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The impact of the financial crisis on the Gross Domestic Product: Technical Analysis

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Management Summary

According to the existing literature in macroeconomics, a recession reduces output and employment in the short run; after an adjustment process, however, the output is expected to return to its long-term equilibrium and employment to come back to its natural level. Theory notwithstanding, many economists shed doubts on this idea; according to them, a recession may permanently reduce potential output by destroying capital, human capital, and knowledge. This thesis seeks to evaluate the impact of the European financial crisis on the potential output of different European countries. To answer the research question – *For the so-defined "PIIGS" countries: how did the differential between potential GDP and observed GDP develop after the financial crisis of 2008?* – the Box-Jenkins technique is implemented to shape an autoregressive integrated moving average model, which can forecast the development of the potential Gross Domestic Product. Additionally, an application of the Long Short-Term Memory Networks based on an Artificial Recurrent Neural Network architecture is proposed as a starting point on which to develop a more in-depth analysis. The outcomes resulting from the empirical analysis are mainly uniform across countries: a small impact is detected in the proximity of the financial crisis, which, however, expands over time. The only circumstance where it is possible to report a complete economic recovery is in Ireland. All the other economies reflect a situation in which the potential GDP forecasted is significantly above the observed GDP.

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1. Introduction

According to the existing literature in macroeconomics, a recession reduces output and employment in the short run; after an adjustment process, however, the output is expected to return to its long-term equilibrium and employment to go back to its natural level (Tobin, 1975). Theory notwithstanding, many economists have shed doubts on this idea; according to them, a recession may permanently reduce potential output by destroying capital, human capital, and knowledge (Tasci & Zaman, 2010).

The purpose of this thesis is to evaluate the impact of the European financial crisis on the potential output of different European countries. Since countries adjust to recessions in specific ways, parallel studies on different countries are possible. Those countries worst hit by the crisis – Portugal, Ireland, Italy, Greece and Spain – are of particular interest in this regard since it is expected, as also other studies have demonstrated, to identify a more substantial impact of the financial crisis there and thus a more significant difference between potential Gross Domestic Product and observed Gross Domestic Product (Liapis, Rovolis, Galanos, & Thalassinos, 2013).

The modus operandi that will be used in the thesis is the following; firstly, a résumé of the financial crisis will be given so that the reader will have a clear starting picture of the causes, evolution, and consequences of the latter. Secondly, the theoretical framework together with the analysis of the previous research will be illustrated. Thirdly, an accurate analysis of the available data will be provided in order to better visualize and understand the characteristics of the analyzed dataset. Finally, to respond to the research question – *For the so-defined "PIIGS" countries: how did the differential between potential GDP and observed GDP develop after the financial crisis of 2008?* –, and therefore to estimate the potential output loss of the analyzed countries, the autoregressive integrated moving average model will be employed in the empirical analysis.

As Ball (2014) asserts, it is possible to measure the long-term effects of the global recession of 2008-2009 through a comparison of the current estimates of the potential output (observed GDP) and the path that potentially would have followed in 2008 (forecasted GDP). Consequently, the difference between the observed GDP from 2008 to 2018 and the forecasted GDP, computed by using data before 2008 for the period 2008 to 2018, will be considered, in part, as the long-term impact of the financial crisis.

However, since there may have been other factors that had an influence on the observed GDP during the period 2008-2018, it is not possible to affirm with certainty that the difference between the observed and forecasted path can be tagged entirely as potential GDP loss. Finally, a qualitative analysis of the results and a short comparison between the selected countries will be exposed with the help of the available data and literature.

1.1 The causes, evolution, and consequences of the financial crisis of 2008

Once the early 2000s crisis had eased, the global economy went through a period characterized by a downward long-term inflation trend and improved overall macroeconomic stability with consequently increased confidence in monetary and fiscal policies. The descending expectations towards nominal inflation, inflation-adjusted interest rates and government bond yields reoriented many investors to other placements with more significant gains. Simultaneously, countries like China gradually accumulated substantial foreign exchange reserves that were invested mainly in securities of financial institutions of the United States, Europe, and Asia. Conversely, it increased the expenditures of companies and households with an implicit intensification in debt appetite (Thakor, 2015).

The result of these developments and events was a sustainable long-term (2002-2007) growth with low inflation level and low long-term interest rates. With the onset of the signs and effects of the financial crisis in 2008, all market participants entered into a reverse trend characterized by a hostile climate. The economic growth was the most affected, the governments and central banks of all interested countries began to implement short and medium-term structural reforms to counteract the dramatic effects of the crisis and limit the likelihood of another systematic crisis in the future (Thakor, 2015).

However, it is of fundamental importance to appreciate that the manner of manifestation of the crisis depended on the state of macroeconomic equilibrium at the time of its propagation; the vulnerabilities of each economy and the responses to the effects which the crisis induced were not homogenous (Ball, 2014).

The financial crisis began in August 2007 when the loss of American investors' confidence in the securitized mortgages led to a liquidity crisis that forced the Federal Reserve Bank, the Bank of England and the European Central Bank to an urgent injection of capital into the markets. The first signs of financial tension were felt already in the first half of 2007 when some relevant financial institutions reduced their exposure in securities linked to particularly risky mortgage loans (the so-called subprime securities). The turbulence further intensified during the summer, bringing the interbank markets to a standstill in August. The TED spread, which can be interpreted as an indicator of the perceived credit risk in the general economy, increased in August 2007, oscillated for one year and later on rose again in September 2008, reaching its maximum record level of 4.65 in October 2008. The crisis intensified rapidly, and it extended in a few months to all the main markets and areas. In fact, in the second quarter of 2008, the economic activities started to slow down in all the major economies. The crisis worsened in 2008 as the stock market collapsed and entered in a period of acute instability. A large number of financial institutions such as banks, creditor institutions and insurance companies went bankrupt. In 2008, a large share of stocks offered in the exchange markets lost between 20 and 70 percent of their market value (Westrupp, Giovannetti, & De-Losso, 2013).

The recession triggered by the financial crisis, which affected the world economy in 2008-2009, was of exceptional significance in terms of size, speed, and distribution. According to the estimates of the OECD, the Gross Domestic Product of the industrial countries fell by 4 percent in the period between October 2008 and March 2009. The contraction affected all the major economies and the synchronicity of the decline in the gross world product was reflected in the exceptional collapse of the international trades, whose volumes were reduced by about one-sixth in the same period. The response of the economic, monetary and fiscal policies was with no historical comparisons; for the extent of the interventions, for their nature and breadth and for the degree of international coordination quickly reached in the more acute phases of the crisis. For the first time since the 1930s, the global economy experienced a systemic financial crisis: on September 2008 the international financial system was on the verge of collapse with a credit market which did not work correctly for the next four weeks. The bankruptcy of large financial institutions and the massive government interventions around the globe were signs of an economic depression comparable to the Great Depression of 1929-1933 (Thakor, 2015).

However, for a better understanding of the financial crisis of 2008, it might result interesting to clarify the concept of crisis to better appreciate the interconnections prevailing in the economic system.

A crisis can be defined as a situation characterized by a pronounced instability being supplemented, as a consequence, with high volatility in the markets and high uncertainty with regard to economic growth.

In fact, in periods of crises, there is a permanent state of restlessness and uncertainty about the future with time frames of fear or panic. The defense and preservation instinct urge irrational behaviors with consequent accentuation of volatility. Each market participant has different cognitive capability skills, filters information differently and understands the phenomenon in his own way; this translates into a specific market-related behavior (Schinasi, 2004).

The problem with the definition of such "events" is to designate how high the volatility or the fall in market prices should be to classify such an evolution as a crisis. How high should be the level of inflation, the unemployment rate or the declining in Gross Domestic Product (GDP) in order to confirm that a country is experiencing a crisis? Conventionally it is established that a country is facing a recession if after two consecutive quarters the level of GDP suffers reductions. The National Bureau of Economic Research (NBER) defines an economic recession as: "*a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales.*" (Eslake, 2009).

Some specialists classify these crises into social crises manifested by rising in inflation, unemployment and poverty; financial crises characterized by increased volatility in the stock markets; political crises that can degenerate into wars; local or international crises; crises caused by natural disasters or global economic crises (Halvorsen, 2016).

A prominent feature of the global economic development was the persistence of some conspicuous current account imbalances. For many years in the United States, Europe, and the United Kingdom, the authorities supported substantial current account deficits, funded by surpluses registered in China, Japan, and Germany. In the United States, the total domestic consumptions and the level of investments substantially exceeded the level of national product and the difference generated was compensated with borrowings. Countries with surpluses bought financial assets contributing to the maintenance of the long-term interest rates at a low level and supported in such a way imbalances in current accounts. Unsatisfied with the level of revenues generated by assets such as treasury bills, these countries, together with their national investors, bought more complex and opaque financial products with a higher promised return (Obstfeld & Rogoff, 2009).

A second feature of the global economic development was the rapid internationalization with regard to production, investment and financial interconnections – in short, globalization – without an appropriate development of supervision and other forms of regulation at an adequate level. In fact, global institutions were still reflecting the geopolitical realities of the period following the Second World War. This lack in regulation was mainly "formed" due to the competitions in regulatory jurisdictions in areas such as taxation, corporate law and financial regulation. The absence of an effective global governance allowed to further intensify the inherent issue of current account imbalances (Mendoza & Quadrini, 2010). Moreover, as a result of these deficiencies, but also as a result of the significant political turns towards "advanced" capitalism, many countries were following a process sustained by the withdrawal of state interventionism from the economy. Besides that, state properties and even financial institutions were reduced. Labor market and public welfare state institutions were weakened, traded, or privatized (Thomsson, 2009). The state of "strict regulations" was abandoned in favor of codes of conduct privileging the so-called "Self-regulation" (Helleiner, Pagliari, & Zimmermann, 2010). The social and legal constraints on the code of business conduct and the influence of the labor unions were sharply reduced, in favor of new approaches that focused on the optimization of price/earnings ratio for shareholders (Lee, Atkinson, & Blundell-Wignall, 2009). These trends, also embedded in the technological developments, led to significant changes in the revenue distribution in the majority of the most advanced capitalist countries: an increased disparity in personal income was present with a consequent greater differentiation between the different social classes. A significant part of the resources was allocated in the "hands" of those who used this capital to speculate on the financial markets rather than consuming it in real goods and services. Meanwhile, at the other end of the income scale, poor people were forced to increase loans to maintain the same living standard (Gornick & Jäntti, 2014).

It is challenging to understand how these realities interacted with the "financialization" of the economy. This "umbrella" term covers various trends such as the increasing size of the financial sector; the expanded volume of transactions and financial products in relation to the Gross Domestic Product; the increased use of share options and other forms of incentives for senior managers; the growth in importance of the CEOs' role and other significant changes in the structure of the financial industry (Epstein, 2005).

The increased share of profits in national income in most countries was not complemented by an increase in the share of investments. The activities of corporate managers had never been like this; intense short-term focus and targeting high profits, which may explain in part the low level of investments. A secondary phenomenon was the migration of the potential funds available for investment in real assets towards more sophisticated and opaque financial assets (Kirkpatrick, 2009). Another critical aspect of the "financialization" of the economy was the securitization process, which can be defined as a procedure whereby an issuer creates a financial product by merging several financial assets and sells layers of the repackaged instrument to investors. Technology evolution and competition between deregulated and globalized financial institutions led to a proliferation of increasingly complex financial products. This occurred despite the increased demand for saving opportunities from institutional investors flooded by the retirement savings as a result of the demographic processes and the privatization of the pension sector (Covitz, Liang, & Suarez, 2013). The lack of understanding of the nature of the risk concerning the consumers who were poorly informed by the original contractors, together with the impossibility to trace and monitor the quality of the various tranches, created several complications. Buyers of such products were forced to put their trust in the credit rating agencies that had a quasi-legalized institutionalized oligopoly and were paid by the issuers of these products. These facts resulted in a significant increase in the leverage measures: higher rate of the household debt to GDP ratio, reversed balance positions between equity and debt financing, and increased debt ratio (Utzig, 2010).

The structural features analyzed previously, and in particular the role of the financial sector, have been long discussed. However, many analysts overlooked a series of aggregate demand shocks that have affected the European economy, and that in a related manner can be considered as the proximate causes of the financial crisis. The primary contractionary "impulses" were as follows:

- The sharp increase of commodities prices: the oil price increased by more than 100% from the beginning of 2007 to the summer of 2008; similar developments were recorded for other commodities as well. In general, the price of the goods (energy sector apart) increased from 2007 to 2008 (quarter to quarter relation) by about 10%. The increase in commodity prices enlarged firms' costs and reduced the real income of the employees. A reduction of the aggregate demand was registered.

- The keen appreciation of the euro: from the beginning of 2006 to the summer of 2008, the euro appreciated against the dollar by about 33% (from EUR/USD 1.20 to EUR/USD 1.60). Meanwhile, there was also a parallel appreciation of the Japanese Yen. The nominal exchange rate of the currency euro increased by approximately 15% compared to its average in 2005. If, on the one hand, the appreciation of the currency euro set off the rise in prices of the commodities, on the other hand, it also narrowed the companies' profit rates in the tradable goods and reduced net exports. As a result, the trades in the euro area (EU27), as well as the current account balances, went from surplus to deficit and the export orders reached an unprecedented level since the 90's recession.
- The delayed effect of high-interest rates: European Central Bank began raising the interest rates at the beginning of 2006, regardless of the increase in the inflation rate resulting from the rise in imported goods' prices.

On top of these three major restrictive factors that negatively affected all European economies (especially those in the euro area), there were specific problems that some European countries were facing. In particular, Great Britain, Ireland and Spain shared some "characteristics" of the American economy: housing bubble, high-level of loans denominated in a non-national currency and current account deficits (Obstfeld & Rogoff, 2009).

In conclusion, for the countries on which this master thesis focuses, it is possible to distinguish three main phases in the evolution of the crisis. In the first phase, the macroeconomic framework showed the first signs of weakening, although the financial turbulence connected with the subprime securities exercised minimal effects on economic activities. Corporate credit grew at a rapid pace and there were no clear indications of supply restrictions. In the first half of 2008, the external framework was dominated by repeated increases in the prices of raw materials associated with a progressive increase in actual and expected inflation in the whole euro area. International trades, although less vigorous than in previous years, did not indicate a significant deterioration even if the foreign sales were already in a substantial stagnation phase. Finally, in the second quarter of 2008 the phase of contraction of the GDP begun. The second phase, which lasted from the end of summer 2008 until March 2009, was characterized by the bankruptcy of Lehman Brothers Holdings Inc. and was the most acute phase of the crisis. Risk premiums on interbank rates suffered a sudden leap upwards. In an exceptional context of uncertainty about the quality of bank assets, the market capitalization of the main European banks collapsed in a few weeks. The signs of deterioration in the conditions of credit offer multiplied. The crisis affected the real economy; industrial production was contracting intensively, up to failure at the end of 2008. The exceptional drop in exports and investments, connected to the tightening of credit conditions and the fall of the demand prospects, coincided with the unprecedented drop in the world trades between November 2008 and January of the following year. All these events induced a forceful contraction of the Gross Domestic Product which, in some cases, returned to similar levels of the previous decade. Moreover, the fall in production begun to weigh on employment. The response of the economic policies intensified progressively. In October 2008, the central banks of the major world economies coordinated a cut in the interest rates policy; the reduction phase continued until May 2009, which brought the interest rate to a historic low level; approximately 1 percent on ECB refinancing operations (minimum value since the introduction of the euro). Additionally, a series of unconventional monetary policies were applied to ensure that the credit continued to flow into the economy. The third phase, which started in the second quarter of 2009, was characterized by a reduction of the fall in economic activities; the qualitative indicators began to signal the thinning of pessimism even if the uncertainty remained high. The risk premiums, which were already dropping since December 2008, continued to fall favored by the improved financial market stability. The tightening of credit conditions gradually faded until they completely stopped at the end of 2009. The decrease in industrial production, which was underway for almost a year, stopped in April. In autumn, GDP was again expanding as in the pre-crisis period, albeit at a slower pace compared to other major European economies. At the same time, the weaknesses of the labor market were fading away. The improvement of the international context and the support of the monetary policy, still exceptionally expansive, foreshadowed a gradual recovery of the economic activities in February 2010, which however did not strengthen before 2011 (Poole, 2010).

As support for the three phases previously mentioned, Table 1 offers a quantitative overview of the most relevant short-term economic indicators for the selected countries. The consequences of the financial crisis of 2008 appear to be self-evident: all the main economic indicators were affected negatively.

Table 1: Key Short-Term Economic Indicators

	2007	2008	2009	2010
Gross Domestic Product (annual)		Growth rate		
Portugal	2.50%	0.20%	-3.00%	1.90%
Ireland	5.30%	-4.40%	-5.00%	1.90%
Italy	1.50%	-1.10%	-5.50%	1.70%
Greece	3.30%	-0.30%	-4.30%	-5.50%
Spain	3.80%	1.10%	-3.60%	0.00%
Imports		Growth on the same period of the previous year		
Portugal	15.60%	15.00%	-24.20%	8.10%
Ireland	14.20%	0.60%	-25.90%	0.80%
Italy	15.70%	9.10%	-26.30%	17.40%
Greece	25.70%	13.80%	-23.20%	-6.90%
Spain	18.00%	7.20%	-30.10%	11.50%
Exports		Growth on the same period of the previous year		
Portugal	16.50%	8.60%	-22.50%	11.50%
Ireland	11.20%	3.40%	-8.00%	1.50%
Italy	19.80%	8.00%	-25.30%	9.90%
Greece	23.10%	17.80%	-19.70%	11.90%
Spain	18.30%	9.70%	-18.70%	11.70%
Current Account % of GDP		Level, ratio or index		
Portugal	-9.70%	-12.10%	-10.40%	-10.10%
Ireland	-6.50%	-6.20%	-4.60%	-1.20%
Italy	-1.40%	-2.80%	-1.90%	-3.40%
Greece	-15.20%	-15.10%	-12.30%	-11.40%
Spain	-9.60%	-9.20%	-4.30%	-3.90%
Private Consumption (volume)		Growth on the same period of the previous year		
Portugal	2.50%	1.40%	-2.30%	2.40%
Ireland	6.60%	0.30%	-5.10%	0.40%
Italy	1.20%	-1.10%	-1.60%	1.20%
Greece	4.10%	3.60%	-1.70%	-6.50%
Spain	3.30%	-0.70%	-3.60%	0.30%
Industrial Production		Growth on the same period of the previous year		
Portugal	-1.70%	-5.40%	-10.60%	1.00%
Ireland	5.20%	-2.20%	-4.50%	8.50%
Italy	2.30%	-4.10%	-18.60%	7.00%
Greece	2.30%	-4.20%	-9.70%	-6.10%
Spain	1.80%	-7.70%	-15.60%	0.80%
Harmonised Unemployment Rate		Level, ratio or index		
Portugal	9.10%	8.80%	10.70%	12.00%
Ireland	5.00%	6.80%	12.70%	14.60%
Italy	6.10%	6.70%	7.80%	8.40%
Greece	8.40%	7.80%	9.60%	12.80%
Spain				
Consumer Prices - Annual inflation		Growth on the same period of the previous year		
Portugal	2.50%	2.60%	-0.80%	1.40%
Ireland	4.90%	4.10%	-4.50%	-0.90%
Italy	1.80%	3.30%	0.80%	1.50%
Greece	2.90%	4.20%	1.20%	4.70%
Spain	2.80%	4.10%	-0.30%	1.80%
Long-term interest rates		Level, ratio or index		
Portugal	4.42%	4.52%	4.21%	5.40%
Ireland	4.33%	4.55%	5.23%	5.99%
Italy	4.49%	4.68%	4.31%	4.04%
Greece	4.50%	4.80%	5.17%	9.09%
Spain	4.31%	4.36%	3.97%	4.25%
Euribor-3M	4.30%	4.60%	1.20%	1.10%

Source: Data from Eurostat

2. Theoretical Framework

This section provides a basic overview of the theoretical framework on which this thesis is based. The main macroeconomics notions regarding the effects and dynamics of the financial crisis of 2008 are illustrated together with the fundamental forecasting theories.

A preliminary insight regarding the effects of a recession on the potential output is stated in the first sub-chapter. After the illustration of the essential idea behind the Gross Domestic Product, the initial "vision" regarding the temporary effects of the recession on the potential output of a country is discussed and further analyzed following other economists' points of view.

The second sub-chapter offers an overview of the forecasting methods employed in the thesis. Firstly, as a short introduction it is explained the difference between two forecasting approaches; Judgment-based and Model-based forecast. The latter is further analyzed, together with the autoregressive model. In fact, the core part of the sub-chapter is focused on illustrating the theory behind the autoregressive integrated moving average model (ARIMA); the determination of the ARIMA parameters is explained, as well as the forecasting theory regarding static and dynamic forecasting. Finally, it is provided an overview of the methods employed in order to assess the quality of the models and their relative predictive accuracy.

2.1 Macroeconomics Theory

According to textbooks in macroeconomics, a reduction of the aggregate demand causes a recession in which output drops temporary below its potential level (Ball, 2014). However, before questioning this theory, it might be interesting to provide some preliminary definitions concerning the output of a country and to illustrate the straightforward macroeconomic dynamics behind the effects of the financial crisis on the key short-term economic indicators. The measure of the aggregate output in the national income accounts is represented by the Gross Domestic Product, which can be defined according to Giavazzi, Amighini, & Blanchard (2010) in three different ways:

- *"GDP is the value of the final goods and services produced in the economy during a given period";*
- *"GDP is the sum of value added in the economy during a given period";*
- *"GDP is the sum of incomes in the economy during a given period".*

The Gross Domestic Product, in short GDP, can also be subdivided into nominal GDP and real GDP. The former can be constructed by the sum of the quantities of final goods produced multiplied by their current prices, while the latter can be defined as the sum of the production of final goods multiplied by constant prices.

The level of the real GDP gives information about the economic size of a country, however, to correctly assess the performance of a specific economy it is necessary to compute the rate of growth of the real GDP; the so-called GDP growth (Giavazzi et al., 2010).

The potential output can be defined as the highest level of real GDP that can be sustained over the long term, given the economy’s resources and technology, without generating a rise in inflation (Ball, 2014). Since the potential output is representing the economy’s supply side, it helps over the medium term to determine the pace of sustainable growth. On the other hand, in the short term it is helpful to estimate the gap between actual and potential output in order to assess possible inflationary pressures. In fact, potential output, as well as the output gap, is employed in the calculation of cyclically adjusting variables which are useful to reflect the levels that would exist if the economy is in neither a recession nor an inflationary expansion (Giorno, Richardson, Roseveare, & Van den Noord, 1995).

As pointed out in the preceding chapter, the financial crisis started in the USA rapidly affected all major advanced economies through two major channels of transmission:

- Balance sheet of banks;
- Trades.

Giavazzi et al. (2010) argued that the first channel of transmission of the financial crisis to the real economy was the composition of the banks' balance sheet; as their capital fell, banks started to shrink credit to firms, and this hit investment. As a consequence, industrial production decreased together with the level of confidence in the macroeconomics expectations. Moreover, all the countries affected by the financial crisis were operating under an open economy, and such openness implied that consumers and firms spent part of their disposable income on foreign goods. When the disposable income fell, consumption followed this trend jointly with the demand for foreign goods (imports). Considering that the largest importer of goods in the world (USA) had experienced such a drastic reduction in the fundamental economic indicators, it appears evident that the likelihood of a contagion was quite significant; such a huge collapse in imports represented a large decrease in exports for other countries exporting to the USA, creating a real vicious circle. The effects of the international contagion were extensive in countries where the degree of openness was high, in particular, those with stronger trade ties with the USA; European countries suffered a lot, and the degree of contagion was even more amplified for those countries in which domestic banks were facing liquidity problems similar to those of US banks (Giavazzi et al., 2010).

As support of the pattern of the transmission of the financial crisis to the real economy presented previously, it is possible to observe the practical repercussions of the financial crisis in Table 1 on page 9. The economic indicators of the so-called "PIIGS" country which were significantly affected by the financial crisis (such as private consumption, industrial production, imports, and exports) are precisely those highlighted by Giavazzi et al. (2010).

As clarified on page 4, it is established that a country is facing a recession when after two consecutive quarters the level of GDP suffers reductions. In this regard, it might be interesting to decompose the GDP into more components:

$$Y \equiv C + I + G + X - IM$$

Where,

Y=Output;

C=Consumption (goods and services purchased by consumers);

I=Investment (sum of non-residential investment and residential investment);

G=Government spending (purchases of goods and services by the governments);

X= Exports (purchases of domestic goods and services by foreigners);

IM=Imports (purchases of foreign goods and services).

Once again, the components of the GDP are a "duplicate" of those which Giavazzi et al. (2010) illustrated as the key indicators which were affected by the financial crisis. Therefore, it is possible to debate that GDP represents a good indicator of the presence of a crisis. Consequently, the accurate estimation of the GDP is of primary importance with regard to the analysis of the impact which the latter had on the long-term growth. Please note that it is not necessary to estimate all the single components of the Gross Domestic Product, but rather focus on the estimation of the GDP on its own (Frankel & Saravelos, 2012).

With reference to the introductory textbooks theory proposed at the beginning of this subchapter, which states that a reduction of the aggregate demand causes a recession where output drops temporary below its potential level, it is possible to argue that many economists have shed doubts about this theory (Ball, 2014). According to them, a recession might have persistent effects on potential output since it is very likely that a crisis destroys capital, human capital and knowledge. Haltmaier (2013) and Reifschneider, Wascher, & Wilcox (2015) pointed out that a permanent reduction in the potential output could be generated by recessions which reduce capital accumulation, psychologically and economically affect workers, and disrupt the economic activities that produce technological progress. Therefore, during a recession, investment generally contracts; a reduction of the investment usually results in a long-lasting lower level of capital stock and technical progress, even though the investment recovers to its initial level (Ball, 2014). According to Reinhart & Rogoff (2014), the output of several countries was still negatively affected by the recession in 2014 and authorities such as the IMF at that time were forecasting only little recovery for the next five years.

2.2 Forecasting Theory

Based on statistics and macroeconomics literature, a wide range of methods for forecasting macroeconomic variables is available. One of the most common is the so-called Judgment-based forecast, which implies the observation of the empirical irregularities and regularities in the economy. However, the result of such forecasting method is primarily dependent on the forecaster's ability involved in the observation of the latter. It is challenging to assess, from an outside point of view, the quality of the model and the reliability of the data analyzed (Robertson & Tallman, 1999).

A valid alternative to the Judgment-based forecast is based on a statistical approach. The Model-based forecast allows tracing sampling errors and therefore, from an outside point of view, it simplifies the assessment process regarding the quality of the proposed model. According to Robertson & Tallman (1999), the most common Model-based forecast is the autoregressive model, which can be described as a representation of a type of stochastic process which describes specific time-varying processes; more precisely, it defines that the output variable depends linearly on its previous values and a stochastic term.

Thus, the notation of an autoregressive model of order k can be generalized as follows:

$$X_t = c + \sum_{i=1}^{k} \varphi_i X_{t-i} + \varepsilon_t$$

Where,

$\varphi_1, \dots, \varphi_i$ = parameters of the model;

c = constant;

ε_t= white noise.

The use of an autoregressive model in the field of macroeconomic model-based studies is very convenient since it allows to learn from a series of past steps and to take measurements from previous actions. All the information about the past is gathered together to produce a regression model which is able to predict values of the next steps. The basic idea beyond autoregression modeling is the measuring of the correlations between past time steps (the so-called lag variables) to predict future values (Brockwell, Davis, & Calder, 2002).

There are several ways to estimate the parameters of an autoregressive model. A valid option suggests that an AR model can be formulated as an extended form of an ordinary least square (OLS) prediction problem. For instance, if the following AR(1) model is taken under consideration:

$$X_t = \varphi X_{t-1} + \varepsilon_t$$

the ordinary least squares estimator ($\hat{\varphi}$) for a sample of size T will be:

$$\hat{\varphi} = \frac{\sum_{t=2}^{T} X_{t-1} X_t}{\sum_{t=2}^{T} X_{t-1}^2}$$

$$\hat{\varphi} = \varphi + \frac{\sum_{t=2}^{T} X_{t-1} \varepsilon_t}{\sum_{t=2}^{T} X_{t-1}^2}$$

$$\hat{\varphi} = \varphi + \sum_{t=2}^{T} \left(\frac{X_{t-1}}{\sum_{t=2}^{T} X_{t-1}^2} \right) \varepsilon_t$$

where ε_t is independent of X_{t-1}, which implies that $\mathrm{E}(X_{t-1}\varepsilon_t) = 0$. Please note that the error term will be dependent of the sum $\sum_{t=2}^{T} X_{t-1}^2$. For this reason, it is possible to affirm that generally the OLS estimates of an autoregressive model are biased. Nevertheless, the consistency of the estimators might be guaranteed under certain conditions. In fact, one of the asymptotic properties, supported by the Law of Large Numbers jointly with the

Central Limit Theorem, states that a sequence of estimates is said to be consistent if it converges to the true value of the estimated parameter. Obviously, there is the possibility to base a forecasting analysis on different values representing the time lags; AR(0) represents the simplest process since there are no dependencies between the terms. Essentially, it means that only the noise term contributes to the output of the process, and therefore it is possible to affirm that AR(0) corresponds to the white noise. However, for an AR model of order (1) the output of the process is strictly dependent on the magnitude of φ. With positive values of φ, the previous term in the process together with the noise term contribute to the final output. When φ approaches 0 the output tends to be closer to the white noise, but as φ gets closer to 1 the output gets a larger contribution from the previous term. With an AR(2) process, not only the previous term contributes to the output, but also the second one. Clearly, as the number of lags increases, it is possible to generalize an autoregressive model of order (k) in a similar way as illustrated previously (Brockwell et al., 2002).

Since most of the macroeconomic times series grow over time, it is not possible to describe them by a simple autoregressive model such as $X_t = \varphi X_{t-i} + \varepsilon_t$. This type of model actually does not impart any trend to the series, which cannot be considered as a realistic and correct "scenario". That being said, the question of whether the macroeconomic time series has a unit root can be phrased as whether the latter has a deterministic time trend or a stochastic trend. A time series which has a deterministic time trend can be represented by:

$$X_t = \alpha + \delta t + \varphi X_{t-1} + \varepsilon_t$$

while a time series which has a stochastic trend can be considered as a unit root with drift and therefore can be represented by the following equation:

$$X_t = \delta + X_{t-1} + \varepsilon_t$$

The autoregressive model, together with the moving-average model, can be used as key components of a more complicated stochastic structure model: the so-called autoregressive integrated moving average (ARIMA). Such a model is a generalization of the autoregressive moving average (ARMA), and it is characterized by three features:

- Autoregressive (AR);
- Integrated (I);
- Moving Average (MA).

The ARIMA model allows forecasting every time series which can be transformed into stationary. According to Brockwell et al. (2002), a time series is said to be stationary if its statistical properties are all constant over time; in fact, a stationary time series has no trend, its variations around its mean have a constant amplitude and it wiggles consistently. The autoregressive (AR) part of the autoregressive integrated moving average (ARIMA) models implies that the evolving variable is regressed on its own lagged values. While the moving average (MA) component of the model indicates that the regression error can be seen as a linear combination of error terms whose values occurred several times simultaneously in the past. The last element “I” stands for integrated and indicates that the model uses a differencing process which can be performed if requested; this process replaces the data values with the difference between the values themselves and the previous ones. All these features guarantee that the model fits the data as accurately as possible (Brockwell et al., 2002).

Moreover, according to the statistics literature, it is possible to further split ARIMA models into:

- Non-Seasonal ARIMA models: denoted as ARIMA(p,d,q) where p stands for the number of time lags, d for the degree of differentiation and q for the order of the moving average model;
- Seasonal ARIMA models: denoted as ARIMA(p,d,q)(P,D,Q)m where (P,D,Q) refer to the seasonal part of the ARIMA model and m refers to the number of periods in each season.

Hence, the following equation can represent a straightforward ARMA(p',q) model:

$$\left(1-\sum_{i=1}^{p'} \propto_i L^i\right)X_t = \left(1+\sum_{i=1}^{q} \theta_i L^i\right)\varepsilon_t$$

Where,

X_t = series of data where t is an integer index;

L = lag operator;

$\propto_i$ = parameters of the autoregressive part of the model;

θ = parameters of the moving average part;

ε_t = error terms.

If the first polynomial of the previous equation

$$\left(1 - \sum_{i=1}^{p'} \propto_i L^i\right)$$

is characterized by a unit root of multiplicity d, it implies that:

$$\left(1 - \sum_{i=1}^{p'} \propto_i L^i\right) = \left(1 - \sum_{i=1}^{p'-d} \phi_i L^i\right)(1 - L)^d$$

As a consequence, the polynomial factorization property can be represented mathematically by an ARIMA(p,d,q) process where:

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1 - L)^d X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right)\varepsilon_t$$

Thus, if it is taken under consideration a process with drift $\frac{\delta}{1-\sum \phi_i}$, it is possible to state the following equation as a generalization of the ARIMA(p,d,q) process:

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1 - L)^d X_t = \delta + \left(1 + \sum_{i=1}^{q} \theta_i L^i\right)\varepsilon_t$$

The question which now arises is quite important: how can be the order of an ARIMA model determined? A useful criterion which helps to determine the order of a Non-Seasonal ARIMA model, respectively the order of a Seasonal ARIMA model, can be the Akaike Information Criterion (AIC). This criterion can be denoted as:

$$AIC = -2\log(L) + 2(p + q + k)$$

Where,

L = maximized value of the likelihood function for the estimated model;

p = order of the autoregressive part;

q = order of the moving average part;

k = intercept of the ARIMA model.

Another criterion which might help in the definition of the order of a non-seasonal/seasonal ARIMA model is the Bayesian Information Criterion. Mathematically it can be defined as:

$$BIC = AIC + (\log(N) - 2)(p + q + k)$$

Where,

AIC = Akaike Information Criterion;

N = number of data points (=sample size);

p, q, k = as for AIC.

The creation of a respectable model implies that these two criterions must be minimized: the lower the value, the better the model will suit the data. However, the purpose of the AIC is to approximate models towards reality while the BIC is commonly used to find the perfect fit. For this reason, the last criterion is quite criticized by researchers since it is rather impossible to perfect fit models with real-life complex data (Harvey & Todd, 1983).

The iteration of all the possible combinations of parameters, with regard to the minimization problem of the above criterion, allows discovering the perfect combination of parameters. As Harvey & Todd (1983) pointed out, the goodness of the forecast ARIMA model is strictly related to the assumptions that the residuals should be uncorrelated and normally distributed. If either of these assumptions is not respected, the forecasted variables might assume imprecise values. For this reason, it is good practice to analyze the autocovariance/autocorrelation function and to visually inspect the histogram of the residuals before producing any forecast. Once the correctness of the model has been assessed, it is finally possible to employ the ARIMA model with the established combination as a base for forecasts.

Since the ARIMA model can be interpreted as a conjunction of two models constructed on non-stationary and stationary time series based processes, Brockwell et al. (2002) argued that it is possible to use the autoregressive method as a forecasting generalization. According to Marcellino, Stock, & Watson (2006), within the model-based forecasting methods used in macroeconomics literature, the most used model is the iterative model. In fact, forecasts of macroeconomic time series are predominantly made by using the "one-step-ahead" approach.

For example, if the general notation of the autoregression is taken under consideration

$$X_t = c + \sum_{i=1}^{k} \varphi_i \, X_{t-i}$$

it appears clear that such a model can be used to predict the first future value of the estimated variable. In fact, the "one-step-ahead" forecasting autoregressive model can be mathematically expressed as:

$$X_{t+1} = c + \sum_{i=1}^{k} \varphi_i \, X_{t+1-i} + \varepsilon_t$$

Where,

X_{t+1} = estimated value (next period);

$\varphi_1, \dots, \varphi_i$ = parameters of the model;

c = constant;

ε_t = expected value of the unobserved error term (0).

Such a process can be repeated as many times as desired to create a series of future forecasted values. More precisely, there are two possible ways to deal with lagged dependent variables: the first option implies the use of static forecasting which uses the actual value of the lagged dependent variable to predict the subsequent forecast, while the second one, dynamic forecasting, uses the previous predicted value of the dependent variable to compute the next prediction. The predictive performance can be assessed through a cross-validation approach: the dataset is divided into training-sample and test-sample; the first one includes an initial portion of the available data as a base for forecasting, while the second one is used for the validation of the predictions.

Please note that the use of the dynamic approach is mandatory in order to consider the forecasting technique reliable. It actually represents the only feasible method which can guarantee a certain degree of external validity. In fact, the actual data are not available in the "true" out-of-sample period (Brockwell et al., 2002). For this reason, the validation of the forecasting model proposed in this thesis was done following both static and dynamic forecasting approaches. However, the final leverage of the seasonal ARIMA time series towards future forecasted values was achieved via dynamic forecasting since it represents better a real case scenario.

There are four significant sources of uncertainty regarding the predictive performance of the dynamic forecasting approach:

1. The goodness of the autoregressive model;
2. The accuracy of the forecasted values which are further used as lagged values;
3. The uncertainty of the autoregressive coefficients;
4. The uncertainty of the error term's value for the forecasted period.

Especially the last three sources of uncertainty can be quantified and combined to form a confidence interval for the predictions. As a consequence of the estimation procedure of the dynamic forecasting, the confidence interval becomes wider when the number of predicted values increases. The accuracy of the predicted values is in fact negatively "correlated" with the number of lags (Tashman, 2000).

Furthermore, to better asses the forecasting accuracy, it might be useful to compute the Mean Squared Error (MSE) of the model which is based on the forecast error whose value is represented by the difference between the actual value (X_t) and the forecasted value (F_t):

$$E_t = X_t - F_t$$

Once the forecast error has been computed, it is finally possible to compute the MSE of the predictive model as Tashman (2000) suggested:

$$MSE = \frac{\sum_{t=1}^{N} E_t^2}{N}$$

As in the case of AIC and BIC, by lowering the value of the Mean Square Error, the quality of the forecasting model will increase.

In conclusion, neither the MSE nor any coefficient previously illustrated gives an accurate indication of the validity of a forecasting model, but rather indicates the prediction accuracy. The external validity of a forecasting model cannot be accomplished so easily, even if the perfect fit has been achieved within the context of a particular study.

3. Previous Research

By a first overview of the available literature regarding the impact of the financial crisis on the Gross Domestic Product, it emerged that further studies about the topic in question are needed.

In order to have a comprehensive understanding and a complete overall picture, the following papers were principally used as a reference to explain the general causes and consequences concerning the financial crisis:

- Covitz, D., Liang, N., & Suarez, G. A. (2013). The evolution of a financial crisis: Collapse of the asset-backed commercial paper market. *The Journal of Finance*, *68*(3), 815–848.
- Epstein, G. A. (2005). *Financialization and the world economy*. Edward Elgar Publishing.
- Eslake, S. (2009). The Difference between a Recession and a Depression. *Economic Papers: A Journal of Applied Economics and Policy*, *28*(2), 75–81. https://doi.org/10.1111/j.1759-3441.2009.00013.x
- Kirkpatrick, G. (2009). The corporate governance lessons from the financial crisis. *OECD Journal: Financial Market Trends*, *2009*(1), 61–87.
- Lee, S. H., Atkinson, P., & Blundell-Wignall, A. (2009). The current financial crisis. *OECD Journal: Financial Market Trends*, *2008*(2), 1–21. https://doi.org/10.1787/fmt-v2008-art10-en
- Mendoza, E. G., & Quadrini, V. (2010). Financial globalization, financial crises and contagion. *Journal of Monetary Economics*, *57*(1), 24–39.
- Obstfeld, M., & Rogoff, K. (2009). *Global imbalances and the financial crisis: products of common causes*.

- Poole, W. (2010). Causes and Consequences of the Financial Crisis of 2007-2009. *Harv. JL & Pub. Pol'y*, *33*, 421.
- Thakor, A. V. (2015). The Financial Crisis of 2007–2009: Why Did It Happen and What Did We Learn? *The Review of Corporate Finance Studies*, *4*(2), 155–205. https://doi.org/10.1093/rcfs/cfv001

The papers of Poole (2010) and Thakor (2015) represented, among the other options, a valid source of information with regard to the events leading to the crisis, the short-term and long-term causes, the consequences, and finally the learnings from the financial crisis. The evolution of the financial crisis together with the necessary clarifications regarding specific terms were extrapolated from Covitz et al. (2013), Epstein (2005) and Obstfeld and Rogoff (2009) papers. The remaining ones were used predominantly as a support for further explanations or clarifications of related topics.

The subsequent literature was used as a base for the definition of the theoretical framework on which this thesis is founded:

- Brockwell, P. J., Davis, R. A., & Calder, M. V. (2002). *Introduction to time series and forecasting* (Vol. 2). Springer.
- Giavazzi, F., Amighini, A., & Blanchard, O. J. B. (2010). *Macroeconomics: A European Perspective*. Financial Times Prentice Hall.
- Giorno, C., Richardson, P., Roseveare, D., & Van den Noord, P. (1995). *Estimating potential output, output gaps and structural budget balances*.
- Harvey, A. C., & Todd, P. H. J. (1983). Forecasting economic time series with structural and Box-Jenkins models: A case study. *Journal of Business & Economic Statistics*, *1*(4), 299–307.
- Marcellino, M., Stock, J. H., & Watson, M. W. (2006). A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series. *Journal of Econometrics*, *135*(1–2), 499–526.

- Robertson, J. C., & Tallman, E. W. (1999). Vector autoregressions: forecasting and reality. *Economic Review-Federal Reserve Bank of Atlanta*, *84*(1), 4.

As presented in the sub-chapter "Macroeconomics Theory", Giavazzi et al. (2010) offered a comprehensive overview of the critical macroeconomic dynamics regarding the financial crisis from a European perspective, whereas the other papers' contents were used primarily as a reference for the forecasting theory on which to base the empirical analysis.

The following papers were used to identify which countries to analyze, and even more important, they contain useful information with regard to the selection of a suitable model and methodology to forecast economic variables such as GDP Growth:

- Andersson, J. (2007). *Forecasting Swedish GDP Growth*.
- Ball, L. (2014). *Long-Term Damage from the Great Recession in OECD Countries* (No. w20185). https://doi.org/10.3386/w20185
- Bassanetti, A., Caivano, M., & Locarno, A. (2010). Modelling Italian potential output and the output gap. *Bank of Italy Temi Di Discussione (Working Paper) No*, *771*.
- Cushman, D. O. (2012). Mankiw vs. DeLong and Krugman on the CEA's Real GDP Forecasts in Early 2009: What Might a Time Series Econometrician Have Said? *Econ Journal Watch; Fairfax*, *9*(3), n/a.
- d'Italia, B. (n.d.). Bank of Italy - Macroeconomic models. Retrieved May 10, 2019, from https://www.bancaditalia.it/compiti/ricerca-economica/modelli-macroeconomici/index.html
- Dritsaki, C. (2015). Forecasting real GDP rate through econometric models: an empirical study from Greece. *Journal of International Business and Economics*, *3*(1), 13–19.

