Facultad de Ciencias Económicas y Empresariales
Universidad de Navarra

Working Paper nº 06/03

Structural Changes in Volatility and Stock Market Development: Evidence for Spain

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Working Paper No.06/03
April 2003
JEL No. C32, C59, G10

ABSTRACT

In this paper we review the factors that may lead to structural changes in stock market volatility and present an analysis that assesses whether Spanish stock market volatility has changed significantly over the period 1941-2001. This period corresponds to the years of more profound development of both the financial and the productive sides of the economy in this country. We use alternative methodologies of endogenous breakpoint detection that estimate the dates at which the behavior of stock market volatility changed. The analysis of the Spanish stock market suggests that volatility has behaved in a different manner over the period 1941-2001: From 1972 to 2001, the years of more intense development of the stock market, the Spanish stock market has been characterized by a higher level of volatility and a lower persistence. This effect is partly attributable to the increased growth of trading volume brought about by the economic development process

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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 and Poterba 2000). This relates to the wealth effect of the stock market in consumption that became especially relevant after the drop in stock prices in the first semester of 2000: If before the decline in prices consumption had been growing at a steady pace given the increased wealth felt by consumers because of the continuous stock appreciation, the sizable fall in consumer wealth provoked by the stock market crash was expected to directly lower consumer spending. 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 economic growth (Levine and Zervos 1996 and Arestis et al. 2001). Investors interpret a raise in stock market volatility as an increase in the risk of equity investment and consequently they may shift their funds to less risky assets. This reaction would tend to raise the cost of funds to firms and new firms might bear the brunt of this effect as investors gravitate toward the purchase of stock in larger, well known firms. Finally, extremely high volatility could also disrupt the smooth functioning of the financial system and lead to structural or regulatory changes. Changes in market regulations 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, the Spanish economy could be counted among the most developed of the world, its capital markets were fully liberalizad and it had qualified to become a founding member of the European Monetary Union. Our sample, therefore, covers those years of development of the stock market, and of economic and financial opening and integration of the country. The analysis of the impact of all these events and of the different stages of financial development in the behavior of the stock market appears relevant for our understanding

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

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

of the functioning of financial markets and for those countries that are now undergoing similar processes, such as the transition countries in Europe and other developing countries.

We attempt to ascertain *when* significant changes in the structure of Spanish stock market volatility have happened through time and to place those changes in the context of the recent history of the Spanish economy. We are interested in the events that coincide with both transitory and structural changes in volatility. The evolution of stock return volatility confirms that the volatility of the Spanish stock market has changed significantly throughout the sample years. More specifically, not only there is evidence of ARCH-type effects, where the conditional volatility is allowed to change over time, but also of changes in unconditional volatility. This suggests the existence of changes - structural breaks - in the statistical model generating return volatility. Given that we do not want to impose the dates of the breaks, 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, 2002, 2003) which have already been successfully applied by Bekaert et al. (2002a, b) to investigate multiple structural changes in the stock markets of emerging economies. We then test for robustness of our results by using two additional tests for endogenous breaks in volatility (Kokoszka and Leipus 2000, and Inclán and Tiao 1996). We finally complement and extend 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 main factors that may drive changes in stock market volatility. Section 3 analyzes changes in the Spanish stock market volatility using a battery of methodologies, placing emphasis on the detection of structural breaks and on the relationship of volatility to trading volume. Section 4 elaborates and 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 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 may be interpreted in two different ways. First, one may look for changes in conditional volatility, in the way implied by ARCH-type models or by the volatility in levels framework in Lamoreux and Lastrapes (1990). This would refer to the value of volatility given a specific realization of past returns or of other relevant variables. Second, one may be interested in changes in unconditional volatility which would imply looking for modifications in the data generating process. As a matter of fact, all the reasons we review in this Section can be consistent with changes in conditional volatility - for example, volatility tends to increase significantly after an unusually big negative return, which would be evidence of "incoming bad times" for the company that might last for a few periods - but also with changes in the unconditional volatility - this unusually negative return might signal the onset of the decline in the business conditions of some company or it may have been triggered by a change in consumer preferences that will have a permanent effect on that specific company.

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). Thus, changes in market volatility would merely reflect changes in the local or global economic environment. Others claim that volatility is caused mainly by changes in trading volume, practices or patterns, which in turn are driven by factors such as modifications in macroeconomic policies, shifts in investor tolerance of risk and increased uncertainty.

More recently, researchers have noticed fundamental changes in investor behavior. This has led to the abandonment of the efficient market hypothesis in favor of behavioral finance. 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 fundamentals: Investor behavior seemed to be driven less by fundamental variables and more by other factors that led to higher and sustained volatility. Among these, Shiller mentions sociological and psychological factors - US triumphalism, cultural changes favoring business success, the impact of baby boomers in the market - 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. These researchers would explain changes in market volatility as 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.

Other factors that have been identified by researchers as leading to changes in market volatility are the improved speed and efficiency with which financial transactions are carried out, the increased interdependence and interconnectivity of markets and the greater homogeneity of investor behavior. All these factors are related to the speed at which the market accommodates shocks and incorporates the relevant information into the prices. Thus, it could be argued that they may lead to different characteristics of volatility dynamics. For instance, persistence of volatility may change: A market where the information gets incorporated faster into the price must revert to the "normal" level of volatility faster, and thus it must have a reduced persistence of volatility shocks. These factors driving changes in volatility would correspond, therefore, to the stage of development of the domestic stock market and to its degree of integration with other markets.

As we review in Section 4, the specific country we analyze, Spain, has evolved in the last sixty years from being a developing and closed country to being currently a developed country, integrated with the rest of Western economies. Consequently, one would expect to see significant changes in the behavior of volatility during these years. In particular, the general level of volatility should have increased substantially over time due to the multiplication of the volume of trading by some orders of magnitude. Furthermore we would expect the Spanish stock market to have become more developed and more efficient, aided by the incorporation of new trading technologies and by the integration with international capital markets.[3] We believe that at least indirectly a link between improved efficiency of the market and changes in volatility dynamics can be expected. The faster the information is incorporated into prices, the lower the volume of trading necessary to bring prices to their correct levels. Thus, periods of increased volatility due to the arrival of new information should be shorter, and volatility should revert to "normal" levels faster. In other words, one would expect lower persistence of abnormal volatility, or faster "mean reversion" of volatility.[4]

We postulate that the development process of the Spanish stock market should be manifest in changes both in the level of volatility - by the increased trading induced - and its dynamic characteristics - by the deep structural changes in investor behavior and trading practices and by the increase in market efficiency. We focus our analysis therefore on characterizing the dynamic evolution of volatility in the Spanish stock market data and on placing that evolution in the context of the historical events related to 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 the behavior of stock market volatility in the Spanish market over the last sixty years. The events that took place in Spain during this period of study provide us with a natural experiment that will allow 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. Even though there are four stock markets in Spain, the Madrid Stock Exchange handles

[3] We define efficiency in the 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. Therefore, efficiency is generally operationalized as the stock market following a martingale process conditional on some set of information - this set determining the form of efficiency: Weak, semi-strong or strong - although usually no relationship is postulated with respect to the volatility of the market.

[4] 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.

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 has been reduced 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.

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 which shows the dynamic behavior of volatility over the years. Events that coincide with temporary increases in volatility are easily identified. Up to this point, our analysis follows that in Campbell et al. (2001) for US stocks. We depart from the cited paper, given that there does not appear to be evidence of a trending behavior of volatility: We focus on a different structure in the time evolution of stock market volatility by examining conditional heteroskedasticity over time. This allows us to complement the previous analysis on the specific events that have caused surges in stock market volatility and 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 points in time where more profound changes in volatility dynamics, and therefore in stock market behavior, have taken place. We test for robustness of our results by using two additional 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, the impact of shocks and make some comments on the frequency components of return oscillations. A final section 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 table includes the average return, standard deviation, skewness and kurtosis coefficients, first order autocorrelation, a Ljung-Box test for significance of the first four autocorrelations, an ARCH-LM test for existence of conditional heteroskedasticity and the Jarque-Bera test of normality. The coefficients of skewness and kurtosis reveal significant departures from normality in the data, confirmed by the value of the Jarque-Bera test. The Ljung-Box Q-statistic and the first order autocorrelation indicate the presence of significant, but mild, autocorrelations of returns and the ARCH-LM(4) test reveals the presence of ARCH-type effects in volatility.

[Insert Table 1 here]

The dynamics of stock market volatility can be seen in Figure 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:

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

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.[5]

[Insert Figure 1 here]

The variance of returns of the Spanish stock market index, which seems to have been relatively low by historical standards before the 1970's, rose significantly in the last periods of the sample: In these last two decades 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 years, there have been three important peaks in stock market volatility, when the annualized standard deviation of returns became greater than 100%. These peaks can be dated in 1987, 1991 and 1999: The first peak corresponds to the crash of October 1987, the second peak to the Gulf War and the last one to the Brazilian and Russian crises. Peaks of this intensity are not present in the first decades of the sample: It is only in recent years that the Spanish stock market has suffered from intense temporary instability, mainly induced by international financial crises, although the unstable episodes appear to be quite short lasting. Note, therefore, 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.[6] The GARCH(1,1) model specifies the behavior of returns as following the process:

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

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

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 (the term $\alpha_1 \sigma_{t-1}^2$). We estimate a simple GARCH(1,1)

[5] We calculate returns as $12(\log P_t - \log P_{t-1})$. Notice that in the subsequent analysis we assume that the behavior in mean of stock returns is an AR(1) process. Given that there is some mild evidence for autocorrelation of returns over time, we allow for the existence of that autocorrelation, even though it is not our main interest.

