Facultad de Ciencias Económicas y Empresariales
Universidad de Navarra

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Stock Market Cycles and Stock Market Development in Spain

Javier Gómez Biscarri and Fernando Pérez de Gracia

Facultad de Ciencias Económicas y Empresariales
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ABSTRACT

In this paper we use Spanish stock market data to identify the bull and bear phases of the market and to analyze its characteristics during the period 1941-2002. We compare these characteristics with those of the US and of two other European countries (Germany and the UK). Our sample is divided in two subperiods in order to account for differences induced by the process of development undergone by Spanish capital markets in the late 1980's and early 1990's. We find that the Spanish stock market has become increasingly more similar to those of the more developed countries, although some differences still persist. Additionally, we show that concordance of the Spanish stock market with other developed markets has increased quite significantly.

JEL classification: C22, G15
Key words: Stock market cycle, data generating process, financial development

Javier Gómez Biscarri
Universidad de Navarra
Depto. Economía
Campus Universitario
31080 Pamplona
jgbiscarri@iese.edu

Fernando Pérez de Gracia
Universidad de Navarra
Depto. de Economía
Campus Universitario
31080 Pamplona
fgracia@unav.es

1 Introduction

Financial markets are part of the core institutions in any developed economy. They facilitate the channeling of savings decisions into productive investment, and are therefore key in order to guarantee stable long-term growth. The literature that links economic growth and financial development in countries is by now quite extensive (e.g., King and Levine 1993, Arestis and Demetriades 1997, Levine and Zervos 1998, Levine et al. 2000, Bekaert, Harvey and Lundblad 2002). The last few decades of sustained growth, therefore, have come hand in hand with an unparalleled process of development in the financial institutions of all developed, and most of the emerging, economies.

These processes of financial development (i.e. capital market opening, financial liberalization or integration processes, and institutional development of the stock markets) lead to substantial changes in stock market behavior. A number of papers in the early 1990's examined the effects of stock market development and liberalization processes on the integration of stock markets (see for example Errunza et al. 1992, Buckberg 1995, Bekaert 1995 and Bekaert and Harvey 1995). After the financial crises of the 1990's, the more recent literature has focused on the evolution of stock market comovements, analyzing how the financial crises have affected these comovements, while still putting the results in the context of financial liberalization. Examples in this line are Ramchand and Susmel (1998), Edwards (2000), Bekaert, Harvey and Lumsdaine (2002a,b), Bekaert, Harvey and Ng (2002), Chakrabarti and Roll (2002), Chen et al. (2002) and Forbes and Rigobon (2002). The main conclusions from this strand of literature point at the increased synchronicity of the stock markets of emerging countries after the financial liberalization episodes, a synchronicity that seemed to become more intense during financial crises.

However, little work has been done on examining the characteristics of domestic stock market behavior and how these characteristics may change as the market develops. A couple of recent contributions (Edwards et al. 2003 and Kaminsky and Schmukler 2003) have done this: These papers have structured their analysis around the relationship between financial liberalization in emerging countries and stock market cycles. They both analyze the stock markets of different countries focusing on the cross-country comparison of the characteristics of upward ("booms" or "bull phases") and downward ("crashes" or "bear phases") movements in the market. They conclude that financial liberalization processes induce significant differences in stock market behavior and the characteristics of the stock markets in emerging countries become more similar with those of developed markets.

Most of the literature so far has focused, not surprisingly given their relevance in the light of recent crises, on emerging countries with or without reference to the US. However, very little work has been done on the countries that are now considered developed, but that went through their own development processes a few years earlier.

Spain is an example of a currently developed market that has gone through its development process not long ago: In 1941 it was still an autarkic, closed economy with an incipient and underdeveloped stock market. By the end of the 1990's, 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. This recent evolution makes Spain a relevant subject for analysis of the impact of the process of economic and financial development on the medium and long term characteristics of its stock market behavior.

This paper focuses on the analysis of the behavior of the Spanish stock market, following an approach similar to that of Edwards et al. (2003) and Kaminsky and Schmukler (2003). More specifically, we are interested in addressing three questions.

First, what are the characteristics of the Spanish stock market in the medium-term and, specifically, of the market cycles? We characterize the bull and bear phases of the Spanish stock market by identifying the cycle phases and measuring a number of their features. We also analyze the degree of similarity of Spanish cycles with those of the US and of two other European stock markets (Germany and the UK): We compare the features across the four countries and test whether cycle phases tend to occur simultaneously in the different countries, a feature we call *concordance of the stock market phases*.

Second, have any changes been induced by the process of market development that Spain went through in the late 1980's and early 1990's? Thus, we qualify the analysis above by comparing the cycle characteristics and the concordance across the four markets before and after 1990. We assess to what extent the development of the Spanish stock market brought it more in line with the markets of more developed countries. Our findings confirm that the Spanish stock market is now substantially more similar to other developed markets and it evolves in a more parallel way, both in short term and medium term fluctuations.

Third, can traditional statistical processes correctly characterize the stock cycles of the Spanish market or are there features of the empirical cycles that deserve further attention? We use alternative data generating processes (DGPs) to replicate the features of the Spanish stock price data, comparing the empirical cycles with those generated by DGPs. Even though this analysis may seem too technical, it allows us to detect features of the data that are not well captured by these DGPs and therefore warrant further analysis and attention. We find that simple statistical models can generate cycles that are very similar to those in the empirical data, but we uncover a specially interesting feature: During the last few years, stock market returns seem to accelerate both at the end of the expansions and of the contractions, a behavior that cannot be well accounted for by statistical models.

The rest of the paper is organized as follows. Section 2 explains the algorithm used to locate the cycle phases and the battery of measures used to characterize the behavior of the stock market. Section 3 shows the results of applying these techniques to the Spanish stock market and comments on the similarities of these phases with those of other developed stock markets. Special emphasis is placed on the differences induced by the process of market development of the late 1980's and on the issue of concordance and correlation of the stock markets across countries. Section 4 examines alternative statistical models in an attempt to replicate the empirical features of the Spanish data both pre and post market development. Section 5 concludes.

2 Identifying and Describing Market Phases: Methodological Issues

2.1 Identifying Market Phases

Our analysis of the cyclical behavior of the stock market is based on the location of the two different phases of the cycle: Bull phases (or "booms") and bear phases (or "crashes"). Bull and bear phases in the stock market have been usually defined as periods of generalized upward trend and generalized downward trend in stock prices, respectively. However, there is not a more formal definition of these phases: Practitioners, for example, have used a rule of thumb by which periods during which the stock market has fallen more than a 20% are identified with bear phases and periods during which the stock market has increased more than a 20% are called bull phases. As a consequence of the direct applicability of business cycle techniques, and of the increased general interest in the stock market, the behavior of bull and bear markets in stock prices has received considerable attention in the recent literature, which has analyzed both the reasons for finding such cyclical behavior and the methodologies that should be used to identify and characterize the cycles.

Two explanations have been put forward for the existence of bull and bear markets. One view considers that major bull and bear markets are purely due to irrational "animal spirit" (see for example Keynes 1936, Galbraith 1954 and Shiller 1989). An alternative view states that, although prices deviate from fundamentals in the short run, that is, in periods of months or a few years, in the long run - decades or even generations - proportional differences between market prices and fundamentals are kept within bounds (see DeLong, 1992 and Siegel, 1998 among others). Under this interpretation, the major bull and bear markets reflect large shifts in consensus perceptions of fundamentals and expectations of the future.[1]

On the methodological side, there are two main approaches to locating and analyzing the expansionary / contractionary phases of the cycles in an economic variable. One, pioneered by Hamilton (1989) advocates a parametric specification of the data generating process of the variable, where two different regimes are allowed, one that corresponds to the expansions and another that corresponds to the contractions.[2] The second approach takes a nonparametric perspective and looks at the original data series in search for the specific features of the cycle. More specifically, this procedure attempts to find periods of generalized upward trend, which will be identified with the expansions, and periods of generalized downward trend which will be identified with the contractions. The key feature of the analysis is the location of turning points (peaks and troughs) which correspond to local maxima and minima in the series. These turning points determine the different phases of the cycle, which can then be subsequently analyzed. This procedure was first applied by Bry and Boschan

[1] The already famous debates between Shiller and Siegel are direct consequence of these two points of view: See for example Shiller (2000) and Siegel (1998).

