality test introduced by Breitung and Candelon (2006). The methodological framework is similar to that of Granger (1969), Geweke (1982) and Hosoya (1991), but the novelty of B&C is that through a bivariate vector auto-regressive (VAR) model, made possible to determine the short and long run predictive power that one variable could have on another. One other thing that seems to distinguish B&C frequency domain causality test from the others mentioned, is that we can indentify non-linear causal relationships and also due to the fact that allows us to test for Granger causality over specific alternative frequencies, provides us a more consolidative understanding of how exactly this causal relationship is being structured.

To explain this causality test, let us consider $z_t = [x_t, y_t]'$ to be a two-dimensional time series vector, with $t = 1, 2, \ldots, T$ observations.

In this paper, $x_t$ will be consumer's sentiment and $y_t$ will be the WTI oil prices. It is assumed that $z_t$ has a finite order VAR representation of the form:

$$\theta(L) z_t = \varepsilon_t$$  \hspace{1cm} (1.18)

$$z_t = \theta(L)^{-1} \varepsilon_t = \Phi(L) \varepsilon_t, \text{ with } \theta(L)^{-1} = \Phi(L)$$  \hspace{1cm} (1.19)
with \( \Theta(L) = I - \theta_1 L - \cdots - \theta_p L^p \) is a 2x2 matrix of polynomials with \( L^k z_t = z_{t-k} \).

Furthermore we assume that the error vector \( \varepsilon_t \), with positive definite covariance \( E(\varepsilon_t \varepsilon'_t) = \Sigma \) and mean equals to zero \( E(\varepsilon_t) = 0 \).

Also, let \( G \) be the lower triangular matrix of the Cholesky decomposition \( C' C = \Sigma^{-1} \), such that \( E(u_t u'_t) = I \) and \( u_t = C \varepsilon_t \). Hence, due to the \( u_t \) the systems can be rewritten as:

\[
\begin{align*}
    z_t &= \Phi(L) \varepsilon_t = \begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} = \\
    &= \Psi(L) u_t = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix},
\end{align*}
\]

where \( \Theta(L)^{-1} = \Phi(L) \) and \( \Theta(L)^{-1} C^{-1} = \Psi(L) \). So, the spectral density of \( x_t \) can be presented as:

\[
f_x(\omega) = \frac{1}{2\pi} \left\{ |\Psi_{11}(e^{-i\omega})|^2 + |\Psi_{12}(e^{-i\omega})|^2 \right\}
\]

The non causality hypothesis proposed by Geweke (1982) and Hosoya (1991) is defined from the following Fourier transformation:

\[
M_{y\rightarrow x}(\omega) = \log \left[ \frac{2\pi f_x(\omega)}{|\Psi_{11}(e^{-i\omega})|^2} \right] = \log \left[ 1 + \frac{|\Psi_{12}(e^{-i\omega})|^2}{|\Psi_{11}(e^{-i\omega})|^2} \right]
\]

In case where \( y_t \) (oil prices) does not cause \( x_t \) (consumer's sentiment) at frequency \( \omega \), the above measure is equal to zero and therefore \( |\Psi_{12}(e^{-i\omega})|^2 = 0 \).

Regarding the fact that \( |\Psi_{12}(e^{-i\omega})| \) is a complicated non linear function of the VAR parameters, B\&C offers a much simpler approach to test the null hypothesis that is imposed on the estimated VAR coefficients. As we have already mentioned, during the null hypothesis \( M_{y\rightarrow x}(\omega) = 0 \) if \( |\Psi_{12}(e^{-i\omega})|^2 = 0 \). Meanwhile, using \( \Psi(L) = \Theta(L)^{-1} C^{-1} \), we get:

\[
\Psi_{12}(L) = -\frac{1}{\epsilon_{22}} \frac{\theta_{12}(L)}{\epsilon_{22}} \quad (1.23)
\]

where \( \frac{1}{\epsilon_{22}} \) is the lower diagonal element of \( C^{-1} \) and \( |\Theta(L)| \) is the determinant of \( \Theta(L) \). Since \( \frac{1}{\epsilon_{22}} \) is positive, \( |\Psi_{12}(e^{-i\omega})|^2 = 0 \) is equivalent to:

\[
|\theta_{12}(e^{-i\omega})| = |\sum_{k=1}^{p} \theta_{12,k} \cos(k\omega) - \sum_{k=1}^{p} \theta_{12,k} \sin(k\omega)i| = 0
\]

(1.24)
where $\theta_{12,k}$ is the upper right element of $\Theta_k$. Subsequently, the sufficient set of restrictions under which $y_t$ does not cause $x_t$ at frequency $\omega \left( |\theta_{12}(e^{-i\omega})| = 0 \right)$, are:

$$\sum_{k=1}^{p} \theta_{12,k} \cos(k\omega) = 0$$  \hspace{1cm} (1.25)

$$\sum_{k=1}^{p} \theta_{12,k} \sin(k\omega) = 0$$  \hspace{1cm} (1.26)

The B&C approach is actually based on the above two linear restrictions. For simplicity, we take $a_j = \theta_{11,j}$ and $\beta_j = \theta_{12,j}$, hence the VAR equation for $x_t$ may be written as:

$$x_t = a_1 x_{t-1} + a_2 x_{t-2} + \cdots + a_p x_{t-p} + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t$$  \hspace{1cm} (1.27)

Therefore, the hypothesis $M_{y \rightarrow x}(\omega) = 0$, is equivalent to the following linear restrictions:

$$H_0: R(\omega) \beta = 0, \text{ where } \beta = \left[ \beta_1, \beta_2, \ldots, \beta_p \right]'$$

and $R(\omega) = \begin{bmatrix} \cos(\omega) & \cos(2\omega) & \cdots & \cos(p\omega) \\ \sin(\omega) & \sin(2\omega) & \cdots & \sin(p\omega) \end{bmatrix}$  \hspace{1cm} (1.28)

The above linear restrictions are asymptotically distributed for $\omega \in (0, \pi)$. To assess the significance of the B&C causal relationship we have to compare the obtained statistic with the 5% critical value of a chi-square distribution $\chi^2$, with two degrees of freedom.

3.8. Lemmens et al. Causality test

Another way that makes possible the assessment of the relationship between oil prices and consumer’s sentiment, in the frequency domain, is by implementing the Lemmens et al. (2008) causality test. This test reconsiders the original framework, proposed by Pierce (1979) and relies on a modified version of the coefficient of coherence for which the study derives the distributional properties.

Let $x_t$ (consumer’s sentiment) and $y_t$ (oil prices) be two stationary time series of length $T$ (here $T=408$). In order to measure if $x_t$ Granger causes $y_t$ at a given frequency $\lambda$, we perform on the univariate innovations series $u_t$ and $v_t$, derived from $x_t$ and $y_t$. The latter are modeled as univariate Autoregressive Moving Average (ARMA) processes:

$$\Theta^x(L)x_t = C^x + \Phi^x(L)u_t$$  \hspace{1cm} (1.29)
\[ \Theta^Y(L)y_t = C^Y + \Phi^Y(L)v_t \]  \hspace{1cm} (1.30)

where \( \Theta^X(L) \), \( \Theta^Y(L) \) are autoregressive polynomials, \( \Phi^X(L) \) and \( \Phi^Y(L) \) are moving average polynomials and \( C^X \), \( C^Y \) are potential deterministic components. If we filter the series with the ARMA models described in equations (1.29, 1.30), we obtained the innovation series \( u_t \) and \( v_t \) (white noise processes) which have zero mean and could be probably correlated with each other at different leads and lags. Series \( u_t \) and \( v_t \) are the series of significance in Granger causality test introduced by Lemmens et al. (2008).

