The Uncertainties About the Relationships Risk – Return – Volatility in the Spanish Stock Market

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Summary

The relationships between the market risk premium, its conditional variance and the risk free rate in the Spanish stock market are studied in this paper. Using daily data, the above mentioned relations are analyzed by quasi maximum likelihood for an EGARCH-M(1,1) model with normal innovations and by nonparametric maximum likelihood for a semiparametric EGARCH-M(1,1) model with arbitrarily distributed innovations. It is worth mentioning that the conclusions differ from one model to the other.

Keywords: market risk premium, nonparametric estimation, bootstrap.

1. **Introduction**

The use of conventional assets pricing models, as the CAPM version for which market risk premium is proportional to its own variance, has brought much attention to the analysis of the relationship between the market risk premium and the conditional market variance.

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There are plenty of empirical works in the existing literature that study this relation. However, it does not exist a total agreement about this issue. Thus, while Harvey (1989), Turner et al. (1989) and Scruggs (1998) find some significant positive relation, some other authors as Fama and Schwert (1977), Breen et al. (1989), Campbell (1987), Nelson (1991), Glosten et al. (1993) and Whitelaw (2000) obtain a negative relation, which is significant in a considerable number of cases. Recently, Girard et al. (2001) analyzed the relation return – risk in nine Asian stock markets and in the US market, before, during and after the financial crisis in Asia, showing the sign changes that take place in the mentioned relation.

In the Spanish market, the analysis of the relation between the market return and its risk has been carried out by Alcalá et al. (1993), who followed the procedure proposed by French et al. (1987), and Alonso and Restoy (1995), that used the methods in Chou et al. (1992). In both cases it is found some time dependent relation between the market risk premium and its conditional variance.

On the other hand, the relation between the risk free rate and the market volatility has been studied, in an international context, by Campbell (1987), Breen et al. (1989), Shanken (1990), Glosten et al. (1993) and Scruggs (1998), among others. All these authors find a significant positive relation using monthly data. Lobo (2000) focuses on the variation of the interest rate and analyzed the impact of the announcements of changes in the interest rates by the US Federal Reserve on the risk aversion and the market volatility.

In the case of the Spanish Market, only Alonso and Restoy (1995) have studied the relation between the conditional market variance and the risk free rate. These authors find no significant relation.

Without a clear agreement, the aim of this work is to study the relation between the market risk premium and its conditional variance via a classical parametric model and a new semiparametric model, which does not impose the normality assumption for the innovations. Comparison of the results using both approaches is useful to understand how important are the assumptions in the model and how different may be conclusions. Of course, these models incorporate the possible influence of the risk free rate on the mentioned relation.

Daily data will be used in this paper. This frequency is of rather common use when analyzing the return given by a market index, which is a standard approach to the market portfolio. However the daily frequency is not so usual in the previous works that have studied the behaviour of the market with respect to the risk free rate. Undoubtedly it is difficult to determine the optimal choice of the frequency to be used when selecting the risk free assets. Thus Nelson (1991), in spite of using daily data in the portfolio analysis, makes use of monthly T-Bills return, assuming that this return is constant throughout every month.

One of the novel aspects included in this paper is the use of the overnight general collateral government repo rate expressed as continuously compounded daily return. This procedure eliminates the “maturity mismatch” problem that appears in previous studies in which the risk free rate has longer maturity (e.g. one month) than the market returns. Also, we think that this rate is the best approach to the risk free rate, since it is subjected to less external effects than other interest rates used in many other approaches. In other studies of the Spanish market, as in Alonso and Restoy (1995), two alternatives have been used to measure the risk free assets return: the weighted average interest rate of the intermediate aggregated between M3 and M2 and the rate corresponding to the one-month government repos. However, we consider that these return and frequency are the most appropriate due to the confidence reported by the data revealed by a risk free transaction.

The period of time studied is January 1994 - December 2001. This is a recent period that exhibits different changes in return and risk of the Spanish market within a European and international high volatility context.

The rest of the paper is organized as follows. Section 2 describes the procedure used to obtain the data to be analyzed. The classical EGARCH-M(1,1) model used in this analysis is presented in Section 3, while the new semiparametric model is introduced in Section 4. Finally, Section 5 is devoted to the conclusions.

