An empirical analysis on the impact of ECB unconventional monetary policy on European banks' performance: The case study of Greece and Cyprus.

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Abstract

This paper examines the impact of the European Central Bank's unconventional monetary policy on the European banking performance and credit supply, through comparing the evolution of bank specific variables, before and after its implementation. Our analysis is carried out on the sample of SSM banks and on Greek and Cypriot banks as well, in order to capture any undermined correlation between the peripheral economies' banks' behavior and ECB's UMP impact. Our empirical findings highlight the inability of the central bank to enhance the effectiveness of banks' lending channel after 2009, while it negatively affects their profitability ratios (ROE). Moreover, the lending strategy of Greek and Cypriot banks is found to be driven by future expectations for economic growth, positively correlated to credit risk during the whole time period of analysis, while non-performing loans' impact is underestimated and therefore mismanaged.

Keywords: European Central Bank, Unconventional monetary policy, Bank performance, Credit supply.

1. Introduction.

In the aftermath of the financial crisis that has started in 2008, the effectiveness of the European Central Bank (ECB) unconventional monetary policy (UMP) transmission mechanism is under assessment, due to the limited ability of the European banking industry to provide credit to the real economy. The UMP, as mainly defined by the longer-term refinancing operations, the fine tuning and structural reverse operations, the marginal lending facility as well as the securities held for monetary policy purposes, was designed to replace the wholesale funding market to the banks, restore financial stability and re-establish confidence to the European banking system.

Regarding the credit supply provided by the euro zone banks to the real economy, Reichlin (2013) noted that even though long term refinancing operations increased and their horizon lengthened, bank lending remained weak, especially when considering the decline in industrial production and the dynamics of broad money. However, Gambacorta and Shin (2016) found that higher capitalized banks provided greater lending due to lower funding costs. Similarly, Kapan and Minoiu (2013) confirmed that financial institutions with strong balance sheets and well capitalized were better able to provide liquidity to the real economy, during the crises.

Similarly, Salachas, Laopodis and Kouretas (2017) have shown that an increase in asset purchases by central banks reduced the financial institutions' (in the US, UK, Japan, Germany, France and Italy), balance sheet dependence to extend financing. Therefore, the implementation of UMP was effective in stimulating credit growth in the post crisis of 2007 sub period. However, Peek and Rosengren (2013) emphasized on the effectiveness of the monetary policy's bank lending channel during the global financial crisis and reported that liquidity crunches had a direct, adverse impact on the monetary policy transmission mechanism.[1]

Therefore, the contribution of this paper is twofold, since it highlights differences of bank lending and performance strategies implemented by the Greek and Cypriot banks in comparison to the rest SSM banks, as well as the impact of the ECB Monetary Policy (MP) and UMP.

2. Hypotheses to be tested.

Our first testing hypothesis examines the impact of ECB UMP on the loans net for both country samples, before and after the program implementation. We also take into consideration the GDP and non-performing loans to total loans ratio, as control

[1] Taking a glimpse on other central banks' expansionary monetary policy measures and their policy transmission on the bank credit channel, Lucjan and Orlowski (2015) observe that "massive liquidity injected by the Fed into the banking system, particularly in the aftermath of the financial crisis, has restrained bank credit". Furthermore, "U.S. banks have been prone to allocating the borrowed liquidity to excess reserves and to investments in securities (predominantly foreign) but not to loans". Bowman, Cai, Davies and Kamin (2015) found that even the Bank of Japan reserve injections boosted bank liquidity significantly, much of the effect was offset as banks reduced their lending to each other.

independent variables, widely used by the relative literature. Moreover, we analyze the impact of capitalization, ROE, ROEA and other loan specific variables in order to capture their impact on the credit supply strategy.

Carpinelli and Crosignani (2016) showed that Italian banks exposed to the foreign wholesale market experience a run and reduce credit supply before the central bank's intervention and expand it after the central bank liquidity provision. Therefore, banks hit by the run are entirely responsible for the transmission to credit supply and other intermediaries use central bank refinancing to increase their holdings of liquid assets. ECB liquidity injection had a 2% positive effect on bank credit supply. However, Krainer (2014) rejected the traditional demand oriented model of bank lending model and failed to reject the capital budgeting model of bank lending for banks in the euro area. It appears that the stock market plays a key role in the lending decisions and allocation of resources in Europe, even though Europe is a bank-based financial system.

Our second testing hypothesis examines the correlation of banks' performance to the ECB UMP. By using either ROA or ROE, we also test the impact of capitalization, liquidity risk and cost of capital. Mamatzakis and Bermpei (2016) analyzed the impact of UMP on the performance of US banks and found that UMP had a negative impact on the performance of commercial and savings banks with a high level of asset diversification and low deposit funding.

3. Data and Specification Model-Empirical Methodology.

As presented in Table 1, our annual data are derived from the Bankscope[2]. As Ashcraft (2006) found, by comparing the results collected from annual data to those captured from quarterly data of respective samples, annual data provided the same information as quarterly data.

Our methodology is based on a panel data approach by the usage of the Fixed Effects, Random Effects model and pooled least squares. The sample is divided into: a) 373 SSM banks (without Greece and Cyprus) and b) 27 Greek and Cypriot banks. In order to avoid the existence of selection bias, we use data from the euro-zone financial institutions that have also been merged or acquired by other financial institutions.

The time range is separated into the period 2001-2008, during which traditional monetary policy measures had taken place and 2009-2016 which has been highly characterized by the ECB UMP implementation.

In order to examine the bank lending supply, we use the loans net, as dependent variable. Respectively, we use the return on earnings (ROE) and the return on assets[3] (ROA), as the dependent variables for measuring profitability. All of our variables are

[2] I would like to thank Mr Conrad Felix Michel, PhD Candidate of Athens University of Economics and Business, for his valuable help in downloading the data.

