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Structural changes in volatility and stock market development: Evidence for Spain

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Abstract

In this paper we review the factors that lead to changes in stock market volatility and use alternative methodologies of endogenous breakpoint detection in order to analyze whether the volatility of the Spanish stock market has changed significantly over the period 1941–2001. This period corresponds to years of profound development of both the financial and the productive sides of the economy in this country. The analysis of the Spanish stock market suggests that volatility has behaved in a different manner over the period 1941–2001: After three decades of low volatility, a structural break in volatility is detected in 1972, coinciding with the opening of the Spanish economy. From 1972 to 2001, the years of more intense financial development, the stock market presents a higher level of volatility and lower persistence. This effect is partly attributable to the increased growth of trading volume brought about by the economic development process.

JEL classification: C32; C59; G10
Keywords: Volatility; Trading volume; Stock market development; Multiple structural breaks

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1. Introduction

Financial markets and institutions play a key role in the economy by channeling funds from savers to investors. Volatility in the prices of financial assets becomes a normal part of the process of allocating investable funds among competing uses. However, excessive or extreme volatility of interest rates, exchange rates or stock prices may be detrimental because such volatility may impair the smooth functioning of the financial system and adversely affect economic performance. [1]

Stock market volatility, in particular, could harm the economy through a number of channels. [2] One way that stock price volatility hinders economic performance is through consumer spending (e.g., Campbell, 1996; Starr-McCluer, 1998; Ludvigson and Steindel, 1999; Poterba, 2000). This relates to the wealth effect of the stock market in consumption that became especially worrisome after the drop in stock prices in the first semester of 2000. In addition, the likely subsequent weakening in consumer confidence could contribute to a further reduction in expenditure. Stock price volatility may also affect business investment spending (Zuliu, 1995) and, consequently, economic growth (Levine and Zervos, 1996; Arestis et al., 2001): Investors interpret a raise in stock market volatility as an increase in the risk of equity investment and they shift their funds to less risky assets. This reaction raises the cost of funds for firms and new firms might bear the brunt of this effect as investors gravitate toward the purchase of stock in larger, better known firms. Finally, extremely high volatility could also disrupt the smooth functioning of the financial system and lead to structural or regulatory changes that may be necessary to increase the resiliency of the market in the face of greater volatility.

In this paper we analyze whether the volatility of the Spanish stock market has changed significantly over the period 1941–2001. The choice of this country makes the analysis especially relevant. Our data start in 1941, when Spain was a closed economy with an incipient and underdeveloped stock market. By the end of the sample, in 2001, Spain could be counted among the most developed economies of the world, its capital markets were fully liberalized and it had qualified to become a founding member of the European Monetary Union. Our sample, therefore, covers the years of development of the stock market and of economic and financial opening and integration of the country. The analysis of the possible impact of these events in the behavior of the stock market becomes relevant for our understanding of the functioning of financial markets and for those countries that are now undergoing similar processes, such as the transition countries in Europe.

Our objective is to ascertain *when* significant changes in the structure of Spanish stock market volatility have occurred and to place those changes in the context of the

[1] Becketti and Sellon (1989) analyze the economic impact of financial market volatility. Walsh (1984) or Ferderer (1993) analyze similar issues for interest rate volatility while Goldberg (1993), Glick (1998), Campa and Goldberg (1999) and, more recently, Baum et al. (2001) focus on exchange rate volatility.

[2] Campbell et al. (2001) and Schwert (2002) are among the most recent papers focused on the behavior and evolution of volatility in the stock market.

recent history of the Spanish economy. We are interested in both transitory and structural changes in volatility: An examination of the evolution of stock market volatility in Spain in the last six decades not only shows evidence of ARCH-type effects, i.e. periods of persistently higher/lower volatility that arise because of the arrival of new information, but also of shifts in unconditional volatility. The latter suggest the existence of changes – structural breaks – in the statistical model generating return volatility. We detect these structural changes, although in order to not impose a priori when the changes occur we use methodologies based on the estimation of endogenous breakpoints. Moreover, since the richness of the period analyzed suggests the possibility of more than one change in the behavior of the stock market we allow for multiple breaks in the series, moving into the estimation of a (still unspecified) number of structural breaks. Our analysis follows the procedures suggested by Bai and Perron (1998, 2003a,b) which have already been successfully applied by Bekaert et al. (2002a,b) to investigate multiple structural changes in the stock markets of emerging economies, but we test for robustness of our results by using two additional tests for endogenous breaks in volatility (Kokoszka and Leipus, 2000; Inclán and Tiao, 1994). We finally complement the results of the structural break analysis by looking at the relationship of volatility to trading volume.

The structure of the paper is as follows. In Section 2 we briefly review the factors that may drive changes in stock market volatility. Section 3 analyzes changes in the Spanish stock market volatility using a battery of methodologies. Emphasis is placed on the detection of structural breaks and on the relationship of volatility to trading volume. Section 4 comments on the results in the light of the relevant historical events related to the evolution of the Spanish economy. Finally, Section 5 concludes.

2. Changes in stock market volatility

While there is a general consensus on what constitutes stock market volatility and, to a lesser extent, on how to measure it, there is far less agreement on the causes of changes in stock market volatility. The question can be approached from two different angles since one may look for changes in conditional volatility, that is, the value of volatility given a specific realization of past returns or of other relevant variables or, alternatively, one may be interested in changes in unconditional volatility, i.e. in the data generating process. [3] The factors we review in this section can be consistent with both, and thus in our analysis we will emphasize that distinction.

Some economists see the causes of volatility in the arrival of new, unanticipated information that alters expected returns on a stock (Engle and Ng, 1993) so that changes in market volatility merely reflect changes in the local or global economic environment. Others claim that volatility is caused mainly by trading volume, practices or patterns. All these reasons hinge on the efficiency of the market: Volatility

[3] Examples of the first approach are ARCH-based or stochastic volatility models or the volatility in levels framework in Lamoreux and Lastrapes (1990).

would just be a consequence of the process by which new information is incorporated into prices. [4]

More recently, however, researchers have noticed fundamental changes in investor behavior. This has led to the abandonment of the efficient market hypothesis in favor of behavioral finance: Changes in market volatility would be mainly determined by changes – temporary, as in the dot-com frenzy, or permanent, as in the generalized surge in interest for the stock market of recent years – in investor behavior. According to Shiller (2000) stock prices in the last few years – prior to the bursting of the dot-com bubble – were too high and volatile to be explained by fundamental variables. The stock market seemed to be driven, instead, by sociological and psychological factors – US triumphalism, cultural changes favoring business success, the impact of baby boomers – as well as behavioral factors directly related to trading practices – increasingly optimistic forecasts by analysts, the enormous expansion of trading volume and an increase in the frequency of trading.

Other factors that have been identified as leading to changes in market volatility are the improved speed with which financial transactions are carried out – the stage of development of the domestic stock market – and the increased interdependence and interconnectivity of markets – the degree of integration of the domestic market with other stock markets. All these factors relate to the speed at which the market accommodates shocks and incorporates the relevant information into the prices. Thus, at least indirectly, a link between improved efficiency of the market and changes in volatility dynamics could be expected. The faster the information is incorporated into prices, the lower the volume of trading necessary to bring prices to their correct levels and periods of increased volatility due to the arrival of new information should be shorter: Volatility should revert to "average" levels faster. In other words, one would expect lower persistence of abnormal volatility, or faster "mean reversion" of volatility. [5]

As we review in Section 4, the stock market of our country of interest, Spain, has developed quite intensely in the last sixty years: Trading volume has multiplied by some orders of magnitude, a process facilitated by the incorporation of new trading technologies, and it has become increasingly integrated with international capital markets. In the light of the above discussion, we posit that this evolution should be manifest in changes both in the level of volatility – because of intense trading and the increase in the availability of alternative investment opportunities – and in its dynamic characteristics – because of changes in investor behavior and trading practices and enhanced market efficiency. We focus our analysis on characterizing the dynamic evolution of volatility in the Spanish stock market data, in order to

[4] We define efficiency in a broad sense as the speed at which the market incorporates the relevant information into the prices of stocks. If information is incorporated immediately into the prices, then there is no possibility of obtaining extra returns when trading on that information.

[5] This, of course, does not mean that persistence of volatility in more developed and efficient markets should be *low*. We see nowadays highly developed markets where volatility is quite persistent. We do believe, though, that volatility in an efficient and developed market would be *less persistent* than it would be if the market was less developed.

put it afterwards in the context of the history of the development of the Spanish economy in both its productive and financial sides. The next sections develop the methodologies we use and present the results of our analysis.

3. Volatility behavior in the Spanish stock market

In this section we analyze the evolution of Spanish stock market volatility over the last sixty years. The events that took place in Spain during this period provide us with a natural experiment that allows us to analyze how such events may have affected the behavior of stock market volatility.