Consider \( S_u(\lambda) \) and \( S_v(\lambda) \) be the spectral density functions of \( u_t \) and \( v_t \) at frequency \( \lambda \in ]0, \pi[ \), defined by:

\[
S_u(\lambda) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_u(k) e^{-i\lambda k}  \hspace{1cm} (1.31)
\]

\[
S_v(\lambda) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_v(k) e^{-i\lambda k}  \hspace{1cm} (1.32)
\]

where \( \gamma_u(k) = \text{Cov}(u_t, u_{t-k}) \) and \( \gamma_v(k) = \text{Cov}(v_t, v_{t-k}) \), representing the autocovariances of \( u_t \) and \( v_t \) at lag \( k \). In the spectral representation, each time series may be expressed as integration of many uncorrelated components, each related to a particular frequency \( \lambda \) (see Koopmans 1995, Warner 1998). To investigate the relationship between \( u_t \) and \( v_t \), we consider the cross-spectrum \( S_{uv}(\lambda) \) that can be expressed as:

\[
S_{uv}(\lambda) = C_{uv}(\lambda) + i Q_{uv}(\lambda) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_{uv}(k) e^{-i\lambda k} \hspace{1cm} (1.33)
\]

where \( C_{uv}(\lambda) \) and \( Q_{uv}(\lambda) \) are the cospectrum and quadrature spectrum respectively, representing at the same time the real and imaginary parts of the cross-spectrum. In the above equation (1.33), \( \gamma_{uv}(k) = \text{Cov}(u_t, v_{t-k}) \) represents the cross-covariance of \( u_t \) and \( v_t \), with lag equals to \( k \).

The non parametric estimation of the cross-spectrum can be defined as:

\[
\hat{S}_{uv}(\lambda) = \frac{1}{2\pi} \left\{ \sum_{k=-M}^{M} w_k \hat{y}_{uv}(k) e^{-i\lambda k} \right\}  \hspace{1cm} (1.34)
\]
where $\hat{\gamma}_{uv}(k) = \hat{\text{Cov}}(u_t, v_{t-k})$, the empirical cross-covariances and $w_k$, representing the window weights for $k = -M, ..., M$. This cross-spectrum allows us to determine the coefficient of coherence $h_{uv}(\lambda)$, defined as:

$$h_{uv}(\lambda) = \frac{S_{uv}(\lambda)}{\sqrt{S_u(\lambda)S_v(\lambda)}}$$  

(1.35)

It is worth mentioning that the coefficient of coherence defines the strength of the linear association between two time series, frequency by frequency. However, does not provide any information regarding the direction of the relationship between the two processes. The squared coefficient of coherence has a similar interpretation with the R-squared in a regression context. The values that coherence can take are between 0 and 1. That derives from the fact that, R-squared of a $v_t$ regression on all past, present and future values of $u_t$, is the integral, across frequencies, of the squared coefficient of coherence (Pierce, 1979). Lemmens et al. (2008) have concluded that under the null hypothesis, that $h_{uv}(\lambda) = 0$, the estimated squared coefficient of coherence at frequency $\lambda$ ($0 < \lambda < \pi$) when appropriately rescaled, converges to a chi-squared distribution with two degrees of freedom, indicated by $\chi^2_2$

$$2(n-1)\hat{h}_{uv}(\lambda) \xrightarrow{d} \chi^2_2$$  

(1.36)

with $\xrightarrow{d}$ being the convergence in distribution, with $n = T/(\sum_{k=-M}^{M} w_k^2)$. The null hypothesis can be rejected if:

$$\hat{h}_{uv}(\lambda) > \sqrt{\frac{\chi^2_{1-\alpha}}{2(n-1)}}$$  

(1.37)

where $\chi^2_{1-\alpha}$ stands for the $1 - \alpha$ quantile of the chi-squared distribution with two degrees of freedom. As we already said, coefficient of coherence does not give any information as far as the direction of the relationship between oil prices and consumer’s sentiment is concerned. Because we want to take the direction of that relationship into account, following Pierce (1979) and Lemmens et al. (2008), we have to split the cross-spectrum (eq 1.33) into three parts: (i) $S_{u \rightarrow v}$, the instantaneous relationship between $u_t$ and $v_t$; (ii) $S_{u \rightarrow v}$, the directional relationship between $v_t$ and the lagged values of $u_t$; (iii) $S_{v \rightarrow u}$, the directional relationship between $u_t$ and the lagged values of $v_t$, i.e.,

$$S_{uv}(\lambda) = [S_{u \rightarrow v} + S_{u \rightarrow v} + S_{v \rightarrow u}]$$
The Granger causality spectral measure that have been proposed, is based on the assumption that $x_t$ (oil prices) does not Granger cause $y_t$, if and only if $\gamma_{uv}(k) = 0$ for all $k < 0$.

Therefore, if the goal is to measure the predictive content of $x_t$, relative to $y_t$, we have to focus on the second part of the above equation:

$$S_{u\rightarrow v}(\lambda) = \frac{1}{2\pi} \left[ \sum_{k=-\infty}^{-1} \gamma_{uv}(k) e^{-i\lambda k} \right]$$

(1.39)

The Granger coefficient of coherence is then given by:

$$h_{u\rightarrow v}(\lambda) = \frac{S_{u\rightarrow v}(\lambda)}{\sqrt{S_u(\lambda)S_v(\lambda)}}$$

(1.40)

So, under the null hypothesis where Granger causality not exist, $h_{u\rightarrow v}(\lambda) = 0$ for every $\lambda \in ]0, \pi[$. Granger coefficient of coherence at frequency $\lambda$ can be estimated by the estimator below and can take values between zero and one,

$$\hat{h}_{u\rightarrow v}(\lambda) = \frac{|\hat{S}_{u\rightarrow v}(\lambda)|}{\sqrt{\hat{S}_u(\lambda)\hat{S}_v(\lambda)}}$$

(1.41)

with

$$\hat{S}_{u\rightarrow v}(\lambda) = \frac{1}{2\pi} \left\{ \sum_{k=-M}^{M} w_k \tilde{\gamma}_{u\rightarrow v}(k) e^{-i\lambda k} \right\}$$

where $\tilde{\gamma}_{u\rightarrow v}(k) = \tilde{Cov}(u_t, v_{t-k})$, the empirical cross-covariances and $w_k$, representing the window weights, for $k \geq 0$ put equal to zero. The distribution of the estimator of the Granger coefficient of coherence can be derived from the distribution of the coefficient of coherence (see eq. 1.36). Under the null hypothesis, where $h_{u\rightarrow v}(\lambda) = 0$, the distribution of the squared estimated Granger coefficient of coherence at frequency $\lambda$ ($0 < \lambda < \pi$), is given by:

$$2(n' - 1)\hat{h}_{u\rightarrow v}^2(\lambda) \overset{d}{\rightarrow} \chi^2_2$$

(1.42)

with $\overset{d}{\rightarrow}$ again, being the convergence in distribution and $n' = T/(\sum_{k=M}^{-1} w_k^2)$. When computing $\hat{S}_{u\rightarrow v}(\lambda)$, window weights $w_k$ (with $k > 0$) are set equal to zero and consequently only the $w_k$ with negative indices is taken into account. Hence the null hypothesis can be rejected if:

$$\hat{h}_{u\rightarrow v}(\lambda) > \sqrt{\frac{\chi^2_{1,1-\alpha}}{2(n'-1)}}$$

(1.43)
4. Data Empirical Application

In the framework of this chapter, we are going to present the WTI oil price and consumer's sentiment time series in more details. Additionally, we are going to further analyze the nature of the two variables and assess their dynamic relationship through the application of causality tests. We will also demonstrate the key findings obtained through the implemented methodology and an analytical discussion of the final results will be performed.

