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ABSTRACT

This paper examines nonlinearities in the dynamics of volatility expectations using benchmarks of implied volatility for the US and Japanese markets. The evidence from Markov regime-switching models suggests that volatility expectations are likely to be governed by regimes featuring a long memory process and significant leverage effects. Market volatility is expected to increase in bear periods and decrease in bull periods. Leverage effects constitute thus an important source of nonlinearities in volatility expectations. There is no evidence of long swings associated with financial crises, which do not have the potential of shifting volatility expectations from one regime to another for long protracted periods.

JEL Classification: C32, C51, G13, G15

Keywords: Markov Regime Switching, Implied Volatility Index, Nonlinear Modelling.

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1. INTRODUCTION

The behavior of asset prices and their reaction to economic information was the impetus behind the development of a rich literature on market efficiency. But, changes in speculative prices do not only provide evidence on the validity of equilibrium models of asset pricing and have implications for investment management and risk hedging. Market volatility has also strong bearing for financial regulation, monetary policymaking and international market integration as well, given the growing evidence of volatility spillovers across markets and countries, particularly during financial crises. Forecasting market volatility is however a difficult exercise in quantifying uncertainty, which further gains in complexity when perceptions of periodic economic reports and theoretical relationships by market participants are not consistent over time.

Arguably, anticipations of market volatility may shed light on how new information interacts with investors' beliefs to produce changes in asset prices. As such, *ex ante* measures of volatility can be reflective of investors' perception of market risk. Traditionally, the time-series of historical returns allows for the modelling of market volatility in order to capture important features such as shock persistence, volatility clustering and leverage effects reflected by the asymmetric impact of news. The present study focuses rather on *ex ante* measures of short-term market volatility implied by stock index option prices. The empirical analysis is aimed at providing evidence on mean reversion and regime shifts in implied volatility dynamics, and thus investors' anticipations of price fluctuations.

The importance of these empirical issues is evident for instance, in the explicit reference to the implied functions from options markets in the Bank of England's monetary policy meetings. This growing interest from policymakers is consistent with evidence from many recent studies such as Carr and Wu (2006), who suggest that the S&P 500 new implied volatility index is reflective of the increasing uncertainty that precedes monetary policy decisions about the Fed Fund Target rate. Similar evidence is obtained from alternative markets including the results by Neely (2005) which indicate that changes in implied volatility from Eurodollar interest rates coincide with major events related to monetary policy decisions, real economy and equity markets. Also, Fornari (2004) suggests that implied volatility from swaptions markets is reflective of market participants' reaction to macroeconomic announcements about the release of US economic indicators.

This close connection between monetary policy decisions and changes in implied volatility adds to the early evidence on the informational content of implied volatility, which is rather mixed. Indeed, the empirical studies by Day and Lewis (1992) based on S&P 100 index options, and by Lamoureux and Lastrapes (1993) based on individual stock options, suggest that implied volatility is a biased and inefficient estimate of market volatility. Canina and Figlewski (1993) provide also evidence of insignificant correlation between S&P 100 implied volatility and future market volatility. However, other empirical results are more supportive of the informational content of implied volatility. For instance, Harvey and Whaley (1992) suggest that implied volatility provides an efficient forecast of future volatility. The empirical evidence from Fleming (1998) also suggests that despite the upward bias, the forecast errors associated with S&P 100 implied volatility are orthogonal to parameters included in ARCH models. Moreover, Christensen and Prabhala (1998) find that the forecasting performance of implied volatility is higher than historical volatility. Furthermore, Blair, Poon and Taylor (2001) find that the S&P 100 implied volatility index is more accurate for out-of-sample forecasting than realized volatility, irrespective of data frequency and the forecasting horizon. The empirical tests by Becker, Clemens and White (2006) suggest that the S&P 500 implied volatility index is efficient with respect to some but not all the information set available for forecasting purposes. More recently, there is evidence from Nishina, Maghrebi and Kim (2006) of higher out-of sample forecasting power for the S&P 500 and Nikkei 225 implied volatility indices.[1]

The informational content of implied volatility has been traditionally examined using conventional regression analysis and GARCH modelling. The present study examines the nonlinear dynamics of the relationship between implied volatility and realized volatility using Markov regime-switching models introduced by Hamilton (1989). The economic motivation for modelling the dynamics of implied volatility with regime-switching processes lies in the changing likelihood for market volatility to fluctuate between regimes of higher versus lower volatility and/or slower against faster mean reversion. Much like the return-generating process, the dynamics of anticipated volatility can be also governed by different regimes characteristic of periods of bearish or bullish markets and associated with the troughs and peaks of economic cycles.

In contrast, the literature on implied volatility provides little empirical evidence based on regime-switching dynamics. This study constitutes, to the best knowledge of the authors, the first attempt to test for the existence of Markov regime switches in anticipations of stock market volatility.[2] The regime switching approach is rather widely applied to account for structural breaks in a range of financial variables including interest rates, equity

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1 There is evidence from Jorion (1995) for instance that implied volatility provides efficient estimates of future volatility in currency markets as well.

2 Guo and Wohar (2006) identify regime changes in stock market volatility implied by S&P 100 and S&P 500 options prices using Bai and Perron (1998) method to determine structural breaks in the mean level of market volatility. Their approach differs however from Markov regime-switching modelling proposed by Hamilton (1989), which is applied in the present paper. Furthermore, this model allows for regime-dependent speed of adjustment and tests for leverage effects and the impact of past realized volatility.

and foreign exchange markets. Using a bivariate regime-switching model, Hamilton and Lin (1996) find evidence of higher stock market volatility during periods of economic recession. Also, Engel and Hakkio (1996) provide evidence based on regime-switching models that periods of high volatility in the bilateral exchange rates in the European Monetary System are associated with speculative attacks and subsequent realignment. Dahlquist and Gray (2000) investigate also the effect of currency target zones in the EMS on mean reversion and speed of adjustment of short-term interest rates.