Our dataset consists of a monthly series of an index of Spanish stock prices, that covers the period from 1941:01 to 2001:12. This series has been obtained from the Research Department of the Madrid Stock Exchange. [6]

We use a battery of methodologies in order to detect and measure the changes in volatility over time. We start by resorting to a graphical analysis of the dynamic behavior of volatility over the years. Events that coincide with temporary increases in volatility are easily identified. We then examine conditional heteroskedasticity. This complements the analysis of the specific events that have caused surges in stock market volatility and allows us to elaborate on how much and how persistently volatility is affected by these events. We then go one step further and analyze evidence of unconditional heteroskedasticity by detecting (possibly multiple) structural breakpoints in the volatility series. These breakpoints locate the moments in time when more substantial changes in volatility dynamics, and therefore in stock market behavior, have taken place. We test for robustness of our results by using three alternative tests for endogenous breaks in volatility. Once the breaks have been located, we comment on the dynamic behavior of volatility in the different subperiods identified by the breaks: We characterize the persistence of volatility and the impact of shocks. A final subsection looks at the historical relationship between trading volume and volatility.

3.1. A first look at the data

Table 1 reports some basic univariate statistics for the Spanish stock returns throughout the entire sample. The skewness and kurtosis coefficients reveal departures from normality in the data, confirmed by the Jarque–Bera test, whereas the Ljung–Box *Q*-statistic and the first order autocorrelation indicate the presence of significant, but low, autocorrelation of returns. An ARCH-LM(4) test suggests ARCH effects in volatility.

[6] There are four stock markets in Spain. However, the Madrid Stock Exchange handles more than 90% of the total volume of trading, while the other three markets – Barcelona, Bilbao and Valencia – are declining in importance and currently their activity is limited to the trading of local stocks. Thus, we believe that focusing on the Madrid Stock Exchange is a reasonable simplification which can be justified as the most accurate way of capturing the behavior of the national Spanish market.

Table 1
Some basic statistics on the returns of the Spanish stock market, 1941:01–2001:12

Mean	SD	SK	κ	ρ_1	$Q(4)$	ARCH(4)	JB
0.119	0.612	−0.418*	6.701*	0.145*	17.652*	18.490*	438.550*

Returns are calculated as $12(\ln P_t - \ln P_{t-1})$, where P_t is the value of the stock index at month t.
SD: standard deviation; SK: skewness coefficient; κ: kurtosis coefficient; ρ_1: first order autocorrelation coefficient; $Q(4)$: Ljung–Box(4) statistic for autocorrelation of returns; ARCH(4): ARCH-LM test with four lags. The value in the table is the asymptotic χ^2 test, using TR^2 of the auxiliary regression; JB: Jarque–Bera normality test.
* Significant at 5% level.

The dynamics of stock market behavior can be seen in Fig. 1. This figure shows the evolution of the Spanish stock returns during the sample period and a nonparametric measure of return volatility. This measure is a 12-month window rolling variance calculated as follows:

$$\sigma^2(r_t) = \left[\sum_{k=1}^{12}(r_{t-k} - \mu_{12})^2/11\right] \tag{1}$$

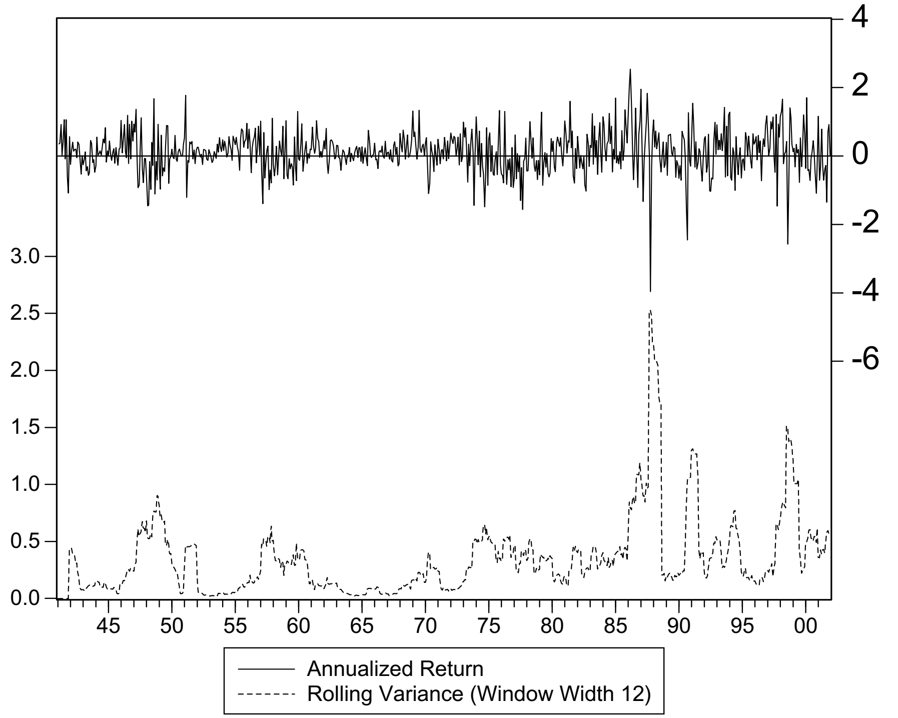

Fig. 1. Evolution of Spanish stock market returns and rolling variance, 1941–2001.

where r_t is the annualized return of the stock market index over period t and μ_{12} is the sample mean over the 12-month window. [7]

Fig. 1 shows that the variance of returns, which seems to have been low before the 1970s, rose significantly in the last two decades of the sample, when the Spanish market shows increased average volatility. That is, stock return variance fluctuates, as it did in the first years of the sample, but around a higher average level. Also, in the last decade and a half, there have been three important peaks in stock market volatility, when the annualized standard deviation of returns became greater than 100%. These peaks correspond to the crash of October 1987, the Gulf War and the Brazilian and Russian crises. Peaks of this intensity are not present in the first decades of the sample: It is only in the most recent years that the Spanish stock market has suffered from intense temporary instability, mainly induced by international financial crises. The unstable episodes, though, appear to be quite short lasting: It is noticeable the contrast with the longer, but less intense, periods of increased volatility in the first decades of the sample.

Since the seminal papers by Engle (1982) and Bollerslev (1986), GARCH models have been successfully applied to financial data and have become the most popular tools to study the behavior over time of financial market volatility. [8] The GARCH(1,1) model specifies the behavior of returns as:

$$r_t = \beta_0 + \beta_1 r_{t-1} + u_t, \quad u_t \to \text{iid}(0, \sigma_t^2), \tag{2a}$$

$$\sigma_t^2 = \varpi_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 u_{t-1}^2, \tag{2b}$$

where (2a) is the mean equation and (2b) is the variance equation. The variance σ_t^2 is modeled as a deterministic function of past innovations (u_{t-1}) and is allowed to be persistent. We estimated a simple GARCH(1,1) process for the full sample of stock market returns. The coefficient estimates, shown in Table 2, indicate that stock market volatility has been quite persistent ($\alpha_1 = 0.86$ and $\alpha_2 = 0.13$, for a value of $\alpha_1 + \alpha_2 = 0.99$). [9] The unconditional level of the annualized standard deviation has been of 72%. Fig. 2 plots the 12-month rolling variance, together with the GARCH forecasts of the conditional variance – the series of estimated σ_t^2 derived from

[7] We calculate returns as $12(\log P_t - \log P_{t-1})$. In the subsequent analysis we assume that the behavior in mean of stock returns is an AR(1) process: The a.c.f. of returns shows significant autocorrelation at lag one and we allow for that effect, even though it is not our main interest.

[8] Pagan and Schwert (1990) and Pagan (1996) show that GARCH models perform quite well in comparison with alternative methods for modelling conditional volatility of stock returns and that, except for a possible asymmetric leverage effect, a GARCH(1,1) is enough to account for the volatility dynamics of most financial time series. Most recently, Schwert (2002) used a GARCH(1,1) to model conditional variance for the Nasdaq. In the case of the Spanish stock market, Peña (1992), Alcalá et al. (1993), Alonso and Restoy (1995), Jimeno (1995) and León and Mora (1999) among others, have used GARCH-based models.

[9] A GARCH(1,1) can be rewritten so that squared returns follow an ARMA(1,1) process where the autoregressive parameter, usually identified as the persistence parameter that determines how much of a shock is transmitted into the next period, is precisely $\alpha_1 + \alpha_2$. The sum of these two coefficients is given as the measure of persistence of the variance.