4.1 Data Analysis

The consumer's sentiment (CS) as well as the West Texas Intermediate (WTI) spot oil prices data, used in this study, are monthly observations which obtained from the Federal Reserve Bank of St. Louis (FRED) database. The period examined spans from January 1, 1978, to March 1, 2013 and includes 423 observations in total. The WTI nominal prices and the CS are presented in figures 6 and 7 below.

![Figure 6. WTI nominal prices (1978-2013)](image1)

![Figure 7. CS index (1978-2013)](image2)
The time series we used, as far as the WTI oil prices is concerned, referring to non-seasonal adjusted, nominal oil prices. In order to proceed and starting to analyze the relationship between consumer sentiment and oil prices, it would be better to use the real WTI oil prices (US dollars per barrel, or in short $/bbl). By doing so, we would have a better understanding of the actual movement of the oil prices, without taking into consideration economic factors that could cause the oil prices to change over time, such as the inflation does. As we already know, a rise in the inflation creates almost simultaneously a downward movement in an economy, because it increases the general level of the commodity’s and service’s prices, making the purchase of certain goods even harder.

To get rid of that macroeconomic variable in our calculations, we used another time series called Consumer Price Index (CPI). CPI is an index that measures the changes occurred in the prices of a market basket, containing a sample of representative items, purchased by households during a certain period of time. So, we obtain CPI time series again from the FRED database, for the same period, from January 1, 1978 to March 1, 2013. Hence, in order to get the real WTI oil prices we have to divide the nominal WTI oil prices with the CPI (decimal) for each month of study, as shown below:

\[
Real \ Price_i = \frac{Nominal \ Price_i}{\% CPI_i}
\]

(1.44)

where, \( i \) is the corresponding month. The WTI nominal and real prices, along with the CPI are depicted in Figure 8 and 9 respectively.

![Figure 8. Graphical comparison between the nominal and real WTI oil prices (1978-2013)](image)
The next variable that we are going to use in order to construct our bivariate model is the Consumer Sentiment Index. As we mentioned earlier in the literature review, Consumer Sentiment Index is a telephone survey conducted by the Michigan's University. The basic principle and purpose behind this survey, is to acquire information about the expectations and concerns of the consumer, concerning the overall economy. More specifically, the questionnaire of the Consumer Sentiment Index is being presented in the following table:

<table>
<thead>
<tr>
<th>Current Personal Finances</th>
<th>Would you say that you (and your family) are better off or worse off financially than you were a year ago?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected Personal Finances</td>
<td>Do you think that a year from now you (and your family) will be better off financially, or worse off, or just about the same as now?</td>
</tr>
<tr>
<td>One-year Economic Outlook</td>
<td>Do you think that during the next 12 months we will have good times financially, or bad times, or what?</td>
</tr>
<tr>
<td>Five-year Economic Outlook</td>
<td>Looking ahead, which would you say is more likely—that in the country as a whole we will have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?</td>
</tr>
<tr>
<td>Buying Conditions</td>
<td>Do you think now is a good or a bad time for people to buy major household items?</td>
</tr>
</tbody>
</table>

Table 1. Questions in the Consumer Sentiment Index
The formula that the University of Michigan is using, in order to construct the Index of Consumer Sentiment, is expressed in term of the observed sample proportions as described below:

\[ CSI_t = \sum_{n=1}^{5} (V_{nt}^\lambda - V_{nt}^\xi) \times 100 \div 100 \quad (1.45) \]

where, \( V_{nt}^\lambda \) is the observed sample that gives favorable replies to the \( n \) question at time \( t \) and \( V_{nt}^\xi \) is the observed sample proportion that gives unfavorable replies to the \( n \) question at time \( t \). At the same manner, the above formula can be expressed in terms of the individual responses, as:

\[ CSI_t = \sum_{n=1}^{5} \sum_{i=1}^{j} X_{int} (100) + 100 \quad (1.46) \]

where,

\( X_{int} = 1 \), in the case of a favorable response to question \( n \) by respondent \( i \) at a time \( t \),

\( X_{int} = -1 \), in the case of an unfavorable response to question \( n \) by respondent \( i \) at a time \( t \),

\( X_{int} = 0 \), in the case of a same or pro-con response to question \( n \) by respondent \( i \) at a time \( t \).

So, in order to proceed further and starting to analyze the WTI and CS time and test the possible causal relationship between them, we use the econometric software eviews 8.

### 4.2. Seasonality Adjustment

So, after we have obtained the real WTI oil prices, we need to take seasonality out of the CS and WTI time series. By extracting seasonality from the series, we purify in a way the data sample since seasons seem to influence the economic and social activity worldwide. For instance, holidays, such as Easter or Christmas produce movements related to purchases of certain goods. Therefore, before the Christmas holydays many toys are sold and purchases of different kind of presents are occurred. Furthermore, as far as the seasons and the oil consumption is concerned, when the weather becomes warmer the residential oil consumption is tending to be zero, while in the case where weather becomes colder, the consumption rises significantly. Figures 10 and 11 below, present the two time series before and after the seasonal adjustment.
4.3. Unit Root Tests

With the extraction of seasonality from the two variables, we are ready to proceed and test for stationarity. So, the first step we have to take in order to determine if the two time series are stationary or not, is by graph observation. At first sight, the CS and WTI time series seem to be non-stationary, because they have not a constant mean and constant variance. On the other hand their logarithmic differences do seem as stationary ones. The following figures, present the log differences of the CS and WTI time series.
Regarding the graph observation, the CS and WTI time series are seem to be integrated of order one, I(1). In order though to demonstrate a more solid and cognitive judgment about the order of integration of the two variables, we have to proceed to the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) unit root test, the Augmented Dickey-Fuller GLS (ADF-GLS) (Elliot, Rothenberg and Stock, 1996) unit root test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al. 1992) stationarity test. All the above unit root tests will be implemented both, with and without a time trend, firstly to the levels and afterwards to the first logarithmic differences of the two time series. It is also worth mentioning that the applied lag length, in all stationarity tests that we are going to implement, corresponds to the optimal lag length derived from the Schwarz Info Criterion[2].

So, when we apply the ADF test (no trend) to the level of CS variable, we fail to reject the null hypothesis (non-stationary) for the 1% and 5% significance level, but we reject the null hypothesis (stationary) for the 10% of significance level. One way to determine though, if the results are reliable, is by taking into consideration the Durbin-Watson stat (see appendix). If the Durbin-Watson stat is equal or near the value of 2, then the results of the ADF stationarity test are reliable. However, in the case where this criterion does not met, the results are not reliable probably due to autocorrelation problems. In our case, the Durbin-Watson stat is equal to 1.9819, meaning that we can rely on the simple ADF test and take the CS variable as stationary, in the 10% significance level.

[2] The econometric program that we use in order to obtain the stationarity results (eviews 8), automatic selects the optimal lag length with a maximum of 17 lags.
Null Hypothesis: CS has a unit root  
Exogenous: Constant  
Lag Length: 0 (Automatic - based on SIC, maxlag=17)

<table>
<thead>
<tr>
<th>Test Case</th>
<th>t-Statistic</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Augmented Dickey-Fuller test statistic</td>
<td>-2.739660</td>
<td>0.0682</td>
</tr>
<tr>
<td>Test critical values:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1% level</td>
<td>-3.445627</td>
<td></td>
</tr>
<tr>
<td>5% level</td>
<td>-2.868169</td>
<td></td>
</tr>
<tr>
<td>10% level</td>
<td>-2.570366</td>
<td></td>
</tr>
</tbody>
</table>

Table 2. ADF unit root test for the CS variable (no trend)

The next stationarity test that we are going to apply is the ADF-GLS test. That test, implements the same concepts as the simple ADF unit root test and the results of which, are presented in the table below.

