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# Models for GDP nowcasting

A thesis submitted in the fulfillment of the requirements for the degree of Master of Science in Applied Economics and Administration.

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*The most reliable way to forecast the future, is to try to understand the present.*

John Naisbitt.

**Abstract**

This thesis has been conducted as a part of the MSc program of Applied Economics and Administration, at the department of Economic and Regional Development of Panteion University in Athens. The dissertation took place from September of 2018 to June of 2019. The aim of this thesis is to contribute to the corpus of the literature about the subject of nowcasting the Greek GDP, through the implementation of bridge models.

Initially, special reference is made to forecasts regarding the field of macroeconomics, whereas next, the most important methods which have been applied, regarding the forecasts with econometric models, are listed. What is more, a substantial number of studies, which have been published not only internationally, but also for the case of Greece, are referred.

Then, collecting data of 30 macroeconomic variables (containing real Greek GDP, which is the dependent variable), we estimate Bridge Models over the period 2000Q3-2012Q4, through the package E-views 10 University Edition. Out of a total of 70 models were constructed and estimated, we present the top seven Bridge Models, which meet the basic assumptions (residual diagnostics test-stationarity,cointegration tests among the variables), have the best values in information criteria, as well as in the value of coefficient of determination $R^2$. In addition, in order to make comparison among the models, we estimate the models, Naïve Average Constant Growth model and the ARIMA (1,1,2) model.

Subsequently, for the aforementioned econometric models we make an out of sample evaluation, by using rolling estimations and forecasts within the period 2013Q1-2018Q4, taking into account the values of the models in the respective forecasting evaluation criteria.

Regarding the results of the analysis, we extract three main conclusions: First, the variables of the Composite Leading Indicator of Organism for Economic Co-operation and Development (OECD), the economic sentiment indicator (ESI) of IOBE, the Industrial production index, Turnover Index and Volume Index in Retail Trade of ELSTAT, proved to be liable predictors for the Greek Real GDP, second, the model which contained the proxies of the Industrial Production Index (IPI) and the Volume Index in Retail Trade had the best performance of all models, achieving the lowest value in the Root Mean Squared Error and third, the 7 Bridge models surpassed the models Naïve Average Constant Growth and ARIMA(1,1,2)), due to the fact that those models, take advantage of the information contained in the proxies, which published every month, before the official announcement of the data for the real Greek GDP.

*Key words: time series, Nowcasting, Forecasting, Greek real GDP, bridge models, forecasting ability evaluation criteria.*

## Περίληψη

Η παρούσα διπλωματική εργασία εκπονήθηκε ως μέρος του προγράμματος Μεταπτυχιακών Σπουδών του τμήματος Οικονομικής και Περιφερειακής Ανάπτυξης του Παντείου Πανεπιστημίου με τίτλο Εφηρμοσμένα Οικονομικά και Διοίκηση, κατά το χρονικό διάστημα Σεπτέμβριος 2018-Ιούνιος 2019. Σκοπός της εν λόγω εργασίας είναι να συμβάλει στο σώμα της βιβλιογραφίας σχετικά με την πρόβλεψη τρέχοντος τριμήνου (nowcasting) του Ελληνικού πραγματικού ΑΕΠ, μέσω της εφαρμογής οικονομετρικών μοντέλων Bridge.

Καταρχάς, γίνεται ιδιαίτερη αναφορά στις προβλέψεις που άπτονται του πεδίου της μακροοικονομίας, ενώ εν συνεχεία, παρατίθενται οι πιο σημαντικές μέθοδοι που έχουν εφαρμοσθεί σχετικά με τις προβλέψεις των οικονομετρικών μοντέλων. Επιπρόσθετα, αναφέρονται οι κυριότερες έρευνες που έχουν δημοσιευθεί όχι μόνο διεθνώς, αλλά και για την περίπτωση της Ελλάδος.

Εν συνεχεία, συλλέγοντας δεδομένα 30 μακροοικονομικών μεταβλητών (συμπεριλαμβανομένου του πραγματικού Ελληνικού ΑΕΠ, η οποία συνιστά την εξαρτημένη μεταβλητή), προβαίνουμε σε εκτίμηση μοντέλων Bridge κατά το χρονικό διάστημα 2000Q3-2012Q4, μέσω του στατιστικού πακέτου E-views 10 University Edition. Από το σύνολο των 70 μοντέλων που δημιουργήθηκαν και εκτιμήθηκαν, παρουσιάζονται τα καλύτερα επτά μοντέλα Bridge, τα οποία πληρούν τις βασικές υποθέσεις (έλεγχοι καταλοίπων, στασιμοτητας-έλεγχος συνολοκλήρωσης μεταξύ των μεταβλητών), έχουν τις καλύτερες τιμές στα πληροφορικά κριτήρια Akaike και Scwarch, καθώς και στον συντελεστή προσδιορισμού $R^2$. Επιπροσθέτως, για να γίνουν συγκρίσεις μεταξύ των ανωτέρω μοντέλων, εκτιμώνται τα μοντέλα Naïve Average Constant Growth και ARIMA(1,1,2).

Ακολούθως, για τα εν λόγω οικονομετρικά μοντέλα διενεργείται εκτός δείγματος αξιολόγηση μέσω των κυλιόμενων παλινδρομικών εκτιμήσεων και προβλέψεων για το χρονικό διάστημα 2013Q1-2018Q4, λαμβάνοντας υπόψη τις τιμές των μοντέλων στα αντίστοιχα κριτήρια προβλεπτικής ικανότητας.

Σχετικά με τα αποτελέσματα της ανάλυσης, τα κύρια συμπεράσματα που εξάγονται είναι τρία: Πρώτον, οι μεταβλητές Composite Leading Indicator (CLI) του Οργανισμού Οικονομικής Συνεργασίας και Ανάπτυξης (ΟΟΣΑ), ο δείκτης οικονομικού κλίματος του ΙΟΒΕ καθώς και οι δείκτες κύκλου εργασιών και όγκου στο λιανικό εμπόριο της Ελληνικής Στατιστικής Αρχής (ΕΛ.ΣΤΑΤ), αποδείχθηκαν αξιόπιστοι δείκτες για την πρόβλεψη του πραγματικού Ελληνικού ΑΕΠ, δεύτερο, το μοντέλο που περιείχε τις μεταβλητές δείκτης βιομηχανικής παραγωγής και δείκτης όγκου στο λιανικό εμπόριο, αναδείχθηκε το καλύτερο ως προς την προβλεπτική ικανότητα, διότι είχε την μικρότερη τιμή στο κριτήριο Root Mean Squared Error και τρίτο, τα επτά μοντέλα Bridge υπερείχαν έναντι των μοντέλων Naïve Average Constant Growth και ARIMA(1,1,2)), γεγονός που οφείλεται στο ότι τα εν λόγω μοντέλα, εκμεταλλεύονται τις πληροφορίες που εμπεριέχονται στις μεταβλητές που δημοσιεύονται κάθε μήνα, πριν την επίσημη ανακοίνωση των στοιχείων για το πραγματικό ΑΕΠ.

*Λέξεις κλειδιά: χρονολογικές σειρές, nowcasting, πρόβλεψη, Ελληνικό πραγματικό ΑΕΠ,bridge models, κριτήρια αξιολόγησης προβλεπτικής ικανότητας.*

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Dimitrios G. Mananas,
Athens, June 2019

## Chapter 1: Introduction

It is an undisputed fact that forecasting is a process, which is used by the individuals, in many aspects of their life. Specifically, it should be noted that forecasts form an integral part of people's daily life, are inseparably linked with human nature and involve the procedure of decision making.

Generally speaking, the future is unknown and we are not aware of what it holds. Also, it is characterized by a great deal of uncertainty and risk. Both of them are factors, which affect human's decision making to a large extent. On the other side, people want to plan their lives, as well as their future by taking the right decisions, that target to improve the conditions of their everyday life. However, it is likely to confront with situations and other possible contingencies, that may have unforeseeable repercussions, including either economic or non-economic losses. So, people want to be prepared for such events, and for this reason, they use widely the economic activity of insurance industry and the probability theory. It is noteworthy, that such basic mechanisms implement fruitful techniques, which enhance people's protection against the risk and help them, to mitigate the negative impact of uncertainty.

Except for the human predictions, forecasting is a commonly applied practice in the economy, both in the public and the private sector, especially in the branch of macroeconomics, as a task, which is implemented by the macroeconometricians (Stock, & Watson, 2001). Even more, macroeconomic forecasting entails data with macroeconomic proxies and it is considered, as a prerequisite for a forward macroeconomic policy making (Hawkins, 2005). As a consequence, it must be mentioned that forecasting is a fundamental part of economic policies. To elucidate further, I consider it necessary to give the following illustrative examples of forecasting, that are associated with policy making:

- National governments make forecasts in order to plan their budget and implement their allocative policies.
- The European Central Bank (ECB) want to maintain price stability and has the privilege of making decisions for the monetary policy in the euro area, which are its key priorities. As a result, macroeconomic projections are produced four times a year and published on the ECB's website.

- The international monetary fund (IMF) generates forecasts for a variety of macroeconomic data, through its Word Economic Outlook, which is published twice a year.
- Private firms predict their sales for the purpose of planning the input, which is needed to be purchased.
- In Greece, predictions for the majority of macroeconomic variables are prepared and executed mainly by organizations and other institutions, such as the Bank of Greece, the Ministry of Finance, the Hellenic Statistical Authority (ELSTAT), the centre of planning and economic research (KEPE) and the foundation for economic & industrial research (IOBE).

When it comes to forecasting, we should take into consideration, that is not a safe experiment, due to the fact, that data are not abundant and often are not reliable, because of the measurement errors (Iacovello, 2001). Consequently, qualitative information regarding the economy is of paramount importance for the macroeconomic forecasts. As a matter of fact, it is a sine qua non condition for the effectiveness of forecasting. Besides, another indispensable feature is the awareness of the current stance of the economy, while its evaluation is one of the cornerstones in macroeconomic forecasting. Jin-Kyu Jung, Manasa Patnam, & Anna Ter-Martirosyan, (2018) claimed that, *΄΄ knowing the current and future state of the economy enables timely responses and policy measures to maintain economic and financial stability as well as boost resilience to episodes of crises and recessions ΄΄.*

However, it is a well-known fact that the present state of the economy is not known and the needed information about the actual economic conditions is inadequate and incomplete. Nevertheless, this matter can be confronted with the index of the real gross domestic product (GDP), which its use is proposed by the economists for the assessment of the overall economy. The explanation they give, is that it depicts more accurately the current economic activity, than any other economic indicator. This view was claimed by Stock, & Watson (1989), as they supported that *΄΄ the cyclical component of real GDP is a useful proxy for the overall business cycle΄΄*. Also, Banbura, Giannone, & Reichlin, (2010), support the use of real GDP, as they mention that, *΄΄the emphasis on GDP is justified by the fact that this is the key statistic describing the state of the economy΄΄*. But, one of the most important advantages of real GDP is that its value is counted in constant prices, without taking into account the effect of inflation and is more reliable than the nominal, which uses current prices.

Whereas the proxy of GDP is the epicenter of our research in this study and before we move to the main part of this thesis, it would be useful to provide an insight, by giving some fundamental elements about the term. The index can be measured in three different ways: First, the production approach, which is called output or value-added approach and refers to the difference between the value of output less the value of goods and services that are used in the production process of these outputs, within an accounting period. Second, the income approach records GDP as the sum of the incomes, which are generated from the production of goods and services in all the sectors of an economy. As for the expenditure approach, which is the last, Mankiw, (2010) refers that GDP is the sum of the four following components. Thus, he gives the fundamental identity of national income accounts[1]:

$$Y = C + I + G + NX,$$

Y: National Income

C: Consumption

I: Investment

NX: Net exports= Exports-imports

Furthermore, the prevailing definitions of the GDP, which are extensively used in the global economy, enabling a deeper understanding about the indicator, are described, as follows: According to OECD (2001)[2], ¨*Gross Domestic Product, is an aggregate measure of production equal to the sum of the gross values added of all resident institutional units engaged in production (plus any taxes, and minus any subsidies, on products not included in the value of their outputs). The sum of the final uses of goods and services (all uses except intermediate consumption) measured in purchasers' prices, less the value of imports of goods and services, or the sum of primary incomes distributed by resident producer units*¨.

[1] Y is the symbol, which is used instead of GDP.
[2] The definition of OECD was based on the System of National Accounts, 1993. (United Nations and others, 1993, p.54)

Tim Callen (2017) one of the assistant directors of IMF gives the following definition: ¨*GDP measures the monetary value of final goods and services- that is, those are bought by the final user-produced in a country in a given period of time (in a quarter or a year). It counts all of the output generated within the borders of a country and is composed of good and services produced for sale in the market and also includes some nonmarket production, such as defense or education services provided by the government*¨.

In addition, the World Bank states that ¨*GDP represents the market value of all final goods and services produced within a country's borders, during the course of one year*¨.

Nevertheless, it is observed that the official statistics for the real greek GDP are published once in a quarter and with a considerable delay[3], while other macroeconomic variables are sampled at higher frequency. Therefore, there is an asynchrony regarding the time of the publication among the variables. Under these circumstances, several modelling approaches were established and valuable ways were provided, leading to efficient estimations, while at the same time, circumvent the problem of the non-concurrent publications.

To summarize, the ultimate goal of this dissertation is to develop and apply nowcasting models for the quarterly real GDP about the case of Greece, through the use of bridge models. After their estimation, we evaluate and compare the out of sample forecasting performance of the proposed models, by using the common statistical measurement errors.

The rest of this dissertation consists of the successive undermentioned chapters:

Chapter 2 reviews the bibliography and presents the main approaches related to the subject, the comparative studies among the approaches as well as the studies which have been made for Greece and main conclusions concerning the literature.

Chapter 3 describes the data, the methodology and the estimation method. Also, the estimated proposed models and the benchmarks models are presented.

[3] By the time of writing the chapter 1, according to the release calendar of Hellenic Statistical Authority, the provisional data of the quarterly national accounts including real GDP of the fourth quarter of 2018 were published in 07-03-2019 and the data of the first quarter of 2019 are going to be published in 04-06-2019. Thus, it is observed a two-month delay (approximately) in the official announcement of GDP, after the end of the reference quarter.

Chapter 4 contains the results of the nowcasts of the forecasting competitive models, the evaluation by doing a comparison among them and the main findings.

In the end, in chapter 5 is provided an overview of the findings and recommendations for future research are made.

## Chapter 2: Literature review

The aim of this chapter is to provide the theoretical framework of the thesis. A wide range of literature is encompassed, in which the multitude of main modeling approaches related to forecasting/nowcasting of the real GDP is mentioned, as well as important studies, in which comparison have been executed and have been published not only worldwide, but also for the case of Greece.

### 2.1 Main issues, challenges and benefits of nowcasting

The decision making of central banks, fiscal authorities, private agents and other economic institutions is depended on the ascertainment of current and future economic conditions. Similarly, fiscal stability can be consolidated by the reliable evaluation of the current and future movement of GDP. Those tasks are difficult (Angelini, Banbura, & Rustler, 2008), while there are several impediment factors. For its execution, it is required the application of economic models that relate theories to the actual economy and the choice of the suitable forecasting technique, which should be well-grounded to the forecasting theory. It is easy to understand, that a construction of a model that is susceptible to be inefficient, leads to forecasting failure. As a result, the effects of the failure can be summarized into an incorrect depiction of the total economy.

Before we create a valid econometric model, that is ready to give good forecasts, one of the most central questions in the field of forecasting arises: What information should be included in the forecasting model? The answer pertains to an abundance of factors. Primarily, it is well reported that exists a large variety of predictors available (Heij, Dijk, & Groenen, 2008), which include useful information that could be exploited to the fullest and improve the assessment of real GDP growth in the current quarter and its development in the near future. In addition, the selected data should be valuable and be updated frequently for the forecast of GDP. As a result, the researchers have to investigate thoroughly every indicator in order to be incorporated in the model and in an optimal way, striving to avoid any information loss.

Also, forecasters have to decide which method is the most suitable for the deployment of the collected data, while several econometric and statistical approaches have been recently developed and established in the forecasting literature. The views of the researchers that exported from the established studies in the literature, vary and differ and as a matter of fact, it is not possible to claim which approach is more effective, while it depends on a number of parameters. Nevertheless, the main goal of forecasters is the creation of an unbiased forecasting model (Itkonen, & Junoven, 2017), which means that an accurate model does not give higher or lower forecasting results than the actual values of the dependent variable.

It is well-accepted that several issues and challenges are posed by taking advantage of auxiliary information for forecasting of real GDP in the immediate short run period (Jansen, Win, &Winter, 2012). First, a significant issue regarding the macroeconomic data is that they have been noticed with a number of irregularities, despite the fact that usually, this type of data (being in time-series form) are currently used in analysis of macroeconomic forecasting, due to its simplicity and good performance (Artis, Banerjee, & Marcellino, 2001). Second, traditional forecasting has relied on economic indicators that have same publication time, which means that some information of high frequency variables involved in forecasting process, have been omitted or treated poorly. As a consequence, the observation and the monitor of the economy should be done in the present time and not to wait for the next quarter.

One challenge that macroeconometricians face, is the issue of dealing with different types of data, that have dissimilar periods in which, their observations are collected. Such situation indicates that a mixed frequency problem is present, while accessible proxies are sampled at a variety of periods, like daily,weekly,monthly and quarterly. Also, it should be stressed that the dating of the most recent observation may differ across indicators, because of differences in publication lags. This issue is called by Wallis, (1986) as a ΄ragged edge problem΄.

Another challenge derives from the necessity of the incorporation of new information that becomes known, in the forecasting model. With the new release of data, it is vital to incorporate the additional information into the model for the purpose of improving the forecasting accuracy for the proxy of GDP growth. A last challenge is the attempt to measure the impact of new release on the accuracy of nowcasting and bridges monthly data releases with the nowcast of quarterly GDP.

For all those reasons, researchers apply and use nowcasting approach (Giannone, Reichlin, & Small, 2008 ; Banbura et.al 2013). From a methodological point of view, nowcasting targets to solve the problem of frequency asymmetry between the dependent and independent variables of econometric models. It is easily concluded that econometric equations that are used for the construction of the models, in nowcasting method have to be in a similar frequency, in order to produce reliable estimates and forecasts. The main benefit of nowcasting models is that aim to use all the available information, which is published earlier and possibly at higher frequencies than the target variable of interest, achieving to obtain its early estimate before its official announcement (Giannone, Reichlin, & Small, 2008 ; Banbura, Giannone, & Reichlin 2010). Consequently, an advantage of nowcasting models is that their performance is enhanced as more information is being released. Thus, it is obviously that they can deal with unbalanced and ever-growing information sets successively. All those benefits of nowcasting lead to a result, that its widely experiment and application through useful econometric techniques, can tackle successively or to the best scenario eliminate the aforementioned challenges.

In general, concerning the existing literature, it should be noticed that the vast majority of the published papers were published during the last 20 years. The models that are mentioned in those studies, can be distinguished in two big categories: the non-factor models from the one-side and the factor models from the other side, while the two approaches are diametrically opposed. In the following sub-sections the main techniques, which are employed through the operation of statistical models as well as the predominant studies are presented.

## 2.2 Non-factor and factor models

First and foremost, the methods which are commonly used, are the univariate time series models[4]. Typical examples of non-factor models are the naïve constant models (usually referred as random walk with drift, (D'Agostino, Giannone, & Surico, 2006)), the random walk without drift model, the naïve model of four quarter moving averaging of GDP, the simple univariate autoregressive AR(1) model (Barhoumi et al., 2008), the moving average(ma) models, the combination of AR and MA models, which is called ARMA and the autoregressive integrated moving average models (ARIMA).

[4] Quarterly models is the else term that is also used in literature.

It should be noted that a major work in the forecasting of time series was done by Box and Jenkins (1976), in which for the first time ARIMA models were used. The main characteristics of such models is that simple time series are applied, but the additional information from the other series that have high correlation with GDP series is not incorporated, fact that could enhance the forecast in short-term horizons.

One of the most significant procedures which has the advantage of linking the monthly variables to quarterly, is the bridge equations. In fact, in those equations, linear regression models are employed and the approach can be highlighted as a commonly used method for nowcasting and easy applicable for the generation of short-term forecasts, especially by the central banks and other financial institutions (Angelini et al 2008; Banbura et al 2013). The backbone of the method is that the nowcast of the quarterly GDP can be produced, by using a single monthly indicator that has been transformed to the quarterly level. Those models are not pure macroeconometric models and require that the whole set of regressors should be known over the projection period. A key advantage of bridge models is that the forecasting results can be explained according to the principles of economic theory.

The first systematic study of the models was reported by Trehan (1989), who investigated the case of nowcasting the GDP in the USA. The author gathered data from sectors like agriculture, industrial production and retail sales. After the estimation of the models, he found that its forecasting ability was better than those of models, which combined the forecasts from other macroeconomic variables. Similarly, studies about the nowcasting of USA GDP through the bridge models were implemented by the Fitzerald, & Miller, (1989); Ingenito, & Trehan, (1996); Kitchen, & Monaco, (2003). Those studies showed the importance of bridge-modelling approach, as it was proved to be quite effective in the generation of the nowcasts.

Apart from the direct nowcast of GDP, in the literature we can identify the nowcasting of the components of GDP. Parigi, & Schlizer, (1995), nowcasted separately the components of the Italian GDP and after its nowcast, they were aggregated each nowcast, in order to shape the nowcast for the overall Italian GDP. Similarly, another significant study was carried out by Baffigi, Golineli, & Parigi, (2004), in which the components of the GDP have been also examined for the cases of Germany, France and Italy as well as for the total GDP of the euro area.

The application of the bridge models was also implemented in the French economy (Barchoumi, Darne, & Ferara, 2012). The authors modelled the quarterly

GDP growth and its main components by creating bridge equations, using a large set of hard and soft data, in both supply and demand side. The forecast experiment was done for the horizons of the current and the next one quarter. The results showed that the supply side encapsulated more accurate predictors than the demand side. Also, a main finding was that supply components are strongly associated with the proxy of industrial production (IPI). It was revealed that the forecast accuracy was higher for the equations that are more specifically selected to forecast GDP at particular monthly stages in the quarter, compared to the equations that are kept unchanged over the whole quarter. As a result, it is implied that changing the set of equations over the quarter, by including or excluding IPI data, is superior to keeping the same equations over time.

In the same vein, another significant study was carried out by Antipa et all (2012), in which the authors applied bridge models for the nowcasting of German GDP. The models were proposed with the proxy of IPI and without IPI. The second set of models had better performance than the first, but the most notable fact was that, keeping the same equation over time, could lead to more reliable projections. A number of studies that have confirmed the usefulness of the method for the purpose of forecasting the GDP growth are the following (Iacovello ,2001; Runstler, & Sedillot, 2003; Golinelli, & Parigi, 2007; Diron, 2006; Angelini et al.,2008; Barhoumi et al, 2008).

Another option in bridge equations, is the system of bridging with factors, which was first introduced in the research of Giannone, Reichlin, & Sala., (2004). Else application of this method can be identified in the study of Giannone, Reichlin, & Small, (2005). The key points of the method is that they use bridge equations and from a large set of data, the estimated common factors are extracted by using the principal components analysis (PCA).

One more approach in the field of nowcasting is the vector autoregressive models (VAR), which was introduced by Sims, (1980). It can be described, as an econometric method that it is oriented to employ linear models, in which each explanatory variable base his interpretation in its own past and current values. The epitome of the such models can be summarized in the fact that while the dynamics in the multiple time series can be monitored, the data can be described more reliably and conclusively, the forecasts are improving and their results can be used for policy making. Such models have many similarities to the bridge models and use the information which is derived from the GDP for the forecasting of GDP (Camba-Mendez, Kapetanios, Smith, & Weale, 2001). This method targets to take advantage of the independence between the separate indicator and real GDP dynamics. Usually, this type of models which are also called bivariate VARS, are executed by including quarterly GDP and the monthly indicator, which has been transformed in a quarterly shape. After that, the forecasting average is done through the indicators. Moreover, a VAR model uses the information which is related to a total quarter. An else form of VAR is the Bayesian vector autoregressive model, whose main benefit is that their specification can be achieved in levels.

Three distinct methods for handling mixed frequency data in a VAR model have been proposed in the literature. Schorfheide, & Song, (2015) show how to specify a VAR on monthly frequency. The quarterly series which are treated as having missing monthly observations, can be estimated with a Kalman smoother.

McCracken et al, (2015) provide an alternative approach, in which a VAR on quarterly frequency is specified in a way that for monthly series, the three-monthly observations within a quarter are treated as separate variables. A third approach for handling mixed frequency data is the specification of two separate VARS, one for the monthly and one for the quarterly variables. First, we use the monthly VAR to fill in quarters with missing monthly observations (usually the last quarter of the data). Second, we sum the monthly series to quarterly frequency whereas treating forecasted monthly variables as noisy signals. The precision of the noisy signal is obtained from the forecast error variance-covariance matrix of a Kalman filter/smoother. Finally, the combination of the monthly and quarterly series has been done and the quarterly VAR is ready for its forecasting. Generally speaking, as opposed to traditional univariate models, var models can exploit the information from the majority of the variables, that are used in the research.

An extra method which is applied in the nowcasting process is the Mixed Data sampling (MIDAS) regression models. Preliminary work in MIDAS models was undertaken by Ghysels et al, (2004). The main characteristic of the models is that they strive to overcome the different frequencies of the independent and explanatory proxies, that are confronted with, by using the distributed lags of regressors that are collected at a higher frequency than that of the dependent variables. One main upside of the approach is that the forecast of GDP can be produced in a direct way. MIDAS is a single horizon-specific equation that relates the quarterly GDP to various lags of a monthly indicator (Ghysels, Sinko & Valkanov, 2006; Schumacher, 2014). Economizes on the number of parameters requiring an estimation by adopting a parsimoniously parameterized lag polynomial. The efficiency gains of such an approach come at the cost of potential efficiency loses, if the implied restrictions on the lag structure between the monthly indicator and quarterly real GDP happen to be invalid.

As for the significant studies of the approach, in a study of Ghysels, Santa-clara, & Valkanov, (2005), the relationship between the conditional mean and the conditional variance of the aggregate market return has been analyzed. The authors reported that there was a positive and robust relation between risk and return and that MIDAS estimator generated better forecasts than those of the rolling windows and GARCH.

Also, Ferrara, Marsilli, & Ortega, (2013) combined the data of stock prices and commodity indexes and wanted to improve the forecasting ability of a MIDAS model. The main feature of their study was, that they used data, which were collected from 2007 to 2009, period which coincided with the outbreak of the global financial crisis. The results showed that by using the above data, the forecasting results can be enhanced and improved.

A different approach for tackling the mixed-frequency problem was the MF-VAR model. Gotz, & Hecq, (2013) showed in their paper that the data which were sampled for example in a monthly basis are correlated with the aggregated data and its lagged values. Moreover, they established the nowcasting causality for mixed-frequency VAR models, by investigating the relationship between nowcasting and Granger Causality. Another outcome of the research was, that the nowcasting causality can have a profound effect on the significance of lagged high-frequency variables in the MIDAS regressions models.

Last but not least, a study that was executed by Asimakopoulos, Paredes, & Warmedinger´s, (2013), with the application of Midas models, had a subject of forecasting a number of fiscal time series in different euro area countries. The authors used fiscal proxies collected in several frequencies and constructed MIDAS models for the purpose of analyzing annually or year-end the fiscal variables. They illustrated that using quarterly information was of paramount importance for the improvement of the forecast.

On the other hand, a rather separate approach in contrast with the others that we have mentioned earlier, being at the forefront of nowcasting literature, is the factor models. This method is associated with the use of the Kalman filter, which allows for an efficient handling of the non balancedness of the dataset and the variety of the frequencies of the data. Factor analysis is divided in two basic approaches: the static factor models and the dynamic factor models. Its general concept is that are used in order to achieve better forecasts and they constitute a valuable mechanism in the short-term forecasting, while there is a slew of studies in the literature that prove that fact.

The DFM has been displayed to provide accurate forecasts for the USA, the euro area, Spain and Netherlands. Also, its use has been implemented by the central banks in the eurozone following the Banbura, & Runstler, (2011). Despite the fact, that those models are capable of dealing with large unbalanced datasets and generally with all challenges, their main disadvantage is that the results cannot be explained by economic sense. In such models, the nowcasting is defined as the projection of quarterly GDP on the common factors extracted from the panel of the monthly data.

A prominent experiment about the factor analysis has been done by Artis et all (2001). To clarify, the authors a dynamic factor model for the case of the UK, by collecting data for 80 variables. First, they created three groups of series including real variables, prices and financial variables. One of the most vital results of the study was that six factors could explain the 50% of the fluctuation of all the variables in the data set. Specifically, those factors underlined the main economic indicators for the economy of the UK, which were the interest rates, monetary aggregates, prices, housing and labour markets variables and stock prices. In terms of an out of sample forecasting evaluation, it was made a comparison with various standard models such as the AR and VAR. The results showed that forecasts which were generated from the factor model achieved better results than those of the normal time series approaches.