Table 2
GARCH(1,1) model for Spanish stock return volatility, 1941:01–2001:12

	1941:01–2001:12
β_0	0.103
	(5.62)
β_1	0.136
	(3.28)
ϖ_0	0.006
	(3.38)
α_1	0.861
	(15.49)
α_2	0.128
	(0.99)
Unconditional variance	0.5263

$r_t = \beta_0 + \beta_1 r_{t-1} + u_t, \quad u_t \rightarrow \mathrm{iid}(0, \sigma_t^2)$ [mean equation]

$\sigma_t^2 = \varpi_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 u_{t-1}^2$ [variance equation]

r_t is the rate of return to the Spanish stock market at period t. σ_t^2 is the conditional variance of the stock return at period t. t-statistics use QML standard errors. The sample size is 732 months.

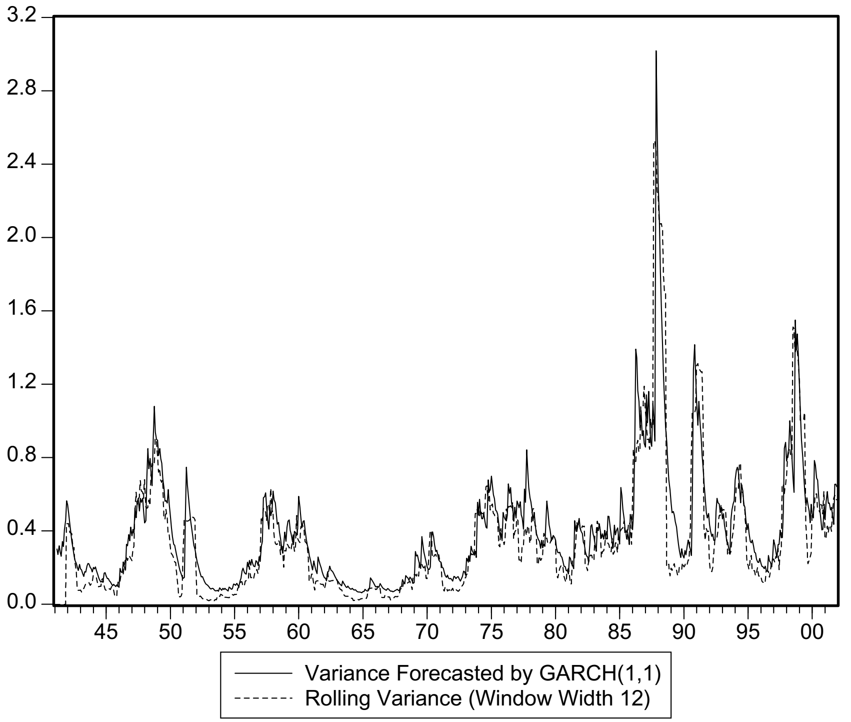

Fig. 2. Comparison of variance forecasted with simple GARCH and rolling variance.

recursively evaluating Eq. (2b). The GARCH-fitted variance very closely approximates the nonparametric rolling variance, especially during periods of high volatility (Schwert, 2002). This gives evidence in favor of the GARCH model, which is able to replicate quite nicely a model-free local estimate of the variance. In order to compare more formally both estimates, we take the rolling variance as the "true" variance and perform a chi-square test of similarity of the distributions of volatility implied by the two measures. [10] The test does not allow to reject the similarity of both distributions: The distribution of volatility implied by the GARCH model is statistically similar to that of the model-free estimate of the variance. [11] There is, therefore, strong evidence of conditional heteroskedasticity in the Spanish stock market, by which volatility is a positive function of both past volatility (GARCH effect) and past innovations to the return process (the "news", or ARCH effect). Volatility appears to have been highly persistent: The half-life of shocks implied by the persistence coefficient turns out to be 63 months. [12] These results were to be expected, and they add little to what has already been found in other analyses of the Spanish stock market, and of most stock markets for that matter. Still, it is interesting to notice the excellent fit that the GARCH variance gives to the rolling variance both in terms of the time evolution and in terms of the implied distribution of volatility.

An eyeball analysis of the more general features of the estimates of the evolution of volatility is warranted now. Beyond the obvious unstable periods, that are quite well accounted for by both measures, some distinct features in the volatility dynamics over the complete period 1941–2001 are worth noting. First, there seems to be an increase in the amplitude of return fluctuations in the last years. Second, and related to the previous feature, the variance measure suggests that the average level of volatility has gone up significantly starting in the early 1970s. Finally, recent instances of an upsurge in market volatility, those recorded in 1987, 1991 and 1999, present higher intensity than in prior periods but the resulting increase in conditional variance is shorter lasting: In the last decade and a half the stock market has been hit more intensely by large good and bad news, but the effect of these shocks or innovations, in terms of increased instability, is less persistent and the market returns faster to average levels of volatility. These features suggest a changing behavior of volatility throughout the sample. The last three decades are characterized by a higher

[10] The test is based on a histogram constructed by dividing the range of the rolling variance in bins of equal length. Given that there are no simple rules as to the number of bins to be used, we have performed the test for all possible integer numbers of bins between the upper ($4(2T^2/c_\alpha^2)^{1/5}$, where T is the number of observations and c_α is the α-critical value of the standard normal) and lower ($1.88T^{2/5}$) values recommended by Mann and Wald (1942) and Schorr (1974). Thus, we do not provide a single value of the test, although the different values are available upon request. None of the test values allowed to reject the similarity of the distributions at 10% confidence level.

[11] One should not interpret the rolling variance as being the true variance. It is, however, a model-free estimate of the local behavior of volatility. The fact that one simple parametric model – the GARCH with three parameters – is able to replicate so closely the local behavior of volatility for the full sample as good evidence in favor of the model.

[12] Half-life of shocks is the time it takes for half of the impact of the shock to die out. It is calculated as $\ln(0.5)/\ln(\phi)$, where ϕ is the persistence coefficient.

level of volatility and lower persistence, although it is only starting in the mid 1980s that episodes of high instability seem to hit the Spanish market. Three distinct periods could thus be identified: The earlier years from the beginning of the sample until the early 1970s, the fifteen years that correspond to the oil crises and before the 1987 stock market crash, and the years post-1987. We comment in further detail in Section 4 how these periods correspond to distinct stages in the evolution of the Spanish economy and identify some of the relevant events and economic trends in each period. For the moment, we believe that there is enough evidence that suggests the presence of structural changes in stock market volatility.

3.2. Structural breaks in the Spanish stock market volatility

In this section we study the evidence for structural changes in the process that generates stock market volatility, that is, the evidence for changes in unconditional variance. The previous section showed results that pointed in that direction, and two possible dates around which we could expect to find significant changes in volatility behavior were identified: The early 1970s and halfway through the 1980s. We use now techniques for the location of endogenous structural breaks in order to detect possible times of changes in the parameters of the variance equation.

In order to capture the changing behavior of volatility we use the baseline GARCH model presented above and test for breaks at unknown times in the parameters of the variance equation. Thus, we do not impose a priori the dates of the breaks, but test simultaneously for the existence of a change in the parameters of the process – ϖ_0, α_1 and α_2 – and for the date of the change. We allow for the existence of more than one break in the parameters following a sequential process.

3.2.1. Locating the structural breaks

The location of endogenous structural breaks in time series has been a matter of intense research in the last few years. [13] Most of the techniques have been developed for estimation and location of endogenous breaks in the mean parameters of trend models. However, as Bai and Perron (1998) mention, they can also accommodate changes in the variance. Given the richer structure of the GARCH variance process, we have to be cautious about how immediately these tests can be extended to changes in the GARCH parameters. [14] In this paper we use the critical values and limiting distributions of the tests for changes in the mean parameters but warn in advance that further results on the asymptotic distributions of our tests might modify the critical values or limiting distributions to be used. Therefore, with this caveat in mind and notwithstanding the fact that some of the results, such as the expression

[13] See, for example, Banerjee et al. (1992), Ghysels et al. (1997) and Bai et al. (1998). Papers by Andrews et al. (1996), García and Perron (1996), Bai (1997, 1999), Lumsdaine and Papell (1997) and Bai and Perron (1998, 2003a,b) analize how to estimate the number and location of multiple endogenous structural breaks.

[14] Formal evidence that these tests can be extended to GARCH processes is cited in Andreou and Ghysels (2002).

for the calculation of a confidence interval for the breakpoint, cannot be directly applied, we use the general framework in Bai and Perron (1998, 2003a,b) and use their sequential procedure and estimated critical values.

This sequential procedure consists of locating the breaks one at a time, conditional on the breaks that have already been located. Thus, we locate the first break and test for significance against the null hypothesis of no break. If the null hypothesis is rejected, we then look for the second break conditional on the first break being the one already found, and test for significance of that second break against the null of one single break, and so on.