[2] Examples of this approach are Goodwin (1993), Diebold and Rudebusch (1996) and those in the book by Kim and Nelson (1999) for real cycles and Hamilton and Lin (1996), Ramchand and Susmel (1998) and Maheu and McCurdy (2000) for stock market cycles.

(1971) to the analysis of business cycles.[3]

In this paper we use the nonparametric approach to detect the expansionary and contractionary phases of the stock market.

Throughout the paper, p_t denotes the natural log of the stock price, $\ln(P_t)$. It is clear that the peaks and troughs for both series have to be the same. A peak/trough in the series of stock prices P_t is defined if p_t is the highest/lowest in a window of width 8.[4] That is, there is a peak at t if

$$[p_{t-8}, ..., p_{t-1} < p_t > p_{t+1}, ..., p_{t+8}] \tag{1}$$

and there is a trough if

$$[p_{t-8}, ..., p_{t-1} > p_t < p_{t+1}, ..., p_{t+8}] \tag{2}$$

In order to ensure that we do not identify spurious phases we include the following four censoring criteria:

1) We eliminate turns within eight months of the beginning / end of the series.

2) Peaks or troughs next to the endpoints of the series are eliminated if they are lower/higher than the endpoints.

3) Complete cycles of less than 16 months of total duration are also eliminated.

4) Phases of less than four months are eliminated unless the fall / rise exceeds 20% (the traditional rule of thumb for identifying a stock market cumulative movement as bullish or bearish).

After every censoring operation, alternation is enforced so that a peak will always follow a trough and viceversa. Alternation is achieved by taking the highest (lowest) of two consecutive peaks (troughs).

2.2 Describing Bull and Bear Phases

Once the bear and bull phases have been identified, we calculate a battery of statistics that describe the behavior of stock prices in each of the phases. This behavior can then be compared across countries and across phases, in search for relevant differences that may shed light on the determinants of stock market evolution. We use four different measures of cyclical behavior: *Duration* of the phases, average return /loss during the complete phase (*amplitude*), *shape* of the phase and *volatility* within the phase.

In order to compute the different statistical measures we construct an indicator of whether the market is in a bull or bear phase at that particular point in time: We

[3]This approach has recently been used by Watson (1994) and Harding and Pagan (2000, 2002) for business cycles, and by Edwards et al. (2003), Kaminsky and Schmukler (2003) and Pagan and Sossounov (2003) for stock markets. We do not comment on the advantages and disadvantages of one approach vs. the other. A fascinating discussion can be found in the exchange between Hamilton (2003) and Harding and Pagan (2003a,b).

[4]The results may be slightly sensitive to the choice of the window width. We use eight months as suggested by Pagan and Sossounov (2003): The usual choice of window width for business cycle analysis, based on the characteristics of this type of cycles, is 12 months or 4 quarters. It is reasonable that stock market cycles must be allowed to be shorter than business cycles, and so 8 months seems to be a good compromise in that it is not too short - so as to avoid identifying spurious short phases - and it is smaller than the width used for real cycles.

define two dummy variables: S_t, which takes the value 1 if there is a bull market at time t and $B_t = 1 - S_t$, which is an indicator for a bear market. Throughout the paper we refer to Δp_t as returns, given that our data series is adjusted for dividends, though it literally corresponds to capital gains. Most of the parallel studies (Pagan and Sossounov, 2003; Aggarwal et al., 1999) use capital gains of dividend adjusted prices, and we follow that approach. Two ancillary statistics can then be calculated: *Total time* spent in an expansion is $\sum_{t=1}^{T} S_t$ and total time spent in a contraction is $\sum_{t=1}^{T} B_t$. The *Number of peaks* (expansions) can be counted as $NTP = \sum_{t=1}^{T} S_t(1 - S_{t+1}) - 1$ (NTP is short for "Number of Trough to Peak") and the *Number of troughs* (contractions) is $NPT = \sum_{t=1}^{T} B_t(1-B_{t+1})-1$.[5] We also define the cumulated change over any expansion as $Z_t^{bull} = S_t Z_{t-1} + S_t \Delta p_t$, $Z_0 = 0$. Z_t contains the running sum of returns Δp_t for bull markets (similar definition with B_t for bear markets) with the sum reset to zero whenever $S_t = 0$.

The four characteristics of the phases of the market that we study are:

1) *Duration (D):* Average duration in months of expansions and contractions can be calculated as

$$\widehat{D}_{bull} = \frac{1}{NTP} \sum_{t=1}^{T} S_t, \; \widehat{D}_{bear} = \frac{1}{NPT} \sum_{t=1}^{T} B_t \tag{3}$$

2) *Amplitude (A):* Average gain or loss throughout the phase, in percentage, is calculated as

$$\widehat{A}_{bull} = \frac{1}{NTP} \sum_{t=1}^{T} S_t \Delta p_t, \; \widehat{A}_{bear} = \frac{1}{NPT} \sum_{t=1}^{T} B_t \Delta p_t \tag{4}$$

3) *Excess Index (EX):* An index that measures the excess with respect to a triangular approximation can be calculated as

$$\widehat{EX} = \frac{\left(\widehat{C} - 0.5\widehat{A} \cdot \widehat{D} - 0.5\widehat{A}\right)}{\widehat{D}} \tag{5}$$

for both expansions and contractions. The first and second terms in the numerator approximate the area between the real path followed by the series (area $\widehat{C}$) and the triangular path (area measured by $0.5\widehat{A} \cdot \widehat{D}$). The third term corrects for the discrete approximation used in computing the real path with $\widehat{C}$.[6] The denominator makes

[5] Given that we only analyze complete phases, the initial and final phases are not counted. That is the reason for the "-1" term in the formulas. However, if the initial and final phase are the same, then the adjustment does not apply to the other type of phase. For example, if the initial and final phases are bullish, the number of complete bull phases would be $NTP = \sum_{t=1}^{T} S_t(1 - S_{t+1}) - 1$ and the number of bear phases would be $NPT = \sum_{t=1}^{T} B_t(1 - B_{t+1})$.

[6] The *average cumulated change* (C) for both phases of the cycle can be calculated as

$$\begin{aligned} \widehat{C}_{bull} &= \frac{1}{NTP} \sum_{t=1}^{T} Z_t^{bull} = \frac{1}{NTP} \sum_{t=1}^{T} \sum_{j=1}^{t} S_j \Delta p_j \\ \widehat{C}_{bear} &= \frac{1}{NPT} \sum_{t=1}^{T} Z_t^{bear} = \frac{1}{NPT} \sum_{t=1}^{T} \sum_{j=1}^{t} B_j \Delta p_j \end{aligned}$$

the measure relative to the size of the phase.

4) *Volatility* (V): We use a measure of *variability* within each phase, which is a simple indicator of how volatile the price is in each of the two phases. Instead of the squared changes in prices Δp_t^2 we use the absolute value $|\Delta p_t|$, to make sure that the index is less sensitive to unusually big changes which frequently occur in stock markets. We measure variability by the average size of the return in bull and bear phases:

$$V^{bull} = \frac{1}{\sum_{t=1}^{T} S_t} \sum_{t=1}^{T} S_t \left|\Delta p_t\right|, \; V^{bear} = \frac{1}{\sum_{t=1}^{T} B_t} \sum_{t=1}^{T} B_t \left|\Delta p_t\right| \tag{6}$$

One of the advantages of our approach is that it allows us to compare the actual stock market cycle to benchmarks characterized by random walk-based models. As pointed out above, if the true data generating process is indeed a random walk, the actual cyclical behavior would follow a triangular path. If, however, actual cycles depart from those coming from a random walk, the cyclical pattern could take a number of alternative forms. Figure 1 depicts the four possible shapes of the market behavior depending on whether the market is bull or bear and the *EX index* is positive or negative.[7]

[Insert Figure 1]

Given that we can estimate the parameters of any statistical model for our candidate countries, we can use those parameters to simulate the time series under that data generating process as null hypothesis. Thus, we can construct a distribution of the different measures under that null hypothesis and perform a formal test. All four measures can be used to test some statistical model and in Section 4 we provide critical values, and therefore formal tests, for *duration*, *amplitude*, the *EX index* and the *volatility* measure. However, the finding that a statistical model cannot correctly replicate the values of the *EX index* - and this happens to be the case quite often, in fact more often than with the other measures - is especially interesting. As it can be seen in Figure 1, a value of the *EX index* significantly different from that implied by the statistical model shows a differing behavior of the return variable at the beginning and the end of the phase. Thus, it points at the existence of a certain type of predictability that is quite difficult to capture with traditional statistical models.