2. Data description

The daily risk premium in the Spanish stock market in the period January 1994 - December 2001 will be considered. The market proxy is the IBEX-35 index, which is a value-weighted index comprising the 35 most liquid Spanish stocks traded in the continuous auction market system. The market risk premium is computed as the difference between the IBEX-35 return and the risk free rate.

The one-day return for an investment in IBEX-35, R_t, is determined as the difference of the logarithms of the series of daily closing prices, multiplied by 100:

$$R_t = \left(Ln\left(Ib_t\right) - Ln\left(Ib_{t-1}\right)\right) \cdot 100,$$

where Ib_t is the closing price of IBEX-35 on the day *t*. This series has been obtained from Madrid Stock Markets Society (Sociedad de Bolsas de Madrid).

In order to compute the one-day risk free investment return, x_t, one has to take into account the settlement process of the repo transactions in the Spanish Public Debt market and the interest rate to be used. This rate is the average interest rate of the Treasury bills and bonds overnight repo transactions, weighted with the negotiated cash of that day (These data are available at the Bank of Spain (Banco de España) web page: www.bde.es). The settlement process of this market implies the application of this interest rate during the calendar days between the buy and the sale of the alternative risky investment, in other words, the days between two consecutive trading sessions. Consequently, the return to be discounted to the market portfolio return is:

$$x_t = Ln\left(1 + i_{t-1} \cdot \frac{n}{360}\right) \cdot 100,$$

where

i_{t-1} is the interest rate of the overnight repo transactions in the session of the day *t*-1, that corresponds to the session in which the market portfolio (IBEX-35) is bought.

n is the number of calendar days between two consecutive trading sessions that correspond to days t and t -1.

As in Aggarwal and Schatzberg (1997), we will use these logarithmic returns since they represent geometric return rates, which lead to more conservative estimations of the deviations with respect to the assumption of normal distribution for these returns.

The market risk premium, y_t, is computed using the two variables (R_t, x_t). It is the one-day excess of the market portfolio return, after discounting the return of a risk free investment:

$$y_t = R_t - x_t .$$

where

R_t is the total IBEX-35 return of day *t*.

x_t , is the free risk return of day *t*.

After obtaining the daily risk premium series of the Spanish market we performed a standard statistical analysis, which reveals the absence of daily seasonality (see Table 1). Rejection of the Dickey-Fullertest for unit roots and simple observation of figure 1 shows that this series is stationary (This is not an asymptotically distribution free test, so the value of the test statistic has to be compared with the critical value, approximated by simulation, pertaining to the sample size used.). In spite of this, a high first order autocorrelation is evident. This is a very important issue when designing the econometric model to be applied. The significance of this autocorrelation is confirmed using the Q test statistic of Ljung-Box, with approximated distribution given by a Chi-squared with as many degrees of freedom as lags involved in the test (in this particular case, only one).

PUT TABLE 1 ABOUT HERE

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3. Market risk premium, volatility and risk free rate under normality assumptions

3.1. Quasi Maximum Likelihood Estimators

To analyze the relation among the market risk premium, its conditional variance and the risk free rate we start by assuming that the innovations in the model have normal distribution.

Our model requires the specification of the market risk premium and its conditional variance in two separate equations. Motivated by the existing empirical literature about the market volatility, we assume here that second order moments fit to an EGARCH (1,1) process, introduced by Nelson (1991). EGARCH models are an important extension of GARCH, where the conditional variance can respond asymmetrically to the sign of the innovations appearing in the market portfolio return. Demos and Sentana (1998) is an example of some work analyzing these responses. Engle and Bollerslev (1986) and Bollerslev (1986) carried out an extensive study on the GARCH and GARCH-M models in a financial context. Applications of these models can be found in Bollerslev et al. (1992), Engle et al. (1990), Engle and González (1991), Sentana (1995), Sentana (1997), Sentana (1998), Sentana (2004) and Sentana and Fiorentini (2001).

Of course, nonnegativeness of the conditional variance, h_t, has to be imposed. The EGARCH-M models (EGARCH in mean) introduce the conditional variance in the equation that models the market risk premium. These are the models that will be used along this paper (Engle et al. (1987) also used this model).