Our framework consists of a model for stock market returns of the form in (2). We believe that at some points in time, $\mathbf{t} = \{t_1, t_2, \dots t_m\}$ the process generating the variance may change, that is, the parameters ϖ_0, α_1 and α_2 change at each of the t_i. The specific number of breaks allowed will be determined by the data through the application of the sequential process outlined above, so here we keep the discussion at a general level.

Given a set $\mathbf{t}$ of l points in time at which q of the parameters of the process change, we want to test if there is an additional break and, if so, when the break takes place and the value of the q parameters before and after the new break. The likelihood of the model that contains the l breaks in $\mathbf{t}$ is specified as $L(\mathbf{t}, \theta)$. θ is the set of all parameters and it contains both the parameters that do not change over time and the l values of each of the q parameters allowed to change at the breakpoints. In our specific model, and disregarding some constants,

$$\begin{aligned} L(\mathbf{t}, \theta) = &-\frac{1}{2}\sum_{t=1}^{t_1}\left[\log \sigma_{1,t}^2 + \frac{u_{1,t}^2}{\sigma_{1,t}^2}\right] - \frac{1}{2}\sum_{t=t_1+1}^{t_2}\left[\log \sigma_{2,t}^2 + \frac{u_{2,t}^2}{\sigma_{2,t}^2}\right] - \cdots \\ &-\frac{1}{2}\sum_{t=t_1}^{T}\left[\log \sigma_{1,t}^2 + \frac{u_{1,t}^2}{\sigma_{1,t}^2}\right] \end{aligned} \tag{3}$$

where $u_{i,t} = r_t - \beta_{0,i} - \beta_{1,i} r_{t-1}$ and $\sigma_{i,t}^2 = \varpi_{0,i} + \alpha_{1,i}\sigma_{i,t-1}^2 + \alpha_{2,i} u_{i,t-1}^2$.

The alternative model is specified as one which contains an additional break at time τ. Thus, the set of $l+1$ breakpoints becomes now $\mathbf{t}^* = \{\mathbf{t}, \tau\}$, and the log-likelihood associated with the alternative model is $L(\mathbf{t}^*, \theta(\mathbf{t}^*))$. The procedure for the detection and timing of the break consists in finding the series of likelihood-ratio statistics of the alternative (unrestricted model) of $l+1$ breaks against the null (restricted model) of l breaks:

$$LR_\tau(l+1|l) = -2[L(\mathbf{t}, \hat{\theta}(\mathbf{t})) - L(\mathbf{t}^*, \hat{\theta}(\mathbf{t}^*))] \tag{4}$$

where $\mathbf{t} = \{t_1, t_2, \dots t_l\}$ is the first set of l breaks (under the null of no additional break) and $\mathbf{t}^* = \{t_1, t_2, \dots t_{l+1}\}$ is the set of $l+1$ breaks that includes τ as a new possible time for a break. $L(\mathbf{t}, \hat{\theta}(\mathbf{t}))$ is the value of the log-likelihood of a model that includes the breaks in $\mathbf{t}$, where $\hat{\theta}(\mathbf{t})$ are the ML estimates of all the parameters of the model. The new breakpoint is located by using the $\sup LR$ test:

$$\sup LR : \sup_{\tau \in \mathbf{T}^*} LR_\tau(l+1|l) \tag{5}$$

where $\mathbf{T}^*$ is the set of possible tunes for the new break. The date of the new breakpoint $\hat{t}$ is

$$\hat{t} = \arg\max_{\tau \in \mathbf{T}^*} L(\mathbf{t}^*, \hat{\theta}(\mathbf{t}^*)) = \arg\max_{\tau \in \mathbf{T}^*} [\sup LR_\tau(l+1|l)]. \tag{6}$$

If the sup LR test is above the critical value, then the null of no additional breakpoint is rejected and the date for the new breakpoint is estimated to be $\hat{t}$. The values of the parameters before and after the break correspond to the estimates in $\hat{\theta}(\mathbf{t}^*)$.

The set of possible times for the break, $\mathbf{T}^*$, must exclude a number of observations around the initial and final dates and around the dates in $\mathbf{t} = \{t_1, t_2, \ldots t_i\}$. This ensures that each subperiod defined by the breakpoints contains enough observations for the parameters to be accurately estimated. In our analysis we have used a trimming proportion of 0.15. That is, we start by locating the first breakpoint in $\mathbf{T}^* = \{0.15T, 0.85T\}$ and then every time we locate a new breakpoint, we exclude from $\mathbf{T}^*$ the 15% observations to both sides of the last breakpoint estimated.

In Table 3 we present the critical values for the sup LR test (Bai and Perron, 1998) for one to three breaks in three parameters along with the empirical values of the sup LR test for our Spanish stock market data.

3.2.2. Empirical results of the endogenous break analysis

We comment now on the results of the endogenous break sequential analysis. We focus on the final model with the number of breaks suggested by the data. Similarly to our presentation of the simple GARCH model, we put emphasis on the comparison of the fitted conditional variance coming from the final model with breaks with the rolling variance.

Before moving into the results, we point out that we do not comment on the parameters of the mean equation. Our estimates for the β_0 and β_1 parameters of the return process are very stable throughout all estimations, with some mild evidence of autocorrelation of returns (values of β_1 around 0.15, and statistically significant) and a mean return $(\beta_0/(1-\beta_1))$ in the 9–12% range.

Model I: The first model used as baseline is the simple GARCH(1,1) without break. The parameter estimates were shown in Table 2. Fig. 2 depicted how the estimated conditional variance reproduces quite well the behav-

Table 3
Asymptotic critical values and empirical estimates of the sequential $LR(l+1|l)$ test for a change in $q = 3$ parameters

α	l		
	0	1	2
90%	13.43	15.26	16.38
95%	15.37	17.15	17.97
Empirical	18.28	15.45	11.46

See Table II, Bai and Perron (1998).

ior of the rolling variance. This model, which already confirms that volatility of the stock market changes over time, represents our benchmark.

Model II: We perform now the test for one break in the three parameters of the variance equation. We take the maximum of the series of *LR* statistics as the test value – to be compared with the critical value for the chosen level of significance – and the date of that maximum value as the date of the break. Fig. 3 presents the series of the *LR* statistics along with the Spanish stock returns over the period 1941–2001. The sup *LR* statistic corresponds to June 1972 and the value of the test is 18.28, well above the critical value (see Table 3). Estimated parameter values appear in Table 4.

Model III: We now test for a possible second break, conditional on the first break being identified with June 1972. The second break is detected in observation 129 that corresponds to September 1951 (see Table 4). However, the sup *LR* statistic to test the null hypothesis of a break in the three parameters of the variance equation against the alternative of two breaks only allows to reject, and marginally, the null at the 10% significance level, so the evidence for a second break in all parameters seems weak. Table 5 contains the estimated parameter values for the three subperiods identified.

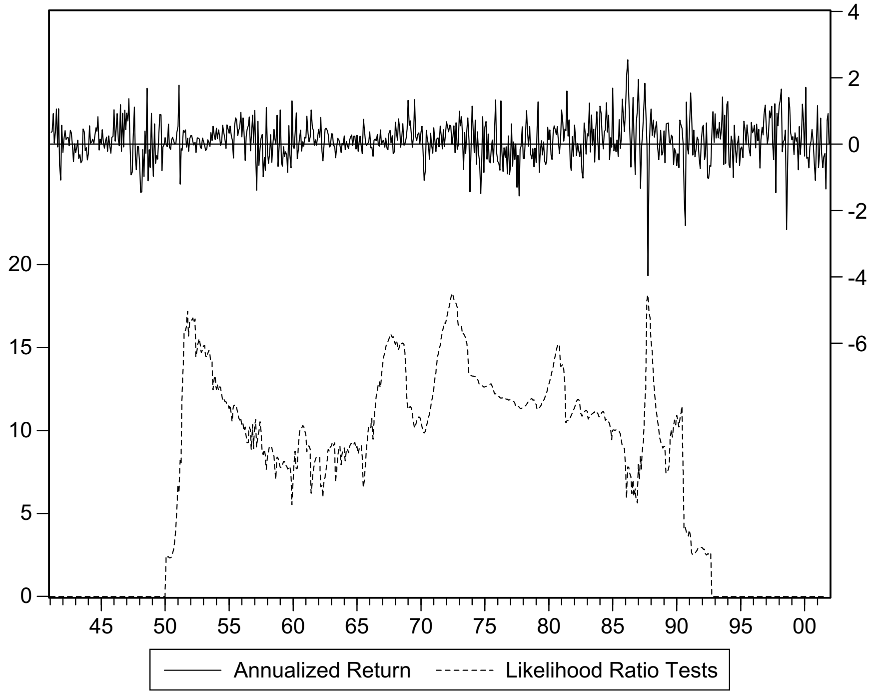

Fig. 3. Returns and series of *LR* tests.

