Quantitative Finance
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/rquf20

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Published online: 15 Apr 2011.

To cite this article: Shu-Mei Chiang, Huimin Chung & Chien-Ming Huang (2012) Volatility behavior, information efficiency and risk in the S&P 500 index markets, Quantitative Finance, 12:9, 1421-1437, DOI: 10.1080/14697688.2010.547512

To link to this article: http://dx.doi.org/10.1080/14697688.2010.547512

Quantitative Finance, Vol. 12, No. 9, September 2012, 1421–1437

Volatility behavior, information efficiency and risk in the S&P 500 index markets

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(*Received 4 June 2008; revised 5 December 2010; in final form 9 December 2010*)

We propose an ARJI-Trend model—a combination of the ARJI and component models—to capture the distinguishing features of US index returns, with the results indicating that our model has a good fit for the volatility dynamics of spot, floor- traded and E-mini index futures in US markets. Although certain analogous characteristics are discernible amongst the three indices (such as the responses by the transitory components to innovations, the high persistence in the trends, and the relative importance of jump variance), the reaction to news is found to be heterogeneous amongst the S&P 500 indices. Furthermore, the out-of-sample forecasting performances of both the ARJI-Trend model and the GARCH model are found to have general equivalence for the S&P 500 indices. Our analyses further show that the mini-sized index market is the most efficient with regard to the transmission of information in both the short and long run. This suggests that, following the introduction of E-mini futures, these instruments have come to play a dominant role in price discovery. Overall, our empirical results are very encouraging, insofar as the proposed ARJI-Trend model is found to be a useful tool for helping practitioners to gain a better understanding of the differential attributes between spot, general and mini-sized products in US stock markets.

Keywords: ARJI-Trend model; Components; Jumps; S&P 500 index

1. Introduction

Despite a general worldwide trend which has witnessed the transfer of trading systems from open outcry to electronic trading, both types of trading systems are simultaneously operated during normal trading hours in the index futures markets of the US. Given that E-mini and floor-traded index futures are the counterparts of the spot index, significant linkages may be found to exist between the spot and the corresponding index futures.¶

Furthermore, it is quite reasonable to assume that both spot and index futures should be driven by, and result in, similar reactions to the same news arrivals; nevertheless, several prior studies have demonstrated that there are certain properties of the index markets that are not necessarily found to be the same (Chiu *et al*. 2006, Chung and Chiang 2006).⊥

Asset volatility refers to fluctuations in stock returns irrespective of direction, with volatility having been recognized for a considerable period of time as playing an important and predominant role in the field of finance. Andersen (1996) notes that changes in return volatility are directly related to the rate of news flows entering into the market. There are also many examples of other studies within which various approaches have been applied to the measurement of volatility and hedging.‖ Hence, it is essential for investors, speculators and hedgers to have a firm understanding of the features of volatility so as to avoid investment risk and try to defeat the market.

Structural change refers to long-term changes in the parameters of a structure generating a time series, and,

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¶Refer to Chung and Chiang (2006) for a detailed description of the differences between the contract specifications for floor-traded and E-mini futures indices.

⊥Chiu *et al*. (2006) demonstrate that there are divergent responses to news arrivals for the S&P 500 index spot and futures, whilst Chung and Chiang (2006) also note that there are different degrees of price clustering between the index spot and futures.

‖See Giot and Laurent (2004), Chiu *et al*. (2005b) and Hung *et al*. (2006).

Quantitative Finance
ISSN 1469–7688 print/ISSN 1469–7696 online © 2012 Taylor & Francis
http://www.tandfonline.com
http://dx.doi.org/10.1080/14697688.2010.547512

indeed, as stated by Perron (1997), if such structural changes are not taken into consideration with the occurrence of certain events, the outcomes may differ markedly from expectations. Accordingly, in a highly uncertain and volatile economy, policymakers must have a firm understanding of any potential transition. Of particular importance is the need to explore potential occurrences of structural changes in markets characterized by a rapid pace of change, a prime example of which is the financial markets.