[6] Pagan and Schwert (1990) show that the GARCH model performs quite well in comparison with many alternative methods for modelling conditional volatility of stock returns. 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, use GARCH models to account for the time evolution of conditional variance.

process for the full sample of stock market returns. The coefficient estimates appear in Table 2. According to these estimates, stock market volatility in these years has been quite persistent ($\alpha_1 = 0.86$ and $\alpha_2 = 0.13$, for a value of $\alpha_1 + \alpha_2 = 0.99$).[7] The unconditional level of the annualized standard deviation has been of 72%. Figure 2 plots the 12-month rolling variance, together with the forecasts of the conditional variance - the series of estimated σ_t^2 derived from the variance equation - coming from the GARCH model. As we can see in the figure, the GARCH forecasts of the conditional variance very closely approximate 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 took the rolling variance as the "true" variance and performed a chi-square test of similarity of the distributions of volatility implied by the two measures.[8] The test did 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.[9] There is, therefore, strong evidence of conditional heteroskedasticity in the Spanish stock market, by which volatility is a positive function of both past volatility (persistence, or 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.[10] These results were, of course, 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. However, it is anyway noticeable 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.

[Insert Figure 2 here]

[7]It can be shown that 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 therefore given as the measure of persistence of the variance.

[8]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 ($4\left(\frac{2T^2}{c_\alpha^2}\right)^{\frac{1}{5}}$, 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 (1972). 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.

[9]Of course, 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. We interpret the fact that one model - the GARCH variance with merely 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.

[10]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.

[Insert Table 2 here]

An eyeball analysis of the more general features of both 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, one can notice an increase in the frequency of price and return oscillations over the last years of the sample, especially starting after 1987. Second, there seems to be also an increase in the amplitude of return oscillations in those last years. Third, and related to the previous feature, the variance measure suggests that the average level of volatility has gone up significantly starting in the early 1970's, having been relatively lower prior to that moment. 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: That is, it seems that 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. All these features suggest the existence of different behaviors of stock market volatility throughout our sample. The last years seem to be characterized by a higher level of volatility and lower persistence. Furthermore, return oscillations seem to be more frequent in those last years. Three distinct periods could be identified: The earlier years from the beginning of the sample until the early 1970's, 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 three periods correspond to three distinct periods 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. In the next subsection we proceed in that direction and attempt to confirm the presence of these structural breaks.

3.2 Structural Breaks in Spanish Stock Market Volatility

In this Section we study whether volatility in the Spanish stock market has changed over the sample period. We are interested in assessing the evidence for structural changes in the process that generates stock market volatility, that is, the evidence for changes in unconditional volatility. The previous Section showed evidence in that direction, and in fact it already pointed at two possible dates around which we would expect to find significant changes in volatility behavior: The early 1970's and around the time of the 1987 crash. We use now techniques for the location of endogenous structural breaks in order to detect the possible time of the change in the parameters of the variance equation.

The GARCH(1,1) process was presented above.[11] In order to capture the

[11] Pagan and Schwert (1990) and Pagan (1996) note that it is usually enough with a GARCH(1,1) model to account for most of the time structure in conditional variance. Except maybe for an asymmetric leverage effect, most series we are aware of can be conveniently

changing behavior in the Spanish volatility we use this baseline GARCH model 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. The following section explains the procedure in greater detail.

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: One can look at Banerjee et al. (1992), Ghysels et al. (1997), Bai et al. (1998) or Dufour and Ghysels (1996) to realize that the topic is still in its early development stages. The issue of how to estimate the number and location of multiple endogenous structural breaks is also being currently intensely researched and results on the procedure and properties of the tests involved are now being published. Papers by Andrews et al. (1996), García and Perron (1996), Bai (1997, 1999), Lumsdaine and Papell (1997) or Bai and Perron (1998, 2002, 2003) are some of the most noticeable examples.

Most of the techniques in the above papers 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.[12] 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 for the calculation of a confidence interval for the breakpoint cannot be directly applied, we use the general framework in Bai and Perron (1998, 2002, 2003) 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 its 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 the existence 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, $\mathbf{t} = \{t_1, t_2, ...t_m\}$ 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

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explained by a GARCH(1,1) model.

[12] Formal evidence that this type of tests can be extended to GARCH processes is cited in Andreou and Ghysels (2002).

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,

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

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

The alternative model is specified as one which contains an additional break at time τ. Thus, the set of $l+1$ breakpoints becomes now $\mathbf{t}^* = \{\mathbf{t}, \boldsymbol{\tau}\}$, 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:

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

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

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

where $\mathbf{T}^*$ is the set of possible times for the new break. Of course, given the series of LR tests and the $\sup LR$ test, the date of the new breakpoint $\widehat{t}$ is:

$$\widehat{t} = \underset{\tau \in \mathbf{T}^*}{\arg\max} L\left(\mathbf{t}^*, \widehat{\theta}(\mathbf{t}^*)\right) = \underset{\tau \in \mathbf{T}^*}{\arg\max}\left[\sup LR_\tau(l+1 \mid l)\right] \tag{6}$$

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 $\widehat{t}$. The values of the parameters before and after the break correspond to the estimates in $\widehat{\theta}(\mathbf{t}^*)$. The different versions of this statistic (Bai et al.,1998, Bai and Perron, 1998, 2002, 2003) have a limiting distribution that depends on a

q-dimensional Brownian motion, where q is the number of parameters allowed to change at the time of the break. Thus, the critical values of the $LR(l+1 \mid l)$ test depend on l and on q and are usually calculated by simulation of the q dimensional Brownian motion.

One final comment is that $\mathbf{T}^*$, the set of possible times for the break, must exclude a number of observations around the initial and final dates and around the dates in $\mathbf{t} = \{t_1, t_2, ...t_l\}$ that 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.[13] 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.

We stress again that the procedure outlined corresponds to a *sequential* location of breakpoints. That is, given that $\mathbf{t} = \{t_1, t_2, ...t_l\}$ is the set of l estimated breakpoints, the $(l+1)^{th}$ breakpoint is located conditional on the other l. An alternative way of locating multiple breakpoints (Bai and Perron, 1998) would compare the value of the likelihood for the l estimated breakpoints with that of all possible partitions of the sample that come from a model with $(l+1)$ breaks. This "simultaneous" location of all breakpoints may lead to different inferences about the breakpoints, but it also yields consistent estimates of the breaks.

The critical values have been tabulated by the authors, and are available in their papers. We present those critical values for the sup $-LR$ test for a break in three parameters in Table 3.

[Insert Table 3 here]

It also has to be said that the tests explained above can consistently estimate not the *dates* of the breaks but the *proportion* of the total sample at which the breaks occur. That is, we estimate consistently that the break happens at "the 0.2 quantile" of the sample. Of course, one can then back up the specific time of the event, given a fixed number of observations T in the sample.

3.2.2 Empirical Results of the Endogenous Break Analysis

We comment now on the results of the endogenous break sequential analysis. The models that are rejected by the data are briefly described, although the focus of our comments is the final model with the number of breaks suggested by the data. Similarly to our presentation of the simple GARCH model, the estimated conditional variance coming from the model with breaks can be compared to the rolling variance, both visually and through a formal goodness-of-fit

[13] This proportion is usually taken to be 0.15. The results are not sensitive to the choice of this trimming proportion, unless the break is located too close to the endpoints of the sample. In small samples or in settings where low frequency data are used a trimming proportion of 0.1 may be more advisable out of data availability considerations, although then the endpoint problem becomes more acute.

test. We perform and comment on those comparisons only for the final model resulting from the breakpoint analysis.

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, that we already commented on, were shown in Table 2. Figure 2 gave an idea of how the conditional variance estimated by the GARCH(1,1) reproduces quite well the behavior of the rolling variance and we mentioned that the goodness-of-fit test of the similarity of the distribution of the implied variance did not allow to reject the similarity of both distributions. This model represents our benchmark. It already confirms the fact that the volatility of the stock market changes over time. We now proceed to estimating the models that allow for breaks in the intercept of the variance equation (level shifts in volatility) and in the persistence (α_1) and news-effect (α_2) parameters.

Model II: We perform now the test for one break in the three parameters of the variance equation. We calculate the series of LR statistics and take the maximum of those 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. Figure 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.

[Insert Table 4 here]

[Insert Figure 3 here]

Model III: Given the above, we now test for a possible second break, conditional on the first break being located at June, 1972. The second break is detected in observation 129 that corresponds to September 1951 (see Table 4). However, when we apply 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, we can only reject, and marginally, the null at the significance level of 10%, so the evidence for a second break in all parameters seems weak. Table 5 contains the estimated parameter values, for the three subperiods identified.

[Insert Table 5 here]

Given the very weak evidence in favor of a second break we look at the implied conditional variance fitted by the two-break model. Figure 4 compares the rolling variance with the conditional variance fitted by the two-break model: It can be seen that the two-break model excessively overestimates the volatility during the observations that correspond with the period January 1941 to January 1951, the period "created" by the second break. In addition, most of the peaks in the volatility behavior present a much reduced persistence compared with the rolling variance. Thus, Model III is giving 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.[14]

[Insert Figure 4 here]

We now comment on the behavior of volatility implied by the parameters - shown in Table 4 - of 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 the sup-type tests tend to be quite sensitive to outliers.[15] All three parameters change at the date of the break: The estimated GARCH effect varies 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. Therefore, there seems to be significant evidence for a decrease in the degree of persistence of conditional variance by 0.09 (from 0.96 down to 0.87): Before the break date, half-life of shocks to volatility can be estimated at around seventeen months, whereas after the break it has been reduced to only five months. 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 Figure 5, along with the rolling variance. The model-estimated 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 both 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.

