1.1 Time-series Econometrics

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FORECASTING ECONOMIC TIME SERIES IN THE PRESENCE OF VARIANCE INSTABILITY AND OUTLIERS

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ABSTRACT

Very often in actual macroeconomic time series there are causes that disrupt the underlying stochastic process and their treatment is known as «linearization». In addition, variance non-stationarity is in many cases also present in such series and is removed by proper data transformation. The impact of either of them (data transformation - linearization) on the quality of forecasts has not been adequately studied to date. This work examines their effect on univariate forecasting considering each one separately, as well as in combination, using twenty of the most important time series for the Greek economy. Empirical findings show a significant improvement in forecasts' confidence intervals, but no substantial improvement in point forecasts. Furthermore, the combined transformation-linearization procedure improves substantially the non-normality problem encountered in many macroeconomic time series.

Keywords: applied time series analysis, time series «linearization», time series transformation, outliers, forecasting of macroeconomic time series, Greek macroeconomic time series.

1. Introduction

A univariate AutoRegressive Integrated Moving Average (henceforth ARIMA) model is a concise quantitative summary of the internal dynamics of a time series in a linear framework, as such, is useful for several reasons, amongst others for forecasting and model-based time series decomposition in unobserved components. This work will deal with the former and, in particular, with univariate forecasts, which usually serve either as short-term, or benchmark forecasts. However, economic time series from the real world are not usually "ready" to be used for forecasting purposes and they need to undergo some statistical preparation and pre-adjustment. This is because in time series of raw data variance non-stationarity may be present. Furthermore, very often there exist causes that disrupt the underlying stochastic process (existence of outliers, calendar effects, etc.). Their treatment is known as «linearization».

Within that line of reasoning, statistical forecasts can be made after a series itself, or some variance stabilizing transformation of it, is "linearized" according to the general framework (Kaiser and Maravall 2001):

$$y_t = w_t' b + C_t' \eta + \sum_{j=1}^{m} \alpha_j \mu_j(B) I_t(t_j) + x_t \tag{1}$$

where: $y_t = f(z_t), f$ is some transformation of the raw series z_t, which may be necessary to stabilize the variance;

$b = (b_1, \ldots, b_n)$ is a vector of regression coefficients;

$w_t' = (w_{1t}, \ldots, w_{nt})$ denotes n regression or intervention variables;

C_t' denotes the matrix with columns possible calendar effect variables (e.g. trading day) and η the vector of associated coefficients;

$I_t(t_j)$ is an indicator variable for the possible presence of an outlier at period t_j;

$\mu_j(B)$ captures the transmission of the j-th effect and α_j denotes the coefficient of the outlier in the multiple regression model with m outliers;

x_t follows in general a multiplicative seasonal ARIMA$(p,d,q)(P,D,Q)_s$ model:

$$\varphi(B)\Phi(B^s)\nabla^d\nabla_s^D x_t = \theta(B)\Theta(B^s)\varepsilon_t \tag{2}$$

where:

- $\varphi(B) = 1 - \phi_1 B - \ldots - \phi_p B^p$ is the so–called autoregressive polynomial of order p;
- $\theta(B) = 1 - \theta_1 B - \ldots - \theta_q B^q$ is the so–called moving average polynomial of order q;
- $\nabla^d \equiv (1-B)^d$ is the arithmetic difference operator of order d;
- $\nabla_s^D \equiv (1-B)_s^D \equiv (1-B^s)^D$ is the seasonal arithmetic difference operator of order D and seasonality s;
- $\Phi(B^s) = 1 - \Phi_1 B^s - \ldots - \Phi_P B^{P\cdot s}$ is the so–called seasonal autoregressive polynomial of order P and seasonality s;
- $\Theta(B^s) = 1 - \Theta_1 B^s - \ldots - \Theta_Q B^{Q\cdot s}$ is the so–called moving average polynomial of order Q and seasonality s;
- ε_t is the stochastic disturbance.

As far as variance stabilization is concerned, if variance is somehow functionally related to the mean level it is possible to select a transformation to stabilize the variance. Widely used transformations to tackle this problem belong to the class of the power Box and Cox transformation (Box and Cox 1964). For example, very often used transformations are given by:

$$f(z_t) = \begin{cases} z_t^{\lambda} \ if \ \lambda > 0 \\ lnz_t \ \ if \ \lambda = 0 \\ -z_t^{\lambda} \ if \ \lambda < 0 \end{cases} \quad (3)$$

On the other hand, outliers are major changes in values that especially stand out in a time series In the TSW[1] framework, of which use will be made in this work, three types of outliers are detected according to their effect in a time series: Additive outliers (AO), Transitory Change outliers (TC), and Level shifts (LS). In an additive outlier the value of only one observation is affected. In a transitory change the value of one observation is extremely high or low and then the size of the deviation is gradually reduced. In the level shift the level of the time series is changed. As far as the detection of outliers is concerned within the TSW framework, outliers are automatically detected, classified and corrected using the Chen and Liu (1993) approach (further details in Section 3).

So, there are two effects with potential influence on forecasting: «linearization» and transformation, each of which separately, as well as in combination, may play an important role on time series forecasting.

At the empirical level, studies which have considered the merits of mathematical transformations on forecasting have demonstrated that a data transformation often does not have a positive effect on forecast accuracy (Nelson and Granger 1979; Makridakis and Hibon 1979; Makridakis *et al*. 1998; Meese and Geweke 1984).

On the other hand, at the theoretical level, Granger and Newbold (1976) found that such forecasts are not optimal in terms of minimization of Mean Square Forecast Error (MSFE). More specifically, for instance for the most popular transformation, namely the logarithmic one, they showed that the minimum MSFE h-step ahead forecast is not equal to $\hat{z}_{T+h} = exp(\hat{y}_{T+h})$, as implied by the previous discussion, but is given by the expression $\hat{z}_{T+h} = exp\left(\hat{y}_{T+h} + \frac{1}{2}\sigma_h^2\right)$, where σ_h^2 is the h-step ahead forecast error variance. Pankratz and Dudley (1987), building up further on the work of Granger and Newbold (1976), relate the bias in using simply the inversely transformed value of the forecasts on the transformed time series (as compared to the minimum MSFE forecast) amongst others to the value of the exponent λ of the power transformation. The two most frequent transformations, namely the logarithmic and the square root ones, under certain conditions may be associated with serious biases (Pankratz and Dudley 1987).

Regarding time series linearization, such a procedure is utilized thus far mainly as a preadjustment task for seasonal adjustment (Kaiser and Maravall 2001), so its effect on forecasting has not been examined systematically, but only indirectly and

[1] TSW stands for TRAMO-SEATS for Windows, a Windows version of the DOS programmes TRAMO and SEATS (see Gomez and Maravall 1996), and is freely available by the provider (Bank of Spain).

fragmentally.[2] It is also remarked that even in studies coping with forecasting with transformed data the attention focuses almost exclusively on point forecasts, by and large disregarding interval forecasts.

Aiming at covering this research gap in the literature the objective of this work is in fact twofold: a) to examine the effect of «linearization» and transformation separately, as well as in combination, on both point forecasts and confidence interval forecasts; b) as a further application, we rank main economic indicators of the Greek economy in terms of statistical «forecastability». The intended approach will be practical.

The structure of the paper is as follows: In Section 2 details about the data to be used for the empirical analysis are given; Section 3 presents the empirical results and relevant comments; Section 4 summarizes and concludes the paper.

2. Data

The data set comprises some of the most important macroeconomic time series for the Greek economy, which refer to: GDP; unemployment; prices of consumer goods and services; monetary aggregates; and balance of payments statistics. Particularly, in the balance of payments, a distinction is made between imports – exports of all goods and imports - exports of goods without fuels and ships, as according to a study by the Bank of Greece (Oikonomou *et al.* 2010), the dependence of the Greek economy on oil was high and was rising at the fastest pace among the euro area countries. Furthermore, from the same study it is noted that the balance of payment of sea transport is significant in the Greek balance of current transactions (4% of GPD in 2008) and will be considered separately from other BOP transactions on transport. The share of revenue from maritime transport in the country's GDP is significant. During the period 2015-2021, it averaged 7.5% of GDP, while in 2021 it amounted to 9.4% of GDP (Papaconstantinou 2022). During the period 2015-2021, revenue from maritime transport accounted for over 40% of service exports and approximately 21% of total exports of goods and services, highlighting their decisive role in promoting the outward orientation of the Greek economy. It should be noted that revenue from maritime transport contributed significantly to limiting the negative effects of the pandemic on the Current Account Balance and the country's GDP in 2020, as they decreased by 15%, but much less than revenue from travel services, which recorded a 76% decline. In 2021 revenues from maritime transport services, amounted to €17.2 billion. Net revenue from maritime transport (i.e., revenue minus payments) amounted to EUR 6.2 billion and covered about a quarter of the trade deficit in 2021, contributing positively to the Current Account Balance. 2022 was a remarkable year for revenue from maritime transport, amounted to €21.0 billion and exceeded the historically high level of 2008, €17.6 billion (Governor’s Annual Report 2022).

As of January 1st, 2022, the leading countries in terms of both dead-weight tonnage and commercial value for ship ownership remained the same as in previous

[2] An additional advantage of “linearizing” the outliers is that such a procedure makes the original data distribution shift closer towards normality. This is important, especially for actual economic data in view of their extreme non-normality in many cases.

years, with Greece, China, and Japan taking the top three places (see Appendices 1 and 2). According to data from the United Nations Conference on Trade and Development (UNCTAD 2022), Greece is at the forefront in terms of tonnage (dwt), even though only 17.63% of the ships owned or managed by Greece are registered under the Greek flag, while China is leading in terms of commercial value.

The Bank of Greece recognizing the importance of Greek shipping for the Greek economy places special emphasis on collecting reliable data in the maritime shipping sector. To this end, it has developed a model for estimating Greek shipping activity and for preparing the accounts of marine transport in the balance of payments (Balance of payments: Revision of sea transport statistics 2018). The imposition of capital controls in 2015 resulted in a significant reduction of incoming capital inflows from the second half of that year, according to the external transactions data of the domestic banking system. However, there were no indications of a corresponding reduction in the real economic activity of the sector and therefore its contribution to the Greek economy. To address and rectify this inconsistency, the Bank of Greece developed a model for estimating Greek shipping activity. Starting from September 2018 (reference month), the Bank of Greece uses data from international shipping databases and administrative sources, instead of the bank settlements data used until August 2018 to calculate sea transport statistics in the balance of payments. This new method will accurately reflect international shipping transactions carried out within or outside the domestic banking system, in accordance with international balance of payment guidelines. Using these new sources will enable the Bank of Greece to calculate receipts and expenses in detail on a monthly basis, combining information from domestic administrative sources and global databases recommended by reliable international organizations such as the International Monetary Fund (IMF). This new approach was developed in collaboration with shipping experts from academia and the industry as part of the quality assurance process for the statistics underlying the Macroeconomic Imbalances Procedure (MIP).

This development confirms the opinion of Milionis (Newspaper of the University of the Aegean 2010) that when the economy was operating under a regime of multiple and strict restrictions and controls (before 1990), the corresponding statistical system, despite its simplicity, functioned satisfactorily, precisely because of these constraints. Unfortunately, however, in relation to the rapidly changing economic reality from then on, the above-mentioned statistical system was totally inadequate. Specifically, radical changes were required: a) at the institutional-legal framework level and b) at the level of statistical methodology. As for a), it was initially necessary to separate the two main sources of official statistical information in the country - the Hellenic Statistical Authority and the Bank of Greece - from the general government. As regards the Bank of Greece, its independence was established in 1997 (Law 2548/97), while as regards the Hellenic Statistical Authority, its abolition as a general secretariat was legislated and the establishment of the Hellenic Statistical Authority, as a new Independent Administrative Authority, was proposed in its place (Law 3832/9.3.2010). Regarding b), a new method of statistical approach and thinking was created for the development of a new statistical culture, in which the knowledge of statistics itself should be combined with a deep understanding of the particularly complex new macroeconomic-financial developments in order to achieve the desired goal. Therefore, in addition to the unquestionable responsibility of policymakers, there was also a scientific-academic responsibility for the deafening weaknesses of the Greek statistical system, for the lack of specialized knowledge of young scientists related to the subject, and consequently for the unreliability of Greek statistical data.

More specifically about the data, twenty economic time series were used, of which nineteen were monthly time series, while one was quarterly time series (sources: Bank of Greece (BoG) and Hellenic Statistical Authority (ELSTAT)). The list of time series used is given in Table 1.

Table 1. *Data*

Time Series	Observation frequency	Source
Gross Domestic Product (GDP)	Quarterly	ELSTAT
Industrial Production Index (IPI)	Monthly	ELSTAT
Consumer Price Index (CPI)	Monthly	ELSTAT
Harmonised Index of Consumer Prices (HICP)	Monthly	ELSTAT
Unemployment – thousands	Monthly	ELSTAT
Unemployment – percentage	Monthly	ELSTAT
Retail sales	Monthly	ELSTAT
M1	Monthly	BoG
M2	Monthly	BoG
M3	Monthly	BoG
Balance of payments (BOP) – Transport – Payments	Monthly	BoG
Balance of payments (BOP) – Transport – Receipts	Monthly	BoG
Balance of payments (BOP) – Travelling – Payments	Monthly	BoG
Balance of payments (BOP) – Travelling – Receipts	Monthly	BoG
Balance of payments (BOP) – Sea transport – Payments	Monthly	BoG
Balance of payments (BOP) – Sea transport – Receipts	Monthly	BoG
Exports of Goods	Monthly	BoG
Exports of Goods without fuels and ships	Monthly	BoG
Imports of Goods	Monthly	BoG
Imports of Goods without fuels and ships	Monthly	BoG

The monthly time series data cover the period from January 2004 to August 2018 and consist of one hundred and seventy-six (176) observations, except for Industrial Production Index, where available data existed from January 2010 to August 2018 (104 observations). The quarterly time series is that of Gross Domestic Product and covers the period from 1995 Quarter 1 to 2018 Quarter 3 (95 observations).

3. Empirical results and comments

As mention in section 1, the effect of transformation and the effect of linearization on forecasting will be examined at first each one separately and, subsequently, in combination. The aforementioned effects will be studied utilizing TSW.

Typical statistics to be used for the assessment of the quality of point forecasts are the following:

i) the Mean Absolute Percentage Error (MAPE) statistic given by:

$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$,

ii) the Mean Square Forecast Error (MSFE) statistic given by:

$MSFE = \frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2$, and

iii) the Mean Absolute Error (MAE) statistic given by:

$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t|$,

where A_t is the actual value and F_t is the forecast value.

Furthermore, as far as interval forecasts are concerned, the width of the forecast confidence interval (CI), or the forecast standard error, will be considered.

Best forecast will obviously be perceived the one with the minimum value of each time utilized statistic from the ones mentioned above.

3.1 The effect of «linearization» on forecast quality

We will investigate how time series linearization affects the quality of both point forecasts and confidence interval forecasts. Here linearization will not be considered in its generality, as described in Section 1, but will be confined to outliers' detection and adjustment[3]. Table 2 presents the number of best forecasts with data in levels. Auxiliary Table 3 presents the number of best forecasts with log-transformed data indistinguishably for all time series, as it is often the case to use log-transformed data in econometric analyses. It is noted that in one time series with levels (that of unemployment expressed in percentages) and one time series in logs (that of industrial production index) no outliers were detected, hence, the total number of time series considered reduced to nineteen for each case.

From the results of Table 2 and Table 3 it is apparent that, when outliers are considered, forecasts are better in every single case in terms of the width of the forecast confidence interval. In contrast, there is no obvious improvement in point forecasts. One point that should be stressed is that such results are in general dependent upon the specific characteristics of each time series, especially upon whether an outlier lays among the first, the middle or the last observations. For this reason, it would be desirable to use a large number of time series, so as to draw conclusions of indisputable confidence. Although the number of time series used in this work is relatively small (though comparable to that of other similar works, see for instance Nelson and Granger 1976) the evidence that lead to the above conclusions, in particular regarding the width of the forecast confidence interval, is so convincing that it really stands far and beyond any concern related to micronumerosity.

[3] Calendar effects such as the trading day and leap effects were considered and indeed were found to be statistically significant on some occasions. All series were properly adjusted for calendar effects before further analysis.

Table 2. *Summary table - Number of best forecasts (levels)*[4]

Point Forecast	With detected Outliers	Without Outliers
MAPE	10/19	9/19
MSFE	8/19	11/19
MAE	9/19	10/19
Confidence Interval	**With detected Outliers**	**Without Outliers**
Standard error (SE)	19/19	0/19

Table 3. *Summary table - Number of best forecasts (log-data)*

Point Forecast	With detected Outliers	Without Outliers
MAPE	9/19	10/19
MSFE	11/19	8/19
MAE	10/19	9/19
Confidence Interval	**With detected Outliers**	**Without Outliers**
Standard error (SE)	19/19	0/19

3.2 The effect of Level Shifts (LS), in particular, on forecast quality

After a level shift outlier, all observations subsequent to the outlier move to a new level. In contrast to additive and transitory outliers a level shift outlier reflects a major change in the stochastic process and affects many observations, as it has a permanent effect. For this reason, the case with only additive and transitory outliers (i.e. excluding level shifts) was examined separately, performing the same analysis as in Section 3.1. It is noted that this time only fifteen time series were considered, i.e. those including all types of outliers. The results are presented in Table 4 and Table 5.

Table 4. *Summary table - Number of best forecasts (levels)*

Point Forecast	All Outliers	Outliers without LS
MAPE	6/15	9/15
MSFE	5/15	10/15
MAE	6/15	9/15
Confidence Interval	**All Outliers**	**Outliers without LS**
Standard error (SE)	14/15	1/15

Table 5. *Summary table - Number of best forecasts (log-data)*

Point Forecast	All Outliers	Outliers without LS
MAPE	6/15	9/15
MSFE	5/15	10/15
MAE	6/15	9/15
Confidence Interval	**All Outliers**	**Outliers without LS**
Standard error (SE)	13/15	2/15

From the results above it is obvious that there is a trade-off: confidence interval forecasts are better with level shift outliers included and, conversely, point forecasts are better excluding level shifts. Given the influence of the level shift outliers it would be desirable to possibly consider stricter identification criteria for them relative to the other two types of outliers. It is noted that in existing statistical software specializing on time

[4] In all cases the hold out sample for ex-post forecasts was set to twelve time periods for the monthly series and ten time periods for GDP.

series analysis there is no such an option and a purpose-built routine should be created by the researcher.

3.3 The effect of a data transformation on forecast quality

As far as the effect of a data transformation is concerned, at first it is important to note that the effect of a transformation in meant in two ways: 1) direct and 2) indirect (through its influence on outlier detection). Indeed, regarding the later, it has been shown that data transformation affects the number and the character of outliers in a time series (Milionis 2003; Milionis 2004).

The possible need for a data transformation of the original time series data will be examined using the TSW routine. Once a decision about the proper data transformation is made, TSW will be used for further analysis on statistical forecasting.

Table 6 presents the results on the decision about, transforming or not, the original time series data. The twenty series were analyzed following the standard TSW procedure. It is noted that the only alternatives available with TSW are either the log-transformation, or no transformation. Using the TSW routine for these twenty cases, TSW suggested the logarithmic transformation of the original data for eighteen cases. It is remarkable that only for the two series of unemployment TSW suggests no transformation.

Table 6. *Decision about data transformation*

TIME SERIES	LOG-LEVEL PRETEST (Output from TSW)
Gross Domestic Product (GDP)	SSlevels/(SSlog*Gmean(levels)^2)= 1.1380170 LOGS ARE SELECTED
Consumer Price Index (CPI)	SSlevels/(SSlog*Gmean(levels)^2)= 1.0781750 LOGS ARE SELECTED
Harmonised Index of Consumer Prices (HICP)	SSlevels/(SSlog*Gmean(levels)^2)= 1.0954455 LOGS ARE SELECTED
Industrial Production Index (IPI)	SSlevels/(SSlog*Gmean(levels)^2)= 1.0224433 LOGS ARE SELECTED
Unemployment – thousands	SSlevels/(SSlog*Gmean(levels)^2)= 0.87725642 LEVELS ARE SELECTED
Unemployment – percentage	SSlevels/(SSlog*Gmean(levels)^2)= 0.86356273 LEVELS ARE SELECTED
Retail sales	SSlevels/(SSlog*Gmean(levels)^2)= 1.2755206 LOGS ARE SELECTED
M1	SSlevels/(SSlog*Gmean(levels)^2)= 0.98393639 LOGS ARE SELECTED
M2	SSlevels/(SSlog*Gmean(levels)^2)= 1.0714007 LOGS ARE SELECTED
M3	SSlevels/(SSlog*Gmean(levels)^2)= 1.0422806 LOGS ARE SELECTED
Balance of payments (BOP) – Transport – Payments	SSlevels/(SSlog*Gmean(levels)^2)= 1.0351033 LOGS ARE SELECTED
Balance of payments (BOP) – Transport – Receipts	SSlevels/(SSlog*Gmean(levels)^2)= 1.1641507 LOGS ARE SELECTED
Balance of payments (BOP) – Travelling – Payments	SSlevels/(SSlog*Gmean(levels)^2)= 1.1509645 LOGS ARE SELECTED
Balance of payments (BOP) – Travelling – Receipts	SSlevels/(SSlog*Gmean(levels)^2)= 4.3996100 LOGS ARE SELECTED

Balance of payments (BOP) – Sea transport – Payments	SSlevels/(SSlog*Gmean(levels)^2)= 0.98863656 LOGS ARE SELECTED
Balance of payments (BOP) – Sea transport – Receipts	SSlevels/(SSlog*Gmean(levels)^2)= 1.1948699 LOGS ARE SELECTED
Exports of Goods	SSlevels/(SSlog*Gmean(levels)^2)= 0.95751942 LOGS ARE SELECTED
Exports of Goods without fuels and ships	SSlevels/(SSlog*Gmean(levels)^2)= 0.96487436 LOGS ARE SELECTED
Imports of Goods	SSlevels/(SSlog*Gmean(levels)^2)= 1.1118244 LOGS ARE SELECTED
Imports of Goods without fuels and ships	SSlevels/(SSlog*Gmean(levels)^2)= 1.2957291 LOGS ARE SELECTED

The possible effect of transforming time series on forecasting quality is examined through Table 7. From the results below it is concluded that point forecasts with TSW transformation method are the same in comparison with that of no transformation in terms of MAPE and MAE, and slightly worse in terms of MSFE. As already explained, forecasts on transformed variables are not optimal in terms of MSFE. Similarly, confidence interval forecasts are shorter in only eight out of the eighteen cases using transformations with the TSW approach. Thus, data transformations using the TSW routine do not seem to improve either point forecasts or forecasts confidence intervals. We note, however, that in this case a larger data set is needed for more solid conclusions. Moreover, the outcome may be a result of the restriction of TSW to use only the logarithmic transformation. Further research is needed on that matter allowing for a wider range of transformations.