The numerical derivation of volatility implied by option prices faces however impediments stemming from measurement errors, as well as theoretical difficulties associated with the option pricing model. There is indeed evidence of volatility smiles and smirks, where different estimates of Black-Scholes implied volatility are derived for options with different exercise prices and same maturity. This empirical evidence is inconsistent with the assumption of constant volatility underlying the option pricing theory by Black-Scholes (1973).[3] These difficulties were conducive to the development of a rich literature of model-free approaches to the estimation of implied volatility. These include inter alia, the methodology suggested by Ait-Sahalia and Lo (1998) based on polynomials and splines smoothing, and by Britten-Jones and Neuberger (2000) based on the adjustment of the volatility process to option prices in the same way that interest rates are fitted to bond prices.

[3] The need to reconcile theoretical assumptions with empirical observations was partly the impetus behind the development of alternative option valuation models including Hull and White (1987) and Heston (1993), where the volatility parameter is substituted by the entire joint probability distribution of returns and volatility changes. More recent studies by Duan, Gauthier and Simonato (1999) and Ritchken and Trevor (1999) examine option pricing under GARCH processes.

Thus, in order to reduce measurement errors and avoid problems of numerical convergence, this study uses two indices of implied volatility, namely the new VIX index on the S&P 500 benchmark disseminated by the Chicago Board of Options Exchange and a new index similarly computed from Nikkei 225 stock average options traded on Osaka Securities Exchange. The model-free approach used in estimating these implied volatility indices takes into account the term structure of implied volatility and possible nonlinearities such as the volatility smiles. It aggregates information across different options maturities and exercise prices and expectations about future volatility across market participants including hedgers, arbitrageurs and speculators.

This study differs from previous studies on several accounts. It provides new evidence on regime shifts in expectations of stock market volatility implied by options prices. It allows for the identification of regimes characterized by expectations of lower volatility and bursts of turbulence, the speed of mean reversion and the length of the memory process. Furthermore, it tests for the existence of leverage effects in options markets in the sense that good and bad news from the stock market exert asymmetric effects on expectations of short-term volatility. It also addresses the important question of whether the regimes of expected volatility are reflective of a feedback process through which anticipations of future market volatility adapt to changes in realized volatility. Thus, new evidence from regime switching models is provided on the relationship between implied volatility and realized volatility, which is examined using conventional regression analysis.

Furthermore, it provides empirical results from an international perspective as it uses implied volatility indices for the US and Japanese stock markets. In the absence of implied volatility benchmark readily available for the Japanese equity market, this study uses the Nikkei 225 implied volatility index reported in Nishina, Maghrebi and Kim (2006). The construction of an implied volatility index for the Japanese equity market is important since the Nikkei 225 index constitutes the underlying asset of financial derivatives traded on two other major Asia Pacific derivatives markets, namely the Chicago Mercantile Exchange, and Singapore Exchange Derivatives Trading Division. The regime-switching models are estimated over a sample period that covers important events such as the Asian financial crisis, the Russian debt crisis, the Long Term Credit Management crisis, the burst of the information technology bubble, and the Japanese economic recession, among others.

The remainder of the paper is structured as follows. The next section describes the Markov regime-switching models used to examine the nonlinearities in implied volatility dynamics. Section 3 presents the sample data and distributional properties of implied volatility indices. Section 4 discusses the empirical results for the Japanese and US markets. The regime-switching models include various conditioning variables and are estimated using both the levels and first differences in implied volatility. Section 5 concludes the paper.

2. REGIME-SWITCHING MODELLING OF IMPLIED VOLATILITY

In the absence of perfect knowledge of when structural breaks in implied volatility can take place, regime shifts are incorporated in the volatility-generating process following the Markov regime-switching model by Hamilton (1989). The two-regime Markov process used in the present study accounts for latent states of the relationship between implied volatility and the set of past information. The sign and significance of model parameters which describe the dynamics of implied volatility are driven by discrete switches in the indicator variable. This unobservable variable takes the value of $z_t = i$, for $i = 1, 2$, and determines which regime governs the volatility dynamics at time t. With each observation being drawn from a distribution conditional on the prevailing regime, the model parameters are likely to differ in sign and/or magnitude across regimes. These regime-dependent parameters allow for the characterization of each state with various features such as higher or lower volatility, slower or faster reversion to the long-run mean, strong or insignificant leverage effects.

The regime-switching models described below the behavior of implied volatility function of past returns and other conditioning variables. The following model (1) tests for regimes of volatility expectations depending on the long-run mean and leverage effects

$$v_t = w_i + \beta_i r_{t-1} + \zeta_t \qquad (1)$$

where the error terms are distributed as $\zeta_t \sim i.i.d.\ N(0, \sigma_\zeta^2)$. This model defines regimes in terms of higher and lower implied volatility judging from the magnitude of drifts and the sign and significance of slope coefficients. A negative coefficient suggests that the implied volatility index tends to increase during bearish markets relationship, providing a measure following Whaley (2000) of investors' fear and anxiety. It is also possible to test for mean reversion in expectations of future volatility by accounting for information contained in past observations of implied volatility.

$$v_t = w_i + \delta_i v_{t-1} + \beta_i r_{t-1} + \zeta_t \qquad (2)$$

According to model equation (2), the dynamics of implied volatility can be driven by past levels of implied volatility as well as past returns. An extension of model (1) to include the squared returns provides a more appropriate test for asymmetric effects of news on implied volatility as model (3) accounts for both the sign and magnitude of shocks to the return-generating process.

$$v_t = w_i + \beta_i r_{t-1} + \gamma_i r_{t-1}^2 + \zeta_t \qquad (3)$$

It is also possible to integrate models (2) Model (3) to allow for long-run mean reversion in implied volatility as well as leverage effects. Model (4) allows for the presence of nonlinearities in the relationship between expected volatility and market returns across regimes and examines the issue of whether the presence of leverage effects affects the significance of mean reversion and/or the length of the memory process.