3 Cycles and Development in the Spanish Stock Market

In this Section we analyze the bull and bear phases in the stock market in Spain placing special emphasis in the comparison with the stock markets in Germany, the

This measure is a discrete time approximation to the integral below (above) the bull (bear) market.

[7] These shapes can be thought as telling when the phase "accelerates," that is, where in the phase, either at the beginning or at the end, the biggest returns are located. A positive excess measure in a bullish market denotes that the first periods of the phase are those of higher (accelerated) returns whereas a positive excess measure in a bearish market shows that it is at the end of the phase that the bigger negative returns happen. The opposite would be true of negative excess measures.

UK and the US. In order to do this, we first apply the dating algorithm to locate the different phases. Once the phases have been identified, we compare the main characteristics of the bull and bear phases: *Duration*, *amplitude*, *EX index* and *volatility*. We then use a *concordance* index and a measure of *correlation* of returns during the bull and bear phases to compare how aligned the cycle phases are in pairs of countries. We thus study the comovement or synchronization of the Spanish stock market with the other three developed markets.

The analysis of bull and bear phases by definition focuses on the medium to long-term evolution of the stock market and thus requires the use of a long time series of data. A problem that arises - and that, given the increasing importance of financial markets, seems especially relevant in our context - is that there may be structural breaks in the evolution of the stock market. For example, both Edwards et al. (2003) and Kaminsky and Schmukler (2003) find evidence for significant differences in stock market behavior in emerging countries before and after the financial liberalization episodes of the early 1990's. European countries are not an exception, especially in the light of the recent processes of development and opening to international flows that their financial markets have gone through. These processes most likely have affected the way domestic stock markets behave and the way they move with respect to one another. This is probably more relevant in the case of Spain, since in the last decades its stock market has undergone profound changes, both because of the growing importance of the financial system and because of the capital market liberalization required by the joining of the European Union (EU). In order to address this issue, in the analysis that follows we divide the sample in two subperiods, setting the break in 1990. In order to rationalize the choice of the breakpoint, we briefly outline now some of the relevant events that affected the Spanish stock market around that date.

3.1 Stock Market Development in Spain

At the end of the 1980's the Spanish stock market was affected by several events, the most important of which were probably the passing of the Stock Market Law of 1988 and the requirement, stemming from 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.

The Stock Market Law of 1988, enacted in July 1989, gave a new legal framework to the Spanish stock market that brought about profound institutional changes and facilitated its complete incorporation into the international stock exchange system. A new monitoring institution (the National Stock Market Commission) was created, along with a sanctioning system for individuals and corporations participating in the markets. More stringent informational requirements were specified for primary markets. The reform also outlined the creation of Securities Companies and Agencies (SCA's) which would become the authorized operators in the secondary market. In conjunction with these reforms, which affected the institutional and constitutive aspects of the Madrid, Barcelona, Valencia and Bilbao Stock Markets, the Continuous Market began to function in April of 1989. This electronic system represented a leap forward in the efficiency of transactions since the matching of buy and sell orders was done in real time over the computerized system. Most of the activity in the markets began to be channeled through this Continuous Market with the subsequent increase in both trading and the speed of trade.

The institutional development of the Spanish stock market did not finish with the passing of the Stock Market Law: Other secondary markets, most noticeably those for financial derivatives, were added shortly afterwards and authorization to act as an organized AIAF market, a fixed income market for wholesalers, was obtained during these years. For all purposes, the Spanish stock market currently presents all the necessary systems and institutions to function as competitively and efficiently as the markets in other developed economies.

Almost simultaneously to the passing of the Stock Market Law, and the subsequent surge in activity, Spain went through the stages required by the Maastricht Treaty to participate in EMU. The Treaty was signed in late 1991, but the Delors Report, released on 17 April 1989, had already suggested a three-stage plan towards full monetary union. Stage One of this plan was implemented in July 1990, when the requirement that capital markets be fully liberalized among EU members and progressively opened to international flows was enacted for most EU members - Spain was allowed to delay this process until the end of 1992.[8] This contributed to the creation of an EU-wide financial market, and the volume of intra-EU financial transactions - and also of transactions from without the EU - increased by orders of magnitude.

Both the legal and operational development of the market and the deepening of its integration with other EU and international markets had noticeable effects on the behavior of the Spanish stock market and its relationship with other markets. Thus, and given that both events occurred in the early 1990's, we consider 1990 as a year marking a "before and after" in the history of the Spanish market. Consequently, in the analysis that follows the sample period has been divided into two subperiods, the first one comprising the years from 1950 until the end of the last cycle before 1990. The second subperiod contains the remaining data up to 2002.[9]

3.2 Bull and Bear Characteristics

In order to investigate the basic features of the Spanish stock market we use a monthly series of an index of Spanish stock prices from 1/1941 to 12/2002 obtained from the Research Department of the Madrid Stock Exchange. The stock market indices for Germany, the UK and the US have been obtained from the DRI database (former CITIBASE). The sample period for these indices goes from 1/1949 to 12/2002, so we restrict our analysis of the Spanish data to this slightly shorter sample. Table 1 presents the results, for the two subperiods, of the basic measures of the bull and bear phases of the four stock markets. Also, Figure 2 presents the evolution of the stock index for Spain, where the bull periods have been shaded to facilitate visual

[8] The Delors Report encompassed the requirements of Directives 86/566/EEC and 88/361/EEC. The former provided for the unconditional liberalization of capital movements associated with long-term credits related to commercial transactions and with the integration of the national securities markets. The latter lifted all remaining restrictions on capital movements between EU member states, giving Greece, Ireland, Portugal and Spain a transitional period.

[9] Alternative results using 1973 as the splitting date are available from the authors. Those results do not add much to the ones we present in the paper.

inspection.

[Insert Table 1]

[Insert Figure 2]

Stylized facts of cycle behavior can be summarized as follows. First, bull markets tend to be significantly longer than bear markets. Second, *volatility* within the phase is similar both for bear and bull markets suggesting an average size of monthly returns (in absolute terms) of around 4% in both upward and downward periods. Even so, the value of the volatility tends to be slightly higher during the bear phases, thus suggesting increased market instability during contractions. Third, *amplitudes* of bull markets tend to be much larger than those of bear markets. The values of the *EX index* seem to point at the fact that expansions deviate from a triangle approximation much more than contractions. It would be tempting to conclude from this finding that we have uncovered significant departures from the random walk behavior similar to those mentioned in Pagan and Sossounov (2003). However, we perform formal significance tests in Section 4 and show that these empirical value of the excess measure is consistent with traditional statistical models.[10]

Across countries, some regularities arise. Bear phases are very similar across all four countries, although those in the more developed markets (the UK and the US) seem to be slightly shorter and have less *amplitude*. Bull phases, however, are quite different in terms of *duration* and the value of the EX *index*. *Amplitude* of bull phases is similar, especially in the second subperiod. The measure of *volatility* is also comparable for both phases: There does not seem to be a clear pattern across countries, although European countries have higher volatility than the US.