[3] ROA, as a measure for profitability is analyzed when the regressions' results differ from the impact on ROE.

expressed as annual percentage changes, in order to capture the rate of growth. The specifications are constructed as following:

$$\text{LOANS NET}_{it} = C + ECB_{it} + GDP_{it} + CAP_{it} + ROE_{it} + ROEA_{it} + INT_{it} + NPLTTL_{it} + LLCR_{it} + TLTTD_{it} + u_{it} \quad \textbf{(1)}$$

$$ROE_{it} = C + ECB_{it} + GDP_{it} + CAP_{it} + NPLTTL_{it} + TLTTD_{it} + INT_{it} + u_{it} \quad \textbf{(2)}$$

Table 1. *Data set - definitions and sources.*

Variable	**Definition**	**Explanation** *(according to Worldscope quide)*	**Frequency**	**Source**
Dependent	**LOANS NET**	total amount of money loaned to customers after deducting reserves for loans losses	Annual Percentage Change	Bankscope
Independent	**ECB**	conventional (1999-2008) and unconventional (2009-2016) monetary policy		ECB
	CAP	**capitalization** common equity/total assets		Bankscope
	ROE	**return on equity** net income		
	ROA*	**return on assets** net income		
	ROEA	**return on earning assets** neti income from investments and loans		
	INT	**interbank loans** transactions between banks that are not classified as cash		
	LLCR	**loans loss coverage ratio** (pre tax income+provisions for loans losses)/net loan losses		
	TLTTD	**total loans to total deposits** liquidity risk		
Control	**GDP**	**growth domestic product**		
	NPLTTL	**non performing loans/total loans** credit risk		

4. Empirical Results.

We confirm the existence of stationarity of our variables by using several Unit-Roots, as depicted on Table 2, where we reject the null hypothesis for the selected variables' second level differences, for the whole time period. Hausman test helps us to evaluate and finally reject the usage of the random effects methodology (due to high p values associated with the initial hypothesis), while the redundant test, which stands for the existence of redundant effects, offers (close to or-) zero p values. Therefore, the fixed effects estimator results are more appropriate than the common constant ones.

Moreover, to deal with residual auto correlation we run the regressions with Period Sur-Cross section Clustering, according to the methodology of Panel Corrected Standard Error.

Table 2. *Unit Root Tests.*

	Unit Root tests							
Variable	Levin, Lin and Chu		Im,Pesaran and Swihn W-test		ADF-Fisher Chi-square		PP-Fisher Chi-square	
	t-statistic	p	t-statistic	p	t-statistic	p	t-statistic	p
d(LOANS NET,2)	-10.926	0.000	-6.198	0.000	108.561	0.000	149.015	0.000
d(CAP,2)	-20.620	0.000	-13.949	0.000	199.192	0.000	260.609	0.000
d(ECB,2)	-18.704	0.000	-23.526	0.000	436.075	0.000	458.712	0.000
d(GDP,2)	-16.100	0.000	-10.774	0.000	204.147	0.000	236.631	0.000
d(ROE,2)	-10.804	0.000	-6.801	0.000	110.902	0.000	214.283	0.000
d(ROEA,2)	-14.060	0.000	-11.737	0.000	165.191	0.000	247.401	0.000
d(INT,2)	-14.449	0.000	-10.287	0.000	139.931	0.000	242.322	0.000
d(NPLTTL,2)	-7.892	0.000	-3.779	0.000	43.962	0.000	60.563	0.000
d(LLCR,2)	-16.375	0.000	-14.372	0.000	75.182	0.000	87.806	0.000
d(TLTTD,2)	-14.612	0.000	-10.929	0.000	167.932	0.000	257.628	0.000
d(ROA,2)	-31.781	0.000	-14.534	0.000	138..661	0.000	190.124	0.000

Note: Unit root tests are conducted for the second level differences of the variables used, during 1999-2016.

Our empirical results for the Greek and Cypriot banks are displayed in Table 3 and for the SSM banks in Table 4. We find that although monetary policy was positively correlated to the credit supply and is statistically significant for both country samples during 1999-2008, it becomes ineffective after 2009 (since it is statistically insignificant), indicating its inability to influence the bank lending supply. Moreover, in Table 4, we see that GDP is found to be positively correlated and statistically significant to the bank credit supply for the SSM banks, whilst for the Greek and Cypriot banks it is negatively correlated and statistically significant, during the whole time period, as depicted in Table 3. The assumption behind this finding is the existence of the “boom and bust cycle” theory according to which, banks’ management increase their bank lending in view of the improvement of economic conditions.

As presented in Table 3, the significance of capitalization ratio and return on equity, that capture the markets’ volatility, on bank lending decisions is decreased after 2009 for Greece and Cyprus, probably substituted by other loan specific variables’ impact. However, the impact of capitalization remains negatively correlated to the SSM banks’ credit supply, as depicted in Table 4.

In Table 3, we observe that the return on earning assets becomes negatively correlated only to the Greek and Cyprian banks’ lending decisions, after 2009. As a result, interbank loans that represent the cost of capital, become determinative on the Greek and Cypriot banks’ lending decisions after 2009, which is a rather expected finding if we considerate the long period of economic instability and uncertainty, that forced the Greek and Cyprian banks to access low cost financing from the interbank market. Furthermore, we should take into consideration the impact of the exclusion of Greece from the QE program, a factor that adds negative pressure on the returns from earning assets and increases the need for low cost of capital.

