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Spot Market Volatility and Futures Trading: The Pitfalls of Using a Dummy Variable Approach

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Spot Market Volatility and Futures Trading: The Pitfalls of Using a Dummy Variable Approach*

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Abstract

This paper challenges the existing literature examining the impact of the introduction of index futures trading on the volatility of its underlying. To overcome econometric shortcomings of previously published work using the dummy variable approach, we employ a Markov-switching-GARCH technique. This approach endogenously identifies distinct volatility regimes rather than modelling an exogenously defined one-step change in the volatility process. We investigate stock market volatility in France, Germany, Japan, the UK and the US. Our empirical results indicate that index futures trading does neither stabilize nor destabilize the underlying spot market.

JEL Classification: C32, G10, G14, G20

Keywords: Stock Index Futures, Stock Market Volatility, Markov-Switching-GARCH Model

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1 Introduction

The process of arbitrage closely links futures markets with their underlying spot markets. A broad empirical literature has examined if the introduction of futures markets stabilizes or destabilizes respective spot markets. However, an unanimous answer has not yet been found. A number of theoretical papers result in conflicting predictions. (Cagan, 1981; Stein, 1987; Kyle, 1985; Stoll and Whaley, 1988; for example). Hence, empirical investigations are crucial to scrutinize if and how the introduction of futures markets impacts the underlying.

The vast majority of recent empirical papers approaches the issue of volatility spillovers by estimating GARCH-type models augmented by dummy variables. (Antoniou et al., 1998; Gulen and Mayhew, 2000; McKenzie et al., 2001; Antoniou et al., 2005). This dummy approach enables distinction between pre- and post-futures markets periods. As a result, the impact of the introduction of futures markets on spot return volatility can be examined.

However, the dummy variable approach can be challenged because it relies on an exogenous determination of the shift in stock return volatility. By definition, it can only model an abrupt one-step change in the volatility process, which may not represent a realistic pattern. Moreover, the dummy variable is unable to capture any kind of gradual adjustment from one volatility regime to another. In addition, this approach is unable to correctly reflect transient changes. If a change in the volatility pattern does not exactly coincide with the date of the futures market introduction and therefore does not follow a one-step change, the dummy variable approach mis-specifies the process. Therefore, any economic conclusions based on this econometric approach are likely to be misleading.

Hence, the present paper employs a Markov-switching-GARCH model instead of the dummy variable approach to examine financial markets in France, Germany, Japan, the United Kingdom (UK) and the United States (US). Our model provides both empirical and graphic evidence of whether and how the introduction of futures markets changes the volatility structure of returns in the underlying spot markets. We endogenously model switches between different volatility regimes. This is all the more interesting as the existing literature has not found unanimous empirical evidence on our research question for these particular mature markets under consideration.

Our study therefore contributes to the literature on the matter by using an econometric approach that has not yet been applied in this context and overcomes apparent shortfalls of the well-established dummy approach. Moreover, it explores the five most important mature financial markets, that were among the first to introduce index futures trading. Our estimation results indicate that the introduction of futures trading has no effect on spot market volatility at all. It neither stabilizes nor destabilizes the underlying.

The rest of the paper proceeds as follows: Section 2 briefly summarizes the available literature on the matter. Section 3 presents the data and econometric technique employed. Section 4 presents our main empirical findings and section 5 concludes.

2 Literature overview

This section focuses on summarizing time series investigations which compare spot market volatility before and after the introduction of index futures trading.[1] Overall, the existing empirical literature yields mixed evidence. Some papers report empirical evidence in favour of the stabilization hypothesis, stating that the introduction of derivatives trading is likely to reduce volatility in the underlying stock market. Others support the destabilization hypothesis, asserting that futures trading will induce higher stock market volatility. A third group finds no significant impact of the introduction of futures markets on the volatility of the underlying at all.

The introduction of S&P500 index futures trading has been the first in a long line of subsequent investigations: Edwards (1988) reports a decrease in the volatility of the S&P500 index after the introduction of its index futures. In contrast, Santoni (1987) finds no significant difference in the volatility of the S&P500 index before and after the

[1] See Sutcliffe (2006) for a comprehensive review of the relevant theoretical and empirical literature regarding stock index futures and the question whether the introduction of futures markets stabilizes or destabilizes the underlying.

introduction of its futures in April 1982. In line with this, Pericli and Koutmos (1997) show that the creation of S&P500 stock index futures did not cause any shift in the volatility of the underlying. Darrat et al. (2002) conclude that index futures trading is not to blame for the observed volatility in the S&P500 spot market. Rather, they find more support for the alternative view that volatility in the futures market is an outgrowth of a turbulent cash market.

In contrast, Maberly et al. (1989) ascertain evidence in favour of the destabilizing hypothesis as it increased volatility of the S&P500 index. However, the authors emphasize that this finding critically depends upon the selection of the sample size, i.e. the length of the pre- and post-futures periods. Brorsen (1991) states futures trading to have reduced autocorrelation and increases volatility of the S&P500 stock index. Further empirical evidence in favour of the destabilizing hypothesis is provided by Lockwood and Linn (1990) and Baldauf and Santani (1991). While Damodaran (1990) reports an increase in daily price volatility of all the S&P 500 shares increased after the introduction of the S&P 500 futures contract, this increase was not statistically significant.

Turning to other mature markets, Lee and Ohk (1992) find evidence in favour of the destabilizing hypothesis in reporting that spot market volatility in Australia, Hong Kong, Japan, the UK and the US has significantly increased following the introduction of index futures. However, Bacha and Vila (1994) confirm the stabilization hypothesis for the Japanese market and Reyes (1996) for both the French and Danish market.

Several studies examine a great number of different markets at once: Antoniou and Holmes (1995) scrutinize the British market and ascertain increasing spot market volatilities after the introduction of the FTSE100 stock index futures. However, they report that the nature of volatility has not changed post-futures and futures have improved the speed and quality of information flowing to the spot market. In line with this, Antoniou et al. (1998) use a GJR-GARCH approach to examine markets in Germany, Japan, Spain, Switzerland, the UK and the US. They find no evidence in favour of the stabilization hypothesis for spot markets in Japan, Spain, the UK and the US. However, they find evidence in favour of the stabilizing hypothesis for the German and Swiss market.