We focus now on the differences between the two subperiods. Panel A shows the main characteristics in the pre-development period. Across countries, average *duration* for both bull and bear phases are greatest in the case of Spain. Also, the *amplitude* for the bull phase is significantly larger for Spain. Bear markets have similar characteristics across the board, although still the bear markets of Germany and Spain are larger than those of the US and the UK. These features - longer bear phases and larger bear and bull phases - have been found to be characteristic of less developed markets (Edwards et al., 2003). Here the differences are not as marked as they are in the case of emerging markets, but still the evidence supports that Spain - the less developed market in our group during the subperiod years - tended to have larger phases in terms of amplitude that, in the case of bear markets, were also longer. *Volatility* in Spain is similar to that of the other European markets but significantly higher in both phases than that of the US. To sum up, the Spanish stock market was significantly different from the other three - which were more homogeneous despite some existing differences, especially in volatility - during the years prior to 1990.

[10] In particular, simulation of a random walk with drift shows that such a process generates cycles with positive *EX* index during the bull phase and negative during the bear phase. This is contrary to the general statement in Harding and Pagan (2000, 2003a) that random walks - with or without drift - generate cycles with zero excess measure. In the case of a random walk with drift, if the drift is significantly large compared to the standard deviation of the innovation, the distribution of the *EX* index is not centered at zero, but at a positive value for bull phases and a negative value for bear phases. We do not present these simulation results - the simulated statistics in Table 5 all correspond to models with autocorrelated returns - but they are available from the authors.

Moreover, these differences were similar to those reported for less developed markets with respect to the US.

In the post-development subsample (Panel B) it can be seen that the *amplitude* of the bull phases and the *duration* of the bear phases decrease in the case of Spain, bringing the Spanish market more in line with the characteristics of the other markets: Less time is now spent on bear phases, and the swings during the bull phase are less acute. Except for the short duration of bull phases, the market in Spain post-1990 has become more similar to the other, more developed markets.[11] Furthermore, the numbers for Spain look significantly more similar to those in Germany - except for bull *duration* - than in the pre-development period, thus giving evidence, which will be reinforced in the next subsection, that the deepening of the integration of European financial markets had a significant effect of equalizing stock market behavior in the members of EMU. It is noticeable that *volatility* in both Germany and Spain - this result is not so clear for the US or the UK - increases significantly in this second subperiod. This finding is not surprising, given that one of the effects of the internationalization and development of capital markets is a surge in trading activity that generates an increase in volatility. The reduced volatility in the case of the UK - whose market goes from being more volatile than those of Germany and Spain to being significantly less so - is a little more puzzling, though that effect may be attributed to their leaving the European Monetary System in 1992. Further regularities appear in this second subperiod: Expansions are bigger whereas contractions are smaller. We defer our comments on the *EX index* to Section 4, where a more interesting picture can be obtained.

In conclusion, the evidence seems to point at the fact that the behavior of the Spanish stock market did indeed change after the process of market development, becoming more similar to that of older, more developed markets.[12]

3.3 Concordance of Cycle Phases

We study now the evolution of the concordance or synchronicity of the stock market in Spain with that of the other three countries. We use the *concordance index* (CI) of cycle phases. This index compares how aligned or concordant the cycle phases in two different countries are and has been used for example in Harding and Pagan (2000, 2002) and Edwards et al. (2003). The CI is calculated, for countries i and j, as

$$CI_{ij} = \frac{1}{T} \sum_{t=1}^{T} \left[S_t^i \cdot S_t^j + B_t^i \cdot B_t^j \right] \tag{7}$$

where $S_t^i = 1$ identifies a bull market at time t in country i and $B_t^i = 1$ identifies a bear market at time t in country i. This index calculates the number of periods for

[11] The time series for the post-development period is significantly shorter than that of the first subperiod. This could influence the post-development results. It seems that only the result of duration of Spanish bull phases is distorted by two short bull phases in the early 1990's. The values for all other characteristics, including those for bear markets, are quite consistent with the increased similarity of the Spanish stock market with the more developed markets.

[12] Edwards et al. (2003) found a similar result for Latin American stock markets following the processes of financial liberalization that these countries went through during the late 1980's.

which the two countries are in the same phase, either bull or bear, and averages out over the T periods.

Additionally, we calculate cross-correlations of returns, a more traditional measure of comovement. We believe that both measures are complementary: Correlation coefficients tend to place more emphasis on the short-term movements of the market, since they are quite sensitive to outliers. The use of a binary variable in the CI to identify the phase circumvents this problem, and the CI focuses more on the medium-term movements that determine the different phases of the cycle.

In Table 2 we present the bilateral CI among the different stock index series over the subperiods. Critical values for significance testing of the concordance indexes have been obtained by simulation: First, we simulated independent bivariate series of stock prices with the same drift, variance and autocorrelation coefficient of returns as the country series.[13] We then calculated the simulated distribution of all bilateral coincident indexes and found the 2.5% and 97.5% critical values. If the empirical values lie outside of this simulated confidence interval, one can reject the hypothesis that the two series have phases that come from independent processes.[14]

[Insert Table 2]

Values of the index are usually bigger than 0.5,[15] but they are in some cases not big enough to justify the claim that the markets are subject to phases that are significantly correlated. In Panel A we present the concordance indices during the pre-1990 period. Only the index of Germany and the UK is above the critical level of positive concordance. Thus, evidence for concordance of stock market phases before 1990 is very weak: The markets of these four countries seemed to be in different phases at different points in time, with no clear tendency to be in the same phase. The results in Panel B, which correspond to the post-development period, are on the other hand, quite striking: All pairs of countries exhibit now concordance indices well above the critical values for significance. These results point at the fact that the process of stock market development and integration - which took place in the other countries as well as in Spain - has contributed to a more intense synchronization of the stock markets, which now tend to be simultaneously in the same phase.[16] Of course, the analysis of phase concordance refers to a medium-term synchronicity of the stock markets. The analysis of simple return correlations might shed a little light on the shorter term evolution of these markets.

Table 3, also divided in two panels, presents the simple correlation coefficients for returns, which tell the same story as the concordance indices: During the last ten

[13] A GARCH/EGARCH process could have been used alternatively. We show in Section 4 that these two models, along with the simple AR(1)-returns used here, are the models which best replicate the features of the data.

[14] Note that this procedure is a parametric bootstrap procedure suggested, for instance, by Maddala and Li (1996).

[15] This is the mean of the simulated distributions: If the phases in two countries were perfectly aligned, we would find a CI of 1, and if they were perfectly misaligned we would find a CI of 0.

[16] It is worth nothing that the pair Spain - Germany presents the higher CI in the post - development period whereas in the pre-development period their CI was the smallest of all pairs. The greater openness of intra-EU financial markets induced by the integration process may be behind this result. Also, the CI for Spain - UK increases quite noticeably during the second subperiod.

years the short-term movements in the four stock markets have become increasingly synchronized, and the markets now move closely together, this being more noticeable for the European countries among themselves.

[Insert Table 3]

The static coefficients in Tables 2 and 3 are enough to give evidence in favor of the significant increase in comovement or synchronicity between European markets and the US. An interesting complement to this analysis comes from calculating rolling CI's and rolling cross-correlations. By using a moving window and representing the evolution of the comovement measures we can track how the increased comovement has evolved over time. Figure 3 shows the rolling CI's and cross-correlations for all six country-pairs using a window of width 50. These graphs tell a story similar to that of the static coefficients: An increase in comovement - measured by either coefficient - is apparent in all country pairs during the last two decades. However, the case of Spain is worth mentioning. Before the mid 1980's, the Spanish stock market was not synchronized with the US and it even moved in the opposite direction to those of Germany and the UK. Notice that the CI's of Spain with Germany and the UK are the only that drop below 0.5 for long periods of time, indicating that the countries tended to be in opposite phases of the cycle. This completely changes after the mid 1980's, and the Spanish market enters in phase, and very significantly so, with the other three markets. Additionally, it can be seen that Germany and the UK have always been quite concordant markets, but in the last years their concordance with the US has also increased. All these findings put together tell an important story: The more developed European markets and the US have tended to be quite concordant in the last fifty years, but that was not the case with Spain. In the last decade and a half, however, the Spanish market has become highly concordant with its European neighbors, and with the US.

