COST ECONOMIES AND MARKET POWER IN THE GREEK FOOD INDUSTRY

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Abstract

This paper investigates the role of scale economies and market power in Greek food manufacturing industries over the period 1987-2010. A model representing the supply and demand structure,which allows simultaneous estimation of price-cost margins andreturns to scale is formulated and estimated. This supply model is based on a dynamic cost framework involving the specification of a restricted variable cost function, withtwo variable inputs ('Labour' and 'Materials & Energy'), as well as aquasi-fixed input (Capital). Empirical results point to the presence of strongscale economies especiallyover the more recent period. At the same time persistent markups are present in a number of sectors butlong term profitability is rather low.

1. Introduction

Measurement of market power has been a prominent issue in industrial organization literature. In the New Empirical Industrial Organization (NEIO) literaturethe degree of market power is inferredon the basis ofmodels involving some representation of demand and cost characteristics.Depending on the specific focus,models may be distinguished according to whether structural or reduced form equations are estimated. A further distinction may be made according to whether the focus lies with supply, demand or price setting components of the model.

Following Hall (1986, 1988 and 1990) and Roeger (1995),reduced form approaches, based on an underlying model of firm behavior,utilize the observed variation in output and input factorsto estimate price-cost margins.The estimation of markups in most reduced form studies is carried out under the assumptions of constant returns to scale (CRTS) andconstant markups over time. However both assumptions are too stringent. If CRTS is assumed the scale component is effectively ignored and instead incorporated in the markup estimate, which is rendered biased. Econometric studies,however, do not support often support the CRTS assumption. Diewert and Fox (2008) find evidence of strong increasing returns to scale and positive monopolistic markups for most sectors for US manufacturing at the aggregate and sectoral levels over the period 1949-2000concluding that US economic growth has been driven by increasing returns to scale. Similar findings appeared in other authors Morrison, 1992; Morrison and Siegel, 1997. Some reduced form models extent Hall's approach to allow for variable returns (Klette (1999), Konings et al. (2011)).Diewert and Fox (2008) is also a type of reduced form model.

Turning to the structural models, it appears that the most active area of research has been the exploration for more sophisticated richer demand structures. Over the last two decades industrial organization has made substantial progress on the estimation of demand systems (see Ackerberg, et al., 2007 for an overview). Based on rich data on prices, quantities and characteristics of the products and consumers, as well as the use of flexible functional forms,thisbody of empirical models allows for consumer and product specific elasticities of demand. However, typically, models focusing on the demand side employ a very poor cost specification. Many studies have estimated costs as a single parameter; while, in some cases, a linear or log-linear function of production cost factors has been used (Besanko et al. 1998, Sudhir 2001).

Anincreasing body of the (NEIO) literature recognizes the importance of cost structures and focuses on the supply side of a structural model of economic behavior to provide inference on market power.Examples of contributions to this literature have been the work of C. Morrison (2001), Lopez et al. (2002) and also the work of Maioli (2003), Hatirli et al., 2006. Also, De Loecker (2011) underlines the value of recovering markups from production.

Lopez et al. (2002) distinguish between oligopoly power and economies of scale effects for the US industry sector at the four digit level. They estimate model of pricing, input and output demand equations which allows them to test the null hypotheses of competitive behavior and constant returns to scale, and assess the effect of concentration on cost efficiency and output price. They find evidence, for the US industry sector, of non-competitive behavior in most industries included in their study. Maioli (2003) applies a similar model on the French two digit manufacturing industries. Morrison (2001) employs a dynamic flexible cost model as well as a representation of demand function in order to study cost economies and market power on the U.S. meat packing industry. She finds that increased consolidation and concentration has been motivated by cost economies, but concludes that little excess profitability exists.

The above results underline the significance of model specification and in particular the treatment of fixed inputs which may have important implications on empirical estimates. In fact, as shown by Konings et al. (2011), ignoring the presence of fixed input may result in an overestimation of theprice-cost margins. However, most reduced form approaches ignore thepresence of fixed inputs. Similarly almost all structural models estimating markups and scale effects are static, the only exception being the Morrison (2001) paper.

The purpose of this work is to formulate and estimate a dynamic structural model to estimate jointly markups and returns to scale, for the Greek food industry. Over the past few years, many Greek industries have experienced significant industrialization and consolidation, but these changes and trends could have spawn more efficient firms even as markets became more concentrated. The issue of economies of scale becomes crucial in this set up.

The Model addresses all the issues outlined above, providing estimates for scale and market power for the period 1988-2010 at the three-digit level of Greek food industry. The parametric model is similar to the one employed by Morrison (2001) even though in a single-product context as opposed to Morrison's multiproduct one. At the same time, unlike Morrison, long term effects are computed analytically in the present study.

2. The structural model

Let production technology be characterised by a variable cost function of the form,

$$VC = VC(Pi;\, Xj, Q, t) \tag{1}$$

VC stands for variable cost,*Q* for the output level, and *P* and Xare price and quantity vectors for the variable and fixed inputs respectivelyand *t* is a time variable representing technical change. Equation (1) provides a short-run characterisation of technology, when the optimisation problem of the production unit is to minimise the variable cost of production for given quantities of fixed inputs.Using Shephard's lemma, demand functions for variable inputs can be obtained by direct differentiation of VC:

$$X_i = \partial CV / \partial P_i \tag{2}$$

The long-run equilibrium canalso be inferred from the variable cost function using is a result due to Samuelson, according to which, the derivative of the variable cost function with respect to the quantity of a fixed inputs equals the negative of its rental price,in long-run equilibrium.

$$\partial \mathrm{CV} / \partial \mathrm{X_j} = \mathrm{h(P_i, X_j, Q)} = -\mathrm{P_j} \tag{3}$$

Equation (3) defines the shadow price of fixed inputs, which equals the actual price at long-run equilibrium.Therefore optimal levels of fixed inputs can be obtained by solving (3) for X^{*}_{j}.

Since the long-run is defined as the state where total cost of production is minimised, we can write long-run total cost,

$$TC = VC(Pi;\ Xj, Q, t) + X_j^{*} P_j \qquad (4)$$

Also, long and short-term marginal cost of production can be obtained from the derivatives of total cost function with respect to output.

$$\mathrm{MCS} = {\partial \mathrm{VC}}/{\partial \mathrm{Q}} \text{ and } \mathrm{MCL} = {\partial \mathrm{VC}}/{\partial \mathrm{Q}} + \sum_{j} \mathrm{P_j}\, {\partial \mathrm{X_j^*}}/{\partial \mathrm{Q}} \qquad (5)$$

Note that, in the short run, the component of total cost attributed to a fixed input in equation (4) is given by the product of actual price with observed quantity.

Having defined the cost structure in the short and long-run, the next step is to describe the demand side. A simple demand for output takes the form of an inverse demand function,

$$P_Q = P(Q) \qquad (6)$$

Finally, the output pricing equation derived by the profit maximization condition, namely that marginal revenue equalslong-run marginal cost takes the form.

$$\mathrm{P}_{\mathrm{Q}} = -\,\mathrm{Q}\left({\partial P(Q)}/{\partial \mathrm{Q}}\right) + {\partial \mathrm{TC}}/{\partial \mathrm{Q}} \qquad (7)$$

Given a parametric model for the variable cost function, estimates of the production parameters can be obtained by simultaneous estimation of functions for variable inputs together with the output pricing equation. Measures of overall and input-specific cost economies and market power may be constructed from this model framework through elasticities of costs and input demands with respect to output. The focus presently will be on measurement of market power and cost economies.

3. Empirical Implementation

3.1 *The parametric Model*

For empirical implementation, the Variable Costfunction is represented by a non-homothetic Generalized Leontief (GL) function capable of capturing the cross-effects among all arguments of the function and therefore not imposing *a priori* restrictions on the estimated elasticities.

$$\begin{aligned} VC = & \sum_i \sum_j \alpha_{ij} P_i^{0.5} P_j^{0.5} + \sum_i \delta_{iK} P_i K^{0.5} + \sum_i \delta_{iQ} P_i Q^{0.5} + \sum_i \delta_{it} P_i t^{0.5} \\ & + \sum_i \gamma_{Qk} P_i K^{0.5} Q^{0.5} + \sum_i P_i \gamma_{tk} K^{0.5} t^{0.5} + \gamma_{kk} K \qquad (8) \end{aligned}$$

The model involves one quasi-fixed input, K, and two variable inputs; Labour (L) and the energy and material mix (ME). The output variable is represented by Gross production value.

Demand functions for the variable inputsare derived directly from the Shephard's lemma as follows:

$$L = \alpha_{LL} + \alpha_{LM}\left(\frac{P_{ME}}{P_L}\right)^{0.5} + \delta_{LK}K^{0.5} + \delta_{LQ}Q^{0.5} + \delta_{Lt}t^{0.5}$$
$$ME = \alpha_{MM} + \alpha_{LM}\left(\frac{P_L}{P_{ME}}\right)^{0.5} + \delta_{MK}K^{0.5} + \delta_{MQ}Q^{0.5} + \delta_{Mt}t^{0.5} \quad (9)$$

The shadow price of capital equation

$$P_{KZ} = -0.5K^{-0.5}\left(\delta_{LK}P_L + \delta_{MK}P_{ME} + (P_L + P_{ME})\gamma_{QK}Q^{-0.5} + \gamma_{tK}t^{0.5}\right) - \gamma_{KK}(1) \quad (10)$$

The long-run quantity of capital, K*, which can be obtained by solving the shadow price of capital equation takes the form,

$$K^* = \left[\left(\sum_i \delta_{iK} P_i + \sum_i P_i \gamma_{KQ} Q^{0.5} + \sum_i P_i \gamma_{tQ} t^{0.5}\right)\Big/ 2(P_K + \gamma_{KK})\right]^2 \quad (11)$$

Demand for output is represented by an inverse demand function, P(q), assumed to take the form : P

$$P_Q = \beta_0 + \beta_1 Q + \beta_2 Q^{0.5} \quad (12)$$

Therefore the output pricing equation is given by:

$$\begin{aligned} P_Q = {} & -Q\,(0.5\beta_1 Q + \beta_2 Q^{0.5}) \\ & + 0.5\, Q^{-0.5}\left(\sum_i \delta_{iQ} P_i + \sum_i P_i \gamma_{KQ} K^{0.5}\right. \\ & \left. + \frac{P_K \sum_i \gamma_{KQ} P_i}{2(P_K + \gamma_{KK})^2}\left(\sum_i \delta_{iK} P_i + \sum_i P_i \gamma_{KQ} Q^{0.5} + \sum_i P_i \gamma_{tQ} t^{0.5}\right)\right) \end{aligned} \quad (13)$$

This system of equations to be estimated incorporates the input demand functions and the output equation, as well as the long term equilibrium condition(equations 9, 10 and13). It comprises supply behaviour but also demand behaviour due to the incorporation of the inverse demand function. Once estimated it is used to make inferences forbothshort and long-run behaviour.

The elasticities of Total Cost with respect to Output provide cost-based scale economymeasures, which are equal to the inverse of production side scale effects. Taking superscripts S and L to denote short and long–run respectively,elasticities are defined as$\varepsilon^{\mathrm{S}}_{\mathrm{TC,Q}} = MCS(Q/TCS) and\ \varepsilon^{\mathrm{L}}_{\mathrm{TC,Q}} = \left(\frac{\partial VC}{\partial Q} + P_K \frac{\partial K^*}{\partial Q}\right)(Q/TCL)$.

Therefore,

$$\varepsilon^{\mathrm{S}}_{\mathrm{TC,Q}} = 0.5\frac{Q^{0.5}\left(\sum_i \delta_{iQ} P_i + \sum_i P_i \gamma_{KQ} K^{0.5}\right)}{(VC + P_K K)} \quad (14)$$

$$\varepsilon_{TC,Q}^{L} = \frac{0.5\, Q^{\,0.5}}{(VC + P_K K^{*})}\left(\sum_i \delta_{iQ}\, P_i + \sum_i P_i\, \gamma_{KQ} K^{0.5} + \frac{P_K \sum_i \gamma_{KQ}\, P_i}{2(P_K + \gamma_{KK})^2}\left(\sum_i \delta_{iK}\, P_i + \sum_i P_i\, \gamma_{KQ} Q^{0.5} + \sum_i P_i\, \gamma_{tQ}\, t^{0.5}\right)\right) \quad (15)$$

The short and long-run mark-ups over marginal cost are defined as (P_Q/MC)are readily obtained from the estimated equations.

3.2 *Econometric Estimation*

The model is estimated for the nine three-digit sectors of the Food Industry over the period 1987-2010.Following standard approach in the empirical production literature involving systems of interrelated input demand functions I use an Iterative Seemingly Unrelated estimation method. In particular I estimate separate structural models for the following sectors.

Sector 151: Production processing and preserving of meat and meat-products

Sector 152: Processing and preserving of fish and fish products

Sector 153: Processing and preserving of fruit and vegetables

Sector 154: Manufacture ofvegetable and animal oils and fats

Sector 155: Manufacture ofdairy products

Sector 156: Manufacture of grain mill products starches and starch products

Sector 157: Manufacture of prepared animalfeeds

Sector 158: Manufacture of other food products

Sector 159: Manufacture of beverages

The basic source of data that can serve the purpose of the present study is the *Annual Industrial Survey* (AIS) of ELSTAT.The AIS contains information on a great number of economic variables at the three digit level. The most complete and detailed information refers to the large scale manufacturing industry, that is establishments employing ten or more persons. Further information from other sources is also used. Such information includes the evolution of value added and intermediate input prices, for which the basic source of data is the sectoral annual National Accounts data.

The labour input is measured in terms of full-time equivalent employment. The capital input in the production is defined as the service provided by the stock of capital in the production process at any given point in time. To create a capital stock series the periodic inventory method was used:$K_t = K_{t-1} - K_{t-1} + GFI_t = (1-\delta)\ K_{t-1} + GFI_t$,where GFI_t, stands for fixed investment in period t and δ for the depreciation rate.

The Price of capital is calculated according to a standard user cost of capital formula$P_{Kit} = P_{It}(r_{it} - \delta_{it})$, where$P_I$ is an investment deflator, $r$is the real cost of finance andδ_i is the effective depreciation rate for sector i.It should be mentioned that Pz, the unobservable shadow price of capital was approximated by the ratio of the residual value of output (having subtracted the cost of variable inputs) to the quantity of Capital.

The estimation output for each sector is presentedin tables 1-9. With the exception of sector 159, where the demand for labour equation has a negative R^2, the model appears to fit the data well.

Table 1 : Estimated parameters for sector 151			
parameter	Estimate	Std. Error	t-Statistic
α_{LM}	2089284.	490277.0	4.261435
α_{LL}	-27591.02	7922.242	-3.482729
α_{MM}	-5.74E+08	51616294	-11.11339
δ_{LK}	0.115328	0.394451	0.292376
δ_{LQ}	0.416460	0.181460	2.295049
δ_{LT}	1417.347	2174.611	0.651770
δ_{MK}	-14642.39	5415.879	-2.703604
δ_{MQ}	42122.10	3066.231	13.73742
δ_{MT}	9436099.	25747483	0.366486
γ_{KK}	0.229175	0.184241	1.243887
γ_{QK}	1.80E-05	1.34E-05	1.344149
γ_{TK}	-0.198927	0.101199	-1.965706
β_1	-1.80E-09	3.46E-10	-5.192918
β_2	9.16E-05	1.90E-05	4.829223

Equation	Adjusted R^2	Durbin-Watson
L	0.53	1.81
ME	0.98	2.31
P_{KZ}	0.80	1.52
P_Q	0.96	1.92

Table 2 : Estimated parameters for sector 152			
parameter	Estimate	Std. Error	t-Statistic
α_{LM}	205809.0	20480.11	10.04921
α_{LL}	-3447.485	329.3816	-10.46654
α_{MM}	-53273270	12881377	-4.135681
δ_{LK}	0.224992	0.034685	6.486778
δ_{LQ}	0.146754	0.009043	16.22786
δ_{LT}	-48.43155	48.80983	-0.992250
δ_{MK}	2111.746	390.6228	5.406101
δ_{MQ}	11674.97	839.9920	13.89891
δ_{MT}	-8218822.	2161433.	-3.802487
γ_{KK}	-0.019186	0.001078	-17.79056
γ_{QK}	-5.24E-06	1.70E-06	-3.081285
γ_{TK}	-0.056773	0.010795	-5.259206
β_1	2.19E-08	1.96E-09	11.20875
β_2	-0.000885	8.00E-05	-11.06394

Equation	Adjusted R^2	Durbin-Watson
L	0.893541	1.882160
ME	0.955615	1.326990
P_{KZ}	0.772953	0.927714
P_Q	0.938347	1.746053

Table 3 : Estimated parameters for sector 153

parameter	Estimate	Std. Error	t-Statistic
α_{LM}	483611.8	291326.9	1.660031
α_{LL}	-13708.62	7980.710	-1.717720
α_{MM}	-1.56E+09	7.92E+08	-1.968057
δ_{LK}	0.013127	0.192461	0.068204
δ_{LQ}	0.618788	0.045765	13.52095
δ_{LT}	88.95929	289.0127	0.307804
δ_{MK}	-4606.315	1290.102	-3.570505
δ_{MQ}	40626.95	2431.710	16.70715
δ_{MT}	2.16E+08	1.42E+08	1.515270
γ_{KK}	-0.008829	0.006902	-1.279134
γ_{QK}	-4.59E-06	1.43E-06	-3.199595
γ_{TK}	-0.015693	0.031403	-0.499727
β_1	1.44E-10	1.53E-10	0.943392
β_2	483611.8	291326.9	1.660031

Equation	Adjusted R^2	Durbin-Watson
L	0.93	1. 67
ME	0.97	2.56
P_{KZ}	0. 93	0.55
P_Q	0.93	0.88

Table 4 : Estimated parameters for sector 154

parameter	Estimate	Std. Error	t-Statistic
α_{LM}	174813.5	130821.5	1.336275
α_{LL}	1190.039	2440.167	0.487688
α_{MM}	-7.46E+08	8.35E+08	-0.893361
δ_{LK}	-0.138045	0.244504	-0.564592
δ_{LQ}	0.101344	0.078971	1.283314
δ_{LT}	-162.6066	529.1570	-0.307294
δ_{MK}	-11382.00	2710.372	-4.199423
δ_{MQ}	22703.87	2344.382	9.684371
δ_{MT}	1.46E+08	1.49E+08	0.983193
γ_{KK}	0.269958	0.142947	1.888525
γ_{QK}	-2.79E-05	1.71E-05	-1.633819
γ_{TK}	0.114006	0.100219	1.137573
β_1	8.67E-10	1.65E-09	0.524830
β_2	-0.000111	8.85E-05	-1.253557

Equation	Adjusted R^2	Durbin-Watson
L	0.82	2. 01
ME	0.82	1.90
P_{KZ}	0. 38	1.38
P_Q	0.87	1.93

Table 5 : Estimated parameters for sector 155

parameter	Estimate	Std. Error	t-Statistic
α_{LM}	998082.7	240466.1	4.150617
α_{LL}	-26946.82	4167.082	-6.466592
α_{MM}	-1.27E+09	92054671	-13.78274
δ_{LK}	0.043214	0.175448	0.246309
δ_{LQ}	0.843244	0.116559	7.234464
δ_{LT}	-584.5623	1021.547	-0.572232
δ_{MK}	-13220.93	1766.395	-7.484693
δ_{MQ}	57914.14	2540.948	22.79234
δ_{MT}	90710931	17709721	5.122098
γ_{KK}	0.068354	0.017267	3.958510
γ_{QK}	-1.36E-05	7.33E-06	-1.848617
γ_{TK}	0.011034	0.047470	0.232452
β_1	-7.61E-10	1.47E-10	-5.184215
β_2	5.76E-05	1.19E-05	4.838072

Equation	Adjusted R^2	Durbin-Watson
L	0.68	1. 10
ME	0.87	0.92
P_{KZ}	0.81	1.46
P_Q	0.87	1.34

Table 6 : Estimated parameters for sector 156

parameter	Estimate	Std. Error	t-Statistic
α_{LM}	121498.6	66403.52	1.829701
α_{LL}	196.8359	1750.719	0.112431
α_{MM}	-1.31E+09	3.65E+08	-3.593462
δ_{LK}	-0.153533	0.082633	-1.858020
δ_{LQ}	0.162691	0.027539	5.907652
δ_{LT}	286.5502	139.1797	2.058851
δ_{MK}	-7362.320	1384.594	-5.317313
δ_{MQ}	29720.71	1643.450	18.08435
δ_{MT}	2.10E+08	61442250	3.419402
γ_{KK}	0.072298	0.016262	4.445744
γ_{QK}	-1.75E-05	4.73E-06	-3.704686
γ_{TK}	0.105290	0.012402	8.489472
β_1	7.31E-10	3.96E-10	1.847451
β_2	-5.26E-05	2.02E-05	-2.597308

Equation	Adjusted R^2	Durbin-Watson
L	0.95	2. 20
ME	0.99	3. 10
P_{KZ}	0.43	0.72
P_Q	0.97	1.61

Table 7 : Estimated parameters for sector 157			
parameter	Estimate	Std. Error	t-Statistic
α_{LM}	-4663.906	46315.74	-0.100698
α_{LL}	-1701.152	1296.010	-1.312606
α_{MM}	-2.21E+08	63291635	-3.493904
δ_{LK}	0.182812	0.096728	1.889953
δ_{LQ}	0.057687	0.017566	3.284015
δ_{LT}	-129.5824	54.49784	-2.377753
δ_{MK}	-2890.662	1662.802	-1.738428
δ_{MQ}	27869.86	758.5201	36.74241
δ_{MT}	9174221.	12182714	0.753052
γ_{KK}	0.045995	0.022687	2.027373
γ_{QK}	-2.14E-05	1.46E-05	-1.466918
γ_{TK}	0.009553	0.054927	0.173915
β_1	-2.73E-09	6.36E-10	-4.298886
β_2	6.60E-05	2.22E-05	2.971306

Equation	Adjusted R^2	Durbin-Watson
L	0.87	1. 77
ME	0.98	2. 43
P_{KZ}	0.36	2.26
P_Q	0.99	1.69

Table 8 : Estimated parameters for sector 158			
parameter	Estimate	Std. Error	t-Statistic
α_{LM}	3621922.	321141.8	11.27827
α_{LL}	-25257.73	9434.257	-2.677235
α_{MM}	-2.24E+09	70398926	-31.75331
δ_{LK}	-1.213775	0.380331	-3.191361
δ_{LQ}	0.570027	0.134717	4.231288
δ_{LT}	9923.300	2303.310	4.308277
δ_{MK}	-4651.800	1060.264	-4.387398
δ_{MQ}	83372.12	2180.904	38.22825
δ_{MT}	-90068497	7840691.	-11.48732
γ_{KK}	0.591184	0.383690	1.540783
γ_{QK}	-7.44E-06	4.59E-06	-1.621451
γ_{TK}	0.498965	0.114392	4.361904
β_1	-1.54E-09	3.02E-10	-5.115039
β_2	0.000117	2.33E-05	5.021128

Equation	Adjusted R^2	Durbin-Watson
L	0.35	2. 39
ME	0.97	1. 75
P_{KZ}	0.94	1.13
P_Q	0.77	2.23

Table 9 : Estimated parameters for sector 159

parameter	Estimate	Std. Error	t-Statistic
α_{LM}	4728882.	549423.2	8.606994
α_{LL}	-105731.4	30051.62	-3.518325
α_{MM}	-1.24E+09	2.88E+08	-4.308361
δ_{LK}	-0.138493	0.319920	-0.432901
δ_{LQ}	0.238429	0.246788	0.966132
δ_{LT}	17576.67	4435.438	3.962781
δ_{MK}	-434.8400	3004.512	-0.144729
δ_{MQ}	40883.29	5963.750	6.855299
δ_{MT}	-84895405	26487809	-3.205075
γ_{KK}	0.090758	0.008027	11.30667
γ_{QK}	-4.26E-05	6.51E-06	-6.539430
γ_{TK}	0.164542	0.056717	2.901091
β_1	6.43E-10	3.55E-10	1.809085
β_2	-7.13E-05	3.18E-05	-2.241905

Equation	Adjusted R^2	Durbin-Watson
L	-0.22	1. 70
ME	0.93	1. 48
P_{KZ}	0.95	1.76
P_Q	0.99	1.75

3.3 *Estimated scale and MarkupMeasures*

Tables 10 and 11 present scale and Mark-up Measures for each one of the three-digit food sectors. The results show strong support for the presence of substantial increasing returns to scale, particularly in the more recent period. Significant long-run scale effects are present in most sectors, especially, 152, 153, 154, 155 (after 2000), 156, and 157 (after 1995). Sectors 151 and 158 exhibits diseconomies for the most part of the period and are close to constant returns in the most recent period.

Substantial long term mark-ups are present in sectors 151(after 1995), 152, 153 and 154. In the other sectors the mark-up is only short term, while in the long run is either rather small (below 10%) as in sectors 155 and 157 or zero or negative, sectors 156 and 158 respectively.

Overall the results show that substantial mark-ups coincide with strong scale effects. The extents of market power and scale effects differ considerably among sectors and they differ between short and long run periods.

This market power measure is based on marginal cost. In the presence of cost economies, however, marginal cost may not be an accurate measure of the costs faced by the producer. In such a case, setting output price equal to marginal cost does not guarantee that normal profit is being made. Moreover setting output price higher than marginal cost does not guarantee that economic profit is being made. Hence, the information that P_Y/MC exceeds unity is not sufficient to indicate the presence of market power, in an economic sense.

What is needed is a measure of economic profit that takes into account the presence of cost economies. This can be provided by utilizing the ratio of output price to average cost instead of marginal cost: P_Q/AC, which, can also be re-formulated as:$P_Q/AC=\varepsilon_{TC,Q}(P_Q/MC)$. The elasticity of total cost with respect to output, $\varepsilon_{TC,Q}$, is the cost-based scale-economy measure. Hence this formulation provides an indicator which combines the market power measure with the elasticity of total cost with respect to output, yielding a profitability indicator which is more intuitive, than simply P_Q/MC, when cost economies are present.

Profitability, as defined by the ratio of price to average cost is presented in Table 12. The existence of strong increasing returns, which implies that average cost is higher than marginal,results in rather low profitability,especially in the long term where we have negative values in the sectors 153, 155, 156 and 157 and 159. From this perspective, it appears that costs economies have been the dominant factor driving market trends. These results have significance for future developments as for most food sectors these economies have not been exhaustedyet.

4. Conclusions

The starting point of this research has been the notion that cost economies may be a significant factor underlying firm consolidation in many markets,thus, properly conducted market power studies must account for possible cost effects that are associated with higher degree of concentration.

A structural model was formulated which represents both supply and demand and allows simultaneous estimation of price-cost marginsand scale economies. Themodel was employed to investigate the role that market power and scale economies may have played in Greek food manufacturing industries over the period 1987-2010.

The results show substantial increasing returns to scale in most three-digit sectors, particularly in the more recent period. Economies of scale are present in both short and long-run periods, while in some cases they are more pronounced in the long run.

Substantial long term mark-ups are present in only less than half of the sectors examined. In the other sectors the mark-up is only short term, while in the long run is either rather small or close to zero.

Estimated profitability, defined by the ratio of price to average cost,is rather low, especially in the long term. From this perspective, it appears that costs economies have been the dominant factor driving market trends. These results have significance for future developments, as, for most food sectors, these economies have not yet been exhausted.

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Liquidity creation through M&As. A viable solution for vulnerable banking systems? Evidence from a stress test under a PVAR methodology.

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Abstract

The recent financial turmoil has distorted the stability of sophisticated and less developed banking sectors and their role as a financial intermediaries. According to the deposit insurance hypothesis banks with higher levels of deposit insurance create higher level of liquidity around mergers. Employing new measures of liquidity creation and using a sample of all commercial banks for the period 1993-2010. On one hand, we investigate whether potential M&As can be proved vital in alleviating the terms of the memorandum between Greece and the so-called Troika, enhancing the real economy, households and firms, with the creation of additional credit channels in the spectrum of a severe country default risk. On the other hand, we exploit potential social welfare benefits in the UK banking system through potential M&As. We conduct a comparative and a forecasting analysis pre-crisis and post-crisis with crucial implications regarding the trade off between shareholders' personal gains and society's economic prosperity that triggers M&A activity. Lastly, we propose a novel methodology to evaluate and compare the robustness of mergers and acquisitions in the spectrum of a panel vector autoregressive (PVAR) framework and we employ recent half life measures of the associated impulse response functions in order to examine thoroughly the robustness and the total effect on liquidity creation of the Greek and UK banks' M&As, due to adverse macroeconomic, financial and bank specific conditions, in line with recently implemented regulations on banking supervision under the Basel III Accord. We provide a strong empirical evidence of increased liquidity that is created after potential M&A activity of two and three banking institutions in the pre-crisis and post-crisis era. Empirical investigation highlights potential

M&As that could be proven more robust towards macroeconomic, financial and bank specific shocks. Additionally, our results cast doubts towards the true origins of M&As and conduce to major policy implications towards the stability of vulnerable banking systems.

Keywords: capital structure, liquidity creation, bank distress, M&As

JEL classification: G21, G28, G32, G34

1 Introduction

Regulators counteracted the crisis with drastic monetary and fiscal expansion and are currently designing a stricter and more stable future financial system that would ensure less wild economic fluctuations and, hopefully, no repetition of the adverse events we are living through today. Comparing to credit risk, there are fewer literature to discuss with liquidity risk. Basel I Accord (Basel Committee on Banking Supervision, 1988) set out regulatory standards for credit risk Besides, Basel II Accord (Basel Committee on Banking Supervision, 2004) even takes operational risk into account. However, they seldom mention the liquidity risk. Landskroner and Paroush (2008) also indicated that there has been an extensive academic and regulatory discussion of the different major banking risks: credit risk, market risk and even operation risk. However relative little attention has been paid to liquidity risk that has become one of the major risks faced by banks and other financial institutions in recent years. Throughout the global financial crisis many banks struggled to maintain adequate liquidity. Unprecedented levels of liquidity support were required from central banks in order to sustain the financial system and even with such extensive support a number of banks failed, were forced into mergers or required resolution. The crisis illustrated how quickly and severely liquidity risks can crystallize and certain sources of funding can evaporate.

1.1 Greek sovereign debt crisis in the spectrum of the banking sector

In October 2008 the Greek government had announced a €28bn support package for Greek banks, consisting of €5bn of capital injections, €15bn of state loan guarantees and €8bn of liquidity in the form of special bonds. Greece's largest banks opted to participate in the capital-raising scheme, designed to bring their Tier 1 capital ratios above 8.5%.

By June 2009, around 80% of the available state-supported capital injections were taken up. The banks took up 80% by June 2009, but then asked for the remaining €17bn of €28bn in the following April.

Greek banks lost access to the international wholesale market in early 2010 because of .increasing perceived risks stemming from the fiscal crisis and the downgrading of Greek government debt to junk bond status in April 2010. As a result, they have relied almost exclusively on the E.C.B for funding, using government and other bonds as collateral. In May 2010, the Eurozone countries and the International Monetary Fund (IMF) agreed on a €110 billion bailout loan for Greece.

Nevertheless, one year after Greece is still in serious danger of running out of cash and defaulting on its debt. The latter enforces the urgent need to find new sources of liquidity as it is globally highlighted in various articles (see, Katie Martin, June 1 2011, Wall street Journal) and is noted. that the basic problem of Greek banks is not capital but liquidity (June 7 2011, Reuters). European Central Bank (E.C.B) is the only source of lending for Greek banks. The banks complain that the E.C.B. is pressuring them to reduce their dependence on central bank funding, hurting not only the banks but Greek businesses and consumers who are unable to get credit. (June 21 2011, New York Times). In October 2011, Eurozone leaders consequently agreed to offer a second €130 billion bailout loan for Greece, conditional not only the implementation of another austerity package (combined with the continued demands for privatisation and structural reforms outlined in the first programme), but also that all private creditors holding Greek government bonds should sign a deal accepting lower interest rates and a 53.5% face value loss. The second bailout deal was finally ratified by all parties in February 2012, and became active one month later

1.2 UK Financial Crisis

A bank rescue package totalling some £500 billion (approximately $850 billion) was announced by the British government on 8 October 2008, as a response to the ongoing global financial crisis. After two unsteady weeks at the end of September, the first week of October had seen major falls in the stock market and severe worries about the stability of British banks. The plan aimed to restore market confidence and help stabilise the British banking system, and provided for a range of short-term loans and guarantees of interbank lending, as well as up to £50 billion of state investment in the banks themselves. The plan provides for several sources of funding to be made available, to an aggregate total of £500 billion in loans and guarantees. Most simply, £200 billion will be made available for short terms loans through the Bank of England's Special Liquidity Scheme. Secondly, the Government will support British banks in their plan to increase their market capitalisation through the newly formed Bank Recapitalisation Fund, by £25 billion in the first instance with a further £25 billion to be called upon if needed. Thirdly, the Government will temporarily underwrite any eligible lending between British banks, giving a loan guarantee of around £250 billion. However, only £400 billion of this is 'fresh money', as there is already in place a system for short term loans to the value of £100 billion.

A second bank rescue package totalling at least £50 billion was announced by the British government on 19 January 2009, as a response to the ongoing global financial crisis. The package was designed to increase the amount of money that banks could lend to businesses and private individuals. This aid comes in two parts: an initial £50 billion being made available to big corporate borrowers, and a second undisclosed amount that forms a form of insurance against banks suffering big losses.

1.3 Intuition

Consolidated banks after mergers create more liquidity because the resources reallocation through an internal money market allows them to take advantage of their improved ability to screen borrowers., (Panetta et al. 2009, Journal of Money, Credit and Banking). Recently it was shown that banks with higher levels of deposit insurance create higher levels of liquidity around mergers., (Pana, Park, Query, 2010). A finding which is consistent with the *deposit insurance* hypothesis. Recently it was shown that banks with higher levels of deposit insurance create higher levels of liquidity Furthermore, Berger and Bouwman (2009) acknowledged the fact that lately banks get involved into various risky activities which are not being reported in their balance sheet. Consequently, they constructed four new measures of liquidity creation of banks that account not only for *on* but for *off* balance sheet bank activities as well. Their results, revealed that recently-merged banks create most of the industry's overall liquidity.

To the best of our knowledge, this is the first empirical work in the literature, that attempts to test the liquidity creation of all the Greek and UK mergers and acquisitions that have taken place by using recently developed measures of liquidity creation (Berger and Bouwman 2009), which take into consideration both *on* and *off* balance sheet activities of banks. Additionally, is the first study to address the question of whether potential M&As of Greek and UK banks could lead to an increase of liquidity in the banking sector and consequently to the creation of new credit channels for the Greek economy on one hand , in the spectrum of a severe country default risk and for the UK economy on the other hand in the context of an increasing public debt resulting of the ample use of unconventional measures from the Bank of England such as £375 billion in QE programmes in the end of 2012. The last point is of extreme importance as it highlights whether ineffectual past attempts of M&As were due to limited personal potential gains of the shareholders or due to limited enhancement of the social welfare. Moreover, we provide a comparative analysis regarding the performance of potential Greek and UK banking M&As in terms of liquidity creation before and during the crisis. Last but not least, we propose a novel methodology to evaluate and compare the robustness of mergers and acquisitions by quoting a stress test scenario in the spectrum of a panel vector autoregressive (PVAR) framework which enables to infer major policy implications towards the stability of vulnerable banking systems especially in the era of the recent financial crisis. Thus, we examine thoroughly and in a more integrated way the robustness of the Greek banking sector on liquidity creation due to adverse macroeconomic, financial and bank specific conditions. The aforememtioned point is very crucial, since the new Basel III accord imposes a strong emphasis on the liquidity standards of banks, and as a consequence it introduces two additional ratio, the *liquidity coverage ratio* (LCR) and the *net stable funding ratio* (NSFR).

2 Theoretical Framework

2.1 Measurement of Liquidity

Berger and Bouwman (2009) averred that the LT gap is a step forward, but argued that it is not sufficiently comprehensive by highlighting a few differences between their approach and the LT gap developed by Deep and Schaefer (2004). Firstly, the Berger/Bouwman model includes almost all commercial banks and compares findings for large and small banks rather than including only the largest institutions. The Berger/Bouwman model also classifies loans by category, rather than maturity and finally, the Berger/Bouwman model employs measures which include off-balance sheet activities, consistent with the arguments of Kashyap et al. (2002), and Repullo (2004)..

Berger and Bouwman(2009) as we aforementioned construct their liquidity creation measure using a three step approach. In step 1, they classify all bank balance sheet and off-balance sheet activities as liquid, semi-liquid, or illiquid based on the ease, cost, and time for banks to dispose of their obligations to obtain liquid funds to meet customers' demands. Within each category, shorter maturity items are defined as more liquid than longer maturity items because they self-liquidate without as much effort. Loans are classified by category ("cat") or entirely by maturity ("mat") because bank Call reports split loans into various loan categories and into different maturity classes.

In step 2, Berger and Bouwman assign weights to the activities classified in step 1. The weights are based on the liquidity creation theory where banks create the most liquidity when they transform illiquid assets into liquid liabilities and maximum liquidity is destroyed when liquid assets are transformed into illiquid liabilities. Therefore positive weights are applied to both illiquid assets and liquid liabilities and negative weights to liquid assets and illiquid liabilities. The magnitudes of the weights are based on simple dollar-for-dollar adding up constraints, so that \$1 of liquidity is created (destroyed) when banks transform \$1 of illiquid (liquid) assets into \$1 of liquid (illiquid) liabilities.

In step 3, the authors combine the activities as classified in step 1, an weighted according to step 2, to construct four liquidity measures. The measures classify loans by category or maturity ("cat" vs "mat") and whether banks include off-balance sheet activities ("fat") or exclude them ("nonfat"). Thus, liquidity creation measures are constructed based on the four combinations "cat fat", "mat fat", "cat nonfat", "mat nonfat".

In turn, the four liquidity measures obtain the following form:

$$
\begin{aligned}
&\text{"}cat\ fat\text{"}{:}LC = \\
&\left\{\tfrac{1}{2}\times illiquidassets(cat) + 0\times semiliquidassets(cat) - \tfrac{1}{2}\times liquidassets\right\} \\
&+\left\{\tfrac{1}{2}\times liquidliabilities + 0\times semiliquidliabilities - \tfrac{1}{2}\times illiquidliabilities - \tfrac{1}{2}equity\right\} + \\
&\left\{\begin{matrix}\tfrac{1}{2}\times illiquidguarantees + 0\times semiliquidguarantees \\ -\tfrac{1}{2}\times liquidguarantees - \tfrac{1}{2}liquidderivatives\end{matrix}\right\}
\end{aligned}
$$

$$
\begin{aligned}
&\text{"}cat\ nonfat\text{"}{:}LC = \\
&\left\{\tfrac{1}{2}\times illiquidassets(cat) + 0\times semiliquidassets(cat) - \tfrac{1}{2}\times liquidassets\right\} \\
&+\left\{\tfrac{1}{2}\times liquidliabilities + 0\times semiliquidliabilities - \tfrac{1}{2}\times illiquidliabilities - \tfrac{1}{2}equity\right\}
\end{aligned}
$$

$$
\begin{aligned}
&\text{"}mat\ fat\text{"}{:}LC = \\
&\left\{\tfrac{1}{2}\times illiquidassets(mat) + 0\times semiliquidassets(mat) - \tfrac{1}{2}\times liquidassets\right\} + \\
&\left\{\tfrac{1}{2}\times liquidliabilities + 0\times semiliquidliabilities - \tfrac{1}{2}\times illiquidliabilities - \tfrac{1}{2}equity\right\} + \\
&\left\{\begin{matrix}\tfrac{1}{2}\times illiquidguarantees + 0\times semiliquidguarantees \\ -\tfrac{1}{2}\times liquidguarantees - \tfrac{1}{2}liquidderivatives\end{matrix}\right\}
\end{aligned}
$$

$$
\begin{aligned}
&\text{"}mat\ nonfat\text{"}{:}LC = \\
&\left\{\tfrac{1}{2}\times illiquidassets(mat) + 0\times semiliquidassets(mat) - \tfrac{1}{2}\times liquidassets\right\} + \\
&\left\{\tfrac{1}{2}\times liquidliabilities + 0\times semiliquidliabilities - \tfrac{1}{2}\times illiquidliabilities - \tfrac{1}{2}equity\right\}
\end{aligned}
$$

3 Data

For the estimation of the model we will use data that consist of an unbalanced panel of all the commercial banks that were operating in the Greek or the 1993-2010 period and UK banking system for the 1987-2011 period. The sources for our data set will be based upon[1]:

a. Bankscope database of Bureau van Dijk's company (data of 2011 are not reported for Greek banks and yet and are incomplete for the UK banks).

b. The official websites of the Greek and UK banks

c. The annual reports of the Governor of the Bank of Greece (1993-2010) and of the Bank of England (1987-2011).

3.1 Model

l

We base our analysis on the preferred liquidity measure of Berger and Bouwman (2009), more specifically the "$catfat$". We test all the M&As that took place during our sample, to check the level of their liquidity the years after M&A activity had been completed.

Following (Pana et al. 2010), in order to examine the financial fragility-crowding out and risk absorption hypotheses, the following regression equations are estimated:

$$\left(\frac{catfat}{GTA}\right)_{i,t+1} - \left(\frac{catfat}{GTA}\right)_{i,t-1} = a_0 + a_1\left(\frac{uninsuredDeposits}{GTA}\right)_{i,t-1} + a_2\left(\frac{Bankcapital}{GTA}\right)_{i,t-1}$$
$$+a_3 \operatorname{Re} lativesize_{i,t-1} + a_4 pub\_st_{i,t-1} + a_5 GDPdeflator_{i,t-1} + \varepsilon_{i,t}$$

In order to measure the bank's ability to absorb shocks occurring from the merges and acquisitions, we use HHI of revenue diversification measure:

$$HHI_{REV=}\left(\frac{NON}{NETOP}\right)^2 + \left(\frac{NET}{NETOP}\right)^2$$
$$NETOP = NON + NET$$

4 Empirical Results

4.0.1

4.0.2 Greek historical M&As

4.0.3 UK historical M&As

Table 5. Greek historical M&As regression results							
Source	SS	df	MS			Number of obs	18
						F(5, 12)	1.6100
Model	0.2325	5	.046507498			Prob > F	0.2303
Residual	0.3461	12	.028837527			R-squared	0.4019
						Adj R-squared	0.1527
Total	0.5786	17	.034034577			Root MSE	0.1698
catfat_gta~1	Coef.	Std. Err.	t	P>t	[95% Conf.		Interval]
pub_st	-0.0184	.0864469	-0.21	0.8350	-0.2068		0.1699
rel_size	0.0000	3.80e-06	-1.65	0.1250	0.0000		0.0000
undep_gta	-6.7068	3.797316	-1.77	0.1030	-14.9805		1.5668
capit_gta	0.1145	.4262736	0.27	0.7930	-0.8143		1.0433
gdpdefl	0.0046	.0040556	1.13	0.2790	-0.0042		0.0134
_cons	-0.2106	.3539828	-0.59	0.5630	-0.9818		0.5607

Table 6. Greek historical M&As regression results with revenue diversification							
Source	SS	df	MS	Number of obs =			18
				F(7, 10)			1.5600
Model	0.3019	7	.043134718	Prob > F			0.2527
Residual	0.2766	10	.027664478	R-squared			0.5219
				Adj R-squared			0.1872
Total	0.5786	17	.034034577	Root MSE			0.1663
catfat_gta~1	Coef.	Std. Err.	t	P>t	[95% Conf.		Interval]
rel_size	0.0000	3.73e-06	-1.66	0.128	-0.0000		0.0000
pub_st	0.0082	0.1083	0.08	0.941	-0.2331		0.2495
undep_gta	-9.5326	4.1274	-2.31	0.044	-18.7291		-0.3362
capit_gta	0.0528	0.4347	0.12	0.906	-0.9157		1.0213
gdpdefl	0.0090	0.0057	1.57	0.148	-0.0038		0.0218
hhirev	0.3701	0.4126	0.90	0.391	-0.5493		1.2894
hhirev2	-0.4945	0.3470	-1.43	0.185	-1.2676		0.2786
_cons	-0.6089	0.4473	-1.36	0.203	-1.6056		0.3877

Table 7. Greek historical M&As regressions results NO EQUITY

Source	SS	df	MS			
					Number of obs	18
					F(5, 12)	1.6900
Model	0.2374	5	.047472119		Prob > F	0.2107
Residual	0.3365	12	.028039236		R-squared	0.4136
					Adj R-squared	0.1693
Total	0.5738	17	.03375479		Root MSE	0.1675
catfat_noe~a	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
undep_gta	-7.2837	3.744388	-1.95	0.0760	-15.4420	0.8746
capit_gta	-0.1145	.420332	-0.27	0.7900	-1.0303	0.8013
gdpdefl	0.0048	.0039991	1.21	0.2510	-0.0039	0.0135
rel_size	0.0000	3.75e-06	-1.67	0.1210	0.0000	0.0000
pub_st	-0.0226	.085242	-0.27	0.7950	-0.2084	0.1631
_cons	-0.2089	.3490489	-0.60	0.5610	-0.9694	0.5516

Table 8. Greek historical M&As and regression results NO EQUITY with revenue diversification

Source	SS	df	MS			
					Number of ob	18
					F(7, 10)	1.53
Model	0.29680954	7	.042401363		Prob > F	0.2612
Residual	0.27702188	10	.027702188		R-squared	0.5172
					Adj R-squarec	0.1793
Total	0.57383142	17	.03375479		Root MSE	0.16644
catfat_noe~a	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
rel_size	-0.00000619	3.73e-06	-1.	0.128	-0.0000145	0.00000212
hhirev	0.2770307	.4128787	0	0.517	-0.6429205	1.196982
hhirev2	-0.4261221	.3472068	-1	0.248	-1.199747	0.3475029
undep_gta	-9.904116	4.130241	-2	0.037	-19.10687	-0.701366
capit_gta	-0.1500164	.4349464	-0	0.737	-1.119137	0.8191046
gdpdefl	0.0094453	.0057538	1	0.132	-0.0033749	0.0222654
pub_st	-0.0102979	.1083655	-0	0.926	-0.2517513	0.2311556
_cons	-0.5984328	.4476035	-1	0.211	-1.595755	0.3988898

Table 9. UK potential M&As and regression results							
Source	**SS**	**df**	**MS**		**Number of obs**		**19**
					F(5, 13)		**0.7700**
Model	0.1839	5	.036782222		**Prob > F**		**0.5900**
Residual	0.6237	13	.047978228		**R-squared**		**0.2277**
					Adj R-squared		**-0.0693**
Total	0.8076	18	.044868226		**Root MSE**		**0.2190**
catfat_gta~1	**Coef.**		**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
ret_size	-0.0055		.0182166	-0.30	0.769	-.0448173	0.0339
undep_gtat1	-10.3070		5.296779	-1.95	0.074	-21.74995	1.1360
capit_gtat1	-0.4894		1.877193	-0.26	0.798	-4.544821	3.5660
gdpdef	0.0009		.0053858	0.17	0.868	-.0107242	0.0125
pub_st	0.0434		.1080967	0.40	0.695	-.1901673	0.2769
_cons	0.0391		.5238181	0.07	0.942	-1.092527	**1**

Table 10. UK historical M&As and regression with revenue diversification							
Source	**SS**	**df**	**MS**		**Number of obs =**		19
					F(7, 11)		0.7400
Model	0.2589	7	.036984001		**Prob > F**		0.6438
Residual	0.5487	11	.049885461		**R-squared**		0.3206
					Adj R-squared		-0.1118
Total	0.8076	18	.044868226		**Root MSE**		0.2234
catfat_gta~1	**Coef.**		**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
ret_size	-0.0061		.0187822	-0.33	0.751	-.0474485	0.0352
pub_st	0.0961		.1192826	0.81	0.437	-.1664138	0.3587
hhirev	5.2036		4.767642	1.09	0.298	-5.28986	15.6972
hhirev2	-10.2529		9.140506	-1.12	0.286	-30.37097	9.8653
undep_gtat1	-11.6262		6.661501	-1.75	0.109	-26.28808	3.0357
capit_gtat1	-0.4162		2.327434	-0.18	0.861	-5.538835	4.7065
gdpdef	0.0019		.0055489	0.34	0.743	-.0103494	0.0141
_cons	-0.0310		.5650918	-0.05	0.957	-1.274776	1.2127

Table 11. UK historical M&As and regression results NO EQUITY							
Source	SS	df	MS			Number of obs	19
						F(5, 13)	0.7000
Model	0.1746	5	.034920752			Prob > F	0.6349
Residual	0.6509	13	.050069333			R-squared	0.2115
						Adj R-squared	-0.0918
Total	0.8255	18	.045861394			Root MSE	0.2238
catfat_noe~a	Coef.	Std. Err.		t	P>t	[95% Conf.	Interval]
pub_st	0.0504	.1104272		0.46	0.6550	-0.1881	0.2890
ret_size	-0.0040	.0186094		-0.21	0.8330	-0.0442	0.0362
undep_gtat1	-10.0917	5.410977		-1.87	0.0850	-21.7815	1.5980
capit_gtat1	-0.7463	1.917665		-0.39	0.7030	-4.8892	3.3965
gdpdef	0.0009	.0055019		0.17	0.8660	-0.0109	0.0128
_cons	0.0404	.5351115		0.08	0.9410	**-1**	1

Table 12. UK historical M&As and regression results NO EQUITY with revenue diversification							
Source	SS	df	MS			Number of obs	19
						F(7, 11)	0.6900
Model	0.2523	7	.036035716			Prob > F	0.6790
Residual	0.5733	11	.052114098			R-squared	0.3056
						Adj R-squared	-0.1363
Total	0.8255	18	.045861394			Root MSE	0.2283
catfat_noe~a	Coef.	Std. Err.		t	P>t	[95% Conf.	Interval]
ret_size	-0.0046	.0191972		-0.24	0.8140	-0.0469	0.0376
hhirev	5.3267	4.872976		1.09	0.2980	-5.3986	16.0521
hhirev2	-10.4867	9.342452		-1.12	0.2860	-31.0493	10.0759
pub_st	0.1039	.121918		0.85	0.4120	-0.1644	0.3722
undep_gtat1	-11.3797	6.808677		-1.67	0.1230	-26.3655	3.6061
capit_gtat1	-0.6526	2.378855		-0.27	0.7890	-5.8884	4.5832
gdpdef	0.0019	.0056715		0.34	0.7420	-0.0106	0.0144
_cons	-0.0335	.5775766		-0.06	0.9550	-1.3048	1.2377

The regression results deriving from the historical M&As that have taken place (see tables 5-12) reveal that in both countries, reveal strong support for the insurance deposit hypothesis. The negative, statistically significant coefficient of the uninsured deposit variable indicates that banks with a high level of insured deposits complete mergers that result in a higher level of liquidity creation over a short period of time.

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4.1 Comparative and Forecasting analysis

We measure the liquidity creation of potential M&As according to the aforementioned "speculated" cases. As additional scenarios of Ḿ&As we create potential mergers and acquisitions among the 10 most important banks in terms of assets, loans and deposits for both the Greek and the Uk banking sector

4.2 Stress test scenario

In order to judge the resilience of banking on various macroeconomic shocks, Vector Autoregressive (VAR) approach has been adopted as done by Hoggarth, Sorensen and Zicchino (2005), Marcucci and Quagliariello (2005) and Renato Filosa (2007). The advantage of VAR model is that, it allows to fully capture the interaction among macroeconomic and financial variables and bank's specific variables. It also captures the entailed feedback effect. We use a panel-data vector autoregression methodology (Holtz et al. 1988).This technique combines the traditional VAR approach, which treats all the variables in the system as endogenous, with the panel-data approach, which allows for unobserved individual heterogeneity

In order to be able to compare among the various combinations of potential M&As and the current situation where there is no M&A activity taking place in an appropriate way,. we calculate the half life for each specific potential M&As and for easch specific shock. We manage to make presice comparisons among the M&As cases under investigation we utilized recently proposed in the literature half life measures (Chortareas and Kapetanios, 2012)

$$\int_o^{h^*} \mid \phi_i \mid d_i = \int_{h^*}^{\infty} \mid \phi_i \mid d_i$$

[1]The year 1993 is the staring year for the Greek banking sector as after this year the deregulation period has commenced.

4.2.1 Greek - Uk potential M&As

Impulse response functions

5 Concluding Remarks

Our analysis reports interesting results of potential M&As that could be proven more robust towards macroeconomic, financial and bank specific shocks. Regarding the Greek banking sector, it's noteworthy that in some cases we report contradictory situations of M&As than those that have been recently agreed to taken place and than those that have been speculated lately that will emerge. We argue that the latter results are of extreme importance as they cast doubts towards the true origins of M&As. To be more specific, our findings raise questions of whether a recent M&A activity occurred to pursue managerial and shareholder's strategic opportunistic decisions rather to enhance the stability of the banking sector in it's presumably the most critical moment after it's deregulation back in 1993.

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Forecasting sales and intervention analysis of durable products in the Greek market. Empirical evidence from the new car retail sector.

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Abstract

The Great Recession in Europe and the Greek economic crisis in the last five years and their impact the new car sales market, are the main focus of our analysis. This research paper tries to analyse, model and investigate the intervention impacts on new car sales levels and evaluate the accuracy of various forecasting techniques to predict car demand before and after the inclusion of intervention events (recession of the Greek economy), for a couple of car representatives operating in the Greek car market. The forecasting methods used in this study include: 1) simple Naïve, 2) seasonal Naïve models, 3) seasonal Autoregressive Integrated Moving Average (SARIMA) models, and 4)Exponential Smoothing State Space (ETS) models. Data on car sales are treated as time series observations and indicate the actual number of monthly new car registration numbers officially recorded in Greece, from January 1998 to December 2011. The data are obtained from the Greek Association of Motor Vehicle Importers - Representatives (AMVIR) statistical data base. The research focus on different Motor Vehicle importers- representatives operating in the Greek auto mobile retail market. Two different firms (Toyota and Opel), out of 10 included in the final research, are presented in this summary paper in order to display the forecasting process and the conclusions of this survey. This study focuses on the importance for forecasting accuracy of allowing for intervention events in the modelling process. All models are estimated both with and without intervention effects in an out-of-sample forecasting experiment for two different periods. Forecasting accuracy is assessed using two “standard ”average loss functions defined as: the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE). Results show the importance of different models for forecasting car demand levels of each car representative for the two chosen periods. Additionally this research gives evidence that the implementation of the austerity measures in Greece during the period 2008-2011 had negative impacts on new car demand in the Greek market place.

Keywords: Time Series forecasting, Intervention impacts, Seasonal ARIMA models, Exponential Smoothing (ETS) models, car sales

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1 Introduction

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 that started in early 2008. This phase became even worse since 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 country, conditional on the implementation of austerity measures. The euro area Member States and the IMF have been providing financial support to Greece through an Economic Adjustment Programme and the release of the disbursements were based on observance of quantitative performance criteria and the positive evaluation of progress made with respect to policy criteria initially detailed in Council Decision 2001/734/EU of 12 July 2011 (as amended in November 2011, 13 March and 4 December 2012) and the Memorandum of Understanding setting the economic policy conditionality (with the last update signed on 7 December 2012). The impact 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 impact of recession, on the new car sales levels, in the Greek retail market and how sales can be modelled and analysed is the focus of this study. Firstly, we point out the importance for forecasting accuracy of allowing for intervention events in the modelling process by estimating all models both with and without intervention effects and generate forecasts for one year ahead. Two periods are estimated for each model: period (A)January 1998 - December 2007 and period (B) January 1998 - December 2010 generating out-of-sample forecasts for: (A) 2008 and (B) 2011 respectively. Secondly, the focus of this study is to examine the impact on car demand, for a sample of automobile retail firms operating in the Greek market, and how their sales level can be evaluated, modelled and forecasted.

There is not much research on car sales level forecasting in Greece. Generally there are some papers for forecasting car sales demand in the American automobile market with the use of disaggregate choice models (Berkovec, 1985), 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 data and include forecasting methods used in time series analysis, like the Naïve, the Seasonal Autoregressive Integrated Moving Average (SARIMA) models (Franses,1991, Greene,1993, Hamilton 1994), and the Exponential Smoothing State Space (ETS) models(Hyndman et al 2008) while we include intervention analysis in the sample data (Chen, 2006).

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 forecasting 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.

2 Data

The dataset used in this study consists of monthly car registration numbers officially recorded by the Greek authorities. The Greek Association of Motor Vehicle Importers - Representatives (AMVIR) statistical data base provide us 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 2011. Time series data from different Motor Vehicle importers –representatives, which operating in the Greek auto mobile retail market, are analysed. For convenience, the sample of this summary paper includes only two (2) different firms. They are selected from a group of ten (10) retail firms of the final research study. Both, Toyota and Opel, have two of the highest monthly sales levels in the Greek car market.

- **Toyota** had a rapid increase of their new car sales level for 2 years (1998-2000) and then maintain a stable high market share in sales with very small upward and downward movements throughout the next years up until 2010. After 2010 the firm had a rapid downfall in new car sales until the end of 2011.

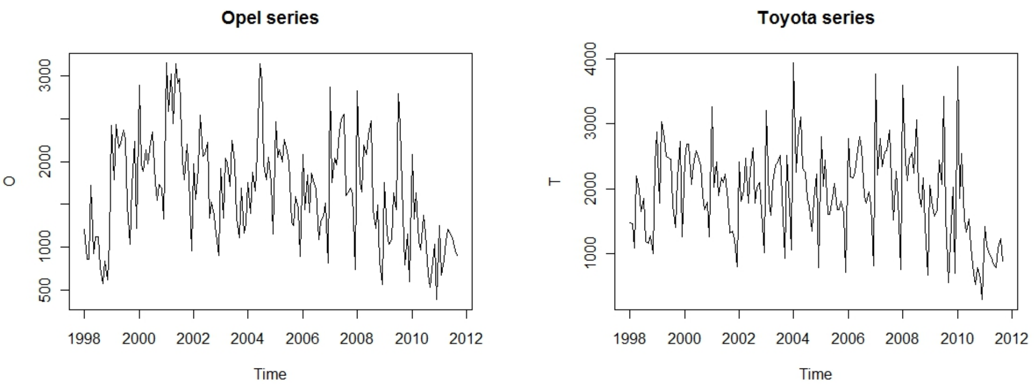
- **Opel** new car sales had been increasing rapidly from 1998 until 2001 but then stated falling until 2004. The company managed to regain its market share in 2005 but sales decreased again. In 2007 the company had managed to regain sales level at a lower but more stable level and kept it stable for the next two years. Unfortunately after 2009 the company had started a downfall movement on its sales level that became dramatic during and after 2011.

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

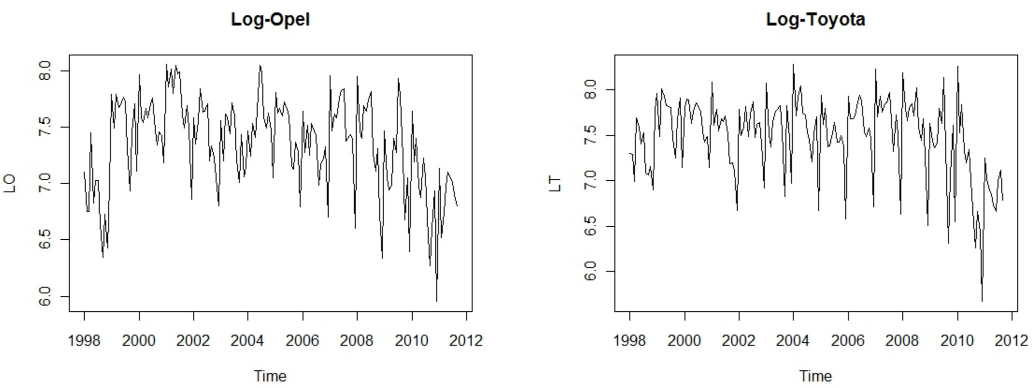
Descriptive statistics (1998:1-2011:12)				
	OPEL		TOYOTA	
	Level	Log	Level	Log
Mean	1.666	7,34	1.928	7,48
Median	1.675	7,42	1.904	7,55
Max	3.154	8,06	3.938	8,28
Min	384	5,95	290	5,67
Standard Deviation	624	0,42	711	0,44
Skewness	0,28	-0,63	0,14	-1,07
Kurtosis	-0,51	0,06	-0,05	1,35
Jarque Bera test	$3,73^{*}$	11,04	$0,54^{*}$	45,42
Shapiro Wilk's test	$0,98^{**}$	0,96	$0,98^{**}$	0,93
Dickey-Fuller Tests	-4,06	-3,98*	-3,88	-0,40*

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

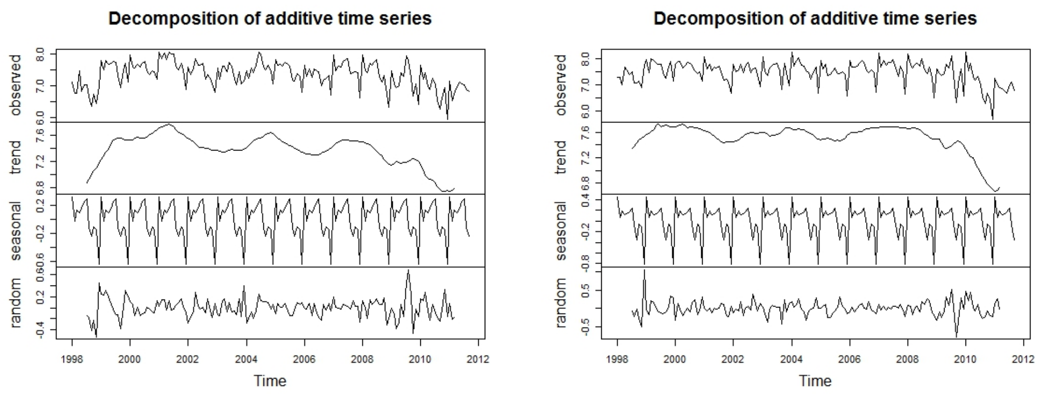
More details are given in Table 1 where descriptive statistics are reported for the total sample period. *Jarque –Bera test* for normality in raw and in log value series of new car sales rejects the null hypothesis that the series are normally distributed only in the case of the log series. So the raw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



(a) New car sales



(b) Log new car sales



(c) Decomposition of log new car sales

Figure 1: Monthly new–car sales in Greek market(1998:1-2011:12)
Note:The graphs in this figure present in panel (a)monthly number of new car sales, in panel (b) log sales and in panel (c) Decomposition of the log series for Opel (in the left panel) and for Toyota (in the right panel).

3 Forecasting Models

Forecasting methods do not exploit the understanding of time series behaviour as economic values 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). Table 2 briefly illustrate the forecasting models, while Table 3 illustrate the measures of forecasting accuracy for periods :

A. January 1998 till December 2007 $\xrightarrow{forecast}$ 2008

B. January 1998 till December 2010 $\xrightarrow{forecast}$ 2011

The first period covers ten (10) years of quite stable Greek economy, while the second period covers thirteen (13) years, including a period of 3 years (2008-2010) with dramatic changes in the Greek economy. The forecasting methods used in this research are:

1. **Simple Naïve Method.** In Naïve forecasting method the next step forecasts value of this period (t) equal to the observed value of the last period (t-1). Empirical evidence show that this method works remarkably well for many economic and financial time series especially in the short run predictions (Makridakis et al, 1998).This is happening as a consequence in an efficient market.

2. **Seasonal Naïve Method.** In 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 future January value equals to the last observed January value (Hyndman and Athanasopoulos, 2012).

3. **Seasonal Autoregressive Integrated Moving Average (SARIMA).** In 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 term ε_t is assumed to be serially independent and have zero mean and constant variance (white noise process).

4. **State space model with exponential smoothing.** The State space model or Dynamic linear model 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 for the initials **E**rror, **T**rend, **S**easonal or as **E**xponen**T**rial **S**moothing (Hyndman and Athanasopoulos, 2012).

4 Forecasting Accuracy Measures

Forecast accuracy is assessed using two standard loss functions:

- the Root Mean Square Error (RMSE) and
- the Mean Absolute Percentage Error (MAPE)

Table 2: Equations of Time Series Forecasting Models

Forecasting Method/Model	Definition
Naïve Method	
$\hat{x}_{n+h\|n} = x_n$	n=number of time periods
	$\hat{x}_{n+h\|n}$=the estimated forecast value
	x_t=the observed car sales at time t
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
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 component ord.q,
	$\Phi_P(B^s)$=seasonal autoregressive component ord.P,
	$\Theta_Q(B^s)$=moving average components order Q,
	$\bigtriangledown^d = (1-B)^d$=ordinary difference component,
	$\bigtriangledown_s^D = (1-B^s)^D$=seasonal difference component,
	d= degree of consecutive differencing,
	D=degree of seasonal differencing,
	ε_t=error with white noise $\sim iidN(0,\sigma^2)$
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

The RMSE is frequently used for evaluating a model's performance for fitting the data or forecasting them. It calculates the differences between values predicted by a model and the values actually observed. These differences can be the residuals, if the calculation is performed over data sample that was for estimation, or prediction errors if the calculation is in an out-of-sample estimation. The root of the squared sum of these prediction errors divided by the number of time periods results in the RMSE measure. It is usually best to report the RMSE rather than the MSE, because the RMSE is measured in the same units as the data, and not in squared units like MSE, and is therefore representative of the size of a typical error. RMSE is scale-dependent and is not preferred in comparing accuracy across time series with different scales or different variables. However RMSE is a good measure of accuracy to compare forecasted errors of different models for a particular variable.

The MAPE evaluation criterion is a great tool for model evaluation and forecasting accuracy because it is not scale-dependent. It is also known as mean absolute percentage deviation and it expresses accuracy as a percentage. The absolute values in the MAPE calculation is summed for every fitted or forecasted point and divided again by the number of fitted points n. Multiplying by 100 makes is a percentage error. MAPE is often preferred because apparently managers understand percentages better than squared errors (Hyndman, Koehler 2006). The only limitations of this measure is in case the data contain zero values (may result in an infinite MAPE) or in case the data contain very small numbers (may result in huge MAPE). However these limitations are of minor importance for this study because our data do not have zero or very small values.

Both RMSE and MAPE are calculated for evaluating the out of sample performance of the forecast models. Table 3 illustrate the equations of the accuracy measures used in this study.

Table 3: Equation of Error Magnitude 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

5 Empirical Evidence - Conclusions

Empirical evidence are given in Table 4. Each one of the four (4) forecasting method is evaluated in two different time periods (A and B) in order to estimate the impact of the economic crisis in sales level. Evidence suggest that the Greek economic crisis had influenced the consumption of durable products, like new car sales, as concluded in this study. In time period A (1998-2007) the sample period stops before the recession started. The error measures for this period indicate that a seasonal Naïve model can best capture the fluctuations of sales in the market. That gives evidence of a stable economic activity and an efficient market since the seasonal Naïve model resulted as the best technique in forecasting car sales levels in the Greek retail market.

However after the addition of the next 3 years (2008-2010) we have the sample period B, which covers the great recession in Europe and the economic crisis in Greece. During that period all sales level had dramatically fallen and the seasonal Naïve models do not seem to capture the sales level fluctuations any more. In case B, the error magnitude measurements RMSE and MAPE indicate the Holt Winters seasonal model with additive errors as the best model for the out of sample forecast modelling. The ETS models are selected via a state space modelling with exponential smoothing parameters. 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). It is also worth noticing that the Seasonal ARIMA models are the second best choice for forecasting the data in both cases A and B. That shows the quite good and stable way these models fit the data but also indicates that they are not very sensitive in capturing the features or changing movements of the data.

In the current turbulent economic situation where customers are reluctant to invest in durable products and buy new cars, there is evidence that exponential smoothing state space models can best forecast the sales level of new cars in the Greek market. However the small sample of this study is not enough to make safe conclusions for all the car representatives operating in the national car market. Therefore this research will be enriched focusing in additional car representatives samples and additional time series forecasting models in order to be completed in the future.

Table 4: Evaluations of Forecasting Performances

Model		**RMSE**		**MAPE**
{Estimation Period}: Forecasting Period	Opel	Toyota	Opel	Toyota
(1)Naïve Forecasting Method				
(A){Jan.1998-Dec.2007}:Jan.2008-Dec.2008	0,89(4)	1,07(4)	10,78(4)	13,07(4)
(B){Jan.1998-Dec.2010}:Jan.2011-Dec.2011	0,91(4)	1,24(4)	12,53(4)	17,65(4)
(2)Seasonal Naïve Forecasting Method				
(A){Jan.1998-Dec.2007}:Jan.2008-Dec.2008	**0,24(1)**	**0,13(1)**	**2,40(1)**	**1,40(1)**
(B){Jan.1998-Dec.2010}:Jan.2011-Dec.2011	0,40(3)	0,71(3)	5,10(3)	8,81(3)
(3)SARIMA Forecasting Method				
(A){Jan.1998-Dec.2007}:Jan.2008-Dec.2008	0,26(2)	0,15(2)	2,99(3)	1,83(2)
(B){Jan.1998-Dec.2010}:Jan.2011-Dec.2011	0,29(2)	0,57(2)	3,61(2)	5,56(2)
(4)ETS Forecasting Method				
(A){Jan.1998-Dec.2007}:Jan.2008-Dec.2008	0,24(1)	0,16(3)	2,75(2)	1,90(3)
(B){Jan.1998-Dec.2010}:Jan.2011-Dec.2011	**0,26(1)**	**0,48(1)**	**3,22(1)**	**4,93(1)**

Note:Figure in parenthesis denote ranking

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