National And Kapodistrian
University of Athens

ANALYSIS OF BUSINESS CYCLES AND FLUCTUATIONS IN GREECE, BASED ON DYNAMIC AND ECONOMETRIC MODELS AND ANALYSIS OF THEIR CAUSATION

A THESIS SUBMITTED
TO THE DEPARTMENT OF ECONOMICS
AND THE COMMITTEE ON GRADUATE STUDIES OF
THE NATIONAL AND KAPODISTRIAN UNIVERSITY OF ATHENS
IN FULLFILMENT OF THE REQUIREMENT
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY IN ECONOMICS

Aleka D. Sargenti

UADPhilEcon, Department of Economic Sciences,
National And Kapodistrian University of Athens

September 2023, Athens Greece

«This research is co-financed by Greece and the European Union (European Social Fund-ESF) through the Operational Programme «Human Resources Development, Education and Lifelong Learning» in the context of the project "Strengthening Human Resources Research Potential via Doctorate Research" (MIS-5000432), implemented by the State Scholarships Foundation (IKY)»

Ευρωπαϊκή Ένωση
European Social Fund

Operational Programme
Human Resources Development, Education and Lifelong Learning

Co-financed by Greece and the European Union

ΕΣΠΑ 2014-2020
ανάπτυξη - εργασία - αλληλεγγύη

I certify that I have read this dissertation and that in my opinion it is fully adequate in scope and quality, as a dissertation for the degree of Doctor of Philosophy

---

Prof. Ioannis Leventides

(Principal Adviser)

I certify that I have read this dissertation and that in my opinion it is fully adequate in scope and quality, as a dissertation for the degree of Doctor of Philosophy

---

Emeritus Prof. Vasileios Dalamagas

I certify that I have read this dissertation and that in my opinion it is fully adequate in scope and quality, as a dissertation for the degree of Doctor of Philosophy

---

Prof. Stylianos Kotsios

Other Committee members

Georgios Argeitis, Professor, Department of Economics, National and Kapodistrian University of Athens.

Georgios Dotsis, Associate Professor, Department of Economics, National and Kapodistrian University of Athens.

Nikolaos Theocharakis, Professor, Department of Economics, National and Kapodistrian University of Athens.

Nikolaos Michelakakis, Professor, Department of Economics, University of Piraeus.

To my lovely daughter, Ioanna,
my husband, Nikos,
my siblings, Yiota and Tasos
and my parents, Dionysios and Eftychia.

Acknowledgements

I am grateful to my Ph.D. advisor Prof. Ioannis Leventides for his brilliant guidance all these years. His sharp feedback was critical for me to accelerate my progress toward our common goal. His deep domain knowledge of both mathematics and economics, as well as his rich research experience had a strong influence on me. He believed in my efforts and provided generous resources and continuous encouragement to make possible what seemed impossible in the beginning. His considerate approach allowed me to be creative and explore diverse paths in my research agenda; for instance, experimenting with ML-based econometric approaches.

Special thanks go to the members of my committee, Profs. Vasileios Dalamagas and Stylianos Kotsios for their continuous support and suggestions. Specifically, Prof. Dalamagas through his thorough review of all chapters, and especially the economic model and the econometric analysis, provided excellent feedback, which was critical for shaping the dissertation at its current state. Without his deep knowledge of macroeconomics and his sharp and critical comments, the current work would not have been as comprehensive and self-contained.

I am very fortunate to have worked alongside many exceptional individuals all these years, many of them have been great mentors through my PhD journey. To name a few, Prof. Giorgos Argeitis was one of the first to encourage me to target my research to a more well-defined direction and adopt a school of economic thought. I would like to also express my appreciation to Prof. Nikolaos Theocharakis for his valuable input for polishing the final text, and especially the literature review. Prof. Dimitris Moschos is a charismatic lecturer, whose econometric class had great educational value and impacted my understanding of econometrics in a substantial way. Besides these mentors, there were many collaborators and friends who collaborated with me over the years in several projects, and through our discussions I learned a lot and made these years unforgettable.

Finally, I would like to acknowledge the unconditional support of my husband, Nikos. His belief in me and his continuous will were very influential not only toward my research path, but in our life in general. To my twin-sister Yiota, as we went through this path from the very beginning, always supporting each other and making a profound impact to each other at every new chapter in our lives. Her help during all these years was invaluable and important towards the final success. She is always there for me, and I will always be there for her.

To my brother Tasos, the supporting system and the calm force. He has been a mentor as well for me. To my parents, Dionysios and Eftychia, who were always there at every big step, to whom this dissertation is dedicated.

Last but not least, to my last addition in this life, my everything, my daughter, Ioanna. I will always be there for you, and I will honor you, my love.

Aleka Sargenti
Athens, September 2023

Abstract

One of the biggest challenges in macroeconomic research has always been the econometric analysis of how aggregate economies fluctuate between peaks and troughs of economic activity, as well as what policies can either prevent or mitigate economic downturns in the future. The purpose of this dissertation is to analyse the principal macroeconomic time series of business cycles in Greece over the period of 1960-2021, provide econometric tools for estimation and forecast of the Gross Domestic Product given the key determinants and conclude with policies that target to improve the fundamental Greek economic indicators.

This dissertation expands previous seminal studies in the literature and examines the period from 1960 to the end of 2021, including Great Recession, the Adjustment program between Greece and the Troika and the arrival of the COVID-19 pandemic, which led to some interesting macro-economic phenomena, which are accounted in the economic model in Ch. 4. In Ch. 5 the econometric analysis is expanded to study the properties of the GDP business cycle in relation to the cycles of its determinants, such as procyclicality, synchronicity, correlation between the cyclical variations, cross-correlation among GDP and the other times series. Analysis is conducted to study the effect of all explanatory variables that are part of the examined economic model, as well as the residual factors, which represents the effect of all other remaining variables that are not included in the model formulation in Ch. 4. In Ch. 6, several econometric and Machine Learning models are utilized from the literature (e.g., ARMA, Markov Switching, VAR, FFT, LSTM) to estimate and forecast the GDP cycle as a function of the key macroeconomic cycles and compare their performance and interpretation power. 6-variable VAR and 2-variable LSTM achieve the best estimation of the GDP cycle.

The examined time period of the last 62 years captures the time series of fundamental macroeconomic variables of the Greek economy, which have a significant impact to the economic, political, control monetary and fiscal policy of the country. The examined time window of business cycles characterizes the significant events of economic and political life of Greece. Furthermore, the comparison between the fluctuations of business cycles of the macroeconomic variables and the noteworthy events that occurred in the Greek economy in this period provides the foundation to analyze this period. Ch. 7 summarizes the main conclusions of this dissertation.

Table of Contents

List of Figures

List of Tables

Chapter 1 – Introduction

The business cycle theory has captured the attention of economists ever since the very beginning of economics as a science. The importance of Business Cycle is related to the fact that the economic fluctuations in the fundamental macro-econometric variables of the economy such as the government expenditure and the private consumption among many others, correspond to wide-scale economic phenomena. To control and often reverse these phenomena the economic policy and, by extension, the fiscal one is an important tool for the government.

This dissertation can be viewed as an extension of [Christodoulakis et al., 1995] and [Michaelides et al., 2007]; these authors examined the business cycle in Greece from 1960 until the date that their study was completed, specifically 1995 and 2007, respectively. In this literature, the analysis of empirical facts has often been used as basis for the formulation and evaluation of theoretical models of the business cycle. The analysis in this dissertation focuses on the Greek business cycle with the hypothesis that the dynamics of the main indicators already capture the contribution of the European and global business cycles due to the propagation mechanism. Moreover, due to this the process of European integration should not be a problem as far as business cycle is concerned [Christodoulakis et al., 1993].

In this dissertation we analyze the macroeconomic fundamentals of the business cycle in Greece for the time period of 1960-2021, using different econometric tools, models and checking whether each model is sufficient to explain and provide comprehensive estimation and forecast of the examined data. Naturally, the quality and availability of collected data play a crucial role on what stylized facts we end up looking at. This research is focused on analysis of a dataset of 62 years of key explanatory macroeconomic variables of the Greek economy output. Giving the shape and the behavior of business cycles of these fundamental variables in the examined time period, the analysis has implications to the interpretation of the major macroeconomic events of this period.

In the second chapter we present a comprehensive study of the Business Cycles literature. We discuss studies of business cycles and how pioneering mechanisms shape this theory. This overview does not only cover the Greek business cycle, but also expands to the European and the US business cycles. Real Business Cycle (RBC) models emphasize the role of real shocks, particularly technology shocks, in driving business fluctuations. These studies present principal macroeconomic series of business cycles in post-war Greece, as well as the synchronization of business cycles within the EMU. Also, fundamental techniques are described, analyzing business cycles, including the Hodrick-Prescott filter to generate business cycle dynamics, methods that use time-frequency analysis, autoregressive models, and Recurrent Neural Network-based techniques.

In the third chapter, fundamental econometric techniques from the business cycle literature are described. The Hodrick-Prescott filter is a tool for detrending the time series of macroeconomic variables, namely for separating the business cycle from the trend. Next, popular econometric and data-driven machine learning models for estimation and forecasting are introduced, for which extensive experimentation and analysis is shown in Chapter 6.

Our method of analysis consists of characterizing the stylized facts or empirical regularities of the business cycle of the Greek economy by computing certain simple statistics of the underlying data series. The ARMA model, is an autoregression and moving average model, which is used in time series analysis to describe stationary time series. This model represents time series that are generated by passing white noise through a recursive and through a nonrecursive linear filter, consecutively. The number of autoregressive terms is determined from the correlogram of each examined variable using a statistical significance threshold (5%).

As an extension of ARMA, VAR is a model with temporal correlation through the autoregressive terms as well as correlation across multiple variables that can be co-integrated; in this case, GDP and its major determinants such as Consumption, Government Expenditure, Exports, Imports and Investment. In this analysis, VAR demonstrates estimations and forecasts of GDP using the information from two, four and six determinant variables of the GDP, respectively. Additionally, experimentation is conducted for different number of autoregressive terms in the VAR formulation.

Markov Switching is also examined, which provides a unified mechanism to model different economic states, such as crisis or recession and growth period. There are many studies that show that macroeconomic variables may display different behavioral patterns over time. Thus, Markov Switching model combines more than one dynamic model through a mechanism called Markovian Switching. This model estimates the crisis and growth periods of the Greek business cycles.

Also, Fast Fourier Transform (FFT) is explored in our research as a way to model the Greek business cycle. The magnitude and phase of the dominant cycle is determined using the dominant Fourier frequency. The cycle of GDP and its determinants are approximated with the dominant FFT cycle.

Finally, Recurrent Neural Networks (RNNs) are used to provide a highly non-linear approximation and learn to model temporal dependencies of macroeconomic time series through learning. LSTM is an artificial neural network used in the fields of artificial intelligence and deep learning for time series. LSTM captures long-term temporal dependencies and is used for estimating and forecasting the GDP business cycle. Compared to RNNs, LSTMs have higher memory capacity over long time series, which enables modeling and interpreting longer-term dynamics.

In the fourth chapter, we introduce the economic model that will shape and be the centerpiece of our dissertation. Based on the examined variables in this model, which are selected from the literature review and the available data sources, we utilize the Augmented Dickey Fuller test to check the stationarity of these variables. Also, a co-integration test is assessed for the fundamental equations of the linear system via the Johansen Cointegration test. Last but not least, coefficients are calculated via OLS regressions for the variables that are empirically shown to be co-integrated. Through these econometric tests, we narrow down the final variables, which are found to be statistically significant as determinant factors of GDP. These are the main economic indicators, which will be used in Ch. 5 and 6 for the econometric analysis, estimation, and forecasting.

In the fifth chapter, the variation of each GDP determinant is examined in comparison to the Greek business cycle to create a taxonomy into procyclical and countercyclical variables. This analysis is performed using the real GDP variable as well as its residual between the actual and the fitting values from the output equation as this was estimated in Ch. 4. The cross-correlations between time series of GDP determinants (i.e., Consumption, Investment, Government Expenditure, Exports and Imports) and real GDP is shown for various lead and lag terms for each variable. Based on the cross-correlation each business cycle is either leading, synchronous, or lagging by a certain number of years the cycle of the output, respectively. This provides evidence on the phase-shift of each variable relative to the GDP cycle. Moreover, following the methodology from [Christodoulakis et al., 1995] each series is classified in procyclical, countercyclical or contemporaneously uncorrelated with the output cycle.

Finally, we correlate the quantitative findings with significant historical, political and economic facts that had a major impact and have shaped the Greek Economy over the examined time period. The prosperity of large groups of people depends on the success with which each government tackles an economic recession or crisis. The experience so far in Greece and other countries of the European Union, indicates that these challenges are not controllable and fiscal policy is not always adapted to the specific features and requirements of every country. The present analysis will capture in graphs but will also analyze the Business Cycles in the Greek economy during the period of 1960 - 2021.

In the sixth chapter, we conduct thorough experimentation on the examined macroeconomic times series using various dynamic and non-dynamic models. Auto-Regressive Moving Average (ARMA) and Vector Auto Regressive (VAR) models are used to capture the temporal dependencies of time-series data through autoregressive and moving-average terms. VAR also models the dynamics across multiple variables. Markov switching models consist of two autoregressive AR(1) expressions with a switching variable, which allows to combine two (or more) dynamic models. This formulation naturally enables the categorization of the economy into two or more states (e.g., crisis or recession, growth period, etc.) Next, an efficient approximation of Discrete Fast Transform (DFT), termed as Fast Fourier Transform (FFT), is applied for its capacity to model complex time series in the frequency domain. Finally, Long Short-Term Memory (LSTM) is selected as an Artificial Neural Network (ANN) model for financial time series that can learn to model temporal dependencies through machine learning. Across all the examined models the forecast error is compared, while both the estimation and forecast are plotted. Different variants are considered to identify the econometric models that are more effective to model the Greek business cycles.

Finally, this dissertation concludes by comparing the stylized events of the examined period with the estimation from the presented econometric models and concludes on the most performant models to estimate and interpret the historical and political events of this period.

Chapter 2 – Literature Review

In this chapter a comprehensive study of the Business Cycles literature is presented. Sect 2.1 discusses econometric techniques that investigate the Greek business cycle with focus on post-war Greece. Based on the analysis and correlation with stylized events, various works have divided Greece's economic performance in distinct phases. Sect 2.2 expands this analysis to include the European and the US business cycle. Central mechanisms such as the European Central Bank (ECB) control the monetary policy and the Economic and Financial Affairs Council (ECOFIN) control the fiscal policy in the Economic and Monetary Union (EMU), therefore causing synchronicity and propagation of business cycles across the EMU countries, and thus affecting the Greek Business Cycle.

Sect 2.3, first, discusses works that study the patterns in the economic literature of business cycles, and then introduces pioneering works that shaped the theory of business cycles and examined the real output using aggregate economic time series. Real Business Cycle (RBC) models are described, as they emphasized the role of real shocks, particularly technology shocks, in driving business fluctuations. Moreover, RBC models are used as simulators for policy analysis, and in particular for the study of optimal fiscal and monetary policy. Next, Sect 2.4 presents a series of econometric studies about the principal macroeconomic series of business cycles in post-war Greece, as well as the synchronization of business cycles within the EMU. Sect 2.5 describes fundamental techniques in analyzing business cycles, including the Hodrick-Prescott filter to generate business cycle dynamics, methods that use time-frequency analysis, autoregressive models, and Recurrent Neural Network-based techniques.

Finally, Sect 2.6 discusses the effectiveness and limitations of business cycles and Sect 2.7 concludes to summarize the techniques that are adopted in the present dissertation.

2.1 Business Cycles in Greece

Empirical research in business cycles for Greece has been relatively scarce. Apergis and Panethimitakis [2007] examined the behavior of basic macroeconomic variables in the context of business cycles and their connection to stylized facts of the Greek economy over the period of 1960–2005. The authors' conclusion was that real shocks drive the economy, implying that demand policies are ineffective. Kollintzas and Vassilatos [1996] built a Real Business Cycle

(RBC) model for Greece and analyzed its predictive power in terms of stylized facts of Greece after World War II. This work concluded that an increase in government consumption has an adverse effect on output and productivity although it is likely to increase foreign asset holdings.

Christodoulakis et al. [1995] compared the cyclical part of business cycles of the Greek economy to other European Community economies. They identified the slower assimilation pace of institutions and policies for the peripheral economies, such as Greece, following their entry in the E.U. and the impact of uncertainties about the future political situation on investment as the underlying causes for the phase transition from a high-growth period in the 1960s and early 1970s to an economic slowdown in the 1980s. All these works outlined that the Greek economy entered a long period of recession in the mid-1970s, after the steady growth that characterized an era of industrialization and increased investment in the 1960s, as also discussed by Mouzelis [1977].

The above-mentioned authors described the emphasis of macroeconomic policies on the demand side and consumption, neglecting both investments and the supply side of the economy. Next, they outlined a policy shift in the 1990s, which led to growth acceleration and a partial restoration of economic stability in the country.

Michaelides et al. [2013] used econometric techniques to investigate the Greek business cycles from 1960 to 2008. This paper examined the stationarity properties of the time series and their first differences using the Augmented Dickey-Fuller test [Dickey & Fuller, 1979], deployed various detrending methods to decompose the series into trends and cycles, and used spectral analysis to identify the length of the cycle. As a result of this analysis, periodization of the phases of development of the Greek economy was performed, which was found to be consistent with the previous literature.

Various works have divided Greece's economic performance in distinct phases [Ioakimoglou and Milios, 1993]. Alogoskoufis [1995] considered the end of the military dictatorship in 1974 as the turning point between the industrialization of 1960s and the slowdown of the 1980s. Similarly, Bosworth and Kollintzas [2001] perceived two distinct phases in the growth patterns of the Greek economy and placed 1973 as their demarcation year. Tsouma [2014] established a chronology for the Greek business cycle from early 1970 to late 2012 using both non-parametric and parametric procedures and relying on quarterly GDP data and selected monthly indicators. This study concluded that the Greek economy entered a period of recession in 2008 that lasted until the end of the examined period, as confirmed by Michaelides et al. [2013]. Alogoskoufis [2021] has expanded the taxonomy of the Greek economy to over 200 years from the Greek Independence in 1821 to today. His overview separated this historical period into three major cycles, namely, the cycle of state and nation building in 1821-1898, the cycle of national expansion and consolidation in 1899-1949 and the post-1950s' cycle of economic and social development.

Bosworth and Kollintzas [2001] attributed the reduction in Total Factor Productivity (TFP) growth to a highly inefficient labor market and a deterioration of various macroeconomic factors, such as large fiscal deficits and very high rates of inflation. As in [Alogoskoufis, 1995], Bosworth and Kollintzas [2001] do not explicitly identify the European Union accession as a primary factor for this TFP fall-off, but they insinuate such connection by pointing out the lack of competitiveness of its tradeable goods sectors and the reputation as an unattractive market for foreign capital. On the other hand, the main argument in [Giannitsis, 1993] is that the liberalization of trade worsened the competitive position of Greek industries and led to a profit squeeze for domestic industries [Stournaras, 2005].

Tavlas et al. [2001] identified two structural breaks, namely one in the early 1980s which led to the low-growth regime, and a second one in 1994, when a more stable macroeconomic environment and the implementation of structural reforms led to a period of steady growth. Giannitsis [2005] pinpointed macroeconomic policies followed in the 1980s after the government change in 1981 and the liberalization of financial markets after joining the European Union as the main macroeconomic drivers behind this growth. Belegri-Roboli and Michaelides [2007] have outlined four main sources for Greece's performance in this era: (a) financial market liberalization, (b) EMU membership, (c) growing activity in export markets in south-eastern Europe and (d) the stimulus given by the Olympic Games in 2004.

All in all, this literature converges on three distinct phases of the Greek economy since 1960: (i) a period of rapid growth from 1960 until the mid-1970s; (ii) a slowdown period until the mid-1990s, and (iii) a period of steady growth from the middle of 1990s until the current recession of the Greek economy.

2.2 European Business Cycles and their impact to the Greek Business Cycle

Central mechanisms such as the European Central Bank, the Stability and Growth Pact and the Economic and Financial Affairs Council control the monetary and fiscal policy in the Economic and Monetary Union (EMU), therefore causing synchronicity and propagation of business cycles across the EMU countries. There is extensive research on the synchronicity of the business cycles in the European Union (EU).

Christodoulakis et al. [1995] compared the business cycle features of the European Community (EC) economies using quarterly and annual data since 1960 and the Real Business Cycle model. Their analysis suggested that there were remarkable similarities between the business cycle patterns of these countries, despite significant differences in fiscal and monetary policy and the terms of trade. This work concluded that the type of shocks and the propagation mechanism is similar across the EC countries. Gouveia and Correia [2008] focused the synchronization analysis on the case of small countries of the EMU. The study argued that the business cycles of the larger member states were increasingly synchronized with the aggregate Eurozone cycles, with the exception of Spain, while the results are rather mixed in the case of smaller countries. They also identified weaker synchronization since 1997 in several smaller members states such as Belgium, the Netherlands and Greece. The business cycles of Finland, Greece and Portugal were found to have the lowest correlation with the Euro-area business cycles, and those experiencing greater volatility.

There are several studies that revealed lack of synchronicity of Greece's business cycles compared to the Eurozone. Papageorgiou et al. [2010] found that whereas in the post-Maastricht period synchronization among the EMU countries seemed to increase, in the period after the introduction of the common currency, divergence was observed for the peripheral EMU countries, especially Greece and Ireland. Gallegati et al. [2004] found weak links among Mediterranean countries, including Greece, and the core EU countries, i.e., Germany, France, Spain, Austria, and the Benelux countries. The latter ones are defined as the core-periphery distinction in [Papageorgiou et al., 2010]. Based on the stage of development of Mediterranean countries, Gallegati et al. [2004] concluded that there is variation of the output volatility. They also found that Greece was more synchronized with Algeria, Egypt, and Tunisia than with the other European countries.

Leon [2007] reached to similar conclusions by using spectral analysis to quantitatively analyze the stochastic shocks of Greece and the Eurozone for 1980–2005 and concluded that the synchronization of the cycles in terms of correlation and their transmission mechanism becomes weaker over time. Crowley and Lee [2005] used Wavelet transform to analyze the frequency components of European business cycles and classified the Euro-area countries into three clusters: high and dynamic correlations at all frequency cycles (e.g., France, Belgium, and Germany), low static and dynamic correlations with little sign of convergence (e.g., Greece) and those with low static correlation but convergent dynamic correlations (e.g., Italy and Ireland).

Furthermore, various works have specifically studied the propagation mechanisms between the USA and the EU countries. Michaelides and Papageorgiou [2012] divided the 1960–2011 period into two sub-periods (1960–1999 and 2000–2011) and found that output fluctuations in the US economy cause output fluctuations in the EU-15 economy. Regarding the timing pattern, the changes in the US GDP cycle are transmitted very rapidly to the EU-15 countries. Michaelides et al. [2013] similarly conducted empirical analysis on the international influences on the domestic business cycles by examining the Greek business cycles between 1960 and 2011. This work showed increasing convergence rates of the Greek economy towards the U.S. economy and the peripheral countries of the E.M.U., such as the Italian and the Spanish, while being disassociated from the "core" of the EU, i.e., the German and French economies. The Greek GDP fluctuations were found to be caused, to a certain extent, by the EMU and US fluctuations, implying a transmission mechanism of business cycles from the EMU and the US to the Greek economy.

As for the transmission of the U.S. shocks to Europe, Canova and Marrinan [1998] discovered that technology trends are more critical than government expenditure disturbances to interpret the data. According to [Osborn et al., 2005] high annual US. growth was found to be more influential on other G7 countries compared with average or low US growth. Finally, according to [Osborn et al., 2005], the U.S. economy leads the economies of Europe and the opposite direction of causality is not as significant. However, the EU-15 impact to the US business cycles has increased over the years, while the effects of the US on Europe have been most significant during the 1970s and the late 1990s [Perez et al., 2003].

2.3 Fundamental Economic Theories of Business Cycles

Historically, economic developments have led to a rise of relevant literature, namely notions, ideas, and theory areas in conjunction with specific policy issues and problems over the course of an economic cycle, specifically during the crisis and recession phases. To point out this phenomenon, “panics produce texts” is a notion that was frequently cited in the literature, such as in [Fabian, 1989] and [Mills, 1868]. This hypothesis does not only refer to the cyclicality in the literature per se, but it also points out to causality from certain phases of the economic cycle. In specific, economic crises and recessions produce an increased interest in the discussion and interpretation of these events, out of necessity for government response and policy making. Mills [1867] made the observation that every commercial crisis that has occurred in the US was promptly followed by a “literature of pamphlets”.

As a similar notion, it is noteworthy that Keynes’s *General Theory* [Keynes, 1936] and the subsequent rise of Keynesianism came as a response to the ‘Great Depression’ of the 1930s. While, undoubtedly, Keynes’s theory was more than a business cycle theory, it has been argued, e.g., by Johnson [1971] that its success can be at least partially attributed to its explaining urgent problems for economic policy such as unemployment caused by the Great Depression, which previous literature failed to resolve.

Aside from qualitative interpretation about cyclicality in the literature, there were also quantitative studies on both the bibliometrics of the business cycles and crises theory and their connection to economic history. Besomi [2011] documents the cumulated absolute frequencies of the titles of different kinds of contributions (journal articles, books, pamphlets, etc.) from various sources of economic literature, namely JSTOR, EconLit and the author’s own records, which contain terms related to crises and business cycles. Subsequently, Besomi [2011] focused their bibliometric analysis on answering the question of whether “panics produce texts”, i.e., whether the discussion of economic crises and business cycles is more prevalent during economic hardship.

Most recently, Geiger and Kufenko [2015] revisited the abovementioned theses through comprehensive quantitative analysis, i.e., (1) whether there were patterns in the economic literature on business cycles, and (2) whether these were correlated with actual events in the economic activity. This study examined time series for income, unemployment, investments, industrial production, inflation rates, SP stock market index and bankruptcy rates in the USA. The cycles were estimated via time-series detrending using the Kalman filter, the causation between economic developments and activity in the academic literature was examined by Granger causality tests, and finally IRF analysis was deployed for quantitative assessment of the effects from economic to bibliometric variables. The results confirmed the hypothesis of positive effect of business cycles and crises in economic variables on the related literature.

Kydland and Prescott [1982] was one of the pioneering works that shaped the theory of business cycles. Their work was developed to explain the autocovariances of real output and the co-variances of cyclical output with other aggregate economic time-series. Kydland and Prescott [1982] introduced three revolutionary ideas; the first idea, which built on [Lucas and Prescott, 1971] was that business cycles can be studied using dynamic general equilibrium models, which featured atomistic agents operating in competitive markets and formed rational future expectations. The second idea was that it is possible to unify business cycle and growth theory. The third idea was that beyond the qualitative comparison of model properties with stylized facts, model parameters can be calibrated using microeconomic studies and long-run properties of the economy.

Kydland and Prescott [1982] found that simulated data from their model showed the same patterns of volatility, persistence, and co-movement as were present in the U.S. data. This finding was particularly surprising, because the model was abstracted from monetary policy, which previous economists such as [Friedman, 1968] considered an important element of business fluctuations. [Kydland and Prescott, 1982] was followed by a series of models that are referred to as Real Business Cycle (RBC) models because of their emphasis on the role of real shocks, particularly technology shocks, in driving business fluctuations. The RBC models became a point of departure from many former theories in which technology shocks do not have a central role.

Moreover, the RBC models were used as simulators for policy analysis, and in particular for the study of optimal fiscal and monetary policy. To that end, the RBC models met the challenge outlined by Lucas [1980] as “one of the functions of theoretical economics is to provide fully articulated, artificial economic systems that can serve as laboratories in which policies that would be prohibitively expensive to experiment with in actual economies can be tested out at much lower cost.”

As one of the seminal papers in the RBC literature, Long and Plosser [1983] emphasized the co-movement of different sectors of the economy as an important feature of business cycles. They proposed a multisector model that exhibits strong sectoral co-movement. However, many properties of the model do not generalize once we move away from the assumption of full depreciation. A simplified version of the model in [Kydland and Prescott, 1982] is deployed by Rebelo [2005]. Their model eliminated features that are not central to their main results: time-to-build in investment, non-separable utility in leisure, and technology shocks that include both a permanent and a transitory component. Rebelo [2005] showed that the correlation between industry hours and total hours workers were employed by the private sector is above roughly 50% except in mining, tobacco, and petroleum and coal. These strong patterns of sectoral co-movement motivated Lucas (1977) to argue that business cycles are driven by aggregate shocks, not by sector-specific shocks. Rebelo [2005] provided an overview of the contribution of the RBC models to understanding economic fluctuations and discussed open issues in business cycle research.

2.4 Econometric Studies for the Greek Business Cycle

Many economists studied and interpreted the existence of fluctuations in the macro-econometric variables using various econometric or dynamic models. Christodoulakis et al. [1995] applied a Real Business Cycle (RBC) model with quarterly and annual time-series data from 1960-1993 to compare the behavior of the Greek Economy with the European Community (EC) economies and their propagation mechanism. This analysis concluded that these countries exhibited similar business cycles, despite significant differences in fiscal and monetary policy and the terms of trade.

Following the RBC framework, Kollintzas and Vassilatos [1996] developed the Dynamic Stochastic General Equilibrium (DSGE) model to analyze the business cycles in Greek economy with data from 1960-1992. This work discovered that the volatility, persistence, and co-movement properties of the business cycle component of the data generated by the model are consistent with the corresponding actual data of the Greek economy in this period. The proposed model was used to investigate the response of major macroeconomic variables to temporary and permanent changes in government policy variables, foreign transfers, and the rate of return on foreign assets.

Michaelides et al. [2007] analyzed the principal macroeconomic series of business cycles in Greece during the period of 1960-2008 using an econometric approach. First, they investigated the stationarity properties of time series and their first differences using the augmented Dickey-Fuller test. Next, they used five different de-trending methods to decompose the original series into a trend and a cyclical component. Furthermore, they used Fourier Transform to extract periodograms to estimate the length of the business cycle. The empirical results suggested that strong cyclical regularities were present. Michaelides et al. [2013] expanded the empirical analysis on the Greek business cycle between 1960-2011 and studied the international influences on it. They showed that the Greek GDP cycles were caused, to a certain extent, by the EMU and US fluctuations, implying a transmission mechanism of business cycles from the EMU and the US to the Greek economy.

Tsouma [2014] attempted to create a time-series chronology for the Greek Business Cycle from the early 1970s to late 2012. Considering the global recession and the recent domestic developments in the late 2000s, they used quarterly GPD data and selected monthly indices covering important sectors of the Greek economic activity. Using both non-parametric and parametric procedures, this work proposed a reference chronology for Greece and outlined stylized facts of the Greek business cycle and suggested that the Greek economy entered a recessionary business cycle regime in 2008 which was continued throughout 2012. Apergis and Panethimitakis [2011] analyzed the stylized events of the Greek economy while considering the changes in the political regime. They focused on 1960-2005 and their results designated that they were real disturbances that drove the economy, suggesting that demand management policies were ineffective.

Other econometric studies have focused on a specific sector of the economy. Konstantakis et al. [2019] explored the impact of the local and international business cycle on Greek maritime transport and investigated the key determinants of maritime transport fluctuations in the three major ports of Piraeus, Volos, and Thessaloniki, considering macroeconomic variables from 1998-2015, capturing, at least partly, the global financial crisis and the local crisis, as well. To this end, various quantitative techniques were used, such as Granger causality, Dufour and Renault multistep causality and SURE system estimation. They discovered that Greek maritime transport traffic was not influenced by the Greek business cycle, implying that the country’s maritime sector was practically independent of the macroeconomic conditions of the total economy.

Gogas [2013] used an econometric analysis to study the synchronization of business cycles within the E.U. The business cycles of twelve E.U. countries and two groups of countries were extracted for the period 1989Q1-2010Q2 using as a benchmark series the cycle of G3, i.e., Germany, France, and Italy. The Hodrick-Prescott and Baxter-King filters were used for detrending, while various parameter specifications and leads/lags were tested. The strength of cycle synchronization was measured using linear regressions, cross-correlation coefficients, and the Cycle Synchronization Index. Two subsamples pre- and post-EMU (1999Q1) were evaluated to assess whether synchronization is stronger after the introduction of the common currency. The analysis concluded that cycle synchronization within the Eurozone became stronger in the common currency period.

2.5 Popular Methods and Models for Business Cycle Research

Cogley [1995] demonstrated that when applied to macroeconomic time series, the Hodrick-Prescott filter [Hodrick, 1997] can generate business cycle dynamics from the original data. That is, even if cyclicality is present in the HP filtered data, it is not necessary that these cycles are pronounced in the original data. They empirically showed that stylized facts were determined primarily by the HP filter as opposed to the dynamics of the underlying data.

Andersson [2003] surveyed various methods for detecting turning points in business cycles. Three likelihood-based methods were compared by using the theory of statistical surveillance and by simulations; one method was a parametric likelihood ratio method, another included a non-parametric estimation procedure, and a third one was based on a Hidden Markov Model. Different characteristics were compared such as curve shape and parameters, types and probabilities of transitions and smoothing. The models were assessed for predicting correct alarms and their expected delay time with real data from the Swedish industrial production.

Škare [2016] presented a synopsis of problems related to the measurement and identification of business cycles. They suggested that spectral analysis methods for measuring business cycles may have advantages over existing methodologies to tackle issues such as nonlinearity and stationarity, and to identify structural breaks in time series when analyzing business cycles. They also considered fractional integration to be important in proper monitoring and explaining business cycles. Finally, they pointed out that the link between cycles and economic growth should not be neglected by implying money neutrality.

Various works have advocated using time-frequency analysis for analyzing business cycles. Crowley [2005] analyzed the European business cycles and their real GDP by employing Multiresolution Decomposition (MRD) with the use of Maximal Overlap Discrete Wavelet Transforms (MODWT). Static correlation analysis via wavelets and dynamic conditional correlation via GARCH models were performed within the Euro area to evaluate synchronicity of cycles through time. They discovered that the Euro area members fell into three categories: i) high and dynamic correlations at all frequency cycles, ii) low static and dynamic correlations, with little sign of convergence occurring, and iii) low static correlation but convergent dynamic correlations. Most recently, Aloui [2016] examined the business cycle synchronization in the Gulf Cooperation Council (GCC) countries, as the prerequisite for the monetary union establishment among them. Using the real growth rates as proxies for business cycles and a continuous wavelet approach, they revealed co-movement of the real growth rates over the short and medium terms, while long-term co-movement of real growth rates was only found in seven out of the 15 country pairs, while the two major countries of the GCC, Saudi Arabia and the United Arab Emirates, shared common growth cycles with the remaining countries.

The Box-Jenkins method [Box and Jenkins, 1970] applies autoregressive moving average (ARMA) or autoregressive integrated moving average (ARIMA) models to find the best fit of a time-series model to past values of a time series. Vector auto-regressive (VAR) models provide a generalization to multiple variables and are prevalent in the business cycle literature. Savva [2010] studied the business cycle synchronization between the Euro aggregate and the countries that acceded or were currently negotiating at the end of 2010s. They used a bivariate VAR-GARCH model with a time-varying correlation. This work discovered that the business cycle synchronization of new EU members and negotiating countries had at least doubled over time, or the correlation changed from negative to positive, since the early 1990s.

The Global Vector Autoregressive (GVAR) methodology provides a general, global macroeconomic modeling framework for the quantitative analysis of the relative importance of different shocks and channels of transmission mechanisms. Michaelides [2018] investigated the dynamic interdependencies among the EU-12 economies using a general equilibrium GVAR network system representation. They estimated the equilibrium price system of the network, while characterizing each economy (node) in the network in terms of its degree of pervasiveness. This work identified the dominant units and estimated the dynamic linkages between the economies. One main finding was that the economy of Germany acted as weakly dominant entity in the EU12 economy. Finally, all shocks disappeared in the short run, without any long-lasting effect.

Tsionas [2016] leveraged Bayesian techniques to estimate the GVAR system of equations (Bayesian System GVAR) in order to study the transmission of shocks (e.g., financial, monetary) between a selection of world economies that account for more than 90% of global production. They examined how the dominant economies of the USA and EU-17 would be affected by a potential slowdown in the BRICS. They empirically discovered that both monetary and financial variables, such as interest rates and total credit, had a significant impact on the transmission of shocks. They finally uncovered that the EU-17 economy seemed to be more vulnerable than the US economy to shocks from the BRICs.

An econometric framework based on a real time Vector Autoregressive (VAR) - Vector Error Correction (VEC) model was employed by Konstantakis [2016] to identify the determining factors of non-performing loans in the Greek banking sector during the Greek recession from the financial crisis of 2008 until the article's publication. They used quarterly aggregate data from the Greek economy in 2001-2015. The empirical findings showed that both macroeconomic and financial factors had a significant impact on non-performing loans.

Vector Autoregressive Moving Average (VARMA) processes [Lutkepohl, 2004] are suitable models for producing linear forecasts of sets of time-series variables. Poskitt [2016] explored new techniques for inferential procedure in VARMA times-series models targeting the analysis of real business cycle. A fully automated data-driven approach was proposed which relied on a new technique to determine the Kronecker invariants. An efficient macroeconomic modeling algorithm was employed based on a canonical, scalar ARMAX representation in which the exogenous regressors were given by predetermined contemporaneous and lagged values of other variables in the VARMA system. The proposed algorithms were applicable to both stationary and unit-root, as well as partially non-stationary time-series models.

Most recently, there is a trend in time-series analysis to combine the merits of Auto-Regressive Integrated Moving Average (ARIMA), as popular linear models in time series forecasting, and the predictive power of Artificial Neural Networks (ANNs) for sequential data, and specifically Recurrent Neural Networks (RNNs). Fathi [2019] used a hybrid methodology combining Box and Jenkins Auto-Regressive Integrated Moving Average (ARIMA) for seasonal component modeling and RNN for trend forecasting. Their results showed that the hybrid model performed better than the component models individually. The selected datasets were Wolf's sunspot data and the US dollar/British pound exchange rate data.

In this PhD dissertation both linear (ARMA, VAR) and non-linear (LSTM) models are presented in order to model the dynamics of the Greek business cycles and correlate them with the macroeconomic events in Greece. Compared to ARMA, VAR has the advantage of estimating and predicting from multiple variables jointly, where the latter ones have been identified as determining factors of GDP. Due to its higher-order non-linearity by design, LSTM is explored as a deep learning-based method to estimate the Greek business cycle. FFT is evaluated as a representative method for analyzing business cycles in the frequency domain. Finally, Markov Switching is defined as a linear, autoregressive model with two states to explicitly model the growth and crisis/recession phases of the economy individually.

2.6 Discussion on Business Cycles and their Effectiveness

The interest in business cycle theory has presented fluctuations over time, which can be attributed to different stages of the economy. Economic downturns can inspire works on analyzing those turning points, e.g., economic crises and business cycle theories, while during the economically prosperous times there is a shrinking volume of work and interest in the area. An intriguing question was posed in the famous volume edited by Bronfenbrenner, titled 'Is the Business Cycle Obsolete?'. However, the volume's emphasis was on high growth rates [Allsopp, 1971], which dominated the economic literature, leading to decreased interest in Business Cycle and Economic Crises (BCCT) theory in 1960s. Another symbolic example of positive economic developments causing limited interest in BCCT theory was expressed by Lucas [2003] during the period of 'Great Moderation' (from mid-1980s to 2007) and shortly before the onset of 'Great Recession' of 2008, when he anecdotally commented that "the central problem of depression prevention has been solved".

Other works have come to debate the usage of the Hodrick-Prescott (HP) filter, as the prevalent choice for business cycle detrending. Hamilton [2018] stated four arguments against the HP filter. In specific: 1) It produces spurious dynamic relations that have nothing to do with the real data, 2) its filtered values at the end of the sample are especially sensitive to these spurious dynamics, compared to filtered samples in the middle, 3) the smoothing hyperparameter from the estimation algorithm is often not aligning with the practice, 4) an alternative was proposed using regression on the four most recent values, which was claimed by the authors to be a more robust approach and achieved all the objectives of the HP filter without the previous drawbacks.

Recent publications have attempted to identify the main drivers of the business cycle. Angeletos [2020] proposed a new algorithm for analyzing sparse and medium-scale business cycles, which better captured the data. They discovered certain factors that were not statistically significant for shaping the business cycle, namely technology or other shocks that lead to Total Factor Productivity (TFP) movements, such as news about future productivity, and inflationary demand shocks. All in all, they concluded that demand-driven cycles better represented the business cycle, as opposed to a strict reliance on nominal rigidity.

Several works address the policy-related tools for business cycles both in the context of a monetary union and when dealing with country-specific fluctuations. Papageorgiou [2016] acknowledged the significant role of fiscal policy and examined the determinants of business cycles in the EMU in 1995-2012. They found that the elections played a crucial role towards a shift of the fiscal policy mix from countercyclical to pro-cyclical policies. Specifically, the increase in taxation right after the elections, as well as the shift from social benefits to capital investment are the reasons of the pro-cyclicality of the elections. Thus, they discovered that social benefits is the most important variable, whereas capital expenditures and indirect taxes are the major pro-cyclical variables. On the other hand, the formation of the EMU, along with the increasing trade openness, caused a countercyclical effect. In other words, the common monetary policy and the financial integration within the EMU constituted reasons for the decrease in the magnitude of the fluctuations.

Konstantakis [2015] also studied the business cycles determinants focusing on fiscal variables in the EU economies, using quarterly data in 1996–2013. Similarly, they identified that Social Benefits, Social Transfers and Gross Debt are the most significant policy variables with a counter-cyclical character, while taxation was found to have a destabilizing effect. Furthermore, they pointed out the significant role of the quality of institutions and the elections in a political business cycles framework.

2.7 Conclusion

In this dissertation econometric techniques in alignment with the ones in [Michaelides et al, 2013] are deployed to study the Greek business cycles from 1960 to 2021. The time series are detrended into trend and cycle, before examining stationarity, co-integration and performing parameter estimation across a variety of models. Seminal works in business cycles such as [Kydland and Prescott, 1982], which shaped the theory of business cycles are followed in order to explain the autocovariances of real output and the co-variances of cyclical output with other macroeconomic time series. The described economic model shares with the Real Business Cycle (RBC) models the emphasis on the role of real shocks, particularly technological shocks, in driving business fluctuations. Moreover, Lucas' inspiration of using "fully articulated, artificial economic systems as laboratories in which policies that would be prohibitively expensive to experiment with in actual economies can be tested out at much lower cost" [Lucas, 1980] is advocated by initiating a data-driven policymaking dialogue.

As for detrending the Hodrick-Prescott filter [Hodrick, 1997] is leveraged to generate business cycle dynamics [Cogley, 1995]. To study the business cycle synchronization, econometric analysis as in [Gogas, 2013] is used for identifying the major macroeconomic GDP determinants, as leads/lags are tested using both GDP and its residual. The strength of cycle synchronization is measured using cross-correlation coefficients. Econometric and machine learning models are used for fitting actual data for estimation and forecasting. As surveyed by Andersson [2003], Markov Switching Autoregressive models are used for detecting turning points and estimating one-step-ahead transition probabilities in business cycles. Business cycle modeling is examined at frequency domain as well [Crowley, 2005], including estimation of the dominant business cycle. For studying the time-varying correlation across macroeconomic indicators VAR models are also explored, similar in principle to the general equilibrium GVAR network system in [Michaelides, 2018], Bayesian System GVAR in [Tsionas, 2016], Vector Autoregressive (VAR) - Vector Error Correction (VEC) model in [Konstantakis, 2016] and VARMA time-series models in [Poskitt, 2016]. Finally, following recent work using a hybrid methodology combining Box and Jenkins Auto-Regressive Integrated Moving Average (ARIMA) for seasonal component modeling and Recurrent Neural Network (RNN) for trend forecasting [Fathi, 2019], RNN-based approaches using Long-Short Term Memory (LSTM) models are investigated to model the highly non-linear phenomena in the examined variables.

Chapter 3 – Methodology

In this chapter fundamental techniques and econometric models from the business cycle literature will be described, as the foundation for the econometric analysis in Chapters 4, 5 and 6. In specific, the Hodrick-Prescott filter is described in Section 3.1.2, which is a tool for detrending the time series of the macroeconomic variables for the graphs in Sections 5.5 and 5.6, as well as input for the econometric models in Chapter 6. Sections 3.2.1-3.2.5 formally define the econometric and machine learning models that will be examined in Chapter 6, as well as advantages, disadvantages and related literature for all these techniques.

In specific, section 3.2.1 outlines the ARMA model, whose autoregressive and moving-average terms model the temporal correlation of the macroeconomic indicators. The number of autoregressive terms is determined from the correlogram of each examined variable using a statistical significance threshold. In Section 6.1 this model estimates the GDP data, as well as the GDP determinant variables. As an ARMA extension, VAR is defined in Section 3.2.2. The latter one can model both the temporal correlation through the autoregressive terms as well as correlation across the major GDP determinants such as Consumption, Government Expenditure, Investment, Exports and Imports. VAR is used in Section 6.4 to provide estimates and forecasts of GDP using the information from two, four and six macroeconomic variables, respectively. Section 3.2.3 defines Markov Switching, which provides a unified mechanism to model different economic states, such as crisis or recession and growth period. Empirical evidence suggests that the behavior of macroeconomic variables may show different patterns over time. Instead of using one model for each pattern, Markov Switching combines two or more dynamic models through a mechanism called Markovian Switching. This model is shown in Section 6.2 to model and estimate the crisis and growth periods of the Greek business cycle.

Next, Section 3.2.4 describes Discrete Fourier Transform and its efficient approximation, known as Fast Fourier Transform (FFT). The magnitude and phase of the dominant cycle is determined using the dominant Fourier frequency. The experiments with FFT are conducted in Section 6.3, where the cycle of GDP and its determinants are approximated with the dominant FFT cycle. Finally, Recurrent Neural Networks (RNN) are used to provide a highly non-linear approximation and learn the temporal dependencies of macroeconomic time series through training. LSTM as an efficient RNN approximation captures long-term temporal dependencies and is used for estimating and forecasting the GDP business cycle in Section 6.5.

3.1 Fundamentals of Business Cycles

Among the various topics that have been reported in the theory of Business Cycles, the ones that have been shown to be the most important in their analysis and characterization [Burns and Mitchell, 1946] are the following: First, how a cycle can be extracted from a time series, and second, how the turning points can be determined in a Business Cycle. These are primary methods to identify noteworthy events in a business cycle and serve as a foundation for the cyclical series that are analyzed in Chapters 4-6. Next, these methods are formally described.

3.1.1 Extraction of the Business Cycle

Given the following time series:

$$\boldsymbol{y_t = \mu_t + \psi_t}, \tag{1}$$

there are many algorithms to estimate the cyclical component $\boldsymbol{\psi_t}$. A simple algorithm is to compute the moving average, where the mean of a given observation along with a fixed number of neighboring observations is computed [Massmann, Mitchell, Weale, 2003].

The resulting value is interpreted as the trend component $\boldsymbol{\mu_t}$ of the total signal $\boldsymbol{y_t}$. In that case, the residual $\boldsymbol{\psi_t}$ defines the cyclical component, as follows:

$$\boldsymbol{\psi_t = y_t - \mu_t}. \tag{2}$$

To extract a Business Cycle, a series of data is required. The process by which the cycle is extracted is referred to as signal extraction or filtering. In particular, some economists refer to this process as 'filtering', when a component, or signal, is extracted using information from a dataset up to that point. To the contrary, it is described as 'smoothing', when information from the entire sample, including future values is leveraged [Massmann, Mitchell, Weale, 2003].

Similar to the simple moving average, more complex filters and smoothing techniques typically use weighted averages of data as hyperparameters, where the distribution of weights is the defining characteristic of a given technique.

Therefore, depending on the extraction method that is chosen, the resulting cyclical series may have different properties, and their suitability depends on a variety of factors. For example, they may differ in terms of the mean length and amplitude of the resulting cycle in the time domain, by the self-scattering function or the spectrum in the frequency domain.

Detrending methods may also differ depending on whether the cyclical sequence is stationary or not, i.e., whether the process removes all non-stationary components, both deterministic and stochastic, from the data under consideration. The evaluation of the estimated cyclical components can be achieved by comparing cycles with each other. More important, however, is examining their relationship to a common point of reference, namely the datasets in question. This allows us to answer questions about whether the detrending method causes spurious cycles or whether there is a phase change.

3.1.2 Hodrick-Prescott Filter

The proposed filter in [Hodrick and Prescott, 1997] is a widely used tool in macroeconomics to fit a smooth curve to a set of points. The Hodrick-Prescott filter is similar to the moving average method but is calculated differently in an attempt to achieve two goals. First, to produce a new series that is as close as possible to the original and second, the new series to be as smooth as possible. This new series is an estimation of the underlying ‘trend’.

HP minimizes the variance of $\boldsymbol{\psi_t}$ and adds a smoothing term through the second-order discrete derivatives of $\boldsymbol{\mu_t}$, that is:

$$\min_{\mu_t} \sum_{t=1}^{T} (y_t - \mu_t)^2 + \lambda \sum_{t=2}^{T-1} [(\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1})]^2 \qquad \textbf{(8)}$$

The decomposition of time series into trend, cycle and noise is fundamental to many macroeconomic analyses.

The Hodrick-Prescott (HP) filter is often used to extract the trend from time series, but as shown by [Harvey and Jaeger, 1993] and [Cogley and Nason, 1995], improper use of the filter can lead to false (spurious) cycles [Pedregal, 2001].

Harvey and Jaeger assumed that the extraction of the trend was best achieved by adapting a structural time series model that contains unobserved components for trend, cycle, and error. In the classical approach, the model is estimated in the state-space form where the components are extracted with the Kalman filter and the smoothing effect that is associated with it.

3.1.3 Detection of turning points

The examined signal is described by a quantitative series, which represents the trend and the cycle. These measures are widely used in economic policy and analysis, such as for measuring the output gap of an economy.

While these series are critical for this estimation, they are not necessary when the goal is to simply locate the turning points of the underlying signal. In such cases, methods that recognize peaks and troughs without splitting the signal into trend and cycle components could be used. For example, the period between two turning points can be defined as a Business Cycle, which is often called a 'Classical Cycle'. In contrast, 'Growth Cycles' result from the extraction of trend, however measured, from the time series under consideration [Andersson, Bock, Frisén, 2003].

3.2 Econometric Models

3.2.1 ARMA (Autoregressive Moving Average)

In this section the Autoregressive Moving Average (ARMA) model is presented as a method to estimate and make a forecast of future values of GDP and other fundamental macroeconomic indicators. This model captures the temporal dependencies of time-series data through autoregressive and moving-average terms. The estimated and forecast data from this model can help us assess its suitability for interpreting the business cycles for the examined time period.

3.2.1.1 Formulation

Regression models define a variable (dependent) as a function of some other independent variables. In linear regression models the dependent variable is a linear combination of the independent variables.

Autoregressive models (AR) [Sargan, 1961] are linear regression models, where we consider as a dependent variable the time-series variable at time $\boldsymbol{t}$, $\boldsymbol{x_t}$, and as independent variables we consider the time-series variable at previous times, $\boldsymbol{x_{t-1}}$, …, $\boldsymbol{x_{t-p}}$. The number of lags that we include is called the autoregressive model *order* $\boldsymbol{p}$. An autoregressive model of order $\boldsymbol{p}$ is denoted by AR($\boldsymbol{p}$) and is defined as:

$$\boldsymbol{x_t = \Phi_0 + \Phi_1 x_{t-1} + \ldots + \Phi_p x_{t-p} + z_t,} \qquad \textbf{(3)}$$

where $\boldsymbol{\Phi_0}$, $\boldsymbol{\Phi_1}$, ..., $\boldsymbol{\Phi_p}$ are the coefficients of the model and $\{\boldsymbol{z_t}\}\sim\boldsymbol{iid}$ with mean value 0 and standard deviation $\boldsymbol{\sigma_z^2}$. The AR model is well-defined if we know the coefficients and the standard deviation of white noise. In practice the coefficients of the AR($\boldsymbol{p}$) model as well as the standard deviation of white noise (iid) are estimated by the time series and their estimates are used to predict the time series in the following time instances $\boldsymbol{x_{t+1}}$, …, $\boldsymbol{x_{t+k}}$.

According to the model AR($\boldsymbol{p}$) the time series variable at time $\boldsymbol{t}$ is partly explained by the linear combination of the last $\boldsymbol{p}$ values of the time series $\boldsymbol{x_{t-1}}$, …, $\boldsymbol{x_{t-p}}$. The rest, which is not explained by the previous values of the time series, is purely stochastic and is due to external factors at time $\boldsymbol{t}$, which are summarized in random variable $\boldsymbol{z_t}$. For instance, in finance $\boldsymbol{z_t}$ is referred as the *shock* of the time series.

In some cases, we assume that external factors in earlier times can also affect the time series variable at time $\boldsymbol{t}$. Including this moving average part, the general linear model for stationary time series prediction is the Autoregressive Moving Average (ARMA) model [Park, 1996], which is given as:

$$\boldsymbol{x_t = \Phi_0 + \Phi_1 x_{t-1} + \ldots + \Phi_p x_{t-p} + z_t - \theta_1 z_{t-1} - \ldots - \theta_q z_{t-q}}. \tag{4}$$

The autoregressive part (AR) is of order $\boldsymbol{p}$ and the moving average part (MA) is of order $\boldsymbol{q}$ and the model is denoted by ARMA($\boldsymbol{p}$, $\boldsymbol{q}$). The ARMA($\boldsymbol{p}$, $\boldsymbol{q}$) model is a combination of $\boldsymbol{p}$ autoregressive terms and $\boldsymbol{q}$ moving average terms. It is obvious that a purely autoregressive model or a purely moving average model can be considered as special cases of an ARMA model. These reductions can be written as: AR($\boldsymbol{p}$)=ARMA($\boldsymbol{p}$, $\boldsymbol{0}$) and MA($\boldsymbol{q}$)=ARMA($\boldsymbol{0}$, $\boldsymbol{q}$).

The simplest form of an ARMA($\boldsymbol{p}$, $\boldsymbol{q}$) procedure is the ARMA(1, 1) model. In that case, the model will be simplified as:

$$\boldsymbol{x_t = \Phi_0 + \Phi_1 x_{t-1} + z_t - \theta_1 z_{t-1}}. \tag{5}$$

In general, the ARMA autocorrelation starts with an initial value $\boldsymbol{\Phi_0}$ and $\boldsymbol{x_t}$ and depends on both parameters $\boldsymbol{\Phi_1}$ and $\boldsymbol{\theta_1}$. While time window $\boldsymbol{s}$ increases, the autocorrelation decreases geometrically, if the AR parameter $\boldsymbol{\Phi_1}$ has absolute value less than one. The above formulation also reflects the fact that the MA part of the time series has memory of only one period.

As explained in Section 3.1, an observed time series can be decomposed into components that are characterized as stochastic functions of time and are designed to exhibit dynamic characteristics, such as trend, cycle, and error. It is customary in the macroeconomic time-series modeling for the trend to be modeled as a slowly evolving process, while the cycle is based on a deterministic Autoregressive Moving Average (ARMA) process [Box and Jenkins, 1970] and the noise is often modeled as a Gaussian white noise process. The dynamics for the cyclical component can be imposed by the presence of complex characteristic roots in the autoregressive polynomial. Additional terms can be introduced such as explainable variables, interventions, and seasonality components into an Unobserved Component (UC) model. The UC model can be considered as a special case of the state space model.

3.2.2 VAR (Vector Autoregressive)

In the case of multivariate time series, VAR is an extension of the AR model which can estimate and predict future values using the past information from multiple variables. Past samples of GDP and its determinant variables are used to estimate and forecast unseen values. The forecast error is compared when using a different subset of GDP determinants to identify which variables are the most critical for GDP forecasting. The predictive power is also compared with ARMA, which performs forecasting for each variable independently. Following the success of previous works ([Savva, 2010], [Tsionas, 2016], [Michaelides, 2018]), various VAR models are studied in Section 6.4 in terms of predictive power in the context of GDP forecasting.

3.2.2.1 Formulation

Since the seminal work of [Sims, 1980] that demonstrated the relationship between abstract macroeconomic variables and historical facts using statistical time series models, Vector Autoregressive (VAR) models of the form:

$$\boldsymbol{A}(\boldsymbol{B})\boldsymbol{y_t} = \boldsymbol{u_t}, \;\; \boldsymbol{t} = \boldsymbol{1}, \dots, \boldsymbol{T}, \tag{6}$$

have become popular in macroeconomic modeling. In this equation the vector $\boldsymbol{y_t} = (\boldsymbol{y_{1t}}, \dots, \boldsymbol{y_{vt}})'$ denotes a $\boldsymbol{v}$-dimensional observable process. The $\boldsymbol{v} \times \boldsymbol{v}$ matrix operator $\boldsymbol{A}(\boldsymbol{z}) = \boldsymbol{A_0} + \boldsymbol{A_1}\boldsymbol{z^1} + \dots + \boldsymbol{A_p}\boldsymbol{z^p}$ as in the backward shift operator $\boldsymbol{B}$, that is $\boldsymbol{By_t} = \boldsymbol{y_{t-1}}$, determines the time-shift properties of the observed process $\boldsymbol{y_t}$ and the stochastic disturbance, $\boldsymbol{u_t} = (\boldsymbol{u_{1t}}, \dots, \boldsymbol{u_{vt}})'$, which is unobserved, captures the influence of random events to the system.

Two common limitations of VAR are the following: first, they are not closed under aggregation, marginalization, or the presence of measurement error ([Fry and Pagan, 2005] and [Lutkepohl, 2005]). Secondly, economic models often imply that the observed processes have a Vector Autoregressive Moving Average (VARMA) representation with a non-trivial moving average component [Fernandez-Villaverde, Rubio-Ramirez, Sargent and Watson, 2007].

3.2.2.2 VARMA (Vector Autoregressive Moving Average)

In order to expand Eq. 6 into the more general VARMA model, let us assume that $\boldsymbol{u}_t$ is a full rank, zero mean, $\boldsymbol{p}$-dependent stationary process with covariance $\boldsymbol{E}[\boldsymbol{u}_t \boldsymbol{u}'_{t+\tau}] = \boldsymbol{\Gamma}_{\xi}(\boldsymbol{\tau}) = \boldsymbol{\Gamma}_{\xi}(-\boldsymbol{\tau})',\ \boldsymbol{\tau} = \mathbf{0}, \pm\mathbf{1}, \pm\mathbf{2}, \dots, \pm\boldsymbol{p}$. This denotes a sequence of zero mean, uncorrelated random variables $\boldsymbol{\varepsilon}_t$, defined on the same probability space as $\boldsymbol{u}_t$, such that $\boldsymbol{u}_t = \boldsymbol{M}(\boldsymbol{B})\boldsymbol{\varepsilon}_t,\ \ \boldsymbol{t} = \mathbf{1}, \dots, \boldsymbol{T}$, where $\boldsymbol{E}[\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}'_t] = \boldsymbol{\Sigma} > \mathbf{0}$ and, without loss of generality, the $\boldsymbol{v} \times \boldsymbol{v}$ matrix operator $\boldsymbol{M}(\boldsymbol{z}) = \boldsymbol{M}_0 + \boldsymbol{M}_1 \boldsymbol{z}^1 + \dots + \boldsymbol{M}_p \boldsymbol{z}^p$ satisfies $\mathbf{det}(\boldsymbol{M}(\boldsymbol{z})) \neq \mathbf{0}, |\boldsymbol{z}| < \mathbf{1}$.