[Insert Figure 3]

This analysis of market comovement also supports the story that during the last fifteen years and after the deepening of the integration of European capital markets and the further development of the stock market in Spain, this market has started to behave much more similarly to the more developed markets of the world.

4 Can Statistical Models explain Spanish Stock Market Cycles?

In this section we analyze alternative data generating processes (DGPs) for stock returns and investigate whether they produce cycles with similar features to those encountered in the historical data. The motivation is clear: We run a horse-race of statistical models previously applied to the stock market in order to check whether these models can replicate the relevant characteristics of the Spanish stock market both before and after the financial development process, and if not, which features are well accounted for and which are not and therefore should be analyzed in greater detail. Previous research has shown that traditional statistical models can usually not replicate correctly the characteristics of the cycle phases (Pagan and Sossounov,

2003) and that less developed markets usually present more marked deviations from the behavior implied by statistical models (Edwards et al., 2003). Thus, given the above results we would expect that the behavior of the Spanish stock market in the last two decades can be better replicated by statistical models, and we carry out a simulation experiment that tries to examine this effect.

The models considered can be fitted to the data and used to forecast future returns. They all fare well when fitting the data in sample and quite poorly when forecasting out of sample returns. It is, therefore, difficult to discriminate between them on the basis of fit of return behavior. One way to discriminate effectively between models is by looking at their ability to replicate the empirical features of the stock market cycles. These features, some of which we described in Section 3, characterize the behavior of stock prices during both bull and bear phases. By comparing the features of the phases implied by statistical models and those of the empirical data, we can discern whether the statistical models correctly characterize the behavior of the stock market. More importantly, not only are we going to be able to discard some of the models in terms of their inability to replicate the empirical features of the data, but also we may be able to uncover regularities in the market that cannot be accounted for by statistical models. Hence, we are not only interested in the - purely statistical - question of whether formal models can account for the behavior of an empirical measure, but also in the more relevant question of whether developed markets behave more in line with random walk-based models of unpredictable - or predictable with a simple structure - returns.

4.1 Simulation of the Return Process

The models estimated parallel the list in Pagan and Sossounov (2003), although we include a stochastic volatility model and do not include duration dependence in the Markov switching model. The DGPs analyzed are:

I) AR(1) returns (AR).

II) AR(1)-GARCH(1,1) returns (GARCH).

III) AR(1)-EGARCH(1,1) returns (EGARCH).

IV) AR(1) returns with stochastic volatility (SV).

V) AR(1) returns with Markov switching mean returns and volatilities (MS).

The Appendix develops these five models in greater detail. We have estimated the models using the Spanish data. Parameter estimates for the two subperiods are shown in Table 4. Notice that the table has the coefficients split into those relating to the mean equation (constant of the mean equation, autoregressive component of returns and the regime means in the case of the regime switching model) and those in the variance. The coefficients for the variance equation are presented in the Table in the same order as in the Appendix.

[Insert Table 4]

The estimated coefficients were then used to generate simulated time series of stock prices. The simulations consisted of series of 10,000 observations.[17] We then

[17] We also simulated series of the specific length of the Spanish time series. The results did not change significantly, and consequently we do not include them in Table 4.

identified the turning points, dated the cycle phases and calculated the cycle characteristics for each simulated series. The same procedure would be repeated 1,000 times, the resulting characteristics averaged and critical values were calculated from the empirical distribution of the simulated characteristics.

4.2 Results of the Simulation Experiment

Table 5 shows the average and the 95% critical values of the simulated distribution of the four characteristics for each of the models considered. We have highlighted in bold font the characteristics for which the empirical measure of the Spanish market is contained in the 95% interval of the simulated distribution - i.e, the specific model considered generates cycles compatible with the empirical measure.

[Insert Table 5]

Panel A shows the average and critical values of the simulated DGPs using the parameters from the estimation with the Spanish data for the subperiod 1950-1989. The models that best replicate the empirical features of the data are the GARCH, EGARCH and the SV models, all of which specify a changing volatility structure to the data. Specifically, of the eight possible measures that the models could replicate - four for each type of phase - the SV model captures six of them, the EGARCH five and the GARCH three. It is especially noticeable that the GARCH and EGARCH models overestimate the value of *volatility* in both phases, which gives special relevance to the SV model as being flexible enough to capture both the evolution in mean and the volatility with relatively few parameters. The three models replicate fairly well the behavior during bull phases whereas they fail to explain correctly bear phases. In particular, only the EGARCH model generates bear phases of similar *amplitude* and none of the five models can account for the *duration* of the bear phases. The AR and the MS models perform quite poorly, capturing only two and one of the eight features respectively. In all cases the value of the *EX index* for bull phases is well captured and, at least, the EGARCH and the SV models generate also bear phases with similar value of the index. Thus, it seems that these simple models can account quite well for the behavior and shape of the cycles in the Spanish stock market prior to 1990, without having to resort to more complicated models such as two-regime specifications.

Things change quite a bit when we analyze the results in Panel B, that correspond to the period post-1990. Now both the EGARCH and the SV models fail to capture the behavior of the post-1990 market - they replicate two and none of the eight features respectively. It is the GARCH model that now fares better, being able to explain five of the features, including the two values of *volatility*. *Duration* of the bull phases is not correctly replicated by any DGP, although this can be due to the bear phase of 1998 which gives rise to two shorter bull phases. In any case, both the *amplitude* and the *volatility* of bull phases is well captured by the AR and the GARCH. Bear phases are well explained by the GARCH model, which perfectly replicates *duration*, *amplitude* and *volatility.* However, the most striking finding comes from looking at the values of the *EX index.* None of the models can generate cycles with shapes similar to those we find in the empirical data. This is true for both bull and bear phases, and, what is more relevant, the direction of the failure is always the same: All five DGPs generate bull phases that have too large *EX index* and bear phases that have too negative *EX index*. In other words, given the behavior that our simple models would imply, the bull phases of the Spanish stock market in the 1990's have had the shape in Figure 1B and bear phases have had the shape in Figure 1C. In both cases we see that the bigger positive returns during market expansions and the more negative returns during market contractions are located at the end of the phase. This finding has not been pointed out, to our knowledge, before. It is relevant in the light of seeing how simple models such as a GARCH specification can correctly explain all other characteristics of the cycle phases. This departure - that we term *return acceleration* - of the empirical *EX index* from what is implied by the statistical DGP is pointing at the existence of a different, or at least non-traditional, predictability in the market, which definitely warrants further attention. The analysis of the bull and bear phases has been able to uncover this behavior, which was concealed in market analyses that did not differentiate between the two types of market phases.

5 Conclusions

This paper uses monthly stock market data to study the characteristics of bull and bear phases of the Spanish stock market during the period 1/1950-12/2002. In order to detect cyclical patterns in stock prices we use the Bry-Boschan business cycle dating algorithm and measure some characteristics of the bull and bear phases of the stock cycles: Average *duration*, average *amplitude*, *excess* from a triangle approximation and *volatility* within the phase. We compare these characteristics with those of Germany, the UK and the US. We divide our sample into two subperiods corresponding to the years before and after the financial development process that Spain and other EU countries went through in the late 1980's and early 1990's. Our results show that after the development period the Spanish market has behaved more similarly to other developed markets, although some differences still remain - mostly with respect to the US, although it could be argued that the behavior of the US stock market has been itself a little unusual. More relevantly, the evolution of the Spanish market became significantly more concordant in both short and medium-term movements, especially with Germany and the UK, that were direct partners in the process of financial unification. Once we identify the main characteristics of bull and bear markets we simulate some typical data generating processes associated with the stock market in order to identify which of these processes can successfully replicate the characteristics of the empirical cycles. Our main results regarding Spanish bull and bear cycles agree closely with those in the traditional literature about other developed countries, where it is found that some simple models of stock market behavior can do a good job at replicating the features of the empirical data, whereas more sophisticated models (and more difficult to estimate) offer very little, if any, improvement. However, no model is able to replicate all the features of the cycles, and some of those that perform the best present some puzzling results (e.g. GARCH models tend to overestimate the volatility of the market whereas a simple autoregressive process does not). The most interesting result comes from the fact that none of the models is able to explain the shape of the Spanish cycles after the development process: Returns in the market tend to *accelerate* at the end of both bull and bear phases. This was not the case before market development, a subperiod for which the statistical models could actually generate cycles with the same shape as the empirical ones. Finding a reason for this market acceleration at the end of the phase, and why this is happening now and not before, becomes an interesting question for future research.