Table 4
GARCH(1,1) model with one break in intercept, GARCH and ARCH effects for Spanish stock return volatility, 1941:01–2001:12

	1941:01–1972:06	1972:07–2001:12
β_0	0.114	0.074
	(5.08)	(1.89)
β_1	0.146	0.135
	(2.70)	(2.26)
ϖ_0	0.007	0.065
	(0.14)	(1.31)
α_1	0.827	0.787
	(2.80)	(5.25)
α_2	0.149	0.095
	(0.26)	(0.66)
Unconditional variance	0.288	0.549
Break date	1972:06	

$r_t = \beta_0 + \beta_1 r_{t-1} + u_t, \quad u_t \to \mathrm{iid}(0, \sigma_t^2)$ [mean equation]

$\sigma_t^2 = \varpi_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 u_{t-1}^2$ [variance equation]

r_t is the rate of return to the Spanish stock market at period t. σ_t^2 is the conditional variance of the stock return at period t. t-statistics use QML standard errors. The full sample size is 732 months.

A graphical analysis of the fitted variance shows that the two-break model excessively overestimates the volatility during the observations that correspond with the period January 1941 to January 1951, the period "generated" by the second break. [15] In addition, most of the peaks in the volatility behavior present a much reduced persistence compared with the rolling variance. Thus, Model III gives a poor fit to the data, probably because of overfitting, and we decided to accept the null of one single break against the alternative of a second break. [16]

We now comment on the behavior of volatility implied by the model with one break, which we believe is the one favored by the data. The date of the break is identified with June 1972. Inspection of the series of returns reveals that indeed there seems to be a change in the variance of the series around that time whereas at the same time no outlier is present in the months around the break date. This is quite relevant, given that sup-type tests tend to be quite sensitive to outliers. [17] All three parameters change at the date of the break: The estimated GARCH effect varies

[15] We have opted for not including this graph in the body of the paper. The graph can be found in the working paper version, Cunado et al. (2003).

[16] We looked at the possibility of three breaks in the volatility series but do not report the results for the sake of brevity and because, as it was to be expected given the rejection of the two-break model, the three-break model was rejected as well.

[17] Note that the other two local peaks of the series of *LR* tests correspond to the 1987 crash and to an unusually large negative return in 1951.

Table 5
GARCH(1,1) model with two breaks in intercept, GARCH and ARCH effects for Spanish stock return volatility, 1941:01–2001:12

	1941:01–1951:09	1951:10–1972:06	1972:07–2001:12
β_0	0.098	0.112	0.074
	(2.61)	(4.75)	(1.89)
β_1	0.106	0.176	0.135
	(1.04)	(2.67)	(2.25)
ϖ_0	0.047	0.004	0.065
	(0.41)	(0.22)	(0.41)
α_1	0.458	0.853	0.786
	(3.79)	(6.09)	(5.25)
α_2	0.454	0.133	0.095
	(2.84)	(0.45)	(0.67)
Unconditional variance	0.541	0.251	0.549
Break date	1951:09	1972:06	

$r_t = \beta_0 + \beta_1 r_{t-1} + u_t, \quad u_t \to \mathrm{iid}(0, \sigma_t^2)$ [mean equation]

$\sigma_t^2 = \varpi_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 u_{t-1}^2$ [variance equation]

r_t is the rate of return to the Spanish stock market at period t. σ_t^2 is the conditional variance of the stock return at period t. t-statistics use QML standard errors. The full sample size is 732 months.

from 0.82 to 0.78 and the news effect or ARCH effect from 0.14 in the first subperiod to 0.09 in the second. The level of the unconditional variance increases from 0.28 to 0.54, representing an increase of annualized volatility from 53% to 73%. With regards to the dynamic evolution implied, the estimated conditional variances are shown in Fig. 4, along with the rolling variance. The fitted variance follows quite closely the nonparametric measure, and again a goodness-of-fit test does not allow to reject the similarity of the empirical distributions: The model captures quite well the behavior before the break, the increase in unconditional variance around the time of the break, the high volatility episodes in 1987, 1991 and 1999, and the lower persistence in volatility in the recent years.

Our discussion so far has been focused on the statistical results of the estimation, and not on the meaning of the results in the historical context of the Spanish economy. We defer our comments until Section 4.

3.2.3. Some robustness checks

Alternative tests for endogenous breaks in unconditional variance are available, although these tests are more nonconstructive in nature. The paper by Andreou and Ghysels (2002) reviews the most recently developed tests. We use two of those tests – based on cumulative sums – as robustness checks for our results on the endogenous breaks. As in traditional CUSUM tests, the tests rely on the fact that if there is a change in the behavior of the series, cumulative sums should depart at some point from what would be implied if the behavior over the full sample were uniform. The

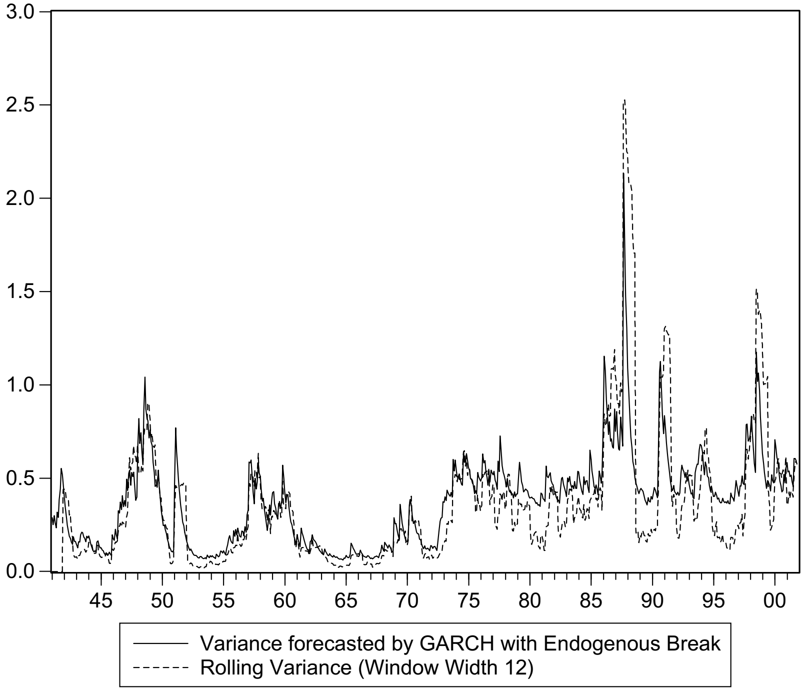

Fig. 4. Comparison of variance forecasted with GARCH with endogenous break and rolling variance.

two tests that we apply are those in Kokoszka and Leipus (KL, 2000), and Inclán and Tiao (IT, 1994). Both can be applied to squared returns or to absolute returns, and are designed to test for the most likely location of a change in the unconditional variance of the series. The asymptotic distribution of both tests is exactly the same, although the KL test is more general: The null under the IT test is that the series is i.i.d. and the alternative is that it has a level shift in variance. The KL test applies to a much wider range of series, including long memory, GARCH-type and some non-linear time series. Thus, it is expected to be more powerful in a time series context, where the i.i.d. assumption is highly dubious. [18]

We have carried out the test for both the squared and the absolute returns. [19] Both tests locate the first break at a similar date as the sup *LR* test, in October 1972 (using absolute returns) and August 1973 (using squared returns). The break in squared returns is statistically significant in both cases, although the evidence for the absolute returns is weaker. We interpret the results as giving evidence in favor

[18] We have noticed that the IT test tends to give evidence of too many breaks (see Aggarwal et al. (1999) for an analysis of emerging markets volatility that uses this test). The results of the two tests are in accordance with the sup *LR*, but the IT test is clearly biased towards detecting more breaks in time series.

[19] An AR(1) was first fitted to the returns, so that the tests are carried out on the residuals of that AR estimation. Further details on the two tests can be found in Cunado et al. (2003).

of a single break in the variance of the return series. This break is located around 1972–1973. Thus, the results of these CUSUM tests are in perfect consonance with those of the supLR test.

3.2.4. Volatility: News effect and persistence

Once the final model that includes one structural break has been estimated, two different subperiods are identified: 1941:01–1972:06 and 1972:07–2001:12. In this section we analyze more in depth the volatility behavior that corresponds to both subperiods. In particular, we comment on the news impact (Engle and Ng, 1993) and on the persistence of volatility.