As pointed out in the previous section after identifying a significant first order autocorrelation our model needs to include the first lag in the equation for the market risk premium. In this way we prevent the resulting residuals to be correlated.

The general equation for the market risk premium is:

$$y_t = \lambda_0 + \lambda_r y_{t-1} + \lambda_M h_t + \lambda_f x_t + u_t \tag{1}$$

where

y_t is the market risk premium at day *t*;

h_t is the conditional variance at day *t*;

λ_0 is a constant that involves those aspects not explained by the variables included in the model;

λ_r is the parameter that measures the relation between the market risk premium and its first lag;

λ_M is the parameter that accounts for the increment or decrement of the risk premium by volatility unit. This is the reason why it is often called *volatility price* when it takes positive values;

λ_f explains how the risk free rate influences the market risk premium;

u_t is the innovation in the risk premium at day *t*.

The general formula for the conditional market variance in our EGARCH-M (1,1) model is the following:

$$Ln(h_t) = w_M + \alpha_M \cdot (|v_{t-1}| - E_{t-1}(|v_{t-1}|)) + \theta_M v_{t-1} + \beta_M \cdot Ln(h_{t-1}) + \gamma_M \cdot x_t \quad (2)$$

where

$v_{t-1} = \frac{u_{t-1}}{\sqrt{h_{t-1}}}$ is the conditional standardized innovation;

$E_{t-1}(|v_{t-1}|) = \sqrt{2/\Pi}$, is the conditional expectation of the absolute innovation (which may be explicitly computed under normality);

$\alpha_M \cdot (|v_{t-1}| - E_{t-1}(|v_{t-1}|)) + \theta_M v_{t-1}$ is a term that includes the response of the conditional variance to the sign and to the magnitude of the lagged innovations. If θ_M is zero, the response is symmetric and only depends on the absolute value of the lagged innovation. The parameter θ_M measures the asymmetric response of the conditional variance to the sign of the lagged return innovation. If $0 \le \theta_M \le 1$, $(-1 \le \theta_M \le 0)$, conditional variance increases more in response to positive (negative) innovations than to negative (positive) innovation of the same magnitude. If $\theta_M = 1$, $(\theta_M = -1)$, the news response function is positive for $v_{t-1} > 0$ $(v_{t-1} < 0)$ and zero otherwise. Finally, if $\theta_M > 1$, $(\theta_M < -1)$, the news response function is upward (downward) sloping in v_{t-1}.

β_M measures the persistence of the conditional market variance. This parameter can be used to measure the half-life of return shocks. The half-life of return shocks, *h*, can be computed by solving the equation $\beta_M^h = 0.5$. It can be interpreted as the number of trading days needed until vanishing of the response of the conditional variance to the lagged innovation.

γ_M is the parameter that accounts for the relation between the risk free interest rate and the market conditional variance.

The Quasi Maximum Likelihood (QML) method will be used for the simultaneous estimation of the parameters in Eq. (1) and (2) that govern the risk premium and its conditional variance. The

QML estimations are computed by just obtaining the value of the vector $P = (\lambda_0, \lambda_r, \lambda_M, \lambda_f, w_M, \alpha_M, \theta_M, \beta_M, \gamma_M)$ that maximizes the logarithm of the likelihood function:

$$L = \sum_{t=1}^{T} \ell_t(P) \tag{3}$$

In this section the log-likelihood function will be determined under the assumption that the innovation of the market risk premium is normally distributed. Thus, a general term in (3) has the form:

$$\ell_t(P) = -\frac{1}{2} \cdot Ln(2\Pi) - \frac{1}{2} Ln(h_t) - \frac{1}{2}\left(\frac{u_t^2}{h_t}\right) \tag{4}$$

The nonlinear function of the parameter P, obtained by substituting the u_t and h_t -in Eq. (1) and (2)- into Eq. (3) and (4), can not be maximized explicitly. Consequently, the QML estimation is computed as some numerical approximation of that maximizer. Bollerslev and Wooldridge (1992) have proved that the QML estimator of P is consistent provided that

$$E_{t-1}\left(u_t \big/ \sqrt{h_{M,t}}\right) = 0$$

$$E_{t-1}\left(u_t^2 / h_t\right) = 1$$

These authors also obtained formulas for the standard error that are robust to deviations from normality. These are the standard error formulas that will be used in this paper. The numerical procedure to approximate the maximizer of the likelihood function is the algorithm by Berndt et al. (1974).