More research is warranted in order to explain the relevant features of the data and why these features change with market development. Current theoretical models that generate stock market cycles do not do a good job at replicating the features of the market - Pagan and Sossounov (2003) calibrate some well-known theoretical models and find that they do not perform well when generating the empirical cycles - and thus it seems necessary to put further effort in developing new models that can successfully account for the behavior of the data.

6 Appendix: Models Simulated for Spanish Data

I) **AR(1) returns (AR)**. Given that $p_t = \ln(P_t)$, $\Delta p_t = p_t - p_{t-1}$ is identified with the return on the stock market index, our first model is:

$$\Delta p_t = \mu + \rho \Delta p_{t-1} + \sigma \varepsilon_t, \;\; \varepsilon_t \rightarrow nid(0,1) \tag{8}$$

This model postulates that there may be some autocorrelation in returns, denoted by ρ, which makes the return somehow predictable.[18]

II) **AR(1)-GARCH(1,1) returns (GARCH)**. This model allows for the variance to change over time, depending on the value of the last return (ARCH effect) and on the value of the variance in the previous period (GARCH effect).

$$\begin{aligned} \Delta p_t &= \mu + \rho \Delta p_{t-1} + \sigma_t \varepsilon_t, \varepsilon_t \rightarrow nid(0,1) \\ \sigma_t^2 &= \alpha + \beta u_{t-1}^2 + \gamma \sigma_{t-1}^2 \end{aligned} \tag{9}$$

III) **AR(1)/EGARCH(1,1) returns (EGARCH)**. This model complements the previous one by allowing for a leverage effect in the variance equation by which negative past returns would have a higher impact on the variance. Given the features of the data, this is the most complete specification: It includes the drift and autocorrelation in the mean equation for returns, and the conditional heteroskedasticity, with the implied excess kurtosis, and asymmetric effect on volatility in the variance equation. One would expect this model to be the best in replicating the features of the Spanish cycles. The model can be expressed as

$$\begin{aligned} \Delta p_t &= \mu + \rho \Delta p_{t-1} + \sigma_t \varepsilon_t, \;\; \varepsilon_t \rightarrow nid(0,1) \\ \ln \sigma_t^2 &= h_t = \phi_0 + \phi_1 \varepsilon_{t-1} + \phi_2 \left| \varepsilon_{t-1} \right| + \phi_3 \ln \sigma_{t-1}^2 \end{aligned} \tag{10}$$

[18] If P_t contains dividends, as our stock prices do, then Δp_t indeed corresponds to market returns. The dating of phases with capital gains (i.e. using stock indexes that have been adjusted for dividends) could in principle be different, especially in the light of recent changes in dividend policies. However, at least in the case of our countries the dating of the cycle phases does not differ substantially when using capital gains instead of returns.

IV) **AR(1) returns with Stochastic Volatility (SV)**. Stochastic Volatility models have the advantage that they allow for a richer time structure on the volatility. An SV model looks like

$$\begin{aligned} \Delta p_t &= \mu + \rho \Delta p_{t-1} + \sigma_t \varepsilon_t, \ \varepsilon_t \to nid(0,1) \\ \ln \sigma_t^2 &= h_t = \phi_0 + \phi_{SV} h_{t-1} + v_t, \ v_t \to nid(0, \sigma_v^2) \end{aligned} \tag{11}$$

This model is very intuitive, for it is capturing most of the features of the time series with a simple AR(1) structure on the variance, that includes now an innovation (unlike GARCH or EGARCH models, where the volatility is adapted to the information set I_{t-1}). However, the model is quite difficult to estimate: The volatility process contains an unobserved disturbance and is itself unobservable, so the likelihood function cannot be computed in the usual way. We follow one of the traditional procedures for estimating SV models and use quasi-maximum likelihood to estimate the parameters. Details can be found in the comprehensive review by Ghysels et al. (1996) or in Ruiz (1994).

V) **AR(1) returns with Markov Switching mean returns and volatilities (MS)**, with two states. This model has become the traditional parametric framework for analyzing business cycles, where the two states are identified with expansions / contractions, and stock market cycles, where the states are identified with bull / bear markets. We estimate a simple two state regime switching model.

Think of a model with two states, 1 and 0, where 1 indicates "bull" and 0 indicates "bear." The behavior of returns in the two states is allowed to differ, and can be expressed as

$$\Delta p_t = \mu_S + \rho_S \Delta p_{t-1} + \sigma_S \varepsilon_t, \ S_t = 1, 0 \tag{12}$$

At each point in time the process followed by returns is in one of the states, but there is a transition matrix that contains the probabilities that, given that the state at time t is S_t, the state at time $t+1$ will be S_{t+1}. This matrix is $\begin{pmatrix} p_{11} & 1-p_{22} \\ 1-p_{11} & p_{22} \end{pmatrix}$. A comprehensive treatment of the model and how the likelihood can be constructed from the transition probabilities is found in Hamilton (1994). This model has a total of eight parameters, three for each state and the two transition probabilities, but we reduce it to 7 by forcing the AR(1) parameter to be equal across states. Thus, we can write the process for Δp_t as

$$\begin{aligned} \Delta p_t &= (\mu_1 + \rho \Delta p_{t-1} + \sigma_1 \varepsilon_t) S_t + (\mu_0 + \rho \Delta p_{t-1} + \sigma_0 \varepsilon_t)(1 - S_t) \\ p(S_t &= j | S_{t-1} = i) = p_{ji} \end{aligned} \tag{13}$$

where 1 refers to the parameters in the bull state and 0 to the parameters in the bear state.

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Table 1. Characteristics of the bull and bear markets

Panel A: Pre-1990

	SPAIN	*GERMANY*	*UK*	*US*
N	483	432	487	462
T	7/49-9/89	2/52-1/88	2/49-8/89	7/49-12/87
Bull				
D	37.4	24.9	31.9	22.2
A	0.872	0.598	0.667	0.426
EX	0.161	0.033	0.068	0.080
V	0.035	0.039	0.038	0.026
Bear				
D	18.3	16.6	12.4	13.4
A	-0.310	-0.321	-0.353	-0.206
EX	-0.030	-0.013	-0.029	0.011
V	0.036	0.036	0.045	0.027

Panel B: Post-1990

	SPAIN	*GERMANY*	*UK*	*US*
N	123	164	145	165
T	10/89-2/00	2/88-9/01	9/89-9/01	1/88-9/01
Bull				
D	20.3	30	34	47.3
A	0.707	0.715	0.523	0.675
EX	0.062	0.091	-2e-4	0.116
V	0.050	0.044	0.029	0.023
Bear				
D	10.5	11	10.8	7.7
A	-0.272	-0.333	-0.227	-0.186
EX	0.023	0.049	0.024	-0.011
V	0.046	0.055	0.042	0.032

N: number of observations. T: period. D: average duration. A: average amplitude. EX: excess from a triangle approximation. V: volatility within the phase.

Table 2. Concordance index (CI)

Panel A: Pre-1990

CI	$SPAIN$	$GERMANY$	UK	US
$SPAIN$	1	0.507	0.563	0.622
$GERMANY$		1	0.768*	0.645
UK			1	0.645
US				1

Panel B: Post-1990

CI	$SPAIN$	$GERMANY$	UK	US
$SPAIN$	1	0.865*	0.808*	0.731*
$GERMANY$		1	0.827*	0.853*
UK			1	0.846*
US				1

The * indicates that the value is outside of the 5% confidence interval. The confidence intervals have been calculated from simulated series using a Random Walk with Drift and AR(1) increments,

$$\Delta p_t = \mu + \rho \Delta p_{t-1} + \sigma \varepsilon_t, \ \ \varepsilon_t \rightarrow nid(0,1)$$

that represents the best fitting model to the bull and bear cycles characteristics. Parameters of this model were estimated for all four countries, and then 10,000 series of length 302 were simulated and the CI calculated. The 2.5% and 97.5% quantiles of the simulated distribution of the CI are used as critical values. The specific values are available upon request. The critical values should be in the 0.35-0.66 range, which is the common range for the rest of the series.