In a broad study, Gulen and Mayhew (2000) investigate the time-series properties of daily stock index returns in 25 different countries before and after the introduction of stock index futures. They use a multivariate GARCH framework to compare volatility, futures trading volume and open interest for a large cross section of different markets. Their empirical results indicate that the futures introduction increases spot market volatility in the US and Japan but has a dampening impact in 16 other countries, such as Germany and the UK. The authors find no change in the volatility of spot markets in the remaining seven countries.

Yu (2001) reports evidence in favour of the destabilizing hypothesis for stock index markets in the US, France, Japan and Australia, while no significant increase in spot market volatility following the introduction of index futures markets is found for the UK and Hong Kong.

Antoniou et al. (2005) point out that inference about possible volatility spillovers depends upon the presence of feedback traders in futures market. They investigate daily stock index data between 1969 and 1996 from Canada, France, Germany, Japan, the UK and the US. In all countries but the US, the introduction of futures trading coincides with a reduced influence of feedback trading on the constituents of the underlying stock index. Spot market volatility has not increased in any country.

As can be seen, a vast amount of empirical literature has dealt with our research question. However, the introduction of index futures trading in the five mature markets we consider here has so far only been examined based on the dummy variable approach, which imposes an exogenous shift date for and a permanent character of possible changes in spot market volatility on the time series investigated.

3 Data and econometric technique

Our data set comprises daily closing price observations of the CAC40 (France), the DAX30 (Germany), the NIKKEI225 (Japan), the FTSE100 (UK) and the S&P500 (US).[2] All data is taken from Global Financial Data. For each stock market index, the sample period centers around the year of the introduction of its respective index futures with a plus/minus five year window span. We therefore focus on the dates that are key to answering our research question. At the same time, we ensure that the data set contains enough observations to enable us to obtain reliable empirical results.

Futures contracts on the CAC40 were introduced on 9 November 1988, the ones on the DAX30 on 23 November 1990, on the NIKKEI225 on 3 September 1986, on the FTSE100 on 3 May 1984 and on the S&P500 on 21 April 1982. After having eliminated extreme outliers caused by the stock market crash of October 1987, we construct the following sample periods: 1 January 1983 to 31 December 1993 for the CAC40, 1 January 1985 to 31 December 1995 for the DAX30, 1 January 1981 to 31 December 1991 for the NIKKEI225, 1 January 1979 to 31 December 1989 for the FTSE100 and 1 January 1977 to 31 December 1987 for the S&P500. We define daily returns as $R_t \equiv 100 \cdot [\ln(\text{Index}_t) - \ln(\text{Index}_{t-1})]$.

In order to model endogenous volatility shifts in the index return time series R_t, we use the Markov-switching-GARCH model developed in Gray (1996b) and refined afterwards. We assume the data generating process (DGP) of the return R_t to be affected by a latent random variable representing the state of the DGP at date t. A latent state variable S_t is used to discriminate between two distinct volatility regimes: $S_t = 1$ indicates that the DGP is in the high-volatility regime, while $S_t = 2$ indicates that the DGP is in the low-volatility regime.

The basic element of our Markov-switching-GARCH model is the well-known probability density function of a mean-shifted t-distribution with ν degrees of freedom, mean μ and variance h, $t_{\nu,\mu,h}$. Based on this parametric density function, we can specify stochastic processes for the mean and the volatility in regime i, which we denote by

[2] The CAC40 is represented by the CAC General prior to 9 July 1987. Further, we use the Financial Times All Share index instead of the FTSE100 before 1 January 1984.

μ_{it} and h_{it}, according to which R_t is generated conditional upon the regime indicator $S_t = i, i = 1, 2$.

Hence, the conditional distribution of the respective stock return is a mixture of two mean-shifted t-distributions:

$$R_t|\phi_{t-1} \sim \begin{cases} t_{\nu_1,\mu_{1t},h_{1t}} & \text{with probability } p_{1t} \\ t_{\nu_2,\mu_{2t},h_{2t}} & \text{with probability } (1-p_{1t}) \end{cases} \tag{1}$$

where ϕ_{t-1} defines the information set at date $t-1$ and $p_{1t} \equiv \Pr\{S_t = 1|\phi_{t-1}\}$ denotes the *ex-ante* probability of being in regime 1 at time t.

Our regime-dependent mean equation reads:

$$\mu_{it} = a_{0i} + a_{1i}R_{t-1} + a_{2i}R_{t-1}^{\text{SP}} \qquad \text{for } i = 1, 2. \tag{2}$$

By including R_{t-1}, we account for first-order autocorrelation in index returns. The lagged S&P500 index return R_{t-1}^{SP} captures the international interdependence of the stock markets under consideration.[3]

In contrast to the mean equation (2), specifying an adequate GARCH process for the regime-specific variance h_{it} is less straight forward. Without going into technical detail, we first consider an aggregate of conditional stock index-return variances from both regimes at date t:[4]

$$\begin{aligned} h_t &= E\left[R_t^2|\phi_{t-1}\right] - \{E\left[R_t|\phi_{t-1}\right]\}^2 \\ &= p_{1t}\left(\mu_{1t}^2 + h_{1t}\right) + (1-p_{1t})\cdot\left(\mu_{2t}^2 + h_{2t}\right) - \left[p_{1t}\mu_{1t} + (1-p_{1t})\,\mu_{2t}\right]^2. \end{aligned} \tag{3}$$