- Granger, C. W. J., & Newbold, P. (1986). *Forecasting economic time series* (2nd ed). Orlando: Academic Press.

- Halvorsen, K. (2016). Economic, Financial, and Political Crisis and Well-Being in the PIGS-Countries. *SAGE Open*, *6*(4), 215824401667519. https://doi.org/10.1177/2158244016675198

- Hendry, D. F. (2018). Deciding between alternative approaches in macroeconomics. *International Journal of Forecasting*, *34*(1), 119–135. https://doi.org/10.1016/j.ijforecast.2017.09.003

- Kennedy, P. (2003). *A guide to econometrics*. MIT press.

- Liapis, K., Rovolis, A., Galanos, C., & Thalassinos, E. (2013). The Clusters of Economic Similarities between EU Countries: A View Under Recent Financial and Debt Crisis. *European Research Studies*, *16*(1), 41.

- Maity, B., & Chatterjee, B. (2012). Forecasting GDP growth rates of India: An empirical study. *International Journal of Economics and Management Sciences*, *1*(9), 52–58.

- Marcellino, M., Stock, J. H., & Watson, M. W. (2006). A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series. *Journal of Econometrics*, *135*(1–2), 499–526.

- Stock, J. H., & Watson, M. W. (2011). *Introduction to econometrics* (3rd ed). Boston: Addison-Wesley.

Halvorsen (2016) analyzed to what extent the financial crisis of 2008 has influenced the well-being of the population living in the four hardest affected European countries (the so-called PIGS); the regressions employed in his paper demonstrated a significant fall in average life's satisfaction. According to Ball (2014) and many other economists, one of the reasons whereby a recession might have persistent effects on potential output is that a crisis might destroy human capital and knowledge. For this reason, from a behavioral economics' point of view, it is possible to link these two findings in order to debate the possibility of an increased impact of the crisis in the "PIGS" countries. Since the financial crisis affected the population's satisfaction of these countries, and according to Florida, Mellander, & Rentfrow (2013) the population's satisfaction is related to the creation of human capital and knowledge, the linkages between these two outcomes appear quite obvious.

Moreover, Liapis et al. (2013) analyzed the clusters of similarities among EU members and pointed out that the high current account deficit and the unsustainable public debt were typical peculiarities of the so-called PIIGS countries (Portugal, Ireland, Italy, Greece, and Spain). In fact, during the financial crisis such countries' ratings were strongly affected by the Credit Rating Agencies. Nevertheless, these countries in the first decade of the euro's existence faced inflation levels above the euro-area average level due to the massive amount of capital inflow. As a result of these facts, the real appreciation led to a deterioration in competitiveness. In conclusion, it is possible to debate that the effects of the financial crisis on the "PIIGS" countries were significantly high, for this reason they are also much easier to identify in an empirical analysis. The thesis' focus is consequently on the "PIIGS" countries, and since the scope of the latter is to perform a technical analysis of the impact of the financial crisis on the Gross Domestic Product, a considerable amount of effort was put in with regard to the literature review of the available forecasting methods.

Cushman (2012) and Bassanetti et al. (2010) pointed out the possibility to use univariate forecasting methods to forecast economic variables such as GDP growth. In fact, contrary to what one might expect, an ARIMA model represents a valid approach in terms of forecasting economic variables, even if it does omit the economic theory behind the estimated variable. As Hendry (2018) stated in his recent paper, macroeconomic time-series data rarely match theoretical concepts since the degree of aggregation, inaccuracy, collinearity, and complexity can be quite significant, meaning that "data-driven" approaches represent an excellent alternative to the classic "theory-driven" models.

According to Stock & Watson (2011), a statistical model can perform better at forecasting economic variables than a purely theory-based approach. An autoregressive model, which basically is the purest form of an autoregressive integrated moving average model, can provide statistically significant results just by using the lags of the process to explain the process itself. In fact, if some theoretical relationship determines the correct process, the lag variables will already contain this information; for this reason, it is not necessary to include it again in the model.

By following the forecasting theory illustrated in the previous chapter, it appears clear that ARIMA models do capture all the statistical properties of the underlying relationships embedded in the process; the forecasting performance of "simple" methods might even outperform more sophisticated models. More precisely, Granger & Newbold (1986) pointed out that simple models are only marginally less accurate compared to the more sophisticated methods. In fact, Stock & Watson (2011) suggested that if the scope of the study is to understand and explain the underlying causal relationships, then the restrictions implied by economic theory must be included for inference. However, under a purely forecasting point of view, it can be even inconvenient to include economic theory. Indeed, this point is brought up frequently in Machine Learning scientific studies, since the algorithms are extremely efficient for predictions but not suitable to comprehend the underlying causal relationship.

According to Kennedy (2003), ARIMA models are the main "competitors" of theory-based econometric models. Univariate Box-Jenkins models ignore the explanatory variables that form the foundation of econometric models since they use past values of the variable being analyzed to generate future forecasts. Kennedy (2003) has identified several reasons why economists should be interested in such models:

- *"thanks to improved computer software, they are easy and cheap to produce";*
- *"the extra information required to estimate a proper econometric model may be expensive to obtain";*
- *"forecasts from such models can serve as a useful benchmark for comparison purposes";*
- *"forecasts from this process can be combined with other forecasts to produce improved forecasts";*
- *"they are useful as a preliminary step for further modeling";*
- *"they clarify the nature of the data and make clear what behavior patterns require explanation".*

With regard to the second argument, it is possible to debate that even with what Kennedy (2003) has pointed out, not only the extra information required to estimate a proper econometric model may be expensive but as a consequence also the degree of complexity of the latter might result huge. For example, if the model file of the Bank of Italy quarterly econometric model (d'Italia, n.d.) is taken into consideration, only the primary model includes 800 equations with more than 700 explanatory variables. Therefore, creating such models requires a lot of resources and the necessary data are not always available. One might debate that there is the possibility of implementing a vector autoregression model to forecast economic variables with the scope of including also the underlying causal relationship as explanatory variables. In fact, Andersson (2007) evaluated which model, among autoregressive and vector autoregressive models (VAR), represents the best linear time series model to forecast Swedish real GDP Growth. In the study lag GDP, unemployment and inflation were included as explanatory variables in the vector autoregressive model; however, the performance obtained by the two models were essentially identical. This should not be surprising considering that the most essential component of a VAR model is the autoregressive part. As a matter of fact, if the lag variables of the analyzed variable have higher standardized coefficients compared to the other variables included in the model, it is very likely that the model behaves similarly to a simple autoregressive model. As support for this statistical principle, in sub-chapter 5.2 is provided a short comparison between the autoregressive and the vector autoregressive regressions obtained from the analysis of the countries on which this thesis is focused.

In conclusion, as the primary concern is the selection of a suitable model which is able to forecast economic variables, the papers from Ball (2014), Dritsaki (2015), Maity & Chatterjee (2012), and Bassanetti, Caivano, & Locarno (2010) were analyzed in depth and used as a methodology reference for this thesis. More specifically, in order to derive the effects of the financial crisis on the Gross Domestic Product of the so-called "PIIGS" country, it was decided to follow a similar approach to the one used by Ball (2014). To assess the effects of the financial crisis, Ball (2014) estimated the levels of the potential output that a country would have attained assuming that the recession had never existed. The estimations proposed was done via an examination of the path of the potential output following the year 2007. All the other papers listed above proposed the autoregressive integrated moving average model as an effective approach to forecast quarterly GDP growth.

4. Data analysis

This section provides a basic overview of the data on which the methodology of this thesis is based and it outlines the main descriptive statistics. Later, it offers a time series analysis to verify if the main requirements of forecasting models are fulfilled.

In the first sub-chapter, a preliminary insight regarding the sample period is stated. After the explanation of the reasoning on which the sampling period is based, it is provided the source of the data together with the peculiarities of the dataset.

The second sub-chapter offers a general overview of the trends embedded in the time series and the relative main descriptive statistic. Firstly, any trend present in the time series is identified and briefly commented. The core part of the sub-chapter is, however, focused on the descriptive statistics of the different variables involved in the analysis part.

The last sub-chapter offers further explanations with regard to the dependence structure of the time series. Since the final scope of the thesis is to provide accurate forecasts, one of the most important factors to consider is the stationarity of the time series.

4.1 Data

As illustrated in sub-chapter 1.1, once the early 2000s crisis eased, the global economy went through a period characterized by an improved overall macroeconomic stability. The result of this development was a sustainable long-term growth from 2002 to 2007. For this reason, the dataset sample period which was chosen covers the period from Q4-2001 to Q3-2018 in order to exclude any possible major macroeconomic event which could have influenced the time-series before the start of the financial crisis. With this regard, the dataset was divided to differentiate the period before and after the crisis into two data frames:

- from Q4-2001 to Q4-2007 considered as the pre-crisis period;
- from Q1-2008 to Q3-2018 considered as the after-crisis period.

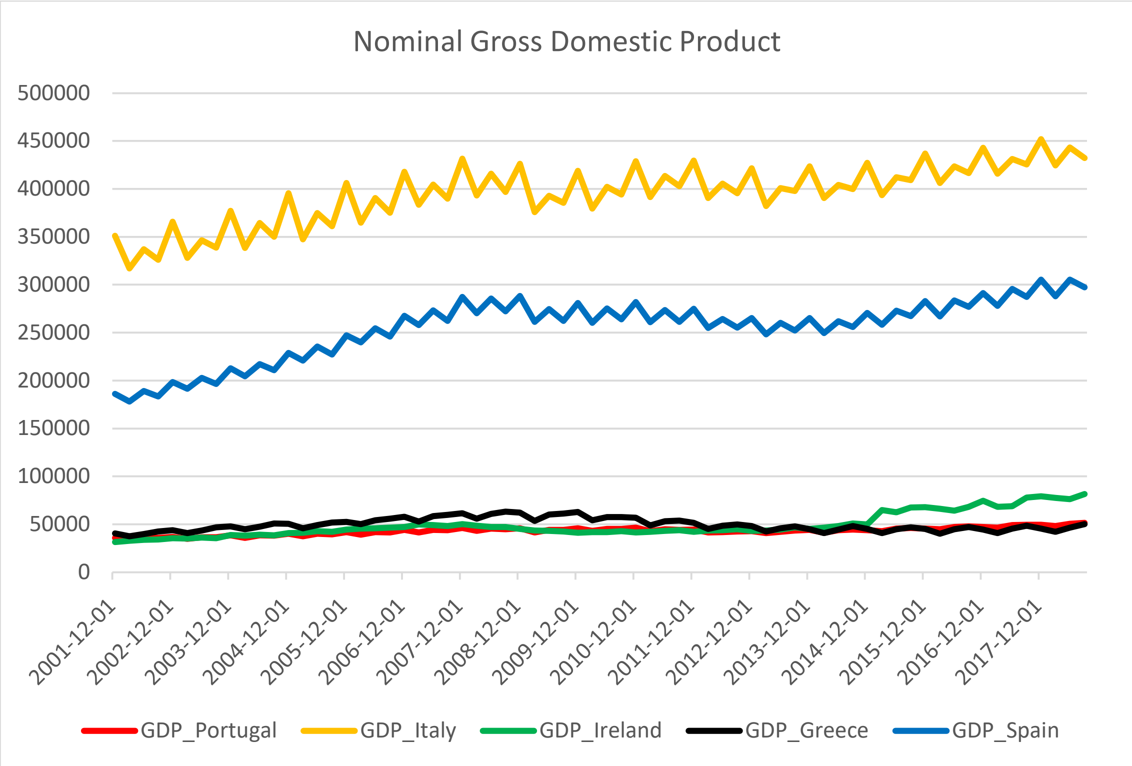
This choice imposes some limits from a statistical point of view considering that the pre-crisis period is relatively short, which implies that the analysis is based on a relatively small sample. However, this strategy brings many advantages considering that by doing so, any anomalies deriving from events which were not taken into consideration are excluded. Furthermore, it allows to significantly simplify the complexity of the model as the implementation of dummy variables is not required to filter out any crises that occurred in the period before the crisis of the 2000s. Besides that, since the most significant event that caused a strong reduction of the GDP is attributable to the financial crisis of 2008, and because the aim of the thesis is to analyze the impact of the financial crisis on the GDP, it was decided to reduce the size of the dataset to be able to base the predictions exclusively on expansive data. In fact, it is assumed that without the occurrence of the 2008 financial crisis, the expansionary trend which had been prevailing in the pre-crisis period would have been present throughout all the sample period (see sub-chapter 5.3 for more information regarding this choice). The decision to base the analysis on the nominal GDP instead of real GDP is because of, according to Ewing, Gruen, & Hawkins (2005), in the last two decades the nominal GDP forecasts have been more accurate than those of real GDP. This can be attributed to the predominance of unanticipated supply-side shocks over recent years which have moved real output and prices in opposite directions. The dataset created contains raw data which was collected from the statistical office of the European Union (Eurostat) and is composed of three different time-series:

- Gross Domestic Product (GDP);
    - Quarterly data;
    - Expenditure approach;
    - Current prices, million euro;
    - Neither seasonally nor calendar adjusted;
- Harmonized Index of Consumer Prices (HICP);
    - Quarterly data;
    - All items HICP approach;
    - Index, 2015=100;
    - Neither seasonally nor calendar adjusted;
- Harmonized Unemployment rate (UN);
    - Quarterly data;
    - All persons approach;
    - Level as a percentage;
    - Neither seasonally nor calendar adjusted.

4.2 Descriptive statistics

From a first visual inspection of the following figure (1) representing the nominal Gross Domestic Product of the so-called “PIIGS” countries, some significant disparities emerge with regard to the GDP level.

Figure 1: Nominal GDP – “PIIGS” countries



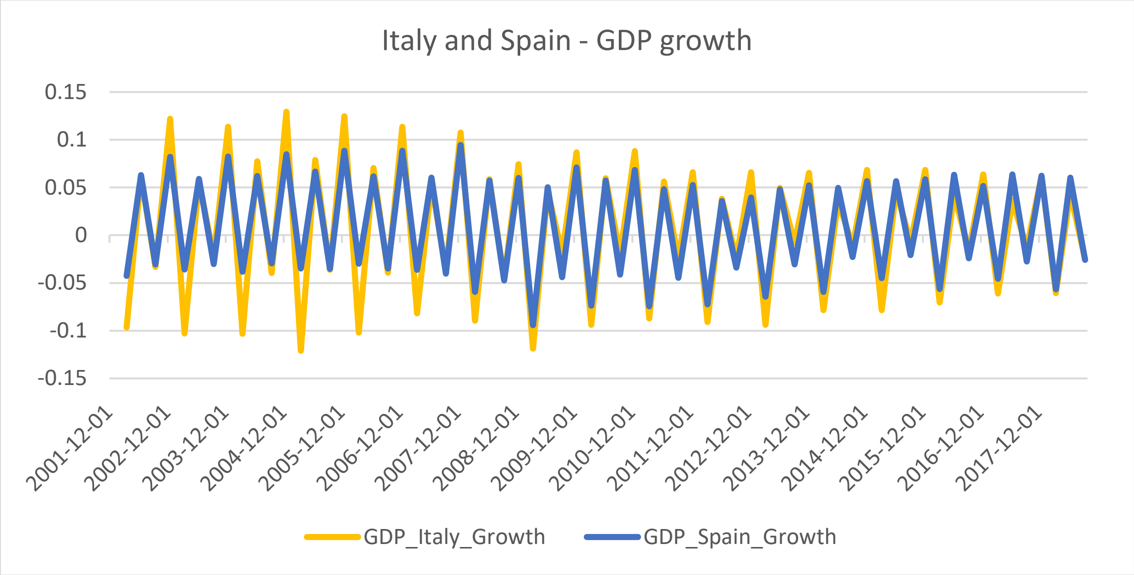
In absolute terms, the leading time series is the one represented by Italy. Spain follows immediately after, whereas the remaining three countries can be clustered together. It is also possible to remark that Italy and Spain develop almost identically; the effects of the financial crisis are easily noticeable and comparable, as well as the slow recovery starting in 2014. Portugal and Greece progress similarly, however, rather than showing an expansionistic trend, they express a stagnant situation. Looking at Ireland’s GDP development, signs of recovery from the year 2014 are clearly visible. In this case, due to the difficulty of identifying possible trends, it results challenging to properly asses the effect of the financial crisis on the Gross Domestic Product. Hence, it might result convenient to compute the GDP growth rate by following this simple formula:

$$GDP_{growth} = \frac{GDP_t^i}{GDP_{t-1}^i} - 1$$

where GDP_t^i is GDP for country *i* at time *t*, and GDP_{t-1}^i is GDP for country *i* at time *t-1.*

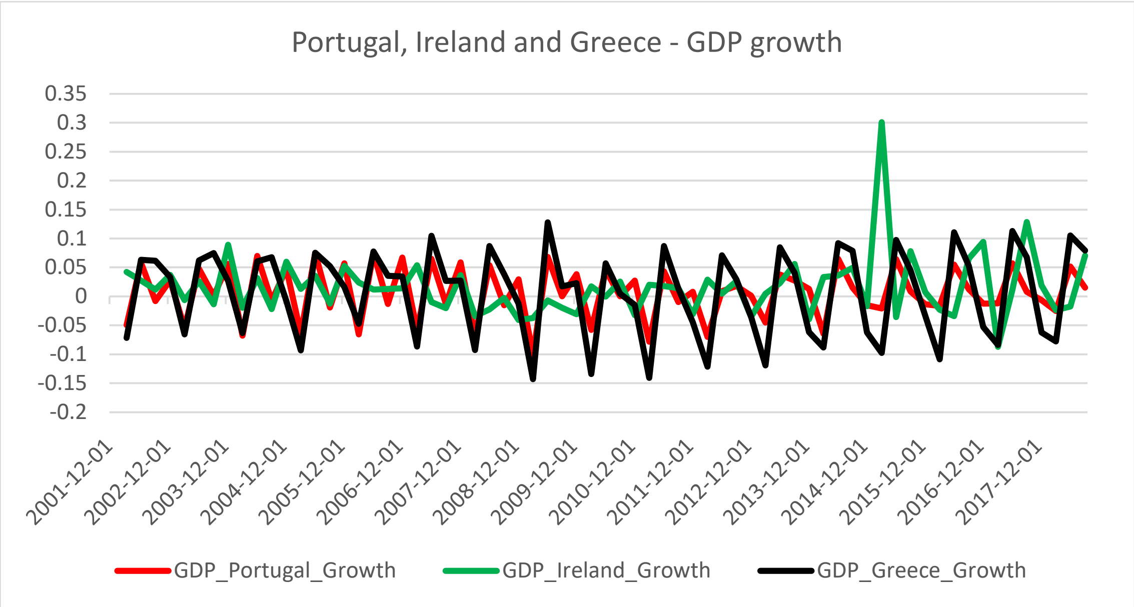
The following figure (2) represents the results obtained from the application of the previous formula on the GDP of Italy and Spain.

Figure 2: GDP growth – Italy and Spain



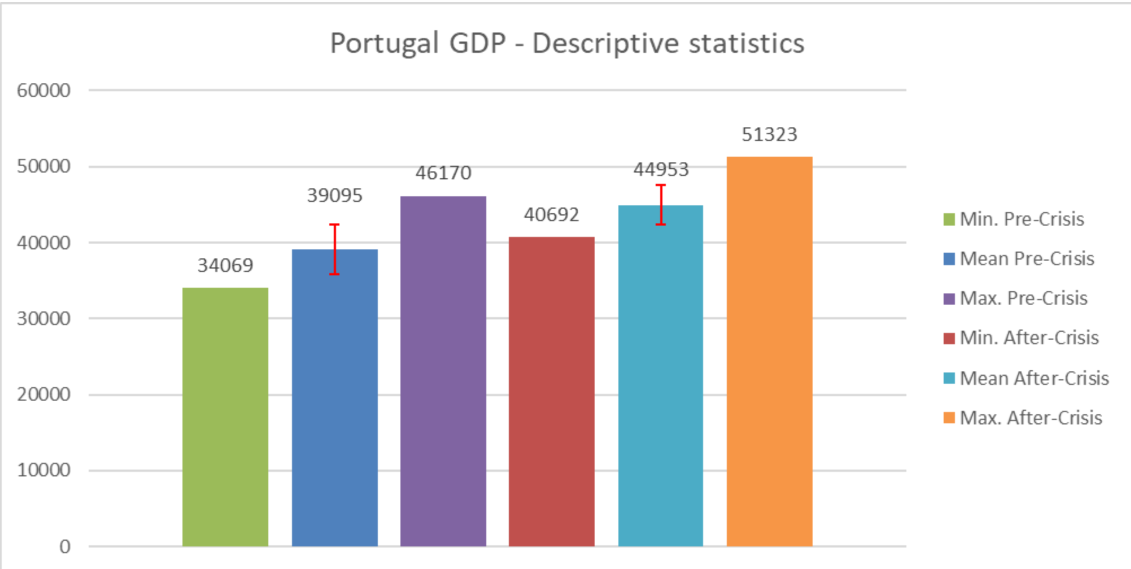
As mentioned previously, the GDP of the two countries develop similarly. The only noteworthy difference is the more significant fluctuation of Italy's GDP compared to Spain's. Thanks to the figure below (3), it emerges that, among the other three countries, Greece and Portugal evolve almost synchronized, whereas Ireland generally presents lower variation. The only exception is present in the period between 2014 and 2015, which is characterized by a positive spike.

Figure 3: GDP growth – Portugal, Ireland, and Greece



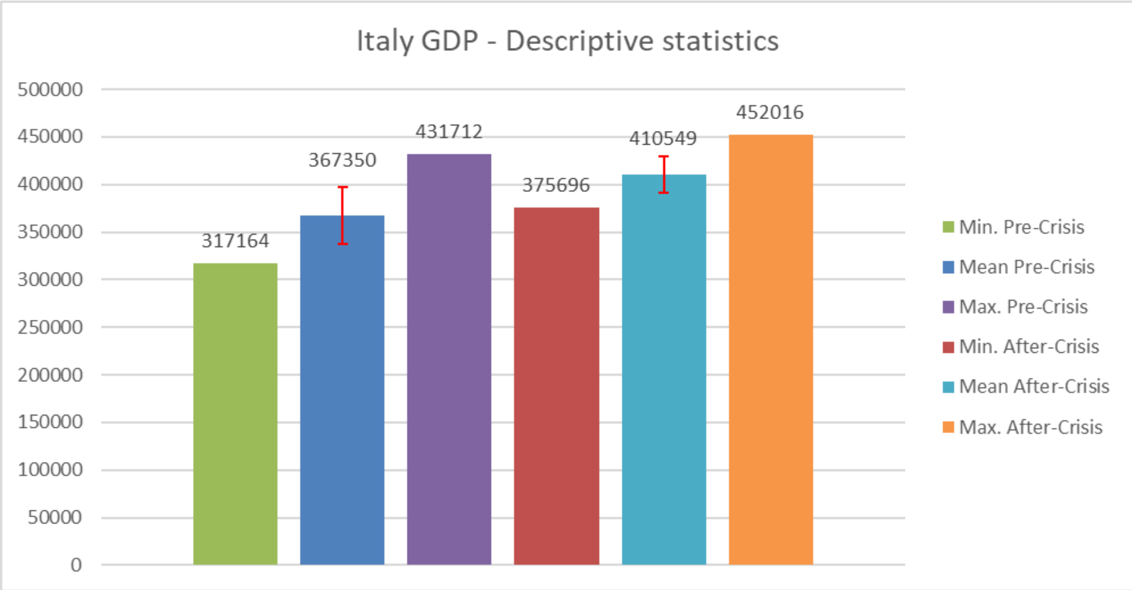
The following figure (4) depicts the main descriptive statistic of Portugal GDP. The first three bars represent the minimum, mean and maximum level of GDP in the period pre-crisis, while the remaining three symbolize the levels of the after-crisis period. The pre-crisis period is characterized by a maximum level, which results to be higher compared to the minimum level of the period after-crisis. In other words, the highest level observed in the first period is higher than the lowest level reached in the second, indicating that the GDP does not reflect a constant expansionistic evolution. The relatively low level of the standard deviation in the period after-crisis suggests a prolonged period of slow economic growth. In fact, the difference between the maximum and minimum level in the period pre-crisis results to be higher compared to the period after-crisis: 12’101 million, respectively 10’631 million.

Figure 4: Portugal GDP – Descriptive statistics



Regarding Italy’s GDP (figure 5), it is possible to note a similar descriptive statistic as for Portugal. The minimum level reached in the period after-crisis is lower compared to the maximum of the second sub-sample, indicating that Italy GDP is not exclusively characterized by positive trends. The standard deviation of the first period is slightly higher compared to the second; this can be easily identified also in figure (2) where higher fluctuations of the GDP growth distinguish the first part of the plot. Moreover, the difference between the maximum and minimum level of the two sub-samples is quantified as 114’548 million for the pre-crisis sub-sample, and respectively, 76’320 million for the period following the crisis.

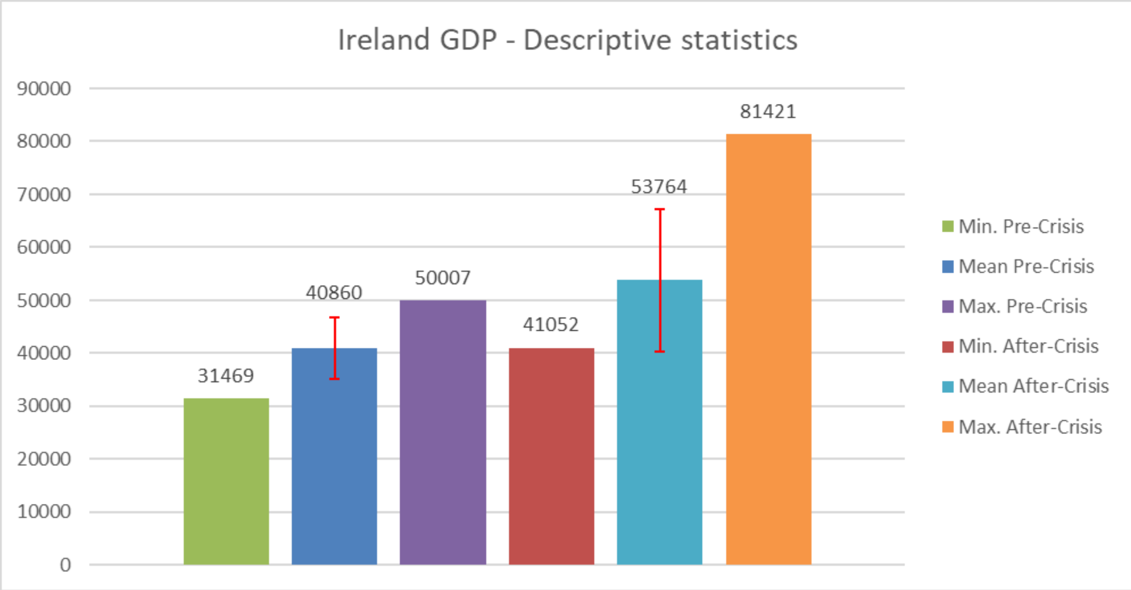
Figure 5: Italy GDP – Descriptive statistics



The descriptive statistic of Ireland represented in figure (6) indicates significant disparities between the two periods. Indeed, the maximum level reached in the first sub-sample is higher compared to the minimum level of the second, indicating a non-constant increasing pace. Moreover, the pre-crisis period presents a lower standard deviation compared to the after-crisis period. As figure (3) shows, the evolution of the GDP growth is characterized by a positive spike; in fact, the maximum level almost doubles the minimum level reached in the same period.

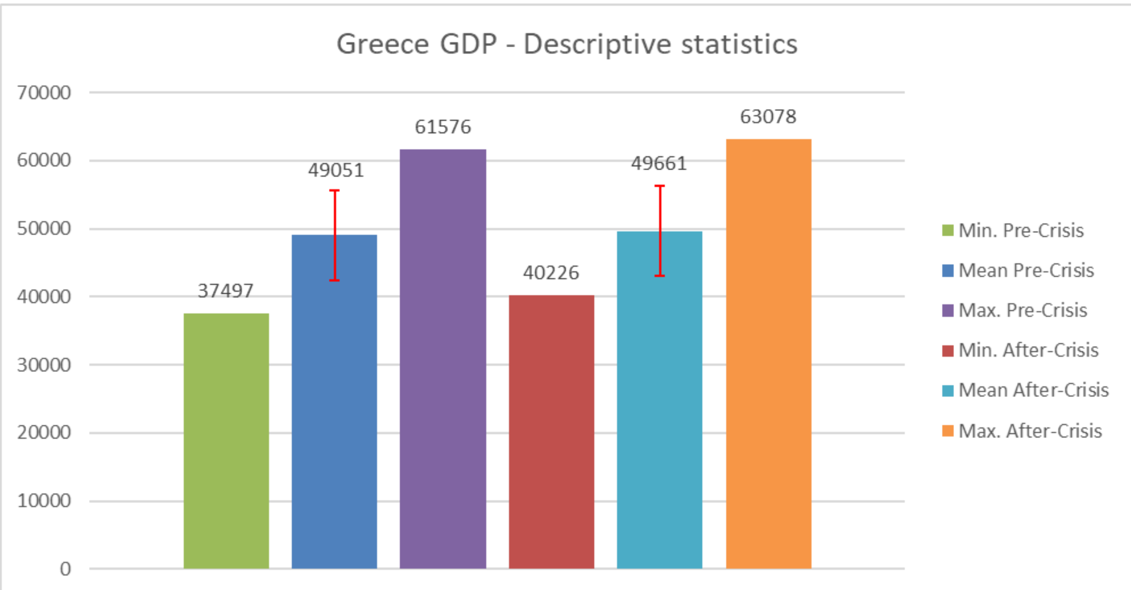
Among the so-called "PIIGS" countries, Ireland is the only nation presenting such "positive" results in the period following the crisis, for which reason it could be interesting to investigate further this development. According to Fitzgerald (2014), the recession was confined to the building and construction sector. The tradable sector was only limitedly affected. In fact, the lost competitiveness did not cause massive wholesale closures. Indeed, the tradable sector rapidly recovered. Noteworthy is also the recovery in the private sector's earnings, which came back in 2014 at the pre-crisis level. Moreover, the high degree of specialization in activities that require skilled labor had increased the service exports, which in 2014 accounted for over half of the total exports. As a result of these facts, the exports of goods and services in 2014 were around 14 percent above their previous peak in 2007. In conclusion, the fluctuating recovery continued to pick up pace in the period between 2014 and 2018.

Figure 6: Ireland GDP – Descriptive statistics



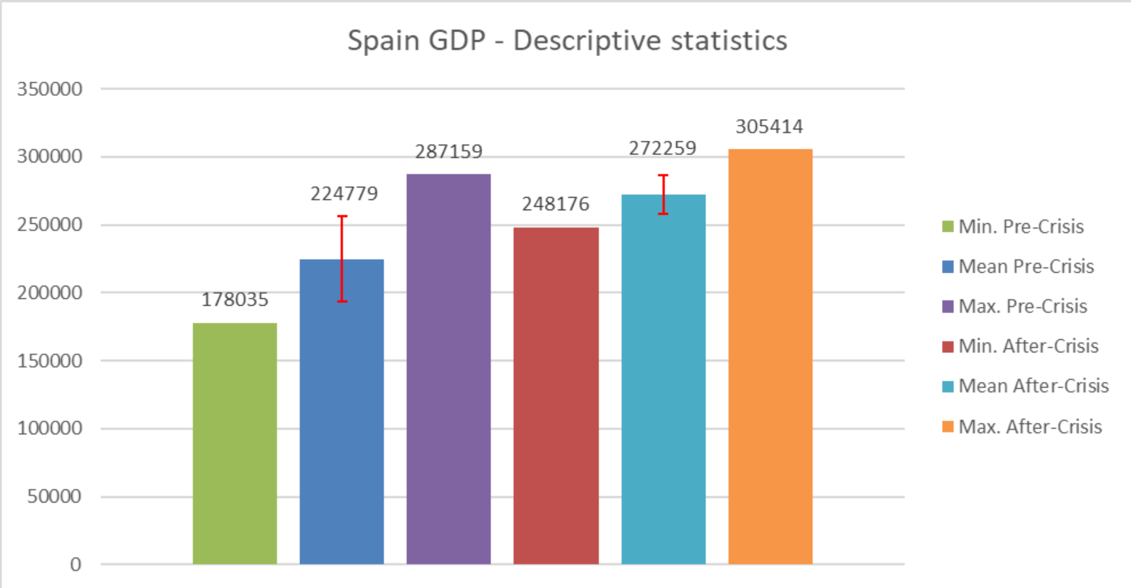
The descriptive statistics of Greece (figure 7) clearly illustrates the effects of the financial crisis on the Gross Domestic Product. The after-crisis period presents nearly the same statistics as the pre-crisis one. The minimum value recorded by the GDP in the after-crisis period is lower by 34.6% compared to the maximum level reached in the pre-crisis sub-sample. No signs of recovery are visible since both minimum, mean, and maximum levels are consistent throughout the entire sample. In conclusion, it is possible to debate whether or not the financial crisis "erased" almost the entire GDP progress from Q4-2001 to Q4-2007.

Figure 7: Greece GDP – Descriptive statistics



Finally, the descriptive statistic of Spain GDP is presented in the following figure (8).

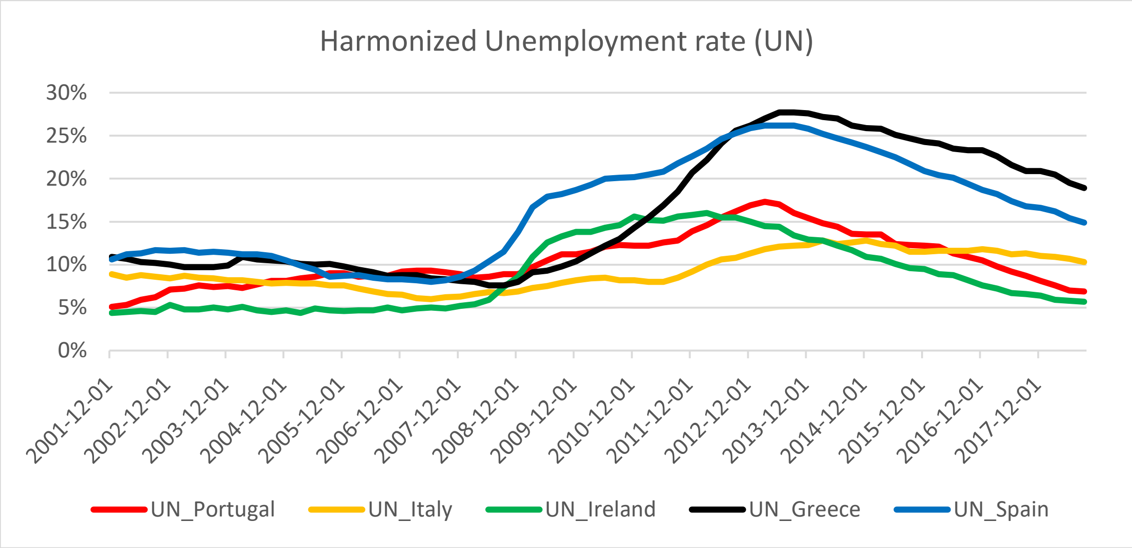
Figure 8: Spain GDP – Descriptive statistics



From a first visual inspection, it emerges that a relatively high standard deviation characterizes the pre-crisis period. The difference between the minimum and maximum level in the first sub-sample is considerable high, both in absolute and relative terms. If the first figure (1) is analyzed, it is possible to observe a higher growing pace of the Spanish GDP, which might explain the higher standard deviation registered in the pre-crisis period. As for the other countries under analysis, the minimum level reached in the period following the crisis results to be lower if compared to the maximum level of the first sub-sample. This is an indication that the development of the time series is not always expansionistic, i.e., the financial crisis impacted the Gross Domestic Product.

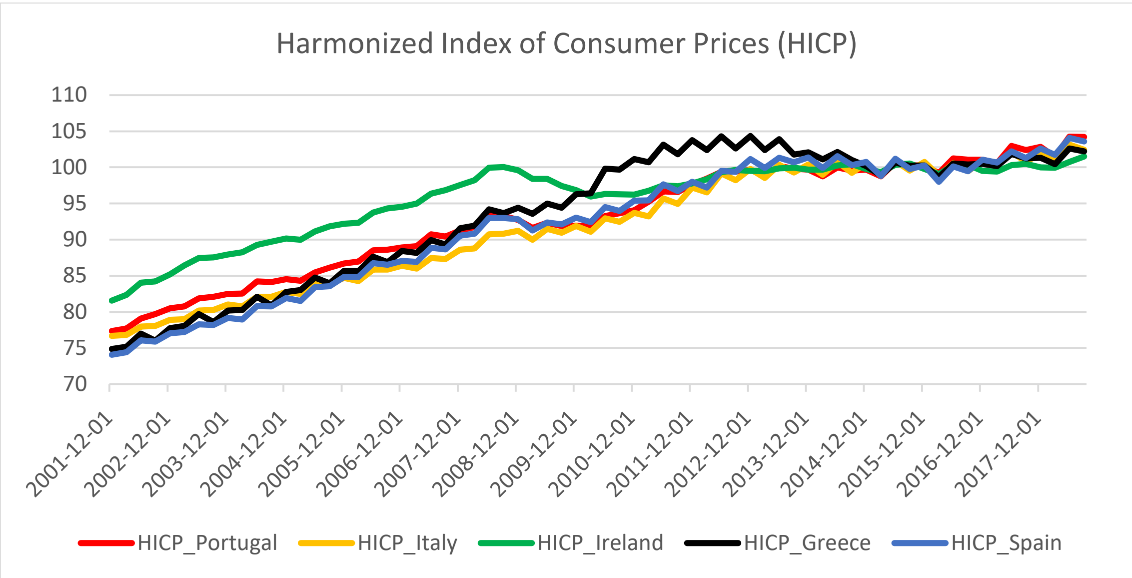
Figure (9) illustrates the development of the Harmonized Unemployment rate throughout the sample period. The highest level of Harmonized Unemployment rate registered in the 4th quarter of 2001 belongs to Greece; follow in order Spain, Italy, Portugal, and Ireland. The same "distribution" characterizes the 3rd quarter of 2018. However, the differences in rates present different magnitudes. Initially, the differences between the registered rates are not significantly high; notwithstanding, as time passes, a greater amplitude is visible. Also noticeable is the relatively similar path of the time series: all unemployment rates started to increase in 2007. From a pure macroeconomic point of view this confirms Okun's law, which implies in his "gap version" that for every 1% increase of the UN, the GDP will be roughly an additional 2% lower than its potential level (Prachowny, 1993).

Figure 9: Harmonized Unemployment rate – "PIIGS" countries



The development of the Harmonized Index of Consumer Prices is depicted in the following figure (10). By analyzing the plot, it emerges that Portugal, Italy, Greece, and Spain started more or less at the same level. Ireland is the only country which presents a significantly higher starting point. After the financial crisis, it is possible to observe a general deflationary trend. Greece represents the only exception since the time series seems to be only marginally affected by the financial crisis and presents an inflationary trend until 2012. In 2015, the index was reset to 100. The magnitudes of the differences in the indexes at the end of the sample period (Q3-2018) result to be lower if compared at the starting point. All indexes are in fact included in the range from 100 to 105.

Figure 10: Harmonized Index of Consumer Prices – "PIIGS" countries



4.3 Time series analysis

From a visual inspection of the plots representing the variables GDP, HICP and UN, it emerges that some time-dependent structure characterizes the time-series; some seasonality patterns, as well as an overall increasing trend of the variables GDP and HICP, are easily distinguishable.

The classification of the time series into non-stationarity and stationarity is crucial in order to perform a proper analysis; a stationary variable fluctuates around a constant mean, without trending or wandering; conversely, a non-stationary variable shows upward or downward trends, and perhaps can wander up and down. More precisely, a stationary variable must respect the so-called mean-reversion property, which implies:

- constant mean;
- constant variance;
- constant covariance.

Since one of the autoregressive model assumptions imposes that the variable under analysis must be stationary, the application of an integration approach is required in order to build an adequate and efficient model. The approaches which were used to transform the data into stationary can be summed up as the calculation of either:

- the change of the variable X from t-1 to t: $\Delta X_t = X_t - X_{t-1}$ or;
- the growth rate of the variable X from t-1 to t: $\Delta X_t / X_{t-1}$.

Initially, the growth rate of the variable GDP was computed in order to derive GDP growth. Secondly, where required, the first (or higher) order differentiation to the variables HICP, UN, and GDP growth was applied. Finally, the confirmatory evidence of the time series classification was done through the Augmented Dickey-Fuller test (ADF).

The ADF test represents a valid option to assess the presence of a unit root in the time series. This test is based on an autoregressive model, and it aims to optimize a specific information criterion concerning the multiple different lag values. The null hypothesis of the test states that the time series can be represented by a unit root (non-stationary), while the alternative hypothesis expresses that the time series is stationary.

The following table (2) represents an overview of the results obtained from the ADF test on the sub-sample "Portugal".