Table 3. Simple Correlations of Returns (ρ)

Panel A: Pre-1990

ρ	$SPAIN$	$GERMANY$	UK	US
$SPAIN$	1	0.203	0.230	0.275
$GERMANY$		1	0.334*	0.367
UK			1	0.395
US				1

Panel B: Post-1990

ρ	$SPAIN$	$GERMANY$	UK	US
$SPAIN$	1	0.678*	0.641*	0.447*
$GERMANY$		1	0.651*	0.450*
UK			1	0.498*
US				1

The * indicate that the CI in Table 2 is outside of the 5% confidence interval.

Table 4. Parameter estimates for the Spanish series

Panel A: Pre-1990

Model	*RW*	*GARCH*	*EGARCH*	*SV*	*MS*
Mean					
μ	0.009	0.009	0.01	0.009	0.013
ρ	0.174	0.150	0.159	0.174	0.168
μ_2					0.010
Variance					
σ, α, ϕ_0	0.047	4.5e-5	-0.268	0.038	
β, ϕ_1		0.154	0.082		
$\gamma, \phi_3, \phi_{SV}$		0.840	0.983	0.981	$p_{11} = 0.975$
ϕ_2			0.209		$p_{22} = 0.981$
σ_1					0.024
σ_2					0.058

Panel B: Post-1990

Model	*RW*	*GARCH*	*EGARCH*	*SV*	*MS*
Mean					
μ	0.009	0.009	0.006	0.009	0.143
ρ	0.101	0.097	0.158	0.101	0.093
μ_2					-0.177
Variance					
σ, α, ϕ_0	0.062	0.003	-11.25	0.055	
β, ϕ_1		0.200	0.019		
$\gamma, \phi_3, \phi_{SV}$		0.004	-0.900	0.463	$p_{11} = 0.983$
ϕ_3			0.356		$p_{22} = 0.278$
σ_1					0.054
σ_2					0.045

Table 5. Characteristics of the bull and bear markets for simulated data

Panel A: Pre-1990

Model	*RW*	*GARCH*	*EGARCH*	*SV*	*MS*
Bull					
D	32.4	**33.6**	**34.1**	**40**	48.9
2.5% *CV*	29.2	**30.1**	**30.7**	**35.2**	42.7
97.5% *CV*	35.8	**37.5**	**37.7**	**45.4**	56.1
A	0.743	**0.876**	**0.884**	**0.788**	1.079
2.5% *CV*	0.673	**0.755**	**0.789**	**0.708**	0.958
97.5% *CV*	0.816	**1.065**	**0.989**	**0.874**	1.221
EX	**0.16**	**0.153**	**0.126**	**0.196**	0.344
2.5% *CV*	**0.112**	**0.093**	**0.076**	**0.132**	0.23
97.5% *CV*	**0.222**	**0.228**	**0.19**	**0.285**	0.497
V	0.04	0.048	0.046	**0.034**	**0.036**
2.5% *CV*	0.039	0.041	0.042	**0.031**	**0.034**
97.5% *CV*	0.041	0.059	0.051	**0.037**	**0.038**
Bear					
D	12.8	13.3	12.4	12.6	12.7
2.5% *CV*	11.7	12.1	11.3	11.2	11
97.5% *CV*	14	14.7	13.6	14	14.7
A	-0.253	-0.389	**-0.313**	-0.235	-0.263
2.5% *CV*	−0.273	−0.567	**−0.359**	−0.275	−0.3
97.5% *CV*	−0.233	−0.291	**−0.273**	−0.198	−0.222
EX	-0.009	**-0.042**	**-0.025**	**0.002**	0.039
2.5% *CV*	−0.028	**−0.128**	**−0.057**	**−0.037**	−0.027
97.5% *CV*	0.023	**0.016**	**0.016**	**0.072**	0.191
V	**0.037**	0.056	0.048	**0.037**	0.041
2.5% *CV*	**0.036**	0.044	0.043	**0.033**	0.039
97.5% *CV*	**0.038**	0.079	0.053	**0.041**	0.044

D: average duration in months. A: average amplitude in % return (or loss). EX: excess from a triangle approximation. V: volatility within the phase in average size of % return per month. The Table includes the 2.5% and 97.5% values of the simulated distributions of all four measures. Boldface numbers indicate that the empirical value for the Spanish stock market data is contained in the 95% simulated confidence interval.

Table 5 (Continued). Characteristics of the bull and bear markets for simulated data

Panel B: Post-1990

Model	*RW*	*GARCH*	*EGARCH*	*SV*	*MS*
Bull					
D	27.8	28.7	25.1	27.6	32.6
2.5% *CV*	25.4	26.1	23	25.1	29.6
97.5% *CV*	30.1	31.3	27.5	30	35.6
A	**0.748**	**0.749**	**0.661**	0.864	0.843
2.5% *CV*	**0.687**	**0.687**	**0.607**	0.786	0.77
97.5% *CV*	**0.811**	**0.816**	**0.721**	0.943	0.926
EX	0.139	0.14	0.112	0.155	0.174
2.5% *CV*	0.096	0.097	0.078	0.103	0.12
97.5% *CV*	0.192	0.19	0.159	0.22	0.241
V	**0.051**	**0.05**	0.048	0.054	0.047
2.5% *CV*	**0.05**	**0.049**	0.047	0.052	0.046
97.5% *CV*	**0.052**	**0.051**	0.049	0.056	0.047
Bear					
D	13.9	13.5	15.1	14.0	12.3
2.5% *CV*	12.7	12.4	13.9	12.8	11.1
97.5% *CV*	15.1	14.8	16.3	15.2	13.5
A	-0.342	-0.331	-0.374	-0.46	**-0.355**
2.5% *CV*	−0.367	−0.357	−0.4	−0.5	**−0.389**
97.5% *CV*	−0.317	−0.306	−0.347	−0.422	**−0.321**
EX	-0.023	-0.02	-0.035	-0.036	**-0.018**
2.5% *CV*	−0.042	−0.04	−0.055	−0.067	**−0.048**
97.5% *CV*	0	0.008	−0.014	−0.002	**0.027**
V	0.048	**0.048**	**0.046**	0.059	0.052
2.5% *CV*	0.047	**0.046**	**0.045**	0.056	0.049
97.5% *CV*	0.05	**0.049**	**0.047**	0.061	0.054

D: average duration in months. A: average amplitude in % return (or loss). EX: excess from a triangle approximation. V: volatility within the phase in average size of % return per month. The Table includes the 2.5% and 97.5% values of the simulated distributions of all four measures. Boldface numbers indicate that the empirical value for the Spanish stock market data is contained in the 95% simulated confidence interval.