[Insert Figure 5 here]

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 on the relevance of the date of the break and the two subperiods 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

[14] We did look at the possible existence of three breaks in the volatility series. We do not report these 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.

[15] 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.

those tests as robustness checks for our results on the endogenous breaks. Both tests are based on cumulative sums of either the squared returns or the absolute returns. 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 two tests that we apply are those in Kokoszka and Leipus (KL, 2000) and Inclán and Tiao (IT, 1996). 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 of returns. 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.[16]

The KL test for existence of a break in the variance of a return series r_t is constructed by first calculating the series of cumulative sums:

$$U_T(k) = \left(1/\sqrt{T} \sum_{j=1}^{k} X_j - k/\left(T\sqrt{T}\right) \sum_{j=1}^{T} X_j \right) \tag{7}$$

where X_j is either the squared return r_j^2 or the absolute return $|r_j|$ at time j. The estimator of the date of the break is then taken to be the maximum of the values of the test:

$$k = \min\left\{ k : |U_T(k)| = \max_{1 \leq j \leq T} |U_T(j)| \right\} \tag{8}$$

The asymptotic distribution of the normalized test $KL = \sup\{|U_T(k)|\}/\widehat{\sigma}$, where $\widehat{\sigma}$ is some estimator of the long run variance, is a Kolmogorov-Smirnov type distribution, with critical values 1.22 and 1.36 for the 90% and 95% confidence levels respectively.[17]

The IT test is constructed with a different series of cumulative sums:

$$D_k = \left(\frac{\sum_{j=1}^{k} X_j}{\sum_{j=1}^{T} X_j} - k/T \right) \tag{9}$$

and again the date of the break is taken to be that of the maximum D_k, with the test statistic being rescaled as follows:

$$IT = \sqrt{T/2} \max_k D_k \tag{10}$$

[16]In fact, 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 can be seen to be in line with the sup $-LR$, but the IT test is clearly biased towards detecting more breaks in time series.

[17]We use a Newey-West heteroskedasticity and autocorrelation-consistent estimator of the long run variance, with truncation lag determined by the rule $4(T/100)^{2/9}$.

The asymptotic distribution followed by this rescaled IT test is exactly the same as that of the normalized KL test.

Both tests can be applied sequentially in order to find multiple breaks. The sequential procedure detects the first break, and then applies the test again to the two subperiods identified by the first break. The date of the higher $\sup U_T$ or $\sup D_k$ of both subperiods is taken as the estimate of the second break, which in turn determines three subperiods and so on.

Table 6 reports the results of applying the KL and IT tests to our series of returns. We have carried out the test for both the squared and the absolute returns.[18] It can be seen that 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). Both tests yield a statistically significant break in squared returns, although the evidence for the absolute returns is a little weaker. The second break is located in 1960, but this break is not statistically significant according to the KL test. The IT test would, however, allow to reject the null of one single break in favor of the alternative of two breaks, but given the i.i.d. assumption underlying the test we believe that the evidence is not strong enough in favor of this second break.

We interpret the results in Table 6 as giving evidence in favor of a single break in the variance of the return series. This break is located around 1972-1973. Thus, the results of these CUSUM-type tests are perfectly in consonance with the results of the $\sup -LR$ test.

[Insert Table 6 here]

3.2.4 Volatility: News Effect, Persistence and Frequency Components

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, the persistence of volatility and the frequency components of return oscillations.

Engle and Ng (1993) developed the news impact curve, that relates past shocks to the return process (news) to current volatility. This curve measures how new information is incorporated into volatility. The news impact curve can be calculated as:

$$\sigma_{t,n}^2 = A + \alpha_2 u_{t-1}^2 \tag{11}$$

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. Figure 6 presents the news impact curve implied by the full sample GARCH and the curves that correspond to the two subperiods identified

[18] An AR(1) was first fitted to the returns, so that the tests are carried out on the residuals of that AR estimation.

by the break. The 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, but large shocks (news) do not have such a considerable effect on variance. In other words, in the second subperiod stock market volatility is less affected by good or bad news.

[Insert Figure 6 here]

Persistence of volatility also changes in the second subperiod. The sum of the α_1 and α_2 coefficients decreases from 0.96 to 0.87, thus representing a decrease in the half life of the shocks from seventeen months to 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 much shorter, even though they are significantly 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 1980's and 1990's have been twice or three times bigger than any pre-1980 shock.

Finally, we mentioned briefly that the frequency of return fluctuations - some cyclical behavior is apparent - appears to be higher after the break. We examine this problem by looking at the spectral density of the variance of the return innovations, calculated from the seasonally adjusted residuals after an AR(1) model is fitted to the returns. We compare the spectral density of the data prior to June 1972 with those of the 1972:07-2001:12 and 1987:11-2001:12 subperiods. Apart from some peaks that correspond to cyclical elements at frequencies other than the seasonals, the densities show that in the two latter periods a higher proportion of the variance is explained by components in the medium-high frequencies. We calculated the area under the spectral density between the frequencies $(0.4, 2)$, which correspond to cycle periods between sixteen and three months - lower frequencies can be attributable to noise components, although the result is robust to using the $(0.4, 3)$ range instead. The areas contained under that interval of frequencies - out of a total area in the $(0, \pi)$ range of π - for the periods 1941:01-1972:06, 1972:07-2001:12 and 1987:11-2001:12 are 1.2, 1.8 and 1.7 respectively. Therefore, the spectral density of the variance of the post-1972 or even post-1987 stock market returns contains more mass in high frequency components - approximately 14%-16% more of the total variance is accounted for by those frequencies - which we understand in terms of the return process suffering more frequent oscillations. The estimated spectral densities are shown in Figure 7, for frequencies in the $(0.4, 2)$ interval.[19]

[Insert Figure 7 here]

Apart from the changes in volatility dynamics, we have already noted that the unconditional level of volatility goes up significantly in the second subperiod, raising from an annualized value of 53% to 73%. Most of this impact is probably attributable to the increase in trading volume experienced in these years as the stock market followed its development and international integration process. We proceed now to analyze 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. Karpoff (1987) surveys 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.

We have already noted that our sample includes the years during which the Spanish stock market went through its development stages. Significant changes in trading volume have been taking place during these years: An upward trend in volume would in fact be expected throughout those years. This trend is likely to have had an influence in the evolution of stock market volatility.

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 daily 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.[20] The trading volume has been converted to euros for the full sample.[21]

Figure 8 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 analysis of the graphs, given the trending behavior of trading volume. It is not clearly noticeable that trading volume affects the variance of the stock market. However, it is clear that given that volume has been increasing over time, to expect a relationship between the level of volume and the volatility would be forcing 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 tends to

[19] We use the Bartlett-smoothed estimate of the spectral density in the graphs.

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

[21] 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.

increase throughout 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. That is, periods of higher than normal growth in trading should correspond to periods of increased volatility, and periods of a relatively stable growth in trading volume should correspond to low volatility periods. Figure 9 shows evidence in this regard, by representing the growth rate in trading volume along with the evolution of stock returns. Even though the figure gives evidence that high growth in trading volume seems to correspond to periods of increased volatility of returns, some statistical evidence is called for.

[Insert Figures 8 and 9 here]

In view of the results in Section 3.2 on the structural break in the behavior of the variance of the stock market, we first examine the possibility of a break in the behavior of trading volume at the time of the break in variance. For that purpose, we fit a time series model to the evolution of trading volume in the Spanish stock market. We take the (log)volume and fit a simple AR(1) plus time trend model. Then, a Chow test for the presence of a structural break of the three 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 42.1, much larger than the relevant 5% critical value for an F(3,581)). 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 7. We performed an additional analysis: It may be advisable to perform a test for an endogenous break in volume instead of forcing the break to be simultaneous to that of the volatility series. We performed the endogenous test by using a similar analysis to that of volatility, trimming the first and last 15% observations and estimating the model for all possible values of the break. We then take the maximum of the value of the $F-$ tests against the null of no break as the date of the break.[22] This $max-F$ test identifies the break date in volume with April, 1971.[23] Thus, the evidence seems to favor the existence of a break in volume slightly before the break in volatility, which is perfectly consistent with the story of the break in volatility being determined by a structural change in trading volume. The parameters of this second equation, which are almost identical to those coming from using the date of the break in volatility, appear in the second column in Table 7.

Figure 10 compares the forecasted value of (log)volume given the two models estimated above - using the exogenous and the endogenous break - and the true

[22] This simple 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 statiscal features to (log)Volume.

[23] The value of the max $-F$ test is 42.7, which is quite close to the value of the test for the exogenous break. In fact, the series of F tests is quite flat around those years: There is quite strong evidence of a break, but the specific date of the break could be a few months before/after 1971:04.

evolution of (log)volume. Both models capture quite well the upward trend - and therefore the average growth - of trading volume, and its acceleration at some point in the early 1970's.