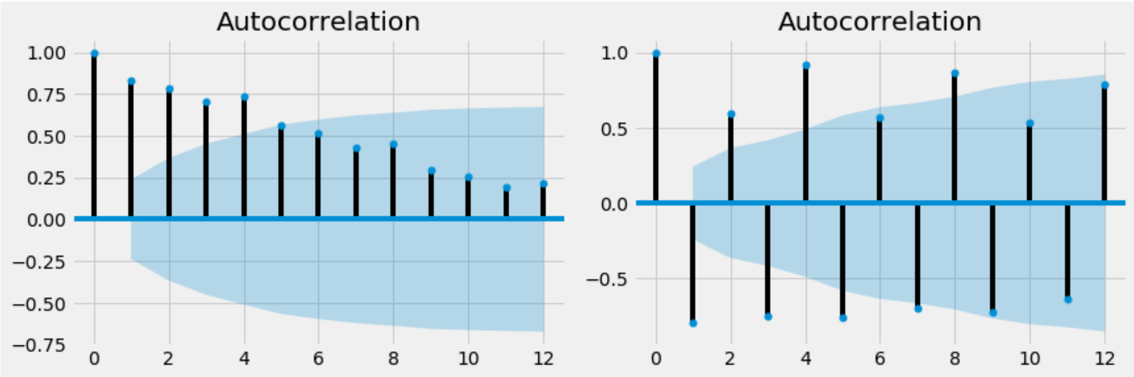
Table 2: ADF Test - Portugal

		Raw data	Growth rate	First-order Differencing	Second-order Differencing
Gross Domestic Product					
ADF Statistic		-0.99	-2.13	-33.24	n/a
P-value		0.76	0.23	**0.00**	n/a
Critical values:					
	1%	-3.54	-3.54	-3.54	n/a
	5%	-2.91	-2.91	-2.91	n/a
	10%	-2.59	-2.59	-2.59	n/a
Harmonized Index of Consumer Prices (HICP)					
ADF Statistic		-2.27	n/a	-2.38	-4.49
P-value		0.18	n/a	0.15	**0.00**
Critical values:					
	1%	-3.55	n/a	-3.55	-3.55
	5%	-2.92	n/a	-2.91	-2.91
	10%	-2.60	n/a	-2.59	-2.59
Harmonized Unemployment rate (UN)					
ADF Statistic		-1.58	n/a	-3.87	n/a
P-value		0.50	n/a	**0.00**	n/a
Critical values:					
	1%	-3.54	n/a	-3.53	n/a
	5%	-2.91	n/a	-2.91	n/a
	10%	-2.59	n/a	-2.59	n/a

Typically, if the GDP time-series is not strongly affected by fluctuations (e.g., by particular events), the simple computation of the growth rate should be enough in order to transform the time-series into stationary. Due to the significant effects which the financial crisis had on the GDP time series of Portugal, the p-value of the ADF test decreases only by 0.53, going from 0.76 to 0.23. As a result, the coefficient reported is too high if compared with the respective critical values. For this reason, it is necessary to compute the first order differentiation of the GDP growth to obtain a lower p-value which can ensure that the time series is stationary, even if this leads to a loss of two data points.

For a more precise analysis, it is also possible to visually compare the autocorrelation plots of the Portugal GDP time series. The left plot is constructed on the raw data (i.e., Nominal GDP), and respectively the right plot is based on the first-order differentiation of the GDP growth. The results are illustrated in figure (11) below.

Figure 11: Autocorrelation - GDP Portugal



It is possible to observe that all the autocorrelation coefficients are positive in the case of the raw data, indicating a non-stationary time series. While the right plot, which represents the first-order differentiation of the GDP growth, shows an alternation of positive and negative autocorrelation coefficients, indicating a stationary time series. In conclusion, both the ADF test and the autocorrelation coefficients confirm that the first-order differentiation of the GDP growth time series is stationary and can be used to build forecasting models.

Regarding the Harmonized Index of Consumer Prices time series, it is possible to observe that the results obtained confirm the failure of the ADF test since the p-value is above all alpha levels. By applying the first-order differentiation to the HICP time series, the ADF test statistic decreases by 0.11, bringing the p-value to a level of 0.15. However, to consider a time series stationary, the p-value must necessarily be less than or equal to 10%. Therefore, it is required to apply the second-order differentiation; in this way, the p-value decreases to a level of approximately 0%, which is why is it possible to affirm that the "second-order differentiation HICP" time series is stationary with a confidence level of 99%.

The ADF test statistic of the "Harmonized Unemployment rate raw" time series assumes a value which is too high considering the critical values. After the first-order differentiation, the value of the latter decreases to approximately 0, consequently it is possible to confirm that the time series is stationary with a confidence level of 99%.

The results obtained from the ADF test applied to the time series regarding Italy are represented in the following table (3).

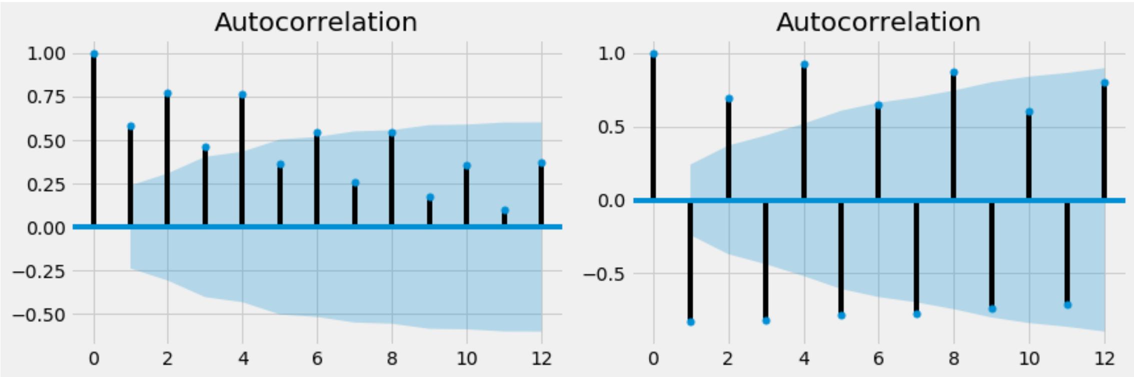
Table 3: ADF Test - Italy

		Raw data	Growth rate	First-order Differencing	Second-order Differencing
Gross Domestic Product					
ADF Statistic		-2.01	-2.75	n/a	n/a
P-value		0.28	**0.07**	n/a	n/a
Critical values:					
	1%	-3.54	-3.54	n/a	n/a
	5%	-2.91	-2.91	n/a	n/a
	10%	-2.59	-2.59	n/a	n/a
Harmonized Index of Consumer Prices (HICP)					
ADF Statistic		-1.73	n/a	-2.62	n/a
P-value		0.42	n/a	**0.09**	n/a
Critical values:					
	1%	-3.55	n/a	-3.55	n/a
	5%	-2.91	n/a	-2.91	n/a
	10%	-2.60	n/a	-2.60	n/a
Harmonized Unemployment rate (UN)					
ADF Statistic		-1.30	n/a	-2.95	n/a
P-value		0.63	n/a	**0.00**	n/a
Critical values:					
	1%	-3.54	n/a	-3.53	n/a
	5%	-2.91	n/a	-2.91	n/a
	10%	-2.59	n/a	-2.59	n/a

In this case, contrary to what happened in the GDP time series of Portugal, the only calculation of the growth rate of GDP is sufficient to state that, with a confidence level of 10%, the time series representing GDP growth is stationary. In fact, the ADF test statistic decreases from -2.01 (raw data) to -2.75 (growth rate), bringing the probability value to an acceptable level of 7%.

The trend of the autocorrelation coefficients represented in figure 12 reflects similar signs of progress to the ones recorded by Portugal; a negative path is easily identifiable in the case of the raw data (left plot of the figure).

Figure 12: Autocorrelation - GDP Italy



The decrease in the autocorrelation coefficients goes hand in hand with the increase in the number of lags. However, compared to Portugal, it is much easier to identify a peak every four lags. This should not be surprising considering how the autocorrelation coefficient is computed. According to Box & Jenkins (1976), the autocorrelation function can be defined as:

$$r_k = \frac{\sum_{i=1}^{N-k}(X_i - \bar{X})\,(X_{i+k} - \bar{X})}{\sum_{i=1}^{N}(X_i - \bar{X})^2}$$

Where,

k = lag operator;

X_i = series of data where i is an integer index.

Thus, it appears evident that since the time series is composed of quarterly data, the autocorrelation of every 4^{th} lag will result in a high positive coefficient. Since the time series representing the Portugal GDP is far from being considered stationary (p-value of 0.76), the autocorrelation coefficient of every 4^{th} lag will not be able to register an increase equal to what it could do in the case of a stationary process. The downward trend of the coefficient in the Portugal case is very smooth, while in Italy's case, it is much easier to identify every 4^{th} lag an increase in the autocorrelation coefficient since the starting time series (raw data) of Italy has a significant lower p-value compared to Portugal. However, after the application of the first order differentiation on the Portugal GDP growth, the autocorrelation plot appears almost identical to the one of the Italy GDP growth (right plot of the figure). In fact, as it should be, every 4^{th} lag the autocorrelation coefficient must assume a relatively high positive value. Furthermore, the presence of an alternation of positive and negative coefficients is required in order to define the time series stationary; therefore it is possible to affirm, with a confidence level of 10%, that Italy's GDP growth time series is stationary.

Both in the case of the HICP time series and in the case of the UN time series, the p-value resulting from the ADF test confirmed that it is not possible to consider the latter stationary. The ADF test statistic assumes in fact a value of -1.73 in the case of the HICP time series, respectively of -1.30 in the case of the UN time series, which suggests that is not possible to consider the two time series as stationary. On both time series is applied the first-order differentiation with the purpose of reducing the p-value. The p-value falls from 0.42 to 0.09 in the case of the HICP time series, respectively from 0.63 to approximately 0 in the case of the UN time series, which ensures that the two time series can be considered stationary when the first-order differentiation is applied.

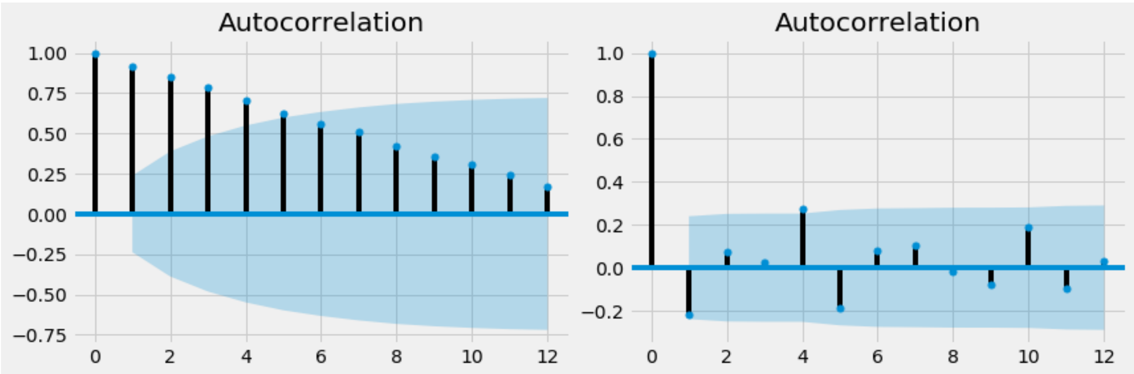
Table 4: ADF Test - Ireland

		Raw data	Growth rate	First-order Differencing	Second-order Differencing
Gross Domestic Product					
ADF Statistic		0.21	-9.94	n/a	n/a
P-value		0.97	**0.00**	n/a	n/a
Critical values:					
	1%	-3.54	-3.53	n/a	n/a
	5%	-2.91	-2.91	n/a	n/a
	10%	-2.59	-2.59	n/a	n/a
Harmonized Index of Consumer Prices (HICP)					
ADF Statistic		-2.02	n/a	-3.23	n/a
P-value		0.28	n/a	**0.02**	n/a
Critical values:					
	1%	-3.54	n/a	-3.54	n/a
	5%	-2.91	n/a	-2.91	n/a
	10%	-2.59	n/a	-2.59	n/a
Harmonized Unemployment rate (UN)					
ADF Statistic		-2.23	n/a	-1.61	-5.83
P-value		0.19	n/a	0.48	**0.00**
Critical values:					
	1%	-3.54	n/a	-3.54	-3.54
	5%	-2.91	n/a	-2.91	-2.91
	10%	-2.59	n/a	-2.59	-2.59

Table 4 allows, as in the previous cases, to have an overview of the results obtained from the ADF tests on the time series of Ireland.

As for Italy, the mere application of the growth rates on the GDP is sufficient to be able to consider the time series stationary since the p-value drops from 0.97 to approximately 0. Even if the ADF test confirms that with a confidence level of 1% the Ireland GDP growth time series is stationary, it might be important to pay attention to the distribution of the autocorrelation coefficients.

Figure 13: Autocorrelation - GDP Ireland



Given the very high p-value, the smooth decreasing trend of the autocorrelation coefficients should not be surprising. However, what attracts the attention is the non-regular alternation of positive and negative autocorrelation coefficients in the right plot of the figure representing the Ireland GDP growth time series.

Figure 14: GDP Comparison between Portugal and Ireland

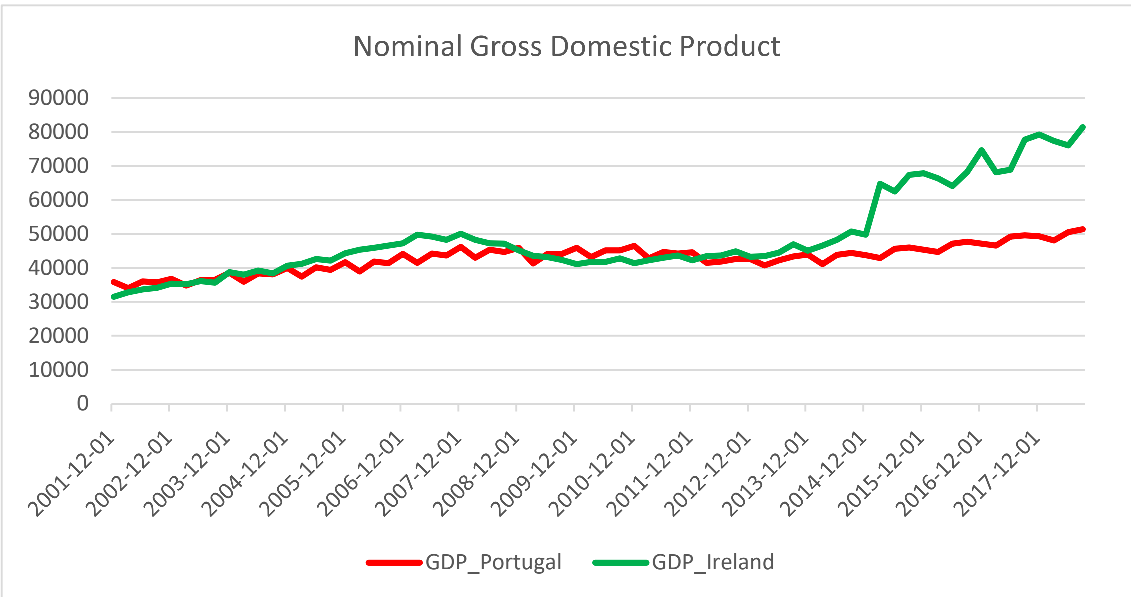


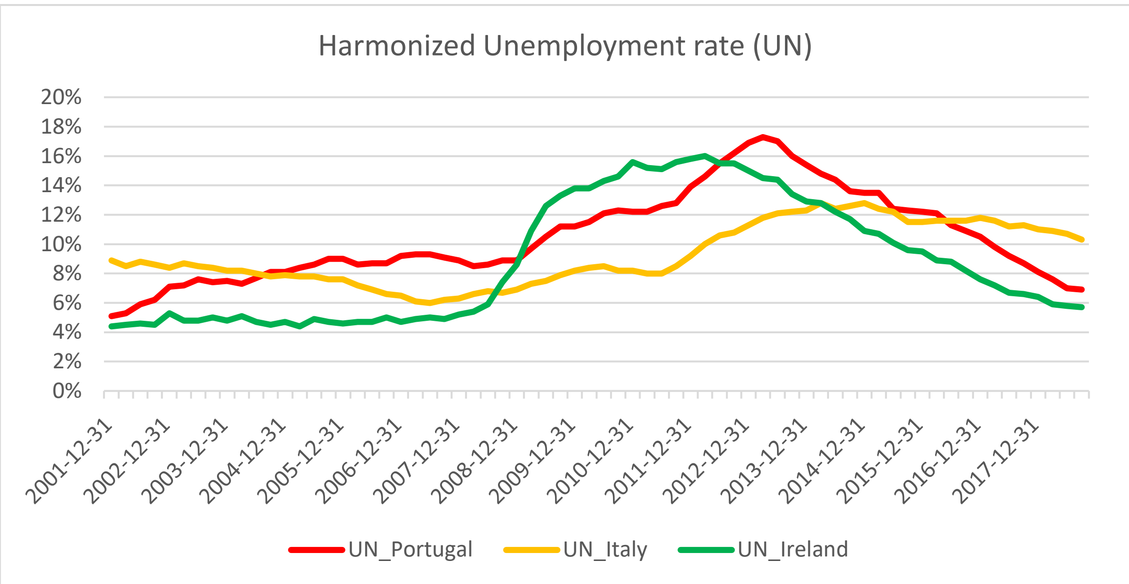
Figure (14) depicts the trend of the Nominal GDP of the countries Portugal and Ireland. From a visual inspection of the time series, it results that the financial crisis' impact on the Portugal GDP is less significant than in the Ireland case. Indeed, it is possible to observe that Portugal experiences more a slowdown rather than a real decrease. Portugal's time series results to be more smooth if compared to the one of Ireland. In fact, after the sharp reduction due to the financial crisis, Ireland's GDP increases again from 2011, reaching a steady growth rate in the period between 2014 and 2018.

Surely the thing that mostly catches the eye is a certain irregularity present in the time series; the "volatility" of Ireland's time series is much higher if compared to Portugal. The period between 2014 and 2018 is in fact characterized by sharp irregularities which are not present in the Portugal GDP time series. Please note that this might pose problems with regard to the calculation of the autocorrelation coefficients since such irregularities are automatically transmitted to the lagged version of the time series.

The Ireland HICP time series based on raw data has an ADF test statistic of -2.02, which translates into a p-value of 0.28. Considering the critical values, it is not possible to deliberate the original time series as stationary. For this reason, the first-order differentiation is applied to reach a p-value lower than 10%. With an ADF test statistic of -3.23, the HICP first-order differentiation time series can be considered as stationary with a confidence level of 5%.

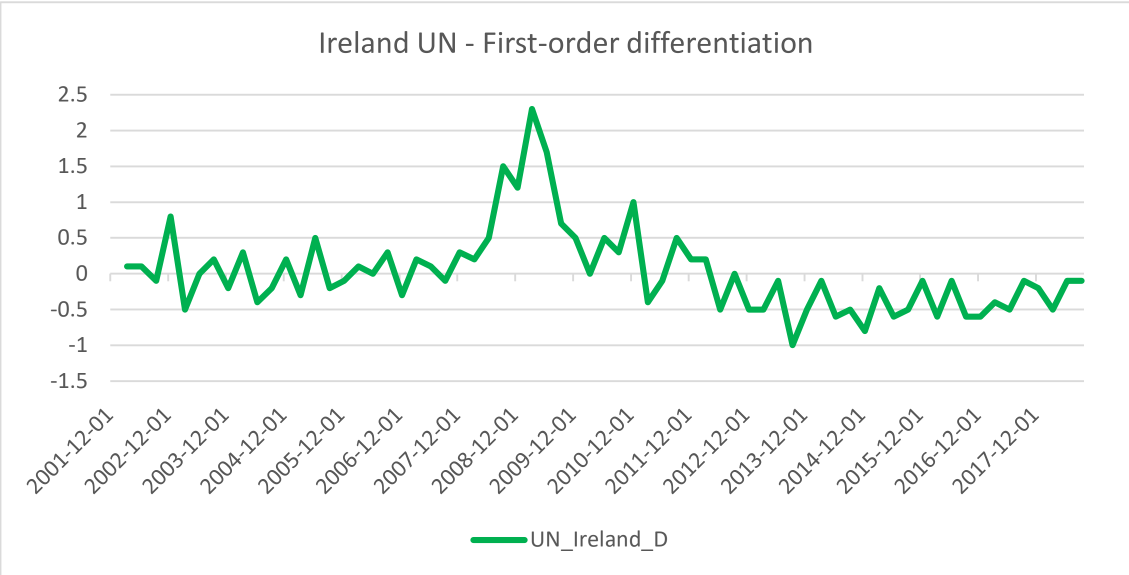
As regards the UN time series, it is possible to debate that the p-value is relatively low compared to the ones of Portugal and Italy.

Figure 15: UN Comparison between Portugal, Italy, and Ireland



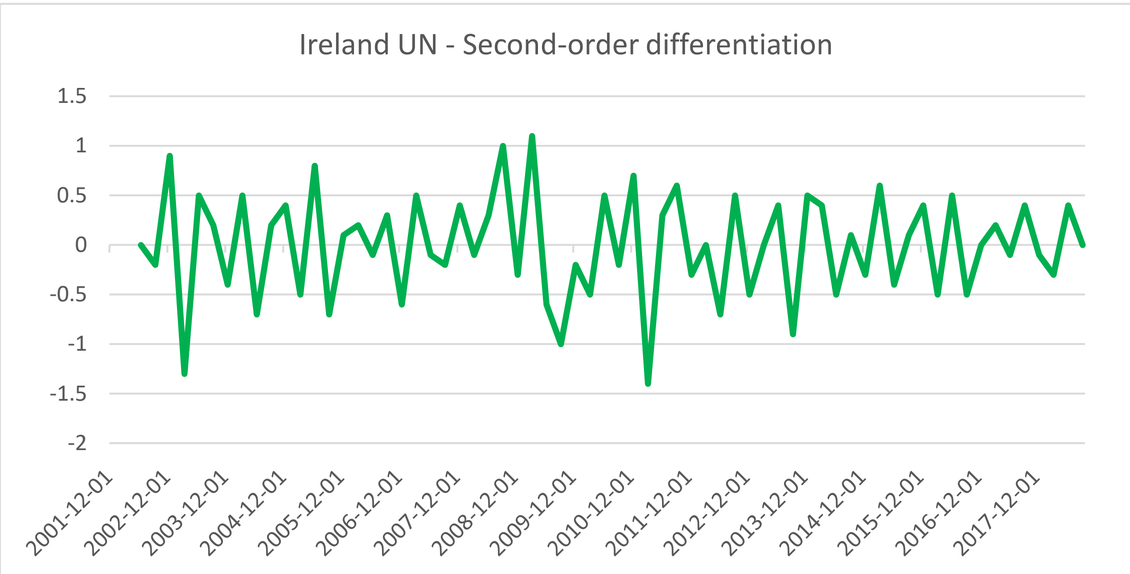
Since a stationary variable fluctuates around a constant mean, the greater the volatility of the time series, the higher the probability of obtaining a lower ADF test statistic. In fact, from a visual inspection of the figure (15), it results that the volatility of the UN time series based on raw data is higher compared to the other two countries, which might explain the lower p-value. However, the p-value of the Ireland first-order differentiation time series is higher compared to the p-value of the original time series. Due to the high volatility of the raw data and to the huge spike shown in the figure below, the first-order differentiation time series cannot be considered stationary.

Figure 16: Ireland UN – First-order differentiation



The following figure represents the Ireland UN second-order differentiation time series.

Figure 17: Ireland UN – Second-order differentiation



What emerges from the latter plot is that the second-order differentiation time series fluctuates around a constant mean, without trending or wandering. Moreover, the lower ADF statistic test confirms with a confidence level of 99% that the Ireland UN second-order differentiation time series is stationary.

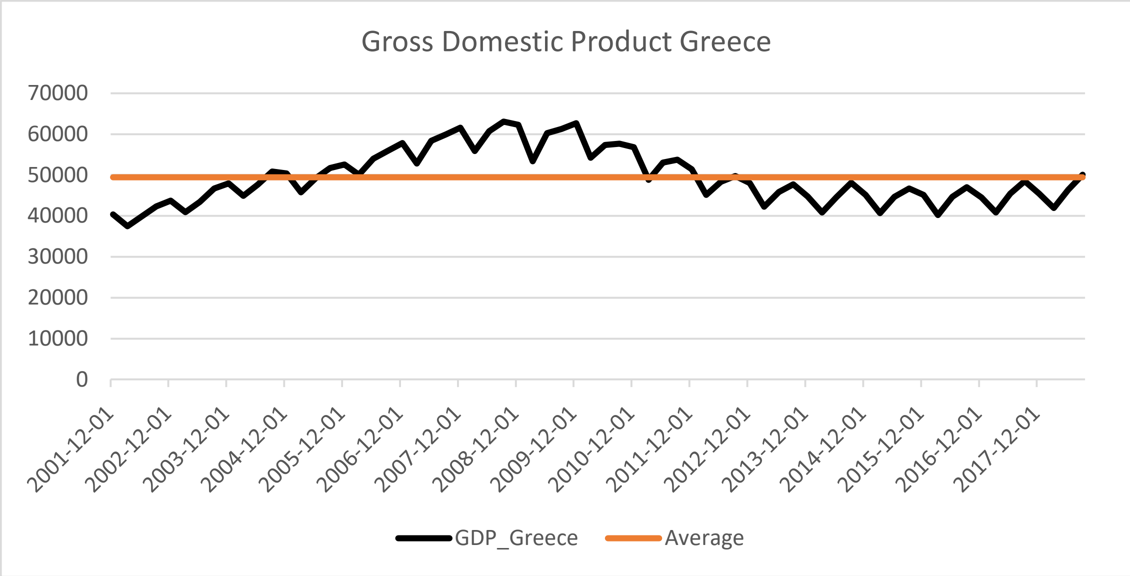
The following table (5) includes the results obtained from the ADF test for the GDP, HICP, and UN time series of Greece.

Table 5: ADF Test - Greece

		Raw data	Growth rate	First-order Differencing	Second-order Differencing
Gross Domestic Product					
ADF Statistic		-2.96	-1.86	-2.44	-7.77
P-value		**0.04**	0.35	0.13	**0.00**
Critical values:					
	1%	-3.55	-3.55	-3.55	-3.55
	5%	-2.91	-2.91	-2.91	-2.91
	10%	-2.59	-2.60	-2.60	-2.60
Harmonized Index of Consumer Prices (HICP)					
ADF Statistic		-1.82	n/a	-1.65	-14.75
P-value		0.37	n/a	0.45	**0.00**
Critical values:					
	1%	-3.54	n/a	-3.54	-3.54
	5%	-2.91	n/a	-2.91	-2.91
	10%	-2.59	n/a	-2.59	-2.59
Harmonized Unemployment rate (UN)					
ADF Statistic		-2.40	n/a	-1.26	-8.02
P-value		0.14	n/a	0.65	**0.00**
Critical values:					
	1%	-3.54	n/a	-3.54	-3.54
	5%	-2.91	n/a	-2.91	-2.91
	10%	-2.59	n/a	-2.59	-2.59

If it is taken under consideration the GDP time series, the first thing that attracts attention is the considerable negative value of the ADF statistic test. The p-value of time series based on raw data is 0.04, which involves that the GDP time series based on raw data is stationarity. However, it could be interesting to visualize the time series in a plot.

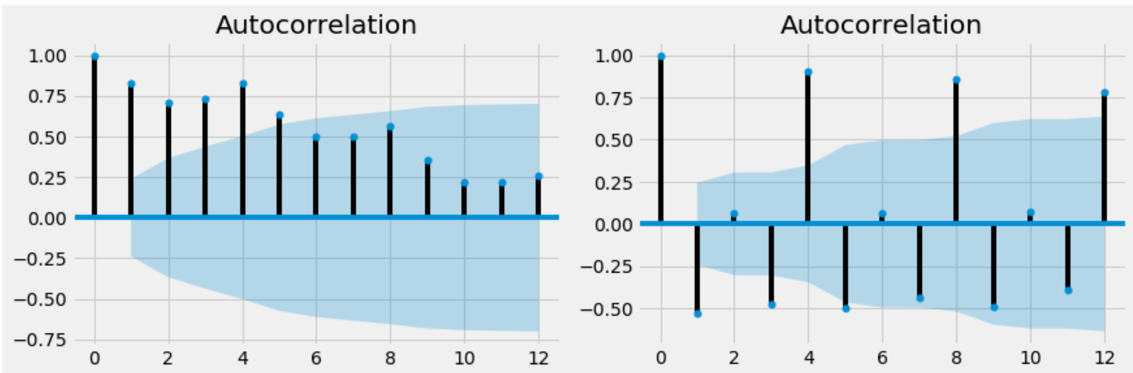
Figure 18: Gross Domestic Product - Greece



In the above figure (18) is it possible to observe that the time series fluctuates around a constant mean. In common practice, the GDP time series are considered non-stationary since they usually reflect an expansionistic trend. However, due to the financial crisis effects, the GDP growth of Greece slows down immediately after the crisis. Indeed, the time series suggests a stagnation phase in the period between 2012 and 2018, where no trend can be easily identified.

However, considering that the purpose of the thesis is to provide forecasts with regard to macroeconomic variables, the sole consideration of the results of the ADF test might provide misleading information with regard to the characteristics of the time series. In fact, if the autocorrelation coefficients presented in the figure below are taken into consideration, it is possible to observe a smooth negative trend of the coefficients.

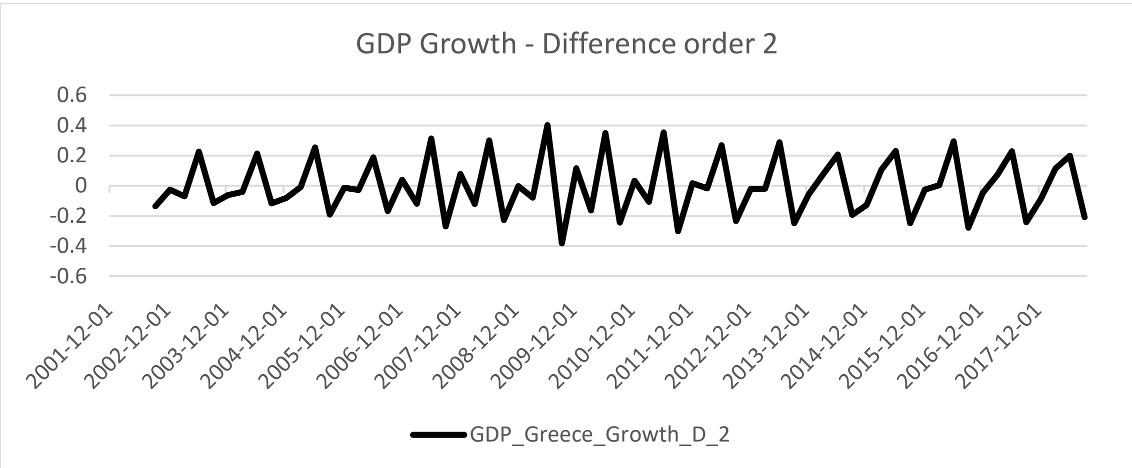
Figure 19: Autocorrelation - GDP Greece



For forecasting purposes, a similar distribution of the autocorrelation coefficients might pose problems in the modeling phase. For this reason, it is necessary to compute first the growth rate of the GDP and afterward, considering the high p-value obtained from the ADF test, apply the first-order differentiation. Unfortunately, the results of the ADF test do not allow to consider the first-order differentiation of the GDP growth time series as stationary since the ADF statistic test is still too high and generates a p-value of 0.13. As a consequence, the second-order differentiation must be applied.

The second-order differentiation of the GDP growth time series presents an ADF statistic test of -7.77 and a p-value of approximately 0, meaning that the series can be considered stationary with a confidence level of 99%. Nevertheless, the autocorrelation coefficients represented in the right plot of the previous figure (19) alternate with positive and negative values. However, relatively low levels of the coefficients in the lags two, six, and ten are reported; from a strictly forecasting point of view, this should not cause concerns considering that the time series includes quarterly data. In fact, the analysis of the quarterly GDP implies the use of four growth rate means (quarters 1 to 4), which as a consequence leads to obtain a larger 4^{th} quarter mean growth rate. Moreover, from a visual inspection of the following figure (20) representing the second-order differentiation of the GDP growth time series, it appears evident that the time series can be considered stationary.

Figure 20: Greece GDP Growth – Second-order differentiation



Both HICP and UN time series required a second-order differentiation in order to be considered stationary. The ADF statistic test of -14.75 for the HICP time series, respectively -8.02 for the UN time series, guarantees a p-value of approximately 0 in both cases. Hence, the time series are stationary with a confidence level of 99%.

The next table (6) shows the results of the ADF test for the Spanish time series.

Table 6: ADF Test - Spain

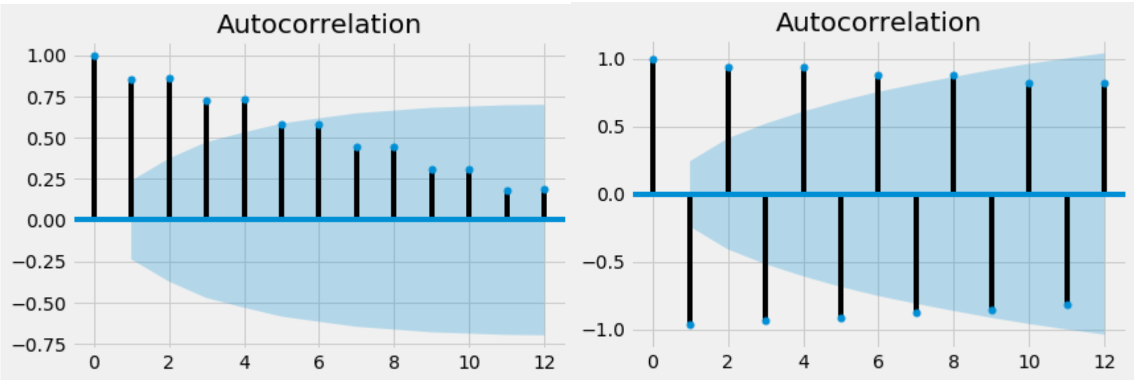
		Raw data	Growth rate	First-order Differencing	Second-order Differencing
			Gross Domestic Product		
ADF Statistic		-1.72	-1.85	-5.23	n/a
P-value		0.42	0.36	**0.00**	n/a
Critical values:					
	1%	-3.55	-3.54	-3.54	n/a
	5%	-2.91	-2.91	-2.91	n/a
	10%	-2.59	-2.59	-2.59	n/a
			Harmonized Index of Consumer Prices (HICP)		
ADF Statistic		-1.89	n/a	-3.08	n/a
P-value		0.34	n/a	**0.03**	n/a
Critical values:					
	1%	-3.54	n/a	-3.54	n/a
	5%	-2.91	n/a	-2.91	n/a
	10%	-2.59	n/a	-2.59	n/a
			Harmonized Unemployment rate (UN)		
ADF Statistic		-1.66	n/a	-1.92	-7.06
P-value		0.45	n/a	0.32	**0.00**
Critical values:					
	1%	-3.54	n/a	-3.54	-3.54
	5%	-2.91	n/a	-2.91	-2.91
	10%	-2.59	n/a	-2.59	-2.59

In this case, no particular anomalies are observed. The raw data GDP time series has an initial ADF statistic test of -1.72 with a p-value of 0.42. Considering the critical values, it is not possible to confirm that the time series is stationary. After the calculation of the growth rate, the ADF statistic test slightly decreases; however, the resulting change is not sufficient considering that the p-value decreases only by 0.06.

The first-order differentiation GDP time series has an ADF statistic test of -5.23; sufficient to determine a p-value of approximately 0. Therefore, it is possible to affirm, with a confidence level of 99%, that the time series can be considered stationary.

The analysis of the autocorrelation coefficients confirms what affirmed previously. The sinister plot of the following figure (21) represents the trend of the autocorrelation coefficients of the original time series based on raw data. It is possible to observe a smooth decreasing trend indicating clearly that the time series is non-stationary. The right plot, however, confirms that the GDP first-order differentiation time series has an alternation of positive and negative autocorrelation coefficients, which suggests the presence of a stationary process.

Figure 21: Autocorrelation - GDP Spain



As far as it concerns the other two time series, for the HICP time series, is sufficient the simple application of the first-order differentiation to lower the p-value from 0.34 to 0.03, while for the UN time series is required a second calculation since the first-order differentiation time series presents an ADF statistic test of -1.92. The HICP first-order differentiation time series can be considered stationary with a confidence level of 95%, whereas the UN second-order time series can be considered stationary with a confidence level of 99%.

Since the dataset was divided with the scope of differentiating the period before and after the crisis, the time series analysis was replicated for both periods running from

- Q4-2001 to Q4-2007 and,
- Q1-2008 to Q3-2018.

The results obtained ensure that the time series employed in the modeling phase are stationary.

5 Empirical analysis

This chapter provides an overview of the methodology, and it outlines the results obtained from the empirical analysis. Subsequently, it offers a critical assessment of the limitations and finally suggests possible improvements.

In the first sub-chapter, a preliminary insight with regard to the different statistical methods employed is stated. More precisely, the application methodology of the vector autoregressive model, autoregressive model, and seasonal autoregressive integrated moving average model to the GDP growth time series is explained. After the presentation of the models, the well-known Box-Jenkins' methodology is provided. This methodology suggests the correct procedure which has to be applied in the case of an empirical analysis which aims to provide accurate time series forecasting with ARIMA models. Following this methodology, further elucidations regarding the application of this specific procedure are provided.

The second sub-chapter offers a general overview of the empirical analysis' results. Firstly, both vector autoregressive and autoregressive models results are illustrated and compared to each other. Secondly, after explaining the reasons for which the development of the last two models was stopped, the diagnostic of the results obtained from the ARIMA models is explained. The core part of the sub-chapter is therefore focused on the forecasting results obtained from the autoregressive integrated moving average model. The last part concerns the validation of the forecasts, the production, and respectively, the visualization of the forecasts.

The last sub-chapter offers further explanations with regard to the limitations of the applied methodology. Since the final scope of the thesis is to provide accurate forecasts, one of the most important factors to consider is the causal impact that the financial crisis has exerted on the GDP. With this regard, possible improvements which can be applied to the methodology used in this thesis are provided.

5.1 Methodology

The primary method employed in the time series forecasting of this thesis is the autoregressive integrated moving average model. However, before proceeding with the fitment of the ARIMA model to the time series data, it was opted to verify the effectiveness of other models considered as "appropriate" methods to forecast macroeconomic variable such as GDP growth.

After the due attention dedicated to the problems inherent the presence of unit roots in the analyzed time series (see sub-chapter 4.3), the model proposed by Andersson (2007) was replicated following this vector autoregression model definition:

$$GDP_t = \alpha + \beta_1 GDP_{t-1} + \beta_2 GDP_{t-2} + \cdots + \beta_j GDP_{t-j} + \gamma_1 HICP_{t-1} + \gamma_2 HICP_{t-2} + \cdots + \gamma_j HICP_{t-j} + \delta_1 UN_{t-1} + \delta_2 UN_{t-2} + \cdots + \delta_j UN_{t-j} + \varepsilon_t$$

Which implies that:

$$GDP_t = \alpha + \sum\nolimits_{j=1}^{k} \beta_j GDP_{t-j} + \sum\nolimits_{j=1}^{k} \gamma_j HICP_{t-j} + \sum\nolimits_{j=1}^{k} \delta_j UN_{t-j} + \varepsilon_t$$

Where GDP at time t represents the GDP growth and depends, as also Marcellino et al. (2006) have suggested, on past values of GDP growth, Harmonized Index of Consumer Prices (HICP), and Harmonized Index of Consumer Prices (HICP).

A second method analyzed is the purest form of the autoregressive integrated moving average model. This choice is dictated by the fact that the autoregressive model turns out to be essential to understand the feasibility of a more advanced approach such as the ARIMA model. With this regard, it was decided to create an autoregressive model with order 4 with the scope of verifying both the statistical significance of the explanatory variables and the feasibility of the ARIMA model. In this case, the order four was chosen arbitrarily, and no order-optimization method was applied since in most of the cases the lag variables following the 4^{th} lag were not statistically significant. Therefore, the autoregressive model used can be represented mathematically by the following equation:

$$GDP_t = c + \sum_{i=1}^{4} \varphi_i \, GDP_{t-i} + \varepsilon_t$$

Where GDP at time t represents the GDP growth and depends on the past value of GDP growth.

Please note that both vector autoregression model and autoregression model were not further developed since their performance resulted to be lower in comparison to the forecasting performance which can be achieved with an ARIMA model. As Marcellino et al. (2006) suggested, the key procedure, which guarantees the perfect fit of the ARIMA models, is the iterative process regarding the identification of the parameters. The regression outputs of the two models are presented in appendix 1.

The autoregressive moving average model employed to fit the different time series can be generalized as follows:

$$GDP_t = \varphi_o + \varphi_1 GDP_{t-1} + \varphi_2 GDP_{t-2} + \cdots + \varphi_p GDP_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t$$

The first autoregressive part can be summarized as an autoregressive model:

$$GDP_t = c + \sum_{i=1}^{p} \varphi_i \, GDP_{t-i} + \varepsilon_t$$

While the second moving average part can be denoted as a moving-average model:

$$GDP_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \, \varepsilon_{t-i}$$

Which implies that the complete ARMA model can mathematically be express, in his final version, as a combination of the two models:

$$GDP_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i \, GDP_{t-i} + \sum_{i=1}^{q} \theta_i \, \varepsilon_{t-i}$$

Where,

c = constant;

ε_t= white noise;

$\varphi_1, \ldots, \varphi_i$ = parameters of the autoregressive model;

$\theta_1, \ldots, \theta_i$ = parameters of the moving average model model.

However, considering the seasonal time series and the required integration, the model which was optimized is the so-called SARIMA model. The parameters are the same as the ones illustrated in the "Forecasting Theory" sub-chapter. Hence, according to Durbin & Koopman (2012), the univariate structural model can be represented as

$$\emptyset_p(L)\widetilde{\emptyset_p}(L^s)\Delta^d \Delta_s^D GDP_t = A(t) + \theta_q(L)\tilde{\theta}_Q(L^s)\varepsilon_t$$

Where,

$\emptyset_p(L)\widetilde{\emptyset_p}(L^s) \equiv$ reduced form lag polynomials;

$\theta_q(L)\tilde{\theta}_Q(L^s) \equiv$ reduced form lag polynomials;

$A(t)$ = unobserved series of state vectors.

The methods employed in the empirical analysis follow the well-known Box-Jenkins' methodology, which can be summarized into the following phases (Pankratz, 2009):

1. Confirmation of the Stationarity of the time series;
2. Identification of the parameters of the SARIMA model;
3. Estimation of the model;
4. Diagnostic checking;
5. Validation of the forecasts;
6. Production and visualization of the forecasts.

The stationarity was tested through the analysis of the autocorrelation function and the Augmented Dickey-Fuller test. The first phase was presented in the sub-chapter 4.3 "Time series analysis".