The news impact curve relates past shocks to the return process (news) to current volatility and so it measures how new information is incorporated into volatility. The news impact curve can be calculated as

$$\sigma^2_{t,n} = A + \alpha_2 u^2_{t-1} \tag{7}$$

where $A = \varpi_0 + \alpha_1 \frac{\varpi_0}{1-\alpha_1-\alpha_2}$ is a function of the persistence and of the unconditional variance. Fig. 5 presents the news impact curve implied by the full sample GARCH and the curves that correspond to the two subperiods identified by the break. The

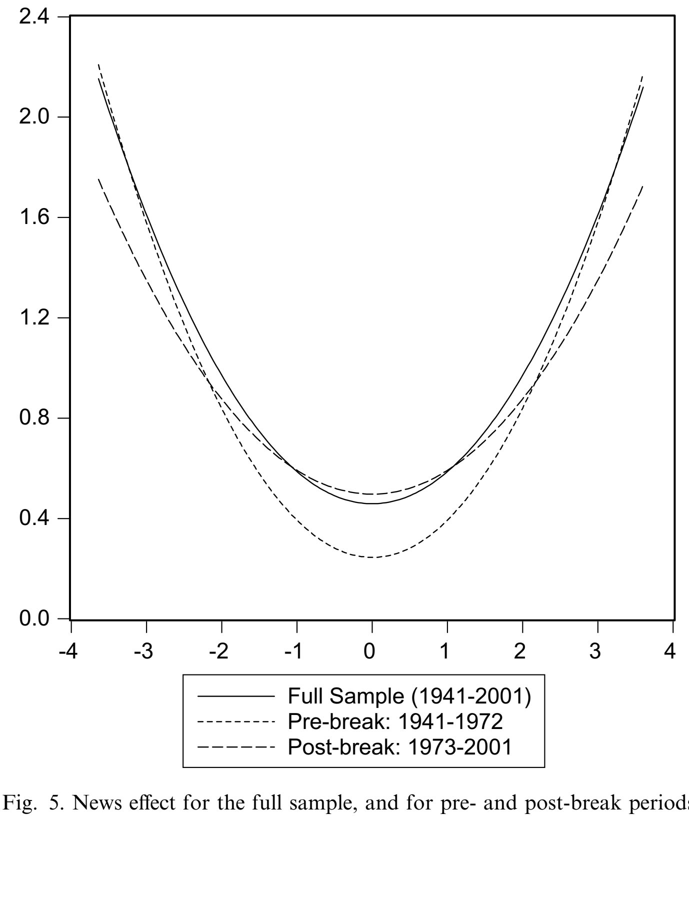

Fig. 5. News effect for the full sample, and for pre- and post-break periods.

impact of news in the period 1941:01–1972:06 can be seen to be much smaller for "small news", although the effect for big news is amplified. This is a consequence of the lower unconditional variance of the pre-1972 process and of the higher value of the α_2 coefficient: New information tended to have a bigger impact on stock market volatility during the early years. After 1972, the news impact shifts up, as a consequence of the higher variance of the market – the *average size* of news has been larger –, but large shocks (news) do not have such a considerable effect on variance. In other words, in the second subperiod the stock market volatility is less affected by good or bad news.

Persistence of volatility decreases markedly in the second subperiod. The sum of the α_1 and α_2 coefficients drops from 0.96 to 0.87, significantly reducing the life of shocks: Before the break date, half-life of shocks to volatility can be estimated at around seventeen months, whereas after the break it decreases to only five months. In other words, shocks that affect stock market volatility die out much faster in the second subperiod, and the time necessary for volatility to return to "average" levels is reduced quite significantly. This can be seen in the series of estimated variances: The unstable episodes in the second half of the sample tend to be shorter, even though they are much more intense than in the earlier years. This is not in contradiction with the above result on the news impact curve: The large negative shocks of the 1980s and 1990s have been twice or three times bigger than any pre-1980 shock.

Apart from the changes in volatility dynamics, we have already noted that the unconditional level of volatility goes up in the second subperiod, raising from an annualized 53% to 73%. Most of this impact may be attributable to the increase in trading volume experienced in these years as the stock market followed its development and international integration process. We analyze now the relationship between stock market volatility and trading volume.

3.3. Trading volume and volatility

Empirical evidence of a positive relationship between trading volume and stock price volatility has been documented by a number of researchers. [20] In this subsection we utilize a newly collected series of monthly trading volume that ranges from 1953:01 to 2001:12.

Such a long series of volume data was not previously available for the Spanish stock market: We recorded trading volume – obtained from the archived issues of the Daily Bulletin of the Madrid Stock Exchange (*Boletín Diario de Cotización de Bolsa de Madrid*) – and aggregated the daily volume into monthly figures. [21] The

[20] Karpoff (1987) surveyed the earlier evidence. More recent support for this relation is found in Jain and Joh (1988), Schwert (1989), Lamoreux and Lastrapes (1990), Gallant et al. (1992), Lang et al. (1992), Jones et al. (1994), Foster and Vishwanathan (1995), Andersen (1996) and Ané and Geman (2000) among others.

[21] Total daily trading volume data prior to January 1953 are not reported by the *Boletín Diario de Cotización.*

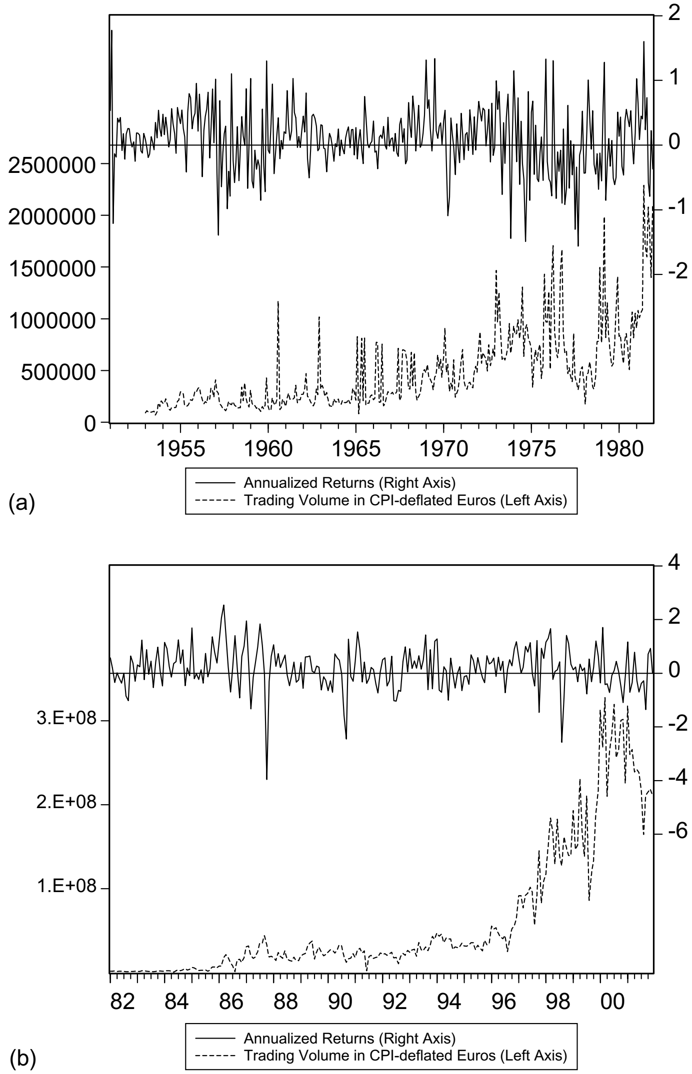

Fig. 6. Evolution of stock returns and real trading volume: (a) 1951–1981 and (b) 1982–2001.

trading volume has been converted to euros for the full sample and expressed in real terms. [22]

Fig. 6 presents the trading volume and the stock returns in the Spanish stock market over the period 1953–2001. The sample is split in 1981 for easiness of visual

[22] From 1941 until 2001, the official Spanish currency was the peseta. Volume data for the pre-2001 years – which was recorded in pesetas – have been converted to euros by using the fixed conversion rate of 166.386 pesetas per euro. The trading volume in real terms is constructed using the consumer price index.

analysis of the graphs, given the trending behavior of trading volume. It is not easily noticeable that trading volume affects the variance of the stock market. However, given that real volume has been increasing over time, a relationship between the level of volume and the volatility would force an upward trend into volatility: This does not seem to be reasonable in a long-term analysis such as ours. Consequently, we believe that the relationship, at least in a developing stock market where volume increases steadily through time, cannot be postulated in terms of the level of volume, but more likely in terms of changes – or, better, growth rates – in that level: Periods of high growth in trading should correspond to periods of increased volatility, and