There are certain characteristics of volatility which have been shown to exist in financial stock returns, such as time-varying conditional volatility (Jacquier *et al.* 1994), time-varying conditional jumps (Maheu and McCurdy 2004, Daal *et al.* 2007) and permanent and transitory components (Engle and Lee 1999, Ané 2006).† Despite this, there is a distinct lack of studies with a focus on empirically exploring the existence of these three features. Although the results reported by Chen and Shen (2004) did provide some evidence on these three features with regard to the Taiwanese exchange rate, their analysis was confined to the consideration of constant jumps. According to Maheu and McCurdy (2004), it is of crucial importance to allow for both time variations and clustering in the process governing jumps. Nevertheless, despite the successful development of E-mini index futures in the US, very few studies have set out to examine the potential co-existence of time-varying GARCH and jump components, and the related responses to the arrival of news in the index markets.‡

It has already become clear that E-mini futures provide traders with greater advantages than those provided by floor-traded index futures, in terms of lower margins, operational efficiency, quotation transparency and anonymity. Chung and Chiang (2006) also note that the differences between E-mini and open-outcry futures, with regard to contract size and tick size, are quite distinct. Furthermore, the absence of human intervention and the almost 24-hour trading period for E-mini futures may well have succeeded in attracting more day traders or speculators.

An issue of particular importance is the fact that, according to the Chicago Mercantile Exchange (CME) trading rules, during those periods when unexpected events occur but the floor-traded futures markets are closed, investors in floor-traded futures can write off their positions through the corresponding E-mini futures. Therefore, if such investors were capable of recognizing the information transmission efficiency, risk and volatility dynamics of each market, they would be in a position to adopt appropriate hedging and arbitrage policies. Given the peculiarity of the market trading mechanism in the US, we are provided with an ideal environment to directly and empirically compare the volatility dynamics, information efficiency and risk amongst spot, regular and E-mini index futures.

In an attempt to capture the stochastic process of volatility for S&P 500 index spot and futures, we combine the Engle and Lee (1999) 'component' model with the Chan and Maheu (2002) 'autoregressive jump intensity' (ARJI) model, creating an ARJI-Trend model to undertake this challenging task.§ Furthermore, the structural change analysis of Bai and Perron (2003) is also applied in advance to enable us to determine whether the market reverses; if this is the case, then we must consider the existence of structural changes for the three indices. Finally, we go on to compare the responses to news by the S&P 500 spot, regular and E-mini index futures markets.

Despite the patterns of public information arrival to financial markets having been documented by Berry and Howe (1994) as non-constant, distinct, displaying seasonality and having an insignificant relationship with price volatility, their study did not consider potential jumps, time-varying volatility and components. They may, therefore, have failed to completely capture the actual characteristics of the volatility. In the present study, we set out to investigate volatility behavior and to carry out a risk comparison with the impacts of news arrivals on the S&P 500 index in an attempt to resolve this issue.

It is anticipated that such contrasts amongst the spot, open-outcry and E-mini futures indices will be particularly informative, not only because the three financial products are simultaneously traded during regular trading hours, but also because their prices are highly correlated; consequently, investors can readily achieve a complete understanding of the microstructure in the S&P 500 index markets. Thus, based upon our results, S&P 500 index market participants would be in a position to make appropriate investment and financial allocation decisions. This could also result in making market supervision much easier for government regulators.

This study makes several contributions to the literature, as follows. Firstly, the results show that a new model, incorporating long- and short-run GARCH dynamics

†Although the 'long memory' phenomenon is also one of the characteristics of volatility in stock returns, the models generally applied to test this long-memory phenomenon include ARFIMA, FIGARCH and so forth; however, it seems that, to date, the empirical models are still unable to deal with a combination of ARJI-Trend plus the long-memory phenomenon.

‡There have been many studies exploring the price efficiency resulting from the changes from regular to electronic trading (Naidu and Rozeff 1994, Blennerhassett and Bowman 1998), the effects of electronic trading on the spot or futures market (Aitken *et al.* 2004, Chung and Chiang 2005) and the intraday price discovery process between floor-traded and E-mini index futures (Ates and Wang 2005); however, seldom has there been any focus on this particular topic.