Surprisingly, credit risk remains positively correlated to credit supply, for the Greek and Cypriot banks, after 2009. Comparing the results presented in Table 3 and Table 4, non-performing loans to total loans ratio remains positive and becomes more statistically significant after 2009, in contradiction to the SSM banks. Therefore, we assume that, the Greek and Cypriot banks underestimate or show a delay of assessing the increasing rate of NPLs and the necessity of their effective management.

Moreover, although the loans loss coverage ratio de-motivates the SSM countries from lending, during the whole time period of analysis, Greek and Cypriot banks change their attitude only after 2009. Their lending decisions become positively and significantly affected by the coverage ratio. This finding suggests that Greek and Cyprian banks add collateral requirements on the existing loans or they require collaterals for the new loans, only after 2009, as presented in Table 3.

Furthermore, liquidity risk significantly de-motivates Greek and Cypriot banks from lending only after 2009, as depicted in Table 3, whilst SSM banks have been more conservative since 1999, as presented in Table 4. The impact of this ratio could have been much worse since the Greek and Cypriot banks went (Greek banks are still) under the regime of capital controls. Therefore, the capital restrictions seem to have prevented (and still prevent the Greek banks) the Greek and Cypriot banks from facing a greater liquidity risk.

Regarding profitability, we find that ECB monetary policy is negatively correlated to the ROE of both samples (although statistically significant to the SSM banks), actually converting the UMP ineffective on profitability, after 2009, as displayed in Table 3 and Table 4. This finding probably implies the reduction of lending rates and the depression in interest margins. However this statement does not apply, regarding the impact on Greek and Cypriot banks' ROA since the correlation remains positive after 2009. This finding probably highlights the impact of UMP on the markets (which is depicted through ROE instead of ROA) as well as the impact of Assets Quality Review on Greek and Cypriot banks' total assets' value (as a fundamental of the stress tests carried out). Moreover, GDP impact becomes negatively correlated on ROA for both samples after 2009, reflecting the high correlation between the economic cycle and income-profitability. Moreover, the economic cycle does not seem to have any significant effect on Greek and Cypriot banks' ROE after 2009, as presented in Table 3, since it is mainly driven by markets' future expectations.

As expected, capitalization remains positively and significantly correlated to both samples' profitability after 2009, as presented in Table 3 and Table 4. This finding, as expressed by ROE, implies the benefits of low cost of capital, which affect banks' liquidity ratios.

As presented in Table 3, credit risk enhances its negative effect and statistical significance on Greek and Cyprian banks' ROE, whilst in Table 4, we observe that SSM banks' ROE reveals a more stabilized negative correlation to profitability, probably as a result of their less risky loans' portfolio. Moreover, liquidity risk gets highly significant and still negatively correlated to the Greek and Cypriot banks ROE whilst SSM banks' ROE is less affected. As it is well known, if banks increase their loans without increasing their deposits, their bank performance deteriorates.

Moreover, the cost of capital as expressed by the interbank loans, seems to have a stabilized positive effect on SSM's banks' ROE after 2009, as presented in Table 4. Furthermore, Greek and Cypriot banks' profitability seems to become less affected by interbank loans, after 2009, as depicted in Table 3. However, the impact of the cost of capital on Greek and Cypriot banks' ROA becomes more positive and statistically significant.

On a long term (1999-2016) regression analysis, we observe that Greek and Cyprian banks' lending decisions have always been positively correlated on credit risk and more statistically significantly from the SSM banks. Regarding monetary policy, it played a key positive role on the SSM banks' lending decisions while it positively affects only Greek and Cypriot banks' profitability as expressed by ROA (does not apply for ROE).

We also confirm that Greek and Cypriot banks based their lending supply decisions on the GDP upcoming growth (boom and bust cycle theory). As expected, capitalization has a statistically significant negative impact on SSM banks' credit supply, while Interbank loans positively affect profitability only for the Greek and Cypriot banks.

Table 3. *Panel regression results – Greek and Cypriot banks.*

Table: Greece-Cyprus	Fixed Effects		Panel Corrected Standard Error		
Dependent Variable: LOANS NET					
	1999-2008	**2009-2016**	**1999-2008**	**2009-2016**	**1999-2016**
ECB	2.19	-474735.5	2.19	-474735.5	8054255
	(1.85)	-(0.185)	(2.2231)	-(0.145)	(0.321)
GDP	-7.177	-18.40	-7.177	-18.40	-6.860
	(-1.32)	(-3.37)	(-1.235)	(-2.647)	(-0.758)
CAP	-2.74	-64281	-2.74	-64281	-363249
	(-1.280)	(-0.629)	(-1.281)	(-0.0602)	(-0.251)
ROE	-341131	-2452	-341131	-2452	-4371
	(-1.352)	(-0.567)	(-1.142)	(-0.539)	(-0.803)
ROEA	200026	-878186	200026	-878186	160989
	(2.999)	(-1.084)	(2.835)	(-0.966)	(1.482)
INT	5.1389	14.230	5.1389	14.230	7.064
	(2.150)	(7.17)	(2.059)	(5.881)	(2.259)
NPLTTL	436409	432804	436409	432804	361401
	(0.841)	(2.137)	(0.899)	(1.801)	(1.394)
LLCR	-711863	696433	-711863	696433	-150805
	(-1.643)	(2.087)	(-1.764)	(1.992)	(-0.508)
TLTTD	5515.219	-494751.5	5515.219	-494751.5	24594
	(0.051)	(-4.430)	(0.055)	(-3.761)	(0.157)
Diagnostics					
Number of Obs.			29	37	66
Adj. R squared			0.532	0.7119	0.302
Redundant FE test			48.254	83.7706	109.248
probability			0.0000	0.0000	0.0000
Hausman Test			40.213	155.199	199.023
probability			0.0000	0.0000	0.0000
Dependent Variable: ROE					
ECB	122.5080	-12.038	122.5080	-12.038	-385.956
	(0.951)	(-0.015)	(1.250)	(-0.023)	(-1.012)
GDP	9.63	4.43	9.63	4.43	6.32
	(1.495)	(0.261)	(1.352)	(0.277)	(0.576)
CAP	77.495	9939	77.495	9939	1860
	(2.093)	(4.039)	(2.408)	(2.953)	(2.176)
NNLTTL	-0.9080	-8.553	-0.9080	-8.553	-0.342
	(-1.744)	(-1.489)	(-2.044)	(-1.560)	(-0.129)
TLTTD	-0.204	-4.493	-0.204	-4.493	-4.312
	(-1.745)	(-1.544)	(-1.793)	(-1.243)	(-1.813)
INT	5.18	5.09	5.18	5.09	1.65
	(2.126)	(0.917)	(2.031)	(0.641)	(0.345)
Diagnostics					
Number of Obs.			40	46	86
Adj. R squared			0.222	0.284	0.093
Redundant FE test			28.0671	13.9922	16.2837
probability			0.0032	0.2334	0.1309
Hausman test			15.600	7.825	10.289
probability			0.016	0.2512	0.113