The quantity h_t now provides the basis for the specification of the regime-specific conditional variance $h_{it+1}, i = 1, 2$ in the form of a parsimonious GARCH(1,1)-structure. We follow the suggestion of Dueker (1997) and first parameterize the degrees of freedom of the $t_{\nu,\mu,h}$-distribution by $q = 1/\nu$, so that $(1-2q) = (\nu-2)/\nu$. We then specify our regime-specific GARCH equation as:

$$h_{it} = b_{0i} + b_{1i}(1-2q_i)\epsilon_{t-1}^2 + b_{2i}h_{t-1} \tag{4}$$

[3] When examining the return of the S&P500, the mean equation includes one lagged return only.
[4] See Gray (1996b) for a formal discussion.

with h_{t-1} given according to Eq. (3) and ϵ_{t-1} obtained from:

$$\begin{aligned} \epsilon_{t-1} &= R_{t-1} - E\left[R_{t-1}|\phi_{t-2}\right] \\ &= R_{t-1} - \left[p_{1t-1}\mu_{1t-1} + (1-p_{1t-1})\,\mu_{2t-1}\right]. \end{aligned} \tag{5}$$

For $i = 1, 2$ the sums $b_{1i}(1-2q_i) + b_{2i}$ of the coefficients from Eq. (4) constitute convenient measures of the regime-specific persistence of volatility shocks. The higher their value, the more time it takes for a shock to die out. A regime-specific volatility shock will die out in finite time if the sum of the coefficients is less than 1. If the coefficient sum exactly to 1 (i.e. for an integrated GARCH(1,1) process) volatility shocks have a permanent effect and the unconditional variance of the process becomes infinitely large.

Finally, we close our model by parameterizing the regime indicator S_t as a first-order Markov process with constant transition probabilities. Letting π_i be the probability of the DGP prevailing in regime i (for $i = 1, 2$) between the dates $t-1$ and t, we specify:

$$\begin{aligned} &\Pr\left\{S_t = 1|S_{t-1} = 1\right\} = \pi_1, \qquad &&\Pr\left\{S_t = 2|S_{t-1} = 1\right\} = 1 - \pi_1, \\ &\Pr\left\{S_t = 2|S_{t-1} = 2\right\} = \pi_2, \qquad &&\Pr\left\{S_t = 1|S_{t-1} = 2\right\} = 1 - \pi_2. \end{aligned} \tag{6}$$

The log-likelihood function of our model can be obtained by performing similar calculations to Gray (1996b). The exact form of the function is presented in Wilfling (2009). It contains the *ex-ante* probabilities $p_{1t} \equiv \Pr\{S_t = 1|\phi_{t-1}\}$ which can be estimated via a recursive scheme. They are useful in forecasting one-step-ahead regimes based on an information set that evolves over time. In our context, the *ex-ante* probability p_{1t} reflects market perceptions of the one-step-ahead volatility regime and therefore represents an adequate measure of stock market volatility sentiments. We also compute the so-called *smoothed* probabilities $\Pr\{S_t = 1|\phi_T\}$ by applying filter techniques after the estimation of our model.[5] The *smoothed* probabilities are based on the full sample-information set ϕ_T and enable us to infer *ex post* if and when volatility regime switches occur.

[5]We do so based on a filter algorithm provided by Gray (1996a).

4 Empirical results

Before turning to the regression results of our Markov-switching-GARCH model, we first discuss estimates of a GARCH model with a single regime only. We augment the standard model by a multiplicative dummy variable in the conditional variance equation, which takes on the value of zero before and the value of one after the introduction of the respective index futures. Antoniou et al. (1998), Gulen and Mayhew (2000) and Antoniou et al. (2005) employ a similar approach. Table I summarizes our estimation results.

[Insert Table I about here.]

With regard to the mean equation, all but the one for the DAX30 returns show positive first-order autocorrelation as reflected by highly significant a_1 coefficients. Estimates for the different a_2 coefficients indicate that the US stock market has a strong impact on the other markets under consideration. Throughout all indices examined, the GARCH parameter estimates indicate highly persistent and stationary volatility processes. However, the estimated c_0-coefficients capturing the possible impact of the index futures introduction vary in sign and size. While the introduction of index futures markets is found to increase volatility in the CAC40 and the NIKKEI225, it has a calming impact on the DAX30. Spot return volatility of both the FTSE100 and the S&P500 are not found to be affected by the introduction of their respective futures markets.

Next, table II presents the maximum-likelihood estimates of the Markov-switching-GARCH model for all five indices. We accomplished maximization of the log-likelihood function using the BFGS-algorithm, heteroscedasticity-consistent estimates of standard errors and suitably chosen starting values for all parameters. The majority of the coefficients in both the mean and volatility equations (2) and (4) are statistically significant at the 1% level for all return series.[6]

[6] Some comments on the probability distribution of the conventional t-statistic within our Markov-switching-GARCH framework are in order. It has to be noted that its exact finite-sample distribution is generally unknown. However, owing to some well-known asymptotic properties of general maxi-

[Insert Table II about here.]

In the mean equations, 6 out of the 10 autoregressive coefficients a_{11} and a_{12} are statistically significant and positive. This shows a positive first-order autoregressive structure in the stock index returns and is commonly reported in the literature. It can be explained by non-synchronous trading (Lo and MacKinlay, 1990), time-varying expected returns (Conrad and Kaul, 1988), transaction costs (Mech, 1993) and feedback trading (Shiller, 1989; Sentana and Wadhwani, 1992). For the CAC40, the DAX30, the NIKKEI225 and the FTSE100, the coefficients a_{21} and a_{22} on the lagged S&P500 index returns R_{t-1}^{SP} are statistically significant and positive in both regimes, which underlines the strong interdependence between US and international stock markets.

Regarding the estimated GARCH parameters, we find that their sums $b_{1i}(1-2q_i)+b_{2i}$ are less than 1 for all series and both regimes. This suggests that we have stationary conditional volatility processes in all regimes: Volatility shocks die out in finite time. Our estimates of the transition probabilities π_1 and π_2 are close to one, which indicates a high degree of regime persistence.

The bottom part of table II presents diagnostic checks to examine the model fit. It provides Ljung-Box Q-statistics testing for serial correlation of the squared standardized residuals for lags 1, 2, 3, 5 and 10. With exception of the CAC40, the null hypothesis of no autocorrelation cannot be rejected up to lag 10 at any conventional significance level. This result provides evidence in favour of our two-regime Markov-switching-GARCH model specification.