3.2 Results

Already existing empirical studies have shown that the market volatility is persistent, it responds asymmetrically to the lagged innovations and it is related to the risk free rate. Several authors have observed that the market volatility tends to increase when the risk premium innovations are negative. Christie (1982) explains the negative relation between price and volatility through the changes in the financial leverage of the companies (leverage effect). In this respect, Table 2 shows a high persistence of the market volatility and a larger response of the conditional variance to the innovations with negative sign. In order to examine the robustness of the results in terms of the time period the sample has been split into two parts and these two half-samples have been analyzed.

PUT TABLE 2 ABOUT HERE

The existing relation between the risk free interest rate and the volatility is negative, with a p-value of 0.17. This means that this relation is not significant for standard levels of 1% or 5%. However, this is not caused by a small value of the estimated parameter γ_M but by the high variability of its estimation. The negative sign seems to be a consequence of the behaviour of the risk free rate that has decreased throughout the studied time period, while the volatility behaved the opposite.

When focusing on the market risk premium equation, there is only one parameter that is significant. This is λ_r, that explains the effect of the lagged premium. The results confirm the significant first order autocorrelation already found in the first statistical analysis of the series.

The relation market risk premium – volatility, measured through the parameter λ_M, is positive. However, this estimated parameter is not significant. This indicates the insignificant effect that the changes in the conditional variance have in the demanded market risk premium.

The effect of the risk free rate on the market risk premium is not significant in any case. The negative sign found for this coefficient coincides with the results in Scruggs (1998). In the same way the effect of the conditional variance on the risk premium is not significant, which was not the case in the paper by Scruggs (1998).

Most of the previous comments remain true for the two half-samples analyzed. However, it is worth mentioning that the estimated relation between the risk free interest rate and the volatility has different signs (although not significant) in the two time periods. This is also the case of the relationship between the risk free interest rate and the market risk premium, as a consequence of the opposite trends in both rates during the first time period.

In summary, the main conclusion is the absence of effect of the volatility on the risk premium in the Spanish market. However, it is very important to remark that this conclusion has been drawn under the normality assumption for the innovations. Consequently, it is very reasonable to check if this statement remains true when the model does not rely on this parametric assumption. To do this, we will present in the next section a semiparametric model whose parameters will be estimated by nonparametric maximum likelihood.

4. Market risk premium, volatility and risk free rate without normality assumptions

4.1. Nonparametric Maximum Likelihood Estimators

We now deal with model (1)-(2) without assuming that the standardized innovations, v_t, have normal distribution. We just assume that the v_t are independent random variables with a common (unknown) density function, f, which needs not to be normal. To produce some nonparametric version of the likelihood function that does not rely on normality assumptions we follow the lines of Cao et al. (2003) (see also the paper by Engle and González (1991) for a similar proposal in the context of ARCH models).

In this nonparametric framework, the logarithm of the likelihood function in (3) can be replaced by:

$$L^{NP} = \sum_{t=1}^{T} \ell_t^{NP}(P) , \tag{5}$$

where

$$\ell_t^{NP}(P) = -\frac{1}{2} Ln(h_t) + Ln\left(\hat{f}\left(\frac{u_t}{\sqrt{h_t}}\right)\right) \tag{6}$$

and $\hat{f}$ is a nonparametric kernel density estimator of f (see, for instance, Silverman, 1986) that can be constructed using the residuals of the model after a parametric fit.