[Insert Table 7 here]

[Insert Figure 10 here]

Having ascertained that there is evidence that points at a significant change in the rate of growth of trading volume around or slightly before the time of the break in volatility behavior, we proceed now to linking volatility and trading volume. We estimate a GARCH model for the Spanish stock returns where we include volume as a regressor in the variance equation. This analysis is similar to that in Lamoreux and Lastrapes (1990), although in our case we follow Ané and Geman (2000) and make the variance depend on the growth rate in volume instead of the level.[24] We allow for the effect of volume and for the intercept of the variance equation to change at the date of the break. In this way, we gain evidence of a change in the relationship of variance to trading volume at the break date. Thus, the model we estimate is:

$$\begin{aligned} r_t &= \beta_0 + \beta_1 r_{t-1} + u_t, \qquad u_t \longrightarrow iid(0, \sigma_t^2) \\ \sigma_t^2 &= \varpi_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 u_{t-1}^2 + \gamma_1 DVOL_t + \gamma_2 D1972_t + \gamma_3 \left(DVOL_t \cdot D1972_t \right) \end{aligned} \tag{12}$$

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

Table 8 reports the results of this model estimated over the period 1953:01-2001:12. The parameter estimates tell quite an interesting story. There is a significant volume effect in the variance of the Spanish stock market, but that effect does not change at the time of the break. In other words, the relationship between increases 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 an increased average volatility - the structural break in volume mentioned above implies that the term $DVOL_t$ has a higher average after 1972 - but there seems to be something more to the story, given the significant change captured by the dummy $D1972_t$. Thus, this 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, but to a change in the average growth rate of volume - higher average value of $DVOL_t$ - and to factors other than volume - significant value of the coefficient attached to $D1972_t$.

[Insert Table 8 here]

[24] We tried to include the volume effect in the same manner as in Lamoreux and Lastrapes (1990), namely, by including the level of volume in the variance equation. 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.

We have calculated the series of forecasts for conditional variance coming from the model with the volume effect in the variance equation. Figure 11 represents the nonparametric measure of volatility (a 12 month rolling variance of returns) and the estimates of this conditional variance estimated using the sample from January 1953 through December 2001. The estimated series of variances passes a goodness-of-fit test with very 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 quite wiggly.

[Insert Figure 11 here]

We believe that the results of this Section are quite enlightening. There seems to be clear 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 opted for including the growth rate of volume as the regressor, so our results mean that periods when trading volume accelerates tend to 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, but rather to the acceleration that trading volume suffered around the time of the break in variance and, maybe, to factors other than volume, which are captured in the equation above by the significant coefficient of $D1972_t$. We believe the acceleration in volume to be due to the continued development of the Spanish stock market and the profound changes the Spanish economy was going through. 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

A quick look at recent Spanish economic and financial history can help put all of the above findings in their context. Spain has evolved from being a developing - and closed - country in the early 1940's to being currently a member on its own right of the group of most developed countries in the world. This evolution has taken place both in the productive and in the financial sides of the economy: Literature that links development of the financial side with real growth is by now abundant (see Levine, 1997, for a survey). In view of our findings, it would appear that this link is more intense whenever a country - like Spain - is facing its early stages of development and that the causality issue goes from the real side to the financial side. We begin this Section by quickly reviewing some of the most important events in the economic and financial development of Spain.

After a few years of autarchic behavior following the Civil War and World War II, the "Stabilization Plan" in 1959 brought an important change of strategy in Spanish economic policy: Frontiers were to be opened to the entry of goods and - more restrictively - to foreign capital. This commercial opening, together with the low competitiveness of the Spanish economy and the great need for capital goods and raw materials, produced a chronic deficit in the balance of trade, which was financed by the entry of capital into Spain, mostly through the tourist boom and through foreign direct investment. This new model produced high growth in production and national income. The stock market began to develop and financial activity - as is already clear from the behavior of trading volume - accelerates during these years. An increasingly higher number of companies go public and activity in the secondary market also steps up.

Following this period of prosperity, however, the opening of the Spanish economy brought with it increased sensitivity to international economic conditions. The oil crises hit, and the crisis years in the 1970's and 1980's represented a decade and a half marked by intense turmoil and instability in economic activity. Neither economic policies nor businesses responded with the necessary flexibility to the new economic conditions. The reasons were twofold. Firstly, given the higher world instability, these years were characterized by more intense state intervention than in the previous two decades, as the Government yielded to the temptation of protecting the economy. This had the unintended consequence of making the economy more sluggish in responding to evolving market forces. Secondly, the economic crises coincided with the end of one political regime - dictatorship - and the transition towards another very different one - democracy: This diverted some of the attention from the economy to sociopolitical issues. After the transition, and in view of the seemingly backward path the economy was taking, severe measures of macroeconomic adjustment were adopted in 1977 with the so-called "Moncloa Pacts." These included a currency devaluation, accompanied by a moderately restrictive monetary policy, and a commitment to deepen the structural reforms that had begun before the crises period.

At the end of 1970's most of the countries were involved in industrial reconversion plans. The first of these plans in Spain was adopted in 1981-1982 and the second in 1983-1986. In 1986 the economy had already adjusted to market conditions and the macroeconomic imbalances had been reduced. Then, a phase of economic growth came about which was principally due to a high increase in investment demand. This increase responded to an improvement in business expectations and the strong need to capitalize the Spanish economy to deal with greater foreign competition after accession - that same year - to the EEC. In the financial side, it was at the end of the 1980's that we witnessed important changes in the Spanish stock market, the most important of which were probably the passing of the Stock Market Law of 1988 and the requirement, stemming from the process of economic and monetary integration set by the EU in the Maastricht Treaty, 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. We are now probably witnessing the beginning of a new period, with the creation of the Eurozone and the European Monetary

Union, of which Spain was one of the founding members. It is probably too early, however, to attempt to study the effects induced by the introduction of the euro.

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 1970's. As we mentioned in Section 3.1, the mid 1980's seemed to point out at an additional change in stock market behavior, although the statistical evidence here turned out to be weak, and the results could be too influenced by the 1987 crash. These two dates - June, 1972 and October, 1987 - determine three subperiods that roughly correspond to the three distinct periods that the Spanish economy has gone through since the early 1940's and that we very briefly reviewed. 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 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. It was also during these years that the transition to democracy took place, and that the development of the financial markets gained new momentum - which would accelerate even more afterwards, with the joining of the EU. The third period (1986- 2001) corresponds to the integration in the European environment.

The evidence suggests that the most substantial change in stock market behavior - both in trading volume and in volatility - happened in the early 1970's, coinciding with the economic development, and not in the late 1980's, which correspond to the years of more intense development of the financial side. This is indeed quite relevant, and two conclusions should be drawn from this evidence. 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 - in our case, a significant acceleration of trading volume with the subsequent increase in volatility. Second, the results suggest that most of the stock market activity in Spain still takes place in the domestic market, given that the period of financial market opening does not seem to bring about significant changes. It is true, though, that international instability is now transmitted to Spain and we witness that the unstable periods of the Spanish stock market coincide with internationally unstable periods. One is led to think, therefore, that 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 significantly the way the stock market behaved. The Spanish stock market seems to have gone through the more important changes earlier on. By the time the markets opened, we found an already developed and mature market. However, the evidence may be suggesting that flows in and out of other markets may still be low, given that no significant structural change is evident after the opening of the markets.

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 trying to identify the causes of such changes. Given that these years correspond to the years of development of the Spanish stock market and, more generally, of the Spanish economy, structural changes are likely to appear. Detecting when those changes take place can shed light on the mechanisms that cause or influence stock market volatility. Thus, the choice of Spain as the country object of our analysis becomes quite relevant.

The time evolution of Spanish stock market volatility reveals that, apart from the periods of momentary 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 low during the earlier years. Also, periods of abnormally high market volatility in the last years - the most important being those recorded in 1987, 1991 and 1999 - present a much higher intensity but a reduced persistence when compared to unstable periods at the beginning of the sample. Thus, there is not only a change in the average value of volatility but also in its dynamic behavior, so that volatility after the break appears to be less persistent. In order to analyze these effects, we estimated a GARCH volatility model and looked for endogenous structural breaks in the parameters of the model. 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 the growth in trading volume had a significant impact on stock market volatility, although this relationship seems to have been stable through the years. It was the acceleration in trading volume in the mid 1970's and not a change in the underlying relationship that seemed to bring about the structural break in volatility. This period coincided with the intensification of the process of economic integration and opening of the Spanish economy, and we offer some comments on the most relevant events that may have affected stock market behavior.

We interpret all the above effects as signs - and consequences - of the development and maturing of the Spanish stock market, and therefore as what would be expected also in the stock markets of countries undergoing financial and economic liberalization. Given the recent excellent performance of the Spanish economy, the results shed a ray of hope for those countries in the process of economic and financial openness.

In the light of the recent instances of financial instability and crises, further research on this topic becomes of top priority. Given the extreme 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.

Acknowledgements

An earlier version of this paper has been presented at the X Foro de Finanzas (Sevilla, 2002) and the XXVII Simposio de Análisis Económico (Salamanca, 2002). Financial assistance from the Spanish Ministry of Science and Technology (SEC2002-01839) is gratefully acknowledged. We especially thank Vicent Aragó and José Enrique Galdón for their helpful comments and suggestions. We also thank Domingo García (Servicio de Estudios de Bolsa de Madrid) for providing us with the stock price data. Finally, we appreciate the valuable research assistance of José Suarez and Pablo Vega. None of the above are responsible for errors in this paper.

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Table 1

Some basic statistics on the returns of the Spanish Stock Market, 1941:1-2001:12

Mean	SD	SK	κ	ρ_1	Q(4)	ARCH(4)	JB
0.1186	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 4 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

Table 2

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

$r_t = \beta_0 + \beta_1 r_{t-1} + u_t, \qquad u_t \longrightarrow iid(0, \sigma_t^2)$ [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.