Null Hypothesis: CS has a unit root  
Exogenous: Constant  
Lag Length: 0 (Automatic - based on SIC, maxlag=17)

<table>
<thead>
<tr>
<th>Test Case</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elliott-Rothenberg-Stock DF-GLS test statistic</td>
<td>-2.651828</td>
</tr>
<tr>
<td>Test critical values:</td>
<td></td>
</tr>
<tr>
<td>1% level</td>
<td>-2.570453</td>
</tr>
<tr>
<td>5% level</td>
<td>-1.941576</td>
</tr>
<tr>
<td>10% level</td>
<td>-1.616196</td>
</tr>
</tbody>
</table>

Table 3. ADF-GLS unit root test for the CS variable (no trend)

As table 3 depicts, the t-statistic is equal to -2.6518. At the same time, the absolute values of the critical values in the 1%, 5% and 10% level of significance are lower than the t-statistic, meaning that we reject the null hypothesis. Hence, CS variable is stationary in all levels of significance. Again, if we take a look at Durbin-Watson stat, we can say that we can reject the autocorrelation and take the ADF-GLS results as reliable.

The final unit root test that we are going to apply is the KPSS test. As we have already mentioned during the previous chapter, the KPSS test is quite different as far as the interpretation of the results is concerned. In that test, the t-statistic value has to be greater than the critical values of the 1%, 5% and 10% of significant levels, in order to say that a particular variable is stationary. According to table 3, t-statistic is equal to 0.3521 and it is smaller than the critical values of the 1% and 5% respectively, levels of significance. However, t-statistic is greater than the critical value in the 10% significance level and that enables us to say that we reject the null hypothesis. Therefore, CS time series is stationary in the 10% of the significance level.
Null Hypothesis: CS is stationary  
Exogenous: Constant  
Bandwidth: 16 (Newey-West automatic) using Bartlett kernel

|-------------------------------------------------|----------|
| Asymptotic critical values*:  
1% level | 0.739000 |
| 5% level | 0.463000 |
| 10% level | 0.347000 |

Table 4. KPSS unit root test for the CS variable (no trend)

All the above results, derived from the implementation of the ADF, ADF-GLS and KPSS unit root tests, leads us to the conclusion that the CS variable is a stationary variable, integrated of order zero, I(0).

The tables above, presents the implemented unit root tests without a trend due to the fact that with the time trend, we have obtained almost similar results (see appendix). The exact same procedure is applied for the next variable, WTI. First and foremost, as we did for the CS variable, we are going to apply the simple ADF unit root test. As presented in the table 4 below, we fail to reject the null hypothesis (WTI time series is not stationary) due to the fact that the absolute value of t-statistic is smaller than that of the critical values. Also, if we look again the Durbin-Watson stat, we can say that the simple ADF's results are reliable (DW stat≈2).

Null Hypothesis: WTI has a unit root  
Exogenous: Constant  
Lag Length: 1 (Automatic - based on SIC, maxlag=17)

<table>
<thead>
<tr>
<th>Augmented Dickey-Fuller test statistic</th>
<th>t-Statistic</th>
<th>Prob.*</th>
</tr>
</thead>
</table>
| Test critical values:  
1% level | -3.445664  
5% level | -2.868186  
10% level | -2.570375 |

Table 5. ADF unit root test for the WTI variable (no trend)

The next step is to implement the ADF-GLS stationarity test, for the WTI time series. The results seem to be different from that obtained from the simple ADF test. According to the table 5, we fail to reject the null hypothesis for the critical value of 1% significant level. However, in 5% and 10% level of significance, we reject the null hypothesis which means that the variable is stationary after all.
The final unit root test that we are going to apply is the KPSS test. The result we retrieve from that particular stationary test, is a t-statistic with a value of 0.5769. Because the t-statistic is smaller than the critical value of 1% significance level, we fail to reject the null hypothesis (WTI is not stationary). If we see though, what happens with the 5% and 10% of the significance level, we reject eventually the null hypothesis and we conclude to the fact that the WTI time series is stationary as shown in the following table.

Null Hypothesis: WTI is stationary
Exogenous: Constant
Bandwidth: 16 (Newey-West automatic) using Bartlett kernel

<table>
<thead>
<tr>
<th>Test</th>
<th>LM-Stat.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kwiatkowski-Phillips-Schmidt-Shin test statistic</td>
<td>0.576939</td>
</tr>
</tbody>
</table>

Table 7. KPSS unit root test for WTI variable (no trend)

So, according to the above tables, which represents the unit root tests that have been implemented in the two variables, CS and WTI, we conclude to the fact that both variables are stationary and integrated of order zero, I(0). The table below shows the results obtained, after the application of the ADF, ADF-GLS and KPSS unit root tests, from the corresponding time series, both with and without time trend (see also the appendix for the stationarity tests, applied to the first differences).

The following table shows the test statistics of the logarithmic differences of the two time series, in order to get a broader aspect of CS and WTI variables.
### Panel A - ADF unit root test

<table>
<thead>
<tr>
<th>Variable</th>
<th>Levels</th>
<th>First differences</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>No trend</td>
</tr>
<tr>
<td></td>
<td>t-stat. (k)</td>
<td>t-stat. (k)</td>
</tr>
<tr>
<td>CS</td>
<td>-2.739 (0)*</td>
<td>-2.733 (0)</td>
</tr>
<tr>
<td>WTI</td>
<td>-2.070 (1)</td>
<td>-2.145 (1)</td>
</tr>
</tbody>
</table>

### Panel B - ADF-GLS unit root test

<table>
<thead>
<tr>
<th>Variable</th>
<th>Levels</th>
<th>First differences</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>No trend</td>
</tr>
<tr>
<td></td>
<td>t-stat. (k)</td>
<td>t-stat. (k)</td>
</tr>
<tr>
<td>CS</td>
<td>-2.651 (0)**</td>
<td>-2.701 (0)*</td>
</tr>
<tr>
<td>WTI</td>
<td>-2.079 (1)**</td>
<td>-2.141 (1)</td>
</tr>
</tbody>
</table>

### Panel C - KPSS stationarity test

<table>
<thead>
<tr>
<th>Variable</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No trend</td>
</tr>
<tr>
<td>CS</td>
<td>0.352*</td>
</tr>
<tr>
<td>WTI</td>
<td>0.576**</td>
</tr>
</tbody>
</table>

Table 8. ADF, ADF-GLS, KPSS test statistics

Note: k represents the selected lag length (based on the Schwarz criterion with $k_{min}=0$ and $k_{max}=17$). *, ** and *** denote rejection of the null hypothesis at the 10%, 5% and 1% significance levels, respectively.

### 4.4. Granger Causality Test

The reliability of the Granger causality test depends on the order of the VAR model and also on the variables that taking place. According to Geweke et al. (1983), the reliability of the granger causality test becomes lower as long as the variables that participate in the test are non stationary.

As we have already mentioned and showed above, the corresponding CS and WTI variables are stationary and integrated of order zero, I(0). So, in order to determine the causal relationship between the two variables, we have to proceed to the following hypotheses testing of the Granger causality test:

$$H_0: \text{WTI does not Granger cause CS}$$

$$H_1: \text{CS does not Granger cause WTI}$$

In Granger causality test, the value that plays the most significant role in the determination of whether one variable might cause another, is the p-value. An empirical rule says that, a p-value greater than 0.05 is evidence that can lead us to fail rejecting the given hypothesis. On the other hand, a p-value below that level of significance enables us to reject the null ($H_0$) or the alternative hypothesis ($H_1$). The table below presents the results taken after the implementation of the Granger causality test.
Pairwise Granger Causality Tests
Sample: 1978M01 2013M03
Lags: 2

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>Obs</th>
<th>F-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTI does not Granger Cause CS</td>
<td>421</td>
<td>7.21090</td>
<td>0.0008</td>
</tr>
<tr>
<td>CS does not Granger Cause WTI</td>
<td>0.61141</td>
<td>0.5431</td>
<td></td>
</tr>
</tbody>
</table>

Table 9. Granger causality test between WTI and CS variables

As we can see from table 9, the lags (2) that the econometric program has applied derived from the optimal lags proposed by the sequential modified LR test statistic (LR), the Schwarz information criterion (SC) and the Hannan-Quinn information criterion. The above results show the existence of a one direction linear causal relationship between the two variables. In particular, according to the p-values presented in the table 9, we reject the null hypothesis due to the fact that the corresponding p-value is much smaller than the 0.05 (5%). On the other hand and as far as the alternative hypothesis is concerned, the p-value (0.5431 or 54.31%) is way larger than the 0.05 (5%) value, making as fail to reject the alternative hypothesis. So, regarding the above mentioned we conclude to the fact that, the WTI variable does Granger cause CS variable.