Table 7. *Summary table - Number of best forecasts (TSW versus benchmark)*

Point Forecast	**TSW - no outliers**	**Levels-no outliers (Benchmark)**
MAPE	9/18	9/18
MSFE	7/18	11/18
MAE	9/18	9/18
Confidence interval	**TSW - no outliers**	**Levels-no outliers (Benchmark)**
Standard error (SE)	8/18	10/18

3.4 The combined effect of a linearization and data transformation

The results of the examination of the forecasting performance combining both linearization and data transformation are presented in Table 8. The conclusion that is derived is that, by and large, the combined effect does not lead to better point forecasts but leads to improved confidence interval forecasts. The conclusion about the forecast confidence interval is reasonable and, to a large extent, expected, as with the adjustment for outliers the process variance is reduced. It is possible to exploit this reduction in obtaining forecasts with increased confidence.

Appendix 3 presents the ARIMA models for the benchmark model and the combination of TSW variance stabilizing method - linearization. It is noted that the differences in the ARIMA models for the two time series where no transformation was needed (that of unemployment expressed in percentages and thousands) should be attributed to the existence of outliers adjusted by linearization.

Table 8. *Summary table - Number of best forecasts (TSW versus benchmark)*

Point Forecast	TSW	Levels-no outliers (Benchmark)
MAPE	8/18	10/18
MSFE	8/18	10/18
MAE	8/18	10/18
Confidence interval	**TSW**	**Levels-no outliers (Benchmark)**
Standard error (SE)	12/18	6/18

3.5 Sensitivity Analysis: Outliers (Dependence of Outlier Detection on the Parameter τ)

Let $\hat{Y}_{T+1}/\Phi_T$ denote the optimal one-step-ahead linear forecast of Y_{T+1} given the information set Φ_T, which includes information up to time T, $e_{T+1} = Y_{T+1} - \hat{Y}_{T+1}/\Phi_T$ denote the associated forecast error, and $\sigma_{T+1}^2 = [Y_{T+1} - \hat{Y}_{T+1}/\Phi_T]^2$ denote the associated variance. The observation Y_{T+1} is considered as an outlier if the null Hypothesis: $H_0: e_{T+1} = 0$ is rejected. The appropriate statistic to test H_0 is: $\tau = \frac{e_{T+1}}{\sigma_{T+1}}$.

However, theory cannot predict the critical value of $\boldsymbol{\tau}$ above which the corresponding observation can be considered as an outlier. A usual practice is to relate the critical value of $\boldsymbol{\tau}$ with the length of a time series. The default values of TSW for $\boldsymbol{\tau}$ are presented in Table 9[5]. In the course of our experimentation it was observed that outlier detection (as well as ARIMA models for the linearized-transformed series), were very sensitive to the value of parameter $\boldsymbol{\tau}$. In order to examine, whether or not, the critical $\boldsymbol{\tau}$ values could have any noticeable effect on our final conclusions, as an alternative set of critical values for $\boldsymbol{\tau}$ we used those suggested by Fischer and Planas (2000), who examined a very large number of time series. Their critical values for $\boldsymbol{\tau}$ were set at 3.5, 3.7 and 4.0 for series lengths of less than 130 observations, between 131 and 180, and more than 180 observations, respectively.

The comparison of the results based on default critical $\boldsymbol{\tau}$ values, as well as on Fischer – Planas recommendations are presented in Table 10, while the detected outliers for each time series and each set of values for the parameter $\boldsymbol{\tau}$ are presented in Appendix 4. Looking at Appendix 4 it is observed that the detection of outliers is indeed sensitive even to the examined small changes in the value of $\boldsymbol{\tau}$. On the other hand, however, from the results of Table 10, it is apparent that using the Fisher and Planas critical values for

[5] In the TSW framework the subroutine TERROR is designed especially for outlier detection. Incoming data volume in institutions like EUROSTAT, ECB, OECD, NCBs, NSOs etc. may be enormous. Such data may be contaminated by errors of various types and origins. Using TERROR is a convenient, yet formal way to spot aberrant observations (outliers). It is highly possible that if erroneous data do exist, they will be included in the set of observations characterized as outliers by TERROR, hence, in a second stage, their possible identification is focused exclusively on that data set. In this work we used the first stage only.

$\boldsymbol{\tau}$ leads to mixed results regarding the effect on forecast quality. By and large, there is only very weak evidence of improvement using the Fischer – Planas recommendations[6].

Table 9. *Critical values for $\boldsymbol{\tau}$*

Observations	**Default values for τ in TSW**
164	0.358E+01
165 – 168	0.359E+01
169 – 172	0.360E+01
173 – 175	0.361E+01

Table 10. *Results based on Fischer – Planas recommendations*

Time series	**Improvement of forecast quality**	**Same forecast quality**	**Deterioration of forecast quality**
Gross Domestic Product (GDP)		MAPE, MSFE, MAE, SE (TSW)	MAPE, MSFE, MAE, SE (Levels - all outliers)
Consumer Price Index (CPI)	MAPE, MSFE, MAE (TSW)	MAPE, MSFE, MAE, SE (Levels – all outliers)	SE (TSW)
Harmonised Index of Consumer Prices (HICP)	MAPE, MSFE, MAE (Levels – all outliers) MAPE, MSFE, MAE, SE (TSW),		SE (Levels – all outliers)
Industrial Production Index (IPI)	MAPE, MSFE, MAE (Levels – all outliers)	MAPE, MSFE, MAE, SE (TSW)	SE (Levels – all outliers)
Unemployment – thousands	MSFE (Levels - all outliers, and TSW)		MAPE, MAE, SE (Levels – all outliers, and TSW)
Unemployment – percentage	MAPE, MSFE, MAE (Levels – all outliers, and TSW)	SE (Levels – all outliers, and TSW)	
Retail sales	MAPE, MSFE, MAE (Levels – all outliers)		SE (Levels – all outliers) MAPE, MSFE, MAE, SE (TSW)
M1		MAPE, MSFE, MAE, SE (Levels – all outliers, and TSW)	
M2	MAPE, MAE (Levels – all outliers)		MSFE, SE (Levels – all outliers) MAPE, MSFE, MAE, SE (TSW)
M3	MAPE, MSFE, MAE (Levels – all outliers)		SE (Levels - all outliers) MAPE, MSFE, MAE, SE (TSW),
Balance of payments (BOP) – Transport - Payments	MAPE, MSFE, MAE (TSW)		SE (TSW) MAPE, MSFE, MAE, SE (Levels – all outliers)
Balance of payments (BOP) – Transport – Receipts	MSFE (Levels – all outliers)		MAPE, MAE, SE (Levels - all outliers)

[6] Indeed, setting the Fisher –Planas critical values instead of the default ones, the results pertaining to those of Table 8 they are identical in terms of the standard error, and 8/18 for MAPE, MAD and MSFE with TSW, as compared to 7/18 using the default critical values.

	MAPE, MSFE, MAE, SE (TSW)		
Balance of payments (BOP) – Travelling - Payments		MAPE, MAE, SE (TSW)	MSFE (TSW) MAPE, MSFE, MAE, SE (Levels – all outliers)
Balance of payments (BOP) – Travelling – Receipts		SE (TSW)	MAPE, MSFE, MAE (TSW) MAPE, MSFE, MAE, SE (Levels - all outliers)
Balance of payments (BOP) – Sea transport - Payments	MAPE, MSFE, MAE (Levels – all outliers, and TSW)		SE (Levels – all outliers, and TSW)
Balance of payments (BOP) – Sea transport – Receipts	MAPE, MSFE, MAE (Levels - all outliers, and TSW)		SE (Levels - all outliers, and TSW)
Exports of Goods	MAPE, MSFE, MAE (Levels – all outliers, and TSW)		SE (Levels - all outliers, and TSW)
Exports of Goods without fuels and ships			MAPE, MSFE, MAE, SE (Levels – all outliers, and TSW)
Imports of Goods		MAPE, MSFE, MAE, SE (Levels - all outliers)	MAPE, MSFE, MAE, SE (TSW)
Imports of Goods without fuels and ships	MAPE, MSFE, MAE (TSW)	MAPE, MSFE, MAE, SE (Levels - all outliers)	SE (TSW)

3.6 An ad-hoc evaluation of models' forecasting performance

The skill of a forecast can be assessed by comparing the relative proximity of both the forecast and a benchmark to the observations. The presence of a benchmark makes it easier to compare approaches and for this reason a benchmark is proposed to establish a common ground for comparison. In the present case an obvious benchmark is to use the twenty-time series described in section 2, non-linearized and non-transformed. Although there exist established formal tests for forecast evaluation (Hansen P.R. 2005; Hansen *et al*. 2011; White H. 2000) in this work, in line with its practical character, it suffices to use a very simple and transparent ad-hoc forecasting evaluation approach based on point and interval forecasts.

More specifically, for the point forecasts for each time series and for each model an arithmetic value is assigned in ascending order based on the corresponding value of the MSFE statistic (i.e. 1 for the minimum MSFE value, 2 and 3 for the second and third lower MSFE value respectively, 4 for the maximum MSFE value). Then, adding up the arithmetic values for all series for a particular model their sum will represent the performance of the model. Models will be ranked according to the value of the corresponding sum. Apparently, the model with the lowest sum will be considered as the best one. For interval forecasts the same procedure will be followed replacing the value of the MSFE statistic with the value of the corresponding standard error around the point forecasts. The results are shown in Tables 11 and 12[7] and more detailed results are quoted in Appendix 5. It is clarified that TSW transformation approach is coupled with the outlier detection-adjustment approach.

Table 11. *Ranking of forecasting performance according to MSFE (point forecasts)*

Time series	Benchmark	Logs - no outliers	Levels - all outliers	TSW
Consumer Price Index (CPI)	2	1	4	3
Harmonised Index of Consumer Prices (HICP)	1	2	3	4
M3	1	2	3	4
M2	3	1	2	4
Gross Domestic Product (GDP)	4	1	3	2
M1	4	2	3	1
Industrial Production Index (IPI)	1	3.5	2	3.5
Retail sales	1	3	2	4
Unemployment – thousands	2	1	3.5	3.5
Balance of payments (BOP) – Transport – Receipts	2	1	4	3
Balance of payments (BOP) – Sea transport – Receipts	1	2	4	3
Unemployment – percentage	3	1	3	3
Balance of payments (BOP) – Transport – Payments	1	2	3	4
Imports of Goods without fuels and ships	3	4	1	2
Exports of Goods without fuels and ships	4	2	3	1
Exports of Goods	3	2	4	1
Balance of payments (BOP) – Sea transport – Payments	3	4	2	1
Imports of Goods	3	4	2	1
Balance of payments (BOP) – Travelling – Receipts	3	2	4	1
Balance of payments (BOP) – Travelling – Payments	2	3	4	1
SUM	47	43.5	59.5	50

[7] If for two models the value of MSFE or SE is exactly the same, the mid-point will be used for both.

__Table 12.__ Ranking of forecasting performance according to SE (interval forecasts)

Time series	Benchmark	Logs – no outliers	Levels – all outliers	TSW
Harmonised Index of Consumer Prices (HICP)	3	4	1	2
Consumer Price Index (CPI)	3	4	1	2
M1	3	4	1	2
M3	4	3	2	1
M2	4	3	2	1
Gross Domestic Product (GDP)	4	3	2	1
Unemployment – percentage	2	4	2	2
Industrial Production Index (IPI)	2	3.5	1	3.5
Unemployment – thousands	3	4	1.5	1.5
Exports of Goods without fuels and ships	2	4	1	3
Retail sales	4	2	3	1
Exports of Goods	2	4	1	3
Balance of payments (BOP) – Transport – Receipts	3	4	1	2
Balance of payments (BOP) – Transport – Payments	2	4	1	3
Balance of payments (BOP) – Sea transport – Receipts	4	3	2	1
Imports of Goods without fuels and ships	4	3	2	1
Balance of payments (BOP) – Sea transport – Payments	2	4	1	3
Imports of Goods	4	3	2	1
Balance of payments (BOP) – Travelling – Payments	4	2	3	1
Balance of payments (BOP) – Travelling – Receipts	2	4	1	3
SUM	61	69.5	31.5	38

From the results of Tables 11 and 12 it is evident that the performance of TSW approach for point forecasts is not better than that of the benchmark model (as a matter of fact is slightly worse). On the other hand, for the forecast confidence intervals the Levels - all outliers method has a better performance than TSW and the benchmark model. Furthermore, TSW outperforms the benchmark model. A rather crude way to procced to an overall evaluation of the four models is to add up their performances in the two categories (i.e. point and interval forecasts). The addition gives the values of

108, 113, 91 and 88 for the benchmark model, Logs – no outliers, Levels – all outliers and TSW method respectively, which means that TSW method performs clearly better that the benchmark model and further the overall performance of the TSW method is slightly better than that of the "levels-all outliers model" and clearly better than that of the other two models.

Nelson and Granger (1979) utilized the Box-Cox transformations, amongst others, for forecasting purposes (point forecasts) using twenty-one actual economic time series. As they failed in getting superior forecasts, they reached to the rather pessimistic conclusion that it is not worthwhile to make use of these transformations bearing in mind the extra inconvenience, effort and cost. Their point of view was subsequently adopted by other researchers as well, as already mentioned in the introductory section. Lest to get too disappointed, despite the fact that cost and effort are much lower nowadays than what they were at that time, we further note that Nelson and Granger (1979) did not associate forecasts on transformed time series with an outlier detection-adjustment approach. Furthermore, their conclusion was based only on point forecasts, disregarding forecast confidence intervals. The latter are of much importance especially in cases where the focus is on best-worst forecast scenarios. For instance, such is the case with actuarial time series on mortality rates, which may be used further for the construction of pension plans. As shown above, the combination of transformation-linearization leads to shorter forecast confidence intervals.

It should also be stressed that neither in the existing research works thus far, nor in the present one, the treatment of the effect of data transformation on time series forecasting is complete for the simple reason that no work extends the analysis in a bivariate (in general multivariate) framework. Indeed, the existence of variance non-stationarity in time series will contaminate the pre-whitening process (for details about the pre-whitening process see Box and Jenkins 1976), consequently, the sample cross correlation function, so it will mask the true dynamic relationship between two series, one of which is supposed to be the leading indicator, thus affecting negatively the conditional (in this case) forecasts.

3.7 The Shift towards Normality

Another serious concern expressed by Nelson and Granger (1979) was the fact that the problem of acute non-normal distributions they found in most macroeconomic time series they analyzed was restored only very little by their use of data transformations. Table 13 presents the results for the Jarque-Bera statistic for normality (Jarque and Bera 1987). This statistic is distributed as chi-square with two degrees of freedom. An asterisk right next to an arithmetic value of Table 13 indicates a rejection of the null hypothesis of normality at the 5% significance level (critical value = 5.99).

The results of Table 13 allow, again, for a more optimistic view, inasmuch as it is evident that there is a general shift towards normality from the benchmark model to TSW transformation-linearization procedure. The phenomenon on some occasions is really very pronounced indeed (e.g. in the series of M1 and Balance of Payments–transport-payments). This allows for computational algorithms such as maximum likelihood estimation, as well as standard statistical tests, to be legitimately employed with transformed-linearized data.

Table 13. Values of the Jarque –Bera statistic (statistically significant values are indicated with an asterisk)

Time series	Benchmark	Logs - no outliers	Levels – all outliers	TSW
Consumer Price Index (CPI)	2.889	1.931	0.423	0.999
Harmonised Index of Consumer Prices (HICP)	6.289*	3.923	8.263*	5.850
M3	19.78*	30.85*	12.44*	14.72*
M2	16.71*	19.27*	16.31*	7.519*
Gross Domestic Product (GDP)	14.17*	2.967	3.699	0.541
M1	152.6*	376.3*	3.597	2.879
Industrial Production Index (IPI)	1.118	0.996	1.118	0.996
Retail sales	2.328	0.771	0.145	0.771
Unemployment – thousands	9.745*	12.58*	7.613*	7.613*
Balance of payments (BOP) – Transport – Receipts	5.526	5.788	0.7983	0.563
Balance of payments (BOP) – Sea transport – Receipts	7.447*	5.991*	0.874	0.9231E-01
Unemployment – percentage	7.584*	11.30*	7.584*	7.584*
Balance of payments (BOP) – Transport – Payments	137.5*	169.3*	5.289	1.651
Imports of Goods without fuels and ships	7.938*	23.30*	2.159	0.928
Exports of Goods without fuels and ships	28.26*	12.84*	0.593	0.473
Exports of Goods	0.404	0.282	0.180	0.380
Balance of payments (BOP) – Sea transport – Payments	210.5*	253.3*	4.598	4.633
Imports of Goods	1.589	4.108	0.924	4.115
Balance of payments (BOP) – Travelling – Receipts	15.31*	6.740*	26.78*	4.696
Balance of payments (BOP) – Travelling – Payments	2.286	0.326	2.013	1.978

3.8 Statistical benchmark forecasting

Seizing the opportunity of the above analysis, it is useful to assess the forecastability of the twenty time series of the Greek economy. Here forecastability will be perceived in both point and confidence interval forecasts. For the former the MAPE statistic will be employed. For the latter the percentage standard error statistic will be introduced as the mean average of the ratio of the forecasts' standard error over the corresponding actual value, so as to make forecasts of the various series mutually comparable. In all cases one-step-ahead forecasts will be performed. It is stressed that although these forecasts are technically perfectly acceptable, nevertheless they are purely statistical, hence, a-theoretical, and they can only serve as benchmark forecasts in order to evaluate the merit of more structural econometric forecasts. Tables 14-15 show the results in terms of statistical forecastability, according to the combined transformation-linearization effect (denoted as TSW). More specifically, point forecasts in Table 14 are presented in descending ordered according to the value of the Mean Absolute Percentage Error (MAPE) statistic for the combined transformation-linearization effect (fourth column), and interval forecasts in Table 15 are presented in descending order according to the value of the Percentage Standard Error statistic for the combined transformation-linearization effect (fourth column).

From the results of the Tables 14 – 15, it is observed that although there are many similarities in the two Tables, the ordering is not exactly the same. For this reason, the linear correlation coefficient between orderings based on MSFE and the percentage standard error was used. In all cases there is a strong positive correlation (see Table 16). The method of Levels – all outliers has the highest correlation, while TSW has the lowest.

From Tables 14 and 15 it is also noticeable that the BOP series are the least forecastable in both Tables. Regarding imports-exports it is noted that the former are less forecastable than the latter. Furthermore, imports-exports excluding fuels and ships are clearly more forecastable than imports-exports including them. This justifies, here from the statistics point of view, the separate recording and usage of the imports-exports without the inclusion of fuels and ships, as presented in the official BOP statistics for Greece (Bank of Greece web-site).

Table 14. *Forecastability of main economic indicators. Greece. Point forecasts*

MAPE				
Time series	**Benchmark**	**Logs – no outliers**	**Levels – all outliers**	**TSW**
Harmonised Index of Consumer Prices (HICP)	0.241%	0.238%	0.252%	0.257%
Consumer Price Index (CPI)	0.238%	0.233%	0.328%	0.289%
M2	0.625%	0.645%	0.697%	0.650%
M1	0.786%	0.730%	0.706%	0.652%
M3	0.561%	0.627%	0.661%	0.653%
Gross Domestic Product (GDP)	0.760%	0.704%	0.745%	0.729%
Industrial Production Index (IPI)	1.011%	1.111%	1.019%	1.111%
Retail sales	1.424%	1.718%	1.594%	1.666%

Exports of Goods without fuels and ships	3.718%	2.793%	3.208%	2.517%
Unemployment – thousands	2.170%	1.925%	2.608%	2.608%
Balance of payments (BOP) – Sea transport – Receipts	2.789%	2.674%	4.003%	2.902%
Unemployment – percentage	2.917%	2.265%	2.917%	2.917%
Balance of payments (BOP) – Transport – Receipts	2.748%	2.717%	2.868%	2.922%
Imports of Goods without fuels and ships	3.032%	3.412%	2.582%	3.026%
Balance of payments (BOP) – Transport – Payments	2.929%	2.955%	3.134%	3.309%
Balance of payments (BOP) – Sea transport – Payments	5.515%	5.918%	5.077%	3.883%
Exports of Goods	5.021%	3.969%	5.129%	4.238%
Imports of Goods	6.027%	6.093%	5.705%	5.750%
Balance of payments (BOP) – Travelling – Receipts	12.194%	8.171%	13.314%	7.729%
Balance of payments (BOP) – Travelling – Payments	12.553%	11.624%	13.994%	11.775%

Table 15. *Forecastability of main economic indicators. Greece. Interval forecasts*

Percentage Standard Error				
Time series	**Benchmark**	**Logs - no outliers**	**Levels – all outliers**	**TSW**
Harmonised Index of Consumer Prices (HICP)	0.439%	0.441%	0.423%	0.427%
Consumer Price Index (CPI)	0.454%	0.464%	0.419%	0.443%
M3	1.451%	1.283%	1.180%	1.013%
M2	1.455%	1.321%	1.219%	1.090%
M1	1.290%	1.475%	1.142%	1.272%
Gross Domestic Product (GDP)	2.145%	1.868%	1.855%	1.745%
Unemployment – thousands	2.809%	3.865%	2.572%	2.572%
Unemployment – percentage	2.737%	3.841%	2.737%	2.737%
Industrial Production Index (IPI)	2.808%	2.890%	2.805%	2.890%
Retail sales	5.110%	3.728%	4.188%	3.636%
Imports of Goods without fuels and ships	7.151%	6.478%	5.184%	4.833%
Balance of payments (BOP) – Transport – Receipts	5.565%	5.586%	4.930%	5.348%
Balance of payments (BOP) – Sea transport – Receipts	6.514%	6.164%	5.524%	5.394%
Exports of Goods without fuels and ships	4.582%	6.263%	4.008%	5.483%
Balance of payments (BOP) – Transport – Payments	5.817%	7.217%	4.469%	6.101%

Exports of Goods	5.495%	7.831%	5.294%	7.552%
Imports of Goods	8.170%	7.875%	7.700%	7.559%
Balance of payments (BOP) – Travelling – Receipts	24.967%	8.695%	20.433%	7.679%
Balance of payments (BOP) – Sea transport – Payments	7.234%	9.847%	5.807%	7.779%
Balance of payments (BOP) – Travelling – Payments	17.607%	14.935%	16.151%	14.157%

Table 16. *Linear correlation coefficient between MSFE and percentage SE ordering*

Method	Correlation
Benchmark	95.40%
Logs - no outliers	96.73%
Levels - all outliers	97.23%
TSW	93.05%

4. Summary and Conclusions

This work dealt with the effect of data transformation for variance stabilization and linearization for outlier adjustment on the quality of univariate time series forecasts, following a practical approach.