§There are several reasons for our examination of the dynamic process in the S&P 500 index spot and futures markets. Firstly, since both S&P 500 regular and E-mini index futures were the first commodities to be traded in the futures markets, they play a leading role in these markets. Secondly, the S&P 500 index is a market-value-weighted index of 500 stocks traded on the NYSE, AMEX and NASDAQ. The weights ensure that the influence of each firm on the performance of the index is proportional to the market value of the firm; hence, the index is an accurate substitute for a fully diversified equity portfolio. Thirdly, the S&P 500 stock index has long been the investment industry standard for measuring performance; thus, it is a comparable gauge for studying the reaction, in terms of volatility, to specific events.

and autoregressive conditional jump dynamics, provides a good fit for the S&P 500 index markets. Secondly, we find that there are certain similarities in some of the characteristics of volatility within the S&P 500 spot and futures; that is, it would seem that, in the long run, the risks in the S&P 500 index markets may be controllable. Thirdly, despite the fact that open-outcry and mini-sized futures are counterparts of the corresponding spot index, their reactions to news are found to be heterogeneous. Fourthly, E-mini index futures are the most efficient instrument in terms of the transference of information; hence, they appear to play a dominant role in price discovery within the index markets.

The remainder of this paper is organized as follows. Descriptions of the data and the empirical methodology adopted for this study are provided in section 2, followed in section 3 by presentation and discussion of the empirical results. Finally, the conclusions drawn from this study are summarized in the closing section.

2. Data and methodology

2.1. *Data description*

Our analysis of volatility dynamics is based upon the daily closing prices of the S&P 500 spot, futures and E-mini futures indices; the details are obtained from Tickdata Inc. Nearby floor-traded and E-mini futures contracts are selected for our discussion since these are the most actively traded futures contracts in their classifications. Given that the E-mini index futures contracts were introduced on the S&P 500 index of the CME on 9 September 1997, in order to unify the trading period for the three indices, the sample period used for our analysis covers the 10 years from 11 September 1997 to 31 August 2006. All of the analyses undertaken in this study are carried out on returns data.

2.2. *Methodology*

The primary aim of the present study is to determine whether the permanent and transitory components, in conjunction with the dynamic jump process, can explain volatility behavior in the S&P 500 spot and futures indices. In order to gain a complete understanding of whether these three singular features coexist in the three indices, we combine the Engle and Lee (1999) component model with the Chan and Maheu (2002) ARJI model to decompose the GARCH conditional variance into permanent and transitory components. We hypothesize that jump intensity will follow an ARMA process, and also incorporate the GARCH effect of the return series.

2.2.1. *ARJI model*

The ARJI model of returns can be expressed as†:

$$R_t = \mu + \sum_{i=1}^{p} \phi_i R_{t-i} + \sqrt{h_t} Z_t + \sum_{k=1}^{n_t} \pi_{t,k}, \tag{1}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}, \tag{2}$$

$$\lambda_t = \lambda_0 + \sum_{i=1}^{r} \rho_i \lambda_{t-i} + \sum_{i=1}^{s} \gamma_i \xi_{t-i}, \tag{3}$$

$$Z_t \sim NID(0,1), \quad \pi_{t,k} \sim N(\theta, \delta^2),$$

where R_t is the return series of the S&P 500 spot and futures. The conditional jump size, $\pi_{t,k}$, is assumed to be independent and normally distributed with mean θ and variance δ^2; h_t denotes the conditional volatility dynamics for the return, following a GARCH(p, q) process with $\varepsilon_t = R_t - \mu - \sum_{i=1}^{p} \phi_i R_{t-i}$; n_t is the discrete counting process governing the number of jumps arriving between $t-1$ and t, which is distributed as a Poisson random variable with a time-varying conditional intensity parameter, λ_t.