4.5. Breitung & Candelon frequency domain causality test

After the implementation of the simple Granger causality test that showed us the existence of a strong causality from the oil price to the consumer's sentiment, we can now investigate further at which specific frequencies the Granger causality is significant. We begin testing for causality by focusing on the levels of the WTI and CS time series. The hypothesis that we are going to examine is whether the WTI variable causes the CS one. For that reason, a frequency domain causality test is going to be implemented, proposed by the Breitung and Candelon (2006).

The results of this causality test are presented in the Figure 14 and reveal a strong non-linear causal relationship between the two variables, for certain frequencies $\omega \in (0, \pi)$, along with the 5% critical value (dashed line). It turns out that the null hypothesis of no causality is rejected at the significance level of 5%, for the ranges $\omega \in (0.93, \pi)$ which corresponds to frequencies with a wave length between 2 and 7 months$^{[3]}$. We have also found causality at frequencies less than 0.28, corresponding to a cycle length of 22 months$^{[4]}$.

$^{[3]}$ $^{[4]}$ the frequency $\omega$ presents a period of $T$, by $T = 2\pi/\omega$ (for monthly data, in months)
Figure 1. WTI oil price cause Consumer's Sentiment (WTI → CS)

It is worth mentioning, that the lag length that we applied in order to draw the above graph, derived from the optimal lag length proposed by the sequential modified test statistic (LR), the Schwarz information criterion (SC) and the Hannan-Quinn information criterion (HQ) and is equal to 2. On the other hand, Akaike information criterion (AIC) along with the Final prediction error (FPE), proposed a different optimal lag length equals to 5. The drawing result of the 5-lag-length causal relationship is being depicted below.

Figure 14. WTI oil price cause Consumer's Sentiment (WTI → CS)

Figure 15. WTI oil price cause Consumer's Sentiment (WTI → CS)
According to Figure 15, the strong non-linear causal relationship still exist but in slightly different frequencies. So, there is a short-run causality from WTI to CS for the ranges $\omega \in (1.77, \pi]$ which corresponds to frequencies with a wave length between 2 and 4 months. We have also long-run causality at frequencies less than 0.26, corresponding to a cycle length of approximately 25 months. The table below presents the results obtained from the implementation of the Breitung & Candelon causality test, for certain frequencies.

Considering now the hypothesis of the opposite direction, that Consumers' Sentiment cause WTI oil price (CS $\rightarrow$ WTI), the Breitung & Candelon test reveals significant outcomes both with 3 (Figure 16) and 5 lag length (Figure 17), derived from the optimal lag length described previously. More specifically and as far as the 3-lag-length test is concerned, we fail to reject the null hypothesis that CS does not Granger cause WTI, for every frequency $\omega \in (0, \pi]$. On the other hand, when the test is re-applied (5 lags), the causality testing results become significant. It seems that the null hypothesis is failed to be rejected in the long-run, however it turns to be rejected in the short-run. In particular, for frequencies $\omega \in (0,1.48]$ the null hypothesis is failed to be rejected, concluding to the fact that the CS variable does not Granger cause the WTI variable in the long-run. Regarding the frequencies $\omega \in (1.48, \pi)$, there seem to be a strong causal relationship in 5% and 1% significance levels between the two variables, in the short-run, corresponding to a cycle length between 2 and 4 months.
Figure 17. Consumer's Sentiment causes WTI oil price (CS → WTI)

Table 10. Summary of the B&C causality test for certain frequencies

<table>
<thead>
<tr>
<th>Causality direction</th>
<th>Selected spectrum values</th>
<th>Causality inference</th>
<th>Causality interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level series</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WTI→CS (3 lags)</td>
<td>10,28*** 4,61 8,45** 9,17** 9,32**</td>
<td>⬇️</td>
<td>(0,0.28) (0.93,π]</td>
</tr>
<tr>
<td>WTI→CS (5 lags)</td>
<td>10,48*** 0,94 5,25** 8,76** 9,89**</td>
<td>⬇️</td>
<td>(0,0.26) (1.77,π]</td>
</tr>
<tr>
<td>CS→WTI (3 lags)</td>
<td>2,61 0,65 0,59 0,74 0,78</td>
<td>⬆️</td>
<td>(0,π]</td>
</tr>
<tr>
<td>CS→WTI (5 lags)</td>
<td>1,89 0,63 6,35** 15,09*** 15,16***</td>
<td>⬇️</td>
<td>(1.48,π]</td>
</tr>
</tbody>
</table>

Notes: (1)*** and *** denote rejection of the null hypothesis at the 10%, 5% and 1% significance levels, respectively; (2) The arrow indicates causality's direction; (3) symbols ⬇️, ⬆️, denote the causality's existence over the entire frequency domain, the existence of causality over parts of the frequency domain and no causal relationship over the entire frequency domain, respectively; (4) 0° denotes the first spectrum value; (5) The final column refer to causality at the 1% significance level.
4.6. Lemmens *et. al* frequency domain causality test

Another one test, which makes possible the investigation of Granger causality between the WTI oil prices and Consumer's sentiment in the frequency domain, is the Lemmens *et al.* (2008) causality test. To perform this test we are focusing again on the stationary levels of the two variables. The figure below, presents the estimated Granger coefficient of coherence for WTI and CS variables. According to Pierce, that coefficient assesses whether and to what extent, the WTI oil prices are Granger causing the consumer's sentiment at that frequency. Figure 18 shows that Granger causality exist both at low (long-run) and high (short-run) frequencies. In particular, Granger coefficient of coherence is close to 40% in the very long run and reaches 28% in the short run, meaning that Granger causality remains more significant at the lower frequencies that at higher ones.

![Figure 18. Granger coefficient of coherence](image)

According to Figure 18 it turns out that the null hypothesis of no causality is rejected at the significance levels of 5%, for the ranges $\omega \in (0,0.3)$ which corresponds to frequencies with a wave length of approximately 2 years. We have also found causality at higher frequencies that ranges $\omega \in (1.59,2.03)$, corresponding to a cycle length between 3 and 4 months and finally at frequencies $\omega \in (2.44,2.54)$ which corresponding to a cycle length of approximately 2.5 months.
If we consider again the hypothesis of the opposite direction (CS → WTI), we induced again to the same conclusion that CS has no predictive power over the WTI on the long-run, but eventually it turns out to Granger cause one another on the short-run. In particular, we fail to reject the null hypothesis for frequencies ranges $\omega \in (0,1.51)$ and $\omega \in (1.63,2.39)$. However, the null hypothesis is rejected at frequencies $\omega \in (1.52,1.62)$ and $\omega \in (2.39,\pi]$, corresponding to a cycle length between 2 and 4 months. The results obtained from the implementation of the Lemmens et al. causality test, depicted in the following graph and being further described in the table 9.