The parameters of a seasonal autoregressive integrated moving average model $(p,d,q)(P,D,Q)_m$ have to be optimized with the scope of achieving the best possible fit. The identification of the parameters was made through a process which optimizes a specific metric of interest. With this regard, it was opted to use the AIC criterion, since it allows to approximate the SARIMA model towards reality. The parameter selection was organized through a process known as "grid search," which iteratively explores the different combinations of parameters. The concept which stays behind this process is also known in machine learning as hyperparameter optimization, and it consists of four specific phases:

1. Definition of the parameters (p,d,q);
2. Generation of all the different possible combination of (p,d,q) triplets;
3. Definition of the parameters (P,D,Q);
4. Generation of all the different possible combinations of seasonal (P,D,Q) triplets.

Once all the triplets were defined, it is possible to automate the process through the iteration of all the seasonal autoregressive integrated moving average models based on all the different triplets of parameters generated. All the generated AIC criterions can now be evaluated and compared to each other. In this case, the model which yields the lowest AIC value is the one that fits the data as best as possible; considering also the overall complexity of the model.

The estimation of the model was made through a nonlinear iterative process which follows the maximum likelihood estimation as a technique. The regression coefficients are treated as additional parameters to be estimated via maximum likelihood.

The diagnostic checking was assessed in order to verify if the residuals of the model are uncorrelated and normal distributed with zero mean. In this case, the relevant plots analyzed are the following:

- Standardized residual plot;
- Histogram plus estimated density plot;
- Normal Q-Q plot;
- Correlogram plot.

The validation of the forecasts was performed through a cross-validation approach. As illustrated in the sub-chapter 2.2 “Forecasting Theory”, the dataset has to be divided into training-sample and test-sample. In this case, since the scope of the thesis is to predict the development of the GDP growth in the after-crisis period (Q1-2008 to Q3-2018), it was opted to split the pre-crisis period (Q4-2001 to Q4-2007) into two parts. The first one represents the training-sample and includes the quarter data from Q4-2001 to Q4-2003. The second one is considered as test-sample, and it includes the data from Q1-2004 to Q4-2007. The subdivision of the dataset was chosen according to an arbitrary criterion following a conservative approach. Both dynamic and static forecasting approaches were used to validate the models.

The final production of the forecasts is based on the pre-crisis data frame (Q4-2001 to Q4-2007) following the dynamic forecasting approach. The resulting forecasts are finally confronted with the observed GDP (after crisis data frame) with the scope of quantifying the impact which the financial crisis has had on the Gross Domestic Product of the so-called “PIIGS” countries.

5.2 Results analysis

The purpose of the empirical analysis is to provide an accurate time series forecasting of the GDP growth of those countries worst hit by the crisis (Portugal, Italy, Ireland, Greece, and Spain). According to the methodology, the primary method employed in the time series forecasting of this thesis is the autoregressive integrated moving average model. However, before proceeding with the visualization of the results obtained from the ARIMA model, it might result interesting to verify the effectiveness of the other two models considered as "appropriate" methods to forecast macroeconomic variables. The regression outputs of the vector autoregressive and the autoregressive model are therefore presented in appendix 1.

As it is possible to observe from appendix 1, all the OLS regression results regarding the vector autoregressive models present a higher coefficient of determination (R-squared between 0.905 and 0.983). The only exception is represented by Ireland's model, which only reached an R-squared of 0.296. The relatively low level of the coefficient of determination can be in part attributed to what illustrated in sub-chapter 4.3 "Time series analysis". In fact, the "volatility" of Ireland's time series is much higher if compared with the one of the other countries. This might pose some problems with regard to the calculation of the autocorrelation coefficients since such irregularities are automatically transmitted to the lagged version of the time series. If only the R-squared is taken under consideration, the vector autoregressive model can represent a valid option. However, from a pure statistical point of view, the R-squared only provides a measure of how well the observed outcomes are replicated by the model since it represents the proportion of the variance in the dependent variable (GDP growth) that can be explained from the independent variables (GDP growth lags, HICP, and UN). If the OLS regression results are further explored, it emerges that by using so many variables, the degrees of freedom result to be too high. This might pose some problems with relatively short data samples. Moreover, the statistical significance of the independent variables in most of the cases cannot be guaranteed for the explanatory variables HICP and UN. Please note that the major component of the vector autoregressive model remains the autoregressive part. Additionally, the standardized regression coefficients of the lag variables HICP and UN are relatively low. Which indicates that, even if the explanatory variable might be considered statistically significant, the explanatory variable in question would have a low effect on the dependent variable. By following the forecasting theory and the previous research illustrated in the previous chapters, it appears clear that the autoregressive models can capture all the statistical properties of the underlying relationships embedded in the process in any way. Therefore, in order to avoid the so-called "Freedman's paradox", it was opted to not further develop the vector autoregressive model and, consequently, not to base the forecasts on such a model considering that the more the number of independent variables increases, the more the likelihood of overfitting increases.

The autoregressive models were used as a starting point on which to base the more advanced autoregressive integrated moving average methods. As it is possible to observe from appendix 1, the autoregressive models' performance can be considered acceptable. The difference of the determination coefficients between the vector autoregressive models and the "pure" autoregressive models is minimal. Moreover, most of the explanatory variables result to be statistically significant. Even more important is the fact that all the 4^{th} lag explanatory variables can be considered statistically significant and have high standardized regression coefficients, which indicate a strong relationship with the dependent variable. In fact, as also explained previously in sub-chapter 4.3 "Time series analysis", the use of four growth rate means implies that the 4^{th} quarter mean growth rate will have a more significant impact.

In conclusion, the vector autoregression and the autoregression models were not further developed because of their relatively weak performance compared to the one that can be obtained via an autoregressive integrated moving average model.

In order to produce reliable forecasts, the seasonal autoregressive integrated moving average model was used to fit the time series containing the GDP growth rates. As explained in the methodology, the hyperparameter optimization approach was used. The deriving parameters are the following:

- Portugal: ARIMA $(0,0,0)x(1,0,0)_4$;
- Italy: ARIMA $(0,0,1)x(1,0,0)_4$;
- Ireland: ARIMA $(1,0,0)x(1,0,0)_4$;
- Greece: ARIMA $(0,0,0)x(1,0,0)_4$;
- Spain: ARIMA $(0,0,0)x(1,0,0)_4$.

The statespace model results of Portugal's ARIMA model are portrayed in the following figure (22):

Figure 22: Portugal – Statespace Model Results

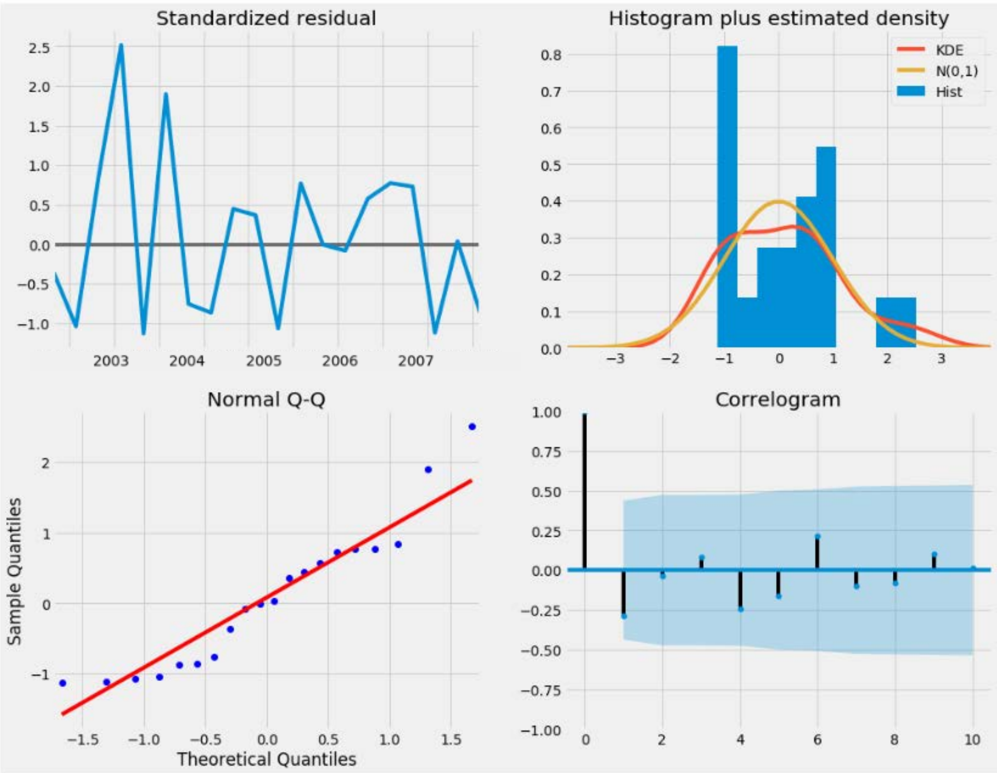
	coef	std err	z	P>|z|	[0.025	0.975]
ar.S.L4	1.0195	0.062	16.552	0.000	0.899	1.140
sigma2	0.0001	4.25e-05	2.853	0.004	3.8e-05	0.000

Ljung-Box (Q):	16.03	Jarque-Bera (JB):	1.47
Prob(Q):	0.66	Prob(JB):	0.48
Heteroskedasticity (H):	0.25	Skew:	0.66
Prob(H) (two-sided):	0.09	Kurtosis:	2.88

The model is based on the pre-crisis data frame, and therefore, it includes 25 observations. The algorithm used automatically decides whether or not to transform the AR parameters to enforce stationarity in the autoregressive component of the model. Moreover, it decides if it is necessary to transform the MA parameters by enforcing the invertibility in the moving average component of the model. In this case, both coefficients result to be statistically significant at a 99% confidence level. Moreover, it is possible to observe that the first coefficient has a significant impact on the dependent variable.

The following figure (23) represents the model diagnostics of Portugal's ARIMA model:

Figure 23: Portugal – ARIMA Diagnostics



As illustrated in sub-chapter 2.2 "Forecasting Theory", the primary concern is to ensure that the residuals of the autoregressive integrated moving average model are normally distributed and uncorrelated. From a visual inspection of the diagnostics, it emerges that the residuals do not display evident seasonality, and apparently they can be considered as white noise. The "Correlogram plot" displays a relatively low correlation of the time series residuals with the lagged version (in general less than ± 0.25). The relation between the theoretical quantiles and sample quantiles shows that the ordered distribution of the residuals follows a positive linear trend taken from a "fictitious" sample created from a standard normal distribution $N(0,1)$. Since the "Histogram plus estimated density plot" confirms that residuals follow a normal distribution, it is possible to conclude that the model produces a satisfactory fit.

The penultimate step of the Box-Jenkins' methodology suggests that before proceeding with the production and visualization of the forecasts, it is essential to first validate the model. The validation implies the comparison of the predicted values with the observed values of the complete time series. As illustrated in sub-chapter 5.1 "Methodology", the backtesting was executed by using the training-sample data to predict future forecasts. The predicted values are subsequently compared with the data contained in the test-sample.

The following figure (24) represents the results obtained from the static approach based on the one-step-ahead forecasts:

Figure 24: Portugal – Static approach

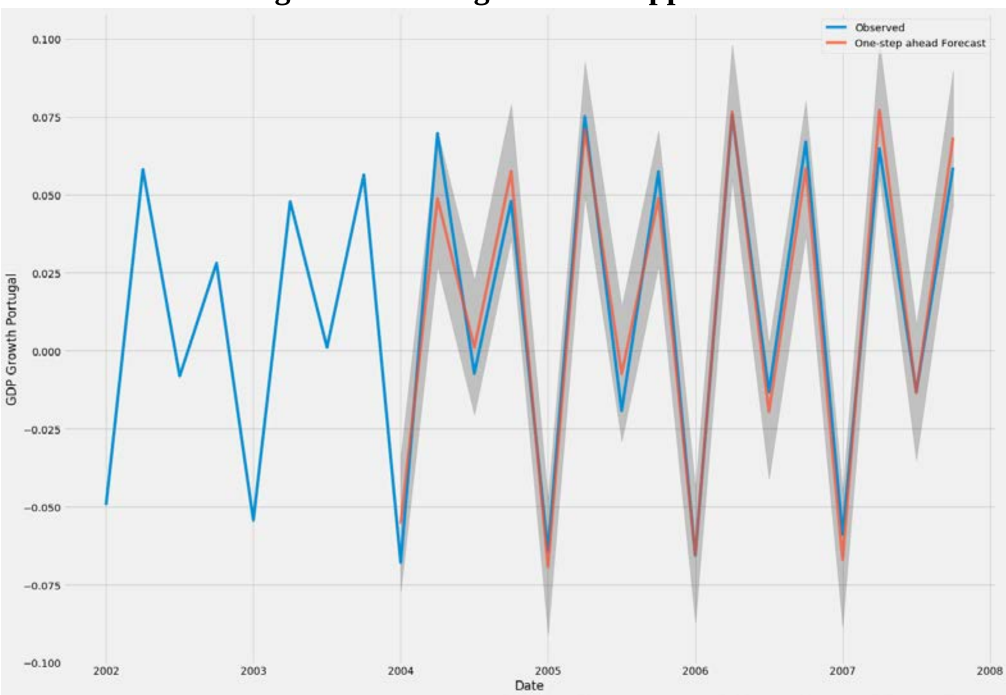
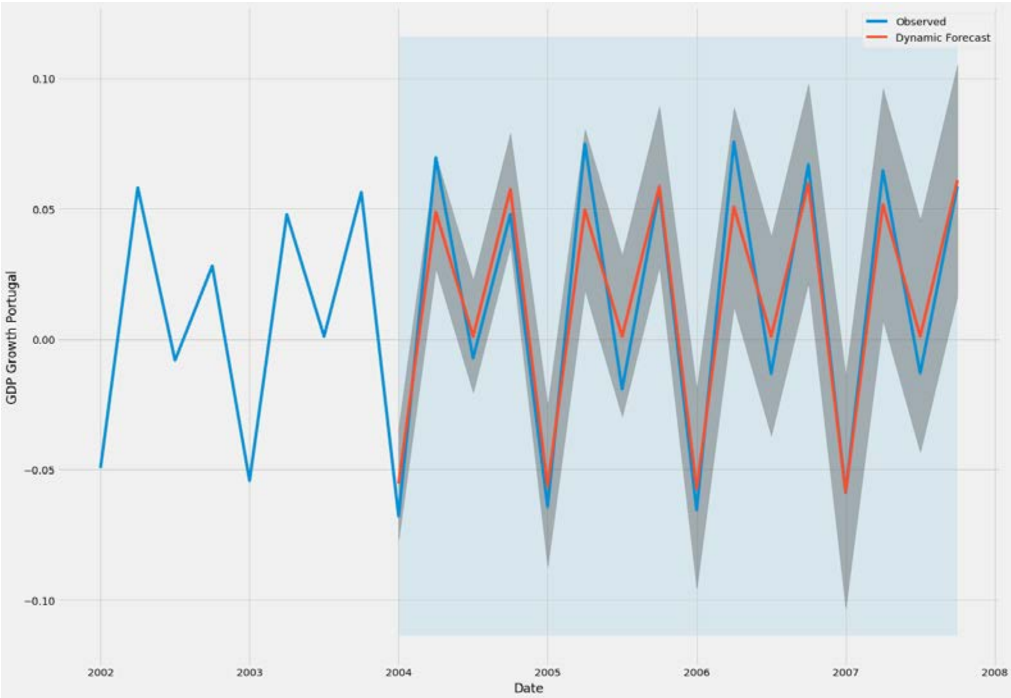


Figure (24) indicates that the one-step-ahead forecasts follow faithfully the observed data in the test sample indicating, therefore, a good forecasting accuracy of the model. In fact, the static approach yields a Mean Squared Error (MSE) of 0.037.

The true predictive power of the model can be obtained using a dynamic approach where the forecasts are generated using values from the previous forecasted time points. The following figure (25) represents the visualization of the dynamic forecasts:

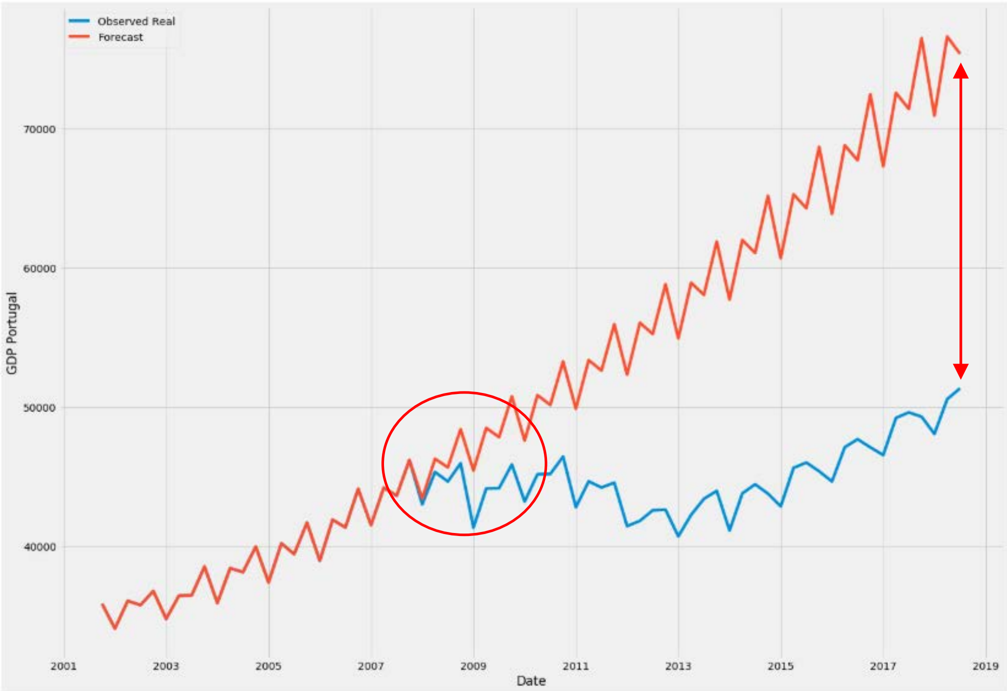
Figure 25: Portugal – Dynamic approach



As for the static approach, it is possible to observe from the figure (25) that the dynamic forecasts follow the observed data faithfully. However, in comparison to the one-step-ahead approach, it is possible to detect small differences between the two paths. The dynamic forecasts are well within the confidence intervals of the forecast. In fact, the width of the latter increases as time passes, indicating that the reliability of the model decreases when the dynamic forecasts “move away” from the last observed data time point. The further away in the time the forecasts are executed, the less the model’s ability to produce accurate forecasts will be. In conclusion, the dynamic approach yields an MSE of 0.19, which turns out to be after all reasonably low, considering also that the dynamic approach relies on less historical data compared to the static approach. Both static and dynamic approaches confirm a certain degree of internal validity of the model.

Once the back-testing confirmed the validity of the model, it is finally possible to produce and visualize the forecasts. With this regard, the following figure (26) depicts the forecasts in relation to the observed GDP in the years succeeding the financial crisis.

Figure 26: Portugal – GDP forecast



Due to the expansionistic period preceding the financial crisis, the forecasts were influenced by this positive trend. In fact, it is possible to observe a smooth increasing of the GDP forecasts. The blue line represents the observed GDP in the after-crisis period and shows clearly the impact that the financial crisis has had on the development of the GDP. In this case, the difference between the forecasted GDP and observed GDP can be partially considered as the impact of the financial crisis.

As illustrated for the figure (25), the forecasting error increases over time since the confidence intervals widen when the dynamic forecast approach is used. For this reason, it is not possible to affirm with certainty that the difference between the two lines represents exclusively the impact that the financial crisis has had. Most likely, the difference detected in the proximate steps of the financial crisis (i.e., red oval) can be attributed with a certain degree of confidence as the impact of the financial crisis. Conversely, as time passes, the degree of confidence decreases, whereby the difference observed in 2018 (i.e., red double arrow) cannot be entirely attributed to the financial crisis.

The following figure (27) represents the statespace model results of the dependent variable Italy GDP growth:

Figure 27: Italy – Statespace Model Results

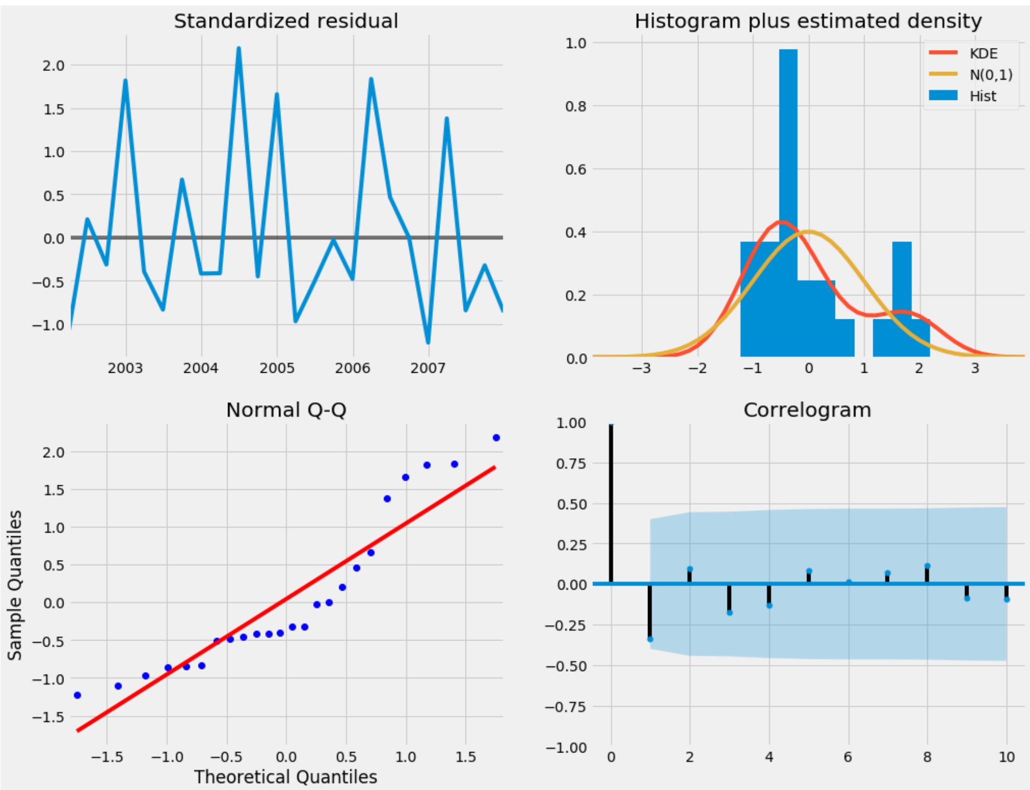
	coef	std err	z	P>|z|	[0.025	0.975]
ma.L1	-0.7588	0.222	-3.412	0.001	-1.195	-0.323
ar.S.L4	0.9928	0.009	104.607	0.000	0.974	1.011
sigma2	7.02e-05	2.77e-05	2.537	0.011	1.6e-05	0.000

Ljung-Box (Q):	17.20	Jarque-Bera (JB):	3.24
Prob(Q):	0.80	Prob(JB):	0.20
Heteroskedasticity (H):	1.39	Skew:	0.86
Prob(H) (two-sided):	0.65	Kurtosis:	2.47

The results demonstrate that all the different variables are statistically significant. Furthermore, the variable inherent the moving average component of the model has a negative coefficient of -0.7588, while the autoregressive variable yields a positive coefficient of 0.9928, indicating that both explanatory variables influence the dependent variable quite markedly.

The diagnostic of the Italian ARIMA *(0,0,1)x(1,0,0)$_4$* model is presented in the following figure (28):

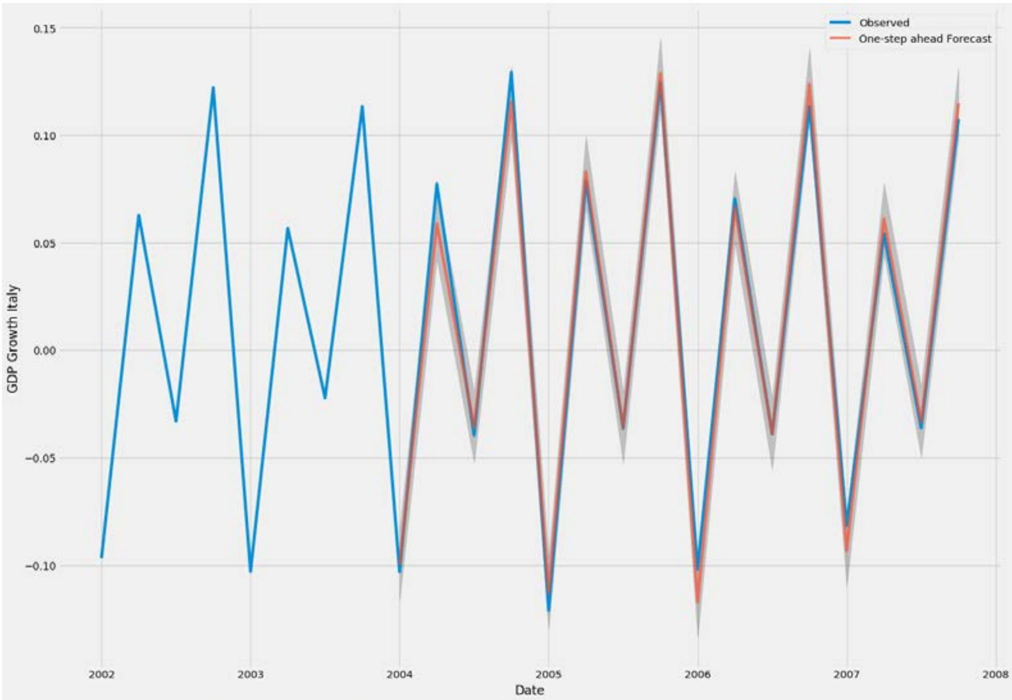
Figure 28: Italy – ARIMA Diagnostics



The standardized residuals can be considered as white noise since no clear trends and seasonality are recognizable in the "Standardized residuals plot". The "Normal Q-Q plot" shows a positive relationship between the theoretical quantiles and the sample quantiles. In fact, the blue dots representing the ordered distribution of the residuals follow approximately the theoretical red line; given the limited number of data available in the sample, the fit can be considered after all sufficient. Additionally, the "Correlogram plot" shows a relatively low correlation of the time series residuals with the lagged version, whereas the "Histogram plus estimated density plot" confirms that the bars of the histogram representing the residuals can be approximated to a normal distribution. All these indications suggest the presence of a model which produces a satisfactory fit.

The validation process through the static approach yields an MSE of 0.012, and the visualization of the forecasts based on the training-sample are represented in the following figure (29):

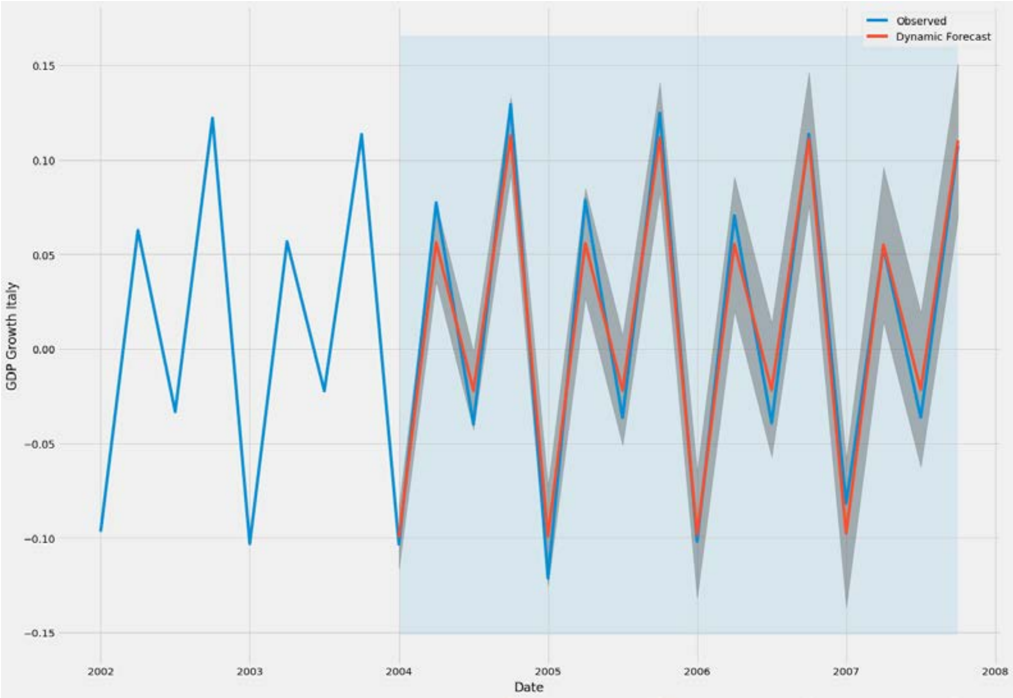
Figure 29: Italy – Static approach



The one-step-ahead forecasts based on the training-sample follow narrowly the GDP observed in the test-sample, indicating an overall good quality of the model in forecasting future data points. The dynamic approach yields an MSE of 0.019, which is slightly higher than the value obtained from the static method.

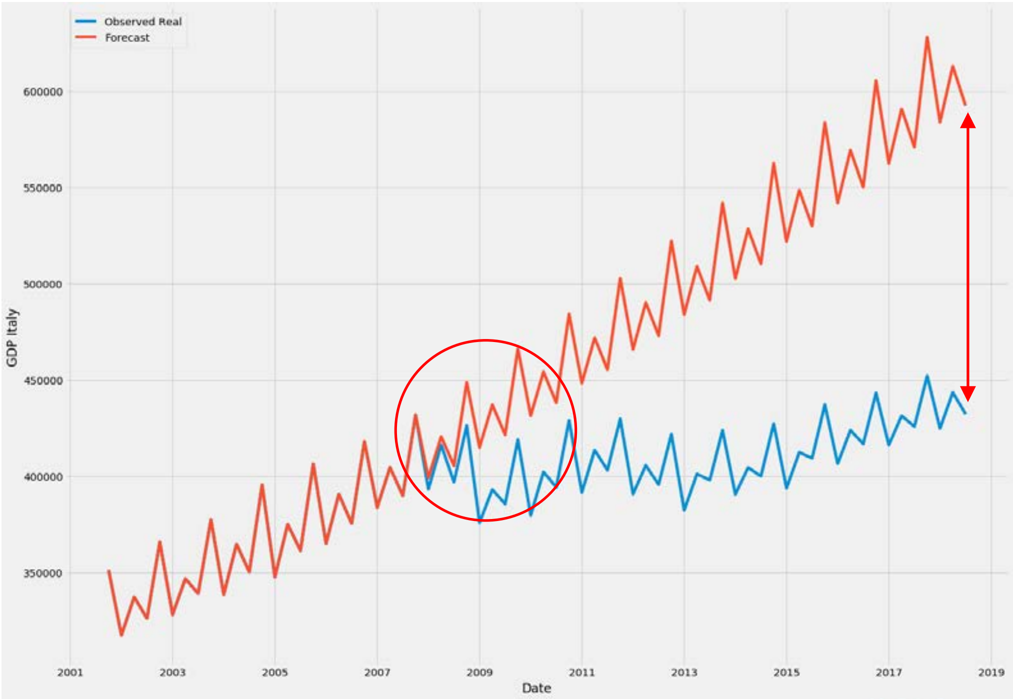
Figure (30) depicts the development of the dynamic forecasts in relation to the real observed data:

Figure 30: Italy – Dynamic approach



As for the static approach, the dynamic forecasts reflect the observed data indicating a reasonable degree of internal validity of the model. Finally, it is now possible to visualize in the following figure (31) the leverage of the seasonal ARIMA:

Figure 31: Italy – GDP forecast



The results show, as in the case of Portugal, an increasing trend of the variable being forecasted. The difference between the two paths can be partially considered as the impact of the financial crisis on the GDP. As time passes, the decreasing degree of confidence is dictated by the increasing of the confidence intervals generated by the model. Therefore, it is challenging to assess the impact of the financial crisis when the data points are far away from the last "true" observed GDP (i.e., red double arrow). The data points generated in the proximity of the financial crisis (i.e., red oval) will likely present a higher degree of accuracy.

The statespace model results of Ireland 's ARIMA model are portrayed in the following figure (32):

Figure 32: Ireland – Statespace Model Results

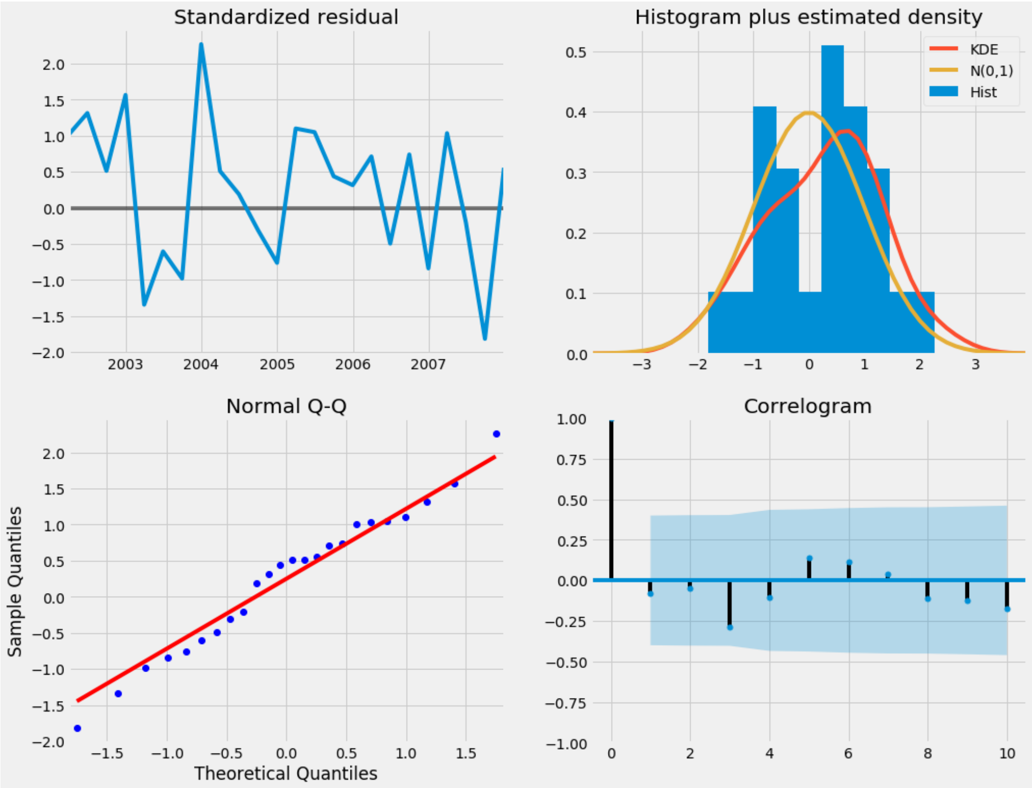
	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.4334	0.189	-2.291	0.022	-0.804	-0.063
ar.S.L4	0.8030	0.124	6.469	0.000	0.560	1.046
sigma2	0.0005	0.000	2.620	0.009	0.000	0.001

Ljung-Box (Q):	20.84	Jarque-Bera (JB):	0.40
Prob(Q):	0.59	Prob(JB):	0.82
Heteroskedasticity (H):	0.49	Skew:	-0.19
Prob(H) (two-sided):	0.33	Kurtosis:	2.50

Ireland's ARIMA model output indicates that all the explanatory variables are statistically significant; the "ar.L1" variable is statistically significant with a 95% confidence level, while the "ar.S.L4" can be considered significant with a 99% confidence level. The first variable has a negative coefficient of -0.4334, whereas the second one has a positive coefficient of 0.8030, indicating that both explanatory variables exercise a significant impact on the explanatory variable due to their relatively high standardized coefficients.

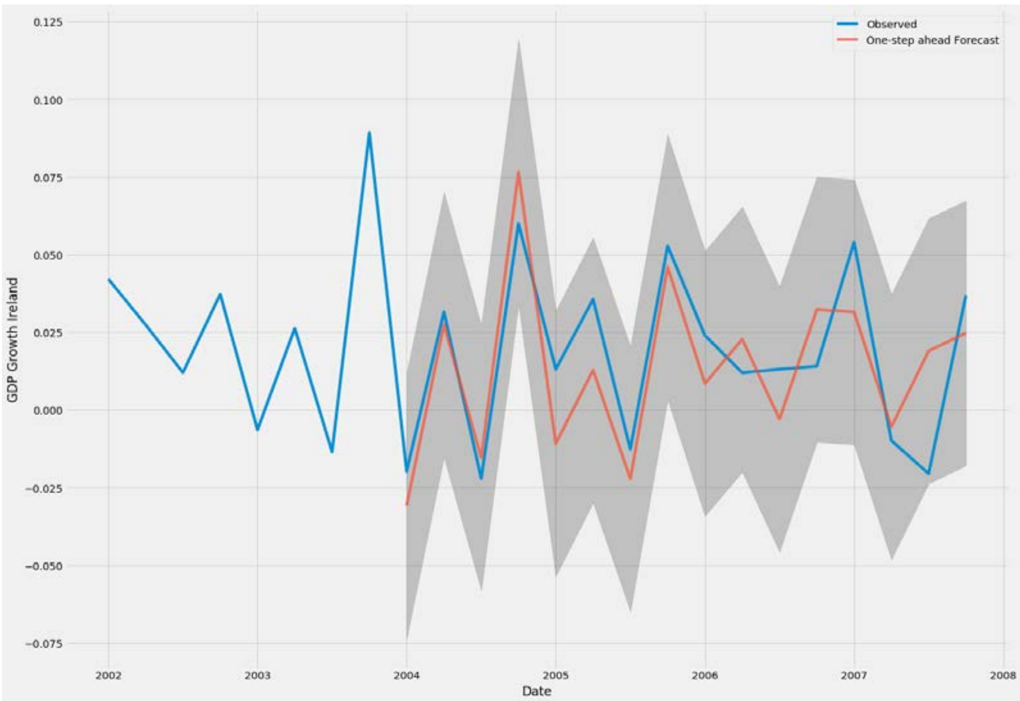
The diagnostics of the model summarized in figure (33) on page 66 confirms that the residuals of the model are uncorrelated and normally distributed. In fact, from a visual inspection of the "Standardized residual plot", it is possible to debate that no particular problems emerge concerning the presence of seasonality in the residuals. The "Correlogram plot" shows consistent results since the relatively low correlation of the time series residuals with the lagged version is constant. The "Quantile-Quantile plot" indicates a good fit of the blue dots representing the ordered distribution of the residuals with the theoretical red line. The "Histogram plus estimated density plot" finally confirms that the residuals are normally distributed.

Figure 33: Ireland – ARIMA Diagnostics



The one-step-ahead forecast approach was used to assess the validity of the model. The results obtained are represented in the succeeding figure (34), which depicts the paths according to the static approach and to the “real” observed GDP:

Figure 34: Ireland – Static approach



Unlike the two previous countries, it is possible to observe a minor fit of the one-step-ahead forecasts to the observed data points. In this case, the predictions do not always faithfully follow the real data. Fortunately, in the first two years of the test-sample, the difference between the two paths is not so marked. Conversely, the differences appear to be more prominent over time. Another detail which is worth mentioning is the relatively high confidence intervals throughout the test-sample. This peculiarity is usually "reserved" for the dynamic approach, indicating that Ireland's GDP time series is not easily predictable. An explanation of this behavior could be the anomalous behavior of the GDP during the training-sample period. Indeed, Portugal and Italy exhibit a homogenous behavior, while Ireland presents higher volatility in the period preceding the financial crisis. All these facts are reflected in a higher MSE, which assumes a value of 7.57%. For more information regarding the difference in the GDP time series of Portugal, Italy, and Ireland, please see sub-chapter 4.2 "Descriptive statistics" and sub-chapter 4.3 "Time series analysis".

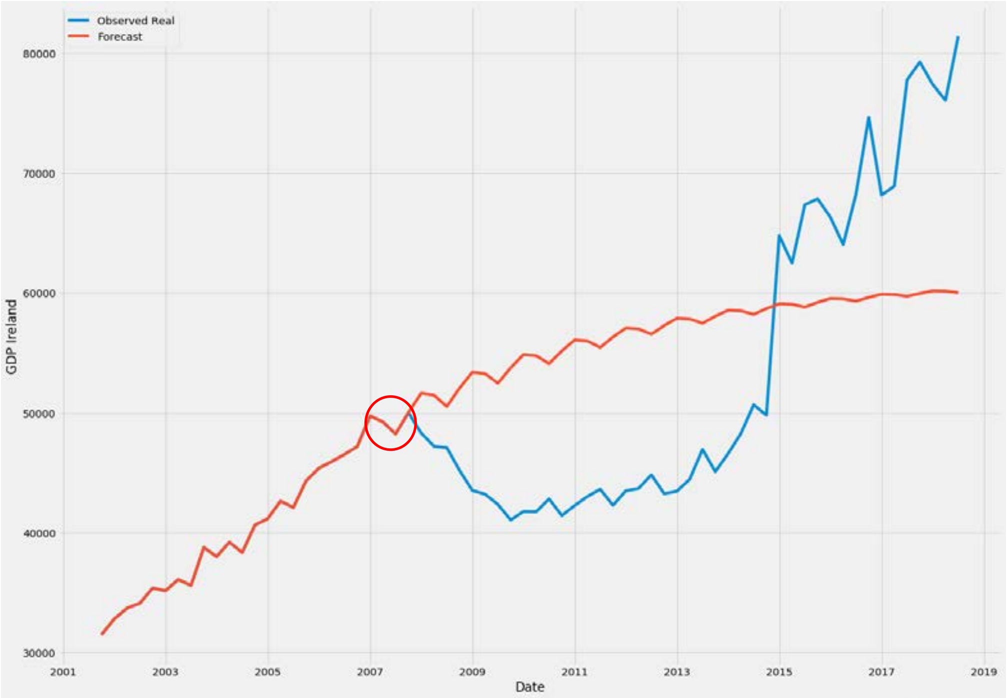
Evidently, as also shows the following figure (35), the dynamic approach encounters greater difficulty in accurately predicting future data points.

Figure 35: Ireland – Dynamic approach

The short-term predictions remain fortunately of moderate quality. However, the predictive accuracy of the model decreases over time, indicating a lower degree of internal validity of the model. The dynamic validation yields an MSE of 8.02%.