More precisely, using $\hat{P}^{QML}$, the QML estimator of the parameter P, and considering $\hat{v}_t^{QML}$, the residuals of the model given in (1) and (2), we compute the values u_t and h_t in (6) –depending on the components of the parameter vector P - as follows:

$$h_1 = c^{\beta_M} \exp(w_M + \gamma_M \cdot x_1)$$

$$u_1 = y_1 - \lambda_0 - \lambda_r \frac{1}{T}\sum_{s=1}^{T} y_s - \lambda_M h_1 - \lambda_f x_1$$

$$v_1 = \frac{u_1}{\sqrt{h_1}} \text{ and, for } t = 2,3,\ldots,T$$

$$h_t = h_{t-1}^{\beta_M} \exp\left(w_M + \alpha_M \cdot \left(\left|v_{t-1}\right| - b\right) + \theta_M v_{t-1} + \gamma_M \cdot x_t\right)$$

$$u_t = y_t - \lambda_0 - \lambda_r y_{t-1} - \lambda_M h_t - \lambda_f x_t$$

$$v_t = \frac{u_t}{\sqrt{h_t}}$$

where

$$a = \frac{1}{T}\sum_{t=1}^{T} \hat{v}_t^{QML}, \quad \tilde{v}_t = \hat{v}_t^{QML} - a \quad (t = 1,2,\ldots,T), \quad b = \frac{1}{T}\sum_{t=1}^{T}\left|\tilde{v}_t\right|, \quad c = \frac{1}{T}\sum_{t=1}^{T}\tilde{v}_t^2.$$

The estimator, $\hat{f}$, of the innovation marginal density is defined as

$$\hat{f}(z) = \frac{1}{T \cdot s}\sum_{t=1}^{T} K\left(\frac{z - \hat{v}_t^{QML}}{s}\right) \tag{7}$$

where the kernel function K has been chosen to be Gaussian (a standard normal density function) and the smoothing parameter, s, has been selected according to the smoothed bootstrap method proposed by Cao (1993). Finally, the nonparametric maximum likelihood estimator, $\hat{P}^{NPML}$, is obtained as the maximizer in P of the function $L^{NP} = \sum_{t=1}^{T} \ell_t^{NP}(P)$ in (5). This has to be done, of course, by using numerical methods. The microgenetic algorithm of ModGA has been used to this aim. Developed by Zheng (1997), ModGA is a simulation-optimization model which couples genetic algorithms, a global search technique inspired by biological evolution.

In practice it is not enough to compute the estimated components of the parameter vector P. One has to report some p-values in order to judge their statistical significance. In order to do this we have considered a smooth bootstrap approach similar to the one already used by Cao et al.(1997) in an autoregressive setting.

Roughly speaking the smoothed bootstrap method proceeds as in (1) and (2) but replacing the unknown parameter P by its estimator $\hat{P}^{NPML}$ and the unknown innovations u_t by some artificial innovations, u_t^*, simulated from the estimated density $\hat{f}$ in (7). The new bootstrap series y_t^* $(t = 1, 2, \ldots, T)$ is then computed and the bootstrap version of the nonparametric maximum likelihood estimator, $\hat{P}^{*NPML}$, is also found. This process has been repeated 1000 times and the 1000 bootstrap replications of $\hat{P}^{*NPML}$ are used to approximate the sampling distribution of $\hat{P}^{NPML}$. Finally, the bootstrap approximation of the p-value is just the frequency of bootstrap resamples for which the absolute value of the difference between the considered component of $\hat{P}^{*NPML}$ and $\hat{P}^{NPML}$ is greater than the absolute value of the pertaining component of $\hat{P}^{NPML}$. Let us illustrate this with an example.

Suppose, for instance, that we want to study the relation between the risk premium and the risk free rate. Mathematically we have to test the hypothesis H_0: $\lambda_f = 0$ versus the alternative that this coefficient is not zero. Using the previous bootstrap approach we obtain 1000 bootstrap versions of the NPML estimator, $\hat{\lambda}_f^{*NPML(i)}$, for $i = 1, 2, \ldots, 1000$ and approximate the p-value by

$$p = \frac{\#\left\{ i = 1, 2, \ldots, 1000 : \left| \hat{\lambda}_f^{*NPML(i)} - \hat{\lambda}_f^{NPML} \right| > \left| \hat{\lambda}_f^{NPML)} \right| \right\}}{1000}.$$

Some alternative bootstrap resampling plan that sets $\lambda_f = 0$ (which is closer to the null hypothesis) was also used but the results were very similar to those of the one presented above.