$$v_t = w_i + \delta_i v_{t-1} + \beta_i r_{t-1} + \gamma_i r_{t-1}^2 + \zeta_t \tag{4}$$

The model parameters are assumed to evolve according to a first-order Markov process, which is not path-dependent in the sense that the current regime z_t depends only on regime z_{t-1} prevailing over the preceding period. This process is governed by the following transition probability conditional on past information.

$$\text{Prob}(z_t = 1 \mid z_{t-1} = 1) = p_{11} \tag{5-1}$$

$$\text{Prob}(z_t = 2 \mid z_{t-1} = 1) = p_{12} \tag{5-2}$$

$$\text{Prob}(z_t = 1 \mid z_{t-1} = 2) = p_{21} \tag{5-3}$$

$$\text{Prob}(z_t = 2 \mid z_{t-1} = 2) = p_{22} \tag{5-4}$$

The typical transition probability is denoted by $p_{ij} = \text{Prob}(z_t = j \mid z_{t-1} = i)$ with $\sum p_{ij} = 1$. The probability p_{ii} in the transition matrix denotes the likelihood that implied volatility remains in regime $z = i$ given that the same regime prevailed at time $t-1$. The probability of a switch from regime $z = i$ at time $t-1$ to regime $z = j$ at time t is $p_{ij} = 1 - p_{ii}$. The Markov model allows for multiple switches between regimes and the dynamics of these shifts depend on the conditional transition probabilities, with the average duration of a given regime i expressed as $(1 - p_{ii})^{-1}$. The stochastic process z_t can be shown to follow an autoregressive process

$$z_t = (1 - p_{11}) + \pi \, z_{t-1} + \varsigma_t \tag{6}$$

where $\pi = p_{11} + p_{22} - 1$ and ς_t denotes innovation terms which are assumed to be uncorrelated with lagged values of the state variable z. In the model specifications (1) to (4), implied volatility is defined as a function of the history of stock market returns and realized volatility. It is not assumed that the explanatory variables follow Markov regime-switching processes. Under the assumption that the error terms ζ_t in implied volatility models are normally distributed conditional upon the history $\Im_{t-1}$, the cumulative density function depends on the regime indicator z. Given the above specifications of implied volatility, the density function depends on the conditioning variables of past returns and realized volatility as well. This conditional density of implied volatility can be obtained from the joint density of implied volatility and state variable as follows.

$$f\left(v_t \mid z_t ; \Im_{t-1}, \vartheta\right) = \sum f\left(v_t \mid z_t = i ; \Im_{t-1}, \vartheta\right) \cdot \mathrm{Prob}\left(z_t = i \mid \Im_{t-1}, \vartheta\right) \tag{7}$$

where ϑ represents the vector of model parameters. The unknown parameters in the implied volatility models are estimated using maximum likelihood. Hamilton (1990) shows that the maximum likelihood estimates of the transition probabilities can be expressed as

$$\hat{p}_{ij} = \frac{\sum_{t=2} \mathrm{Prob}\left(z_t = j, z_{t-1} = i \mid \Im_T ; \hat{\vartheta}\right)}{\sum_{t=2} \mathrm{Prob}\left(z_{t-1} = i \mid \Im_T ; \hat{\vartheta}\right)} \tag{8}$$

where $\hat{\vartheta}$ denotes the maximum likelihood estimates of model parameters. This estimation procedure is applied to each model specification for the levels and first differences in implied volatility in the Japanese and US stock markets.

3. INDEX DESCRIPTION AND DISTRIBUTIONAL PROPERTIES

The empirical evidence on the dynamics of implied volatility is based on regime-switching tests using the new implied volatility index disseminated by the CBOE and a similar index for Nikkei 225 index options traded on Osaka Securities Exchange. Whereas the new VIX index is available from CBOE database, this study uses the Nikkei implied volatility index introduced in Nishina, Maghrebi and Kim (2006) to measure volatility expectations in the Japanese market. The new VIX index gathers consensus information on options market’s expectations about future stock market volatility, without relying on any theoretical model of option pricing. The methodology provides an approximate measure of stock market volatility from a hypothetical option with exercise price equal to the futures price and with thirty days remaining to maturity. As such, the new VIX index provides an estimation of a thirty-day return variance swap rate from a portfolio of options spanning the nearest two maturities. The contribution of each option to the implied volatility index is an increasing (decreasing) function of the exercise price for put (call) options.[4]

The empirical analysis is based on the daily time-series of the implied volatility indices for a sample period extending from January 1990 to December 2004, and spanning 180 options maturities. Figure 1 describes the behavior of spot prices and implied volatility indices for the U.S. and Japanese markets. There is a tendency for the S&P 500 index to increase monotonously until the burst of the information technology bubble. This pattern contrasts with the tendency for Nikkei 225 index to decrease from its height in early 1990, reflecting the persistent recession of the Japanese economy during the 1990s. Although there appears a tendency for implied volatility across markets to converge in more recent years, the Nikkei 225 implied volatility seems to remain typically higher than expectations of US market volatility.

There are instances of sharp increases in implied volatility in both markets. The occasional spikes in implied volatility tend to be associated with sharp decreases in stock market prices. These events are seemingly associated with significant economic events such

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[4] The model-free methodology for the calculation of S&P 500 implied volatility index is thoroughly explained in CBOE documentation. It follows the original VIX index based on S&P100 American options calculated using Black-Scholes pricing model. The rationale underlying the calculation of these indices and their major differences are discussed in Carr and Wu (2006).

as the onset of the Asian financial crisis in 1997, Russian debt default and LTCM crisis in 1998. The increase in implied volatility associated with the burst of the IT bubble in 2000 is less pronounced than that related to the Latin American debt crisis in 2002. These implied volatility patterns may be indicative of a negative relationship between market volatility and returns, which can be formally examined with Markov regime-switching modelling.