The following figure (36) represents the development of the GDP forecasts in relation to the “real” observed development:

Figure 36: Ireland – GDP forecast



As illustrated previously, the pre-crisis period recorded a different trend compared to the one registered by the other countries under analysis; this influenced the development of the forecasts. The after-crisis period presents a tendency of the forecasts which can be considered more like a stagnant situation rather than expansionistic. Furthermore, the blue line representing the development of the “real” observed GDP displays a significant recovery of the economic situation in the period between 2013 and 2015. This recovery de facto has allowed the observed GDP to outpace the development of the forecasts. Among the so-called “PIIGS” countries, Ireland is the only nation presenting such positive results in the period following the crisis. Please note that a brief explanation concerning the brilliant performances reached by Ireland was made available in sub-chapter 4.2 “Descriptive statistics”. In this case, care must be taken with regard to the predictive accuracy of the model over time. In fact, only by shortening the pre-crisis sample by three quarters, the predictions would assume a different development. Indeed, if the trend marked inside the red oval would not be taken into consideration, the forecast would assume an expansionistic trend. These circumstances would therefore no longer allow claiming that the Irish economy has completely recovered from the financial crisis.

The statespace model results of Greece's ARIMA model are represented in the following figure (37):

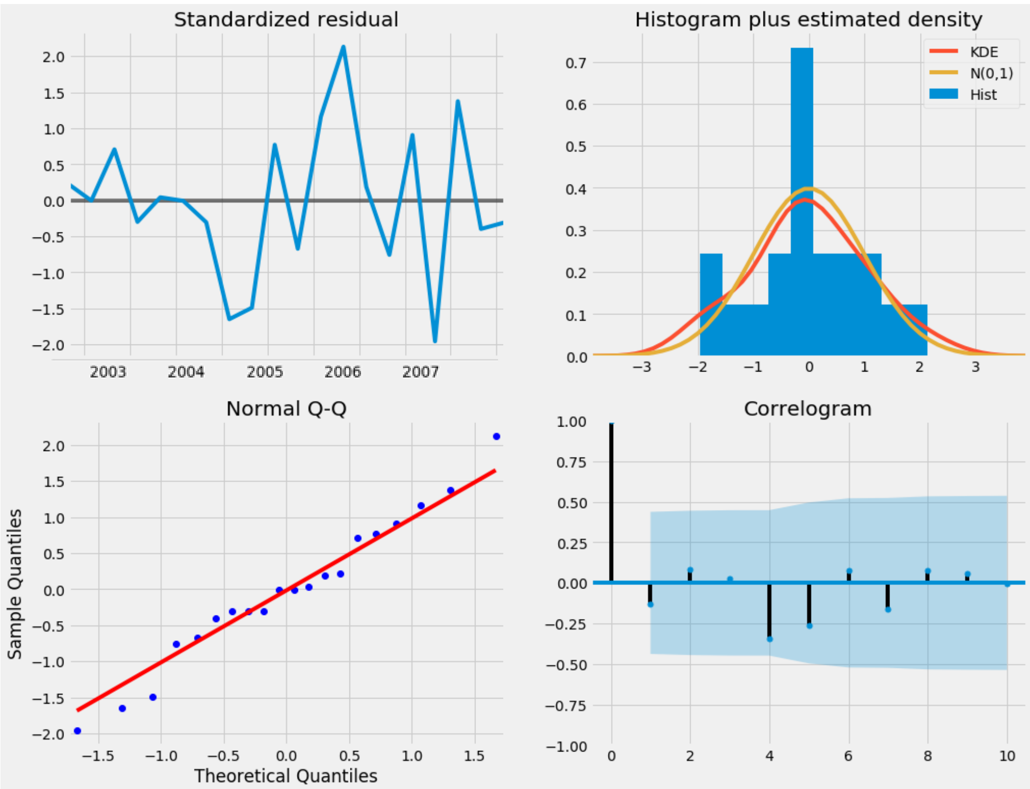
Figure 37: Greece – Statespace Model Results

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.S.L4        0.9812      0.074     13.302      0.000       0.837       1.126
sigma2         0.0004      0.000      2.916      0.004       0.000       0.001
===================================================================================
Ljung-Box (Q):                        9.00   Jarque-Bera (JB):                 0.06
Prob(Q):                              0.97   Prob(JB):                         0.97
Heteroskedasticity (H):              10.08   Skew:                             0.01
Prob(H) (two-sided):                  0.01   Kurtosis:                         2.74
===================================================================================
```

The standardized coefficient of the explanatory variable "ar.S.L4" presents a value of 0.9812, indicating that the variable has an important impact on the dependent variable. The p-value of approximately 0 allows confirming that the variable is statistically significant with a 99% confidence level.

As it is possible to observe from the model diagnostics represented in the following figure (38), the model presents a good overall quality:

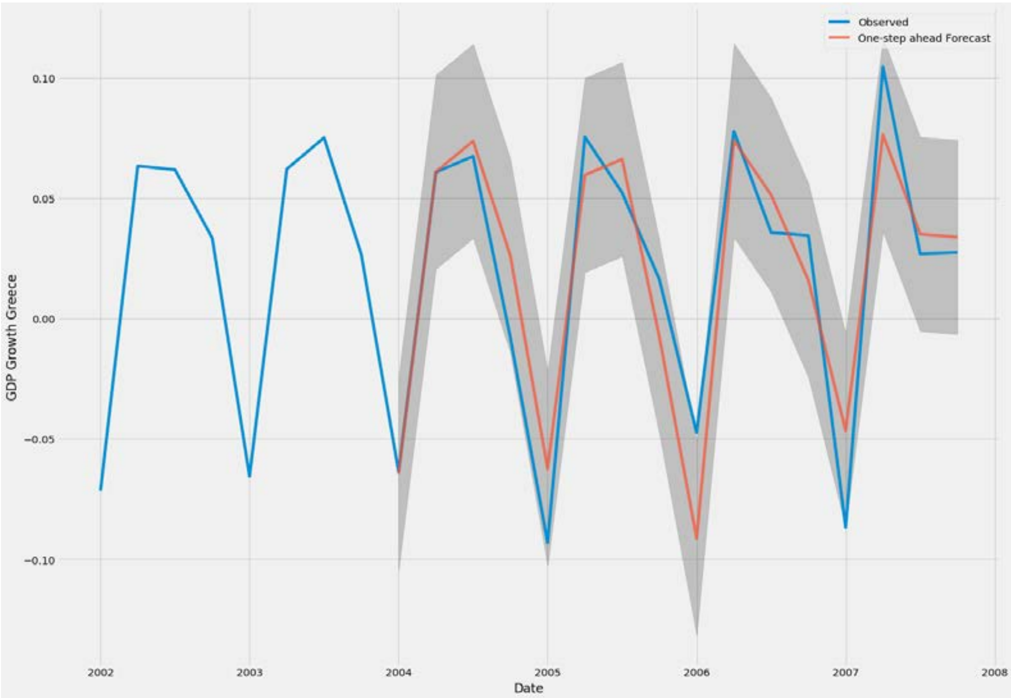
Figure 38: Greece – ARIMA Diagnostics



The "Correlogram plot" presents constant low coefficients, and the "Standardized residuals plot" confirms that apparently, no seasonality is present in the residuals. The blue dots of the "Q-Q plot" follow the theoretical red line indicating a good approximation of the residuals towards a normal distribution. To further support the quality of the model, the "Histogram plus estimated density plot" confirms that the shape of histogram's bars can be approximated as a normal distribution $N(0,1)$. Among the so-called "PIIGS" countries, Greece's ARIMA model presents on paper the best diagnostics results. The residuals of the model can be considered, therefore, as uncorrelated and normally distributed.

The validation of the model through the static approach yielded the following representation:

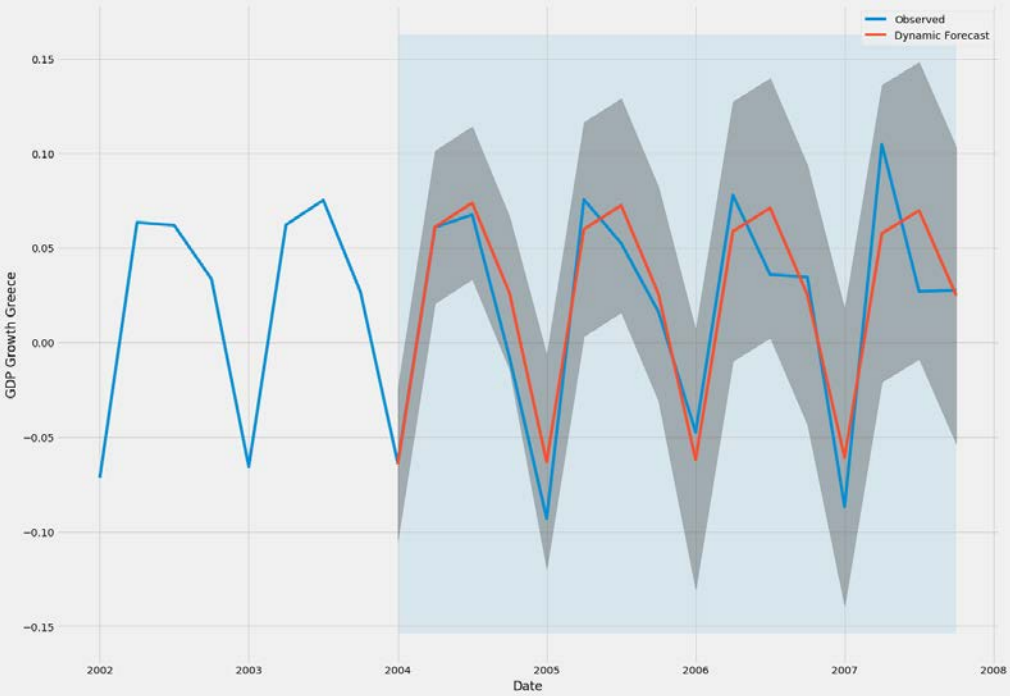
Figure 39: Greece – Static approach



Despite the confirmed goodness of the model in terms of diagnostics, the one-step-ahead forecasts did not map the development of the observed GDP faithfully. Fortunately, the distance between the observed and forecasted data points is not considerable. Moreover, the main directional movements were picked up by the forecasts, indicating, therefore, a functional capacity of the model to "reconstruct" the trend of the GDP in the test-sample. The static approach yields an MSE value of 5%.

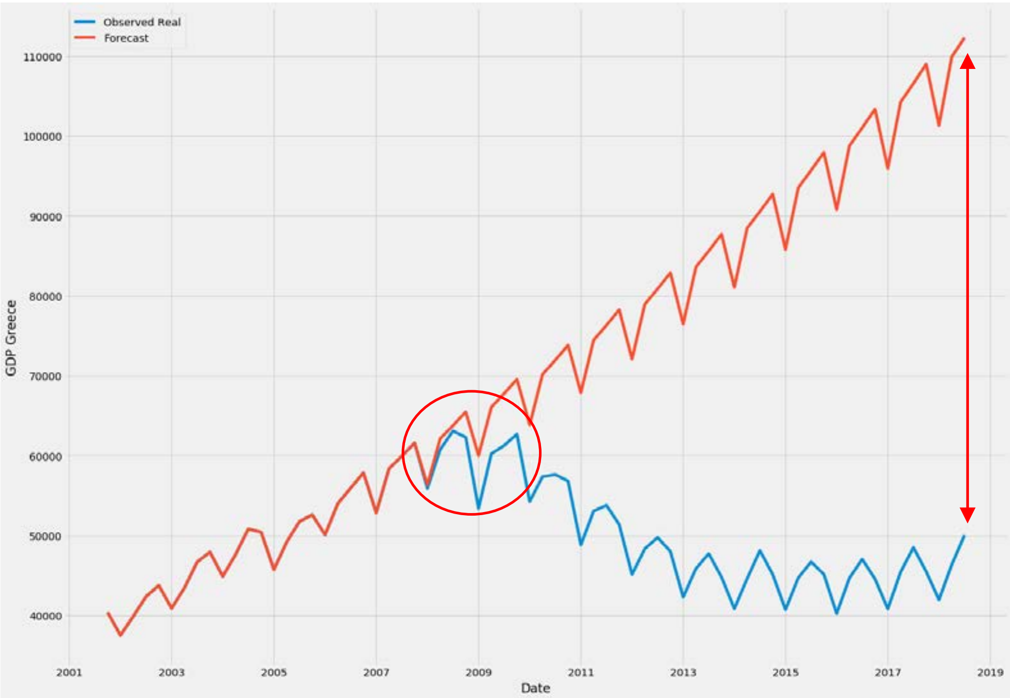
On page 71 are represented in figure (40) the results obtained from the dynamic approach.

Figure 40: Greece – Dynamic approach



The employment of the dynamic approach implies an increase in the confidence intervals over time. The forecasted data points (red line) match in an approximate way the "true" observed data. However, as in the case of the static approach, it is not possible to claim with absolute certainty that the forecasts are reliable over time. The MSE of the dynamic forecasts assumes in fact a value of 5.6%. The next figure (41) represents the development of the forecasts in relation to the observed GDP registered in the after-crisis period:

Figure 41: Greece – GDP forecast



In this case, what immediately catches the eye is the relatively high difference evidenced by the red double arrow. In fact, the development of the "real" observed GDP shows no apparent signs of recovery. In the proximity of the financial crisis (i.e., red oval), no particular observations can be stated since no significant differences compared to other countries are present.

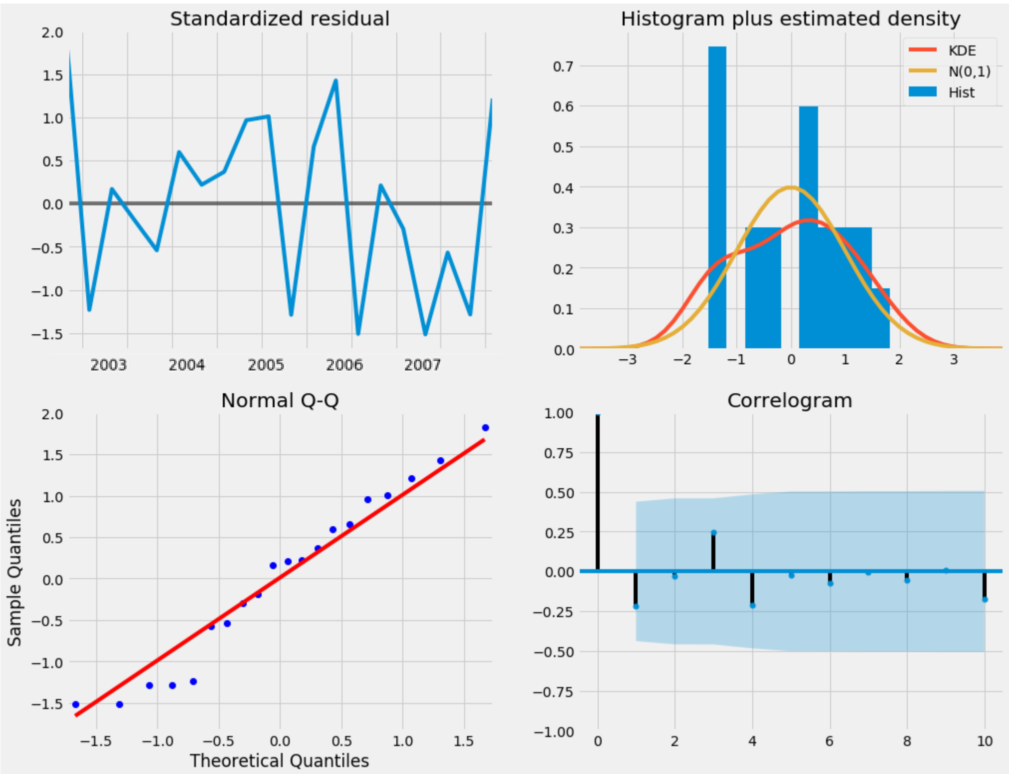
Finally, the statespace model results of the last country are presented in the following figure (42):

Figure 42: Spain – Statespace Model Results

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.9973	0.009	-112.969	0.000	-1.015	-0.980
ma.L1	0.9620	0.067	14.351	0.000	0.831	1.093
ar.S.L4	0.8775	0.073	12.006	0.000	0.734	1.021
sigma2	9.038e-05	1.18e-05	7.672	0.000	6.73e-05	0.000

All the explanatory variables are statistically significant with a confidence level of 99%. Considering the values assumed by the standardized coefficients, it is possible to affirm that the impact that the independent variables exercise on the dependent variable is significant. The diagnostic of the model is presented in the next figure (43):

Figure 43: Spain – ARIMA Diagnostics



It is possible to observe from the "Standardized residual plot" that no seasonality is present in the residuals. Moreover, the "Correlogram plot" confirms that the correlation coefficients are relatively low and constant. The "Normal Q-Q plot" indicates a good fit of the blue dots to the theoretical red line, while the "Histogram plus estimated density" shows that the estimated density of the histogram's bars follows approximately the shape of a normal distribution. That being said, it can be stated that the model diagnostics confirm that the residuals follow a normal distribution and are not correlated.

The validity of the model was assessed through the visualization of the forecasts computed via static and dynamic approach. The resulting forecasting is in fact compared with the development of the "real" observed GDP in the test-sample.

Figure 44: Spain – Static approach

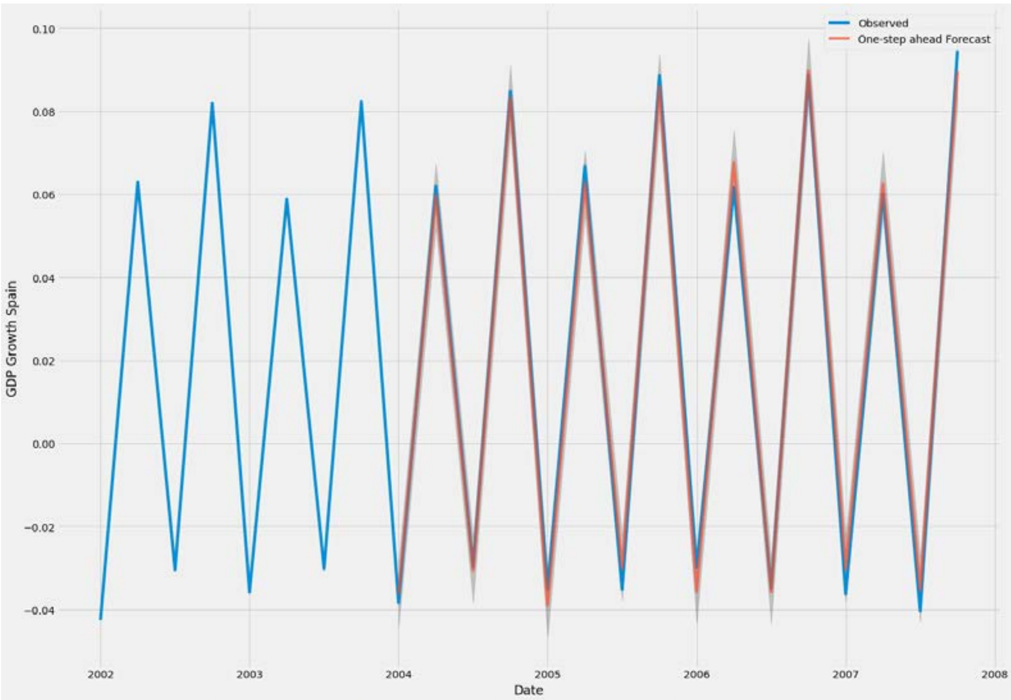
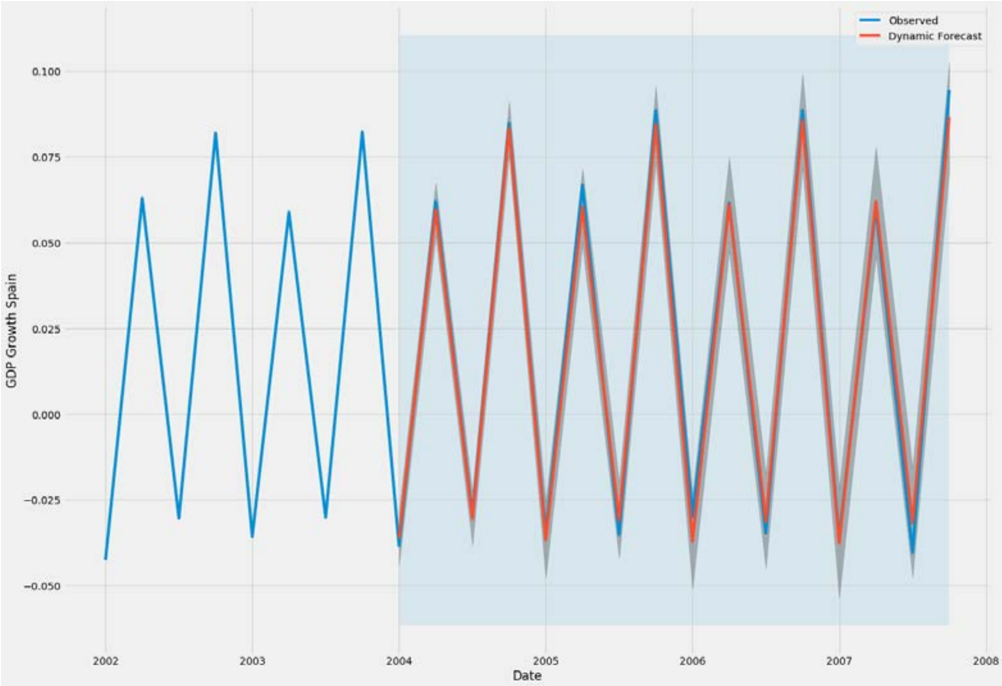


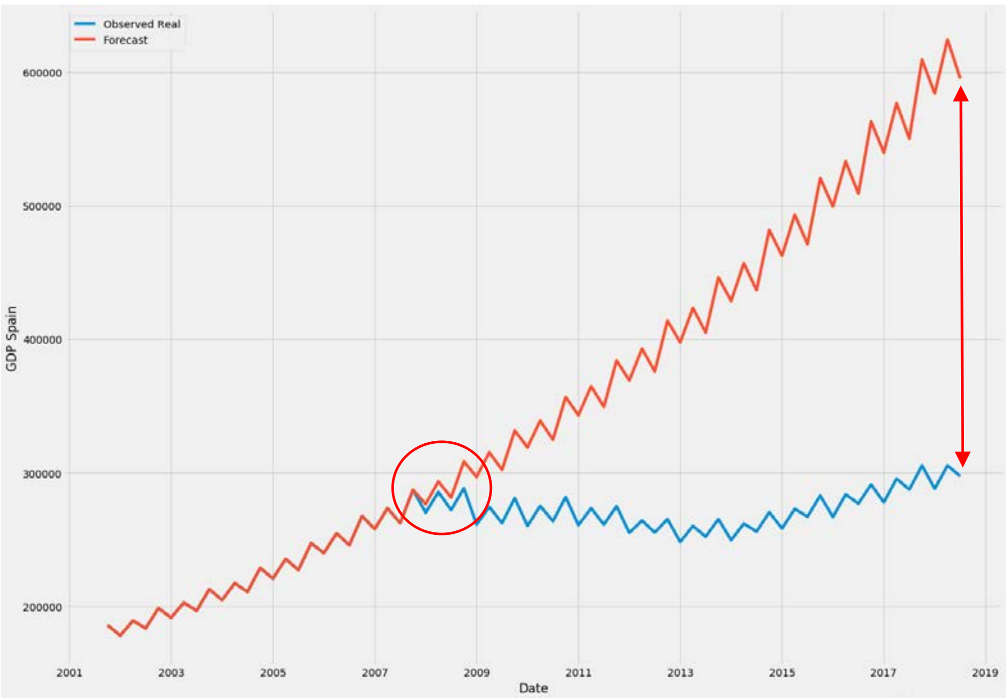
Figure (44) represents the one-step-ahead forecasts in relation to the observed GDP and indicates that the forecasts align perfectly with the actual values. The accuracy of the model can be represented by the average error of the forecasts measured by the MSE, which assumes, in this case, a considerable low value: 0.01. This perfect synchronization of the forecasts with the observed data points can be attributed to the presence of a consistent expansionistic trend in the pre-crisis period.

Figure 45: Spain – Dynamic approach



Similar behavior is also recorded in the dynamic approach; the forecasts map almost entirely the "true" observed GDP. The MSE results to be slightly higher than in the static approach: 0.015. However, considering the results obtained by the diagnostics and by the validation of the model, it is possible to affirm with a certain degree of confidence that the model can be used to produce reliable forecasts. Consequently, in the next figure (46), it is represented the development of the forecasts in relation to the observed GDP.

Figure 46: Spain – GDP forecast



In the proximity of the financial crisis (i.e., red oval) it is possible to observe that in the first two quarters following the financial crisis, the impact that the latter had on the GDP was minor compared to the impact that the crisis had on the other countries under analysis. A slight improvement in the economic situation is also reported in the period between 2004 and 2018, however not sufficient to reduce the difference created (i.e., red double arrow).

5.3 Limitations

As it emerged from the empirical analysis, the main limitations regarding the methodology employed can be summarized as follows:

- Sample of limited size;
- Confidence intervals of the forecasts widening over time;
- Uncertainties associated with the events that have been taken place in the period after-crisis;
- Unrealistic optimism bias;
- Uncertainties regarding the events that took place in the period preceding the sample period;
- Uncertainty with regard to the causal impact that the financial crisis has had on the GDP;
- Apparent good internal validity, uncertain external validity;
- Existence of other machine learning models which can perform better in forecasting macroeconomic variables.

The forecasts were based on a limited sample containing only 25 data points. As demonstrated by the validation results illustrated in the previous sub-chapter, a similar dimension of the database allows, from a statistical point of view, to perform accurate forecasts. However, the selection of the period on which to base the analysis influence significantly the forecasts generated. The choice of both the starting date and the final date of the time series being forecasted plays a crucial role in the development of the forecasts. For example, if it has been opted to exclude data by reducing the overall length of the time series to produce forecasts on a specific time frame, the results obtained will be consequently influenced by this choice. More precisely, if the data frame contains expansionistic data, the forecasted data will likely present a similar development. In this specific study, the sample contains data from Q4-2001 to Q4-2007. This period was characterized by an expansionistic trend; consequently the forecasts were also influenced positively by the trend embedded in the time series being forecasted. This obviously does not represent a real and sustainable scenario, in fact, it is necessary to start from the presupposition that if the financial crisis had never existed, the GDP would have registered a growth similar to the one recorded in the six years prior to the financial crisis. The key element that could improve the validity of the study would be the verification of the state of the economy in the period on which the forecasts are based. It was assumed that the period characterized by the expansionistic trend was "synonymous" of economy in equilibrium (all the economic indicators at their natural level and stable growth) and this presupposition obviously represents an unrealistic optimism bias.

As expected, from a quick analysis of the forecasts based on a larger dataset, it emerges that generally the forecasts present different values. As it is possible to observe in appendix 2, the different values encountered in the forecasts involve different final results. No major differences are revealed between the two methods (long and short database) in the case of Italy and Spain. However, for Portugal and Greece, the forecasts obtained result to be higher to the ones based on the short data frame. The outlook changes completely in the case of Ireland, where, according to the forecasts based on the extended dataset, the recovery of the GDP was delayed until 2017. Therefore, it is possible to conclude that the choice of the period on which to base the analysis is crucial.

According to the common practice in machine learning, all the available data must be investigated. However, particular attention must be dedicated to the events that could have influenced the time series in the investigated period. Since the purpose of the study is to measure the impact that the financial crisis has had on the GDP, no major events that could have influenced the development of the GDP have to be identified in the time series under analysis. This, in fact, represents the main reason why in this thesis the initial longer database was reduced.

Moreover, to properly evaluate the impact that the financial crisis has had on the GDP, it is necessary to collect all the information regarding the other events that have influenced the GDP in the period before and after-crisis. Finally, with all the information gathered together, it is possible to re-adjust the forecasts to increase the overall validity of the study. The differences between forecasted and actual GDP can exclusively be attributed as the impact of the financial crisis only if the forecasts are adjusted. The uncertainty related to the events that have been taken place in the period after-crisis together with the uncertainties regarding the events that took place in the period preceding the sample period makes this goal difficult to achieve.

Furthermore, the confidence intervals of the forecasts widen over time, indicating that the model employed in the thesis might produce accurate forecasts in the short future, however, it loses efficiency with predictions far in time. In order to increase the quality of the predictions, it is possible to employ more advanced forecasting models based on Artificial Neural Networks.

Finally, the most critical limitation regards the uncertainty of the causal impact that the financial crisis has had on the GDP. In fact, according to Brodersen, Gallusser, Koehler, Remy, & Scott (2015), to properly infer the causal impact of a specific market event, it is necessary to generalize the widely used difference-in-differences approach by modeling the counterfactual of a time series, before and after-crisis. Therefore, the following improvements could be applied to the methodology:

- Impact analysis of other crisis preceding the sample period analyzed through the implementation in the model of dummy variables;
- Causal impact analysis through the difference-in-differences approach;
- Implementation of forecasting models based on Artificial Neural Networks.

With regard to the last recommendation, it is possible to visualize in appendix 3 the results obtained from the implementation of a deep learning approach. The model employed in the production of the forecasts of the GDP time series is known as Long Short-Term Memory networks, or in short LSTMs, and is based on an Artificial Recurrent Neural Network (RNN) architecture. The application proposed might result useful in the development of further studies since it represents a valid starting point on which to develop a more in-depth analysis.

6. Conclusion

The purpose of this thesis is to evaluate the impact of the European financial crisis on the potential output of different European countries. Those countries worst hit by the crisis – Portugal, Ireland, Italy, Greece and Spain – are, of course, of particular interest, since a more substantial impact of the financial crisis was detected there and thus a more significant difference between potential Gross Domestic Product and observed Gross Domestic Product.

Following the Box-Jenkins technique, the autoregressive integrated moving average model was employed to forecast the development of the potential Gross Domestic Product. The complete database contained a total of 68 quarterly observations covering the period from Q4-2001 to Q3-2018. The database was divided into two different data frames:

- from Q4-2001 to Q4-2007 considered as the pre-crisis period;
- from Q1-2008 to Q3-2018 considered as the after-crisis period.

The pre-crisis data frame was further split into training-sample (36%) and test-sample (64%) to validate the models. The parameters of the ARIMA models were decided with the aim of minimizing the AIC criterion through a process known as "grid search," which iteratively explores the different combinations of parameters. The concept which stays behind this process is also known in machine learning as hyperparameter optimization. The estimation of the model was made through a nonlinear iterative process which followed the maximum likelihood estimation as a technique. The regression coefficients were treated as additional parameters to be estimated via maximum likelihood.

With the assumption that the forecasts generated, based on a time series containing data from Q4-2001 to Q4-2007, would hypothetically represent the potential Gross Domestic Product in the after-crisis period, it was possible to debate that the differences between the potential Gross Domestic Product (forecasts) and the observed Gross Domestic Product would potentially represent the impact of the financial crisis.

The results emerged from the empirical analysis were mainly uniform across all countries: a small impact was detected in the proximity of the financial crisis, which however expanded over time. The only case in which it was possible to report a complete economic recovery was Ireland's case. All the other economies were still reflecting a situation in which the potential GDP forecasted was significantly above the observed GDP.

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Appendix 1 – Vector Autoregressive and Autoregressive Models

Portugal

Vector Autoregressive - Andersson's method

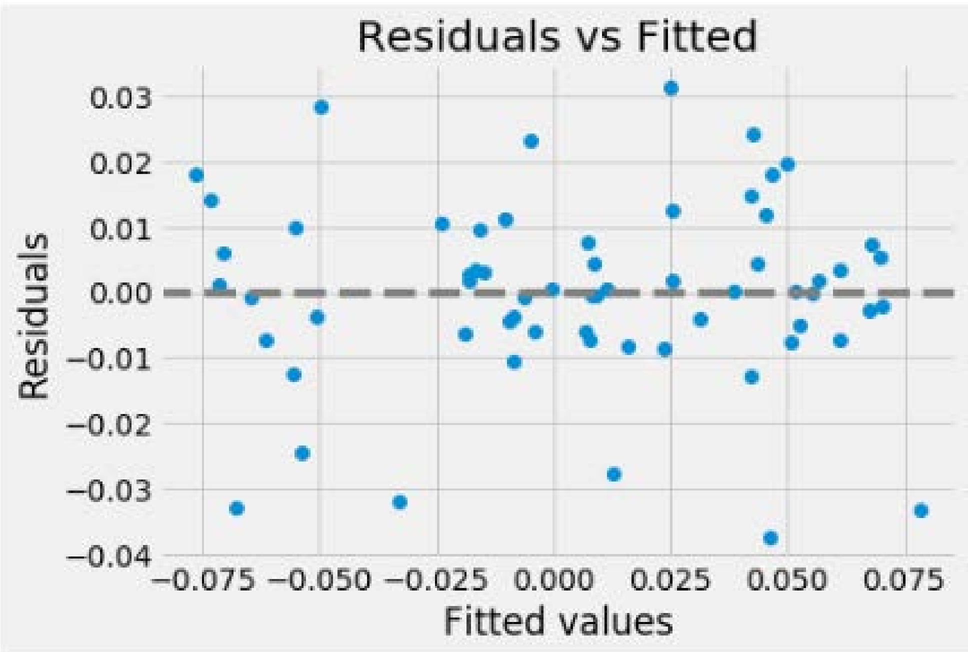
OLS Regression Results

Dep. Variable:	GDP_Portugal_Growth	R-squared:	0.905
Model:	OLS	Adj. R-squared:	0.882
Method:	Least Squares	F-statistic:	39.73
Date:	Sat, 04 May 2019	Prob (F-statistic):	2.40e-21
Time:	18:43:19	Log-Likelihood:	179.47
No. Observations:	63	AIC:	-332.9
Df Residuals:	50	BIC:	-305.1
Df Model:	12		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0095	0.004	2.521	0.015	0.002	0.017
GDP_Portugal_Growth_1	-0.1869	0.103	-1.818	0.075	-0.393	0.020
GDP_Portugal_Growth_2	-0.0847	0.105	-0.811	0.421	-0.295	0.125
GDP_Portugal_Growth_3	-0.0493	0.100	-0.493	0.624	-0.250	0.152
GDP_Portugal_Growth_4	0.8077	0.102	7.939	0.000	0.603	1.012
HICP_Portugal_D_1	-0.0014	0.003	-0.430	0.669	-0.008	0.005
HICP_Portugal_D_2	-0.0047	0.003	-1.357	0.181	-0.012	0.002
HICP_Portugal_D_3	-0.0067	0.004	-1.872	0.067	-0.014	0.000
HICP_Portugal_D_4	-0.0039	0.004	-1.040	0.303	-0.012	0.004
UN_Portugal_D_1	0.0002	0.006	0.038	0.969	-0.012	0.012
UN_Portugal_D_2	-0.0027	0.007	-0.418	0.678	-0.016	0.010
UN_Portugal_D_3	0.0018	0.007	0.276	0.784	-0.011	0.015
UN_Portugal_D_4	0.0064	0.006	1.113	0.271	-0.005	0.018

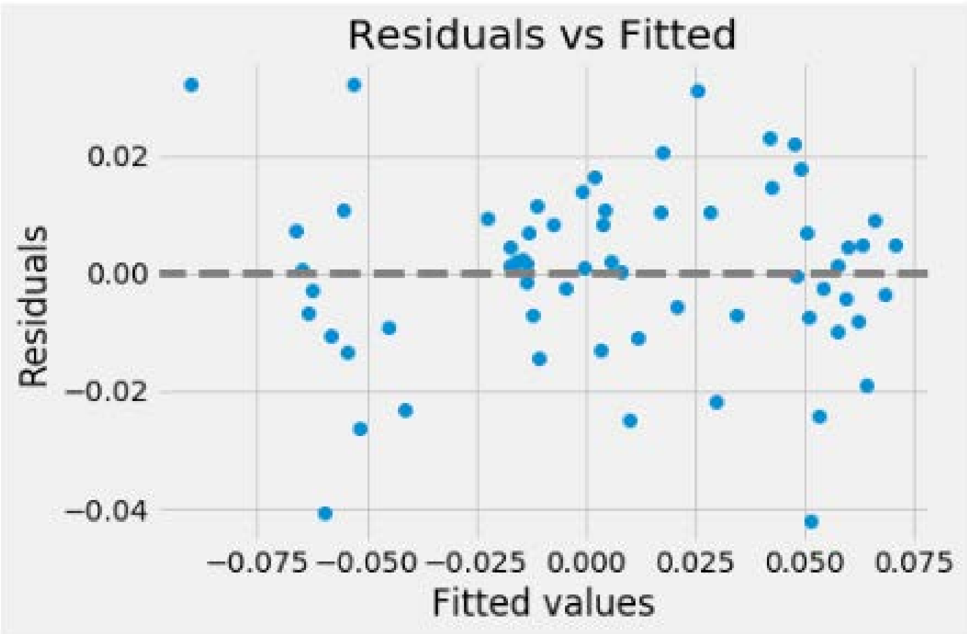
Omnibus:	5.022	Durbin-Watson:	2.266
Prob(Omnibus):	0.081	Jarque-Bera (JB):	4.163
Skew:	-0.484	Prob(JB):	0.125
Kurtosis:	3.805	Cond. No.	111.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

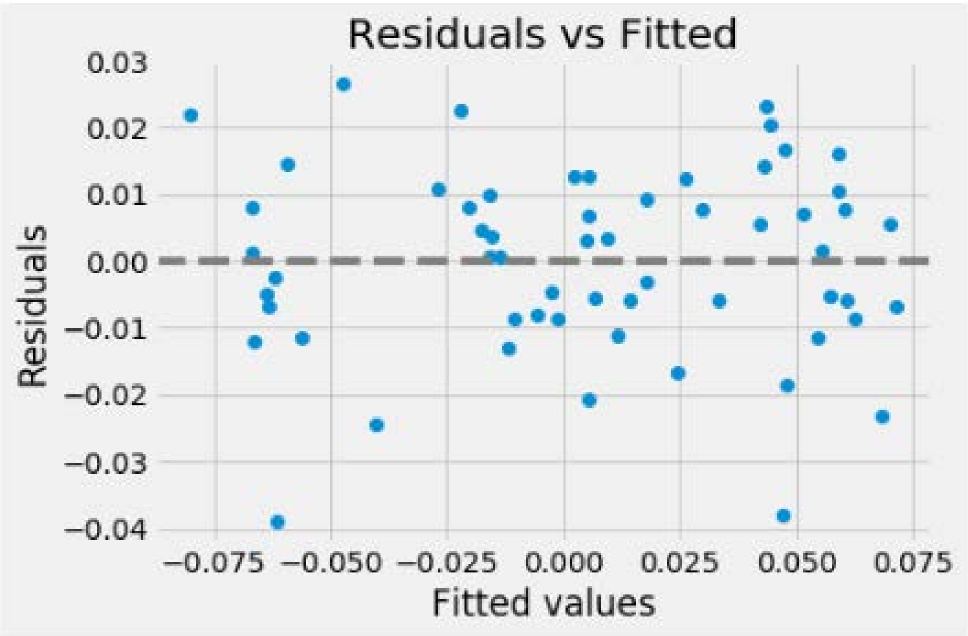


Autoregressive method

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      GDP_Portugal_Growth   R-squared:                       0.888
Model:                              OLS   Adj. R-squared:                  0.880
Method:                   Least Squares   F-statistic:                     114.7
Date:                  Thu, 23 May 2019   Prob (F-statistic):           7.55e-27
Time:                          14:11:01   Log-Likelihood:                 174.20
No. Observations:                    63   AIC:                            -338.4
Df Residuals:                        58   BIC:                            -327.7
Df Model:                             4
Covariance Type:              nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
Intercept                 0.0038      0.003      1.434      0.157      -0.002       0.009
GDP_Portugal_Growth_1    -0.1782      0.079     -2.266      0.027      -0.336      -0.021
GDP_Portugal_Growth_2    -0.1188      0.081     -1.458      0.150      -0.282       0.044
GDP_Portugal_Growth_3    -0.0899      0.082     -1.099      0.276      -0.254       0.074
GDP_Portugal_Growth_4     0.8042      0.079     10.235      0.000       0.647       0.961
==============================================================================
Omnibus:                        2.959   Durbin-Watson:                   2.043
Prob(Omnibus):                  0.228   Jarque-Bera (JB):                2.084
Skew:                          -0.357   Prob(JB):                        0.353
Kurtosis:                       3.534   Cond. No.                         68.4
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```



```
                            OLS Regression Results
==============================================================================
Dep. Variable:      GDP_Portugal_Growth   R-squared:                       0.907
Model:                              OLS   Adj. R-squared:                  0.892
Method:                   Least Squares   F-statistic:                     60.72
Date:                  Thu, 23 May 2019   Prob (F-statistic):           4.40e-23
Time:                          14:11:01   Log-Likelihood:                 168.49
No. Observations:                    59   AIC:                            -319.0
Df Residuals:                        50   BIC:                            -300.3
Df Model:                             8
Covariance Type:              nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
Intercept                 0.0038      0.003      1.365      0.178      -0.002       0.009
GDP_Portugal_Growth_1    -0.2251      0.133     -1.699      0.096      -0.491       0.041
GDP_Portugal_Growth_2     0.0811      0.132      0.613      0.543      -0.185       0.347
GDP_Portugal_Growth_3     0.1313      0.130      1.010      0.317      -0.130       0.392
GDP_Portugal_Growth_4     0.6336      0.130      4.876      0.000       0.373       0.895
GDP_Portugal_Growth_5     0.0044      0.130      0.034      0.973      -0.257       0.266
GDP_Portugal_Growth_6    -0.2596      0.130     -1.991      0.052      -0.521       0.002
GDP_Portugal_Growth_7    -0.2138      0.134     -1.597      0.117      -0.483       0.055
GDP_Portugal_Growth_8     0.1864      0.133      1.399      0.168      -0.081       0.454
==============================================================================
Omnibus:                        3.818   Durbin-Watson:                   1.938
Prob(Omnibus):                  0.148   Jarque-Bera (JB):                2.948
Skew:                          -0.521   Prob(JB):                        0.229
Kurtosis:                       3.339   Cond. No.                         104.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```