	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)
Unc. Var.	0.5263

Table 3
Asymptotic critical values of the sequential test $LR(l+1 \mid l)$ for a change in q parameters

		l		
q=3	α	0	1	2
	90%	13.43	15.26	16.38
	95%	15.37	17.15	17.97
	Estimated	18.28	15.45	11.46

See Table II, Bai and Perron (1998).

Table 4

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

$r_t = \beta_0 + \beta_1 r_{t-1} + u_t, \qquad u_t \longrightarrow iid(0, \sigma_t^2)$ [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.

	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)
Unc. Var.	0.288	0.549
Break Date	1972:06	

Table 5

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

$r_t = \beta_0 + \beta_1 r_{t-1} + u_t, \qquad u_t \longrightarrow iid(0, \sigma_t^2)$ [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.

	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)
Unc. Var.	0.541	0.251	0.549
Break Date	1951:09	1972:06	

Table 6

Alternative tests for one and two breaks in Spanish stock market volatility, 1941:01-2001:12

	Kokoszka and Leipus (2000)		Inclan and Tiao (1996)	
	Test	Break	Test	Break
One Break				
$(r_t)^2$	1.4581	August 1973	4.0090	August 1973
$\|r_t\|$	1.0616	October 1972	2.2068	October 1972
Two Breaks				
$(r_t)^2$	1.0512	March 1960	2.6104	March 1960
$\|r_t\|$	0.7518	March 1960	1.4846	March 1960

The critical values are 1.22 (90%) and 1.36 (95%).

Table 7

AR(1) plus time trend estimate for trading volume, 1953:01-2001:12

$VOL_t = \gamma_0 + \gamma_1 VOL_{t-1} + \gamma_2 TREND_t + \gamma_3 D_t + \gamma_4 (VOL_{t-1} * D_t) + \gamma_5 (TREND_t * D_t) + \varepsilon_t$

D_t is a dummy that is zero for t <1972:06 and one otherwise in the first colum (exogenous break determined by volatility); in the second colum, D_t is zero if t <1971:04 and one otherwise (endogenous break for volume).

	Exogenous	Endogenous
γ_0	8.179	8.381
	(11.48)	(11.57)
γ_1	0.278	0.262
	(4.46)	(4.15)
γ_2	0.008	0.007
	(9.98)	(9.77)
γ_3	-6.939	-7.118
	(-9.34)	(-9.44)
γ_4	0.484	0.502
	(6.78)	(6.97)
γ_5	-0.0013	-0.001
	(-1.07)	(-1.21)

Table 8

GARCH(1,1) model for Spanish stock return volatility with trading volume, 1953:01-2001:12

$r_t = \beta_0 + \beta_1 r_{t-1} + u_t, \qquad u_t \longrightarrow iid(0, \sigma_t^2)$ [Mean equation]

$\sigma_t^2 = \varpi_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 u_{t-1}^2 + \gamma_1 DVOL_t + \gamma_2 D1972_t + \gamma_3 DVOL_t * D1972_t$ [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 <1972:6 and one otherwise. t-statistics use QML standard errors.

	1953:01-2001:12
β_0	0.107 (5.02)
β_1	0.149 (3.37)
ϖ_0	0.023 (5.20)
α_1	0.6969 (15.52)
α_2	0.145 (3.98)
γ_1	0.075 (2.49)
γ_2	0.063 (3.71)
γ_3	-0.021 (-0.24)

Figure 1
Evolution of Spanish Stock Market Returns and Rolling Variance, 1941-2001

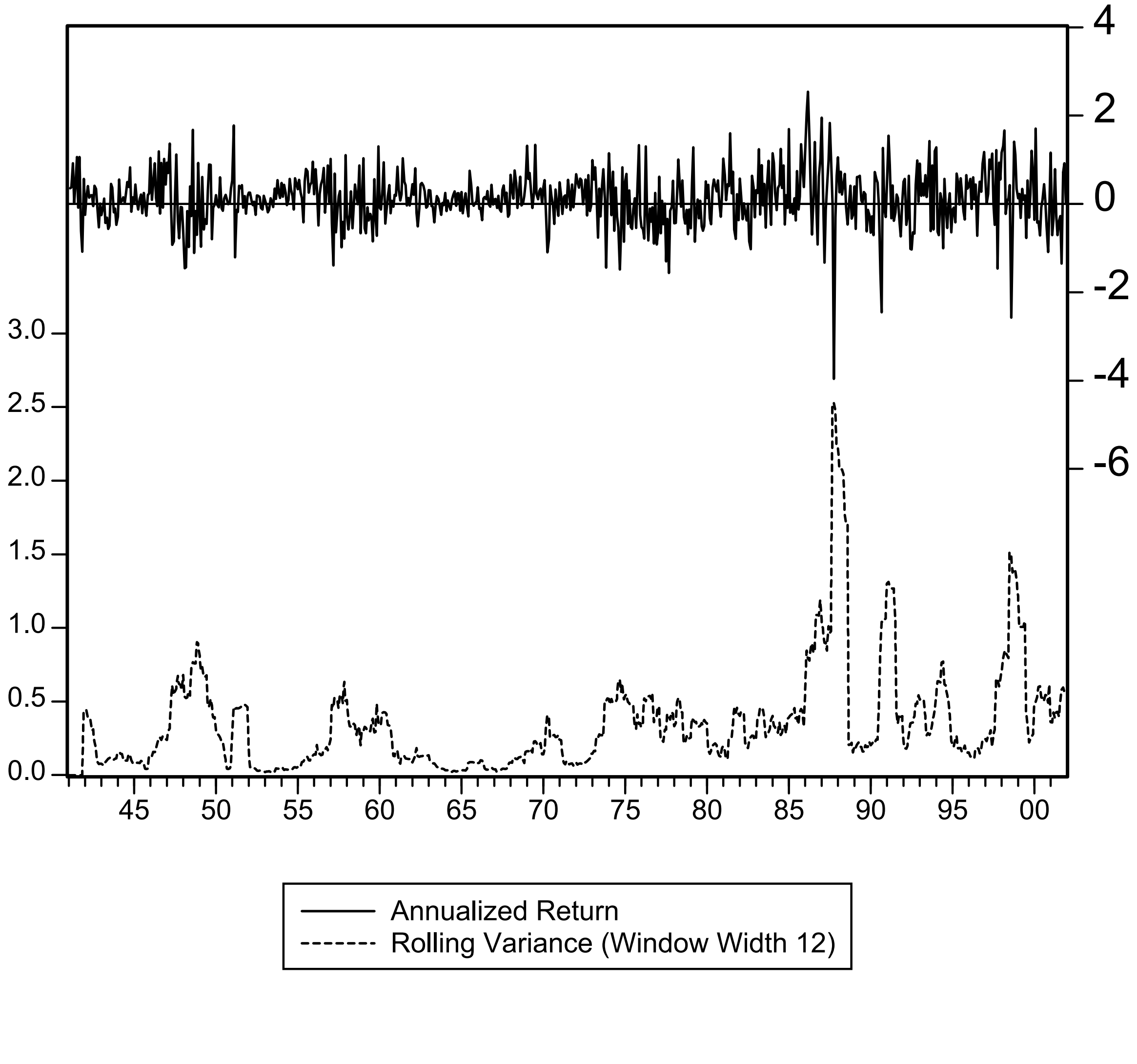

Figure 2
Comparison of Variance forecasted with simple GARCH and Rolling Variance