There is clear evidence that linearization improves the forecasts' confidence intervals, but not such evidence for the data transformation. Furthermore, no evidence was found that either transformation or linearization leads to better point forecasts. The combined effect of transformation-linearization improves leads to better forecast confidence intervals and improves substantially the non-normality problem encountered in many macroeconomic time series, but worsens point forecasts. There is also evidence that the overall forecasting performance using the TSW data transformation procedure is somewhat better than that of the other used models.

It is also noticeable that the BOP series are the least forecastable time series. Regarding imports-exports it is noted that imports-exports excluding fuels and ships are clearly more forecastable than imports-exports including them. This justifies, here from the statistics point of view, the separate recording and usage of the imports-exports without the inclusion of fuels and ships.

It must be remarked that the above results regarding the effect of data transformation were obtained within the restrictive framework, which allows the logarithmic transformation as the only alternative. Further research is needed on that mater using a larger dataset and the whole Box-Cox transformations framework.

References

Balance of payments: Revision of sea transport statistics (2018). Bank of Greece, available at https://www.bankofgreece.gr/en/news-and-media/press-office/news-list/news?announcement=cf2e8b48-c801-4963-b8a6-64da23985e35 (accessed 20 November 2018).

Box, G. E. P., and Cox, D. R. (1964). 'An Analysis of Transformations', *Journal of the Royal Statistical Society*, 26:2, 211-243.

Box, G. E. P. and Jenkins, G. M. (1976). *Time series analysis: forecasting and control*. Revised Edition, Holden – Day, San Francisco.

Chen, C. and Liu, L.-M. (1993). 'Forecasting Time Series With Outliers', *Journal of Forecasting*, 12:1, 13-35.

Fischer, B. and Planas, C. (2000). 'Large scale fitting of regression models with ARIMA errors', *Journal of Official Statistics*, 16:2, 173-184.

Gomez, V. and Maravall, A. (1996). 'Programmes SEATS and TRAMO: instructions for the User', Bank of Spain Working Paper 9628.

Governor's Annual Report (2022). Bank of Greece (in Greek), available at https://www.bankofgreece.gr/Publications/ekthdkth2022.pdf (accessed 7 April 2023).

Granger, C. W. J. and Newbold, P. (1976). 'Forecasting Transformed Series', *Journal of the Royal Statistical Society*, 38:2, 189 – 203.

Hansen, P. R. (2005). 'A test for superior predictive ability', *Journal of Business & Economic Statistics*, 23:4, 365-380.

Hansen, P. R., Lunde, A. and Nason, J. M. (2011). 'The model confidence set', *Econometrica*, 79:2, 453-497.

Jarque, C. and Bera, A. (1987). 'Efficient tests for normality homoscedasticity and serial independence of regression residuals', *Econometric Letters*, 6:3, 255-259.

Kaiser, R. and Maravall, A. (2001). *Measuring business cycles in economic time series*. Springer, New York

Makridakis, S. and Hibon, M. (1979). 'Accuracy of Forecasting: An Empirical Investigation', *Journal of the Royal Statistical Society*, 142:2, 97-145.

Makridakis, S., Wheelwright, S. C. and Hyndman, R. J. (1998). *Forecasting Methods and Applications*. 3rd Edition, Wiley, Hoboken, NJ.

Meese, R. and Geweke, J. (1984). 'A comparison of autoregressive univariate forecasting procedures for macroeconomic time series', *Journal of Business & Economic Statistics*, 2:3, 191-200.

Milionis, A. E. (2003). ‘Modeling economic time series in the presence of variance non-stationarity’, Bank of Greece Working Paper No 7.

Milionis, A. E. (2004). ‘The importance of Variance Stationarity in Economic Time Series Modelling; a Practical Approach’, *Applied Financial Economics*, 14:4, 265-278.

Milionis, A. E. (2010). Greek Statistics: Politicians are not the only ones responsible (in Greek). Newspaper of the University of the Aegean, issue 5, page 6, available at http://www1.aegean.gr/newspaper/archive.htm (accessed May 2010).

Nelson, H. L. and Granger, C. W. J. (1979). ‘Experience with using the Box-Cox transformation when forecasting economic time series’, *Journal of Econometrics*, 10:1, 57-69.

Oikonomou, G., Sampethai, I. and Symigiannis, G. eds (2010). *Greece's balance of payments: reasons for imbalances and policy proposals* (in Greek). Bank of Greece Publications

Pankratz, A. and Dudley, U. (1987). ‘Forecasts of power-transformed series’, *Journal of Forecasting*, 6:4, 239-248.

Papaconstantinou, C. (2022). The prospects of the Greek economy and the contribution of Greek shipping to the GDP (in Greek). Bank of Greece, available at https://www.bankofgreece.gr/enimerosi/grafeio-typoy/anazhthsh-enhmerwsewn/enhmerwseis?announcement=96c4f968-d0f0-4851-a449-021f469e45e0 (accessed 6 June 2022).

UNCTAD (2022). Review of Maritime Transport 2022, available at https://unctad.org/system/files/official-document/rmt2022_en.pdf (accessed 24 November 2022).

White, H. (2000). ‘A reality check for data snooping’, *Econometrica*, 68:5, 1097-1126.

Appendix 1

Table A1 – Ownership of the world fleet, ranked by commercial value (million US$), 2022

Country or Territory of Ownership		Total
1	Chine	154.827
2	Greece	148.157
3	Japan	144.477
4	United States	85.966
5	Germany	81.649
6	Singapore	70.481
7	United Kingdom	60.336
8	Hong Kong, China	58.704
9	Norway	56.325
10	Republic of Korea	45.929
11	Switzerland	41.404
12	Denmark	38.932
13	Taiwan Province of China	35.983
14	Bermuda	29.784
15	Netherlands	23.935
16	France	22.307
17	Italy	22.225
18	Brazil	16.580
19	Monaco	15.317
20	Türkiye	14.706
21	Indonesia	13.953
22	Russian Federation	12.901
23	United Arab Emirates	12.350
24	Belgium	11.011
25	Malaysia	10.158
	Others	129.874

	World Total	1.358.270

Appendix 2

Table A2. Ownership of the world fleet, ranked by carrying capacity in dead-weight tons, 2022, national – and foreign – flagged fleet

Country or Territory of Ownership		Deadweight tonnage		
		Total	Foreign flag as a % total	Total as a% of world
1	Greece	384.430.215	85.51	17.63
2	China	277.843.335	59.19	12.74
3	Japan	236.638.365	84.8	10.85
4	Singapore	136.243.709	50.16	6.25
5	Hong Kong, China	111.587.729	35.39	5.12
6	Republic of Korea	92.302.014	84	4.23
7	Germany	79.592.915	91.23	3.65
8	Bermuda	63.407.273	99.96	2.91
9	Norway including Svalbard and Jan Mayen Islands excluding Bouvet Island	59.931.039	68.33	2.75
10	United Kingdom of Great Britain and Northern Ireland including Channel Islands and Isle of Man	58.746.865	84	2.69
11	United States of America including Puerto Rico	55.113.272	81.23	2.53

12	China, Taiwan Province of	54.974.072	88	2.52
13	Denmark	40.637.122	49.59	1.86
14	Monaco	38.011.632	100	1.74
15	Switzerland	30.887.688	97.05	1.42
16	Türkiye	30.433.830	81.04	1.4
17	Belgium	29.445.947	68.96	1.35
18	Indonesia	29.065.796	14.06	1.33
19	United Arab Emirates	27.363.741	97.68	1.26
20	India	25.979.620	36.53	1.19
21	Russian Federation	24.317.936	61.92	1.12
22	Iran (Islamic Republic of)	19.441.051	4.27	0.89
23	Netherlands	17.911.737	69.9	0.82
24	Saudi Arabia	17.358.885	21.54	0.8
25	France, Metropolitan	15.335.183	71.59	0.7
26	Italy	15.278.786	40.83	0.7
27	Viet Nam	14.934.404	23.88	0.69
28	Brazil	13.773.954	66.02	0.63
29	Cyprus	13.758.739	67.64	0.63
30	Canada	9.835.479	74.67	0.45
31	Oman	9.332.147	99.94	0.43
32	Malaysia	8.985.167	26.22	0.41
33	Nigeria	7.520.054	53.03	0.34
34	Qatar	7.208.940	89.82	0.33
35	Kuwait	5.252.184	8.51	0.24
	Subtotal, top 35 shipowners	2.062.880.823	71.44	94.63

	Rest of the world unknown	117.177.484	48.46	5.37
	World	2.180.058.307	71.08	100

Appendix 3

Table A3. Univariate ARIMA models with and without transformation-linearization

Time series	Benchmark	TSW
Gross Domestic Product (GDP)	ARIMA (0,1,1) (0,1,1)4	ARIMA (1,1,0) (0,1,1)4
	$\nabla\nabla_4 Y_t = (1+0.118B)(1+0.425B^4)\varepsilon_t$	$(1-0.160B)\nabla\nabla_4 \ln Y_t = (1+0.267B^4)\varepsilon_t$
Industrial Production Index (IPI)	ARIMA (2,0,0) (0,1,1)12	ARIMA (1,1,0) (0,1,1)12
	$(1+0.379B+0.547B^2)\nabla_{12} Y_t = (1+0.950B^{12})\varepsilon_t$	$(1-0.554B)\nabla\nabla_{12} \ln Y_t = (1+0.831B^{12})\varepsilon_t$
Consumer Price Index (CPI)	ARIMA (0,1,0) (0,1,1)12	ARIMA (1,1,0) (0,1,0)12
	$\nabla\nabla_{12} Y_t = (1+0.260B^{12})\varepsilon_t$	$(1+0.146B)\nabla\nabla_{12} \ln Y_t = \varepsilon_t$
Harmonised Index of Consumer Prices (HICP)	ARIMA (0,1,0) (0,1,1)12	ARIMA (0,1,0) (0,1,1)12
	$\nabla\nabla_{12} Y_t = (1+0.347B^{12})\varepsilon_t$	$\nabla\nabla_{12} \ln Y_t = (1+0.326B^{12})\varepsilon_t$
Unemployment – thousands	ARIMA (3,2,1) (0,1,1)12	ARIMA (3,2,1) (0,1,1)12
	$(1-0.681B-0.674B^2+0.062B^3)\nabla^2\nabla_{12} Y_t = (1+0.758B)(1+0.938B^{12})\varepsilon_t$	$\begin{pmatrix}1-1.153B-1.123B^2\\ -0.340B^3\end{pmatrix}\nabla^2\nabla_{12} Y_t = (1+0.614B)(1+0.907B^{12})\varepsilon_t$
Unemployment – percentage	ARIMA (2,2,1) (0,1,1)12	ARIMA (2,2,1) (0,1,1)12
	$(1-0.726B-0.715B^2)\nabla^2\nabla_{12} Y_t = (1+0.734B)(1+0.816B^{12})\varepsilon_t$	$(1-0.726B-0.715B^2)\nabla^2\nabla_{12} Y_t = (1+0.734B)(1+0.816B^{12})\varepsilon_t$
Retail sales	ARIMA (0,1,1) (0,1,1)12	ARIMA (0,1,1) (0,1,1)12
	$\nabla\nabla_{12} Y_t = (1+0.364B)(1+0.566B^{12})\varepsilon_t$	$\nabla\nabla_{12} \ln Y_t = (1+0.334B)(1+0.631B^{12})\varepsilon_t$
M1	ARIMA (0,2,1) (0,1,1)12	ARIMA (3,1,0) (0,1,1)12
	$\nabla^2\nabla_{12} Y_t = (1+0.838B)(1+0.682B^{12})\varepsilon_t$	$\begin{pmatrix}1+0.0001B+0.178B^2\\ +0.422B^3\end{pmatrix}\nabla\nabla_{12} \ln Y_t = (1+0.685B^{12})\varepsilon_t$
M2	ARIMA (3,1,0) (1,0,1)12	ARIMA (1,1,1) (0,1,1)12
	$(1+0.328B+0.040B^2+0.307B^3)(1+0.868B^{12})\nabla Y_t = (1+0.656B^{12})\varepsilon_t$	$(1+0.933B)\nabla\nabla_{12} \ln Y_t = (1+0.627B)(1+0.800B^{12})\varepsilon_t$
M3	ARIMA (0,2,1) (0,1,1)12	ARIMA (0,2,1) (0,1,1)12
	$\nabla^2\nabla_{12} Y_t = (1+0.695B)(1+0.824B^{12})\varepsilon_t$	$\nabla^2\nabla_{12} \ln Y_t = (1+0.660B)(1+0.838B^{12})\varepsilon_t$
Balance of payments (BOP) – Transport – Payments	ARIMA (0,1,1) (0,1,1)12	ARIMA (0,1,1) (0,1,1)12
	$\nabla\nabla_{12} Y_t = (1+0.188B)(1+0.847B^{12})\varepsilon_t$	$\nabla\nabla_{12} \ln Y_t = (1+0.440B)(1+0.841B^{12})\varepsilon_t$
Balance of payments (BOP) – Transport – Receipts	ARIMA (3,1,1) (0,1,1)12	ARIMA (3,1,0) (0,1,1)12
	$(1-0.393B-0.050B^2+0.264B^3)\nabla\nabla_{12} Y_t = (1-0.288B)(1+0.950B^{12})\varepsilon_t$	$(1-0.208B-0.110B^2+0.229B^3)\nabla\nabla_{12} \ln Y_t = (1+0.895B^{12})\varepsilon_t$
	ARIMA (1,0,0) (0,1,1)12	ARIMA (1,0,0) (1,0,0)12

Balance of payments (BOP) – Travelling – Payments	$(1+0.339B)\nabla_{12}Y_t = (1+0.506B^{12})\varepsilon_t$	$(1+0.328B)(1+0.608B^{12})\ln Y_t = \varepsilon_t$
Balance of payments (BOP) – Travelling – Receipts	ARIMA (1,0,0) $(1,1,0)_{12}$	ARIMA (1,0,0) $(1,1,0)_{12}$
	$(1+0.731B)(1-0.371B^{12})\nabla_{12}Y_t = \varepsilon_t$	$(1+0.598B)(1-0.422B^{12})\nabla_{12}\ln Y_t = \varepsilon_t$
Balance of payments (BOP) – Sea transport – Payments	ARIMA (0,1,1) $(0,0,0)_{12}$	ARIMA (0,1,1) $(0,1,1)_{12}$
	$\nabla Y_t = (1+0202B)\varepsilon_t$	$\nabla\nabla_{12}\ln Y_t = (1+0.334B)(1+0.824B^{12})\varepsilon_t$
Balance of payments (BOP) – Sea transport – Receipts	ARIMA (3,1,1) $(0,1,1)_{12}$	ARIMA (3,1,1) $(0,1,1)_{12}$
	$(1-0.388B-0.020B^2+0.281B^3)\nabla\nabla_{12}Y_t = (1-0.262B)(1+0.848B^{12})\varepsilon_t$	$\left(\begin{matrix}1-0.676B-0.187B^2\\+0.170B^3\end{matrix}\right)\nabla\nabla_{12}\ln Y_t = (1-0.515B)(1+0.867B^{12})\varepsilon_t$
Exports of Goods	ARIMA (0,1,1) $(0,1,1)_{12}$	ARIMA (0,1,2) $(0,1,1)_{12}$
	$\nabla\nabla_{12}Y_t = (1+0.414B)(1+0.950B^{12})\varepsilon_t$	$\nabla\nabla_{12}\ln Y_t = (1+0.349B+0.111B^2)(1+0.950B^{12})\varepsilon_t$
Exports of Goods without fuels and ships	ARIMA (0,1,1) $(0,1,1)_{12}$	ARIMA (0,1,1) $(0,1,1)_{12}$
	$\nabla\nabla_{12}Y_t = (1+0.485B)(1+0.922B^{12})\varepsilon_t$	$\nabla\nabla_{12}\ln Y_t = (1+0.605B)(1+0.753B^{12})\varepsilon_t$
Imports of Goods	ARIMA (0,1,1) $(0,1,1)_{12}$	ARIMA (0,1,1) $(1,1,1)_{12}$
	$\nabla\nabla_{12}Y_t = (1+0.495B)(1+0.950B^{12})\varepsilon_t$	$(1-0.096B^{12})\nabla\nabla_{12}\ln Y_t = (1+0.502B)(1+0.912B^{12})\varepsilon_t$
Imports of Goods without fuels and ships	ARIMA (0,1,1) $(0,1,1)_{12}$	ARIMA (0,1,1) $(0,1,1)_{12}$
	$\nabla\nabla_{12}Y_t = (1+0.434B)(1+0.785B^{12})\varepsilon_t$	$\nabla\nabla_{12}\ln Y_t = (1+0.363B)(1+0.778B^{12})\varepsilon_t$

Appendix 4

Table A4. Detected outliers for the different values of parameter τ (the first number indicate the serial number of the corresponding observation, then follows the type of outlier and within the parentheses the corresponding month, or quarter, and year).

Time series	τ -default TSW critical values	τ –Fisher-Planas
Gross Domestic Product (GDP)	OUTLIERS: 57 AO (1 2009)	OUTLIERS: 57 AO (1 2009)
Industrial Production Index (IPI)	OUTLIERS: NO OUTLIERS DETECTED	OUTLIERS: NO OUTLIERS DETECTED
Consumer Price Index (CPI)	OUTLIERS: 93 LS (9 2011), 119 AO (11 2013)	OUTLIERS: 119 AO (11 2013)
Harmonised Index of Consumer Prices (HICP)	OUTLIERS: 119 AO (11 2013)	OUTLIERS: 119 AO (11 2013)
Unemployment – thousands	OUTLIERS: 60 LS (12 2008), 95 LS (11 2011), 98 TC (2 2012), 126 LS (6	OUTLIERS: 60 LS (12 2008), 95 LS (11 2011), 98 TC (2 2012), 126 LS (6

	2014), 148 TC (4 2016), 156 TC (12 2016)	2014), 148 TC (4 2016), 156 TC (12 2016)
Unemployment – percentage	OUTLIERS: NO OUTLIERS DETECTED	OUTLIERS: NO OUTLIERS DETECTED
Unemployment – thousands	OUTLIERS: NO OUTLIERS DETECTED	OUTLIERS: 113 AO (5 2013), 139 AO (7 2015)
M1	OUTLIERS: 139 LS (7 2015)	OUTLIERS: 139 LS (7 2015)
M2	OUTLIERS: 100 AO (4 2012), 102 AO (6 2012), 133 LS (1 2015), 138 TC (6 2015)	OUTLIERS: 100 AO (4 2012), 102 AO (6 2012), 138 TC (6 2015)
M3	OUTLIERS: 100 AO (4 2012), 102 AO (6 2012), 133 LS (1 2015), 138 TC (6 2015)	OUTLIERS: 100 AO (4 2012), 102 AO (6 2012), 133 LS (1 2015), 138 TC (6 2015)
Balance of payments (BOP) – Transport – Payments	OUTLIERS: 60 LS (12 2008), 133 LS (1 2015)	OUTLIERS: 60 LS (12 2008), 133 LS (1 2015)
Balance of payments (BOP) – Transport – Receipts	OUTLIERS: 59 LS (11 2008)	OUTLIERS: 36 TC (12 2006), 59 LS (11 2008)
Balance of payments (BOP) – Travelling – Payments	OUTLIERS: 92 AO (8 2011)	OUTLIERS: 92 AO (8 2011)
Balance of payments (BOP) – Travelling – Receipts	OUTLIERS: 2 AO (2 2004), 113 LS (5 2013)	OUTLIERS: 2 AO (2 2004), 113 LS (5 2013)
Balance of payments (BOP) – Sea transport – Payments	OUTLIERS: 60 LS (12 2008), 113 LS (5 2013), 133 LS (1 2015)	OUTLIERS: 59 LS (11 2008), 113 LS (5 2013), 133 LS (1 2015)
Balance of payments (BOP) – Sea transport – Receipts	OUTLIERS: 36 TC (12 2006), 59 LS (11 2008), 129 AO (9 2014)	OUTLIERS: 36 TC (12 2006), 59 LS (11 2008), 129 AO (9 2014)
Exports of Goods	OUTLIERS: 81 AO (9 2010)	NO OUTLIERS DETECTED
Exports of Goods without fuels and ships	OUTLIERS: 60 LS (12 2008), 81 AO (9 2010)	OUTLIERS: 60 LS (12 2008), 81 AO (9 2010)
Imports of Goods	OUTLIERS: NO OUTLIERS DETECTED	OUTLIERS: NO OUTLIERS DETECTED
Imports of Goods without fuels and ships	OUTLIERS: 39 AO (3 2007), 59 LS (11 2008), 75 AO (3 2010), 82 AO (10 2010), 139 TC (7 2015)	OUTLIERS: 39 AO (3 2007), 59 LS (11 2008), 75 AO (3 2010), 82 AO (10 2010), 139 TC (7 2015)

Appendix 5

Table A5. Detailed forecast quality statistics: MSFE, MAE and Forecast Standard Error

Time series	Benchmark	Logs – no outliers	Levels – all outliers	TSW
Consumer Price Index (CPI)	0.074 0.241 0.461	0.069 0.236 0.471	0.163 0.332 0.426	0.123 0.293 0.450
Harmonised Index of Consumer Prices (HICP)	0.100 0.255 0.466	0.102 0.252 0.467	0.107 0.267 0.448	0.114 0.272 0.452
M3	1,551,599 947 2,448	1,939,771 1,060 2,166	1,947,577 1,116 1,989	2,166,840 1,100 1,709
M2	2,410,091 1,048 2,440	2,014,253 1,085 2,220	2,224,942 1,165 2,046	2,479,304 1,094 1,831
Gross Domestic Product (GDP)	252,244 371 1,004	208,470 342 878	230,028 363 869	212,606 354 819
M1	1,318,053 908 1,490	997,812 844 1,704	1,138,385 815 1,319	849,764 752 1,470
Industrial Production Index (IPI)	1.618 0.955 2.665	1.639 1.049 2.751	1.619 0.963 2.663	1.639 1.049 2.751
Retail sales	3.159 1.423 5.111	4.366 1.731 3.740	3.815 1.591 4.194	4.389 1.671 3.646
Unemployment – thousands	546.2 20.8 26.6	469.1 18.4 36.9	819.2 24.8 24.4	819.2 24.8 24.4
Balance of payments (BOP) – Transport – Receipts	1,919 36.0 70.3	1,789 35.7 71.2	2,585 38.9 62.2	2,225 38.5 68.0
Balance of payments (BOP) – Sea	1,215 31.2	1,259 30.2	2,803 45.1	1,574 32.6

transport – Receipts	70.2	66.9	59.4	58.5
Unemployment – percentage	0.399 0.584 0.544	0.285 0.454 0.773	0.399 0.584 0.544	0.399 0.584 0.544
Balance of payments (BOP) – Transport – Payments	1,002 25.4 49.7	1,083 25.6 61.9	1,106 27.3 37.9	1,217 29.0 51.8
Imports of Goods without fuels and ships	12,479 98.1 224.7	14,750 108.9 203.5	11,069 83.7 163.0	12,246 96.5 152.1
Exports of Goods without fuels and ships	6,020 67.3 81.3	3,476 50.1 111.6	4,520 58.4 71.0	2,793 45.5 97.7
Exports of Goods	20,174 130.6 138.8	17,024 101.8 199.6	20,562 133.4 133.9	16,877 108.5 192.8
Balance of payments (BOP) – Sea transport – Payments	1,276 31.0 39.8	1,418 33.4 54.5	1,095 28.7 31.8	711.8 21.8 42.9
Imports of Goods	97,620 263.4 345.1	99,541 266.2 333.7	93,509 250.3 324.0	93,330 252.6 319.3
Balance of payments (BOP) – Travelling – Receipts	19,885 87.7 96.6	16,863 84.6 113.7	34,684 135.3 79.2	13,120 78.6 98.9
Balance of payments (BOP) – Travelling – Payments	1,563 24.4 28.8	1,564 23.2 24.3	1,687 26.9 25.7	1,560 23.4 23.0

Constructing the Greek Yield Curve using Differential Evolution

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Abstract

In this paper, we use Differential Evolution (DE) algorithm to estimate monthly values of the Greek Government Bond Yields, for a time period from March 1999 to June 2022, using an appropriately combined dataset of observed short and long maturity yields. Although we compare the estimations with the Nelson-Siegel family of models (Nelson-Siegel, Nelson-Siegel-Svensson and Diebold-Li), we intend to avoid using parametric models for yield curve estimation. We take this course of action due to issues arising, namely the optimization problem and the collinearity problem, which several papers mention and discuss. Highly encouraging results in terms of the estimation accuracy for the model's parameters, bond yields' values and the model parameters' economic structure are obtained through the application of the DE method. These in-sample results are reported on along with other interesting conclusions.