The distributional properties of stock returns and implied volatility are described by Table 1. There is evidence that the Japanese market tends to be associated with lower mean returns and higher volatility. The average implied volatility, as well as first differences, is found to be higher than comparable statistics in the US market. Based on unit-root tests following Augmented Dickey-Fuller and Phillipps-Perron tests, the time-series of stock market returns and volatility are also found to be stationary in both markets.

4. Empirical Evidence

4.1. Regime SWITCHING and THE LEVEL OF Implied Volatility

The estimation results of the various first-order Markov regime-switching models with respect to implied volatility levels are reported in Table 2 and 3 for the US and Japanese markets, respectively. Model 1 allows for regime-dependency in the relationship between expected volatility levels and stock market returns. There is evidence that the slope coefficients in both regimes are negative for the US market, but insignificant for the Japanese market. Evidence of negative slope suggests that market volatility is expected to increase in bear periods and decrease in bull periods. Given the acceptance of the null of equal slopes for both markets, it is the magnitude of drifts which defines regimes of high and low expected levels of volatility.

Model 2 expresses the relationship between past returns and volatility upon the inclusion of autoregressive terms. There is a significant increase in the log-likelihood function compared to the previous Model 1 for both markets. For the US market, two regimes of implied volatility are identified, one with longer memory and negative correlation with stock market returns (regime 1) and another with shorter memory and positive correlation with returns (regime 2). Again, there is no evidence of a negative relationship between implied volatility and stock market returns for the Japanese market. The regime of low expected volatility is characterized by shorter memory and positive correlation with returns.

Testing for the asymmetric impact of news on market volatility should take into account both the sign and magnitude of returns. Thus, Model 3 describes the level of implied volatility as a function of past return levels as well as squared innovations, while excluding autoregressive terms. There is evidence of significant leverage effects since both the sign and magnitude of returns are likely to affect volatility expectations. However, the negative relationship with returns is not found to be regime-dependent in both markets since the null of equal β parameters across regimes cannot be rejected. Given the positive γ coefficients, shocks to the return-generating process, are irrespective of their sign, conducive to expectations of higher volatility. Thus, the evidence of leverage effects is found to be regime-dependent in both markets.

The estimation of Model 4, which is comparable to Model 3 but inclusive of autoregressive terms, reveals the existence of two regimes featuring equal intercepts and positive serial correlation for the US market. The two regimes differ only with respect to the relationship of volatility expectations with market returns. The presence of leverage effects is manifested by the significance of both β and γ parameters, with the level of expected volatility in regime 1 being less responsive to variations in market returns. In contrast, the estimation results for the Japanese market suggest that drift terms and autoregressive parameters are regime-dependent. Regime 1 is identified with expectations of low volatility, long memory and significant leverage effects while regime 2 is associated with expectations of high volatility, and significant mean reversion in the absence of leverage effects.

The inferred probabilities of regime 1 from Model 4 are reported in Figures 2 and 3 for the US and Japanese markets, respectively. These figures suggest that in the absence of long swings, the process of volatility expectations tends to switch randomly and abruptly between regimes. It is clear from Figure 2 that there is a stronger likelihood for volatility expectations to be governed by regime 1, which features positive serial correlation and relatively less significant leverage effects. There are more frequent regime shifts in S&P 500 implied volatility index, particularly over the period associated with the onset of the Russian debt default and LTCM crises in 1998 until the Latin American debt crisis in 2002. The higher frequency of regime switches may be reflective of the increased uncertainty generated by financial crises. Such events have the potential of increasing the likelihood of the alternative regime, typically characterized by stronger leverage effects.

With respect to the Japanese market, it appears from Figure 3 that regime 1 tends to prevail over the sample period, except for very short-lived switches to the alternative regime. The predominant regime is characterized by expectations of low volatility levels, longer memory, and significant leverage effects. Significant events such as the Asian financial crisis seem to trigger shifts towards the volatility regime featuring expectations of higher volatility, and significant mean reversion. Judging from the inferred probabilities reported for both markets, it seems that financial crises are not associated with long swings in the sense that they do not have the potential of shifting volatility expectations from one regime to another for long protracted periods.

4.2. REGIME SHIFTS AND CHANGES IN VOLATILITY EXPECTATIONS

The dynamics of volatility expectations are also estimated with respect to first differences in implied volatility. While retaining the features of previous regime-switching models in terms of mean reversion and asymmetric impact of returns (leverage effects with respect to changes in expected volatility), it is also possible to test for nonlinearities in the relationship between changes in implied volatility and the dynamics of realized volatility.

$$\Delta v_t = w_i + \delta_i \Delta v_{t-1} + \beta_i r_{t-1} + \gamma_i r_{t-1}^2 + \varphi_i \Delta \sigma_{r,t-1} + \zeta_t \tag{9}$$

Given the definition of the new implied volatility index as the approximation of volatility implicit in a hypothetical option with thirty days remaining to maturity, realized volatility is defined at time t as the ex post annualized measure of standard deviation of returns until option expiration, from $t+1$ to $t+30$. The sign and significance of parameters φ in Model (9) across regimes can provide evidence on the adjustment process that governs the formation of expectations about market volatility. It allows for the examination of the important issue of whether implied volatility rises following a marginal increase in realized volatility.

Tables 4 and 5 report the estimation results for Models (1) to (5) with respect to changes in implied volatility for the US and Japanese markets, respectively. Judging from the LR test, the dynamics of expected volatility are better described according to Model 5 based on all conditioning variables, including past changes in realized volatility. The degree of mean reversion does not differ across regimes in the US market. In the Japanese market instead, it is the sensitivity to the magnitude, as opposed to the sign, of shocks in the return-generating process that is hardly different across regimes.

There is at least, one regime of expectations for decreasing volatility in both markets (regime 2). Anticipations of decreasing volatility are characterized by the asymmetric impact of news and positive relationship with changes in realized volatility. This evidence suggests that marginal decreases in realized volatility are conducive to expectations of lower volatility. With respect to the Japanese market, this regime is also associated with slower mean reversion. The alternative regime featuring anticipations of increasing volatility is characterized by faster mean reversion, symmetric impact of news and negative relationship with past changes in realized volatility.