Remaining in factor analysis, I found a study that carried out by D'Agostino, McQuinn, & O'Brien, (2011) presented a DFM, which produced nowcasts and backasts of Irish quarterly GDP using timely data from a dataset of 35 indicators. To the authors point of view, they followed the case of Giannone, Reichlin, & Small, (2008), which generated nowcasts of output for the US, using dynamic factor model. Its main advantage was that data related with macroeconomic had a major content about the relative information. Hence, the newest information can be incorporated within the similar quarter.

In addition, Shumacher, (2009) highlighted the role of international data for forecasting German GDP, by using a dataset of 500 indicators following the Bai and NG procedure. In this analysis, he used the principal component analysis following Stock, & Watson, (2002) methodology. The author also followed Bai and Ng (2008) and employed penalized regression techniques to identify ´´targeted predictors ´´that can be used for estimating the factors rather than the whole data. Taking account the preselection of data, international indicators do not contain additional information for forecasting. But in the case we preselect variables prior to factor estimation by LARS-EN, international data improve forecasts. So, in accordance with previous findings from Boivin, & Ng (2006), more data is not always better for factor forecasting and only by careful preselection of predictors, it would be feasible to exploit the additional information from a large and heterogenous data set.

Furthermore, Stakenas, (2012) used a large monthly dataset for the short-term Lithuanian GDP forecasting. The method he applied was the factor models by attempting a variety of specifications for an out of sample forecasting accuracy. Also, he explored and stressed the effect of using weighted principal components models. It is remarkable that weights had a dependence on variables with absolute correlation with GDP. Finally, he displayed that a small-scale factor model consisted of 5 variables is capable of nowcasting the GDP better than models with a full dataset of 52 variables, indicating that for the Lithuanian economy such models, may be more appropriate.

### 2.3 Comparative studies among the models.

A paper produced by Iacovello, (2001) was referred to the employment of bridge model and Var model for the short-term forecasting of Italian GDP. In his study, the author used variables such as industrial production and a coincident promptly indicator, which contained useful information. Also, he mentioned that bridge models refer to an indicator approach, which exploits early cyclical indicators, with a vast majority of them to be available on a monthly frequency. Moreover, he stressed the significance of industrial production index, as it was by far the most correlated variable with GDP growth and in his specified modes includes a trend. The next stage of his analysis was the estimation of a VAR model, by using 7 variables of GDP and he highlighted that such a model has the drawback of overparameterization, which in fact means that too many parameters have to be estimated. Another key thing to remember from the analysis, is that the author suggested to tackle the issue of multicollinearity, by using Bayesian Var models.

In a comparative study among standard benchmarks, small autoregression, leading indicator model, models for inflation, unemployment models based on the Phillip Curve and factor models, Stock, & Watson, (2002a) used 215 macroeconomic proxies. The researchers found that only 6 factors accounted for much of the variance of their 215 time-series. In addition, just a few factors were needed to forecast real activity and the most accurate forecasts of inflation used lags of its own values together with a single factor. This suggests that a small state vector may be essential for the prediction of macroeconomic time series.

Another empirical comparative study was conducted by the same authors (Stock, & Watson,) in 2004. In their experiment, the dataset they used consisted of 131 US time series and the forecasts were produced for a 30-year horizon. Their analysis also contained benchmark models like univariate, OLS using all predictors and combined ADL models. The main findings were two: First, the factors models gave best results in comparison with the else models and second that a large data set can be encapsulated by a few numbers of extracted factors.

As I have just highlighted before, Baffigi, Gollineli, & Parigi, (2004) separated the models they used in their analysis in two parts: Demand side and supply side and after that they evaluated their forecasting ability by using as comparative models the following: ARIMA, multivariate VAR and a cointegrated VAR model. The major finding they reached was that the performance of the BMs improved, due to the fact that more information was being incorporated. Finally, they revealed that the bridge models outperformed the other three models, bearing in mind, that some indicators are available over the whole forecasting horizon and proved that the aggregation of the national forecasts forecasted more precisely the euro area GDP and its components.

In the area of MIDAS models I gleaned the following papers: Tay (2006) estimated an AR(1) GDP growth model based on MIDAS approach and a common AR(1) GDP growth(usual naïve model) and made a comparison with the explanatory variable of stock price index. His main finding was that for the prediction of GDP is valuable to use the stock returns and that MIDAS models had better forecasting performance than those of the naïve model.

The German GDP has been investigated by Marcellino, & Shumacher, (2007) via the application of MIDAS models. The authors used macroeconomic variables by doing different specifications of MIDAS models as wells as of other alternative models and they proved that Midas with one lag had the best performance of all competitive models.

In Clements, & Galvao, (2008) study, the collected data which were sampled weekly and monthly, were used in the analysis for the generation of the USA GDP growth forecasts. They included in the MIDAS models an AR component, creating the MIDAS-AR model and showed that this model achieved better forecasts than those of the traditional AR and the AR distributed lag model.

Another study was that of Kuzin, Marcellino, & Shumacher, (2009). In their analysis, they tried to investigate MIDAS and MF-VAR models for the forecasting and nowcasting of GDP in the euro area by using a dataset of 20 variables. The outcome of the research was that the MF-VAR model surpassed the MIDAS models in longer horizons, while the MIDAS models was better in short term predictions.

A relatively recent study regarding the nowcasting of Philippine GDP growth has been documented (Rufino, 2019). The author used seven different nowcasting models, of which the three were traditional models and the other four were variants of MIDAS Models. Also, he contained in the dataset five macroeconomic variables(inflation, growth of industrial production, psei return, interest and exchange rate return). From those indicators, he used the first three and specified them in an ARDL form. 500 models were evaluated and the best model proved to be the ARDL(1,4,0,1). Therefore, he continued his analysis by estimating the seven competitive models with the ARDL (1,4,0,1) shape and the main findings of the research was that the step-weighting MIDAS had the lowest values in the measurement forecasting errors among the other models, result that underlined the supremacy of the MIDAS Models over the other common models in the nowcasting of economic growth in Philippines.

Two noteworthy subsequent comparative studies were published by Angelini et al the same year (2008). In the first study, the authors estimated and forecasted quarterly GDP in the euro area, by applying bridge equations and the system of bridging via factors. The main finding of the study was that the technique of bridging via factors offered more reliable predictions than those of bridge equations. Another key point of the research was that data based on surveys and other called soft, proved to be essential for the nowcasting procedure.

In the second study, the researchers tested a dynamic factor model for the euro area, estimating and generating forecasts for the monthly GDP growth and its components, comparing it to other models like the typical quarterly models. Ultimately, they concluded that the factor model had the best performance among the other models, highlighting their superiority. The supremacy of the dynamic factor models has been also confirmed in Barhoumi et al (2008) study, where the comparison was done with usual quarterly models. The main conclusions exported from this paper were two: The dynamic factor models had the best nowcasting ability and the models, which use data collected in monthly basis, tend to surpass models that use purely quarterly data.

Moreover, Heij, Dijk, & Groensen, (2011) tried to investigate the predictive performance of the Composite leading indicator by using ten monthly indicators and four coincident indicators. Especially, they employed in their analysis models with the proxies of the CCI and the IP and evaluated their forecasting errors for a variety of horizons (one,three and six months). The foremost outcomes were that the CLI seemed to be as not valuable as the univariate AR model, which had lower RMSE., Also another important feature of the research was that using the PCA can lead to more precise forecasts for both the IP and CCI growth rates, which were used as alternatives to CLI.

Last but not least, in Antipa et al, (2012) study which was introduced before, the authors made a comparison, as they implemented bridge and factor models for the case of the German Economy, for different forecasting periods. The first models were built by a variety of data like quarterly national accounts, the index of industrial production and financial and three forecasts per quarter were generated. Also, two common benchmarking models which were the AR and the naïve, were used. Concerning the forecasting results the RMSES for the BMs and DFMs were lower than those generally of the naïve and AR predictions. Another key finding was that the bridge models with IPI had a lower RMSEs for the second and the third forecast, highliting the significance of the IPI in the effectiveness of forecasting. Overall, the results of the experiment revealed that BMs fared better in comparison with DFMs,, as their errors were smaller than those of DFMs and that the improvement of the forecasts derived from the change in bridge equations, while new information was being included.

### 2.4 Review of studies about the case of Greece and discussion on literature.

Until recently, only a few works in literature, demonstrate the use of forecasting and nowcasting models about the Greek GDP. In this part, the two most notable studies are referred and highlighted with chronological order during the last eight years.

To the best of the author’s knowledge, no previous study has investigated nowcasting models for the Greek economy, until the first, which was pioneered by the Eurobank Global Markets Research (Thomakos, & Monokroussos, 2012). According to their empirical case study, they developed a model, which was oriented to deal with the publication lags of the data, revisions and other significant sides of the daily flow of macroeconomic information. In fact, they tried to derive high-frequency and real estimates of Greek GDP. The results underlined the importance of the economic climate index (ESI). After, they continued their analysis by applying MIDAS models and achieved to link the past evolution between the economic climate index and GDP growth. Also, a subsequent number of studies based on the same methodology were published by the Eurobank, until the third quarter of 2016. It is worth mentioning that those papers produced preliminary estimates for the quarterly GDP in real-time and ahead of the publication of the provisional data of the GDP.

Moreover, the most significant and representative study regarding the bridge models for the Greek economy was published by Lamprou, (2015). Specifically, the author proposed the implementation of bridge models for the nowcasting of Greek GDP, by using three of the most important monthly domestic indicators as the explanatory variables. The proxies she used, were the indexes of industrial production, the total turnover of retail sales and the volume of retail sales. The proposed models contained the following combinations: each variable individually, the two out of the three monthly variables as a pair and all three monthly variables together. After that, the estimated models were compared to AR(1) and AR(AIC) models for their nowcasting performance. The conclusion she reached was that more precise forecasts for the real GDP can be generated, by incorporating information that have become accessible recently and before the official release of the quarterly GDP growth.

In view of all that have been mentioned so far, the main conclusion that can be drawn from the thorough study of the above literature, leads to the fact that the most effective model has not been found yet, despite the plethora of available modelling approaches. The method that is used at each time, has to take into consideration the specificities of the research, such as the sample of the experiment, the structure, the peculiarities and the weak points of each economy. Also, it must be stressed that each model has its strengths and weaknesses, and its choice cannot be done on purely theoretical basis. The ranking of the models in terms of forecasting capacity and the extent to which this varies with the prediction horizon or the economic circumstances, has to be determined by empirical analysis. The vast majority of the papers differ in the size of information set and the sample period. As a general rule, when we build a nowcasting model it is important to collect proxies that are valuable for the prediction of GDP growth, timely and be updated frequently.

To conclude, despite the fact that some of the studies are conflicting, however, the significance of the bridge models has been confirmed by their widespread application in the field of short-term forecasting-nowcasting of real GDP.

## Chapter 3: Data, Methodology and Proposed models

### 3.1 Data

In this study, the dataset is composed of 30 macroeconomic variables, including real Greek GDP, as our target variable. The data were collected during the January and February 2019, from institutions and organisms like Hellenic Statistical Authority (ELSTAT), Bank of Greece (BoG), European Central Bank (ECB), the foundation for Economic and Industrial Research (IOBE), the Organization for Economic Co-operation and Development (OECD), the European Money Markets Institute (EMMI) and private companies, such as the CBOE Global Markets and HIS Markit Economics.

The sample ranges between the date of the first observation which begins in the first quarter of 2000 and ends in the fourth quarter of 2018, date which coincides with the last observation (76 observations in total). The data for the real Greek GDP were downloaded from the website of the Hellenic Statistical Authority.

What is more, I decided to include time-series that relate to the total economy. As a result, in the dataset are contained the main components of the Greek GDP, as they actually have a strong relation with GDP, a fact derived from the economic theory, other significant indicators of the Greek Economy, not only from the demand side, but also from the supply side, covering thus, a satisfiable part of various types of data, with the most of them to be published in monthly basis mainly from the ELSTAT. The vast majority of the indicators have been used in a number of studies in nowcasting literature (Antipa, Barhoumi, Brunes-Lesage & Darbe, 2012; Baffigi, Golineli, & Parigi, 2004; Diron, 2006, Monokrousos, & Thomakos 2012, Lamprou, 2015),. Also, in line with Monokrousos, &Thomakos, (2012), I incorporated in the dataset indexes of the European and international market activity, Eonia Rate and VIX[5]. For those indicators, we use the end of day to day closing values, respectively.

[5] As for the proxies of Eonia Rate and VIX, the transformations to monthly frequency were done in Excel.

Before we turn our focus in main analysis, it would be helpful to present detailed information about the series (see appendix A for graph of each variable). Also, in table 1 the source, the frequency and the type of data of each variable is depicted.

Athens stock exchange (the official term is Athens Exchange) supports Greece's capital markets by operating the equities and derivatives markets. (www.investopedia.com). Due to the fact that the initial series was available from January 2001, I found the data for the year of 2000 from the monthly statistical bulletin of the HELEX group headquarters[6], in order to have the same range of observations, as the other proxies. Also, it is worth mentioning that the Athens Stock Exchange suspended his operations on 27 June of 2015 and remained closed until 3 August of 2015. Thus, for the values of July, I used the respective values of June for the simplification of the analysis and due to the fact that no difference was observed.

Consumer confidence index provides an indication of future developments of households consumption and saving, based upon answers regarding their expected financial situation, their sentiment about the general economic situations, unemployment and capability of savings. (www.oecd.com)

Composite leading indicator offers early signals of turning points in business cycles showing fluctuation of the economic activity around its long-term potential level. Also, shows short-term economic movements in qualitative rather than quantitative terms. (www.oecd.com)

Construction confidence indicator is a statistical indicator based on the results from business surveys interrogating enterprises on their current economic situation and their expectations about future developments. The indicator is calculated as the simple arithmetic average of (the seasonally adjusted) balances of positive and negative answers to specific questions. (www.ec.europa.eu)

Consumer price index measures the change over time in the prices of consumer goods and services acquired. (www.ec.europa.eu).

Harmonized index of Consumer prices measures the change over time in the prices of consumer goods and services acquired, used or paid by euro area households. (www.ecb.europa.eu)

[6] I need to thank Mr. Kamaroulis, who offered his help in order to find the monthly data of the ASE index for the year of 2000.

Deposits (households and business entities) refer to the money of physical and legal persons that are placed in the Greek banks for safekeeping. (www.investopedia.com)

Economic sentiment indicator is a composite indicator made up of five sectoral confidence indicators with different weights. It is measured as an index with mean value of 100 and standard deviation of 10 over a fixed standardized sample period (www.ec.europa.eu)

Eonia (Euro overnight index average) rates the 1-day interbank interest rate for the Eurozone. (www.emmi-benchmarks.eu).

Exports of goods and services is the transferring process of domestic goods and services to a foreign country, where goods and services will be processed, used , sold or re-imported. It has a positive effect in the trade balance. (www.investopedia.com)

Final consumption expenditure is referred to the amount of money that is spent by the households on individual consumption of goods and services. (www.oecd.com)

General government expenditure is the sum of all government current expenditures for purchases of goods and services (including compensation of employees). Also, contains the most expenditures on national defense and security, but excludes government military expenditures that are part of government capital formation. (www.worldbank.org)

Gross fixed capital formation is the variable, which is used for the component of investments according to SNA 2008[7]. It is calculated by deducting the total value of fixed assets acquired by a producer, within one accounting period certain specific costs that increase the value of non-produced assets. (www.oecd.com). Moreover, it should be noted that GFCF is a cost element, which shows how much of the value added to the economy is invested, but it does not include in their calculation, the purchases and the sales of lands as well as the consumption of fixed assets (depreciation).

Imports of goods and services is the transferring process of goods and services from a foreign country to another, where goods and services will be processed, used, sold or re-exported. It is the opposite of exports and have a negative affect the trade balance. (www.investopedia.com)

[7] The quarterly national accounts are compiled in agreement with the European System of accounts-ESA 2010 of the council Regulations (EU) No 549/2013 of the European Parliament and of the council of 21 May 2013.

Long-term interest rates: It is referred to central government bond yields on the secondary market, gross of tax, with a residual maturity of around 10 years. (www.ec.europa.eu)

Sales of motor vehicles (index) measures the activity of the investigated sectors on the market, in terms of value. Specifically, the index is calculated net of VAT and includes the total amounts invoiced by the enterprise during the reference period(quarter), which correspond to sales of (vehicles) goods and services supplied to third parties. (www.statistics.gr)

Short term interest rates are the rates at which short-term borrow-lings are affected between financial institutions or the rate at which short-term government paper is issued or traded in the market. Generally, are averages of daily rates, measured as a percentage and are based on three-month money market rates. (www.oecd.com)

Industrial production index refers to the output of industrial establishments and covers sectors such as mining, manufacturing, electricity, gas, steam and air-conditioning. This index is measured during a specific period and expresses change in the vol

Motor trades index includes wholesale and retail trade, repair of motor vehicles and motorcycles. (www.statistics.gr)

Price indices for new Residential Buildings Construction((Output) Price Index of Work Categories): The index reflects the changes in the prices paid to the constructors-contractors for the different individual construction stages of new residential buildings, when ordering the construction of the works. (www.statistics.gr)

Production index in construction is a significant business cycle indicator, which shows the quarterly activity in the production of building construction and the production of civil engineering sectors. (www.statistics.gr)

Producer price index (total market) measures the monthly rates of change in the prices of goods that are produced in the total market and either sold in this market or are exported to the same market. (www.oecd.com)

Retail trade confidence indicator is based on the results from business surveys interrogating enterprises on their current economic situation and their expectations about future developments. The index is calculated as the simple arithmetic average of (the seasonally adjusted) balances of positive and negative answers to specific questions concerning retail trade. (www.ec.europa.eu)

Standard unemployment rate (total all ages): The share of the labor force that is jobless, expressed as a percentage. It is a lagging indicator, meaning that it generally rises or falls in the wake of changing economic conditions, rather than anticipating them. (www.ec.europa.eu). For instance, when the economy is characterized by the recession, the unemployment rate is expected to rise. On the other hand, when the economy is growing, the percentage is expected to decline.

Volume index of retail trade: The index is calculated by deflating the Retail trade Turnover index using the Harmonized Index of Consumer Prices at constant tax rates (HICP-CT) as deflator. (www.statistics.gr)

The Purchaser Manufacturing Index (PMI) is measured by the HIS Markit[8] and is derived from monthly surveys of supply chain managers, covering both upstream and downstream activity. (www.ihsmarkit.com). Also, it is an index of the prevailing direction of economic trends in manufacturing and service sectors and contains a diffusion index that summarizes if the market conditions are expanding, staying stable or contracting. The foremost purpose of the index is to provide information about current and future business conditions to company decision makers, analysts and investors.

The CBOE Volatility index is a measure of the stock market's expectation of volatility implied by S& P 500 index options. (www.cboe.com). It is calculated by the Chicago Board Options Exchange. It is a useful tool for investors, research analysts and portfolio managers who take into consideration the VIX values, as a way to measure market risks, before they undertake investment decisions.

Turnover index retail trade is a business cycle indicator which shows the monthly activity of the retail sector in value. It is a short-term indicator for the domestic demand. (www.ec-europa.eu)

Wholesale trade index: The purpose of the index is to measure in value terms the activity of wholesale trade in the market. The turnover excludes VAT and comprises

[8] Special thanks are given to Ms Sian Jones, economist of HIS Markit, who provided the data for the Greek manufacturing PMI after my request.

the totals invoiced by the enterprise during the reference period(quarter), which correspond to sales of goods and services supplied to third parties. (www.statistics.gr).

Table 1. Series, source, frequency and type of data

| **Series** | **Source** | **Frequency** | **Type of data** |
|---|---|---|---|
| ASE Index | BoG | Monthly | Economic |
| Consumer Confidence Index | OECD | Monthly | Survey |
| Composite leading Indicator (CLI) | OECD | Monthly | Economic |
| Construction Confidence Indicator | IOBE | Monthly | Survey |
| Consumer Price Index (CPI) | ELSTAT | Monthly | Economic |
| Deposits (Households and Business Entities) | BoG | Monthly | Financial |
| Eonia Rate | EMMI | Daily | Financial |
| Economic Sentiment Indicator (ESI) | IOBE | Monthly | Survey |
| Exports of Goods and Services | ELSTAT | Quarterly | Economic |
| Final Consumption Expenditure | ELSTAT | Quarterly | Economic |
| General Government Expenditure | ELSTAT | Quarterly | Economic |
| Gross Fixed Capital Formation | ELSTAT | Quarterly | Economic |
| Harmonized Consumer Price Index | ELSTAT | Quarterly | Economic |
| Imports of Goods and Services | ELSTAT | Quarterly | Economic |
| Industrial Production Index | ELSTAT | Monthly | Financial |
| Long-term interest rates | OECD | Monthly | Financial |
| Motor Trades Index | ELSTAT | Monthly | Economic |
| Output Price Index of work categories (Price Indices for New Residentials Buildings Construction) | ELSTAT | Monthly | Economic |
| Producer Price Indices (Total market) | OECD | Monthly | Economic |
| Production Index in Construction | ELSTAT | Monthly | Economic |
| Manufacturing Purchasing Managers Index (PMI) | HIS Markit | Monthly | Survey |
| Retail Trade Confidence Indicator | IOBE | Monthly | Survey |
| Sales of Motor Vehicles Index | ELSTAT | Monthly | Economic |
| Short-term interest rates | OECD | Quarterly | Financial |
| Standardized Unemployment Rate (total all ages) | ECB | Monthly | Economic |
| Turnover Index Retail Trade | ELSTAT | Monthly | Economic |
| Volatility Index (VIX) | CBOE | Daily | Financial |
| Volume Index Retail Trade | ELSTAT | Monthly | Economic |
| Wholesale Trade Index | ELSTAT | Monthly | Economic |

In table 2 the essential descriptive statistics, which were calculated for all variables used in the study, by using the option from Eviews-10, are presented. To facilitate the readers' understanding of the table, it is clarified, that the descriptive statistics for the Greek Real GDP, the components and for the deposits are in billion

Euro. Also, the proxies of Eonia Rate, short-term interest rates, long-term interest rates, standardized unemployment rate, volatility index are in percentage rate. The ASE index takes values below or above 1000 points and the other indicators take values below or above 100.

Table 2. Descriptive statistics

| Series | Mean | Median | Max | Min | St. Deviation |
|---|---|---|---|---|---|
| ASE Index | 2086,58 | 1783 | 5186,33 | 549 | 1354,37 |
| Consumer Confidence Index | 99,18 | 99,28 | 102,99 | 95,64 | 1,98 |
| Composite Leading Indicator (CLI) | 99,71 | 99,81 | 102,35 | 96,58 | 1,36 |
| Construction Confidence Indicator | 83,25 | 75,05 | 144,60 | 32,96 | 30,58 |
| Consumer Price Index (CPI) | 96,91 | 99,98 | 110,86 | 74,26 | 11,24 |
| Deposits (Households and Business Entities) | 154032,2 | 145179,5 | 236257,7 | 97804,33 | 37744,90 |
| Eonia Rate | 3,01 | 2,75 | 5,06 | 1,97 | 1 |
| Economic Sentiment Indicator (ESI) | 97,81 | 100,95 | 119,96 | 77,96 | 11,06 |
| Exports of Goods and Services | 12544,76 | 11974,50 | 20374 | 7397 | 2979,599 |
| Final Consumption Expenditure | 46646,84 | 45024,50 | 57037 | 38626 | 5114,48 |
| General Government Expenditure | 11140,72 | 11037 | 14070 | 9173 | 1253,314 |
| Gross Fixed Capital Formation | 9460,46 | 10420,50 | 17545 | 4383 | 3476,21 |
| Harmonized Consumer Price Index | 91,73 | 94,68 | 104,36 | 69,80 | 10,85 |
| Imports of Goods and Services | 16371,50 | 16270,50 | 24055 | 12814 | 2451,266 |
| Industrial Production Index | 106,42 | 106,10 | 123,97 | 86 | 13,79 |
| Long-term interest rates | 7,65 | 5,38 | 30,66 | 3,37 | 5,62 |
| Motor Trades Index | 188,60 | 220,20 | 322,80 | 75,30 | 83,19 |
| Output Price Index of work categories (Price Indices for New Residential Buildings Construction) | 92,59 | 92 | 100,60 | 80,50 | 5,99 |
| Producer Price Indices (Total market) | 94,63 | 96 | 116,13 | 70,70 | 13,58 |
| Production Index in Construction | 123,84 | 117,97 | 337,36 | 26,08 | 81,78 |
| Manufacturing Purchasing Managers Index (PMI) | 49,41 | 50,60 | 58,03 | 38,73 | 4,50 |
| Retail Trade Confidence Index | 93,13 | 96,88 | 128 | 54,30 | 19,36 |
| Sales of Motor Vehicles Index | 214,36 | 253,25 | 417,50 | 71,10 | 108,17 |
| Short-term interest rates | 1,97 | 1,52 | 8,91 | -0,32 | 2,16 |
| Standardized Unemployment Rate (Total all ages) | 15,55 | 11,29 | 27,73 | 7,58 | 7 |
| Turnover Index in Retail Trade | 115,40 | 106,88 | 159,36 | 81,90 | 20,15 |
| Volatility Index (VIX) | 19,70 | 17,45 | 58,59 | 10,30 | 8,00 |
| Volume Index in Retail Trade | 128,25 | 126,41 | 174,6 | 97,8 | 24,08 |
| Wholesale Trade Index | 123,93 | 113 | 188,5 | 81,6 | 27,8 |
| Real Greek GDP | 52501,41 | 50926,50 | 65000 | 42633 | 6371,475 |

## 3.2 Methodology

### 3.2.1 Data transformations

In this part we analyze the conversion of the proxies of our dataset, in order to use them in the construction of valid models and for the purpose of giving us accurate estimates and forecasts.

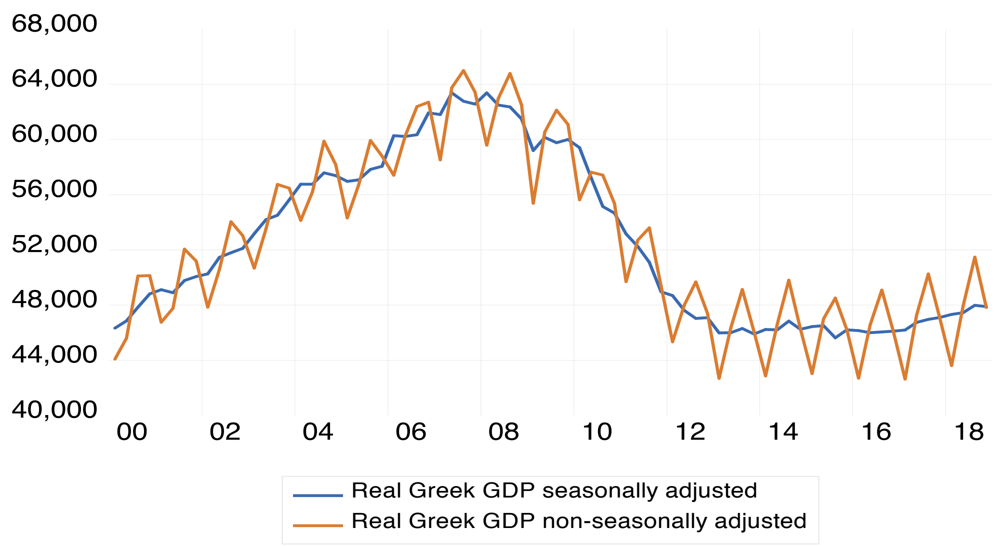
The first stage in our methodology, is to check the variables about seasonality. In an econometric analysis, it is a well-known fact that the existence of seasonality leads to not valid models and creates issues such as, unreliable estimates and not precise predictions. As a result, it has to be overcome. Regarding the Greek real GDP, it must be noted that the Hellenic Statistical Authority stopped to produce seasonally adjusted data in 2011. Thus, the downloaded data for the Greek Real GDP in this analysis was downloaded in a non-seasonally adjusted form. Also, some time-series were collected with seasonally adjusted data (table 3). So, I decided to test the presence of seasonality for the rest of the variables, in order to have a common time-series data set. Therefore, seasonality was tackled, through the TRAMO/SEATS option of E-views 10 University Edition, which was implemented by Gomez and Maravall (1996). When seasonality was present, each variable was transformed to a new with the seasonally adjusted data. In figure 1, we plot together the non-seasonally and the seasonally adjusted series for the GDP and we observe the result of the adjustment in the Real Greek GDP series, which illustrates, that the seasonal effects have been eliminated.

The next step in our analysis after the monitoring of seasonality, is the use of log-transformation of the variables, which is a commonly applied technique by the econometricians. The main concept is that we take logarithms for each variable, apart from survey and financial data (Barhoumi et al 2008) and those, which were in growth rate or percentage rate (they have been mentioned in part 3.1). The foremost goal of this transformation is to make our data more normal and symmetrical. So, the proxies were logarithmised, by the following specification: $\log x_t = \log(x_t)$.

Table 3. Seasonally adjusted time-series

| |
|---|
| Industrial Production Index |
| Motor Trades Index |
| Production Index in Construction |
| Purchasers Manufacturing Index (PMI) |
| Sales of Motor Vehicles Index |
| Standardized unemployment rate |
| Turnover Index Retail Trade |
| Volume Index Retail Trade |
| Wholesale Trade Index |

Figure1. Quarterly Real Greek GDP levels (in billion Euro) at constant 2010 prices, non-seasonally and seasonally adjusted series, 2000Q1-2018Q4




### 3.2.2 Stationarity test

The concept of stationarity is one of the most important key features of a time series. Even more, in order to prevent the phenomenon of spurious regression, we strive to regress and estimate models that its variables are stationary. Actually, it is a prerequisite for the validity of every regression.