Substituting $\boldsymbol{u}_t = \boldsymbol{M}(\boldsymbol{B})\boldsymbol{\varepsilon}_t$ into Eq. 6 gives us the VARMA form:

$$\boldsymbol{A}(\boldsymbol{B})\boldsymbol{y}_t = \boldsymbol{M}(\boldsymbol{B})\boldsymbol{\varepsilon}_t \tag{7}$$

The process $\boldsymbol{y}_t$ is assumed to evolve over the time period $\boldsymbol{t} = \mathbf{1}, \dots, \boldsymbol{T}$, starting from initial values given by $\boldsymbol{y}_t = \boldsymbol{\varepsilon}_t = \mathbf{0},\ \boldsymbol{t} \leq \mathbf{0}$. The stochastic behavior of $\boldsymbol{y}_t$ is now dependent on the operator pair $[\boldsymbol{A}(\boldsymbol{z}) : \boldsymbol{M}(\boldsymbol{z})]$ with random variation induced by the random disturbances, or shocks, $\boldsymbol{\varepsilon}_t$.

In general, the VARMA models are frequently encountered in econometrics, particularly in time series analysis to reveal the correlation across co-integrated time series, exceeding the isolated analysis of the individual time series, as in ARMA.

3.2.3 Markov Chain theory

In the Markov switching model dynamic specifications are permitted through the use of lagged dependent variables as explanatory variables and through the presence of auto-correlated errors. [Hamilton, 1989] specified a two-state Markov switching model in which the mean growth rate of GNP is subject to regime switching, and where the errors follow a regime-invariant AR(4) process. We follow this paradigm and choose a two-state Markov switching to estimate the growth and recession eras of the Greek economy. We use this model to estimate the GDP determining factors and predict whether the economy is in a state of growth or crisis and recession. The hypothesis is that modeling the two main states of the economy independently can increase the predictive power of this econometric model.

3.2.3.1 Formulation

These models took their name from the great Russian mathematician Markov who in the early 20th century, while trying to interpret the alternation of vowels and consonants in the poem "Onegin" by the poet Pushkin, introduced a simple probabilistic model. Markov chains are classified into two categories: Markov chains in discrete time and continuous time.

Stochastic process $\{X_n, n = 0, 1, \dots\}$ with a space of states I is called discrete-time Markov chain, if for all times $n = 0, 1, \dots$ and for all states $i_0, i_1, \dots, i_{n+1} \in I$:

$$P\{X_{n+1} = i_{n+1} | X_n = i_n, X_{n-1} = i_{n-1}, \dots, X_1 = i_1, X_0 = i_0\} \\ = P\{X_{n+1} = i_{n+1} | X_n = i_n\} = P_{ij}. \quad \textbf{(9)}$$

The transition probabilities P_{ij} are called first-order transition probabilities and satisfy the following properties: $P_{ij} > 0, i, j \in I$ and $\sum_{j \in I} P_{ij} = 1, i \in I$.

A Markov chain $\{X_n, n = 0, 1, \dots\}$ is fully determined by the probability function of the initial state X_0 and the probabilities of first-order transitions P_{ij}.

The future probabilistic behavior of the chain depends only on its current state and not on its history, which is known as *Markovian property*. First-order transition probabilities can be used to calculate the probability of transition from state i to state j following n steps.

State transition probabilities are defined as: $\boldsymbol{P_{ij}^{(n)} = P\{X_n = j \mid X_0 = i\}, n = 1, 2, \dots, i, j \in I}$. It holds that $\boldsymbol{P_{ij}^{(1)} = P_{ij}}$ and we also define: $\boldsymbol{P_{ij}^{(0)} = 1}$, if $\boldsymbol{j = i}$, and $\boldsymbol{P_{ij}^{(0)} = 0}$, if $\boldsymbol{j \neq i}$.

Chapman-Kolmogorov equations provide a method for calculating the $\boldsymbol{n}$-step state transition probabilities $\boldsymbol{P_{ij}^{(n)}}$ of a Markov chain [Burke and Rosenblatt, 1958]. It holds that $\boldsymbol{P_{ij}^{(n+1)} = \sum_{k \in I} P_{ik}^{(n)} P_{kj}}$ for each time step $\boldsymbol{n = 1, 2}$, ... and each state $\boldsymbol{i, j \in I}$ as we consecutively have:

$$
\begin{aligned}
\boldsymbol{P_{ij}^{(n+1)}} &= \boldsymbol{P\{X_{n+1} = j | X_0 = i\}} \\
&= \boldsymbol{\sum_{k \in I} P\{X_{n+1} = j \mid X_n = k, X_0 = i\} P\{X_n = k \mid X_0 = i\}} \\
&= \boldsymbol{\sum_{k \in I} P\{X_{n+1} = j \mid X_n = k\} P\{X_n = k \mid X_0 = i\}} \\
&= \boldsymbol{\textstyle\sum_{k \in I} P_{ik}^{(n)} P_{kj}, i, j \in I, n = 0, 1, \dots} \qquad \textbf{(10)}
\end{aligned}
$$

The second equation results from the application of the Total Probability theorem, where it is conditioned to the state at which the chain is at time $\boldsymbol{n}$. The third equation is a result of the Markovian property. The first-order transition probabilities are grouped in a matrix called the chain's one-step transition probability matrix. This matrix is usually denoted as $\boldsymbol{P}$ and since it satisfies the properties in Eq. 10 it is called a stochastic matrix.

The possible values of $\boldsymbol{X_i}$ form a countable set $\boldsymbol{S}$ that defines the chain state space. Markov Chains are often described by a directed graph whose edges indicate the probabilities of transition from one state to another.

3.2.3.2 Categorization of the states of a Markov chain

State $\boldsymbol{i}$ is called accessible from state $\boldsymbol{j}$ (denoted as $\boldsymbol{i \to j}$), if for some integer $\boldsymbol{n \geq 0}$ we have: $\boldsymbol{p_{ij}^{(n)} > 0}$. Two states that are accessible to each other are said to 'communicate', which is denoted as $\boldsymbol{i \leftrightarrow j}$, if it holds that $\boldsymbol{i \to j}$ and $\boldsymbol{j \to i}$. Allowing $\boldsymbol{n}$ to be able to be zero means that each state is accessible by itself.

A pair of states $\boldsymbol{C}$ is a 'communication class', if every pair of states in $\boldsymbol{C}$ communicates with each other but no state of $\boldsymbol{C}$ communicates with a state outside of $\boldsymbol{C}$. For each state in $\boldsymbol{C}$, an equivalence class is the set of states that it communicates with. A communication class is closed if the probability of leaving the class is zero, that is, if $\boldsymbol{i}$ is in $\boldsymbol{C}$ and $\boldsymbol{j}$ is not in $\boldsymbol{C}$, $\boldsymbol{j}$ is not accessible by $\boldsymbol{i}$. A Markov chain is 'irreducible' if the state-space has only one communicating class, that is, it is possible to go from any state to any other state.

3.2.3.3 Markov-Switching Model of Conditional Mean

Much empirical evidence suggests that the behavior of macroeconomic variables may show different patterns over time. Instead of using one model for the conditional mean of a variable, it is natural to use different models to represent these patterns. The Markov Switching model was created by combining two or more dynamic models through a mechanism called Markovian Switching ([Goldfield and Quandt, 1973], [Engel, 1994]).

Naïve Model

Suppose that $\boldsymbol{s_t}$ is an unobservable state variable assuming a value of one or zero. A simple Markov Switching model for variable $\boldsymbol{z_t}$, including two AR expressions is as follows:

$$\boldsymbol{z_t} = \begin{cases} \boldsymbol{a_0 + \beta z_{t-1} + \varepsilon_t,\ s_t = 0} \\ \boldsymbol{a_0 + a_1 + \beta z_{t-1} + \varepsilon_t,\ s_t = 1,} \end{cases} \tag{11}$$

where $|\boldsymbol{\beta}| < \mathbf{1}$ and $\boldsymbol{\varepsilon_t}$ are random variables, with zero mean and variation $\boldsymbol{\sigma^2_\varepsilon}$. This is a stationary $AR(1)$ process with mean $\boldsymbol{\alpha_0}/(\mathbf{1}-\boldsymbol{\beta})$ when $\boldsymbol{s_t} = \mathbf{0}$ and a constant $AR(1)$ process with mean $(\boldsymbol{\alpha_0}+\boldsymbol{\alpha_1})/(\mathbf{1}-\boldsymbol{\beta})$, when $\boldsymbol{s_t}$ changes from 0 to 1. Assuming that $\boldsymbol{\alpha_1} \neq \mathbf{0}$, this model recognizes two different dynamic structures at different levels, depending on the value of the variable state $\boldsymbol{s_t}$.

In this case, $\boldsymbol{z_t}$ is driven by two distributions with separate means and $\boldsymbol{s_t}$ guides the switching between these two distributions. When $\boldsymbol{s_t} = \mathbf{0}$ for $\boldsymbol{t} = \mathbf{1}, \dots, \boldsymbol{\tau_0}$ and $\boldsymbol{s_t} = \mathbf{1}$ for $\boldsymbol{t} = \boldsymbol{\tau_0} + \mathbf{1}, \dots, \boldsymbol{T}$, the model in Eq. 11 exhibits a unique transition in which the model parameter experiences an abrupt change after $\boldsymbol{t} = \boldsymbol{\tau_0}$. When $\boldsymbol{s_t}$ are independent random variables, this is a "random" switching model [Quandt, 1972].

In the random switching model, the instantiation of $\boldsymbol{s_t}$ is independent of past and future states, so that $\boldsymbol{z_t}$ can be "jumpy" and therefore switches back and forth between different states. If $\boldsymbol{s_t}$ is considered as the variable index $\mathbf{1}_{\{\lambda_t<c\}}$, so that $\boldsymbol{s_t} = 0$ or 1 depending on whether the value of $\boldsymbol{\lambda_t}$ is greater than the value of threshold $\boldsymbol{c}$, Eq. 11 becomes a "threshold" model. It is quite common to choose a dependent variable $\boldsymbol{z_t}$ as variable $\boldsymbol{\lambda_t}$.

While these models are all capable of characterizing time-series behaviors in two modes, each has its own limitations. First, such model switches are solely determined by the time variable, which is an exogenous factor to the model. Second, for the model with one structural switch, it is very restrictive, because more than two modes might arise in practice, such as crisis, recession, growth, trough, etc. Although extending this model to allow multiple switches is theoretically simple, the resulting model estimation and *hypothesis testing* are usually cumbersome in practice [Bai and Perron, 1998]. In this dissertation, a Markov Switching model with two states is chosen in favor of simplicity and easier estimation with the existing data.

The state variables of the "random" switching model are still exogenous to the dynamic structures of the model. This model, moreover, suffers from the disadvantage that state variables are independent of time and therefore may not be well applicable to time-series data.

However, the switch in the threshold model is time dependent, intrinsic to the model and includes multiple switches. Choosing a suitable variable $\boldsymbol{\lambda_t}$ and threshold value $\boldsymbol{c}$ is usually difficult. One approach to circumvent these problems is to consider a different formulation for $\boldsymbol{s_t}$. Specifically, assume a first-order Markov Chain with the following transition matrix:

$$\begin{aligned}\boldsymbol{P} &= \begin{bmatrix} \mathbb{P}(\boldsymbol{s_t} = \mathbf{0} \mid \boldsymbol{s_{t-1}} = \mathbf{0}) & \mathbb{P}(\boldsymbol{s_t} = \mathbf{1} \mid \boldsymbol{s_{t-1}} = \mathbf{0}) \\ \mathbb{P}(\boldsymbol{s_t} = \mathbf{0} \mid \boldsymbol{s_{t-1}} = \mathbf{1}) & \mathbb{P}(\boldsymbol{s_t} = \mathbf{1} \mid \boldsymbol{s_{t-1}} = \mathbf{1}) \end{bmatrix} \\ &= \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix}, \end{aligned} \quad \textbf{(12)}$$

where $\boldsymbol{p_{ij}}$ $(\boldsymbol{i}, \boldsymbol{j} = \mathbf{0}, \mathbf{1})$ indicate the transition probabilities from $\boldsymbol{s_{t-1}} = \boldsymbol{i}$ to $\boldsymbol{s_t} = \boldsymbol{j}$ with the constraint $\boldsymbol{p_{i0}} + \boldsymbol{p_{i1}} = \mathbf{1}, \boldsymbol{i} = \mathbf{0}, \mathbf{1}$. The transition matrix governs the random behavior of the variable state and contains only two parameters ($\boldsymbol{p_{00}}$ and $\boldsymbol{p_{11}}$). The model with the Markovian variable state in Eq. 12 is known as the Markov Switching Model [Goldfeld and Quandt, 1973].

[Hamilton, 1989] presented a detailed analysis of the Markov Switching Model, as well as the estimation method ([Hamilton, 1994] and [Kim and Nelson, 1999]). In this model, the properties of $\boldsymbol{z_t}$ are jointly determined by the random characteristics of the driving innovations $\boldsymbol{\varepsilon_t}$ and the variable state $\boldsymbol{s_t}$. Specifically, the Markovian state variable attributes random switches and the probabilities of transition determine the persistence of each regime.

Compared to the threshold model, the Markov Switching model is simpler to implement as it does not require the a-priori selection of threshold variable $\boldsymbol{\lambda_t}$. Instead, the classification to a regime is probabilistic and determined by the data. However, one challenge with the Markov Switching model is that it might be hard to interpret because its state variables are not observable. Nevertheless, due to the implementation not being dependent on selecting a threshold, in this dissertation a two-state Markov Switching model is adopted.

3.2.3.4 Extensions

The model in Eq. 11 is easily extensible to allow for more general dynamic structures. A simple extension is as follows:

$$\boldsymbol{z_t = \alpha_0 + \alpha_1 s_t + \beta_1 z_{t-1} + \ldots + \beta_k z_{t-k} + \varepsilon_t} \qquad \textbf{(13)}$$

where $\boldsymbol{s_t = 0, 1}$ are the Markovian state variables with the transition matrix from Eq. 12, and $\boldsymbol{\varepsilon_t}$ are random variables with zero mean and variance $\boldsymbol{\sigma_\varepsilon^2}$. This is a model with a general AR($\boldsymbol{k}$) dynamic structure and displacements. For $\boldsymbol{d}$-dimensional time series $\{\boldsymbol{z_t}\}$, this is written as:

$$\boldsymbol{z_t = \alpha_0 + \alpha_1 s_t + B_1 z_{t-1} + \ldots + B_k z_{t-k} + \varepsilon_t} \qquad \textbf{(14)}$$

where $\boldsymbol{s_t = 0, 1}$ remain the variables of the Markovian state with the transition matrix of Eq. 12, $\boldsymbol{B_i, i = 1, \ldots, k}$ are $\boldsymbol{d} \times \boldsymbol{d}$ matrices of parameters, and $\boldsymbol{\varepsilon_t}$ is iid random vectors with zero mean and lattice variance - co-variance $\boldsymbol{\Sigma_0}$. Eq. 14 is a displacement VAR model. This extension is theoretically easy, but it might not always be realistic, as $\boldsymbol{d}$ variables are required for simultaneous switching.

3.2.4 Fast Fourier Transform (FFT)

In this section a classical algorithm for analyzing business cycles in the frequency domain is presented, i.e., Discrete Fourier Transform and its efficient approximation, known as Fast Fourier Transform (FFT). The magnitude and phase of the dominant cycle is determined using the dominant Fourier frequency. Despite being a crude approximation, it allows suppressing the noise of the examined time series by focusing on the dominant cycle, while its efficient implementation is very fast to compute. The experiments with FFT are conducted in Section 6.3, where the cycle of GDP and its determinants are approximated by the dominant FFT cycle.

3.2.4.1 Introduction

The Fast Fourier Transform (FFT) algorithm calculates the discrete Fourier transform (DFT) of a sequence. Fourier analysis converts a signal from its original state to a representation in the frequency domain. FFT is efficient by factorizing the DFT matrix into a sparse factor product. As a result, it manages to reduce the complexity of calculating DFT from $\boldsymbol{O(n^2)}$, when the DFT definition is simply applied, to $\boldsymbol{O(nlogn)}$, where $\boldsymbol{n}$ is the data size. FFT is widely used in engineering, science, and mathematics. The basic ideas became popular by [Cooley and Tukey, 1965], but some algorithms had been around since 1805 [Gauss, 1805].

3.2.4.2 Theory of Continuity

For a continuous function with a variable $\boldsymbol{f(t)}$, the Fourier transform $\boldsymbol{F(f)}$ can be defined as:

$$\boldsymbol{F(f) = \int_{-\infty}^{\infty} f(t) e^{-j2\pi ft} dt.} \tag{15}$$

And the reverse transformation as

$$\boldsymbol{f(t) = \int_{-\infty}^{\infty} F(f) e^{j2\pi ft} df,} \tag{16}$$

where $\boldsymbol{j}$ is the square root of -1 and $\boldsymbol{e}$ the natural exponent $\boldsymbol{e^{j\theta} = \cos(\theta)\, j\ \sin(\theta), \theta = 2\pi ft}$.

3.2.4.3 Discrete Fourier Transform

Consider a complex series $\boldsymbol{x(k)}$ with $\boldsymbol{N}$ samples of the form $\boldsymbol{x_0, x_1, \dots, x_k, \dots, x_{N-1}}$, where $\boldsymbol{x}$ is complex number: $\boldsymbol{x_i = x_{real} + x_{imag} i}$. Furthermore, we assume that the sequence outside the interval $[\boldsymbol{0, N-1}]$ is an extended $\boldsymbol{N}$-periodic, i.e., $\boldsymbol{x_k = x_{k+N}}$ for all $\boldsymbol{k}$.

The FT of this series is denoted by $\boldsymbol{X(k)}$ with $\boldsymbol{N}$ samples. The forward transform is defined as:

$$\boldsymbol{X(n) = \frac{1}{N}\sum_{k=0}^{N-1} x(k)\, e^{-jk2\pi n/N}, n = 0, \dots, N-1} \quad \textbf{(17)}$$

The inverse transformation is defined as:

$$\mathrm{x}(\boldsymbol{n}) = \boldsymbol{\sum_{k=0}^{N-1} X(k)\, e^{jk2\pi n/N}, n = 0, \dots, N-1}. \quad \textbf{(18)}$$

Although the functions are described here as a complex series, the real series can be represented by setting the imaginary part to 0. In general, the transformation in the frequency domain will be a complex function, i.e., with magnitude and phase:

$$\begin{aligned} \boldsymbol{magnitude} &= \|\boldsymbol{X(n)}\| = (\boldsymbol{X_{real} * X_{real} + X_{imag} * X_{imag}})^{\mathbf{0.5}} \\ \boldsymbol{phase} &= \mathbf{tan}^{-\mathbf{1}}\left(\frac{\boldsymbol{X_{imag}}}{\boldsymbol{X_{real}}}\right). \end{aligned} \quad \textbf{(19)}$$

3.2.4.4 FFT algorithm

While the DFT transform can be applied to any complex series, in practice for large arrays it may take long time to calculate, as the corresponding time is proportional to the square of the number of data points. A much faster algorithm was developed by [Cooley and Tukey, 1965] called FFT (Fast Fourier Transform). The only requirement of the most popular implementation of this algorithm (Radix-2 Cooley-Tukey) is that the number of points in the series is a power of 2. The calculation time for FFT radix-2 is proportional to $\boldsymbol{Nlog_2(N)}$. For example, a 1,024-point transformation using DFT takes about 100 times longer than using FFT.

The FFT algorithm operates in the frequency domain and can suppress noise by identifying the dominant frequency. Despite a coarse approximation, this property allows the analysis to focus on the dominant cycle of the examined time series. This characteristic is leveraged in Section 6.3 where the dominant cycle is identified for GDP and its determining factors.

3.2.5 Deep Learning Models

Despite their widespread use in the business cycle literature, the autoregressive models still have some limitations that have to do with their modeling capacity. Nonlinear models are needed to describe the data-generating mechanisms of inherently asymmetric realizations, because linear autoregressive or ARMA models are only capable of generating realizations with symmetrical cyclical fluctuations [Terasvirta and Anderson, 1992]. To this end, recent advances in Deep Neural Networks [LeCun, Bengio, Hinton, 2015] have expanded their use in predicting econometric time series [Fathi, 2019]. Next two paragraphs review two popular machine learning models for time-series prediction.

3.2.5.1 Recurrent Neural Networks (RNNs)

RNNs are used to process sequential data, that is a sequence of inputs $\mathbf{x_1}, \dots, \mathbf{x_m}$. At time $\mathbf{t}$, they calculate their output according to the input $\mathbf{x_t}$ but also the state of the hidden layer at the previous time $\mathbf{h_{t-1}}$. Thus, they develop an internal state that acts as a short-term memory and captures the temporal dependencies of the input sequence.

The simplest RNN representation is the following. Let: $\mathbf{n}, \mathbf{k}, \mathbf{p} \in \mathbf{N}, \mathbf{x_0}, \dots, \mathbf{x_m}$, where $\boldsymbol{x_t} \in \boldsymbol{R_n}, \boldsymbol{W} \in \boldsymbol{M_{kn}}(\boldsymbol{R}), \boldsymbol{W_h} \in \boldsymbol{M_{kk}}(\boldsymbol{R}), \boldsymbol{O} \in \boldsymbol{M_{pk}}(\boldsymbol{R})$ and $\boldsymbol{h_{-1}} \in \boldsymbol{R_k}$. Then, the dynamics of the associated RNN is described by:

$$\begin{aligned} \boldsymbol{h_t} &= \boldsymbol{\sigma}(\boldsymbol{W x_t} + \boldsymbol{W_h h_{t-1}}) \\ \boldsymbol{y_t} &= \boldsymbol{O} \cdot \boldsymbol{h_t}, \end{aligned} \qquad \textbf{(20)}$$

where $\boldsymbol{h_t} \in \boldsymbol{R_k}$ is the state of the hidden layer and $\boldsymbol{y_t} \in \boldsymbol{R_p}$ is the state of the output layer. As an initial condition, we often assume that $\boldsymbol{h_{-1}} = \mathbf{0}$.

Conventional recurrent neural networks often suffer from the problem of “vanishing gradient” that prevents them from learning from sufficiently long time periods in the past. To update its parameters, a neural network backpropagates its gradients from the loss function through the network by calculating the derivative of its activation functions. A classic RNN, by not selecting which time-series terms to keep and treating them all uniformly, is causing the gradient information to decrease exponentially over time. The network falsely stops learning because it believes that the error is near zero. To that end, the Long Short-Term Memory models are devised to alleviate this vanishing gradient problem.

3.2.5.2 Long Short-Term Memory (LSTM)

The Long Short-Term Memory (LSTM) network is the most widely used architecture in practice to address the problem of vanishing gradient. This network structure was proposed by [Hochreiter and Schmidhuber, 1997]. The idea associated with the LSTM is that each computational unit is linked not only to a hidden state $\boldsymbol{h}$ but also to a state $\boldsymbol{c}$ of the cell that plays the role of memory. The change from $\boldsymbol{c_{t-1}}$ to $\boldsymbol{c_t}$ is done by constant gain transfer equal to 1, so that errors are propagated at previous steps without significant gradient loss. The status of the cell can be modified through a gate that allows or blocks the update (input gate). Similarly, a gate controls whether the state of the cell is communicated at the output gate of the LSTM unit (output gate). The most common version of LSTMs also uses a gate to reset the cell state (forget gate). The dynamic equations of this model are as follows:

$$\begin{aligned}
&\boldsymbol{F_t} = \boldsymbol{\sigma}(\boldsymbol{W_F x_t} + \boldsymbol{U_F h_{t-1}} + \boldsymbol{b_F}) \textbf{ (forget gate)}\\
&\boldsymbol{I_t} = \boldsymbol{\sigma}(\boldsymbol{W_I x_t} + \boldsymbol{U_I h_{t-1}} + \boldsymbol{b_I}) \textbf{ (input gate)}\\
&\boldsymbol{O_t} = \boldsymbol{\sigma}(\boldsymbol{W_O x_t} + \boldsymbol{U_O h_{t-1}} + \boldsymbol{b_O}) \textbf{ (output gate)}\\
&\boldsymbol{c_t} = \boldsymbol{F_t} \circ \boldsymbol{c_{t-1}} + \boldsymbol{I_t} \circ \boldsymbol{tanh}(\boldsymbol{W_C x_t} + \boldsymbol{U_C h_{t-1}} + \boldsymbol{b_C})\\
&\boldsymbol{h_t} = \boldsymbol{O_t} \circ \textbf{tanh}\,(\boldsymbol{c_t})\\
&\boldsymbol{o_t} = \boldsymbol{f}(\boldsymbol{W_o h_t} + \boldsymbol{b_o})
\end{aligned} \qquad \textbf{(21)}$$

The terms $\boldsymbol{b_F}$, $\boldsymbol{b_I}$, $\boldsymbol{b_O}$, $\boldsymbol{b_C}$ and $\boldsymbol{b_o}$ represent the different biases across gates. Operator $\circ$ represents Hadamard's product (element-wise product). Initially, we take $\boldsymbol{c_O} = \boldsymbol{h_O} = \boldsymbol{0}$.

With the advent of deep architectures, LSTM is widely used today in sequence learning and has demonstrated great modeling power. In 2014, a simplified version of LSTM called GRU (Gated Recurrent Unit) was introduced by [Chung, Gulcehre, Cho, Bengio, 2014]. GRU has the advantage of being less computationally cumbersome because it has fewer parameters and equations. Nevertheless, it remains as effective as its predecessor.

In Section 6.5 different formulations of LSTM for macroeconomic time series are explored. A different number of past samples are considered as the model input, specifically, a period of 1, 2 and 6 years, respectively. The size of the input sample is equivalent to the order P of the autoregressive models. Next, a comparison between a univariate and multivariate LSTM is presented, where the LSTM input $\boldsymbol{x}$ either consists of individual variables (for instance, GDP) independently or jointly along with the other GDP determining factors (e.g., Consumption, Government Expenditure, Exports, Imports).

3.3 Summary

Various works have leveraged ARMA for modeling the temporal dynamics of business cycle time series. [Davidson et al., 1990] used ARMA to study the political business cycle and partisan theories of politico-economic interaction and tested the hypothesis that model dynamics vary over electoral periods and party regimes. Several works have extended this framework to VAR modeling, such as GVAR to investigate the dynamic interdependencies among the EU-12 economies [Michaelides, 2018], Bayesian System GVAR to study the transmission of shocks (e.g., financial, monetary) between a selection of world economies [Tsionas, 2016]. All these works exploited the temporal correlation across macroeconomic variables, exceeding the isolated analysis of the individual time series, as in ARMA.

Markov Switching provides a unified framework for modeling more than one dynamic states. [Engel, 1994] used a Markov Switching model to estimate exchange rates at quarterly frequencies and concluded that its forecasts are superior at predicting the direction of change of the exchange rate. Other works have operated in the frequency domain to build models that are tolerant to noise. [Crowley, 2005] analyzed the European business cycles by employing Multiresolution Decomposition with Maximal Overlap Discrete Wavelet Transforms. Nonlinear models can generate asymmetric data, while linear autoregressive, ARMA or VAR models are only capable of generating realizations with symmetrical cyclical fluctuations [Terasvirta and Anderson, 1992]. Among the nonlinear models, [Fathi, 2019] used a hybrid methodology combining Auto-Regressive Integrated Moving Average (ARIMA) for seasonal component modeling and Recurrent Neural Networks (RNN) for trend forecasting.

This dissertation provides a comprehensive econometric analysis in order to empirically identify the statistically significant determining factors of GDP and then leverage them along with the above-mentioned methods to quantify the estimation and forecast error for each of them. Thus, this analysis determines the most fitting modeling approaches for the Greek business cycle in terms of both estimation and forecasting. Moreover, this work provides correlation between the time series characteristics and stylized events based on political, economic, and historical events.

Chapter 4 – Economic Model

This chapter describes the macroeconomic variables of our economic model with a focus on the Greek Gross Domestic Product (GDP) and its main determining factors. Initially, we introduce the fundamental equations of GDP and proceed to briefly describe functions for the determining factors as well (e.g., Consumption, Government expenditure, Exports, Imports). Next, we formulate a system of equations for GDP, which comprises of the GDP expenditure equation as the identity and the GDP production function as an equation to estimate its coefficients. Next, we applied the econometric methods and models described in Ch. 3 to empirically investigate the cyclical behaviour of the examined macroeconomic time series of the Greek economy as defined in the aforementioned linear system.

More specifically, this dissertation regards business cycles as fluctuations around a trend, i.e., "deviation cycles" [Lucas, 1977]. The business cycle component is regarded as the movement in the time series around a trend [Burns and Mitchell, 1946]. In this chapter we first examine the stationarity of the observed time series, followed by extracting its cyclical component. The use of the Augmented Dickey-Fuller (ADF) test [Dickey & Fuller, 1979] provides a critical step towards checking for integration of the examined indicators. That is, we investigate whether there is a unit root for each time series, in order to ultimately examine the stationarity properties of these variables. Ensuring the stationarity of the differenced variables is a critical step towards checking for cointegration among these variables.

After examining the stationarity properties, a de-trending method is used in order to extract the cyclical component from each time series. The utilized method is the Hodrick-Prescott (HP) filter due to its widespread acceptance in the literature ([Christodoulakis et al, 1993], [Michaelides, 2013]). The Hodrick-Prescott (HP) filter decomposes a time series into a trend and a cyclical component.

After extracting the cyclical part of the series, we assess the hypothesis whether the cyclical component corresponds to a white noise process [Michaelides, 2013]. White noise is a data generating process where autocorrelation is zero between lagged versions of the variable. When this is the case, the occurrence of an event is not related to previous phenomena. In order to discover if there is autocorrelation between lagged time series, we use the Q-stat test [Ljung and Box, 1978] and the probability of the null hypothesis (Ho). If the null hypothesis is rejected, then the examined time series is not a white noise process and might well represent a cycle.

Next, we investigate the cointegration among two or more indicators for the equations of the examined linear system, except for the identity. The Johansen test is adopted to estimate the cointegration of the involved time series [Johansen & Juselius, 1990]. The hypothesis is that two or more variables are cointegrated when they have a long-run equilibrium relationship. Thus, even though shocks may have permanent effects on the specific variables, they only have temporary effects with regards to the system as a whole and consequently the return to the presumed equilibrium relationship will occur. Finally, the linear system is solved via Ordinary Least Square regressions, so that the coefficients of the macroeconomic variables are estimated.

In the next sections we review various fundamental macroeconomic functions using references from the related literature.

4.1 Closed Economy

In a closed economy, where all transactions take place domestically, the national income can be partitioned into three factors, i.e., consumption, investment, and government spending, as:

$$\mathbf{Y} = \mathbf{C} + \mathbf{I} + \mathbf{G}, \tag{1}$$

where $\boldsymbol{Y}$ is the national income, $\boldsymbol{C}$ is the total consumption, $\boldsymbol{I}$ is the total investment and $\boldsymbol{G}$ is the total government expenditure.

4.2 Open Economy

An open economy makes transactions with the rest of the world, where some goods are imported, while others are exported abroad. Imports $\boldsymbol{M}$ are the goods which are produced abroad and are purchased in our country, while Exports $\boldsymbol{X}$ are the goods that are produced domestically and are sold abroad. Given that the imports are not part of the domestic product, but are part of the total expenditure, they should be subtracted by the total expenditure so that the remaining spending equals to the domestic product. Thus:

$$\mathbf{Y} = \mathbf{C} + \mathbf{I} + \mathbf{G} + \boldsymbol{X} - \boldsymbol{M}. \tag{2}$$

This can be refactored for Net Exports $\mathbf{X - M}$ to be as output $\boldsymbol{Y}$ minus domestic spending:

$$\mathbf{X - M = Y - (C + I + G)}, \qquad \textbf{(3)}$$

If output exceeds domestic expenditure, that is exports surpass imports, then there is a "trade surplus" with size $\mathbf{X - M}$. On the other hand, when domestic spending exceeds output $\boldsymbol{Y}$ and equivalently imports surpass exports, then there is a "trade deficit" with size $\boldsymbol{M - X}$. If $\mathbf{X - M}$ is equal to zero, there is "balanced trade" and the value of imports equals the value of exports.

The Gross Domestic Product (GDP) can be expressed using only domestic terms by absorbing the Imports components within the Expenditure terms, as follows:

$$\begin{aligned}\mathbf{Y} &= \mathbf{C + I + G + X - M} \\ &= \mathbf{C + I + G + X} - \left(\boldsymbol{C^f} + \boldsymbol{I^f} + \boldsymbol{G^f}\right) \\ &= (\mathbf{C} - \boldsymbol{C^f}) + (\mathbf{I} - \boldsymbol{I^f}) + (\mathbf{G} - \boldsymbol{G^f}) + \mathbf{X} \\ &= \boldsymbol{C^d} + \boldsymbol{I^d} + \boldsymbol{G^d} + \mathbf{X}. \qquad \textbf{(4)}\end{aligned}$$

The sum of the first three terms, $\boldsymbol{C^d} + \boldsymbol{I^d} + \boldsymbol{G^d}$, is domestic spending on domestic goods and services. The fourth term, $\mathbf{X}$, is foreign spending on domestic goods and services (i.e., the value of exports). Therefore, the sum of them corresponds to the expenditure of an open economy $\boldsymbol{Y}$.

4.3 International capital flows and trade balance

By subtracting **C** and **G** from both sides in Eq. 2 and introducing the taxes, we obtain:

$$\begin{aligned}&\mathbf{Y - C - G = I + X - M} \\ &\mathbf{(Y - C - T) + (T - G) = I + X - M}, \qquad \textbf{(5)}\end{aligned}$$

where $\mathbf{Y - C - G}$ is the national saving $\mathbf{S}$, which equals the sum of private saving, $\mathbf{Y - C - T}$, and public saving, $\mathbf{T - G}$, and $\mathbf{T}$ stands for Taxes. Therefore,

$$\mathbf{S = I + X - M}. \qquad \textbf{(6)}$$

Subtracting **I** from both sides of the equation, we have:

$$\mathbf{S - I = X - M}. \qquad \textbf{(7)}$$

Net exports are also known as the “trade balance” and is equal to the difference between savings $\mathbf{S}$ and investment $\mathbf{I}$. The latter difference is also known as “net capital outflow” $\mathbf{S} - \mathbf{I}$, which is equal to the amount that domestic residents are lending abroad minus the amount that foreigners are lending to home economy. If it is positive, national saving exceeds investment, then the home economy is lending to foreigners, which makes it a “net lender”. On the contrary, when investment exceeds national saving, other countries are lending to the home country, which acts as a “net borrower” and there is a “net capital inflow”. In summary, Eq. 7 shows that Net Capital Outflow is equal to Trade Balance.

4.4 General Form for Gross Domestic Product Determination

In its more general form, Eq. 2 can be written as:

$$\mathbf{Y} = \mathbf{C}(\mathbf{Y} - \mathbf{T}(\mathbf{Y})) + \mathbf{I}(\mathbf{r}) + \mathbf{G} + \mathbf{NX}(\mathbf{Y}), \tag{8}$$

where Consumption $\mathbf{C}$ is a function of the disposable income $\mathbf{Y} - \mathbf{T}(\mathbf{Y})$, where Taxes $\mathbf{T}$ are an increasing function of Income $\mathbf{Y}$, $\mathbf{I}(\mathbf{r})$ represents business Investment decreasing as a function of the real Interest Rate $\mathbf{r}$ and $\mathbf{NX}(\mathbf{Y}) = \mathbf{X} - \mathbf{M}(\mathbf{Y})$ represents Net Exports (Exports minus Imports) increasing as a function of Income.

4.5 Production Function

In its most standard form, the production equation for a single good has been formulated in [Cobb and Douglas, 1928] as follows:

$$\boldsymbol{Y = AL^{\beta}K^{\alpha}}, \tag{9}$$

where $\boldsymbol{Y}$ is the total production, $\boldsymbol{L}$ is the Labor force and $\boldsymbol{K}$ is the Capital. $\boldsymbol{A}$ is the Total Factor Productivity, which is typically measured as the ratio of aggregate output to aggregate inputs. The Total Factor Productivity (TFP) is used as the technology variable in production equation, as its residual component is considered to quantify the cyclical evolution of technological innovation [Michaelides, 2013]. The exponents $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are the output elasticities of $\boldsymbol{K}$ and $\boldsymbol{L}$ and are determined by the available technology.

The production function often exhibits constant returns to scale, that is doubling the resources of capital $\boldsymbol{K}$ and labor $\boldsymbol{L}$ will also double output $\boldsymbol{Y}$. In this case, the production function is first-order homogeneous, i.e., $\boldsymbol{\alpha} + \boldsymbol{\beta} = \mathbf{1}$, and Eq. 9 is simplified as follows:

$$\boldsymbol{Y = AL^{\beta}K^{1-\beta}}. \quad \textbf{(10)}$$

Equivalently, the Cobb-Douglas function can be estimated as a linear relationship by using the logarithms in the following expression:

$$\mathbf{ln}(\boldsymbol{Y}) = \mathbf{ln}(\boldsymbol{A}) + \boldsymbol{\beta ln}(\boldsymbol{L}) + (\mathbf{1} - \boldsymbol{\beta})\mathbf{ln}\ (\boldsymbol{K}). \quad \textbf{(11)}$$

4.6 Investment Function and Interest Rate

Prior literature on interest rate policy, e.g., [McCallum & Nelson, 1997], argues the case for ignoring investment in business cycles on the premise that there is little connection at cyclical frequencies between capital stock movements and those in aggregate output and consumption. One argument is that a typical year's investment is very small in relation to the existing capital stock and physical investment is ignored by assuming a fixed capital stock [Benhabib et al., 2001]. In these models the interest rate affects output solely through the consumption-savings decision of the household, and not through the investment decision of the firm.

On the contrary, [Dupor, 2001] emphasizes that investment is a significant fraction of GDP and cite the fact that quarterly investment is more than four times as volatile as consumption in the post-war US to provide further motivation for modeling investment. In Eq. 8 investment **I** can be written as a function of the real interest rate $\boldsymbol{r}$:

$$\boldsymbol{I = I(r)} \quad \textbf{(12)}$$

[Dupor, 2001] shows that a temporary, exogenous increase in the nominal interest rate causes a temporary increase in output $\boldsymbol{Y}$ and investment $\boldsymbol{I}$. However, in the long run an interest rate increase causes decrease in output, since higher rates are accompanied by lower liquidity. Additionally, with neoclassical investment, they show that uniqueness determinacy results are reversed: a passive interest rate rule, where the monetary authority responds to inflation by lowering the real interest rate $\boldsymbol{r}$, leads to a unique equilibrium, as opposed to an active policy, which leads to either indeterminacy or no equilibria that converge to a stationary steady state.

4.7 Consumption Function

According to the conventional Keynesian definition, consumption $\mathbf{C}$ is a function of nominal income $\boldsymbol{Y}$ and income taxes $\boldsymbol{T^{Inc}}$, as it is introduced in Eq. 8:

$$\mathbf{C} \;=\; \mathbf{C}(\mathbf{Y} - \boldsymbol{T^{Inc}}(\mathbf{Y})). \tag{13}$$

This formulation assumes that a perfect foresight in the short run implies that the transitory shock is zero. However, the objective factors include surprises to a variety of short-term variables, which have been proposed by [Wolfson, 1994] to be modeled as the price levels of consumption goods $\boldsymbol{P^C}$. Furthermore, assuming that wealth $\boldsymbol{W}$ is an important component of consumption, then to the extent that long-term expectations $\boldsymbol{E^C}$ and uncertainty $\boldsymbol{U^C}$ are relevant to investment demand, they must also be relevant to the evaluation of wealth, which mainly consists of capital goods. Similarly, human capital is also likely to depend on these factors. Purchases of consumer durables, which comprise roughly half of consumption spending, can often be postponed with little immediate impact on consumption, giving uncertainty and long-run expectations another way for influencing output.

Combining the abovementioned assumptions, the following extension of the consumption function is discussed in [Wolfson, 1994]:

$$\mathbf{C} \;=\; \mathbf{C}(\mathbf{Y} - \boldsymbol{T^{Inc}}(\mathbf{Y}), \mathbf{W}(\boldsymbol{E^C}, \boldsymbol{U^C}), \mathbf{w}, \boldsymbol{P^C}\,), \tag{14}$$

where $\mathbf{Y}$ is real Income, $\boldsymbol{T^{Inc}}$ is income Taxes, $\mathbf{W}$ is real Aggregate Wealth, both tangible and human, $\boldsymbol{E^C}$ is the long-run expectations, $\boldsymbol{U^C}$ is the uncertainty associated with these expectations, $\mathbf{w}$ is the Money Wage, and $\boldsymbol{P^C}$ is the Price Level of consumption goods.

4.8 *Government Expenditure Function*

[Ganelli, 2005] describes a Blanchard-type Open-Economy Macroeconomics model of government spending, where expenditure $\boldsymbol{G}$ and real interest payments $\boldsymbol{r}$ on outstanding debt $\boldsymbol{D}$ can be financed by seigniorage, lump-sum taxes $\boldsymbol{T}$ and issuing of new debt $\boldsymbol{D}$, according to the single-period budget constraint at time $\boldsymbol{t}$:

$$\boldsymbol{G_t} + (\mathbf{1} + \boldsymbol{r_t})\boldsymbol{D_t} \;= \boldsymbol{T_t} + \frac{\boldsymbol{B_t} - \boldsymbol{B_{t-1}}}{\boldsymbol{P_t^C}} + \boldsymbol{D_{t+1}}. \tag{15}$$

$\boldsymbol{B_t}$ is the nominal Money Balance and $\boldsymbol{P_t^C}$ the Price Level of goods held at time $\mathbf{t}$. $\boldsymbol{D_{t+1}}$ is the outstanding Government Debt for year $\boldsymbol{t+1}$ as fiscal spillover from the previous year $\boldsymbol{t}$, which is not financed by taxes $\boldsymbol{T_t}$ or seigniorage $\frac{\boldsymbol{B_t - B_{t-1}}}{\boldsymbol{P_t^C}}$.

This model can restore the traditional Mundell-Fleming result, but it is also able to distinguish between the effects of different types of fiscal policy, such as a debt-financed tax cut, a balanced-budget increase in government spending and debt-financed increase in government spending. The Government Expenditure equation can be written in functional form as:

$$\mathbf{G} = \mathbf{G}(\mathbf{T}, \mathbf{D}, \mathbf{r}, \mathbf{B}, \boldsymbol{P^C}). \qquad \textbf{(16)}$$

4.9 Tax Function

[Andrejovska et al, 2018] examined different factors based on the intensity of correlation between the dependent variable of total tax revenues $\mathbf{T}$ from direct and indirect taxes at current prices and a series of independent variables, as follows:

$$\mathbf{T} = \mathbf{T}(\mathbf{Y}, \mathbf{E}, \mathbf{D}, \mathbf{N}, \boldsymbol{T_c}, \mathbf{F}), \qquad \textbf{(17)}$$

where $\boldsymbol{Y}$ is Gross Domestic Product at current prices, **E** is Employment rate, **D** is Public Debt, **N** is the Rate of Inflation measured on the basis of the harmonized index of consumer prices, $\boldsymbol{T_c}$ is the corporate Tax Rate and **F** is direct Foreign Investments. The analysis for 28 European Union countries in [Andrejovska et al, 2018] confirms that the strongest correlation is between tax revenues and employment rate, followed by direct Foreign Investment and GDP. Interestingly, the nominal and effective Tax Rate is shown to have small impact to tax revenue.

4.10 Net Exports Function

From Eq. 3 Net Exports **NX** have been defined as the difference between exports **X** and imports **M**, which equals to subtracting the sum of Consumption $\mathbf{C}$, Investment $\boldsymbol{I}$ and Government Expenditure $\boldsymbol{G}$ from GDP **Y**, i.e., $\boldsymbol{X - M = Y - (C + I + G)}$.

When it comes to identifying the main determinants for the export **X** and import **M** functions, the prevailing approach explains exports as well as imports in form of a demand equation for imports. The demand function for real goods exports is modeled by [Joebges et al., 2008] as:

$$\boldsymbol{X} = \boldsymbol{X}(\boldsymbol{Y}^*, {}^{\boldsymbol{pxg}}/_{\boldsymbol{p}^*}), \tag{18}$$

where $\boldsymbol{Y}^*$ represents a proxy for income of the importing economies, $\boldsymbol{pxg}$ stands for the export goods price index, and $\boldsymbol{p}^*$ is a broad price index of the importing economies. The ratio of the prices thus serves as a proxy for the price competitiveness of the exported goods and services.

Conversely, the standard approach models the long-run demand for real goods imports as a function of domestic activity $\boldsymbol{Y}$ and a proxy for the price competitiveness of imported goods and services:

$$\boldsymbol{M} = \boldsymbol{M}(\boldsymbol{Y}, {}^{\boldsymbol{pmg}}/_{\boldsymbol{p}}), \tag{19}$$

where the activity variable can be expressed as real GDP $\boldsymbol{Y}$ and the price term for imports should consist of the ratio of import prices $\boldsymbol{pmg}$ and an overall price index $\boldsymbol{p}$, which can be expressed by the GDP deflator or the Consumer Price Index (CPI).

The import and export price indexes measure the change in prices of goods and services purchased from abroad by Greek consumers and businesses (imports) and sold to foreign buyers (exports). The indexes provide information as to the strength of the Greek economy and consumer spending, the demand for Greek goods abroad, and the pace of rising import prices.

4.11 Linear System for GDP Estimation

Next, the empirical analysis is focused on the Greek GDP estimation. Combining Eqs. 2 and 9, the linear system for GDP estimation can be written as follows:

$$\begin{aligned} &\boldsymbol{Y} = \boldsymbol{C} + \boldsymbol{I} + \boldsymbol{G} + \boldsymbol{X} - \boldsymbol{M} \\ &\boldsymbol{Y} = \boldsymbol{A}\boldsymbol{L}^{\boldsymbol{\beta}}\boldsymbol{K}^{\boldsymbol{\alpha}}, \end{aligned} \tag{20}$$

where $\boldsymbol{Y}$ is the gross domestic product, $\boldsymbol{C}$ is the consumption, $\boldsymbol{I}$ is the investment, $\boldsymbol{G}$ is the government expenditure, $\boldsymbol{X}$ is the exports, $\boldsymbol{M}$ is the imports, $\boldsymbol{A}$ is the total factor productivity, $\boldsymbol{L}$ is the labor force and $\boldsymbol{K}$ is the capital.

A series of dummy variables are introduced in this system to model the effect of certain macroeconomic events that had an independent effect on output following the paradigm of [Dalamagas, 1995]. Dummy variable $\boldsymbol{D_1}$ is constructed for years 2010-2017 to capture the influence of the memorandum that was signed between Greece and the Troika, as part of the economic adjustment program that Greece entered to cope with the government debt crisis. Dummy variable $\boldsymbol{D_2}$ is constructed for years 2020-2021 to model the impact of the COVID-19 Pandemic to GDP and the other macroeconomic variables.

Dummy variable $\boldsymbol{D_3}$ is constructed for years 1960-1979 to model a growth policy which concentrates to efficiency target, which was characterized by sustained growth and investment. This period was succeeded by a social policy in 1980-1995, when the resources and the social funds were distributed throughout society. This governance led to currency devaluation twice and a negative growth rate for the Greek economy. Dummy variable $\boldsymbol{D_4}$ is constructed for years 2008-2012 to model the Great Recession, which started from the United States as a financial crisis and emerged in Greece as a fiscal crisis due to the national fiscal deficit. The dummy vectors are set to 1 for the impacted years and 0 for the rest of the examined time period. With the dummy variables and the corresponding elasticities, the system is formulated as follows:

$$\begin{aligned}\boldsymbol{Y} &= \boldsymbol{C} + \boldsymbol{I} + \boldsymbol{G} + \boldsymbol{X} - \boldsymbol{M}\\ \boldsymbol{Y} &= \boldsymbol{D_1 D_2 D_3 D_4 A L^{\beta} K^{\alpha}},\end{aligned} \tag{21}$$

In the following sections, the Augmented Dickey Fuller test is performed in Sec 4.12 to check the stationarity of the examined variables from Eqs. 21, de-trending via HP filter is performed to extract the cycle and white noise test is conducted in Sec. 4.13 for the extracted business cycle. Next, co-integration is examined for the equations of the linear system in Eqs. 21 via the Johansen Cointegration test in Sec. 4.14 and finally coefficients are estimated via OLS regressions for whole system in Sec 4.15.

Data for the 9 variables in Eqs. 21 are sourced from OECD [Florence, 2023] and AMECO [AMECO European Database] for the Greek economy and the period between 1960 and 2021. In specific, complete time-series data are sourced for Gross Domestic Product, Consumption, Government Expenditure, Investment, Exports and Imports from OECD, while time series for Labor Force, Capital and Total Factor Productivity are sourced from AMECO. Finally, the two dummy variables are constructed following the methodology from [Dalamagas, 1995].

4.12 Stationarity Check for Model Variables with Augmented Dickey Fuller Test

Next, we perform Augmented Dickey Fuller (ADF) test [Dickey & Fuller, 1979] to check whether the examined variables in Eq. 20 or their first derivative are stationary. To this end, we define the Null Hypothesis as "Given variable has a unit root". Not rejecting the hypothesis $\boldsymbol{H_0}$ is equivalent to empirically showing that the given variable has a unit root and thus is non-stationary. The lag length is automatically determined based on the Schwarz Information Criterion (SIC).

Null Hypothesis: Y has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.764709	0.3942
Test critical values:	1% level	-3.544063	
	5% level	-2.910860	
	10% level	-2.593090	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(Y)
Method: Least Squares
Date: 04/27/23 Time: 16:10
Sample (adjusted): 1962 2021
Included observations: 60 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Y(-1)	-0.026830	0.015203	-1.764709	0.0830
D(Y(-1))	0.437776	0.119171	3.673519	0.0005
C	5802.982	2644.062	2.194722	0.0323

R-squared	0.259193	Mean dependent var	2558.955
Adjusted R-squared	0.233200	S.D. dependent var	7513.103
S.E. of regression	6579.007	Akaike info criterion	20.46986
Sum squared resid	2.47E+09	Schwarz criterion	20.57458
Log likelihood	-611.0959	Hannan-Quinn criter.	20.51082
F-statistic	9.971582	Durbin-Watson stat	1.898863
Prob(F-statistic)	0.000193		

Figure 1: ADF test statistics for GDP.

Null Hypothesis: D(Y) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.378163	0.0008
Test critical values:	1% level	-3.544063	
	5% level	-2.910860	
	10% level	-2.593090	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(Y,2)
Method: Least Squares
Date: 04/27/23 Time: 16:19
Sample (adjusted): 1962 2021
Included observations: 60 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(Y(-1))	-0.520733	0.118939	-4.378163	0.0001
C	1411.909	910.3385	1.550971	0.1263

R-squared	0.248396	Mean dependent var	165.6200
Adjusted R-squared	0.235437	S.D. dependent var	7659.993
S.E. of regression	6697.842	Akaike info criterion	20.48972
Sum squared resid	2.60E+09	Schwarz criterion	20.55953
Log likelihood	-612.6917	Hannan-Quinn criter.	20.51703
F-statistic	19.16831	Durbin-Watson stat	1.911745
Prob(F-statistic)	0.000051		

Figure 2: ADF test statistics for first differenced GDP.

In Figs. 1 and 2 the ADF test statistics are shown for GDP and its first derivative, respectively. The p-value of GDP is 0.3942 and thus larger than 0.05 (that is, the ADF test significance level), which means that the Null hypothesis is not rejected and therefore the time series is non-stationary. Next, the p-value of D(GDP) is 0.0008, thus smaller than 0.05, which means that the differenced time series has no unit root and therefore it is stationary. Therefore, the ADF test shows that GDP is integrated of degree 1, i.e., $I(1)$.

In Figs. 1 and 2 the ADF test is performed for both the original and the differenced GDP time series, respectively. Since GDP is $I(1)$, from the original equation [Michaelides et al., 2013]:

$$\boldsymbol{\Delta Y_t = \alpha + bt + \rho Y_{t-1} + \sum_{i=1}^{m} \zeta \Delta Y_{t-i} + \varepsilon_t,} \tag{22}$$

it holds that $\boldsymbol{b = 0}$ and $\boldsymbol{\rho = 0}$, which correspond to a difference stationary model. Based on Fig. 2 the ADF coefficients are $\boldsymbol{\alpha = 1411.9}$ and $\boldsymbol{\zeta = -0.52}$.

Based on [Michaelides et al., 2013] the different cases for Eq. 22 are:

a) If $\boldsymbol{b \neq 0}$ and $\boldsymbol{\rho = -1}$ implies a trend stationary (TS) model.
b) If $\boldsymbol{b = 0}$ and $\boldsymbol{-1 < \rho < 0}$ implies an ARMA Box/Jenkins class of models.

c) If $\boldsymbol{b} = \mathbf{0}$ and $\boldsymbol{\rho} = \mathbf{0}$ implies a difference stationary (DS) model, where Y variable is integrated of degree one $I(1)$, which is the case with the Greek GDP in Eq. 22.

Next, the statistics associated with the ADF test equation are explained. The Durbin-Watson (D-W) statistic ranges in value from 0 to 4. A value near 2 indicates non-autocorrelation; a value toward 0 indicates positive autocorrelation; a value toward 4 indicates negative autocorrelation. Based on Fig. 2, GDP is characterized by positive autocorrelation. In Table 3 the ADF test estimation statistics are shown for all examined variables. The Durbin-Watson statistic indicates positive autocorrelation across all variables, except for Government Expenditure and Total Factor Productivity, which have negative error autocorrelation. The latter implies that the increase observed in a time interval leads to a proportionate decrease in the lagged time interval. That means that by plotting the observations with a regression line, it shows that a positive error will be followed by a negative one and vice versa, which indicates instability in those time series.

R-squared (R^2) is a statistical measure that represents the proportion of the variance for a dependent variable that is explained by an independent variable in a regression model. Essentially, R^2 measures the model fitness. R^2 only works as intended in a simple linear regression model with one explanatory variable. With a multiple regression made up of several independent variables, the Adjusted R^2 measure must be used. Every predictor added to a model increases R^2 and never decreases it. Thus, a model with more terms may seem to have a better fit just for the fact that it has more terms, while the Adjusted R^2 compensates for the addition of variables; it only increases if the new term enhances the model above what would be obtained by probability and decreases when a predictor enhances the model less than what is predicted by chance. Based on Table 3 Exports achieve the highest Adjusted R^2 measure. The low R^2 values for the other macroeconomic indicators indicate that even noisy, high-variability data can have a significant trend.

The Hannan-Quinn (H-Q) Criterion evaluates the fitness of the estimation, where smaller values indicate higher fitness. In Table 3 the H-Q Criterion is the smallest for Capital and Total Factor Productivity, which means higher fitness. Similar trends are observed by the Akaike Information criterion (AIC), which estimates the amount of information loss, where smaller values show a higher quality estimation. The Schwarz criterion is an index that quantifies and chooses the less complex probability model among a set of models. A smaller value shows a better fitting model. In line with the previous criteria the Capital, Total Factor Productivity and then Government Expenditure estimations achieve the best fitness.

In Tables 1 and 2 the ADF T-statistic and P-value (Prob.) are shown for all variables in their original and differenced version. The test is performed by including the intercept (C) and then both the trend and intercept (C+T) in the test equation. Since the P-values in Table 2 are smaller than 0.05, we conclude that all differenced variables except for the Labor Force are stationary, and thus the original variables are integrated of degree 1 (i.e., $I(1)$). The Labor Force is $I(2)$, that it $\boldsymbol{D^2}$(Labor) is stationary, where T-statistic for C is -14.08148, Probability for C is 0.0000 and Probability for C+T is 0.0000.

Table 1: ADF statistics for the original variables.

Variable	T-stat for C	Prob for C	Prob for C+T	Stationary
GDP	-1.764709	0.3942	0.7191	No
Consumption	-1.360300	0.5957	0.5038	No
Government Expenditure	-1.775557	0.3889	0.3969	No
Investment	-2.326416	0.1672	0.6953	No
Exports	0.319051	0.9775	0.2891	No
Imports	0.168243	0.9683	0.3416	No
Capital	-2.378686	0.1520	0.4498	No
Labor	-1.192072	0.6724	0.8579	No
Total Factor Productivity	-2.855627	0.0567	0.5804	No

Table 2: ADF statistics for first differenced variables.

D(Variable)	T-stat for C	Prob for C	Prob for C+T	Stationary
D(GDP)	-4.378163	0.0008	0.0034	Yes
D(Consumption)	-3.786953	0.0050	0.0232	Yes
D(Government Expenditure)	-4.711961	0.0003	0.0010	Yes
D(Investment)	-6.093536	0.0000	0.0000	Yes
D(Exports)	-8.905042	0.0000	0.0000	Yes
D(Imports)	-5.493008	0.0000	0.0001	Yes
D(Capital)	-5.300459	0.0000	0.0003	Yes
D(Labor)	-2.654345	0.0882	0.2958	No
D(Total Factor Productivity)	-5.289755	0.0000	0.0001	Yes

Table 3: Statistics from the ADF test estimation.

D(Variable)	T-stat	Prob	Adj R^2	D-W	H-Q	Schwarz	Akaike
D(GDP)	-4.378163	0.0008	0.2354	1.9117	20.5170	20.5595	20.4897
D(Consumption)	-3.786953	0.0050	0.1844	1.7235	19.3913	19.4338	19.3640
D(Government Expenditure)	-4.711961	0.0003	0.2644	2.1964	17.0411	17.0846	17.0138
D(Investment)	-6.093536	0.0000	0.3798	1.9923	19.8700	19.9125	19.8427
D(Exports)	-8.905042	0.0000	0.5702	1.9955	19.4500	19.4925	19.4227
D(Imports)	-5.493008	0.0000	0.3309	1.8030	19.5644	19.6069	19.5371
D(Capital)	-5.300459	0.0000	0.3147	1.8885	5.3353	5.3778	5.3080
D(Total Factor Productivity)	-5.289755	0.0000	0.3138	2.0975	5.1969	5.2394	5.1696

Given that we have verified that the examined variables are $I(1)$, the Johansen co-integration test is performed in Sec. 4.14. Ahead of this, in Sec 4.13 Hodrick-Prescott (HP) detrending is conducted for the examined variables, and each extracted cycle is tested whether it corresponds to a white noise process.

4.13 Ljung and Box White Noise Test

After having extracted the cyclical component via HP detrending, we test whether the detrended series represent a cycle by testing if it corresponds to a white noise process. White noise is a data generating process where autocorrelation is zero between lagged versions of the macroeconomic variable. To test for auto-correlation we use the Ljung and Box test [Ljung & Box, 1978], which tests the null hypothesis of white noise for a maximum lag length k.