Let $\lambda_t \equiv E[n_t | \Phi_{t-1}]$ be the conditional expectation of the counting process, which is assumed to follow an ARMA(r, s) process, where λ_t is related to r past lags of the conditional jump intensity plus lags of ξ_t. Thus, ξ_{t-1} is the innovation to λ_{t-1} which is measured, *ex post*, by the econometrician. The jump intensity residual is then computed as

$$\xi_{t-i} \equiv E[n_{t-i} | \Phi_{t-i}] - \lambda_{t-i} = \sum_{i=0}^{\infty} j P(n_{t-i} = j \,|\, \Phi_{t-i}) - \lambda_{t-i}, \tag{4}$$

and the conditional density of n_t, following a Poisson distribution, is

$$P(n_t = j \,|\, \Phi_{t-1}) = \frac{e^{-\lambda_t} \lambda_t^j}{j!}, \quad j = 0, 1, 2, \ldots. \tag{5}$$

Maheu and McCurdy (2004) propose a further *ex-post* distribution for the number of jumps, n_t, within which the filter is contracted as

$$P(n = j \,|\, \Phi_t) = \frac{f(R_t | n_t = j, \Phi_{t-1}) P(n_t = j \,|\, \Phi_{t-1})}{P(R_t | \Phi_{t-1})}, \quad j = 0, 1, 2 \ldots. \tag{6}$$

After integrating out all of the jumps during a one-unit interval, the conditional probability density function of the returns can be expressed as

$$P(R_t | \Phi_{t-1}) = \sum_{j=1}^{\infty} f(R_t | n_t = j, \Phi_{t-1}) P(n_t = j \,|\, \Phi_{t-1}). \tag{7}$$

On the condition that the j jumps which occur during the conditional density of returns are normal, the likelihood function can be constructed as

$$f(R_t | n_t = j, \Phi_{t-1}) = \left(2\pi(h_t + j\delta^2)\right)^{-1/2} \exp \times \left(- \frac{\left(R_t - \mu - \sum_{i=1}^{p} \phi_i R_{t-i} - \theta j\right)^2}{2(h_t + j\delta^2)} \right). \tag{8}$$

†Refer to Chiu *et al.* (2005a) for a detailed description.

The log-likelihood function can then be written as

$$L(\Psi) = \sum_{t=1}^{T} \log f(R_t|\Phi_{t-1};\Psi), \tag{9}$$

where $\Psi = (\mu, \phi_i, \omega, \alpha_i, \beta_i, \theta, \delta, \lambda_0, \rho_i, \gamma_i)$ are the parameters to be estimated.

Given that the log-likelihood function in equation (9) involves an infinite summation, in order to ensure that our estimations are feasible, as the truncation point for the distribution determining the number of jumps, we select a large value of five as the maximum number. The reason for this is that, in practice, we find that within our model estimates, the conditional Poisson distribution of equation (5) has a zero probability in the tail for all values of $n_t > 5$; thus, in the present study, we set the maximum number of jumps (n_t) as five.

2.2.2. Component model. The component model, which was devised by Engle and Lee (1999) to describe both long- and short-run volatility, is stated as

$$h_t = q_t + \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta(h_{t-1} - q_{t-1}), \tag{10}$$

$$q_t = \omega + \rho q_{t-1} + \phi\left(\varepsilon_{t-1}^2 - h_{t-1}\right), \tag{11}$$

where q_t is the permanent (or trend) component within the GARCH conditional variance which captures the time-varying long-term volatility, with the mean reversion speed being determined by ρ.

It should be noted that equation (2.4) in the GARCH(1,1) model of Engle and Lee (1999) can also be represented as

$$h_t = (1-\alpha-\beta)\sigma^2 + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} = \sigma^2 + \alpha\left(\varepsilon_{t-1}^2 - \sigma^2\right) + \beta(h_{t-1} - \sigma^2).$$

It is therefore quite easy to recognize that equation (10) in the present study is simply a reinterpretation of equation (2.4) in the Engle and Lee (1999) study, albeit with the constant long-run volatility, σ^2, being replaced by the time-varying trend, q_t, and its past value. The difference between h_t and q_t is simply the transitory component of the conditional variance which dies out with time.

The forecasting error term, $\varepsilon_{t-1}^2 - h_{t-1}$, which is zero-mean and serially uncorrelated, drives the evolution of the permanent component, whilst $\alpha+\beta$ refers to the persistence of the short-run component. The term ρ is an autoregressive root, for which a typical value is between 0.9 and 1; therefore, q_t will approach the unconditional variance very slowly. The stability terms of ρ are $\rho < 1$ and $\alpha+\beta < 1$. When $\rho > \alpha+\beta$, the transitory component will converge more rapidly than the permanent component.