As a general rule, each time-series is stationary, when it swings around the average. To be more specific, the values it takes at different times over a period of time, have the same average, the same variance and the value of its covariance between two periods of time, depends only on the delay between the two time periods. In fact, it is the distance between these two time points and not the actual time period, where the covariance is calculated. It must be mentioned that, stationarity of a variable entails the acceptance of the following fundamental assumptions:

1. The median: $E(X_t) = \mu$, is constant for all the t.
2. The variance: Var$(X_t) = E(X_t - \mu)^2 = \sigma^2$, is constant over the period of time t.
3. Covariance: Cov $(X_t, X_{t+k})$= E$[(X_t - \mu)(X_{\tau+\kappa} - \mu)] = \gamma_\kappa$ , is constant for all the t and k$\neq 0$.

In this project, the proxies are checked for stationarity, by using the Augmented Dickey-Fuller test. It should be noted that in most cases, when we use macroeconomic data for the construction of an econometric model, it is customary for the variables, to show a trend or seasonality. As a consequence, the time series are not stationary and we have to take the first differences (differencing), in order to achieve stationarity. However, the Dickey fuller unit-root test examines the following hypothesis:

Ho: The variable is not stationary (there is a unit root)

$H_1$: The variable is stationary. (there is not a unit root).

Therefore, after the transformation of the proxies in log-levels (as an example, see figure 2 for the log-transformation of the Greek Real GDP ), first of all, we examined the performance of all the variables, including those that were in growth rates or percentage rate in their levels, by doing the Augmented Dickey Fuller test in Eviews-10, following the case of Diebold & Kilian (2000), who stress that the check of unit root in the variables, lead to the selection of better forecasting models. However, all the variables had a unit root in their examined level, except for short-term interest rates, which was stationary. (for further results of stationarity test see appendix B). As a consequence, the null hypothesis was rejected (presence of a unit root) for the rest of the variables, and taking the first differences of each variable, I repeated the test.

Generally, for the transformation of the proxies by taking first differences, I used the following specifications: D[9]log$(X_t)$=log$(X_t)$-log$(X_{t-1})$ and D$(X_t)$=$X_t$-$X_{t-1}$, where t refers to the current quarter and t-1 to the preceding quarter. As we see in table 4, the results revealed, that the investigated time series were stationary in their first

[9] The symbol D is the difference operator and is defined as D=(1-L), where L=Lag. It means the difference between the time t and the time t-1.

differences. Besides, in figure 4 the growth rate of Greek real GDP is plotted (for the other proxies see appendix B).

Figure 2: Quarterly Greek Real GDP in log-levels at constant 2010 prices, 2000Q1-2018Q4

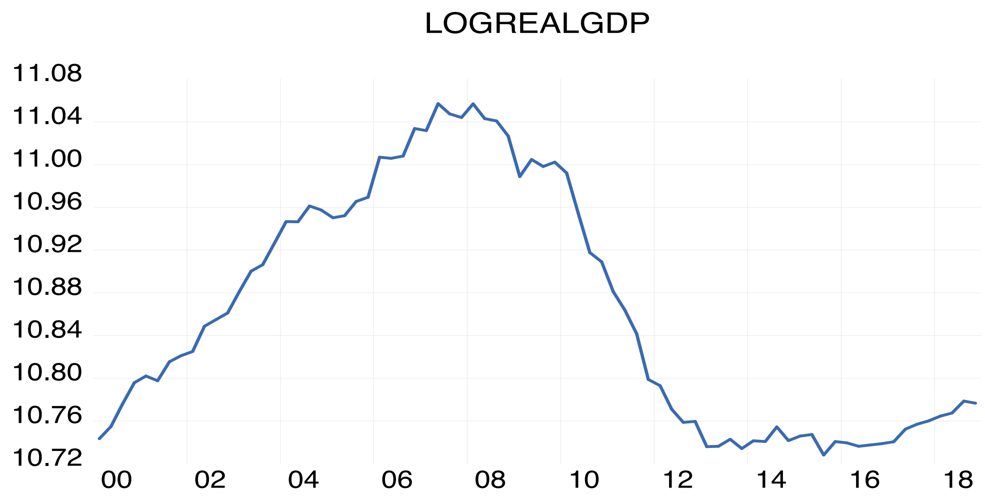
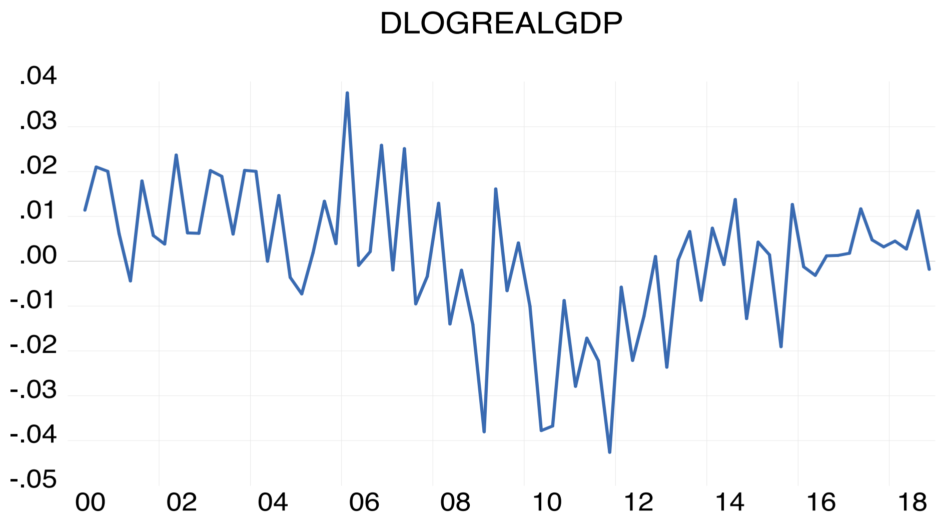


Table 4: Stationarity tests of growth rates of variables

| Variables | ADF (t-stat) | P_value[10] |
|---|---|---|
| DlogrealGDP | -6,121163 | 0,000 |
| Dlogaseindex | -5,868384 | 0,000 |
| Dlogcci | -9,411913 | 0,000 |
| Dlogcli | -6,511533 | 0,000 |
| Dconstrconfind | -8,320597 | 0,000 |
| Dlogcpi | -3,280941 | 0,0013 |
| Dlogdeposits | -3,297042 | 0,0013 |
| Deoniarate | -7,066742 | 0,000 |
| Desi | -6,226259 | 0,000 |
| Dlogexports | -10,69724 | 0,000 |
| Dlogfinconsexpenditutre | -5,921167 | 0,000 |
| Dloggengovnexpenditure | -10,39624 | 0,000 |
| Dloggrosfixcapformation | -10,25336 | 0,000 |
| Dloghcpi | -2,866939 | 0,000 |
| Dlogimports | -11,16313 | 0,000 |
| Dlogipi | -9,953940 | 0,000 |
| Dlongtermintrate | -8,057721 | 0,000 |
| Dlogmotortradesind | -5,338623 | 0,000 |
| Dlogouputpriceindex | -3,743478 | 0,000 |
| Dlogppi | -6,791178 | 0,000 |
| Dlogprodindconstruction | -15,09970 | 0,000 |
| Dpmi | -8,257728 | 0,000 |
| Dretailtradeconfind | -7,415458 | 0,000 |
| Dlogsalesmotorrvehicles | -7,795021 | 0,000 |
| Dunemprate | -2,831123 | 0,000 |
| Dlogturnindexrttrade | -6,989232 | 0,000 |
| Dvix | -9,459207 | 0,000 |
| Dlogvolindexrettrade | -7,157866 | 0,000 |
| Dlogwholesaletradeindex | -7,036677 | 0,000 |

[10] Confidence level of 90%,95% and 99% (p=0,01, 0,05, 0,1)

Figure 3: Quarter-on-quarter Real Greek GDP growth rate (first-differences of log), in billion Euro, 2000Q1-2018Q4.




### 3.2.3 Bridge Models

In this dissertation, we use the established method of Bridge Models. As we stressed in chapter 2, bridge models link quarterly average of the monthly independent variables $X_{j,t}$ to quarterly target variable ($Y_t^Q$). Thus, we rely on a bridge model based on a regression, which has the general following form (Rustler, Sedillot 2003):

$$\rho(L)\Delta Y_t^Q = \sum_{i=1}^{k} \delta_j(L)\Delta\, xj_t^Q + \varepsilon_t^Q,\ \varepsilon_t^Q \sim N(0, \sigma_\varepsilon^2)$$

where,

i) $Y_t^Q$ , is the quarterly target variable (log of real Greek GDP)

ii) Δ is the difference operator

iii) p(L) is the lag polynomial of order p

iv) δj(L) is the lag polynomial of order $q_j$

v) k is the number of lags for the explanatory variables

vi) $xj_t^Q$ refers to the monthly proxies

vii) Q is the number of explanatory variables and

viii) $\varepsilon_t^Q$ the error term distributed as iid[11] Normal with zero mean and constant variance.

ix) t is the number of quarters in the sample.

Also, the average of the monthly indicators which are published before the release of GDP, is denoted as:

$$X_{j,t}^{Q} = \sum_{1}^{3} 1/3\, x_{m,t}^{j}$$

Where $X_{m,t}$ is the monthly indicator observed in month m of quarter t.

In our case, all the monthly variables have been aggregated to quarterly frequency, as the information for the data are known over the whole quarter, which means that we have incorporated the information of the monthly releases of the data. As a consequence, the bridge models are estimated in quarterly basis. Next, we introduce the indispensable tests regarding the residuals.

### 3.2.4 Residuals diagnostics tests

For each bridge model we create, it is of paramount importance to make the necessary residual diagnostics tests, which are described in the following sections. As we know from econometric theory, residuals are defined as the difference between the observed value of the dependent variable and the estimated value. Specifically, suppose that we have the dependent variable called y, then its residuals for a specific time t are defined as:

$$\varepsilon_t = y_t - \widehat{y_t}$$

The residuals have to satisfy the assumptions of no autocorrelation, normality and homoskedasticity.

#### 3.2.4.1 Autocorrelation test

The autocorrelation in our study is investigated through the correlogram-Q Statistics and serial correlation LM Test. The result which gives the first test, contains the autocorrelation, the partial autocorrelation, the shape of their graph, the Q-stat and the probabilities. Q-stat refers to Ljung and Box (1978) statistical function and it is

[11] Independent and identically distributed.

used for the detection of autocorrelation. To be more specific, the null and the alternative hypothesis are:

Ho: No autocorrelation

$H_1$: Autocorrelation

It has to be mentioned that the Ljung Box function is defined as:

$$Q= T\,(T+2)\sum_{k=1}^{i}\frac{r_k^2}{T-k}$$

and follows the Chi-square distribution with i-degrees of freedom.

The serial autocorrelation LM test was firstly introduced by Bresh and Godfrey (1978) and examines the following hypothesis:

$H_0$: ρ1=ρ2=…….= $\rho^{12}{}_{\rho}$=0, (no autocorrelation)

$H_1$: at least one of the p's is not zero, thus autocorrelation.

The test is based on the LM function, which follows the Chi-square distribution with i degrees of freedom and is estimated, by the number of observations multiplied with the $R^2$.[13]

### 3.2.4.2 Normality test

This type of test is associated with the normality of the residuals. To put another way, it is essential for the values of the residuals to follow the normal distribution. In this analysis, the normality is checked by the use of Jargue-Bera test. This test is based on the fact, that skeweness is equal to zero and the kurtosis is equal to 3. So, the following typical assumptions are:

$H_0$: residuals follow the normal distribution $(\varepsilon_t \sim N(0,\sigma^2))$

$H_1$: residuals do not follow the normal distribution $(\varepsilon_t \nsim N(0,\sigma^2))$

[12] ρ= first-order autocorrelation coefficient.

[13] The coefficient of determination $R^2$ expresses the percentage of the observed variance of the dependent variable, which is explained by the independent variables in a given model. It takes values between 0 and 1.

Jargue-Bera[14] test gives us the result of the test, focusing on the value of probability (Prob). If the value is > 0,05 (5%) then, the zero assumption is accepted. Otherwise, we accept the alternative assumption.

### 3.2.4.3 Heteroscedasticity test

Another residual test is the application of the heteroskedasticity test in order to note, if the residuals have the same variance. In this test we make the following assumptions:

$H_0$: The residuals have the same variance. ($\sigma^2 = c$) (homoskedasticity)

$\mathrm{H}_1$: The residuals do not have the same variance. ($\sigma^2 \neq$c) (heteroskedasticity)

For our analysis, the Bresch-Pagan Godfrey heteroscedasticity test and the white-Cross test are used.

The Bresch-Pagan Godfrey test is grounded on the LM statistical function, which is computed by the number of observations multiplied with the $R^2$. In addition, LM follows Chi-square distribution with i-1 degrees of freedom.

White cross test is based on the function of white, which is calculated as the number of the observations multiplied with the $R^2$. Both tests investigate if the null hypothesis is accepted or not, by using the values of probabilities.

### 3.2.5 Cointegration test (Engle-Granger)

The last test we apply in this study, is the test of cointegration. Regarding the relationship among the variables, which are transformed by using first differences, it was observed that only short-term information is available, while at the same time the long-term information is lost, the general interest focuses on the analysis of long-term relations between the Greek Real GDP and the variables of our dataset.

The concept of cointegration is considered as a technique for the estimation of long-term coefficients and general equilibrium parameters in a relationship, where the variables are not stationary and the corresponding rows are characterized by the existence of a unit root. Specifically, for our study we target to give answers if there is a long-term relation equilibrium between the Greek Real GDP and the variables, we

---

[14] JB=T $\left(\frac{S^2}{6} + \frac{k-3^2}{4}\right)$

use in the bridge models. For our analysis, we use the method of Engle-Granger (1987), which is based in the test of residuals stationarity. In accordance with Engle-Grangers methodology, cointegration can be achieved among the variables, when the residuals are integrated in a lower level than those of the level of the rest of the variables. It is notable that the method of Engle-Granger can be applied in the case of a model that has more than two proxies. To put another way, we suppose that we have two variables Y and X. If the variables have the same order of integration (I(1)), we estimate by OLS the long-term equilibrium equation:

$$Y_t = \alpha_0 + \alpha_1 X_t + \varepsilon_t, (1)$$

which is usually called cointegrating regression and the residuals express the deviations from the long-term equilibrium errors state. The next step is to store the estimations of the residuals ($\varepsilon_\tau$), by transforming the equation (1). As a result, the residuals are defined as: $\widehat{\varepsilon_t} = Y_t - \widehat{\alpha_0}$- $\widehat{\alpha_1} X_t$. After, by applying the Augmented Dickey Fuller Test, we investigate if the residuals are stationary in their levels (I(0)) by estimating the equation:

$$\Delta\hat{\varepsilon}_t = \hat{\varepsilon}_{t-1} + u_t$$

Finally, we check the following assumptions:
$H_{0:}\ \beta = 0$ (Residuals are not stationary and the variables are not cointegrated)
$H_1: \beta < 1$ (Residuals are stationary and the variables are cointegrated)
The null hypothesis is rejected if $t\beta < \tau$ (critical value of Engle-Granger table).

### 3.3 Proposed Models

In this part of the thesis we propose different bridge models, following the nowcasting literature. In total, I created seventy (70) Bridge models using the vast majority of the variables of the dataset. All the models were estimated by using ordinary least squares (OLS) via the E-views University Edition 10, over the period 2000Q3-2012Q4. After their estimation, I present the best models according to their score in the information criteria of Swarzch and Akaike (see table 6) and the value of $R^2$. Also, it must be noted that a number of specifications among the variables was done, but the results showed, that the variables were proved statistically insignificant[15], especially the financial proxies.

In addition, I experimented with the variables in their levels as well as with different lags values. Finally, I concluded to present the best seven competitive nowcasting models (the estimation output of each model is in appendix C). Another significant thing of the analysis that should be noticed, is that the models contain a constant and the first autoregressive term of lagged GDP growth (Shumacher,2014). Furthermore, for each proposed model we executed the residual diagnostics test and we found that the assumptions are satisfied. (analytical results in appendix C).

Below, we report the first four of the proposed models, which are single-indicator models. The first model relates the real GDP growth to the Economic Sentiment Indicator (following Diron, 2006). The estimation output of the model gives us the following form:

**Model1:**

$$\mathbf{Dlog(realgdp\_sa)_t = 0.000168 + 0.070626*Dlog(realgdp\_sa)_{t-1}+0.525579*Dlog(realgdp\_sa)_{t-3}+0.001534*DEsi_t+0.000556*DEsi_{t-1}+\varepsilon_t}$$

From the estimation output of the model, we observe that the model explains the 43,1% of the variance of the dependent variable. What is more, from the value of F statitistic[16], we conclude that all the parameters are statistically significant, because the value of prob is 0<0,05. Below, in table 5 we present the results of the ADF test of the cointegration equation 1 and in table 6 we can observe the critical values of Engle-Granger cointegration test.

Table 5. Results of ADF test (residuals stationarity-cointegration equation 1)

Null Hypothesis: RESIDESI has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=0)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -2.220618 | 0.0270 |
| Test critical values: | 1% level | -2.622585 | |

[15] Results are available upon request from the author.
[16] The function F is used for the test of null hypothesis that all the parameters of the models are statistical equal to zero(insignificant) versus the alternative hypothesis that at least one is not equal(significant).

| | |
|---|---|
| 5% level | -1.949097 |
| 10% level | -1.611824 |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESIDESI)
Method: Least Squares
Date: 06/24/19 Time: 10:25
Sample (adjusted): 2000Q4 2012Q4
Included observations: 49 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| RESIDESI(-1) | -0.211425 | 0.095210 | -2.220618 | 0.0321 |

| | | | |
|---|---|---|---|
| R-squared | 0.109567 | Mean dependent var | 43.97620 |
| Adjusted R-squared | 0.109567 | S.D. dependent var | 3117.794 |
| S.E. of regression | 2942.036 | Akaike info criterion | 18.83568 |
| Sum squared resid | 3.46E+08 | Schwarz criterion | 18.87747 |
| Log likelihood | -385.1314 | Hannan-Quinn criter. | 18.85090 |
| Durbin-Watson stat | 1.945418 | | |

Table 6. Critical Values of Engle-Granger (Cointegration Test with 2 Variables)[17]

| Variables | Sample size T | Significance Level 1% | Significance level 5% | Significance Level 10% |
|---|---|---|---|---|
| 2 | 50 | 4,12 | 3,29 | 2,90 |

As can be seen from table 6 the null hypothesis is rejected in all significant levels. Thus, we deduce that the series are cointegrated, while the residuals are stationary at its levels (I(0)).

In the next model, we use the composite leading indicator (CLI) of OECD. Based again in Diron, 2006 study, we estimate the model and take the following specification:

**Model2**:

$$\mathbf{Dlog(realgdp)_t = -0.000606 + 0.014214 * Dlog(realgdp)_{t-1} + 0.505334 * Dlog(realgdp\_sa)_{t-3} + 1.376360 * Dlog(cli\_sa)_t + \varepsilon_t}$$

[17] Engle, F.R. & Yoo, S.B. (1987). ¨ Forecasting in co-integrated systems ¨, Journal of Econometrics 35, North Holland, p. 158.

The $R^2$ of the model is 50%, a quite high percentage. The value of F statistic implies that the sum of the parameters of the model are statistically significant as, prob=0<0,05. In addition, the Real Greek GDP and the CLI are cointegrated, as we see in table 7.

Table 7. Results of ADF (residuals stationarity-cointegration equation 2)

Null Hypothesis: RESID01MODELCLI has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=0)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -2.789482 | 0.0064 |
| Test critical values: | 1% level | -2.622585 | |
| | 5% level | -1.949097 | |
| | 10% level | -1.611824 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESID01MODELCLI)
Method: Least Squares
Date: 06/24/19 Time: 10:48
Sample (adjusted): 2000Q4 2012Q4
Included observations: 49 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| RESID01 MODELCLI(-1) | -0.291012 | 0.104325 | -2.789482 | 0.0080 |

| | | | |
|---|---|---|---|
| R-squared | 0.159979 | Mean dependent var | 180.0497 |
| Adjusted R-squared | 0.159979 | S.D. dependent var | 3112.164 |
| S.E. of regression | 2852.381 | Akaike info criterion | 18.77378 |
| Sum squared resid | 3.25E+08 | Schwarz criterion | 18.81558 |
| Log likelihood | -383.8626 | Hannan-Quinn criter. | 18.78900 |
| Durbin-Watson stat | 1.905860 | | |

The following models 3,4,5,6,7 include the proxies of turnover index of Retail Trade, the volume index of Retail Trade and the Industrial production Index. As can be seen in the figures 4-6, evidence is provided that the Greek Real GDP has a strong correlation with the variables.

Figure 4. Growth rates of Greek Real GDP and Turnover Index in Retail Trade

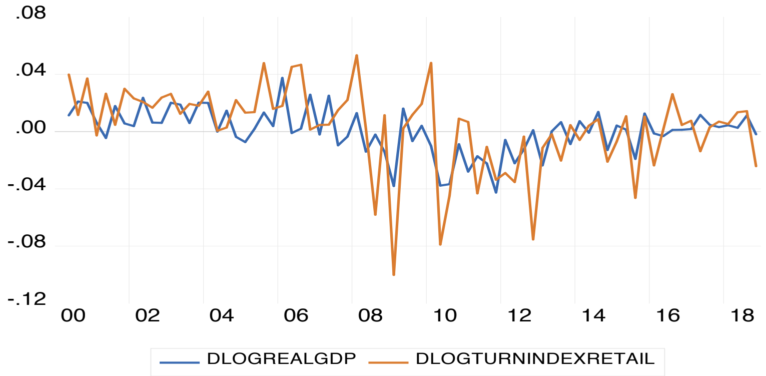



Figure 5. Growth rates of Greek Real GDP and volume Index in retail trade

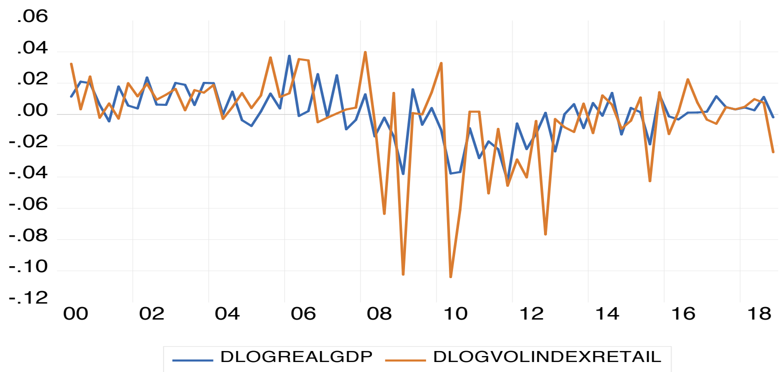
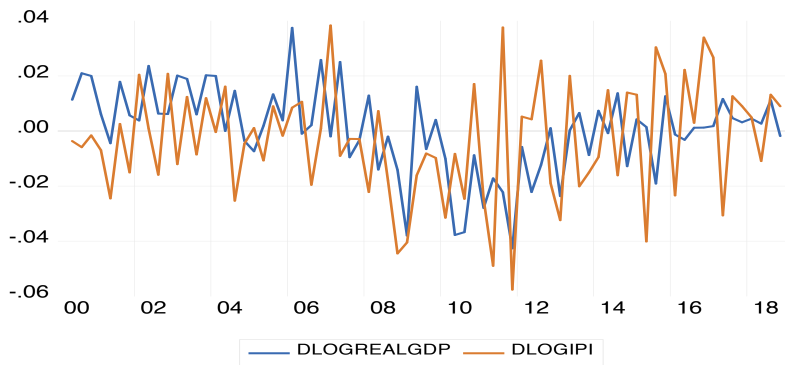



Figure 6. Growth rates of Greek Real GDP and Industrial Production Index




In addition, as we mentioned in the literature review, the variables have been used by Lamprou, (2015). To continue, in model 3 we regress the growth rate of Greek Real

GDP growth, the growth rate of turnover index in retail trade and its lagged value. As a result, the model is specified as follows:

**Model3:**

$$\mathbf{Dlog(realgdp\_sa)_t=-0{,}0001830+0{,}034411*Dlog(realgdp\_sa)_{t-1}}$$
$$\mathbf{+0{,}279311*Dlog(turnrettrdindex\_sa)_t+0{,}099824*Dlog(turnrettrdindex\_sa)_{t-1}+\varepsilon_t}$$

From the estimation output, the 35% of the dependent variable is explained from the model. The parameters of the model are significant and the long-term relation between the variables is confirmed in the following table and in table 6, as we reject the null hypothesis, which means that residuals are stationary.

Table 8. Results of ADF test (residuals stationarity-cointegration equation 3)

Null Hypothesis: RESIDMODELTURN has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=0)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -5.147824 | 0.0000 |
| Test critical values: | 1% level | -2.622585 | |
| | 5% level | -1.949097 | |
| | 10% level | -1.611824 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESIDMODELTURN)
Method: Least Squares
Date: 06/24/19 Time: 11:15
Sample (adjusted): 2000Q4 2012Q4
Included observations: 49 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| RESIDMODELTURN(-1) | -0.818810 | 0.159059 | -5.147824 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.397867 | Mean dependent var | -98.94065 |
| Adjusted R-squared | 0.397867 | S.D. dependent var | 3094.840 |
| S.E. of regression | 2401.511 | Akaike info criterion | 18.42967 |
| Sum squared resid | 2.31E+08 | Schwarz criterion | 18.47147 |
| Log likelihood | -376.8083 | Hannan-Quinn criter. | 18.44489 |
| Durbin-Watson stat | 1.794248 | | |

**Model4**

The next model associates the real Greek GDP with the volume index in retail trade and the lagged value of the volume index in retail trade. The estimation of the models gives us the following specification:

$$\mathbf{Dlog(realgdp\_sa)t=0,001406-0,074587*Dlog(realgdp\_sa)_{t-1}+ 0,379108*Dlog(volindexretail\_sa)_{t}+0,139376*Dlog(volindexretail\_sa)_{t-1}+ \varepsilon_t}$$

From the estimation output, we see that the $R^2$ is quite high (47%) underlining the importance of the index for the Greek economy. All the parameters of the model are statistically significant (prob(f)=0<0,05). Next, comparing again the results with the critical values in table 6, we lead to accept that the residual are stationary at their level and the series are cointegrated.

Table 9. Results of ADF test (residuals stationarity-cointegration equation 4)

Null Hypothesis: RESID01MODELVOL has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on SIC, maxlag=1)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -7.248492 | 0.0000 |
| Test critical values: | 1% level | -2.624057 | |
| | 5% level | -1.949319 | |
| | 10% level | -1.611711 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESID01MODELVOL)
Method: Least Squares
Date: 06/24/19 Time: 10:59
Sample (adjusted): 2001Q1 2012Q4
Included observations: 48 after adjustments

| Variable | Coefficient | Std. Error. | t-Statistic | Prob. |
|---|---|---|---|---|
| RESID01MODELVOL(-1) | -1.337593 | 0.184534 | -7.248492 | 0.0000 |
| D(RESID01MODELVOL(-1)). | 0.565447 | 0.142253 | 3.974943 | 0.0003 |

| | | | |
|---|---|---|---|
| R-squared | 0.587455 | Mean dependent var | 65.44793 |
| Adjusted R-squared | 0.576599 | S.D. dependent var | 3231.508 |
| S.E. of regression | 2102.720 | Akaike info criterion | 18.18856 |

| | | | |
|---|---|---|---|
| Sum squared resid | 1.68E+08 | Schwarz criterion | 18.27300 |
| Log likelihood | -361.7711 | Hannan-Quinn criter. | 18.21909 |
| Durbin-Watson stat | 1.552812 | | |

The next three models contain combinations among the variables of industrial production index, volume index in retail trade and the turnover index in retail trade.

**Model 5**

This model includes the growth rate of realgdp_sa (3 quarter-lag), the growth rate of the IPI, the growth rate of volume index in retail trade and its lagged value. The model has the following form:

$$\mathbf{Dlog(realgdp\_sa)_t=0{,}000966-0{,}306219*Dlog(realgdp\_sa)_{t-1} +0.384049*Dlog(realgdp\_sa)_{t-3}+ 0{,}131689*Dlog(ipi)_t+0{,}309167*Dlog(volindexretailtrd\_sa)_t+ 0{,}175855*Dlog(volindexretailtrd\_sa)_{t-1}+\varepsilon_t}$$

By the estimation output we take that $R^2$ is 58,6%. Also, the statistical significance of the parameters of the models is confirmed, while Prob(F-stat)=0<0,05. By using table 10 & table 11, we prove that the variables have a long-term relation equilibrium. The null hypothesis is not accepted and the series are cointegrated.