In Tables 4 and 5 the white noise test for $k = 8$ is conducted for the GDP Expenditure and Production function determinants. In case the null hypothesis is rejected then the underlying time series is not white noise and is considered a cycle. In other words, the existence of autocorrelation rejects the random walk process hypothesis for these time series. Based on the P-Values in Tables 4 and 5, the null hypothesis is rejected and therefore the detrended time series well represent cycles for the examined macroeconomic indicators.

Table 4: Ljung-Box White Noise test for the GDP Expenditure function determinants.

Lag	GDP		Consumption		Gov Expend		Investment		Exports		Imports	
	Q-stat	Prob	Q-stat	Prob	Q-stat	Prob	Q-stat	Prob	Q-stat	Prob	Q-stat	Prob
1	25.34	0.000	33.06	0.000	27.94	0.000	22.09	0.000	11.66	0.001	20.17	0.000
2	33.76	0.000	42.91	0.000	36.54	0.000	28.25	0.000	11.67	0.003	21.25	0.000
3	34.09	0.000	42.91	0.000	36.76	0.000	30.39	0.000	14.10	0.003	22.52	0.000
4	36.52	0.000	48.26	0.000	40.37	0.000	37.81	0.000	19.53	0.001	28.48	0.000
5	44.54	0.000	60.90	0.000	46.26	0.000	45.33	0.000	21.13	0.001	42.27	0.000
6	52.24	0.000	75.37	0.000	59.31	0.000	50.88	0.000	21.47	0.002	50.31	0.000
7	58.80	0.000	87.39	0.000	68.08	0.000	55.18	0.000	23.65	0.001	50.42	0.000
8	64.10	0.000	94.99	0.000	71.28	0.000	60.33	0.000	23.66	0.003	52.53	0.000

Table 5: Ljung-Box White Noise test for the GDP Production function determinants.

Lag	Capital		Labor		Total Factor Productivity	
	Q-stat	Prob	Q-stat	Prob	Q-stat	Prob
1	54.12	0.000	63.09	0.000	54.92	0.000
2	94.68	0.000	124.63	0.000	101.04	0.000
3	123.63	0.000	183.54	0.000	137.62	0.000
4	141.21	0.000	239.25	0.000	165.90	0.000
5	150.35	0.000	291.16	0.000	187.14	0.000
6	154.19	0.000	338.84	0.000	202.86	0.000
7	155.14	0.000	382.00	0.000	213.73	0.000
8	155.15	0.000	420.50	0.000	220.60	0.000

4.14 Johansen Cointegration Test

In this section we use the Johansen cointegration test to examine the cointegration among the variables which are part of the production function in Eqs. 27. Specifically, $\boldsymbol{Y} = \boldsymbol{A}\boldsymbol{L}^{\boldsymbol{\beta}}\boldsymbol{K}^{\boldsymbol{\alpha}}$, where Gross Domestic Product ($\boldsymbol{Y}$) is the dependent variable and Total Factor Productivity ($\boldsymbol{A}$), Labor Force ($\boldsymbol{L}$), Capital ($\boldsymbol{K}$) are the independent variables. The null hypothesis is that there is no cointegration at all.

Sample (adjusted): 1963 2021
Included observations: 59 after adjustments
Trend assumption: Quadratic deterministic trend
Series: Y TFP L K
Lags interval (in first differences): 1 to 2

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.365519	61.99526	55.24578	0.0113
At most 1 *	0.314733	35.15332	35.01090	0.0483
At most 2	0.189117	12.85446	18.39771	0.2503
At most 3	0.008207	0.486207	3.841465	0.4856

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

The probability for the first two hypotheses is below 0.05, which means that the Null hypothesis is rejected for them, and therefore the criterion indicates 2 cointegrated time series. Moreover, the trace statistics values are larger than the corresponding 0.05 critical values, which confirms again the rejection of the null hypothesis for the first two hypotheses. However, the probability for the two remaining hypotheses is above 0.05, which indicates that the Null hypothesis is accepted for them. All in all, the null hypothesis is rejected since there is empirical evidence for a cointegrating relationship of two time series.

The existence of cointegration implies that the examined variables have a long-run equilibrium relationship. The concept of "long-run equilibrium", in this context, means that despite the fact that shocks may have permanent effects on the specific variables, they only have temporary effects with regards to the system as a whole and consequently the return to the presumed equilibrium relationship will occur [Banerjee et al., 1986].

4.15 System Estimation via Ordinary Least Square (OLS) Regressions

In this section we solve the System of Eqs. 21 defined in Sec. 4.11 in order to compute the estimated (or fitted) values for the Greek GDP in 1960-2021 by relying on its fundamental determinant factors. The GDP Expenditure function is the identity in the examined system, while the GDP Production function is being estimated and its coefficients are calculated for the involved macroeconomic variables.

Based on the OLS regressions, the System of Eqs. 21 is written as:

$$\boldsymbol{Y = C + I + G + X - M}$$
$$\boldsymbol{Y = 0.218 * D_1 * D_2 * D_3 * D_4 * A^{1.72} * L^{0.734} * K^{-0.154}}. \qquad \textbf{(23)}$$

The estimated parameters in this system represent the output elasticities and quantitatively express the relative change between the independent and dependent macroeconomic variables. For instance, 2% increase in Labor Force corresponds to 1.66% increase in GDP. Similarly, 2% improvement in Total Factor Productivity corresponds to 3.29% increase in GDP.

In Figs. 3-7 the fitted and actual GDP data are shown from the estimation of the abovementioned system of equations when using no dummy variables and after consecutively introducing a series of dummy variables to model the effect of certain macroeconomic events that had an independent effect on GDP.

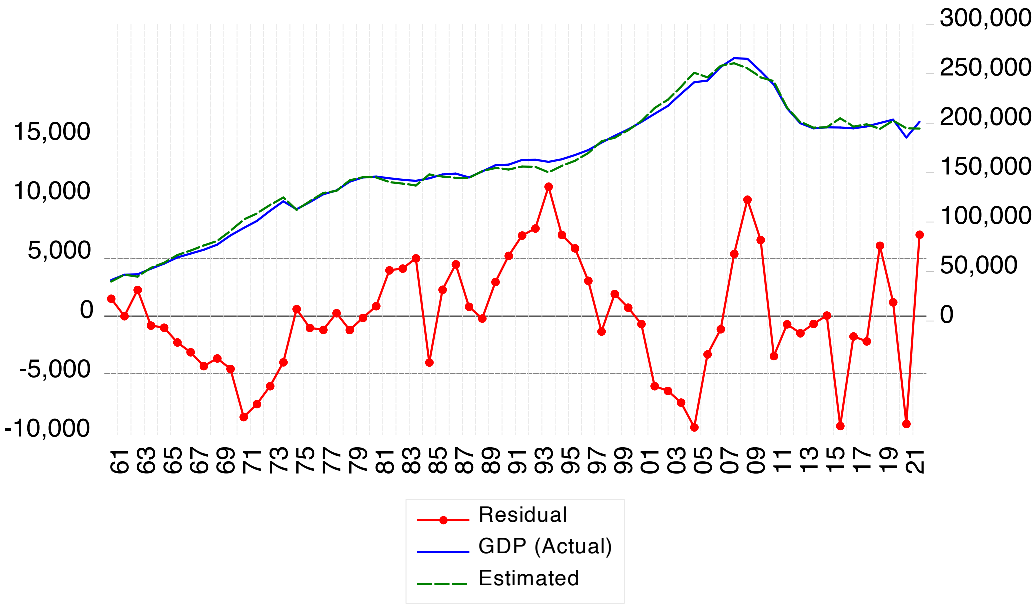


Figure 3: GDP estimation from System of Eqs. 21.

For the GDP estimation in Fig. 3 no dummy variable is constructed. The residual time series is computed as the difference of the actual and estimated series. Although the residual is small in comparison to the actual data, there are certain years such (e.g., 2009) with high residual. Next, dummy variables are used to address rapid changes caused by macroeconomic events.

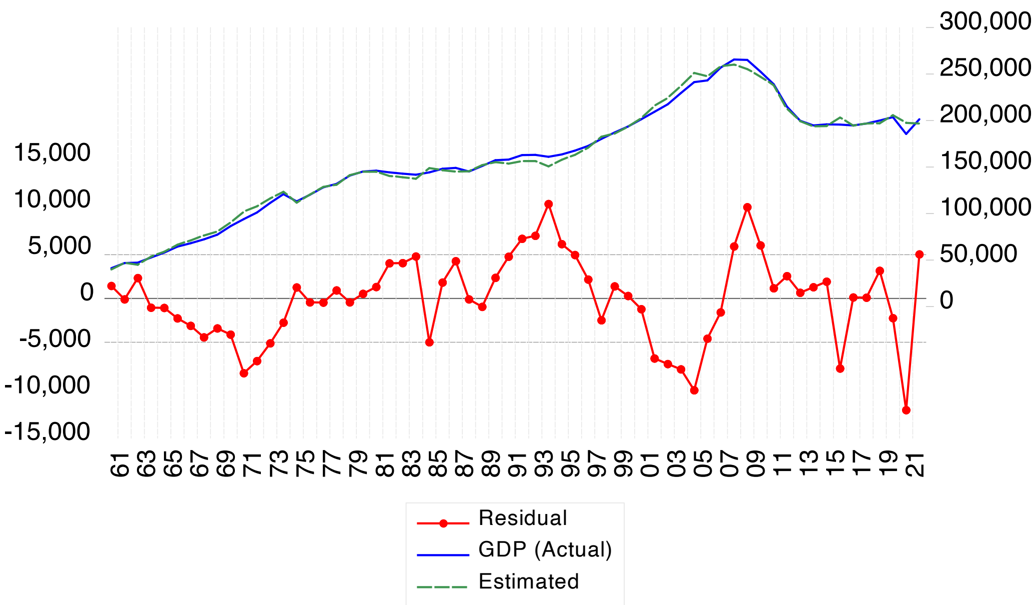


Figure 4: GDP estimation with a dummy variable for Adjustment Program (2010-2017).

In Fig. 4 one dummy variable is constructed for the Adjustment program between Greece and the Troika (2010-2017). The residual error is apparently smaller for the Memorandum period.

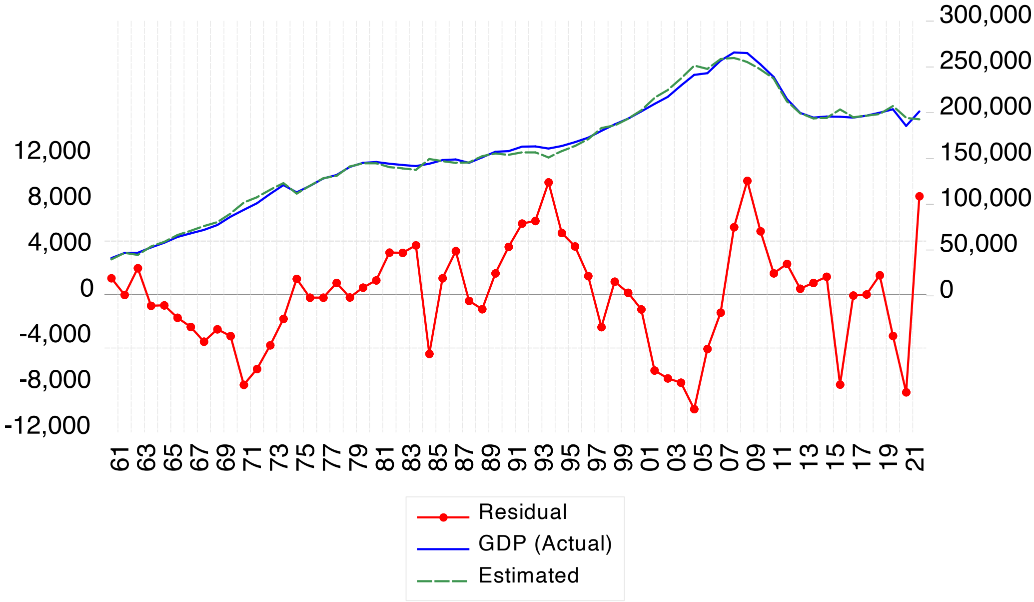


Figure 5: GDP estimation with dummy variables for Adjustment Program (2010-2017) and COVID-19 Pandemic (2020-2021).

In Fig. 5 the GDP estimation is repeated after the construction of one additional dummy variable for the COVID-19 Pandemic (2020-2021). By observing the residual, the estimation is near identical for the period of 1960-2021 compared to the previous estimations, except for the pandemic period, where the residual error is reduced. This comparison demonstrates the effectiveness of the dummy variables to maintain a small residual in the GDP estimation across the 62-year period.

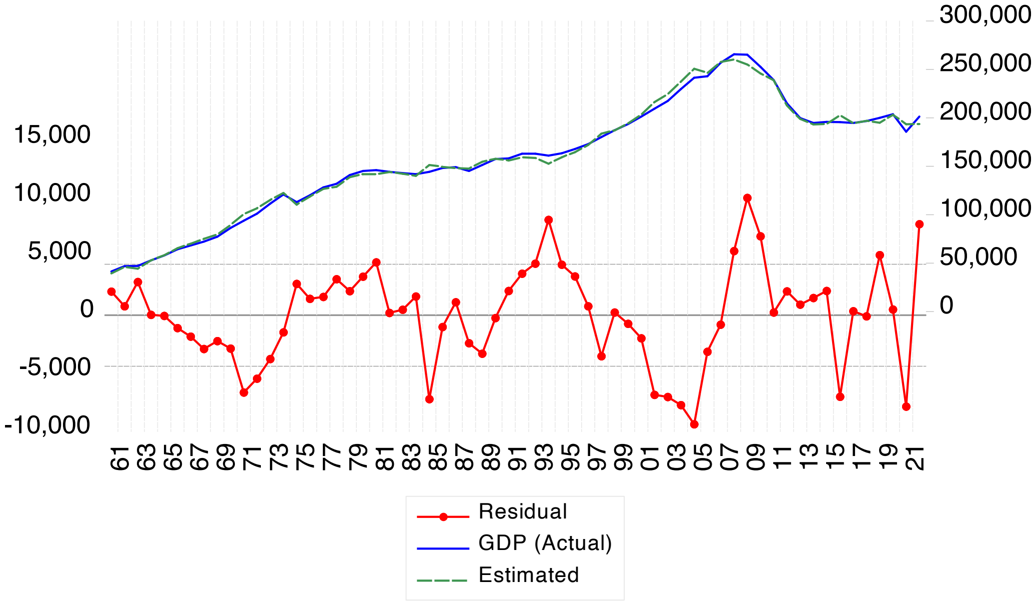


Figure 6: GDP estimation with dummy variables for Adjustment Program (2010-2017), COVID-19 Pandemic (2020-2021) and Growth Policy (1960-1979).

In Fig. 6 an additional dummy variable is constructed for years 1960-1979 to model a fiscal policy which concentrates on efficiency target. The government budget is mainly distributed towards investment to fuel the growth. The government constituted the new development law, which aimed at the determination of the investment, developmental and industrial policy of Greece. By inspecting the residual above, it is reduced for the addressed years.

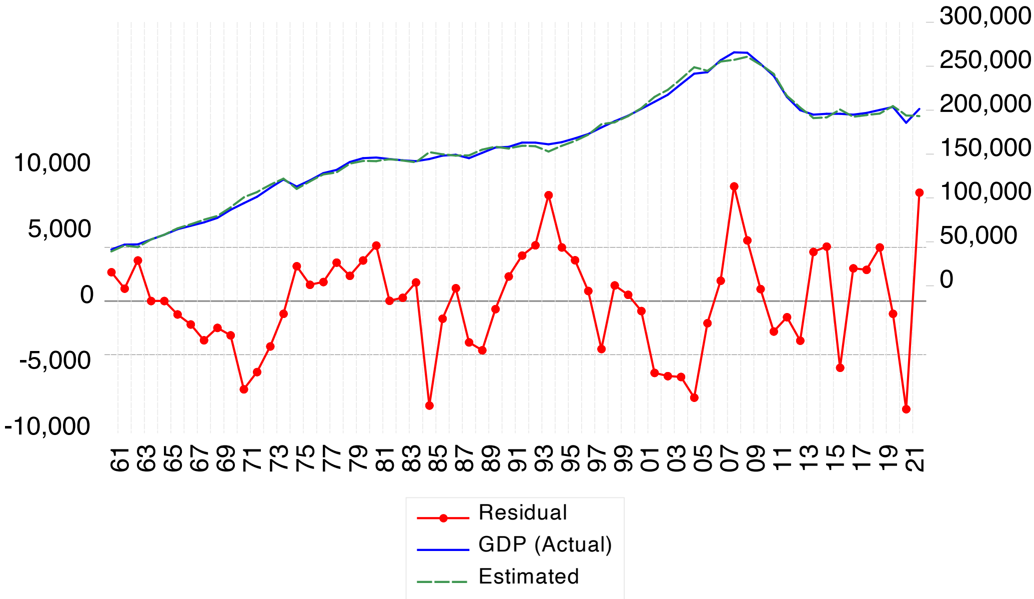


Figure 7: GDP estimation with dummy variables for Adjustment Program (2010-2017), COVID-19 Pandemic (2020-2021), Growth Policy (1960-1979), and Great Recession (2008-2012).

In Fig. 7 one final dummy variable is constructed for years 2008-2012 to model the Great Recession. When the crisis occurred and the Lehman Brothers collapsed, which led to its bankruptcy in 2008, the investors were severely impacted, and in turn Greece was not able to borrow money from the investors in order to finance its fiscal debt. The government bonds were devalued and had half the value compared to before the crisis. The financial crisis was absorbed as fiscal crisis in Greece due to its insolvency and lack of trust among the international investors. As a direct consequence Greece was not in a position to redeem its fiscal debt.

In this graph an overall ascending GDP trend is observed over the years from 1960-2008 with successive periods of higher and lower growth. Specifically, steady high GDP growth occurred in 1960-1974. Then a one-year decline took place after the end of the dictatorship and a slowdown happened in 1975-1979, which was followed by a period of stagflation (1980-1993) [Alogoskoufis, 2021]. GDP growth took place between 1994-2007, which was a period of Recovery and Euro Euphoria that was characterized by Greece joining the European Monetary Union in 2001 and the Greek Olympic Games in 2004. After the advent of the Global Recession the Greek economy entered a period of depression in 2008-2016. Next, a period of economic stabilization followed until the shock of the COVID-19 Pandemic.

Table 6: Coefficients and statistics from GDP estimation for the System of Eqs. 21.

System	Adj R^2	D-W	ε_K	ε_L	ε_A	ε_{D^1}	ε_{D^2}	ε_{D^3}	ε_{D^4}
Eqs. 21	0.9932	0.8404	-0.132	0.824	1.705	N/A	N/A	N/A	N/A
Eqs. 21 w/ D^1	0.9936	0.9483	-0.157	0.854	1.732	-0.021	N/A	N/A	N/A
Eqs. 21 w/ D^1 & D^2	0.9937	0.9510	-0.179	0.873	1.760	-0.033	-0.030	N/A	N/A
Eqs. 21 w/ D^1, D^2 & D^3	0.9944	0.9466	-0.168	0.881	1.740	-0.028	-0.025	0.011	N/A
Eqs. 21 w/ D^1, D^2, D^3 & D^4	0.9952	1.2269	-0.207	0.872	1.800	-0.050	-0.037	0.004	0.029

In Table 6 the estimated coefficients (elasticities) and statistics are shown from the GDP estimation for the different settings described in Figs. 3-7. The R^2 measure is nearly 1 for all estimations, which indicates excellent model fitness. Moreover, we observe that R^2 increases with the addition of each dummy variable, which shows the improved model fitness after explicitly accounting for Adjustment Program, Pandemic, Growth Policy and Great Recession. In all cases the Durbin-Watson statistic is lower than 2 which indicates positive error auto-correlation for the estimated GDP. All in all, the fitted GDP values capture the effect of all explanatory variables in the model, while the GDP residual represents the effect of all other remaining variables that are not included in the model formulation.

4.16 Conclusions

In this chapter the fundamental macroeconomic indicators of GDP are described theoretically with references from the related literature and then introduced into a system of equations to estimate the Greek GDP for 1960-2021. The final estimation shows high model fitness based on the Adjusted R^2 measure, especially after the construction of dummy variables to account for four disruptive macroeconomic phenomena, i.e., the Adjustment program between Greece and the Troika, the Global Covid-19 Pandemic, the Growth Policy in the 1960s and 1970s and the Great Recession. This empirically verifies that the selected macroeconomic indicators are key determining factors for GDP.

To effectively study the system a series of tests is performed in advance to show that most variables are integrated of degree 1, i.e., $I(1)$, the business cycles from detrending do not correspond to white noise process and the analyzed equations are co-integrated. After these diagnostic tests are conducted, the system is estimated using Ordinary Least Square regression in order to calculate the coefficients of the participating variables. The estimated elasticities for each variable quantify the impact of changes in the individual variables to the Greek GDP.

In Chapter 5 we will expand the econometric analysis to study the properties of the GDP business cycle in relation to the cycles of the determinants, such as procyclicality, synchronicity, correlation between the cyclical variations, cross-correlation among GDP and the other times series. In Chapter 6, we will introduce econometric and Machine Learning models to estimate and forecast the GDP cycle as a function of the key macroeconomic cycles and compare their performance and interpretation power.

Chapter 5 – Econometric Analysis of the Greek Business Cycle

The purpose of this chapter is the macro-econometric analysis of data for the Greek Economy for years 1960-2021. Specifically, we process and examine the time series of various macroeconomic indicators as described in Chapter 4 and were formulated as a linear system of equations. First, we detrend the time series of the selected variables into trend and cycle, so that we delve deeper in the observed patterns in relation to stylized events. Next, we draw the cyclical part of multiple macroeconomic variables together, as these are grouped through the equations of Chapter 4 (e.g., Expenditure and Production function) so that we compare the joint patterns and in relation to economic and political events. Main focus of this chapter is to correlate the quantitative findings with significant historical, political and economic facts that had a major impact and have shaped the Greek Economy over the examined time period.

To support the qualitative comparisons, we perform a thorough econometric analysis to study the properties of the GDP business cycle in relation to the cycles of its determinants, such as procyclicality, synchronicity, countercyclicality, correlation between the cyclical variations, cross-correlation among GDP and the other indicators. The analysis is conducted to study the effect of all explanatory variables that are part of the examined economic model, as well as the residual factors, which represent the effect of all other remaining variables that are not part of the economic model in Ch. 4.

5.1 Introduction

The Greek Economy has often faced a structural crisis through its modern history, which is reflected in the rapid deterioration of the economic fundamental factors and the decline of prospects for investments and further economic growth. The importance of the Business Cycles is related to the fact that the economic fluctuations in macro-econometric variables such as unemployment and many others, are economic phenomena that affect economic policy and, by extension, the fiscal one. The prosperity of large groups of people depends on the success with which each government tackles an economic recession or crisis.

The experience so far in Greece and other countries of the European Union, indicates that these challenges are not fully controllable, and a central fiscal policy is not always adapted to the specific features and requirements of every country. The present analysis will capture in graphs but will also analyze the Business Cycles of the Greek economy during the period 1960 - 2021.

In the next sections, we first discuss the real Greek GDP in Sec. 5.2, followed by individual plots with the cyclical and trend components of the key GDP indicators in Sec. 5.3. Next, in Sec. 5.4 comprehensive econometric analysis is performed to study the relative properties among the business cycles, such as procyclicality, synchronicity, leads/lags, cross-correlation, and persistence. In Sec. 5.5 we illustrate joint graphs of the cyclical parts of GDP and its major indicators in order to identify common patterns and correlation with political and historical events. The conclusions are summarized in Sec. 5.6.

5.2 *Gross Domestic Product in modern Greece*

After World War II and the Greek civil war that only ended in 1949, Greece's macroeconomic performance was among the most impressive in Europe with rapid growth. This started changing in the early 1970s, when Greece was negatively affected from the first oil shock of the 1970s, but recovered relatively quickly. Democracy was restored in 1974, after a seven-year dictatorship, and Greece applied to enter the European Economic Community (EEC) in 1975. However, following the second oil shock, admittance into the EEC in 1981, and the election of a socialist government in the same year, Greece entered a period of 'stagflation' and rapid public debt accumulation, which lasted throughout the 1980s [Alogoskoufis, 2012].

After a change in government in 1990, Greece initiated a program of fiscal consolidation and structural reforms, in order to prepare itself for joining the single European currency. Greece was among the signatories of the Maastricht Treaty in 1991, and secured its participation in the

Euro area in the year 2000. Economic growth gradually recovered during the 1990s, inflation was gradually contained and public debt was stabilized relative to GDP.

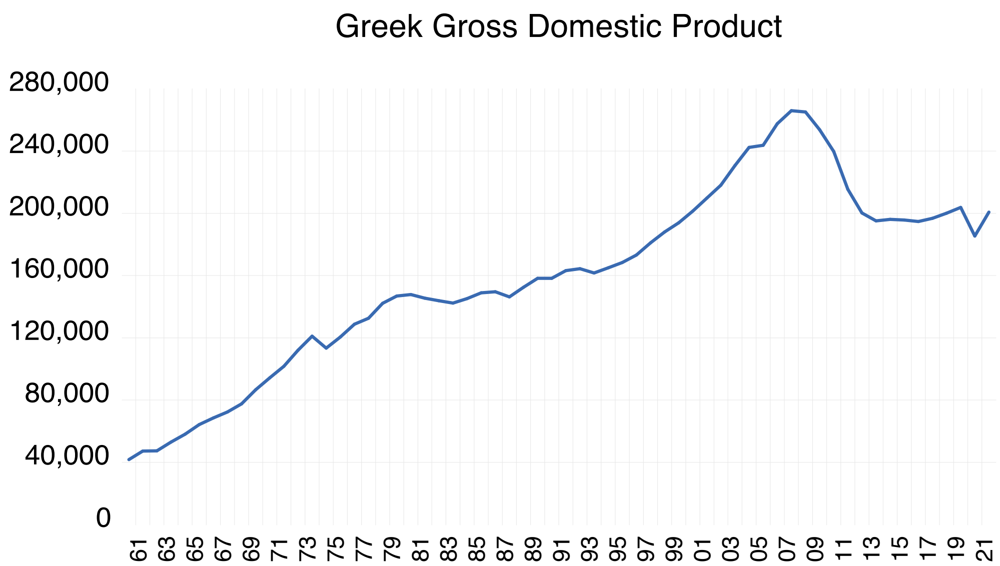


Figure 8: Gross Domestic Product (in millions).

In Fig. 8 real GDP of the Greek economy is drawn for years 1960-2021, sourced from the OECD database. Between 2001 and 2008, after joining the Euro area, a golden era for the Greek economy followed with increased growth rates, subdued inflation despite slightly higher than the Euro area average and reduced unemployment. The public debt to GDP ratio was stabilized at about 100%, which was much higher than the average for the Euro area. In addition, Greece's mechanisms of controlling primary government expenditure remained weak, in areas such as local authorities, social security funds and the health sector, while tax evasion undermined the effectiveness of the tax system.

A peak is observed at 2008 in Fig. 8, which is followed by sovereign debt crisis in the next years. Initiated by the US and specifically the collapse of Lehman Brothers on September 2008, the global financial system entered a phase of malfunctioning credit markets, unprecedented write-downs in asset valuations, risk aversion and instability of the banking section [Alogoskoufis, 2012]. The international financial crisis was quickly spread in the Greek economy. In 2009, the year of the global recession, the Greek deficit of the general government exploded to 13.6% of GDP. After 15 years of economic growth, the Greek economy entered prolonged recession [Bank of Greece, 2014].

The international financial crisis of 2008 hit the Greek economy, while the high public debt that was accumulated over the previous decades had to be refinanced. Despite the improved fundamentals of the economy during its preparation for the entry in the Euro area, public finances and international competitiveness were persistent problems throughout this period. In spite of short periods of improvement in the fiscal situation, there were many instance of relapse, especially around election years.

After its steep rise in 1980s, public debt was stable at about 100% of GDP since the early 1990s, when Greece had no difficulty refinancing its debt. The situation changed in late 2008 when the international financial crisis started and became more serious after the elections of October 2009. Compared to 2008, the deficit widened by 5.8 percentage points of GDP. This widening can be attributed to reduced revenue performance (2008: 40.7% of GDP, 2009: 38.3% of GDP) and increased general government expenditure (2008: 50.6% of GDP, 2009: 54.0% of GDP). Moreover, affected by lower investment and private consumption, GDP fell and the economy entered into recession [Bank of Greece, 2014].

A severe confidence crisis in the Greek economy led the eventual setting up of a special European Support Mechanism, with the participation of IMF, also known as the European Troika. Starting from the end of April 2010, Greece was excluded from international financial markets. In late 2009 and early 2010, the economy's fundamentals were out of track, with a drop in public revenue and increase in public expenditure, deficit and debt, whereas the balance of payments deficit remained at historically high levels. During this period the economic policy and the implementation of measures were delayed due to political cost considerations, which peaked in mid-2011 and resurged in the period of the two election rounds in mid-2012. Next, significant modifications were made to the agreements with the European Troika, to make up for delays in the implementation of the program or errors in initial forecasts.

The first adjustment program viewed the problem as one of liquidity rather than solvency, imposing heavy austerity measures, which accentuated recession and deteriorated the financial situation. The second program included debt restructuring and focused on decreasing labor costs to improve competitiveness. As a result of the two programs and the measures for restoring the financial stability, there was a period of slight growth, but the change of government in 2016 reversed this trend of full recovery and put the country at stake to exit the European Union. In 2017-2018 a strong fiscal policy was implemented, which led to a low growth rate in 2019, while the country exited the Adjustment program. The global crisis led the international investors to turn into less risky investments and far from indebted countries that were in need to fund their fiscal debt. The third program, continued on what was left from the first two programs. Despite deleveraging, both public and private debt as share of GDP continued to grow because of the steep recession, pro-cyclical policy mix, and bank-sovereign 'doom loop'.

To date, despite the successive reform programs, the Greek economy continues to suffer a weak public administration, slow functioning justice system, low savings, high consumption, small average business size, and a still weak export sector [Pagoulatos, 2018]. Prolonged austerity has caused poverty, social vulnerability, and weakened productive capacity, while at the same time steep disinvestment and the decline of employment are limiting factors for economic growth. However, the twin deficits (fiscal and current account) have been eradicated, various structural reforms have been implemented, exports have increased, and the administrative capacity of the state has relatively improved. Driven by domestic demand and deficit-financing, the Greek economy is evolving towards a fiscally disciplined, reform-driven, and more export-oriented growth model.

A period of recovery was disrupted in the early 2020 by the advent of the COVID-19 pandemic. Suddenly, the national income declined and along with the government measures for quarantine and closure of public places, all led to a reduced purchasing power and a widespread fear of the consumers to spend their income. All in all, all macroeconomic indicators were significantly impacted, and the economy as a whole still feels the impact of the pandemic until today.

5.3 *Graphs of Individual Determinants of the Greek Business Cycle*

In this section plots with the cyclical and trend components are dipicted for individual variables that were selected in the System of Eqs. 21 in Ch. 4. The important economic and political events are discussed for each presented plot, along with more context originated from the global macroeconomic events in the same time period.

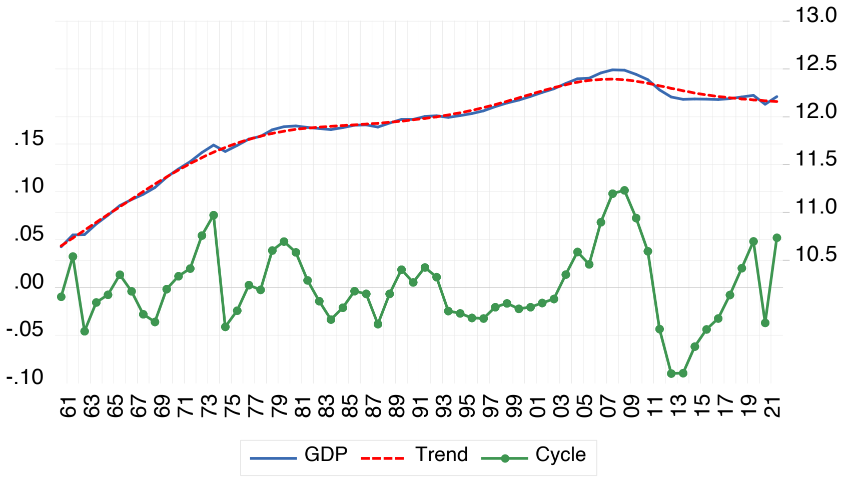


Figure 9: GDP decomposed into Trend and Cycle.

In Fig. 9, a major peak in the GDP cyclical part appears in 2008 when the golder era that characterized the Greek economy after entering the Eurozone comes to an abrupt end with the international financial crisis. Later, another peak appears at the cyclical part in 2019, however the examined time series when combined with the GDP trend shows that the economy still remains in recession. Two other significant peaks of the GDP business cycle took place in 1973 and 1979, which coincide with the last stage of the military dictatorship and the second oil crisis that occurred during the Islamic Iranian Revolution (1979-1980). The political turmoil in Iran had a significant impact on the country's oil sector, reducing production and exports respectively. These events propagated and had adverse effects globally. On the other hand, a significant trough took place in 2012-2013 in the middle of the sovereign government debt crisis.

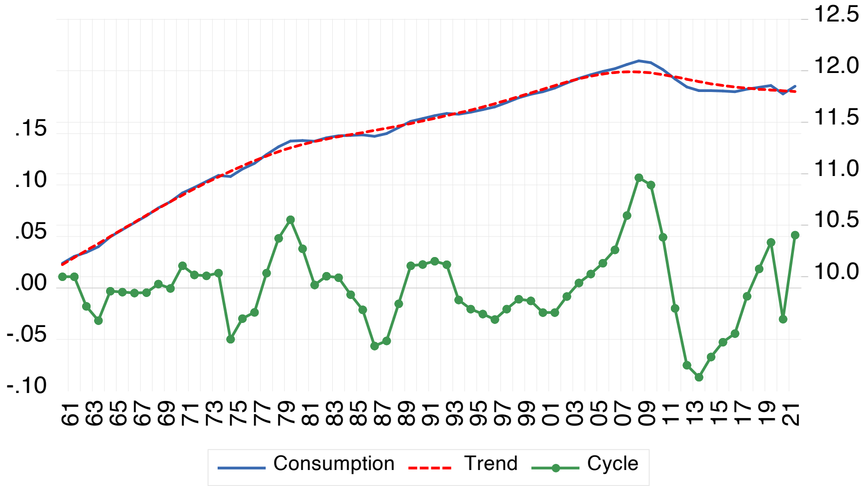


Figure 10: Consumption decomposed into Trend and Cycle.

Analogously to GDP, Household Consumption Expenditure in Fig. 10 has an upward trend, which peaks in 2008 followed by a steep descent as indicated by the cyclical part of the time series. A significant trough appears at 2012-2014 when reduction in GDP is associated with lower investment and private consumption [Bank of Greece, 2014]. This trend is in line with the Eq. 2 in Ch. 4, where Household Consumption Expenditure is a main determinant in the GDP equation.

Despite the ongoing recession, private consumption remains high in years 2016 and afterwards, while the economy suffers from low savings, high unemployment and widespread poverty partially due to prolonged austerity measures [Pagoulatos, 2018]. Similar to GDP, negative shocks in Consumption appear in 1974, while 1986-1987 are characterized by government debt and reduced investment [Charikiopoulou, I., 2022].

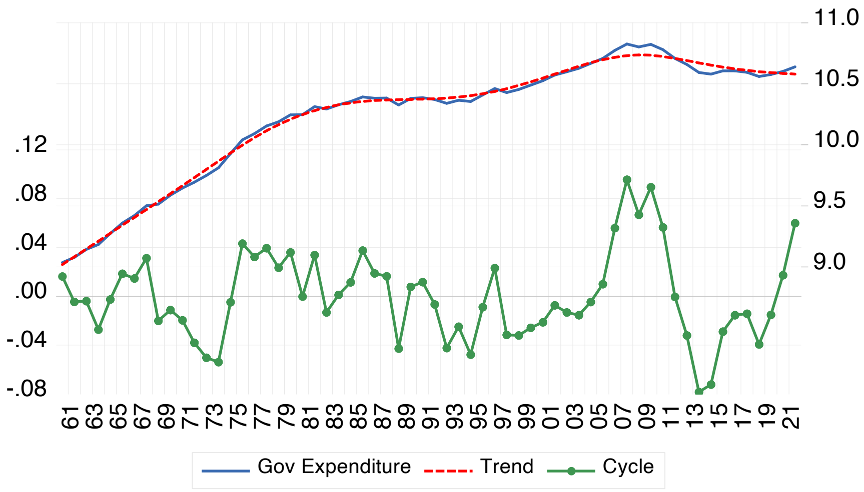


Figure 11: Government Expenditure decomposed into Trend and Cycle.

Government Expenditure in Fig. 11 demonstrates similar trend and cyclical parts for this time period as GDP and Household Consumption Expenditure. A peak is observed in 2007-2009 when the international financial crisis erupted, which was followed by a series of measures to reduce public expenditure, namely a fiscal consolidation plan which included a cut in civil service employment, a freeze in government wages, a 10% cut in elastic budget outlays and a one-off levy on high incomes [OECD, 2009].

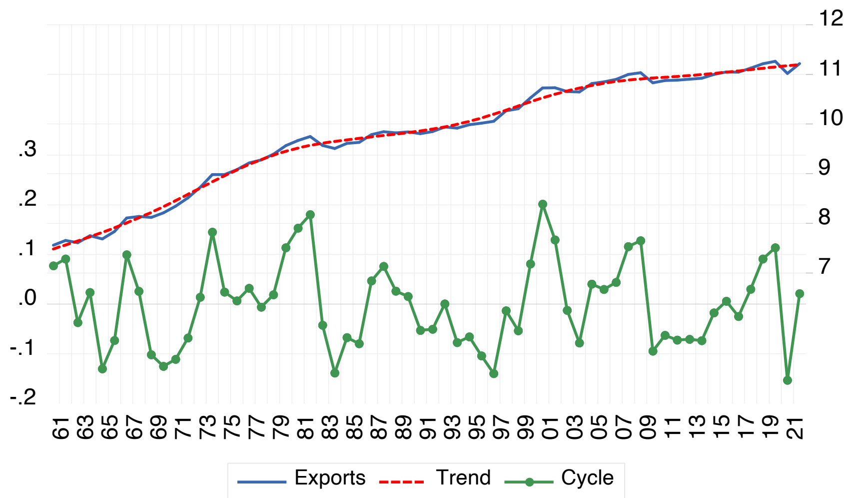


Figure 12: Exports decomposed into Trend and Cycle.

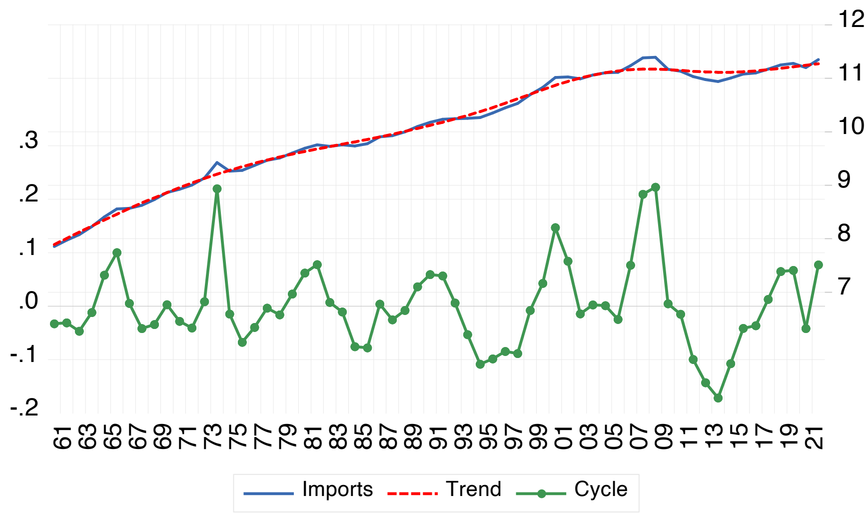


Figure 13: Imports decomposed into Trend and Cycle.

By examining Exports and Imports in Figs. 12 and 13, we observe that both indicators presented an ascending trend, with a steep rise when the country entered the Eurozone in 2001 and onwards. The integration and scale that came with the common currency in the Eurozone made the single market more efficient and less risky, as the costs for exchanging currencies were eliminated, the risks and the lack of transparency in cross-border transactions were resolved.

However, the trade balance of Greece in the Euro era, in general, and in particular within the Member States of the Euro Zone was deteriorated, while the Greek economy observed losses in competitiveness. The structure of production and the foreign trade affected the trade deficit and competitiveness of the Greek economy. Moreover, the more rapid rates of inflation in Greece, compared with its trading partners, led to a re-evaluation of the real exchange rate in the country, affecting its export performance [Magoulios, 2013]. The deterioration in the trade balance, i.e., the gap between Imports and Exports was widened in years 2003-2011, as reflected by Net Exports in Fig. 14.

Figure 14: Exports, Imports and Net Exports in Greece [World Bank, 2019].

Despite the downward trend of Exports after 2008, Net Exports kept increasing during the entire period after the financial crisis and converged to zero after 2014. A reduction in government spending or a tax hike, as it has been observed in Fig. 11, exerts a negative response on output which reduces the import demand. A cut back in government spending boosts exports through the labor cost competitiveness channel further improving net exports. Tax hikes on social security contributions and other indirect taxes reduced export performance. Although real aggregate output declined following a cut in government spending, the tradable sector output responded positively, further boosting Net Exports [Tagkalakis, 2015].

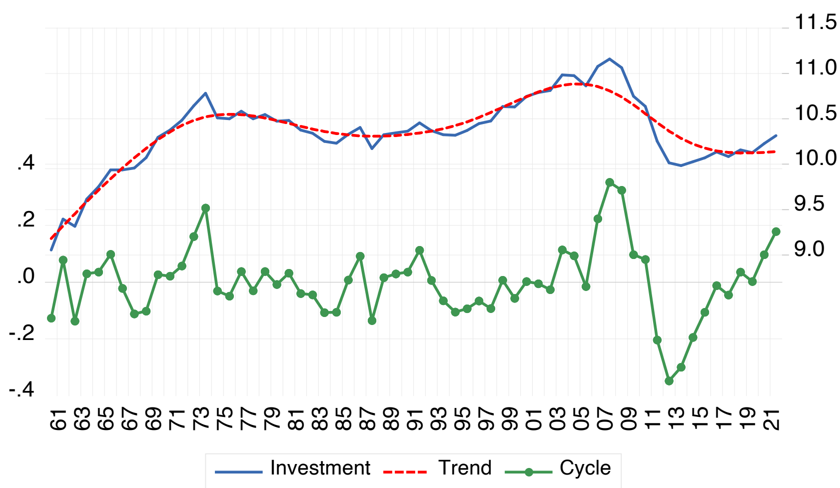


Figure 15: Investment decomposed into Trend and Cycle.

Investment in Fig. 15 shows a high-investment, high-growth period in 1960-1973. In the 1950-1973 period, investment was on average equal to 23.5% of GDP. As a result, the average annual growth rate of GDP rose to 7.4%. Never before had Greece experienced such high growth rates for such a long period. During this period the two main pillars of the development strategy were high investment and monetary stability. The latter was pursued through fiscal discipline and the stabilisation of the drachma's exchange rate vis-a-vis the US dollar, in the context of the Bretton Woods system of fixed but adjustable exchange rates. After 1974 the investment fell. Between 1981 and 1997 it had fallen to an average of 18.4% of GDP. As a result, the annual GDP growth rate fell to 1.7% [Alogoskoufis, 2021].

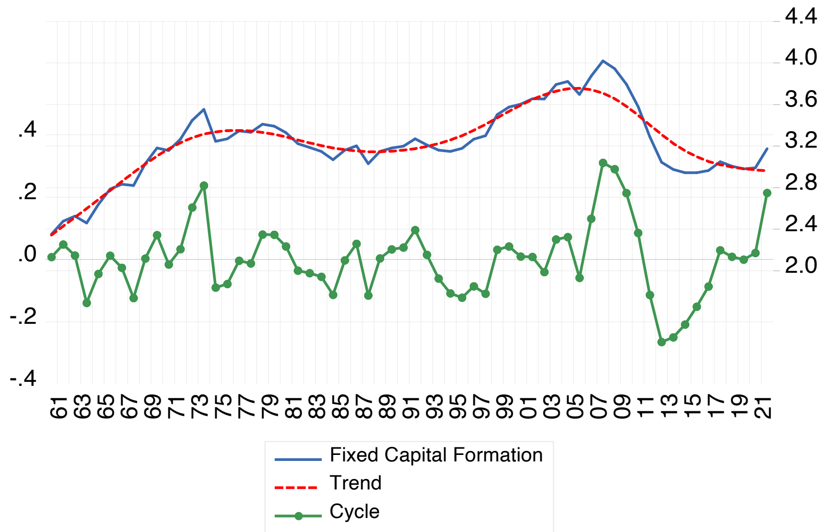


Figure 16: Fixed Capital Formation decomposed into Trend and Cycle.

Gross Fixed Capital Formation is shown in Fig. 16 for the Greek economy. There is a steadily rising trend during 1987-2007, when the average annual growth rate was equal to 3.2%. This period largely coincides with the period of recovery of the Greek economy following by the 'Euro euphoria'. When the international financial crisis occurred in 2008, Capital Formation reached to a peak and then a steady decline in Capital lasted until mid-2010s through the recession of 2008-2009, the Greek 'debt crisis' of 2010, and the 'austerity' policy of 2010-2016, also known as the 'Great Depression' [Alogoskoufis, 2021]. Then a period of steady Capital followed until a steep rise is observed in 2021 after overcoming the shock of the Covid-19 Pandemic.

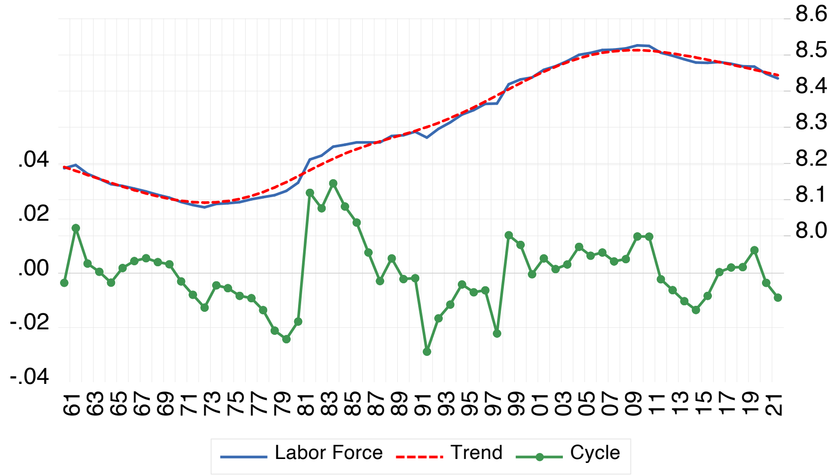


Figure 17: Labor Force decomposed into Trend and Cycle.

Labor Force is shown in Fig. 17. Labor Force includes all people of age 16 and older who are either employed or actively looking for a job. The labor force participation rate represents the number of people in the labor force as a percentage of the civilian population. Labor Force is significantly influenced by population changes and is less dependent on macroeconomic factors, except for major events such as wars and pandemics. Labor Force's slow and steady fall after 2010 can be attributed to both the declining population and the 'brain drain', that is it is estimated that 450,000 Greeks left the country from 2008 to 2016 [KPMG, 2017].

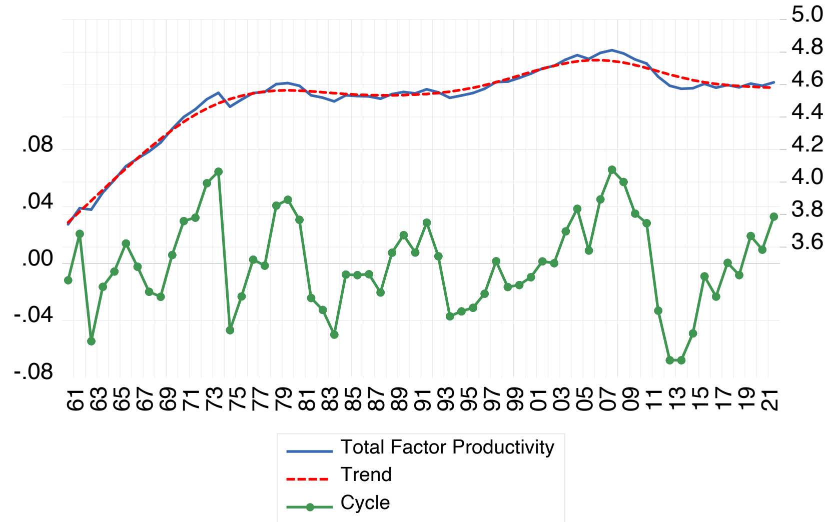


Figure 18: Total Factor Productivity decomposed into Trend and Cycle.

The cyclical component of TFP is considered to quantify the cyclical evolution of technological innovation [Michaelides, 2013]. After a period of rapid growth during the industrialization of the Greek economy in 1960–1973, when foreign investment in dynamic sectors of manufacturing such as chemicals and metallurgy boosted the economy [Mouzelis, 1977], and a period of stagnation after the oil crisis of 1973 until the late 1970s, a sharp decline followed around 1980. This could be attributed to a collapse of investment which took place after 1981 and the subsequent stagnation of technological innovation. Next, a period of recovery and growth followed at the second half of the 1990s and through the 'Euro euphoria' era until the financial crisis of 2008. After the crisis, the recession led to a declining TFP trend until mid-2010s and a later stabilization until today.

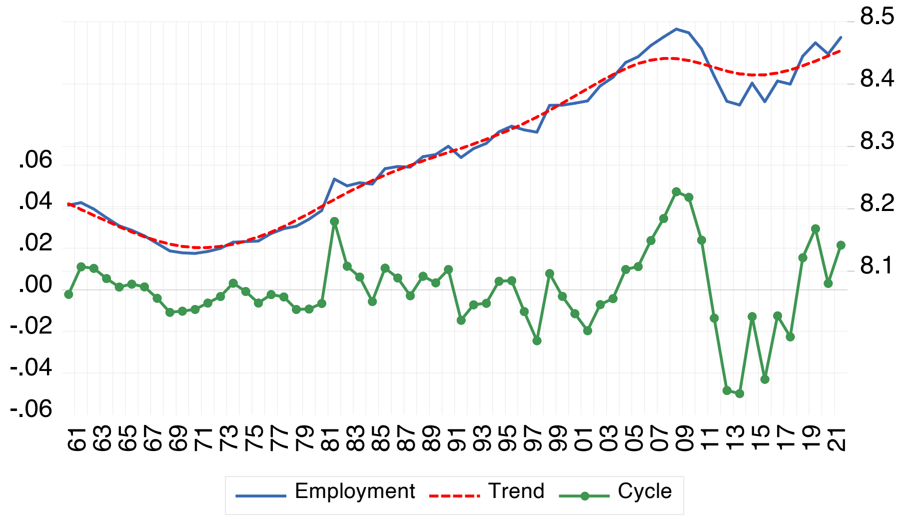


Figure 19: Employment decomposed into Trend and Cycle.

Employment is the portion of Labor Force that is employed, as opposed to Labor Force which includes both the employed and the unemployed part of the population that is actively seeking work. As seen in Fig. 19, a trough is observed in the cyclical part of Employment in 2012-2013. On the contrary, a large peak occurred in 2008, followed by a steep decline in 2009-2013 with a subsequent recovery from 2015 until today. At the early 1970s, the employment rate was not a major problem for most world economies, and similarly for Greece during the last part of the dictatorship and immediately after its resolution when the unemployment reached historical low levels. From that point onwards, however, combined with the two oil crises, the employment rate decreased steadily, simultaneously hitting the European countries, the United States of America and Japan.

The first oil crisis occurred during the Arab – Israeli War (1973-1974), when there was a significant oil price hike, due to the oil embargo of the Arab countries towards the US and the Netherlands. At the same time, oil extraction and supply were reduced under the OPEC agreement [Kotios & Pavlidis, 2011]. The second oil crisis occurred during the Islamic Iranian Revolution (1979-1980). The political turmoil in Iran has had a significant impact on the country's oil sector, reducing production and exports respectively. These events had adverse effect to Employment too.

Later, the growth of the unemployment factor in Europe has been even higher in the last fifteen years, while reaching almost 10% [Ameco European Database, 2019]. Following a similar trend, Greece reached historical high numbers of unemployment after the financial crisis of 2008; unemployment which had fallen during the period of 'Euro Euphoria', exploded during the 'Great Depression', with the unemployment rate peaking at 27.5% of the labor force in 2013, from 7.8% in 2008 [Alogoskoufis, 2021].

Based on Figs. 17 and 19, it is important to note that Employment and Labor Force have in general similar trends during the past 62 years, where there is a steadily rising trend from the early 1970s until 2008-2009, which is followed by a steady decline until today. However, Employment presents a more rapid decline in the post-financial-crisis period of 2010-2014 compared to Labor Force, which can be attributed to prolonged austerity and steep disinvestment that led to this employment decline and dragging down the economy's growth potential [Pagoulatos, 2018]. Moreover, Employment shows an upward trend from 2015 and onwards as opposed to Labor Force which keeps declining until the early 2020s.

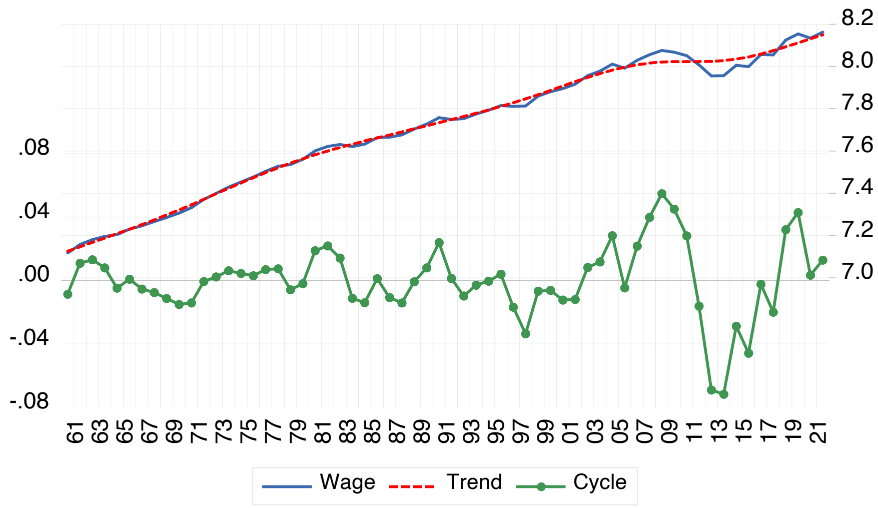


Figure 20: Wage decomposed into Trend and Cycle.

Wage in Greece is plotted in Fig. 20 for years 1960-2021. The wages experienced a continuous upward trend up to the financial crisis of 2008 when Greece endured significant job losses and wage cuts, as well as deep cuts to workers' compensation and welfare benefits, which lasted until 2013. These 5 years Greece became 40% poorer on average, and in 2014 saw the disposable household income drop below 2003 levels.

During 2010-2012, the government instituted several important reforms in the field of employment and social affairs, especially in the areas of employment protection and wage setting. New provisions came into force regarding minimum wages, severance pay, mass dismissals, commercial shop opening hours, temporary work, arbitration, etc. The most important of the reforms entailed: a new type of firm-level wage agreement, a reduction in minimum wages in the private sector, measures to boost part-time work and facilitate more flexible work time, shorter periods of notice for terminating an employment contract, a reduction of the 'non-wage' costs for employers and the introduction of non-subsidized sub-minimum wages for youths. These reforms led to a dramatic decline of the labor cost as a result of wage cuts. Overall, the total contraction of the average nominal wage in the Greek economy for the period 2010-13 reached 30%, bringing down nominal wages to 2000 levels and real wages to 1996 levels [European Parliament's Committee on Employment and Social Affairs, 2013]. The Wage trend shows a recovery from 2015 until today, as an outcome of implementing the reforms and a renewed alignment of productivity and wages.

5.4 Econometric Analysis of Variations of GDP Determinants

In this section the cycle of each key GDP determinant is examined in comparison to the Greek business cycle to study their econometric properties and create a taxonomy into procyclical and countercyclical variables. This analysis is performed using the cycle of the estimated (fitted) GDP time series from the System of Eqs. 23 in Ch. 4 (cf. Table 7) as well as the residual GDP cycle, which is computed from detrending the difference between the actual and fitted values from the System of Eqs. 23 in Ch. 4 (cf. Table 8).

First, we will review core econometric properties of the business cycles, and then we will characterize the cycles based on Tables 7 and 8, and in conjunction with combined graphs of these cycles in Sec. 5.5 to investigate the coincidence with political and historical events.

"Procyclicality" refers to a condition of a positive correlation between the value of a good, a service, or an economic indicator and the overall state of the economy. In the context of business cycles, it describes a state where the behavior of certain macroeconomic indicators moves in tandem with the cyclical condition of the economy, as the latter is captured by the GDP business cycle. On the other hand, indicators that move in opposite directions compared to GDP are characterized by "countercyclicality" and they are mathematically demonstrated by negative cross-correlation. Finally, when an indicator has no relevance to the state of the economy is described as "acyclic". In general, policies and fiscal behavior typically fall into procyclical patterns in periods of economic growth (i.e., boom) and decline (i.e., bust). For instance, when there is economic prosperity, many members of the population will engage in behavior that not only falls in line with that growth but serves to extend the period. This behavior is driven just as much by market and economic fundamentals as it is by investor and consumer psychology [Marx, 1875].

Economists and investors are constantly watching for signs of what is immediately ahead for the markets and for the wider economy. To this end, all indicators fall into one of three categories: "Leading" indicators are considered to point toward future events. "Lagging" indicators are seen as confirming a pattern that is in progress. "Coincident" indicators occur in real-time and clarify the state of the economy. Coincident indicators, such as often GDP, employment levels and real wage, are typically synchronous with the economic change.