Keywords: Differential Evolution, Nelson-Siegel-Svensson, Term Structure, Yield Curve

JEL classification: C10, E43, G12

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1 Introduction

Accurately fitting the term structure of interest rates is vital to many market participants whether central banks, governments or financial market investors. It is crucial for bonds and derivatives pricing, risk management, and reveals market expectations, which is essential for monetary policy decisions, since different levels of the term structure may signal changes in monetary policies, or investment strategies.

A set of unobservable values and the shape of the interest rate curve has led not only to constant study of its estimation, but also to the study of predicting the subsequent values of the curve. A first approach of the study of the interest rate curve uses splines for the estimation procedure.

McCulloch (1971), introduces a new method which fits a polynomial spline curve to observable values of bond prices. Term structure of interest rates is then resulting from this smooth discount function. Vasicek & Fong (1982) propose a similar spline-based procedure propose but they implement exponential splines to fit the discount function. In the same context, Fisher *et al.* (1995) and Waggoner (1997) used splines, imposing penalties for the poor estimated points of the forward curve, while Linton *et al.* (2001) propose a non parametric kernel smoothing based method for yield curve estimation, without assuming a specific form for the discount function, imposing restrictions in their estimation.

From another point of view, a set of models try to represent the term structure of interest rates by its shape. This approach introduced by Nelson & Siegel (1987), which model fits to monotonic, humped and S-shaped yield curves. Diebold *et al.* (2005) claim that the third term of Nelson & Siegel (1987) model explains a small part of the variation of the yield curve. So they exclude this term and propose a model with only two terms. Later on, Diebold & Li (2006) turned Nelson & Siegel (1987) model into a dynamic factor model, stabilized the value of the decay parameter and rearranged the terms of the model, yet described as factors, to identify them as level, slope and curvature of the yield curve. A few years later, Svensson (1994) and Björk & Christensen (1999) added an extra term to Nelson & Siegel (1987), to reflect curve shapes with an extra hump and more recently De Rezende & Ferreira (2013) added a fifth term to Svensson (1994) to improve model performance for inverted yield curves. According to De Pooter (2007), Bliss (1997) propose different decay parameters for the second and third term of Nelson & Siegel (1987).

In the meantime, Ioannides (2003) compared the estimation performance of spline-based methods and Nelson-Siegel type models on the term structure of interest rates on daily UK yields, from January 1995 to January 1999. He

came to the conclusion that parametric models fit better to his dataset, for this specific period.
Recently, Nymand-Andersen (2018) tries out Nelson & Siegel (1987) model, Svensson (1994) model, Waggoner (1997) model and Variance Roughness Penalty model and observes that all models are appropriate to fit the European yield curve, with reliable estimations.
Several papers like Gilli *et al.* (2010), Annaert *et al.* (2013), Giraldo *et al.* (2016), León Valle *et al.* (2018), Lakhany *et al.* (2021) among others report high levels of correlation between the regressors of parametric models for some values of the decay parameter λ and the existence of multiple local optima of the function used to be optimized. For several yield values, this has been flagged as the main problem that parametric models fail to give valid estimations for.
Recent studies, in order to overcome these obstacles, are making efforts to improve the yield curve estimations using non parametric methods, or calibrating parametric models using algorithms. Examples of such papers are Liu & Wu (2021), Lakhany *et al.* (2021), Ayouche *et al.* (2016), Maciel *et al.* (2016) and Maciel *et al.* (2012), Annaert *et al.* (2013) and Gilli *et al.* (2010).
In our paper we are dealing with the Greek Bond Yield Curve which, to the best of our knowledge, only a very few papers have looked into. In their paper, Manousopoulos & Michalopoulos (2009) compare a set of algorithms for yield curve estimation using daily Greek yield curve data for the year 2004 and Balfoussia (2008) estimates Greek nominal bond returns via an affine latent factor model. Also, we choose to estimate the Greek yield surface, using our data following the methodology of Maciel *et al.* (2016), Maciel *et al.* (2012) and Gilli *et al.* (2010) by applying the Differential Evolution algorithm, which is an optimization algorithm proposed by Storn & Price (1997).
The rest of the paper is organized as follows. In section 2, we briefly report the traditional models used for the yield curve estimation and the method we propose for the Greek Yield Curve to be estimated, while section 3 presents the procedure of the empirical analysis used, including the dataset and some results from Differential Evolution estimation. Finally, section 4 offers some concluding remarks.

2 Estimation Models

2.1 Benchmark Models for Zero Coupon Bond Yield Estimation

The most common and widely used parametric models for the estimation of the yield curve are Nelson & Siegel (1987), Svensson (1994) and Diebold & Li (2006). Gürkaynak *et al.* (2007) in their paper estimate and make available the data for US Treasury yield curve in a daily basis and for a large number of maturities, for the period starting from 1961 to the present, using the Svensson (1994) model. Even several central banks use these parametric models to estimate the local yield curves. For instance the bank of Germany uses the model of Svensson (1994) [1].
These models are appealing mainly due to their simplicity ('parsimonious'), with only a small number of parameters needed to be estimated and easy to apply for fitting the yield curve. Also, their closed form and easy to use functions, which they produce smooth curves and accurate yield estimation and forecasts (De Pooter (2007)). These models can be adapted to various shapes of the yield curve (S-shaped, humped shaped, etc).
Another advantage of these models is the use of fundamental estimation methods in order to estimate each model's parameters. Non Linear Least Squares for Nelson & Siegel (1987), Ordinary Least Squares for fixed λ for Diebold & Li (2006) and Maximum Likelihood for Svensson (1994) are respectively needed for the parameters to be estimated.

2.1.1 Nelson-Siegel

An investment starting in a future time τ_1, ending in a future time τ_2, where $\tau_2 > \tau_1$ is called a forward contract and the interest rate curve of this kind of investments is called the forward curve, with respect to maturity τ and is given by (2.1), when estimated by the Nelson & Siegel (1987) model.

$$f_t(\tau) = \beta_{1t} + \beta_{2t} e^{-\lambda_t \tau} + \beta_{3t}(\lambda_t \tau) e^{-\lambda_t \tau} \tag{2.1}$$

The forward rate curve $f_t(\tau)$ is given as the solution of a second order differential equation in the case of two equal roots. Otherwise the differential equation fails to converge to a solution.

[1] https://www.bundesbank.de/dynamic/action/en/statistics/time-series-databases/time-series-databases/759784/759784?listId=www_skms_it03a

The average of forward rates $f_t(\tau)$ over a time period from zero to τ is calculated by (2.2),

$$y_t(\tau) = \frac{1}{\tau} \int_0^{\tau} f_t(u)du \tag{2.2}$$

and results in the zero coupon yield curve $y_t(\tau)$ given by (2.3)

$$y_t(\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau}\right) + \beta_{3t}\left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau}\right) \tag{2.3}$$

where λ_t is the decay factor and β_{1t}, β_{2t} and β_{3t} are the model coefficients, which are estimated using non-linear least squares method, for every t.
Equation (2.3) is the zero coupon yield curve estimation, given from the Nelson & Siegel (1987) model. Nelson & Siegel (1987) transform Equation (2.3) to the form of Equation (2.4), in order to use for fitting yield curves.

$$y_t(\tau) = b_{1t} + b_{2t}\left(\frac{1 - e^{-\lambda_t \tau}}{\lambda_t \tau}\right) + b_{3t}\left(e^{-\lambda_t \tau}\right) \tag{2.4}$$

2.1.2 Diebold-Li

Diebold & Li (2006) set the varying λ_t of Nelson & Siegel (1987) model to a constant $\lambda = 0.0609$, which is the maximum of the loadings for β_{3t}, $\left(\frac{1-e^{-\lambda_t \tau}}{\lambda_t \tau} - e^{-\lambda_t \tau}\right)$ for $\tau = 30$ months and rearranged the terms of Eq.(2.3). They end up in a three factor model for the yield curve, given by Eq.(2.5)

$$y_t(\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1 - e^{-\lambda \tau}}{\lambda \tau}\right) + \beta_{3t}\left(\frac{1 - e^{-\lambda \tau}}{\lambda \tau} - e^{-\lambda \tau}\right) \tag{2.5}$$

They identify these three coefficients β_{1t}, β_{2t} and β_{3t} as dynamic factors and they define the long term factor β_{1t} as the level, the short term factor β_{2t} as the slope and medium term factor β_{3t} as the curvature of the yield curve.
Nelson & Siegel (1987) model's coefficients are identical to Diebold & Li (2006) model's factors, described by Eq.(2.6)

$$\begin{aligned} b_{1t}(NS) &= \beta_{1t}(DL) \\ b_{2t}(NS) &= \beta_{2t}(DL) + \beta_{3t}(DL) \\ b_{3t}(NS) &= \beta_{3t}(DL) \end{aligned} \tag{2.6}$$

Factors β_{1t}, β_{2t} and β_{3t} can be estimated using ordinary least squares method, for every t.

2.1.3 Nelson-Siegel-Svensson

The three factor model of Nelson & Siegel (1987) expanded to a four factor model from Svensson (1994), to fit yield curves with a second hump. The corresponding forward curve, with respect to maturity τ is given by (2.7)

$$f_t(\tau) = \beta_{1t} + \beta_{2t}e^{-\lambda_{1t}\tau} + \beta_{3t}(\lambda_{1t}\tau)e^{-\lambda_{1t}\tau} + \beta_{4t}(\lambda_{2t}\tau)e^{-\lambda_{2t}\tau} \tag{2.7}$$

and the zero coupon yield curve (2.8)

$$y_t(\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1-e^{-\lambda_{1t}\tau}}{\lambda_{1t}\tau}\right) + \beta_{3t}\left(\frac{1-e^{-\lambda_{1t}\tau}}{\lambda_{1t}\tau} - e^{-\lambda_{1t}\tau}\right) + \beta_{4t}\left(\frac{1-e^{-\lambda_{2t}\tau}}{\lambda_{2t}\tau} - e^{-\lambda_{2t}\tau}\right) \tag{2.8}$$

where $\lambda_1 t$ is the first decay factor, $\lambda_2 t$ is the second decay factor and β_{1t}, β_{2t}, β_{3t} and β_{4t} are the model coefficients, which are estimated using maximum likelihood method, for every t.

2.2 Differential Evolution

Differential Evolution algorithm introduced by Storn & Price (1997) and is used to minimize nonlinear functions. In yield curve modelling is described by Maciel *et al.* (2016), Maciel *et al.* (2012), Gilli *et al.* (2010) and Gilli & Schumann (2010).
We adopt Svensson (1994) model to fit the yield curve, using the zero coupon bond yield curve given by (2.8), so we focus on Svensson model parameters estimation, $\beta = (\beta_1, \beta_2, \beta_3, \beta_4)$ and $\lambda = (\lambda_1, \lambda_2)$, via the algorithm.
The objective of the algorithm is the minimization of the mean absolute error function (MAE, 2.9), where the error is defined as the difference of the fitted $\hat{y}_i$ and the observed yields y_i

$$\min_{\beta,\lambda} \sum_{i=1}^{D} |\hat{y}_i - y_i| \tag{2.9}$$

under the general constraints (2.10)

$$\begin{aligned} \beta_1 &> 0 \\ \beta_1 + \beta_2 &> 0 \\ \lambda_1 &> 0 \\ \lambda_2 &> 0 \end{aligned} \tag{2.10}$$

among other papers, Wahlstrøm *et al.* (2022), Lakhany *et al.* (2021), Gilli *et al.* (2010) and Diebold & Li (2006) discuss the setting of these constraints

(2.10) for the models of Nelson & Siegel (1987) and its four parameters extension Svensson (1994). These constraints guarantee that the estimated yield curve behaves reasonably according reality and would have economic interpretations.
The level factor β_1, with a flat loadings function equal to 1, constantly affects the yield curve, as maturity tends to ∞. It is the long term and represents the level of the yield curve. The estimations for β_1 should be positive, as the value of the yield in the long run (Wahlstrøm *et al.* (2022)). Because of the form of the loadings on β_2, where the function of the loadings start from 1 and reaches 0 fast, as monotonically decreasing while maturity τ_1 increases, reflecting the slope of the yield, affects the curve only in the short term. The upward or downward move of the curve, depends on the sign of β_2, which can be positive ($\beta_2 > 0$) for upward yield slope or negative ($\beta_2 < 0$) for downward yield slope. Obviously, we allow negative values of β_2 but cumulatively $\beta_1 + \beta_2$ must be positive as the sum reflects the short end level (Wahlstrøm *et al.* (2022)).
The factor loadings of β_3 and β_4 begin from zero where maturity τ equals zero, increase to address their maximum and decrease to reach zero, without affecting the yield curve neither in short nor in the long run, so it is considered as the medium term factor of the yield curve. β_3 controls hump (if β_3 is positive) or trough (if β_3 is negative) of the shape of the yield curve. β_4 controls a second hump or trough of the yield curve (Wahlstrøm *et al.* (2022)).
Depending on the values of the decay factors λ_1 and λ_2, the value of loadings on β_3 and β_4, respectively maximize. So we restrict them to be positive.

3 Empirical Analysis

3.1 Data

We started by requesting the original database from the Electronic Secondary Securities Market (HDAT[2]) operating by the Bank of Greece[3], which kindly received. This dataset consisted of a set of 5796 daily observations of the price of coupon bonds without the accrued coupon payments (clean prices, Hull (2006)) of Greek Government bond prices and yields, for 7 maturities (3, 5, 7, 10, 15, 20 and 30 years), for the period from March 2^{nd} 1999 to May 19^{th} 2022. We then frequently update this dataset to include the most

[2]https://www.bankofgreece.gr/en/main-tasks/markets/hdat
[3]https://www.bankofgreece.gr/en/homepage

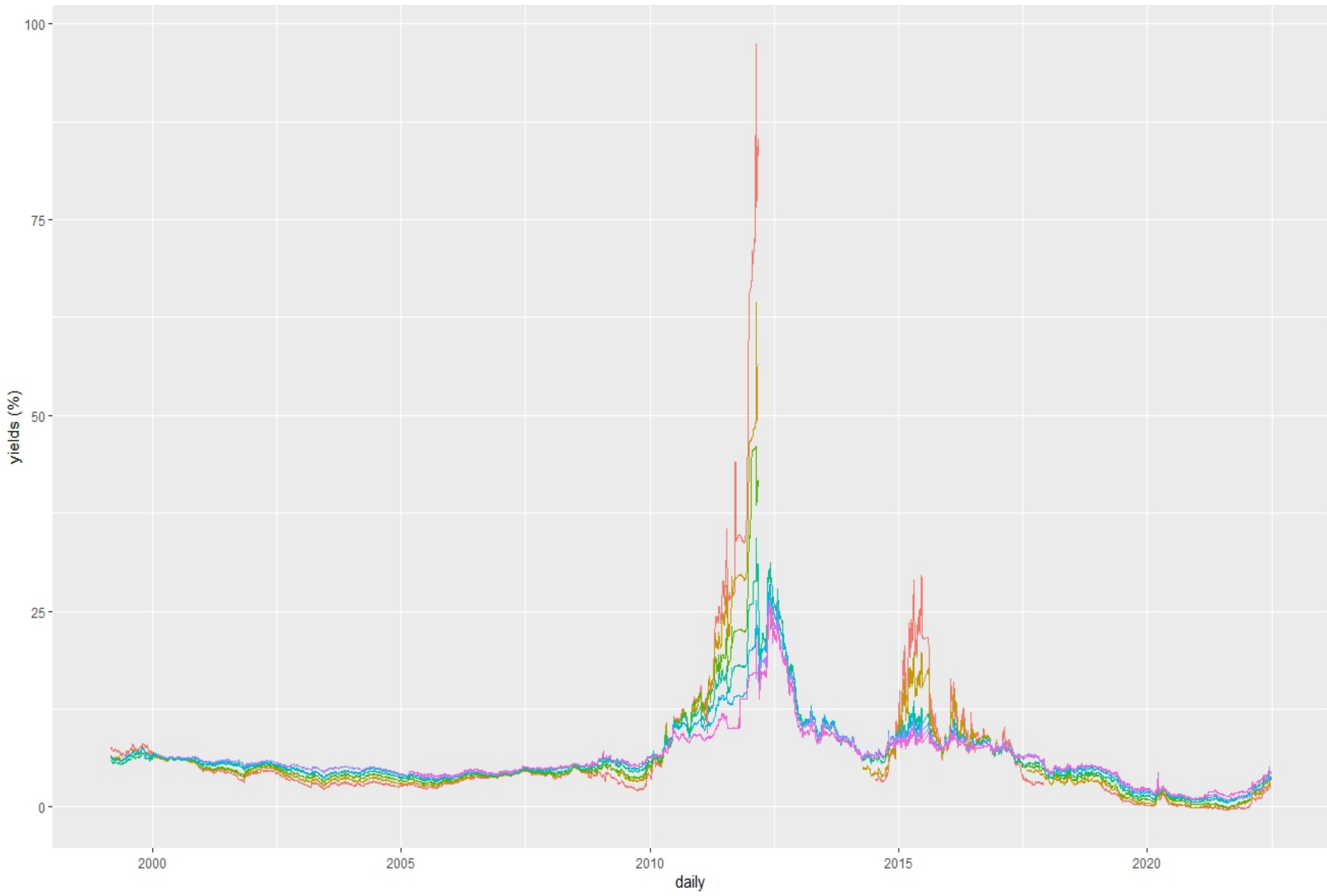


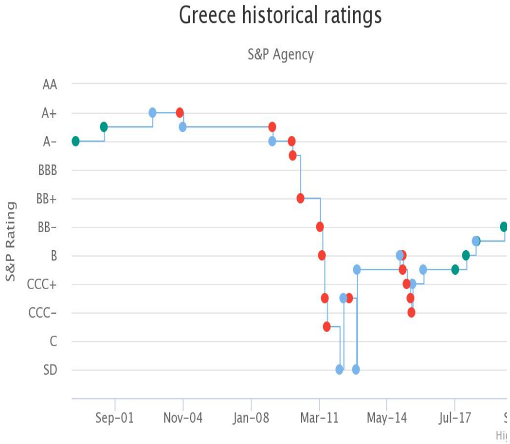
Figure 1. Observed daily Greek Government bond yields for March 1999 - June 2022

recent daily data from the Bank of Greece[4]. This daily dataset is depicted in Figure (1).