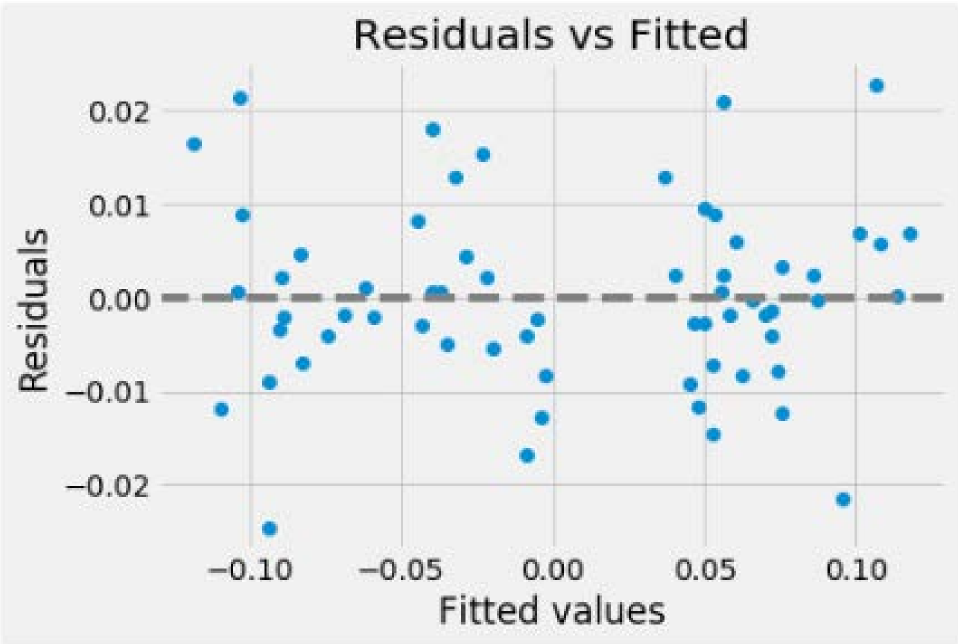
Autoregressive method – HC3

```
                             OLS Regression Results
==============================================================================
Dep. Variable:     GDP_Portugal_Growth   R-squared:                       0.888
Model:                             OLS   Adj. R-squared:                  0.880
Method:                  Least Squares   F-statistic:                     82.34
Date:                 Thu, 23 May 2019   Prob (F-statistic):           3.11e-23
Time:                         14:11:04   Log-Likelihood:                 174.20
No. Observations:                   63   AIC:                            -338.4
Df Residuals:                       58   BIC:                            -327.7
Df Model:                            4
Covariance Type:                   HC3
=========================================================================================
                            coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------------------
Intercept                 0.0038      0.004      1.065      0.287      -0.003       0.011
GDP_Portugal_Growth_1    -0.1782      0.098     -1.819      0.069      -0.370       0.014
GDP_Portugal_Growth_2    -0.1188      0.090     -1.318      0.188      -0.295       0.058
GDP_Portugal_Growth_3    -0.0899      0.083     -1.087      0.277      -0.252       0.072
GDP_Portugal_Growth_4     0.8042      0.091      8.833      0.000       0.626       0.983
==============================================================================
Omnibus:                        2.959   Durbin-Watson:                   2.043
Prob(Omnibus):                  0.228   Jarque-Bera (JB):                2.084
Skew:                          -0.357   Prob(JB):                        0.353
Kurtosis:                       3.534   Cond. No.                         68.4
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC3)
```

Italy

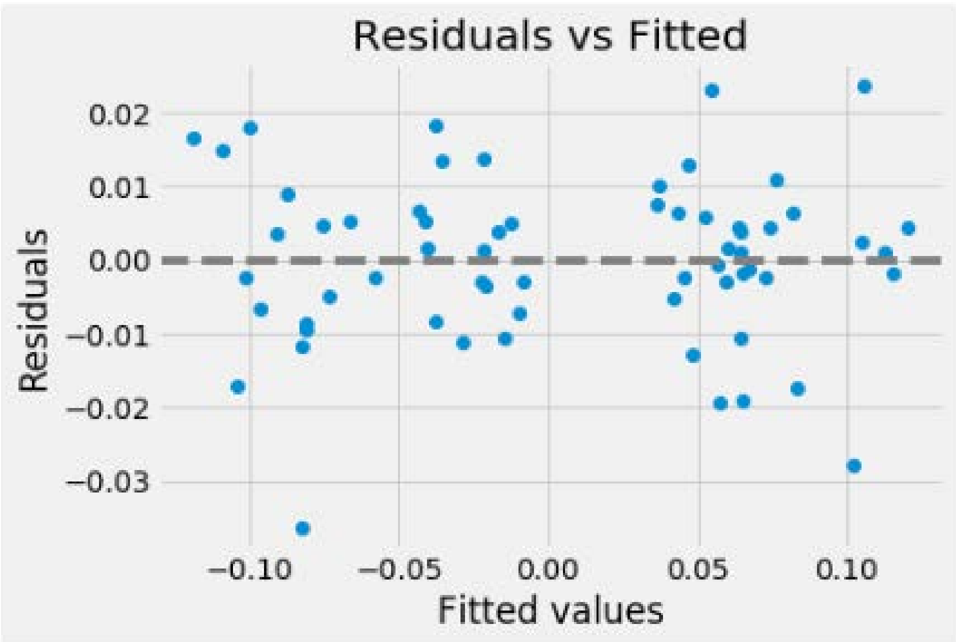
Vector Autoregressive - Andersson's method

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       GDP_Italy_Growth   R-squared:                       0.981
Model:                            OLS   Adj. R-squared:                  0.977
Method:                 Least Squares   F-statistic:                     215.9
Date:                Mon, 13 May 2019   Prob (F-statistic):           1.10e-38
Time:                        03:46:25   Log-Likelihood:                 202.75
No. Observations:                  63   AIC:                            -379.5
Df Residuals:                      50   BIC:                            -351.6
Df Model:                          12
Covariance Type:            nonrobust
======================================================================================
                         coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------
Intercept              0.0098      0.003      3.096      0.003       0.003       0.016
GDP_Italy_Growth_1    -0.2359      0.118     -2.005      0.050      -0.472       0.000
GDP_Italy_Growth_2    -0.0918      0.102     -0.898      0.373      -0.297       0.113
GDP_Italy_Growth_3    -0.1699      0.103     -1.646      0.106      -0.377       0.037
GDP_Italy_Growth_4     0.6665      0.114      5.827      0.000       0.437       0.896
HICP_Italy_D_1         0.0049      0.004      1.091      0.280      -0.004       0.014
HICP_Italy_D_2         0.0007      0.004      0.163      0.871      -0.008       0.010
HICP_Italy_D_3        -0.0105      0.004     -2.709      0.009      -0.018      -0.003
HICP_Italy_D_4        -0.0067      0.004     -1.503      0.139      -0.016       0.002
UN_Italy_D_1          -0.0072      0.006     -1.134      0.262      -0.020       0.006
UN_Italy_D_2          -0.0026      0.007     -0.395      0.694      -0.016       0.011
UN_Italy_D_3           0.0068      0.006      1.102      0.276      -0.006       0.019
UN_Italy_D_4          -0.0046      0.006     -0.792      0.432      -0.016       0.007
==============================================================================
Omnibus:                        1.013   Durbin-Watson:                   1.672
Prob(Omnibus):                  0.603   Jarque-Bera (JB):                0.468
Skew:                           0.165   Prob(JB):                        0.791
Kurtosis:                       3.264   Cond. No.                         334.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

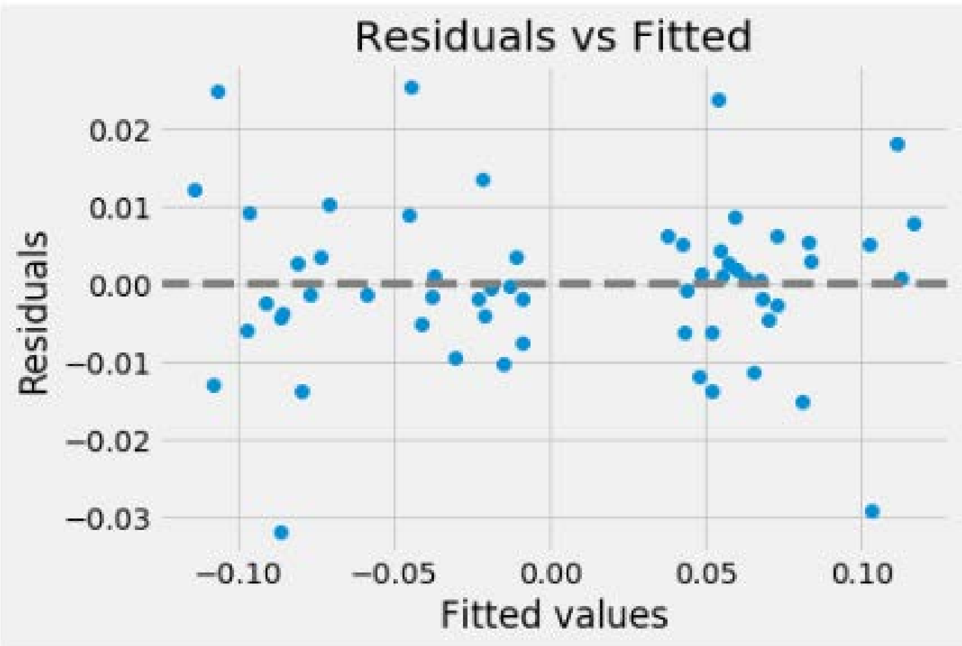


Autoregressive method

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        GDP_Italy_Growth   R-squared:                       0.974
Model:                             OLS   Adj. R-squared:                  0.972
Method:                  Least Squares   F-statistic:                     548.0
Date:                 Mon, 13 May 2019   Prob (F-statistic):           2.46e-45
Time:                         03:46:25   Log-Likelihood:                 193.02
No. Observations:                   63   AIC:                            -376.0
Df Residuals:                       58   BIC:                            -365.3
Df Model:                            4
Covariance Type:             nonrobust
======================================================================================
                         coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------
Intercept              0.0032      0.002      1.391      0.170      -0.001       0.008
GDP_Italy_Growth_1    -0.1361      0.068     -1.988      0.052      -0.273       0.001
GDP_Italy_Growth_2    -0.1043      0.068     -1.536      0.130      -0.240       0.032
GDP_Italy_Growth_3    -0.1209      0.068     -1.780      0.080      -0.257       0.015
GDP_Italy_Growth_4     0.8168      0.068     12.083      0.000       0.681       0.952
==============================================================================
Omnibus:                        5.473   Durbin-Watson:                   1.700
Prob(Omnibus):                  0.065   Jarque-Bera (JB):                4.676
Skew:                          -0.506   Prob(JB):                       0.0965
Kurtosis:                       3.869   Cond. No.                         83.7
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```



```
                            OLS Regression Results
==============================================================================
Dep. Variable:        GDP_Italy_Growth   R-squared:                       0.977
Model:                             OLS   Adj. R-squared:                  0.973
Method:                  Least Squares   F-statistic:                     266.6
Date:                 Mon, 13 May 2019   Prob (F-statistic):           3.05e-38
Time:                         03:46:25   Log-Likelihood:                 184.97
No. Observations:                   59   AIC:                            -351.9
Df Residuals:                       50   BIC:                            -333.2
Df Model:                            8
Covariance Type:             nonrobust
======================================================================================
                         coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------
Intercept              0.0036      0.003      1.434      0.158      -0.001       0.009
GDP_Italy_Growth_1    -0.0426      0.138     -0.308      0.760      -0.320       0.235
GDP_Italy_Growth_2     0.1881      0.136      1.382      0.173      -0.085       0.462
GDP_Italy_Growth_3    -0.1409      0.132     -1.065      0.292      -0.407       0.125
GDP_Italy_Growth_4     0.5578      0.132      4.221      0.000       0.292       0.823
GDP_Italy_Growth_5    -0.1153      0.128     -0.899      0.373      -0.373       0.142
GDP_Italy_Growth_6    -0.3046      0.129     -2.371      0.022      -0.563      -0.047
GDP_Italy_Growth_7     0.0009      0.133      0.007      0.994      -0.266       0.268
GDP_Italy_Growth_8     0.2335      0.131      1.778      0.081      -0.030       0.497
==============================================================================
Omnibus:                        5.076   Durbin-Watson:                   1.904
Prob(Omnibus):                  0.079   Jarque-Bera (JB):                6.208
Skew:                          -0.180   Prob(JB):                       0.0449
Kurtosis:                       4.548   Cond. No.                         139.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```



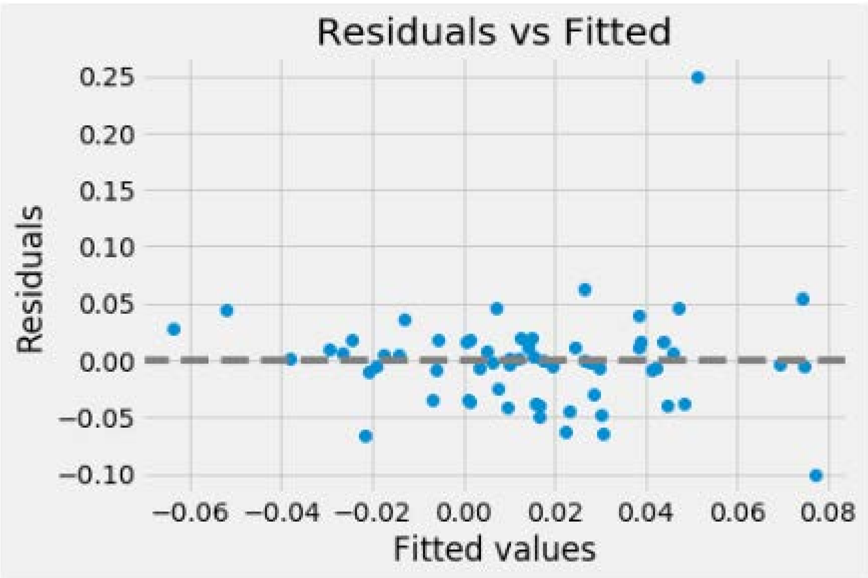
Autoregressive method – HC3

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       GDP_Italy_Growth   R-squared:                       0.974
Model:                            OLS   Adj. R-squared:                  0.972
Method:                 Least Squares   F-statistic:                     397.2
Date:                Mon, 13 May 2019   Prob (F-statistic):           2.08e-41
Time:                        03:46:27   Log-Likelihood:                 193.02
No. Observations:                  63   AIC:                            -376.0
Df Residuals:                      58   BIC:                            -365.3
Df Model:                           4
Covariance Type:                  HC3
======================================================================================
                         coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------------
Intercept              0.0032      0.003      0.992      0.321      -0.003       0.009
GDP_Italy_Growth_1    -0.1361      0.095     -1.427      0.154      -0.323       0.051
GDP_Italy_Growth_2    -0.1043      0.091     -1.146      0.252      -0.283       0.074
GDP_Italy_Growth_3    -0.1209      0.083     -1.457      0.145      -0.283       0.042
GDP_Italy_Growth_4     0.8168      0.090      9.105      0.000       0.641       0.993
==============================================================================
Omnibus:                        5.473   Durbin-Watson:                   1.700
Prob(Omnibus):                  0.065   Jarque-Bera (JB):                4.676
Skew:                          -0.506   Prob(JB):                       0.0965
Kurtosis:                       3.869   Cond. No.                         83.7
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC3)
```

Ireland

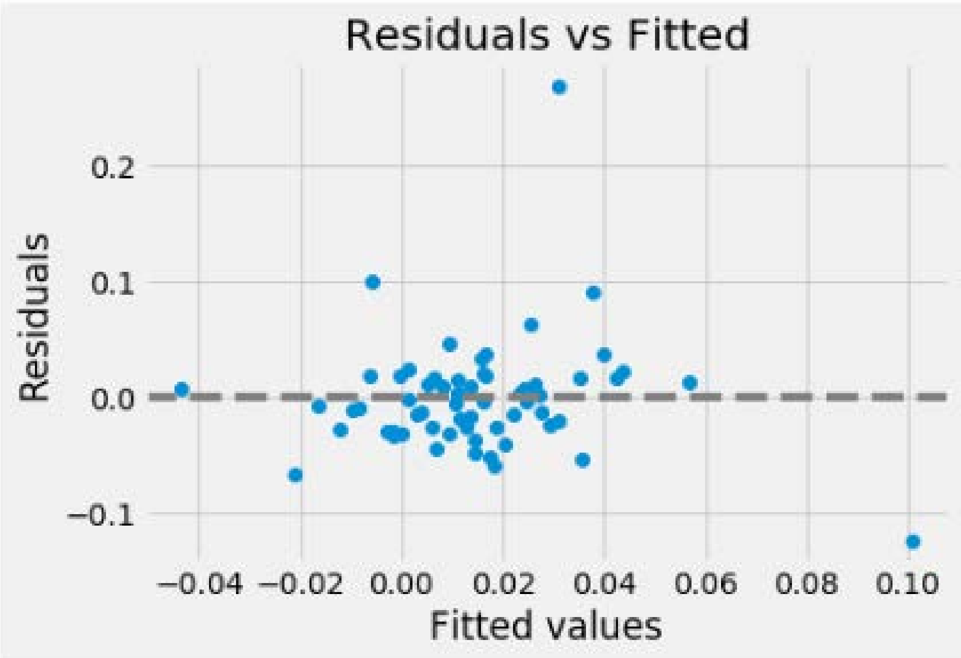
Vector Autoregressive - Andersson's method

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      GDP_Ireland_Growth   R-squared:                       0.296
Model:                             OLS   Adj. R-squared:                  0.127
Method:                  Least Squares   F-statistic:                     1.749
Date:                 Mon, 13 May 2019   Prob (F-statistic):             0.0841
Time:                         04:12:02   Log-Likelihood:                 106.58
No. Observations:                   63   AIC:                            -187.2
Df Residuals:                       50   BIC:                            -159.3
Df Model:                           12
Covariance Type:             nonrobust
=========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
Intercept                0.0240      0.010      2.375      0.021       0.004       0.044
GDP_Ireland_Growth_1    -0.3492      0.138     -2.525      0.015      -0.627      -0.071
GDP_Ireland_Growth_2    -0.1406      0.146     -0.962      0.341      -0.434       0.153
GDP_Ireland_Growth_3    -0.0390      0.148     -0.264      0.793      -0.336       0.258
GDP_Ireland_Growth_4     0.2060      0.137      1.504      0.139      -0.069       0.481
HICP_Ireland_D_1         0.0005      0.011      0.047      0.963      -0.022       0.023
HICP_Ireland_D_2         0.0023      0.011      0.202      0.841      -0.020       0.025
HICP_Ireland_D_3        -0.0139      0.011     -1.237      0.222      -0.036       0.009
HICP_Ireland_D_4        -0.0034      0.011     -0.301      0.765      -0.026       0.019
UN_Ireland_D_1          -0.0201      0.015     -1.302      0.199      -0.051       0.011
UN_Ireland_D_2          -0.0084      0.016     -0.530      0.598      -0.040       0.023
UN_Ireland_D_3          -0.0192      0.016     -1.195      0.238      -0.051       0.013
UN_Ireland_D_4           0.0076      0.015      0.491      0.626      -0.023       0.039
==============================================================================
Omnibus:                       60.813   Durbin-Watson:                   1.917
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              549.117
Skew:                           2.495   Prob(JB):                    5.76e-120
Kurtosis:                      16.575   Cond. No.                         37.2
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

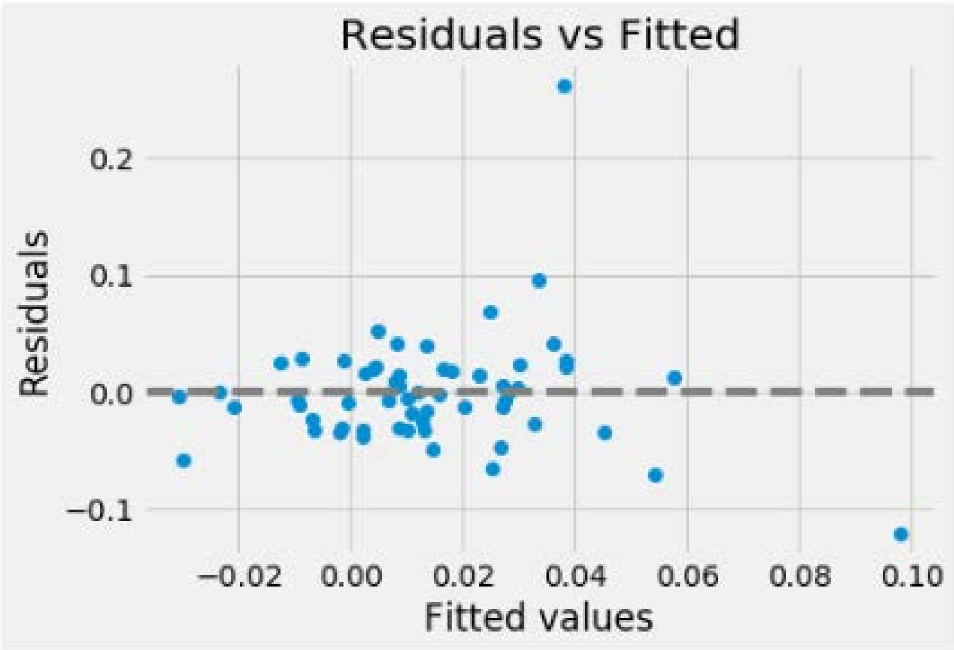


Autoregressive method

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      GDP_Ireland_Growth   R-squared:                       0.143
Model:                             OLS   Adj. R-squared:                  0.084
Method:                  Least Squares   F-statistic:                     2.426
Date:                 Mon, 13 May 2019   Prob (F-statistic):             0.0581
Time:                         04:12:02   Log-Likelihood:                 100.41
No. Observations:                   63   AIC:                            -190.8
Df Residuals:                       58   BIC:                            -180.1
Df Model:                            4
Covariance Type:             nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
Intercept                0.0108      0.008      1.407      0.165      -0.005       0.026
GDP_Ireland_Growth_1    -0.2372      0.126     -1.888      0.064      -0.489       0.014
GDP_Ireland_Growth_2     0.0233      0.129      0.181      0.857      -0.234       0.281
GDP_Ireland_Growth_3     0.1198      0.129      0.926      0.358      -0.139       0.379
GDP_Ireland_Growth_4     0.3135      0.126      2.479      0.016       0.060       0.567
==============================================================================
Omnibus:                       60.298   Durbin-Watson:                   1.932
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              499.821
Skew:                           2.514   Prob(JB):                    2.92e-109
Kurtosis:                      15.850   Cond. No.                         22.4
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```



```
                            OLS Regression Results
==============================================================================
Dep. Variable:     GDP_Ireland_Growth   R-squared:                       0.164
Model:                            OLS   Adj. R-squared:                  0.030
Method:                 Least Squares   F-statistic:                     1.227
Date:                Mon, 13 May 2019   Prob (F-statistic):              0.303
Time:                        04:12:02   Log-Likelihood:                 94.005
No. Observations:                  59   AIC:                            -170.0
Df Residuals:                      50   BIC:                            -151.3
Df Model:                           8
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
Intercept                0.0104      0.009      1.186      0.241      -0.007       0.028
GDP_Ireland_Growth_1    -0.1906      0.140     -1.365      0.178      -0.471       0.090
GDP_Ireland_Growth_2     0.0639      0.143      0.447      0.657      -0.224       0.351
GDP_Ireland_Growth_3     0.1074      0.143      0.749      0.458      -0.181       0.396
GDP_Ireland_Growth_4     0.2733      0.143      1.915      0.061      -0.013       0.560
GDP_Ireland_Growth_5    -0.1324      0.152     -0.871      0.388      -0.438       0.173
GDP_Ireland_Growth_6     0.0007      0.152      0.005      0.996      -0.305       0.307
GDP_Ireland_Growth_7     0.1302      0.156      0.837      0.407      -0.182       0.443
GDP_Ireland_Growth_8    -0.0369      0.155     -0.238      0.813      -0.349       0.275
==============================================================================
Omnibus:                       55.207   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              414.895
Skew:                           2.376   Prob(JB):                     8.07e-91
Kurtosis:                      15.091   Cond. No.                         28.3
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```



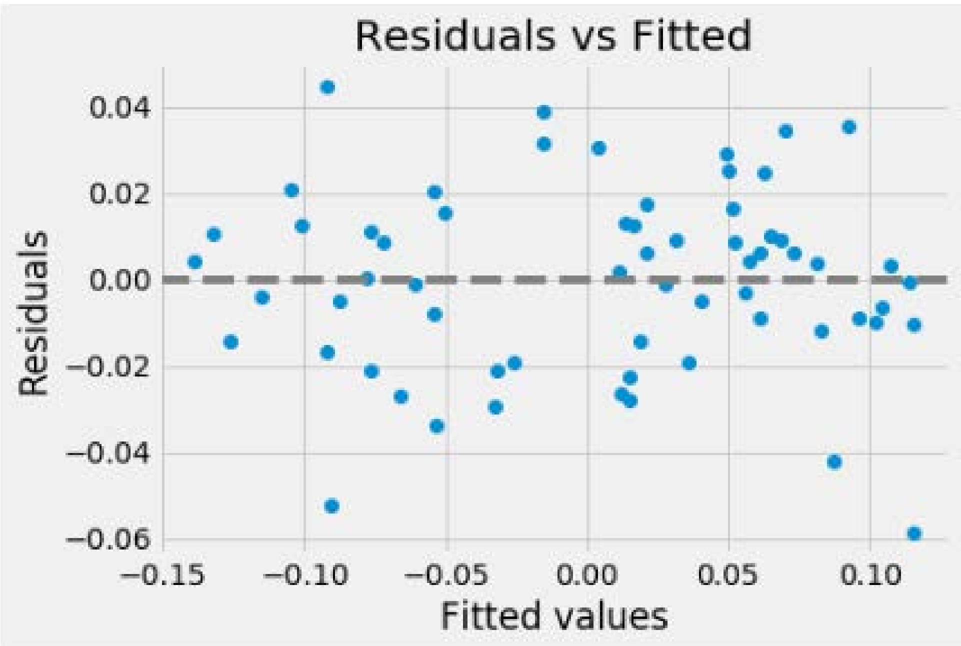
Autoregressive method – HC3

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      GDP_Ireland_Growth   R-squared:                       0.143
Model:                             OLS   Adj. R-squared:                  0.084
Method:                  Least Squares   F-statistic:                     1.975
Date:                 Mon, 13 May 2019   Prob (F-statistic):              0.110
Time:                         04:12:04   Log-Likelihood:                 100.41
No. Observations:                   63   AIC:                            -190.8
Df Residuals:                       58   BIC:                            -180.1
Df Model:                            4
Covariance Type:                   HC3
========================================================================================
                           coef    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------------
Intercept                0.0108      0.007      1.549      0.121      -0.003       0.025
GDP_Ireland_Growth_1    -0.2372      0.088     -2.705      0.007      -0.409      -0.065
GDP_Ireland_Growth_2     0.0233      0.172      0.135      0.892      -0.314       0.361
GDP_Ireland_Growth_3     0.1198      0.125      0.962      0.336      -0.124       0.364
GDP_Ireland_Growth_4     0.3135      0.413      0.758      0.448      -0.497       1.124
==============================================================================
Omnibus:                       60.298   Durbin-Watson:                   1.932
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              499.821
Skew:                           2.514   Prob(JB):                    2.92e-109
Kurtosis:                      15.850   Cond. No.                         22.4
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC3)
```

Greece

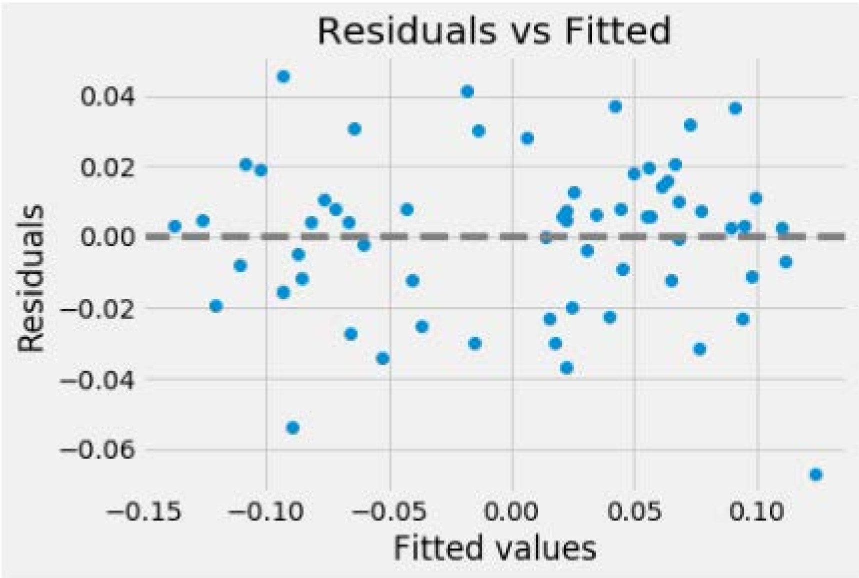
Vector Autoregressive - Andersson's method

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      GDP_Greece_Growth   R-squared:                       0.920
Model:                            OLS   Adj. R-squared:                  0.901
Method:                 Least Squares   F-statistic:                     48.09
Date:                Sat, 04 May 2019   Prob (F-statistic):           3.33e-23
Time:                        18:47:39   Log-Likelihood:                 153.08
No. Observations:                  63   AIC:                            -280.2
Df Residuals:                      50   BIC:                            -252.3
Df Model:                          12
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
Intercept               0.0052      0.004      1.194      0.238      -0.004       0.014
GDP_Greece_Growth_1    -0.1324      0.106     -1.245      0.219      -0.346       0.081
GDP_Greece_Growth_2    -0.1768      0.107     -1.652      0.105      -0.392       0.038
GDP_Greece_Growth_3    -0.0966      0.107     -0.907      0.369      -0.311       0.117
GDP_Greece_Growth_4     0.8102      0.108      7.472      0.000       0.592       1.028
HICP_Greece_D_1         0.0007      0.005      0.143      0.887      -0.009       0.010
HICP_Greece_D_2        -0.0028      0.005     -0.611      0.544      -0.012       0.006
HICP_Greece_D_3        -0.0038      0.005     -0.836      0.407      -0.013       0.005
HICP_Greece_D_4         0.0016      0.005      0.354      0.725      -0.008       0.011
UN_Greece_D_1          -0.0006      0.009     -0.062      0.951      -0.019       0.018
UN_Greece_D_2          -0.0090      0.010     -0.891      0.377      -0.029       0.011
UN_Greece_D_3           0.0025      0.010      0.252      0.802      -0.017       0.022
UN_Greece_D_4          -0.0011      0.009     -0.128      0.898      -0.019       0.016
==============================================================================
Omnibus:                        1.729   Durbin-Watson:                   2.289
Prob(Omnibus):                  0.421   Jarque-Bera (JB):                1.224
Skew:                          -0.336   Prob(JB):                        0.542
Kurtosis:                       3.126   Cond. No.                         132.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

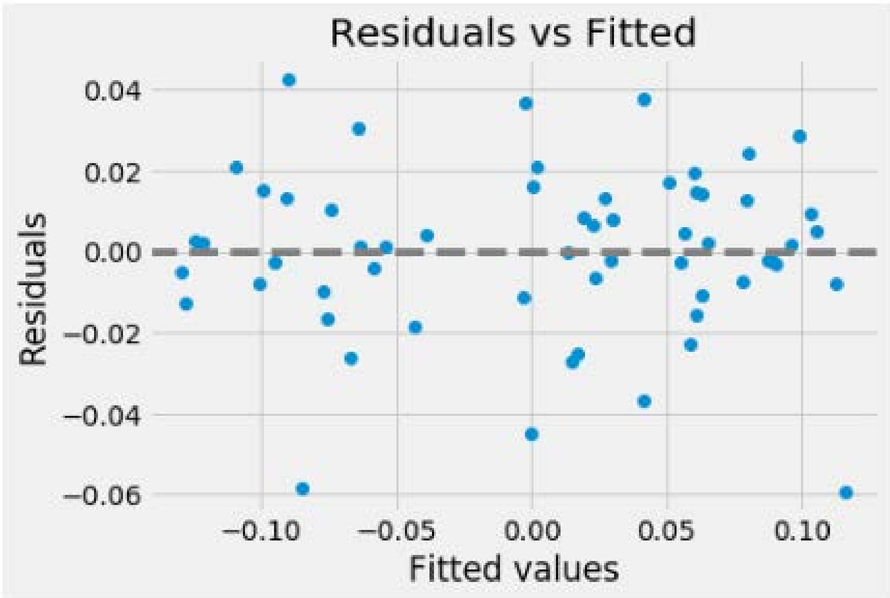


Autoregressive method

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      GDP_Greece_Growth   R-squared:                       0.913
Model:                            OLS   Adj. R-squared:                  0.907
Method:                 Least Squares   F-statistic:                     153.0
Date:                Sat, 04 May 2019   Prob (F-statistic):           4.22e-30
Time:                        18:47:39   Log-Likelihood:                 150.49
No. Observations:                  63   AIC:                            -291.0
Df Residuals:                      58   BIC:                            -280.3
Df Model:                           4
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
Intercept               0.0011      0.003      0.342      0.734      -0.005       0.007
GDP_Greece_Growth_1    -0.0923      0.059     -1.556      0.125      -0.211       0.026
GDP_Greece_Growth_2    -0.1099      0.060     -1.830      0.072      -0.230       0.010
GDP_Greece_Growth_3    -0.0543      0.060     -0.898      0.373      -0.175       0.067
GDP_Greece_Growth_4     0.8920      0.060     14.893      0.000       0.772       1.012
==============================================================================
Omnibus:                        3.219   Durbin-Watson:                   2.242
Prob(Omnibus):                  0.200   Jarque-Bera (JB):                2.369
Skew:                          -0.435   Prob(JB):                        0.306
Kurtosis:                       3.382   Cond. No.                         35.2
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```



```
                            OLS Regression Results
==============================================================================
Dep. Variable:       GDP_Greece_Growth   R-squared:                       0.928
Model:                             OLS   Adj. R-squared:                  0.916
Method:                  Least Squares   F-statistic:                     80.44
Date:                 Sat, 04 May 2019   Prob (F-statistic):           7.40e-26
Time:                         18:47:39   Log-Likelihood:                 145.55
No. Observations:                   59   AIC:                            -273.1
Df Residuals:                       50   BIC:                            -254.4
Df Model:                            8
Covariance Type:             nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
Intercept           -8.782e-05      0.003     -0.029      0.977      -0.006       0.006
GDP_Greece_Growth_1    -0.1950      0.131     -1.493      0.142      -0.457       0.067
GDP_Greece_Growth_2     0.0417      0.133      0.314      0.755      -0.225       0.308
GDP_Greece_Growth_3    -0.0387      0.131     -0.295      0.770      -0.302       0.225
GDP_Greece_Growth_4     0.5374      0.130      4.126      0.000       0.276       0.799
GDP_Greece_Growth_5     0.1006      0.130      0.773      0.443      -0.161       0.362
GDP_Greece_Growth_6    -0.1565      0.131     -1.192      0.239      -0.420       0.107
GDP_Greece_Growth_7    -0.0057      0.132     -0.043      0.965      -0.271       0.259
GDP_Greece_Growth_8     0.3871      0.130      2.977      0.004       0.126       0.648
==============================================================================
Omnibus:                         7.021   Durbin-Watson:                   1.922
Prob(Omnibus):                   0.030   Jarque-Bera (JB):                6.279
Skew:                           -0.637   Prob(JB):                       0.0433
Kurtosis:                        3.965   Cond. No.                         68.5
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```



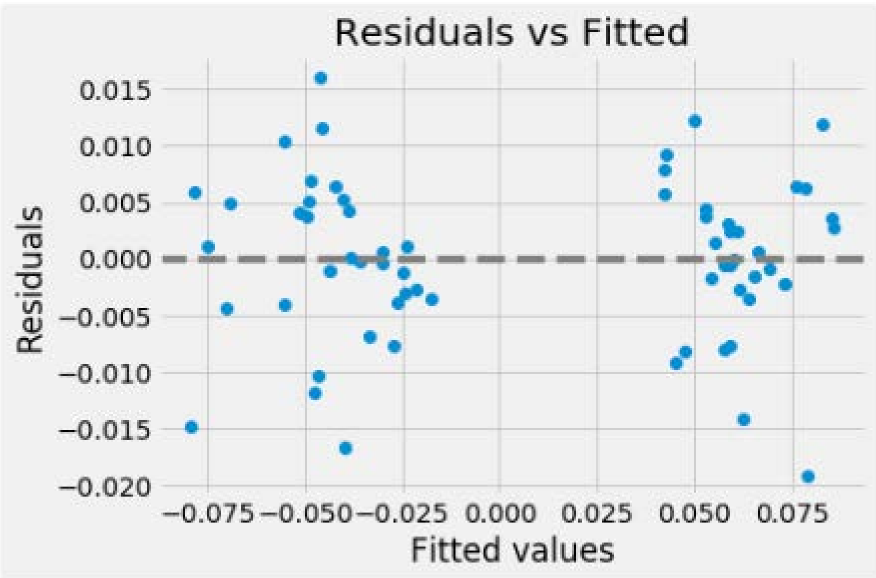
Autoregressive method – HC3

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      GDP_Greece_Growth   R-squared:                       0.913
Model:                            OLS   Adj. R-squared:                  0.907
Method:                 Least Squares   F-statistic:                     140.5
Date:                Sat, 04 May 2019   Prob (F-statistic):           3.98e-29
Time:                        18:47:41   Log-Likelihood:                 150.49
No. Observations:                  63   AIC:                            -291.0
Df Residuals:                      58   BIC:                            -280.3
Df Model:                           4
Covariance Type:                  HC3
=======================================================================================
                          coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------------
Intercept               0.0011      0.003      0.324      0.746      -0.005       0.007
GDP_Greece_Growth_1    -0.0923      0.058     -1.583      0.113      -0.207       0.022
GDP_Greece_Growth_2    -0.1099      0.051     -2.162      0.031      -0.210      -0.010
GDP_Greece_Growth_3    -0.0543      0.064     -0.850      0.395      -0.180       0.071
GDP_Greece_Growth_4     0.8920      0.054     16.406      0.000       0.785       0.999
==============================================================================
Omnibus:                        3.219   Durbin-Watson:                   2.242
Prob(Omnibus):                  0.200   Jarque-Bera (JB):                2.369
Skew:                          -0.435   Prob(JB):                        0.306
Kurtosis:                       3.382   Cond. No.                         35.2
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC3)
```

Spain

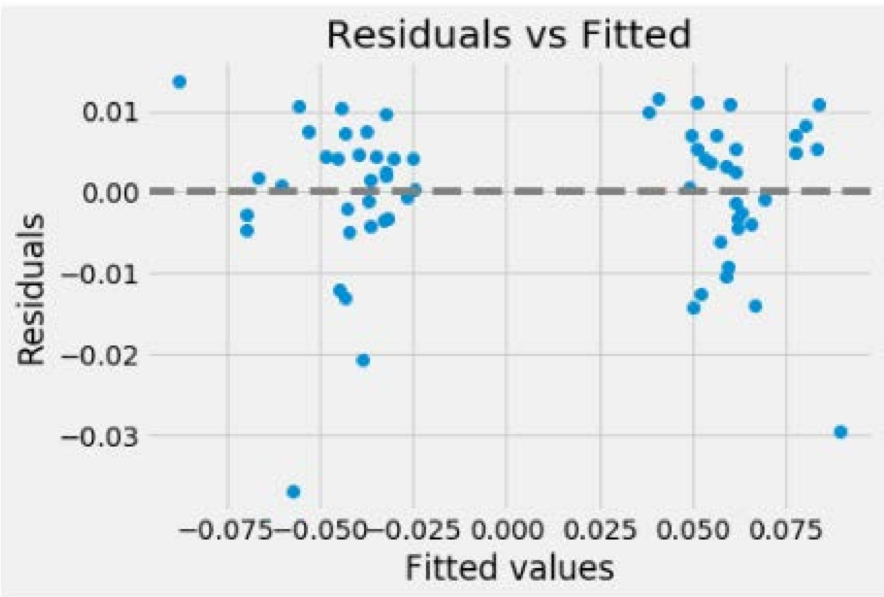
Vector Autoregressive - Andersson's method

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        GDP_Spain_Growth   R-squared:                       0.983
Model:                             OLS   Adj. R-squared:                  0.979
Method:                  Least Squares   F-statistic:                     246.3
Date:                 Sat, 04 May 2019   Prob (F-statistic):           4.43e-40
Time:                         18:41:19   Log-Likelihood:                 222.19
No. Observations:                   63   AIC:                            -418.4
Df Residuals:                       50   BIC:                            -390.5
Df Model:                           12
Covariance Type:             nonrobust
======================================================================================
                         coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------
Intercept              0.0025      0.002      1.323      0.192      -0.001       0.006
GDP_Spain_Growth_1    -0.1271      0.066     -1.922      0.060      -0.260       0.006
GDP_Spain_Growth_2     0.0274      0.068      0.401      0.690      -0.110       0.165
GDP_Spain_Growth_3     0.0364      0.071      0.510      0.612      -0.107       0.180
GDP_Spain_Growth_4     0.8994      0.070     12.780      0.000       0.758       1.041
HICP_Spain_D_1         0.0004      0.002      0.204      0.839      -0.003       0.004
HICP_Spain_D_2        -0.0015      0.002     -0.839      0.406      -0.005       0.002
HICP_Spain_D_3        -0.0017      0.002     -0.878      0.384      -0.005       0.002
HICP_Spain_D_4        -0.0010      0.002     -0.505      0.616      -0.005       0.003
UN_Spain_D_1          -0.0094      0.003     -3.116      0.003      -0.016      -0.003
UN_Spain_D_2          -0.0004      0.004     -0.111      0.912      -0.008       0.007
UN_Spain_D_3          -0.0003      0.004     -0.078      0.938      -0.008       0.007
UN_Spain_D_4           0.0071      0.003      2.539      0.014       0.001       0.013
==============================================================================
Omnibus:                        2.700   Durbin-Watson:                   2.223
Prob(Omnibus):                  0.259   Jarque-Bera (JB):                2.026
Skew:                          -0.426   Prob(JB):                        0.363
Kurtosis:                       3.210   Cond. No.                         175.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