Judging from the inferred probabilities exhibited by Figure 4 for the US market, regime 1 prevails with insignificant drift, significant mean reversion, weaker asymmetric impact of news and weaker adjustment to the dynamics of realized volatility. Similar to patterns revealed by Figure 2, the frequency of regime shifts seems to increase since the mid 1990s, in response to more turbulent periods including the Russian debt default and LTCM debt crises. The onset of financial crises increases the likelihood of the alternative regime of expectations for significant decreases in market volatility, with slower mean reversion, stronger asymmetric reaction to news, and significant positive adjustment to the dynamics of realized volatility.

As illustrated by Figure 5, the inferred probabilities for the Japanese market suggest also that regime 2 is more likely to prevail with expectations of decreasing volatility, slower mean reversion, asymmetric impact of news and significant positive adjustment to changes in realized volatility. Compared to the US market results, there are less frequent switches toward the alternative regime featuring expectations of increasing volatility, with stronger mean reversion, significant though not asymmetric impact of news, and inverse adjustment to changes in realized volatility. These regime changes are seemingly associated with significant events such as the Asian financial crisis and the burst of the Japanese bubble, which heralded a decade-long period of mounting bad debts, deflationary pressures, and economic recession. Arguably, the results suggest that the worsening economic prospects may have been conducive, particularly in the early 1990s, to expectations of increasing volatility even in the presence of positive returns and marginal decreases in market volatility.

5. CONCLUSION

This study examines nonlinearities in the dynamics of market volatility implied in options prices in the Japanese and US markets. The analysis tests for regime switches in volatility expectations using the CBOE new VIX index and a similarly computed index from Nikkei 225 options prices, not available in economic databases. The characterization of these regimes is based on a set of conditioning variables, which includes past returns and realized volatility. The first-order Markov regime-switching models test also for the asymmetric impact of news and the presence of an adjustment mechanism through which volatility expectations respond to the dynamics of realized volatility. The testing approach allows also for the examination of regime switches in volatility expectations in association with financial crises.

The empirical evidence with respect to implied volatility levels suggests that the regime governing volatility expectations in the US market features a long memory process, and relatively less significant leverage effects. The prevailing regime in the Japanese market is characterized by expectations of low volatility levels, longer memory and significant leverage effects. These results indicate that market volatility is expected to be higher in bear periods and lower in bull periods and that leverage effects constitute an important source of nonlinearities in expectations of market volatility. Given the evidence of positive serial correlation, the expected level of volatility in both markets is not likely to be so much whittled down by mean reversion as by leverage effects.

There is also evidence from the first differences in implied volatility that the prevailing regime for the rate of change in expected volatility in the US market is likely to be characterized by significant mean reversion, weaker asymmetric impact of news, and positive, albeit less significant, adjustment to changes in realized volatility. The dynamics of volatility expectations in the Japanese market are likely to be driven by a regime of anticipated decreases in volatility, with slower mean reversion, asymmetric relationship with returns and positive adjustment to changes in realized volatility.

The onset of financial crises does not have the effect of shifting the implied volatility process from one regime to another for long protracted periods. For the Japanese market however, major events such as the burst of the asset bubble and the Asian financial crises seem to trigger the regime characterized by expectations of significant increments in volatility, stronger mean reversion and negative correlation with changes in realized volatility. The immediate reversal to the pre-crisis regime, featuring expectations of decreasing volatility and strong mean reversion, suggests that the impact of financial crises on the dynamics of volatility expectations is short-lived. With respect to the US market, it increases the likelihood of regimes characterized by expectations of decreasing volatility, significant mean reversion, stronger asymmetric impact of news and more significant adjustment process.

Evidence of regime shifts in volatility expectations has some implications for risk-hedging, policymaking and future research in financial economics. It offers new avenues for research on such important issues as to whether market consensus expectations are consistent with rational expectations and whether financial crises may be induced by regimes consistent with self-fulfilling expectations and speculative bubbles. Empirical studies may also shed light on the relationship between the leverage effects and the speed of mean reversion or length of the memory process across regimes. Future research in behavioral finance can benefit from tests of the stochastic properties of investors' attitudes towards risk, regime-dependencies in investor confidence and irrational exuberance. From the risk-hedging perspective, regime shifts imply nonlinear serial dependence in volatility expectations. It is thus important to examine to what extent the quantification of risk exposure is affected, the estimation of dynamic hedge ratios is further complicated, and the composition of asset portfolios is altered.

Finally, the empirical results have important implications for policymaking market regulation. Given the evidence that the release of new information is usually following by rapid changes in asset prices and significant increases in trading activity, the regime-dependencies in market expectations can have some bearing on the scheduled announcement times of economic reports. It is thus interesting to examine the issue of the announcement of monetary policy shifts or changes in margin lending regulation are preceded or followed with regime switches in volatility expectations.

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TABLES

TABLE 1. Distributional moments and unit-root test results

	Mean	*Std.Dev.*	*Skewness*	*Kurtosis*	*JB*	*ADF*	*PP*
Stock Returns							
S&P 500	0.0310	0.0102	-0.1031	6.8986	2485.06	-62.665[c]	-62.877[c]
Nikkei 225	-0.0312	0.0148	0.1961	6.3530	1858.13	-46.979[c]	-63.862[c]
Implied Volatility							
S&P 500	0.1988	0.0635	0.9063	3.7215	620.70	-3.863[b]	-5.379[a]
Nikkei 225	0.2476	0.0647	0.6528	4.1171	481.53	-6.143[b]	-6.907[b]
Changes in Implied Volatility							
S&P 500	-0.0010	0.0122	0.5690	9.2627	6605.84	-22.530[c]	-73.542[c]
Nikkei 225	0.0026	0.0165	0.6450	39.4066	216373.60	-42.551[c]	-84.201[c]

Notes: The sample period extends from January 2, 1990 to December 31, 2004. JB refers to Jarque-Bera statistics for normality tests. ADF refers to Augmented Dickey-Fuller tests using Schwarz information criterion. PP refers to Phillips-Perron tests with Newey-West bandwidth using Bartlett kernel. The superscripts [a], [b] and [c] refer to unit root tests with trend and intercept, with intercept only, with neither trend nor intercept, respectively. The means of return series and volatility first differences are scaled by 10^2.