Examination of the *ex-ante* and *smoothed* probabilities $\Pr\{S_t = 1|\phi_{t-1}\}$ and $\Pr\{S_t = 1|\phi_T\}$ provides empirical evidence about the timing of switches between the high- and low-volatility regimes. Figures 1 to 5 display the different daily stock returns, the regime-1 probabilities and the conditional variance for all indices under consideration. Since the *ex-ante* probabilities are determined on the basis of an evolving and therefore shortening information set, they exhibit a more erratic dynamic behaviour than the

mum likelihood estimators in conjunction with an appropriate limiting distribution result, it can be concluded that under the null hypothesis of a single parameter being equal to zero, our t-statistics should converge in distribution towards a standard normal variate. This implies asymptotic critical values of 2.58, 1.96 and 1.64 for the absolute value of the t-statistic at the 1%, 5% and 10%-levels.

smoothed regime-1 probabilities. The time following the introduction of the respective index futures trading is shaded in grey. Periods of high probabilities are generally associated with periods of high conditional volatility. This reflects that regime 1 is the high-volatility regime.

[Insert Figures 1 to 5 about here.]

If the destabilization hypothesis is valid, we should see a clear-cut and permanent increase in stock market volatility following the introduction of futures trading. In terms of our Markov-switching-GARCH approach, spot market returns should therefore perform a sustained shift to the high-volatility regime accompanied by higher conditional variance following the introduction of the respective futures market.

Figure 1 shows that after roughly 15 months of low volatility for the CAC40 index, a switch to the high-volatility regime takes place at the end of 1985. The CAC40 then remains in the high-volatility regime until the end of our sample period. Prior to its introduction date on 9 July 1987, we use the CAC General instead of the CAC40. The observed pattern could therefore result from lower volatility of the broader index employed during the first 3.5 years of our sample period. In turn, the October 1987 stock market crash appears clearly in the structure of the conditional variance. The introduction of CAC40 index futures on 9 November 1988 falls into the high-volatility regime. Compared to levels reached in 1987 and between 1990 and 1993, the conditional variance is relatively low around the introduction date. Overall, no distinct impact of the introduction of the French index futures market emerges. We therefore do not find evidence in favour of the stabilizing nor the destabilizing hypothesis for the French market.

Our estimation output for the German DAX30 is shown in figure 2 and suggests many short periods of increased volatility. Nonetheless, our model appears to capture the volatility clusters in returns quite well. The crash in October 1987 is reflected in a short period of high-volatility accompanied by an extreme spike in the conditional variance. Around the time of the introduction of DAX30 futures trading on 23 November 1990, other short but distinct periods of high volatility appear. In line with this, the conditional volatility around that time is considerably above its overall average. However, this cannot be regarded as empirical evidence in favour of the destabilization hypothesis as the period of high volatility is only temporary.

Figure 3 summarizes our regression results for the Japanese NIKKEI225. In the first half of our sample, several minor spikes in both the high-volatility regime probabilities and the conditional variance occur. In the second half, two pronounced periods of high volatility between 1986 and 1988 as well as from 1990 onwards emerge. The introduction of NIKKEI225 index futures markets on 3 September 1986 falls into the former, which lasts until the end of 1987. Afterwards, both the regime-1 probabilities and the conditional variance indicate low-volatility for roughly two years. The NIKKEI225 switches back to the high-volatility regime at the beginning of 1990. The temporarily lower volatility from 1988 to 1990 provides evidence against the destabilization hypothesis.

For the British FTSE100 index, our model picks up several distinct periods of high and low volatility, as can be seen in figure 4. A relatively long period of high volatility lasts from September 1983 to December 1984. During this time span, index futures on the FTSE100 were introduced on 3 May 1984. Thereupon, a gradual transition towards the low-volatility regime occurs. With the exception of the month after the stock market crash in October 1987, the FTSE100 remains in the low-volatility regime up to 1989. This empirical finding does not reveal a persistent increase in stock market volatility after the introduction of index derivatives trading.

Lastly, figure 5 presents our results for the S&P500. The evolution of the regime-1 probabilities in our sample shows no lasting periods of high volatility at all. Also, the introduction of S&P500 index futures on 21 April 1982 falls into the low-volatility regime. Six month afterwards, a considerable increase in the conditional variance occurs. However, it is not permanent as the conditional variance gradually moves back to its average. The October 1987 crash is clearly visible both in the regime-1 probabilities and the conditional variance. Again, we can neither confirm empirical evidence either in favour of the stabilizing nor of the destabilizing hypothesis.

Summing up, for all five indices considered, the introduction of index futures trading does not lead to a permanent transition to a high-volatility regime along with a higher conditional variance. We do not find evidence for stabilizing effects, either. In consequence, the introduction of derivatives trading does not seem to be connected with the volatility of the underlying spot market at all. This contradicts our preliminary findings based on the dummy variable approach. Therefore, the approach of imposing an exogenously predetermined shift date for possible changes in spot market volatility seems inappropriate to capture its dynamics.

5 Summary and conclusions

This paper re-examines whether the introduction of index futures trading impacts the volatility of the underlying stock index returns. We investigate five major stock market indices around their respective futures introduction: The CAC40 (France), the DAX30 (Germany), the NIKKEI225 (Japan), the FTSE100 (UK) and the S&P500 (US). By applying a Markov-switching-GARCH model, we allow for endogenous volatility regime shifts and can reveal if the volatility structure of stock index returns has changed transitorily or permanently. We therefore overcome an econometric shortcoming of the existing literature: The vast majority of papers estimates GARCH models that include a dummy variable to capture the introduction of futures trading in the variance equation. This approach relies on an exogenous determination of any possible volatility shift. It only models an abrupt one-step change in the volatility process which may not constitute a realistic pattern of volatility changes. By construction, the one-step dummy variable approach cannot capture gradual adjustment to a new volatility regime and does not allow for a transitory volatility change.