![Figure 19. Granger coefficient of coherence](image)

<table>
<thead>
<tr>
<th>Causality direction</th>
<th>Selected spectrum values</th>
<th>Causality inference</th>
<th>Causality interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level series</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WTI→CS</td>
<td>0.368**</td>
<td>0.06**</td>
<td>0.202**</td>
</tr>
<tr>
<td>CS→WTI</td>
<td>0.059</td>
<td>0.038</td>
<td>0.215**</td>
</tr>
</tbody>
</table>

Table 11. Summary of the Lemmens et al. causality test for certain frequencies

Notes: (1)***, and *** denote rejection of the null hypothesis at the 10%, 5% and 1% significance levels, respectively; (2) The arrow indicates causality's direction; (3) symbols $E$, $\bar{E}$, $\not{E}$, denotes the causality's existence over the entire frequency domain, the existence of causality over parts of the frequency domain and no causal relationship over the entire frequency domain, respectively; (4) $0^\circ$ denotes the first spectrum value; (5) The final column refer to causality at the 1% significance level.
5. Conclusions

With this study, we examined the causal relationship between WTI oil prices and Consumers’ Sentiment (with one-month maturity), for the US economy. The corresponding time period was approximately 40 years, spanning in particular from January 1, 1978, to March 1, 2013 (423 observations in total). After we extract seasonality from the variables, we applied the ADF, ADF-GLS and KPSS unit root tests, to find the order of integration. Hence, we concluded to the fact that both the variables are stationary to the levels, meaning that they are integrated of order zero, I(0). Given that the two time series are stationary, we proceeded to test for linear causality by using the simple Granger causality test. The results of the GC test showed the existence of a one direction linear causal relationship, from WTI to CS and not vice versa. In order to get a more solid understanding of the true nature of this relationship, we also assessed the possible predictive power that the two variables might have on one another, in the frequency domain. Initially, we implemented the B&C test to the levels, using different lag structure in both directions. Our findings denote the following significant characteristics; (a) there is a causality running from the WTI oil prices to the CS. More specifically, the test reveals a short-run causality from WTI to CS, with a wave length between 2 and 4 months and also a long-run causality, with a wave length of 25 months; (b) B&C test shows also a causality running in the opposite direction. Therefore, CS seems to have a short-run predictive power over WTI, corresponding to a wave length of 4 months. Apart from the B&C test, we applied also the Lemmens et al. causality test, in the frequency domain. The derived results also support the same hypothesis that the past values of WTI oil prices, are able to predict future values of the Consumer Sentiment and vice versa, in certain frequencies.

Our analysis shed light on the investigation of the causal relationship between two variables and in particular, between WTI oil prices and Consumer Sentiment. The methodological approach we adopted may be used in order to test different variables, demonstrate the true nature of their causality and determine the policy or take the relative measures.
6. Appendix

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>CS(-1)</td>
<td>-0.035489</td>
<td>0.012954</td>
<td>-2.739660</td>
<td>0.0064</td>
</tr>
<tr>
<td>C</td>
<td>3.015673</td>
<td>1.117442</td>
<td>2.698730</td>
<td>0.0072</td>
</tr>
</tbody>
</table>

R-squared                      | 0.017557 | Mean dependent var | -0.010310 |
Adjusted R-squared             | 0.015218 | S.D. dependent var  | 3.508952  |
S.E. of regression             | 3.482150 | Akaike info criterion | 5.337905 |
Sum squared resid              | 5092.656 | Schwarz criterion    | 5.357076  |
Log likelihood                 | -1124.298| Hannan-Quinn criter. | 5.345481  |
F-statistic                    | 7.505738 | Durbin-Watson stat   | 1.981953  |
Prob(F-statistic)              | 0.006412 |

Table 12. ADF unit root test for the CS variable (no trend)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLSRESID(-1)</td>
<td>-0.032999</td>
<td>0.012444</td>
<td>-2.651828</td>
<td>0.0083</td>
</tr>
</tbody>
</table>

R-squared                      | 0.016421 | Mean dependent var | -0.010310 |
Adjusted R-squared             | 0.016421 | S.D. dependent var  | 3.508952  |
S.E. of regression             | 3.480023 | Akaike info criterion | 5.334225 |
Sum squared resid              | 5098.546 | Schwarz criterion    | 5.343907  |
Log likelihood                 | -1124.542| Hannan-Quinn criter. | 5.338110  |
Durbin-Watson stat             | 1.984598 |

Table 13. ADF-GLS unit root test for the CS variable (no trend)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Augmented Dickey-Fuller test statistic</td>
<td>-2.733694</td>
<td></td>
<td>0.2235</td>
<td></td>
</tr>
</tbody>
</table>

Test critical values:
- 1% level: -3.979954
- 5% level: -3.420507
- 10% level: -3.132944

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>CS(-1)</td>
<td>-0.035452</td>
<td>0.012969</td>
<td>-2.733694</td>
<td>0.0065</td>
</tr>
<tr>
<td>C</td>
<td>3.093961</td>
<td>1.154008</td>
<td>2.681056</td>
<td>0.0076</td>
</tr>
<tr>
<td>@TREND(&quot;1978M01&quot;)</td>
<td>-0.000385</td>
<td>0.001393</td>
<td>-0.276260</td>
<td>0.7825</td>
</tr>
</tbody>
</table>

R-squared                      | 0.017736 | Mean dependent var | -0.010310 |
Adjusted R-squared             | 0.013047 | S.D. dependent var  | 3.508952  |
S.E. of regression             | 3.485986 | Akaike info criterion | 5.342462 |
Sum squared resid              | 5091.728 | Schwarz criterion    | 5.371218  |
Log likelihood                 | -1124.260| Hannan-Quinn criter. | 5.353826  |
F-statistic                    | 3.782775 | Durbin-Watson stat   | 1.982386  |
Prob(F-statistic)              | 0.023541 |

Table 14. ADF unit root test for the CS variable (trended)
### Table 15. ADF-GLS unit root test for the CS variable (trended)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLSRESID(-1)</td>
<td>-0.034553</td>
<td>0.012789</td>
<td>-2.701810</td>
<td>0.0072</td>
</tr>
</tbody>
</table>

| R-squared            | 0.017016    |            | -0.018575   |       |
| Adjusted R-squared   | 0.017016    |            | 3.508952    |       |
| S.E. of regression   | 3.478970    |            | 5.333716    |       |
| Sum squared resid    | 5095.460    |            | 5.343302    |       |
| Log likelihood       | -1124.414   |            | 5.337504    |       |
| Durbin-Watson stat   | 1.982716    |            |             |       |

### Table 16. KPSS unit root test for the CS variable (trended)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLSRESID(-1)</td>
<td>-0.034553</td>
<td>0.012789</td>
<td>-2.701810</td>
<td>0.0072</td>
</tr>
</tbody>
</table>

| R-squared            | 0.017016    |            | -0.018575   |       |
| Adjusted R-squared   | 0.017016    |            | 3.508952    |       |
| S.E. of regression   | 3.478970    |            | 5.333716    |       |
| Sum squared resid    | 5095.460    |            | 5.343302    |       |
| Log likelihood       | -1124.414   |            | 5.337504    |       |
| Durbin-Watson stat   | 1.982716    |            |             |       |