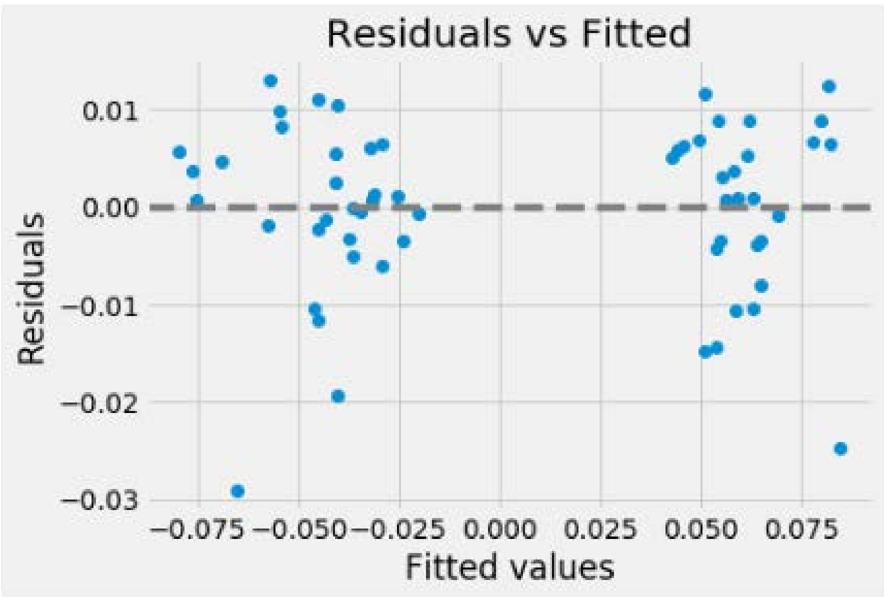


Autoregressive method

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       GDP_Spain_Growth   R-squared:                       0.970
Model:                            OLS   Adj. R-squared:                  0.968
Method:                 Least Squares   F-statistic:                     473.9
Date:                Sat, 04 May 2019   Prob (F-statistic):           1.48e-43
Time:                        18:41:19   Log-Likelihood:                 203.95
No. Observations:                  63   AIC:                            -397.9
Df Residuals:                      58   BIC:                            -387.2
Df Model:                           4
Covariance Type:            nonrobust
======================================================================================
                         coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------
Intercept              0.0010      0.002      0.567      0.573      -0.002       0.004
GDP_Spain_Growth_1    -0.0518      0.065     -0.794      0.430      -0.182       0.079
GDP_Spain_Growth_2     0.0487      0.065      0.747      0.458      -0.082       0.179
GDP_Spain_Growth_3    -0.0251      0.066     -0.384      0.703      -0.156       0.106
GDP_Spain_Growth_4     0.8657      0.065     13.235      0.000       0.735       0.997
==============================================================================
Omnibus:                       27.707   Durbin-Watson:                   1.413
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               49.734
Skew:                          -1.524   Prob(JB):                     1.59e-11
Kurtosis:                       6.108   Cond. No.                         63.8
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```



```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:       GDP_Spain_Growth   R-squared:                       0.975
Model:                            OLS   Adj. R-squared:                  0.971
Method:                 Least Squares   F-statistic:                     243.6
Date:                Sat, 04 May 2019   Prob (F-statistic):           2.75e-37
Time:                        18:41:19   Log-Likelihood:                 195.94
No. Observations:                  59   AIC:                            -373.9
Df Residuals:                      50   BIC:                            -355.2
Df Model:                           8                                         
Covariance Type:            nonrobust                                         
======================================================================================
                         coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------
Intercept              0.0014      0.002      0.830      0.410      -0.002       0.005
GDP_Spain_Growth_1     0.1641      0.139      1.181      0.243      -0.115       0.443
GDP_Spain_Growth_2     0.2627      0.141      1.860      0.069      -0.021       0.546
GDP_Spain_Growth_3     0.0799      0.144      0.554      0.582      -0.210       0.370
GDP_Spain_Growth_4     0.6877      0.139      4.948      0.000       0.408       0.967
GDP_Spain_Growth_5    -0.2951      0.136     -2.174      0.034      -0.568      -0.022
GDP_Spain_Growth_6    -0.2577      0.142     -1.812      0.076      -0.543       0.028
GDP_Spain_Growth_7    -0.0522      0.142     -0.368      0.714      -0.337       0.233
GDP_Spain_Growth_8     0.1970      0.142      1.388      0.171      -0.088       0.482
==============================================================================
Omnibus:                       15.428   Durbin-Watson:                   2.009
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               17.687
Skew:                          -1.135   Prob(JB):                     0.000144
Kurtosis:                       4.428   Cond. No.                         184.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```



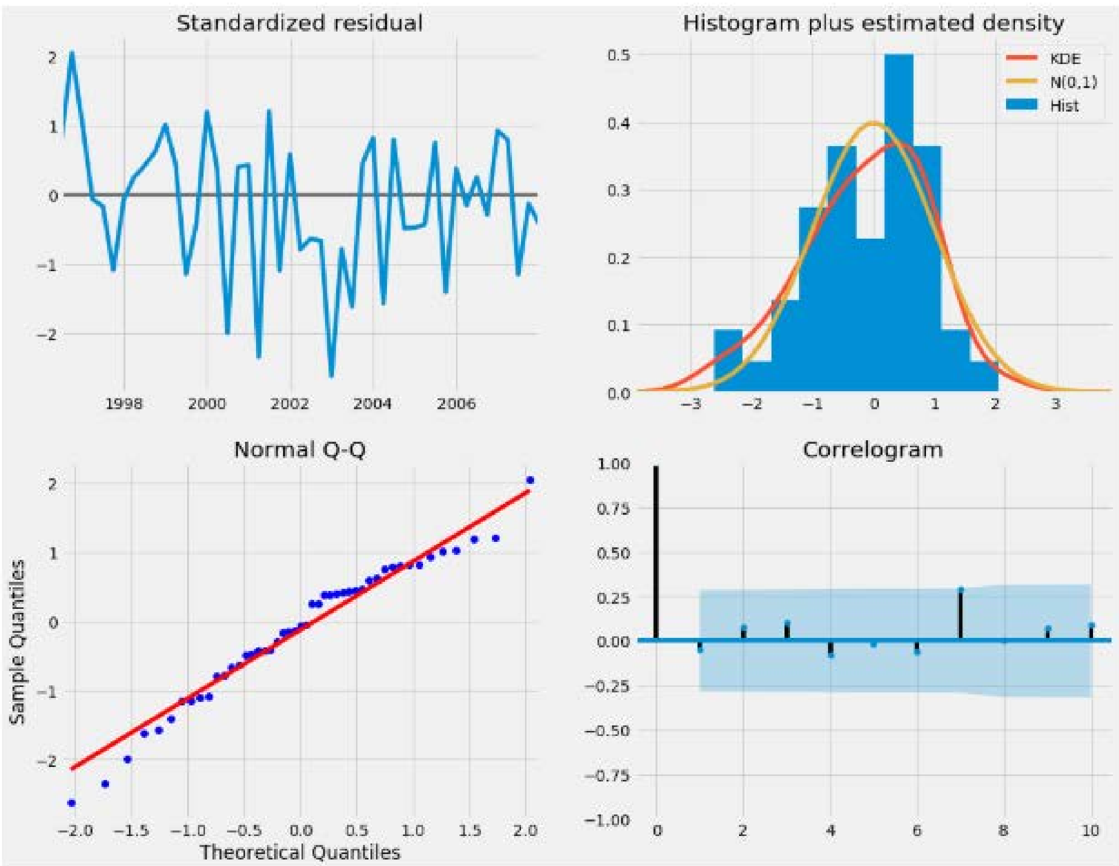
Autoregressive method – HC3

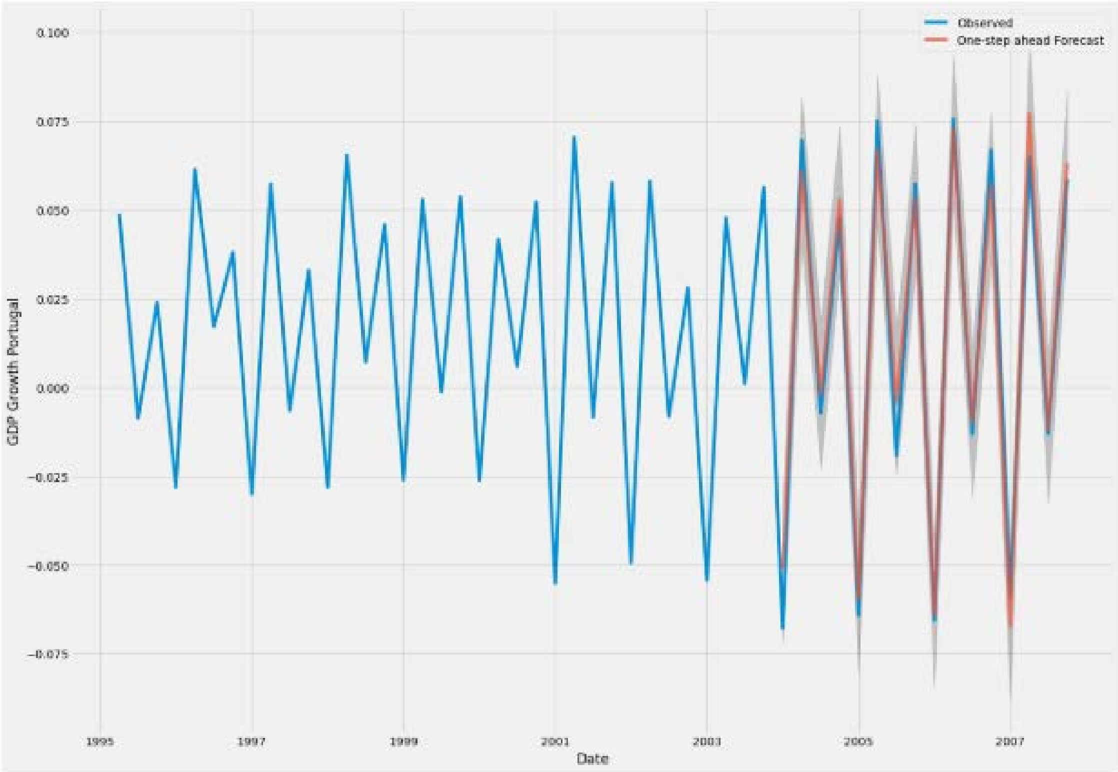
```
                            OLS Regression Results
==============================================================================
Dep. Variable:        GDP_Spain_Growth   R-squared:                       0.970
Model:                             OLS   Adj. R-squared:                  0.968
Method:                  Least Squares   F-statistic:                     501.0
Date:                 Sat, 04 May 2019   Prob (F-statistic):           3.10e-44
Time:                         18:41:22   Log-Likelihood:                 203.95
No. Observations:                   63   AIC:                            -397.9
Df Residuals:                       58   BIC:                            -387.2
Df Model:                            4
Covariance Type:                   HC3
======================================================================================
                         coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------------
Intercept              0.0010      0.002      0.486      0.627      -0.003       0.005
GDP_Spain_Growth_1    -0.0518      0.068     -0.767      0.443      -0.184       0.081
GDP_Spain_Growth_2     0.0487      0.060      0.808      0.419      -0.069       0.167
GDP_Spain_Growth_3    -0.0251      0.066     -0.380      0.704      -0.155       0.105
GDP_Spain_Growth_4     0.8657      0.079     10.976      0.000       0.711       1.020
==============================================================================
Omnibus:                       27.707   Durbin-Watson:                   1.413
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               49.734
Skew:                          -1.524   Prob(JB):                     1.59e-11
Kurtosis:                       6.108   Cond. No.                         63.8
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC3)
```

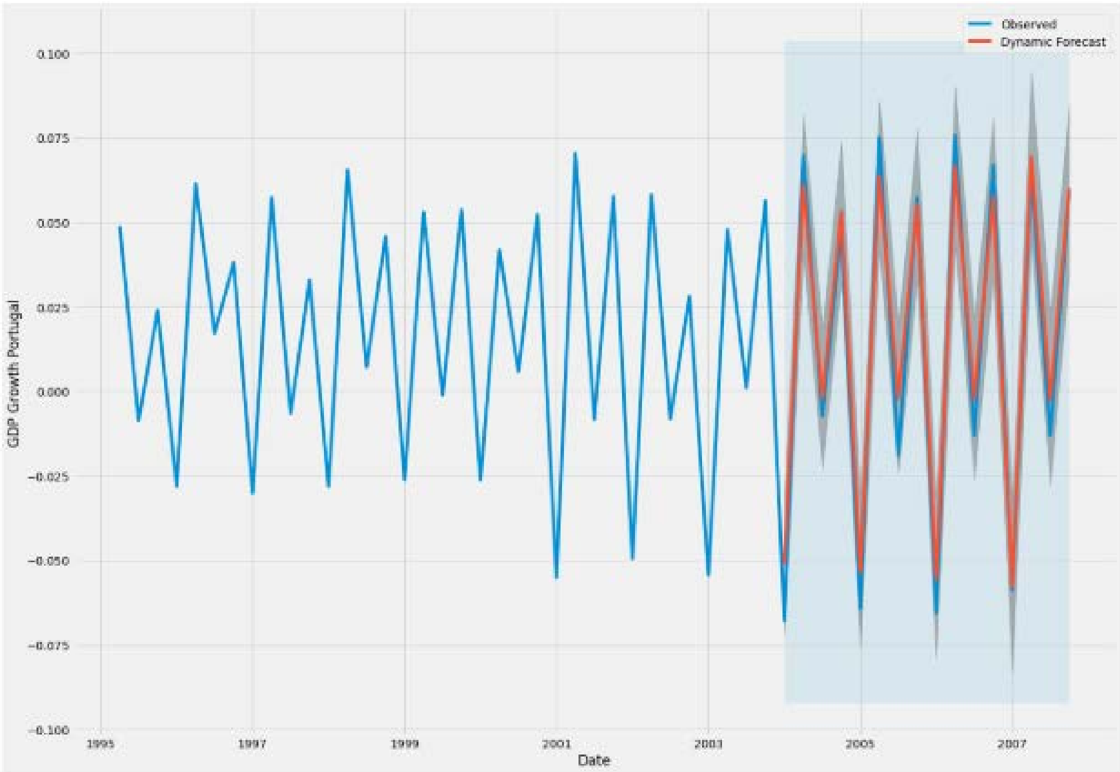
Appendix 2 – Short data frame and Long data frame comparison

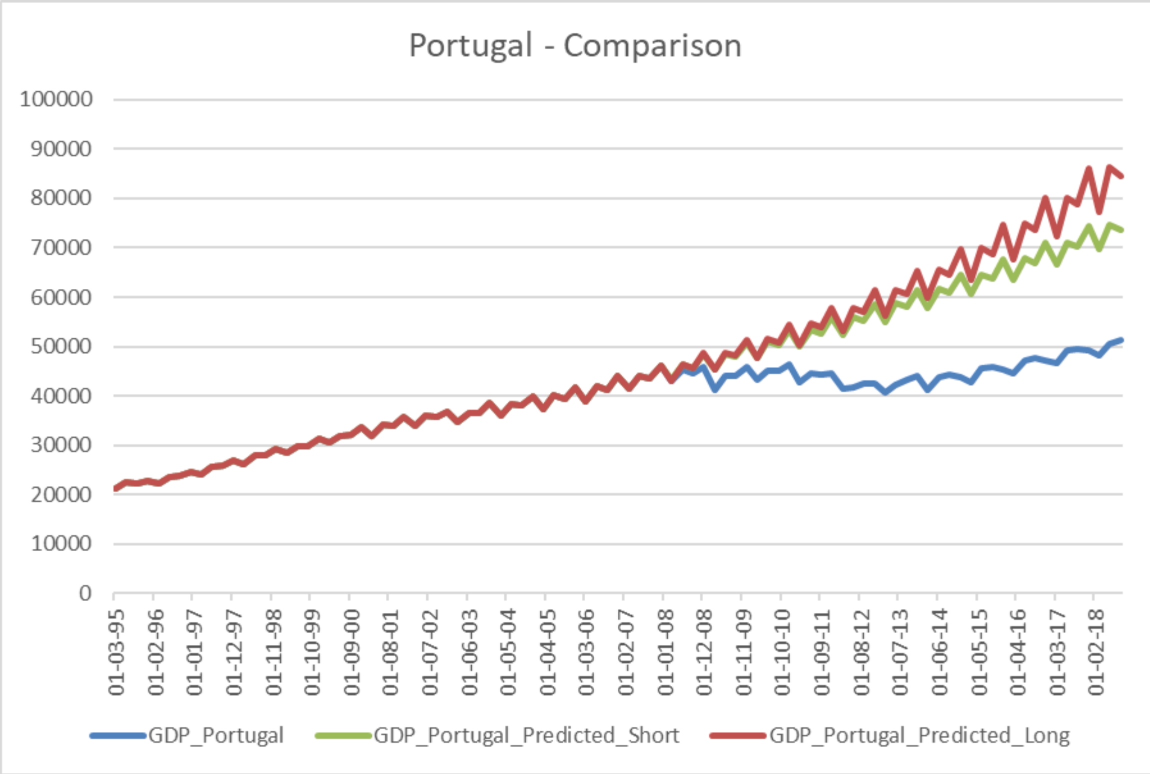
Portugal

```
                           Statespace Model Results
==============================================================================
Dep. Variable:     GDP_Portugal_Growth   No. Observations:                   52
Model:             SARIMAX(1, 0, 1, 4)   Log Likelihood                 145.642
Date:                 Mon, 27 May 2019   AIC                           -285.284
Time:                         15:07:29   BIC                           -279.430
Sample:                     03-31-1995   HQIC                          -283.040
                          - 12-31-2007
Covariance Type:                   opg
=============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------
ar.S.L4        1.0421      0.015     69.935      0.000       1.013       1.071
ma.S.L4       -0.6590      0.138     -4.776      0.000      -0.929      -0.389
sigma2         0.0001   2.59e-05      4.378      0.000    6.27e-05       0.000
===================================================================================
Ljung-Box (Q):                       30.21   Jarque-Bera (JB):                 1.71
Prob(Q):                              0.87   Prob(JB):                         0.43
Heteroskedasticity (H):               0.80   Skew:                            -0.46
Prob(H) (two-sided):                  0.66   Kurtosis:                         2.86
===================================================================================
```



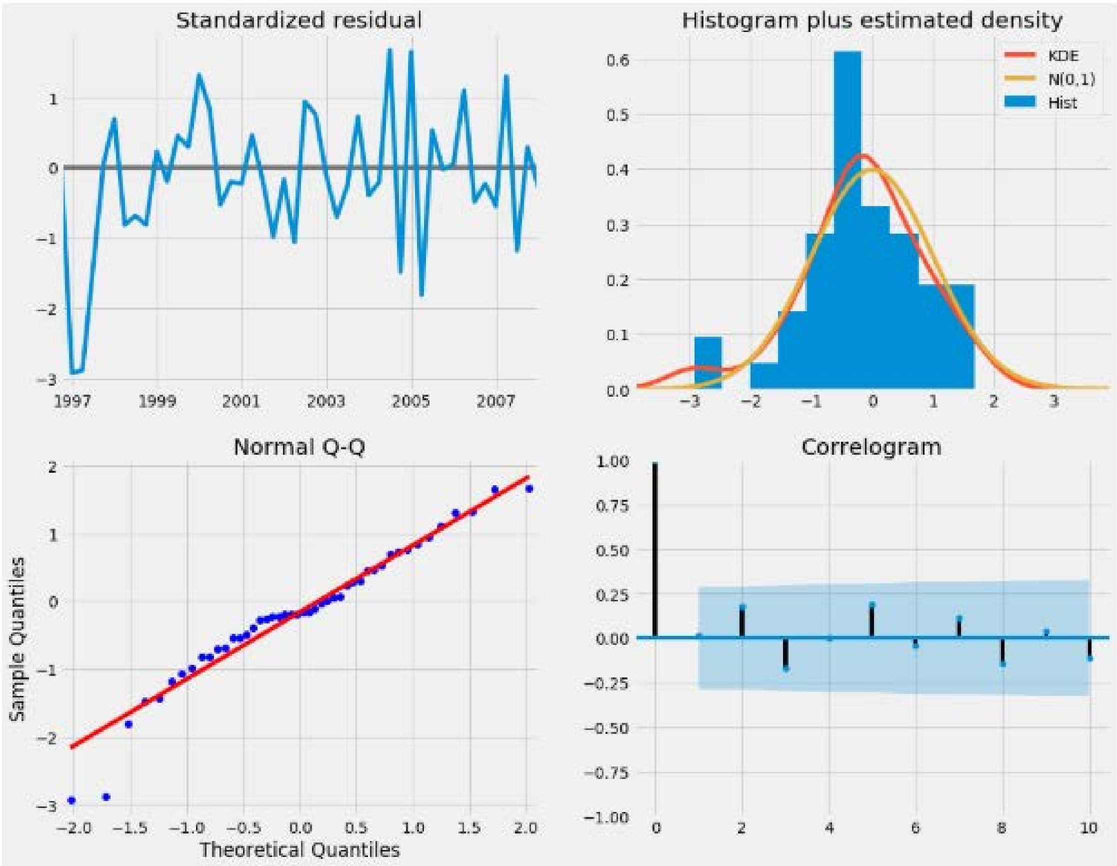

Observed
One-step ahead Forecast
0.100
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
GDP Growth Portugal
1995
1997
1999
2001
2003
2005
2007
Date

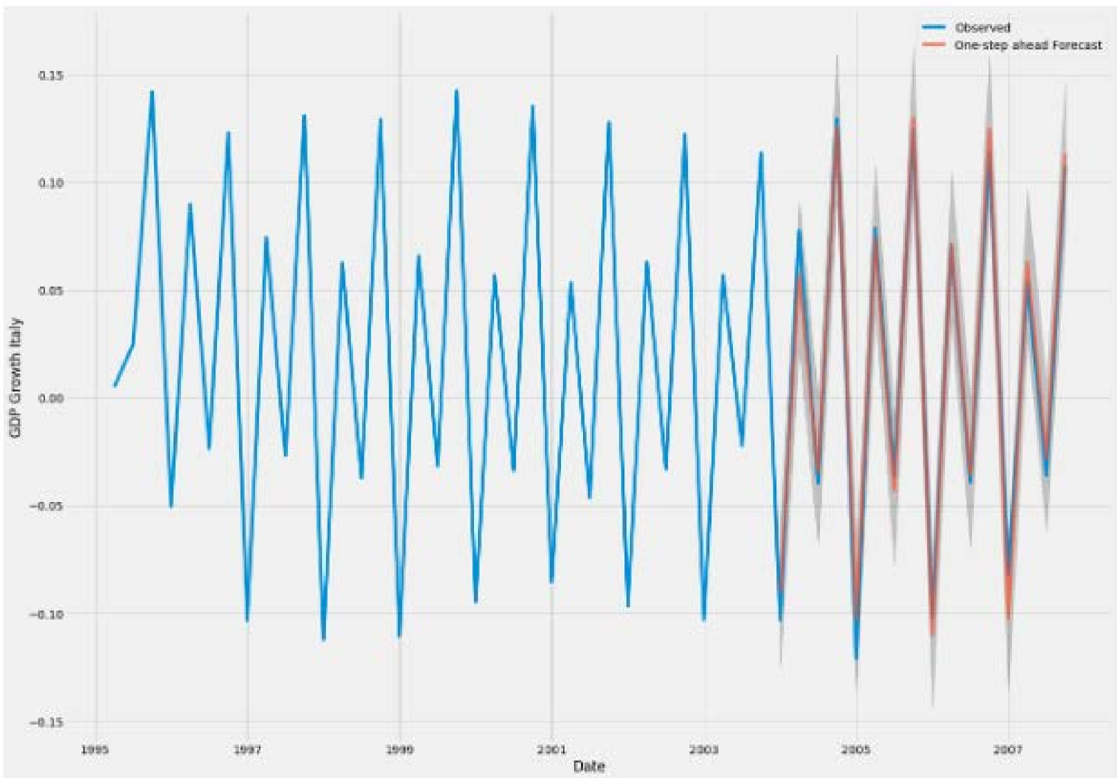

Observed
Dynamic Forecast
0.100
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100
GDP Growth Portugal
1995
1997
1999
2001
2003
2005
2007
Date

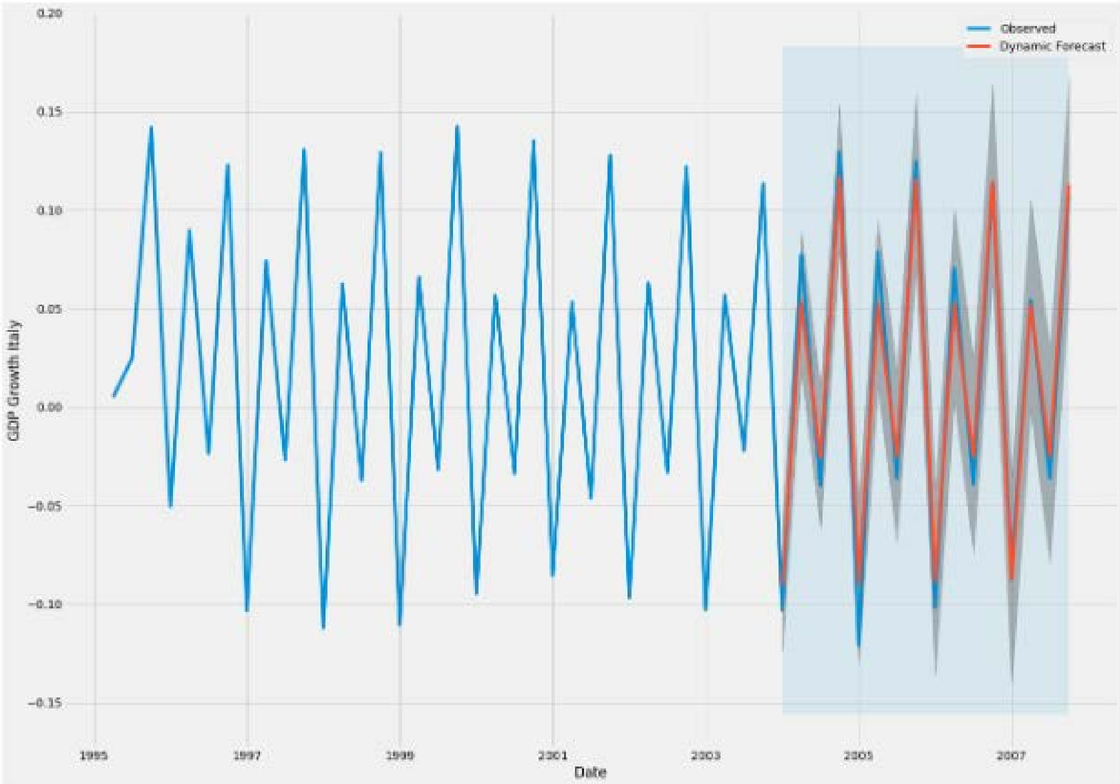


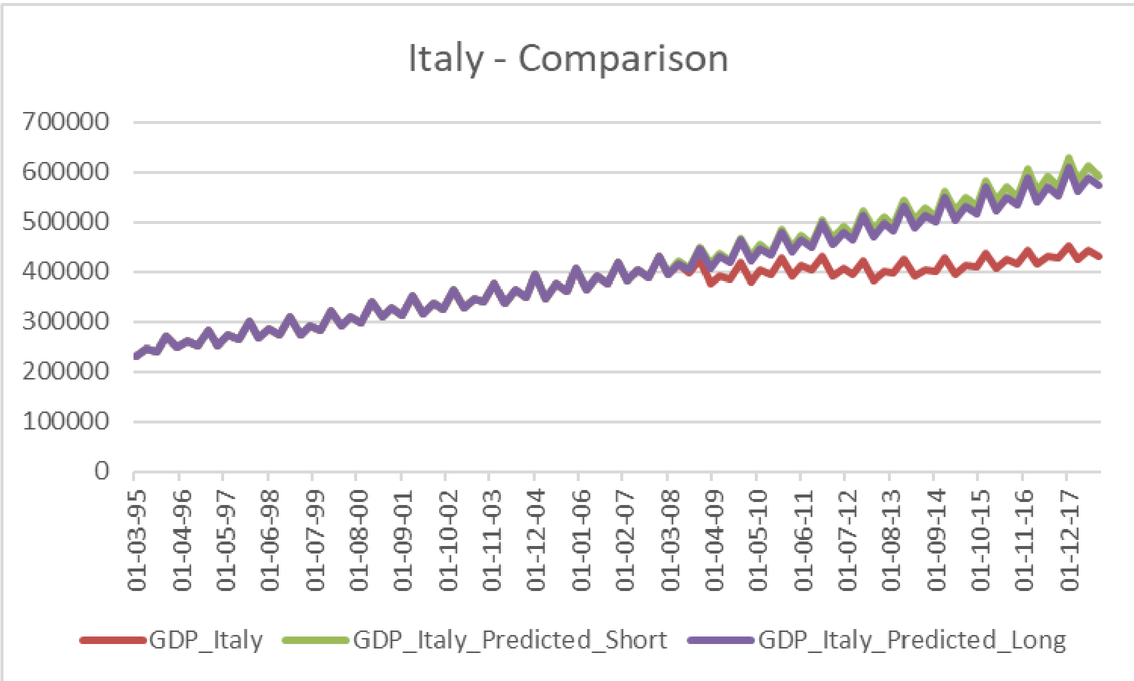
Italy

```
                                 Statespace Model Results
==========================================================================================
Dep. Variable:                     GDP_Italy_Growth   No. Observations:                 52
Model:             SARIMAX(1, 0, 1)x(1, 0, 1, 4)   Log Likelihood                 128.606
Date:                          Mon, 27 May 2019   AIC                           -247.213
Time:                                  15:26:06   BIC                           -237.457
Sample:                              03-31-1995   HQIC                          -243.472
                                   - 12-31-2007
Covariance Type:                            opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.8975      0.113     -7.952      0.000      -1.119      -0.676
ma.L1          0.6315      0.164      3.845      0.000       0.310       0.953
ar.S.L4        0.9899      0.016     60.989      0.000       0.958       1.022
ma.S.L4       -0.6368      0.264     -2.413      0.016      -1.154      -0.120
sigma2         0.0003   6.17e-05      4.927      0.000       0.000       0.000
===================================================================================
Ljung-Box (Q):                       nan   Jarque-Bera (JB):                 94.17
Prob(Q):                             nan   Prob(JB):                          0.00
Heteroskedasticity (H):             0.16   Skew:                              1.70
Prob(H) (two-sided):                0.00   Kurtosis:                          8.72
===================================================================================
```


Standardized residual
Histogram plus estimated density
KDE
N(0,1)
Hist
Normal Q-Q
Sample Quantiles
Theoretical Quantiles
Correlogram

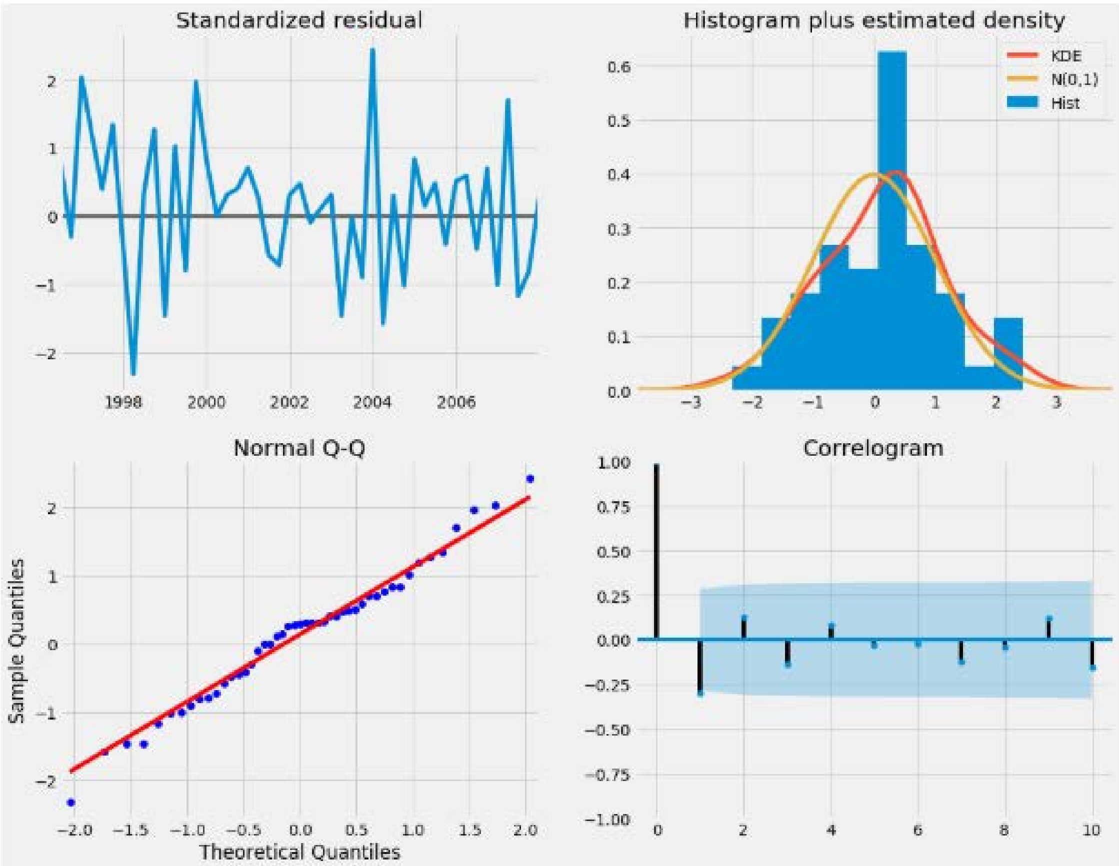

Observed
One-step ahead Forecast
GDP Growth Italy
Date

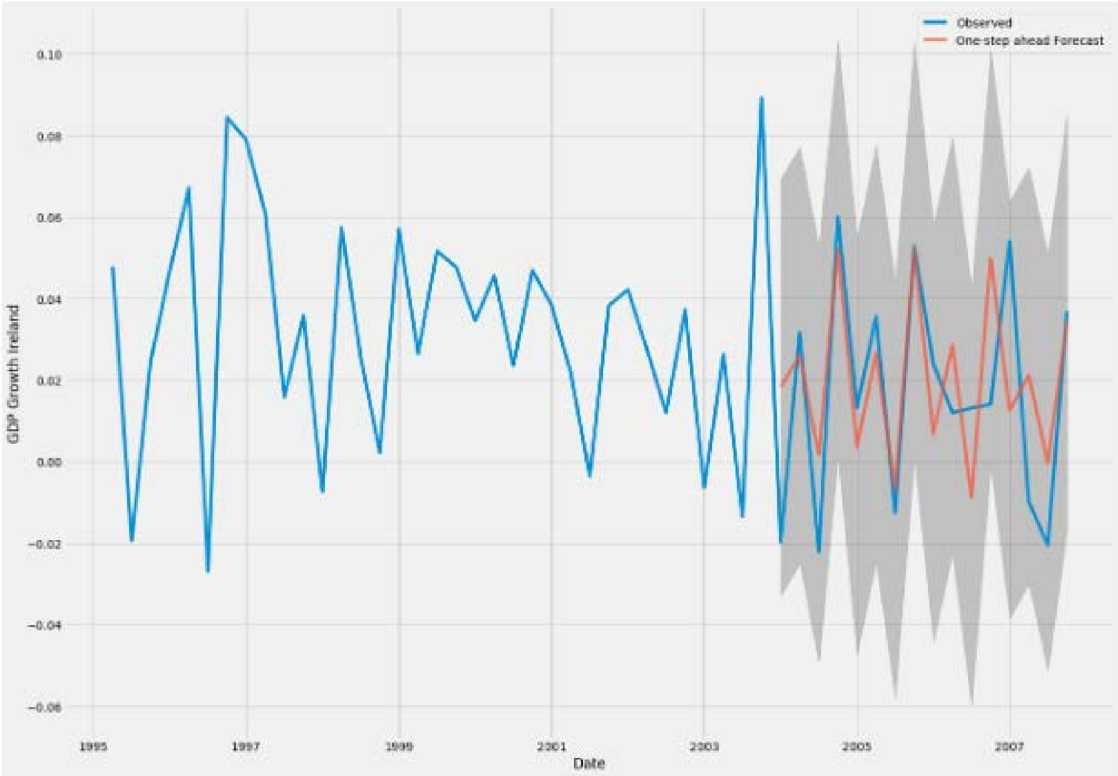

Observed
Dynamic Forecast
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
GDP Growth Italy
1995
1997
1999
2001
2003
2005
2007
Date

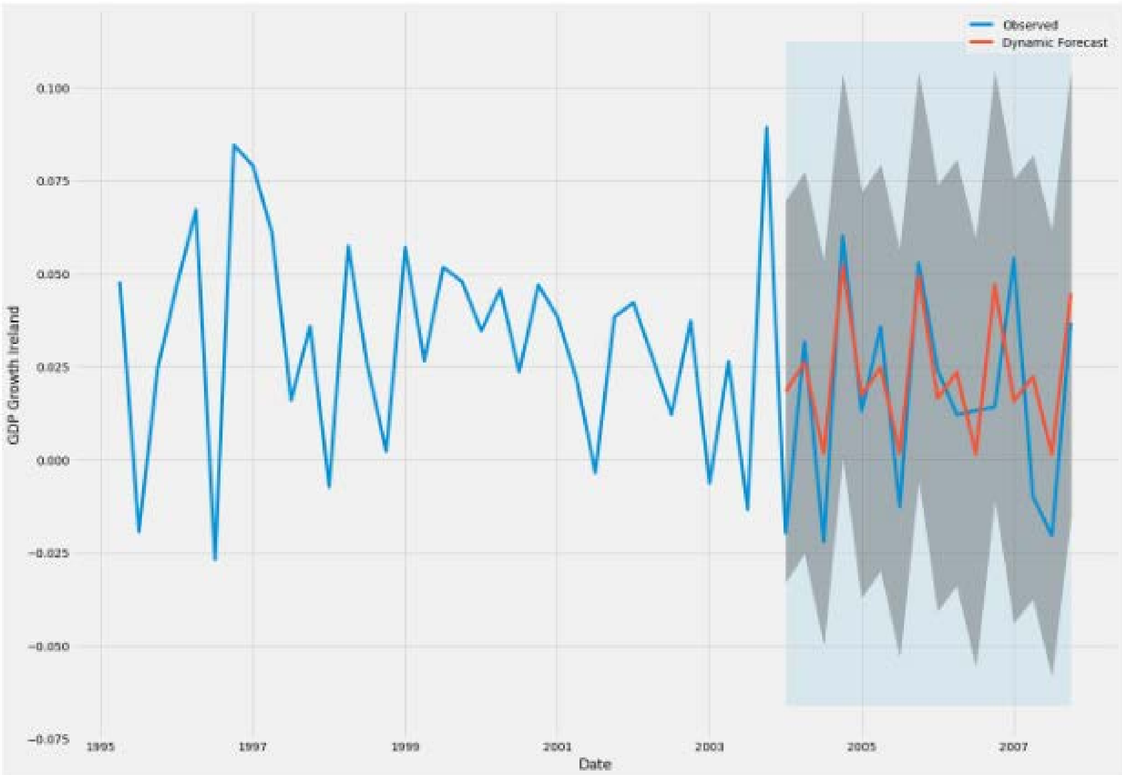

Italy - Comparison
700000
600000
500000
400000
300000
200000
100000
0
01-03-95
01-04-96
01-05-97
01-06-98
01-07-99
01-08-00
01-09-01
01-10-02
01-11-03
01-12-04
01-01-06
01-02-07
01-03-08
01-04-09
01-05-10
01-06-11
01-07-12
01-08-13
01-09-14
01-10-15
01-11-16
01-12-17
GDP_Italy
GDP_Italy_Predicted_Short
GDP_Italy_Predicted_Long

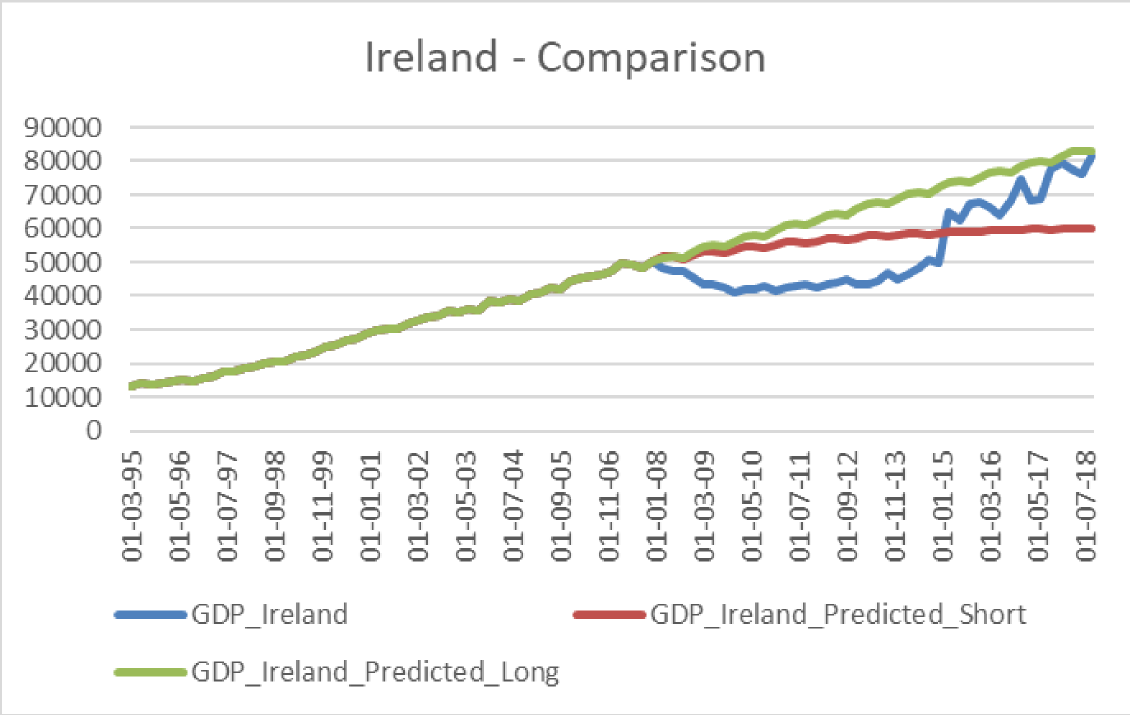
Ireland