2.2.3. ARJI-Trend model. In addition to replacing equation (3) ξ_{t-1} with equation (4), we also combine the ARJI model with the component model and rewrite equation (2) as equations (10) and (11). The resultant equations can be written as follows†:

$$h_t = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(h_{t-1} - q_{t-1}), \tag{12}$$

$$q_t = \omega + \rho q_{t-1} + \phi\left(\varepsilon_{t-1}^2 - h_{t-1}\right), \tag{13}$$

$$\lambda_t = \lambda_0 + (\rho_1 - \gamma_1)\lambda_{t-1} + \gamma_1 E[n_{t-1}|\Phi_{t-1}]. \tag{14}$$

The log-likelihood function of equation (9) is used to estimate the parameters in the present study.‡ Furthermore, in the present study, we carry out the Bai and Perron (2003) procedures in advance, so as to ensure that we can effectively identify the potential structural change within the conditional mean of the returns for the spot and futures markets; this enables us to determine the possible break points in the three series.§

If such structural changes are found to exist, then the dummy variables are added into the mean equation to indicate the existence of a structural transition; that is, equation (1) is subsequently rewritten as

$$R_t = \mu_0 + \sum_{i=1}^{n}\mu_i D_i + \sum_{i=1}^{p}\left(\phi_{i0} + \sum_{j=1}^{n}\phi_{ij}D_j\right)R_{t-i} + \sqrt{h_t}Z_t + \sum_{i=1}^{n}\upsilon_i\sqrt{h_{t-i}}Z_{t-i} + \sum_{k=1}^{n_t}\pi_{t-k}, \tag{15}$$

$$Z_t \sim NID(0,1), \quad \pi_{t,k} \sim N(\theta,\delta^2), \quad n_t \sim Poisson(\lambda_t \mathrm{d}t),$$

where D_i represents the structural change dummy variables captured by the Bai and Perron (2003) procedure.

†If $|\rho| < 1$, and when $\gamma = s$, equation (3) can be rewritten as equation (14).

‡The distribution of the error terms for standardized GARCH-type models is usually non-normal. In order to resolve the potential problem of the residuals not having a conditional normal distribution, we apply the quasi-maximum likelihood estimation (QMLE) approach for our empirical examination. According to Tsai and Chan (2005), the QMLE is asymptotically normal; therefore, our results are robust, producing consistent estimates of the parameters.

§Bai and Perron (2003) note that a total of five breaks should prove to be efficient for empirical applications. In any event, the critical values for choices greater than five are very small. Accordingly, in the present study, the maximum permitted number of breaks allowed is set at five. In addition, to match the maximum number of breaks, we use a trimming of $\varepsilon = 0.15$; thus, the minimal distances between each break are 338 for the spot index, 340 for floor-traded futures and 341 for E-mini index futures. Adhering to the Bai and Perron (2003) approach for determining the potential break points in the spot, floor-traded and E-mini futures, we execute the following steps. Firstly, we construct the supF, UDmax and WDmax tests for the three indices, and then also construct the supF(l + 1 | l) tests. Secondly, we refer to the procedure for selecting the number of breaks using information criteria as the BIC, LWZ and sequential procedures. Finally, we obtain the optimal number of breaks for spot, floor-traded and E-mini futures.

3. Estimation results

In order to illustrate the dynamic properties of S&P 500 spot and futures, we estimate the ARJI-Trend model in conjunction with a structural change test. A description of the data adopted for this study and subsequent analysis of the estimation results based upon the ARJI-Trend model are provided in the following subsections.

3.1. Basic analysis of the data

The summary descriptive statistics for the daily logarithmic returns of the S&P 500 spot, regular and E-mini futures indices over the 10-year sample period are presented in table 1, from which we can see that the mean daily return is found to be the highest (lowest) for the spot (futures) index.