Our regression results suggest that the introduction of index futures trading does neither stabilize nor destabilize the underlying spot market. Futures trading does not seem to influence spot market volatility at all. While we find periods of high volatility for all indices under consideration, they are all likely to be caused by events such as financial turmoil and not by the introduction of derivatives trading. We therefore cast doubt on the various different conclusions drawn from empirical evidence in the available literature.

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Tabel I: Estimates and related statistics for GARCH model with multiplicative dummy variable

	CAC 40		DAX 30		NIKKEI 225		FTSE 100		S&P 500	
Parameters	Estimate	S. E.	Estimate	S. E.	Estimate	S. E.	Estimate	S. E.	Estimate	S. E.
a_0	0.0843***	0.0135	0.0444***	0.0166	0.0608***	0.0114	0.0598***	0.0136	0.0265	0.0183
a_1	0.1044***	0.0181	0.0055	0.0186	0.1158***	0.0174	0.0589***	0.0193	0.1074***	0.0203
a_2	0.3428***	0.0187	0.4076***	0.0223	0.2268***	0.0126	0.2425***	0.0168	-	-
b_0	0.0165***	0.0047	0.0310***	0.0080	0.0241***	0.0048	0.0364***	0.0099	0.0097***	0.0037
b_1	0.1338***	0.0221	0.1038***	0.0183	0.1657***	0.0223	0.0790***	0.0122	0.0486***	0.0087
b_2	0.8418***	0.0248	0.8707***	0.0215	0.7457***	0.0344	0.8660***	0.0245	0.9347***	0.0128
q	0.1463***	0.0167	0.1357***	0.0115	0.1545***	0.0198	0.0399***	0.0113	0.1185***	0.0174
c_0	0.0209**	0.0093	-0.0232***	0.0085	0.0754***	0.0199	0.0019	0.0071	0.0031	0.0041
$[b_1(1-2q)+b_2]$	[0.9365]		[0.9463]		[0.8602]		[0.9387]		[0.9718]	
Log-likelihood	-3583.0280		-3865.1343		-3193.2146		-3417.0838		-3432.6854	
Residual analysis	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
LB_1^2	0.074	0.785	0.017	0.896	0.084	0.772	0.000	0.995	1.499	0.221
LB_2^2	8.494**	0.014	0.088	0.957	0.089	0.957	2.281	0.320	1.643	0.440
LB_3^2	9.585**	0.022	0.171	0.982	0.118	0.989	2.909	0.406	2.717	0.437
LB_5^2	11.216**	0.047	0.363	0.996	0.162	0.999	3.912	0.562	7.021	0.219
LB_{10}^2	12.269	0.267	1.197	0.999	1.284	0.999	7.642	0.664	8.200	0.609

Notes: The table reports estimates for the parameters and standard errors are from the following GARCH model. The conditional distribution of the return R_t is a mean-shifted t-distribution with ν degrees of freedom, mean μ_t and variance h_t:

$$R_t \mid \phi_{t-1} \sim t_{\nu,\mu_t,h_t},$$

where ϕ_{t-1} defines the information set at date $t-1$. The estimated mean equation including R_{t-1} and the lagged S&P 500 return R_{t-1}^{SP} as a control variable is

$$\mu_t = a_0 + a_1 R_{t-1} + a_2 R_{t-1}^{SP}.$$

When we model the return of the S&P 500, the mean equation includes one lagged return only. A parsimonious GARCH(1,1)-structure with ν parameterized by $q = 1/\nu$, so that $(1-2q) = (\nu-2)/\nu$, specifies the conditional variance:

$$h_t = (1 + c_0 D_t)(b_0 + b_1(1-2q)\varepsilon_{t-1}^2 + b_2 h_{t-1}),$$

where $\varepsilon_{t-1} = R_{t-1} - E[R_{t-1} \mid \phi_{t-2}] = R_{t-1} - \mu_{t-1}$ and the multiplicative dummy variable D_t takes the value of 1 after the introduction of index futures trading and 0 otherwise. Maximization of the log-likelihood function was performed by the "MAXIMIZE"-routine within the software package RATS 7.1 using the BFGS-algorithm, heteroscedasticity-consistent estimates of standard errors and suitably chosen starting values for all parameters involved.

LB_i^2 denotes the Ljung-Box Q-statistics for serial correlation of the squared standardized residuals up to i lags. *, **, *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Tabel II: Estimates and related statistics for Markov-switching-GARCH model