4.2 Results

The estimated values of the nine parameters in the EGARCH-M(1,1) model using the nonparametric maximum likelihood estimators are presented in Table 3 for the whole sample and the two half-samples. This table also collects their p-values, that has been approximated using the smooth bootstrap approach presented in the previous section. The results for most of the parameters are very close to those obtained with the QML approach with two exceptions: λ_f and γ_M.

PUT TABLE 3 ABOUT HERE

The estimated values for λ_f, the parameter that measures the relation between the risk premium and the risk free rate, are similar for the QML and NPML methods. However, the p-value obtained when not restricting to normality (NPML) is approximately zero, which leads to a significant relation between these two variables. This was not the case with the QML method, for which the p-value was very large (0.689).

The relation between the risk free rate and the conditional market variance, measured through γ_M, offers a negative estimated value for both approaches. In fact its absolute value is larger when estimated with the QML method than for the NPML. However, the p-value for this estimation using NPML is almost zero and indicates a significant relation between these two variables, which was not the case with QML. The comments about λ_f and γ_M remain valid for the two time periods, although with different signs for the estimated coefficients, as a consequence of the reason explained in Subsection 3.2.

In order to examine the difference between the QML and NPML approaches for different time series models, the data have been fitted to an EGARCH-M(1,1) model with $\lambda_M = 0$ and to the second order autoregressive model: $y_t = \lambda_0 + \lambda_r y_{t-1} + \lambda_s y_{t-2} + \lambda_M h_t + \lambda_f x_t + u_t$ with an EGARCH-M(1,1) error structure. Tables 4 and 5 collect the results of the QML and NPML methods for models 1 and 2. The figures included in these tables lead to a similar relative behaviour of NPML with respect to QML.

PUT TABLE S 4-5 ABOUT HERE

5. Conclusions

The main aim of this paper was to analyze the relation between the risk premium and its conditional variance in the Spanish market, having in mind the possible influence on this relation of the information coming from the risk free rate.

In order to evaluate how important is the normality assumption in the final results, two different models and estimators have been considered in this paper. The first is an EGARCH-M(1,1) model with normal innovations, whose parameters have been estimated by quasi maximum likelihood. The second approach is a semiparametric EGARCH-M(1,1) model with innovations following any arbitrary (unknown) continuous distribution. In this case the parameters have been estimated via nonparametric maximum likelihood following Cao et al. (2003).

Both approaches point out a lack of significance of the parameter that measures the relation between market risk premium and its volatility. However the absence of significance of the relations: risk free rate – market volatility and risk free rate – market risk premium, obtained under the normality assumption, does not hold when this assumption on the innovation is not imposed. This is also a relevant conclusion that reveals how important is to use an appropriate model and estimation procedure when analyzing a time series that clearly violates the normality assumption. This is a very crucial point when analyzing other relations different than the classical market risk premium – market volatility in the Spanish stock market.

Acknowledgments

This research has been partially supported by the Grants MTM2005-00429 (ERDF support included) of the Spanish Ministerio de Educación y Ciencia and PGIDT03PXIC10505PN of the Xunta de Galicia, for the first author and Grant MTM2005-01274 (ERDF support included) of the Spanish Ministerio de Educación y Ciencia for the third author. The authors would like to thank the helpful comments coming from an anonymous referee.

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Table 1. Statistical analysis of the Spanish market risk premium during the period January 1994 – December 2001. The Kruskal-Wallis test under the column "Weakly" is testing the hypothesis of identical distribution of the risk premium along the five days in the week. Under the column "Tuesday" it tests the hypothesis of identical distribution between the risk premium on Tuesdays and the rest of the week. Dickey-Fuller and Ljung-Box tests are applied for the whole data series.

	One-day risk premium (%)					
	Weekly	Monday	Tuesday	Wednesday	Thursday	Friday
Number of observations	1986	392	404	402	395	393
Number of positive observations	1042	200	225	197	199	221
Number of negative observations	944	192	179	205	196	172
Mean	0.020	-0.007	0.119	-0.058	-0.032	0.075
Standard deviations	1.402	1.421	1.381	1.405	1.431	1.369
Median	0.070	0.042	0.141	-0.016	0.015	0.206
Kurtosis	2.481	2.266	1.286	3.114	3.697	1.935
Asymmetry	-0.311	0.022	0.079	-0.145	-0.929	-0.559

	Weekly		Tuesday
Kruskal-Wallis test	5.647		1.801
p-value	(0.227)		(0.180)

Dickey-Fuller	-20.209 [1]
Critical value (1%)	-3.436

Ljung-Box test	8.453 [1]
p-value	(0.004)

NOTE, [1] Rejection of the null hypothesis at a level of 1%.