Table 7: Cross-correlation analysis between GDP and its key determinants.

x	% St Dev/ Rel Var	x(t-4)	x(t-3)	x(t-2)	x(t-1)	x(t)	x(t+1)	x(t+2)	x(t+3)	x(t+4)
GDP	N/A	-0.16	0.00	0.28	0.48	**1.00**	0.48	0.28	0.00	-0.16
Consumption	0.02	-0.40	-0.24	0.07	0.41	**0.69**	0.62	0.47	0.26	0.08
Investment	0.00	0.01	0.03	0.06	0.09	**0.13**	0.06	0.07	-0.03	-0.05
Expenditure	0.02	-0.21	-0.04	0.05	0.28	0.38	**0.47**	0.40	0.26	0.20
Exports	0.01	0.17	0.16	0.05	0.05	**0.30**	0.19	0.27	0.07	-0.21
Imports	0.02	-0.14	0.02	0.19	0.32	**0.56**	0.50	0.37	0.14	-0.07
Capital	0.01	-0.25	-0.10	0.12	0.40	**0.68**	0.67	0.48	0.20	-0.04
Labor Force	0.02	0.13	**0.20**	0.14	0.00	0.08	0.12	0.17	0.17	0.13
TFP	0.02	-0.23	-0.10	0.18	0.45	**0.93**	0.57	0.35	0.05	-0.14

In Table 7 the cross-correlations between the time series of GDP and its key determinants (i.e., Consumption, Investment, Government Expenditure, Exports, Imports, Fixed Capital Formation, Labor Force and Total Factor Productivity) is computed for lag up to $T = 4$, generating T *lead* terms and T *lag* terms for each variable x. If the cross-correlation of x has the largest value (in absolute terms) in entries $x(t-i)$, $x(t)$ or $x(t+j)$, the cycle of x is *leading* by i periods, is *coincident*, or is *lagging* by j periods the cycle of output, respectively. This provides evidence on the *phase-shift* of each variable x relative to the cycle of output. Moreover, this analysis reveals whether each series is *procyclical* or *countercyclical*. In specific, the $x(t)$ column gives the contemporaneous correlation between the cyclical deviations of a given variable x with those of the pertinent output variable. A value larger than a cutoff point indicates that variable x is procyclical, while a value less than this indicates a countercyclical variable x. Otherwise, a value close to the cutoff indicates that x is *contemporaneously uncorrelated* with the output cycle.

Following [Christodoulakis et al., 1995] the cutoff point of 0.35 is adopted for annual data. This point effectively corresponds to the values required to accept the null hypothesis that there is no correlation at the 5% significance level. Additionally, the standard deviation of each detrended series in the first column is given as a measure of the volatility of its cyclical component relative to that of the GDP output variable in percentage terms. Therefore, the first column measures the relative variance of each variable compared to GDP.

Based on Table 7, Consumption, Government Expenditure, Imports, Capital and Total Factor Productivity are procyclical, while Investment, Exports and Labor Force are countercyclical. This observation reinforces the theory that Consumption and Imports are procyclical because they increase the demand, while Investment and Exports are countercyclical as these indicators increase the supply by boosting the domestic production. On the other hand, Capital and Total Factor Productivity appear as procyclical based on this criterion, although theoretically are countercyclical too due to the supply increase.

Additionally, all variables are coincident with GDP, except for the cycle of Labor Force which is leading by 3 periods the cycle of GDP and the cycle of Government Expenditure which is lagging by 1 period the cycle of GDP. Finally, Consumption and Capital present high persistence with value $x(t+1)$ higher than 0.59.

Table 8: Cross-correlation analysis between GDP residual and its key determinants.

Res(x)	% St Dev/ Rel Var	x(t-4)	x(t-3)	x(t-2)	x(t-1)	x(t)	x(t+1)	x(t+2)	x(t+3)	x(t+4)
GDP	N/A	-0.18	-0.01	0.06	0.28	**1.00**	0.28	0.06	-0.01	-0.18
Consumption	0.02	0.13	0.31	0.40	0.35	**0.43**	0.15	-0.04	-0.21	-0.43
Investment	0.00	0.21	0.36	0.32	0.39	0.27	-0.13	-0.28	-0.36	**-0.49**
Expenditure	0.02	0.03	0.11	**0.35**	0.33	0.28	0.10	0.09	-0.02	-0.23
Exports	0.01	-0.08	0.01	0.14	0.07	0.20	0.02	-0.33	**-0.38**	-0.25
Imports	0.02	0.03	0.16	0.22	0.24	0.38	0.02	-0.32	**-0.46**	-0.45
Capital	0.01	0.16	0.23	0.29	0.40	**0.41**	-0.05	-0.25	-0.30	-0.44
Labor Force	0.02	-0.08	**-0.24**	-0.16	-0.13	-0.03	0.02	-0.01	-0.03	-0.11
TFP	0.01	0.26	0.38	**0.40**	0.33	0.05	-0.11	-0.26	-0.29	-0.38

In Table 8 the same analysis is repeated using the GDP residual, which is computed as the difference between the actual values and the fitted values from the System of Eqs. 23 in Ch. 4. Based on the theoretical model definition, the fitted values contain the influence of all interpretive variables in the identity of the GDP output, namely Consumption, Investment, Expenditure, Exports and Imports, whereas the residual captures the remaining variables, such as money supply, nominal wage, nominal interest rate, exchange rate, price level, fiscal deficit, balance of payments deficit, etc., which also affect the output.

The method in Table 8 confirms that Consumption, Imports and Capital are procyclical and Investment is countercyclical. However, there is disagreement between these two methods in terms of synchronicity for most variables: while all variables appeared as synchronous in Table 7, except for Labor Force and Expenditure, on the contrary in Table 9, the cycles of many variables are either leading by 2 to 3 years (i.e., Expenditure, Labor Force, TFP), or lagging by 3 to 4 years (i.e., Investment, Exports, Imports) the output of the GDP. On the other hand, there is agreement between these two methods that Labor Force is leading by 3 years, while Consumption and Fixed Capital Formation are synchronous.

5.5 Graphs of Combined Variables

In this section the cyclical part of multiple variables is jointly examined and in conjunction with historical and political events; namely, indicators in the GDP expenditure equation and the GDP production equation.

As illustrated in Fig. 21, the Government Expenditure cycle follows a similar trend as the GDP cycle with a lag of about 1-2 years observed in certain peaks, such as in 1965, 1973 and 2008. This is in line with the econometric analysis in Sec. 5.4, where it is shown that Government is lagging GDP by 1 year. For instance, when the international financial crisis erupted in 2009, GDP started collapsing, while Government Expenditure experienced a peak. This time a series of measures followed in order to reduce public expenditure, namely a fiscal consolidation plan which included a cut in civil service employment, a freeze in government wages, a 10% cut in elastic budget outlays and a one-off levy on high incomes [OECD, 2009].

As seen in Fig. 22, Household Consumption and GDP are highly synchronized over the last 25 years, as well as during peaks and troughs. This is expected since Consumption is one of the mains determinants of GDP. Government Expenditure has similar behavior with the exception of 2009 when the international financial crisis erupted. This year both GDP and Consumption started falling, but Government Expenditure experienced a peak. However, a series of measures followed in order to reduce public expenditure, and thus the latter one followed GDP and Consumption as the country started falling in Deep Depression. From 2010 onwards these three macroeconomic variables are well-aligned.

According to Exports and Imports in Fig. 23, there is a concurrent trend between these two variables over the years with an increased gap between 2003-2011, which is also measured by Net Exports in Fig. 14. We observe large peaks at the cyclical part of Imports and Exports in 1974, 2001 and 2008. These peaks are coincident with the exit from the dictatorship, Greece's entry in the Eurozone and the arrival of the international financial crisis.

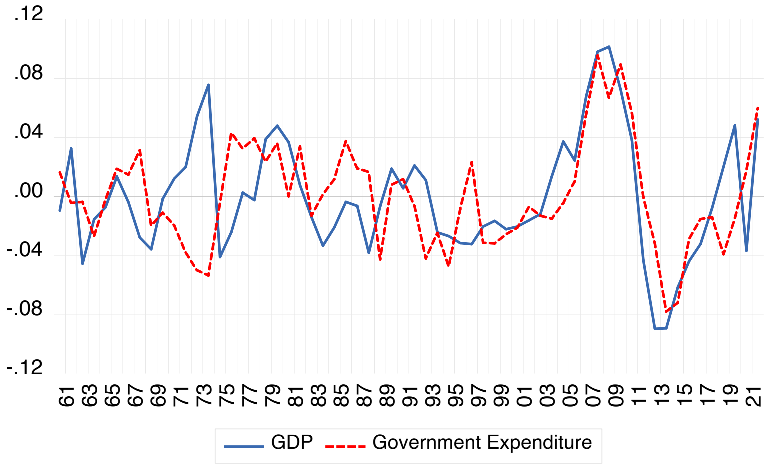


Figure 21: Cyclical Part of GDP and Government Expenditure.

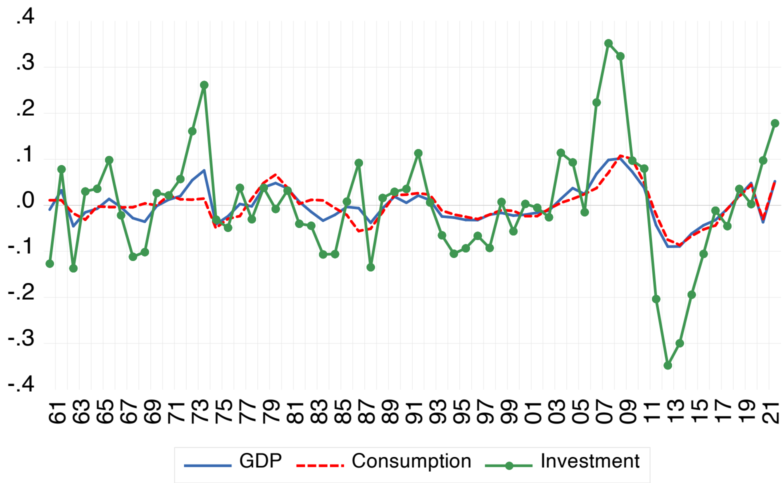


Figure 22: Cyclical Part of GDP, Consumption and Investment.

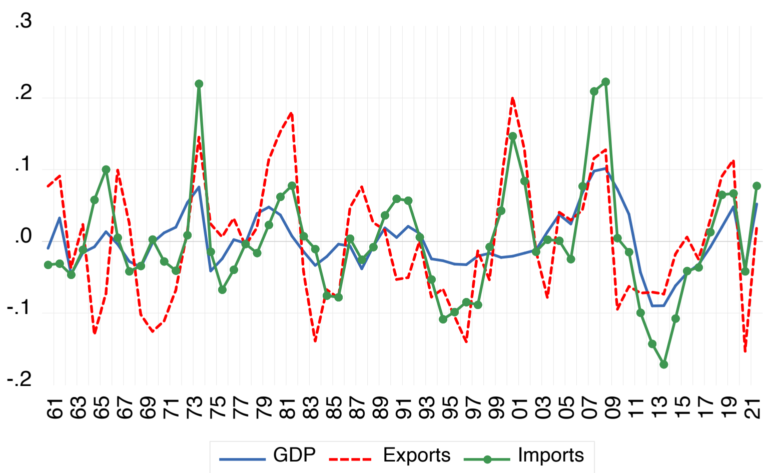


Figure 23: Cyclical Part of GDP, Exports and Imports.

The growth rate of real GDP per capita remained relatively high at 3.2% on average during the 2000-2008 period. This was mainly due to increases in both private consumption and investment because of the low real interest rates, as well as an expansionary fiscal policy. At the same time, the widening savings-investment imbalance and deteriorating international competitiveness led to an unprecedented widening of current account deficits and a steady increase in external debt [Alogoskoufis, 2021]. The fiscal deficit increased during the period of 2008-2010, while the real interest rates for both government and private debt were significantly increased. Greece was unable to reduce the interest rate or devalue its currency due to the Eurozone membership in order to achieve growth. Thus, the country was not able to respond to its fiscal and political needs.

After 2016, a weak recovery began, while the adjustment programs were completed in 2018. However, Greece remained under a regime of enhanced surveillance, in the context of the implementation of the stability and growth pact of the euro area. At the beginning of 2020 Greece was confronted with a new major international economic crisis, due to the COVID-19 Pandemic [Alogoskoufis, 2021].

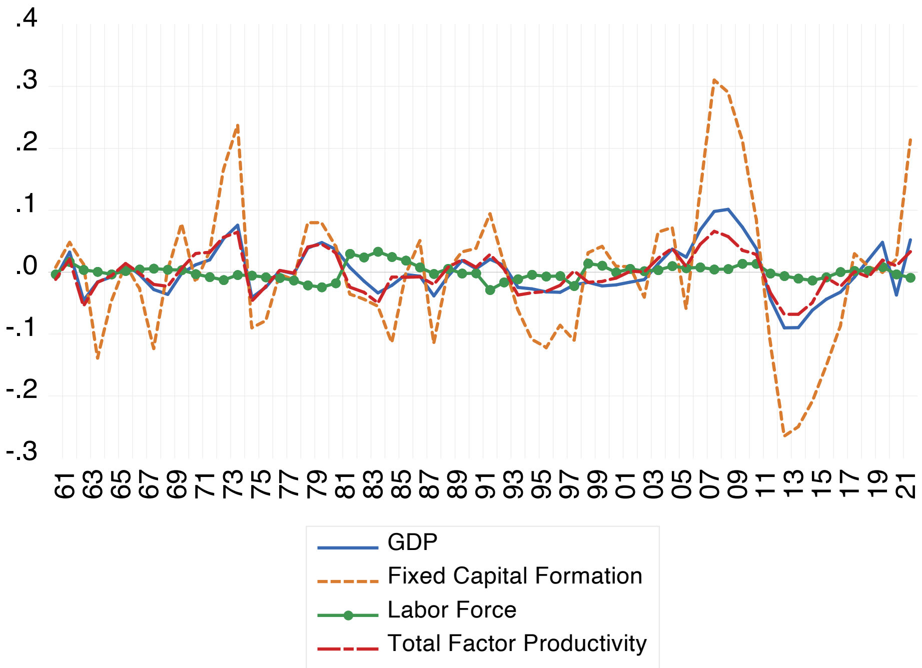


Figure 24: Cyclical Part of the determinants in the GDP Production Function.

Fig. 24 shows the determinants of the GDP production equation. In general, we observe smaller variation in Labor Force and Total Factor Productivity compared to Fixed Capital Formation. Labor Force has relatively smaller fluctuations over the years with a peak in the early 1980s when Governance of Efficiency was implemented and in 2009-2010 when the Global Recession arrived in Greece. TFP peaked at 1973 and 2008 which coincided with the end of the dictatorship and the advent of the financial crisis, while it has been steadily increasing from 2012 until today. The Capital cycle is well aligned with Labor Force and TFP, while presenting a higher variance compared to these cycles due to higher volatility. Capital endured a steady rise from 1995 to 2007, during a period of recovery in the growth rate followed by the 'Euro Euphoria'. Capital Formation reached at its highest level in 2008 and then a steady decline in Capital lasted until 2012 through the financial crisis and recession of 2008-2009, the Greek 'debt crisis' of 2010, and the 'austerity' policy of 2010-2016, also known as the 'Great Depression'. Afterwards, a steady capital growth has been observed until today.

5.6 Discussion

A growth policy was implemented during the 1960s and 1970s, when the Greek economy was characterized by sustained growth and investment. The first and second global oil crises during the Arab – Israeli War (1973-1974) and the Islamic Iranian Revolution (1979-1980) led to significant oil price hikes, which had adverse effects to Employment as well as the GDP growth in Greece too. These events were accompanied by the oil embargo of the Arab countries towards the US and the Netherlands, reduced oil extraction and supply under the OPEC agreement [Kotios & Pavlidis, 2011] and the political turmoil in Iran with a significant impact on the country's oil sector production and exports. All these factors slowed down the imports and subsequently the output of the Greek economy in the second half of 1970s [Alogoskoufis, 2021], while the Imports are procyclical which is confirmed by Table 7 and Fig. 23.

This period was succeeded by a social policy and stagnation in the 1980s, when the resources and the social funds were distributed. This governance led to currency devaluation twice and a negative growth rate for the Greek economy. During the 1990s, despite the deterioration in international competitiveness, the rate of economic growth gradually but significantly improved, as the average annual growth rate of real GDP per capita in the 1990s was 3.4%, compared with 2.7% in the 1980s. This can be attributed to the gradual reduction of real interest rates and the increased confidence of investors and the markets to the eventual Euro zone membership. After the EU summit decided that Greece could join the Eurozone and thus replace the drachma with the euro, a further rapid fall in real interest rates occurred, due to the elimination of the risk of currency devaluation. This led to a reduction in private savings and large increases in aggregate investment.

The growth rate of real GDP per capita remained relatively high at 3.2% on average during the 2000-2008 period. This was mainly the result of high increases in both private consumption and investment because of the low real interest rates. The procyclicality of Consumption is confirmed in Table 7 with high cross-correlation of 0.69 and the coincident behavior in Fig. 22. The Investment cycle has a similarly rising trend in the same period, although Investment demonstrates countercyclicality over the years.

At the same time, the increasing savings-investment imbalance led to an unprecedented widening of current account deficits and a steady increase in external debt. After a brief correction in the early 1990s, the Greek deficit started worsening from the second half of the 1990s. As Greece started securing the Euro area membership, nominal and real interest rates declined, the international competitiveness deteriorated, the current account kept worsening. The international recession of 2008-2009 further pushed the current account deficit, due to the decline in Greece's revenues from exports and tourism. It was only after the crisis of 2010 and the adoption of the subsequent adjustment programs that these trends were gradually reversed, as a result of the improvements in international competitiveness.

Greece was very negatively affected by the international financial crisis of 2008-2009 due to its high external debt, and its deteriorating external and fiscal imbalances. The country's growing indebtedness led to a 'sudden stop' in international lending, thus Greece was forced to sign a 'rescue memorandum' in exchange for the financial support of the rest of the European Union. This provided official financing of its immediate external debt obligations, under the condition of the adoption by Greece of an economic adjustment program as monitored by 'Troika'. Two more programs followed the original adjustment program which involved significant restructuring of Greece's debt. The implementation of these programs gradually led to the restoration of fiscal and external balance, but at the cost of the deepest and longest post-war depression of the Greek economy. Between 2008 and 2016 per capita real GDP fell by 25% and unemployment peaked at 27.5% of the workforce in 2013, compared to 7.8% in 2008

[Alogoskoufis, 2021]. This decline in production is demonstrated by all the macroeconomic indicators in Fig. 24. This is also validated by Table 7, since TFP and Capital are coincident with GDP, while Labor Force is leading GDP by 3 years. After 2016, a slow recovery began, and the adjustment programs were completed in 2018. However, Greece remained under a regime of enhanced surveillance, in the context of the implementation of the stability and growth pact of the euro area.

The cyclical component of TFP is considered to quantify the cyclical evolution of technological innovation [Michaelides, 2013]. The TFP cycle has a profound impact to the GDP cycle as shown in Fig. 24 and demonstrated by the high correlation in Table 7. After a period of rapid growth during the industrialization of the Greek economy in 1960–1973 [Mouzelis, 1977], and a period of stagnation after the oil crisis of 1973 until the late 1970s, a sharp decline followed around 1980. This could be attributed to a collapse of investment which took place after 1981 and the subsequent stagnation of technological innovation. Next, a period of recovery and growth followed at the second half of the 1990s and through the 'Euro euphoria' era until the financial crisis of 2008. After the crisis, the recession led to a declining TFP until mid-2010s and a later stabilization until today.

Labor Force's slow and steady fall after 2010 and until 2014 can be attributed to both the declining population and the 'brain drain', as it is estimated that 450,000 Greeks left the country from 2008 to 2016 [KPMG, 2017]. This reduction coincided with the GDP rapid increase during the Great Recession.

Chapter 6 – Econometric Models

In this chapter econometric models are utilized for modeling the fundamental macroeconomic variables of the Greek business cycle. AutoRegressive Moving Average (ARMA) and Vector AutoRegressive (VAR) models are used to capture the temporal dependencies of time-series data through autoregressive and moving-average terms. Markov switching models consist of two autoregressive AR(1) expressions with a switching variable, which allows to combine two (or more) dynamic models. This formulation naturally enables the categorization of the economy into two or more states (e.g., crisis or recession, growth period, etc.) Next, an efficient approximation of Discrete Fast Transform (DFT), termed as Fast Fourier Transform (FFT), is applied to model complex time series in frequency domain. Finally, Long Short-Term Memory (LSTM) is deployed as an Artificial Neural Network (ANN) model that can learn to model temporal dependencies and non-linearities through training.

The data sample consists of the values of GDP over the last 62 years (1960-2021), as collected from the OECD database. Based on the actual data, the parameters of each model are estimated in order to generate fitted data. Both actual and fitted data are shown in one plot to demonstrate the estimation accuracy of each model. Subsequently, the estimated parameters are used to perform forecasting and calculate the forecast error for each model. Along with GDP, the other determinants of the GDP expenditure equation are included in the experiments, namely Consumption, Government Expenditure, Exports, Imports and Investment. Moreover, we explore the hypothesis whether the historical values of these determinants can increase the predictive power of these models (c.f., VAR, LSTM).

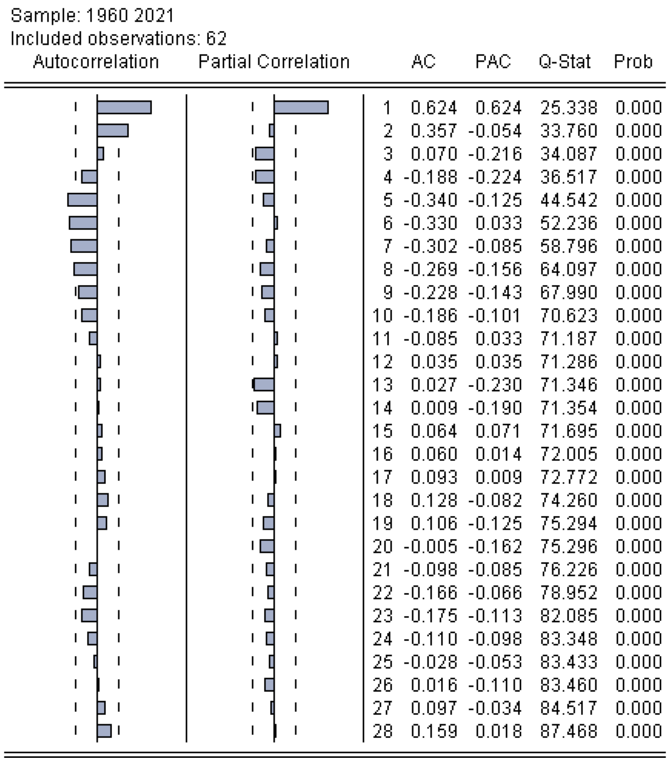
In order to study the fluctuations of the business cycles, the aforementioned variables are detrended using Hodrick-Prescott filter. As a result of this process, the variables are decomposed into a low-frequency long-term component (i.e., the trend) and high-frequency fluctuations, which pertain to the business cycles. The subsequent analysis targets to model the cyclical components of each variable, as they often correlate with macroeconomic events.

6.1 Auto-Regressive Moving Average (ARMA)

For determining the number of autoregressive terms, the correlogram of each variable is used. Based on a cut-off threshold, which approximately coincides with two standard error bounds computed as $\boldsymbol{\sigma} = \pm \mathbf{2}/_{\sqrt{\boldsymbol{N}}}$, it is decided which terms are significant at the $\mathbf{5}\%$ significance level. Specifically, given $N = 62$ years, the error bounds are computed as $\boldsymbol{\sigma} = \pm \mathbf{2}/_{\sqrt{\mathbf{62}}} \cong \pm\mathbf{0.254}$. All AutoCorrelation (AC) or Partial AutoCorrelation (PAC) terms which are within these two bounds, are considered as not statistically significant. This procedure allows us to choose the AR terms $\boldsymbol{p}$ and MA terms $\boldsymbol{q}$ for ARMA($\boldsymbol{p}$, $\boldsymbol{q}$).

6.5.1 GDP

The correlogram of GDP for is shown in Fig. 25. Thus, the AR and MA terms are $\boldsymbol{p} = \mathbf{8}$ and $\boldsymbol{q} = \mathbf{1}$, respectively.



Sample: 1960 2021
Included observations: 62

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.624	0.624	25.338	0.000
		2	0.357	-0.054	33.760	0.000
		3	0.070	-0.216	34.087	0.000
		4	-0.188	-0.224	36.517	0.000
		5	-0.340	-0.125	44.542	0.000
		6	-0.330	0.033	52.236	0.000
		7	-0.302	-0.085	58.796	0.000
		8	-0.269	-0.156	64.097	0.000
		9	-0.228	-0.143	67.990	0.000
		10	-0.186	-0.101	70.623	0.000
		11	-0.085	0.033	71.187	0.000
		12	0.035	0.035	71.286	0.000
		13	0.027	-0.230	71.346	0.000
		14	0.009	-0.190	71.354	0.000
		15	0.064	0.071	71.695	0.000
		16	0.060	0.014	72.005	0.000
		17	0.093	0.009	72.772	0.000
		18	0.128	-0.082	74.260	0.000
		19	0.106	-0.125	75.294	0.000
		20	-0.005	-0.162	75.296	0.000
		21	-0.098	-0.085	76.226	0.000
		22	-0.166	-0.066	78.952	0.000
		23	-0.175	-0.113	82.085	0.000
		24	-0.110	-0.098	83.348	0.000
		25	-0.028	-0.053	83.433	0.000
		26	0.016	-0.110	83.460	0.000
		27	0.097	-0.034	84.517	0.000
		28	0.159	0.018	87.468	0.000

Figure 25: Correlogram of GDP.

Subsequently, the ARMA coefficients are estimated in E-Views. The cyclical component of Log GDP along with the statistically significant terms (i.e., AR(1), AR(2), AR(5), AR(6), MA(1)) are introduced for estimating the model via Maximum Likelihood.

Table 9: ARMA Statistical Estimation of GDP.

Dependent Variable: LOG_Y_CYCLE
Method: ARMA Maximum Likelihood (Kohn-Ansley)
Date: 11/29/22 Time: 16:45
Sample: 1960 2021
Included observations: 62
Convergence achieved after 20 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000501	0.007886	0.063533	0.9496
AR(1)	0.062693	1.202986	0.052115	0.9586
AR(2)	0.324690	0.698932	0.464551	0.6441
AR(5)	-0.318795	0.152542	-2.089886	0.0413
AR(6)	-0.022874	0.428939	-0.053328	0.9577
MA(1)	0.548982	1.191504	0.460747	0.6468
SIGMASQ	0.000841	0.000143	5.876291	0.0000

R-squared	0.464165	Mean dependent var	-5.62E-14
Adjusted R-squared	0.405710	S.D. dependent var	0.039935
S.E. of regression	0.030786	Akaike info criterion	-4.000651
Sum squared resid	0.052128	Schwarz criterion	-3.760491
Log likelihood	131.0202	Hannan-Quinn criter.	-3.906358
F-statistic	7.940575	Durbin-Watson stat	1.880009
Prob(F-statistic)	0.000003		

Inverted AR Roots	.73-.41i	.73+.41i	-.07	-.24-.69i
	-.24+.69i	-.86		
Inverted MA Roots	-.55			

After the parameter estimation, the GDP ARMA model is as follows:

$$\boldsymbol{Y_t = 0.0005 + 0.063Y_{t-1} + 0.325Y_{t-2} - 0.319Y_{t-5} - 0.023Y_{t-6} + z_t + 0.549z_{t-1} + \varepsilon_t.} \quad \textbf{(1)}$$

This function acts as an absorption mechanism for the external shocks that originate from the foreign economies. Specifically, the deviation from the trend for the GDP cycle represents the current value at period $\boldsymbol{t}$, which is equal to $\boldsymbol{0.063}$ of the value at $\boldsymbol{t-1}$ plus $\boldsymbol{0.325}$ of the value at $\boldsymbol{t-2}$, and so on, plus the moving average terms $\boldsymbol{z_t}$, $\boldsymbol{z_{t-1}}$ multiplied by $\boldsymbol{0.549}$ and the residual $\boldsymbol{\varepsilon_t}$.

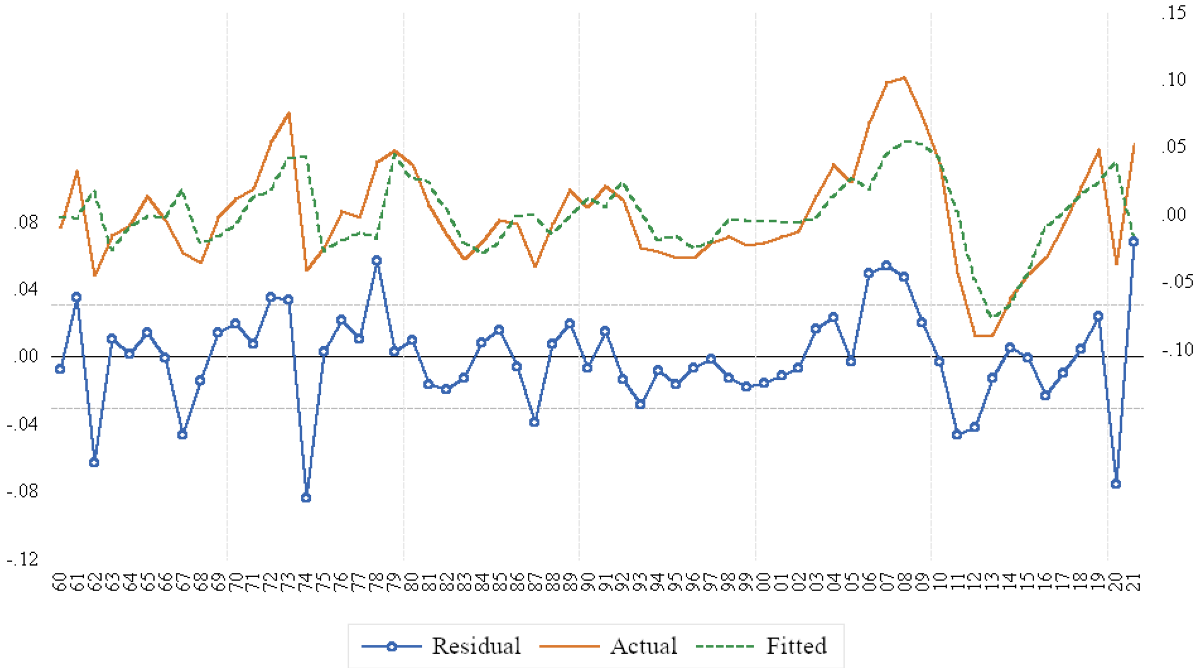


Figure 26: Actual vs Estimated data from ARMA of GDP.

In Fig. 26 the actual and fitted GDP data are plotted, along with the residual time series. The residuals are attributed to domestic shocks and although they contribute to the national business cycle, their causation is characterized by uncertainty due to their chaotic behavior.

Rapid adaptation of prices and wages can act as a stabilization mechanism, which can smooth the GDP cycle by achieving economic equilibrium. However, many classical economists are opposed to the use of fiscal policy as a tool for smoothing the cycle, because they argue that this kind of policy increases GDP and subsequently deteriorates the situation for the employees due to increased taxes [Smith, 1776]. Monetarist economists doubt the ability of governments to regulate the business cycle with fiscal policy and argue that judicious use of monetary policy (essentially controlling the supply of money to affect interest rates) can alleviate the crisis [Jahan et al, 2014].

This mechanism also assumes completely free movement of production factors. For instance, when a country suffers from unemployment, the movement of production factors can compensate the negative consequences. In practice, though, such movement is typically slow in the short term and can be effective in a longer time horizon. Additionally, there should be separation between the movement of production factors and labor force. The capital movement is limited due to the fact that the investments are produced from one country and are absorbed from another country.

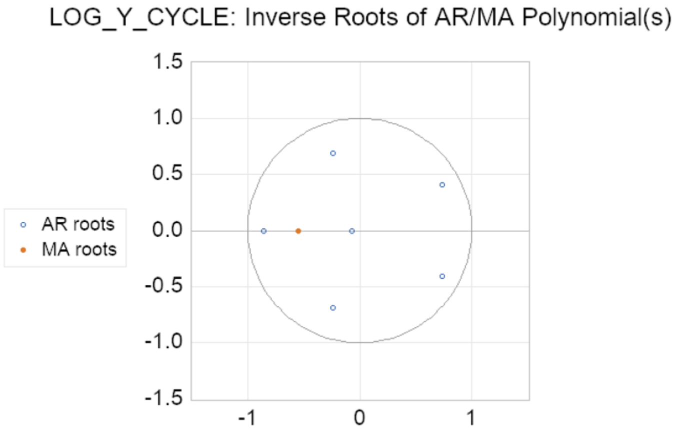


Figure 27: AR and MA roots of GDP.

In Fig. 27 the AR (in blue) and MA roots (in red) are superimposed on the unit circle. Both types of roots lie inside the unit circle and therefore they are characterized by stability.

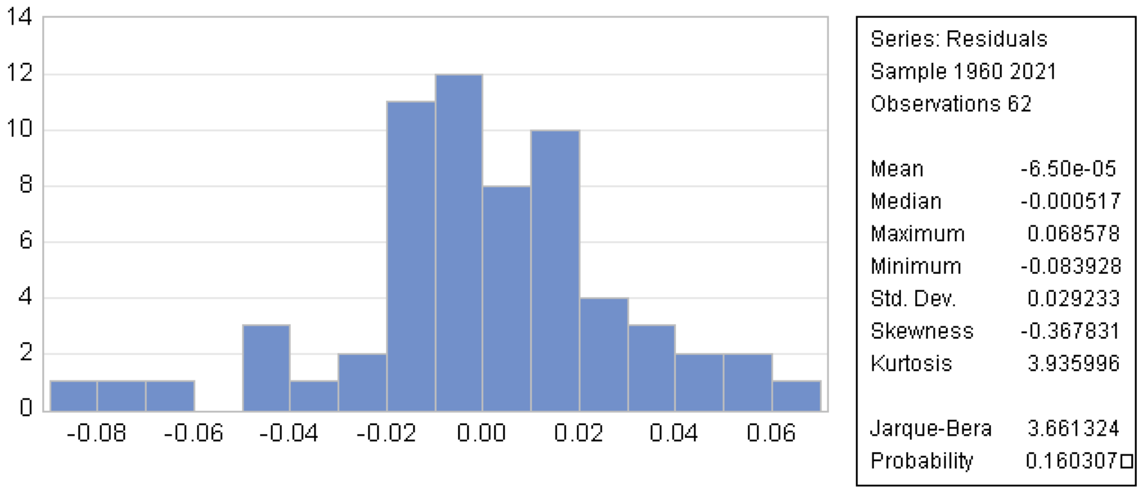


Figure 28: The distribution of GDP Residuals.

The GDP residual is shown in Fig. 26 as the difference between the actual and fitted data, while its histogram is computed in Fig. 28. Typically, values outside ± 2 standard deviations identify the outliers of the residual distribution. In that case, the GDP standard deviation is 0.0292 and therefore values outside $[-0.058, 0.058]$ are considered as outliers, which indicate positive and negative shocks of the Greek economy.

In Fig. 26, in 1974 and 2020 two outliers are presented that correspond to negative shocks, whereas there are positive shocks that fall into the regime between 1 and 2 standard deviations in 1978 and 2007. The positive and negative shocks often coincide with macroeconomic events that took place in Greece at the same years. The standard deviation statistic is used as a method to discriminate between noise and actual events such as crisis, recession and growth period. In 1974 when the country exited the dictatorship, we observe a negative shock in Fig. 26. This was also the case in 2020 when the Pandemic started and was followed by lockdown restrictions. The years ahead of the financial crisis of 2008 and the subsequent recession were characterized by steady growth [Michaelides et al., 2013]. In 2006-2008 high residual values coincide with the peak of GDP before the international financial crisis.

6.1.2 Consumption

The correlogram of Consumption is shown in Fig. 29. Given error bounds $\boldsymbol{\sigma} \cong \pm \mathbf{0.254}$ as in the GDP case, the AR and MA terms are $\boldsymbol{p} = \mathbf{8}$ and $\boldsymbol{q} = \mathbf{20}$, respectively.

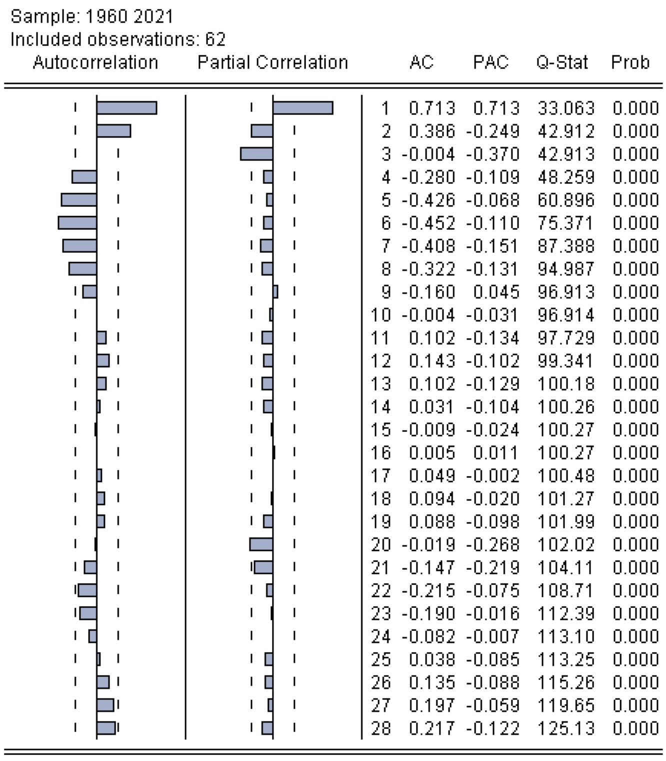


Figure 29: Correlogram of Consumption.

The cyclical component of Log Consumption along with the statistically significant terms (i.e., AR(1), AR(2), AR(4), AR(5), AR(6), AR(7), AR(8), MA(1), MA(3), MA(20)) are introduced in E-Views in order to estimate the ARMA coefficients via Maximum Likelihood.

Table 10: ARMA Statistical Estimation of Consumption.

Dependent Variable: LOG_CN_CYCLE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/28/22 Time: 14:42
Sample: 1960 2021
Included observations: 62
Convergence achieved after 89 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001395	0.004721	0.295541	0.7688
AR(1)	0.067703	0.383959	0.176328	0.8607
AR(2)	0.521105	0.415069	1.255466	0.2151
AR(4)	-0.521225	0.304170	-1.713599	0.0928
AR(5)	-0.065002	0.315638	-0.205938	0.8377
AR(6)	0.084453	0.330238	0.255734	0.7992
AR(7)	-0.030191	0.268522	-0.112434	0.9109
AR(8)	-0.288633	0.223562	-1.291062	0.2026
MA(1)	0.730159	0.414483	1.761616	0.0842
MA(3)	-0.385854	0.261265	-1.476865	0.1460
MA(20)	0.198376	0.305540	0.649265	0.5191
SIGMASQ	0.000456	0.000114	3.994784	0.0002

R-squared	0.677868	Mean dependent var	-8.00E-14
Adjusted R-squared	0.606999	S.D. dependent var	0.037915
S.E. of regression	0.023769	Akaike info criterion	-4.395581
Sum squared resid	0.028249	Schwarz criterion	-3.983877
Log likelihood	148.2630	Hannan-Quinn criter.	-4.233935
F-statistic	9.565067	Durbin-Watson stat	1.865373
Prob(F-statistic)	0.000000		

Inverted AR Roots	.85-.40i	.85+.40i	.43-.67i	.43+.67i
	-.44+.69i	-.44-.69i	-.80-.36i	-.80+.36i
Inverted MA Roots	.90+.14i	.90-.14i	.80+.40i	.80-.40i
	.63+.63i	.63-.63i	.39-.80i	.39+.80i
	.10+.89i	.10-.89i	-.19+.89i	-.19-.89i
	-.48-.81i	-.48+.81i	-.72+.67i	-.72-.67i
	-.86-.45i	-.86+.45i	-.93+.15i	-.93-.15i

After the parameter estimation, the Consumption ARMA model is as follows:

$$\boldsymbol{C_t = 0.001 + 0.068C_{t-1} + 0.521C_{t-2} - 0.521C_{t-4} - 0.065C_{t-5} + 0.084C_{t-6} - 0.03C_{t-7} - 0.289C_{t-8} + z_t + 0.73z_{t-1} - 0.386z_{t-3} + 0.198z_{t-20} + \varepsilon_t.} \quad \textbf{(2)}$$

The actual and fitted data, along with the residual are shown in Fig. 30, while the AR (in blue) and MA roots (in red) are placed in relation to the unit circle in Fig. 31. Both types of roots are characterized by stability, since they lie inside the unit circle.

The histogram of the Consumption residual is shown in Fig. 32. With standard deviation 0.0215, values outside $[-0.043, 0.043]$ are considered as outliers, which are correlated with positive and negative shocks of the Greek economy.

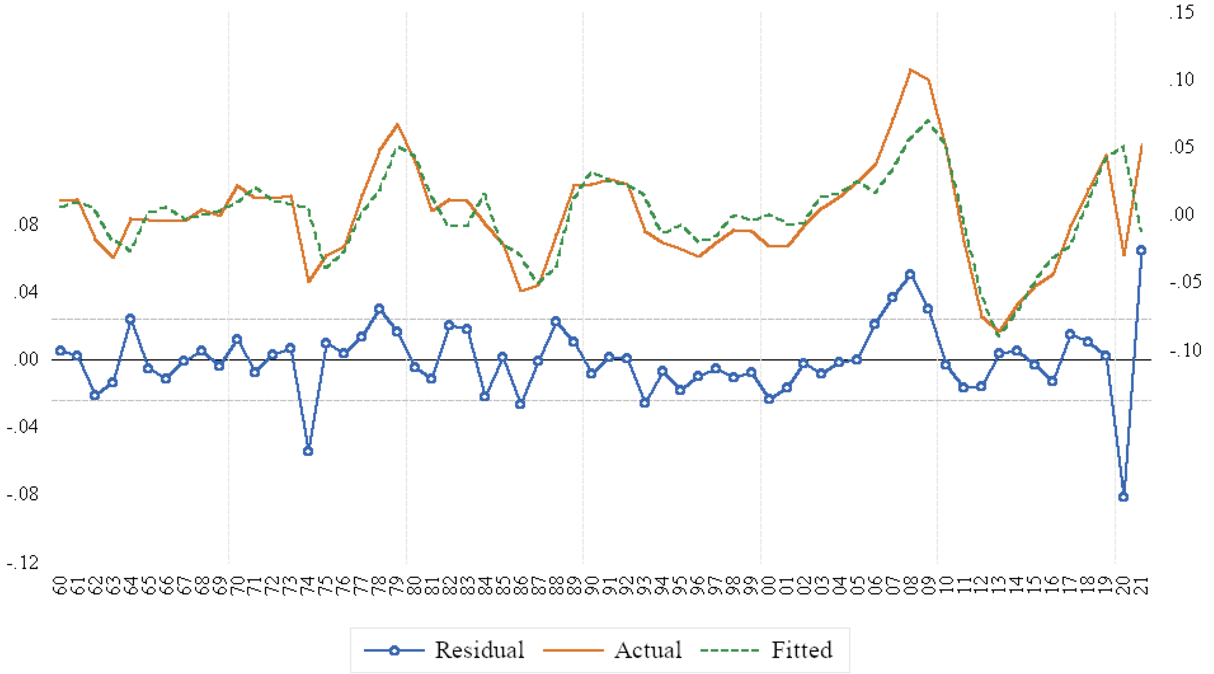


Figure 30: Actual vs Estimated data from ARMA of Consumption.

In Fig. 30 a positive shock is again identified in 2008, which coincides with the arrival of the international financial crisis. Another positive shock appears in 2021, which coincide with one year after the advent of the pandemic. On the other hand, negative shocks occurred in 1974 and 2020, when Greece exited the dictatorship and entered the COVID-19 pandemic, respectively.

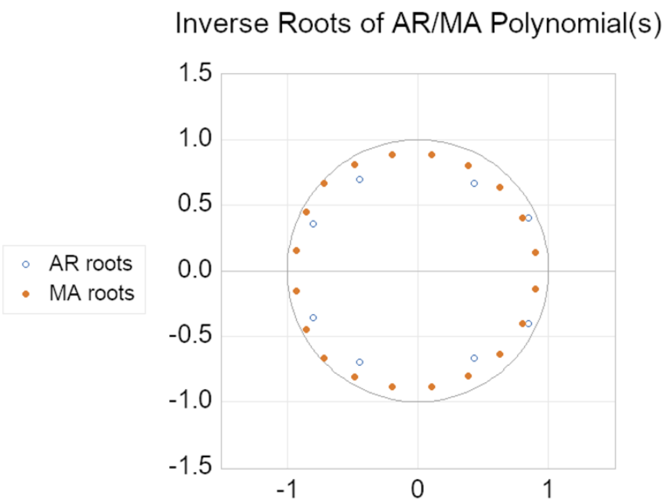


Figure 31: AR and MA roots of Consumption.

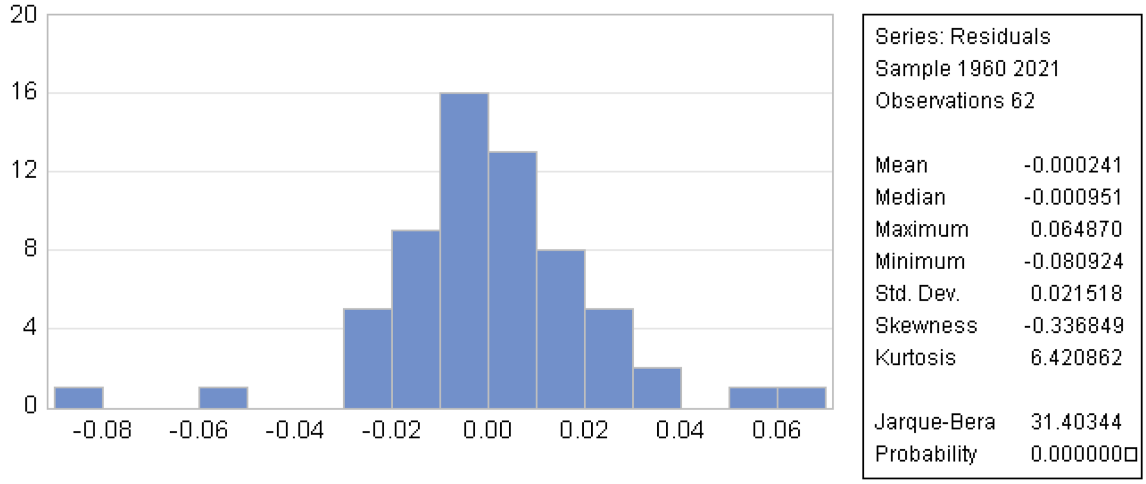
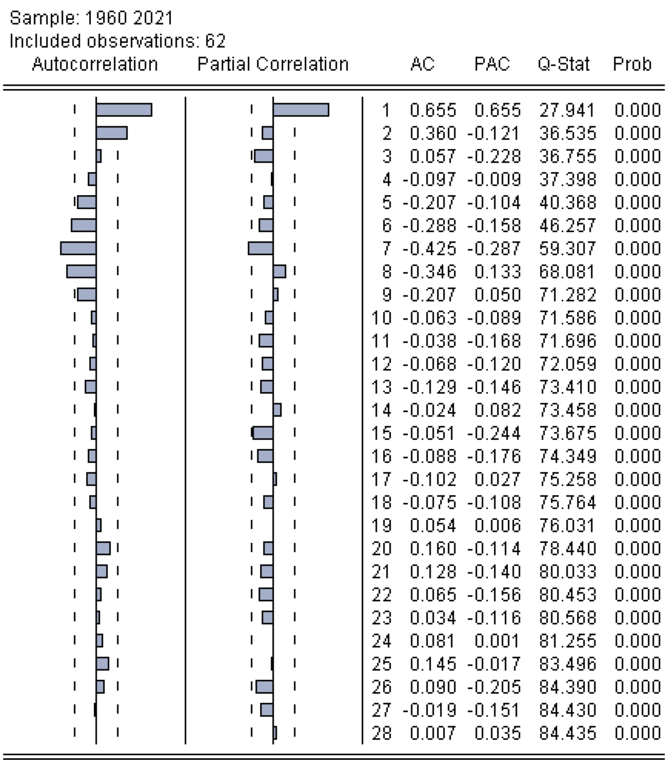


Figure 32: The distribution of Consumption Residuals.

6.1.3 Government Expenditure

The correlogram of Government Expenditure for is shown in Fig. 33. Given error bounds $\boldsymbol{\sigma} = \pm \mathbf{0.254}$, the AR and MA terms are $\boldsymbol{p} = \mathbf{8}$ and $\boldsymbol{q} = \mathbf{7}$, respectively.



	AC	PAC	Q-Stat	Prob
1	0.655	0.655	27.941	0.000
2	0.360	-0.121	36.535	0.000
3	0.057	-0.228	36.755	0.000
4	-0.097	-0.009	37.398	0.000
5	-0.207	-0.104	40.368	0.000
6	-0.288	-0.158	46.257	0.000
7	-0.425	-0.287	59.307	0.000
8	-0.346	0.133	68.081	0.000
9	-0.207	0.050	71.282	0.000
10	-0.063	-0.089	71.586	0.000
11	-0.038	-0.168	71.696	0.000
12	-0.068	-0.120	72.059	0.000
13	-0.129	-0.146	73.410	0.000
14	-0.024	0.082	73.458	0.000
15	-0.051	-0.244	73.675	0.000
16	-0.088	-0.176	74.349	0.000
17	-0.102	0.027	75.258	0.000
18	-0.075	-0.108	75.764	0.000
19	0.054	0.006	76.031	0.000
20	0.160	-0.114	78.440	0.000
21	0.128	-0.140	80.033	0.000
22	0.065	-0.156	80.453	0.000
23	0.034	-0.116	80.568	0.000
24	0.081	0.001	81.255	0.000
25	0.145	-0.017	83.496	0.000
26	0.090	-0.205	84.390	0.000
27	-0.019	-0.151	84.430	0.000
28	0.007	0.035	84.435	0.000

Figure 33: Correlogram of Government Expenditure

The cyclical component of Log Government Expenditure along with the statistically significant terms (i.e., AR(1), AR(2), AR(6), AR(7), AR(8), MA(1), MA(7)) are introduced in E-Views in order to estimate the ARMA coefficients via Maximum Likelihood.

Table 11: ARMA Statistical Estimation of Government Expenditure.

Dependent Variable: LOG_G_CYCLE
Method: ARMA Maximum Likelihood (BFGS)
Date: 11/29/22 Time: 12:51
Sample: 1960 2021
Included observations: 62
Convergence achieved after 44 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000793	0.001393	0.568989	0.5718
AR(1)	1.465687	0.669419	2.189492	0.0330
AR(2)	-0.699124	0.555940	-1.257553	0.2141
AR(6)	0.125077	0.226126	0.553130	0.5825
AR(7)	-0.249739	0.533211	-0.468368	0.6414
AR(8)	0.121125	0.343566	0.352552	0.7258
MA(1)	-0.824043	1.473418	-0.559273	0.5783
MA(7)	-0.170407	0.571835	-0.298001	0.7669
SIGMASQ	0.000504	0.000430	1.172931	0.2461

R-squared	0.601760	Mean dependent var	-3.56E-14
Adjusted R-squared	0.541648	S.D. dependent var	0.035881
S.E. of regression	0.024292	Akaike info criterion	-4.402574
Sum squared resid	0.031276	Schwarz criterion	-4.093797
Log likelihood	145.4798	Hannan-Quinn criter.	-4.281340
F-statistic	10.01068	Durbin-Watson stat	2.081617
Prob(F-statistic)	0.000000		

Inverted AR Roots	.80+.39i	.80-.39i	.64	.36+.68i
	.36-.68i	-.38+.64i	-.38-.64i	-.74
Inverted MA Roots	1.00	.61+.54i	.61-.54i	-.08-.72i
	-.08+.72i	-.62+.33i	-.62-.33i	

The Government Expenditure ARMA model is formulated as follows:

$$\boldsymbol{G_t = 0.0008 + 1.466G_{t-1} - 0.7G_{t-2} + 0.125G_{t-6} - 0.25G_{t-7} + 0.121G_{t-8} + z_t - 0.824z_{t-1} - 0.17z_{t-2} + \varepsilon_t.} \quad \textbf{(3)}$$

The actual and fitted data, along with the residual are shown in Fig. 34, while the AR (in blue) and MA roots (in red) are placed in relation to the unit circle in Fig. 35. All the roots lie inside the unit circle and therefore the solution of this discrete equation is stable.

The histogram of the Government Expenditure residual is shown in Fig. 36. With standard deviation of 0.087, values outside $[-0.17, 0.17]$ are considered as outliers. The Government Expenditure has no outliers in the examined period. Modest positive shocks are observed in 1989 and 2009. The latter one was followed by a series of measures to reduce public expenditure, namely a fiscal consolidation plan which included a cut in civil service employment, a freeze in government wages, a 10% cut in elastic budget outlays and a one-off levy on high incomes [OECD, 2009].

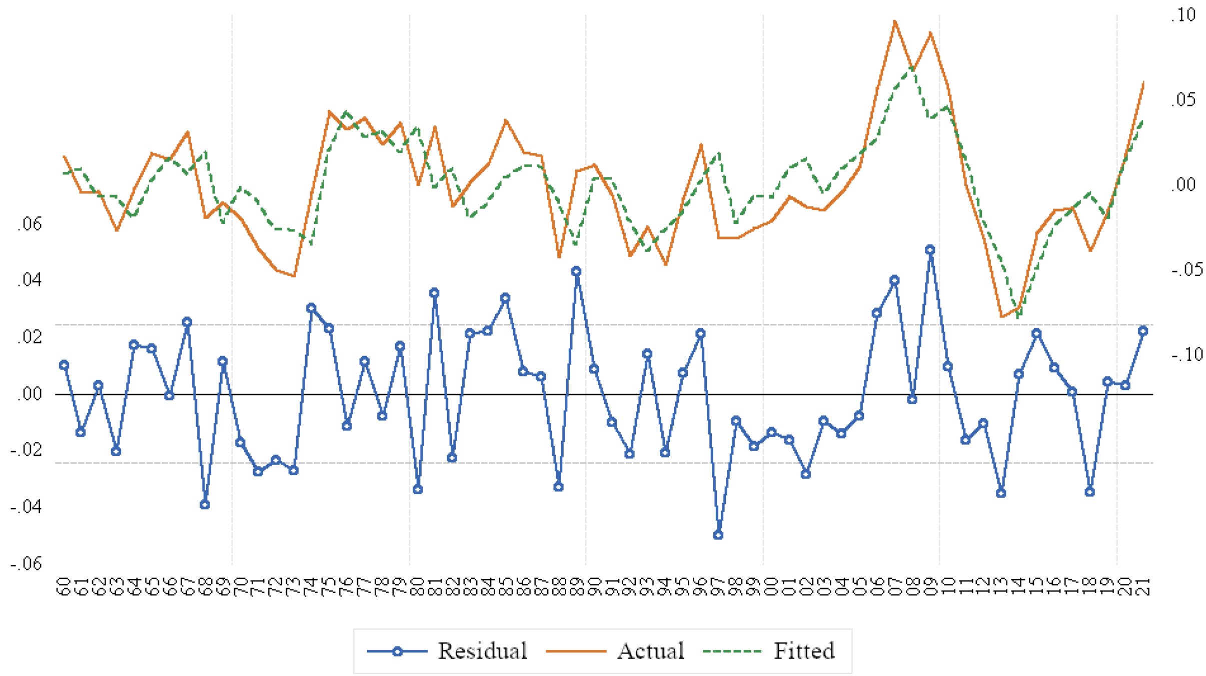


Figure 34: Actual vs Estimated data from ARMA of Government Expenditure.

The year of 1989 was marked by the gravest political and financial scandal in the post-war era [Charikiopoulou, I., 2022]. The victory of the socialist party PASOK in the 1981 elections initially created hopes in Post-Government Greece for growth, while the policies pursued during this first period were for the benefit of the people and to the detriment of capital. However, the debt skyrocketed and, in the next four years, when they won the elections again, they were forced to change their policy completely. This led to reaction from the people and the deterioration of the government.

Reduction in the government spend is observed in 1973 when the country exited the dictatorship, while from 2009 until 2013 the ministry implemented real expenditure cuts that would allow expenditures to grow 3.8% from 2009 to 2013, well below expected inflation at 6.9% [Ameco European Database, 2019]. The latter one was a response to fiscal imbalances developed from 2004 to 2009. Overall revenues were expected to grow 31.5% from 2009 to 2013, secured by new, higher taxes and by a major reform of the ineffective tax collection system. The deficit needed to decline to a level compatible with a declining debt-to-GDP ratio.

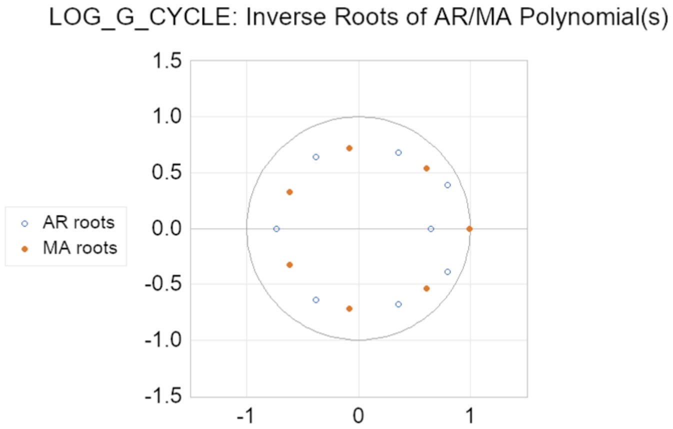


Figure 35: AR and MA roots of Government Expenditure.