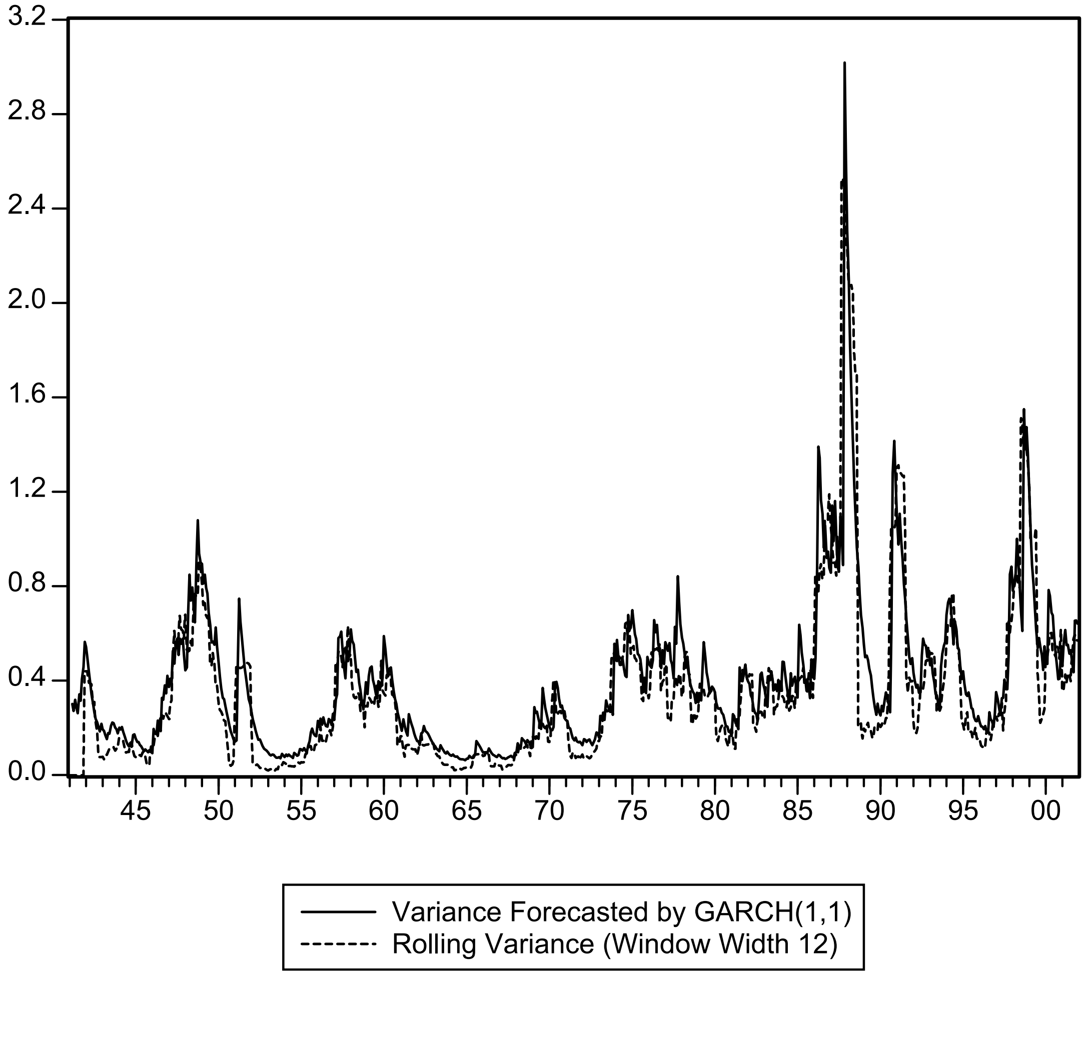

Figure3
Returns and series of LR tests

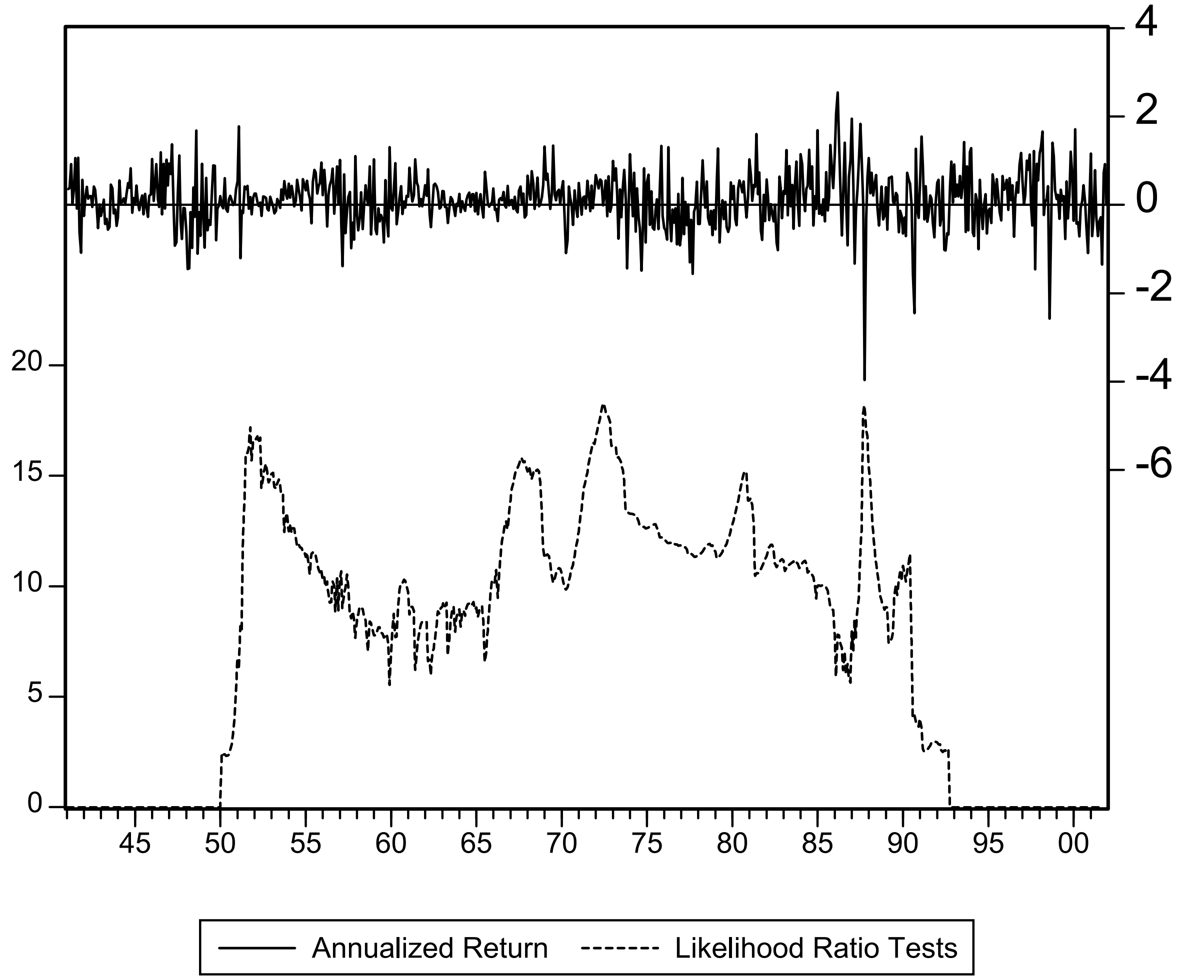

Figure 4
Comparison of Variance forecasted with GARCH with Two Endogenous Breaks and Rolling Variance

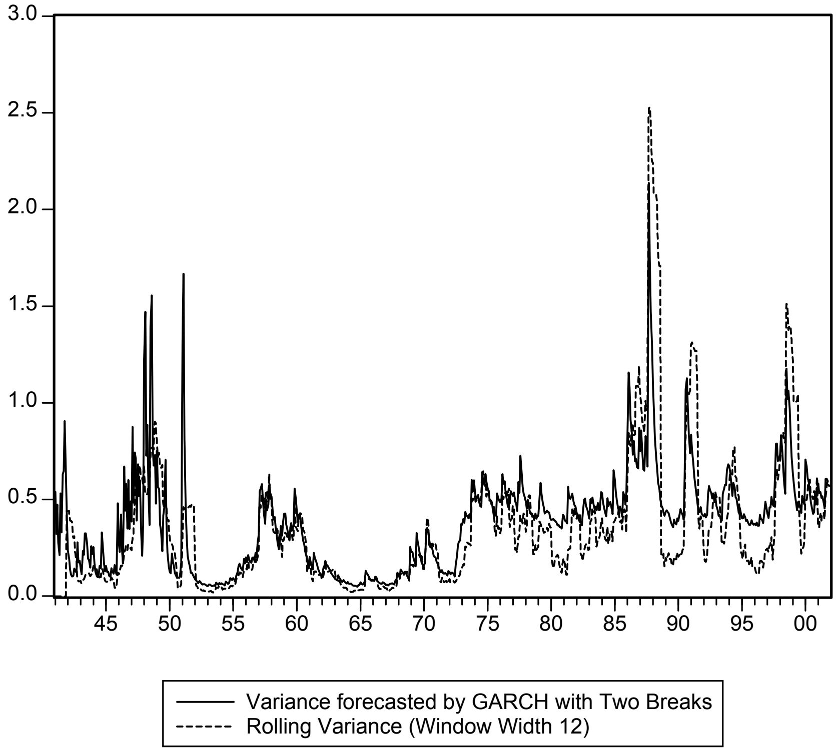

Figure 5
Comparison of Variance forecasted with GARCH with Endogenous Break and Rolling Variance