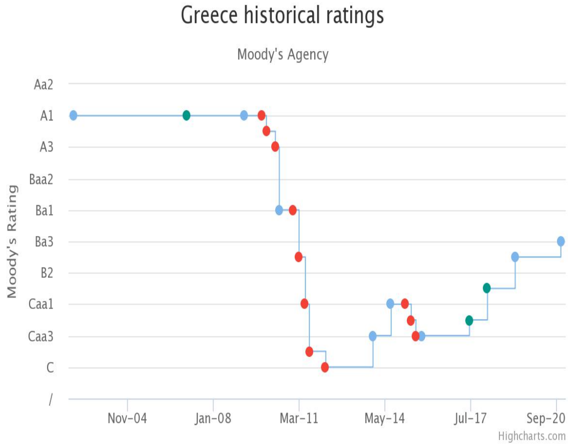
Figure (2) shows the historical credit ratings [5] for Greek economy from four biggest credit rating agencies (S&P, Moody's, DBRS-Mourningstar and Fitch). The graph is enlightening, showing the high rating grades for Greek economy for the period from 2000 to 2009. During that decade, Greece maintained a positive outlook and investment potential in the ratings of credit agencies. From December 2009 until December 2012, during a period of severe world economic liquidity crisis which was striking Greece and credit ratings sharply declined, credit agencies downgrading Greek economy

[4]https://www.bankofgreece.gr/en/statistics/financial-markets-and-interest-rates/greek-government-securities

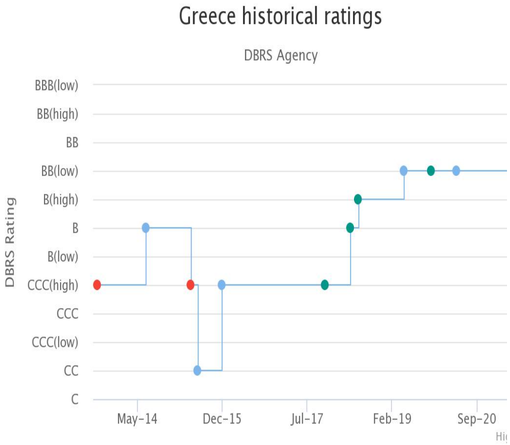
[5]data from http://www.worldgovernmentbonds.com/credit-rating/greece/



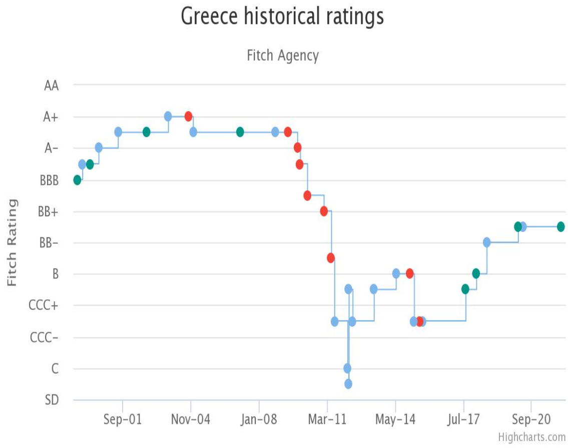
(a) Histrorical credit ratings, for Greece for the period 2001-2021, from S&P.



(b) Histrorical credit ratings, for Greece for the period 2004-2020, from Moody's.



(c) Histrorical credit ratings, for Greece for the period 2014-2022, from DBRS.



(d) Histrorical credit ratings, for Greece for the period 2001-2021, from Fitch.

Figure 2. Histrorical Credit Ratings, for Greece from four Rating Agencies.

to speculative investment state with negative outlook. In 2011 the credit ratings reach default state, which practically meant the bankruptcy of Greek economy. The following three years, until late 2015 and the first months of 2016, credit ratings remained extremely low. The Greek economy started to recover after the middle of 2017 and the last 4-5 years shows positive outlook, according to credit agencies.

High credit ratings for Greek Government Bonds and positive outlook for Greek economy kept zero coupon bond yields to low levels for the period from March 1999 to the end of 2009. After this period and for the next three years, yields steeply rose following the collapse of credit ratings. Unpacking the reasons behind the huge increase of Greek zero-coupon bond yields, which affected most lower maturity bonds, such as 3-year and 5-year maturity zero coupon bonds, is performed by Neely (2012). Greek debt became increasingly unsustainable, with the Federal Reserve Bank of St. Louis projecting that, the debt was 184,001% of GDP in 2011[6]. In an attempt for the Greek debt to be restructured, Greek bond holders, literally Greek debt lenders, should accept a haircut in their prespecified payoff at maturity. This way, in return, they would eliminate the possibility of default, which as a scenario would mean zero payoff for all Greek Bond buyers.

In a theoretical scenario where the lenders expect the full predetermined amount from their contracts and the market expectations recalculate the payoff in a much lower level, would drive the yields to rise extremely. This is what happened in February of 2012 when the 3 years zero coupon bond yield reached its maximum value of 97,51% and the 5 years zero coupon bond yield reached its maximum value of 64,41%. Longer maturity bond yields followed this trend, but the increase was less dramatic.

For over two years after February 2012, three, five and seven years maturity Greek government zero coupon bonds stopped trading in the Greek market, and there are corresponding missing values, depicted in Figures (1) and (3).

In our application we use monthly observations for the Greek Government bond yields, collected from the original dataset on the last day of each month (end-of-month), for the period from March 1999 to June 2022. Because of the lack of short term yields in our dataset, we use short term Greek T-bill interest rates, for 4 maturities (1, 3, 6 and 12 months), in order to optimize our yield curve estimation (Manousopoulos & Michalopoulos (2009)). Greek T-bill interest rates data are available from the site of the Greek Public Debt Management Agency (PDMA)[7]. The latter dataset contains 4 series of short yields, with maturities of 1m, 3m, 6m and 1y. We excluded the series of 1m because of lack of data (this series contained only 3 observations) and we interpolated the series for maturities of 3m and 6m with high order polynomials to contain data for all dates.

After the combination of these two datasets, the one containing short yields and the second containing long yields, we end up covering the period March 1999 - June 2022 with T = 279 months as observations and N = 10 series in total, with maturities 3m, 6m, 12m, 3y, 5y, 7y, 10y, 15y, 20y and 30y.

[6] https://fred.stlouisfed.org/series/GGGDTAGRC188N

[7] https://www.pdma.gr/en/debt-instruments-greek-government-bonds/issuance-calendar-a-syndication-and-auction-results/t-bills-historical-data/t-bills-historical-interest-rates

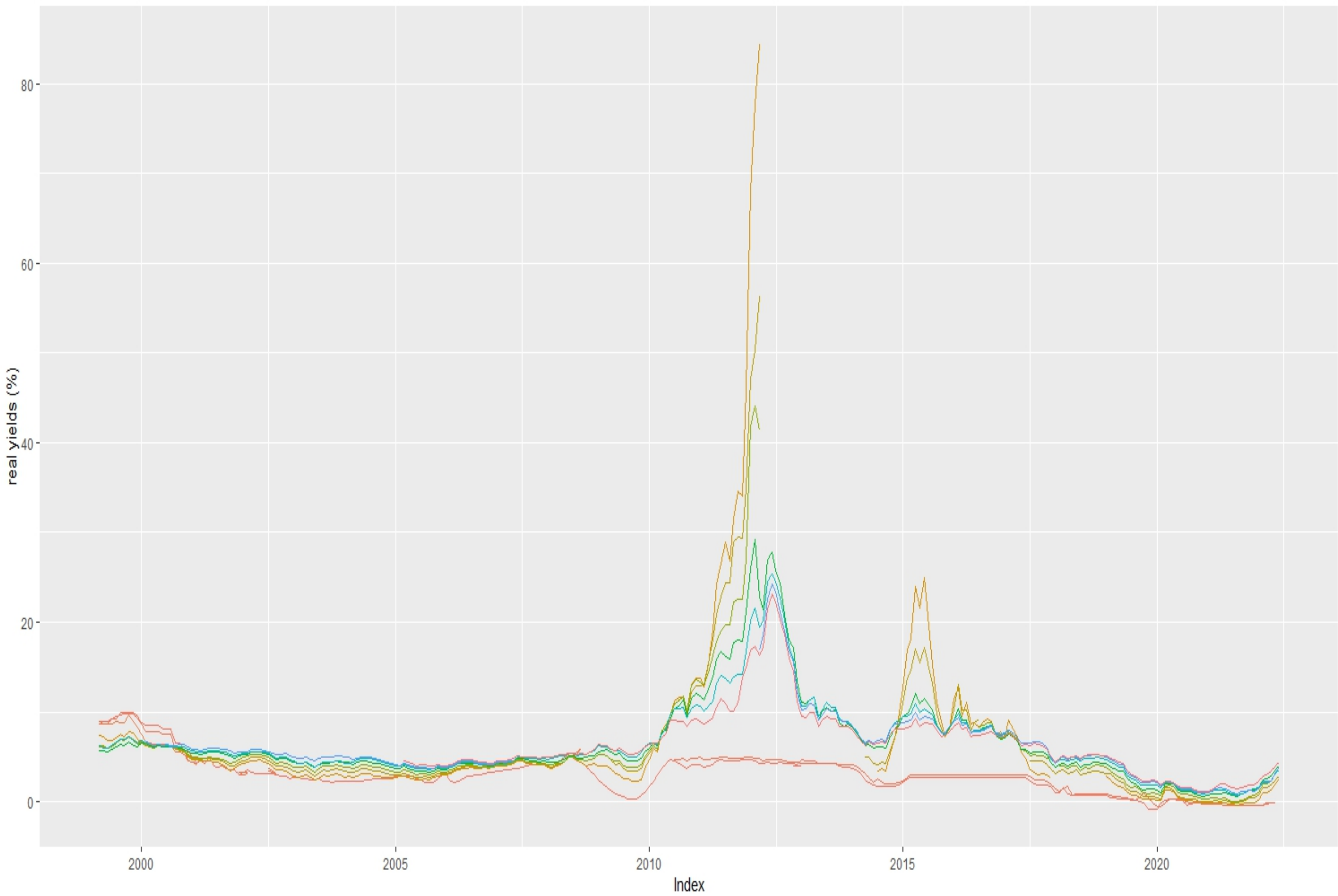
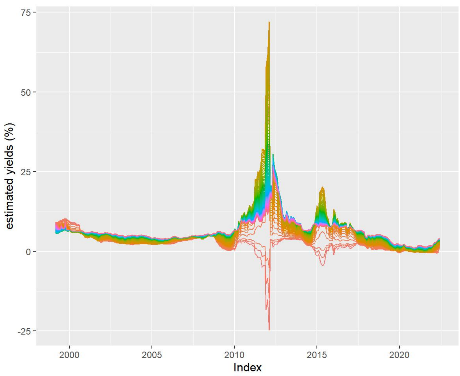


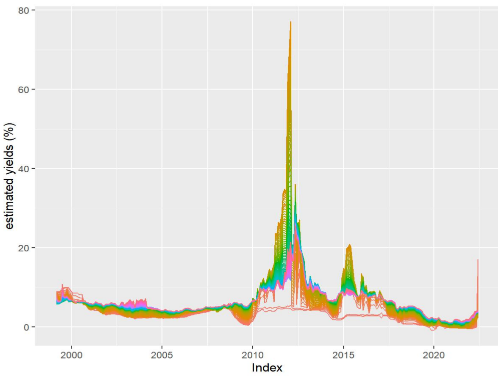
Figure 3. Monthly (end-of-month) Greek Government bond yields for March 1999 - June 2022

3.2 Benchmark Models Issues

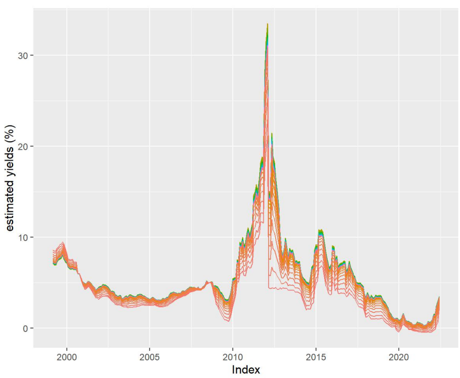
As a first step in our application, we use the monthly dataset to estimate the Greek Yield Curve via the Benchmark models (Nelson & Siegel (1987), Svensson (1994) and Diebold & Li (2006)).
Figure (4) shows the monthly yield curve estimations resulting from each one of the parametric models, for maturities of 1 month and 3,6,9,... to 360 months.
The estimation for all three models is satisfactory for most maturities and months, but problematic for several horizons. The most common remark is the extreme values for maturities of one, two and three months, for all three models, mainly because of lack of short term data. For the last months of 2011 and first months of 2012 and at the end of 2014 to the beginning of 2015 the models collapse and they give extremely negative or extremely



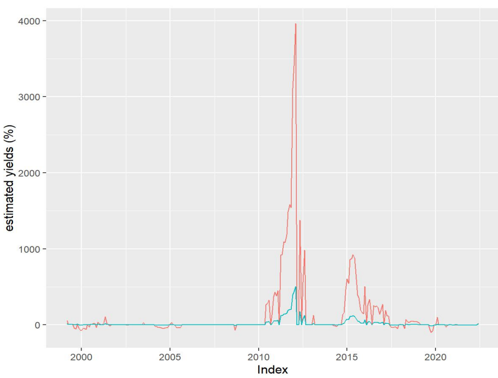
(a) Monthly Greek Yield Curve estimation for the period March 1999 - June 2022, using (Nelson & Siegel (1987).



(b) Monthly Greek Yield Curve estimation for the period March 1999 - June 2022, excluding maturity of 1 month, using Svensson (1994).



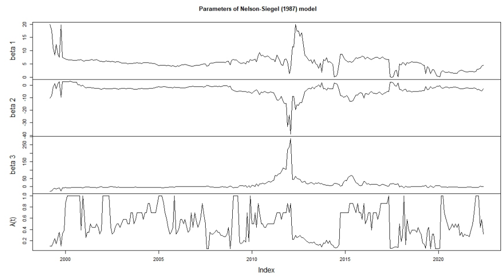
(c) Monthly Greek Yield Curve estimation for the period March 1999 - June 2022, using Diebold & Li (2006).



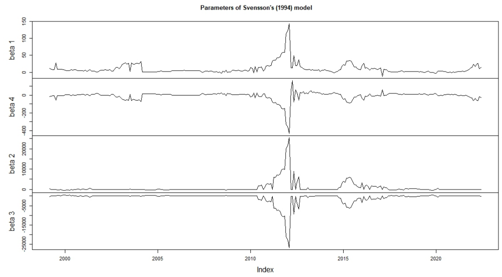
(d) Monthly Greek Yield Curve estimation for the period March 1999 - June 2022, for maturity of 1 and 2 months, using Svensson (1994).

Figure 4. Monthly Greek Yield Curve estimations for the period March 1999 - June 2022, using parametric models (Nelson & Siegel (1987) (4a), Diebold & Li (2006) (4c) and Svensson (1994) (4b and 4d)).

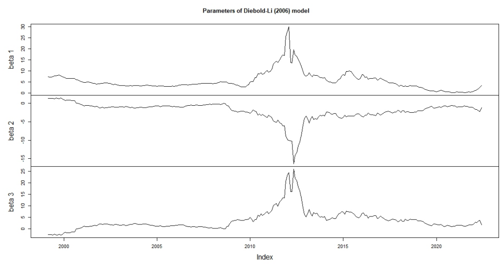
positive estimations. For example, Nelson & Siegel (1987) model estimates the yield -24.73% for February 2012 for maturity of 1 month and -14.48% for maturity of 3 months for the same date. Diebold & Li (2006) estimates the yield 21.09% for 1 month maturity and 22.92% for 3 months maturity for the same month, which is strange since there are data for 3 months maturity for all dates. Svensson (1994) model gives positive estimations for these periods, but irrational values for bond yields (Svensson (1994) model estimates the yield 3961,47% for March 2012). Svensson (1994) model gives an unrealistic estimation for the short yields up to 1 year for June 2022, because there are not available data for this date.



(a) Nelson-Siegel Parameters



(b) Svensson's Parameters

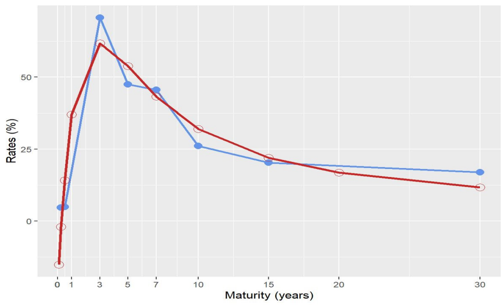


(c) Diebold-Li Parameters

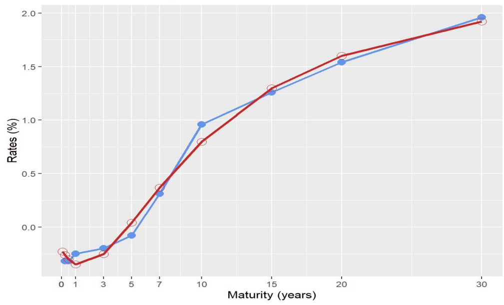
Figure 5. The estimations of the parameters from the parametric models (Nelson & Siegel (1987), Svensson (1994) and Diebold & Li (2006)).

Figure (5) shows the estimation of the parameters produced from the parametric models Nelson & Siegel (1987), Svensson (1994) and Diebold & Li (2006). From figure (5a) it becomes obvious that there is high correlation between the model's parameters. For instance, for Nelson & Siegel (1987) parameter β_2 and β_3 are very close to mirroring, which means that these parameters are highly negative correlated. Also, high levels of correlations are presented in figure (5b) for the parameters of Svensson (1994) model, where β_1 with β_4 and β_2 with β_3 are very close to mirroring. The same applies for Diebold & Li (2006) model's parameters β_2 with β_3.

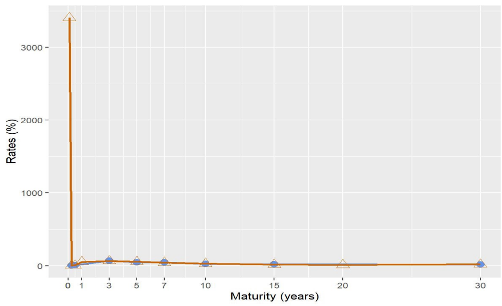
Figure(6a, 6c and 6e) fit the estimations of the Greek yields for January 2012 and Figure(6b, 6d and 6f) fit the estimations of the Greek yields for April 2021 on observed data for the corresponding dates using the parametric models Nelson & Siegel (1987), Svensson (1994) and Diebold & Li (2006) respectively. Svenson's model, obviously collapses for 1-month's maturity estimation, giving a value over 3000% for January 2012 but clearly performs better for April 2021. Apart from an irrational estimation, the estimated values for all other maturities are more accurate.
Nelson & Siegel (1987) model seems to struggle less in its estimations, but the estimated yields for 1-month and 3-months maturities give negative values for January 2012, which is not the case. For April 2021, Nelson & Siegel (1987) produces more accurate estimations. On the contrary, Diebold & Li (2006) model's estimations diverge from observed yields in most maturities.



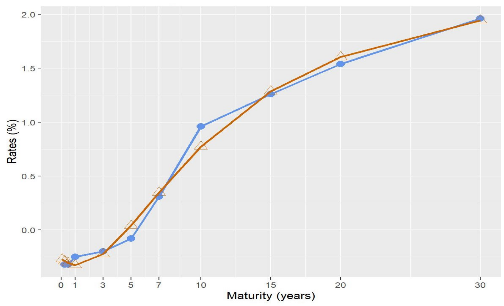
(a) Estimation of the Greek yields for January 2012, from Nelson & Siegel (1987) model.



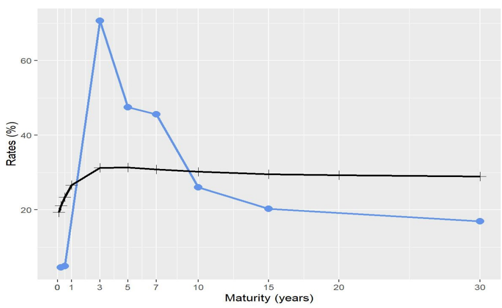
(b) Estimation of the Greek yields for April 2021, from Nelson & Siegel (1987) model.



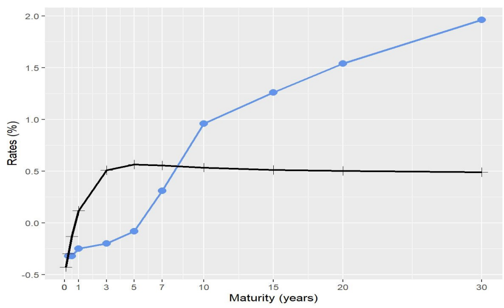
(c) Estimation of the Greek yields for January 2012, from Svensson (1994) model.



(d) Estimation of the Greek yields for April 2021, from Svensson (1994) model.



(e) Estimation of the Greek yields for January 2012, from Diebold & Li (2006) model.



(f) Estimation of the Greek yields for April 2021, from Diebold & Li (2006) model.

Figure 6. Estimation of the Greek yields for January 2012 and April 2021, using the parametric models (Nelson & Siegel (1987), Svensson (1994) and Diebold & Li (2006)).

3.3 Differential Evolution Results

Figure (3) shows observed Greek market Government bond yields for the period from March 1999 to June 2022. Missing data and the lack of a data from unobserved maturities is obvious. Using Differetial Evolution algorithm, all series for Greek market Government bond yields for every maturity can be estimated and Greek government zero coupon bond yield data for all maturities and all dates would be available.
We use the NMOF package by Schumann (2022) concluded in R software (R Core Team (2017)) to implement the estimation, minimizing the mean absolute error function (2.9). In order to estimate the set of parameters from Svensson (1994) model ($\beta = (\beta_1, \beta_2, \beta_3, \beta_4)$ and $\lambda = (\lambda_1, \lambda_2)$), we run Differential Evolution algorithm a number of times for each month of our sample.
The selected constraints for each month separately (3.1) in this case are

$$\begin{aligned} 0 < \beta_1 < 26 \\ -26 < \beta_2 < 30 \\ -190 < \beta_3 < 190 \\ -190 < \beta_4 < 190 \\ 0 < \lambda_1 < 10 \\ 0.2 < \lambda_2 < 30 \end{aligned} \tag{3.1}$$

The algorithm converges to a solution with error less than Svensson (1994) model's error or less than a prespecified barrier for the error and then it gives a valid estimation for the model parameters.