Table 2. Quasi maximum likelihood estimation of the parameters involved in the EGARCH-M (1,1) for the risk premium in the Spanish market. The p-values are reported in brackets. The maximal value of the log-likelihood (ML) is also included.

	Estimated value (p-value)		
	Whole sample	1st half of the sample	2nd half of the sample
λ_0	0.022	0.149	-0.141
	(0.759)	(0.166)	(0.202)
λ_r	0.087 [1]	0.125 [1]	0.039
	(0.000)	(0.000)	(0.226)
λ_M	0.013	0.001	0.027
	(0.704)	(0.986)	(0.514)
λ_f	-0.601	-3.337	5.516
	(0.689)	(0.067)	(0.231)
w_M	0.034 [1]	0.031	0.005
	(0.010)	(0.227)	(0.797)
α_M	0.146 [1]	0.113 [1]	0.167 [1]
	(0.000)	(0.045)	(0.000)
θ_M	-0.055 [1]	-0.042	-0.068 [1]
	(0.000)	(0.118)	(0.000)
β_M	0.967 [1]	0.958 [1]	0.964 [1]
	(0.000)	(0.000)	(0.000)
γ_M	-0.743	-0.878	1.571
	(0.171)	(0.349)	(0.272)
$L\left(\hat{P}^{QML}\right)$	-1,449.16	-533.51	-903.60

NOTE, [1] Statistically significant at a level of 5%.

Table 3. Nonparametric maximum likelihood estimation of the parameters involved in the EGARCH-M (1,1) for the risk premium in the Spanish market. The p-values, approximated using the smoothed bootstrap mechanism described in Section 4.1, are reported in brackets. The values of the nonparametric log-likelihood at the QML estimator and the NPML estimator are also included.

	Estimated value (p-value)		
	Whole sample	1st half of the sample	2nd half of the sample
λ_0	0.025	0.154 [1]	-0.149 [1]
	(0.089)	(0.000)	(0.000)
λ_r	0.075 [1]	0.132 [1]	0.051 [1]
	(0.000)	(0.000)	(0.000)
λ_M	0.016	0.013	0.038
	(0.661)	(0.902)	(0.090)
λ_f	-0.679 [1]	-3.579 [1]	4.741 [1]
	(0.000)	(0.000)	(0.000)
w_M	0.025 [1]	0.018	0.001
	(0.001)	(0.208)	(0.990)
α_M	0.153 [1]	0.124 [1]	0.159 [1]
	(0.000)	(0.000)	(0.000)
θ_M	-0.050 [1]	-0.058 [1]	-0.066 [1]
	(0.000)	(0.000)	(0.000)
β_M	0.967 [1]	0.950 [1]	0.959 [1]
	(0.000)	(0.000)	(0.000)
γ_M	-0.626 [1]	-0.787 [1]	1.574 [1]
	(0.000)	(0.000)	(0.000)
$L^{NP}\left(\hat{P}^{QML}\right)$	-3,283.41	-1,427.72	-1,802.78
$L^{NP}\left(\hat{P}^{NPML}\right)$	-3,243.77	-1,424.01	-1,800.52

NOTE, [1] Statistically significant at a level of 5%.

Table 4. Quasi maximum likelihood and nonparametric maximum likelihood estimation of the parameters involved in the EGARCH-M (1,1) model with $\lambda_M = 0$ for the risk premium in the Spanish market. The values of the parametric log-likelihood at the QML estimator and the nonparametric log-likelihood at the QML estimator and the NPML estimator are also included.