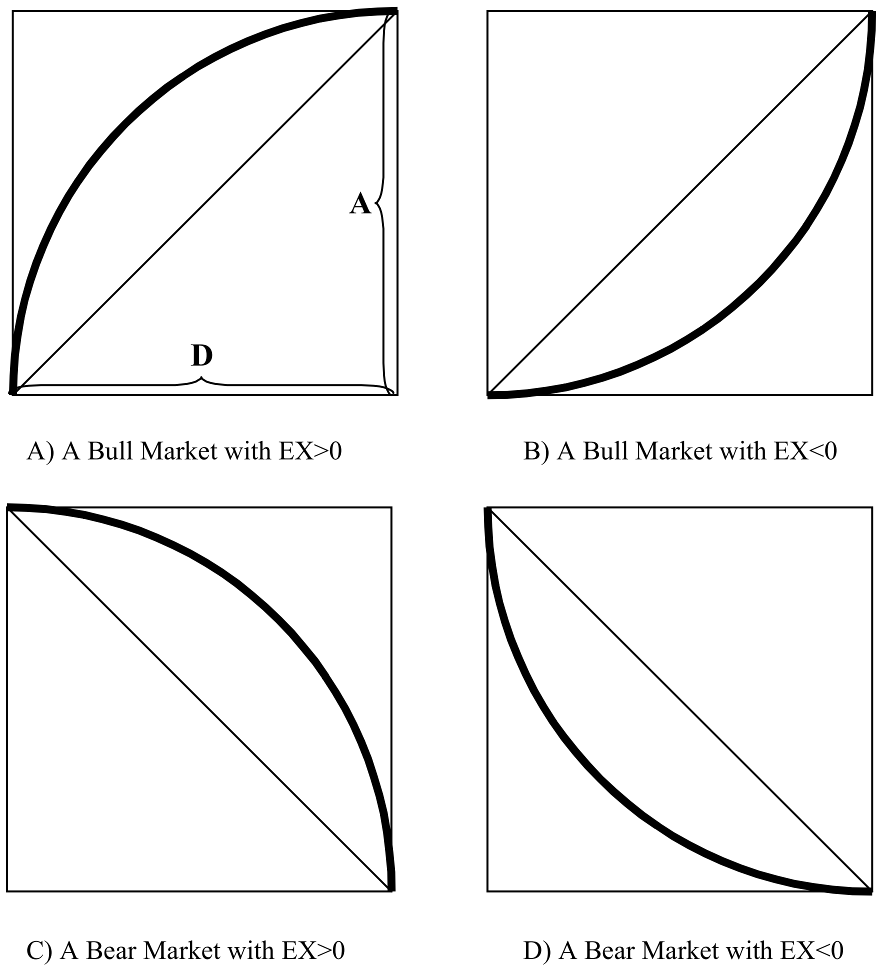

Figure 1: Shape of the Bull / Bear Phases and value of the Excess measure. The axes correspond to time and stock prices. Consequently, D corresponds to our measure of *duration* of the phase and A to the *amplitude*.

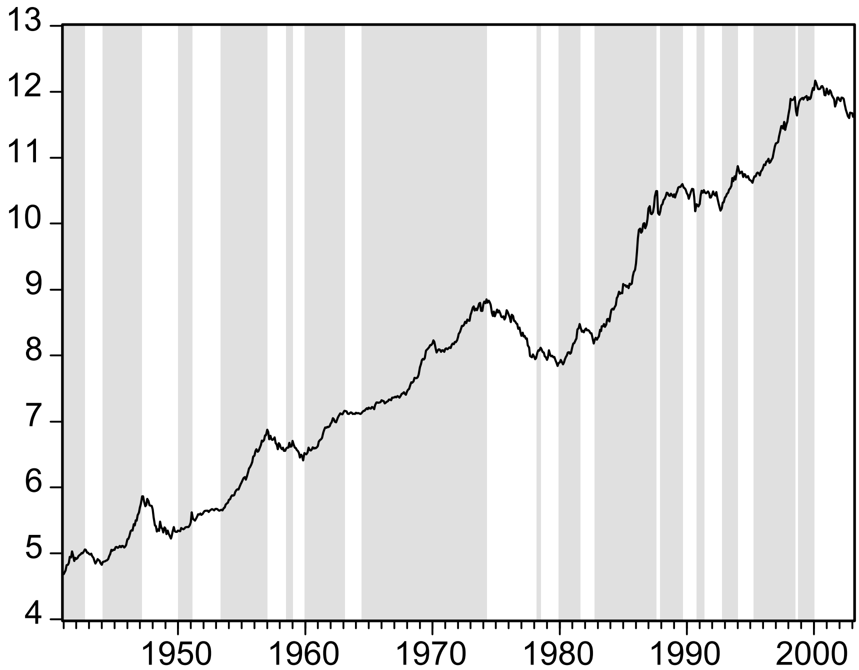

Figure 2: Spanish Stock Index. Evolution of (Log) Prices, 1941-2002. Bullish Phases shaded.

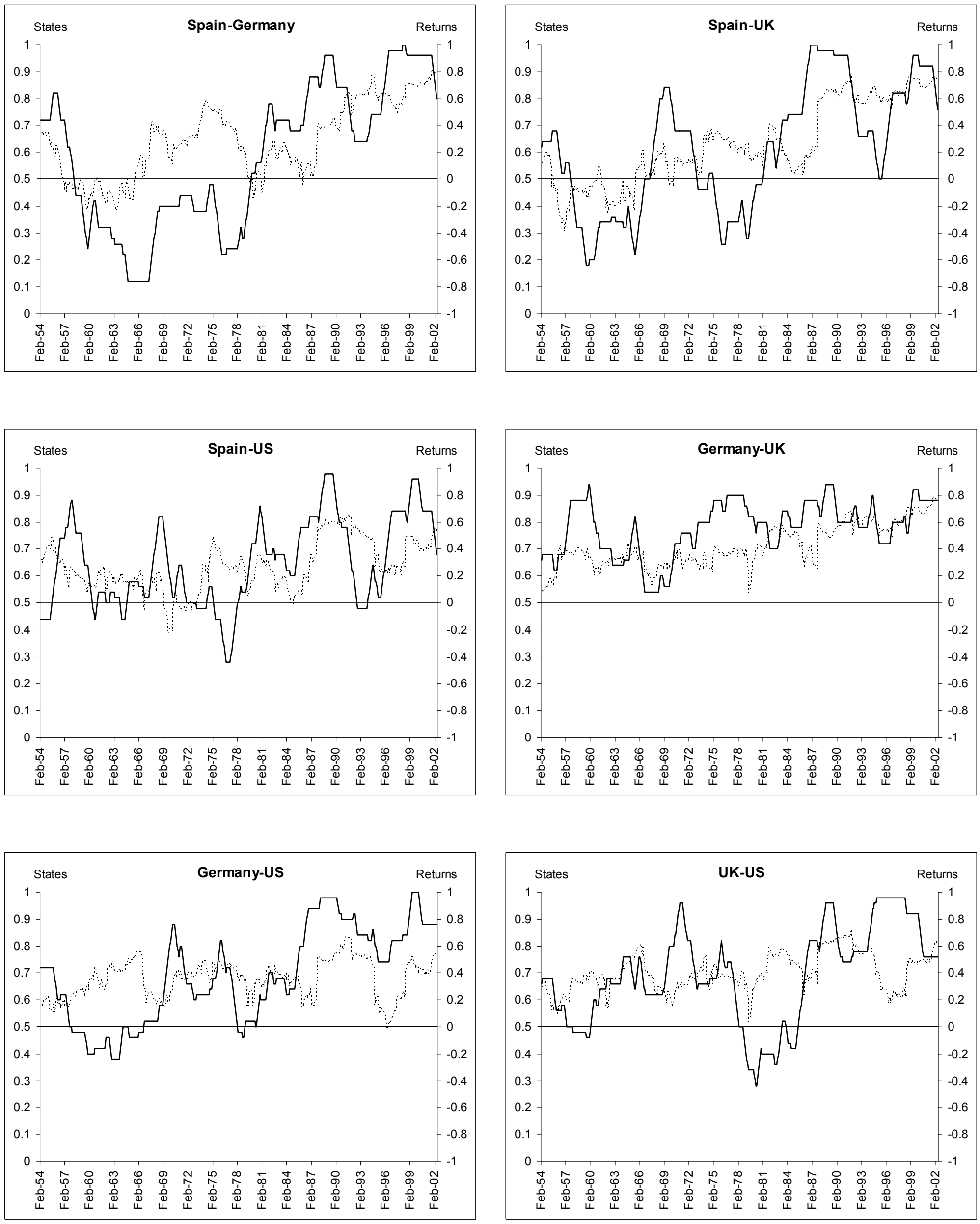

Figure 3: Evolution of market synchronicity in Spain, Germany, the UK and the US: Comparison of rolling correlation indexes of simple returns (dashed line) and rolling concordance indexes of bull/bear states (solid line). The rolling window has size 50.