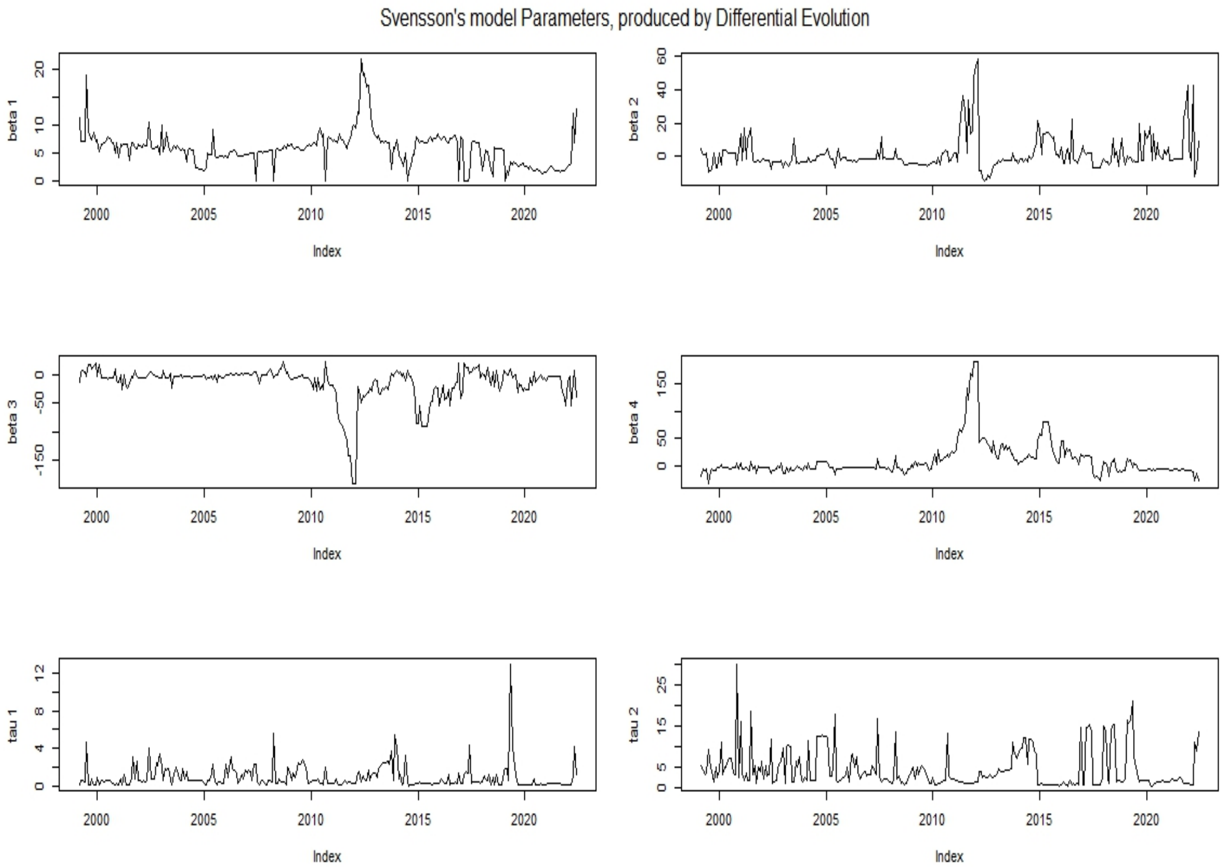


Figure 7. Estimated (monthly) parameters for Svensson (1994) model, via the Differential Evolution algorithm, for March 1999 - June 2022

Figure (7) shows the estimated monthly parameters used for the estimation of the Greek Government yield curve, for the period from March 1999 to June 2022. As shown in Figure (7), the basic identification problem of extremely high levels of correlation among the parameters of Svensson (1994) model is eliminated. Even if the parameters are correlated, they do not seem to continue mirroring, after the estimation using the differential evolution algorithm, correcting the multicollinearity issue of parametric models.

Table (1) reports the correlation coefficients between all the pairs of beta parameters for each of the four models we study and reveals the definite improvement of the correlation coefficient between β_1 and β_2, β_1 and β_3 and β_1 and β_4, after the differential evolution estimation. In addition, table (1) shows a slight improvement in correlation coefficient between β_2 and β_3 and β_2 and β_4. On the other hand, no improvement is shown for the correlation

Table 1. A comparative table for the correlation coefficients between parameters, of Nelson & Siegel (1987) model (Panel A), Diebold & Li (2006) model (Panel B), Svensson (1994) model (Panel C) and Svensson (1994) model estimated using Differential Evolution (Panel D).

Panel A	**beta 1 NS**	**beta 2 NS**	**beta 3 NS**	
beta 1 NS	1			
beta 2 NS	4.66%	1		
beta 3 NS	-81.43%	-41.27%	1	
Panel B	**beta 1 DL**	**beta 2 DL**	**beta 3 DL**	
beta 1 DL	1			
beta 2 DL	-72.68%	1		
beta 3 DL	79.95%	-97.92%	1	
Panel C	**beta 1 NSS**	**beta 2 NSS**	**beta 3 NSS**	**beta 4 NSS**
beta 1 NSS	1			
beta 2 NSS	91.41%	1		
beta 3 NSS	-91.58%	-99.99%	1	
beta 4 NSS	-93.97%	88.4%	88.46%	1
Panel D	**beta 1 DE**	**beta 2 DE**	**beta 3 DE**	**beta 4 DE**
beta 1 DE	1			
beta 2 DE	-19.99%	1		
beta 3 DE	-27.65%	-71.62%	1	
beta 4 DE	22.08%	52.79%	-88.84%	1

Notes. Panel A: We report the correlation coefficients between the beta parameters of Nelson & Siegel (1987) model. **Panel B:** We report the correlation coefficients between the beta parameters of Diebold & Li (2006) model. **Panel C:** We report the correlation coefficients between the beta parameters of Svensson (1994) model. **Panel D:** We report the correlation coefficients between the beta parameters of Svensson (1994) model, estimated using Differential Evolution Algorithm.

Table 2. A comparative table between Mean Errors(ME, Panel A), Mean Absolute Errors (MAE, Panel B) and Root Mean Square Errors (RMSE, Panel C), of Nelson & Siegel (1987) model , Diebold & Li (2006) model (Panel B), Svensson (1994) model (Panel C) and Svensson (1994) model estimated using Differential Evolution (Panel D), for each maturity and overall. All error values in basis points.

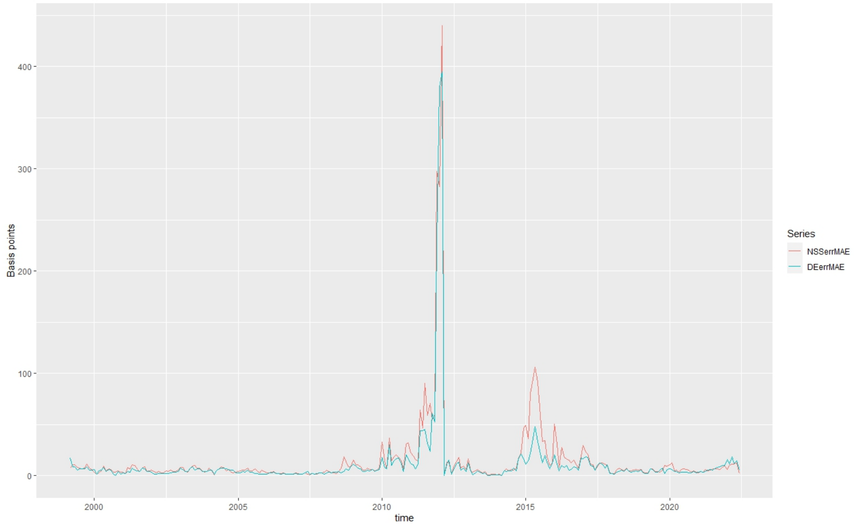
Panel A	**h3m**	**h6m**	**h1y**	**h3y**	**h5y**	**h7y**	**h10y**	**h15y**	**h20y**	**h30y**	**Overall**
NS(ME)	24.46	-35.26	2.98	31.50	-13.78	-8.85	-9.02	-1.20	0.81	13.88	2.59
NSS(ME)	0.01	-1.13	0.71	16.30	-15.64	-6.46	-3.22	13.62	4.10	-10.58	-1.08
DL(ME)	-94.74	-118.75	-44.13	114.15	63.08	51.69	82.26	85.87	122.64	73.45	26.64
DE(ME)	0.038	1.88	0.72	31.21	-2.31	-0.52	-4.84	-1.47	-0.80	3.24	2.46
Panel B	**h3m**	**h6m**	**h1y**	**h3y**	**h5y**	**h7y**	**h10y**	**h15y**	**h20y**	**h30y**	**Overall**
NS(MAE)	36.24	45.59	15.40	38.59	22.61	16.91	19.59	11.86	10.07	19.67	23.93
NSS(MAE)	2.24	4.87	7.18	24.28	24.21	17.47	14.28	19.08	10.10	14.28	13.42
DL(MAE)	108.66	131.77	56.32	190.19	103.83	68.91	101.91	125.42	128.36	152.88	110.06
DE(MAE)	**0.58**	6.80	**2.85**	32.42	**12.03**	**9.70**	**13.44**	**10.72**	**6.76**	**8.91**	**9.47**
Panel C	**h3m**	**h6m**	**h1y**	**h3y**	**h5y**	**h7y**	**h10y**	**h15y**	**h20y**	**h30y**	**Overall**
NS(RMSE)	101.89	137.45	23.38	123.40	70.94	41.39	51.32	21.15	15.66	61.85	61.90
NSS(RMSE)	5.28	8.90	10.32	82.37	88.42	46.61	27.93	69.30	19.54	42.27	37.62
DL(RMSE)	235.91	269.29	66.62	562.57	260.95	158.02	159.90	179.84	155.35	220.79	210.22
DE(RMSE)	**4.75**	17.73	**8.18**	219.46	**28.26**	**46.39**	40.06	**30.11**	**14.78**	**33.08**	40.25

Notes. Panel A: We report the Mean Errors (ME) resulting from estimation using Nelson & Siegel (1987) model, Svensson (1994) model, Diebold & Li (2006) model and Svensson (1994) model, estimated using Differential Evolution Algorithm. **Panel B:** We report the Mean Absolute Errors (MAE) resulting from estimation using Nelson & Siegel (1987) model, Svensson (1994) model, Diebold & Li (2006) model and Svensson (1994) model, estimated using Differential Evolution Algorithm. **Panel C:** We report the Root Mean Square Errors (RMSE) resulting from estimation using Nelson & Siegel (1987) model, Svensson (1994) model, Diebold & Li (2006) model and Svensson (1994) model, estimated using Differential Evolution Algorithm.

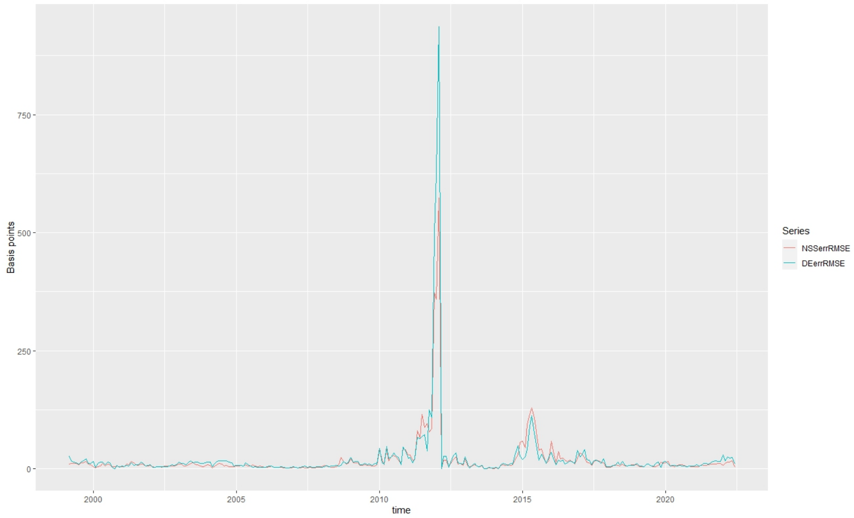
coefficient between β_3 and β_4 of the estimation using Differential Evolution Algorithm, against Svensson (1994) model.

Apart from the identification problem which is solved and the parameters' better economical structure using Differential Evolution Algorithm for the estimation, another goal is achieved. This method manages to deliver better accuracy in bond yields estimation. The in-sample results are reported in Table (2) where we compare the accuracy metrics of Mean Error (ME), the Mean Absolute Errors (MAE) and the Root Mean Square Error (RMSE) from all the models used to estimate the yield curve, like Liu & Wu (2021) and Jeleskovic & Demertzidis (2020). We observe that Differential Evolution estimation manages to show the lowest Overall Mean Absolute Error (Panel B of Table 2), 9.47 basis points. Except for the Overall MAE, this method shows the lowest MAE for 8 out of 10 maturities.
Even for the Root Mean Square Error (Panel C of Table 2), DE method manages to reduce RMSE for 7 out of 10 maturities. The lowest overall RMSE is achieved from traditional Svensson (1994) model, mainly because it manages

to show much lower RMSE against DE method for maturity of three years (82.37 bps against 219.46 bps).



(a) MAE, Svensson (1994) vs Differential Evolution.

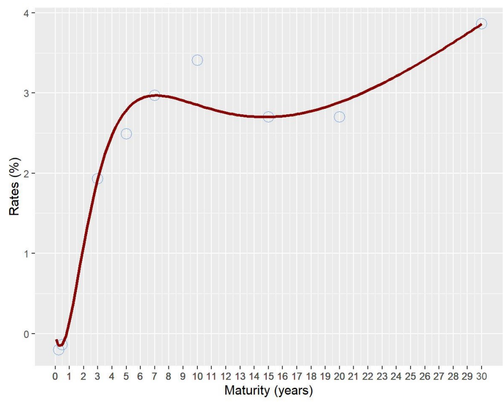


(b) RMSE, Svensson (1994) vs Differential Evolution.

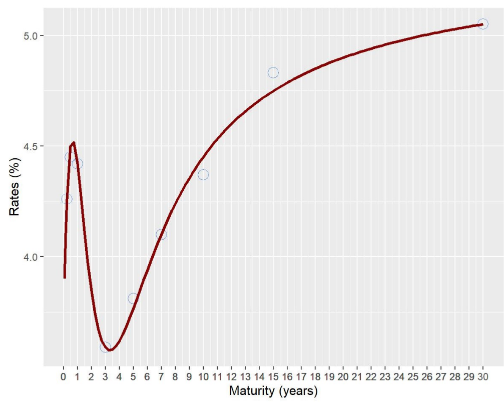
Figure 8. Time Series of difference for Overall Mean Absolute Errors (8a) and Overall Root Mean Square Errors (8b), between Svensson (1994) model and Differential Evolution. All values in basis points.

Figure (8) presents the time series of Mean Absolute Error (8a) and Root Mean Square Errors (8b) for all the time period of our study, between Svensson (1994) model and Differential Evolution. We observe the fact that, re-

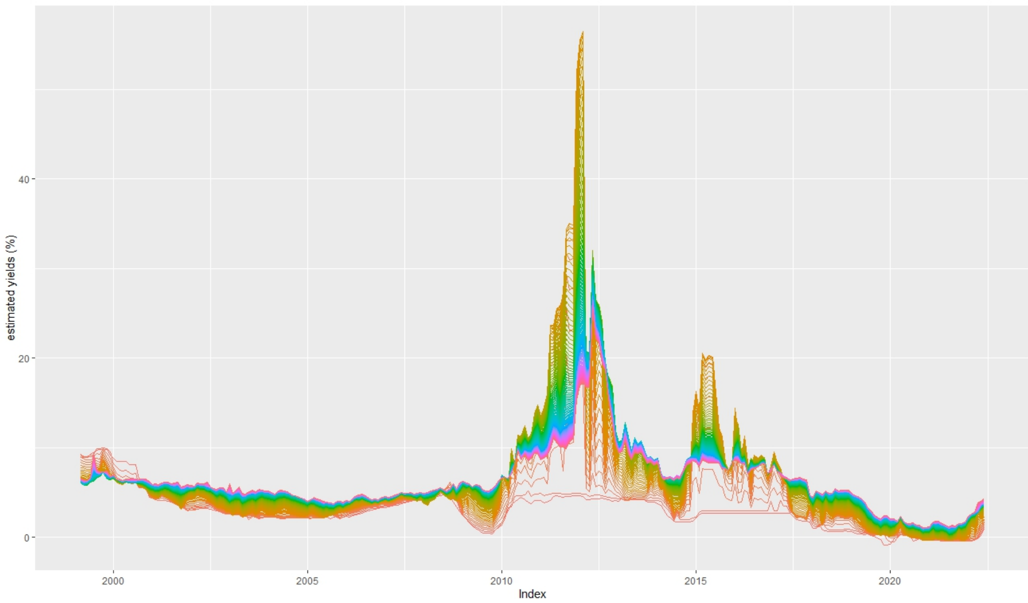
gardless time (month) Overall MAE is lower for Differential Evolution for the majority of months, while RMSE is higher.
If we study the sample for each month, out of the total of 279 months, the error from the differential evolution estimation is less than Svensson (1994) model error for about 240 months.



(a) DE estimation for April 2022



(b) DE estimation for February 2008



(c) DE yield curve estimation for period March 1999 - June 2022.

Figure 9. The estimations of the yields for April 2022 (9a), for February 2008 (9b) and the Greek Yield Curve for the period March 1999 - June 2022 (9c), usimg Differential Evolution. All observed values and estimates are monthly.

Figure (9) shows two example estimations for April 2022 (9a) and for

February 2008 (9b). Figures (9a) and (9b) show the good fit and accuracy in estimations, from the use of DE algorithm.
Figure (9c) depicts the estimation for Greek Yield Curve for the period March 1999- June 2022, for all maturities from 3 months to 360 months for every 3 months. We observe that this estimation is a very good proxy for the observed monthly yield curve (Figure (3)).

4 Concluding remarks

For the estimation of the Greek Yield Curve, we use the Differential Evolution algorithm instead of the traditional and widely used parametric models Nelson & Siegel (1987), Svensson (1994) and Diebold & Li (2006). The reason why we propose the DE method for the Yield Curve estimation is twofold, the multicollinearity problem and the optimization of a highly non linear and non convex objective function, with several local optima. For estimation purposes, we construct our Greek yields dataset by combining a set of three series of short term yields and a set of seven long term yields and based on this dataset we show the aforementioned issues existing in Greek data. We show that using DE algorithm to estimate the Greek yields, two main results are achieved. The former is that the model parameters correlate less than traditional models' parameters and the latter is the better in sample overall accuracy as the Mean Absolute Error is the lowest among the four models. Another side result is the MAE reduction for the maturities of 3 months, 1 year, 5 years, 7 years, 10 years, 15 years, 20 years and 30 years and the RMSE reduction for the maturities of 3 months, 1 year, 5 years, 7 years, 15 years, 20 years and 30 years. Obviously, the most important result is the full range data, for all maturities for the Greek yields, which have become available for everyone to use.
Moving forward, we intend to use these estimations to forecast the Greek yields, in future research projects.

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References

Annaert, Jan, Claes, Anouk GP, De Ceuster, Marc JK, & Zhang, Hairui. 2013. Estimating the spot rate curve using the Nelson–Siegel model: A ridge regression approach. *International Review of Economics & Finance*, **27**, 482–496.

Ayouche, Sofia, Ellaia, Rachid, & Aboulaich, Rajae. 2016. A Hybrid Particle Swarm Optimization-Nelder-Mead Algorithm (PSO-NM) for Nelson-Siegel-Svensson Calibration. *International Journal of Economics and Management Engineering*, **10**(4), 1365–1369.

Balfoussia, Hiona. 2008. An affine factor model of the Greek term structure.

Björk, Tomas, & Christensen, Bent Jesper. 1999. Interest Rate Dynamics and Consistent Forward Rate Curves. *Mathematical Finance*, **9**(4), 323–348.

Bliss, Robert Russell. 1997. Testing term structure estimation methods. *Advances in Futures and Options research*, **9**, 197–232.

De Pooter, Michiel. 2007. Examining the Nelson-Siegel class of term structure models: In-sample fit versus out-of-sample forecasting performance. *Available at SSRN 992748*.

De Rezende, Rafael B, & Ferreira, Mauro S. 2013. Modeling and Forecasting the Yield Curve by an Extended Nelson-Siegel Class of Models: A Quantile Autoregression Approach. *Journal of Forecasting*, **32**(2), 111–123.

Diebold, Francis X, Piazzesi, Monika, & Rudebusch, Glenn D. 2005. Modeling bond yields in finance and macroeconomics. *American Economic Review*, **95**(2), 415–420.

Diebold, F.X., & Li, C. 2006. Forecasting the term structure of government bond yields. *Journal of Econometrics*, **130**(2), 337–364.

Fisher, Mark, Nychka, Douglas W, & Zervos, David. 1995. Fitting the term structure of interest rates with smoothing splines.

Gilli, Manfred, & Schumann, Enrico. 2010. Robust regression with optimisation heuristics. *Pages 9–30 of: Natural computing in computational finance*. Springer.

Gilli, Manfred, Große, Stefan, & Schumann, Enrico. 2010. Calibrating the nelson-siegel-svensson model. *Available at SSRN 1676747*.

Giraldo, Mateo Velásquez, Betancur, Juan Carlos Gutiérrez, & Hurtado, Paula María Almonacid. 2016. Calibración de parámetros de los modelos de tasas de interés NS y NSS para Colombia: una nota técnica. *Journal of Economics, Finance and Administrative Science*, **21**(41), 73–80.

Gürkaynak, Refet S, Sack, Brian, & Wright, Jonathan H. 2007. The US Treasury yield curve: 1961 to the present. *Journal of monetary Economics*, **54**(8), 2291–2304.

Hull, John C. 2006. *Options, futures, and other derivatives*. Pearson Prentice Hall.

Ioannides, Michalis. 2003. A comparison of yield curve estimation techniques using UK data. *Journal of Banking & Finance*, **27**(1), 1–26.

Jeleskovic, Vahidin, & Demertzidis, Anastasios. 2020. Comparing different methods for the estimation of interbank intraday yield curves. *Journal of Corporate Accounting & Finance*, **31**(3), 57–75.

Lakhany, Asif, Pintar, Andrej, & Zhang, Amber. 2021. Calibrating the Nelson-Siegel-Svensson model by genetic algorithm. *arXiv preprint arXiv:2108.01760*.

León Valle, Ángel M, Rubia, Antonio, & Sanchis-Marco, Lidia. 2018. On multicollinearity and the value of the shape parameter in the term structure Nelson-Siegel model.

Linton, Oliver, Mammen, Enno, Nielsen, Jans Perch, & Tanggaard, Carsten. 2001. Yield curve estimation by kernel smoothing methods. *Journal of Econometrics*, **105**(1), 185–223.

Liu, Yan, & Wu, Jing Cynthia. 2021. Reconstructing the yield curve. *Journal of Financial Economics*, **142**(3), 1395–1425.

Maciel, Leandro, Gomide, Fernando, & Ballini, Rosangela. 2012. Modeling the term structure of government bond yields with a differential evolution algorithm. *Pages 1–8 of: 2012 IEEE Conference on Computational Intelligence for Financial Engineering & Economics (CIFEr)*. IEEE.

Maciel, Leandro, Gomide, Fernando, & Ballini, Rosangela. 2016. A differential evolution algorithm for yield curve estimation. *Mathematics and Computers in Simulation*, **129**, 10–30.

Manousopoulos, Polychronis, & Michalopoulos, Michalis. 2009. Comparison of non-linear optimization algorithms for yield curve estimation. *European Journal of Operational Research*, **192**(2), 594–602.

McCulloch, J Huston. 1971. Measuring the term structure of interest rates. *The Journal of Business*, **44**(1), 19–31.