	CAC 40		DAX 30		NIKKEI 225		FTSE 100		S&P 500	
Parameters	Estimate	S. E.	Estimate	S. E.	Estimate	S. E.	Estimate	S. E.	Estimate	S. E.
Regime 1										
a_{01}	0.0576	0.0362	-0.0535	0.0956	-0.0785	0.1616	0.0716	0.0527	-0.0864	0.0728
a_{11}	0.0494**	0.0198	-0.0119	0.1578	0.1583**	0.0630	0.0568	0.0572	0.0885	0.0826
a_{21}	0.3820***	0.0237	0.2523*	0.1522	0.2900*	0.1729	0.4996***	0.0307	-	-
b_{01}	0.0732	0.0568	0.0215	0.0540	0.2925	0.2175	0.0256*	0.0145	0.0685	0.0452
b_{11}	0.1153***	0.0251	0.2446	0.4739	0.1363	0.0848	0.1576***	0.0140	0.3955	0.3718
b_{21}	0.8400***	0.0605	0.7452**	0.3274	0.8158***	0.1613	0.8036***	0.0086	0.5452**	0.2422
q_1	0.0876***	0.0161	0.2841**	0.1296	0.1863***	0.0491	0.1259***	0.0285	0.2722***	0.0316
$[b_{11}(1-2q_1)+b_{21}]$	[0.9351]		[0.8508]		[0.9013]		[0.9215]		[0.7254]	
Regime 2										
a_{02}	0.0934***	0.0274	0.0808***	0.0278	0.0669***	0.0160	0.0607***	0.0142	0.0325*	0.0182
a_{12}	0.2248***	0.0457	0.0085	0.0657	0.1036***	0.0293	0.0666***	0.0193	0.1072***	0.0228
a_{22}	0.3227***	0.0260	0.4727***	0.1592	0.2200***	0.0198	0.1922***	0.0166	-	-
b_{02}	0.1121**	0.0510	0.0211	0.0201	0.0900*	0.0498	0.0476***	0.0006	0.0014	0.0063
b_{12}	0.2168	0.1440	0.0708	0.0570	0.1877	0.1172	0.0653***	0.0071	0.0193	0.0133
b_{22}	0.2530	0.1940	0.9123***	0.0978	0.4119***	0.1940	0.8515***	0.0107	0.9836***	0.0327
q_2	0.1937**	0.0777	0.0029***	0.0001	0.1113	0.0859	0.0029***	0.0003	0.0937***	0.0308
$[b_{12}(1-2q_2)+b_{22}]$	[0.3858]		[0.9827]		[0.55783]		[0.9165]		[0.9993]	
Transition probabilities										
π_1	0.9939***	0.0029	0.9672***	0.0222	0.9606***	0.0289	0.9657***	0.0018	0.9524***	0.0187
π_2	0.9971***	0.0038	0.9838***	0.0058	0.9983***	0.0071	0.9922***	0.0006	0.9950***	0.0095
Log-likelihood	-3554.2805		-3839.2966		-3185.4506		-3409.1503		-3423.8581	
Residual analysis	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
LB_1^2	0.029	0.864	0.011	0.916	0.036	0.849	0.427	0.513	0.855	0.355
LB_2^2	11.664***	0.003	0.038	0.981	0.037	0.981	1.842	0.398	0.948	0.623
LB_3^2	12.719***	0.005	0.091	0.993	0.059	0.996	2.085	0.555	1.311	0.727
LB_5^2	13.110**	0.022	0.242	0.999	0.116	0.999	3.980	0.552	3.412	0.637
LB_{10}^2	13.646	0.190	0.824	1.000	0.997	1.000	6.508	0.771	6.355	0.785

Notes: The table reports estimates for the parameters and standard errors from Eqs. (1) to (6). LB_i^2 denotes the Ljung-Box Q-statistics for serial correlation of the squared standardized residuals up to i lags. *, **, *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Figure 1: Daily returns, regime-1 probabilities and conditional variance (CAC40)

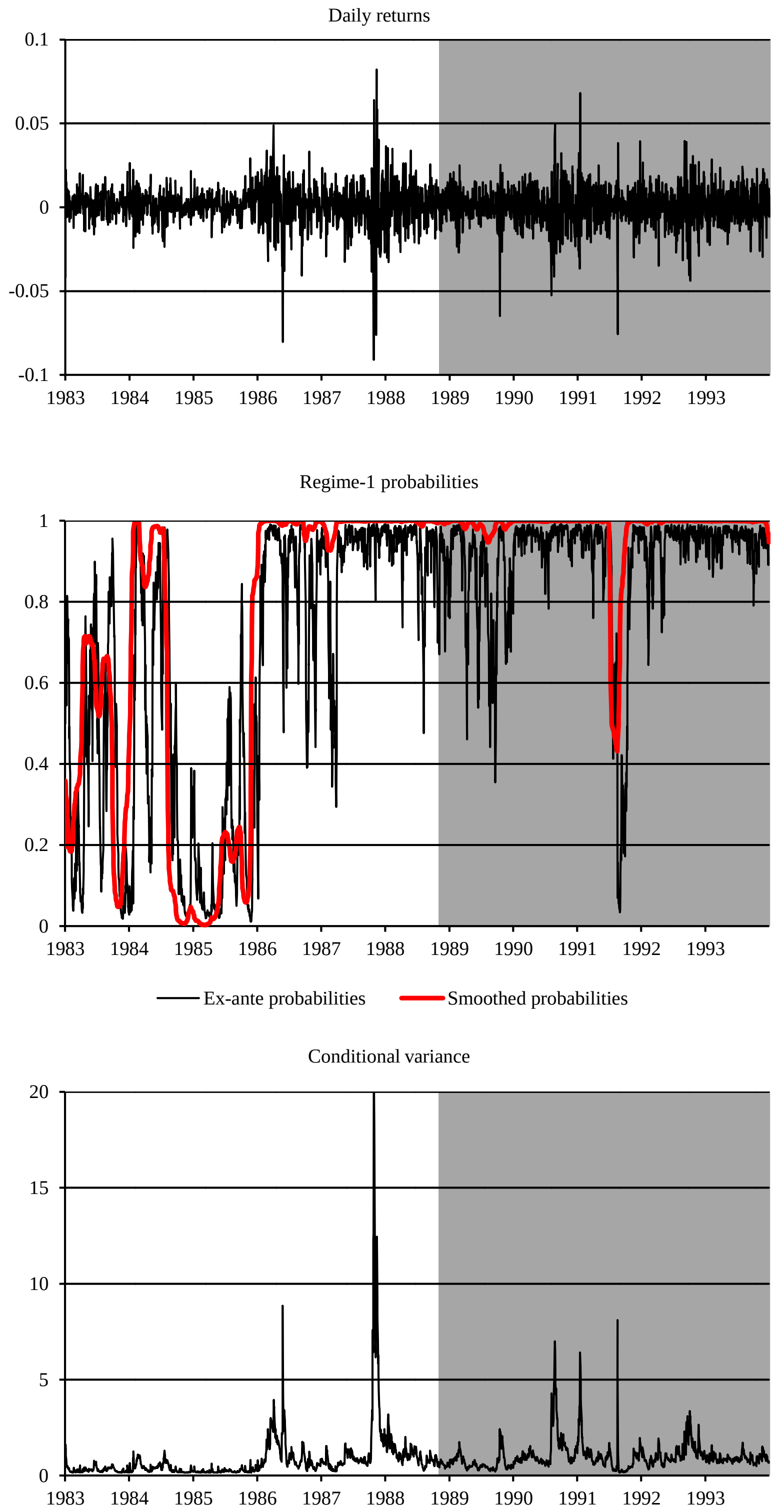

Figure 2: Daily returns, regime-1 probabilities and conditional variance (DAX30)