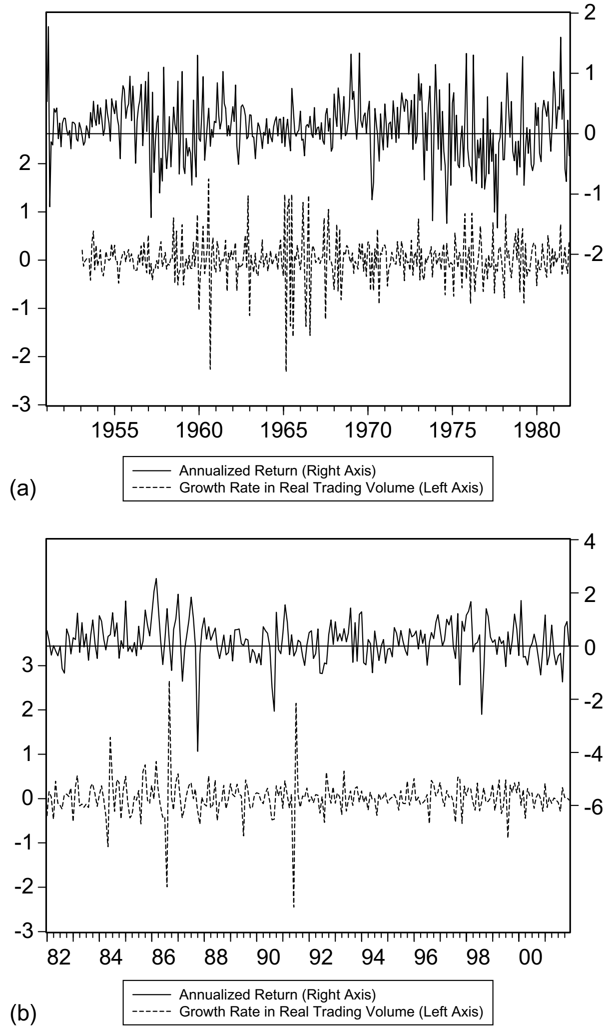

Fig. 7. Evolution of stock returns and growth in trading volume: (a) 1951–1981 and (b) 1982–2001.

periods of low growth in trading volume would be low volatility periods. Fig. 7 shows evidence in this regard, by representing the growth rate in trading volume along with the evolution of stock returns.

In view of the results in Section 3.2 on the structural break in the behavior of the variance of the stock market, we examine the possibility of a break in the behavior of trading volume at the time of the break in variance. We fit a simple AR(1) plus time trend model to the evolution of (log)trading volume in the Spanish stock market. Then, a Chow test for the presence of a structural break of the parameters at a predetermined time – June 1972 – is performed. The test gives ample evidence of the existence of a break in the volume series (the test value is 39.2, much larger than the relevant 5% critical value for an $F(3.58)$). We reestimate the time series model for trading volume using a post-1972 dummy that allows for all three parameters to differ at 1972. The results of this model are shown in the first column of Table 6. Additionally, we tested for an endogenous break in volume instead of forcing the break to be simultaneous to that of the volatility series. This test was carried out similarly to that of volatility, trimming the first and last 15% observations and estimating the model for all possible values of the break. The maximum value of the series of F-tests against the null of no break determines the date of the break. [23] This max-F test identifies the break date in volume with May 1984. [24] The parameters of this second equation, which are similar to those coming from using the date of the break in volatility, appear in the second column in Table 6. It seems, therefore, that the acceleration in trading volume in the Spanish market most likely took place after the increase in volatility.

We now estimate a GARCH model for the Spanish stock returns where we include trading volume as a regressor in the variance equation. We follow Ané and Geman (2000) and make the variance depend on the growth rate in volume instead of the level. [25] We allow for the effect of volume and for the intercept of the variance equation to change at the dates of the two different breaks. More specifically, the model we estimate is:

$$\begin{aligned} r_t &= \beta_0 + \beta_1 r_{t-1} + u_t, \quad u_t \to \mathrm{iid}(0, \sigma_t^2), \\ \sigma_t^2 &= \varpi_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 + \gamma_1 \mathrm{DVOL}_t + \gamma_2 D1972_t + \gamma_3 (\mathrm{DVOL}_t \cdot D1984_t), \end{aligned} \tag{8}$$

where DVOL_t is the first difference in (log)volume at period t, $D1972_t$ is a dummy variable that takes the value one after June 1972, and $D1984_t$ is a dummy variable that takes the value one after May 1984.

Table 7 reports the results of this model estimated over the period 1953:01–2001:12. The parameter estimates tell an interesting story. There is a significant

[23] This procedure, and even the same baseline equation has been used, for instance, by Christiano (1992) to detect a break in (log)GNP, a series that presents very similar statistical features to (log)volume.

[24] The value of the max-F test is 46.6, which is quite close to the value of the test for the exogenous break. The series of F tests is quite flat around the maximum.

[25] We tried to assess the volume effect directly by including the level of volume in the variance equation, as in Lamoreux and Lastrapes (1990). No relationship at all was detected, which is reasonable given the upward trending behavior of trading volume throughout the full sample which volatility does not present.

Table 6
AR(1) plus time trend estimate for real trading volume, 1953:01–2001:12

	Exogenous	Endogenous
γ_0	7.823	6.122
	(11.24)	(11.75)
γ_1	0.296	0.438
	(4.78)	(9.22)
γ_2	0.004	0.003
	(7.22)	(9.92)
γ_3	−6.737	−4.25
	(−9.29)	(−6.57)
γ_4	0.494	0.251
	(7.05)	(3.73)
γ_5	0.0004	−0.002
	(0.52)	(−2.11)

$$\mathrm{VOL}_t = \gamma_0 + \gamma_1 \mathrm{VOL}_{t-1} + \gamma_2 \mathrm{TREND}_t + \gamma_3 D_t + \gamma_4(\mathrm{VOL}_{t-1} \cdot D_t) + \gamma_5(\mathrm{TREND}_t \cdot D_t) + \varepsilon_t$$

D_t is a dummy that is zero for $t < 1972{:}06$ and one otherwise in the first column (exogenous break determined by volatility); in the second column, D_t is zero if $t < 1984{:}05$ and one otherwise (endogenous break for volume). t-statistics use QML standard errors.

volume effect in the variance of the Spanish stock market, but that effect does not change at the time of the break in volume – or at the time of the break in volatility. [26] In other words, the relationship between growth in volume and increased volatility seems to stay constant throughout the two periods. The variance does increase, though, in level, given the significant value of the coefficient attached to $D1972_t$. Consequently, the increased rate of growth in volume contributes to increased volatility – the structural break in volume mentioned above implies that the term DVOL_t has a higher average after 1984 – but there seems to be something more to the story, given the significant change captured by the dummy $D1972_t$. Thus, our analysis confirms that the unconditional level of volatility increases significantly around 1972, although this change is not due to a change in the effect of volume or to an acceleration in trading volume – which did not take place until 1984 – but to factors other than volume – captured by the significant value of the coefficient attached to $D1972_t$. [27]

[26] Alternative models that use $D1984_t$ for the intercept shift or $(\mathrm{DVOL}_t \cdot D1972_t)$ for the volume effect were also estimated. The results were significantly worse, so we do not comment on them.

[27] Note that the specification we have used does not guarantee that the variance of r_t will always be positive, since a very negative value of DVOL_t could make σ_t^2 negative. However, given the empirical estimates, the value of DVOL_t that would be needed to make σ_t^2 negative is an unreasonably big number – which would imply that trading volume virtually stopped. We did reestimate an EGARCH specification, that models $\ln \sigma_t^2$ instead, and therefore guarantees that σ_t^2 is positive at all times. The results, which for the sake of simplicity have been omitted and can be consulted in Cunado et al. (2003), do not change much qualitatively, although the fitted variance from the EGARCH model gives a much worse fit than that from the GARCH model that we present.

Table 7
GARCH(1,1) model for Spanish stock return volatility with real trading volume, 1953:01–2001:12

	1953:01–2001:12	1953:01–2001:12
β_0	0.102	0.105
	(6.92)	(5.25)
β_1	0.135	0.153
	(2.81)	(3.52)
ϖ_0	0.024	0.014
	(2.96)	(2.63)
α_1	0.663	0.775
	(10.39)	(15.11)
α_2	0.184	0.116
	(4.09)	(3.65)
γ_1	0.073	0.069
	(2.35)	(7.92)
γ_2	0.067	0.041
	(3.01)	(2.69)
γ_3	−0.073	
	(−0.68)	–

$r_t = \beta_0 + \beta_1 r_{t-1} + u_t, \quad u_t \to \mathrm{iid}(0, \sigma_t^2)$ [mean equation]

$\sigma_t^2 = \varpi_0 + \alpha_1\sigma_{t-1}^2 + \alpha_2 u_{t-1}^2 + \gamma_1 \mathrm{DVOL}_t + \gamma_2 D1972_t + \gamma_3(\mathrm{DVOL}_t \cdot D1984_t)$ [variance equation]

r_t is the rate of return to the Spanish stock market at period t, σ_t^2 is the conditional variance of the stock return at period t, DVOL_t is first difference in trading volume at period t, $D1972_t$ is a dummy that is zero for $t < 1972{:}06$ and one otherwise. $D1984_t$ is a dummy that is zero for $t < 1984{:}05$ and one otherwise. t-statistics use QML standard errors.