Neely, Christopher J. 2012. The mysterious Greek yield curve. *Economic Synopses*, **2012**(2012-03-02).

Nelson, Charles R., & Siegel, Andrew F. 1987. Parsimonious Modeling of Yield Curves. *The Journal of Business*, **60**(4), 473.

Nymand-Andersen, Per. 2018. *Yield curve modelling and a conceptual framework for estimating yield curves: evidence from the European Central Bank's yield curves*. Tech. rept. ECB Statistics Paper.

R Core Team. 2017. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Schumann, Enrico. 2022. *Numerical Methods and Optimization in Finance (NMOF) Manual. Package version 2.7-0)*.

Storn, Rainer, & Price, Kenneth. 1997. Differential evolution-a simple and efficient heuristic for global optimization over continuous spaces. *Journal of global optimization*, **11**(4), 341.

Svensson, Lars E O. 1994. Estimating and interpreting forward interest rates: Sweden 1992-1994. *NBER Working Paper No. 4871*, sep, 1–47.

Vasicek, Oldrich A., & Fong, H. Gifford. 1982. Term Structure Modeling Using Exponential Splines. *The Journal of Finance*, **37**(2), 339–348.

Waggoner, Daniel F. 1997. Spline methods for extracting interest rate curves from coupon bond prices. *Federal Reserve Bank of Atlanta Working Paper*, 97–10.

Wahlstrøm, Ranik Raaen, Paraschiv, Florentina, & Schürle, Michael. 2022. A comparative analysis of parsimonious yield curve models with focus on the Nelson-Siegel, Svensson and Bliss versions. *Computational Economics*, 1–38.

Investors' Herding Behavior in the Greek Stock market: Evidence from the outbreak of the Covid-19 pandemic

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Abstract

This paper investigates the effect of the Covid-19 on investor herding behaviour in the Greek stock market during the pandemic outbreak. We examine the presence of herding using the cross-sectional absolute deviation of stock returns around the market portfolio return and whether the dispersion of returns differs on rising and declining market days. We reveal that Covid-19 has a herding effect in the Greek stock market in lower levels and it impacts on investors' herding behaviour only on bad days in lower levels.

Keywords. Asset Pricing; Behavioural Finance; Herding behaviour

JEL CLASSIFICATION: G12; G14; G41

1 Introduction

People's investment behavior was influenced by the devastating pandemic period when Covid-19 wreaked havoc on the global financial markets. People tend to imitate the choices of others in panic situations because of uncertainty. Luu and Luong (2020) refer that there is clear evidence of investor herd behavior during the H1N1 and Covid-19 outbreaks as diseases make people emotionally unstable when trading on the markets. This study investigates how the Covid-19 pandemic affects stock market herding in Greece during the Covid-19 outbreak (unconditional herding) and whether the dispersion of returns behaves differently on rising and declining market days when herding behavior prevails (conditional herding).

Portfolio management companies and individual investors seek to differentiate themselves by making better market valuations and, therefore, more targeted investments due to the increased competition and volatility of the stock market. To succeed, they should understand the possibilities provided by the correct interpretation of herd behavior and its results to gain a competitive advantage, increase their financial results, and establish their position inside their task environment.

This study will focus on the measure of cross-sectional absolute deviation (CSAD) of stock returns around the market portfolio return, examining whether rational asset pricing ceases to exist by observing the relationship between the CSAD of ATG stock index and the squared market return ($R^2{}_m$) of the STOXX index. Some studies have examined herd behavior in only one stock market during the pandemic. Dhall and Singh (2020) confirm that the Covid-19 pandemic has provoked herding behavior at the industry level of the Indian stock market. Also, Espinosa-Méndez and Arias (2021) refer that to an increase in the herding behavior in the Australian stock market during the pandemic. However, it is remarkable that there is no research on the herding behavior of investors in the Greek stock market during the Covid-19 outbreak.

Hence, there is a relative research gap in the international literature regarding if the Covid-19 pandemic affects the herding behavior of investors in the Greek stock market. This paper aims to investigate if the pandemic has any effect on the herding behavior in the Greek stock market from July 10, 2019, to July 15, 2020, a period that contains the pre-Covid-19 outbreak and the post-Covid-19 outbreak and examines if the dispersion of returns behaves differently in up and down-market days.

Regarding our findings, neither unconditional nor conditional herding prevails on the Greek stock market using the Classic Newey-West heteroscedasticity and autocorrelation consistent standard errors. Nonetheless, because non-linear regression does not consider extreme values, we validate this estimation using quantile regression Kizys, Tzouvanas and Donadelli (2021) and Gębka and Wohar (2013)) to see how the coefficients behave across quantiles. So, herding occurs only at the highest quantile in the Greek stock market, and especially at the 75% quantile only on declining market days. Summarizing the empirical findings, herding behavior occurs at lower levels in the Greek stock market and only on down-market days during the Covid-19 outbreak.

Conclusively, this research provides insight into the herding behavior in the Greek stock market through a period with extreme market movements, proposes how herding behavior could be measured, and lays the groundwork for future research.

The rest of this study is structured as follows. Section 2 outlines the conceptual framework and the formulated hypotheses. Section 3 clarifies the data and variables that were chosen. Section 4 demonstrates the econometric methodology used to examine herding behavior over the sample periods and determine whether return dispersion behaves differently in up and down market days. Section 5 presents and analyzes the findings, while Section 6 demonstrates the conclusions and mentions the implications for financial decision-makers.

2 Conceptual Framework and Hypothesis Development

Herding behavior has been studied in many contexts in financial markets, including international stock markets. Christie and Huang (1995) initially find that the daily and monthly returns do not demonstrate herd behavior during periods of market stress but rather are consistent with rational asset pricing. Chang et al. (2000) indicate no herding effect for the US and Hong Kong markets, limited evidence of bias in Japan, and findings of herding behavior in South Korea and Taiwan, as a modification of the prior model. Moreover, Hwang and Salmon (2004) show that not only is herding in the direction of the market persistent in the US and South Korean equity markets but that market crises cause a reduction in herding behavior. Furthermore, Chiang and Zheng (2010) argue that herding behavior causes asset price deviations by investigating 18 advanced and developing economies. Finally, Economou et al. (2011) explore whether the recent global financial crisis has resulted in intense herding behavior in the four markets studied (Portuguese, Italian, Spanish, and Greek).

2.1 Herding Behavior and Stock Markets

Several studies have examined herding behavior in stock markets around the world. Chang and Chen (2010) on the Taiwanese stock market found that herding behavior was prevalent during the 2008 global financial crisis. Another study by Gao et al. (2017) on the Chinese stock market also found evidence of herding behavior during both up and down markets. In a study on the Indian stock market, Bhattacharya and Mukherjee (2017) found that herding behavior was influenced by both rational and irrational factors. A study by Arjoon and Bhatnagar (2016) on the South African stock market found that herding behavior was present but not as prevalent as in other markets. Finally, a study by Mitra and Das (2015) on the Brazilian stock market found that herding behavior was significantly influenced by market conditions and investor characteristics.

Another studies that have examined herding behavior around the world is Chang and Cheng (2019) who examined herding behavior in the Taiwan stock market and found evidence of herding during both bull and bear markets. Moreover, Demirer et al. (2018) examined herding behavior in emerging markets and found that herding was more prevalent in countries with weaker institutional quality. A study by Saha and Bhattacharya (2019) examined herding behavior in the Indian stock market and found evidence of herding during both positive and negative market conditions. Another study by Choe et al. (2019) examined herding behavior in the Korean stock market and found that herding was more prevalent during times of high market uncertainty. Finally, a study by Corbet et al. (2020) examined herding behavior in cryptocurrency markets and found evidence of herding during periods of high market volatility. These studies suggest that herding behavior is a phenomenon that occurs in stock markets around the world and is influenced by various factors such as institutional quality, market uncertainty, and volatility.

In terms of global studies, Chang and Zeng (2019) analyzed herding behavior in the stock markets of 11 countries in the Asia-Pacific region and found significant herding behavior in all of the countries studied. Similarly, Shahzad et al. (2020) examined herding behavior in the stock markets of 27 countries and found evidence of herding behavior in all of the countries studied, with stronger herding behavior in emerging markets. On the other hand, Chatziantoniou et al. (2020) investigated herding behavior in 16 European stock markets and found limited evidence of herding behavior during the Covid-19 pandemic, with herding behavior being more prevalent in the early stages of the pandemic. Finally, Frijns et al. (2021) examined herding behavior in the Australian stock market during the Covid-19 pandemic and found evidence of herding behavior, which was more prevalent in the initial stages of the pandemic but reduced as the pandemic progressed.

2.2 Herding Behavior and Greek Stock Market

Over the years, several studies have explored the presence of herding behavior in the Greek stock market. Koutmos (1997) was among the first to examine analyst forecasts in the Athens Stock Exchange and found evidence of herding behavior. This finding was corroborated by Kanas (2000), who also found evidence of herding behavior in the market, although it was not significant enough to affect market efficiency. The research conducted by Vrontos and Vrontos (2004) suggested that herding behavior in the Athens Stock Exchange could be attributed to a combination of social influence and information cascades, while Bekiris et al. (2005) attributed it to the lack of information and the presence of noise in the market.

Other studies have explored the presence of herding behavior in specific sectors of the market. Athanasoglou et al. (2008) found evidence of herding behavior among Greek banks, which they argued was driven by macroeconomic and industry-specific factors. Siriopoulos and Fassas (2009) concluded that herding behavior was more prevalent among retail investors than among institutional investors. Michalopoulos and Milios (2009) also found that herding behavior was more prevalent among retail investors than institutional investors.

Studies conducted in later years have continued to find evidence of herding behavior in the Greek stock market. Daskalakis and Skiadopoulos (2011) revealed that herding behavior was more prevalent during crisis periods and among less-informed investors. Papadamou and Markopoulos (2013) provided evidence of the herding effect in the Greek stock market, particularly during periods of high investor sentiment. Koulakiotis et al. (2015) found evidence of herding behavior in the Athens Stock Exchange, especially during periods of market turbulence, driven by behavioral biases and the lack of available information to investors, which could lead to mispricing and systemic risk in the market.

Other studies have explored the impact of investor sentiment on herding behavior in the Greek stock market. Tsaousis and Kyriakou (2015) found evidence of herding behavior in response to investor sentiment. Konstantakis and Michaelides (2017) found strong evidence of herding and information cascades among Greek investors, which they attributed to the lack of financial education and the presence of sentiment in the market. Gkillas et al. (2018) examined the impact of financial crises on herding behavior in the Greek stock market and found that herding was stronger during crisis periods, due to higher uncertainty and a decrease in the availability of information.

2.3 *Herding Behavior and Greek Stock Market during Covid-19 period*

Numerous studies have investigated herding behavior in stock markets worldwide during Covid-19 pandemic. Zhang et al. (2021) examined herding behavior in the Chinese stock market and found that it was prevalent during the COVID-19 pandemic. They concluded that herding behavior was more likely to occur during periods of high uncertainty and low liquidity. In the Malaysian stock market, Lim et al. (2021) found that herding behavior was significant during the pandemic period and was related to market uncertainty and volatility. In the United States, Cici and Gibson (2020) studied herding behavior during the COVID-19 crisis and found that it was more prevalent among retail investors. They also found that herding behavior was more pronounced for firms with higher market volatility. Finally, in the Indian stock market, Kaur and Kaur (2021) examined the impact of the COVID-19 pandemic on herding behavior and found that it was more likely to occur during periods of high market volatility and uncertainty. They also found that herding behavior was more common among smaller firms. Overall, these studies suggest that herding behavior is prevalent in stock markets during the COVID-19 pandemic and is related to market uncertainty, volatility, and liquidity.

Recent studies have explored the impact of crises on herding behavior in the Greek stock market during the Covid-19 pandemic. Spyrou et al. (2020) analyzed the impact of the sovereign debt crisis and found that herding was present during the crisis period but decreased in the post-crisis period. Ballas et al. (2020) found evidence of herding and suggested that this effect was related to investor sentiment, as measured by Google search queries.

Gavriilidis et al. (2021) investigated the impact of the COVID-19 pandemic on herding behavior in the Greek stock market and found that herding was present during the pandemic period but decreased in the post-pandemic period, attributed to the implementation of fiscal and monetary policies aimed at stabilizing the economy and the financial markets. Koulakiotis et al. (2021) found evidence of herding behavior related to investor sentiment and market uncertainty. Kyriakou et al. (2021) investigated 11 sectors of the Greek stock market, found evidence of herding behavior in most of them, also linked to high market uncertainty and investor sentiment. Christofi et al. (2021) analyzed the impact of investor sentiment on herding behavior in the Greek stock market. Dritsakis and Psillaki (2021) used the methodology of Chang et al. (2000) and found evidence of herding behavior during the pandemic. Skintzi and Antoniou (2021) also found evidence of herding behavior in the Greek stock market during the pandemic, which was linked to market uncertainty and investor sentiment.

However, the existing literature is limited on how the Covid-19 pandemic impacts Greek stock market provoking herding behavior, during the outbreak of the pandemic. More specifically, Koulakiotis, Papathanasiou, and Kyriakou (2021) analyzed the herding behavior in the Greek stock market during the Covid-19 pandemic using a time-varying parameter model. They collected data on the daily returns of the Athens Stock Exchange General Index from January 2018 to July 2020 and found evidence of herding behavior related to investor sentiment and market uncertainty. Also, Dritsakis and Psillaki (2021) used regression analysis to investigate herding behavior in the Greek stock market during the Covid-19 pandemic. Specifically, they used the methodology proposed by Chang et al. (2000), which involves estimating a time-varying beta coefficient that measures the degree of herding behavior among investors. They employed this methodology to examine the herding behavior of investors in the Greek stock market during the period from July 2019 to July 2020.

Overall, we anticipate that the Covid-19 pandemic will underline the presence of investor herding behavior in our study, taking into consideration the surveys. We examine the following hypotheses using the Chang et al. (2000) model, as used in almost all studies, to test whether herding behavior exists among investors in stock markets due to the pandemic's uncertainty that prevails:

Hypothesis 1 (H1): Once $\beta_1 > 0$ and $\beta_2 = 0$ in $CSAD_{m,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + e_t$ proves that there is no herding behavior, we anticipate a negative relation between squared market ($\beta_2 < 0$) and cross-sectional absolute deviation (CSAD) if herding behavior is recognized, or we expect a positive relationship between squared market ($\beta_2 > 0$) and cross-sectional absolute deviation (CSAD) if the anti-herding event happens. If Hypothesis 1 is true, herding behavior exists in stock markets during the period studied, which contains the outbreak of COVID-19 crisis.

Hypothesis 2 (H2): Since $\beta_1 > 0$ and $\beta_2 > 0$ in $CSAD_{m,t} = \beta_0 + \beta_1 D_{up} |R_{m,t}| + \beta_2 (1 - D_{up}) |R_{m,t}| + \beta_3 D_{up} R_{m,t}^2 + \beta_4 (1 - D_{up}) R_{m,t}^2 + e_t$

We note that there are no herding effects, and we anticipate a negative relationship between positive squared market values ($\beta_3 < 0$), negative squared market values ($\beta_4 < 0$), and cross-sectional absolute deviation (CSAD). As a result, if coefficient $\beta_4 < \beta_3$, herding effects are more intense on days with negative market returns. Finally, if Hypothesis 2 is valid, there are links between herding and market periods with rising and falling prices.

3 Data and Methodology

3.1 Data

Our sample includes the ATG stock index, which investigates the Greek stock market to see if the pandemic affects stock investors' herding behavior.

Thomson Reuters DataStream is the source of our information. More specifically, we obtain hourly observations of stock index closing prices. Remarkably, we explore the Greek market from 11:00 am July 10, 2019, to 6:00 pm July 15, 2020. Furthermore, we obtained the hourly closing prices of the general stock index of Europe from the database, which is the market return for each region of our study. The STOXX is the general stock index of the European index.

Table A1 in the Appendix provides an array of descriptive statistics for the ATG. Similarly, Table A2 gives descriptive statistics for the European general stock index. As we'll discover later by examining the measurement of herding behavior, the general stock index reflects the market return of each region.

3.2 Measurement of Herding Behavior

Various methods can be used to investigate herding behavior in stock markets during the COVID-19 pandemic, but we opt to utilize Chang et al. (2000) method due to its widespread and effective application in previous studies. In Section 2, we introduce and explain this method, which measures herding based on the low dispersion of returns around their cross-sectional average, indicating that market participants are disregarding their diverse beliefs and information to conform to the "market consensus" through correlated trading activities. Chang et al. (2000) proposed the cross-sectional absolute deviation (CSAD) of stock returns from the market portfolio return as a suitable measure to capture this phenomenon. This measure is given by:

$$CSAD_{m,t} = \frac{\sum_{t=1}^{N} |\mathrm{R_{i,t}} - \mathrm{R_{m,t}}|}{N} \qquad (1)$$

where $\mathrm{R_{i,t}}$ is the observed stock return of index i on hour t, which is represented by ATG index, and it is the first logarithmic difference of closing prices for stock index i at time t, as given below:

$$R_{i,t} = \; ln\, P_t - ln\, P_{t-1} \qquad (2)$$

N stands for the total number of stocks in the market portfolio. $R_{m,t}$ is the average absolute market return, which is the general stock index and is represented by STOXX for European region. $R_{m,t}$ is the first logarithmic difference of closing prices for general stock index m at time t:

$$R_{m,t} = \; ln\, P_t - ln\, P_{t-1} \qquad (3)$$

Chang et al. (2000) proposed a model to capture herding behavior during market stress defined that the model below is what occurs by market stress:

$$CSSD = \beta_0 + \beta_1 D_t^U + \beta_2 D_t^L + e_t \qquad (4)$$

where D_t^U=1 if the return is in the extreme upper tail of the return's distribution, and $D_t^L = 1$ if the return is in the extreme lower tail of the return's distribution. Asset pricing models, such as the conditional CAPM, assume a linear relationship between returns' dispersion and market returns. However, herding behavior during periods of market stress may result in a non-linear relationship. To test for herding behavior, the following regression model is run for each market i:

$$CSAD_{m,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + e_t \qquad (5)$$

It is expected that the coefficient β_2 will be positive in the absence of herding effects. However, linear asset pricing models assume that the change in cross-sectional dispersion of stock returns during days of extreme market movements will be proportional to the market return. Contrary to this assumption, we observe a negative estimate of coefficient β_1 indicating a nonlinear relationship. Therefore, we examine irrationality and herding behavior in stock markets by testing *Hypothesis 1* (H1).

Furthermore, we investigate whether the returns' dispersion varies in up and down market days. Since market distress is a common indicator of herding, it is reasonable to examine whether herding is affected by such periods. We expect that during days of negative market returns, the cross-sectional dispersion of stock returns will decrease. Hence, we test *Hypothesis 2 (H2)* by examining irrationality and herding behavior in stock markets.

Based on prior research by Christie and Huang (1995), Chang et al. (2000), Demirer et al. (2010) and Chiang and Zheng (2010) have reported that herding effects prevail during periods of abnormal information flows and market downturn, as investors follow public opinion to feel more secure. However, there is no consensus regarding the findings as they depend on the examined market and the sample period. To discover herding in up and down market days (conditional herding), we adopt the approach proposed by Cui et al. (2019) Specifically, we estimate the following model for each market i to examine the asymmetric effect of the market return sign:

$$CSAD_{m,t} = \beta_0 + \beta_1 D_{up}|R_{m,t}| + \beta_2(1 - D_{up})|R_{m,t}| + \beta_3 D_{up}R_{m,t}^2 + \beta_4(1 - D_{up})R_{m,t}^2 + e_t \tag{6}$$

where D_{up} is a dummy variable that takes on a value of one (zero) on days when the general stock index market performance is positive (negative), denoted by $R_{m,t}$. A statistically significant negative coefficient estimation of β_3 (β_4) would provide evidence for herding behavior on days when the average general stock index market performance is positive (negative), respectively.

3.3 Econometric Methodology

We utilize various quantitative methods to investigate the hypotheses mentioned in Section 2, as well as Models (5) and (6). Our first approach is to use classic (Newey and West, 1987) Heteroscedasticity and Autocorrelation consistent (HAC) estimators, which use Bartlett kernel weights as described in (Newey and West, 1994, 1987) to estimate linear regressions and test for the presence of herding behavior in the Greek stock market under consideration. However, using the classic linear Newey-West regression may lead to erroneous conclusions because abrupt changes are typical occurrences in investor herding behavior during extreme conditions, such as the COVID-19 pandemic.

However, quantile regression allows for the estimation of the average relationship between the dependent and explanatory variables at specific quantiles of the distribution of the dependent variable, which reflects extreme values in a fat-tailed or asymmetric distribution. As a result, we utilized the static extension of Chang et al. (2000) analysis to investigate the herding effect in the examined stock market. We perform quantile regressions, as described by Kizys et al. (2021) and Gębka and Wohar (2013) to investigate the behavior of the coefficients across quantiles. For each market i, we run the following regression model:

$$CSAD_{m,t} = Q[\tau|r_{m,t}] = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + e_t \quad \textbf{(8)}$$

where $CSAD_{m,t} = Q[\tau|r_{m,t}]$ is the cross-sectional absolute deviation of stock returns concerning the market portfolio return R_m for each period t and market i and τ represents the τ th quantile (0.05, 0.25, 0.5, 0.75, 0.95) of the conditional distribution of the average absolute market return of the European region. Error term e_t has a zero τ -quantile. Moreover, we examine herding behavior in up and down markets across quantiles in each market i:

$$CSAD_{m,t} = Q[\tau|r_{m,t}] = \beta_0 + \beta_1 D_{up}|R_{m,t}| + \beta_2(1 - D_{up})|R_{m,t}| + \beta_3 D_{up} R_{m,t}^2 + \beta_4 (1 - \mathrm{D_{up}}) R_{m,t}^2 + e_t$$

(9)

by using D_{up} , a dummy variable that takes the value 1 on days with positive values of $R_{m,t}$ and the value 0 otherwise.

4 Results

4.1 Estimating herding behavior

[Insert Table 1 here]

Table 1 shows the results for unconditional herding behavior across the Greek stock market using Newey-West consistent estimators from July 2019 to July 2020. Using the squared market return to the model, we investigate whether this cross-sectional dispersion increases at a decreasing rate during extreme market movements.