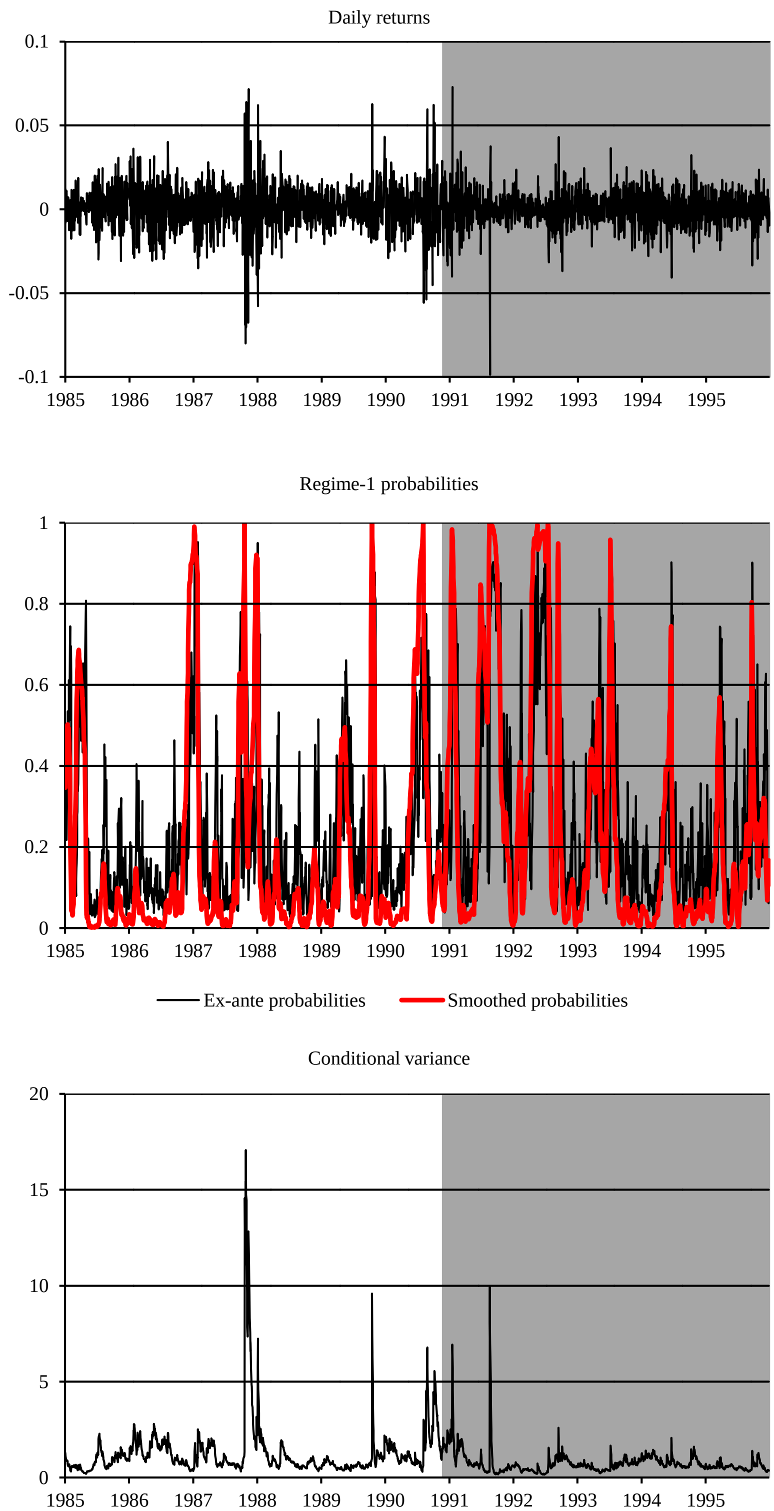

Figure 3: Daily returns, regime-1 probabilities and conditional variance (NIKKEI225)