	Estimated value (p-value)	
	QML	NPML
λ_0	0.044	0.056 [1]
	(0.316)	(0.00)
λ_r	0.086 [1]	0.083 [1]
	(0.00)	(0.00)
λ_f	-0.741	-0.694 [1]
	(0.617)	(0.00)
w_M	0.033 [1]	0.031 [1]
	(0.01)	(0.03)
α_M	0.145 [1]	0.161 [1]
	(0.00)	(0.00)
θ_M	-0.055 [1]	-0.052 [1]
	(0.00)	(0.00)
β_M	0.967 [1]	0.967 [1]
	(0.00)	(0.00)
γ_M	-0.742	-0.827 [1]
	(0.61)	(0.00)
$L\left(\hat{P}^{QML}\right)$	-1,449.26	
$L^{NP}\left(\hat{P}^{QML}\right)$		-3,240.53
$L^{NP}\left(\hat{P}^{QML}\right)$		-3,238.25

NOTE, [1] Statistically significant at a level of 5%.

Table 5. Quasi maximum likelihood and nonparametric maximum likelihood estimation of the parameters involved in the second order autoregressive EGARCH-M (1,1) for the risk premium in the Spanish market. The values of the parametric log-likelihood at the QML estimator and the nonparametric log-likelihood at the QML estimator and the NPML estimator are also included.

Estimated value (p-value)

	QML	NPML
λ_0	0.037	0.025
	(0.621)	(0.35)
λ_r	0.091 [1]	0.076 [1]
	(0.00)	(0.00)
λ_s	0.008	0.022
	(0.818)	(0.112)
λ_M	-0.036	-0.051 [1]
	(0.120)	(0.00)
λ_f	-0.598	-0.507 [1]
	(0.697)	(0.00)
w_M	0.033 [1]	0.031 [1]
	(0.00)	(0.00)
α_M	0.145 [1]	0.176 [1]
	(0.00)	(0.00)
θ_M	-0.0525 [1]	-0.037
	(0.00)	(0.05)
β_M	0.967 [1]	0.966 [1]
	(0.00)	(0.00)
γ_M	-0.758	-0.745 [1]
	(0.159)	(0.00)
$L\left(\hat{P}^{QML}\right)$	-1,447.20	
$L^{NP}\left(\hat{P}^{QML}\right)$		-3,221.31
$L^{NP}\left(\hat{P}^{NPML}\right)$		-3,221.12

NOTE, [1] Statistically significant at a level of 5%.

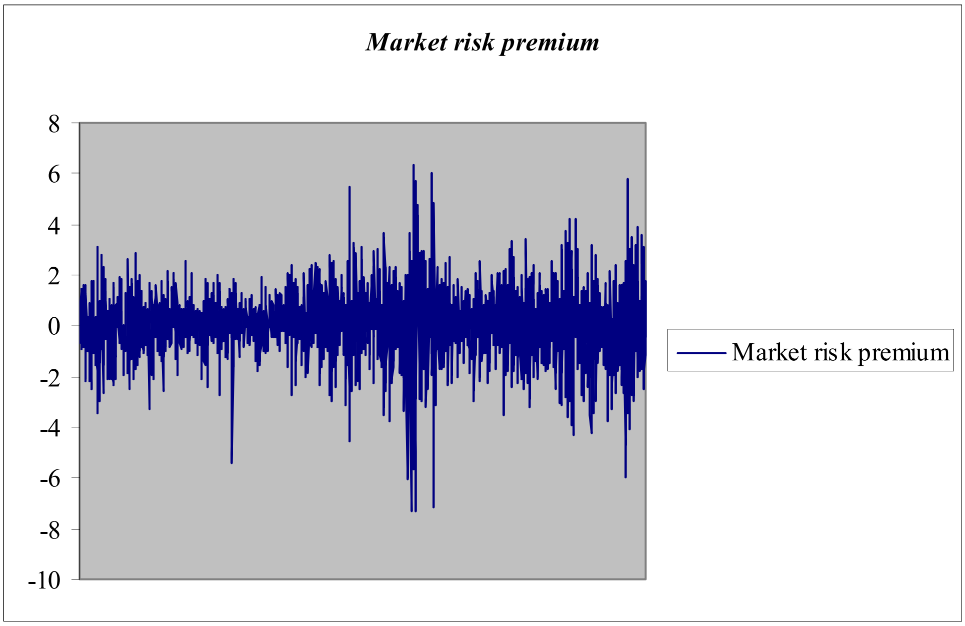

Figure 1. Spanish market risk premium from January 1994 to December 2001.