Amongst the three indices, the standard deviation of the returns is found to be the highest for regular futures, with all of the indices exhibiting large kurtosis, and the Jarque–Bera tests for normality revealing that the stock returns have a non-normal distribution.† Therefore, according to the preliminary results of the skewness, kurtosis and Jarque–Bera tests, the return distribution is more fat-tailed and high-peaked than a normal distribution, which is consistent with the ARCH effect.

3.2. Empirical results for the S&P 500 index markets

3.2.1. Structural break points. The daily stock price trends of the S&P 500 spot index, regular and E-mini futures markets from 11 September 1997 to 31 August 2006 are illustrated in figures 1(a)–(c). We apply the Bai and Perron (2003) procedure to extract the structural break point so as to explore the possible structural break in these indices during the sample period.

The extracted results indicate that the break date in the S&P 500 is 13 August 2002 for the spot index and 30 September 2002 for the open-outcry and E-mini futures indices. At first glance, such a difference in the timing of the structural changes in the two markets implies that, on the one hand, there are divergent responses to news in the spot and futures markets; that is, the S&P 500 spot and futures markets may well have different microstructures. On the other hand, however, the identical date for the structural change in the open-outcry and E-mini index futures markets seems to confirm high homogeneity between the two markets, despite the differences in their trading hours and trading systems.

In order to confirm that the inclusion of such breaks is essential, we first perform likelihood ratio tests to examine the validity of the ARJI-Trend model with structural breaks. The results are presented in tables 2–4, from which we can see that the ARJI-Trend model with structural breaks is an appropriate model for the S&P 500 spot index, floor-traded and E-mini futures markets.

Table 1. Summary descriptive statistics of daily returns for the S&P 500 spot index, floor- traded and E-mini index futures markets.

Variable	Spot index	Floor-traded futures	E-mini futures
Mean	0.0143	0.0137	0.0137
Std. dev.	1.1720	1.2021	1.2004
Max.	5.3080	5.8141	5.9128
Min.	−7.1127	−7.7058	−7.8793
Skewness	−0.0620	−0.0958*	−0.0820
Kurtosis	2.9755***	3.5493***	3.5098***
Jarque–Bera	832.9338***	1192.8664***	1170.2833***
No. of observations	2254	2266	2275

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

In the following subsections, we go on to further examine the null hypotheses on whether the coefficients with break dummies are significantly different from zero (that is, H_0: $\mu_1 = 0$ and H_0: $\phi_{11} = 0$). The F-test results, presented in table 5, reveal that a structural break must be considered when undertaking empirical research using the ARJI-Trend model. An evaluation of the existence of structural change is therefore seen as important when setting out to determine the presence of time-varying, continuous-state GARCH and discrete jump components.

3.2.2. Comparison between ARJI-Trend and GARCH-type models. The ARJI-Trend model proposed in the present study nests the widely adopted classical GARCH structures: GARCH(1,1), component-GARCH and GARCH- Jump with constant jump intensity and size. In order to determine whether it is the ARJI-Trend model which actually provides the best goodness-of-fit, we apply the likelihood ratio (LR) tests to examine the validity of each of the models. The LR results on the S&P 500 spot index, floor-traded and E-mini index futures (tables 2–4) indicate that, for these three markets, the GARCH, component-GARCH and GARCH-Jump models are rejected at the 1% level of significance.

3.3. Empirical results for the ARJI-Trend model

3.3.1. GARCH components. Table 5 also presents the related results for the ARJI-Trend model, from which we can see that, for the three indices, all of the related parameters characterizing the dynamics in the models are significant. Furthermore, almost all of the parameters pass the Ljung–Box $Q(26)$ and $Q^2(26)$ tests, thereby indicating the superior performance of the ARJI-Trend model in describing the behavior of S&P 500 spot and futures indices.

Table 5 further reveals that the permanent component of the GARCH conditional variance exhibits a high degree of persistence, with the autoregressive parameters

†The kurtosis examined here is excess kurtosis, which deviates from the respective means.