Table 2. Regime-switching modelling of implied volatility (S&P 500 index)

	Model 1	***Model 2***	***Model 3***	***Model 4***
	Model parameters			
w_1	0.2664[a]	-0.0129[a]	0.2581[a]	0.0033[a]
w_2	01612[a]	0.0093[a]	0.1561[a]	0.0035[a]
δ_1		1.1093[a]		0.9810[a]
δ_2		0.9393[a]		0.9796[a]
β_1	-0.5693[a]	-0.2328[a]	-0.6094[a]	-0.6226[a]
β_2	-0.3991[a]	0.0632[a]	-0.5627[a]	-1.4508[a]
γ_1			40.4928[a]	7.0033[a]
γ_2			90.7546[a]	9.9678[a]
φ_1				
φ_2				
	Hypothesis tests			
$w_1 = w_2$	6074.104[a]	122.558[a]	5423.406[a]	0.0377
$\delta_1 = \delta_2$		585.366[a]		0.0798
$\beta_1 = \beta_2$	1.588	45.094[a]	0.118	1184.4911[a]
$\gamma_1 = \gamma_2$			50.754[a]	12.8244[a]
$\varphi_1 = \varphi_2$				
$p_{11} = p_{22}$	2.022	50.034[a]	2.626	71.5032[a]
LL	7166.36	11997.22	7369.75	13491.68

Notes: Significance at the 1, 5 and 10 % level is denoted by [a], [b] and [c] respectively. The estimated Markov regime-switching models are represented by $v_t = w_i + \beta_i r_{t-1} + \zeta_t$ for Model 1, $v_t = w_i + \delta_i v_{t-1} + \beta_i r_{t-1} + \zeta_t$ for Model 2, $v_t = w_i + \beta_i r_{t-1} + \gamma_i r_{t-1}^2 + \zeta_t$ for Model 3, and $v_t = w_i + \delta_i v_{t-1} + \beta_i r_{t-1} + \gamma_i r_{t-1}^2 + \zeta_t$ for Model 4. The null hypothesis tests are distributed as $\chi^2(1)$. LL is the log maximum likelihood function.

Table 3. Regime-switching modelling of implied volatility (Nikkei 225 index)

	Model 1	***Model 2***	***Model 3***	***Model 4***
	Model parameters			
w_1	0.3106[a]	0.1522[a]	0.3030[a]	0.0048[a]
w_2	0.2080[a]	0.0088[a]	0.2057[a]	0.3494[a]
δ_1		0.7995[a]		0.9747[a]
δ_2		0.9611[a]		-0.0693[a]
β_1	-0.0339	0.5529[a]	-0.1489[a]	-0.3231[a]
β_2	0.0044	0.0072	-0.0991	0.8789[a]
γ_1			20.5833[a]	5.7630[a]
γ_2			11.6824[a]	-24.6102[a]
φ_1				
φ_2				
	Hypothesis tests			
$w_1 = w_2$	4590.3206[a]	1764.6474[a]	3844.3931[a]	10957.0160[a]
$\delta_1 = \delta_2$		225.7556[a]		9901.6532[a]
$\beta_1 = \beta_2$	0.1639	85.26211[a]	0.3771	430.3168[a]
$\gamma_1 = \gamma_2$			28.2025[a]	432.8464[a]
$\varphi_1 = \varphi_2$				
$p_{11} = p_{22}$	4.5052[b]	20.8045[a]	5.4429[b]	175.5199[a]
LL	6822.32	11007.45	6883.55	11386.28

Notes: Significance at the 1, 5 and 10 % level is denoted by [a], [b] and [c] respectively. The estimated Markov regime-switching models are represented by $v_t = w_i + \beta_i r_{t-1} + \zeta_t$ for Model 1, $v_t = w_i + \delta_i v_{t-1} + \beta_i r_{t-1} + \zeta_t$ for Model 2, $v_t = w_i + \beta_i r_{t-1} + \gamma_i r_{t-1}^2 + \zeta_t$ for Model 3, and $v_t = w_i + \delta_i v_{t-1} + \beta_i r_{t-1} + \gamma_i r_{t-1}^2 + \zeta_t$ for Model 4. The null hypothesis tests are distributed as $\chi^2(1)$. LL is the log maximum likelihood function.

Table 4. Regime-switching modelling for changes in implied volatility (S&P 500 index)

	Model 1	***Model 2***	***Model 3***	***Model 4***	***Model 5***
			Model Parameters		
w_1	-0.0793[a]	-0.0788[a]	-0.0080	-0.1138[a]	-0.0146
w_2	4.3311[a]	4.3243[a]	-0.1302[a]	-0.0133	-0.1106[a]
δ_1		-0.0437[a]		-0.0358[a]	-0.0723[a]
δ_2		-0.1076[b]		-0.0769[a]	-0.0479[a]
β_1	0.0965[a]	0.0592[a]	-0.6216[a]	-1.4887[a]	-0.6243[a]
β_2	0.2078	0.1097	-1.5029[a]	-0.6162[a]	-1.5016[a]
γ_1			5.5455[a]	8.9329[a]	5.8918[a]
γ_2			9.21184[a]	5.7441[a]	9.5776[a]
φ_1					0.0184[c]
φ_2					0.0640[a]
			Hypothesis Tests		
$w_1 = w_2$	912.1114[a]	898.6265[a]	8.6952[a]	6.1134[b]	5.3364[b]
$\delta_1 = \delta_2$		1.9562		6.9142[a]	2.3351
$\beta_1 = \beta_2$	0.6735	0.1177	1306.9559[a]	1364.9120[a]	1298.9449[a]
$\gamma_1 = \gamma_2$			19.6618[a]	15.0836[a]	18.5454[a]
$\varphi_1 = \varphi_2$					5.2107[b]
$p_{11} = p_{22}$	16.6083[a]	13.5024[a]	87.9058[a]	79.8012[a]	84.8625[a]
LL	11893.48	11895.73	13453.93	13470.09	13473.32