Table 10. Results of ADF test (residuals stationarity-cointegration equation 5)

Null Hypothesis: RESID07 has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=0)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -5.340848 | 0.0000 |
| Test critical values: | 1% level | -2.622585 | |
| | 5% level | -1.949097 | |
| | 10% level | -1.611824 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESID07)
Method: Least Squares
Date: 06/29/19 Time: 01:30
Sample (adjusted): 2000Q4 2012Q4
Included observations: 49 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| RESID07(-1) | -0.841494 | 0.157558 | -5.340848 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.416150 | Mean dependent var | 44.85991 |
| Adjusted R-squared | 0.416150 | S.D. dependent var | 3193.581 |
| S.E. of regression | 2440.216 | Akaike info criterion | 18.46165 |
| Sum squared resid | 2.38E+08 | Schwarz criterion | 18.50344 |
| Log likelihood | -377.4638 | Hannan-Quinn criter. | 18.47687 |
| Durbin-Watson stat | 1.824455 | | |

Table 11. Critical values of Engle-Granger (cointegration test with 3 variables)[18]

| Variables | Sample size T | Significance Level 1% | Significance Level 5% | Significance Level 10% |
|---|---|---|---|---|
| 3 | 50 | 4,45 | 3,75 | 3,36 |

**Model 6**

In this model we regress, the growth rate of realgdp_sa (3 quarter-lag), the growth rate of the IPI, the turnover index in retail trade and its lagged value. After the running of the equation, this model is represented in the form:

$$\mathbf{Dlog(realgdp\_sa)_t = -0{,}001453 - 0{,}174025*Dlog(realgdp\_sa)_{t-1} + 0{,}397910*Dlog(realgdp\text{-}sa)_{t-3} + 0{,}195880*Dlog(ipi)_t + 0{,}203303*Dlog(tuninderettrd\_sa) + 0{,}109017*Dlog(turninderettrd\_sa)_{t-1} + \varepsilon_t}$$

The value of $R^2$ is 48%, a quite satisfactory result. The parameters are significant in total (Prob(f)=0<0,05) and in the table 12 we show that there is a long-term relation equilibrium among the examined variables.

Table 12. Results of ADF test (residuals stationarity-cointegration equation 6)

Null Hypothesis: RESID08 has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=0)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -5.916628 | 0.0000 |
| Test critical values: | 1% level | -2.622585 | |

[18] Engle, F.R. & Yoo, S.B (1987). ¨ Forecasting in co-integrated systems ¨, Journal of Econometrics 35, North Holland, p.158.

| | |
|---|---|
| 5% level | -1.949097 |
| 10% level | -1.611824 |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESID08)
Method: Least Squares
Date: 06/29/19 Time: 01:32
Sample (adjusted): 2000Q4 2012Q4
Included observations: 49 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| RESID08(-1) | -0.936503 | 0.158283 | -5.916628 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.466609 | Mean dependent var | -42.91427 |
| Adjusted R-squared | 0.466609 | S.D. dependent var | 3119.064 |
| S.E. of regression | 2277.965 | Akaike info criterion | 18.32404 |
| Sum squared resid | 2.08E+08 | Schwarz criterion | 18.36583 |
| Log likelihood | -374.6428 | Hannan-Quinn criter. | 18.33926 |
| Durbin-Watson stat | 1.912325 | | |

**Model 7**

In this model, the growth rate of turnover index in retail trade, its lagged value and the growth rate of volume index in retail trade are included. The estimation of the equation gives us the following representation:

$$\mathbf{Dlog(realgdp\_sa)_t = 0{,}001546 - 0{,}008371 * Dlog(realgdp\_sa)_{t-1} - 0{,}160974 * Dlog(turnoverindexretailtrd\_sa)_t + 0{,}122010 * Dlog(turnoverindexretailtrd\_sa)_{t-1} + 0{,}521180 * Dlog(volindexretail\_sa)_t + \varepsilon_t}$$

It should be mentioned that the value of $R^2$ is quite high, 49,3%. Furthermore, the statistical significance of the parameters is demonstrated by the value of F-statistic (0<0,05). Regarding the test of cointegration, we reveal that the residuals do not have a unit root at their levels (I(0)), as we observe in table 11 and as a result, the variables are cointegrated.

Table 13. Results of ADF test (residuals stationarity-cointegration equation 7)

Null Hypothesis: RESID09 has a unit root
Exogenous: None

Lag Length: 0 (Automatic - based on SIC, maxlag=0)

| | | | |
|---|---|---|---|
| | | t-Statistic | Prob.* |
| Augmented Dickey-Fuller test statistic | | -6.004561 | 0.0000 |
| Test critical values: | 1% level | -2.622585 | |
| | 5% level | -1.949097 | |
| | 10% level | -1.611824 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESID09)
Method: Least Squares
Date: 06/29/19 Time: 23:31
Sample (adjusted): 2000Q4 2012Q4
Included observations: 49 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| RESID09(-1) | -0.947566 | 0.157808 | -6.004561 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.473990 | Mean dependent var | -36.61267 |
| Adjusted R-squared | 0.473990 | S.D. dependent var | 3146.551 |
| S.E. of regression | 2282.084 | Akaike info criterion | 18.32765 |
| Sum squared resid | 2.08E+08 | Schwarz criterion | 18.36945 |
| Log likelihood | -374.7169 | Hannan-Quinn criter. | 18.34287 |
| Durbin-Watson stat | 1.930625 | | |

The last step in this chapter is to display the values of information criteria which had the estimated proposed models. It is known from the econometric theory that those criteria have been developed on the basis of theoretical information for the selection of a model, which is suitable for forecasting. The information criteria of Akaike and Swarch are used widely methods for the determination of the most desired number of independent variables. Also, they give us the chance to understand the goodness of fit of a model, which means how well it fits every model, in a number of observations. Therefore, to elucidate further, the definitions of Akaike and Schwarz criteria are given in the following table:

Table 14. Information Criteria

| | |
|---|---|
| Akaike Information Criteria | AIC= $2T^{-1}(k-L)$ |
| Schwarz Bayesian Criterion | SC= $2T^{-1}(2^{-1}klog(T)-L)$ |

source: www.modelselection.org

Table 15. Values of Proposed Models in AIC and Swarch Information Criteria

| Models | Akaike criterion | Swarch Criterion |
|---|---|---|
| Model1 | **-5,570233** | **-5,375316** |
| Model2 | **-5,7464121** | **-5,590488** |
| Model3 | **-5,474309** | **-5,321347** |
| Model4 | **-5,686921** | **-5,533959** |
| Model5 | **-5,847448** | **-5,613547** |
| Model6 | **-5,623247** | **-5,389347** |
| Model7 | **-5,679456** | **-5,488253** |

From the table 6 above, we accept that the model5 has the lowest values in accordance with the information criteria.

### 3.4 Benchmark models

For the comparison among the proposed models we apply univariate autoregressive models. Our first benchmark model is the naïve model of average constant growth (Barhoumi, et all 2008). The model is defined by the simple following regression:

$$y_t = \mu + \varepsilon_t, \varepsilon_t \sim N(0, \sigma_\varepsilon^2)$$

Also, the predictions of the model, the growth rate is the sample average up to the more recent observations.

. The other model that will be used for the comparison amongst the other models is the ARIMA model (similar case in Baffigi, Golineli, Parigi, 2004). As mentioned previously in chapter 2, the ARIMA models were introduced by Box, & Jekins, (1970) and their main purpose is to produce predictions for a time-series, based only in past values of the series and without having any structural information. The general form of an ARIMA (p,d,q) is denoted as follows: D$y_t = \alpha + c_1 y_{t-1} + c_2 y_{t-2} + \ldots + c_p y_{t-p} + e_t + d_1 e_{t-1} + d_2 e_{t-2} \ldots\ldots + d_q e_{t-q} + \varepsilon_t$

where,

AR(p): $y_t = c_1 y_{t-1} + c_2 y_{t-2} + \ldots\ldots + c_p y_{t-p} + e_t,$

MA(q): $y_t = a + d_1\varepsilon_{t-1} + d_2\varepsilon_{t-2}\ldots\ldots + d_q\varepsilon_{t-q} + \varepsilon_t$,

a,c,d: constants

p: the number of lagged values of the dependent variable

q: the number of lagged values of the error term

d: The level of integration refers to the number of times that a time series needs to become stationary. As a result, D$y_t$= $y_t$-$y_{t-1}$=(1-L)$y_t$

As we proved in section 3.2, the Real Greek GDP is stationary in the first differences of log, in the ARIMA model, it enters in first difference of its logged value. It must be noticed that the naïve model is specified in log-levels (following Baffigi, Golineli, & Parigi, 2004). The level of p and q orders was found by investigating the correlogram, until the autocorrelation and partial autocorrelation vanishes. (see, Gujarati (1995)). After the estimation of the benchmark models in Eviews-10 package, below we present the following specifications, as observed in their estimation outputs, (see appendix C):

**Naïve model (average constant growth): log($realgdp_{sa_t}$)= 0,998024 +$\varepsilon_t$**

**ARIMA (1,1,2): Dlog( $realgdp_{sa_t}$)= 0,000693 +0,181541*$D$ log($realgdp_{sa_{t-1}}$) +0,740597 *$e_{t-2}$+ $\varepsilon_t$**

The residuals diagnostic tests were executed for the models and the results were satisfactory, where, no discernible irregularities were observed, apart from the Naïve Model (see appendix C for analytical details). In the next part, we examine the nowcasting performance of the models we estimated, by applying an out of sample evaluation and comparing them in accordance their values in the forecasting evaluation ability criteria, fact which leads us to extract reasonable and valuable results.

## Chapter 4: Nowcasting evaluation: Results and Findings

### 4.1 Evaluation of forecasting accuracy-framework of nowcasting experiment

In this chapter we generate forecasts for the estimated models, which we have mentioned in the previous section of this thesis. Undoubtedly, the evaluation of the forecasting ability, is an essential part in the production of forecasting models. As a matter of fact, the evaluation is made, by the comparison between the forecasted values and the actual. Actually, the forecasting measurement errors are measured, extracted and compared with the errors of the other models and a forecaster has to take into consideration, how close are the forecasted to the observed values. In general, one of the main targets of a forecaster is the investigation of models that have the lowest values based on forecasting evaluation criteria (close to zero).

However, it is of vital importance that a model should be unbiased, which means that the outcomes of predictions, should not be higher or lower compared to the actual data.

In addition, another key element for our evaluation that must be mentioned, is that, it is preferable to execute pseudo out of sample forecasts for the evaluation of nowcasting ability, while it is commonly used method, as we observe in a number of studies ( Brahoumi et al, 2008; Baffigi, Golineli, Parigi, 2004; Barhoumi,Darne,Ferrara, & Pluyaud, 2012). Besides, after the publication of GDP series, the data are subject to revision. But, in our thesis it is not available a real-time database and as a result we do not take account any revision. Therefore, it is not possible to apply in this study a true real-time nowcasting exercise and for the performance evaluation of the models we report a ¨ pseudo¨out of sample nowcasting exercise.

In our study, the forecasting experiment was implemented over the period 2013q1-2018q4 and the nowcast of each model is generated one-step ahead, following the general rule of using the one third of the sample (24 observations) for the out of sample evaluation. As a result, one forecast per quarter is done. Also, it is noted that the experiment is called nowcasting exercise, while the data for every single variable are completely known over the whole forecasting horizon (complete information) (see, Baffigi, Golinelli, & Parigi, 2004). This means that if T is the last observation of our estimation sample, the forecast is produced for the T+1 quarter. In obtaining the out of sample evaluation of the models, we use the method of rolling estimations and forecasts for the whole prediction period (Tashman,2000). As a consequence, for each model we constructed an analogous program (relevant code is in appendix D), by applying the programming language of Eviews and computed the common forecasting evaluation criteria, where its definitions are given in table 17.

Table 16. Forecasting ability evaluation criteria

| | |
|---|---|
| ***RMSE*** | $\sqrt{\frac{\sum_{t=1}^{T}(\hat{y}_t - y_t)^2}{T}}$ |
| ***MAE*** | $\sum_{=1}^{T}\left\lvert\frac{\hat{y}_t - y_t}{T}\right\rvert$ |
| ***MAPE*** | $\frac{100}{T}\sum_{t=1}^{T}\left\lvert\frac{y_t - \hat{y}_t}{y_t}\right\rvert$ |
| ***SMAPE*** | $\frac{100\%}{T}\sum_{t=1}^{T}\frac{\lvert\hat{y}_t - y_t\rvert}{(\lvert y_t\rvert + \lvert\hat{y}_t\rvert)/2}$ |

source: http://www.eviews.com/help/helpintro.html#page/content/series-Forecast_Evaluation.html

where,

$\hat{y}_t$, the predicted value of the dependent variable

$y_t$, the observed value of the dependent variable

T: the range of the sample

In the following section we report the results of the experiment by comparing the nowcasts of the estimated bridge models with those of benchmark models.

### 4.2 Nowcasting evaluation of the models - Results & Findings

In the following table 17, we present the results of our nowcasting experiment. All the values of the forecasting evaluation criteria were derived from Eviews University Edition 10.

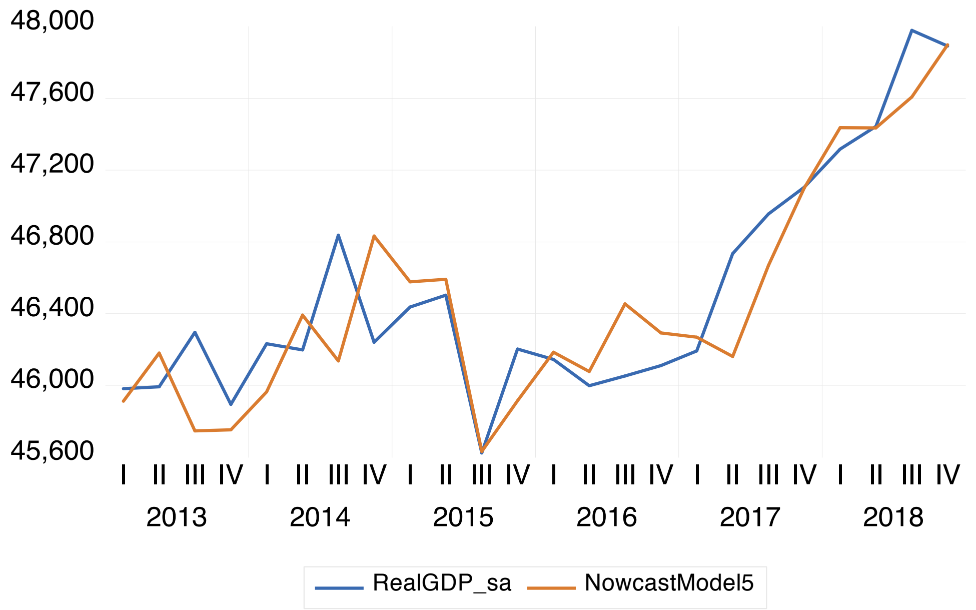
Table 17. Nowcasting Evaluation of the one-step ahead Greek Real GDP forecast (2013 1st quarter-2018 4th quarter)

| **Models** | RMSE | MAE | MAPE | SMAPE |
|---|---|---|---|---|
| **Naïve Average Const. Growth** | 4278,247 | 4278,247 | 8,933107 | 8,551165 |
| **ARIMA (1,1,2)** | 335,9693 | 0,701514 | 0,701514 | 0,699062 |
| **Model1** | 107,8692 | 107,8692 | 0,225234 | 0,224981 |
| **Model2** | 158,4695 | 158,4695 | 0,330889 | 0,330342 |
| **Model3** | 235,4404 | 235,4404 | 0,491607 | 0,49818 |
| **Model4** | 25,51294 | 25,51294 | 0,053272 | 0,053286 |
| **Model5** | **6,507507** | **6,507507** | **0,013588** | **0,013588** |
| **Model6** | 89,24871 | 89,24871 | 0,186354 | 0,186528 |
| **Model7** | 175.2479 | 175.2479 | 0,365923 | 0,365255 |

As we observe from the table above, the first interesting feature is that in the MAPE criterion, the bridge models had low percentages and the second one is the superior performance of model 5. The RMSE of the model is 6,507507, result which demonstrates that the volume index of retail trade and the industrial production index are useful and significant predictors for the Greek GDP, findings which are in line with the study of Lamprou, 2015.

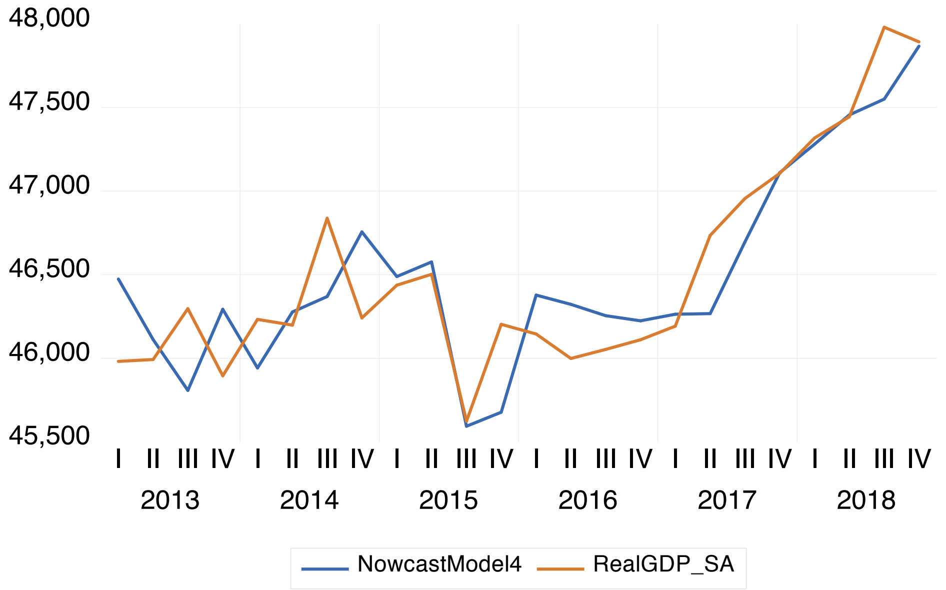
In the next figure, we compare the Greek Real GDP (seasonally adjusted data) with the nowcast of the model 5 (for the outcomes of the nowcast and the difference with the actual data, see appendix E).

Figure 7. Real GDP_sa and nowcast of model 5




Furthermore, Model4 is in the second place and the RMSE of the model is 25,51294, result which is quite satisfactory. In addition, the finding is in line with Lamprou, (2015), as we can say that the Volume Index in Retail Trade has been proved as a reliable predictor for the nowcast of Greek GDP. The comparison of Greek Real GDP (seasonally adjusted data) and the nowcast of model 4 is listed below.

Figure 8. Real GDP_sa and nowcast of model4



Another important finding of our study, that has not been previously mentioned in the nowcasting literature regarding the Greek GDP, is the contribution of the Composite Leading Indicator into the nowcast of the Greek GDP. In the ranking among the models is in the fifth place, as it has the lowest value which is 158,4695 in RMSE criterion is not negligible.

The model with the Economic Sentiment Indicators (ESI) ranks in the fourth place, as the value of 107,0692 is obviously a good outcome. Also, the usefulness of the predictor as an explanatory variable is confirmed, being in line with Monokrousos, & Thomakos (2012). Below, in figures 9,10 the Real Greek GDP and the nowcasts of model1 and 2 are plotted.

Figure 9. Real GDP_sa and nowcast of model1

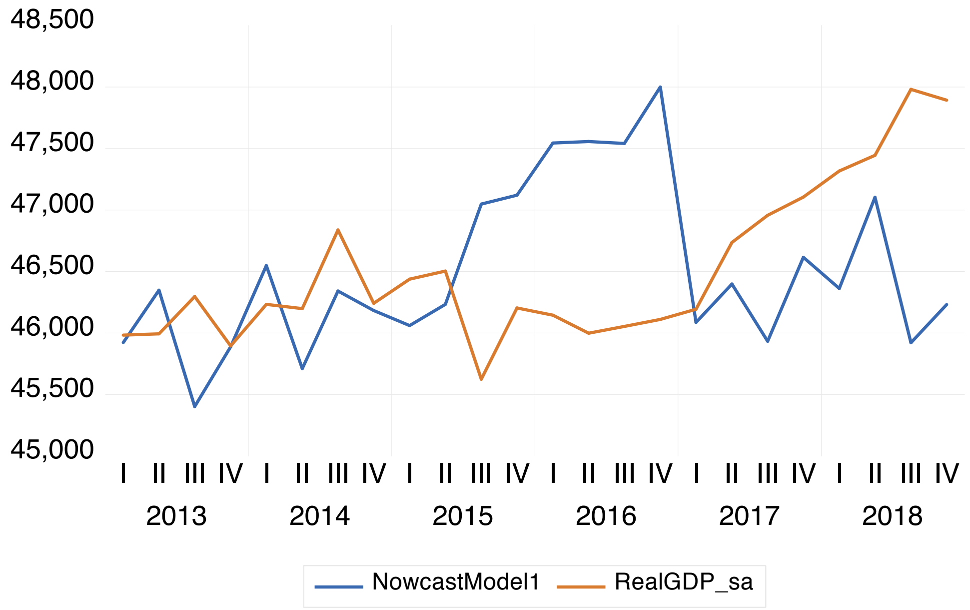
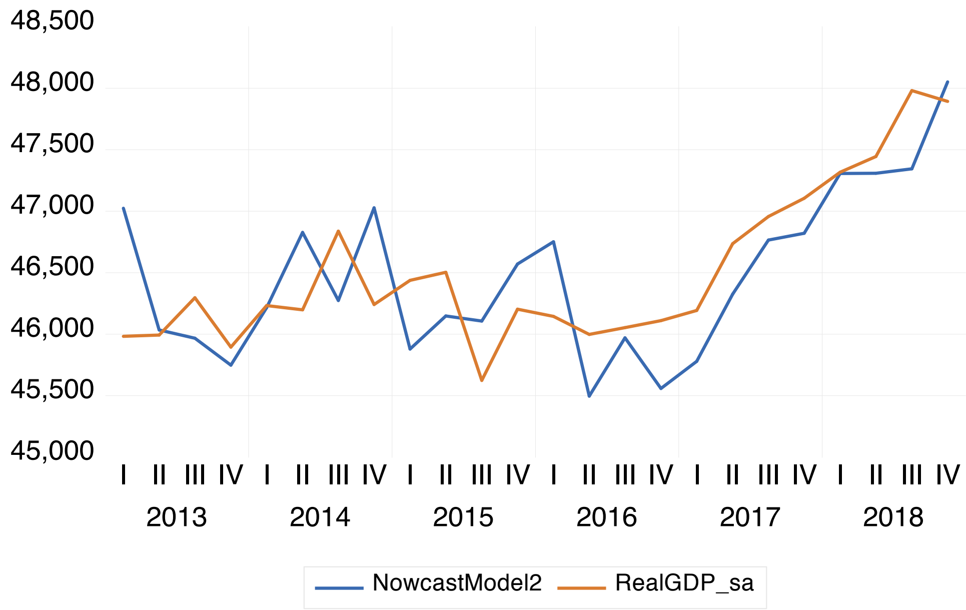


Figure 10. Real Greek GDP and nowcast of model 2




Regarding the Models 3, 6 and 7 we mention, that the model3 had the worst performance amongst the models, a result that was not expected. The model 6 ranked in the third place, while its value of RMSE is 89,24871. It is obvious that the combination of the Industrial Production Index and the Turnover Index in Retail Trade gave extremely good nowcasting results, findings that agree with the literature. Finally, the model 7 was in the sixth place with the value of 175,2479 in the RMSE criterion.

However, a general finding that derives from the evaluation and should be mentioned, is that bridge models with the proxy of IPI obtain better RMSES than the models without IPI. In figures 11-13 we illustrate the comparisons of nowcasts of each model with the Real Greek GDP.

Figure 11. Real GDP_sa and nowcast of model 3

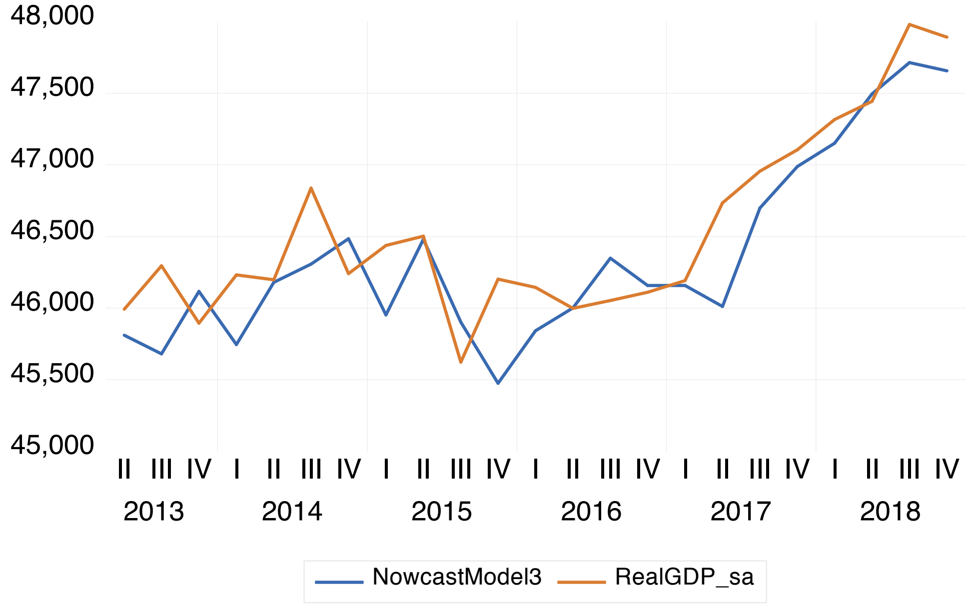



Figure 12. Real GDP_sa and nowcast of model 6

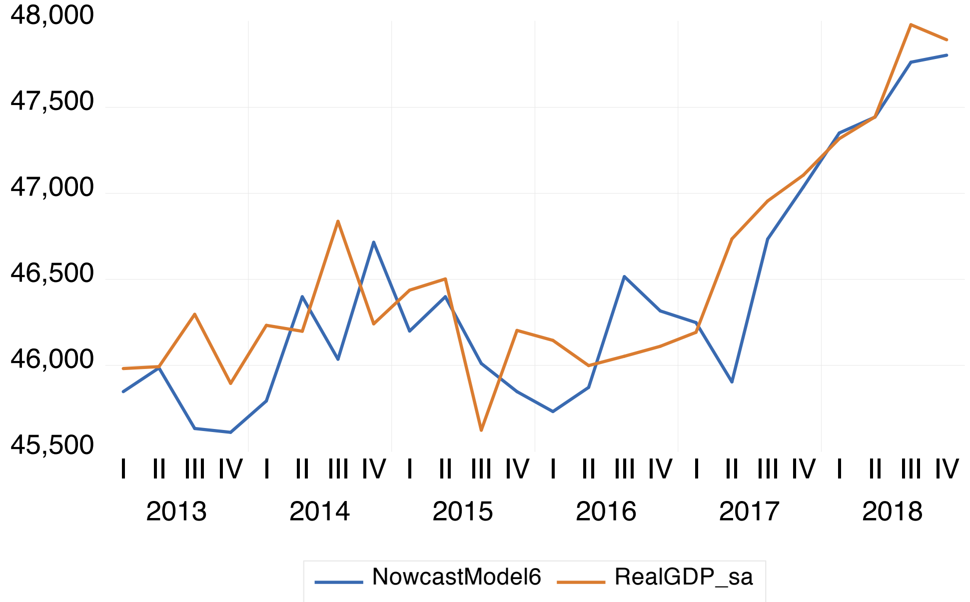
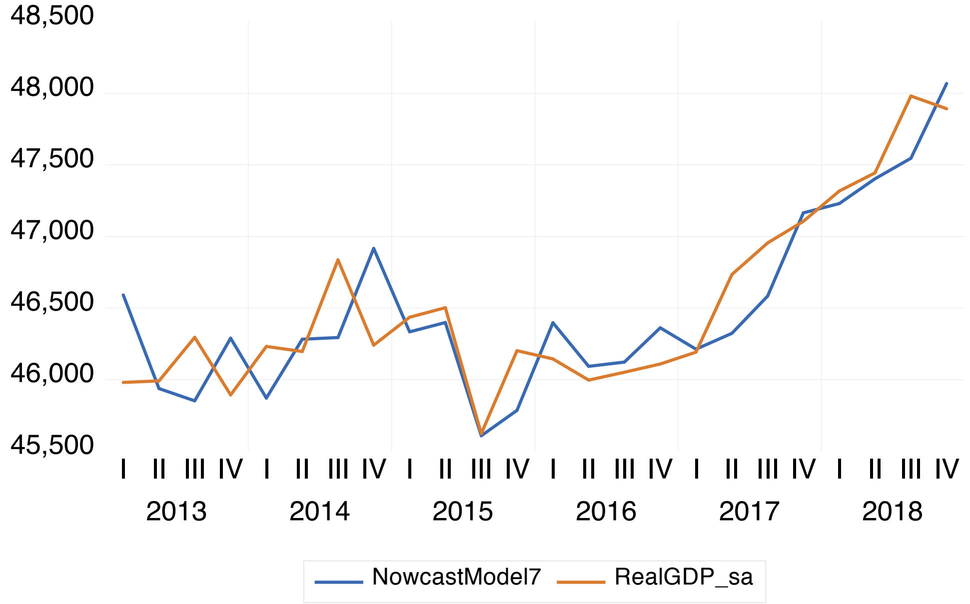


Figure 13. Real GDP_sa and nowcast of model 7




Regarding the benchmark models, the ARIMA model has the best performance, while its projections were more accurate than those of the Naïve Average Constant Growth, as can be seen in figures 14 and 15.