Table 4. *Panel regression results – SSM banks.*

Table: SSM without Greece-Cyprus	Fixed Effects		Panel Corrected Standard Error		
Dependent Variable: LOANS NET					
	1999-2008	**2009-2016**	**1999-2008**	**2009-2016**	**1999-2016**
ECB	1.61	-3068373	1.61	-3068373	1.52
	(1.917)	(-0.229)	(1.677)	(-0.344)	(1.588)
GDP	7.95	26.9730	7.95	26.9730	18.747
	(1.174)	(2.277)	(0.606)	(2.637)	(1.175)
CAP	-1.38	-1.01	-1.38	-1.01	-8.85
	(-4.07)	(-3.695)	(-2.517)	(-6.105)	(-2.112)
ROE	-202.888	-697.84	-202.888	-697.84	-22142
	(-2.13)	(-0.355)	(-1.488)	(-0.445)	(-0.092)
ROEA	476366	6432860	476366	6432860	-1317467
	(2.059)	(0.536)	(1.325)	(1.157)	(-0.108)
INT	2.913	1.848	2.913	1.848	2.141
	(17.172)	(11.769)	(9.141)	(17.948)	(7.017)
NPLTTL	143562	-287712	143562	-287712	466650
	(0.529)	(-0.1950)	(0.318)	(-0.640)	(0.244)
LLCR	-1746.747	-1368.6	-1746.747	-1368.6	-2075.31
	(-0.272)	(-0.1566)	(-0.477)	(-0.508)	(-0.338)
TLTTD	-75398	-291088	-75398	-291088	-178615
	(-1.629)	(-3.611)	(-0.947)	(-4.196)	(-1.994)
Diagnostics					
Number of Obs.			331	275	606
Adj. R squared			0.5909	0.494	0.512
Redundant FE test			600.364	1112.4063	943.543
probability			0.0000	0.0000	0.0000
Hausman Test			50.777	10.1514	29.371
probability			0.0000	0.3384	0.0000
Dependent Variable: ROE					
ECB	51.701	-31.272	51.701	-31.272	-13.874
	(3.214)	(-0.955)	(2.632)	(-1.385)	(-0.749)
GDP	2.73	2.08	2.73	2.08	2.24
	(1.798)	(0.650)	(0.998)	(0.623)	(1.036)
CAP	111.060	440	111.060	440	244.88
	(3.436)	(6.192)	(2.119)	(5.482)	(5.315)
NNLTTL	-4.180	-1.005	-4.180	-1.005	-1.670
	(-9.126)	(-3.648)	(-6.081)	(-2.816)	(-5.620)
TLTTD	-0.146	-0.115	-0.146	-0.115	-0.145
	(-36.826)	(-5.162)	(-19.731)	(-4.660)	(-19.350)
INT	3.06	2.57	3.06	2.57	-1.04
	(0.067)	(0.502)	(0.050)	(0.460)	(-0.231)
Diagnostics					
Number of Obs.			742	502	1244
Adj. R squared			0.684	0.117	0.402
Redundant FE test			1878.677	145.580	522.290
probability			0.0000	0.003	0.0000
Hausman Test			917.600	27.264	161.397
probability			0.0000	0.0001	0.0000

5. Conclusions.

Our research highlights critical differences of the Greek and Cypriot banks' lending strategy compared to the rest of the SSM banks, before and after the implementation of the UMP. Future expectations for economic growth and underestimation or/and mismanagement of the increasing levels of NPLs are the key drivers for their lending decisions. Moreover, UMP does not meet its objectives on providing liquidity to the real economy through banks after 2009, for both country samples. However, it does positively affect profitability when it comes to ROA but it is not a good signal for the markets' expectations since it fails to positively affect the ROE. Moreover, the risky lending strategy of Greek and Cypriot banks is being reflected on their profitability, through the significantly negative impact of credit and liquidity risk.

Overall, we obtain that the bank lending decisions are not UMP driven. A policy implication to reassure the fundamental objective of the UMP to restart the SSM economies through the banks' lending activity should include the establishment of a threshold of banks' lending ratios, to ensure that the liquidity provided by the ECB UMP is allocated to the real economy.

Future research will focus on highlighting any possible correlation between liquidity ratios, lending ratios and regulatory requirements of the euro area banks which are under the European Banking Union, before and after the UMP implementation, using the methodology of the Generalized Method of Moments (GMM).

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Forecasting sales using switching regime models in the Greek market.