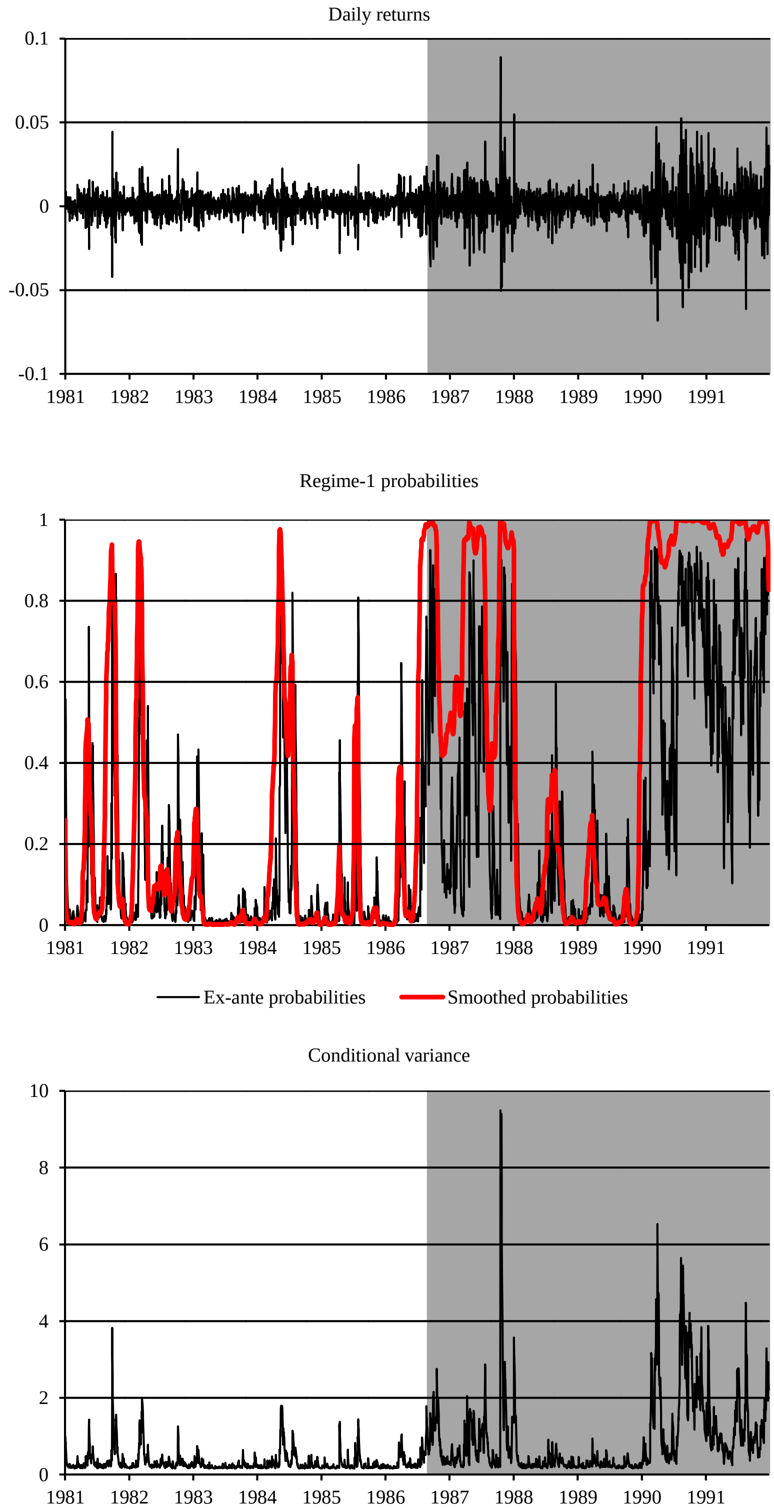

Figure 4: Daily returns, regime-1 probabilities and conditional variance (FTSE100)

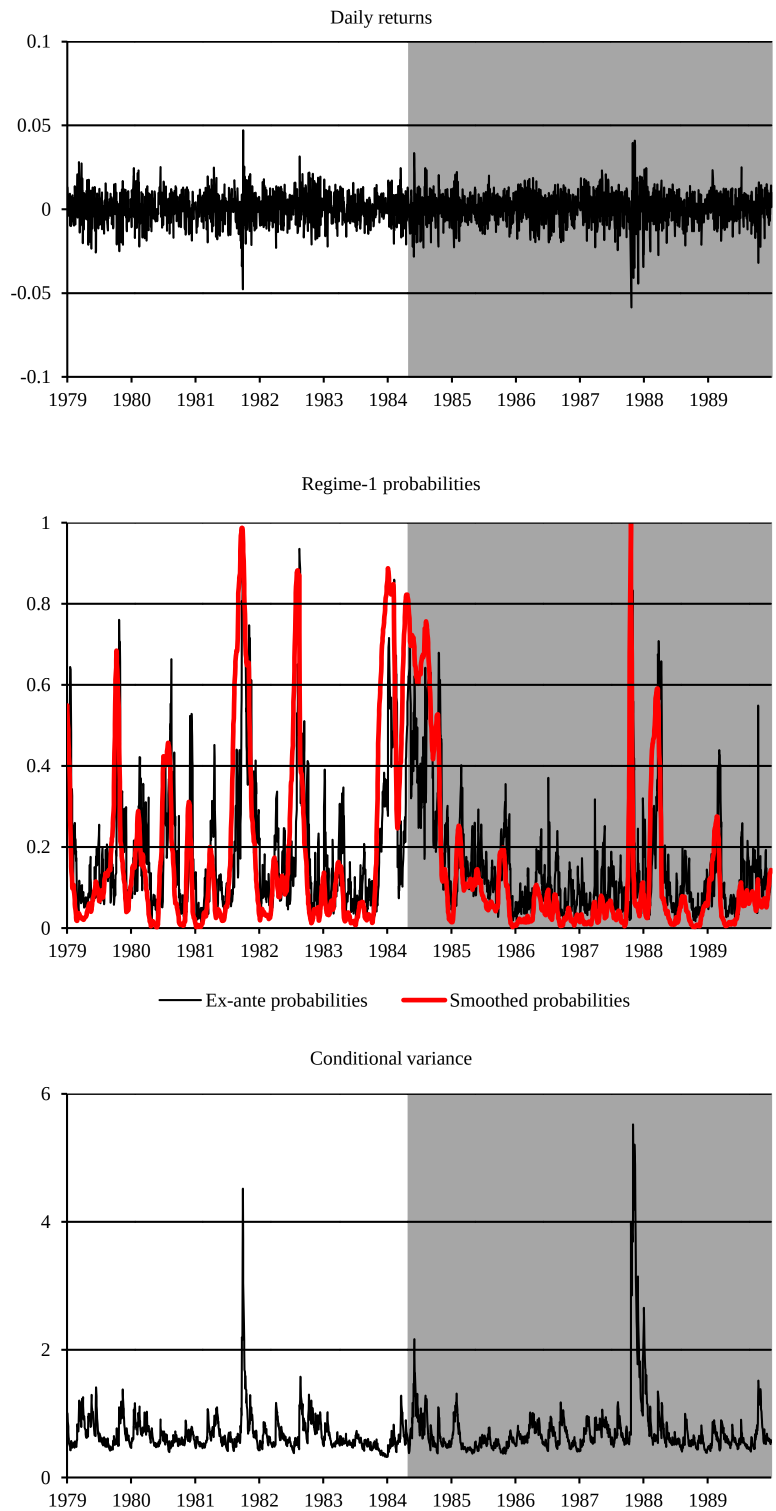

Figure 5: Daily returns, regime-1 probabilities and conditional variance (S&P500)