We have calculated the series of fitted conditional variances from the model with the volume effect in the variance equation, although we have reestimated the equation, eliminating the $(\mathrm{DVOL}_t \cdot D1984_t)$ variable, which is nonsignificant and added a substantial amount of noise to the estimate of the variance during the second subperiod. The estimated parameters without this interaction variable appear in the second column in Table 7 – the estimates in the two cases are quite similar. Fig. 8 represents the rolling variance and the forecasted conditional variance from January 1953 through December 2001. The estimated series of variances passes a goodness-of-fit test with similar values of the chi-square statistic as those of both the simple GARCH and the GARCH with one break models: Its similarity with the rolling variance is again clear, although given the character of the additional regressor included in the variance equation – which is a growth rate – the forecasted variances appear wiggly.

Summing up, there seems to be ample evidence for a relationship of trading volume with stock market volatility in the Spanish stock market during the years of our sample. Given the trending behavior of volume we included the growth rate of volume as the regressor, so our results imply that periods when trading volume

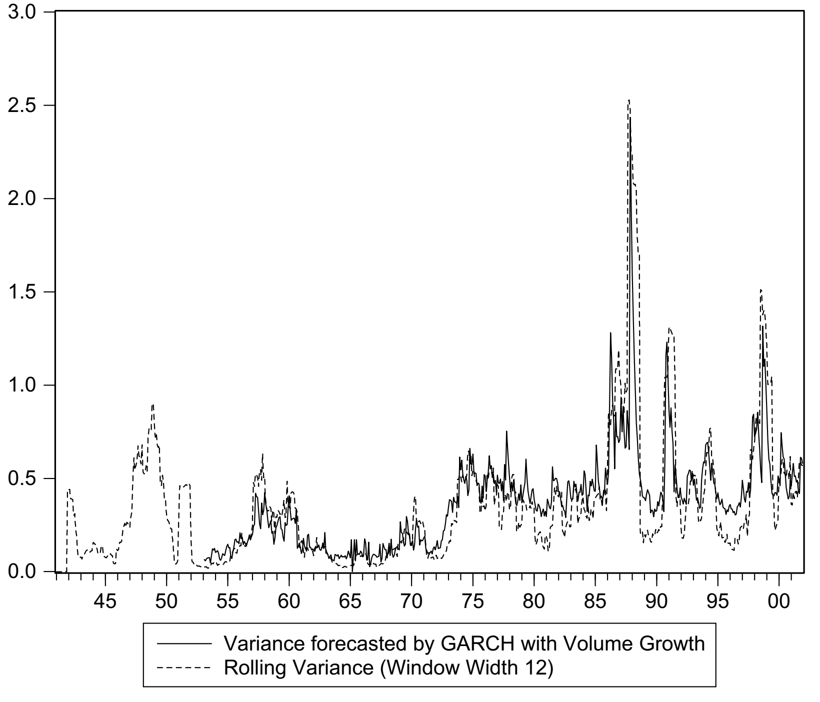

Fig. 8. Comparison of variance forecasted with GARCH with volume and rolling variance.

accelerates bring about a surge in volatility. The evidence also points at a stable relationship between variance and volume, so the structural break found in variance is not attributable to a change in the underlying relationship or to the acceleration in trading volume in the 1980s, but rather to factors other than volume, which are captured by the significant coefficient of $D1972_t$. We place now all our results in their historical context by identifying the most relevant events that have taken place before, around and after the date of the break.

4. Implications in the light of Spanish history

After a few years of autarchic behavior following the Civil War and World War II, the "Stabilization Plan" in 1959 signified a key change of strategy in Spanish economic policy: Frontiers were to be opened to the entry of goods and – more restrictively – to foreign capital. The stock market began to develop and financial activity accelerated during the late 1960s and early 1970s. An increasingly higher number of companies went public and activity in the secondary market stepped up.

Following this period of prosperity, however, the opening of the Spanish economy brought with it increased sensitivity to international economic conditions. The years of the oil crises represented a decade and a half of intense turmoil and instability in economic activity. At the end of the 1970s most of the countries were involved in industrial reconversion plans. In Spain in particular, in view of the seemingly backward path the economy was taking after the transition to democracy, severe measures of macroeconomic adjustment were adopted in 1977 with the so-called "Moncloa Pacts". By 1986, after a few reconversion plans, the economy had adjusted to market conditions and macroeconomic imbalances had been reduced. A phase of economic growth came about which was principally due to a high increase in investment demand caused by an improvement in business expectations and the need to capitalize the Spanish economy to deal with greater foreign competition after accession – that same year – to the EEC. In the financial side, the second half of the 1980s witnessed important changes such as the passing of the Stock Market Law of 1988 and the Maastricht Treaty requirement that financial markets in Spain be completely opened to international capital flows shortly after 1990. These two events were determinant in the development and consolidation of the Spanish stock market, which by now may be counted among the most important and highly developed stock markets in Europe.

Our analysis has shown significant evidence of a change in behavior of Spanish stock market volatility – and, as a by-product, of trading volume – in the 1970s and 1980s. As we mentioned in Section 3.1, the mid 1980s seemed to identify an additional change in stock market behavior, although the statistical evidence turned out to be weak. These two dates, however, – June 1972 and halfway through the 1980s – determine three distinct subperiods. The first period corresponds to the early development years, when Spain gradually came out of an autarchic state and began the opening of the economy to international markets. The stock market was stable, volatility tended to be persistent but no major shocks hit the economy. The second period corresponds to the crisis years (1973–1985), when the opening of the economy consolidated but Spain was hit by the global recessions and competition in the international markets. Volatility increased during this second period and became less persistent, but still no large shocks seemed to hit the economy: The market was basically closed to international capital flows, and volume had not accelerated. The third period (1986–2001) corresponds to the integration in the European environment and the years of financial development. Volume accelerates during this third period, and major shocks – but short-lasting – hit the market, which seems more subject to the influence of international conditions.

Thus, the evidence suggests that the change in stock market volatility occurred in the early 1970s, coinciding with the economic development, and not in the mid-late 1980s, the years of more intense development of the financial side, market integration and the acceleration of trading volume. This suggests two conclusions. First, it is the development of the economy that has led stock market development, and periods of profound changes in the economy bring about changes in stock market behavior. Second, most of the stock market activity in Spain still takes place in the domestic market, given that the period of financial market opening – post 1986 – does not seem to bring about significant changes in volatility behavior. It is true, though, that international instability is now transmitted to Spain and the unstable periods in the domestic market coincide with the episodes of international instability. Therefore, the opening of the financial markets has increased the degree of integration of the Spanish market with or its sensitivity to international stock markets, but this opening has not changed the way the stock market behaved. The Spanish stock market seems to have gone through the more important changes earlier on and by the time the market opened it was already developed and mature.

5. Conclusions

In this paper we have analyzed the behavior of Spanish stock market volatility, placing special emphasis on detecting whether volatility has changed its behavior significantly over the period 1941:01–2001:12 and on identifying the causes of such changes.

The time evolution of Spanish stock market volatility reveals that, apart from the periods of transitory instability induced by shocks to the market, the average level of market volatility has been significantly higher over the period 1972–2001 whereas it was relatively lower during the earlier years. Also, periods of abnormally high market volatility in the last years – stemming from episodes of global financial instability – present a much higher intensity but a reduced persistence when compared to unstable periods at the beginning of the sample. There is therefore a change both in average volatility and in its dynamic behavior: The stock market in the latter years is subject to higher but less persistent instability. In order to analyze these effects, we estimated a volatility model that allowed for endogenous structural breaks. We detected one single structural break in volatility behavior, located around June 1972. The unconditional level of volatility went up significantly at the time of the break, but both persistence and the impact of big shocks decreased after the break.

In view of this, and seeing that the years of stock market development have come in hand with a continuous increase in trading volume, the effect of volume on stock market volatility was analyzed. The results showed that growth in trading volume has a significant impact on stock market volatility, although this relationship has been stable through the years. Moreover, it was not the acceleration in trading volume – that took place around 1984 – that brought about the increased volatility, but most likely the intensification of the process of economic development and opening that the Spanish economy went through in the 1970s.

In the light of the recent instances of financial instability and crises, further research on this topic becomes a top priority. Given the importance of a smooth functioning of stock markets and the continuous increased importance of international financial flows, efforts towards understanding the factors that affect the stock market – by making it more unstable, or changing its dynamic behavior – and the side consequences derived from these changes in behavior are likely to yield benefits both for regulators, investors and for those involved in the processes of economic reform.

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