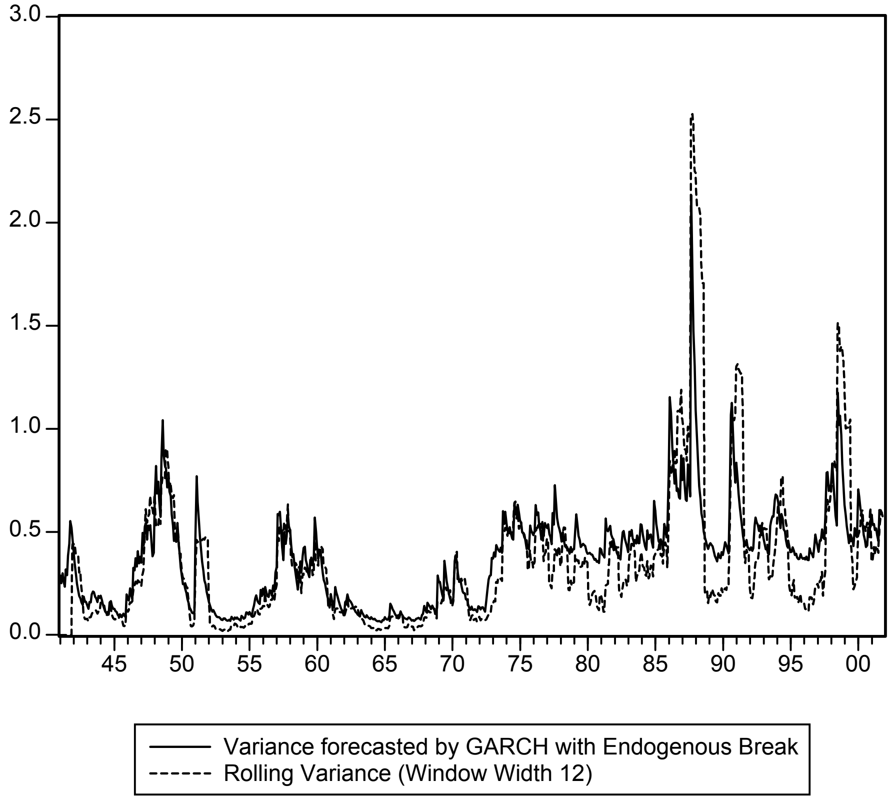

Figure 6
News Effect for the Full Sample, and for Pre- and Post-break Periods

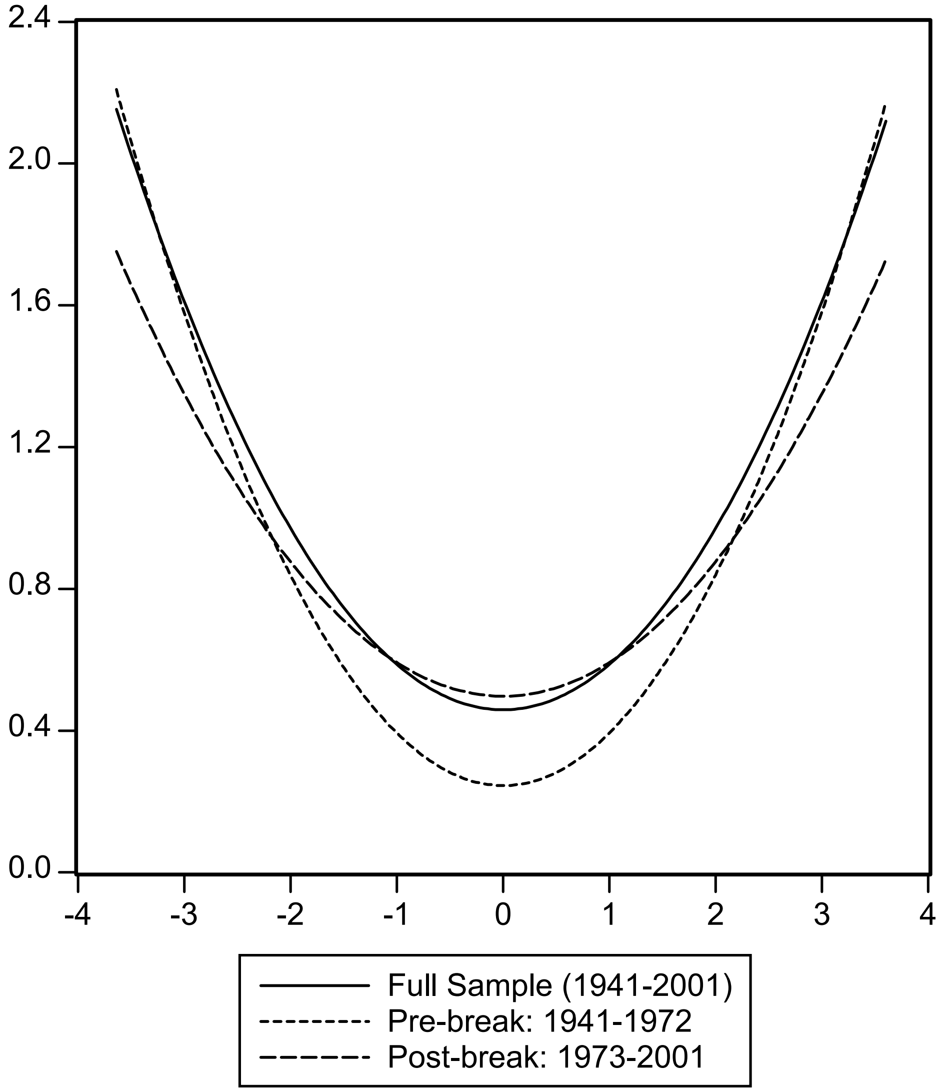

Figure 7: Estimated Spectral Densities of Return Innovations
(All spectra estimated with Bartlett smoothing)