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Abstract

In periods of economic crisis or unpredictable events nonlinearity plays an important role in the prognosis of economic and financial variables. The objective of this paper is to investigate the out-of sample forecasting performance of a regime-switching model for monthly sales levels for a specific retail sector in the Greek market. We first model volatility regime switching within a univariate Markov-Switching framework. Nowadays modeling sales within this context can be motivated by the fact that the change in regime should be considered as an event cause by the economic situation that was not as predictable as we thought. Different regimes are implied by the model, with high and low volatility, providing quite accurately the state of volatility associated with the presence of a rational bubble in the Greek market and shows evidence of regime clustering. In this paper we examine whether the nonlinear regime switching model improves predictions compared to linear (mean and seasonal naïve models) and to nonlinear models (seasonal Autoregressive Integrated Moving Average -SARIMA- and Exponential Smoothing State Space-ETS-models). We first evaluate the models and then compute forecast error criteria. Eventually, the regime switching model of the focus retailer, outperforms the basic linear models and has almost equal predictive power to nonlinear SARIMA and ETS models.

1 Introduction

The behavior of consumers in a specific Greek retail market is the subject of this study that concerns a wide range of people. The Greek economic crisis and the financial agreement of the Greek government with the International Monetary Fund (IMF) gave rise to a deep recession phase in the Greek market place that started in early 2008. This phase became even worse in May 2010 after the announcement of the financial agreement of the Greek government with the eurozone countries and the IMF on a bailout loan for the

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country, conditional on the implementation of austerity measures. The impacts of austerity measures in consumption were dramatic. Consumers postpone or prolong the purchase of durable products, like cars and therefore new car sales levels turned down reaching the lowest level ever recorded in the Greek market.

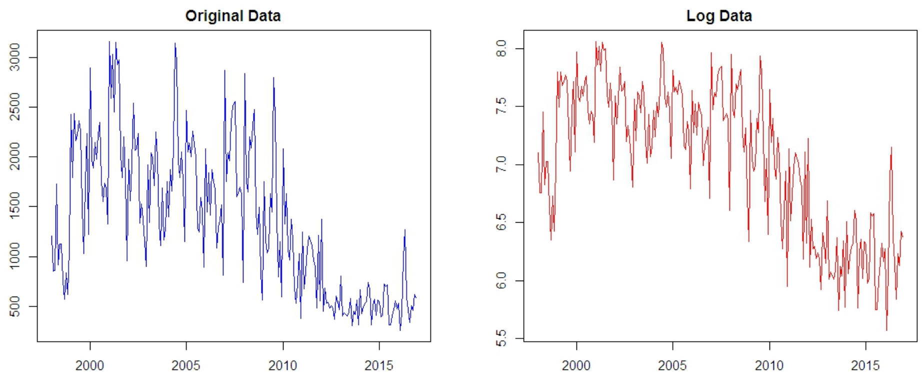
The economic environment seems volatile and many factors affect the sales level and the consumer decision. Linear and nonlinear models are both applied but it is difficult to find an appropriate model to make accurate predictions. We intent to capture nonlinerarities and that is the reason we introduce a regime switching model to analyze and forecast sales levels in new car retail sector. We employ a two state Markov Regime Switching (RS) model introduced by Hamilton (1989) because it moves though time between two regimes. The Exponential State space model (ETS) is empiricaly tested, which consist of an equation that describes the observed data and some transition equations that describe how the unobserved components or states, like level trend and seasonality change over time, which is widely used for its easy application and ability to generate fair forecasts (Winters, 1960). The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is inroduced since it examine the year to year relationship for each month introduced by Box Jenkins & Reinsel(1994) and the basic linear seasonal Naïve model that in stable economic environments seems to capture the fluctuations of sales in the market.

The paper is structured as follows. Section 2 outlines the literature survey. Section 3 reviews the data. In Section 4 we present the models. Section 5 contains full sample estimation results of Markov regime Switching Model. In Section 6 we conduct out of sample forecasts and compare the performance of the regime switching model with other models. Finally in Section 7 we conclude our research.

2 Literature Review

There is not much research on forecasting car retail sales level in market. Generally there are some papers for forecasting car sales demand in the American automobile market with the use of disaggregate choice models (Berkovec, 1985) and forecasting automobile sales in connection to many economic and demographic variables (Shahabuddin, 2009). However in this empirical research we treat our data as time series and include forecasting methods used in time series analysis with nonlinear models and especially those with Markov regime switching models introduced to econometrics by Goldfeld and Quandt (1973), Cosslet and Lee (1985) and Hamilton (1989) assuming that the regime shifts evolve according to a Markov chain. Since then regime switching models have become a popular modeling tool for applied work measuring the economic output and identifying the phases of the business cycle. Examples of such models include Tiao and Tsay (1994), Porter (1995), Hamilton (2001), Clements et al (2004), Kim(2004), Piger(2007) among other. We consider also studies for the Seasonal Autoregressive Integrated Moving Average (SARIMA) models as elaborated in Franses (1991), Greene(1993) and Hamilton (1994) to mention a few and Exponential Smoothing State Space (ETS) models as in Hyndman et al (2008). Since the economic situation in the Greek market is not steady, literature reports that retail sales and other economic variables are often described by seasonality and asymmetry. Regime switching models and generally nonlinear models forecast more accurate than linear models. Nonlinearity is necessary for better results. Therefore we focus our study on nonlinear models specifically on regime-switching model. This summary paper continues by a brief analysis of the data with a graphical presentation of several plots and an illustration of a table with descriptive statistics. Then the forecast-

Figure 1: Monthly new car sales in Greek market(1998-2016)



ing models are specified alone with the accuracy measures used in this study. Lastly, the empirical evidence are presented together with the concluding remarks of the study.