### Table 17. ADF unit root test for the WTI variable (no trend)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTI(-1)</td>
<td>-0.015057</td>
<td>0.007271</td>
<td>-2.070856</td>
<td>0.0390</td>
</tr>
<tr>
<td>D(WTI(-1))</td>
<td>0.315969</td>
<td>0.046719</td>
<td>6.763248</td>
<td>0.0000</td>
</tr>
<tr>
<td>C</td>
<td>0.379979</td>
<td>0.191644</td>
<td>1.982730</td>
<td>0.0481</td>
</tr>
</tbody>
</table>

| R-squared            | 0.102597    |            | 0.035669    |       |
| Adjusted R-squared   | 0.098303    |            | 1.806436    |       |
| S.E. of regression   | 1.715350    |            | 3.924212    |       |
| Sum squared resid    | 1229.935    |            | 3.953020    |       |
| Log likelihood       | -823.0467   |            | 3.935597    |       |
| F-statistic          | 23.89415    |            | 2.054829    |       |
| Prob(F-statistic)    | 0.000000    |            |             |       |
Null Hypothesis: WTI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=17)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Augmented Dickey-Fuller test statistic</td>
<td>-2.145141</td>
<td>0.5185</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Test critical values:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1% level</td>
<td>-3.980006</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5% level</td>
<td>-3.420533</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10% level</td>
<td>-3.132959</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WTI(-1)</td>
<td>-0.015752</td>
<td>0.007260</td>
<td>-2.079878</td>
<td>0.0381</td>
</tr>
<tr>
<td>D(WTI(-1))</td>
<td>0.316230</td>
<td>0.046650</td>
<td>6.778767</td>
<td>0.0000</td>
</tr>
<tr>
<td>C</td>
<td>0.293582</td>
<td>0.228208</td>
<td>1.286465</td>
<td>0.1990</td>
</tr>
<tr>
<td>@TREND(&quot;1978M01&quot;)</td>
<td>0.000486</td>
<td>0.000695</td>
<td>0.698326</td>
<td>0.4854</td>
</tr>
</tbody>
</table>

Table 19. ADF unit root test for the WTI variable (trended)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-squared</td>
<td>0.102495</td>
<td>Mean dependent var</td>
<td>0.035669</td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.100353</td>
<td>S.D. dependent var</td>
<td>1.806436</td>
<td></td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>1.713399</td>
<td>Akaike info criterion</td>
<td>3.919575</td>
<td></td>
</tr>
<tr>
<td>Sum squared resid</td>
<td>1230.074</td>
<td>Schwarz criterion</td>
<td>3.938780</td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-823.0705</td>
<td>Hannan-Quinn criter.</td>
<td>3.927165</td>
<td></td>
</tr>
<tr>
<td>Durbin-Watson stat</td>
<td>2.055080</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Null Hypothesis: WTI has a unit root  
Exogenous: Constant, Linear Trend  
Lag Length: 1 (Automatic - based on SIC, maxlag=17)

<table>
<thead>
<tr>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elliott-Rothenberg-Stock DF-GLS test statistic</td>
</tr>
<tr>
<td>Test critical values:</td>
</tr>
<tr>
<td>1% level</td>
</tr>
<tr>
<td>5% level</td>
</tr>
<tr>
<td>10% level</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLSRESID(-1)</td>
<td>-0.015481</td>
<td>0.007230</td>
<td>-2.141150</td>
<td>0.0328</td>
</tr>
<tr>
<td>D(GLSRESID(-1))</td>
<td>0.315656</td>
<td>0.046609</td>
<td>6.772385</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kwiatkowski-Phillips-Schmidt-Shin test statistic</td>
</tr>
<tr>
<td>Asymptotic critical values*:</td>
</tr>
<tr>
<td>1% level</td>
</tr>
<tr>
<td>5% level</td>
</tr>
<tr>
<td>10% level</td>
</tr>
</tbody>
</table>

Table 20. ADF-GLS unit root test for the WTI variable (trended)

Null Hypothesis: WTI is stationary  
Exogenous: Constant, Linear Trend  
Bandwidth: 16 (Newey-West automatic) using Bartlett kernel

<table>
<thead>
<tr>
<th>LM-Stat.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kwiatkowski-Phillips-Schmidt-Shin test statistic</td>
</tr>
<tr>
<td>Asymptotic critical values*:</td>
</tr>
<tr>
<td>1% level</td>
</tr>
<tr>
<td>5% level</td>
</tr>
<tr>
<td>10% level</td>
</tr>
</tbody>
</table>

Table 21. KPSS unit root test for the WTI variable (trended)
Null Hypothesis: DCS has a unit root  
Exogenous: Constant  
Lag Length: 0 (Automatic - based on SIC, maxlag=17)

<table>
<thead>
<tr>
<th>Augmented Dickey-Fuller test statistic</th>
<th>t-Statistic</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-20.24508</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Test critical values:  
1% level: -3.445664  
5% level: -2.868186  
10% level: -2.570375

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>DCS(-1)</td>
<td>-0.988821</td>
<td>0.048843</td>
<td>-20.24508</td>
<td>0.0000</td>
</tr>
<tr>
<td>C</td>
<td>-0.000203</td>
<td>0.002191</td>
<td>-0.092655</td>
<td>0.9262</td>
</tr>
</tbody>
</table>

R-squared 0.494488  
Adjusted R-squared 0.493282  
S.E. of regression 0.044953  
Sum squared resid 0.846685  
Log likelihood 709.6338  
S.E. of regression 0.063150  
Akaike info criterion -3.361681  
Schwarz criterion -3.342476  
Hannan-Quinn criter. -3.354091  
F-statistic 409.8632  
Prob(F-statistic) 0.000000

Table 22. ADF unit root test for the DCS variable (no trend)

Null Hypothesis: DCS has a unit root  
Exogenous: Constant  
Lag Length: 8 (Automatic - based on SIC, maxlag=17)

<table>
<thead>
<tr>
<th>Elliott-Rothenberg-Stock DF-GLS test statistic</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-2.653260</td>
</tr>
</tbody>
</table>

Test critical values:  
1% level: -2.570573  
5% level: -1.941592  
10% level: -1.616185

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLSRESID(-1)</td>
<td>-0.198557</td>
<td>0.074835</td>
<td>-2.653260</td>
<td>0.0083</td>
</tr>
<tr>
<td>D(GLSRESID(-1))</td>
<td>-0.712508</td>
<td>0.082907</td>
<td>-8.594059</td>
<td>0.0000</td>
</tr>
<tr>
<td>D(GLSRESID(-2))</td>
<td>-0.690102</td>
<td>0.085990</td>
<td>-8.025344</td>
<td>0.0000</td>
</tr>
<tr>
<td>D(GLSRESID(-3))</td>
<td>-0.675466</td>
<td>0.087291</td>
<td>-7.738114</td>
<td>0.0000</td>
</tr>
<tr>
<td>D(GLSRESID(-4))</td>
<td>-0.592253</td>
<td>0.086697</td>
<td>-6.831303</td>
<td>0.0000</td>
</tr>
<tr>
<td>D(GLSRESID(-5))</td>
<td>-0.539661</td>
<td>0.083263</td>
<td>-6.481371</td>
<td>0.0000</td>
</tr>
<tr>
<td>D(GLSRESID(-6))</td>
<td>-0.446284</td>
<td>0.076089</td>
<td>-5.865305</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

R-squared 0.468391  
Adjusted R-squared 0.457864  
S.E. of regression 0.046763  
Sum squared resid 0.883443  
Log likelihood 683.4114  
Durbins-Watson stat 2.033567

Table 23. ADF-GLS unit root test for the DCS variable (no trend)
Null Hypothesis: DCS is stationary  
Exogenous: Constant  
Bandwidth: 17 (Newey-West automatic) using Bartlett kernel

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Asymptotic critical values*:</td>
<td></td>
</tr>
<tr>
<td>1% level</td>
<td>0.739000</td>
</tr>
<tr>
<td>5% level</td>
<td>0.463000</td>
</tr>
<tr>
<td>10% level</td>
<td>0.347000</td>
</tr>
</tbody>
</table>

Table 24. KPSS unit root test for the DCS variable (no trend)

Null Hypothesis: DCS has a unit root  
Exogenous: Constant, Linear Trend  
Lag Length: 0 (Automatic - based on SIC, maxlag=17)