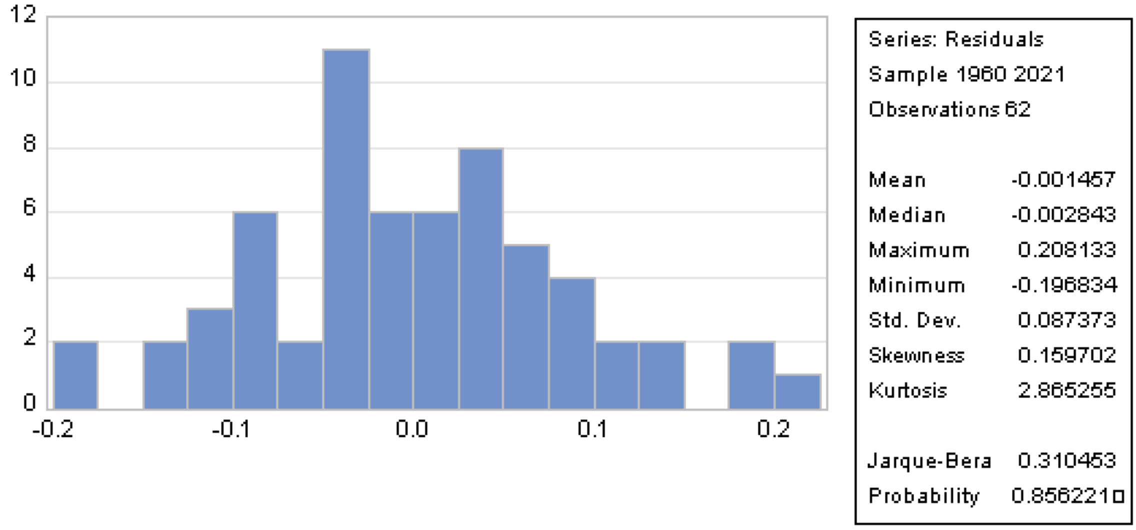
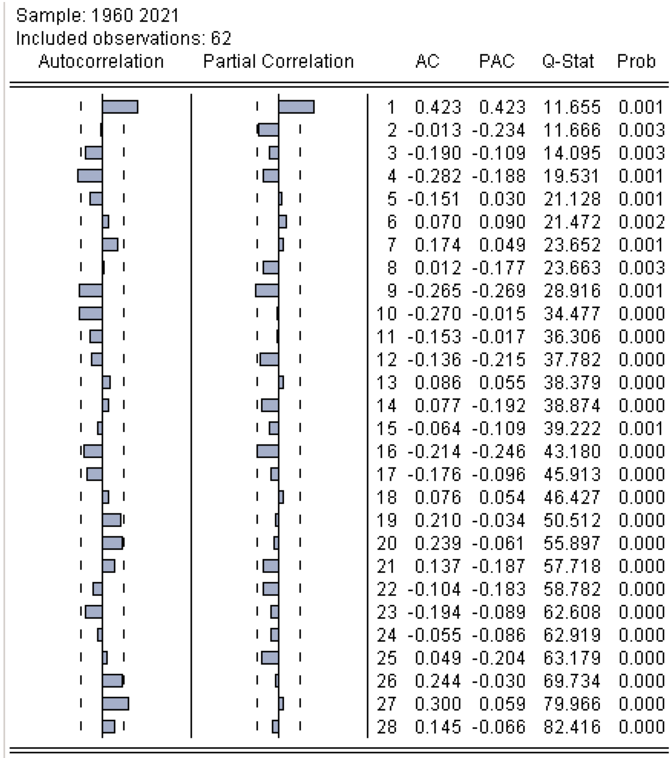


Figure 36: The distribution of Government Expenditure Residuals.

6.1.4 Exports

The correlogram of Exports for is shown in Fig. 37. Given error bounds $\boldsymbol{\sigma = \pm 0.254}$, there are statistically significant terms at $\boldsymbol{p = 27}$ and $\boldsymbol{q = 9}$.



Sample: 1960 2021
Included observations: 62

	AC	PAC	Q-Stat	Prob
1	0.423	0.423	11.655	0.001
2	-0.013	-0.234	11.666	0.003
3	-0.190	-0.109	14.095	0.003
4	-0.282	-0.188	19.531	0.001
5	-0.151	0.030	21.128	0.001
6	0.070	0.090	21.472	0.002
7	0.174	0.049	23.652	0.001
8	0.012	-0.177	23.663	0.003
9	-0.265	-0.269	28.916	0.001
10	-0.270	-0.015	34.477	0.000
11	-0.153	-0.017	36.306	0.000
12	-0.136	-0.215	37.782	0.000
13	0.086	0.055	38.379	0.000
14	0.077	-0.192	38.874	0.000
15	-0.064	-0.109	39.222	0.001
16	-0.214	-0.246	43.180	0.000
17	-0.176	-0.096	45.913	0.000
18	0.076	0.054	46.427	0.000
19	0.210	-0.034	50.512	0.000
20	0.239	-0.061	55.897	0.000
21	0.137	-0.187	57.718	0.000
22	-0.104	-0.183	58.782	0.000
23	-0.194	-0.089	62.608	0.000
24	-0.055	-0.086	62.919	0.000
25	0.049	-0.204	63.179	0.000
26	0.244	-0.030	69.734	0.000
27	0.300	0.059	79.966	0.000
28	0.145	-0.066	82.416	0.000

Figure 37: Correlogram of Exports.

The cyclical component of Log Exports along with the statistically significant terms (i.e., AR(1), AR(4), AR(9), AR(10), AR(27), MA(1), MA(9)) are introduced in E-Views in order to estimate the ARMA coefficients via Maximum Likelihood.

After the parameter estimation, the Exports ARMA model is as follows:

$$\boldsymbol{X_t = -0.0002 + 0.166X_{t-1} - 0.259X_{t-4} - 0.437X_{t-9} - 0.034_{t-10} + z_t + 0.32z_{t-1} + 0.159z_{t-9} + \varepsilon_t}. \quad \textbf{(4)}$$

The actual and fitted data, along with the residual are shown in Fig. 38, while the AR (in blue) and MA root (in red) are drawn onto the unit circle in Fig. 39. All roots lie inside the unit circle and therefore they are characterized by stability.

Table 12: ARMA Statistical Estimation of Exports.

Dependent Variable: LOG_X_CYCLE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/29/22 Time: 16:29
Sample: 1960 2021
Included observations: 62
Convergence achieved after 73 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000294	0.010345	-0.028426	0.9774
AR(1)	0.165874	0.304355	0.545001	0.5880
AR(4)	-0.258625	0.122132	-2.117590	0.0388
AR(9)	-0.436867	0.405697	-1.076831	0.2863
AR(10)	-0.034250	0.280273	-0.122204	0.9032
MA(1)	0.320084	0.312638	1.023819	0.3105
MA(9)	0.159286	0.480434	0.331545	0.7415
SIGMASQ	0.004653	0.000989	4.706798	0.0000

R-squared	0.364549	Mean dependent var	-5.48E-14
Adjusted R-squared	0.282176	S.D. dependent var	0.086274
S.E. of regression	0.073095	Akaike info criterion	-2.244204
Sum squared resid	0.288516	Schwarz criterion	-1.969735
Log likelihood	77.57033	Hannan-Quinn criter.	-2.136441
F-statistic	4.425572	Durbin-Watson stat	1.994034
Prob(F-statistic)	0.000603		

Inverted AR Roots	.86+.35i	.86-.35i	.52-.79i	.52+.79i
	-.08	-.15-.87i	-.15+.87i	-.69+.62i
	-.69-.62i	-.85		
Inverted MA Roots	.74+.28i	.74-.28i	.38-.70i	.38+.70i
	-.18-.80i	-.18+.80i	-.66-.52i	-.66+.52i
	-.86			

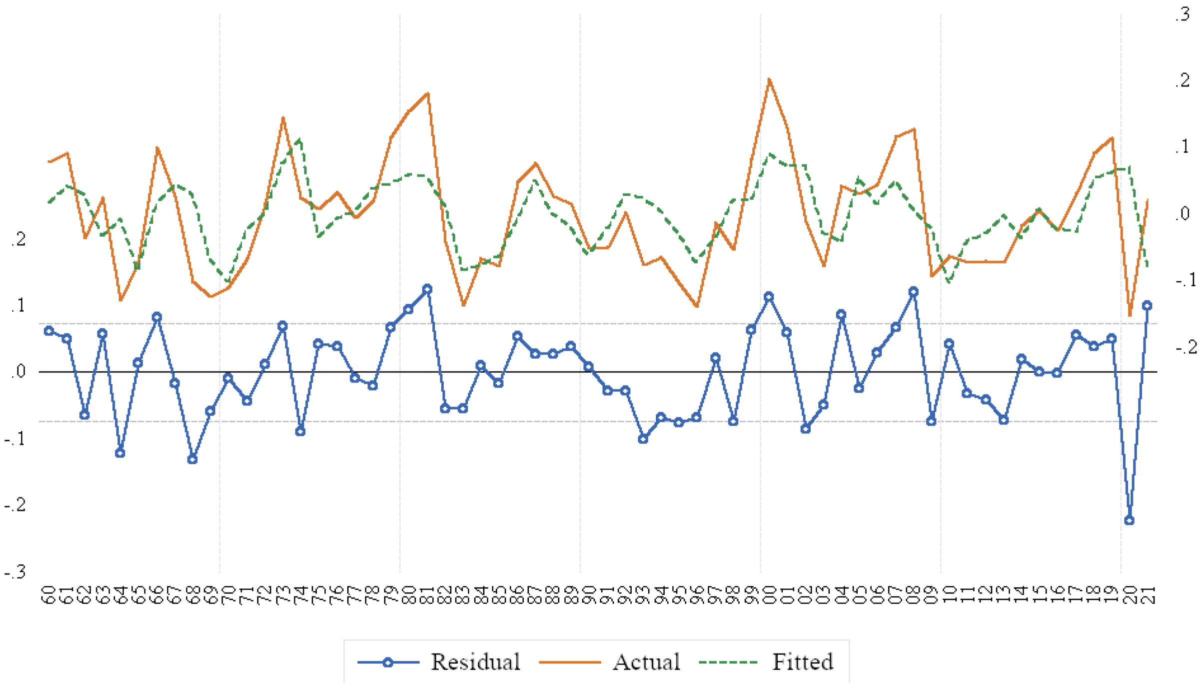


Figure 38: Actual vs Estimated data from ARMA of Exports.

The histogram of the Exports residual is shown in Fig. 40. With standard deviation 0.069, values outside $[-0.14, 0.14]$ are considered as outliers. A negative shock is prominent in 2020, when the COVID-19 shock set back Greece's export and consumption-driven recovery [OECD, 2023]. A positive shock appears in 1981, when the Greek agriculture made up 17% of GDP and 30% of employment, in comparison to 5% of GDP and less than 10% of employment in EU countries excluding Ireland and Italy [Freris, A.F., 1986].

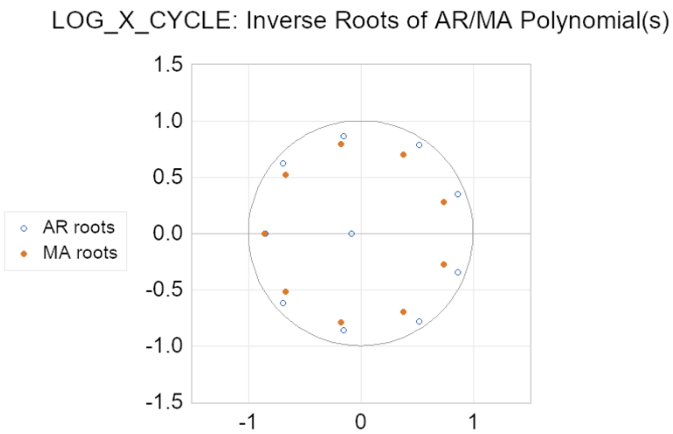


Figure 39: AR and MA roots of Exports.

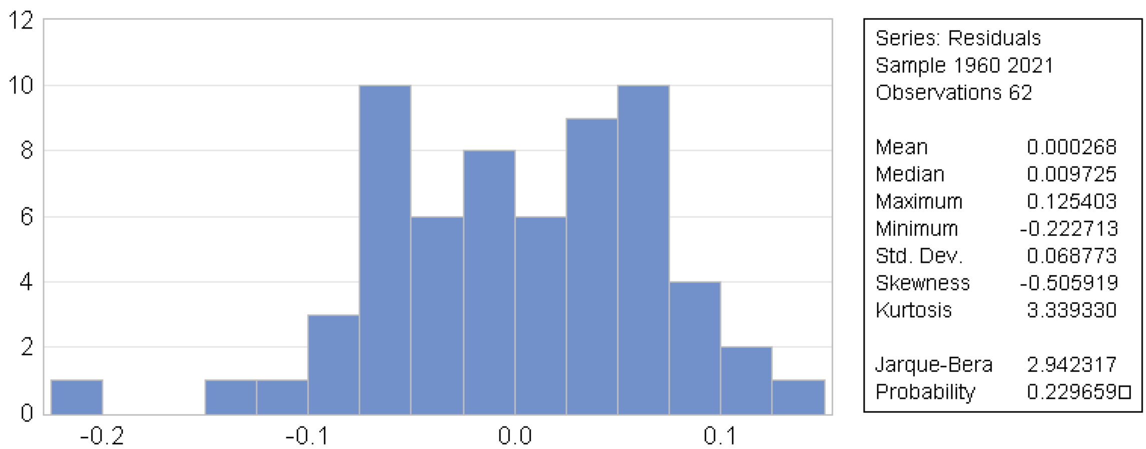
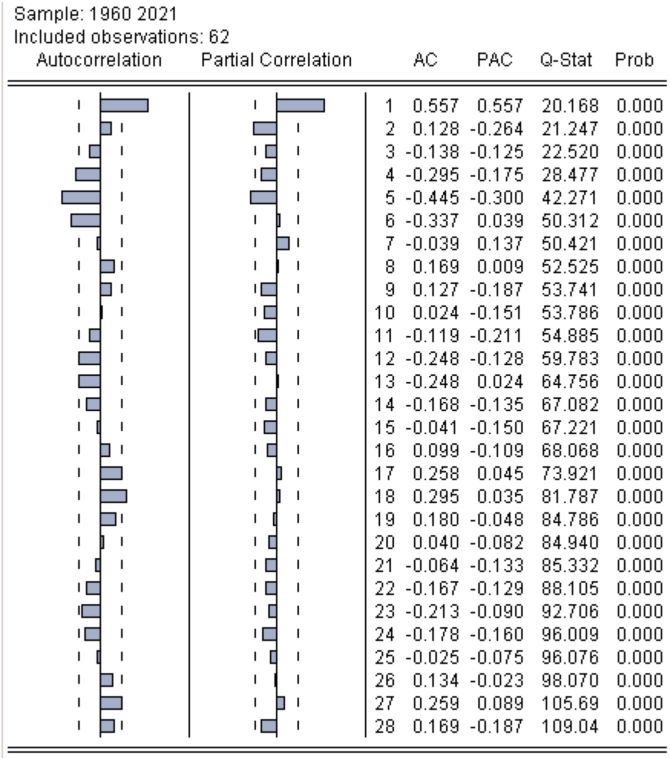


Figure 40: The distribution of Exports Residuals.

6.1.5 Imports

The correlogram of Imports is shown in Fig. 41. Given error bounds $\boldsymbol{\sigma = \pm 0.254}$, the AR and MA terms are $\boldsymbol{p = 18}$ and $\boldsymbol{q = 5}$, respectively.



Sample: 1960 2021
Included observations: 62

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.557	0.557	20.168	0.000
		2	0.128	-0.264	21.247	0.000
		3	-0.138	-0.125	22.520	0.000
		4	-0.295	-0.175	28.477	0.000
		5	-0.445	-0.300	42.271	0.000
		6	-0.337	0.039	50.312	0.000
		7	-0.039	0.137	50.421	0.000
		8	0.169	0.009	52.525	0.000
		9	0.127	-0.187	53.741	0.000
		10	0.024	-0.151	53.786	0.000
		11	-0.119	-0.211	54.885	0.000
		12	-0.248	-0.128	59.783	0.000
		13	-0.248	0.024	64.756	0.000
		14	-0.168	-0.135	67.082	0.000
		15	-0.041	-0.150	67.221	0.000
		16	0.099	-0.109	68.068	0.000
		17	0.258	0.045	73.921	0.000
		18	0.295	0.035	81.787	0.000
		19	0.180	-0.048	84.786	0.000
		20	0.040	-0.082	84.940	0.000
		21	-0.064	-0.133	85.332	0.000
		22	-0.167	-0.129	88.105	0.000
		23	-0.213	-0.090	92.706	0.000
		24	-0.178	-0.160	96.009	0.000
		25	-0.025	-0.075	96.076	0.000
		26	0.134	-0.023	98.070	0.000
		27	0.259	0.089	105.69	0.000
		28	0.169	-0.187	109.04	0.000

Figure 41: Correlogram of Imports.

The cyclical component of Log Imports along with the statistically significant terms (i.e., AR(1), AR(4), AR(5), AR(6), AR(17), AR(18), MA(1), MA(2), MA(5)) are introduced in E-Views in order to estimate the ARMA coefficients via Maximum Likelihood. After the parameter estimation, the Imports ARMA model is as follows:

$$\boldsymbol{M_t = 0.0005 - 0.064M_{t-1} + 0.01M_{t-4} - 0.228M_{t-5} - 0.181M_{t-6} + 0.161M_{t-17} + 0.27M_{t-18} + z_t + 0.653z_{t-1} + 0.227z_{t-2} + \varepsilon_t.} \tag{5}$$

The actual and fitted data, along with the residual are shown in Fig. 42, while the AR (in blue) and MA roots (in red) are shown onto the unit circle in Fig. 43. All roots lie inside the unit circle, which indicate stability. The histogram of the Imports residual is shown in Fig. 44. With standard deviation 0.055, values outside $[-0.11, 0.11]$ are considered as outliers.

Table 13: ARMA Statistical Estimation of Imports.

Dependent Variable: LOG_M_CYCLE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/29/22 Time: 15:05
Sample: 1960 2021
Included observations: 62
Convergence achieved after 40 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000532	0.016911	0.031433	0.9750
AR(1)	-0.063923	0.521253	-0.122634	0.9029
AR(4)	0.010077	0.215932	0.046666	0.9630
AR(5)	-0.228414	0.181905	-1.255676	0.2148
AR(6)	-0.180936	0.235181	-0.769350	0.4452
AR(17)	0.160763	0.321305	0.500344	0.6189
AR(18)	0.270036	0.319781	0.844440	0.4023
MA(1)	0.653376	0.535342	1.220483	0.2278
MA(2)	0.226979	0.355282	0.638871	0.5257
SIGMASQ	0.002964	0.000635	4.669949	0.0000

R-squared	0.503697	Mean dependent var	-4.47E-14
Adjusted R-squared	0.417799	S.D. dependent var	0.077915
S.E. of regression	0.059451	Akaike info criterion	-2.614054
Sum squared resid	0.183791	Schwarz criterion	-2.270968
Log likelihood	91.03568	Hannan-Quinn criter.	-2.479350
F-statistic	5.863867	Durbin-Watson stat	1.929784
Prob(F-statistic)	0.000013		

Inverted AR Roots	.93	.89-.36i	.89+.36i	.74+.62i
	.74-.62i	.45-.81i	.45+.81i	.11-.93i
	.11+.93i	-.19-.93i	-.19+.93i	-.47-.78i
	-.47+.78i	-.71-.55i	-.71+.55i	-.86-.29i
	-.86+.29i	-.90		
Inverted MA Roots	-.33-.35i	-.33+.35i		

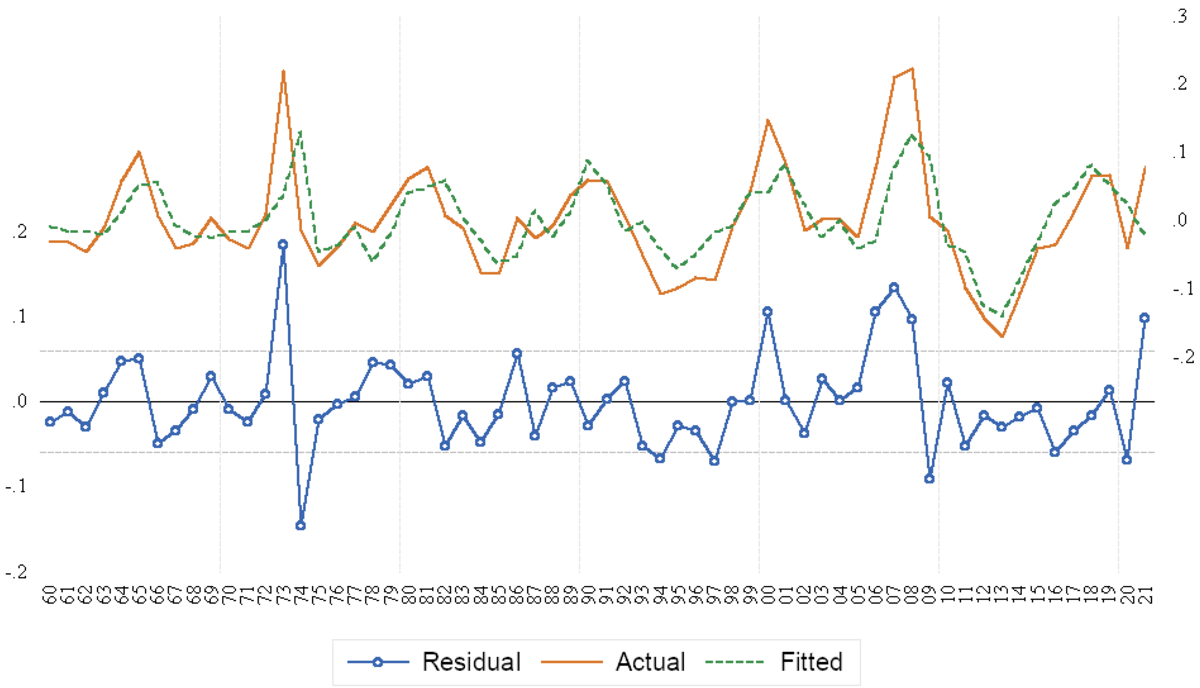


Figure 42: Actual vs Estimated data from ARMA of Imports.

In Fig. 42 significant fluctuation of the Imports cycle is observed between 1973 and 1974. The Greek economy, as any other western economy, was seriously affected by the sudden increase of oil prices, which ushered in a period of international inflation. The abrupt readjustment of the internal price level in 1973 was to a large extent caused by the sudden lifting of the strict price control, which was followed inflexibly by the military regime, in order to keep the cost of living down, but which proved ineffective when the inflationary pressures became persistent.

The following year, 1974, was a turbulent year for Greece. During the first semester prices continued to soar, despite the deflationary policy followed by the military regime, and the balance of payments showed dangerous signs. Then came the Cyprus crisis, which among other things, sealed the end of the dictatorial regime in Greece.

Next, a positive shock appears in 2000, while a negative shock happened in 2009. The positive shock is a precursor of the Imports increase that was observed in early 2000's by entering the Eurozone. The integration and scale that came with the common currency in the Eurozone made the single market more efficient and less risky, as the costs for exchanging currencies were eliminated, the risks and the lack of transparency in cross-border transactions were resolved. However, the trade balance of Greece in the Euro era was deteriorated, while the Greek economy observed losses in competitiveness due to the structure of production and the foreign trade [Magoulios, 2013], which partially explains the negative shock of 2009.

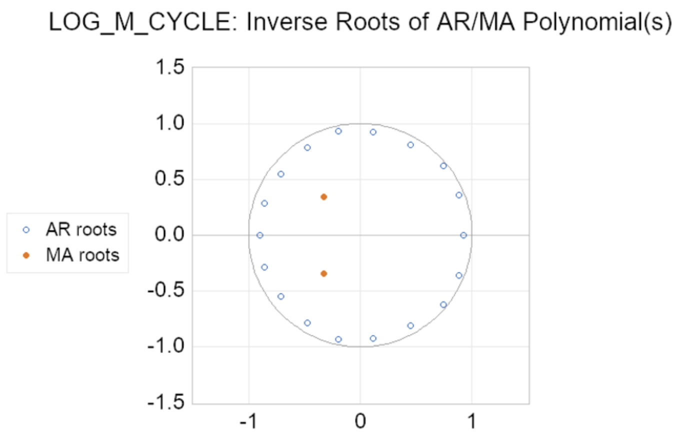


Figure 43: AR and MA roots of Imports.

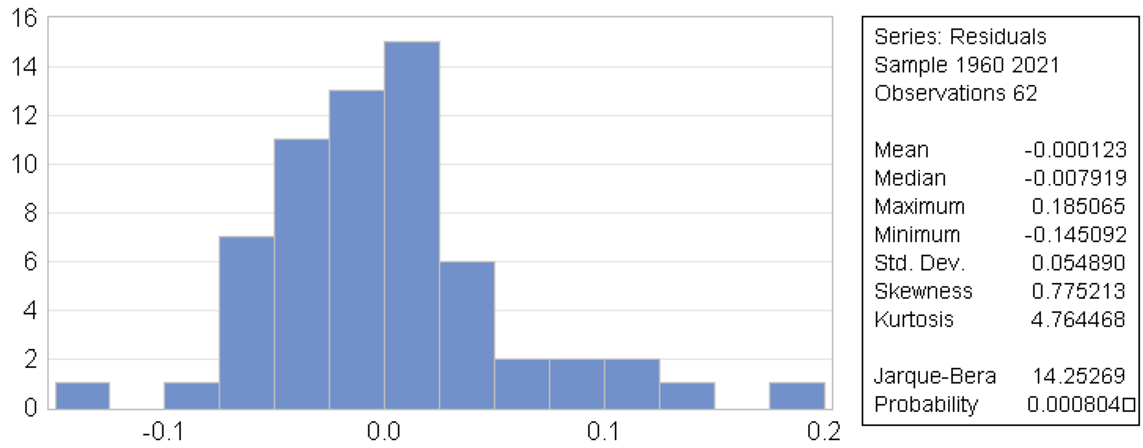
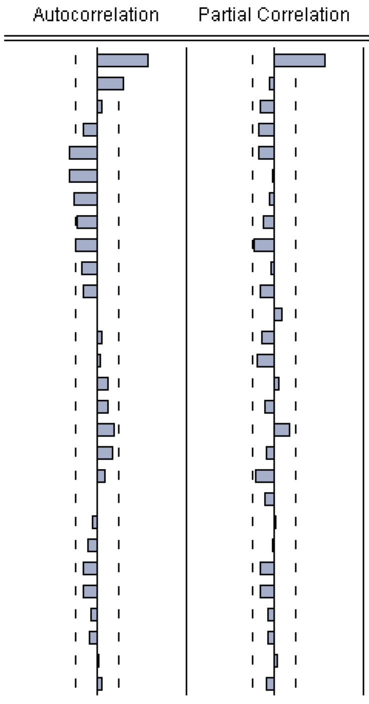


Figure 44: The distribution of Imports Residuals.

6.1.6 Investment

The correlogram of Investment for is shown in Fig. 45. Given error bounds $\boldsymbol{\sigma = \pm 0.254}$, the AR and MA terms are $\boldsymbol{p = 9}$ and $\boldsymbol{q = 1}$, respectively.

Sample: 1960 2021
Included observations: 62



	AC	PAC	Q-Stat	Prob
1	0.583	0.583	22.092	0.000
2	0.305	-0.052	28.246	0.000
3	0.046	-0.168	28.388	0.000
4	-0.171	-0.182	30.389	0.000
5	-0.327	-0.174	37.814	0.000
6	-0.326	-0.019	45.328	0.000
7	-0.277	-0.049	50.877	0.000
8	-0.242	-0.129	55.182	0.000
9	-0.262	-0.233	60.327	0.000
10	-0.178	-0.045	62.741	0.000
11	-0.161	-0.159	64.748	0.000
12	0.000	0.097	64.748	0.000
13	0.044	-0.145	64.905	0.000
14	0.040	-0.204	65.037	0.000
15	0.127	0.051	66.408	0.000
16	0.116	-0.109	67.573	0.000
17	0.201	0.173	71.139	0.000
18	0.186	-0.089	74.273	0.000
19	0.083	-0.207	74.910	0.000
20	-0.003	-0.107	74.910	0.000
21	-0.063	0.015	75.297	0.000
22	-0.107	-0.018	76.436	0.000
23	-0.172	-0.171	79.443	0.000
24	-0.164	-0.158	82.245	0.000
25	-0.066	-0.066	82.714	0.000
26	-0.093	-0.073	83.668	0.000
27	0.010	0.037	83.679	0.000
28	0.058	-0.098	84.066	0.000

Figure 45: Correlogram of Investment.

The cyclical component of Log Investment along with the statistically significant terms (i.e., AR(1), AR(2), AR(5), AR(6), AR(7), AR(9), MA(1)) are introduced in E-Views in order to estimate the ARMA coefficients via Maximum Likelihood.

After the parameter estimation, the Investment ARMA model is as follows:

$$\boldsymbol{I_t = 0.004 + 1.166I_{t-1} - 0.421I_{t-2} - 0.309I_{t-5} + 0.204I_{t-6} - 0.013I_{t-7} - 0.193I_{t-9} + z_t - 0.693z_{t-1} + \varepsilon_t.} \quad \textbf{(6)}$$

The actual and fitted data, along with the residual are shown in Fig. 46, while the AR (in blue) and MA roots (in red) are placed in relation to the unit circle in Fig. 47. All roots lie inside the unit circle, which indicate stability. The histogram of the Investment residual is shown in Fig. 48. With standard deviation 0.087, values outside $[-0.17, 0.17]$ are considered as outliers.

Table 14: ARMA Statistical Estimation of Investment.

Dependent Variable: LOG_I_CYCLE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/29/22 Time: 13:07
Sample: 1960 2021
Included observations: 62
Convergence achieved after 219 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004058	0.007996	0.507480	0.6139
AR(1)	1.165720	0.293205	3.975779	0.0002
AR(2)	-0.421304	0.158796	-2.653121	0.0105
AR(5)	-0.309372	0.146004	-2.118936	0.0388
AR(6)	0.203867	0.227668	0.895456	0.3746
AR(7)	-0.012830	0.169432	-0.075725	0.9399
AR(9)	-0.192901	0.164110	-1.175438	0.2451
MA(1)	-0.693339	0.322970	-2.146760	0.0364
SIGMASQ	0.007513	0.001767	4.252894	0.0001

R-squared	0.512111	Mean dependent var	-6.51E-14
Adjusted R-squared	0.438467	S.D. dependent var	0.125106
S.E. of regression	0.093748	Akaike info criterion	-1.719077
Sum squared resid	0.465805	Schwarz criterion	-1.410300
Log likelihood	62.29140	Hannan-Quinn criter.	-1.597844
F-statistic	6.953902	Durbin-Watson stat	2.053287
Prob(F-statistic)	0.000003		

Inverted AR Roots	.91-.34i	.91+.34i	.62+.64i	.62-.64i
	-.08-.84i	-.08+.84i	-.45+.50i	-.45-.50i
	-.80			
Inverted MA Roots	.69			

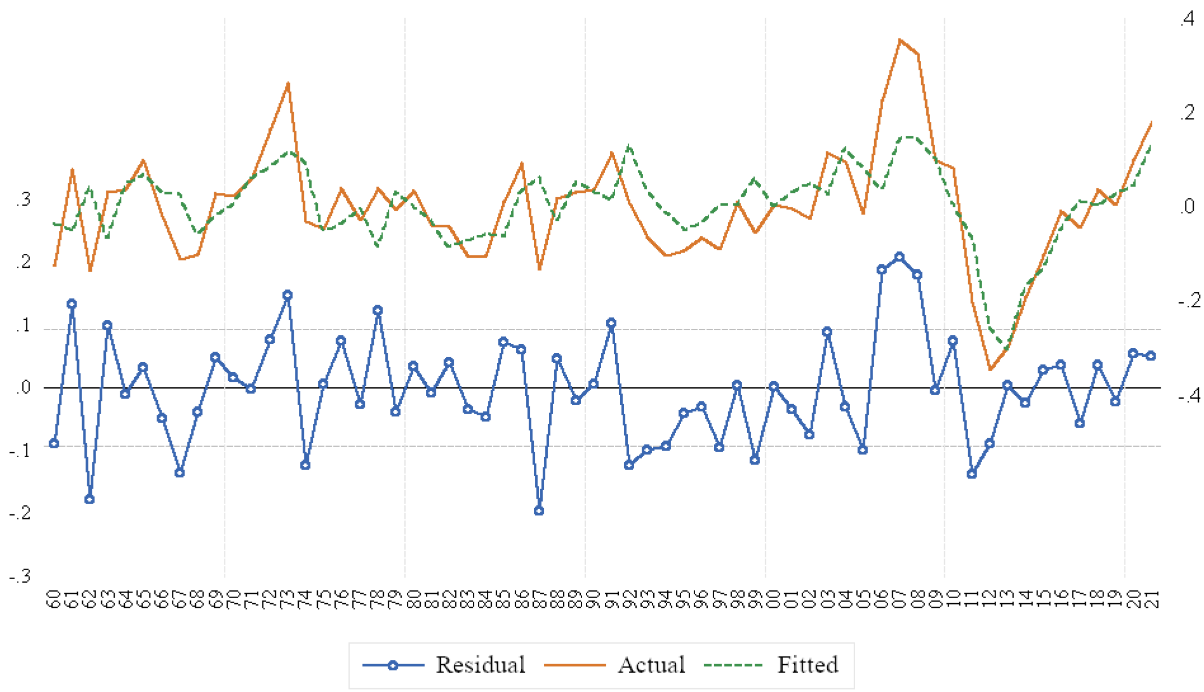


Figure 46: Actual vs Estimated data from ARMA of Investment.

In Fig. 46 positive shocks appear in 1973 and 2006-2008, while negative shocks happened in 1987 and 2011. The year 1973 marks the oil crisis and the end of the Greek economic miracle, which was a period between 1950 and 1973, when the Greek economy was Europe's faster growing economy, with growth rates of 7 per cent a year [Hamish, M., 2015]. The year of 1987 was characterized by government debt and reduced investment [Charikiopoulou, I., 2022]. To the contrary, the investment reached a high ahead of the international financial crisis in 2006-2008. Later, as the Great Recession spread to Europe, the amount of funds lent from the European core countries (e.g., Germany) to the peripheral countries such as Greece began to decline. Reports in 2009 of Greek fiscal mismanagement and deception increased borrowing costs; the combination meant Greece could no longer borrow to finance its trade and budget deficits at an affordable cost [Hale, G., 2013]. This series of events led to a negative shock in private investment in 2011.

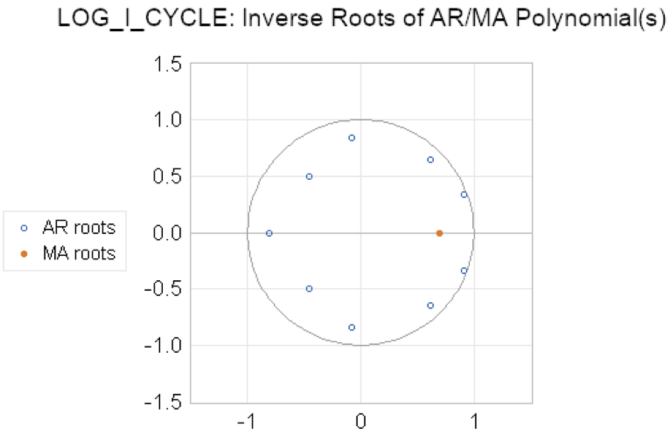


Figure 47: AR and MA roots of Investment.

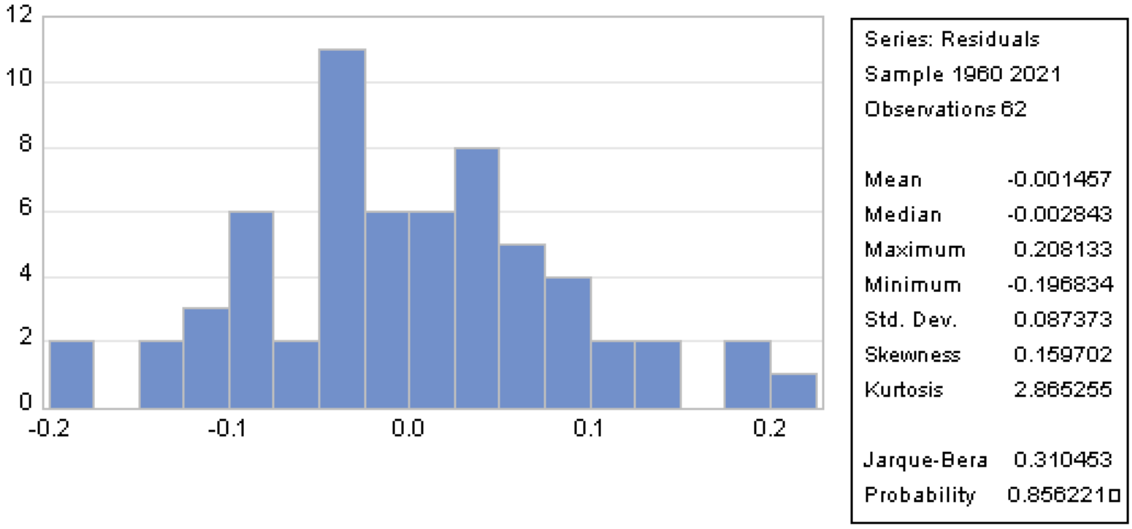


Figure 48: The distribution of Investment Residuals.

6.2 Markov Switching AR

[Hamilton, 1989] proposed an efficient approach to model changes in regime with application to the mean Growth Rate of a nonstationary series. After the initial success for GNP business cycle estimation, this method has been popular in the business cycle literature. It presents an algorithm for performing probabilistic inference in the form of a non-linear iterative filter. This filter permits estimation of popular parameters by the method of Maximum likelihood estimation and provides the foundation for forecasting future values of the series.

The core principle of the Markovian property is that the probability of transitioning to any state is dependent solely on the current state, and not on the sequence of state that preceded it. In economic terms this means that each of the eventualities depends only on its immediate predecessor. The model formulation is as follows:

$$\boldsymbol{z_t} = \begin{cases} \boldsymbol{a_0 + \beta z_{t-1} + \varepsilon_t,\ s_t = 0} \\ \boldsymbol{a_0 + a_1 + \beta z_{t-1} + \varepsilon_t,\ s_t = 1,} \end{cases} \tag{7}$$

where the constant terms $\boldsymbol{a_0}$ and $\boldsymbol{a_1}$ depend on the regime. In this case, the only probability regressor is the constant C since we have time-invariant regime transition probabilities. Thus, a Markov switching model is constructed by combining two or more dynamic models via a Markovian switching mechanism. In the next paragraphs, $\boldsymbol{z_t}$ estimation will be performed for GDP and all its determinants. From the estimated model the Markov Switching Transition probabilities will be illustrated for the statistically significant regimes.

The Markov Switching AR(1) model, which is examined in this study, uses Switching Regression with two regimes, specifically a period of crisis or recession and a growth period. Its estimation is used to calculate the hyperparameters of both model regimes. Compared to the rest of examined models in this dissertation, Markov Switching allows to estimate separate parameters for different phases of the economy. We want to examine the hypothesis that modeling each phase of the economy individually can enable more robust estimation compared to models that unify all phases of the business cycle.

6.2.1 GDP

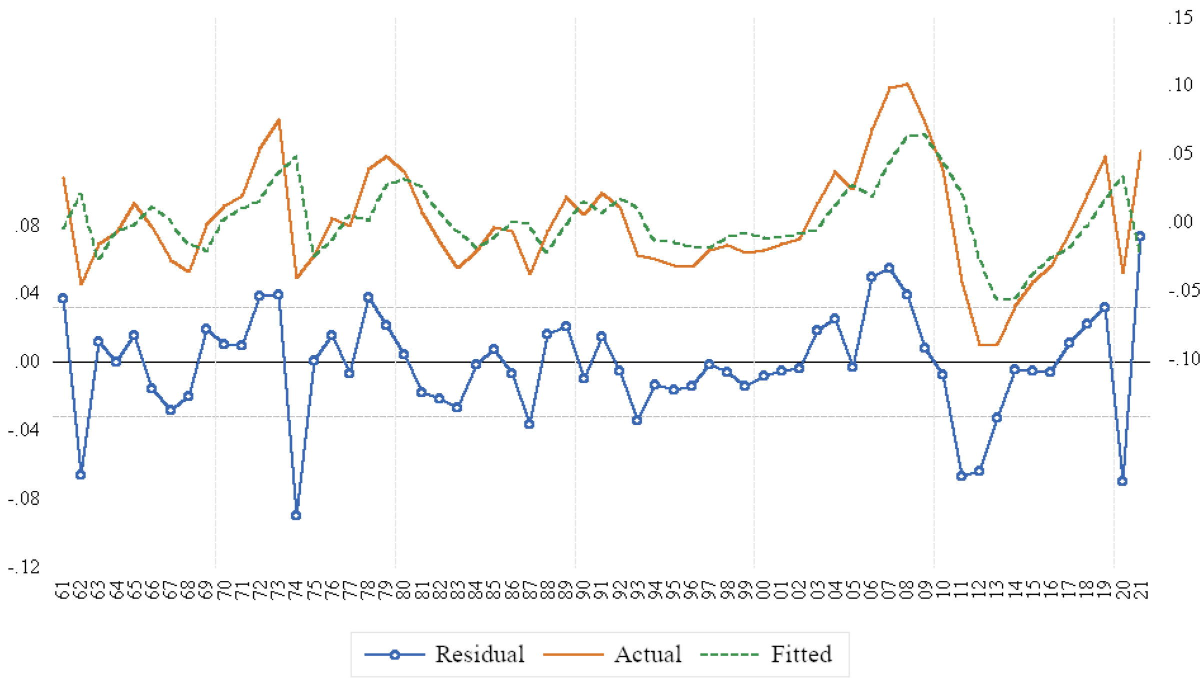


Figure 49: Actual vs Estimated data from Markov Switching of GDP.

In Fig. 49 the actual, fitted and residual series are plotted. In general, the estimation follows well the actual data, except for a large negative shock in 1974 when the country exited the dictatorship and 2011-2012 when the country recession occurred following the global crisis and recession.

In Table 15 the statistical estimation of GDP is shown. In Regime 1, the coefficients are estimated as $\boldsymbol{a_0} = \mathbf{-0.011}$, while in Regime 2 as $\boldsymbol{a_0} + \boldsymbol{a_1} = \mathbf{0.057}$, respectively. These two values correspond to the constants C for each regime in the table above. P-Values are $\mathbf{0.22}$ and $\mathbf{0.00}$ respectively, which is less than $\mathbf{5\%}$ for the 2nd regime, and therefore they indicate that only Regime 2 is statistically significant. To sum up, high values in Regime 1 with negative $\boldsymbol{a_0}$ denote crisis or recession, while high values in Regime 2 with positive $\boldsymbol{a_0} + \boldsymbol{a_1}$ characterize growth or a normal state of the economy. Lastly, $\boldsymbol{\beta} = \mathbf{0.667}$ is the common coefficient in both dynamic states.

The Durbin-Watson stat is less than 2, which indicates positive autocorrelation. The Hannan-Quinn criterion (HQC) is used for model selection, where smaller values indicate fewer explanatory variables or better fit or both. In this section HQC is smaller for Consumption, then for GDP, with the rest of the indicators having higher (worse) values. The Akaike Info criterion (AIC) is an alternative to HQC and estimates the amount of information loss, where smaller values show a higher quality estimation. In this case, again Consumption, GDP and Government Expenditure have the lower information loss based on AIC, while the estimation for Exports, Imports and Investment has higher information loss. The Log Likelihood value is another way to measure the model fitness, where the higher the value the better a model fits a dataset. This criterion is aligned with the previous ones, as Consumption and GDP demonstrate the best fitness. The Schwarz criterion, also known as Bayesian Information Criterion (BIC) is an index that quantifies and chooses the less complex probability model among a set of models. A smaller values shows a better fitting model based on BIC. In line with the previous criteria the Consumption, GDP and Government Expenditure estimations achieve the best fitness.

Table 15: Markov Switching Statistical Estimation of GDP.

Dependent Variable: LOG_Y_CYCLE
Method: Markov Switching Regression (BFGS / Marquardt steps)
Date: 03/23/23 Time: 13:49
Sample (adjusted): 1961 2021
Included observations: 61 after adjustments
Number of states: 2
Initial probabilities obtained from ergodic solution
Standard errors & covariance computed using observed Hessian
Random search: 25 starting values with 10 iterations using 1 standard deviation (rng=kn, seed=1353880255)
Convergence achieved after 8 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Regime 1				
C	-0.011227	0.009146	-1.227514	0.2196
Regime 2				
C	0.057046	0.013163	4.333877	0.0000
Common				
AR(1)	0.666827	0.103439	6.446567	0.0000
LOG(SIGMA)	-3.853592	0.107879	-35.72142	0.0000
Transition Matrix Parameters				
P11-C	2.254522	0.527187	4.276514	0.0000
P21-C	-0.701672	0.771146	-0.909908	0.3629

Mean dependent var	0.000159	S.D. dependent var	0.040247
S.E. of regression	0.031759	Sum squared resid	0.057491
Durbin-Watson stat	1.744242	Log likelihood	130.1670
Akaike info criterion	-4.071050	Schwarz criterion	-3.863424
Hannan-Quinn criter.	-3.989680		

Inverted AR Roots	.67

Table 16: Markov Transition Probabilities for GDP.

Transition summary: Constant Markov transition probabilities and expected durations
Sample (adjusted): 1961 2021
Included observations: 61 after adjustments

Constant transition probabilities:
P(i, k) = P(s(t) = k | s(t-1) = i)
(row = i / column = k)

	1	2
1	0.905040	0.094960
2	0.331442	0.668558

Constant expected durations:

1	2
10.53073	3.017123

From Table 16, we observe that in Regime 1 the probability to remain in this state is 90.5%, while the probability to change state is 9.5%. In Regime 2 the probability to remain in this state is 66.9%, while the probability of transition is 33.1%. The period of crisis and recession lasts 10.5 years, while the normal period or period of growth has 3 years estimated duration.

Next, the regime probabilities are shown for the examined time period. Gaussian smoothing is used to provide a smoother curve for easier interpretation of the statistically significant events, while the noise is filtered.

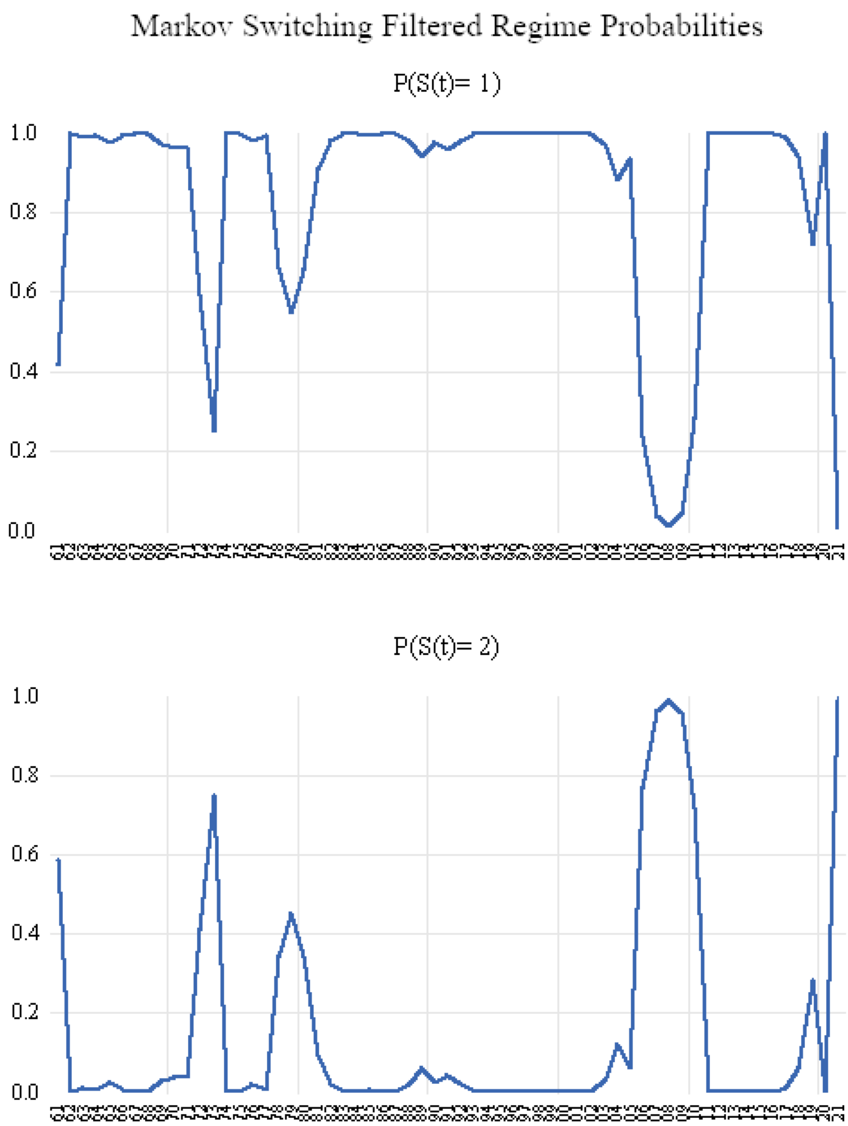


Figure 50: Filtered Regime Probabilities of GDP.

According to Fig. 50, we examine Regime 2, where the prediction is statistically significant based on the P value. We observe that Greece went through growth in 1972-1974, 1978-1981, 2006-2010 and after 2021. The periods coincide with the last years of dictatorship, when Greece joined the European Economic Community (EEC), the crisis and subsequent recession that the country went through at the end of 2010's and the recovery from the pandemic, respectively. Specifically, the EEC membership improved the trade balance as the conditions for imports and exports were improved.

6.2.2 Consumption

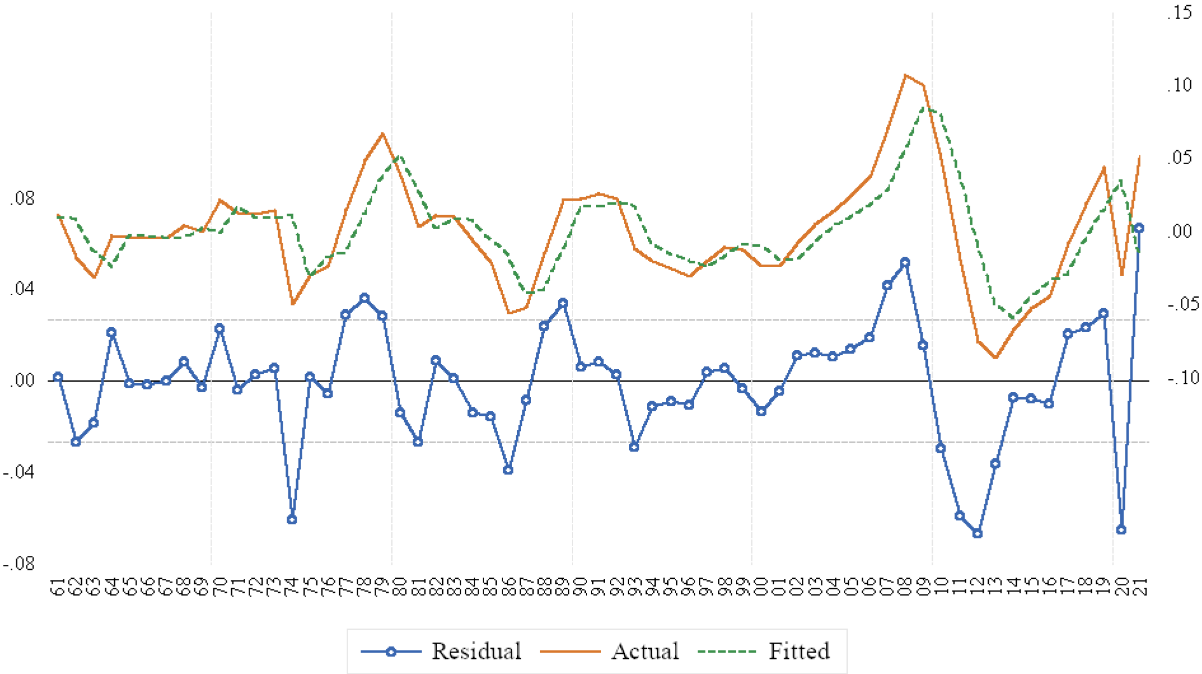


Figure 51: Actual vs Estimated data from Markov Switching of Consumption.

In Fig. 51 the actual, fitted and residual series are plotted. Similarly to GDP, the estimation is reliable except for 1974 after the end of the dictatorship, 2012 as Greece went through the Great Recession and 2020 as the COVID-19 pandemic arrived. All these events caused negative shocks in the economy. Data for 2012 indicated that the Greek "shadow economy" or "underground economy", from which little or no tax was collected, was a full 24.3% of GDP [Florence, 2023]. This led to reduced consumer spending for the basket of goods in 2013. In 2020 when the pandemic started the national income declined and along with the government measures for quarantine and closure of public places, all led to a reduced purchasing power and a widespread fear of the consumers to spend their income.

In Table 17 the statistical estimation of Consumption is shown. In Regime 1, the coefficient is estimated as $\boldsymbol{a_0} = \mathbf{-0.048}$, while in Regime 2 it is $\boldsymbol{a_0} + \boldsymbol{a_1} = \mathbf{0.01}$. The P-Values are $\mathbf{0.03}$ and $\mathbf{0.52}$, respectively, which indicates that Regime 1 is statistically significant. To sum up, high values in Regime 1 with negative $\boldsymbol{a_0}$ denote crisis or recession, while high values in Regime 2 with positive $\boldsymbol{a_0} + \boldsymbol{a_1}$ characterize growth or a normal state of the economy. Lastly, $\boldsymbol{\beta} = \mathbf{0.795}$ is the common coefficient in both states of the economy.

Table 17: Markov Switching Statistical Estimation of Consumption.

Dependent Variable: LOG_CN_CYCLE
Method: Markov Switching Regression (BFGS / Marquardt steps)
Date: 03/23/23 Time: 14:07
Sample (adjusted): 1961 2021
Included observations: 61 after adjustments
Number of states: 2
Initial probabilities obtained from ergodic solution
Standard errors & covariance computed using observed Hessian
Random search: 25 starting values with 10 iterations using 1 standard deviation (rng=kn, seed=1353880255)
Convergence achieved after 9 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	-0.047541	0.021438	-2.217608	0.0266
		Regime 2		
C	0.009712	0.015253	0.636700	0.5243
		Common		
AR(1)	0.795212	0.089337	8.901298	0.0000
LOG(SIGMA)	-3.859905	0.144116	-26.78334	0.0000
		Transition Matrix Parameters		
P11-C	0.643484	1.041781	0.617677	0.5368
P21-C	-2.979600	1.024687	-2.907815	0.0036

Mean dependent var	-0.000178	S.D. dependent var	0.038204
S.E. of regression	0.027012	Sum squared resid	0.041591
Durbin-Watson stat	1.376213	Log likelihood	138.0550
Akaike info criterion	-4.329673	Schwarz criterion	-4.122046
Hannan-Quinn criter.	-4.248302		

Inverted AR Roots	.80

Table 18: Markov Transition Probabilities for Consumption.

Transition summary: Constant Markov transition probabilities and expected durations
Sample (adjusted): 1961 2021
Included observations: 61 after adjustments

Constant transition probabilities:
P(i, k) = P(s(t) = k | s(t-1) = i)
(row = i / column = k)

	1	2
1	0.655541	0.344459
2	0.048356	0.951644

Constant expected durations:

1	2
2.903100	20.67993

In Table 18, we observe that the probability to remain in Regime 1 is 65.6%, while the transition probability is 34.4%. In Regime 2 the probability to remain in this state is 95.2%, while the probability of transition is 4.9%. The period of crisis or recession lasts 2.9 years, while the normal period or period of growth lasts 20.7 years. Consumption and its rate of change appears in Fig. 52. The economy shows long periods of growth, except for the downturns in 1973, 1980, 2008-2012, 2019-2021, when the dictatorship ended, the year before entering the European Community, the Great Recession, and the advent of the pandemic, respectively.

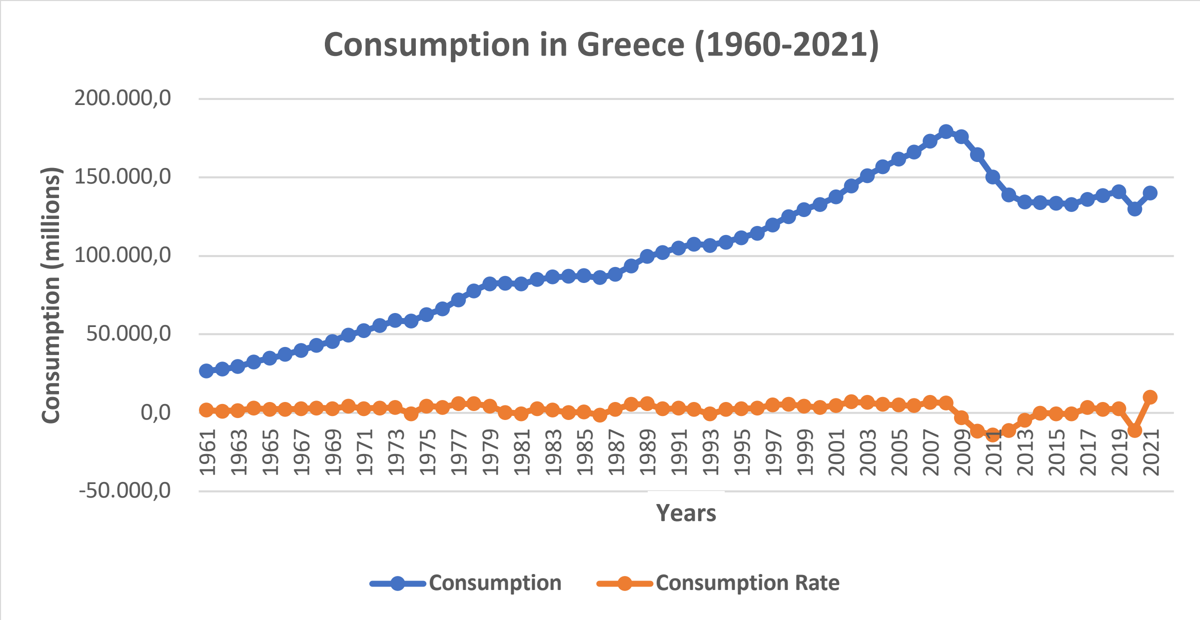


Figure 52: Consumption and its rate of change.

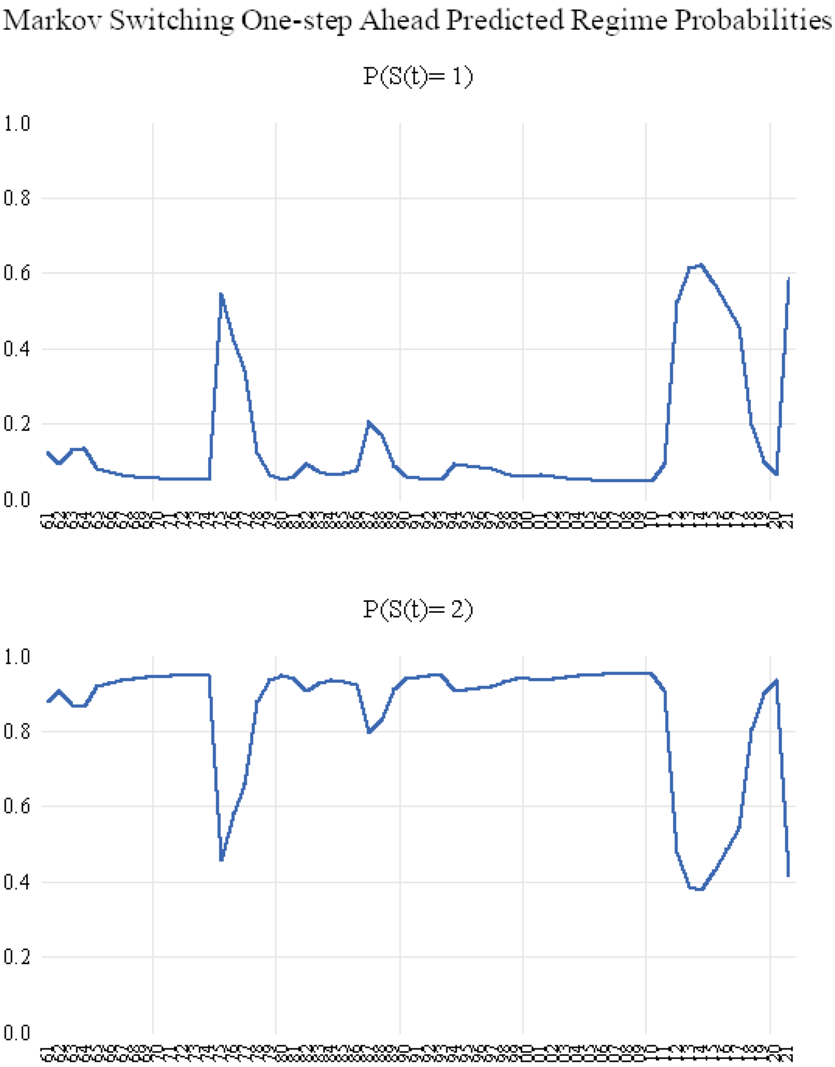


Figure 53: Filtered Regime Probabilities of Consumption.