Notes: Significance at the 1, 5 and 10 % level is denoted by [a], [b] and [c] respectively. The estimated Markov regime-switching models are represented by $\Delta v_t = w_i + \beta_i r_{t-1} + \zeta_t$ for Model 1, $\Delta v_t = w_i + \delta_i \Delta v_{t-1} + \beta_i r_{t-1} + \zeta_t$ for Model 2, $\Delta v_t = w_i + \beta_i r_{t-1} + \gamma_i r_{t-1}^2 + \zeta_t$ for Model 3, $\Delta v_t = w_i + \delta_i \Delta v_{t-1} + \beta_i r_{t-1} + \gamma_i r_{t-1}^2 + \zeta_t$ for Model 4, and $\Delta v_t = w_i + \delta_i \Delta v_{t-1} + \beta_i r_{t-1} + \gamma_i r_{t-1}^2 + \varphi_i \Delta\sigma_{r,t-1} + \zeta_t$ for Model 5. The model parameters w and σ_e are scaled by 10^2. The null hypothesis tests are distributed as $\chi^2(1)$. LL refers to the log maximum likelihood function.

Table 5. Table 4. Regime-switching modelling for changes in implied volatility (Nikkei 225 index)

	Model 1	***Model 2***	***Model 3***	***Model 4***	***Model 5***
			Model Parameters		
w_1	0.0047	-0.3498[a]	-0.1257[a]	1.2607[a]	2.0495[a]
w_2	-3.4197[a]	-0.0030	6.9409[a]	-0.1317[a]	-0.1290[a]
δ_1		-0.6558[a]		-1.4394[a]	-1.7631[a]
δ_2		-0.1233[a]		-0.1352[a]	-0.1145[a]
β_1	-0.0112	-6.3270[a]	-0.3312[a]	4.5286[a]	5.6178[a]
β_2	-7.2362[a]	-0.0434[a]	6.8867[a]	-0.3435[a]	-0.3132[a]
γ_1			3.9584[a]	61.5712[a]	12.1322[a]
γ_2			-164.8804[a]	4.9217[a]	4.4534[a]
φ_1					-2.7179[a]
φ_2					0.0274[a]
			Hypothesis Tests		
$w_1 = w_2$	1248.3519[a]	14.4029[a]	5711.6400[a]	295.9666[a]	338.6405[a]
$\delta_1 = \delta_2$		318.7542[a]		2294.9900[a]	2630.6941[a]
$\beta_1 = \beta_2$	9520.5489[a]	6397.2327[a]	13819.9404[a]	6756.7345[a]	7119.3876[a]
$\gamma_1 = \gamma_2$			4639.8593[a]	523.5600[a]	3.1972[c]
$\varphi_1 = \varphi_2$					1574.2915[a]
$p_{11} = p_{22}$	2.0749	43.6718[a]	33.1734[a]	162.7422[a]	102.2636[a]
LL	10855.93	10930.50	11133.54	11183.11	11209.71

Notes: Significance at the 1, 5 and 10 % level is denoted by [a], [b] and [c] respectively. The estimated Markov regime-switching models are represented by $\Delta v_t = w_i + \beta_i r_{t-1} + \zeta_t$ for Model 1, $\Delta v_t = w_i + \delta_i \Delta v_{t-1} + \beta_i r_{t-1} + \zeta_t$ for Model 2, $\Delta v_t = w_i + \beta_i r_{t-1} + \gamma_i r_{t-1}^2 + \zeta_t$ for Model 3, $\Delta v_t = w_i + \delta_i \Delta v_{t-1} + \beta_i r_{t-1} + \gamma_i r_{t-1}^2 + \zeta_t$ for Model 4, and $\Delta v_t = w_i + \delta_i \Delta v_{t-1} + \beta_i r_{t-1} + \gamma_i r_{t-1}^2 + \varphi_i \Delta \sigma_{r,t-1} + \zeta_t$ for Model 5. The model parameters w and σ_e are scaled by 10^2. The null hypothesis tests are distributed as $\chi^2(1)$. LL refers to the log maximum likelihood function.

FIGURES

FIGURE 1. The behavior of stock prices benchmarks and implied volatility indices (Stock price indices rebased to 100 as of January 2, 1990)