Generally speaking, concerning the bridge models, those findings are in accordance with findings reported by Barhoumi et al (2008), due to the fact that they exploit the information released each month, in contrast with the benchmarks, which based on purely quarterly data. Last but not least, bridge models performed better than the benchmark models.

Figure 14

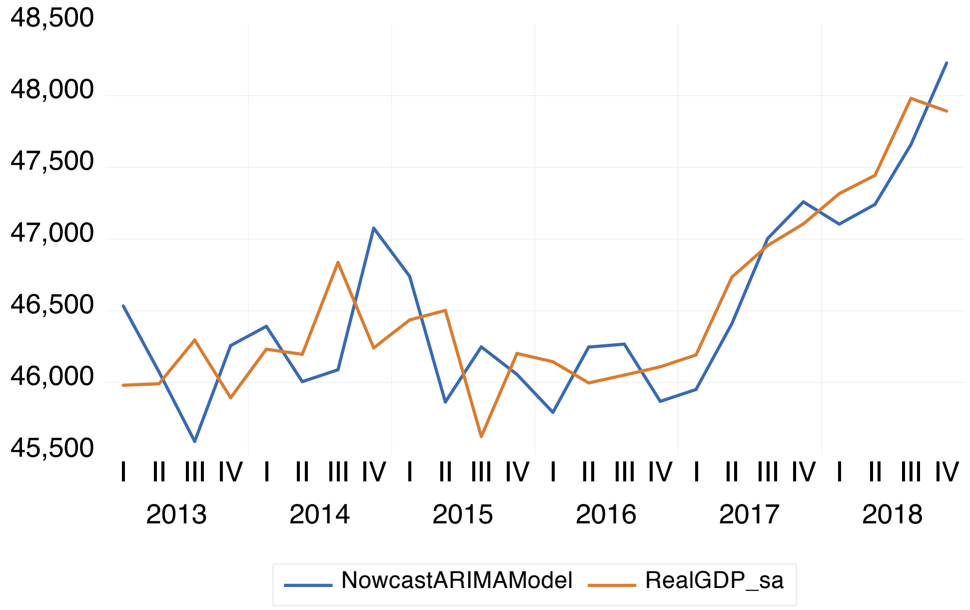
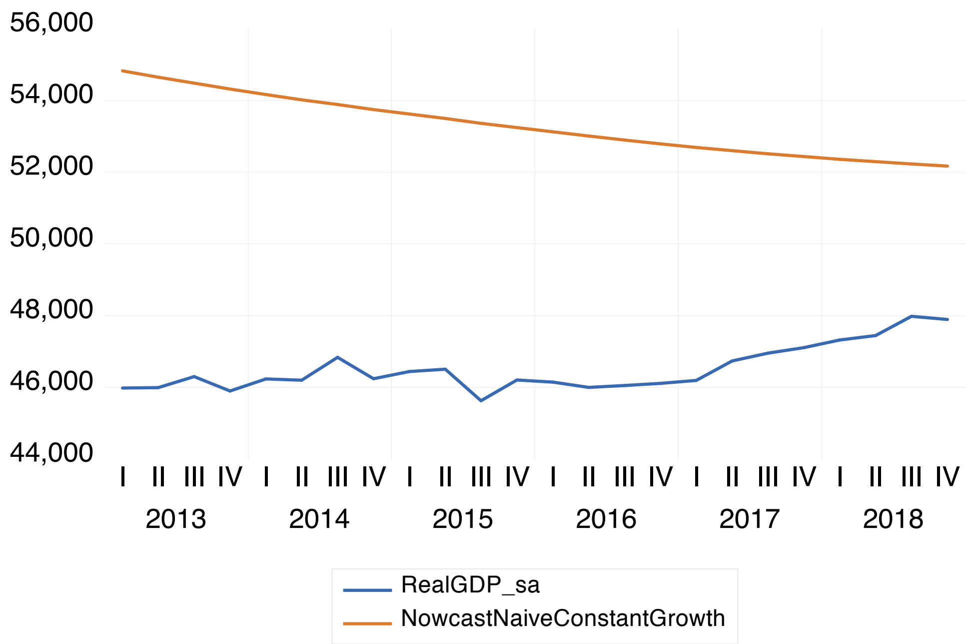



Figure 15



## 5. Conclusions and Recommendations

The aim of this study was to nowcast the real Greek GDP through the use of Bridge models. For this purpose, a dataset of 30 macroeconomic variables was created. Before the production and estimation of the nowcasting models, all the variables were transformed (logarithimization) and checked for seasonality and stationarity. Besides, for each model we constructed, the essential diagnostic tests as well as the investigation of stationarity and cointegration among the proxies were implemented.

Having completed the assessment of the best seven proposed Bridge Models and the out of sample nowcasting comparison for the case of the Greek GDP, we can review the main findings of our research. To the best of the author's knowledge, we point out a finding that has not be stressed in previous studies: The Composite Leading Indicator gave satisfactory results into the nowcast of the Greek GDP and proved to be a liable predictor.

In addition, broadly translated our findings, we show that the variables of Economic Sentiment Indicator, Industrial Production Index, Volume Index in Retail Trade and Turnover Index in Retail Trade gave reliable nowcasts, taking into consideration the values in the forecasting evaluation criteria. The comparison among the competitive models, gave evidence that the model with the Volume Index in Retail Trade and the Industrial Production Index was the best in accordance with the evaluation criteria. A result that was anticipated, if we bear in mind the strong correlation of the indexes with the Greek GDP.

Besides, in general bridge models surpassed the performance of the standard models we estimated for the comparison, a finding that it is consistent with the literature. So, a main conclusion that is demonstrated, is that bridge models make use of the information, regarding data that are published monthly and earlier than the official release of the GDP.

Concerning the limitations of this study, it should be noted that we do not take into account the impact of the revision, while the data are subject to revisions, after each publication of the proxies. Also, another limitation, is that we might ignore proxies that could potentially provide significant improvements in the nowcast of Greek GDP. Last but not least, it is highlighted that nowcasting experiment is done for one forecasting horizon, precisely for the one-step ahead period.

Furthermore, at this point, we note the following recommendations for future study: Research should further develop and confirm these initial findings by using alternative methods that have been reported in the theoretical part of our dissertation, such as Dynamic Factor Models, Midas models (FA-VAR and factor Midas models) or bridging via factors.

Another possible area of research would be the nowcasting by using daily data. Also, it would be very interesting to investigate the impact on the results, in case we expand or decline the number of explanatory proxies, the sample of the analysis and to experiment with various lags. At this juncture, an interesting question is raised: How our results be affected by using different forecasting horizons? It is a reasonable question and the comparison among the horizons could deliver useful and important results.

An interesting avenue for new studies, could be the investigation of the alternative methods which offer numerous benefits, like random forest approach, machine learning and artificial intelligence.

As the forecasting of economy and especially of the most important index which is the real GDP, is associated with our life and taking into consideration its vital significance, it should be noticed that more research is needed to apply and new ways have to be tested for producing more accurate forecasts. The science of econometrics provides the substantial tools in order to research in depth new areas that provide real improvements in the field of forecasting the GDP, striving to deter an outburst of a financial crisis.

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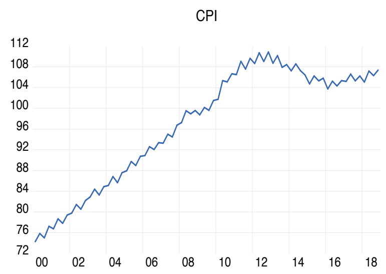
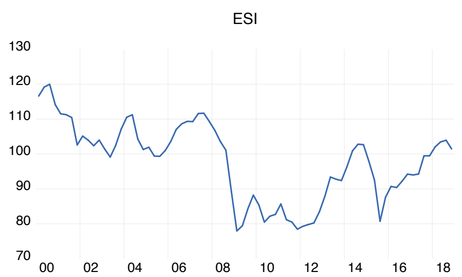
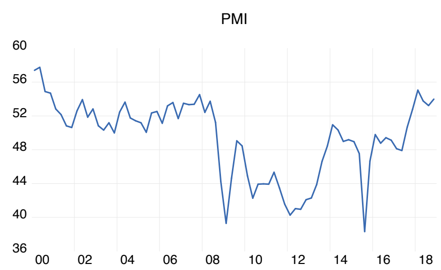
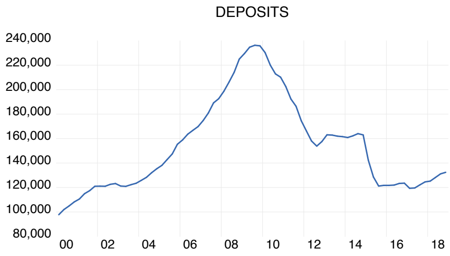
## APPENDIX A: Graphs of variables in levels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180,000
160,000
140,000
120,000
100,000
80,000
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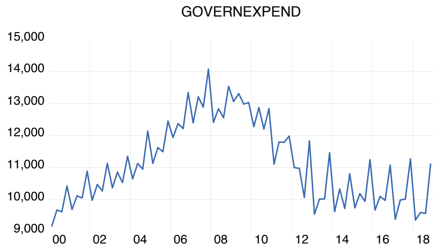
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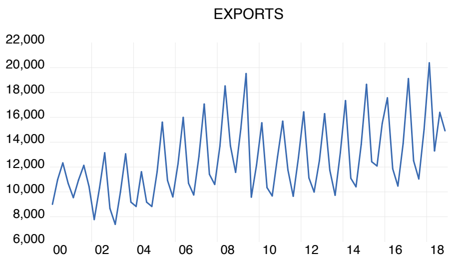
14,000
13,000
12,000
11,000
10,000
9,000
00 02 04 06 08 10 12 14 16 18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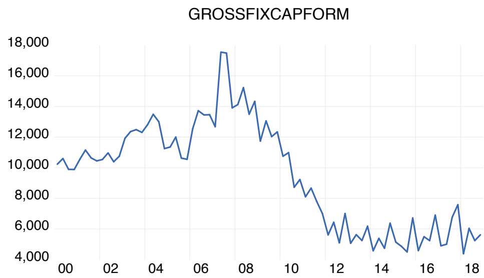
20,000
18,000
16,000
14,000
12,000
10,000
8,000
6,000
00 02 04 06 08 10 12 14 16 18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16,000
14,000
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10,000
8,000
6,000
4,000
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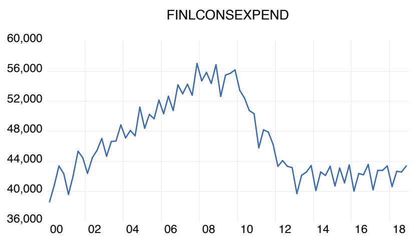
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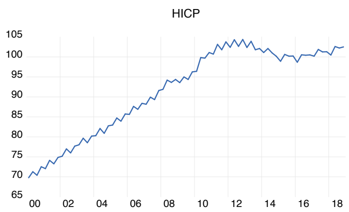
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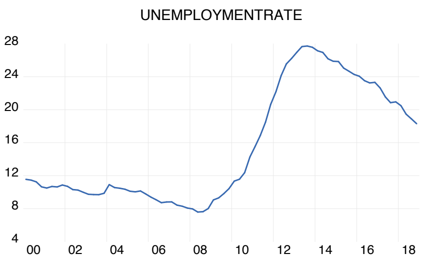
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8
4
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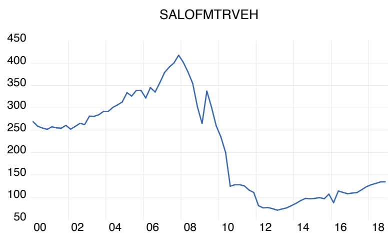
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200
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50
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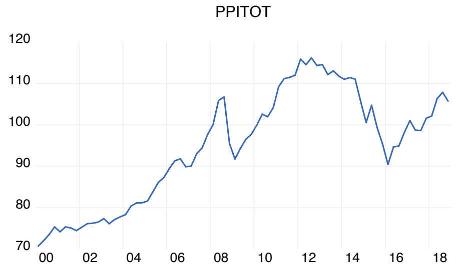
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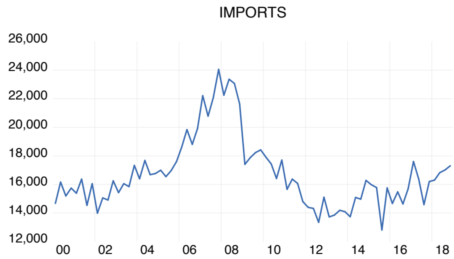
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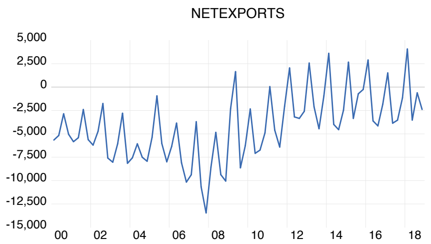
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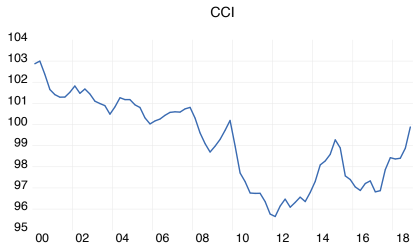
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101
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98
97
96
95
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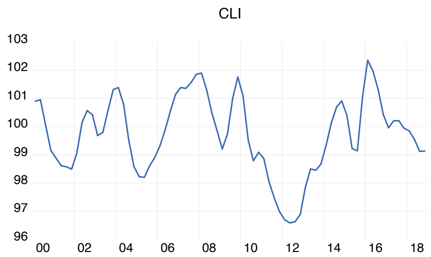
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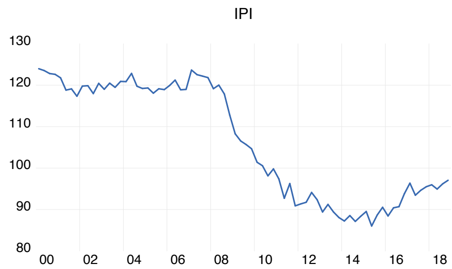
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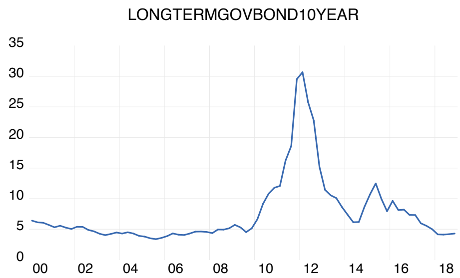
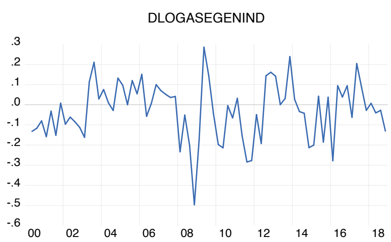
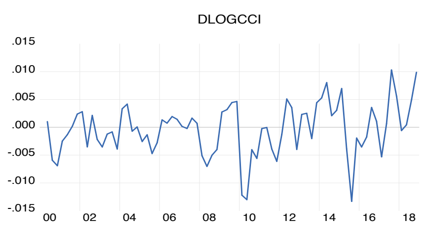

LONGTERMGOVBOND10YEAR
35
30
25
20
15
10
5
0
00 02 04 06 08 10 12 14 16 18

## APPENDIX B: Results of ADF-test of variable in levels, log-levels, percentage rate and graphs of variables in growth rates. (seasonally adjusted data)

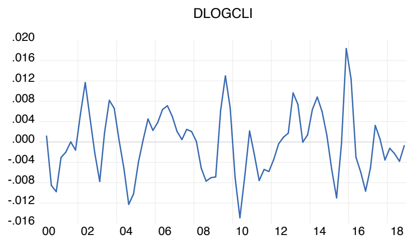
| Series | ADF (t-stat) | P_value[19] |
|---|---|---|
| Logaseindex | -1,780592 | 0,0714 |
| Logcci | -0,748670 | 0,3888 |
| Logcli | -0,317489 | 0,5679 |
| Logcpi | 6,630707 | 1,00 |
| Logdeposits | 1,000670 | 0,9151 |
| Eonia Rate | -0,485857 | 0,5022 |
| Economic Sentiment Indicator (ESI) | -0,718925 | 0,4019 |
| Logexports | 0,779448 | 0,8795 |
| Logfinconssexpend | 0,264565 | 0,7602 |
| Loggengovernexpend | 0,215528 | 0,7461 |
| Loggrossfixcapform | -1,056087 | 0,2603 |
| Loghcpi | 7,521571 | 1,00 |
| Logimports | 0,208560 | 0,7441 |
| Logipi | -1,406671 | 0,1473 |
| long-term interest rates | -0,866087 | 0,3375 |
| Logmotortradesindex | -0,880873 | 0,3312 |
| Logouputpriceindexofworkcateg | 2,219666 | 0,9934 |
| Logppi | 1,651157 | 0,9752 |
| Logprodindconstr | -0,662663 | 0,4268 |
| PMI | -0,399806 | 0,5365 |
| Retail Trade Confidence Indicator | -0,295236 | 0,5762 |
| Logsalofmotorvehindex | -0,903672 | 0,3216 |
| Short-term interest rates | -4,718147 | 0,0000 |
| Unemployment rate | 0,796496 | 0,8826 |
| logturnoverindexretailtrade | 0,767528 | 0,8774 |
| Volatility Index (VIX) | -1,278523 | 0,1837 |
| Logvolindrettrad | -0,502542 | 0,4954 |
| Logwholesaletrdind | 0,827158 | 0,8800 |

### Graphs of growth rates of variables




[19] Confidence level of 90%,95% and 99%. (p=0,01, 0,05, 0,1)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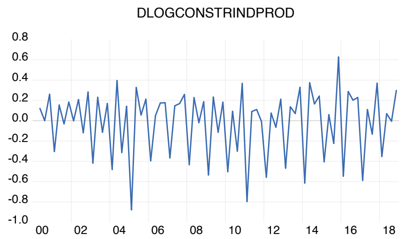
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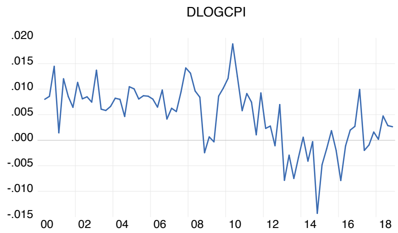
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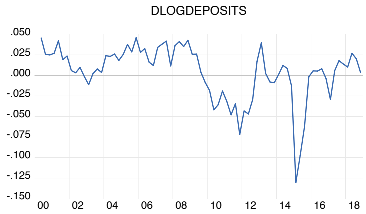
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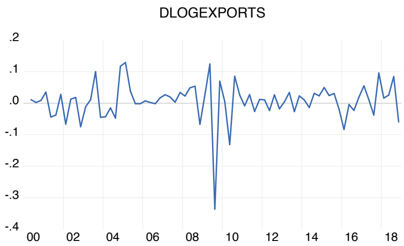
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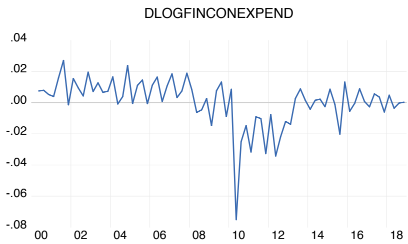
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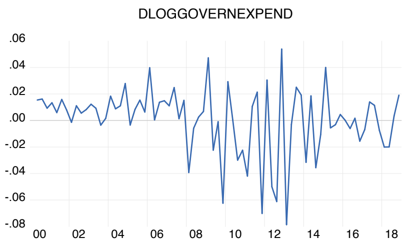
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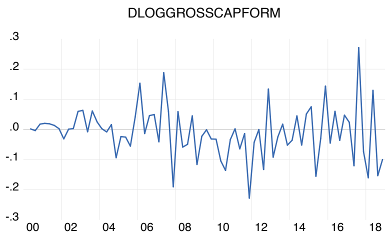
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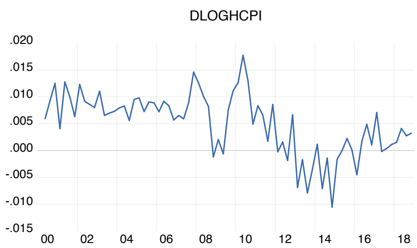
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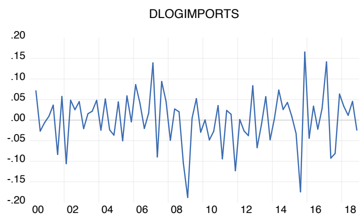
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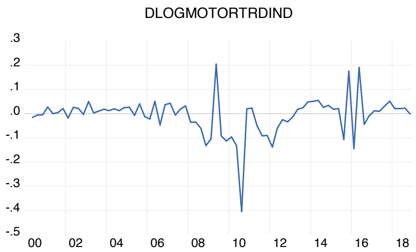
.20 .15 .10 .05 .00 -.05 -.10 -.15 -.20
00 02 04 06 08 10 12 14 16 18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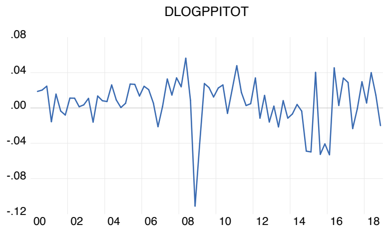
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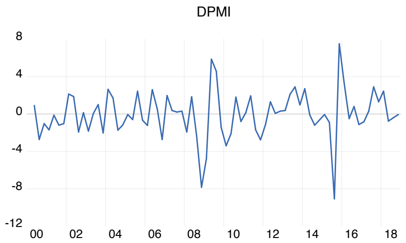
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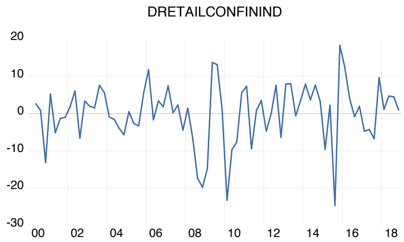
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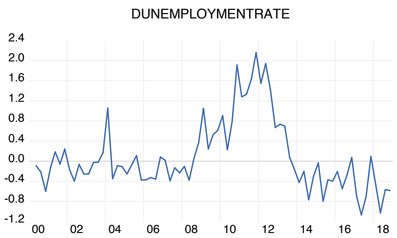
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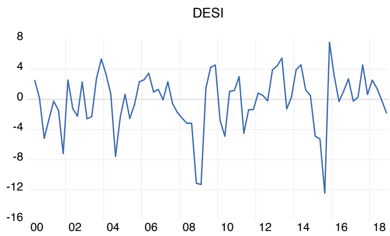
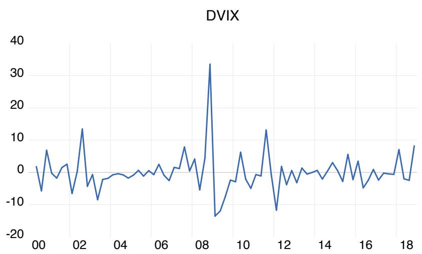
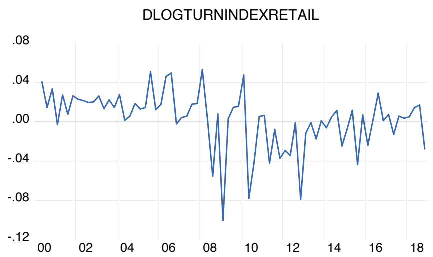

DESI


DVIX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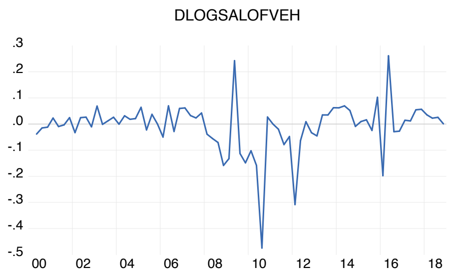
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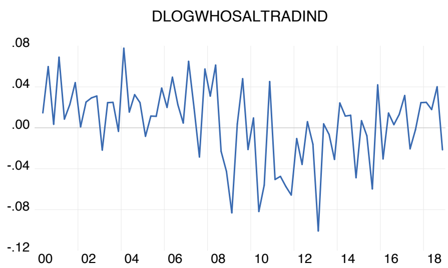
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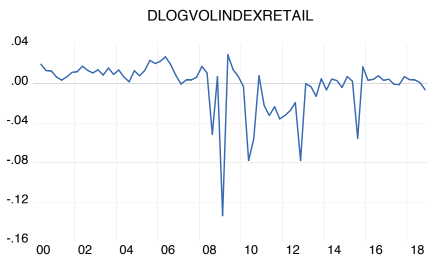
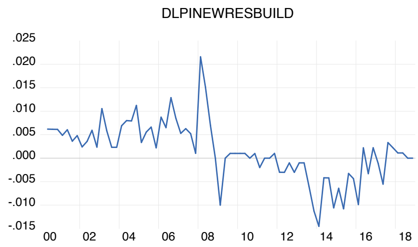
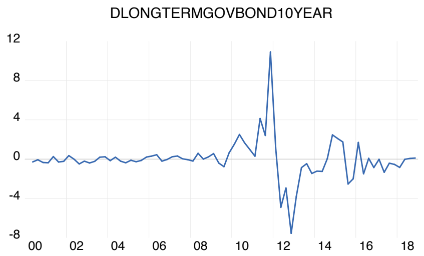
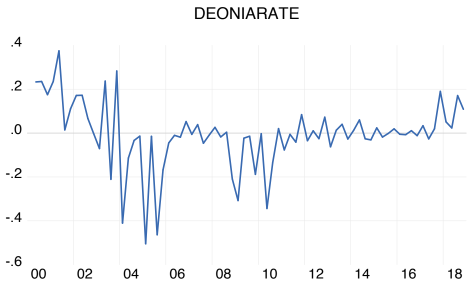
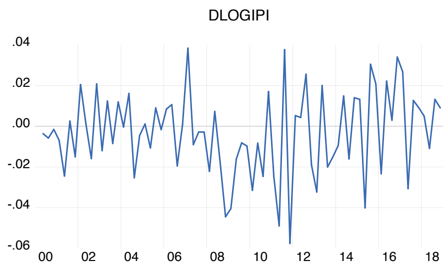
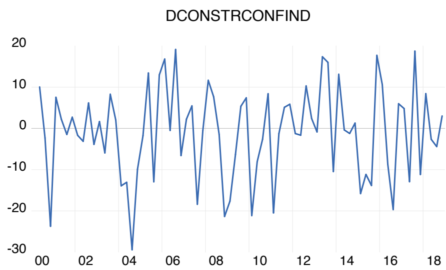



## APPENDIX C: Model estimation outputs and Residuals Diagnostics Tests

Model 1 estimation output

Dependent Variable: DLOG(REALGDP_SA)
Method: Least Squares
Date: 05/30/19 Time: 20:32
Sample (adjusted): 2001Q1 2012Q4
Included observations: 48 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000168 | 0.002119 | 0.079087 | 0.9373 |
| DLOG(REALGDP_SA(-1)) | 0.070626 | 0.133926 | 0.527349 | 0.6007 |
| DLOG(REALGDP_SA(-3)) | 0.525579 | 0.131068 | 4.009973 | 0.0002 |
| DESI | 0.001534 | 0.000612 | 2.506841 | 0.0160 |
| DESI(-1) | 0.000556 | 0.000627 | 0.886727 | 0.3802 |

| | | | |
|---|---|---|---|
| R-squared | 0.431744 | Mean dependent var | -0.000754 |

| | | | |
|---|---|---|---|
| Adjusted R-squared | 0.378883 | S.D. dependent var | 0.018041 |
| S.E. of regression | 0.014218 | Akaike info criterion | -5.570233 |
| Sum squared resid | 0.008693 | Schwarz criterion | -5.375316 |
| Log likelihood | 138.6856 | Hannan-Quinn criter. | -5.496574 |
| F-statistic | 8.167544 | Durbin-Watson stat | 2.094112 |
| Prob(F-statistic) | 0.000054 | | |

Residuals Diagnostics test model1
Date: 05/30/19 Time: 13:04
Sample: 2000Q3 2012Q4
Included observations: 50
Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation Partial Correlation AC PAC Q-Stat Prob*

Date: 05/30/19 Time: 20:34
Sample: 2000Q3 2012Q4
Included observations: 48
Q-statistic probabilities adjusted for 4 dynamic regressors

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| . \| . \| | . \| . \| | 1 | -0.049 | -0.049 | 0.1219 | 0.727 |
| . \|** \| | . \|** \| | 2 | 0.219 | 0.218 | 2.6349 | 0.268 |
| . \| . \| | . \| . \| | 3 | -0.019 | -0.000 | 2.6552 | 0.448 |
| .*\| . \| | .*\| . \| | 4 | -0.098 | -0.154 | 3.1811 | 0.528 |
| . \|** \| | . \|** \| | 5 | 0.260 | 0.274 | 6.9400 | 0.225 |
| . \|*. \| | . \|*. \| | 6 | 0.105 | 0.200 | 7.5665 | 0.272 |
| .*\| . \| | **\| . \| | 7 | -0.118 | -0.298 | 8.3782 | 0.300 |
| . \| . \| | .*\| . \| | 8 | -0.035 | -0.147 | 8.4503 | 0.391 |
| . \| . \| | . \|** \| | 9 | -0.051 | 0.218 | 8.6104 | 0.474 |
| . \| . \| | . \| . \| | 10 | 0.001 | -0.010 | 8.6105 | 0.569 |
| . \|** \| | . \| . \| | 11 | 0.220 | 0.009 | 11.736 | 0.384 |
| .*\| . \| | . \| . \| | 12 | -0.104 | -0.012 | 12.459 | 0.410 |
| . \| . \| | . \| . \| | 13 | 0.029 | 0.071 | 12.516 | 0.486 |
| . \| . \| | . \|*. \| | 14 | 0.035 | 0.079 | 12.605 | 0.558 |
| . \|*. \| | . \|*. \| | 15 | 0.096 | 0.116 | 13.275 | 0.581 |
| . \|*. \| | . \| . \| | 16 | 0.145 | -0.008 | 14.853 | 0.535 |
| . \| . \| | .*\| . \| | 17 | -0.021 | -0.126 | 14.888 | 0.604 |
| **\| . \| | **\| . \| | 18 | -0.251 | -0.268 | 19.910 | 0.338 |
| . \| . \| | . \| . \| | 19 | -0.011 | 0.052 | 19.920 | 0.399 |
| .*\| . \| | .*\| . \| | 20 | -0.173 | -0.103 | 22.486 | 0.315 |

*Probabilities may not be valid for this equation specification.