According to Fig. 53, in Regime 1 the probability is high in 1975-1977, 2012-2018 and 2021. These periods follow the negative shocks of negative Consumption rate which is observed in Fig. 51 in 1973, 2008-2012 and 2019-2021. These correlate with the end of the Greek dictatorship (1967-1974), the Great Recession and the Pandemic. In 1974, a series of events took place, starting from the Athens Polytechnic uprising until Turkish invasion in Cyprus. Regime 2 has high values between 1978-2011 which corresponds to prediction for growth and normal period of the economy. This largely agrees with the actual data in Fig. 52.

6.2.3 Government Expenditure

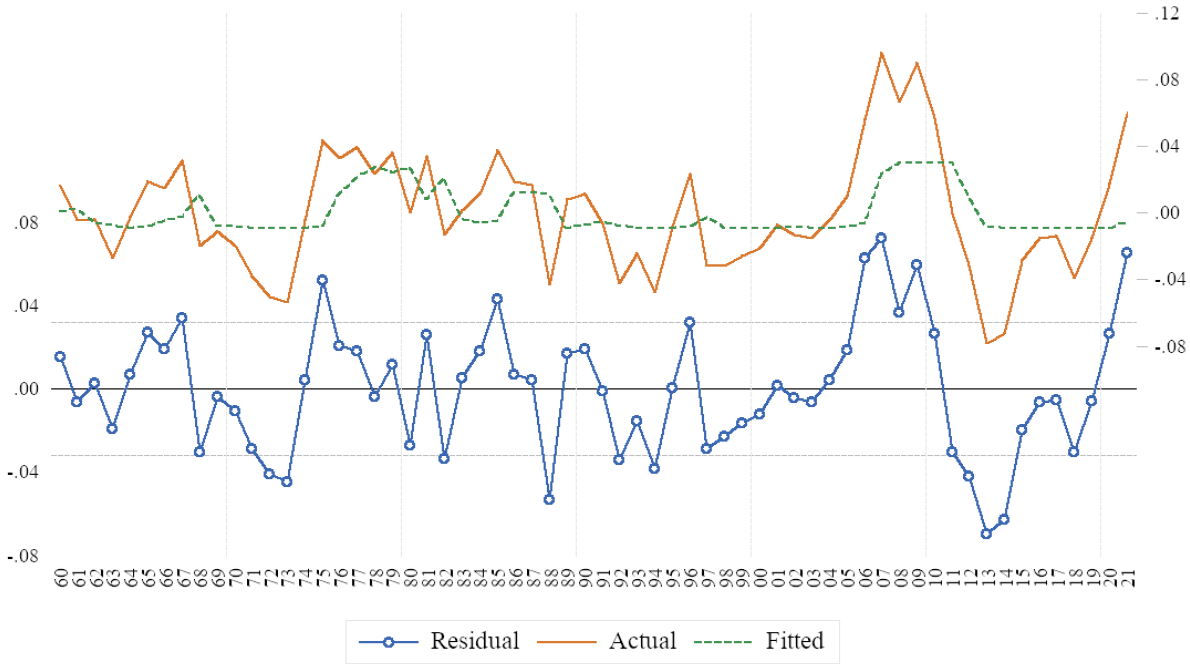


Figure 54: Actual vs Estimated data from Markov Switching of Government Expenditure.

In Fig. 54 the actual, fitted and residual series are shown for the Greek Government Expenditure in 1960-2021. Its residual has higher variance compared to this model's GDP and Consumption estimation. High residual appears in 1975, 2007-2010 and 2021, while low residual appears in 1988 and 2013-2014. These coincide with the macroeconomic events that were described in Fig. 51 for Consumption.

In Fig. 55 the absolute values of Government Expenditure along with its annual rate of change is shown for 1961-2021. In 1988 there was an adjustment Greece entered a multi-year European Community government expenditure program where the national budget is segmented in categories with a spending limit per category. The first programmatic period lasted 5 years and the subsequent one 7 years. Next, the government spending peaks at 2008-2010, which is followed by a period of reduced spending, Consumption and GDP. This phenomenon has been observed earlier by [Hondroyiannis & Papapetrou, 2001], that is the increase in the relative size of public spending is not an important determinant for the growth of income, since the productivity in the public sector is lower than in the private sector.

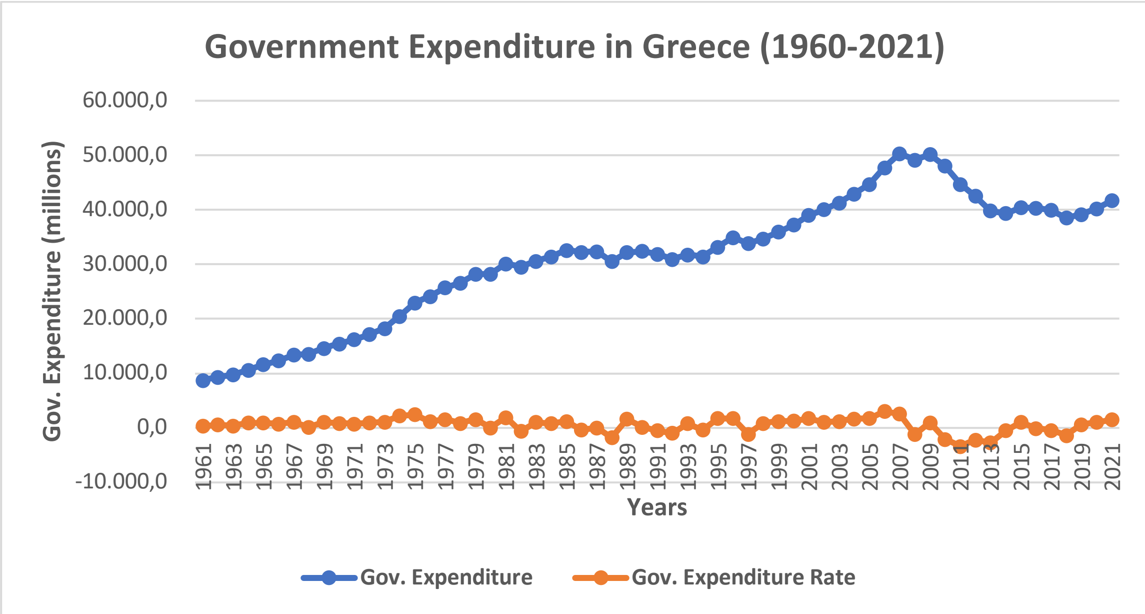


Figure 55: Government Expenditure and its rate of change.

Table 19: Markov Switching Statistical Estimation of Government Expenditure.

Dependent Variable: LOG_G_CYCLE
Method: Markov Switching Regression (BFGS / Marquardt steps)
Date: 03/23/23 Time: 19:05
Sample: 1960 2021
Included observations: 62
Number of states: 2
Initial probabilities obtained from ergodic solution
Standard errors & covariance computed using observed Hessian
Random search: 25 starting values with 10 iterations using 1 standard deviation (rng=kn, seed=404557615)
Convergence achieved after 8 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	0.042774	0.017767	2.407458	0.0161
		Regime 2		
C	-0.013810	0.007511	-1.838535	0.0660
		Common		
LOG(SIGMA)	-3.649675	0.114502	-31.87445	0.0000
		Transition Matrix Parameters		
P11-C	1.236780	0.781256	1.583066	0.1134
P21-C	-2.446615	0.950948	-2.572816	0.0101

Mean dependent var	-3.56E-14	S.D. dependent var	0.035881
S.E. of regression	0.031662	Sum squared resid	0.059145
Durbin-Watson stat	0.981758	Log likelihood	126.7535
Akaike info criterion	-3.927532	Schwarz criterion	-3.755989
Hannan-Quinn criter.	-3.860180		

In Table 19 the statistical estimation for Government Expenditure is presented. In Regime 1, the coefficient is estimated as $\boldsymbol{a_0 = 0.043}$, while in Regime 2 it is $\boldsymbol{a_0 + a_1 = -0.01}$. The P-Values are $\mathbf{0.016}$ and $\mathbf{0.066}$, respectively, which is less than $\mathbf{5\%}$ and therefore statistically significant for Regime 1. To sum up, high values in Regime 1 with positive $\boldsymbol{a_0}$ characterize growth or a normal state of the economy, while negative values in Regime 2 $\boldsymbol{a_0 + a_1}$ denote crisis or recession.

Table 20: Markov Transition Probabilities of Government Expenditure.

Transition summary: Constant Markov transition probabilities and expected durations
Sample: 1960 2021
Included observations: 62

Constant transition probabilities:
P(i, k) = P(s(t) = k | s(t-1) = i)
(row = i / column = k)

	1	2
1	0.775003	0.224997
2	0.079686	0.920314

Constant expected durations:

	1	2
	4.444503	12.54919

From Table 20, we observe that in Regime 1 the probability to remain in this state is 77.5%, while the transition probability is 22.5%. In Regime 2 the probability to remain in this state is 92%, while the transition probability is 8%. The period of crisis and recession lasts 12.5 years, while the normal period or period of growth has 4.4 years duration.

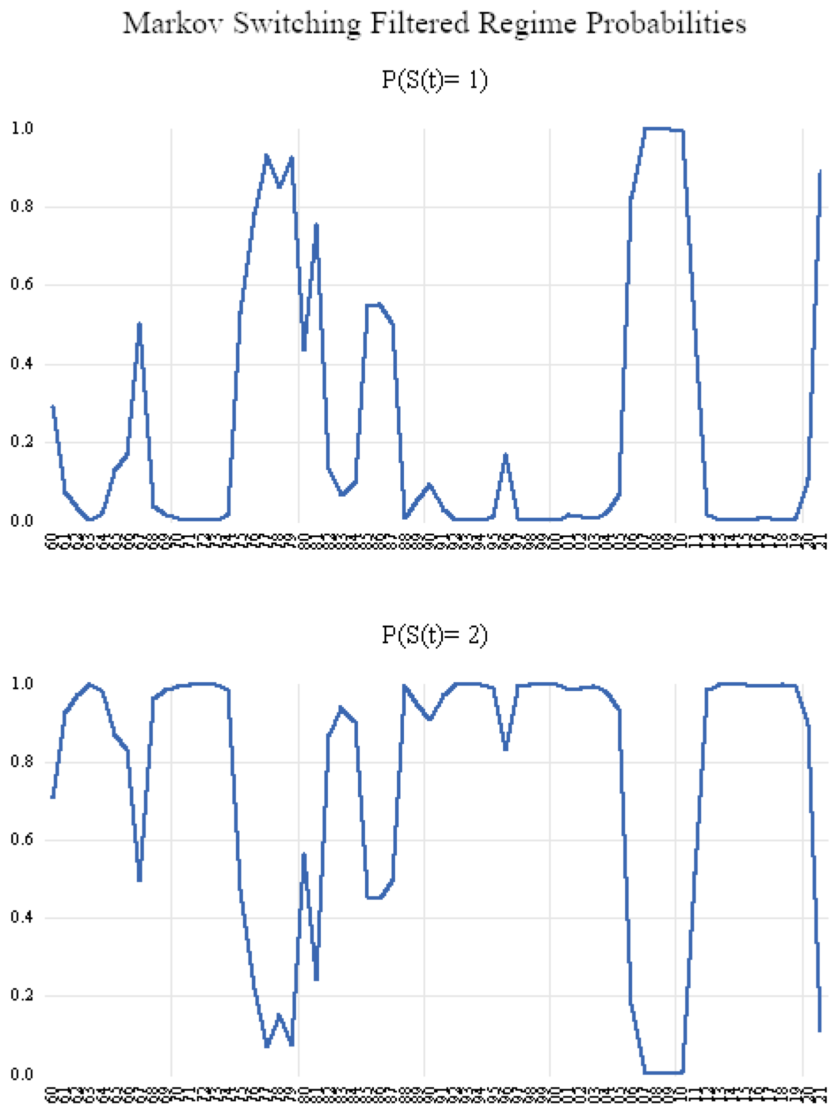


Figure 56: Filtered Regime Probabilities of Government Expenditure.

According to Fig. 56, in Regime 1 the probability for growth is high in 1976-1981, 2006-2011 and 2021 onwards. These growth periods are also reflected in Fig. 55 with the absolute values of Government Expenditure when the spending experiences a growth during these years.

6.2.4 Exports

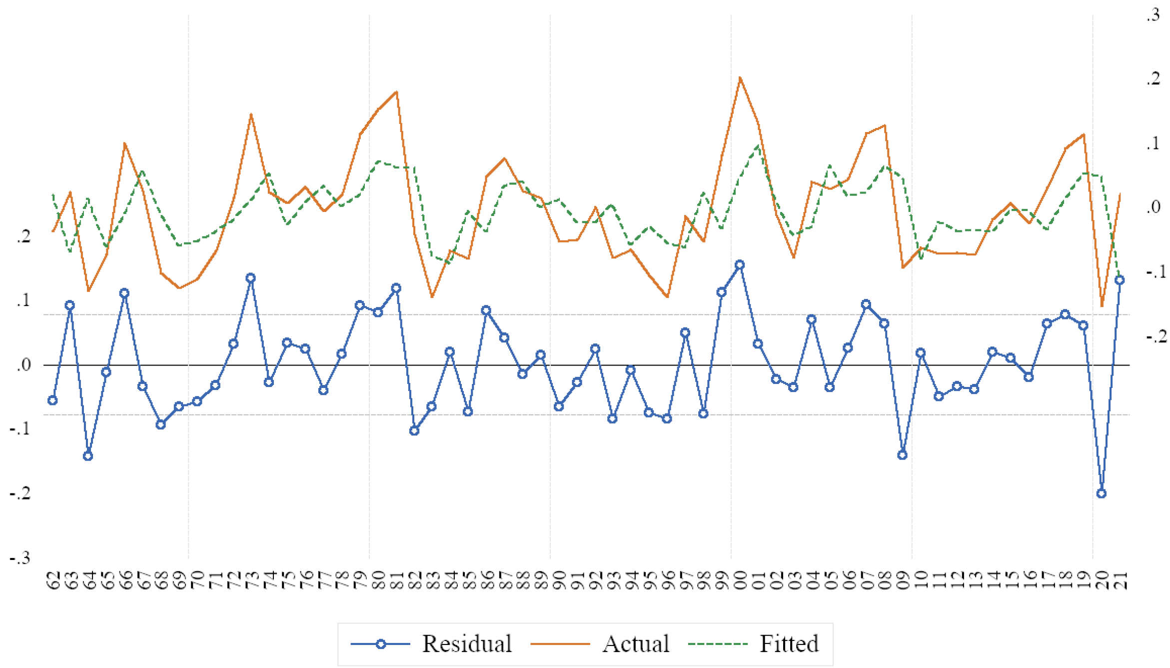


Figure 57: Actual vs Estimated data from Markov Switching of Exports.

In Fig. 57 the actual, fitted, and residual series of Exports are plotted for 1960-2021. In general, the actual data are well fitted, except for large negative shocks in 1964, 1982, 2009 and 2020. These events coincide with the Greek Elections of 1964, the year after joining the European Community due to low competitiveness and expensive labor cost, the Great Recession and the advent of the Covid-19 pandemic.

In Table 21 the statistical estimation of Exports is shown. In Regime 1, the coefficient is estimated as $\boldsymbol{a_0 = 0.058}$, while in Regime 2 it is $\boldsymbol{a_0 + a_1 = -0.069}$. The P-Values are $\mathbf{0.0001}$ and $\mathbf{0.0005}$, respectively, which are both less than $\mathbf{5\%}$, and therefore statistically significant. Regime 1 corresponds to growth or a normal period, while Regime 2 characterizes crisis or recession. Lastly, $\boldsymbol{\beta_1 = 0.59}$ and $\boldsymbol{\beta_2 = -0.43}$ are the common AR(1) and AR(2) coefficients in both dynamic states.

From Table 22, we observe that in Regime 1 the probability to remain in this state is 77.1%, while the probability to change state is 22.9%. In Regime 2 the probability to remain in this state is 74.4%, while the transition probability is 25.6%. The period of crisis and recession lasts 3.9 years, while the normal period or period of growth has 4.4 years duration.

Table 21: Markov Switching Statistical Estimation of Exports.

Dependent Variable: LOG_X_CYCLE
Method: Markov Switching Regression (BFGS / Marquardt steps)
Date: 03/24/23 Time: 15:30
Sample (adjusted): 1962 2021
Included observations: 60 after adjustments
Number of states: 2
Initial probabilities obtained from ergodic solution
Standard errors & covariance computed using observed Hessian
Random search: 25 starting values with 10 iterations using 1 standard deviation (rng=kn, seed=790090216)
Convergence achieved after 12 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	0.058129	0.015303	3.798650	0.0001
		Regime 2		
C	-0.069419	0.019824	-3.501819	0.0005
		Common		
AR(1)	0.592108	0.171308	3.456396	0.0005
AR(2)	-0.430787	0.145822	-2.954201	0.0031
LOG(SIGMA)	-3.027327	0.127691	-23.70831	0.0000
		Transition Matrix Parameters		
P11-C	1.214735	0.602004	2.017819	0.0436
P21-C	-1.066759	0.551923	-1.932803	0.0533

Mean dependent var	-0.002802	S.D. dependent var	0.086293
S.E. of regression	0.078126	Sum squared resid	0.335700
Durbin-Watson stat	2.105136	Log likelihood	72.43668
Akaike info criterion	-2.181223	Schwarz criterion	-1.936883
Hannan-Quinn criter.	-2.085648		

Inverted AR Roots	.30+.59i	.30-.59i

Table 22: Markov Transition Probabilities of Exports.

Transition summary: Constant Markov transition probabilities and expected durations
Sample (adjusted): 1962 2021
Included observations: 60 after adjustments

Constant transition probabilities:
P(i, k) = P(s(t) = k | s(t-1) = i)
(row = i / column = k)

	1	2
1	0.771136	0.228864
2	0.256020	0.743980

Constant expected durations:

1	2
4.369402	3.905947

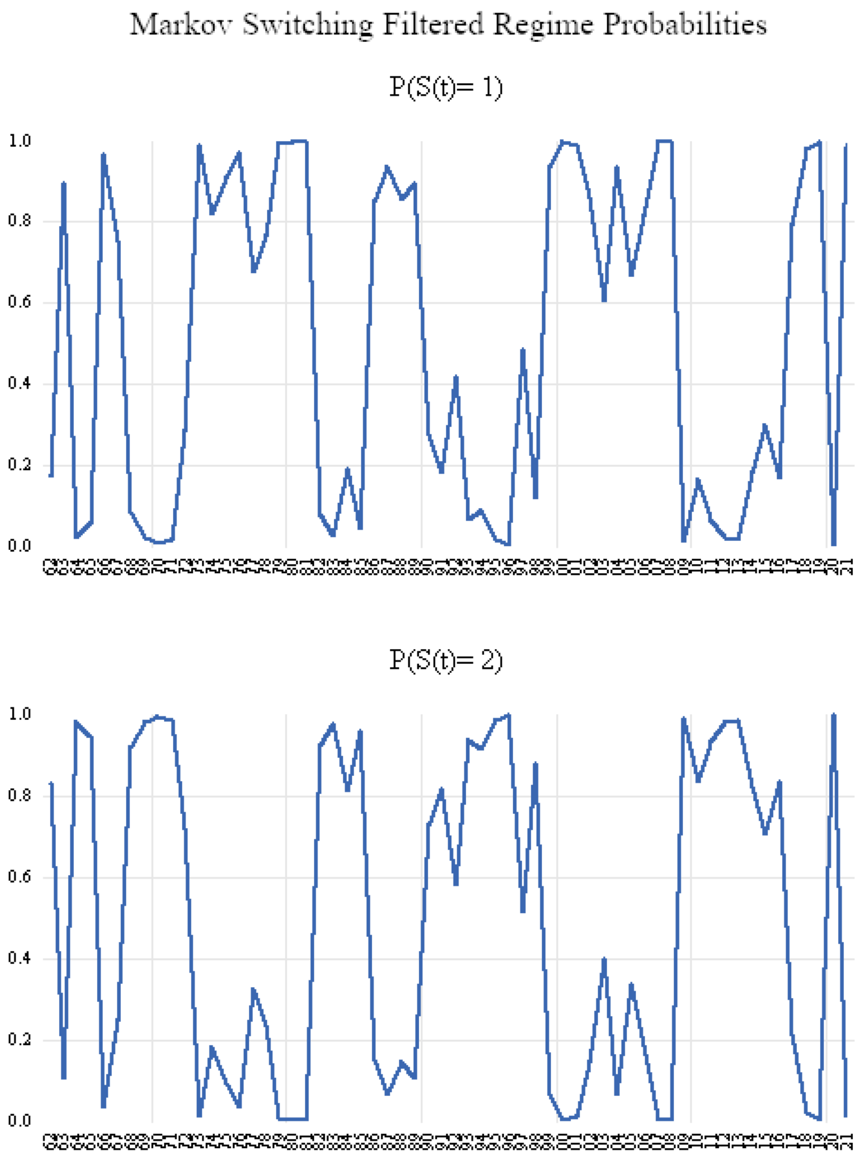


Figure 58: Filtered Regime Probabilities of Exports.

According to Fig. 58, in Regime 1 the probability to stay in growth is high in 1973-1981, 2000-2008, 2017-2019 and 2021, while Regime 2 has high probability for recession or crisis in 1968-2072, 1992-1998 and 2009-2016. The predominant phenomena that characterize these periods are the dictatorship of 1967-1974, Recovery and Euro Euphoria of 1994-2007, Great Depression of 2008-2016 [Alogoskoufis, 2021] and the advent of the pandemic. The insecurity resulting from the take by the Greek military junta in 1967 caused a break in the growth rate in the first two years, which was reflected in Exports too. The period of intensive growth in exports was that of 1973-1981, when the exports of goods increased almost ten-fold, showing an average annual growth of 34% in current prices [Magoulios & Athianos, 2013].

6.2.5 Imports

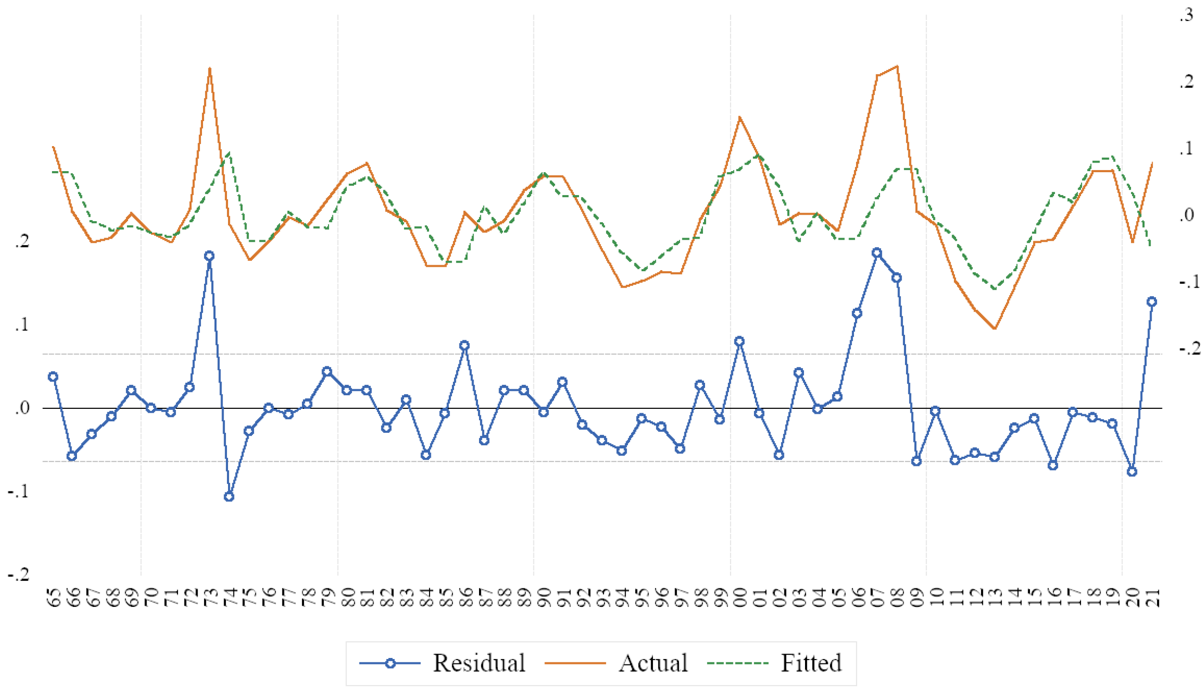


Figure 59: Actual vs Estimated data from Markov Switching of Imports.

In Fig. 59 the actual, fitted, and residual series of Imports are illustrated for 1960-2021. In general, the estimated series fits well the actual data, except for a negative shock in 1974, which follows a spike in Imports in 1973. Imports also peak at 2007-2008 towards the end of Euro Euphoria and ahead of the Great Depression, when Imports started shrinking and reached a low in 2013-2014.

In Table 23 the statistical estimation of Imports is shown. In Regime 1, the coefficient is estimated as $\boldsymbol{a_0} = \mathbf{0.132}$, while in Regime 2 it is $\boldsymbol{a_0} + \boldsymbol{a_1} = \mathbf{-0.016}$. The P-Values are $\mathbf{0.0000}$ and $\mathbf{0.0074}$, respectively, which are both less than $\mathbf{5\%}$, and thus statistically significant. Regime 1 corresponds to growth or a normal period, while Regime 2 characterizes crisis or recession. Lastly, $\boldsymbol{\beta_1} = \mathbf{0.8}$, $\boldsymbol{\beta_2} = \mathbf{-0.37}$, $\boldsymbol{\beta_3} = \mathbf{-0.11}$, $\boldsymbol{\beta_4} = \mathbf{0.24}$ and $\boldsymbol{\beta_5} = \mathbf{-0.45}$ are the common AR coefficients in both dynamic states. More autoregressive terms are introduced for Imports to achieve convergence. From Table 24, we observe that in Regime 1 the probability to remain in this state is 38.5%, while the probability to change state is 61.5%. In Regime 2 the probability to remain in this state is 92.5%, while the probability of transition is 7.5%. The period of crisis and recession lasts 13.3 years, while the normal period or period of growth has 1.6 years duration.

Table 23: Markov Switching Statistical Estimation of Imports.

Dependent Variable: LOG_M_CYCLE
Method: Markov Switching Regression (BFGS / Marquardt steps)
Date: 03/24/23 Time: 15:43
Sample (adjusted): 1965 2021
Included observations: 57 after adjustments
Number of states: 2
Initial probabilities obtained from ergodic solution
Standard errors & covariance computed using observed Hessian
Random search: 25 starting values with 10 iterations using 1 standard deviation (rng=kn, seed=790090216)
Convergence achieved after 16 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	0.132538	0.018314	7.236910	0.0000
		Regime 2		
C	-0.016480	0.006150	-2.679770	0.0074
		Common		
AR(1)	0.803459	0.134571	5.970501	0.0000
AR(2)	-0.371746	0.183592	-2.024843	0.0429
AR(3)	-0.105146	0.203983	-0.515466	0.6062
AR(4)	0.238641	0.193059	1.236105	0.2164
AR(5)	-0.454600	0.148080	-3.069960	0.0021
LOG(SIGMA)	-3.339124	0.105257	-31.72366	0.0000
		Transition Matrix Parameters		
P11-C	-0.468462	0.993555	-0.471500	0.6373
P21-C	-2.512706	0.580721	-4.326875	0.0000

Mean dependent var	0.001119	S.D. dependent var	0.080463
S.E. of regression	0.064214	Sum squared resid	0.202045
Durbin-Watson stat	1.649747	Log likelihood	91.84968
Akaike info criterion	-2.871919	Schwarz criterion	-2.513489
Hannan-Quinn criter.	-2.732621		

Inverted AR Roots	.78-.50i	.78+.50i	.01+.83i	.01-.83i
	-.76			

According to Fig. 60, in Regime 1 the probability to stay in a period of growth is high in 1973 and 2006-2008, towards the end of the dictatorship and the end of the Euro Euphoria. In 1973, the Greek economy was seriously affected by the sudden increase of oil prices, which ushered in a period of international inflation. The abrupt change in price was at a large extent caused by the sudden lifting of the strict price control, which was followed inflexibly by the military regime to keep the cost of living down [New York Times, 1976]. In 1973, capital goods imports came to exceed consumer goods imports for the first time, while in 1975, the share of the EEC-9 in Greek imports of manufactured goods was over 60% [Tsakas, 2018].

Table 24: Markov Transition Probabilities of Imports.

Transition summary: Constant Markov transition probabilities and expected durations
Sample (adjusted): 1965 2021
Included observations: 57 after adjustments

Constant transition probabilities:
P(i, k) = P(s(t) = k | s(t-1) = i)
(row = i / column = k)

	1	2
1	0.384980	0.615020
2	0.074972	0.925028

Constant expected durations:

1	2
1.625964	13.33827

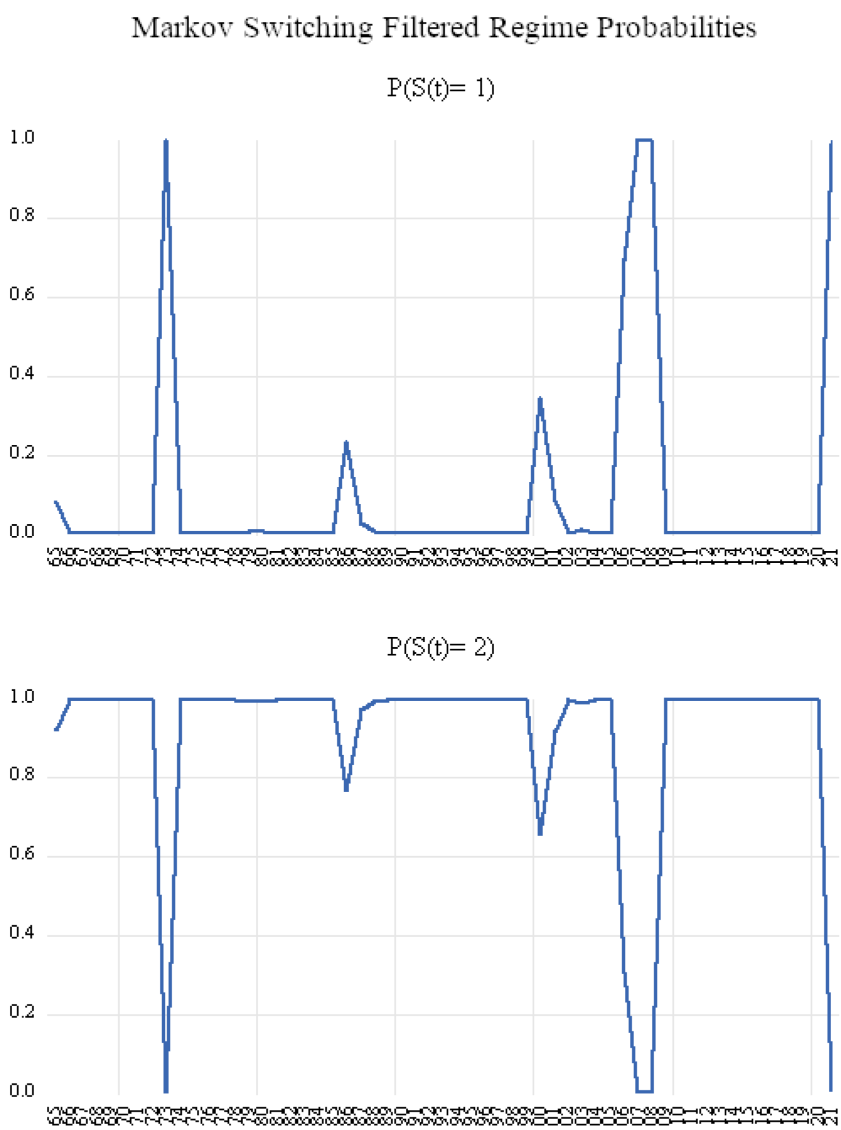


Figure 60: Filtered Regime Probabilities of Imports.

6.2.6 Investment

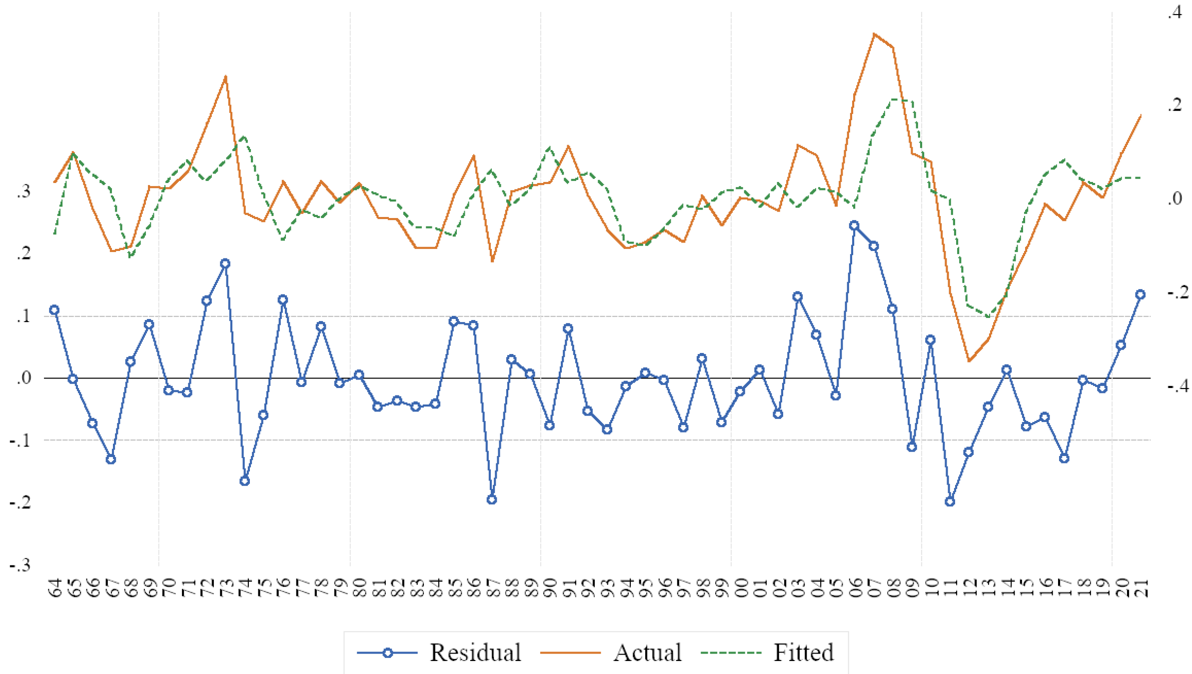


Figure 61: Actual vs Estimated data from Markov Switching of Investment.

In Fig. 61 the actual, fitted, and residual series of Investment are illustrated for 1960-2021. In general, the estimated series fits well the actual data, except for negative shocks in 1974, 1987 and 2011. Investment peaks in 1973 and 2006-2008, while it is descending in 2009-2013 and reaches the lowest point in 2012-2013. The investment between 2009 and 2013 was impacted by the increase in funding costs due to the sudden stop, but thereafter private-sector credit risk, fiscal austerity, and price-markup shocks have been more relevant drivers [Hua et al., 2022].

In Table 25 the statistical estimation of Investment is shown. In Regime 1, the coefficient is estimated as $\boldsymbol{a_0 = 0.14}$, while in Regime 2 it is $\boldsymbol{a_0 + a_1 = -0.04}$. The P-Values are $\mathbf{0.0000}$ and $\mathbf{0.0028}$, respectively, which are less than $\mathbf{5\%}$ and thus statistically significant. To sum up, Regime 1 characterizes growth or a normal state of the economy, while Regime 2 denotes crisis or recession. Lastly, $\boldsymbol{\beta_1 = 0.67}$, $\boldsymbol{\beta_2 = -0.39}$, $\boldsymbol{\beta_3 = -0.6}$ and $\boldsymbol{\beta_4 = -0.05}$ are the common AR coefficients in both dynamic states.

From Table 26, we observe that in Regime 1 the probability to remain in this state is 52.7%, while the probability to change state is 47.3%. In Regime 2 the probability to remain in this state is 85.5%, while the probability of transition is 14.5%. The period of crisis and recession lasts 6.9 years, while the normal period or period of growth lasts 2.1 years.

Table 25: Markov Switching Statistical Estimation of Investment.

Dependent Variable: LOG_I_CYCLE
Method: Markov Switching Regression (BFGS / Marquardt steps)
Date: 03/24/23 Time: 15:20
Sample (adjusted): 1964 2021
Included observations: 58 after adjustments
Number of states: 2
Initial probabilities obtained from ergodic solution
Standard errors & covariance computed using observed Hessian
Random search: 25 starting values with 10 iterations using 1 standard deviation (rng=kn, seed=1575381279)
Convergence achieved after 20 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	0.142352	0.019989	7.121357	0.0000
		Regime 2		
C	-0.042842	0.014353	-2.984902	0.0028
		Common		
AR(1)	0.666663	0.154232	4.322475	0.0000
AR(2)	0.391840	0.165479	2.367907	0.0179
AR(3)	-0.599135	0.135896	-4.408774	0.0000
AR(4)	-0.049437	0.143944	-0.343445	0.7313
LOG(SIGMA)	-2.901999	0.114559	-25.33190	0.0000
		Transition Matrix Parameters		
P11-C	0.106239	0.606970	0.175033	0.8611
P21-C	-1.770674	0.461855	-3.833829	0.0001

Mean dependent var	0.002688	S.D. dependent var	0.126520
S.E. of regression	0.099487	Sum squared resid	0.504779
Durbin-Watson stat	1.709371	Log likelihood	58.75621
Akaike info criterion	-1.715731	Schwarz criterion	-1.396007
Hannan-Quinn criter.	-1.591192		

Inverted AR Roots	.75+.50i	.75-.50i	-.08	-.76

According to Fig. 62, in Regime 1 the probability to stay in a growth period is high in 1972-1973 and 2003-2008, which overlap with the last years of the dictatorship and the last period of Euro Euphoria ahead of the Great Global Depression. The 1967–1973 period was marked by high rates of economic growth coupled with low inflation and low unemployment. Economic growth was driven by investment in the tourism industry, public spending, and pro-business incentives that fostered both domestic and foreign capital spending. Investment grew in 2000’s, while its rate plunged following the Sovereign Debt Crisis (SDC) and remained one of the lowest in the world in 2019 [Hua et al., 2022].

Table 26: Markov Transition Probabilities of Investment.

Transition summary: Constant Markov transition probabilities and expected durations
Sample (adjusted): 1964 2021
Included observations: 58 after adjustments

Constant transition probabilities:
P(i, k) = P(s(t) = k | s(t-1) = i)
(row = i / column = k)

	1	2
1	0.526535	0.473465
2	0.145458	0.854542

Constant expected durations:

	1	2
	2.112088	6.874814

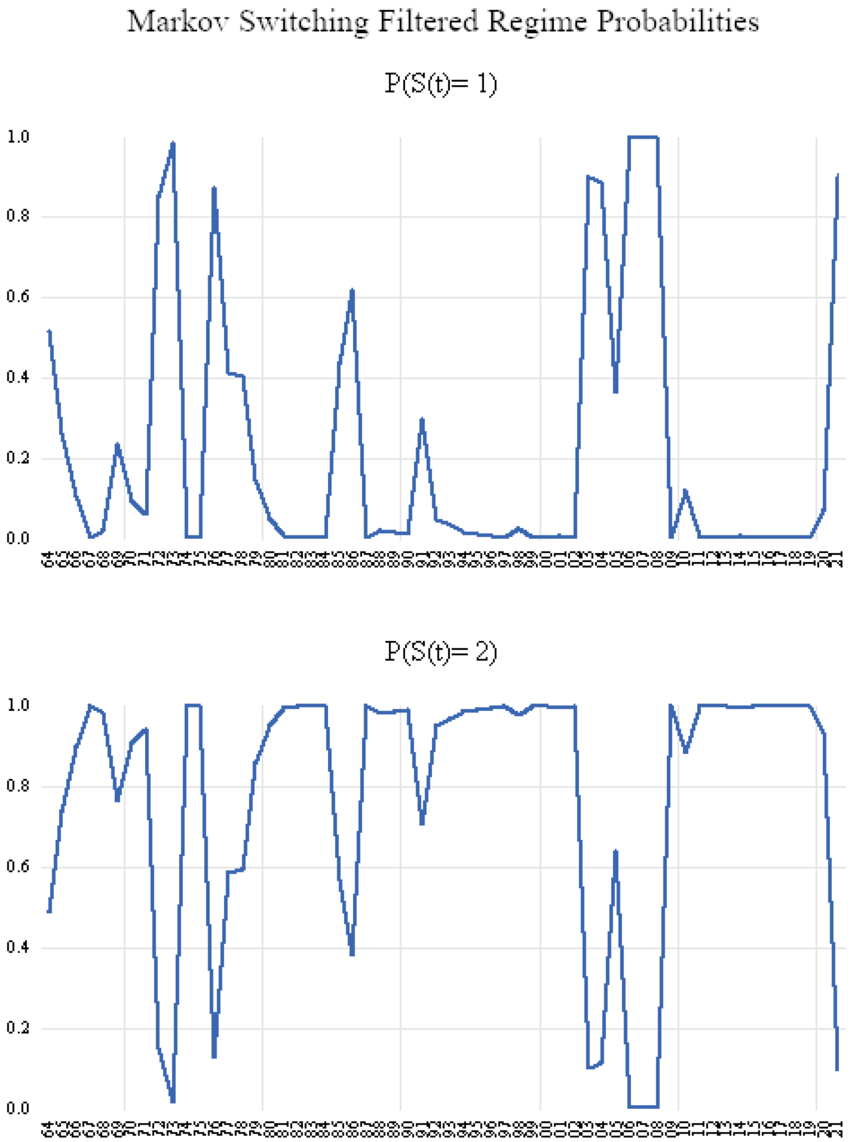


Figure 62: Filtered Regime Probabilities of Investment.

6.3 Fast Fourier Transform (FFT)

In this section the macroeconomic variables are analyzed in the frequency domain using Fast Fourier Transform (FFT). This approach differs from all other techniques in this chapter, which take place in the time domain. The hypothesis to be examined is whether analyzing the data in the frequency domain can give a better estimation and interpretation of the business cycle for GDP and its determinant variables.

The dominant cycle is a crude approximation of the actual data due to its simplicity. In theory, an infinite number of frequencies need to be integrated in FFT to exactly reproduce the actual data. Despite the coarse approximation, the dominant cycle is popular in macroeconomics [Thomson and Van Vuuren, 2016], as it captures the prevalent pattern and frequency of the macroeconomic business cycle and in turn it may generalize better to new data.

The following analysis is conducted in the frequency domain, where the highest point of the spectrum corresponds to the dominant frequency, which in turn defines the dominant cycle. Based on [Cooley & Tukey, 1965], the FFT algorithm shares a transform of length N among growingly smaller pieces, also known as decimation in the time and the frequency domain. After identifying the dominant frequency, the dominant cycle $\boldsymbol{D}$ of the examined variable can be written in polar coordinates $(\boldsymbol{r}, \boldsymbol{\theta})$ as:

$$\boldsymbol{D} = \boldsymbol{r} * \sin\left(\left(2\boldsymbol{\pi} * {}^{\boldsymbol{m}}/_{\boldsymbol{K}}\right) * \boldsymbol{t} + \boldsymbol{\theta}\right), \tag{8}$$

where $\boldsymbol{r}$ is the height of the cycle, $\boldsymbol{\theta}$ is the phase, $\boldsymbol{m}$ is the position of the maximum, $\boldsymbol{K} = \boldsymbol{62}$ is the number of examined years and $\boldsymbol{T} = {}^{\boldsymbol{K}}/_{\boldsymbol{m}}$ is the period of the dominant cycle. These values are computed from the magnitude $\boldsymbol{r}$ and angle $\boldsymbol{\theta}$ of the complex number at position of maximum value $\boldsymbol{m}$ in the spectrum.

6.3.1 GDP

In Fig. 63 the spectrum of GDP peaks at position $\boldsymbol{m} = \boldsymbol{4}$, which corresponds to period $\boldsymbol{T} = {}^{\boldsymbol{62}}/_{\boldsymbol{4}} = \boldsymbol{15.5}$ years. Given the point of maximum in the spectrum represented as a complex number, whose magnitude $\boldsymbol{r} = \boldsymbol{0.0706}$ and angle $\boldsymbol{\theta} = \boldsymbol{0.4195}$ define the height and phase, the dominant cycle $\boldsymbol{Y_D}$ can be written as follows:

$$Y_D = 0.0706 * \sin\left(\left(2\pi * {}^{4}/_{62}\right) * t + 0.4195\right). \tag{9}$$

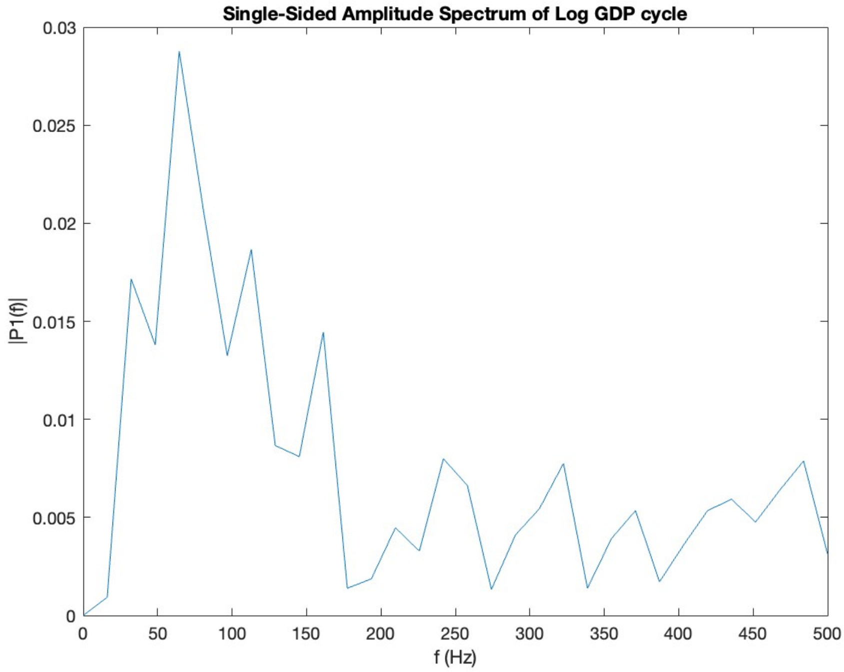


Figure 63: GDP Spectrum (Frequency Domain).

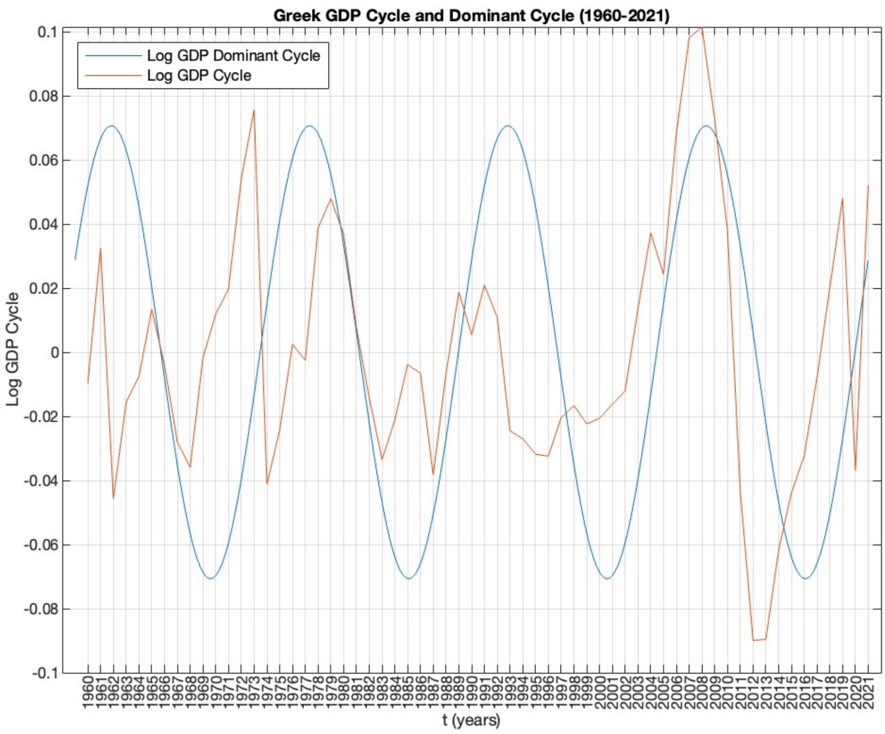


Figure 64: GDP and Dominant Cycle (Time Domain).

In Fig. 64 the GDP cycle is shown along with its dominant cycle. The period of the dominant cycle is $\boldsymbol{T = 15.5}$ years, where the last period starts in 2006 until 2021. The model captures the growth of the Greek economy (i.e., recovery and expansion) from 2001 until 2008, the peak in 2009 and then the recession from 2009 to 2016. Based on the model a trough is observed in 2016, while in practice there is a 3-year lag compared to the actual trough of the economy in 2012-2013. Next, recovery and expansion follow from 2017 to 2021. The GDP dominant cycle does not capture the downturn of the economy in 2020 when the pandemic started. In the previous years the model presents high residual for instance at the peak of the cycle in 1977, which follows the actual peak of 1973 at the end of the dictatorship.

6.3.2 Consumption

In Fig. 65 the spectrum of Consumption peaks at position $\boldsymbol{m = 5}$, which corresponds to period $\boldsymbol{T = {}^{62}\!/_{5} = 12.4}$ years. Given the point of maximum in the spectrum represented as a complex number, whose magnitude $\boldsymbol{r = 0.0845}$ and angle $\boldsymbol{\theta = 0.3029}$ define the height and phase, the dominant cycle $\boldsymbol{C_D}$ can be written as follows:

$$\boldsymbol{C_D = 0.0845 * \sin\left(\left(2\pi * {}^{5}\!/_{62}\right) * t + 0.3029\right)} \qquad \textbf{(10)}$$

In Fig. 66 the Consumption business cycle is shown along with its dominant cycle. The dominant cycle shows growth from 2005-2011, recession from 2012-2017 and recovery from 2018-2021. There is an observed lag compared to the actual data, wherein a peak occurs in 2008 and a trough in 2013. This lag can be attributed to the coarse nature of the dominant cycle.

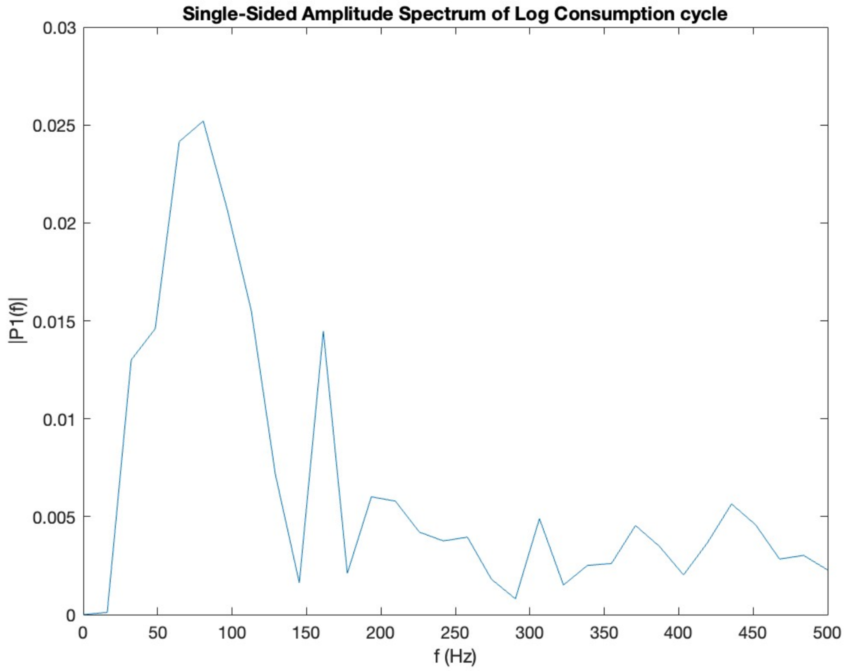


Figure 65: Consumption Spectrum (Frequency Domain).

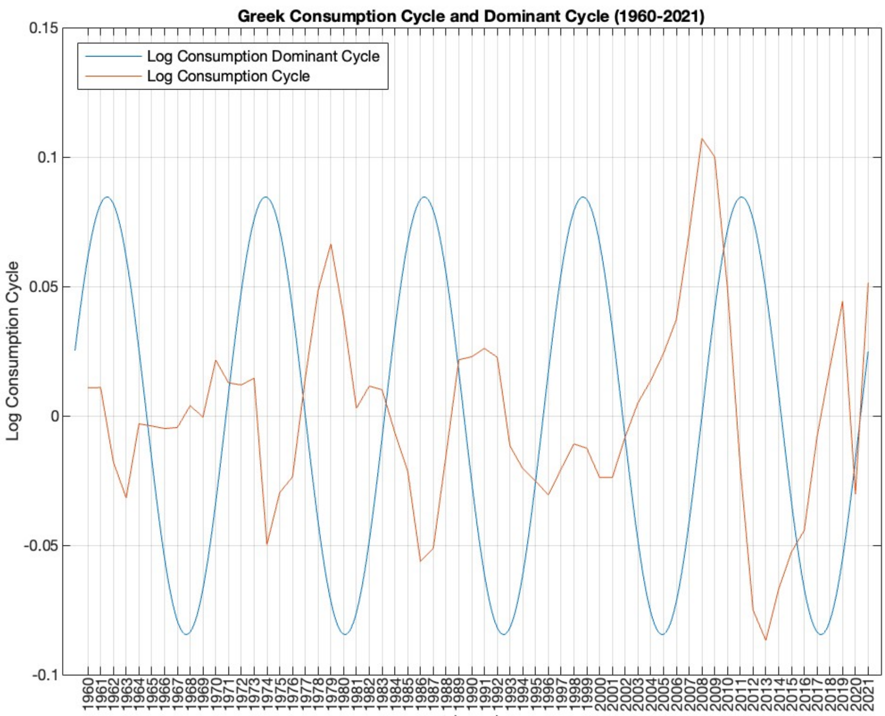


Figure 66: Consumption and Dominant Cycle (Time Domain).

6.3.3 Government Expenditure

In Fig. 67 the spectrum of Government Expenditure peaks at position $\boldsymbol{m} = \mathbf{6}$, which corresponds to period $\boldsymbol{T} = {}^{\mathbf{62}}/_{\mathbf{6}} = \mathbf{10.3}$ years. Given the point of maximum in the spectrum represented as a complex number, whose magnitude $\boldsymbol{r} = \mathbf{0.0995}$ and angle $\boldsymbol{\theta} = \mathbf{0.2353}$ define the height and phase, the dominant cycle $\boldsymbol{G_D}$ can be written as follows:

$$\boldsymbol{G_D} = \mathbf{0.0995} * \mathbf{sin}\left(\left(\mathbf{2}\boldsymbol{\pi} * {}^{\mathbf{6}}/_{\mathbf{62}}\right) * \boldsymbol{t} + \mathbf{0.2353}\right) \quad \mathbf{(11)}$$

In Fig. 68 the Government Expenditure business cycle is shown along with its dominant cycle. The two waveforms of the actual and fitted data are not well aligned in this case, which can be attributed to the fact that many frequencies in the spectrum have large magnitude in comparison to the dominant frequency. Adding these frequencies in the FFT model can further enhance the approximation of the actual data.

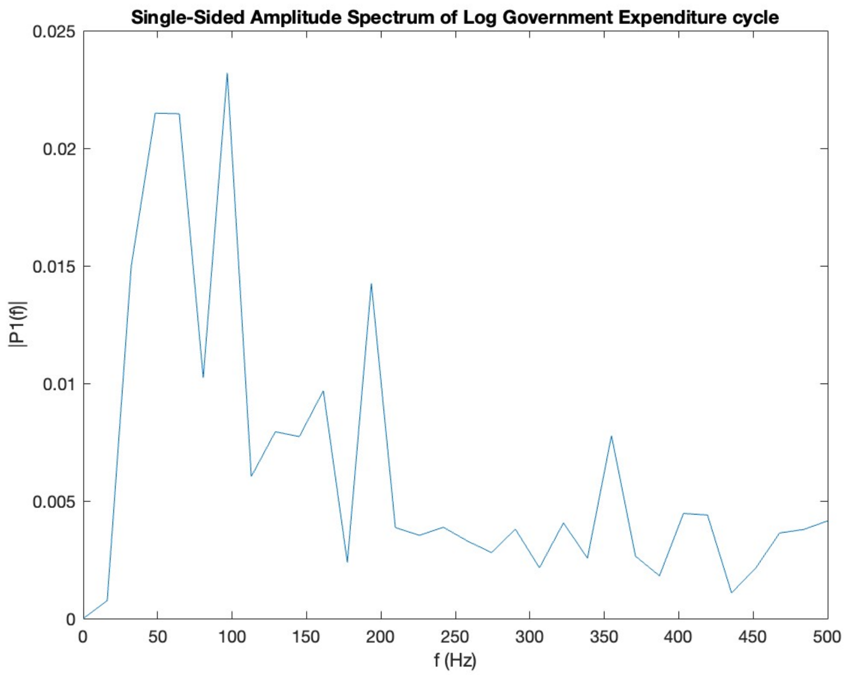


Figure 67: Government Expenditure Spectrum (Frequency Domain).