```
                           Statespace Model Results
==============================================================================
Dep. Variable:      GDP_Ireland_Growth   No. Observations:                   52
Model:             SARIMAX(1, 0, 1, 4)   Log Likelihood                 111.402
Date:                 Mon, 27 May 2019   AIC                           -216.803
Time:                         15:29:29   BIC                           -210.950
Sample:                     03-31-1995   HQIC                          -214.559
                          - 12-31-2007
Covariance Type:                   opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.S.L4        0.9490      0.052     18.358      0.000       0.848       1.050
ma.S.L4       -0.5879      0.195     -3.008      0.003      -0.971      -0.205
sigma2         0.0007      0.000      4.575      0.000       0.000       0.001
===================================================================================
Ljung-Box (Q):                       nan   Jarque-Bera (JB):                  0.25
Prob(Q):                             nan   Prob(JB):                          0.88
Heteroskedasticity (H):             0.63   Skew:                             -0.00
Prob(H) (two-sided):                0.35   Kurtosis:                          2.66
===================================================================================
```



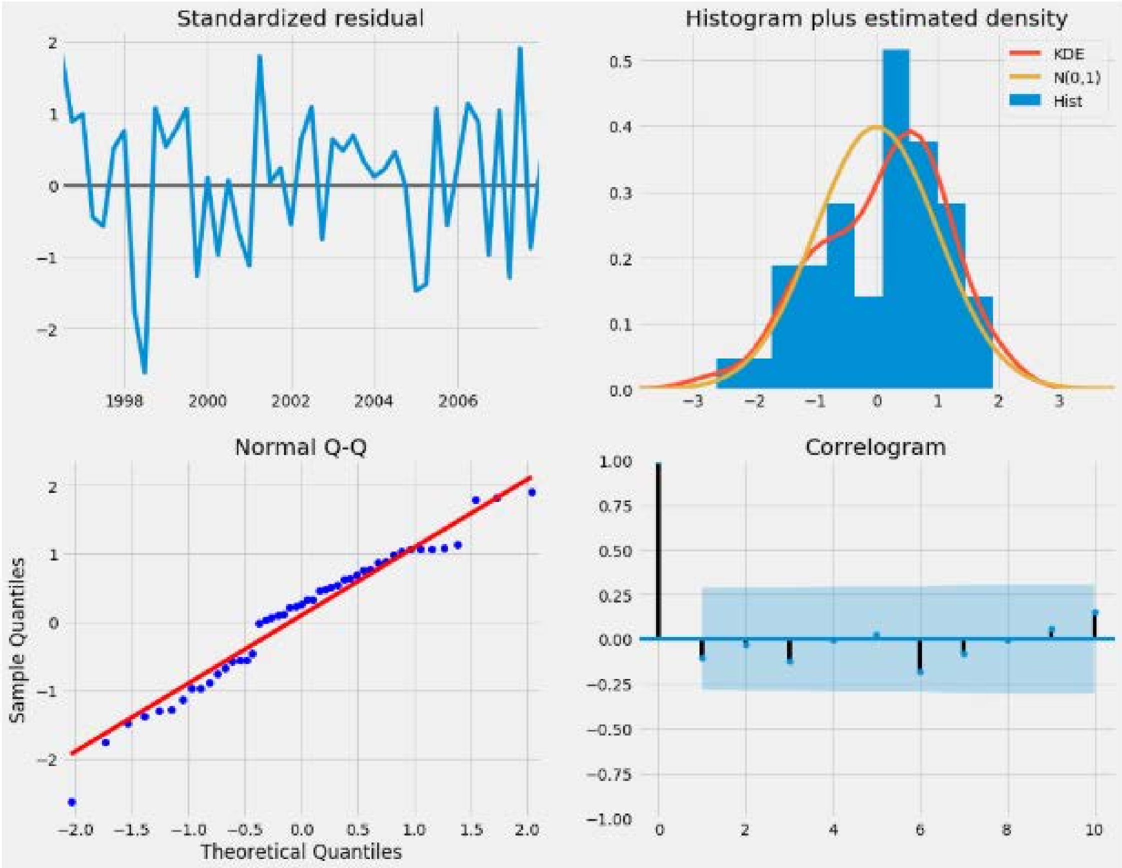

Observed
One-step ahead Forecast
GDP Growth Ireland
Date
0.10
0.08
0.06
0.04
0.02
0.00
−0.02
−0.04
−0.06
1995
1997
1999
2001
2003
2005
2007

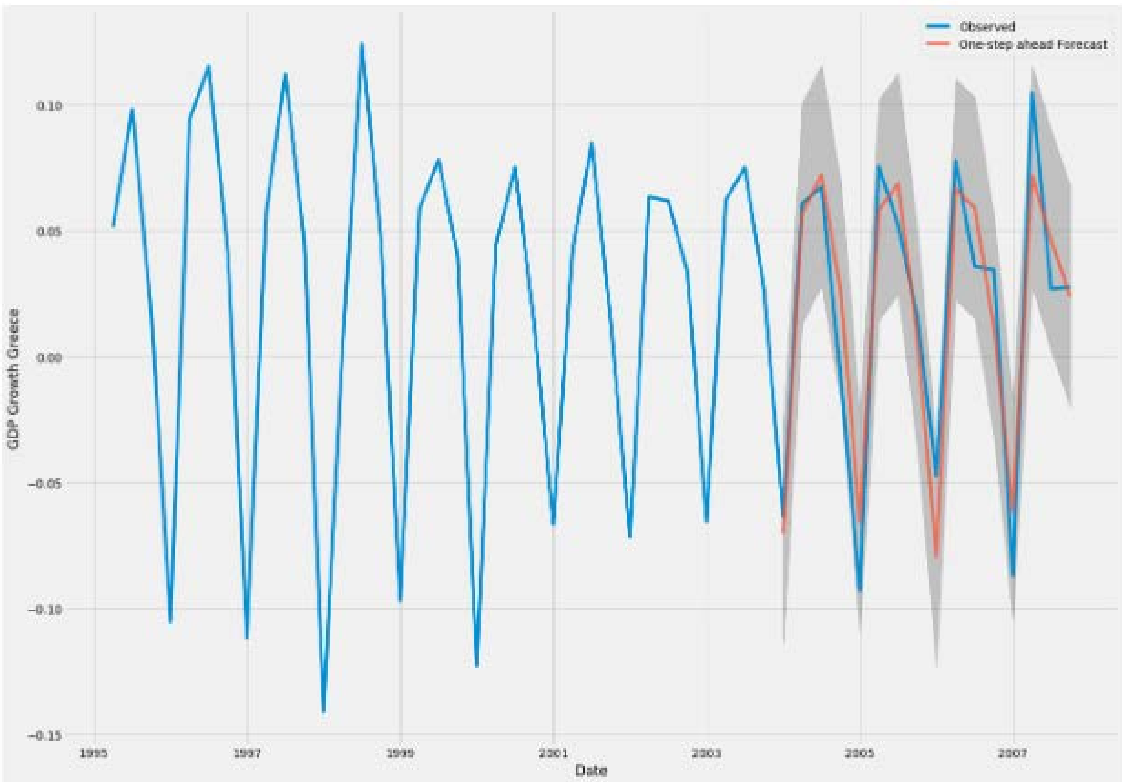

Observed
Dynamic Forecast
GDP Growth Ireland
Date
0.100
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
1995
1997
1999
2001
2003
2005
2007

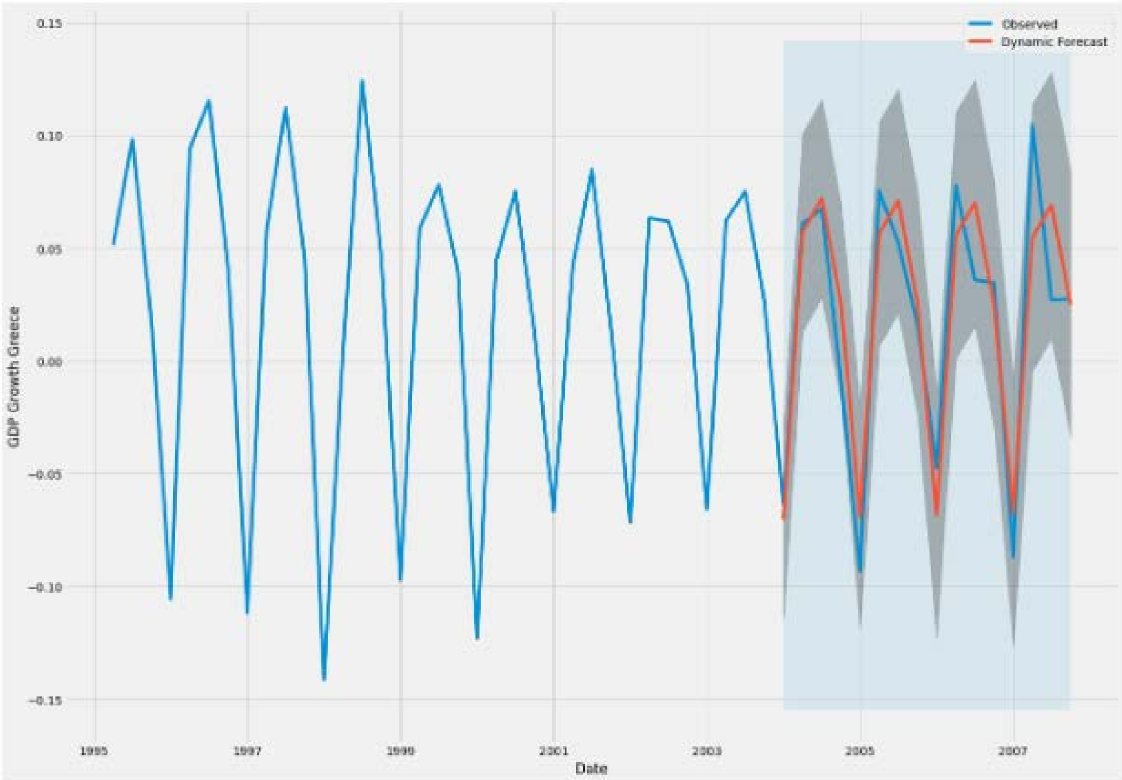


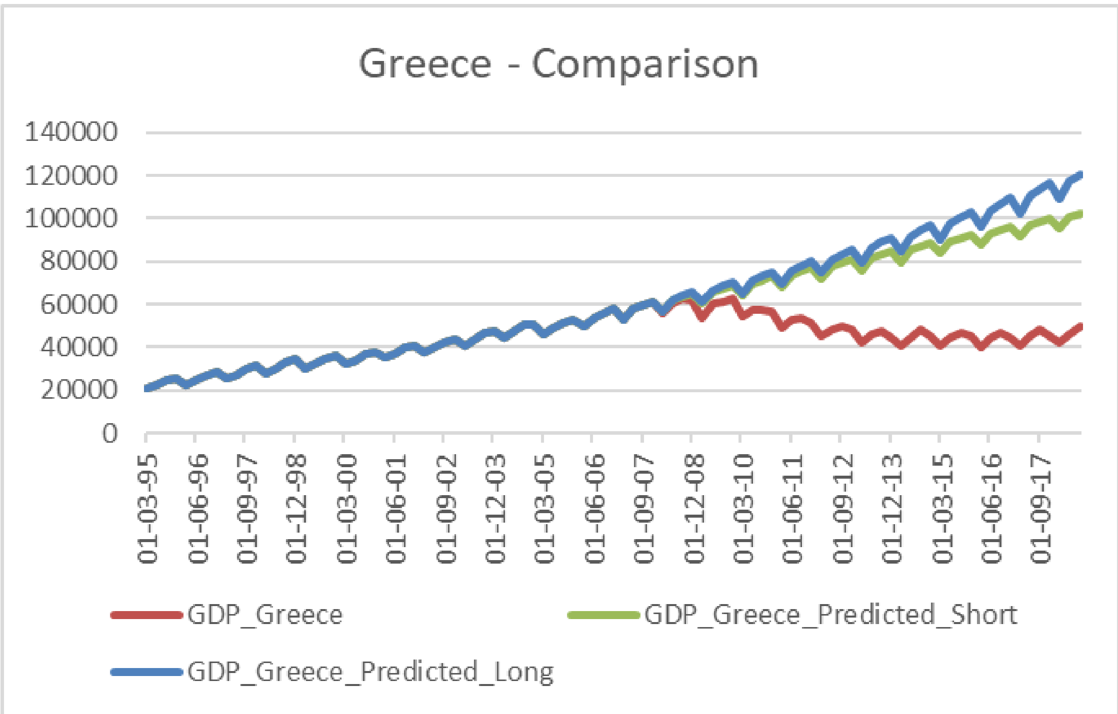
Greece

```
                           Statespace Model Results
==============================================================================
Dep. Variable:        GDP_Greece_Growth   No. Observations:                 52
Model:               SARIMAX(1, 0, 1, 4)   Log Likelihood                116.082
Date:                  Mon, 27 May 2019   AIC                          -226.165
Time:                          15:48:11   BIC                          -220.311
Sample:                      03-31-1995   HQIC                         -223.921
                           - 12-31-2007
Covariance Type:                    opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.S.L4        0.9861      0.015     65.112      0.000       0.956       1.016
ma.S.L4       -0.4583      0.176     -2.600      0.009      -0.804      -0.113
sigma2         0.0005      0.000      4.583      0.000       0.000       0.001
===================================================================================
Ljung-Box (Q):                       nan   Jarque-Bera (JB):                  1.12
Prob(Q):                             nan   Prob(JB):                          0.57
Heteroskedasticity (H):             0.61   Skew:                             -0.34
Prob(H) (two-sided):                0.32   Kurtosis:                          2.74
===================================================================================
```


Standardized residual
Histogram plus estimated density
KDE
N(0,1)
Hist
Normal Q-Q
Sample Quantiles
Theoretical Quantiles
Correlogram

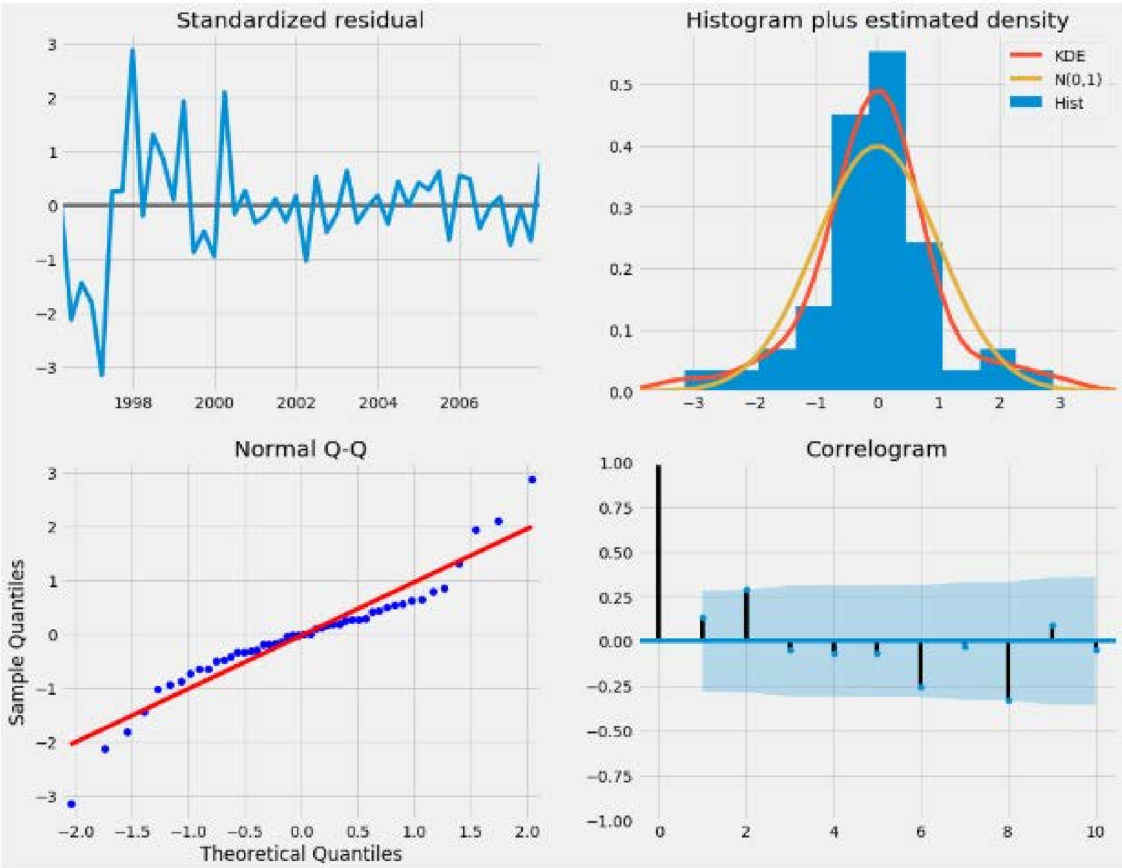

Observed
One-step ahead Forecast
GDP Growth Greece
Date

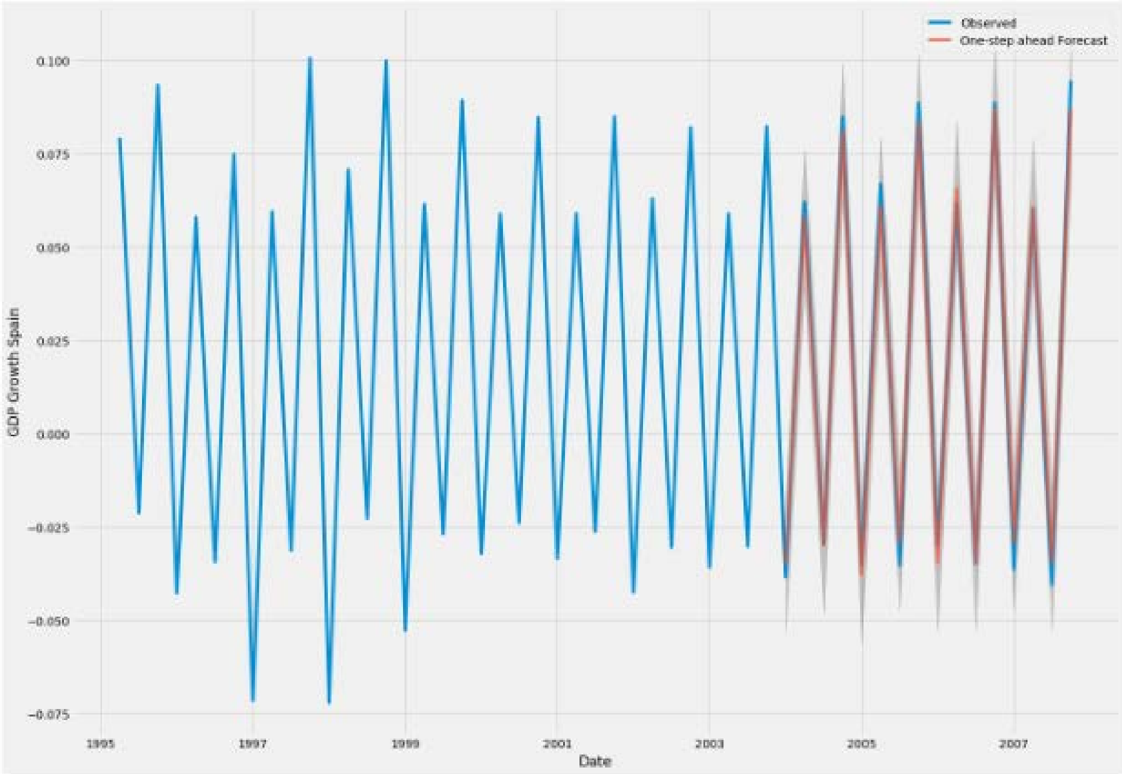

Observed
Dynamic Forecast
GDP Growth Greece
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
1995
1997
1999
2001
2003
2005
2007
Date

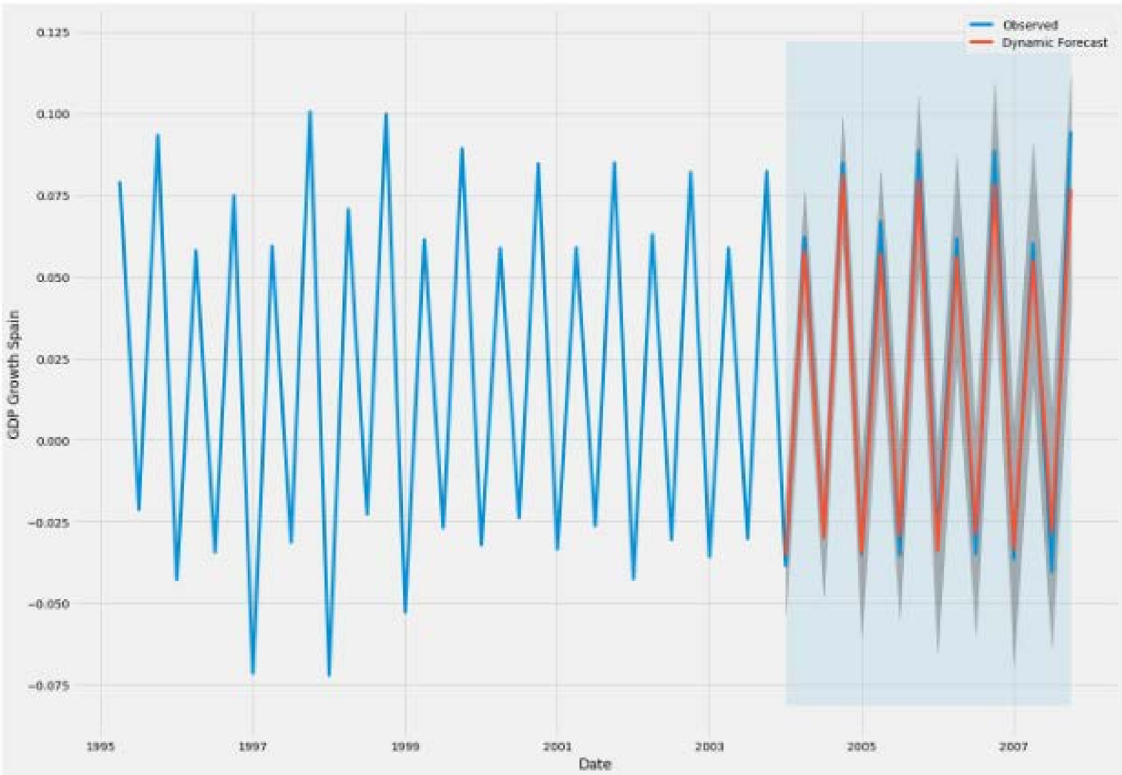

Greece - Comparison
140000
120000
100000
80000
60000
40000
20000
0
01-03-95
01-06-96
01-09-97
01-12-98
01-03-00
01-06-01
01-09-02
01-12-03
01-03-05
01-06-06
01-09-07
01-12-08
01-03-10
01-06-11
01-09-12
01-12-13
01-03-15
01-06-16
01-09-17
GDP_Greece
GDP_Greece_Predicted_Short
GDP_Greece_Predicted_Long

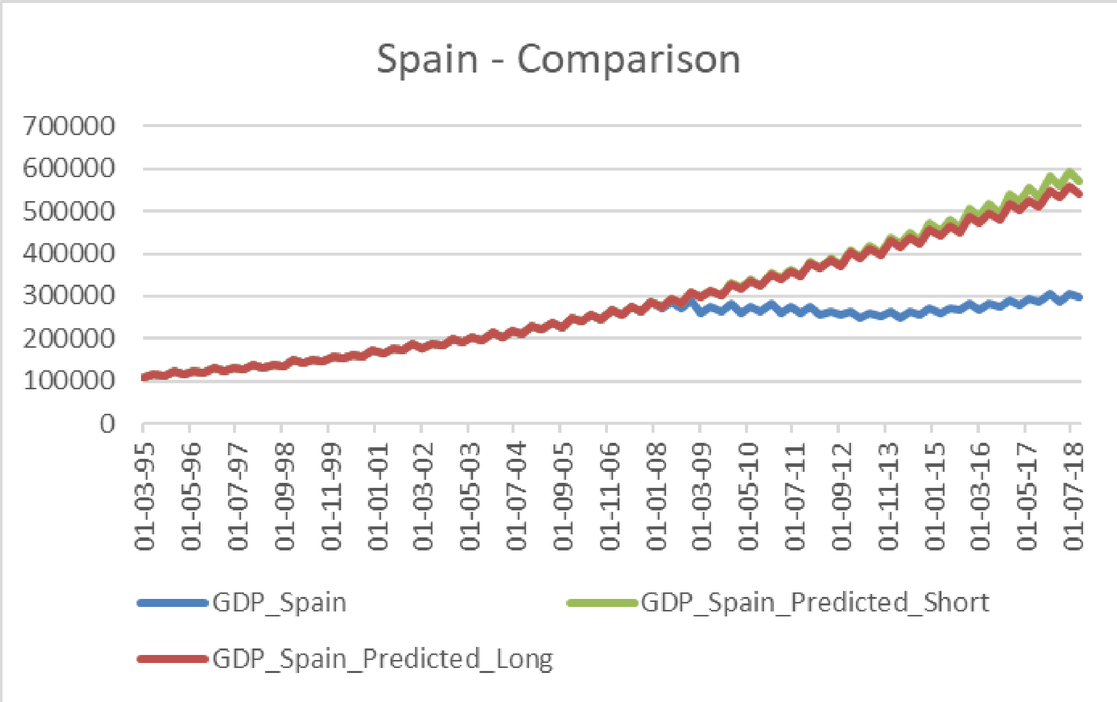
Spain

```
                               Statespace Model Results
==============================================================================
Dep. Variable:          GDP_Spain_Growth   No. Observations:                   52
Model:               SARIMAX(1, 0, 0, 4)   Log Likelihood                 145.012
Date:                   Mon, 27 May 2019   AIC                           -286.024
Time:                           15:53:20   BIC                           -282.121
Sample:                       03-31-1995   HQIC                          -284.528
                            - 12-31-2007
Covariance Type:                     opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.S.L4        0.9831      0.022     45.503      0.000       0.941       1.025
sigma2      8.776e-05   1.27e-05      6.914      0.000    6.29e-05       0.000
===================================================================================
Ljung-Box (Q):                       29.59   Jarque-Bera (JB):               10.45
Prob(Q):                              0.89   Prob(JB):                        0.01
Heteroskedasticity (H):               0.10   Skew:                           -0.09
Prob(H) (two-sided):                  0.00   Kurtosis:                        5.28
===================================================================================
```




Observed
One-step ahead Forecast
GDP Growth Spain
Date
0.100
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
1995
1997
1999
2001
2003
2005
2007


Observed
Dynamic Forecast
GDP Growth Spain
Date
0.125
0.100
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
1995
1997
1999
2001
2003
2005
2007

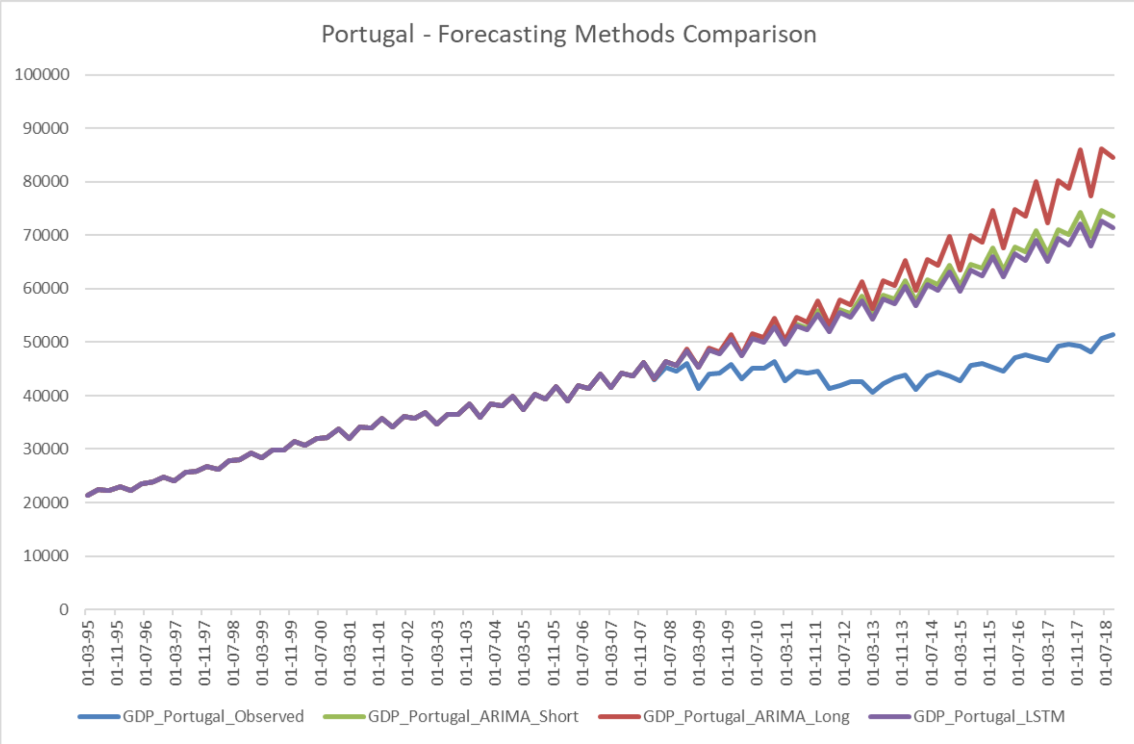

Spain - Comparison
700000
600000
500000
400000
300000
200000
100000
0
01-03-95
01-05-96
01-07-97
01-09-98
01-11-99
01-01-01
01-03-02
01-05-03
01-07-04
01-09-05
01-11-06
01-01-08
01-03-09
01-05-10
01-07-11
01-09-12
01-11-13
01-01-15
01-03-16
01-05-17
01-07-18
GDP_Spain
GDP_Spain_Predicted_Short
GDP_Spain_Predicted_Long

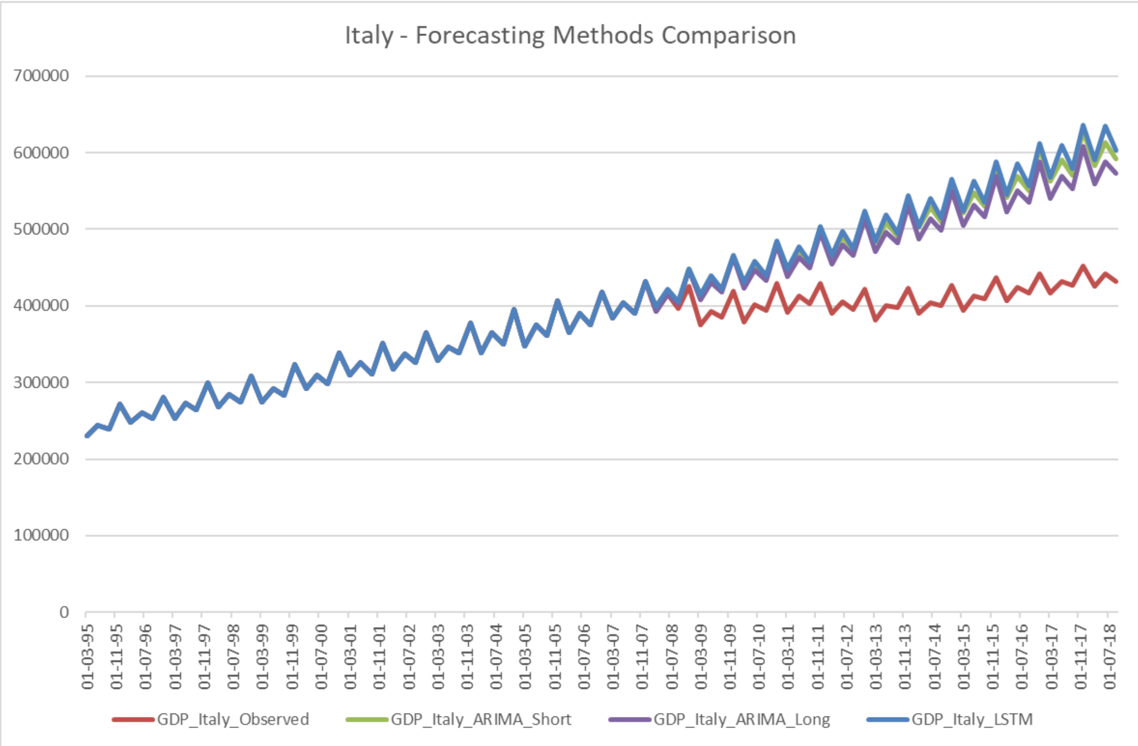
Appendix 3 – Artificial Neural Network – LSTM

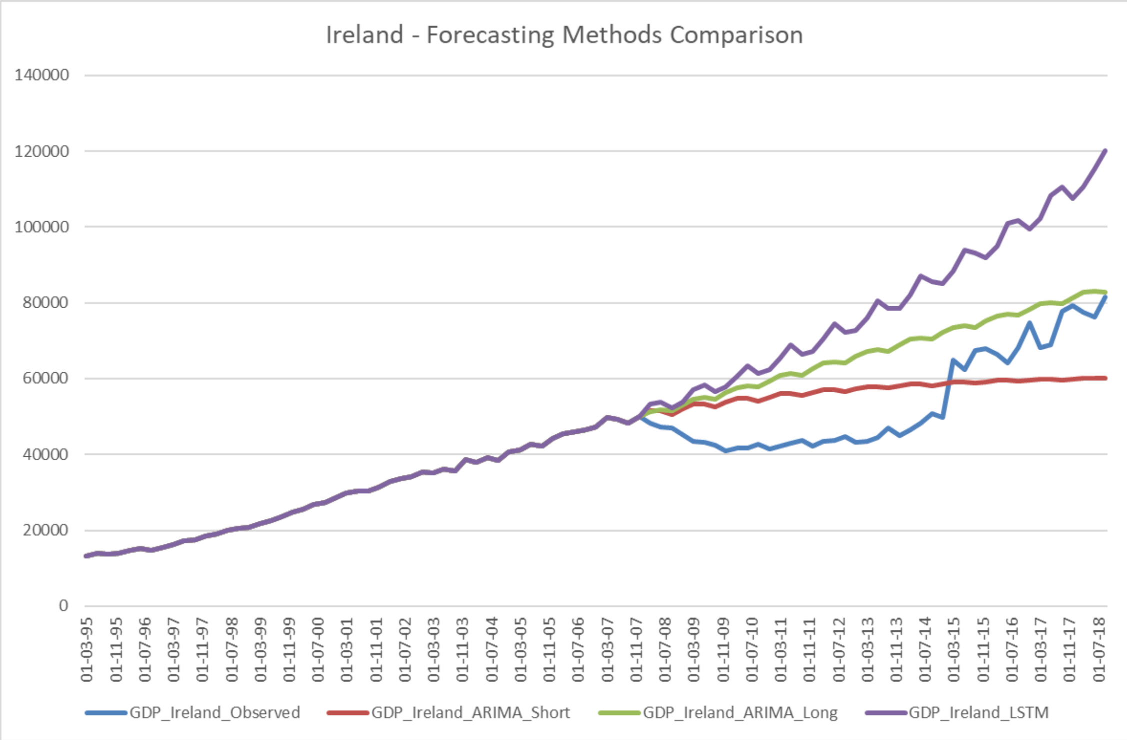
Features of the model:

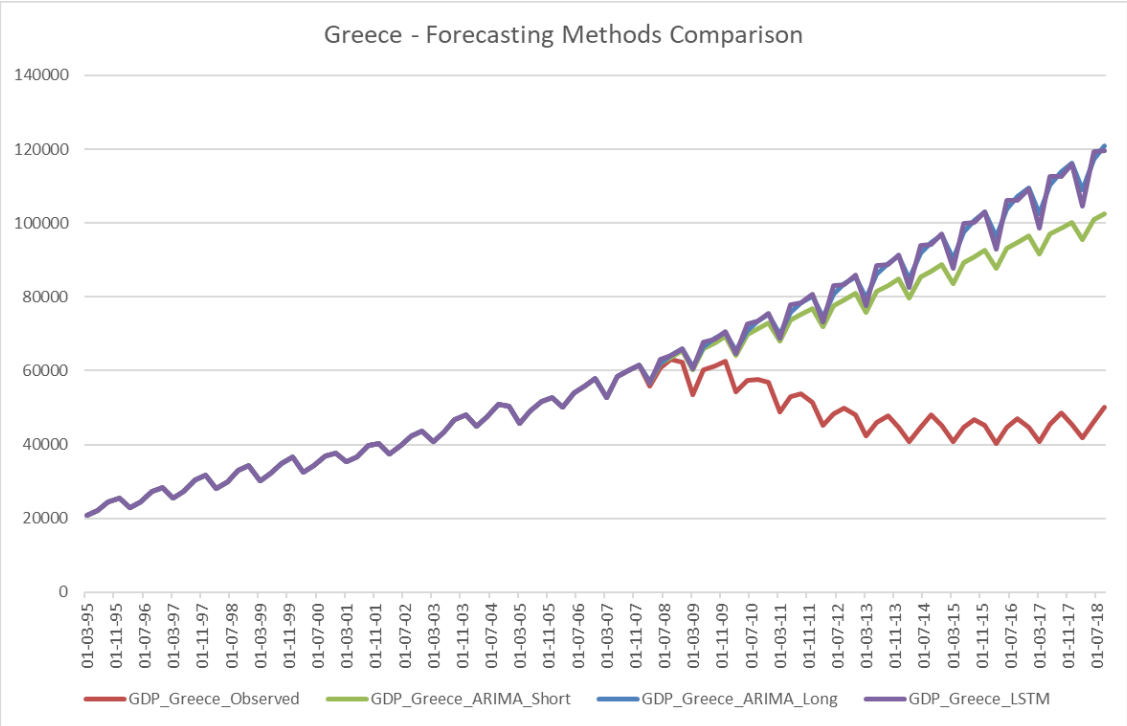
- LSTM model for univariate time series forecasting;
- Learning function which maps a sequence of past observations:
    - Multiple input/output patterns as samples;
        - Three past time steps used as input;
            - One-time step used as output;
- Vanilla LSTM model implementation:
    - Single hidden layer of LSTM units;
    - Single output layer used for prediction purposes;
    - One feature since the analysis is done on a univariate series;
    - 50 units representing the dimensionality of the output space;
    - Rectified Linear Unit (ReLU) Activation Function;
    - Fitted through the Adam version of stochastic gradient descent;
    - Optimized through Mean Squared Error loss function;
    - 3000 Epochs;
- Database: GDP from Q4-2001 to Q4-2007;
- Other possible implementations:
    - Stacked LSTM;
    - Bidirectional LSTM;
    - CNN LSTM;
    - ConvLSTM.

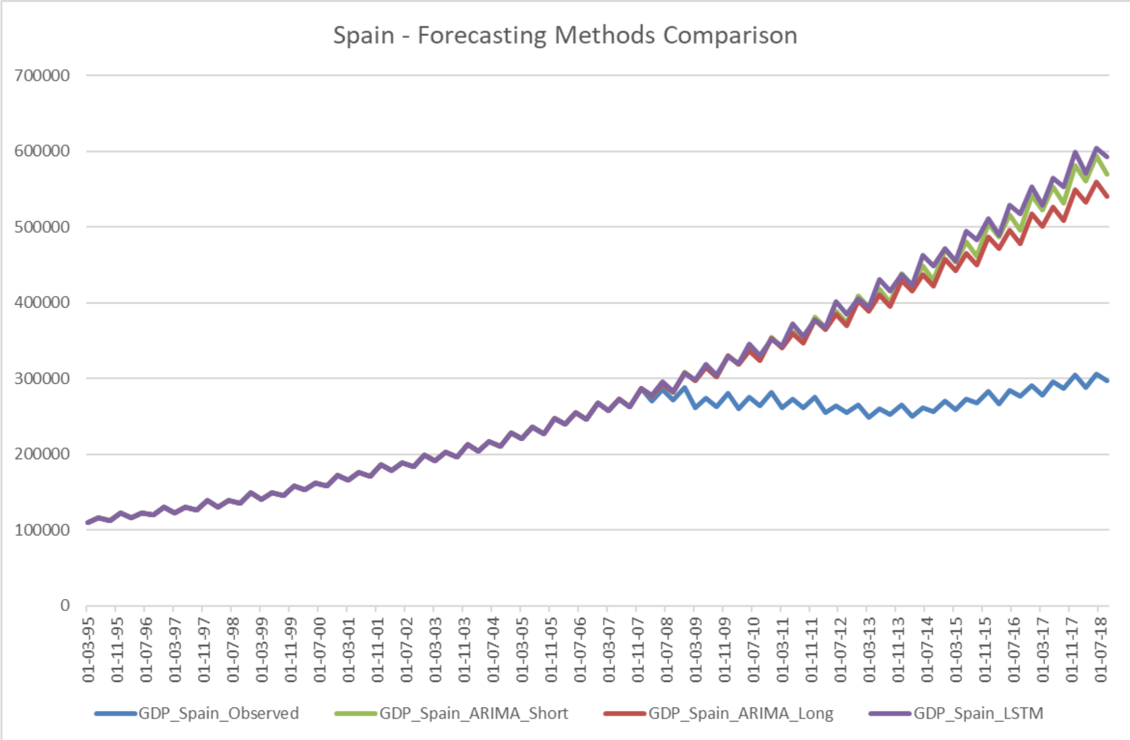
The forecasting methods' comparisons are provided in the following pages.


Portugal - Forecasting Methods Comparison
100000
90000
80000
70000
60000
50000
40000
30000
20000
10000
0
01-03-95
01-07-18
GDP_Portugal_Observed
GDP_Portugal_ARIMA_Short
GDP_Portugal_ARIMA_Long
GDP_Portugal_LSTM


Italy - Forecasting Methods Comparison
700000
600000
500000
400000
300000
200000
100000
0
01-03-95
01-07-18
GDP_Italy_Observed
GDP_Italy_ARIMA_Short
GDP_Italy_ARIMA_Long
GDP_Italy_LSTM


Ireland - Forecasting Methods Comparison
140000
120000
100000
80000
60000
40000
20000
0
01-03-95
01-07-18
GDP_Ireland_Observed
GDP_Ireland_ARIMA_Short
GDP_Ireland_ARIMA_Long
GDP_Ireland_LSTM


Greece - Forecasting Methods Comparison
140000
120000
100000
80000
60000
40000
20000
0
01-03-95
01-07-18
GDP_Greece_Observed
GDP_Greece_ARIMA_Short
GDP_Greece_ARIMA_Long
GDP_Greece_LSTM


Spain - Forecasting Methods Comparison
700000
600000
500000
400000
300000
200000
100000
0
01-03-95
01-11-95
01-07-96
01-03-97
01-11-97
01-07-98
01-03-99
01-11-99
01-07-00
01-03-01
01-11-01
01-07-02
01-03-03
01-11-03
01-07-04
01-03-05
01-11-05
01-07-06
01-03-07
01-11-07
01-07-08
01-03-09
01-11-09
01-07-10
01-03-11
01-11-11
01-07-12
01-03-13
01-11-13
01-07-14
01-03-15
01-11-15
01-07-16
01-03-17
01-11-17
01-07-18
GDP_Spain_Observed
GDP_Spain_ARIMA_Short
GDP_Spain_ARIMA_Long
GDP_Spain_LSTM