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

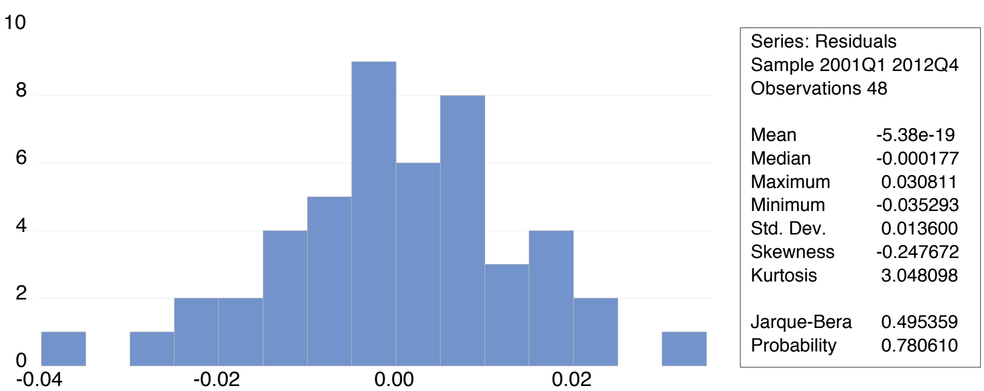
| | | | |
|---|---|---|---|
| F-statistic | 1.104580 | Prob. F(2,41) | 0.3410 |
| Obs*R-squared | 2.454101 | Prob. Chi-Square(2) | 0.2932 |

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 05/30/19 Time: 13:07
Sample: 2001Q1 2012Q4
Included observations: 48
Presample missing value lagged residuals set to zero.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 4.13E-07 | 0.002115 | 0.000195 | 0.9998 |
| DLOGREALGDP_SA(-1) | -0.030221 | 0.219479 | -0.137695 | 0.8912 |
| DLOGREALGDP_SA(-3) | 0.012524 | 0.133192 | 0.094032 | 0.9255 |
| DESI | -2.36E-05 | 0.000620 | -0.038059 | 0.9698 |
| DESI(-1) | -1.35E-05 | 0.000671 | -0.020081 | 0.9841 |
| RESID(-1) | -0.011708 | 0.258226 | -0.045341 | 0.9641 |
| RESID(-2) | 0.230353 | 0.165291 | 1.393621 | 0.1709 |

| | | | |
|---|---|---|---|
| R-squared | 0.051127 | Mean dependent var | -5.38E-19 |
| Adjusted R-squared | -0.087732 | S.D. dependent var | 0.013600 |
| S.E. of regression | 0.014184 | Akaike info criterion | -5.539380 |
| Sum squared resid | 0.008249 | Schwarz criterion | -5.266497 |
| Log likelihood | 139.9451 | Hannan-Quinn criter. | -5.436257 |
| F-statistic | 0.368193 | Durbin-Watson stat | 1.980065 |
| Prob(F-statistic) | 0.894861 | | |

Normality test Model1




Heteroskedasticity Test: Breusch-Pagan-Godfrey

Null hypothesis: Homoskedasticity

| | | | |
|---|---|---|---|
| F-statistic | 0.792377 | Prob. F(4,43) | 0.5366 |
| Obs*R-squared | 3.295169 | Prob. Chi-Square(4) | 0.5097 |
| Scaled explained SS | 2.708027 | Prob. Chi-Square(4) | 0.6078 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 11/04/19 Time: 20:46
Sample: 2001Q1 2012Q4
Included observations: 48

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000180 | 3.94E-05 | 4.560458 | 0.0000 |
| DLOG(REALGDP_SA(-1)) | -0.003776 | 0.002489 | -1.516815 | 0.1366 |
| DLOG(REALGDP_SA(-3)) | 0.001713 | 0.002436 | 0.702994 | 0.4858 |
| DESI | 8.90E-06 | 1.14E-05 | 0.782487 | 0.4382 |
| DESI(-1) | -4.89E-06 | 1.17E-05 | -0.419595 | 0.6769 |

| | | | |
|---|---|---|---|
| R-squared | 0.068649 | Mean dependent var | 0.000181 |
| Adjusted R-squared | -0.017988 | S.D. dependent var | 0.000262 |
| S.E. of regression | 0.000264 | Akaike info criterion | -13.54088 |
| Sum squared resid | 3.00E-06 | Schwarz criterion | -13.34597 |
| Log likelihood | 329.9812 | Hannan-Quinn criter. | -13.46722 |
| F-statistic | 0.792377 | Durbin-Watson stat | 1.815233 |
| Prob(F-statistic) | 0.536634 | | |

Heteroskedasticity Test: White
Null hypothesis: Homoskedasticity

| | | | |
|---|---|---|---|
| F-statistic | 0.854281 | Prob. F(14,33) | 0.6103 |
| Obs*R-squared | 12.76863 | Prob. Chi-Square(14) | 0.5448 |
| Scaled explained SS | 10.49348 | Prob. Chi-Square(14) | 0.7253 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/30/19 Time: 20:49
Sample: 2001Q1 2012Q4
Included observations: 48

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000212 | 7.78E-05. | 2.722899 | 0.0103 |
| DLOG(REALGDP_SA(-1))^2 | -0.051362 | 0.159361. | -0.322299 | 0.7493 |
| DLOG(REALGDP_SA(-1))*DLOG(REALGDP_SA(-3)) | 0.117871 | 0.310245 | 0.379929 | 0.7064 |
| DLOG(REALGDP_SA(-1))*DESI | -0.000659 | 0.001097. | -0.601101 | 0.5519 |
| DLOG(REALGDP_SA(-1))*DESI(-1) | 0.002345 | 0.000986 | 2.378716 | 0.0233 |
| DLOG(REALGDP_SA(-1)) | -0.000229 | 0.002980 | -0.076948 | 0.9391 |
| DLOG(REALGDP_SA(-3))^2 | -0.046744 | 0.150931 | -0.309705 | 0.7587 |
| DLOG(REALGDP_SA(-3))*DESI | 0.000317 | 0.000985 | 0.322053 | 0.7494 |
| DLOG(REALGDP_SA(-3))*DESI(-1) | -0.001165 | 0.001137 | -1.024863 | 0.3129 |
| DLOG(REALGDP_SA(-3)) | 0.000142 | 0.002903 | 0.048926 | 0.9613 |
| DESI^2 | -1.39E-06 | 2.98E-06 | -0.465052 | 0.6449 |
| DESI*DESI(-1) | 6.40E-07 | 3.56E-06 | 0.179771 | 0.8584 |
| DESI | -7.95E-06 | 1.70E-05 | -0.467992 | 0.6429 |
| DESI(-1)^2 | -3.03E-06 | 2.97E-06 | -1.020125 | 0.3151 |
| DESI(-1) | -2.98E-06 | 1.90E-05 | -0.157315 | 0.8760 |

| | | | |
|---|---|---|---|
| R-squared | 0.266013 | Mean dependent var | 0.000181 |
| Adjusted R-squared | -0.045375 | S.D. dependent var | 0.000262 |
| S.E. of regression | 0.000268 | Akaike info criterion | -13.36236 |
| Sum squared resid | 2.37E-06 | Schwarz criterion | -12.77761 |
| Log likelihood | 335.6967 | Hannan-Quinn criter. | -13.14138 |
| F-statistic | 0.854281 | Durbin-Watson stat | 1.734966 |
| Prob(F-statistic) | 0.610346 | | |

Model2 Estimation output

Dependent Variable: DLOG(REALGDP_SA)
Method: Least Squares
Date: 05/30/19 Time: 21:40
Sample (adjusted): 2001Q1 2012Q4
Included observations: 48 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.000606 | 0.001907 | -0.317676 | 0.7522 |
| DLOG(REALGDP_SA(-1)) | 0.014214 | 0.123567 | 0.115032 | 0.9089 |
| DLOG(REALGDP_SA(-3)) | 0.505334 | 0.119900 | 4.214633 | 0.0001 |
| DLOG(CLI_SA) | 1.376360 | 0.328153 | 4.194268 | 0.0001 |

| | | | |
|---|---|---|---|
| R-squared | 0.503268 | Mean dependent var | -0.000754 |
| Adjusted R-squared | 0.469400 | S.D. dependent var | 0.018041 |
| S.E. of regression | 0.013142 | Akaike info criterion | -5.746421 |
| Sum squared resid | 0.007599 | Schwarz criterion | -5.590488 |
| Log likelihood | 141.9141 | Hannan-Quinn criter. | -5.687493 |

| | | | |
|---|---|---|---|
| F-statistic | 14.85967 | Durbin-Watson stat | 2.211155 |
| Prob(F-statistic) | 0.000001 | | |

Residuals Diagnostics test Model2
Date: 05/30/19 Time: 21:42

Sample: 2000Q3 2012Q4

Sample: 2000Q3 2012Q4
Included observations: 50
Q-statistic probabilities adjusted for 3 dynamic regressors

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| .*\| . \| | .*\| . \| | 1 | -0.108 | -0.108 | 0.5906 | 0.442 |
| . \| . \| | . \| . \| | 2 | 0.049 | 0.038 | 0.7168 | 0.699 |
| .*\| . \| | .*\| . \| | 3 | -0.116 | -0.108 | 1.4334 | 0.698 |
| . \| . \| | .*\| . \| | 4 | -0.041 | -0.067 | 1.5266 | 0.822 |
| . \|*** \| | . \|**** \| | 5 | 0.479 | 0.491 | 14.354 | 0.014 |
| . \|** \| | . \|*** \| | 6 | 0.243 | 0.434 | 17.720 | 0.007 |
| .*\| . \| | .*\| . \| | 7 | -0.078 | -0.068 | 18.077 | 0.012 |
| . \| . \| | . \| . \| | 8 | -0.054 | -0.062 | 18.252 | 0.019 |
| .*\| . \| | . \| . \| | 9 | -0.109 | -0.006 | 18.981 | 0.025 |
| . \|*. \| | **\| . \| | 10 | 0.089 | -0.272 | 19.485 | 0.035 |
| . \|** \| | . \| . \| | 11 | 0.322 | -0.050 | 26.207 | 0.006 |
| . \| . \| | . \| . \| | 12 | -0.037 | 0.047 | 26.299 | 0.010 |
| .*\| . \| | .*\| . \| | 13 | -0.095 | -0.104 | 26.919 | 0.013 |
| .*\| . \| | .*\| . \| | 14 | -0.164 | -0.141 | 28.818 | 0.011 |
| . \| . \| | . \|*. \| | 15 | -0.025 | 0.093 | 28.865 | 0.017 |
| . \|** \| | . \|*. \| | 16 | 0.226 | 0.131 | 32.693 | 0.008 |
| . \| . \| | . \| . \| | 17 | 0.060 | -0.041 | 32.972 | 0.011 |
| **\| . \| | **\| . \| | 18 | -0.282 | -0.338 | 39.347 | 0.003 |
| .*\| . \| | . \| . \| | 19 | -0.104 | -0.054 | 40.249 | 0.003 |
| .*\| . \| | .*\| . \| | 20 | -0.178 | -0.087 | 42.956 | 0.002 |

*Probabilities may not be valid for this equation specification.

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

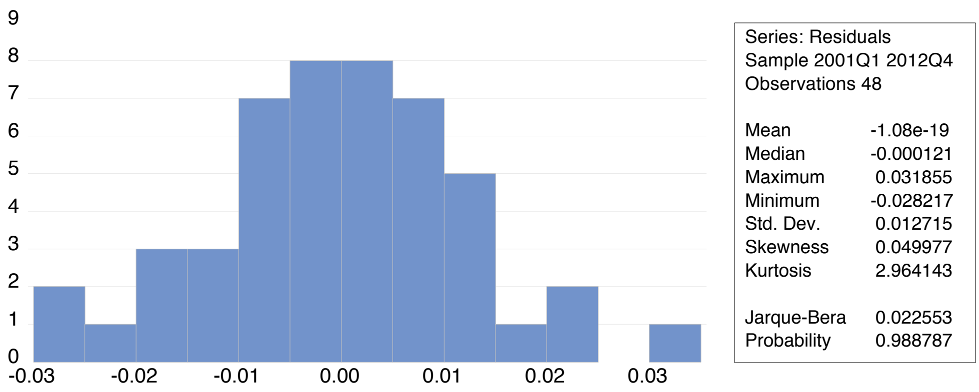
| | | | |
|---|---|---|---|
| F-statistic | 0.548234 | Prob. F(2,42) | 0.5820 |
| Obs*R-squared | 1.221224 | Prob. Chi-Square(2) | 0.5430 |

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 05/30/19 Time: 21:43
Sample: 2001Q1 2012Q4
Included observations: 48
Presample missing value lagged residuals set to zero.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -2.06E-05 | 0.001928 | -0.010660 | 0.9915 |
| DLOG(REALGDP_SA(-1)) | 0.123348 | 0.178332 | 0.691676 | 0.4929 |
| DLOG(REALGDP_SA(-3)) | -0.003306 | 0.121233 | -0.027272 | 0.9784 |
| DLOG(CLI_SA) | -0.122734 | 0.354073 | -0.346634 | 0.7306 |
| RESID(-1) | -0.231467 | 0.232588 | -0.995181 | 0.3253 |
| RESID(-2) | 0.011153 | 0.158581 | 0.070332 | 0.9443 |

| | | | |
|---|---|---|---|
| R-squared | 0.025442 | Mean dependent var | -1.08E-19 |
| Adjusted R-squared | -0.090577 | S.D. dependent var | 0.012715 |
| S.E. of regression | 0.013279 | Akaike info criterion | -5.688859 |
| Sum squared resid | 0.007405 | Schwarz criterion | -5.454959 |
| Log likelihood | 142.5326 | Hannan-Quinn criter. | -5.600468 |
| F-statistic | 0.219294 | Durbin-Watson stat | 2.068271 |
| Prob(F-statistic) | 0.952277 | | |

Normality test Model2




Heteroskedasticity Test: Breusch-Pagan-Godfrey

Null hypothesis: Homoskedasticity

| | | | |
|---|---|---|---|
| F-statistic | 0.327971 | Prob. F(3,44) | 0.8051 |
| Obs*R-squared | 1.049881 | Prob. Chi-Square(3) | 0.7892 |
| Scaled explained SS | 0.866376 | Prob. Chi-Square(3) | 0.8335 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/30/19 Time: 21:48
Sample: 2001Q1 2012Q4
Included observations: 48

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000155 | 3.33E-05 | 4.667754 | 0.0000 |
| DLOG(REALGDP_SA(-1)) | -0.001168 | 0.002155 | -0.542116 | 0.5905 |
| DLOG(REALGDP_SA(-3)) | 0.000821 | 0.002091 | 0.392785 | 0.6964 |
| DLOG(CLI_SA) | -0.003674 | 0.005723 | -0.641997 | 0.5242 |

| | | | |
|---|---|---|---|
| R-squared | 0.021873 | Mean dependent var | 0.000158 |
| Adjusted R-squared | -0.044818 | S.D. dependent var | 0.000224 |
| S.E. of regression | 0.000229 | Akaike info criterion | -13.84444 |
| Sum squared resid | 2.31E-06 | Schwarz criterion | -13.68851 |
| Log likelihood | 336.2667 | Hannan-Quinn criter. | -13.78552 |
| F-statistic | 0.327971 | Durbin-Watson stat | 1.844633 |
| Prob(F-statistic) | 0.805122 | | |

Heteroskedasticity Test: White
Null hypothesis: Homoskedasticity

| | | | |
|---|---|---|---|
| F-statistic | 1.102802 | Prob. F(9,38) | 0.3841 |
| Obs*R-squared | 9.940703 | Prob. Chi-Square(9) | 0.3553 |
| Scaled explained SS | 8.203196 | Prob. Chi-Square(9) | 0.5138 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/30/19 Time: 21:50
Sample: 2001Q1 2012Q4
Included observations: 48

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000135 | 5.99E-05 | 2.251197 | 0.0302 |
| DLOG(REALGDP_SA(-1))^2 | -0.028803 | 0.109134 | -0.263924 | 0.7933 |

| | | | | |
|---|---|---|---|---|
| DLOG(REALGDP_SA(-1))*DLOG(REALGDP_SA(-3)) | 0.126123 | 0.226698 | 0.556350 | 0.5812 |
| DLOG(REALGDP_SA(-1))*DLOG(CLI_SA) | 1.147130 | 0.432695 | 2.651126 | 0.0116 |
| DLOG(REALGDP_SA(-1)) | -0.002621 | 0.002452 | -1.069125 | 0.2918 |
| DLOG(REALGDP_SA(-3))^2 | -0.030722 | 0.109761 | -0.279900 | 0.7811 |
| DLOG(REALGDP_SA(-3))*DLOG(CLI_SA) | -0.729545 | 0.388035 | -1.880103 | 0.0678 |
| DLOG(REALGDP_SA(-3)) | 0.002549 | 0.002292 | 1.112249 | 0.2730 |
| DLOG(CLI_SA)^2 | -0.289953 | 0.769711 | -0.376703 | 0.7085 |
| DLOG(CLI_SA) | -0.001073 | 0.006221 | -0.172507 | 0.8640 |

| | | | |
|---|---|---|---|
| R-squared | 0.207098 | Mean dependent var | 0.000158 |
| Adjusted R-squared | 0.019305 | S.D. dependent var | 0.000224 |
| S.E. of regression | 0.000222 | Akaike info criterion | -13.80439 |
| Sum squared resid | 1.87E-06 | Schwarz criterion | -13.41455 |
| Log likelihood | 341.3052 | Hannan-Quinn criter. | -13.65707 |
| F-statistic | 1.102802 | Durbin-Watson stat | 1.968562 |
| Prob(F-statistic) | 0.384115 | | |

Estimation Output model3
Dependent Variable: DLOG(REALGDP_SA)
Method: Least Squares
Date: 11/30/19 Time: 21:54
Sample: 2000Q3 2012Q4
Included observations: 50

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.001830 | 0.002242 | -0.816450 | 0.4185 |
| DLOG(REALGDP_SA(-1)) | 0.034411 | 0.170775 | 0.201500 | 0.8412 |
| DLOG(TURNINDEXRETAIL_SA) | 0.279311 | 0.076641 | 3.644407 | 0.0007 |
| DLOG(TURNINDEXRETAIL_SA(-1)) | 0.099824 | 0.088322 | 1.130232 | 0.2642 |

| | | | |
|---|---|---|---|
| R-squared | 0.352975 | Mean dependent var | 9.64E-05 |
| Adjusted R-squared | 0.310778 | S.D. dependent var | 0.018164 |
| S.E. of regression | 0.015080 | Akaike info criterion | -5.474309 |
| Sum squared resid | 0.010460 | Schwarz criterion | -5.321347 |
| Log likelihood | 140.8577 | Hannan-Quinn criter. | -5.416060 |
| F-statistic | 8.364872 | Durbin-Watson stat | 2.070531 |
| Prob(F-statistic) | 0.000152 | | |

Residuals Diagnostics test model3
Date: 05/30/19 Time: 21:58
Sample: 2000Q3 2012Q4
Included observations: 50
Q-statistic probabilities adjusted for 3 dynamic regressors

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| .*\| . \| | .*\| . \| | 1 | -0.076 | -0.076 | 0.3057 | 0.580 |
| . \|*. \| | . \|*. \| | 2 | 0.114 | 0.109 | 1.0060 | 0.605 |
| . \|** \| | . \|*** \| | 3 | 0.330 | 0.353 | 7.0453 | 0.070 |
| .*\| . \| | .*\| . \| | 4 | -0.203 | -0.182 | 9.3726 | 0.052 |
| . \|** \| | . \|*. \| | 5 | 0.217 | 0.126 | 12.089 | 0.034 |
| . \|*. \| | . \| . \| | 6 | 0.105 | 0.071 | 12.736 | 0.047 |
| .*\| . \| | . \| . \| | 7 | -0.087 | -0.001 | 13.191 | 0.068 |
| . \| . \| | .*\| . \| | 8 | 0.067 | -0.122 | 13.472 | 0.097 |
| . \| . \| | . \|*. \| | 9 | 0.045 | 0.083 | 13.600 | 0.137 |
| . \| . \| | . \| . \| | 10 | 0.011 | 0.062 | 13.607 | 0.192 |
| . \| . \| | . \| . \| | 11 | 0.051 | 0.002 | 13.780 | 0.245 |
| . \| . \| | . \| . \| | 12 | 0.007 | -0.048 | 13.784 | 0.315 |
| . \| . \| | . \| . \| | 13 | -0.004 | 0.022 | 13.785 | 0.389 |
| . \|*. \| | . \|*. \| | 14 | 0.176 | 0.201 | 16.017 | 0.312 |
| . \| . \| | . \| . \| | 15 | -0.022 | -0.041 | 16.052 | 0.379 |
| . \| . \| | . \| . \| | 16 | 0.013 | -0.064 | 16.065 | 0.448 |
| .*\| . \| | **\| . \| | 17 | -0.139 | -0.287 | 17.577 | 0.416 |
| .*\| . \| | . \| . \| | 18 | -0.099 | -0.023 | 18.380 | 0.431 |
| . \| . \| | . \| . \| | 19 | 0.035 | 0.023 | 18.481 | 0.491 |
| .*\| . \| | .*\| . \| | 20 | -0.159 | -0.074 | 20.679 | 0.416 |
| . \|*. \| | . \|*. \| | 21 | 0.128 | 0.141 | 22.154 | 0.391 |
| . \| . \| | . \|** \| | 22 | 0.055 | 0.218 | 22.436 | 0.434 |
| .*\| . \| | . \| . \| | 23 | -0.133 | -0.056 | 24.144 | 0.396 |
| . \| . \| | **\| . \| | 24 | 0.060 | -0.225 | 24.508 | 0.433 |

*Probabilities may not be valid for this equation specification.

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

| | | | |
|---|---|---|---|
| F-statistic | 3.165141 | Prob. F(2,44) | 0.0520 |
| Obs*R-squared | 6.288742 | Prob. Chi-Square(2) | 0.0431 |

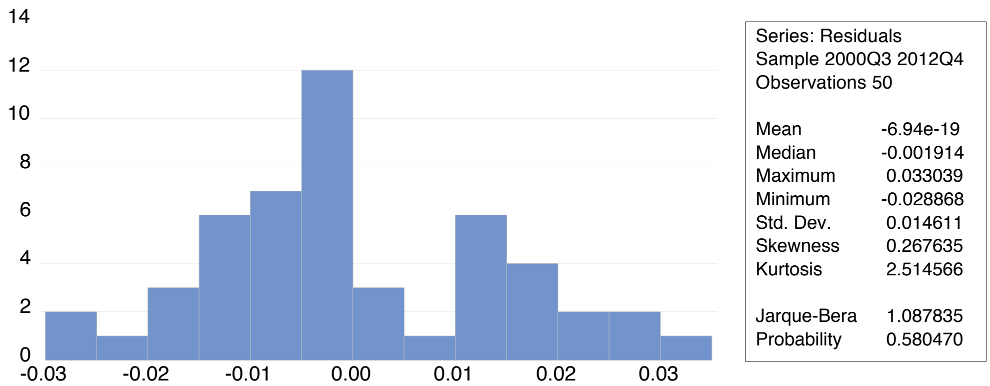
Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 05/30/19 Time: 22:01
Sample: 2000Q3 2012Q4
Included observations: 50
Presample missing value lagged residuals set to zero.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.002207 | 0.002316 | 0.953084 | 0.3458 |

| | | | | |
|---|---|---|---|---|
| DLOG(REALGDP_SA(-1)) | 1.466079 | 0.641110 | 2.286784 | 0.0271 |
| DLOG(TURNINDEXRETAIL_SA) | -0.034429 | 0.074613 | -0.461429 | 0.6468 |
| DLOG(TURNINDEXRETAIL_SA(-1)) | -0.471794 | 0.208261 | -2.265395 | 0.0285 |
| RESID(-1) | -1.494997 | 0.641199 | -2.331567 | 0.0244 |
| RESID(-2) | 0.108105 | 0.166524 | 0.649183 | 0.5196 |

| | | | |
|---|---|---|---|
| R-squared | 0.125775 | Mean dependent var | -6.94E-19 |
| Adjusted R-squared | 0.026431 | S.D. dependent var | 0.014611 |
| S.E. of regression | 0.014416 | Akaike info criterion | -5.528726 |
| Sum squared resid | 0.009145 | Schwarz criterion | -5.299283 |
| Log likelihood | 144.2182 | Hannan-Quinn criter. | -5.441353 |
| F-statistic | 1.266057 | Durbin-Watson stat | 1.983575 |
| Prob(F-statistic) | 0.295554 | | |

Normality test Model3




Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

| | | | |
|---|---|---|---|
| F-statistic | 0.844924 | Prob. F(3,46) | 0.4764 |
| Obs*R-squared | 2.611295 | Prob. Chi-Square(3) | 0.4555 |
| Scaled explained SS | 1.673747 | Prob. Chi-Square(3) | 0.6428 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/30/19 Time: 22:05
Sample: 2000Q3 2012Q4
Included observations: 50

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|

C 0.000211 3.88E-05 5.422111 0.0000
DLOG(REALGDP_SA(-1)) -0.002883 0.002959 -0.974038 0.3351
DLOG(TURNINDEXRETAIL_SA) -0.000559 0.001328 -0.421001 0.6757
DLOG(TURNINDEXRETAIL_SA(-1)) 0.000283 0.001531 0.184750 0.8542

| | | | |
|---|---|---|---|
| R-squared | 0.052226 | Mean dependent var | 0.000209 |
| Adjusted R-squared | -0.009585 | S.D. dependent var | 0.000260 |
| S.E. of regression | 0.000261 | Akaike info criterion | -13.58500 |
| Sum squared resid | 3.14E-06 | Schwarz criterion | -13.43204 |
| Log likelihood | 343.6251 | Hannan-Quinn criter. | -13.52676 |
| F-statistic | 0.844924 | Durbin-Watson stat | 2.339497 |
| Prob(F-statistic) | 0.476402 | | |

Heteroskedasticity Test: White
Null hypothesis: Homoskedasticity

| | | | |
|---|---|---|---|
| F-statistic | 0.809569 | Prob. F(9,40) | 0.6102 |
| Obs*R-squared | 7.704293 | Prob. Chi-Square(9) | 0.5642 |
| Scaled explained SS | 4.938178 | Prob. Chi-Square(9) | 0.8397 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/30/19 Time: 22:08
Sample: 2000Q3 2012Q4
Included observations: 50

Variable Coefficient Std. Error t-Statistic Prob.