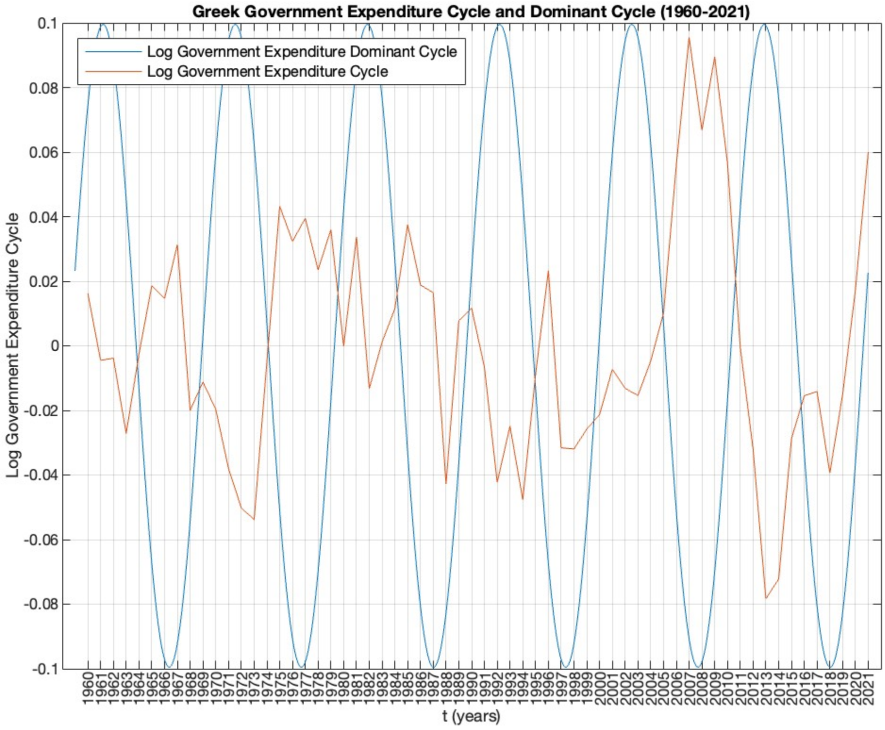


Figure 68: Government Expenditure and Dominant Cycle (Time Domain).

6.3.4 Exports

In Fig. 69 the spectrum of Exports peaks at position $\boldsymbol{m = 9}$, which corresponds to period $\boldsymbol{T = {}^{62}/_{9} = 6.9}$ years. Given the point of maximum in the spectrum represented as a complex number, whose magnitude $\boldsymbol{r = 0.1550}$ and angle $\boldsymbol{\theta = 0.3576}$ define the height and phase, the dominant cycle $\boldsymbol{X_D}$ can be written as follows:

$$\boldsymbol{X_D = 0.1550 * \sin\left(\left(2\pi * {}^{9}/_{62}\right) * t + 0.3576\right)} \qquad \textbf{(12)}$$

In Fig. 70 the Exports business cycle is shown along with its dominant cycle. Overall, in this period the dominant cycle is lagging about 2-3 years compared to the actual business cycle. For instance, the predicted troughs of 1971 and 1984 are lagging compared to the actual troughs of 1969 and 1983, when the Exports reached a low. These years overlap with the dictatorship and the period that Greece joined the European Community due to low competitiveness and expensive labor cost, respectively.

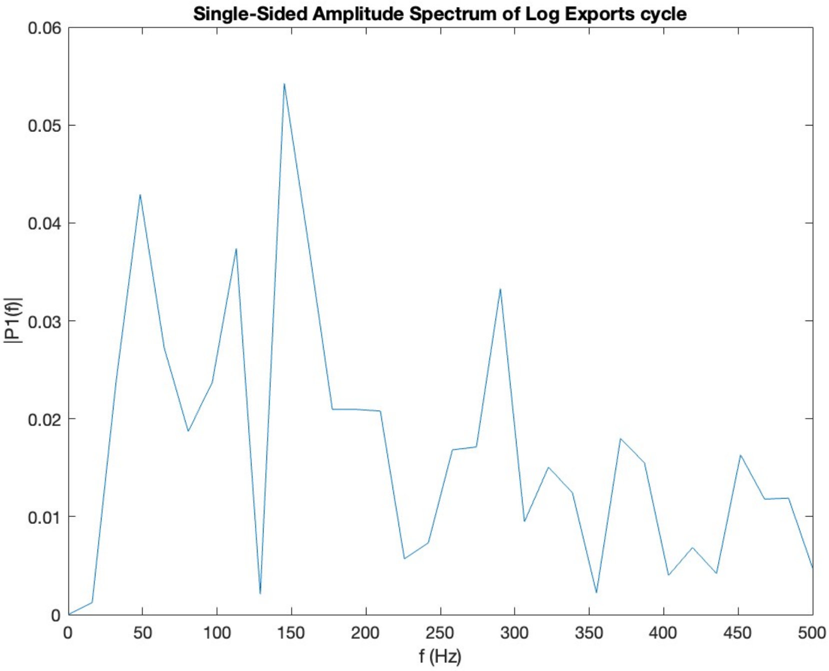


Figure 69: Exports Spectrum (Frequency Domain).

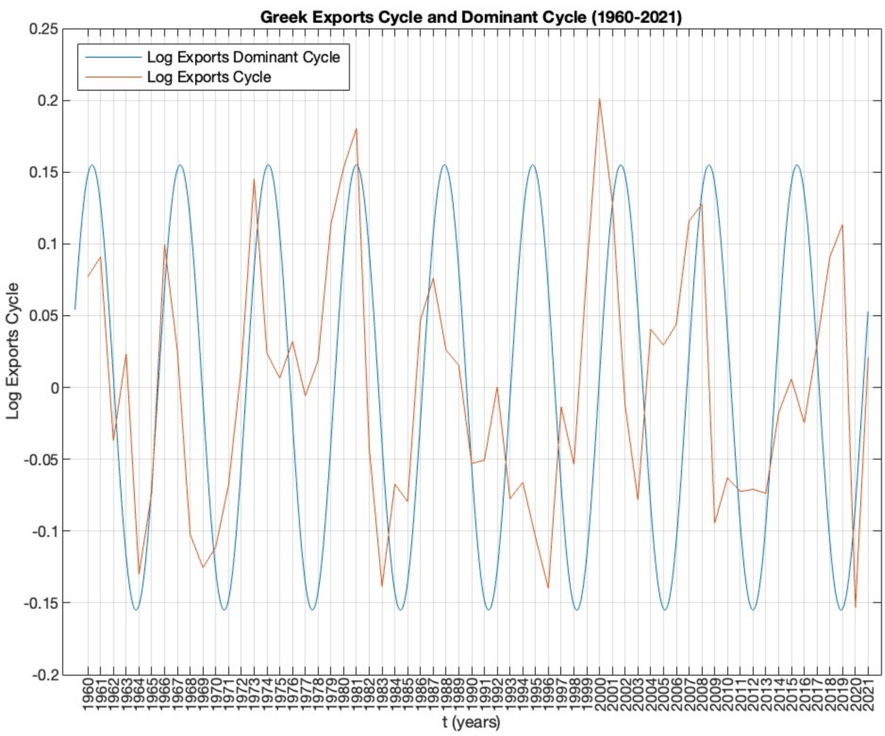


Figure 70: Exports and Dominant Cycle (Time Domain).

6.3.5 Imports

In Fig. 71 the spectrum of Exports peaks at position $\boldsymbol{m} = \mathbf{7}$, which corresponds to period $\boldsymbol{T} = \mathbf{62}/\mathbf{7} = \mathbf{8.9}$ years. Given the point of maximum in the spectrum represented as a complex number, whose magnitude $\boldsymbol{r} = \mathbf{0.1301}$ and angle $\boldsymbol{\theta} = \mathbf{0.5196}$ define the height and phase, the dominant cycle $\boldsymbol{M_D}$ can be written as follows:

$$\boldsymbol{M_D} = \mathbf{0.1301} * \mathbf{sin}\left(\left(\mathbf{2\pi} * \mathbf{7}/\mathbf{62}\right) * \boldsymbol{t} + \mathbf{0.5196}\right) \qquad \textbf{(13)}$$

In Fig. 72 the Imports business cycle is shown along with its dominant cycle. As opposed to Exports, the dominant cycle here appears to be leading the actual business cycle. For instance, the predicted peaks in 1961, 1969, 1978 are leading the actuals in 1965, 1973 and 1981, respectively. This shift pinpoints to a 3-4 year lag of the dominant business cycle.

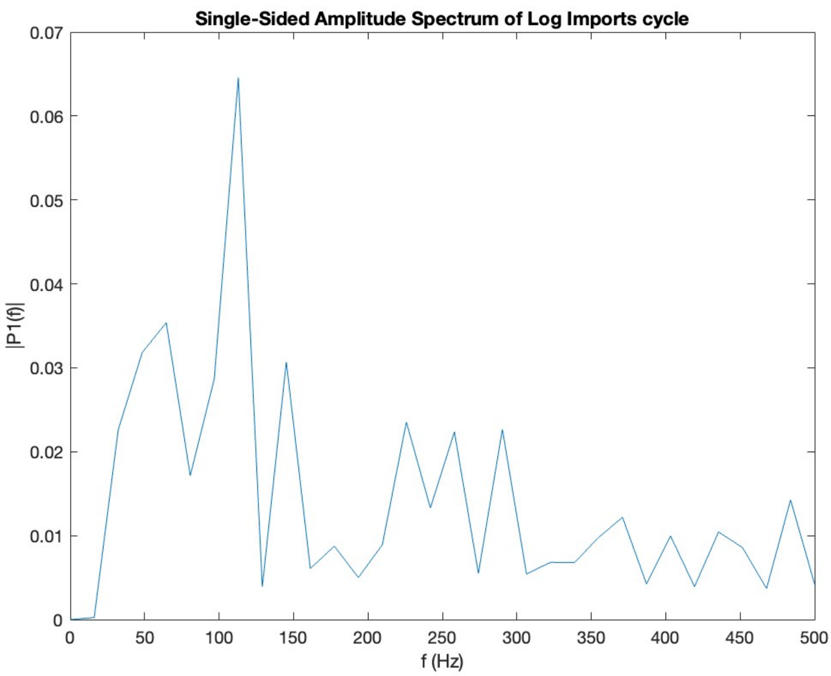


Figure 71: Imports Spectrum (Frequency Domain).

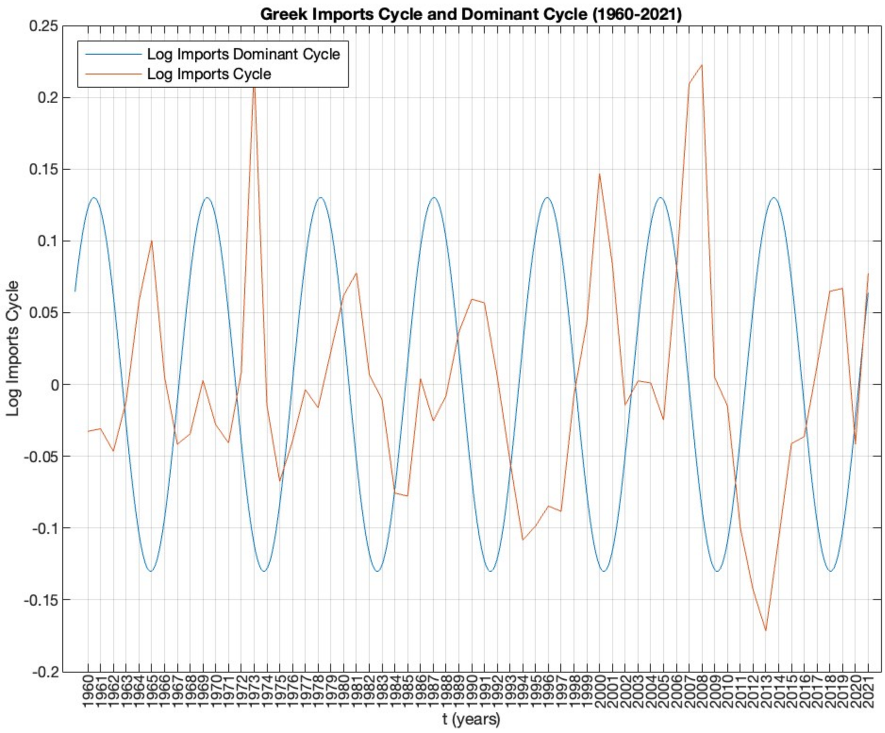


Figure 72: Imports and Dominant Cycle (Time Domain).

6.3.6 Investment

In Fig. 73 the spectrum of Investment peaks at position $\boldsymbol{m} = \mathbf{4}$, which corresponds to period $\boldsymbol{T} = {}^{\mathbf{62}}/_{\mathbf{4}} = \mathbf{15.5}$ years. Given the point of maximum in the spectrum represented as a complex number, whose magnitude $\boldsymbol{r} = \mathbf{0.1136}$ and angle $\boldsymbol{\theta} = \mathbf{0.9669}$ define the height and phase, the dominant cycle $\boldsymbol{I_D}$ can be written as follows:

$$\boldsymbol{I_D} = \mathbf{0.1136} * \mathbf{sin}\left(\left(\mathbf{2\pi} * {}^{\mathbf{4}}/_{\mathbf{62}}\right) * \boldsymbol{t} + \mathbf{0.9669}\right) \quad \textbf{(14)}$$

In Fig. 74 the Investment business cycle is shown along with its dominant cycle. In this case the two cycles are better aligned, while the period is larger than the previous indicators and the same as GDP. In the last 15.5-year period, the business cycle follows closely the actual events, where the investment grows from 2000-2007, it peaks in 2007 and then Greece enters in recession from 2008 to 2015. Finally, recovery and expansion are observed in 2015-2021. One deviation from the actual data occurs with the trough of 2012 when the FFT approximation is characterized by a 3-year lag.

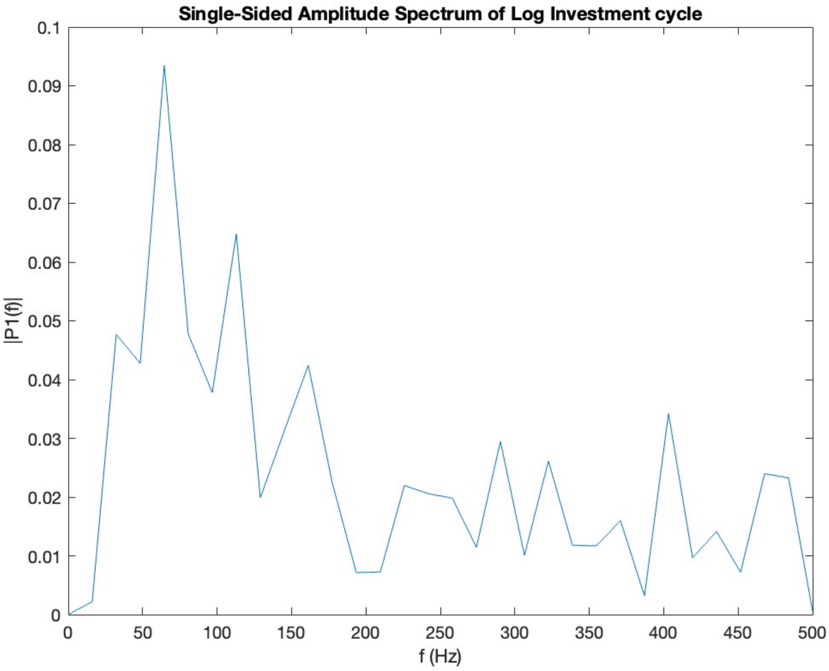


Figure 73: Investment Spectrum (Frequency Domain).

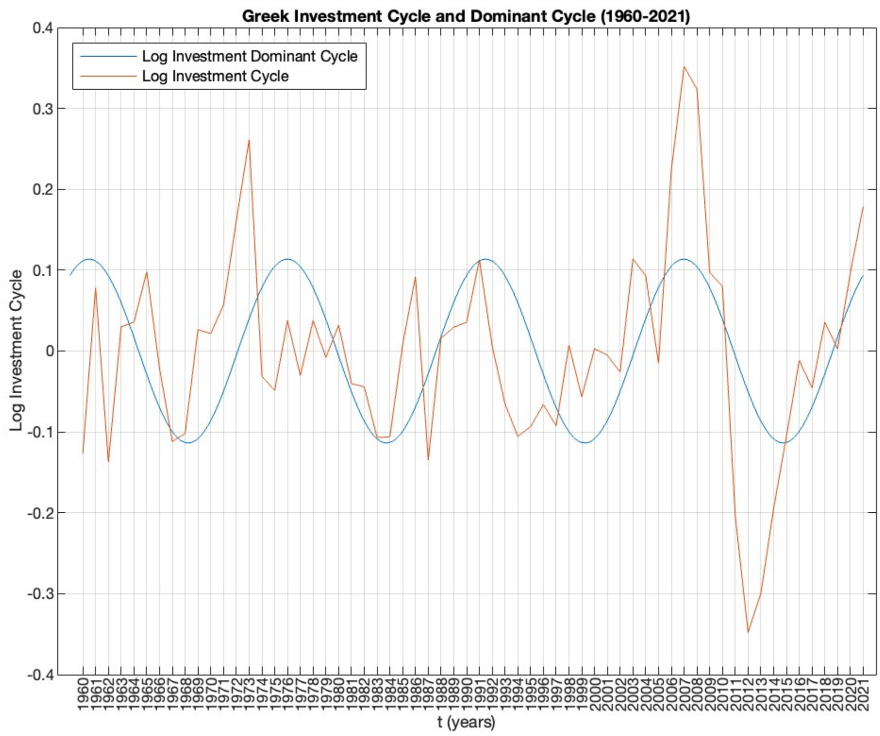


Figure 74: Investment and Dominant Cycle (Time Domain).

6.4 Vector Autoregressive (VAR)

In this section VAR (Vector Autoregressive) is used to model the dependencies of macroeconomic variables of the Greek business cycle both as temporal dependencies of individual variables as well as correlation across co-integrated variables. This model is added to our dissertation for further research because of the functionality of the model to explicitly include more than one variable as determinant factors for GDP. VAR is a statistical model for multivariable time series analysis, where the variables have a relationship that affects each other over time. The predictions made by the model are dependent on the past values of multiple cointegrated indicators. The main difference with ARMA is that the latter one is used for univariate time series. Its popularity for analyzing the dynamics of economic systems rose due to the influential work by Sims (1980). It is suitable for estimation and forecasting and given the leading indicators provides the simplest model to coincident variables (Central Bank of Iceland, 2007).

GDP, Consumption, Government Expediture, Investment, Exports and Imports are selected to explore co-dependencies for the VAR model as cointegrated variables based on Sec. 4.15. We progressively increase the number of co-dependent variables in order to test the hypothesis that more indicators can increase the predictive power of the model. To compare the latter the forecast error of GDP is used. Initially GDP and Consumption are introduced in the formulation, while subsequently Government Expenditure and Investment are added and finally Export and Imports for a 6-variable VAR.

6.4.1 Estimation and Forecasting with 2-variable VAR

For the initial formulation GDP and Consumption are used. Four different VAR systems are created based on the number of autoregressive terms and whether the autoregressive matrix is full or diagonal. In specific, the following models are explored:

- VAR2diag: 2 autoregressive terms and diagonal autoregressive matrix
- VAR2full: 2 autoregressive terms and full autoregressive matrix
- VAR4full: 4 autoregressive terms and full autoregressive matrix
- VAR6full: 6 autoregressive terms and full autoregressive matrix

To estimate the model parameters for each variant, the time series is divided into three periods: presample, estimation, and forecast. The presample period is used to estimate the parameters in Eq. 6 in Sec. 3.2.2.1. Subsequently, the fitted models perform prediction for the forecast period and the forecast data are compared to the actual data to compute the prediction error.

For this analysis the presample period is chosen to be as the first ten years from the 62-year data sample (i.e., 1960-1969), while the last five years are used for forecasting (i.e., 2017-2021). The remaining 47 years are used for model estimation (i.e., 1970-2016).

In the implementation of VAR2diag, MATLAB sets the off diagonal elements as 0 and fixed during estimation, while the main diagonals consist of numerical values. In contrast, the specifications for VAR2full and VAR4full have matrices composed of numerical values, since all elements of the autoregressive matrices are parameters to be estimated.

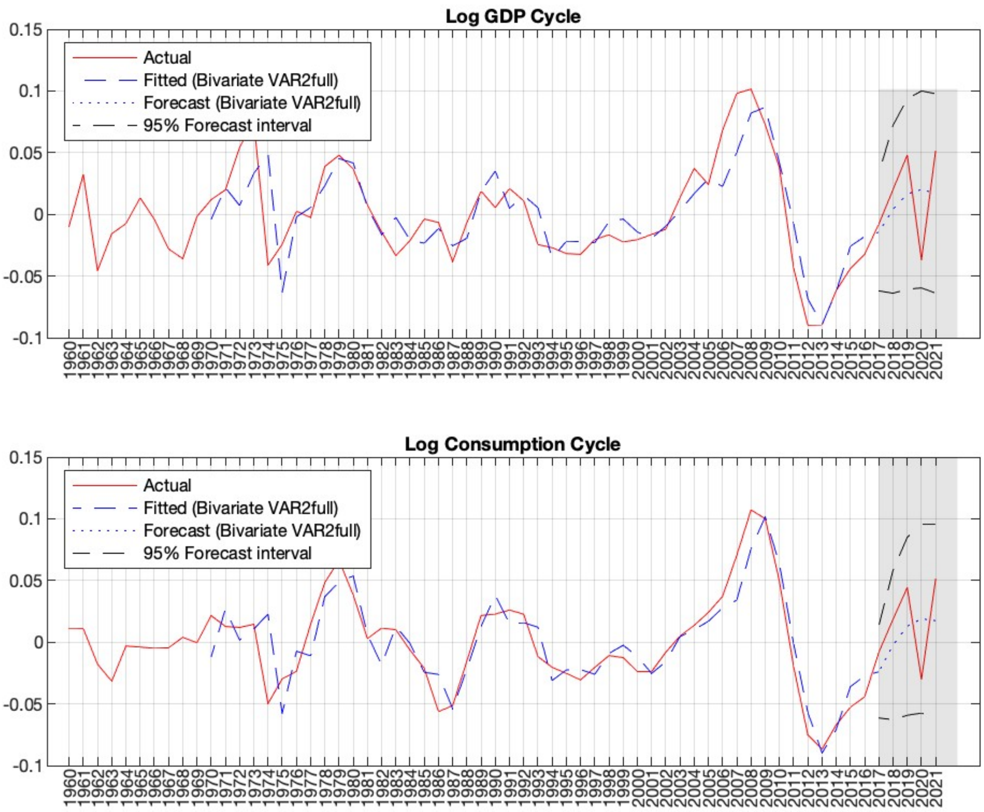


Figure 75: Actual, fitted and forecast data from VAR2full for GDP and Consumption.

To check the model adequacy across these bivariate VAR variants, three criteria are used: 1) Test for stability and invertability, 2) Likelihood ratio test for pair-wise comparison, and 3) Akaike information criterion for the best model in a set.

First, it is checked whether the estimated models are AR-stationary. This provides evidence that the estimated model is stable and invertible. All models are shown to be AR-stationary.

Second, likelihood ratio test is conducted for pair-wise comparison of the estimated models. The test rejects or fails to reject the hypothesis that the restricted model is adequate, with a default 5% tolerance. In that case, the restricted VAR(2) model, VAR2diag, is compared with the unrestricted VAR(2) model, VAR2full. This criterion returns ‘1’, which indicates that the likelihood ratio test rejects the restricted VAR(2) model in favor of the unrestricted VAR(2) model. After all pair-wise comparisons: VAR6full>VAR2full>VAR4full>VAR2diag. In sum, the unrestricted VAR(6) model demonstrates higher adequacy based on this criterion.

Third, the Akaike information criterion is calculated to identify the best model in a set of four models. To find the best model in a set, the Akaike information criterion (AIC) is minimized using in-sample data. The Akaike information is computed as $AIC(\text{VAR2diag}) = -467.4016$, $AIC(\text{VAR2full}) = -473.8066$, $AIC(\text{VAR4full}) = -470.4742$ and $AIC(\text{VAR6full}) = -474.4129$. Since the AIC value is the smallest for VAR6full, the unrestricted VAR(6) model is the best, which also verifies the outcome from the likelihood ratio test.

Next, to further assess the predictive power of these models, forecasting is performed for 2017-2021 using their estimated parameters. As an out-of-sample calculation, function ‘forecast’ in MATLAB returns both a prediction of the mean time series, and an error covariance matrix that gives confidence intervals about the means.

In Fig. 76 the combined error for GDP and Consumption is computed as the sum of squared forecast errors for the two variables within the 5-year forecast period. Next in Fig. 77 the individual errors of GDP are shown for these models. Consistently, the unrestricted model, VAR2full has the smaller error for both variables. Although VAR6full showed the highest adequacy based on AIC and the likelihood ratio test, after considering the forecast errors, VAR6full seems to be overfitting on the estimation data, while VAR2full appears as the best model for forecasting in the bivariate setting.

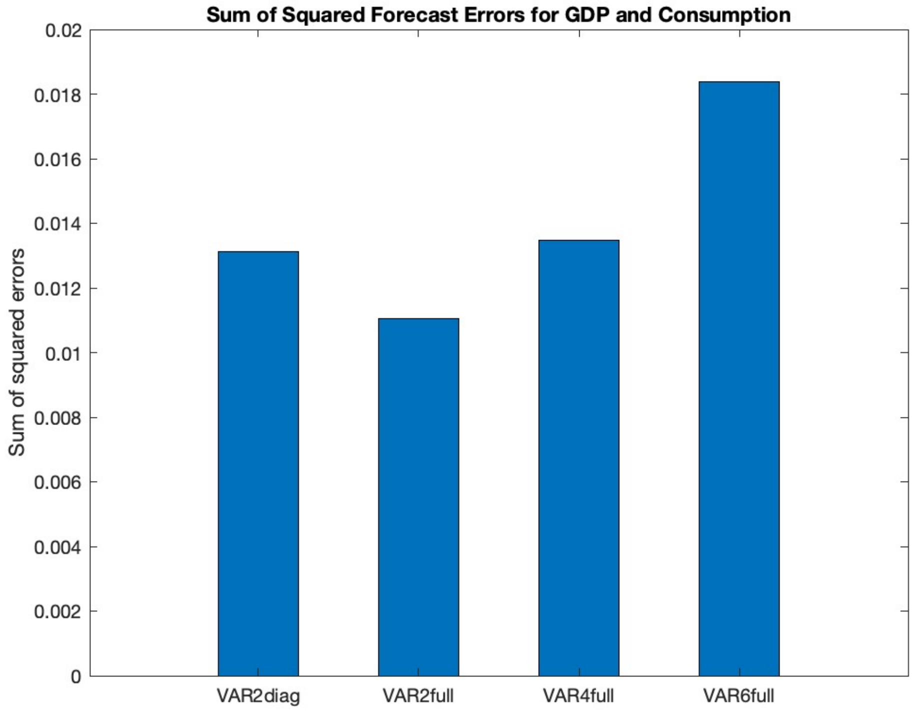


Figure 76: Combined GDP and Consumption Forecast Errors from 2-variable VAR.

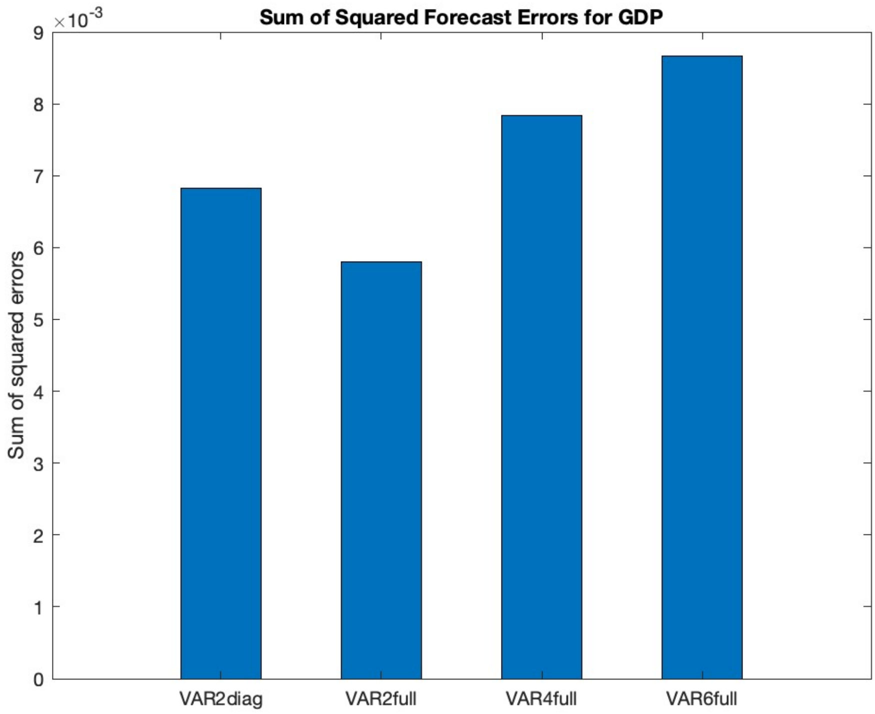


Figure 77: Individual GDP Forecast Errors from 2-variable VAR.

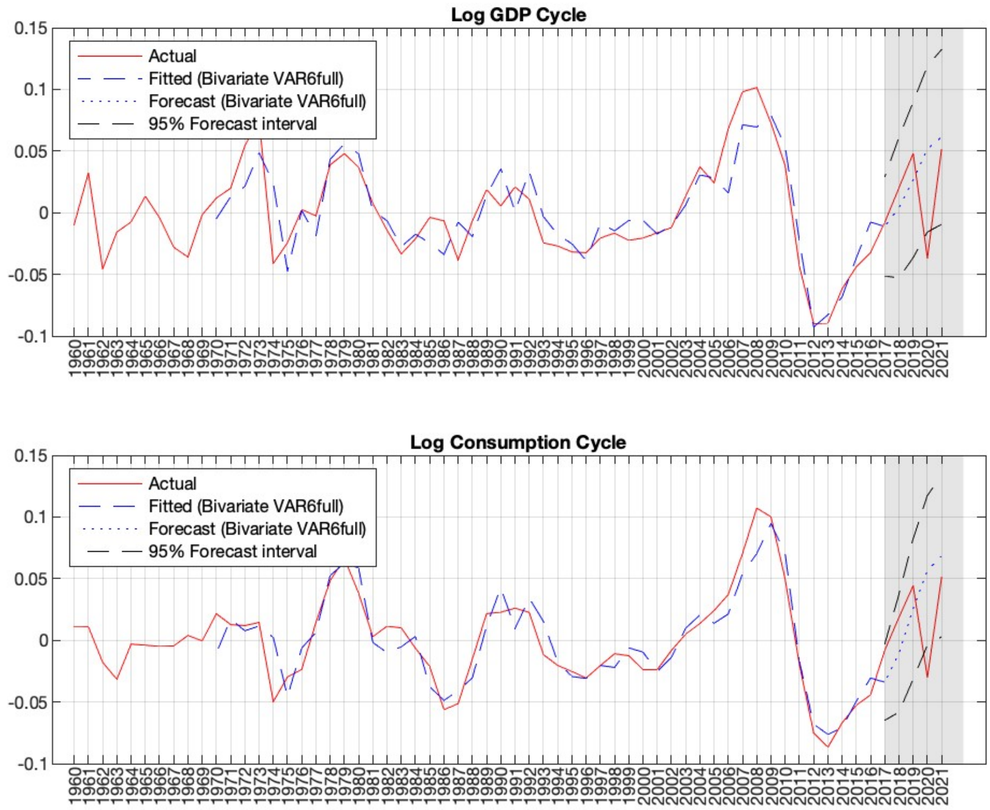


Figure 78: Actual, fitted and forecast data from VAR6full for GDP and Consumption.

The actual and fitted values for GDP and Consumption are plotted for VAR2full in Fig. 75 and VAR6full in Fig. 78. Both plots show the 2017-2021 forecast (dotted blue) along with the actual values (solid red). The fitted values are shown for 1970-2016 (dashed blue). Finally, the upper and lower bounds of the 95% forecast interval are depicted for the forecast years (dashed black).

By inspecting the GDP and Consumption forecasts for the model there are at least three observations. First, VAR2full makes better forecast than VAR6full. The additional parameters do not enable a more robust estimation that generalizes better to unseen data. Second, despite VAR6full fitting the data very well during the estimation period, this model shows strong signs of overfitting and fails to provide a reliable 5-year forecast. Third, VAR2full and VAR6full mostly succeed at including the actual data within their 95% forecast confidence interval, except for VAR6full in 2020 when the pandemic started. All in all, VAR2full is the best model for forecasting in the bivariate case.

6.4.2 Estimation and Forecasting with 4-variable VAR

Next, Government Expenditure and Investment are introduced in the VAR model to examine the hypothesis whether more variables add robustness in the GDP estimation and forecast.

To test the model adequacy, first, it is verified that all models are AR-stationary. This provides evidence that the estimated model is stable and invertible. Second, based on the likelihood ratio test it is shown that: VAR6full>VAR4full>VAR2full>VAR2diag for 1960-2021. In sum, the unrestricted VAR(6) model demonstrates the highest adequacy based on this criterion. Third, the Akaike information is computed as $AIC(\text{VAR2diag}) = -817.9487$, $AIC(\text{VAR2full}) = -828.4256$, $AIC(\text{VAR4full}) = -813.4517$ and $AIC(\text{VAR6full}) = -817.9444$. Based on the AIC values the unrestricted VAR(2) model demonstrates the highest adequacy.

Next, based on the forecast error in Figs. 79 and 80, the 4-variable model with the highest predictive power is VAR2full. This aligns with the outcome of the bivariate estimation.

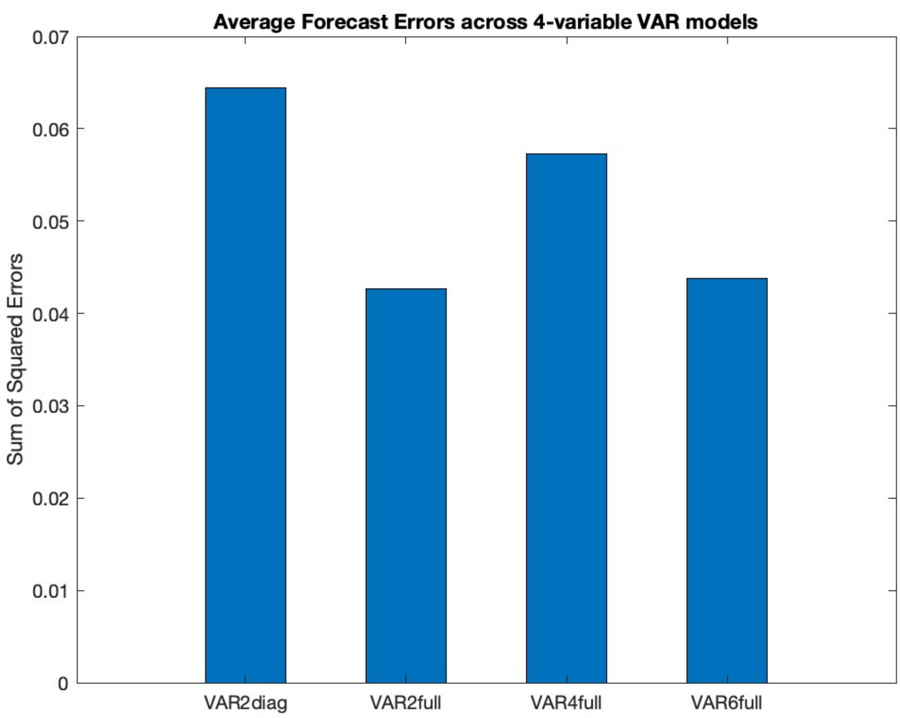


Figure 79: Combined GDP and Consumption Forecast Errors from 4-variable VAR.

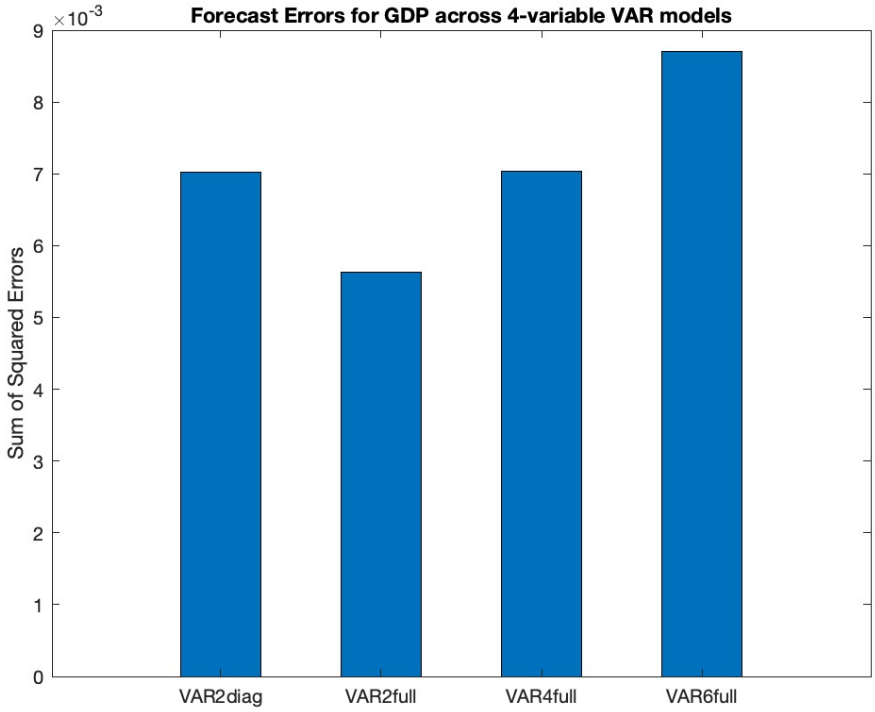


Figure 80: GDP Forecast Errors from 4-variable VAR.

In Fig. 81 the individual forecast errors across the four indicators are illustrated. Except for Investment, the other indicators achieve a low forecast error. The investment error reveals a higher deviation from the real data.

Finally, in Fig. 82 the GDP forecast error from the bivariate and 4-variable VAR2full estimation is drawn. Interestingly, the GDP forecast error is smaller when using 4 variables, which reveals that the additional indicators of Investment and Government Expenditure further enable VAR2full to provide a more accurate forecast for GDP in 2017-2021.

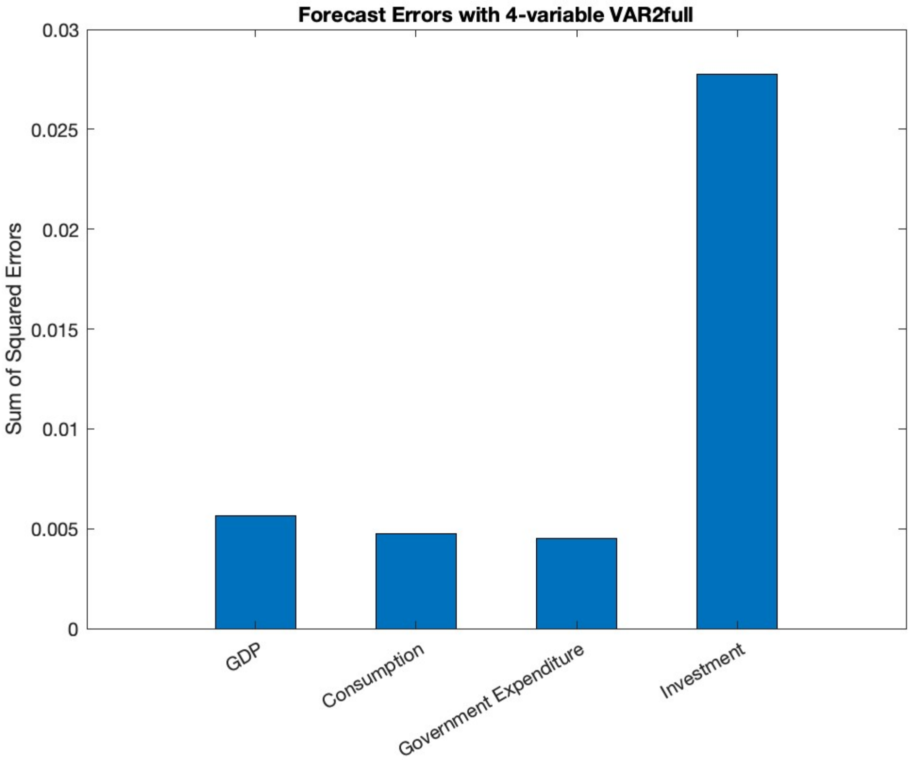


Figure 81: Individual Forecast Errors from 4-variable VAR2full.

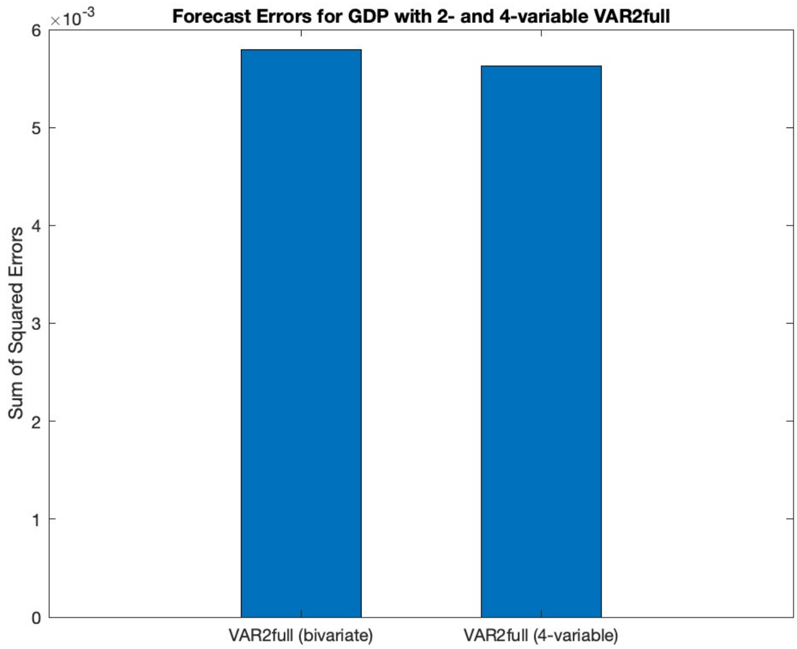


Figure 82: GDP Forecast Errors from 2-variable and 4-variable VAR2full.

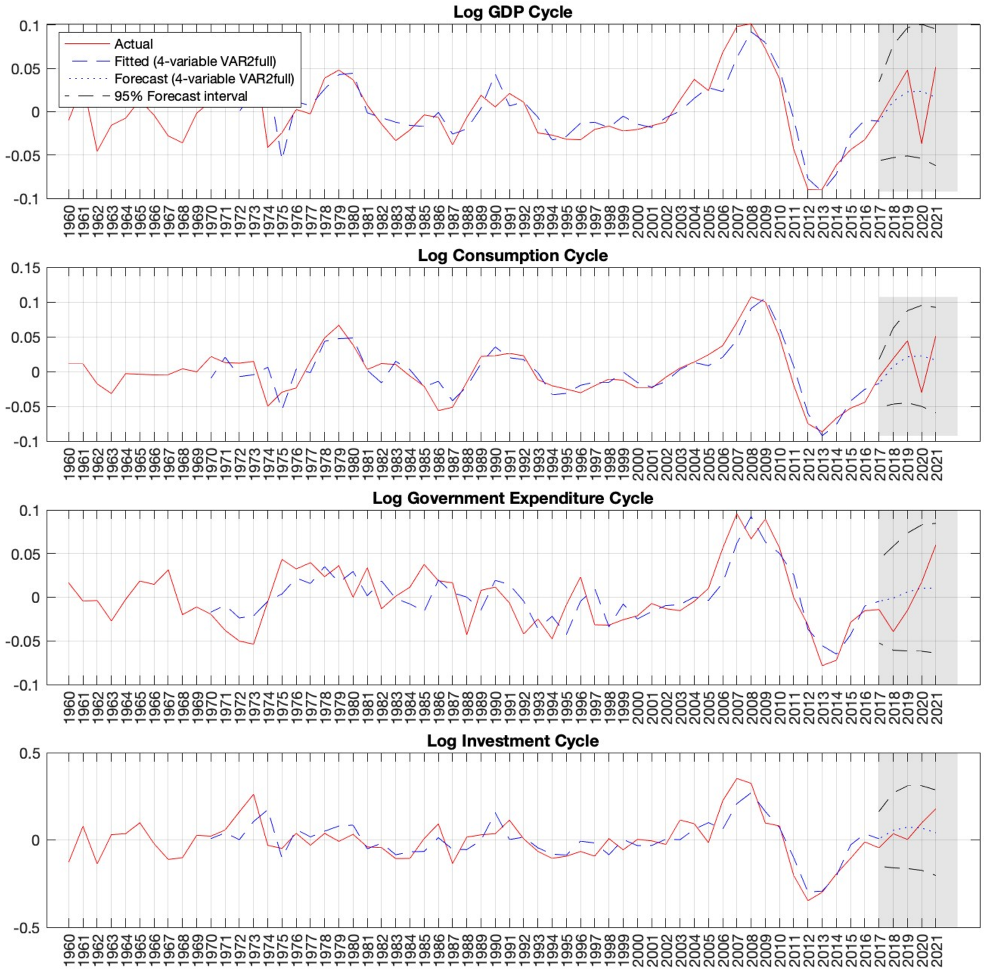


Figure 83: Actual, fitted and forecast data from 4-variable VAR2full.

In Fig. 83 the actual and fitted data from VAR2full are illustrated for all variables, as well as the 95% forecast interval bounds along with the forecast for 2017-2021. The forecast closely follows the real data for GDP and Consumption, while the real data are well within the 95% prediction intervals. The only deviation from the real data appears in 2020 when the COVID-19 pandemic erupted. The forecast for Government Expenditure is within bounds with a deviation in 2018 when the expenditure had a decline due to delays in EU funding and administrative bottlenecks, while the general government primary surplus reached 4.2 percent of GDP. In 2020-2021 Government Expenditure started growing as the economy bounced back from the pandemic.

6.4.3 Estimation and Forecasting with 6-variable VAR

Next, Exports and Imports are introduced in the VAR model to examine the hypothesis whether more macroeconomic indicators improve estimation and forecast for GDP. To test the model adequacy, first, it is verified that all models are AR-stationary. All models are AR-stationary, except for VAR6full. Thus, the estimated model from VAR6full is not stable or invertible. Second, based on the likelihood ratio test it is shown that: VAR4full>VAR2full>VAR2diag for 1960-2021. In sum, the unrestricted VAR(4) model demonstrates the highest adequacy based on this criterion. Third, the Akaike information is computed as $AIC(\text{VAR2diag}) = -1{,}146.7$, $AIC(\text{VAR2full}) = -1{,}157.0$, $AIC(\text{VAR4full}) = -1{,}199.3$. Based on the AIC values the unrestricted VAR(4) model is the most adequate.

Based on the forecast error in Figs. 84 and 85, the 6-variable model with the highest predictive power is VAR2full, when considering either GDP itself or the average across all six variables. This is different than the outcome of the adequacy tests, which may imply overfitting of VAR4full to the estimated data, while VAR2full generalizes better to the forecast period.

In Fig. 86 forecast errors are individually shown for each variable of the 6-variable VAR2full model. GDP, Consumption and Government Expenditure have much smaller error than Exports, Imports and Investment, which shows the higher uncertainty of the latter variables, especially during macroeconomics changes.

Next, the GDP forecast error is compared among the bivariate, 4-variable and 6-variable VAR2full models in Fig. 87. The forecast error gets progressively smaller when introducing more indicators in the VAR2full formulation. Specifically, introducing Government Expenditure and Investment reduces the error, while adding Exports and Imports slightly further improves the predictive power of the model for 2017-2021. We comprehend that as more indicators participate in our econometric analysis, the prediction is more accurate to interpret any economic or political event.

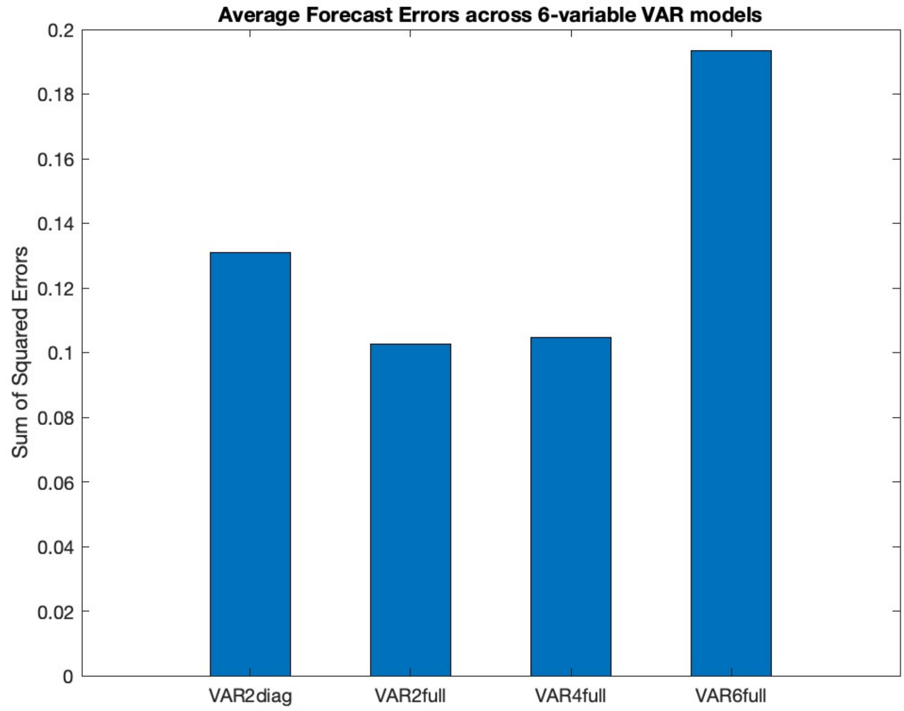


Figure 84: Combined Forecast Errors from 6-variable VAR.

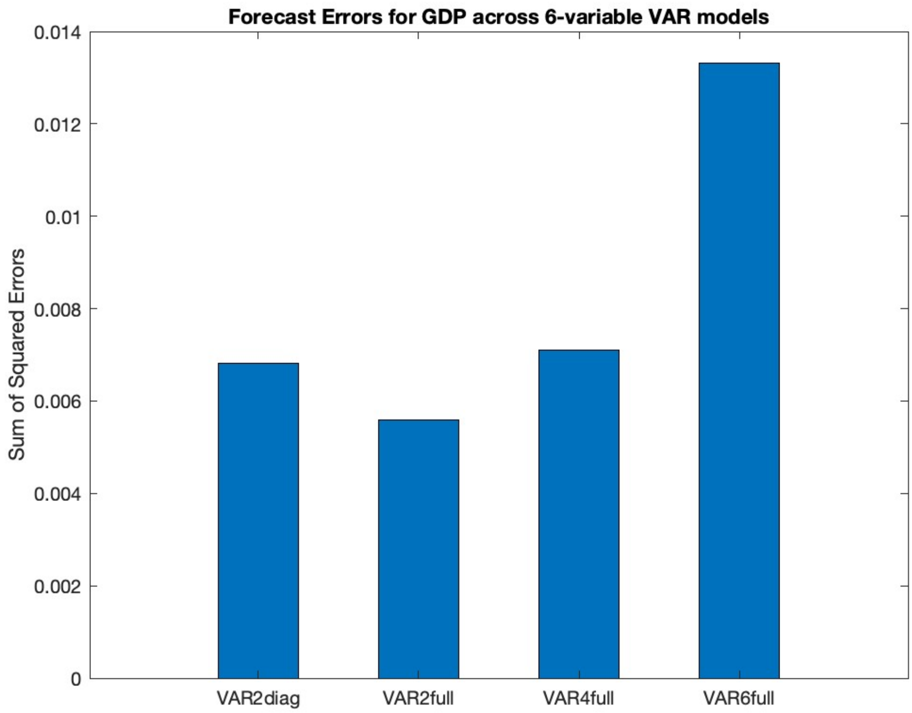


Figure 85: GDP Forecast Errors from 6-variable VAR.

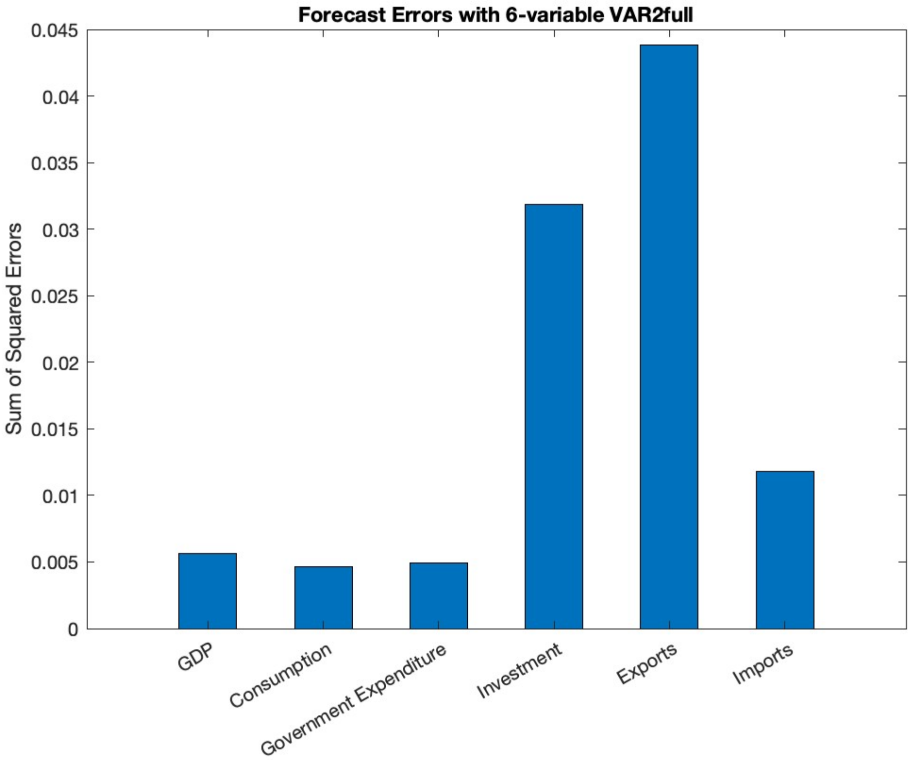


Figure 86: Individual Forecast Errors from 6-variable VAR2full.

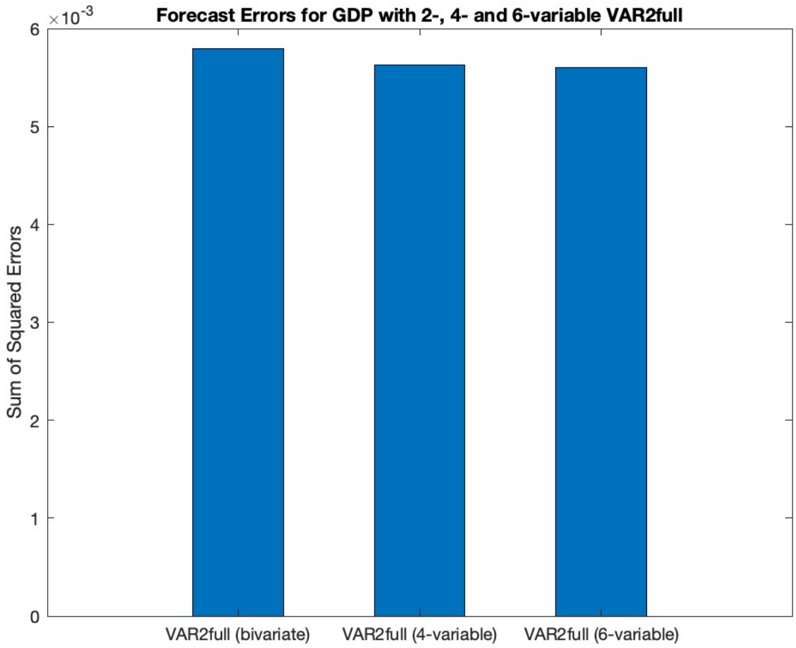


Figure 87: GDP Forecast Errors from 2-variable, 4-variable and 6-variable VAR2full.

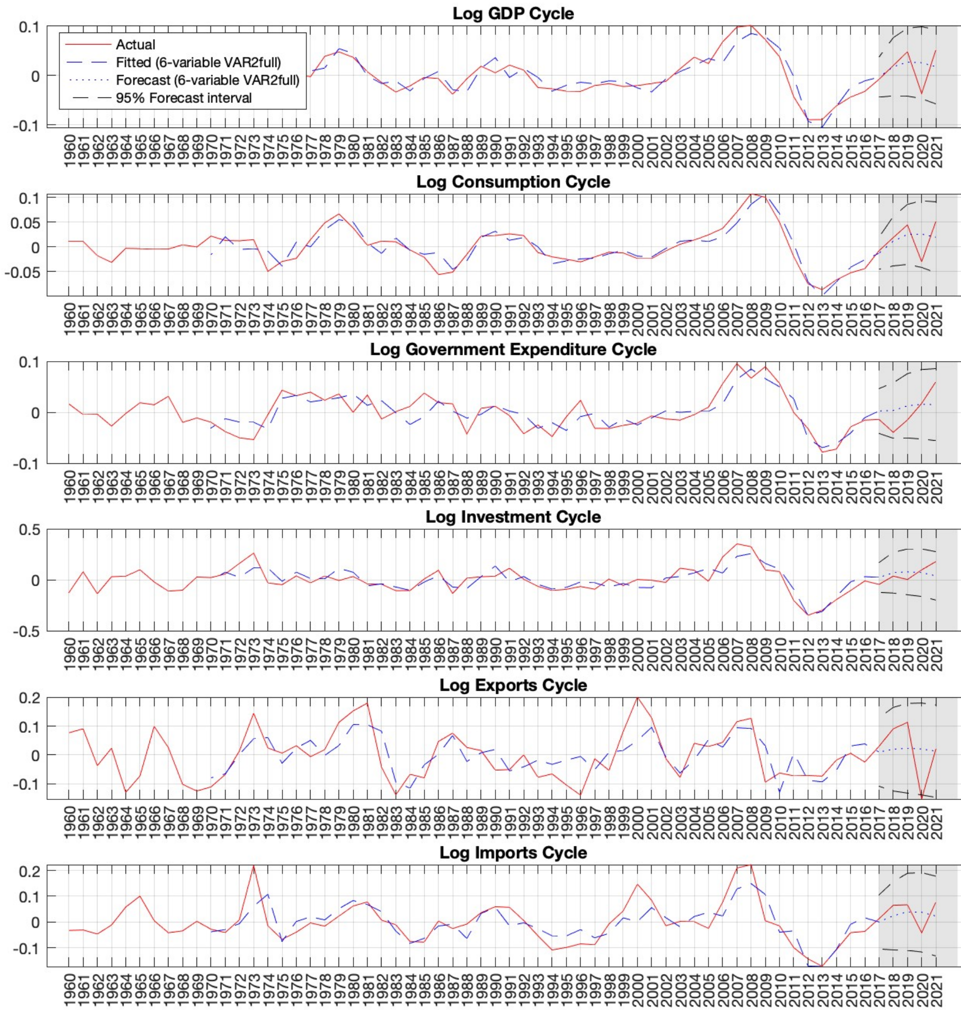


Figure 88: Actual, fitted and forecast data from VAR2full.

In Fig. 88 the actual data are demonstrated along with the fitted data from VAR2full. The latter model is chosen as it has the best predictive power among the 6-variable VAR models.