3 Dataset

3.1 Data

We investigate the sales level of a retailer in the new car market in Greece. The dataset used consists of monthly car registration numbers officially recorded by the Greek authorities. The Greek Association of Motor Vehicle Importers - Representatives (AMVIR) statistical data base provides the detailed information needed for all car representatives operating in Greece (http://www.seaa.gr). Data on monthly new car registration officially recorded by the Greek authorities are equivalent to new car sales in the retail market. The time period recorded starts from January 1998 and ends in December 2016, implying a total of 228 monthly observations but we take two yearly lags in our data so we end up with 204 monthly observations . We take the first 2/3 of the data for the in sample estimations and the remaining 1/3 for the out of sample forecast evaluation. The in sample data spans the period of January 2000 to December 2010 (132 observations, 11 years). The out of sample starts from January 2011 to December 2016 (72 observation, 6 years).

3.2 Graphs

The graphs of the retail new car sales give us some information about their behavior. In Figure 1 we can see the graphs of both levers and log values. The series seems to have no clear trend. Moreover their movement is quite turbulent throughout the years. We observe a steep recession in 2008 at the market. This happens probably due to the great recession in the Greek market that started in early 2008 but it became even worse after the announcement of the financial agreement of the Greek government with the International Monetary Fund (IMF) in the May 2010 and until today the Greek market is under a lot of pressure and instability. This research considers the log transformation of the sample series and not the raw data. The major reason for using the logarithmic transformation of the data is that the variation of the series becomes smaller if the series are in log values it also stabilize the mean and variance of the series. Additionally log transformations squeeze the range of the confidence intervals in the forecasting process and that is very important in the forecasting process. The sales series graphically gives a clear evidence of seasonality as there is an identical pattern repeated in a 12 months circle, which gives a yearly effect for new car sales of each one of the sample car representatives. New car sales series exhibited a consistent seasonal pattern with the highest peak in January and the lowest in December every year.

3.3 Descriptive statistics

In this section we depict some features of the data and their distribution. Table 1 presents the descriptive statistics for the retail sales levels and in log values in the Greek Market.

Table 1: Descriptive Statistics for monthly new-car sales series simple and log-values.

RETAILER	Descriptive statistics	Time period:1998-2016
New Car Sales	Level	Log
Mean	1.666	7,34
Median	1.675	7,42
Max	3.154	8,06
Min	384	5,95
Standard Deviation	624	0,42
Skewness	0,28	-0,63
Kurtosis	-0,51	0,06
Jarque Bera test	$3,73^{*}$	11,04
Shapiro Wilk's test	$0,98^{**}$	0,96
Dickey-Fuller Tests	-4,06	$-3{,}98^{*}$

Note: One or two asterisks denote significance of tests at 5% or 1% levels.

More details are given in Table 1 where descriptive statistics are reported for the total sample period. Jarque –Bera test for normality in raw and in log value series of new car sales rejects the null hypothesis that the series are normally distributed only in the case of the log series. So the raw data seem to be normally distributed and the same result is supported with the Shapiro Wilk test. The unit root test called Augmented Dickey Fuller (ADF) test gives evidence of stationarity only for the log values of the series. Therefore we decided to proceed our research using the log values of both sample data.

4 The Models

Forecasting time series encompass a variety of techniques, which rely primarily on the statistical properties of the data. Forecasting methods do not exploit the understanding of the time series behaviour as an economic value but are rather interested in building simple models which capture the time series behaviour of the data and may be used to provide an adequate basis for predicting the series in the future (Hall, 1994). In this paper our focus is to estimate a model in order to make a good prognosis for the monthly sales of a retailer in the Greek market. Table 2 illustrate the forecasting methods used in this research in more details. More specific we apply the following forecasting methods:

Regime-switching model We apply a univariate two-order Markov switching regime model with two states. This model was firstly introduced by Hamilton (1989). The model is nonlinear and moves through time from one regime to the other abruptly based on a probability law. The probability of being in a regime depends on the previous state and since we have a yearly seasonally effect in our data the previous state equals the previous year and that is the reason our model is of order two because it takes into account the previous values of the same months for the last two years. In addition this probability is constant and is described by a Markov chain. The model allows for different specification in the conditional mean of each regime. This model allows for different variances and so we have heteroskedasticity.

State space model with exponential smoothing. The State space models or Dynamic linear models consist of an equation that describes the observed data and some transition equations that describe how the unobserved components or states, like level (ℓ_t), trend (b_t), and seasonality (s_t) change over time. We denote the state space models as ETS($\cdot, \cdot, \cdot$) for the initials Error, Trend, Seasonal. However according to Hyndman and Athanasopoulos (2012) the model can also be thought as ExponenTrial Smoothing. In our case both data series has an ETS model that has additive errors, with no trend and an additive seasonality which is denoted as an ETS(A,N,A). In other words, both series in this research paper, fit to an exponential smoothing state space model that is equivalent to the Holt-Winters linear model with additive errors. Holt (1957) and Winters(1960) extended Holt 's methods to capture seasonality. The model has the forecast equation and three parameter smoothing equations: one for the level, one for the trend, and one for seasonality. This model is widely used for its easy application and ability to generate fair forecasts (Winters, 1960).

Seasonal Autoregressive Integrated Moving Average (SARIMA). In the SARIMA model we examine the year to year relationship for each month since seasonal relationships are between observations for the same month in successive years (Box Jenkins & Reinsel, 1994). The SARIMA model error terms ε_t are assumed to have a zero mean, constant variance and are assumed to be serially independent which means that the ε_t sequence is a white noise process.