C 0.000240 7.18E-05 3.336050 0.0018
DLOG(REALGDP_SA(-1))^2 -0.380966 0.225522 -1.689266 0.0989
DLOG(REALGDP_SA(-1))*DLOG(TURNINDEXRETAIL_SA) 0.227378
0.179890 1.263980 0.2136
DLOG(REALGDP_SA(-1))*DLOG(TURNINDEXRETAIL_SA(-1)) 0.182419
0.191807 0.951057 0.3473
DLOG(REALGDP_SA(-1)) -0.004268 0.003476 -1.227810 0.2267
DLOG(TURNINDEXRETAIL_SA)^2 -0.024749 0.032822 -0.754058 0.4552
DLOG(TURNINDEXRETAIL_SA)*DLOG(TURNINDEXRETAIL_SA(-1)) -
0.078800 0.065791 -1.197730 0.2381
DLOG(TURNINDEXRETAIL_SA) 0.000832 0.002152 0.386872 0.7009
DLOG(TURNINDEXRETAIL_SA(-1))^2 0.002909 0.053318 0.054562
0.9568
DLOG(TURNINDEXRETAIL_SA(-1)) 0.000642 0.001945 0.330041
0.7431

R-squared 0.154086 Mean dependent var 0.000209

| | | | |
|---|---|---|---|
| Adjusted R-squared | -0.036245 | S.D. dependent var | 0.000260 |
| S.E. of regression | 0.000265 | Akaike info criterion | -13.45870 |
| Sum squared resid | 2.80E-06 | Schwarz criterion | -13.07630 |
| Log likelihood | 346.4676 | Hannan-Quinn criter. | -13.31308 |
| F-statistic | 0.809569 | Durbin-Watson stat | 1.954289 |
| Prob(F-statistic) | 0.610210 | | |

Estimation output model4
Dependent Variable: DLOG(REALGDP_SA)
Method: Least Squares
Date: 05/30/19 Time: 22:12
Sample: 2000Q3 2012Q4
Included observations: 50

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.001406 | 0.001940. | 0.724823 | 0.4722 |
| DLOG(REALGDP_SA(-1)) | -0.074587 | 0.172107 | -0.433375 | 0.6668 |
| DLOG(VOLUMEINDEXRETTR_SA) | 0.379108 | 0.072028 | 5.263362 | 0.0000 |
| DLOG(VOLUMEINDEXRETTR_SA(-1)) | 0.139376 | 0.096005 | 1.451762 | 0.1534 |

| | | | |
|---|---|---|---|
| R-squared | 0.476900 | Mean dependent var | 9.64E-05 |
| Adjusted R-squared | 0.442784 | S.D. dependent var | 0.018164 |
| S.E. of regression | 0.013559 | Akaike info criterion | -5.686921 |
| Sum squared resid | 0.008457 | Schwarz criterion | -5.533959 |
| Log likelihood | 146.1730 | Hannan-Quinn criter. | -5.628672 |
| F-statistic | 13.97908 | Durbin-Watson stat | 2.006115 |
| Prob(F-statistic) | 0.000001 | | |

Residuals Diagnostics Test model4
Date: 11/04/19 Time: 22:19
Sample: 2000Q3 2012Q4
Included observations: 50
Q-statistic probabilities adjusted for 3 dynamic regressors

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| .*\| . \| | .*\| . \| | 1 | -0.069 | -0.069 | 0.2539 | 0.614 |
| . \|*. \| | . \|*. \| | 2 | 0.125 | 0.121 | 1.1044 | 0.576 |
| . \|** \| | . \|*** \| | 3 | 0.330 | 0.353 | 7.1462 | 0.067 |
| **\| . \| | **\| . \| | 4 | -0.266 | -0.263 | 11.153 | 0.025 |
| . \|*. \| | . \|*. \| | 5 | 0.195 | 0.092 | 13.340 | 0.020 |
| . \| . \| | . \| . \| | 6 | 0.010 | -0.020 | 13.346 | 0.038 |
| . \| . \| | . \|*. \| | 7 | -0.055. | 0.093 | 13.529 | 0.060 |

| | | | | | | |
|---|---|---|---|---|---|---|
| . \| . \| | **\| . \| | 8 | -0.002 | -0.206 | 13.529 | 0.095 |
| . \| . \| | . \|*. \| | 9 | 0.040 | 0.162 | 13.630 | 0.136 |
| . \| . \| | .*\| . \| | 10 | -0.035 | -0.074 | 13.709 | 0.187 |
| . \| . \| | . \| . \| | 11 | -0.022 | 0.052 | 13.742 | 0.248 |
| . \|*. \| | . \| . \| | 12 | 0.104 | -0.022 | 14.480 | 0.271 |
| . \| . \| | . \|*. \| | 13 | -0.017 | 0.146 | 14.500 | 0.340 |
| . \|*. \| | . \|*. \| | 14 | 0.144 | 0.074 | 15.992 | 0.314 |
| . \| . \| | .*\| . \| | 15 | -0.009 | -0.067 | 15.998 | 0.382 |
| . \| . \| | . \| . \| | 16 | 0.003 | -0.022 | 15.999 | 0.453 |
| .*\| . \| | **\| . \| | 17 | -0.116 | -0.239 | 17.053. | 0.451 |
| .*\| . \| | . \| . \| | 18 | - 0.110 | -0.020 | 18.037 | 0.453 |
| . \| . \| | . \| . \| | 19 | 0.041 | 0.001 | 18.178 | 0.511 |
| .*\| . \| | . \| . \| | 20 | -0.160 | 0.032 | 20.410 | 0.433 |
| . \|*. \| | . \|*. \| | 21 | 0.138 | 0.095 | 22.119 | 0.393 |
| . \|*. \| | . \|*. \| | 22 | 0.074 | 0.180 | 22.627 | 0.423 |
| .*\| . \| | . \| . \| | 23 | -0.081 | -0.065 | 23.265 | 0.445 |
| . \|*. \| | . \| . \| | 24 | 0.139 | -0.011 | 25.208 | 0.395 |

*Probabilities may not be valid for this equation specification.

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

| | | | |
|---|---|---|---|
| F-statistic | 3.321182 | Prob. F(2,44) | 0.0454 |
| Obs*R-squared | 6.558109 | Prob. Chi-Square(2) | 0.0377 |

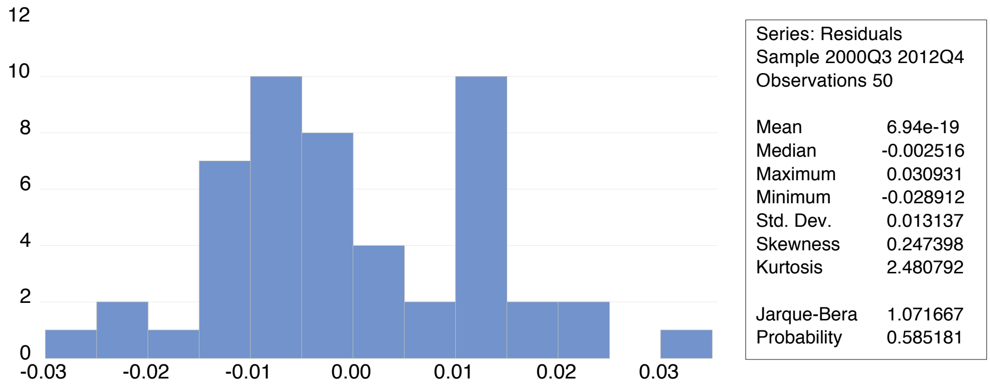
Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 11/04/19 Time: 22:26
Sample: 2000Q3 2012Q4
Included observations: 50
Presample missing value lagged residuals set to zero.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.001929 | 0.002027 | -0.951676 | 0.3465 |
| DLOG(REALGDP_SA(-1)) | 1.419327 | 0.613503 | 2.313480 | 0.0254 |
| DLOG(VOLUMEINDEXRETTR_SA) | -0.044573 | 0.070797 | -0.629579 | 0.5322 |
| DLOG(VOLUMEINDEXRETTR_SA(-1)) | -0.585328 | 0.251062 | -2.331403 | 0.0244 |
| RESID(-1) | -1.428871 | 0.609921 | -2.342714 | 0.0237 |
| RESID(-2) | 0.257929 | 0.172373 | 1.496344 | 0.1417 |

| | | | |
|---|---|---|---|
| R-squared | 0.131162 | Mean dependent var | 6.94E-19 |
| Adjusted R-squared | 0.032431 | S.D. dependent var | 0.013137 |
| S.E. of regression | 0.012923 | Akaike info criterion | -5.747519 |

| | | | |
|---|---|---|---|
| Sum squared resid | 0.007348 | Schwarz criterion | -5.518077 |
| Log likelihood | 149.6880 | Hannan-Quinn criter. | -5.660146 |
| F-statistic | 1.328473 | Durbin-Watson stat | 2.015678 |
| Prob(F-statistic) | 0.269915 | | |

Normality test model4




Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

| | | | |
|---|---|---|---|
| F-statistic | 0.693725 | Prob. F(3,46) | 0.5606 |
| Obs*R-squared | 2.164229 | Prob. Chi-Square(3) | 0.5390 |
| Scaled explained SS | 1.356260 | Prob. Chi-Square(3) | 0.7158 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/30/19 Time: 22:29
Sample: 2000Q3 2012Q4
Included observations: 50

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000166 | 3.00E-05 | 5.530831 | 0.0000 |
| DLOG(REALGDP_SA(-1)) | -0.000771 | 0.002664 | -0.289583 | 0.7734 |
| DLOG(VOLUMEINDEXRETTR_SA) | -0.001034 | 0.001115 | -0.927366 | 0.3586 |
| DLOG(VOLUMEINDEXRETTR_SA(-1)) | -0.000167 | 0.001486 | -0.112526 | 0.9109 |

| | | | |
|---|---|---|---|
| R-squared | 0.043285 | Mean dependent var | 0.000169 |
| Adjusted R-squared | -0.019110 | S.D. dependent var | 0.000208 |
| S.E. of regression | 0.000210 | Akaike info criterion | -14.02339 |
| Sum squared resid | 2.03E-06 | Schwarz criterion | -13.87043 |
| Log likelihood | 354.5848 | Hannan-Quinn criter. | -13.96514 |
| F-statistic | 0.693725 | Durbin-Watson stat | 2.152286 |
| Prob(F-statistic) | 0.560597 | | |

Heteroskedasticity Test: White
Null hypothesis: Homoskedasticity

| | | | |
|---|---|---|---|
| F-statistic | 0.696505 | Prob. F(9,40) | 0.7079 |
| Obs*R-squared | 6.774089 | Prob. Chi-Square(9) | 0.6606 |
| Scaled explained SS | 4.245125 | Prob. Chi-Square(9) | 0.8946 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/30/19 Time: 22:32
Sample: 2000Q3 2012Q4
Included observations: 50

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000191 | 5.39E-05 | 3.543677 | 0.0010 |
| DLOG(REALGDP_SA(-1))^2 | -0.176260 | 0.267686 | -0.658459 | 0.5140 |
| DLOG(REALGDP_SA(-1))*DLOG(VOLUMEINDEXRETTR_SA) | -0.016002 | 0.226349 | -0.070697 | 0.9440 |
| DLOG(REALGDP_SA(-1))*DLOG(VOLUMEINDEXRETTR_SA(-1)) | 0.092029 | 0.279978 | 0.328699 | 0.7441 |
| DLOG(REALGDP_SA(-1)) | 0.000294 | 0.003034 | 0.097024 | 0.9232 |
| DLOG(VOLUMEINDEXRETTR_SA)^2 | -0.029904 | 0.031836 | -0.939314 | 0.3532 |
| DLOG(VOLUMEINDEXRETTR_SA)*DLOG(VOLUMEINDEXRETTR_SA(-1)) | 0.010072 | 0.091445 | 0.110141 | 0.9128 |
| DLOG(VOLUMEINDEXRETTR_SA) | -0.004601 | 0.003081 | -1.493255 | 0.1432 |
| DLOG(VOLUMEINDEXRETTR_SA(-1))^2 | 0.024171 | 0.077389 | 0.312331 | 0.7564 |
| DLOG(VOLUMEINDEXRETTR_SA(-1)) | 0.002447 | 0.003148 | 0.777226 | 0.4416 |

| | | | |
|---|---|---|---|
| R-squared | 0.135482 | Mean dependent var | 0.000169 |
| Adjusted R-squared | -0.059035 | S.D. dependent var | 0.000208 |
| S.E. of regression | 0.000214 | Akaike info criterion | -13.88472 |
| Sum squared resid | 1.83E-06 | Schwarz criterion | -13.50232 |
| Log likelihood | 357.1181 | Hannan-Quinn criter. | -13.73910 |
| F-statistic | 0.696505 | Durbin-Watson stat | 1.886569 |
| Prob(F-statistic) | 0.707931 | | |

Estimation output model5
Dependent Variable: DLOGREALGDP
Method: Least Squares
Date: 05/30/19 Time: 00:59
Sample: 2001Q1 2012Q4
Included observations: 48 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000966 | 0.001858 | 0.519617 | 0.6061 |
| DLOG(REALGDP_SA(-1)) | -0.306219 | 0.168491 | -1.817415 | 0.0763 |
| DLOG(REALGDP_SA(-3)) | 0.384049 | 0.116408 | 3.299155 | 0.0020 |
| DLOGIPI | 0.131689 | 0.094264 | 1.397017 | 0.1697 |
| DLOG(VOLUMEINDEXRETTR_SA) | 0.309167 | 0.069206 | 4.467317 | 0.0001 |
| DLOG(VOLUMEINDEXRETTR_SA(-1)) | 0.175855 | 0.087915 | 2.000281 | 0.0520 |

| | | | |
|---|---|---|---|
| R-squared | 0.586900 | Mean dependent var | -0.000754 |
| Adjusted R-squared | 0.537721 | S.D. dependent var | 0.018041 |
| S.E. of regression | 0.012266 | Akaike info criterion | -5.847448 |
| Sum squared resid | 0.006319 | Schwarz criterion | -5.613547 |
| Log likelihood | 146.3387 | Hannan-Quinn criter. | -5.759056 |
| F-statistic | 11.93405 | Durbin-Watson stat | 1.782312 |
| Prob(F-statistic) | 0.000000 | | |

Residuals Diagnostics test model5
Date: 05/30/19 Time: 23:08
Sample: 2000Q3 2012Q4
Included observations: 48
Q-statistic probabilities adjusted for 5 dynamic regressors

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| . \| . \| | . \| . \| | 1 | 0.044 | 0.044 | 0.0971 | 0.755 |
| . \|*. \| | . \|*. \| | 2 | 0.096 | 0.095 | 0.5825 | 0.747 |
| . \| . \| | . \| . \| | 3 | 0.059 | 0.052 | 0.7694 | 0.857 |
| **\| . \| | **\| . \| | 4 | -0.309 | -0.327 | 5.9844 | 0.200 |
| . \|*. \| | . \|*. \| | 5 | 0.090 | 0.121 | 6.4353 | 0.266 |
| . \| . \| | . \| . \| | 6 | -0.025 | 0.031 | 6.4704 | 0.373 |
| .*\| . \| | .*\| . \| | 7 | -0.131 | -0.136 | 7.4674 | 0.382 |
| . \| . \| | .*\| . \| | 8 | -0.042 | -0.159 | 7.5756 | 0.476 |
| .*\| . \| | . \| . \| | 9 | -0.152 | -0.046 | 9.0000 | 0.437 |
| . \| . \| | . \| . \| | 10 | -0.027 | 0.019 | 9.0470 | 0.528 |
| . \| . \| | . \| . \| | 11 | 0.016 | -0.042 | 9.0628 | 0.616 |
| . \|*. \| | . \| . \| | 12 | 0.078 | 0.061 | 9.4682 | 0.663 |

```
 . | .  |       . | .  |     13        0.025    - 0.033  9.5106 0.733
 . |*.  |       . |*.  |     14        0.130  0.139  10.704 0.709
 . |*.  |       . | .  |     15        0.088  0.057  11.261 0.734
 . | .  |       . | .  |     16        0.044  0.026  11.404 0.784
 .*| .  |       **| .  |     17       -0.107 -0.225  12.295 0.782
 **| .  |       .*| .  |     18       -0.217 -0.184  16.064 0.588
 .*| .  |       . | .  |     19       -0.104 -0.009  16.963 0.592
 . | .  |       . | .  |     20       -0.065  0.024  17.322 0.632
```

*Probabilities may not be valid for this equation specification.

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

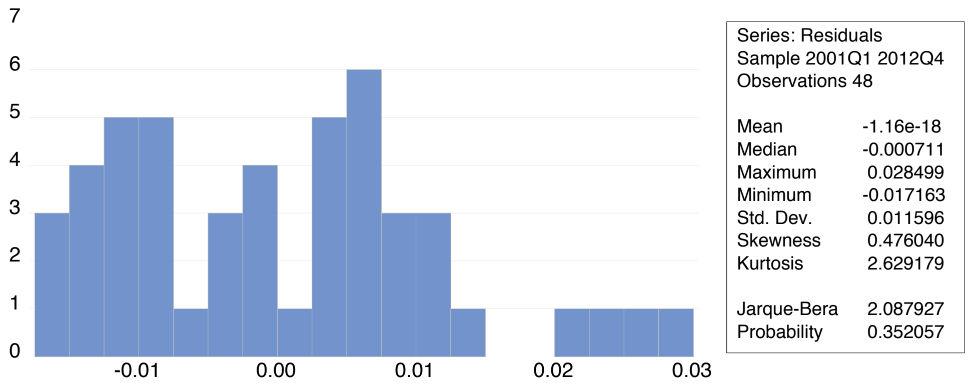
| | | | |
|---|---|---|---|
| F-statistic | 0.362665 | Prob. F(2,40) | 0.6981 |
| Obs*R-squared | 0.854894 | Prob. Chi-Square(2) | 0.6522 |

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 11/04/19 Time: 22:54
Sample: 2001Q1 2012Q4
Included observations: 48
Presample missing value lagged residuals set to zero.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000162 | 0.001901 | 0.085163 | 0.9326 |
| DLOG(REALGDP_SA(-1)) | -0.093976 | 0.295264 | -0.318279 | 0.7519 |
| DLOG(REALGDP_SA(-3)) | 0.009020 | 0.120455 | 0.074885 | 0.9407 |
| DLOGIPI | 0.000147 | 0.095935 | 0.001534 | 0.9988 |
| DLOG(VOLUMEINDEXRETTR_SA) | 0.003564 | 0.070583 | 0.050495 | 0.9600 |
| DLOG(VOLUMEINDEXRETTR_SA(-1)) | 0.014684 | 0.130178 | 0.112798 | 0.9108 |
| RESID(-1) | 0.140594 | 0.314756 | 0.446676 | 0.6575 |
| RESID(-2) | 0.121089 | 0.186781 | 0.648291 | 0.5205 |

| | | | |
|---|---|---|---|
| R-squared | 0.017810 | Mean dependent var | -1.16E-18 |
| Adjusted R-squared | -0.154073 | S.D. dependent var | 0.011596 |
| S.E. of regression | 0.012457 | Akaike info criterion | -5.782085 |
| Sum squared resid | 0.006207 | Schwarz criterion | -5.470218 |
| Log likelihood | 146.7700 | Hannan-Quinn criter. | -5.664230 |
| F-statistic | 0.103619 | Durbin-Watson stat | 1.855033 |
| Prob(F-statistic) | 0.997804 | | |

Normality test model5




Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

| | | | |
|---|---|---|---|
| F-statistic | 1.100964 | Prob. F(5,42) | 0.3743 |
| Obs*R-squared | 5.562201 | Prob. Chi-Square(5) | 0.3512 |
| Scaled explained SS | 3.468979 | Prob. Chi-Square(5) | 0.6281 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/30/19 Time: 23:10
Sample: 2001Q1 2012Q4
Included observations: 48

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000124 | 2.56E-05 | 4.858560 | 0.0000 |
| DLOG(REALGDP_SA(-1)) | 0.000197 | 0.002320 | 0.084762 | 0.9329 |
| DLOG(REALGDP_SA(-3)) | 0.000587 | 0.001603 | 0.365926 | 0.7163 |
| DLOGIPI | -8.11E-05 | 0.001298 | -0.062475 | 0.9505 |
| DLOG(VOLUMEINDEXRETTR_SA) | -0.000899 | 0.000953 | -0.943151 | 0.3510 |

| | | | | |
|---|---|---|---|---|
| DLOG(VOLUMEINDEXRETTR_SA(-1)) | -0.001690 | 0.001211 | -1.395938 | 0.1701 |

| | | | |
|---|---|---|---|
| R-squared | 0.115879 | Mean dependent var | 0.000132 |
| Adjusted R-squared | 0.010627 | S.D. dependent var | 0.000170 |
| S.E. of regression | 0.000169 | Akaike info criterion | -14.41786 |
| Sum squared resid | 1.20E-06 | Schwarz criterion | -14.18396 |
| Log likelihood | 352.0286 | Hannan-Quinn criter. | -14.32947 |
| F-statistic | 1.100964 | Durbin-Watson stat | 1.806666 |
| Prob(F-statistic) | 0.374317 | | |

Heteroskedasticity Test: White
Null hypothesis: Homoskedasticity

| | | | |
|---|---|---|---|
| F-statistic | 0.839270 | Prob. F(20,27) | 0.6527 |
| Obs*R-squared | 18.40110 | Prob. Chi-Square(20) | 0.5610 |
| Scaled explained SS | 11.47622 | Prob. Chi-Square(20) | 0.9329 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 11/04/19 Time: 22:59
Sample: 2001Q1 2012Q4
Included observations: 48

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000184 | 7.01E-05 | 2.622243 | 0.0142 |
| DLOG(REALGDP_SA(-1))^2 | -0.233953 | 0.289091 | -0.809274 | 0.4254 |
| DLOG(REALGDP_SA(-1))*DLOG(REALGDP_SA(-3)) | 0.514522 | 0.283019 | 1.817980 | 0.0802 |
| DLOG(REALGDP_SA(-1))*DLOGIPI | 0.019388 | 0.197338 | 0.098247 | 0.9225 |
| DLOG(REALGDP_SA(-1))*DLOG(VOLUMEINDEXRETTR_SA) | -0.252405 | 0.256289 | -0.984846 | 0.3334 |
| DLOG(REALGDP_SA(-1))*DLOG(VOLUMEINDEXRETTR_SA(-1)) | 0.087746 | 0.320564 | 0.273724 | 0.7864 |
| DLOG(REALGDP_SA(-1)) | -0.000484 | 0.003049 | -0.158719 | 0.8751 |
| DLOG(REALGDP_SA(-3))^2 | -0.172212 | 0.105756 | -1.628384 | 0.1151 |
| DLOG(REALGDP_SA(-3))*DLOGIPI | 0.076172 | 0.121529 | 0.626783 | 0.5361 |
| DLOG(REALGDP_SA(-3))*DLOG(VOLUMEINDEXRETTR_SA) | -0.120826 | 0.236872 | -0.510091 | 0.6141 |
| DLOG(REALGDP_SA(-3))*DLOG(VOLUMEINDEXRETTR_SA(-1)) | -0.062065 | 0.185778 | -0.334083 | 0.7409 |
| DLOG(REALGDP_SA(-3)) | 0.001167 | 0.002288 | 0.509805 | 0.6143 |
| DLOGIPI^2 | -0.023504 | 0.066494 | -0.353474 | 0.7265 |
| DLOGIPI*DLOG(VOLUMEINDEXRETTR_SA) | -0.025951 | 0.132276 | -0.196186 | 0.8459 |

| | | | | |
|---|---|---|---|---|
| DLOGIPI*DLOG(VOLUMEINDEXRETTR_SA(-1)) | 0.007708 | 0.120552 | 0.063937 | 0.9495 |
| DLOGIPI | -0.000140 | 0.002028 | -0.069186 | 0.9454 |
| DLOG(VOLUMEINDEXRETTR_SA)^2 | 0.029050 | 0.053361 | 0.544411 | 0.5906 |
| DLOG(VOLUMEINDEXRETTR_SA)*DLOG(VOLUMEINDEXRETTR_SA(-1)) | 0.123781 | 0.099862 | 1.239513 | 0.2258 |
| DLOG(VOLUMEINDEXRETTR_SA) | -0.002638 | 0.003419 | -0.771622 | 0.4470 |
| DLOG(VOLUMEINDEXRETTR_SA(-1))^2 | 0.021161 | 0.096316 | 0.219705 | 0.8278 |
| DLOG(VOLUMEINDEXRETTR_SA(-1)) | 0.000796 | 0.004765 | 0.167039 | 0.8686 |

| | | | |
|---|---|---|---|
| R-squared | 0.383356 | Mean dependent var | 0.000132 |
| Adjusted R-squared | -0.073417 | S.D. dependent var | 0.000170 |
| S.E. of regression | 0.000176 | Akaike info criterion | -14.15316 |
| Sum squared resid | 8.36E-07 | Schwarz criterion | -13.33451 |
| Log likelihood | 360.6758 | Hannan-Quinn criter. | -13.84379 |
| F-statistic | 0.839270 | Durbin-Watson stat | 1.705346 |
| Prob(F-statistic) | 0.652694 | | |

Estimation output model6
Dependent Variable: DLOG(REALGDP_SA)
Method: Least Squares
Date: 05/30/19 Time: 23:20
Sample: 2001Q1 2010Q4
Included observations: 48 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.001453 | 0.002160 | -0.672427 | 0.5050 |
| DLOG(REALGDP_SA(-1)) | -0.174025 | 0.166799 | -1.043322 | 0.3028 |
| DLOG(REALGDP_SA(-3)) | 0.397910 | 0.129206 | 3.079668 | 0.0036 |
| DLOGIPI | 0.195880 | 0.103421 | 1.894016 | 0.0651 |
| DLOG(TURNINDEXRETAIL_SA) | 0.203303 | 0.072959 | 2.786529 | 0.0080 |
| DLOG(TURNINDEXRETAIL_SA(-1)) | 0.109017 | 0.081502 | 1.337592 | 0.1882 |

| | | | |
|---|---|---|---|
| R-squared | 0.483079 | Mean dependent var | -0.000754 |
| Adjusted R-squared | 0.421541 | S.D. dependent var | 0.018041 |
| S.E. of regression | 0.013721 | Akaike info criterion | -5.623247 |
| Sum squared resid | 0.007908 | Schwarz criterion | -5.389347 |
| Log likelihood | 140.9579 | Hannan-Quinn criter. | -5.534856 |
| F-statistic | 7.850064 | Durbin-Watson stat | 1.916884 |
| Prob(F-statistic) | 0.000027 | | |

Residuals Diagnostics test model6

Date: 05/30/19 Time: 23:25
Sample: 2000Q3 2012Q4
Included observations: 48
Q-statistic probabilities adjusted for 5 dynamic regressors

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| . \| . \| | . \| . \| | 1 | 0.008 | 0.008 | 0.0034 | 0.954 |
| . \|*. \| | . \|*. \| | 2 | 0.076 | 0.076 | 0.3068 | 0.858 |
| . \| . \| | . \| . \| | 3 | 0.033 | 0.032 | 0.3658 | 0.947 |
| **\| . \| | **\| . \| | 4 | -0.276 | -0.284 | 4.5203 | 0.340 |
| . \|*. \| | . \|*. \| | 5 | 0.139 | 0.152 | 5.5925 | 0.348 |
| . \|*. \| | . \|*. \| | 6 | 0.080 | 0.132 | 5.9602 | 0.428 |
| .*\| . \| | **\| . \| | 7 | -0.184 | -0.231 | 7.9373 | 0.338 |
| . \| . \| | .*\| . \| | 8 | 0.030 | -0.072 | 7.9905 | 0.434 |
| .*\| . \| | . \| . \| | 9 | -0.150 | -0.016 | 9.3837 | 0.403 |
| . \| . \| | . \|*. \| | 10 | 0.064 | 0.141 | 9.6419 | 0.472 |
| . \|*. \| | . \| . \| | 11 | 0.097 | -0.044 | 10.249 | 0.508 |
| . \| . \| | . \| . \| | 12 | -0.048 | -0.061 | 10.404 | 0.581 |
| . \| . \| | . \| . \| | 13 | 0.032 | 0.035 | 10.475 | 0.655 |
| . \|*. \| | . \|** \| | 14 | 0.146 | 0.259 | 11.977 | 0.608 |
| . \| . \| | . \| . \| | 15 | 0.069 | 0.069 | 12.323 | 0.654 |
| . \|*. \| | .*\| . \| | 16 | 0.076 | -0.135 | 12.753 | 0.691 |
| .*\| . \| | .*\| . \| | 17 | -0.134 | -0.161 | 14.135 | 0.658 |
| **\| . \| | .*\| . \| | 18 | -0.220 | -0.077 | 17.995 | 0.456 |
| .*\| . \| | . \| . \| | 19 | -0.088 | -0.011 | 18.640 | 0.480 |
| . \| . \| | .*\| . \| | 20 | -0.058 | -0.110 | 18.924 | 0.527 |

*Probabilities may not be valid for this equation specification.