The forecast for GDP, Consumption, Investment and Government Expenditure has similar trends with the 4-variable estimation. Specifically, their forecast data lie within the 95% intervals with a fall in 2020. Similarly, the Exports and Imports have high-fidelity prediction, except for the Exports forecast in 2020 when it falls outside the 95% lower bound, as the pandemic broke out.

6.5 LSTM (Long Short - Term Memory)

Long-Short Term Memory (LSTM) is a family of neural networks that can process sequences of data. They are more accurate in long-term predictions, as they can model longer-term and more complex temporal dependencies compared to linear models, such as ARMA and VAR [Fathi, 2019]. LSTM is inherently capable of addressing mixed-frequency data and learning complex, non-linear relationships in temporal data [Hopp, 2022]. Also, LSTM can scale computationally efficiently as the number of features increases [Fathi, 2019].

LSTM is useful in Economics for analyzing multivariate time series that describe economic indicators. The advantage of LSTM is especially highlighted when it comes to long-term forecasting, compared to linear models such as ARMA and VAR [Fathi, 2019].

6.5.1 Estimation and Forecasting with 1-variable LSTM

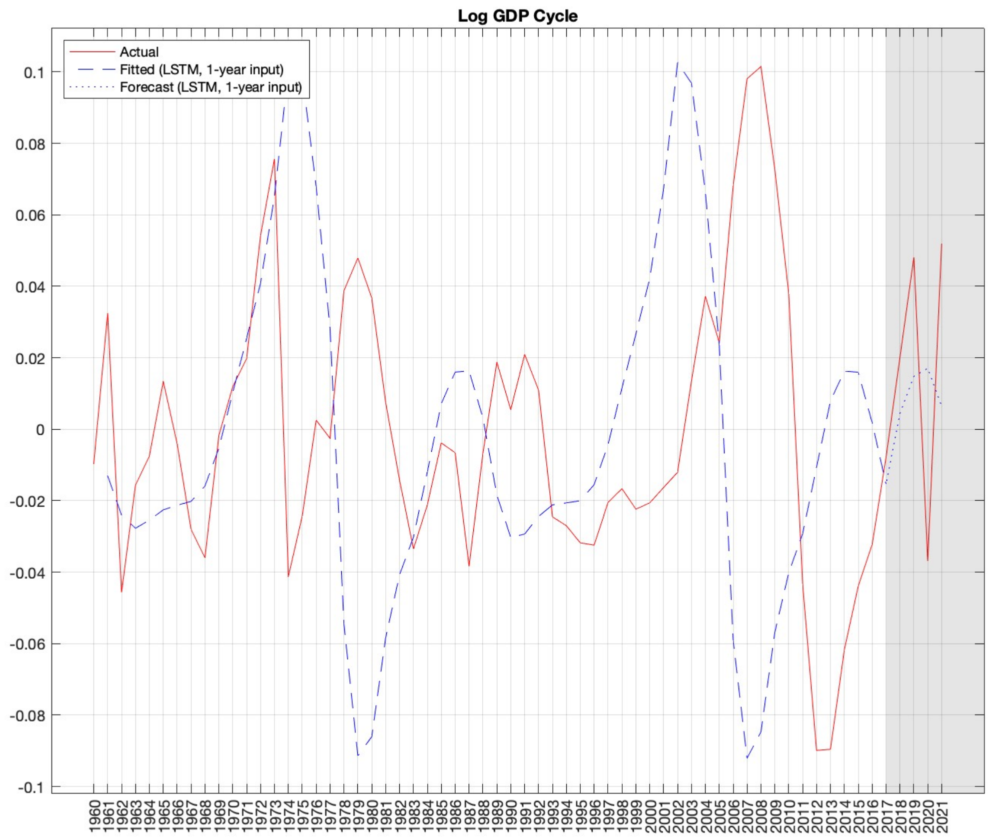


Figure 89: GDP Forecast from 1-year LSTM.

To train LSTM for estimation and forecast, we use a sample of 62 years of annual data (i.e., 1960-2021), as with the previous models, where the first 57 years are used for learning the model parameters and the last 5 years for forecasting. We learn a model by using time series data of GDP and its determinants. Initially, a 1-year time window is used to predict the value of each macroeconomic variable across these 62 years. By applying the learned parameters after learning, the model is able to predict the business cycle in the examined period. Using a 1-year history as model input is a simplified assumption and formulation, which will be expanded in the next section.

In Fig. 89 the fitted data are shown along with the actual data. As expected, the estimated values do not follow the actual data closely, which implies that the 1-year sample of learning does not suffice to learn and interpret the actual data. However, the provided forecast is a crude approximation of the actual data. By inspecting the GDP fitted data for the estimation period, the fitted data are characterized by a 5-year lead compared to the actual data. This reinforces the observation that the 1-year model input is not sufficient.

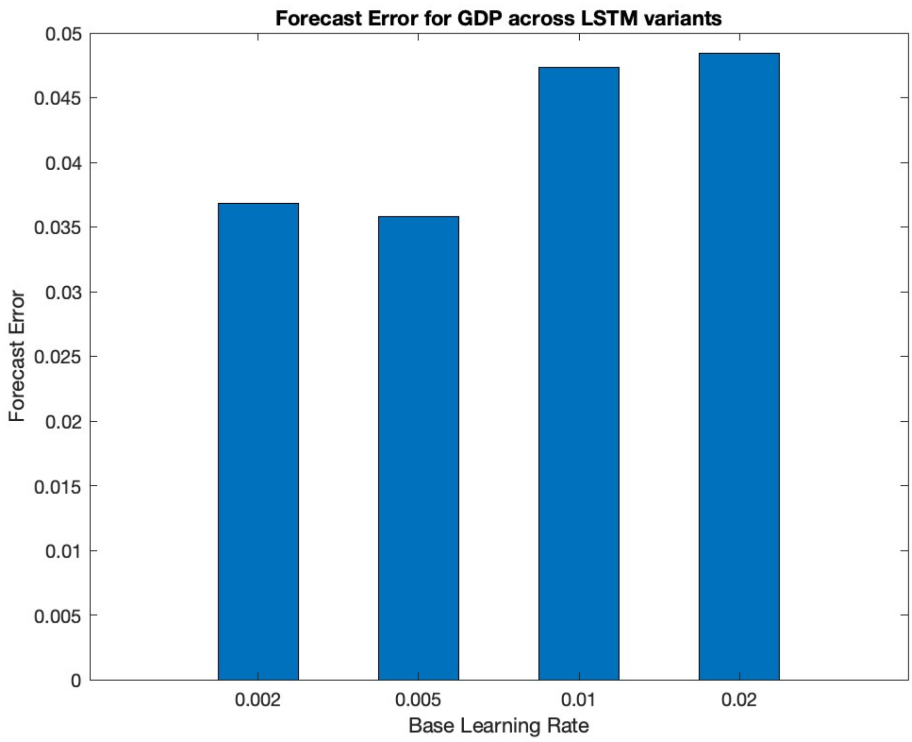


Figure 90: Forecast Error for GDP from LSTM variants.

The learning rate is a hyperparameter that controls how much to change the model in response to the estimated error each time the model weights are updated. This parameter depends on the available data and the nature and complexity of them. Therefore, in Table 27 the base learning rate is ablated to identify the optimal value for this setting. Several initial (base) learning rate values are tried and the RMSE error of the GDP forecast is compared. Initial learning $l = 0.005$ gives the lower RMSE error of 0.0358. The learning schedule consists of 250 iterations of learning rate l and another 250 iterations of learning rate $l/_{10}$. In Table 28 different number of hidden units h is tried for $l = 0.005$.

Table 27: Ablation of base learning rate and number of hidden units.

Base Learning Rate, # of hidden units, # of years	RMSE Error
$l = 0.002$, $h = 200$, y= 1	0.0368
$l = 0.005$, $h = 200$, y= 1	0.0358
$l = 0.005$, $h = 400$, y= 1	0.0399
$l = 0.005$, $h = 100$, y= 1	0.0358
$l = 0.01$, $h = 200$, y= 1	0.0473
$l = 0.02$, $h = 200$, y= 1	0.0484

Next, the model input increases to 2 and 6 years, respectively. The goal is to identify the optimal model input to achieve the best forecast error and therefore the best prediction of the actual data for the examined period. In Table 28 it is shown that the lowest RMSE error is achieved for y= 2 years. This means that for each estimated year, two prior years are used as model input. On the other hand, when y= 6 observations are used the forecast is slightly less accurate for 2017-2021.

Table 28: Ablation of number of years as LSTM input

Initial Learning Rate, # of hidden units, # of years	RMSE Error
$l = 0.005$, $h = 200$, y= 2	0.0302
$l = 0.005$, $h = 200$, y= 6	0.0329

As illustrated in Fig. 91, when 2-year observations are used as input the fitted data of GDP are significantly closer to the actual data. This is in contrast with the 1-year observations used in Fig. 89, which indicates that the model estimation is better with 2-year model input for the examined period. By inspecting the learned curve in Fig. 91, the GDP estimation is getting accurate from the late 1980's until today. This intuitively makes sense as the learning of the time series became progressively better over the years. Moreover, the forecast is improved for the 2-year case, which is reflected by the RMSE error and qualitatively by the predicted curve in Fig. 91.

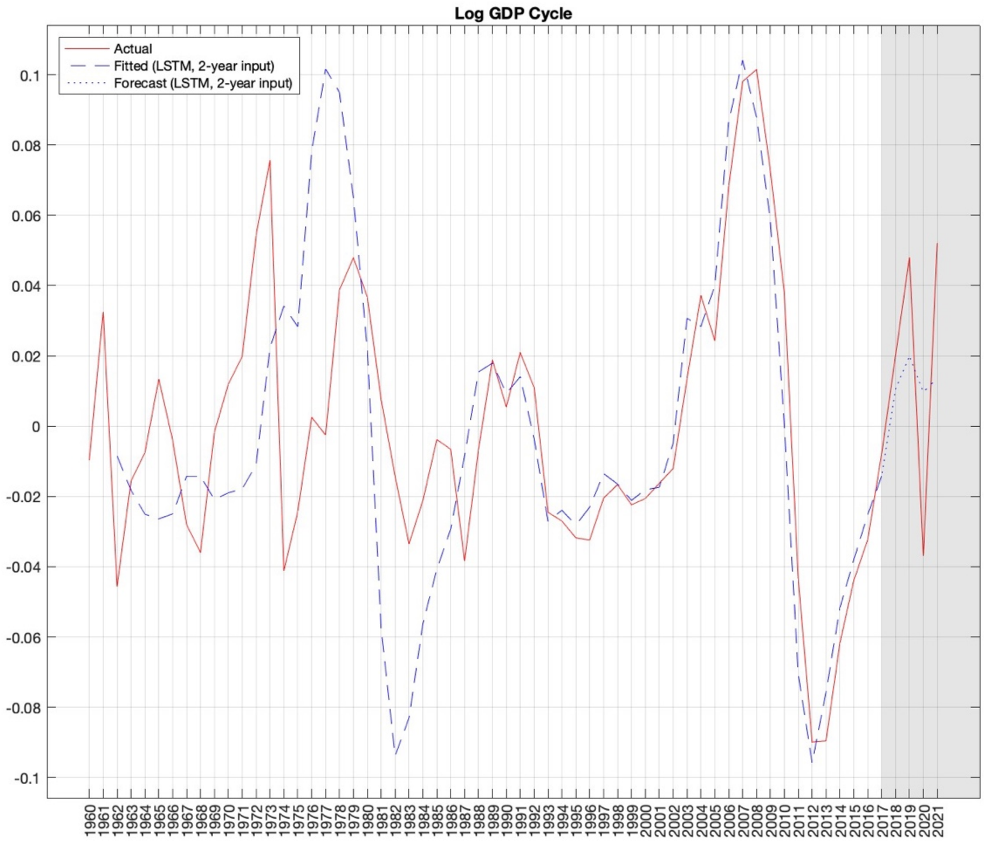


Figure 91: Actual, Fitted and Forecast data of Log GDP Cycle from 2-year LSTM.

6.5.2 Estimation and Forecasting with 2-variable LSTM

Next, the LSTM estimation is extended to the multi-variate case, where both GDP and Consumption participate in the formulation. This is comparable to the VAR model, where multiple variables are used in the model estimation. The hypothesis that is examined is whether multiple macroeconomic indicators can provide better GDP forecast. To this end, various number of years y is tried for the multivariate formulation too in order to minimize the forecast error. It is discovered that for $y = 4$ the 2-variable LSTM achieves an improved forecast error of $RMSE = 0.0276$. Initial learning rate $l = 0.005$, and number of hidden units $h = 50$ are used. The learning process is illustrated in Fig. 92, where the RMSE error and the training loss are minimized through the training iterations. Finally, in Fig. 93 the estimated and forecast curves are shown from the 2-variable LSTM estimation. As in the 1-variable case the estimation improves over time and approximates the real data best, over the last 2 decades. The slower learning curve compared to VAR can be attributed to the relative very small learning sample, as the neural network-based methods are known for being data greedy.

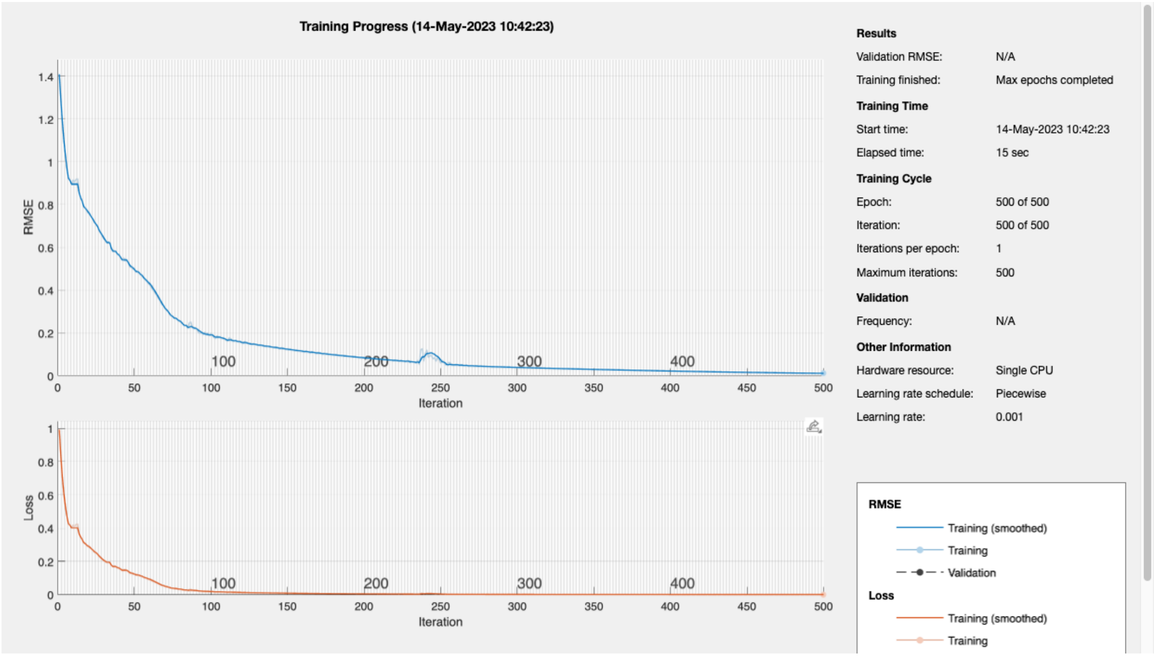


Figure 92: Error and training loss reduction during training.

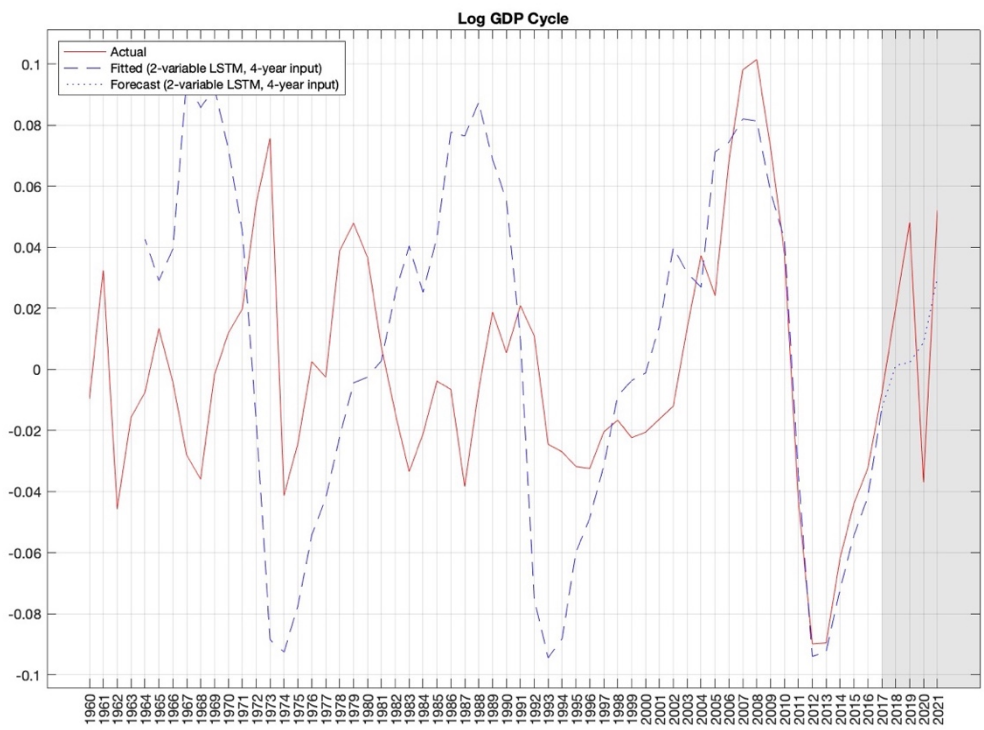


Figure 93: Actual, Fitted and Forecast data of Log GDP Cycle from 4-year LSTM.

6.6 GDP Cycle Estimation Comparison and Discussion

In this section we provide a comparison of the actual GDP cycle with its estimation from all econometric and machine learning models that are presented in this dissertation.

In Fig. 94 we observe the estimation from ARMA and 6-variable VAR. As expected, the VAR estimation is closer to the actual data, since it uses information from multiple macroeconomic indicators, which contribute towards a better estimation of the macroeconomic events that impacted GDP during the examined period. For instance, the global crisis and recession of 2008-2009 as well as the trough of 2013-2014 are more accurately estimated by VAR. Both models fail to accurately predict the pandemic; however, VAR is closer to the actuals, while ARMA has a higher variance in these years without accurately reflecting the GDP cycle.

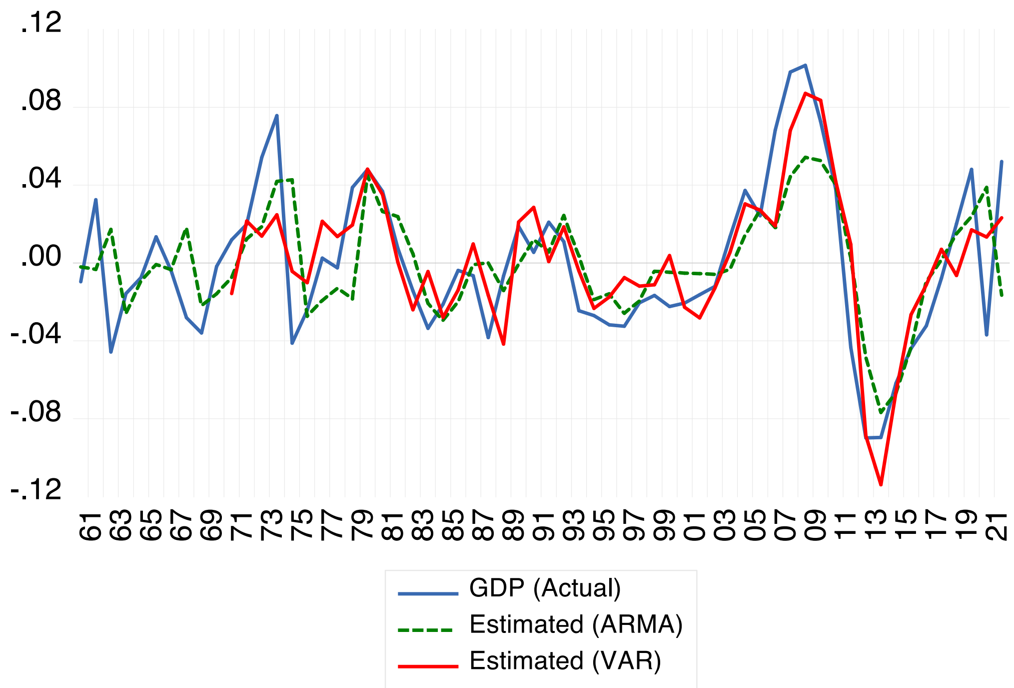


Figure 94: Comparison of the actual GDP cycle with its estimation from ARMA and VAR.

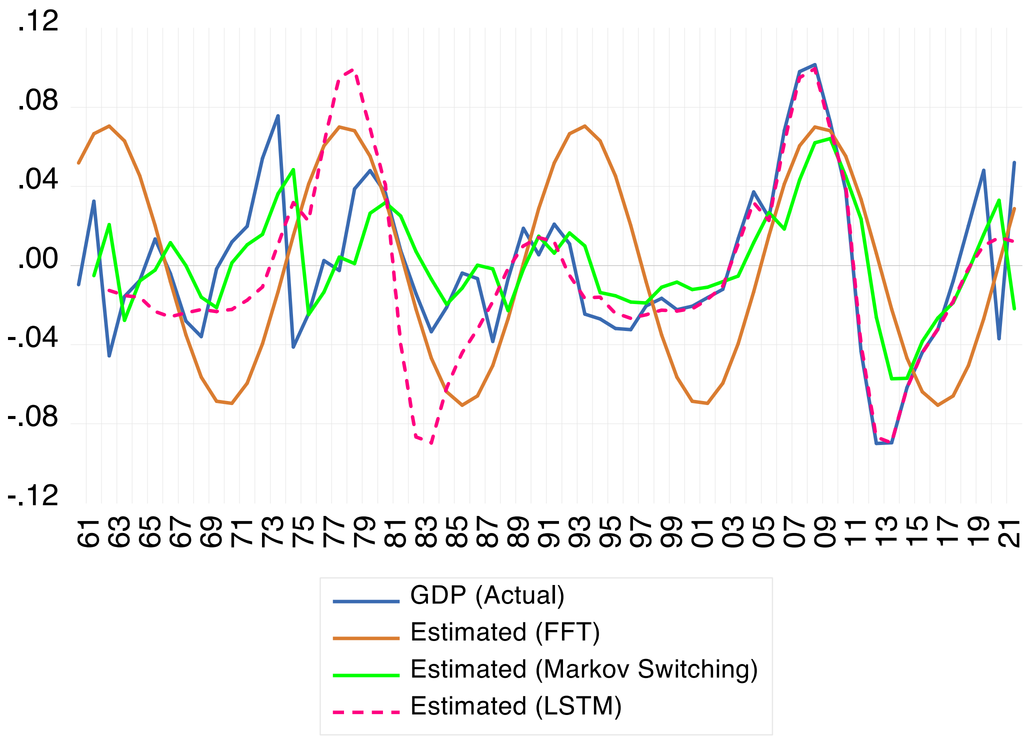


Figure 95: Comparison of the actual GDP cycle with its estimation from LSTM, Markov and FFT.

In Fig. 95 we see the comparison of the actual GDP cycle with its estimation from FFT, Markov Switching and 2-variable LSTM. As expected, FFT provides a coarse approximation of the GDP cycle, while Markov Switching has a satisfactory estimation despite a modest residual error during disruptive macroeconomic events such as the global recession and the advent of the COVID-19 pandemic. The LSTM estimation is remarkably close to the actual data, especially in the second half of the examined time period (i.e., 1990-2021). This is expected given that LSTM needs to learn from sufficient data before providing an accurate prediction.

Table 29: Residual Average Error across various GDP estimation methods.

Estimation Method	Average Residual Error (1960-2021)	Average Residual Error (1990-2021)
ARMA	0.0213	0.0214
Markov Switching	0.0227	0.0232
FFT	0.0447	0.0452
VAR	**0.0180**	0.0178
LSTM	0.0216	**0.0087**

Table 30: Cross-Correlation between the actual GDP cycle and its estimation from various methods.

Estimation Method	Cross-correlation (1960-2021)	Cross-correlation (1990-2021)
ARMA	68.1%	80.1%
Markov Switching	64.0%	74.9%
FFT	30.9%	42.4%
VAR	**83.9%**	87.8%
LSTM	72.1%	**95.0%**

These qualitative findings are quantified in Tables 29 and 30, where Average Residual Error and Cross-Correlation between the actual GDP cycle and its estimation from each method are shown, respectively. Both metrics show that 6-variable VAR presents the best estimation across the entire examined period (1960-2021), while 2-variable LSTM estimates the actual GDP cycle best in the second half of this period (1990-2021). ARMA and Markov Switching are the next best estimators, which is explainable given that they do not leverage information from multiple macroeconomic indicators. Finally, FFT provides the crudest estimation of the GDP cycle, which is expected since the estimation relies on a single dominant cycle.

Chapter 7 – Conclusions

This dissertation analyzes the Greek economy over the last decades by means of various econometric techniques combined with a macroeconomic analysis. This analysis is characterized by presentation of the cyclical component of a number of macroeconomic variables through 8 distinct phases of the Greek economy: a) Growth policy in the 1960s and 1970s (1960-1979), b) Change of economic policy from Efficiency to Equity target (social policy with Stagflation) (1980-1995), c) Stabilization (1995-2003), d) Growth with deficit (2003-2008), e) Great Recession (2008-2009), f) Adjustment Program (2010-2017), g) Growth (2018-2020) and h) COVID-19 Pandemic (2020-2021).

The country achieved steady growth from 1960-1979, when a fiscal policy of growth was followed with an efficiency consideration. Then stagflation followed, as a social policy was adopted in 1980-1995 with the change of economic policy from efficiency to equity consideration. Also, the public debt was tripled as a percentage of GDP because of this policy change. Later, a period of stabilization (1995-2003) and growth with deficit (2003-2008) followed through the 2000s, when it was interrupted by the economic crisis of 2008. Through the Adjustment Program all indicators were severely impacted through the trough of 2013-2014. Then the economy reached a phase of slow growth (2018-2020), which continues until the advent of the COVID-19 pandemic; an ongoing global economic recession began after a year of global economic slowdown. As the new decade started, there was stagnation of economic growth and consumer activity, with lockdowns and other precautions taken in early 2020s, which drove the global economy into recession. To explicitly account for major macroeconomic events which have independent effect to the output, dummy variables are constructed in the economic model for Growth Policy (1960-1979), Adjustment Program (2010-2017), COVID-19 Pandemic (2020-2021) and Great Depression (2008-2012).

In this dissertation, we investigate a large range of econometric and machine learning models and study their properties for the purpose of estimation and forecast error, as well as their interpretability. These models are used to assess the correlation of the fluctuations of business cycles of the Greek economy with the political, economic events that occurred through the last decades in the Greek region. Based on Figs. 94 and 95 we observe the correlation of the estimation from various models compared to the actual troughs and peaks in the GDP cycle, which reflect the examined periods. Specifically, the peak of 2008-2009 is well estimated from all models, while the LSTM and VAR estimation is closer to the actual data, which reflects the period of Great Recession. Next, the majority of models estimate the trough that followed, except for FFT as well as Markov Switching which is slightly lagging. This is the effect of recession through the Adjustment program (Memorandum). Right after the recession all models show the GDP growth, although the FFT estimation is lagging. This ascending trend shows the Growth from 2018-2019, after the Greek economy exited the adjustment program, when the country had redeemed a portion of its debt and the investors started trusting the country again for investing in government bonds. Finally, all models fail to capture the economy downturn from the advent of the COVID-19 Pandemic.

Earlier, the period of growth in 1960-1979 is estimated reasonably well by ARMA, VAR and Markov Switching, while FFT and LSTM show significant residual error. Specifically, ARMA and Markov Switching are lagging the actual data, despite of estimating the higher peaks in 1973-1974 and 1979-1980. These two periods coincide with the last phase of the dictatorship and the second oil crisis which severely impacted the oil prices and Greek GDP, respectively. Next, the trough of 1988 is best estimated by VAR and Markov Switching, although they appear to be slightly lagging the actual GDP cycle, while the other models do not provide a satisfactory prediction. This whole period describes the stagnation in the Greek economy from 1980 to 1995. In the next period leading to the peak of 2008 all models estimate well the GDP growth. This is the period that the Greek economy experienced growth along with an increased deficit.

The qualitative analysis above is confirmed by quantitative results in Tables 29 and 30. The above-mentioned macroeconomic events are best estimated by the 6-variable VAR and the 2-variable LSTM, as shown by the Average Residual Error in Table 29 and Cross-Correlation in Table 30. Specifically, 6-variable VAR achieves the best estimation across all the examined time period of the Greek economy (1960-2021), while 2-variable LSTM provides the best estimation in the second half of this period (1990-2021). Both these models achieve accurate estimation through major macroeconomic events, such as Stabilization, Growth with deficit, Great Recession, Adjustment Program and Growth ahead of the Pandemic. During the Pandemic all models are not able to capture the large fluctuation of the GDP cycle due to the unforeseen event, which had a significant impact on all macroeconomic indicators.

ARMA and Markov Switching are the next best estimators based on Tables 29 and 30 during the 62 years of the Greek Economy. This is expected given that they do not leverage information from multiple macroeconomic indicators, and therefore their estimation of the GDP cycle is less accurate than the VAR and LSTM estimates. Finally, FFT provides the less accurate estimation of the GDP cycle, which is expected since the estimation relies on a single dominant cycle.

This dissertation also correlates the major macroeconomic events qualitatively and quantitatively through econometric analysis in Chapter 5. Based on Table 7, Consumption, Government Expenditure, Imports, Capital and Total Factor Productivity are procyclical, while Investment, Exports and Labor Force are countercyclical. This observation reinforces the economic theory that Consumption and Imports are procyclical because they increase the demand, while Investment and Exports are countercyclical as these indicators increase the supply by boosting the domestic production.

Various events confirm the findings of Table 7. For instance, the growth rate of real GDP per capita remained relatively high during the 2000-2008 period. This was mainly the result of high increases in both private consumption and investment because of the low real interest rates. The procyclicality of Consumption is confirmed in Table 7 with high cross-correlation of 0.69 and the coincident behavior in Fig. 22.

Next, Greece was very negatively affected by the international financial crisis of 2008-2009 due to its high external debt, and its deteriorating external and fiscal imbalances. The country's growing indebtedness led to a 'sudden stop' in international lending, thus Greece was forced to enter Adjustment Program in exchange for the financial support of the rest of the European Union. This provided official financing of its immediate external debt obligations. The implementation of these program gradually led to the restoration of fiscal and external balance. Between 2008 and 2016 per capita real GDP fell by 25%, while this decline in production is demonstrated by all the macroeconomic indicators in Fig. 24. This is confirmed by Table 7, since TFP and Capital are coincident with GDP. Specifically, TFP has a profound impact to the GDP cycle as shown qualitatively in Fig. 24 and by the high correlation in Table 7.

Finally, business cycles have a very useful meaning on policy making, as they can determine monetary and fiscal policy. Due to the strong cyclical behavior of most macroeconomic variables, the fiscal expansion should be aimed at those expenditures that would not lead to acute fluctuations in the economy. Therefore, the focus should be directed at social and structural issues which could reverse this situation. While the Greek fiscal expansion measures are often focusing on achieving a higher total income in the economy, given the current challenges and prospects of the Greek economy, the government should also boost structural competitiveness, address institutional reforms and change the political conditions.

References

- Allsopp, C. J., 1971. [Review of Is the Business Cycle Obsolete?, by M. Bronfenbrenner]. *Economic Journal*, 81 (324), 951–953. https://doi.org/10.2307/2230339
- Alogoskoufis, G., Giavazzi, F., & Laroque, G., 1995. The Two Faces of Janus: Institutions, Policy Regimes and Macroeconomic Performance in Greece. *Economic Policy*, 10 (20), 149–192. https://doi.org/10.2307/1344540
- Alogoskoufis, G., 2012. Greece's Sovereign Debt Crisis: Retrospect and Prospect, GreeSE Paper No.54, Hellenic Observatory Papers on Greece and Southeast Europe, LSE, January. https://www2.lse.ac.uk/Hellenic-Observatory/Assets/Documents/Publications/GreeSE-Papers/GreeSE-No54.pdf
- Alogoskoufis, G., 2021. Historical Cycles of the Economy of Modern Greece from 1821 to the Present (February 10, 2021). Department of Economics Athens University of Economics and Business, Working Paper no. 01-2021, Available at SSRN: https://ssrn.com/abstract=3801664 or http://dx.doi.org/10.2139/ssrn.3801664 .
- Aloui, C., Hkiri, B. and Nguyen, D.K., 2016. Real growth co-movements and business cycle synchronization in the GCC countries: Evidence from time-frequency analysis. *Economic Modelling*, 52, B, pp.322-331.
- Ameco European Database, available at https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/macro-economic-database-ameco/ameco-database_en (retrieved 2023).
- Andersson, E., Bock, D. and Frisén, M., 2003. Detection of turning points in business cycles. *Journal of Business Cycle Measurement and Analysis*, 2004 (1), pp.93-108.
- Andrejovska, A. and Pulikova, V., 2018. Tax revenues in the context of economic determinants. *Montenegrin Journal of Economics*, 14 (1), pp. 133-141.
- Angeletos, G.M., Collard, F. and Dellas, H., 2020. Business-cycle anatomy. *American Economic Review*, 110(10), pp.3030-70.
- Apergis, N. and Panethimitakis, A., 2011. Stylized facts of Greek business cycles: new evidence from aggregate and across regimes data. *International Journal of Economics and Business Research*, *3* (2), pp.147-165.

- Apostolopoulos, N., Psychalis, M., and Liargovas, P., 2022. Discussing EU Policies and Mechanisms towards the COVID-19 Pandemic Crisis: A Case Study of Greece. World. 3(4):772-782. https://doi.org/10.3390/world3040043.
- Bai, J. and Perron, P., 1998. Estimating and testing linear models with multiple structural changes. *Econometrica*, 66 (1), pp.47-78.
- Banerjee, A., Dolado, J.J., Hendry, D. and Smith, G., 1986. Exploring equilibrium relationships in econometrics through static models: some Monte-Carlo evidence. *Oxford Bulletin of Economics & Statistics*, 48 (3), pp. 253-277.
- Bank of Greece, 2014. *The chronicle of the great crisis. The Bank of Greece, 2008-2013*, Athens 2014. Bank of Greece, Athens.
- Belegri-Roboli, A., Michaelides, P., 2007. Estimating labour and output gap: evidence from the Athens Olympic region in Greece. *Applied Economics* 39 (19), 2519–2528.
- Benhabib, J., Schmitt-Grohé, S. and Uribe, M., 2001. Monetary policy and multiple equilibria. *American Economic Review*, 91(1), pp.167-186.
- Besomi, D., 2011. Naming crises: A note on semantics and chronology. In: D. Besomi (ed.), *Crises and cycles in economic dictionaries and encyclopedias*, Routledge, London, p.54.
- Bird, G., 1998. An Open-Economy Macroeconomic Model. In: *International Macroeconomics*. Palgrave Macmillan, London, pp. 7-23.
- Bosworth, B. and Kollintzas, T., 2001. Economic growth in Greece: past performance and future prospects. Available at SSRN 274560.
- Box, G. E., and Jenkins, G. M., 1970. Time Series Analysis Forecasting and Control. Holden Day, San Francisco. [5th edition 2016]
- Burke, C.J. and Rosenblatt, M., 1958. A Markovian function of a Markov chain. *The Annals of Mathematical Statistics*, 29(4), pp.1112-1122.
- Burns, A.F. and Mitchell, W.C., 1946. Measuring Business Cycles. *National Bureau of Economic Research,* New York.
- Canova, F., Marrinan, J., 1998. Sources and propagation of international cycles: common shocks or transmission? *Journal of International Economics* 46 (1), 133–167.
- Center of Planning and Economic Research, 2016. The evolution of the Consumer Price Index (CPI) in Greece and the Eurozone. KEPE, Athens.

- Eklund, B., 2007. Forecasting the Icelandic Business Cycle using Vector Autoregressive Models. Working Paper no 36, Central Bank of Iceland. https://www.sedlabanki.is/lisalib/getfile.aspx?itemid=5377
- Charikiopoulou, I., 2022. The Koskotas scandal and the political unrest of the years 1988-1989 through the Press: The case of Auriani and Eleutheros Tipos newspapers.
- Christodoulakis, N., Dimelis, S. and Kollintzas, T., 1993. 'Comparisons of Business Cycles in Greece and the EC: idiosyncrasies and regularities', *Centre for Economic Policy Research Discussion*, Paper 809.
- Christodoulakis, N., Dimelis, S. and Kollintzas, T., 1995. Comparisons of Business cycles in Greece and the EC: idiosyncrasies and regularities. *Economica*, 62 (245), pp. 1–27.
- Chung, J., Gulcehre, C., Cho, K. and Bengio, Y., 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555.
- Cobb, C.W. and Douglas, P.H., 1928. A theory of production. *American Economic Review*, 18(1), pp. 139-165.
- Cogley, T. and Nason, J.M., 1995. Effects of the Hodrick-Prescott filter on trend and difference stationary time series Implications for business cycle research. *Journal of Economic Dynamics and Control*, 19(1-2), pp.253-278.
- Cooley, J.W. and Tukey, J.W., 1965. An algorithm for the machine calculation of complex Fourier series. *Mathematics of Computation*, *19*(90), pp.297-301.
- Crowley, P.M. and Lee, J., 2005. Decomposing the co-movement of the business cycle: a time-frequency analysis of growth cycles in the euro area. *Bank of Finland Research Discussion Paper*, (12).
- Dalamagas, B., 1995. A reconsideration of the public sector's contribution to growth. *Empirical Economics*, 20 (3), pp. 385-414.
- Dalamagas, B., 2000. Public sector and economic growth: the Greek experience. *Applied Economics*, 32 (3), pp. 277-288.
- Davidson, L.S., Fratianni, M. and Von Hagen, J., 1990. Testing for political business cycles. *Journal of Policy Modeling*, 12(1), pp.35-59.
- Dickey, D.A. and Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366a), pp.427-431.

- Dupor, B., 2001. Investment and interest rate policy. *Journal of Economic Theory*, 98 (1), pp. 85-113.
- Engel, C., 1994. Can the Markov switching model forecast exchange rates?. *Journal of International Economics*, 36(1-2), pp.151-165.
- European Parliament's Committee on Employment and Social Affairs (2013). The Social and Employment Situation in Greece. Retrieved in March 2021.
- Fabian, A., 1989. Speculation on distress: The popular discourse of the panics of 1837 and 1857. *Yale Journal of Criticism*, 3(1), p.127.
- Fathi, O., 2019. Time series forecasting using a hybrid ARIMA and LSTM model. In Velvet Consulting. https://www.velvetconsulting.com/wp-content/uploads/2019/03/Seasonality_modeling_using_ARIMA_LSTM_Hybrid_Model
- Fernández-Villaverde, J., Rubio-Ramírez, J.F., Sargent, T.J. and Watson, M.W., 2007. ABCs (and Ds) of understanding VARs. *American Economic Review*, 97(3), pp.1021-1026.
- Freris, A.F., 1986. The Greek Economy in the Twentieth Century. New York: St. Martin's Press, Friedman, Milton, 1968. "The Role of Monetary Policy," *American Economic Review*, 58 (1), pp. 1-17.
- Friedman, Milton, 1968. "The Role of Monetary Policy," *The American Economic Review*, 58: 1-17.
- Fry, R. and Pagan, A., 2005. Some issues in using VARs for macroeconometric research. CAMA Working Papers 2005-19, Centre for Applied Macroeconomic Analysis, Crawford School of Public Policy, The Australian National University. https://ideas.repec.org/p/een/camaaa/2005-19.html
- Gallegati, M., Gallegati, M. and Polasek, W., 2004. Business Cycles' Characteristics of the Mediterranean Area Countries. In *Proceedings of the Middle East Economic Association*. https://www.researchgate.net/publication/228742437
- Ganelli, G., 2005. The new open economy macroeconomics of government debt. *Journal of International Economics*, 65 (1), pp. 167-184.
- Gauss, Carl Friedrich, 1866 [1805]. Theoria interpolationis methodo nova tractata. Werke (in Latin and German). Vol. 3. Göttingen: Königliche Gesellschaft der Wissenschaften. pp. 265–327. https://archive.org/details/bub_gb_OuYGAAAAYAAJ/page/265/mode/2up

- Giannitsis, T., 1993. World market integration: trade effects and implications for industrial and technological change in the case of Greece. *Greece, the New Europe and the Changing International Order. New York: Pella for the Center for Byzantine and Modern Greek Studies*. Queen's College, City University of New York, pp.217-256.
- Giannitsis, T., 2005. Greece and the future: Pragmatism and illusions. *Athens: Polis Publications* (in Greek).
- Gogas, P., 2013. Business cycle synchronization in the European Union: The effect of the common currency. *OECD Journal: Journal of Business Cycle Measurement and Analysis*, 2013 (1), pp.1-14.
- Goldfeld, S.M. and Quandt, R.E., 1973. A Markov model for switching regressions. *Journal of Econometrics*, 1(1), pp.3-15.
- Gouveia, S. and Correia, L., 2008. Business cycle synchronization in the Euro area: the case of small countries. *International Economics and Economic Policy*, 5(1), pp.103-121.
- Gylfason, T., 1981. Interest rates, inflation, and the aggregate consumption function. *The Review of Economics and Statistics*, pp. 233-245.
- Hale, G., 2013. Balance of Payments in the European Periphery. *Federal Reserve Bank of San Francisco*. Retrieved 3 July 2015.
- Hamilton, J.D., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica: *Journal of the Econometric Society*, pp.357-384.
- Hamilton, J.D. and Susmel, R., 1994. Autoregressive conditional heteroskedasticity and changes in regime. *Journal of Econometrics*, 64(1-2), pp.307-333.
- Hamilton, J.D., 2018. Why you should never use the Hodrick-Prescott filter. *Review of Economics and Statistics*, 100(5), pp.831-843.
- Hamish, M., 2015. "Greece crisis: It needs another economic miracle – and it could happen". The Independent.
- Harvey, A.C. and Jaeger, A., 1993. Detrending, stylized facts and the business cycle. *Journal of Applied Econometrics*, 8(3), pp.231-247.
- Hicks, J.R., 1937. Mr. Keynes and the "classics"; a suggested interpretation. *Econometrica: Journal of the Econometric Society*, pp. 147-159.
- Hochreiter, S. and Schmidhuber, J., 1997. Long short-term memory. *Neural Computation*, 9(8), pp.1735-1780.

- Hodrick, R.J. and Prescott, E.C., 1997. Postwar US business cycles: an empirical investigation. *Journal of Money, Credit, and Banking*, pp.1-16.
- Hondroyiannis, G. and Papapetrou, E., 2001. An investigation of the public deficits and government spending relationship: Evidence for Greece. *Public choice*, *107*(1-2), pp.169-182.
- Hopp, D., 2022. Economic nowcasting with long short-term memory artificial neural networks (LSTM). *Journal of Official Statistics*, 38(3), pp. 847-873.
- Hua, S., Méndez, M. and Xu, X.C., 2022. Greece's Investment Gap. *International Monetary Fund*.
- International Monetary Fund Research Dept, 2004. Export and Import Price Indices. *IMF Staff Papers*, Vol 51, No 1.
- Ioakimoglou, E. and Milios, J., 1993. Capital accumulation and over-accumulation crisis: The case of Greece (1960-1989). *Review of Radical Political Economics*, 25(2), pp. 81-107.
- Jahan, S., Mahmud, A.S. and Papageorgiou, C., 2014. What is Keynesian economics. *International Monetary Fund*, 51(3), pp.53-54.
- Joebges, H. and Herrmann, E., 2008. Euro area exports and imports: Do determinants of intra-and extra-EMU trade differ? (No. 08/2008). *IMK Working Paper*.
- Johansen, S. and Juselius, K., 1990. Maximum likelihood estimation and inference on cointegration—with appucations to the demand for money. *Oxford Bulletin of Economics and Statistics*, 52(2), pp.169-210.
- Johnson, H.G., 1971. The Keynesian revolution and the monetarist counter-revolution. *The American Economic Review*, pp.1-14.
- Keynes, J.M., 1936. The General Theory of Employment, Interest and Money. Ed: Macmillan London.
- Kim, C.J. and Nelson, C.R., 1999. Has the US economy become more stable? A Bayesian approach based on a Markov-switching model of the business cycle. *Review of Economics and Statistics*, 81(4), pp.608-616.
- Kollintzas, T., Vassilatos, V., 1996. A stochastic dynamic general equilibrium model for Greece. *Centre for Economic Policy Research*, Discussion Paper No. 1518.
- Konstantakis, K.N., Michaelides, P.G. and Vouldis, A.T., 2016. Non-performing loans (NPLs) in a crisis economy: Long-run equilibrium analysis with a real time VEC model

for Greece (2001–2015). *Physica A: Statistical Mechanics and its Applications*, 451, pp.149-161.

- Konstantakis, K.N., Papageorgiou, T., Christopoulos, A.G., Dokas, I.G. and Michaelides, P.G., 2019. Business cycles in Greek maritime transport: an econometric exploration (1998–2015). *Operational Research*, 19(4), pp.1059-1079.
- Konstantakis, K.N., Papageorgiou, T., Michaelides, P.G. and Tsionas, E.G., 2015. Economic fluctuations and fiscal policy in Europe: A political business cycles approach using panel data and clustering (1996–2013). *Open Economies Review*, 26(5), pp.971-998.
- Kotios, A., and Pavlidis, G., 2011. *International Financial Crises*. Athens: Rosili.
- Kufenko, V. and Geiger, N., 2016. Business cycles in the economy and in economics: An econometric analysis. *Scientometrics*, 107(1), pp.43-69.
- Kydland, F.E. and Prescott, E.C., 1982. Time to build and aggregate fluctuations. *Econometrica: Journal of the Econometric Society*, pp.1345-1370.
- LeCun, Y., Bengio, Y. and Hinton, G., 2015. Deep learning. *Nature*, 521(7553), pp.436-444.
- Leon, C., 2007. The European and the Greek business cycles: are they synchronized. *MRPA Paper*, No. 1312 (November).
- Ljung, G.M. and Box, G.E., 1978. On a measure of lack of fit in time series models. *Biometrika*, 65(2), pp.297-303.
- Long Jr, J.B. and Plosser, C.I., 1983. Real business cycles. *Journal of Political Economy*, 91(1), pp.39-69.
- Lucas, R.E., 1977. Understanding business cycles. In *Carnegie-Rochester Conference Series on Public Policy* (Vol. 5, No. 1, pp. 7-29). Elsevier.
- Lucas, R.E., 1980. Methods and problems in business cycle theory. *Journal of Money, Credit and Banking*, 12(4), pp.696-715.
- Lucas, R.E. and Prescott, E.C., 1971. Investment under uncertainty. *Econometrica: Journal of the Econometric Society*, pp.659-681.
- Lucas, R.E., 2003. Macroeconomic priorities. *American Economic Review*, 93(1), pp.1-14.
- Lutkepohl, H., 2004. Forecasting with VARMA models. European University Institute, *Economics Working Papers*, (25), p.43.

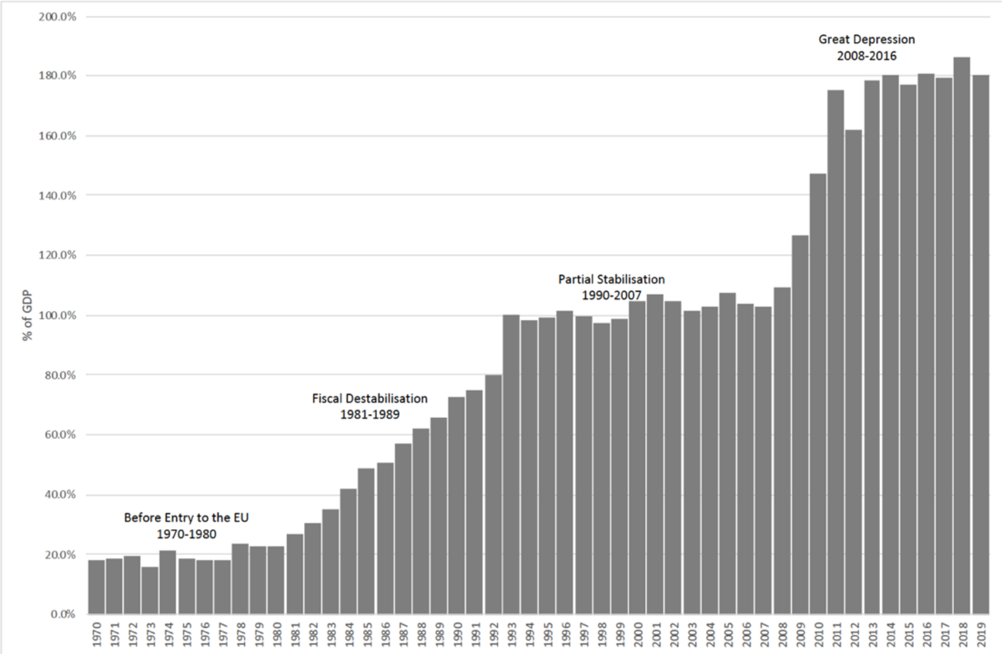
- Lütkepohl, H., 2005. New introduction to multiple time series analysis. *Springer Science & Business Media*.
- Magoulios, G. and Athianos, S., 2013. The trade balance of Greece in the euro era. *South-Eastern Europe Journal of Economics*, 2, pp.187-216.
- Manchester Statistical Society (Manchester, England) and Mills, J., 1867. On credit cycles and the origin of commercial panics.
- Mankiw, N. Gregory, 2007. Macroeconomics. New York: Worth.
- Marx, K., 1875. Le capital. Maurice Lachatre.
- Massmann, M., Mitchell, J. and Weale, M., 2003. Business cycles and turning points: a survey of statistical techniques. *National Institute Economic Review*, 183(1), pp.90-106.
- McCallum, B. and Nelson E., 1997. An Optimizing IS-LM Specification for Monetary Policy and Business Cycle Analysis, NBER Working Paper 5875.
- Meade, J.E., 1937. A simplified model of Mr. Keynes' system. *The Review of Economic Studies*, 4 (2), pp. 98-107.
- Michaelides, P., Milios, J., Vouldis, A. and Lapatsioras, S., 2007. Business cycles in Greece (1960-2008): an econometric investigation. *Journal of Economics and Business*, *2007* (1), pp. 71-106.
- Michaelides, P.G. and Papageorgiou, T., 2012. On the transmission of economic fluctuations from the USA to EU-15 (1960–2011). *Journal of Economics and Business*, 64(6), pp.427-438.
- Michaelides, P.G., Papageorgiou, T. and Vouldis, A.T., 2013. Business cycles and economic crisis in Greece (1960–2011): A long run equilibrium analysis in the Eurozone. *Economic Modelling*, *31*, pp. 804-816.
- Michaelides, P.G., Tsionas, E.G. and Konstantakis, K.N., 2018. Debt dynamics in Europe: A network general equilibrium GVAR approach. *Journal of Economic Dynamics and Control*, 93, pp.175-202.
- Mouzelis, N., 1977. Modern Greek Society: Facets of Underdevelopment. *Exantas Publications*, Athens (in Greek).
- Observatory of Economic Complexity. Greece Exports 1960-2021. www.macrotrends.net (retrieved March 2021).
- OECD, 2009. Government at a Glance.
- Florence, G., 2023. OECD Economic Surveys: Greece 2023. *OECD Economic Surveys*.

- Osborn, D.R., Perez, P.J., Sensier, M., 2005. Business cycles linkages for the G-7 countries: does the US leads the world. *Centre for Growth and Business Cycles Research Discussion Paper Series*, No. 50.
- Pagoulatos, G., 2018. Greece after the bailouts: assessment of a qualified failure. *London School of Economics and Political Science*, Paper 130.
- Papageorgiou, T., Michaelides, P.G. and Milios, J.G., 2010. Business cycles synchronization and clustering in Europe (1960–2009). *Journal of Economics and Business*, 62(5), pp.419-470.
- Papageorgiou, T., Michaelides, P.G. and Tsionas, E.G., 2016. Business cycle determinants and fiscal policy: A Panel ARDL approach for EMU. *Journal of Economic Asymmetries*, 13, pp.57-68.
- Papastamou, A., 2011. 'Global Financial Crises'. Athens: Enastron.
- Park, G., 1996. The role of detrending methods in a model of real business cycles. *Journal of Macroeconomics*, 18(3), pp.479-501.
- Pedregal, D.J., 2001. Some comments on the use and abuse of the Hodrick-Prescott filter. In *Review on Economic Cycles*, International Association of Economic Cycles.
- Perez, P.J., Osborn, D.R. and Artis, M., 2006. The international business cycle in a changing world: volatility and the propagation of shocks in the G-7. *Open Economies Review*, 17(3), pp.255-279.
- Plosser, C.I., 1989. Understanding real business cycles. *Journal of Economic Perspectives*, 3(3), pp. 51-77.
- Poskitt, D.S., 2016. Vector Autoregressive Moving Average identification for macroeconomic modeling: A new methodology. *Journal of Econometrics*, 192(2), pp.468-484.
- Prescott, E.C. and Lucas, R.E., 1972. A note on price systems in infinite dimensional space. *International Economic Review*, pp. 416-422.
- Quandt, R.E., 1972. A new approach to estimating switching regressions. *Journal of the American Statistical Association*, 67(338), pp.306-310.
- Rebelo, S., 2005. Real business cycle models: Past, present, and future (No. w11401). *National Bureau of Economic Research*.
- Sargan, J.D., 1961. The maximum likelihood estimation of economic relationships with autoregressive residuals. Econometrica: *Journal of the Econometric Society*, pp.414-426.

- Savva, C.S., Neanidis, K.C. and Osborn, D.R., 2010. Business cycle synchronization of the euro area with the new and negotiating member countries. *International Journal of Finance & Economics*, 15(3), pp.288-306.
- Sims, C.A., 1980. Macroeconomics and reality. Econometrica: *Journal of the Econometric Society*, pp.1-48.
- Škare, M. and Stjepanović, S., 2016. Measuring business cycles: a review. *Contemporary Economics*, 10(1), pp.83-94.
- Smith, A., 1776. An inquiry into the nature and causes of the wealth of nations: Volume One. London: printed for W. Strahan; and T. Cadell.
- Stournaras,Y., Bakinezou, D., Pantazidis, S., Papadogonas, T., and Papazoglou, C., 2005. Aspects of the Economic and Financial Integration of Greece into the European Union, Bank of Greece, Research Department, July.
- Tagkalakis, A.O., 2015. Fiscal policy, net exports, and the sectoral composition of output in Greece. *International Economics and Economic Policy*, 12(4), pp. 521-539.
- Tavlas, G., Zonzilos, N., 2001. Comment on Bosworth and Kollintzas. In: Bryant, R., Garganas, N., Tavlas, G. (Eds.), Greece's Economic Performance and Prospects. Bank of Greece and the Brookings Institution, Athens, pp. 202–210.
- Terasvirta, T. and Anderson, H.M., 1992. Characterizing nonlinearities in business cycles using smooth transition autoregressive models. *Journal of Applied Econometrics*, 7(S1), pp. S119-S136.
- The New York Times, 1976. "Economic Conditions In Greece".
- Thomson, D. and Van Vuuren, G., 2016. Forecasting the South African business cycle using Fourier analysis. *International Business and Economics Research Journal (IBER)*, *15*(4), pp.175-192.
- Tsakas, C., 2018. Europeanisation under authoritarian rule: Greek business and the hoped-for transition to electoral politics, 1967–1974. *Business History*.
- Tsionas, E.G., Konstantakis, K.N. and Michaelides, P.G., 2016. Bayesian GVAR with k-endogenous dominants & input–output weights: Financial and trade channels in crisis transmission for BRICs. *Journal of International Financial Markets, Institutions and Money*, 42, pp.1-26.
- Tsouma, E., 2014. Dating business cycle turning points: The Greek economy during 1970-2012 and the recent recession. *OECD Journal: Journal of Business Cycle Measurement and Analysis*, *2014* (1), pp. 1-24.

- Wolfson, P. 1994. A simple Keynesian model with flexible wages: A succinct synthesis. *Journal of Macroeconomics*, 16 (1), pp. 129-156.
- World Bank. "Exports and Imports" World Development Indicators. The World Bank Group, 2019. Retrieved from data.worldbank.org in March 2021.
- Zezza, G., 2010. Getting out of the recession?. *Levy Economics Institute*.

Appendix



Source: EU Commission, AMECO Database (November 2020).

Figure 96: Gross Debt of the General Government, 1970-2019.

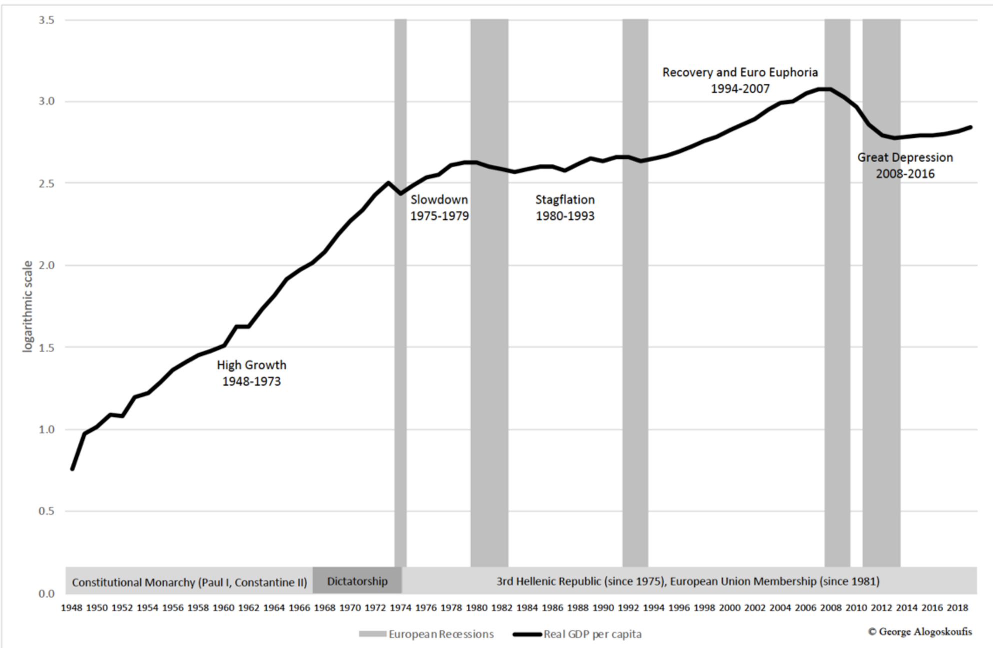


Figure 97: Real GDP Per Capita, 1948-2019 [Alogoskoufis, 2021].