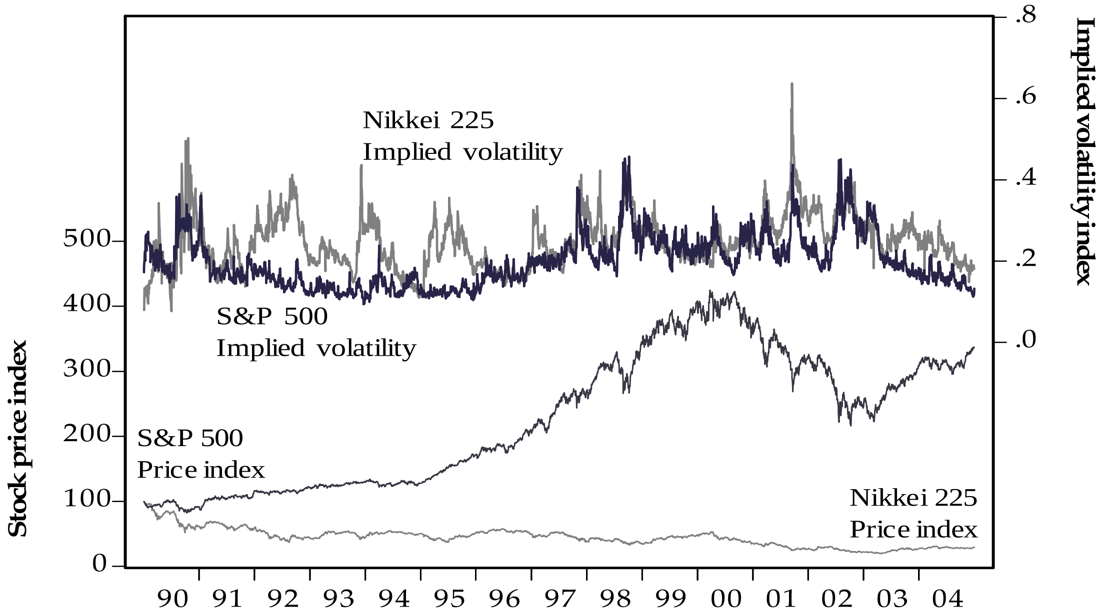

FIGURE 2. Inferred probabilities of regime1 for S&P 500 implied volatility index (Model 4 of expected volatility levels)

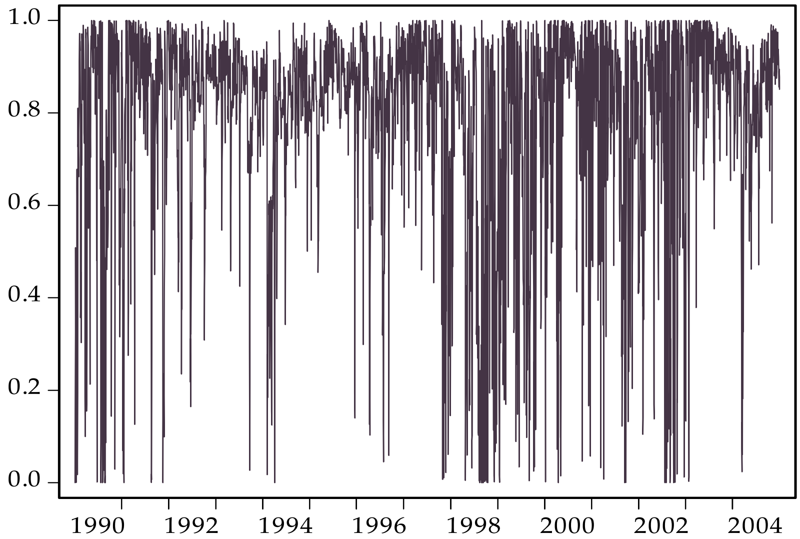

FIGURE 3. Inferred probabilities of regime1 for Nikkei 225 implied volatility index (Model 4 of expected volatility levels)

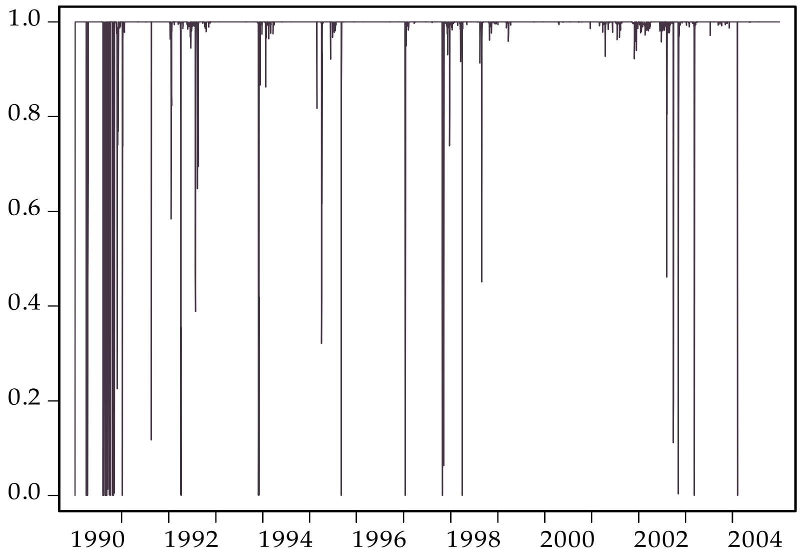

FIGURE 4. Inferred probabilities of regime1 for S&P 500 implied volatility index (Model 5 of first differences in expected volatility)

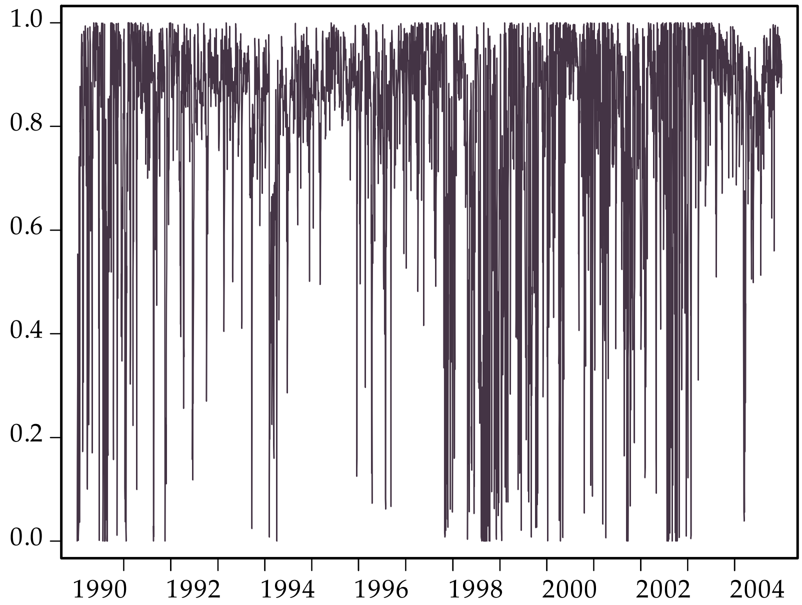

FIGURE 5. Inferred probabilities of regime1 for Nikkei 225 implied volatility index (Model 5 of first differences in expected volatility)