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

| | | | |
|---|---|---|---|
| F-statistic | 0.159630 | Prob. F(2,40) | 0.8530 |
| Obs*R-squared | 0.380077 | Prob. Chi-Square(2) | 0.8269 |

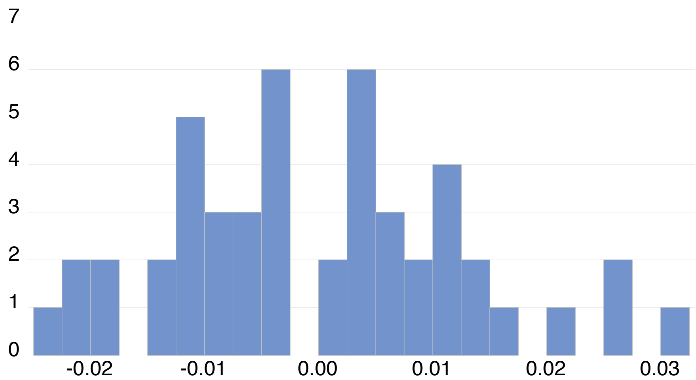
Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 05/30/19 Time: 23:30
Sample: 2001Q1 2012Q4
Included observations: 48
Presample missing value lagged residuals set to zero.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000165 | 0.002270 | 0.072596 | 0.9425 |
| DLOG(REALGDP_SA(-1)) | -0.015431 | 0.300051 | -0.051428 | 0.9592 |

| | | | | |
|---|---|---|---|---|
| DLOG(REALGDP_SA(-3)) | 0.007766 | 0.135638 | 0.057259 | 0.9546 |
| DLOGIPI | 0.004701 | 0.105915 | 0.044382 | 0.9648 |
| DLOG(TURNINDEXRETAIL_SA) | -0.001809 | 0.074535 | -0.024265 | 0.9808 |
| DLOG(TURNINDEXRETAIL_SA(-1)) | -0.013863 | 0.115609 | -0.119908 | 0.9052 |
| RESID(-1) | 0.025481 | 0.318176 | 0.080086 | 0.9366 |
| RESID(-2) | 0.101123 | 0.182083 | 0.555368 | 0.5817 |

| | | | |
|---|---|---|---|
| R-squared | 0.007918 | Mean dependent var | 1.45E-19 |
| Adjusted R-squared | -0.165696 | S.D. dependent var | 0.012971 |
| S.E. of regression | 0.014005 | Akaike info criterion | -5.547864 |
| Sum squared resid | 0.007845 | Schwarz criterion | -5.235997 |
| Log likelihood | 141.1487 | Hannan-Quinn criter. | -5.430009 |
| F-statistic | 0.045608 | Durbin-Watson stat | 1.923567 |
| Prob(F-statistic) | 0.999851 | | |

Normality test model6




| Series: Residuals | |
|---|---|
| Sample 2001Q1 2012Q4 | |
| Observations 48 | |
| Mean | 1.45e-19 |
| Median | -0.001009 |
| Maximum | 0.032285 |
| Minimum | -0.023174 |
| Std. Dev. | 0.012971 |
| Skewness | 0.329365 |
| Kurtosis | 2.710594 |
| Jarque-Bera | 1.035362 |
| Probability | 0.595901 |

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

| | | | |
|---|---|---|---|
| F-statistic | 0.925638 | Prob. F(5,42) | 0.4740 |
| Obs*R-squared | 4.764352 | Prob. Chi-Square(5) | 0.4453 |
| Scaled explained SS | 3.119873 | Prob. Chi-Square(5) | 0.6815 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 11/04/19 Time: 23:14
Sample: 2001Q1 2012Q4
Included observations: 48

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| C | 0.000175 | 3.44E-05 | 5.078656 | 0.0000 |
| DLOG(REALGDP_SA(-1)) | -0.001504 | 0.002657 | -0.565957 | 0.5744 |
| DLOG(REALGDP_SA(-3)) | 0.001557 | 0.002059 | 0.756589 | 0.4535 |
| DLOGIPI | 0.000248 | 0.001648 | 0.150388 | 0.8812 |
| DLOG(TURNINDEXRETAIL_SA) | -0.001092 | 0.001162 | -0.939122 | 0.3530 |
| DLOG(TURNINDEXRETAIL_SA(-1)) | -0.001146 | 0.001299 | -0.882901 | 0.3823 |

| | | | |
|---|---|---|---|
| R-squared | 0.099257 | Mean dependent var | 0.000165 |
| Adjusted R-squared | -0.007974 | S.D. dependent var | 0.000218 |
| S.E. of regression | 0.000219 | Akaike info criterion | -13.90207 |
| Sum squared resid | 2.01E-06 | Schwarz criterion | -13.66817 |
| Log likelihood | 339.6496 | Hannan-Quinn criter. | -13.81368 |
| F-statistic | 0.925638 | Durbin-Watson stat | 1.733228 |
| Prob(F-statistic) | 0.474040 | | |

Heteroskedasticity Test: White
Null hypothesis: Homoskedasticity

| | | | |
|---|---|---|---|
| F-statistic | 1.105499 | Prob. F(20,27) | 0.3977 |
| Obs*R-squared | 21.61025 | Prob. Chi-Square(20) | 0.3620 |
| Scaled explained SS | 14.15119 | Prob. Chi-Square(20) | 0.8227 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/30/19 Time: 23:35
Sample: 2001Q1 2012Q4
Included observations: 48

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000302 | 8.34E-05 | 3.620040 | 0.0012 |
| DLOG(REALGDP_SA(-1))^2 | -0.648132 | 0.228078 | -2.841716 | 0.0084 |
| DLOG(REALGDP_SA(-1))*DLOG(REALGDP_SA(-3)) | 0.396845 | 0.287260 | 1.381485 | 0.1785 |
| DLOG(REALGDP_SA(-1))*DLOGIPI | 0.340689 | 0.185456 | 1.837035 | 0.0772 |
| DLOG(REALGDP_SA(-1))*DLOG(TURNINDEXRETAIL_SA) | 0.307409 | 0.170524 | 1.802735 | 0.0826 |
| DLOG(REALGDP_SA(-1))*DLOG(TURNINDEXRETAIL_SA(-1)) | 0.302490 | 0.188383 | 1.605720 | 0.1200 |
| DLOG(REALGDP_SA(-1)) | -0.003853 | 0.003303 | -1.166440 | 0.2536 |
| DLOG(REALGDP_SA(-3))^2 | -0.138876 | 0.134752 | -1.030610 | 0.3119 |
| DLOG(REALGDP_SA(-3))*DLOGIPI | 0.106079 | 0.152704 | 0.694674 | 0.4932 |
| DLOG(REALGDP_SA(-3))*DLOG(TURNINDEXRETAIL_SA) | -0.209440 | 0.143137 | -1.463212 | 0.1550 |

| | | | | |
|---|---|---|---|---|
| DLOG(REALGDP_SA(-3))*DLOG(TURNINDEXRETAIL_SA(-1)) | -0.094068 | 0.126096 | -0.746004 | 0.4621 |
| DLOG(REALGDP_SA(-3)) | 0.004363 | 0.003318 | 1.314861 | 0.1996 |
| DLOGIPI^2 | -0.056267 | 0.083644 | -0.672697 | 0.5069 |
| DLOGIPI*DLOG(TURNINDEXRETAIL_SA) | -0.151692 | 0.101077 | -1.500754 | 0.1450 |
| DLOGIPI*DLOG(TURNINDEXRETAIL_SA(-1)) | -0.156052 | 0.100599 | -1.551227 | 0.1325 |
| DLOGIPI | 0.001309 | 0.002819 | 0.464413 | 0.6461 |
| DLOG(TURNINDEXRETAIL_SA)^2 | 0.016744 | 0.041302 | 0.405399 | 0.6884 |
| DLOG(TURNINDEXRETAIL_SA)*DLOG(TURNINDEXRETAIL_SA(-1)) | -0.109670 | 0.061251 | -1.790489 | 0.0846 |
| DLOG(TURNINDEXRETAIL_SA) | 0.000457 | 0.002177 | 0.209909 | 0.8353 |
| DLOG(TURNINDEXRETAIL_SA(-1))^2 | -0.023361 | 0.056090 | -0.416491 | 0.6803 |
| DLOG(TURNINDEXRETAIL_SA(-1)) | -0.002977 | 0.002190 | -1.359070 | 0.1854 |

| | | | |
|---|---|---|---|
| R-squared | 0.450214 | Mean dependent var | 0.000165 |
| Adjusted R-squared | 0.042964 | S.D. dependent var | 0.000218 |
| S.E. of regression | 0.000213 | Akaike info criterion | -13.77076 |
| Sum squared resid | 1.23E-06 | Schwarz criterion | -12.95211 |
| Log likelihood | 351.4982 | Hannan-Quinn criter. | -13.46139 |
| F-statistic | 1.105499 | Durbin-Watson stat | 1.697102 |
| Prob(F-statistic) | 0.397738 | | |

Estimation output model7
Dependent Variable: DLOG(REALGDP_SA)
Method: Least Squares
Date: 05/30/19 Time: 23:40
Sample: 2000Q3 2012Q4
Included observations: 50

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.001546 | 0.002221 | 0.696203 | 0.4899 |
| DLOG(REALGDP_SA(-1)) | -0.008371 | 0.153222 | -0.054635 | 0.9567 |
| DLOG(TURNINDEXRETAIL_SA) | -0.160974 | 0.142145 | -1.132462 | 0.2634 |
| DLOG(TURNINDEXRETAIL_SA(-1)) | 0.122010 | 0.079245 | 1.539655 | 0.1306 |
| DLOG(VOLUMEINDEXRETTR_SA) | 0.521180 | 0.147404 | 3.535733 | 0.0010 |

| | | | |
|---|---|---|---|
| R-squared | 0.493645 | Mean dependent var | 9.64E-05 |
| Adjusted R-squared | 0.448636 | S.D. dependent var | 0.018164 |
| S.E. of regression | 0.013488 | Akaike info criterion | -5.679456 |
| Sum squared resid | 0.008186 | Schwarz criterion | -5.488253 |
| Log likelihood | 146.9864 | Hannan-Quinn criter. | -5.606645 |
| F-statistic | 10.96761 | Durbin-Watson stat | 2.188810 |

Prob(F-statistic) 0.000003

Residuals Diagnostics Test model7
Date: 05/30/19 Time: 23:48

Sample: 2000Q3 2012Q4
Included observations: 50
Q-statistic probabilities adjusted for 4 dynamic regressors

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| .*\| . \| | .*\| . \| | 1 | -0.146 | -0.146 | 1.1349 | 0.287 |
| . \|*. \| | . \|*. \| | 2 | 0.170 | 0.152 | 2.7003 | 0.259 |
| . \|** \| | . \|*** \| | 3 | 0.320 | 0.380 | 8.3578 | 0.039 |
| **\| . \| | **\| . \| | 4 | -0.263 | -0.223 | 12.253 | 0.016 |
| . \|*. \| | . \| . \| | 5 | 0.167 | -0.035 | 13.860 | 0.017 |
| . \| . \| | . \| . \| | 6 | 0.019 | 0.033 | 13.881 | 0.031 |
| . \| . \| | . \|*. \| | 7 | -0.059 | 0.094 | 14.093 | 0.050 |
| . \| . \| | .*\| . \| | 8 | 0.031 | -0.112 | 14.152 | 0.078 |
| . \| . \| | . \| . \| | 9 | -0.009 | -0.006 | 14.157 | 0.117 |
| . \| . \| | . \| . \| | 10 | -0.015 | 0.022 | 14.171 | 0.165 |
| . \| . \| | . \| . \| | 11 | -0.032 | -0.015 | 14.238 | 0.220 |
| . \|*. \| | . \|*. \| | 12 | 0.124 | 0.116 | 15.297 | 0.226 |
| . \| . \| | . \| . \| | 13 | -0.008 | 0.056 | 15.302 | 0.289 |
| . \|*. \| | . \|*. \| | 14 | 0.120 | 0.113 | 16.334 | 0.293 |
| . \| . \| | .*\| . \| | 15 | -0.035 | -0.160 | 16.423 | 0.354 |
| . \| . \| | . \|*. \| | 16 | 0.066 | 0.075 | 16.760 | 0.401 |
| .*\| . \| | **\| . \| | 17 | -0.137 | -0.219 | 18.233 | 0.374 |
| .*\| . \| | .*\| . \| | 18 | -0.140 | -0.154 | 19.824 | 0.343 |
| . \| . \| | . \| . \| | 19 | 0.070 | 0.025 | 20.235 | 0.381 |
| .*\| . \| | . \|*. \| | 20 | -0.164 | 0.100 | 22.563 | 0.311 |
| . \|*. \| | . \|*. \| | 21 | 0.111 | 0.117 | 23.676 | 0.309 |
| . \|*. \| | . \|*. \| | 22 | 0.096 | 0.106 | 24.528 | 0.320 |
| .*\| . \| | . \| . \| | 23 | -0.096 | -0.001 | 25.418 | 0.329 |
| . \|*. \| | . \| . \| | 24 | 0.157 | -0.011 | 27.872 | 0.265 |

*Probabilities may not be valid for this equation specification.

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

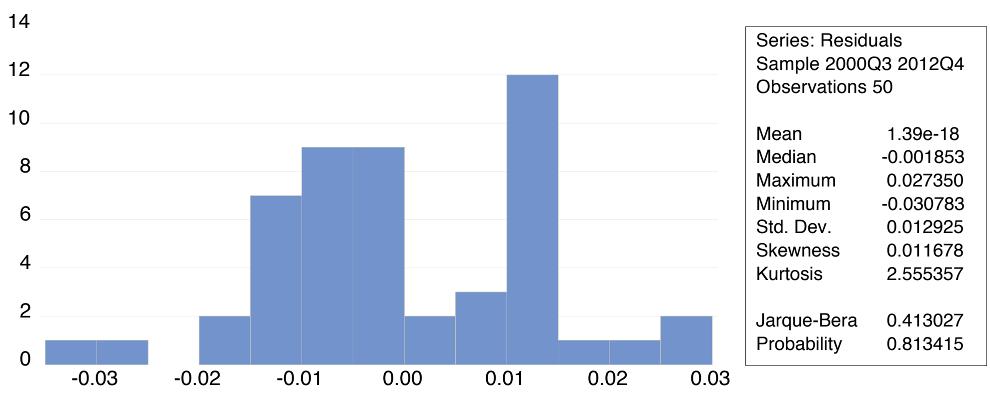
| | | | |
|---|---|---|---|
| F-statistic | 2.678391 | Prob. F(2,43) | 0.0801 |
| Obs*R-squared | 5.538811 | Prob. Chi-Square(2) | 0.0627 |

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 11/04/19 Time: 23:25
Sample: 2000Q3 2012Q4
Included observations: 50
Presample missing value lagged residuals set to zero.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.001486 | 0.002236 | 0.664381 | 0.5100 |
| DLOG(REALGDP_SA(-1)) | 0.472708 | 0.284970 | 1.658799 | 0.1044 |
| DLOG(TURNINDEXRETAIL_SA) | -0.123892 | 0.148675 | -0.833309 | 0.4093 |
| DLOG(TURNINDEXRETAIL_SA(-1)) | -0.148353 | 0.100556 | -1.475319 | 0.1474 |
| DLOG(VOLUMEINDEXRETTR_SA) | 0.114444 | 0.151826 | 0.753781 | 0.4551 |
| RESID(-1) | -0.620498 | 0.329729 | -1.881841 | 0.0666 |
| RESID(-2) | 0.117814 | 0.172810 | 0.681754 | 0.4991 |

| | | | |
|---|---|---|---|
| R-squared | 0.110776 | Mean dependent var | 1.39E-18 |
| Adjusted R-squared | -0.013302 | S.D. dependent var | 0.012925 |
| S.E. of regression | 0.013011 | Akaike info criterion | -5.716862 |
| Sum squared resid | 0.007279 | Schwarz criterion | -5.449179 |
| Log likelihood | 149.9216 | Hannan-Quinn criter. | -5.614927 |
| F-statistic | 0.892797 | Durbin-Watson stat | 1.981015 |
| Prob(F-statistic) | 0.508745 | | |

Normality test Model7




Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

| | | | |
|---|---|---|---|
| F-statistic | 2.555281 | Prob. F(4,45) | 0.0516 |
| Obs*R-squared | 9.254723 | Prob. Chi-Square(4) | 0.0550 |

| | | | |
|---|---|---|---|
| Scaled explained SS | 5.829732 | Prob. Chi-Square(4) | 0.2122 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/30/19 Time: 23:55
Sample: 2000Q3 2012Q4
Included observations: 50

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000183 | 3.20E-05 | 5.733706 | 0.0000 |
| DLOG(REALGDP_SA(-1)) | -0.000733 | 0.002207 | -0.332139 | 0.7413 |
| DLOG(TURNINDEXRETAIL_SA) | -0.004733 | 0.002048 | -2.311614 | 0.0254 |
| DLOG(TURNINDEXRETAIL_SA(-1)) | 0.001473 | 0.001142 | 1.290098 | 0.2036 |
| DLOG(VOLUMEINDEXRETTR_SA) | 0.002853 | 0.002123 | 1.343622 | 0.1858 |

| | | | |
|---|---|---|---|
| R-squared | 0.185094 | Mean dependent var | 0.000164 |
| Adjusted R-squared | 0.112658 | S.D. dependent var | 0.000206 |
| S.E. of regression | 0.000194 | Akaike info criterion | -14.15977 |
| Sum squared resid | 1.70E-06 | Schwarz criterion | -13.96856 |
| Log likelihood | 358.9942 | Hannan-Quinn criter. | -14.08696 |
| F-statistic | 2.555281 | Durbin-Watson stat | 2.248134 |
| Prob(F-statistic) | 0.051636 | | |

Heteroskedasticity Test: White
Null hypothesis: Homoskedasticity

| | | | |
|---|---|---|---|
| F-statistic | 0.994305 | Prob. F(14,35) | 0.4794 |
| Obs*R-squared | 14.22751 | Prob. Chi-Square(14) | 0.4329 |
| Scaled explained SS | 8.962187 | Prob. Chi-Square(14) | 0.8335 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/30/19 Time: 23:58
Sample: 2000Q3 2012Q4
Included observations: 50

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000241 | 5.98E-05 | 4.034416 | 0.0003 |
| DLOG(REALGDP_SA(-1))^2 | -0.310638 | 0.183594 | -1.691977 | 0.0995 |
| DLOG(REALGDP_SA(-1))*DLOG(TURNINDEXRETAIL_SA) | 0.220553 | 0.277420 | 0.795014 | 0.4320 |
| DLOG(REALGDP_SA(-1))*DLOG(TURNINDEXRETAIL_SA(-1)) | 0.159223 | 0.159887 | 0.995845 | 0.3262 |

DLOG(REALGDP_SA(-1))*DLOG(VOLUMEINDEXRETTR_SA) -0.048586
0.375613 -0.129351 0.8978
DLOG(REALGDP_SA(-1)) -0.002191 0.003093 -0.708111 0.4836
DLOG(TURNINDEXRETAIL_SA)^2 0.071992 0.145532 0.494683
0.6239
DLOG(TURNINDEXRETAIL_SA)*DLOG(TURNINDEXRETAIL_SA(-1))
-0.000340 0.132238 -0.002569 0.9980
DLOG(TURNINDEXRETAIL_SA)*DLOG(VOLUMEINDEXRETTR_SA)
-0.103145 0.281226 -0.366768 0.7160
DLOG(TURNINDEXRETAIL_SA) -0.007619 0.005018 -1.518399 0.1379
DLOG(TURNINDEXRETAIL_SA(-1))^2 -0.050042 0.044829 -1.116273
0.2719
DLOG(TURNINDEXRETAIL_SA(-1))*DLOG(VOLUMEINDEXRETTR_SA)
-0.011130 0.149832 -0.074284 0.9412
DLOG(TURNINDEXRETAIL_SA(-1)) 0.000809 0.001825 0.443272
0.6603
DLOG(VOLUMEINDEXRETTR_SA)^2 0.031479 0.148438 0.212065
0.8333
DLOG(VOLUMEINDEXRETTR_SA) 0.006589 0.006728 0.979395
0.3341

| | | | |
|---|---|---|---|
| R-squared | 0.284550 | Mean dependent var | 0.000164 |
| Adjusted R-squared | -0.001630 | S.D. dependent var | 0.000206 |
| S.E. of regression | 0.000206 | Akaike info criterion | -13.88993 |
| Sum squared resid | 1.49E-06 | Schwarz criterion | -13.31632 |
| Log likelihood | 362.2482 | Hannan-Quinn criter. | -13.67149 |
| F-statistic | 0.994305 | Durbin-Watson stat | 2.083091 |
| Prob(F-statistic) | 0.479391 | | |

Estimation output of Naïve Average Constant Growth Model
Dependent Variable: LOG(REALGDP_SA)
Method: Least Squares
Date: 05/31/19 Time: 00:10
Sample: 2000Q3 2012Q4
Included observations: 50

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| MEANLOGREALGDP_SA | 0.998024 | 0.001204 | 828.5980 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.000000 | Mean dependent var | 10.92191 |
| Adjusted R-squared | 0.000000 | S.D. dependent var | 0.093205 |
| S.E. of regression | 0.093205 | Akaike info criterion | -1.888231 |
| Sum squared resid | 0.425672 | Schwarz criterion | -1.849991 |
| Log likelihood | 48.20578 | Hannan-Quinn criter. | -1.873669 |
| Durbin-Watson stat | 0.036944 | | |

Estimation output ARIMA model

Dependent Variable: DLOG(REALGDP_SA)
Method: ARMA Maximum Likelihood (BFGS)
Date: 05/30/19 Time: 00:15
Sample: 2000Q3 2012Q4
Included observations: 50
Convergence achieved after 7 iterations
Coefficient covariance computed using outer product of gradients

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000693 | 0.004968 | 0.139515 | 0.8897 |
| AR(1) | 0.181541 | 0.165676 | 1.095764 | 0.2789 |
| MA(2) | 0.740597 | 0.093038 | 7.960161 | 0.0000 |
| SIGMASQ | 0.000220 | 6.38E-05 | 3.453309 | 0.0012 |

| | | | |
|---|---|---|---|
| R-squared | 0.318724 | Mean dependent var | 9.64E-05 |
| Adjusted R-squared | 0.274293 | S.D. dependent var | 0.018164 |
| S.E. of regression | 0.015474 | Akaike info criterion | -5.389286 |
| Sum squared resid | 0.011014 | Schwarz criterion | -5.236324 |
| Log likelihood | 138.7321 | Hannan-Quinn criter. | -5.331037 |
| F-statistic | 7.173453 | Durbin-Watson stat | 1.957283 |
| Prob(F-statistic) | 0.000475 | | |

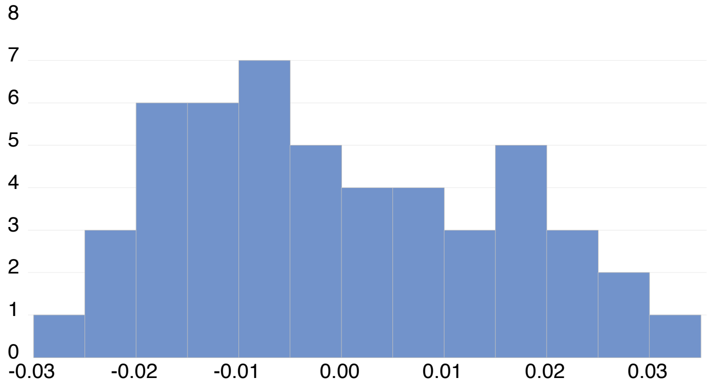
| | | |
|---|---|---|
| Inverted AR Roots | .18 | |
| Inverted MA Roots | -.00+.86i | -.00-.86i |

Date: 05/31/19 Time: 00:20
Sample: 2000Q3 2012Q4
Included observations: 50
Q-statistic probabilities adjusted for 2 ARMA terms

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| . \| . \| | . \| . \| | 1 | 0.006 | 0.006 | 0.0019 | |
| .*\| . \| | .*\| . \| | 2 | -0.172 | -0.172 | 1.6128 | |
| . \|** \| | . \|** \| | 3 | 0.233 | 0.242 | 4.6052 | 0.032 |
| . \| . \| | .*\| . \| | 4 | -0.025 | -0.074 | 4.6402 | 0.098 |
| . \|** \| | . \|*** \| | 5 | 0.326 | 0.455 | 10.768 | 0.013 |
| . \|** \| | . \|*. \| | 6 | 0.248 | 0.153 | 14.409 | 0.006 |
| .*\| . \| | . \|*. \| | 7 | -0.105 | 0.106 | 15.079 | 0.010 |
| . \| . \| | . \| . \| | 8 | 0.071 | -0.036 | 15.394 | 0.017 |
| . \| . \| | .*\| . \| | 9 | -0.005 | -0.126 | 15.396 | 0.031 |
| . \|*. \| | . \| . \| | 10 | 0.112 | 0.010 | 16.212 | 0.039 |
| . \|** \| | . \| . \| | 11 | 0.250 | 0.050 | 20.375 | 0.016 |
| .*\| . \| | .*\| . \| | 12 | -0.113 | -0.094 | 21.253 | 0.019 |
| . \| . \| | . \| . \| | 13 | -0.050 | -0.031 | 21.428 | 0.029 |
| . \| . \| | .*\| . \| | 14 | 0.034 | -0.090 | 21.511 | 0.043 |

| | | | | | | |
|---|---|---|---|---|---|---|
| . \|. \| | . \|*. \| | 15 | 0.053 | 0.094 | 21.721 | 0.060 |
| . \|*. \| | . \|. \| | 16 | 0.191 | 0.067 | 24.503 | 0.040 |
| .*\|. \| | .*\|. \| | 17 | -0.155 | -0.146 | 26.385 | 0.034 |
| .*\|. \| | .*\|. \| | 18 | -0.186 | -0.131 | 29.189 | 0.023 |
| . \|. \| | .*\|. \| | 19 | 0.053 | -0.092 | 29.421 | 0.031 |
| .*\|. \| | .*\|. \| | 20 | -0.108 | -0.169 | 30.429 | 0.033 |
| . \|. \| | . \|. \| | 21 | 0.072 | 0.011 | 30.894 | 0.041 |
| . \|. \| | . \|. \| | 22 | 0.040 | 0.029 | 31.040 | 0.055 |
| **\|. \| | . \|*. \| | 23 | -0.212 | 0.104 | 35.387 | 0.026 |
| . \|. \| | . \|. \| | 24 | -0.044 | 0.036 | 35.579 | 0.034 |

Normality test ARIMA Model




| Series: Residuals | |
|---|---|
| Sample 2000Q3 2012Q4 | |
| Observations 50 | |
| Mean | -0.000395 |
| Median | -0.002996 |
| Maximum | 0.030030 |
| Minimum | -0.026013 |
| Std. Dev. | 0.014987 |
| Skewness | 0.236148 |
| Kurtosis | 2.013005 |
| Jarque-Bera | 2.494215 |
| Probability | 0.287335 |

Heteroskedasticity Test: ARCH

| | | | |
|---|---|---|---|
| F-statistic | 1.151404 | Prob. F(1,47) | 0.2887 |
| Obs*R-squared | 1.171696 | Prob. Chi-Square(1) | 0.2791 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/31/19 Time: 00:30
Sample (adjusted): 2000Q4 2012Q4
Included observations: 49 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000254 | 4.55E-05 | 5.596262 | 0.0000 |
| RESID^2(-1) | -0.155508 | 0.144924 | -1.073035 | 0.2887 |

| | | | |
|---|---|---|---|
| R-squared | 0.023912 | Mean dependent var | 0.000220 |
| Adjusted R-squared | 0.003144 | S.D. dependent var | 0.000224 |
| S.E. of regression | 0.000223 | Akaike info criterion | -13.93685 |
| Sum squared resid | 2.34E-06 | Schwarz criterion | -13.85964 |

| | | | |
|---|---|---|---|
| Log likelihood | 343.4529 | Hannan-Quinn criter. | -13.90756 |
| F-statistic | 1.151404 | Durbin-Watson stat | 1.987751 |
| Prob(F-statistic) | 0.288734 | | |

## APPENDIX D: Code for Eviews environment

Example for Program (model 5).

```
matrix(76,1) forecasts_=na
matrix(76,1) ape_ = na
matrix(76,1) se_=na
matrix(76,4) coef_=na
matrix(76,4) tstat_=na
for !i=52 to 75
  sample ss @first @first+!i
  smpl ss
  equation model5.ls(DERIV=AA) dlog(realgdp_sa) c dlog(realgdp_sa(-1)) dlogipi
dlog(volumeindexrettr_sa) dlog(volumeindexrettr_sa(-1))
  for !j=1 to 4
     scalar c{!j} = @coefs({!j})
     coef_(!i,!j) = c{!j}
     tstat_(!i,!j) = @tstats({!j})
   next
  sample sss @first+!i @first+1+!i
  smpl ss
  model 5. forecast(e,g,f=na) for{!i}
    for !s=1 to 1
       forecasts_(!i,!s) = for{!i}(!i+!s)
 ape_(!i,!s) = abs ((for{!i}(!i+!s) – realgdp_sa(!i+!s)) / realgdp_sa(!i+!s))
 se_(!i,!s) =(for{!i}(!i+!s) – realgdp_sa(!i+!s)) ^2
   next
 delete ss
 delete sss
 delete for{!i}
```

## Appendix E Nowcasting results

| Year/Quarter | RealGdp_sa (in billion Euro) | NowcastModel5 | Difference from actual (in million Euro) |
|---|---|---|---|
| **2013Q1** | 45981 | 45912 | 69 |
| **2013Q2** | 45992 | 46180 | 912 |
| **2013Q3** | 46296 | 45746 | 500 |
| **2013Q4** | 45894 | 45752 | 142 |
| **2014Q1** | 46233 | 45964 | 279 |
| **2014Q2** | 46197 | 46391 | 194 |
| **2014Q3** | 46837 | 46136 | 701 |
| **2014Q4** | 46241 | 46832 | 600 |
| **2015Q1** | 46437 | 46577 | 140 |
| **2015Q2** | 46502 | 46591 | 89 |
| **2015Q3** | 45623 | 45631 | 8 |
| **2015Q4** | 46203 | 45914 | 289 |
| **2016Q1** | 46145 | 46185 | 40 |
| **2016Q2** | 45998 | 46077 | 79 |
| **2016Q3** | 46053 | 46454 | 401 |
| **2016Q4** | 46110 | 46293 | 183 |
| **2017Q1** | 46192 | 46269 | 77 |
| **2017Q2** | 46735 | 46161 | 574 |
| **2017Q3** | 46956 | 46668 | 288 |
| **2017Q4** | 47105 | 47100 | 5 |
| **2018Q1** | 47317 | 47436 | 19 |
| **2018Q2** | 47444 | 47435 | 9 |
| **2018Q3** | 47980 | 47608 | 372 |
| **2018Q4** | 47892 | 47899 | 7 |