In the Greek market, we observe a positive β_1 coefficient with a significance level of 1%. A positive β_1 coefficient indicates that the dispersion of cross-sectional returns increases with the market return magnitude, which is consistent with the standard asset pricing models. However, this cannot be directly interpreted to assess herding behavior. On the other hand, the negative and statistically significant β_2 coefficient denotes intense herding behavior. A negative β_2 coefficient indicates that during extreme market volatility, cross-sectional dispersion increases at a decreasing rate. However, we note that there is a negative β_2 coefficient, which is statistically insignificant during the Covid-19 pandemic outbreak. We cannot provide an accurate estimate for the examined stock market until we investigate and verify the results with quantile regression because nonlinear regression does not consider extreme values, as previously stated.

Our results contradict those of Spyrou et al. (2020) and Ballas et al. (2020), who documented the herding effect in the Greek stock market. Herding is more impactful if the relationship between the CSAD of asset returns and market returns is negative Bernales et al., (2020) which implies that β_1 is negative. In our study, coefficient β_1 was not found to be negative. Thus, stronger herding was not observed in our sample.

4.2 Results of Quantile regressions

[Insert Table 2 here]

Quantile regression is a static model that quantifies the average relationship between the dependent and explanatory variables at specific quantiles, which mirrors abrupt changes that occur under harsh conditions such as COVID-19 disease. To better understand the dynamics of herding, we run Quantile regressions in Table 2 to investigate the effect of various quantiles of return variation on those of herding behavior.

As in Gębka and Wohar (2013), lower quantiles indicate lower CSAD and thus higher levels of herding behavior, whereas upper quantiles indicate higher deviations from the market return and thus lower levels of herding behavior. In the Greek empirical results, we only see herding evidence in the upper quantile of return variation (95%), indicating lower levels of herding behavior. Thus, herding behavior increased in the Greek stock market through Covid-19, but at a lower level. Our results contradict those of Christofi et al. (2021) who discovered evidence of herding behavior in the Greek stock market during the pandemic for all quantiles except the highest analyzing daily data from the Athens Stock Exchange from January 1, 2020, to September 18, 2020.

4.3 Estimating herding behavior on up and down market days

[Insert Table 3 here]

The results of model (6) for conditional herding behavior across the three geographical regions for the sample period of July 2019 – July 2020 are presented in Table 3 above.

Our empirical results provide no evidence of significant herding behavior on up and down-market days in the Greek stock market as the value of β_3 and β_4 is negative and statistical unsignificant. Our evidence is opposite of those of Christofi, Koutmos, and Savva (2021) find that herding behavior is more prevalent on down market days than on up market days, suggesting that investors are more likely to follow the actions of others during times of market stress,

It is worth mentioning that negative values of β_3 (β_4) and significant mean the presence of herding on days of positive (negative) average performance for the examined regions. As for the European geographical region, both β_3 and β_4 are negative and statistically significant, implying herding on positive and negative average market performance, though herding on positive average market performance is stronger as the absolute value of β_3 is higher than the absolute value of coefficient β_4.

4.4 Results of quantile regressions on up and down market days

In Table 4 , we employ quantile regression to understand the dynamics of herding on up and down market days, and to determine if Covid-19 has any effect.

[Insert Table 4 here]

In the conditional Greek quantile regression, there is a decreasing trend in the higher quantiles during the negative average market performance in the Greek stock market. Our results agree with those of Kyriakou et al. (2021), that find herding behavior is more pronounced during periods of high volatility, indicating that investor behavior is more susceptible to market shocks during these times. They used daily data from the Athens Stock Exchange (ASE) from January 2019 to May 2020.

5 Conclusions

Herding behavior has played a role in the Global Financial Crisis (Galariotis et al., 2016), as well as stock price bubbles and other anomalies Devenow and Welch (1996); Hott (2009). Furthermore, herding behavior can increase the co-movement of financial asset returns, reducing the benefits of portfolio diversification (Economou et al., 2011). These unfavorable consequences compel us to define herding behavior in financial markets, as it may contribute to the emergence of a financial crisis. Proper portfolio diversification assumes a strategy that minimizes losses in any market condition.

This paper aims to investigate the impact of herding behavior on the Greek stock market during the COVID-19 outbreak. This study is novel as it examines whether the COVID-19 pandemic affects the Greek stock market during the outbreak of Covid-19, and it investigates whether the dispersion of the returns behaves differently in up and down market days using regression methods to confirm the initial results of the cross-sectional dispersion approach.

The dataset used in this study consists of hourly returns for the general stock index (ATX) between July 2019 and July 2020. The commonly used cross-sectional absolute deviation (CSAD) measure is calculated, which proxies the cross-sectional dispersion of stock returns in the Greek region to examine for potential herding effects. The cross-sectional dispersion approach is conducted, and Quantile Regressions are used to validate potential herding effects.

In testing the 1st Hypothesis of whether herding behavior is present in the examined region (Greek). Our results indicate that there is lack of herding behavior in the Greek region using the Newey and West (1987) approach. However, lower levels of herding were detected using the Quantile Regressions. Our results contrast with those of previous studies by Christofi et al. (2021) who discovered evidence of herding behavior in the Greek stock market during the pandemic for all quantiles except the highest.

Regarding the 2nd hypothesis, our findings reveal that there is no conditional herding behavior using the Newey and West (1987) approach. However, lower levels of herding were detected using the Quantile Regressions on down market days in higher quantiles. These findings contrast with those of Kyriakou, Koulakiotis, and Papathanasiou (2021), that find herding behavior is more pronounced during periods of high volatility, indicating that investor behavior is more susceptible to market shocks during these times..

In general, our findings suggest that herding behavior is stronger during times of heightened uncertainty. These results have important implications for investors and market regulators in times of market turbulence, such as the COVID-19 pandemic. Our study highlights the significance of herding behavior in asset selection for investors and suggests the need for market regulators to issue guidelines on risk disclosure for listed entities. Overall, our study contributes to the understanding of financial stability for the financial community.

In terms of future research, there is an opportunity to investigate the impact of Covid-19 on herding behavior in global stock markets by examining the entire first year of the pandemic. The existing literature is limited in understanding the potential impact of pandemics on financial markets, so it would be worthwhile to compare the first year of the Covid-19 pandemic with other past pandemics. Additionally, further research could explore herding behavior in other markets such as bond markets and examine the stability of herding bias over time. Understanding the motivations behind herding behavior, including the differentiation between spurious herding and intentional herding, as outlined by Bikhchandani and Sharma (2001), is also important to address. Finally, exploring the tension of the herding effect through an examination of trading volume is a promising area for future research. Overall, this study aims to provide insight into investors' herding behavior in financial markets and highlight significant evidence and key issues for future investigation.

6 References

Athanasoglou, P. P., Brissimis, S. N., & Delis, M. D. (2008). Bank-specific, industry-specific and macroeconomic determinants of bank profitability. Journal of International Financial Markets, Institutions and Money, 18(2), 121-136.

Arjoon, V. A., & Bhatnagar, C. (2016). Herding in frontier markets: Evidence from the Mongolia stock exchange. Research in International Business and Finance, 38, 436-453.

Ballas, A. A., Drakos, K., & Kouretas, G. P. (2020). Herding behaviour during extreme events: The role of global information. Journal of Behavioral and Experimental Finance, 28, 100365.

Bekiris, F. V., Georgoutsos, D. A., & Sermpinis, G. J. (2005). Evaluating the forecasting accuracy of five volatility models: A comparison of developed and emerging markets. Applied Financial Economics Letters, 1(5), 267-272.

Bernales, A., Verousis, T., Voukelatos, N., 2020. Do investors follow the herd in option markets? J. Bank. Finance 119, 104899. https://doi.org/10.1016/j.jbankfin.2016.02.002

Bhattacharya, U., & Mukherjee, K. (2017). Dynamic herding analysis in Chinese stock market: a quantile regression approach. Journal of Quantitative Economics, 15(1), 153-176.

Bikhchandani, S., Sharma, S., 2001. Herd Behavior in Financial Markets. IMF Staff Pap. 47, 1–1.

Chatziantoniou, I., Filis, G., & Degiannakis, S. (2020). Financial and political risks in the BRICS. Journal of International Financial Markets, Institutions and Money, 65, 101199. https://doi.org/10.1016/j.intfin.2019.101199

Chang, C.-L., Chen, S.-T. (2010). Herding behavior in the Taiwan stock market: An examination of institutional and individual investors. Pacific-Basin Finance Journal, 18(5), 477-492. doi: 10.1016/j.pacfin.2010.07.003

Chang, C.-L., & Zeng, Q. (2019). Dynamic herding behavior in Pacific-Basin markets: Evidence from a Markov-switching model. International Review of Economics & Finance, 64, 492-510. doi: 10.1016/j.iref.2019.07.009.

Chang, E.C., Cheng, J.W., Khorana, A., 2000. An examination of herd behavior in equity markets: An international perspective. J. Bank. Finance 24, 1651–1679. https://doi.org/10.1016/S0378-4266(99)00096-5

Chiang, T.C., Zheng, D., 2010. An empirical analysis of herd behavior in global stock markets. New Contrib. Retail Paym. Conf. Nor. Bank Cent. Bank Nor. 14–15 Novemb. 2008 34, 1911–1921. https://doi.org/10.1016/j.jbankfin.2009.12.014

Choe, H., & Lee, B. (2019). Herding in the cryptocurrency market: Evidence from Bitcoin, Ethereum, and Ripple. Finance Research Letters, 31, 1-7.

Christie, W.G., Huang, R.D., 1995. Following the Pied Piper: Do Individual Returns Herd around the Market? Financ. Anal. J. 51, 31–37. https://doi.org/10.2469/faj.v51.n4.1918

Corbet, S., Larkin, C., Lucey, B., & Yarovaya, L. (2020). COVID-19, Pandemics and Stock Market Contagion: Evidence from 49 Global Markets. Available at SSRN 3560274.

Cui, Y., Gebka, B., Kallinterakis, B., 2019. Do closed-end fund investors herd? J. Bank. Finance 105. https://doi.org/10.1016/j.jbankfin.2019.05.015

Daskalakis, N., & Skiadopoulos, G. (2011). Should investors include commodities in their portfolios after all? New evidence. Journal of Banking & Finance, 35(10), 2606-2626.

Demirer, R., Kutan, A., Chen, C.-D., 2010. Do investors herd in emerging stock markets?: Evidence from the Taiwanese market. J. Econ. Behav. Organ. 76, 283–295. https://doi.org/10.1016/j.jebo.2010.06.013

Demirer, R., Kutan, A. M., & Zhang, H. (2018). Herding in emerging stock markets: Evidence from the recent financial crises. The Quarterly Review of Economics and Finance, 69, 92-104.

Devenow, A., Welch, I., 1996. Rational herding in financial economics. Pap. Proc. Tenth Annu. Congr. Eur. Econ. Assoc. 40, 603–615. https://doi.org/10.1016/0014-2921(95)00073-9

Dhall, R., Singh, B., 2020. The COVID-19 Pandemic and Herding Behaviour: Evidence from India's Stock Market. Millenn. Asia 11, 366–390. https://doi.org/10.1177/0976399620964635

Economou, F., Kostakis, A., Philippas, N., 2011. Cross-country effects in herding behaviour: Evidence from four south European markets. J. Int. Financ. Mark. Inst. Money 21, 443–460. https://doi.org/10.1016/j.intfin.2011.01.005

Espinosa-Méndez, C., Arias, J., 2021. COVID-19 effect on herding behaviour in European capital markets. Finance Res. Lett. 38, 101787. https://doi.org/10.1016/j.frl.2020.101787

Frijns, B., Tourani-Rad, A., Indriawan, I., & Webb, R. (2021). Intraday herding in international stock markets: Evidence from price and volume dynamics. Journal of International Financial Markets, Institutions and Money, 70, 101314. https://doi.org/10.1016/j.intfin.2020.101314

Galariotis, E.C., Krokida, S.-I., Spyrou, S.I., 2016. Bond market investor herding: Evidence from the European financial crisis. Int. Rev. Financ. Anal. 48, 367–375. https://doi.org/10.1016/j.irfa.2015.01.00

Gao, X., Bian, Y., & Liang, Q. (2017). Herding behavior in the Chinese stock market: Evidence from quantile regression analysis. Physica A: Statistical Mechanics and its Applications, 465, 272-284.

Gębka, B., Wohar, M.E., 2013. International herding: Does it differ across sectors? J. Int. Financ. Mark. Inst. Money 23, 55–84. https://doi.org/10.1016/j.intfin.2012.09.003

Gkillas, K., Konstantaras, I., & Tsagkanos, A. (2018). Does the realized volatility improve VaR forecasts during the global financial crisis? Evidence from the Athens Stock Exchange. Journal of Risk Finance, 19(4), 354-367.

Hott, C., 2009. Herding behavior in asset markets. J. Financ. Stab. 5, 35–56. https://doi.org/10.1016/j.jfs.2008.01.004

Hwang, S., Salmon, M., 2004. Market stress and herding. Spec. Issue Behav. Finance 11, 585–616. https://doi.org/10.1016/j.jempfin.2004.04.003

Kanas, A. (2000). Herding behaviour in cypriot financial markets. Applied Financial Economics, 10(2), 217-227.

Kizys, R., Tzouvanas, P., Donadelli, M., 2021. From COVID-19 herd immunity to investor herding in international stock markets: The role of government and regulatory restrictions. Int. Rev. Financ. Anal. 74, 101663. https://doi.org/10.1016/j.irfa.2021.101663

Konstantakis, K.N., & Michaelides, P.G. (2017). Oil price shocks and uncertainty: How stable is their relationship over time?. Energy Economics, 67, 2-11.

Koulakiotis, A., Papathanasiou, S., & Kiohos, A. (2015). Predicting stock returns with machine learning classifiers. In Proceedings of the 8th International Conference on Computer Science and Education (ICCSE) (pp. 223-228).

Koutmos, G. (1997). On the stock market's reaction to international monetary policy events. Journal of Economics and Finance, 21(1), 33-42.
Kyriakou, A., Koulakiotis, D., & Papathanasiou, S. (2021). Herding behavior in cryptocurrencies revisited: Novel evidence from a TVP model. Journal of Risk and Financial Management, 14(4), 146. doi: 10.3390/jrfm14040146.
Luu, Q.T., Luong, H.T.T., 2020. Herding Behavior in Emerging and Frontier Stock Markets During Pandemic Influenza Panics. J. Asian Finance Econ. Bus. 7, 147–158. https://doi.org/10.13106/JAFEB.2020.VOL7.NO9.147.
Michalopoulos, E., & Milios, J. G. (2009). The efficient market hypothesis and identification of long memory in the Athens Stock Exchange. Applied Economics Letters, 16(1), 79-84.
Mitra, S.K. and Das, A. (2015) 'Herding behavior in the Indian stock market: A multivariate regression analysis', Journal of Advances in Management Research, 12(2), pp. 171-188.
Newey, W.K., West, K.D., 1994. Automatic Lag Selection in Covariance Matrix Estimation. Rev. Econ. Stud. 61, 631–653. https://doi.org/10.2307/2297912
Newey, W.K., West, K.D., 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55, 703–708. https://doi.org/10.2307/1913610
Papadamou, S., & Markopoulos, T. (2013). Stock market liquidity and macroeconomic uncertainty shocks: Evidence from the US and UK markets. Journal of International Financial Markets, Institutions and Money, 26, 219-237. doi: 10.1016/j.intfin.2013.04.005
Saha, A., & Bhattacharya, M. (2019). Does herding lead to market under (over) reaction? Evidence from Indian stock market. Managerial Finance, 45(6), 807-822.
Shahzad, S. J. H., Zakaria, M., Raza, S. A., & Ahmad, S. (2020). Herding behavior in cryptocurrencies revisited: Novel evidence from a TVP model. Technological Forecasting and Social Change, 161, 120307.
Siriopoulos, C., & Fassas, A. (2009). The impact of foreign ownership on the performance of Greek banks. Managerial Finance, 35(11), 955-969.
Tsaousis, I. and Kyriakou, I. (2015). A Review of Multifractal Analysis. Journal of Multivariate Analysis, 139:245-265.
Vrontos, I. D., & Vrontos, S. (2004). A Bayesian approach to marginally specified binomial clustered models, with application to the prediction of the next U.S. president. Journal of Applied Econometrics, 19(5), 605-625.

7 APPENDIX

Table A1: Descriptive Statistics of the ATG stock index

	Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev.**	**Observations**
_ATG	0.0002	0.0000	0.1068	-0.0640	0.0076	2011

Notes: Table A1 reports univariate statistics on number of mean, median, maximum, minimum, standard deviation and observations for the ATG stock index during the examined period of July 2019 – July 2020.

Table A2: Descriptive statistics of STOXX (General Stock Market Index of Europe)

	Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev.**	**Observations**
R_m (STOXX)	2.40E-05	-9.84E-05	0.0801	-0.0425	0.0057	2297

Notes: Table A2 displays the univariate statistics on number of mean, median, maximum, minimum, standard deviation and observations for the general stock index of Europe (STOXX), which is the market return ($R_{m,t}$) during the period July 2019 – July 2020.

Table 1

Herding behavior estimates

	Constant	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	***R^2 adj.***
Greek CSAD	0.0024 (15.67) ***	0.4102 (5.29)***	-3.8936 (-1.23)	7.24%

*Notes: Table 1 presents the estimated coefficients for the benchmark model: $CSAD_{m,t} = \beta_0 + \beta_1 \left| R_{m,t} \right| + \beta_2 R_{m,t}^2 + e_t$ where $CSAD_{m,t}$ stands for cross-sectional absolute deviation of stock returns with respect to the market portfolio return $R_{m,t}$ for each period t and market i. The sample period is July 2019 to July 2020. t-Statistics are given in parentheses, calculated using Newey–West heteroscedasticity and autocorrelation consistent standard errors. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.*

Table 2

Unconditional Quantile regressions

Greek stock market	**5th Quantile**	**25th Quantile**	**50th Quantile**	**75th Quantile**	**95th Quantile**
$\boldsymbol{C}$	0.0001(2.64)***	0.0008(10.99)***	0.0016(18.95)***	0.0030(18.49)***	0.0070(12.75)***
$\lvert \boldsymbol{R_{m,t}} \rvert$	0.049(1.15)	0.1650(3.09)***	0.3271(6.14)***	0.5774(6.12)***	1.1457(3.51) ***
$\boldsymbol{R^2_{m,t}}$	-2.1584(-0.68)	-1.4881(-0.39)	0.1422(0.11)	-3.9816(-0.77)	-22.5790(-2.77)***
Pseudo R^2	0%	1.80%	4.15%	7.15%	8.09%

Notes: Table 3 reports the results for quantile regression equivalents of model: $CSAD_{m,t} = Q[\tau|r_{m,t}] = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R^2_{m,t} + e_t$ *where* $CSAD_t$ *stands for cross-sectional absolute deviation of stock returns with respect to the market portfolio return* R_m *for each period t and* τ *is the* τ^{th} *quantile (0.05, 0.25, 0.5, 0.75, 0.95) of the conditional distribution of the average absolute market return ,* e_t *is the error term with a zero* τ *-quantile. The sample period is July 2019 to July 2020. t-Statistics are given in parentheses, calculated using Huber Sandwich Standard Errors & Covariance. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.*

Table 3

Conditional on up/down market days Herding behavior estimates.

	Constant	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{\beta_3}$	$\boldsymbol{\beta_4}$	$\boldsymbol{R^2}$ ***adj.***
Greek CSAD	0.0024 (15.35)***	0.5165 (4.07) ***	0.3186(4.83) ***	-8.5993(-1.04)	-0.5545(-0.26)	7.48%

Notes: This table reports the estimated coefficients for the model: $CSAD_{m,t} = \beta_0 + \beta_1 D_{up}\left|R_{m,t}\right| + \beta_2\left(1 - D_{up}\right)\left|R_{m,t}\right| + \beta_3 D_{up} R^2_{m,t} + \beta_4\left(1 - D_{up}\right) R^2_{m,t} + e_t$ *, where* $CSAD_{m,t}$ *represents the cross-sectional absolute deviation of stock returns with respect to the market portfolio return* $R_{m,t}$ *for each market i.* D_{up} *is a dummy variable that takes the value 1 on days with positive values of* $R_{m,t}$ *and the value 0 otherwise. The sample period is July 2019 – July 2020. t-statistics are given in parentheses, calculated using Newey–West heteroscedasticity and autocorrelation consistent standard errors. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.*

Table 4

Conditional Quantile Regressions

Greek stock market	**5th Quantile**	**25th Quantile**	**50th Quantile**	**75th Quantile**	**95th Quantile**
$\boldsymbol{C}$	0.0001(2.25)**	0.0007(11.17)***	0.0016(14.11)***	0.0029(20.76)***	0.0069(9.12)***
$\boldsymbol{D_{up}\lvert R_{m,t}\rvert}$	0.0685(1.62)	0.1926(3.62)***	0.4272(2.67)***	0.6228(6.20)***	1.5828(1.22)
$\boldsymbol{(1-D_{up})\lvert R_{m,t}\rvert}$	0.0048(0.05)	0.1271(1.86)*	0.3056(4.22)***	0.5599(8.66)***	0.7956(3.64)***
$\boldsymbol{D_{up}R_{m,t}^2}$	-2.9919(-1.29)	-3.4033(-1.11)	-11.5963(-0.62)	-3.3059(-1.17)	-35.5832(-0.93)
$\boldsymbol{(1-D_{up})R_{m,t}^2}$	1.7094(0.21)	0.0642(0.01)	0.6912(0.41)	-6.2310(-3.98)***	-9.5649(-1.01)
Pseudo R^2	0%	1.85%	4.2%	7.28%	9.18%

Notes: Table 5 reports the results for quantile regression equivalents of model: $CSAD_{m,t} = Q[\tau|r_{m,t}] = \beta_0 + \beta_1 D_{up}|R_{m,t}| + \beta_2(1 - D_{up})|R_{m,t}| + \beta_3 D_{up}R_{m,t}^2 + \beta_4(1 - D_{up})R_{m,t}^2 + e_t$ *where* $CSAD_{m,t}$ *stands for cross-sectional absolute deviation of stock returns with respect to the market portfolio return* R_m *for each period t and market i and* τ *is the* τ^{th} *quantile (0.05, 0.25, 0.5, 0.75, 0.95) of the conditional distribution of the average absolute market return of the geographical region,* e_t *is the error term with a zero* τ *-quantile.* D_{up} *is a dummy variable that takes the value 1 on days with positive values of* $R_{m,t}$ *and the value 0 otherwise. The sample period is July 2019 to July 2020. t-Statistics are given in parentheses, calculated using Huber Sandwich Standard Errors & Covariance. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively*