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Abstract
Recent studies provide evidence that investors participating in the financial markets, decide for their actions using heuristics, according to their feelings and reacting to noise. In this paper, we extract two factors related to the variability of Premium/Discount (P/D): a behavioral and a fundamental. In our opinion Closed-End Funds represent a market where investor sentiment is one key reason for its existence. It seems that the structure of the closed end funds call for the existence of a discount. We provide evidence that using both factors we can achieve a better understanding of discounts as theories and the Closed End Funds Puzzle support it. We believe that one basic reason for that development is the fact that the CEFs being listed companies adds a second component of risk to the market risk that any investor undertakes by investing in a well-diversified portfolio.

Keywords: Behavioral Finance; closed-end funds; premiums/discounts.

JEL: G0.

Introduction

The majority of financial and economic theory is based on the notion of rationality that characterizes the actions of individuals concerning all the available information in the decision making process. In other words the Efficient Market Hypothesis (hereafter EMH), which is actually defined from the above-mentioned sentence, has been the central proposition in Finance for more than thirty years. It states that security prices in financial markets must equal fundamental values, either because investors are rational, or because arbitrage eliminates pricing anomalies (Shleifer, 2000).

An alternative approach has been developed, attempting to better understand and explain how emotions and cognitive errors influence investors and the decision making process. Many researchers believe that the study of psychology and other social sciences can shed considerable light on the efficiency of financial markets and explain many stock anomalies. As an example, some believe that the out-performance of value investing comes from investors' irrational overconfidence in exciting growth companies and from the fact that investors generate pleasure and pride from owning growth stocks. Researchers also believe that these human flaws are consistent, predictable and can be exploited for profit.

Over the past four decades, investment decisions have been guided by efficient market theory. The theory is based on the notion that investors behave in a rational, predictable and unbiased manner. Empirical applications assume that investors aggressively correct stock prices to reflect all publicly available information.

In this paper, we present an empirical investigation of the determinants of the evolution from 1997 to 2004 of the discount on Greek closed end funds. This is achieved using a two-step procedure. Firstly we use a dynamic factor analysis in financial time series and two factors are identified, one fundamental and one behavioral, which quantify the interplay of investor sentiment and arbitrage reaction. Then using these extracted factors, regression analysis is introduced in order to assess their effect on the premium/discount of Greek closed end funds. According to various diagnostic tests, the methodology of Engle *et al.* (1987) has been utilized and maximum likelihood estimation of the ARCH-M model is used to assess the presence of ARCH effect in the data set at hand. In this way, apart from assessing the relative impact of the two factors on the discount, we explore if there were common patterns in premium discount as well as we test if the conditional variance influences significantly the behavior of the premium discount at very high frequencies.

This paper is organized a follows. Section 1 presents a review of the existing literature. Section 2 discusses the various variables that can be used in the formulation of the proposed model. In section 3 we present a theoretical discussion of the factor analysis using for extraction the method of Principal Components to our variables that according to previous research affect or partly explain Premiums/Discounts. Section 4 presents the findings of our empirical study. In section 5 we present a regression model, where we try to capture the relation between the extracted factors derived in section 4 and the premium/discount experienced in the market. The final section concludes the paper discussing the derived results and recommending future further research in this area.

1. Literature review

Closed-End Funds Puzzle has been researched in several studies and several fundamental and behavioural reasons have been proposed. Within the framework provided by EMH approaches, the Net Asset Value (hereafter NAV) miscalculation, the agency costs, the tax-timing hypothesis and the impact of international and domestic market segmentation are included (Dimson and Minio-Kozerski, 1998). Biases in NAV calculation include tax liabilities and liquidity while agency costs include management fees, managerial performance and several other agency problems.

Zweig (1973) and De Long *et al.* (1990a, b) presented first an alternative explanation of the puzzle. Specifically, Zweig was the first to suggest that discounts on closed-end funds reflect expectations of individual investors. Delong *et al.* suggest that fluctuations in investor sentiment can lead to fluctuations in demand for closed-end fund shares, which is reflected in discounts. Lee *et al.* (1990) describe the four important pieces to the closed-end fund puzzle, which also characterize the life cycle of the closed end fund:

1. They start out at a premium of almost 10 percent.
2. They move to an average discount of more than 10 percent within three months of trading.
3. The fluctuations in the discount throughout their life appear to be mean reverting.
4. When they are terminated share prices rise and discounts narrow.

Other findings in the area of Behavioural Finance also provide insights with regard to the puzzle. De Bondt and Thaler (1985, 1987) extended Dreman's (1978) reasoning to predict a new anomaly. They refer to representativeness, that investors become overly optimistic about recent winners and overly pessimistic about recent losers. They found that overreaction lead past losers to become under-priced and past winners to become over-priced. Investors become too pessimistic about past losers and overly optimistic about past winners. As a result they propose a strategy of buying recent losers and selling recent winners.

Schacter *et al.* (1986) demonstrate investors' proclivity to reinforce existing price trends and to reinforce brief price reversals when they become apparent. Also, they found that once a price trend is underway, there is a behavioural tendency for individuals to invest with the direction of the existing price pressure and to exit their positions during brief trend interruptions.

People trade in both cognitive and emotional reasons. They trade because they think they have information when they have nothing but noise and they trade because trading can bring the joy of pride when decisions turn out well. Investors try to avoid the pain of regret by avoiding the realisation of losses, employing investment advisors as scapegoats and avoiding stocks of companies with low reputation.

Hong and Stein (1999) through their research found that under- and over-reactions arise from the interaction of momentum traders and news watchers. Moreover, momentum traders make partial use of the information continued in recent price trends and ignore fundamental news. Finally, they found that fundamental traders rationally use fundamental news but ignore prices.

Hong (2000) found that an increase in the number of investors in a stock demonstrates agreement among a broader base of opinions and forecasts higher returns. The idea of combining fundamental data and behavioural analysis is not a new one. Deaves and Krinsky (1994), show that it is possible to explain some of the findings without abandoning market efficiency. Swaminathan (1996) suggests that discounts may be driven both by sentiment and by fundamentals.

Shefrin (2000) claims that the underlying determinants of the puzzle are heuristic-driven biases and frame dependence. Heuristic-driven bias manifests itself in the form of investor sentiment and volatile investor sentiment is the main driver behind discounts. Loewenstein *et al.* (2001) note that anticipatory affect refers to those emotions and feeling states that are immediate, visceral reactions to perceive risk, uncertainty, or potential rewards. In addition, they note that feelings about risk and cognitive risk perceptions often diverge. Cognitive assessment of risk has a tendency to depend both on probabilities of outcomes and on assessment of outcome severity. In risky situations anticipatory affective reactions often exert a dominating influence on behaviour (over cognitive reactions) and frequently produce behaviours that are not adaptive.

In addition, emotions often produce behavioural responses that depart from what individuals consider as the best course of action. Also note that people tend to be incentive to the statistical probability of a desired or feared outcome occurring when the potential outcome is both emotional and vivid. For example, the thought of receiving an electric shock is enough to arouse individuals emotionally, but the precise likelihood of being shocked has little impact on the level of arousal. They suggest that feelings of fear or worry in the face of decisions under risk or uncertainty have an all-or-none characteristic: they may be sensitive to the possibility rather than the probability of negative consequences. The vividness of a potential reward or catastrophe is more effectively arousing than the probability of its actual occurrence.

2. Variable Selection

From the extensive literature on the subject we can draw a series of alternative variables to use in the formation of a set to examine their explanatory power on Premium and Discount of closed-end funds to their NAV. Malkiel (1977) and Lee *et al.* (1991) provide evidence to support the view that changes in closed-end fund discounts reflect changes in individual investor sentiment using net redemption in the units of open-end funds. Gemmill and Dylan (2002) use as a proxy to trader demand the retail fund flows and find evidence that they account for the variance of discounts of closed-end funds.

Thompson (1978) to conduct his study on the profitability of Discount based strategies uses a two parameter CAPM. Richards *et al.* (1980), Anderson (1986) and Brauer (1988) as Thompson (1978) document significant abnormal returns from assuming long positions on funds with large discounts. In other words those studies suggest the existence of a relation between discounts and market returns. In their studies Brickley *et al.* (1991), Cheng *et al.* (1994) and Minio-Paluello (1998) also use index returns in their models. Finally, Fama and French (1993) propose market as a factor of the discount.

Malkiel (1977) refers to past performance of closed-end funds (NAV performance) as a reason for the existence of premiums or discounts. Another supportive research for the inclusion of NAV in our independent variables comes from Weiss (1989). In this study it is referred that closed-end funds after their listing in the stock exchange move to a discount towards their NAV. Dimson and Minio-Kozerski (1998) also cite the managerial performance versus the funds premium/discount and according to their literature review they discuss the use of NAV versus discounts.

Weiss (1989) suggests that closed-end funds move to a discount to their NAV approximately 120 days after their listing. This evidence implies that time could also be an explanatory variable of the discount. In our analysis we also tried a set of other variables according to Nofsinger (2005) that in his paper cites "…the same social mood can simultaneously influence consumer behavior. An optimistic society is more willing to take on additional debt and increase spending". The author also suggests "… when sentiment investors are optimistic, they are willing to take more risk and buy stocks". As a test to the above propositions we also tried the following variables: the balance of consumer debt, the volume (as a measure of trader demand) and the consumer confidence index as calculated by Eurostat, but unfortunately they did not add to the analysis conducted in this paper.

Table 1: Notation and explanation of variables used

P_D: NAV weighted Premium/Discount using all funds existed during the research period
TIME_12: Time (serial counting of months from 1 to 96)
NAVR: Year to date market capitalization weighted average NAV return
DEURO: Month to month change of equity mutual funds total assets
DSHARES: Month to month change of equity mutual funds number of shares outstanding
LO: Year to date athens stock exchange general index return from the month open
DIN_OUT: Month to month change on the number of equity mutual fund shares issued
MASE: Monthly change of athens stock exchange general index

Source: Association of Greek Institutional Investors and Athens Stock Exchange (1997-2004), Monthly Market Statistics.

Relying on the previous mentioned information, the following table presents the variables included in our analysis. These variables are monthly data from January 1997 to December 2004 (total 96 months).

2.1. Data Set Descriptive Statistics

Although the first closed-end fund incorporated in Greece in 1972, the market really started to exist only after 1990 when several new funds were incepted. The explosion phase for the market came during 1998 and 2000 when almost 30 new funds were incorporated. As we needed standardized NAV calculations in our research we decided to rely only on data gathered by the Association of Greek Institutional Investors. Our decision limited the number of observations to 96 months (full use of AGII database since January 1997), but it provided us with accurate and timely data. Using end of month NAVs and market prices for the same period, we calculated the Premium/Discount per fund using the formula:

$$\text{Premium/Discount} = \frac{\text{Market Price} - \text{Net Asset Value}}{\text{Net Asset Value}}$$

In order to calculate the market Premium/Discount, we calculated a NAV weighted index using all funds existed during the research period. In total we used data from 16 closed-end funds averaging € 25.6 millions and almost 15 years of age at the beginning of the period, i.e. January 1997. Table 2 summarizes the market discount descriptives while Table 3 presents the unit root tests for our original variables as described before. As it can be seen, stationarity is present in all cases.

Table 2: Premium/Discount Descriptive Statistics

Average	-6,98%
High	68,62%
Low	-28,65%
Median	-8,78%
Variance	2,70%
Average Jan-97 to Mar-99	-6,36%
Average Apr-99 to Mar-00	21,13%
Average Apr-00 to Dec-04	-13,82%

Source: Association of Greek Institutional Investors (1997-2004), Monthly Market Statistics.

Table 3: Unit root tests for the original variables and the extracted factors

Variables		**ADF**
DEURO		-3.994
LO		-2.9055
NAVR		-2.9076
DSHARES		-4.6875
MASE		-7.7312
DIN_OUT		-8.5226
P_D		-2.8
FACTOR 1		-2.87
FACTOR 2		-9.2296
Critical values	1%	-2.59
	5%	-1.94
	10%	-1.61

3. A proposed model for the extraction of the components

The idea to perform a Factor Analysis using it as method of extraction the Principal Components came from the fact that according to previous research outcomes all those variables affect or explain partly the closed-end fund puzzle in respect to the premium/discount versus their Net Asset Value. At the same time, suggested variables are expected to present an increased correlation as a result of overlapping variation between them. That would result in multicollinearity in a multiple regression model setup. Researchers suggest the application of factor analysis in order to examine the structure of the overlapping variation between the predictors (Leeflang *et al.*, 2000) claiming that the only problem in this case remains the theoretical interpretation of the final components (Greene, 2000; Gurmu *et al.*, 1999).

Year to date returns as well as monthly changes were selected, as people understand several measures on the basis of data provided to them and the way they are provided this information. In other words the information regarding the Athens Stock Exchange is being given through the level of the ASE General Index. When it comes to returns, investors can get it on a daily or monthly basis or, which is the most popular reference, from the beginning of the year, the year to date return (ytd). This results to an increased correlation between the P_D and the ASE ytd return as opposed to the monthly change in P_D and the monthly ASE return. To be more specific, the correlation coefficient between the monthly ASE return and P_D change is 0.201 and statistically insignificant where it reaches 0.542 significant at 0.01 level when the variables are P_D reading and ASE ytd return at the end of each month.

Specifically referring to the factor model, if we have a p-indicator m-factor model then the basic factor analysis equation is given by

$$X = \Phi\zeta + u \qquad (1)$$

where X is a px1 vector of variables, Φ is a pxm matrix of factor pattern loadings, ζ is an mx1 vector of unobservable factors and u is a px1 vector of unique factors. It is assumed that the factors are not correlated with the error components. The correlation matrix R of the indicators is given by

$$E(XX') = E(\Phi\zeta\zeta'\Phi') + E(uu') \qquad (2)$$

$$\mathrm{R} = \Phi\Lambda\Phi' + \Omega \qquad (3)$$

Where Φ, Λ, Ω matrices are parameter matrices and where R is the correlation matrix of the observables, Λ is the correlation matrix of the factors and Ω is a diagonal matrix containing the unique variances. The diagonal of the R-Ω matrix gives the communalities. The off diagonal of the R matrix give the correlation among the indicators.

The correlation between the indicators and the factors is given as

$$E(X\zeta')=\Phi E(\zeta\zeta')+E(u\zeta') \tag{4}$$

$$A=\Phi\Lambda \tag{5}$$

Where A is the correlation between indicators and factors. Rotations of the factor solution are the common type of constraints placed on the factor model for obtaining the unique solution. In our case we have followed the varimax rotation. The objective of this rotation is to determine the transformation matrix C in such a way as any given factor will have some variables loaded high on it and some loaded low on it. This may be achieved by maximizing the variance of the square loading across variables subject to the constraint that the communalities of each variable remain the same (Johnson and Wichern, 1998; Sharma, 1996).

The factor scores are calculated as

$$\hat{F} = X\hat{B} \tag{6}$$

where $\hat{F}$ is an mxn matrix of m factor scores for n indicators, X is an nxp matrix of observed variables and $\hat{B}$ is a pxm matrix of estimated factor score coefficients. If we standardized our variables

$$\hat{F} = Z\hat{B} \Rightarrow \frac{1}{n}Z'\hat{F} = \frac{1}{n}Z'ZB \Rightarrow \Phi = R\hat{B} \tag{7}$$

as $\frac{1}{n}(Z'Z) = R$ and $\frac{1}{n}Z'\hat{F} = \Phi$

Thus the estimated factor scores coefficient matrix is given as $\hat{B} = R^{-1}\Phi$ and the estimated factor scores by $\hat{F} = ZR^{-1}\Phi$.

The factor scores are extracted using the following expression

$$f_j = w_{j1}X_1 + w_{j2}X_2 + w_{j3}X_3 + ... + w_{jp}X_p \qquad (8)$$

where f_j is the score of the j common factor, w_{ji} are considered unknown and they are estimated using regression. In the Principal Components method applied here for the extraction of the factors the scores are exactly calculated. Residuals are computed between observed and reproduced correlations.

4. Empirical Results

Table 4 presents the factor loadings, communalities and specific variance contributions according to the Principal Components method of extraction in a Factor Analysis setup. Looking at Table 4 it can be seen that variables 1, 6 and 7 define factor 1 (high loadings on factor 1, small or negligible loadings on factor 2), while variables 2, 3, 4 and 5 define factor 2 (high loadings on factor 2, small or negligible loadings on factor 1). The communalities (0.867, 0.676, 0.926, 0.500, 0.518, 0.879, 0.529) being quite high indicate that the two factors account for a large percentage of the sample variance of each variable and is another evidence that the model presents stability.

In an attempt to explain the results of our analysis we can conclude that there are clearly two different sets of independent variables in our sample. The first set consisting of NAV ytd return (NAVR), ASE ytd return (LO) and TIME is the set of variables we can call the Fundamental Factor. It consists basically of those variables that count for the direct fundamental reasons for the variability both in Price (ASE ytd return) and in NAV (NAV ytd return) and as a result the variability of the calculation: (P-NAV)/NAV = P_D. The second set consisting of the change in number of Equity Mutual Funds Shares Outstanding (DSHARES), the change in Inflows/Outflows in Equity Mutual Funds (DIN_OUT), the change in total assets Equity Mutual Funds (DEURO) and the monthly change of the Athens Stock Exchange General Index (MASE), and is the set we can call Behavioral Factor. It includes those variables that (in line with the bibliography) account for the changes in investors' sentiment.

Table 4: Statistical Output of Factor Analysis

Variables	Estimated factor loadings		Rotated factor loadings		Communalities
	F_1	F_2	F_1^*	F_2^*	$\hat{h}_i^2$
NAVR	0.817	-0.448	0.909	0.203	0.867
DSHARES	0.804	0.172	0.290	0.660	0.676
DEURO	0.884	0.378	0.215	0.868	0.926
MASE	0.587	0.394	0.181	0.683	0.500
DIN_OUT	0.428	0.579	-6.04E-02	0.717	0.518
L_O	0.851	-0.392	0.899	0.267	0.879
TIME_12	-0.586	0.431	-0.725	-6.26E-02	0.529
Cumulative Proportion of Total sample Variance explained	0.527	0.172	0.372	0.327	0.699
Kaiser-Meyer-Olkin	0.673				
Bartlett's test of Sphericity	594.333 (Significance = .000000)				

In other words, these variables do not have direct fundamental relation with the variability of P_D and we will examine their actual impact on that. We can also note that as all the Closed End Funds (hereafter CEF) in Greece invest the majority of their assets in listed equities in the Athens Stock Exchange, their performance is directly related to the performance of the market and consequently to a broad market index as the ASE General Index.

5. Performing a Regression Analysis of P_D on the extracted factors

The idea of performing a regression analysis between a dependent variable and extracted factors is not a new one. Dunteman (1989) also suggests this process to cope with multicollinearity in a regression analysis model and it is also an indicated way to minimize the number of independent variables and maximize the degrees of freedom.

Based on the CAPM theory regarding the returns of a stock with respect to the market returns, we consider that the Premium/Discount measure can be a function of the market return. Following the rational model for the financial markets, investors are rational and wealth maximizers. Under this model investors are expected to pay for a share no more than the actual value of it, while arbitrageurs will be always present to make profit out of any mispricing. Literature provides several fundamental reasons for the existence of a discount. The same literature even since early 70's and Zweig (1973) noticing that there is another factor that we can call "investor sentiment" to influence the discounts.

The assumption in the proposed model is that the final output of the existence of a Premium or Discount for the CEFs will be related to the market fundamentals as well as to the sentiment of the investors that changes for other than fundamental reasons. The second factor presented in section 4 will help as a proxy in our attempt to identify the influence of market sentiment in the experienced P_D of the CEFs in the Greek market the previous eight years. The first factor presented in section 4 will help as a proxy of the fundamentals respectively.

Running a regression between P_D and the extracted factors and as it can be seen from Table 5, only the first factor is statistically significant. In the same table some diagnostic statistics and the associated P-values can be found. The first and second rows in the diagnostics give the results of the Box-Pierce test on the residuals and the squared residuals. If the mean equation is correctly specified all Q statistics should be insignificant. The third row gives the result of the Jarque-Bera test for normality of errors, the fourth, fifth and sixth give the LM tests and the P-value for ARCH(1), ARCH(2) and ARCH(3) specifications of the residuals and the seventh the Breusch-Godfrey LM test for serial correlation. The first (simple) model according to the diagnostic tests has normality problems, ARCH effects and autocorrelated errors.

To avoid autocorrelation and increase the explanatory capacity of the model, we decided to incorporate in our analysis as an independent variable the Premium/Discount lagged one month. The idea behind the selection is no other than the effect that the existing (known) Premium/Discount should have on current developments. In financial markets existing situations are very influential.

Running the model with the premium discount lagged one month, gives the constant term (at 10% significance level), both factors and the lagged Premium/Discount variables statistically significant. Lagged Premium/Discount has the strongest relation to P_D. This means that existing situation (in terms of Premium or Discount) is quite important to the reading of P_D in the current month. Both fundamental and behavioral factors should go through important changes to alter existing premium (or more usually discount) into a discount (premium). Of the two factors the first one (fundamental) has a slightly stronger relation to P_D. In other words starting from equilibrium where neither premium nor discount exists, fundamentals will initially drive the market more than behavioral aspects. When a situation has been established, it will replicate itself (lagged P_D) until either fundamental or behavioral reasons, or both of them, strongly change.

Table 5: OLS and ML ARCH-M estimates (Dependent variable P_D)

Parameters	Estimates	P-values	Estimates	P-values	Estimates	P-values
Regression						
Constant	-0.0702	0.000	-0.0151	0.0526	-0.03076	0.000
Factor 1	0.1053	0.000	0.0392	0.000	0.0225	0.020
Factor2	0.0102	0.4305	0.02665	0.000	0.0198	0.000
P_D_{t-1}			0.7655	0.000	0.805	0.000
GARCH					0.4011	0.000
GARCH						
γ_0	-	-	-	-	0.0009	0.000
γ_1	-	-	-	-	0.9249	0.000
R^2 Adjusted	0.41		0.833		0.82	
Log Likelihood	64.46		124.54		155.56	
F-statistic	33.37	0.000	157.88	0.000	70.42	0.000
DW	0.454		2.51		2.59	
Diagnostics						
Q(12)	190.19	0.000	23.862	0.021	7.2083	0.944
Qsq(12)	86.448	0.000	40.273	0.000	1.6167	0.446
Jarque-Bera	21.99	0.000	155.94	0.000	1.088	0.58
ARCH(1)	24.074	0.000	31.9	0.000	1.49	0.222
ARCH(2)	35.62	0.000	33.019	0.000	-	-
ARCH(3)	36.022	0.000	32.983	0.000	-	-
Breusch-Godfrey	58.86	0.000	8.28	0.016	-	-
Engle-Ng	-	-	-	-	2.321	-

It remains on the actual importance of each one of those factors at any given point in time, to define the existence of a premium or a discount for the sector. It can be well understandable, that although fundamental variables have a stronger impact on the P_D of the CEFs, during periods where market sentiment accumulates the actual importance of this factor increases to an extent that its final effect determines the P_D.

The fact that the constant term has a negative sign and is statistically significant can be explained on the basis of the construction of the CEFs market. We believe that one basic reason for the development of discounts is the fact that the CEFs, being listed companies, adds a second component of risk to the market risk that any investor undertakes by investing in a well-diversified portfolio. However we have serious problems with all the diagnostic tests.

In our last step we investigated the need to extend our model to cope with ARCH effects and risk as an explanatory variable. The most common used ARCH and GARCH models as introduced by Engle (1982) and Bollerslev (1986) take h^2 (the conditional variance) as a linear function of lagged conditional variances and squared residuals. Theoretically these models are characterized by linearity as they imply an ARMA equation for the squared prediction errors u_t^2 allowing a full study of the distributional properties of u_t as well as easier statistical inference. A number of alternative parameterizations for the function h have been suggested in the literature.

Researchers have used the ARCH-M class of models as proposed by Engle *et al.* (1987) and Bollerslev *et al.* (1992). According to this model, the conditional mean is an explicit function of the conditional variance or standard deviation of the forecast errors. The basic idea in this model, as in many theories in financial economics, is the use of a measure of risk as an explanatory variable. To the extent that the conditional variance of an error term is a measure of risk it seems reasonable that the variance should enter the regression function as a measure of the risk premium.

In our work, the general form of the model is:

$$P\_D_t = c + a_1\ FACTOR_1 + a_2 FACTOR_2 + b\ P\_D_{t-1} + \delta\, \mathrm{h}_t^2 + \mathrm{u}_t \quad (9)$$

$$\mathrm{u}_t \mid \Omega_{t-1} \sim \mathrm{N}(0,\ h_t^2) \quad (10)$$

$$h_t^2 = \gamma_0 + \sum_{i=1}^{n} \gamma_i u_{t-i}^2 + \zeta Z_t \quad (11)$$

where Z_t is a vector of weakly exogenous conditioning variables. Equation (9) is a ARCH-M regression model for the mean P_D. Equations (10)-(11) give the ARCH structure of its conditional time varying variance where Ω denotes an appropriate information set up to time t-1. Equation (11) is a non-stochastic equation and h_t^2 is the conditional variance of u_t at period t relying on information available up to period t-1.[1]

In Table 5 and in the last two columns we present the estimation results for model (9-11). The first of the last two columns contains the parameters following the notation of relationships (9)-(11). The coefficient γ_1 has a reasonable size and sign and it is significantly different from zero at all levels. This suggests that there is an important ARCH component to the error process. Both coefficients c and b have sensible magnitudes and they are significant suggesting that the risk premium is time varying.

In the case of the ARCH-M model, the diagnostic tests were applied again. Normality of the standardized residuals is present and the variance equation is correctly

[1] The likelihood function was maximized by using the SIMPLEX algorithm in terms of improving the initial starting values and the BHHH algorithm to achieve both convergence and consistency in the estimates of the asymptotic standard errors (Berndt *et al.* 1974).

specified as all Q-statistics of the residuals are insignificant. As the ARCH(1) test shows, the standardized residuals do not exhibit additional ARCH effects. Finally, a joint diagnostic test for nonlinear ARCH effects (following Engle and Ng, 1993) is reported in the last row of table 5. The test relies on the following regression

$$\varepsilon_{it}^2 = a + bS_{t-1}^- + b_2 S_{t-1}^- \varepsilon_{i,t-1} + b_3(1 - S_{t-1}^-)\varepsilon_{it-1} + cZ_i + e_i \qquad (12)$$

where ε_{it} standardized residuals, S_{t-1} dummy variable taking the value of 1 if ε_{it-1} is negative and 0 otherwise and Z a vector of explanatory variables. The test statistic for this test is the LM statistic n $R^2 \sim \chi_\alpha^2$ with 3 degrees of freedom and it is not significant at the usual significance levels implying that the used volatility model is not rejected.

6. Conclusions

In this paper, we extract two main factors related to the variability of P_D. The first consists of NAV ytd return (NAVR), ASE ytd return (LO) and TIME variables, which we call the fundamental factor. The second factor consists of the change in number of Equity Mutual Funds Shares Outstanding (DSHARES), the change in Inflows/Outflows in Equity Mutual Funds (DIN_OUT), the change in total assets Equity Mutual Funds (DEURO) and the monthly change of the Athens Stock Exchange General Index (MASE), which we call the behavioral factor. Although one may has good reason to argue on the economic view point of our classification, the relative bibliography on the subject suggests that the use of our variables have been tested by other researchers and provided similar results. It is also interesting to argue on our classification of the variable "Monthly Change of the ASE" as a behavioral one. Most investors react to the market level regardless of the fundamentals behind it. For example during the 1999 “bubble” in Greece, there were almost 10 times more active investors than three years later.

Using these factors as independent variables in a regression analysis where the experienced premium/discount of the Greek CEFs market is the dependent variable, our results come in line with the literature. First of all it seems that the structure of the closed end funds call for the existence of a discount (we got a negative sign for the constant of the model). We believe that one basic reason for that development is the fact that the CEFs being listed companies adds a second component of risk to the market risk that any investor undertakes by investing in a well-diversified portfolio (broad market index). As a result, in comparison to the market pricing, CEFs should be priced lower as a compensation for that additional risk the investor carries. That lower market price will finally be at discount to the NAV that is calculated on the basis of the market prices.

There have been several researchers trying to explain the existence of the discount on the basis of the efficient market hypothesis. Our model agrees with them. Fundamental factor has a positive relation and a slightly greater impact than behavioral on the development of the P_D of the CEFs. On the other hand sentiment is one reason that can explain why some funds -and in some cases more than some- trade far away from what the literature defines as expected discount and also, with premium. So we would expect that the behavioral effect would have a positive relation with Premium/Discount levels. This is supported form the results of our analysis as the behavioral factor (factor 2), has a positive sign. In other words the higher the level of the market sentiment, the smaller the discount of the closed-end funds, which can also be a premium. Finally in our analysis the coefficient of the risk factor was significant as an explanatory variable to P_D and an ARCH-M model was enough to explain the time variation in the premium discounts.

The more optimist people feel the higher the trading activity, the higher the level of the market (and the positive feedback), the more they invest in mutual funds. As a result positive changes in these "sentiment" indices, result in positive changes in the premium/discount. Our findings follow the literature and provide evidence for the impact of two sets of different factors in the development of premium/discount in the CEFs market in Greece. We believe that future research using other variables, as proxies of the behavioral and fundamental factors will help the community understand better the structure and support the validity of the proposed model.

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