Seasonal Naïve Method. In the Seasonal Naïve forecasting Method we just add the seasonal component to the previous Naïve forecasting method. Thus the forecast value equals to the last value from the same period of time. In other words, when having monthly data the forecast for all future January values is equal to the last observed January value (Hyndman and Athanasopoulos, 2012).This is a basic linear model and sometimes gives quite good forecasting results.

5 Full sample estimation results

We estimate the regime switching model for our retailer sales levels taking into account the whole sample. In Table 3 we see the results of the regression.

5.1 Smoothed and Transition probabilities

The smoothed probabilities of the two (2) different regime volatility for the retailers sales levels is illustrated in Figure 2 shows. The smoothed regime probabilities indicate in

Table 2: Equations of Time Series Forecasting Models

Forecasting Method/Model	Definition
Regime-switching model	
$x_t = c_0 + c_1 x_{t-1} + \epsilon_t, \epsilon_t\ iidN(0, \sigma^2)$	x_t =the sales level at time t
$x_t = c_0^{'} + c_1^{'} x_{t-1} + \epsilon_t, \epsilon_t\ iidN(0, \sigma^{'2})$	x_{t-1}=the sales level at time t-1
	c_0, c_1= the coefficients in first regime
	$c_0^{'}$, $c_1^{'}$=coefficients in second regime
State space model with exponential smoothing (ETS)	
Holt-Winters seasonal method with additive errors	
$\hat{x}_{t+h\|t} = \ell_t + hb_t + s_{t+h-m}$	
$\ell_t = \alpha(x_t - s_{t-m} + (1-\alpha)(\ell_{t-1} + b_{t-1}))$	ℓ_t=estimate of the *level* of the series at time t
$b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$	b_t=estimate of the *trend* (slope) of the series at time t
$s_t = \gamma(x_t - \ell_{t-1} - b_{t-1} + (1-\gamma)s_{t-m})$	s_t=estimate of the *seasonality* of the series at time t
	m=period of seasonality
$(0 \leq \alpha \leq 1)$	α= smoothing constant
$(0 \leq \beta^* \leq 1)$	β^*=smoothing parameters for trend
$(0 \leq \gamma \leq (1-\alpha)$	γ=smoothing parameters for seasonality
Seasonal Autoregressive Integrated Moving Average (SARIMA)	
$\phi_p(B)\Phi_P(B^s) \bigtriangledown^d \bigtriangledown_s^D x_t = c + \theta_q(B)\Theta_Q(B^s)\varepsilon_t$	x_t=dependent variable(car sales at time t),
	$\phi_p(B)$= ordinary autoregressive components order p,
	B=the backshift operator,
	$\theta_q(B)$= ordinary moving average components order q,
	$\Phi_P(B^s)$=seasonal autoregressive components order P,
	$\Theta_Q(B^s)$=moving average components order Q,
	$\bigtriangledown^d = (1-B)^d$=ordinary difference components,
	$\bigtriangledown_s^D = (1-B^s)^D$=seasonal difference components,
	d= degree of consecutive differencing,
	D=degree of seasonal differencing,
	ε_t=error with white noise $\sim iidN(0, \sigma^2)$
Autoregressive Conditional Heteroscedastic (ARCH)	
Mean Method)	
$\hat{x}_{n+h\|n} = \bar{x} = (x_1 + x_2 + \cdots + x_n)/n$	n=number of time periods
	$\hat{x}_{n+h\|n}$=the estimated forecast value
	x_t=the observed car sales at time t
	h=the forecasting horizon
Seasonal Naïve Method	
$\hat{x}_{n+h\|n} = \hat{x}_{n+h-km}$	n=number of time periods
	$\hat{x}_{n+h\|n}$=the estimated forecast value
	h=the forecasting horizon
	m= is the seasonal period
	k=[(h-1)/m]+1

Table 3: Full Sample Regime Switching Model Estimation

	Retailer 1
c_0	0.1096 (0.5153)
$c_0^{'}$	0.1836 (0.3375)
c_1	0.5201 (0.0724)***
$c_1^{'}$	0.7696 (0.0589)***
c_2	0.4227 (0.0877)***
$c_2^{'}$	0.2274 (0.0654)***
$log(sigma)$	0.2638
$log(sigma)^{'}$	0.1856
R^2	0.8003
$R^{2'}$	0.9125

Note: Sigma is the residuals standard deviation. c_0,c_1 and $log(sigma)$ represents regime 1. $c_0^{'}$,$c_1^{'}$ and $log(sigma^{'})$ represents regime 2. The numbers in parentheses are the standard errors. ***, ** and * denote rejection of the null hypothesis at 1%, 5% and 10% significance level respectively. The null hypothesis claims that a coefficient is zero and its rejection means that the coefficients are statistically significant.

which regime the market is throughout the period under scrutiny.
The probabilities that the process moves from one regime to the other are constant and characterized by a Markov chain, so the transition probabilities are called constant Markov transition probabilities and we can see them in table 4. We notice that the transition probabilities from regime 1 to regime 2 and vice versa are very small and as a consequence the probabilities of staying at the same regime are very large. That means that the model remains for long periods at each regime and does not have the tendency to change regime frequently. Furthermore the retailer seems to spend more time at the low volatility state and low volatility indicates less risk for the retailer.

Table 4: Transition probabilities

	Regime 1	Regime 2
Regime 1	0.9392	0.0769
Regime 2	0.6607	0.9230

The implementation for modeling retail sales using a Markov Regime Switching model is visually presented in figure 3

6 Out of sample forecast evaluation

This paper work investigates whether the regime can provide more accurate forecasts that the simple Seasonal Nave model and the more complicated ETS and SARIMA models. So we divide the sample in two parts and keep the last 72 for the out of sample evaluation and we estimate the model using 132 observations. We perform one-step ahead forecasts for the out of sample observations.