<table>
<thead>
<tr>
<th>Augmented Dickey-Fuller test statistic</th>
<th>t-Statistic</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test critical values:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1% level</td>
<td>-3.980006</td>
<td></td>
</tr>
<tr>
<td>5% level</td>
<td>-3.420533</td>
<td></td>
</tr>
<tr>
<td>10% level</td>
<td>-3.132959</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>DCS(-1)</td>
<td>-0.988947</td>
<td>0.048904</td>
<td>-20.22220</td>
<td>0.0000</td>
</tr>
<tr>
<td>C</td>
<td>0.000486</td>
<td>0.004410</td>
<td>0.110253</td>
<td>0.9123</td>
</tr>
<tr>
<td>@TREND(&quot;1978M01&quot;)</td>
<td>-3.25E-06</td>
<td>1.80E-05</td>
<td>-0.180134</td>
<td>0.8571</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>R-squared</th>
<th>Adjusted R-squared</th>
<th>S.E. of regression</th>
<th>Sum squared resid</th>
<th>Log likelihood</th>
<th>F-statistic</th>
<th>Prob(F-statistic)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.494528</td>
<td>0.492109</td>
<td>0.045005</td>
<td>0.846620</td>
<td>709.6501</td>
<td>204.4746</td>
<td>0.000000</td>
</tr>
</tbody>
</table>

| | Mean dependent var | S.D. dependent var | Akaike info criterion | Schwarz criterion | Hannan-Quinn criter. | Durbin-Watson stat ||
|----------|------------------|-------------------|-----------------------|-------------------|----------------------|-------------------|
|          | -1.07E-05        | 0.063150          | -3.357008             | -3.328200         | -3.345623           | 1.996973         |

Table 25. ADF unit root test for the DCS variable (trended)
Null Hypothesis: DCS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=17)

<table>
<thead>
<tr>
<th>t-Statistic</th>
<th>Elliott-Rothenberg-Stock DF-GLS test statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-18.50397</td>
</tr>
</tbody>
</table>

Test critical values:
- 1% level: 3.480000
- 5% level: 2.890000
- 10% level: 2.570000

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLSRESID(-1)</td>
<td>-0.898807</td>
<td>0.048574</td>
<td>-18.50397</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

R-squared: 0.449105
Adjusted R-squared: 0.449105
S.E. of regression: 0.046871
Sum squared resid: 0.922698
Log likelihood: 691.5364
Durbin-Watson stat: 1.999789

<table>
<thead>
<tr>
<th>LM-Stat.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kwiatkowski-Phillips-Schmidt-Shin test statistic</td>
</tr>
<tr>
<td>Asymptotic critical values*:</td>
</tr>
<tr>
<td>1% level</td>
</tr>
<tr>
<td>5% level</td>
</tr>
<tr>
<td>10% level</td>
</tr>
</tbody>
</table>

Table 26. ADF-GLS unit root test for the DCS variable (trended)

Null Hypothesis: DCS is stationary
Exogenous: Constant, Linear Trend
Bandwidth: 17 (Newey-West automatic) using Bartlett kernel

<table>
<thead>
<tr>
<th>LM-Stat.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kwiatkowski-Phillips-Schmidt-Shin test statistic</td>
</tr>
<tr>
<td>Asymptotic critical values*:</td>
</tr>
<tr>
<td>1% level</td>
</tr>
<tr>
<td>5% level</td>
</tr>
<tr>
<td>10% level</td>
</tr>
</tbody>
</table>

Table 27. KPSS unit root test for the DCS variable (trended)
Null Hypothesis: DWTI has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=17)

<table>
<thead>
<tr>
<th>Augmented Dickey-Fuller test statistic</th>
<th>t-Statistic</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>-15.71853</td>
<td>0.0000</td>
<td></td>
</tr>
</tbody>
</table>

Test critical values:

- 1% level: -3.445664
- 5% level: -2.868186
- 10% level: -2.570375

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>DWTI(-1)</td>
<td>-0.743126</td>
<td>0.047277</td>
<td>-15.71853</td>
<td>0.0000</td>
</tr>
<tr>
<td>C</td>
<td>0.000851</td>
<td>0.003509</td>
<td>0.242469</td>
<td>0.8085</td>
</tr>
</tbody>
</table>

R-squared: 0.370939
Adjusted R-squared: 0.369438
S.E. of regression: 0.071932
Sum squared resid: 2.170932
Log likelihood: 511.4307

Table 28. ADF unit root test for the DWTI variable (no trend)

Null Hypothesis: DWTI has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=17)

<table>
<thead>
<tr>
<th>Elliott-Rothenberg-Stock DF-GLS test statistic</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>-14.26933</td>
<td></td>
</tr>
</tbody>
</table>

Test critical values:

- 1% level: -2.570466
- 5% level: -1.941578
- 10% level: -1.616194

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLSRESID(-1)</td>
<td>-0.653569</td>
<td>0.045802</td>
<td>-14.26933</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

R-squared: 0.326505
Adjusted R-squared: 0.326505
S.E. of regression: 0.074391
Sum squared resid: 2.324276
Log likelihood: 497.0636

Table 29. ADF-GLS unit root test for the DWTI variable (no trend)
Null Hypothesis: DWTI is stationary
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0.125022</td>
<td></td>
</tr>
</tbody>
</table>

Asymptotic critical values*:
- 1% level: 0.739000
- 5% level: 0.463000
- 10% level: 0.347000

Table 30. KPSS unit root test for the DWTI variable (no trend)

Null Hypothesis: DWTI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=17)

Augmented Dickey-Fuller test statistic
<table>
<thead>
<tr>
<th>t-Statistic</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>-15.71514</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Test critical values:
- 1% level: -3.980006
- 5% level: -3.420533
- 10% level: -3.132959

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>DWTI(-1)</td>
<td>-0.744296</td>
<td>0.047362</td>
<td>-15.71514</td>
<td>0.000</td>
</tr>
<tr>
<td>C</td>
<td>-0.002587</td>
<td>0.007063</td>
<td>-0.366255</td>
<td>0.714</td>
</tr>
<tr>
<td>@TREND(&quot;1978M01&quot;)</td>
<td>1.62E-05</td>
<td>2.89E-05</td>
<td>0.560963</td>
<td>0.575</td>
</tr>
</tbody>
</table>

R-squared: 0.371412, Mean dependent var: -0.000123
Adjusted R-squared: 0.368405, S.D. dependent var: 0.090647
S.E. of regression: 0.072040, Akaike info criterion: -2.416100
Sum squared resid: 2.169299, Schwarz criterion: -2.387293
Log likelihood: 511.5891, Hannan-Quinn criter.: -2.404715
F-statistic: 123.4913, Durbin-Watson stat: 1.997222
Prob(F-statistic): 0.000000

Table 31. ADF unit root test for the DWTI variable (trended)
Null Hypothesis: DWTI has a unit root  
Exogenous: Constant, Linear Trend  
Lag Length: 0 (Automatic - based on SIC, maxlag=17)

<table>
<thead>
<tr>
<th>t-Statistic</th>
<th>Elliott-Rothenberg-Stock DF-GLS test statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>-15.27461</td>
<td></td>
</tr>
</tbody>
</table>

Test critical values:  
- 1% level: 3.480000  
- 5% level: 2.890000  
- 10% level: 2.570000

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLSRESID(-1)</td>
<td>-0.715535</td>
<td>0.046845</td>
<td>-15.27461</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Table 32. ADF-GLS unit root test for the DWTI variable (trended)

Null Hypothesis: DWTI is stationary  
Exogenous: Constant, Linear Trend  
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

| LM-Stat. | Kwiatkowski-Phillips-Schmidt-Shin test statistic | 0.047231 |

Asymptotic critical values*:  
- 1% level: 0.216000  
- 5% level: 0.146000  
- 10% level: 0.119000

Table 33. KPSS unit root test for the DWTI variable (trended)
7. References