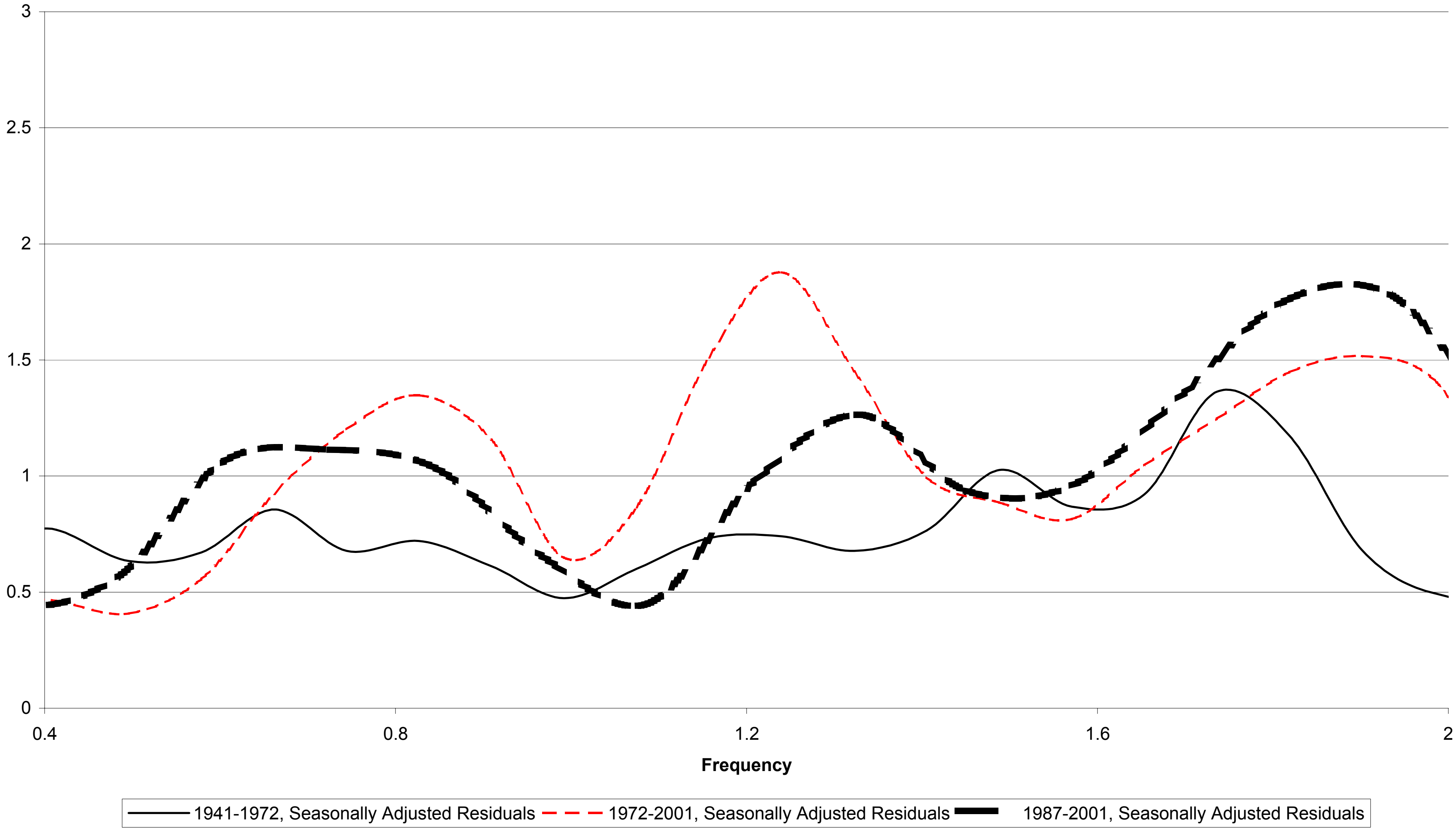

Figure 8a
Evolution of Stock Returns and Trading Volume, 1951-1981

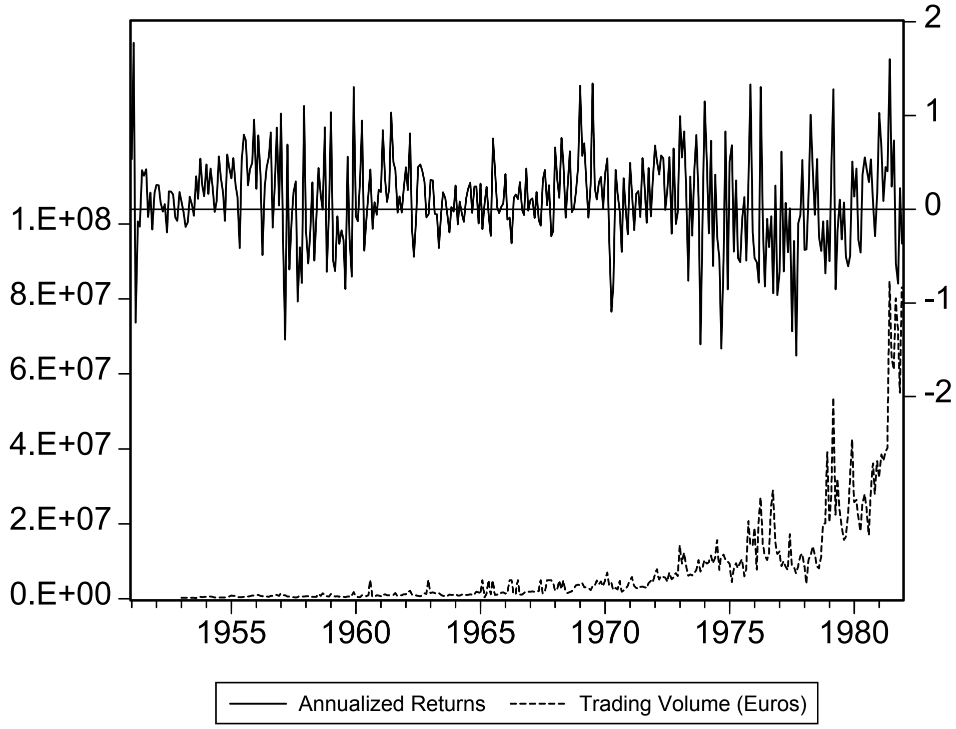

Figure 8b
Evolution of Stock Returns and Trading Volume, 1982-2001

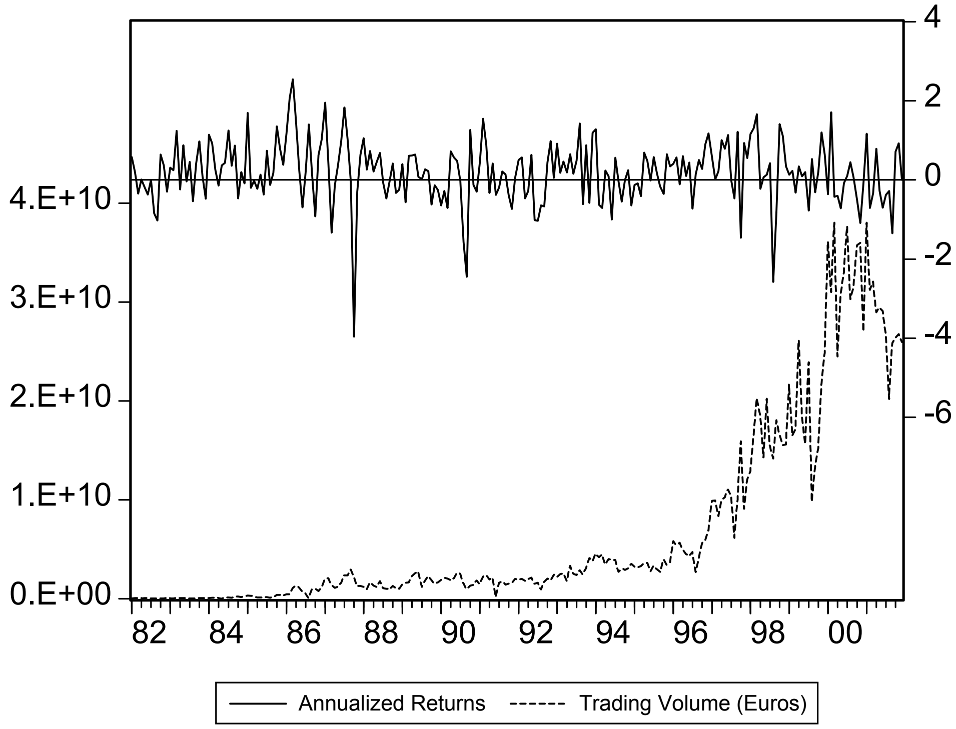

Figure 9a
Evolution of Stock Returns and Trading Volume, 1951-1981

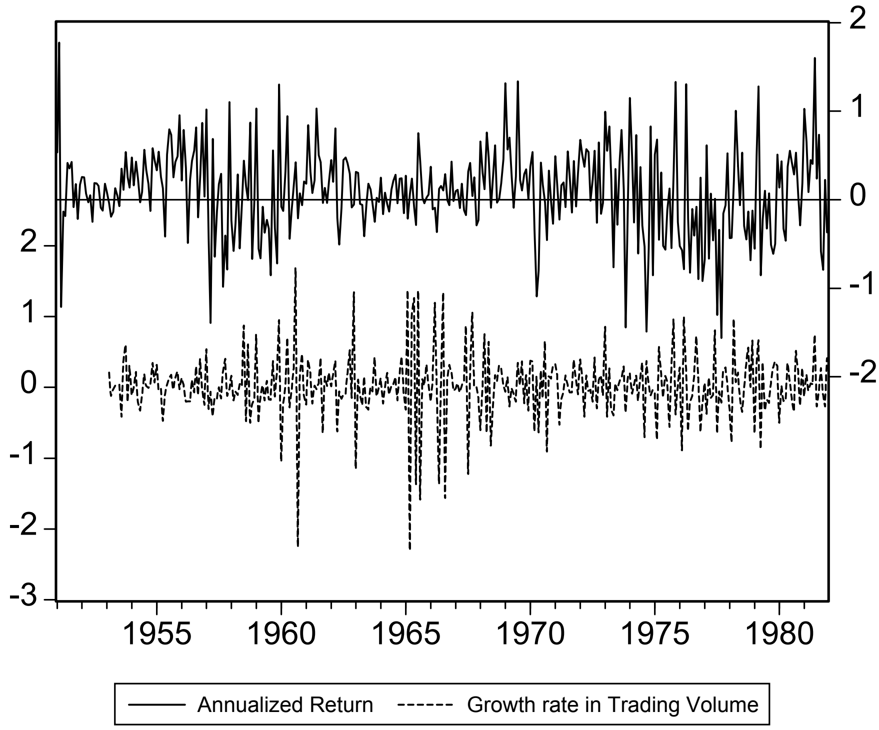

Figure 9b
Evolution of Stock Returns and Trading Volume, 1982-2001

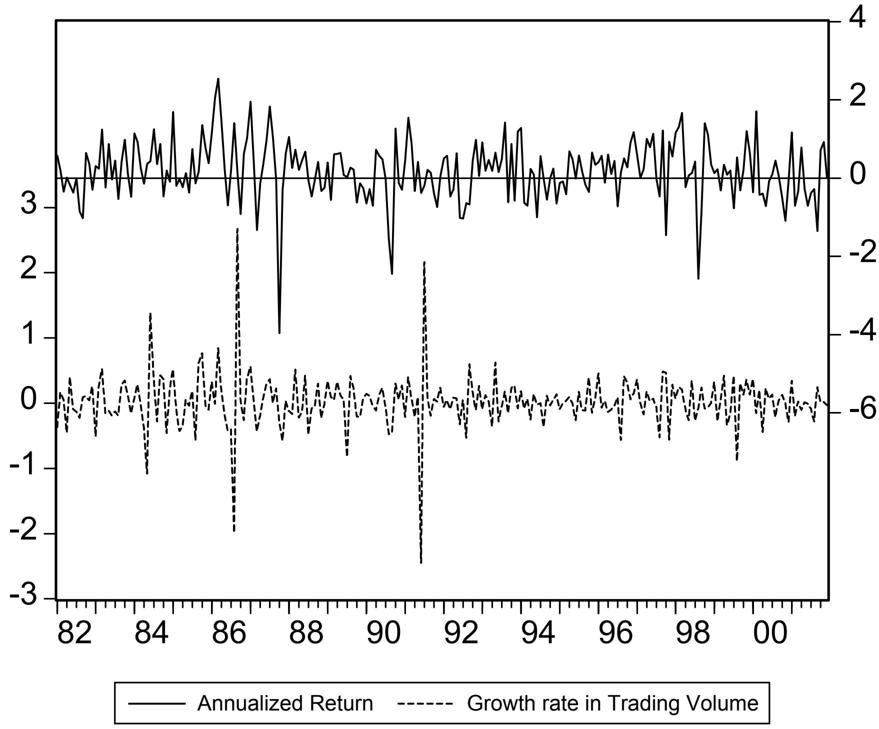

Figure 10
(log)Trading Volume: Real and Forecasted Value (with break in 1972:6 and with endogenous break)

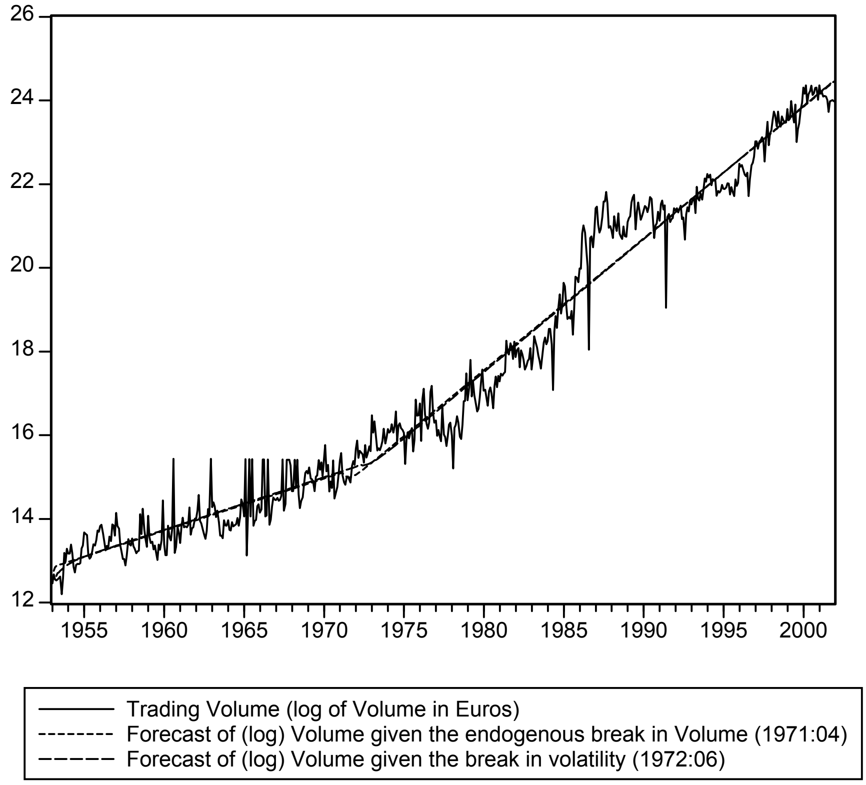

Figure 11
Comparison of Variance forecasted with GARCH with Volume and Rolling Variance