Figure 2: Smoothed Regime Probabilities

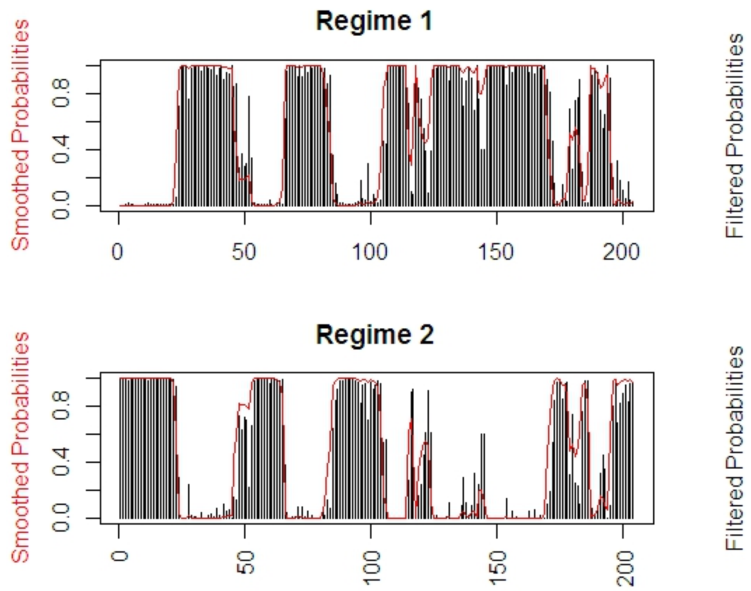


Figure 3: Markov Regime Switching Model

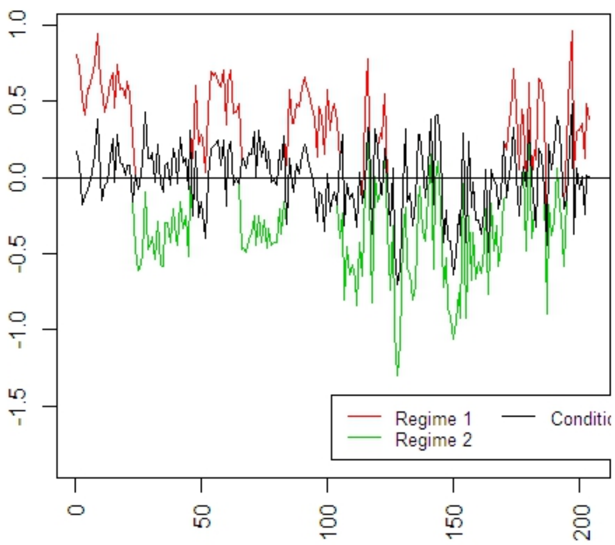


Table 5: Accuracy Measurements

Method/Equation	Definition
Root Mean Squared Error (RMSE)	
$RMSE = \sqrt{n^{-1}\sum\limits_{t=1}^{n}(x_t - f_t)^2}$	n=number of time periods
	x_t=the actual number of car sales in period t
	f_t=the forecast value in time period t
Mean Absolute Persentage Error (MAPE)	
$MAPE = 100n^{-1}\sum_{t=1}^{n}\lvert x_t - f_t\rvert/\lvert x_t\rvert$	n=number of time periods
	x_t=the actual number of car sales in period t
	f_t=the forecast value in time period t

Table 6: Forecasting Performance of Models

	New Car Sales	
RMSE	RW/SNaïve	0.445
	RS/ETS	0.998
	RM/SARIMA	0.996
MAPE	RW/SNaïve	0.345
	RM/ETS	0.978
	RM/SARIMA	0.996

Note:RS=Regime Switching model

6.1 Forecasting error criteria

In order to evaluate the predictive accuracy of the model we employ two different criteria the Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE). The smaller their value is the larger the forecasting strength of the model. We calculate both RMSE and MAPE for evaluating the out of sample performance of the forecast models. Table 5 illustrates the accuracy measures of the models evaluation. To compare the models we take the ratios of the values of the measures. We use the regime-switching model as a benchmark. Particularly we put the value of the RMSE of the regime switching model as the numerator and the value of the RMSE of the other models as the denominator. After, we divide the value of the MAPE of the regime switching model by the value of the MAPE of the other models. In all cases the regime switching model is on the numerator. Consequently if the ratio is less than unity the regime switching model outperforms the model at the denominator otherwise the other model appears to be more reliable. The results are in Table 2 and according to both error criteria there is evidence that regime switching model (RS) has stronger predictive power than the other three models. Evidence shows that the nonlinera regime switching model perform better that the linear Seasonal Naïve model. However the difference between ETS and SARIMA models is not big and we cannot say with confidence that RS outperforms these models.

7 Conclusions

A large number of retailers worldwide are interested in the prognosis of sales levels. Volatility and stability of sales level concerns producers and retailers in a marker. We analyze monthly sales levels of new car market in Greece for almost 17 years. We present a two-order Markov regime switching specification with two states and we initially examine its in sample properties. Thereafter we cut our sample into the in-sample and the out of sample part and evaluate the forecasting power of the regime-switching model relative to that of an ETS, SARIMA and a Seasonal Naïve model. The Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE) are used to assess the results generated the one step ahead forecasting method. The regime switching model outperforms the Seasonal Naïve but has equal predictive ability to the SARIMA and ETS models. To conclude we can argue that in the current turbulent economic situation, our regime switching model has a relatively good fit in sample but the out of sample predictions are not very accurate so we can not consider the regime switching model as a trustworthy model to derive forecasts since ETS and SARIMA perform efficiently. Further research should be done and more parameters have to be consider for a more effective model to be generated.

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