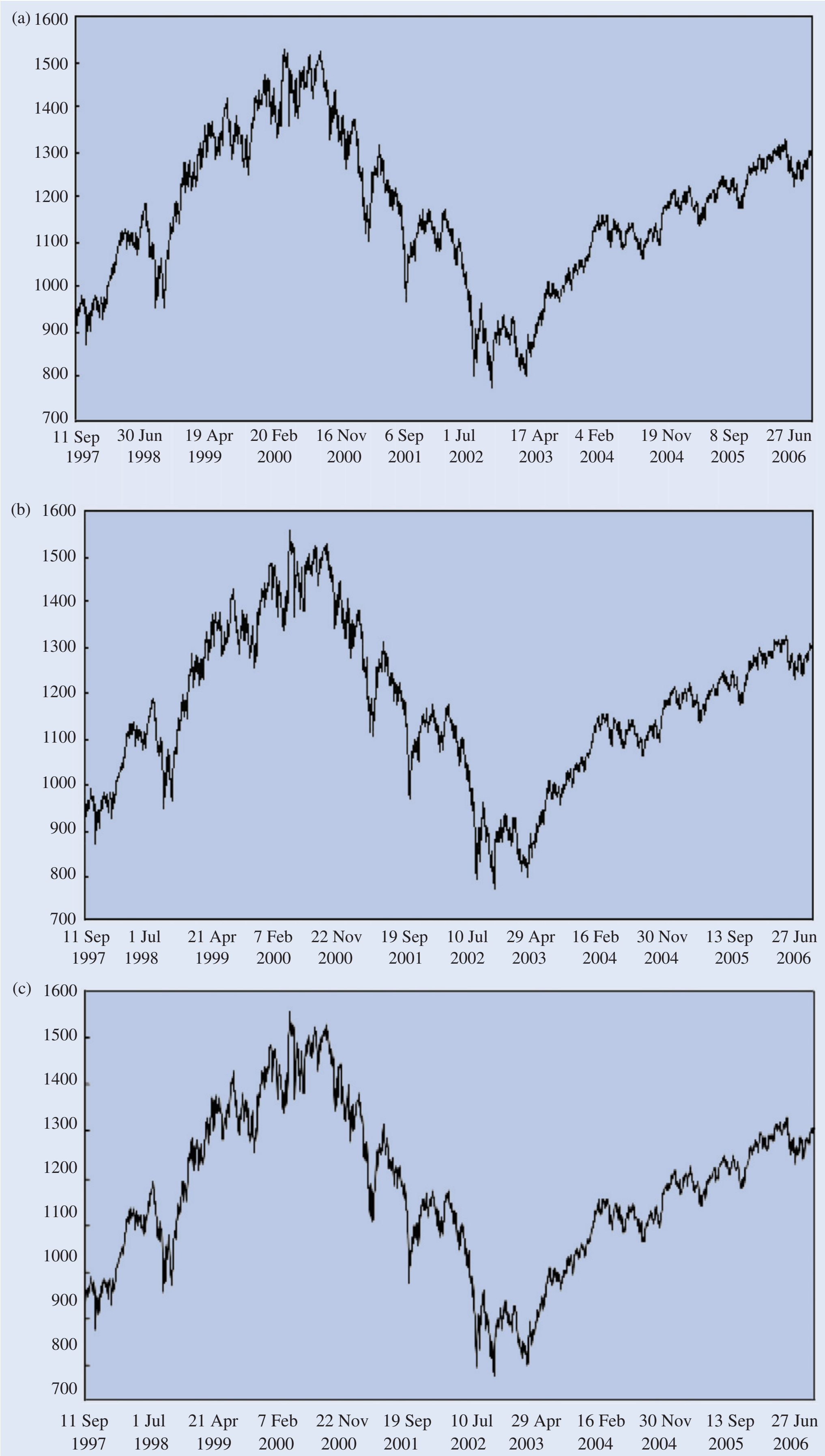

Figure 1. Daily stock price trend on the S&P500 (a) spot index, (b) futures index, and (c) E-mini futures index, September 1997 to August 2006.

Table 2. Parameter estimates of the GARCH-type model for the S&P 500 spot index.

	ARJI-Trend		GARCH(1,1)		Component GARCH		GARCH Jump		ARJI-Trend (no breaks)		ARJI-Trend ($\rho=1$)	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
μ_0	0.3504***	0.0193	0.0396*	0.0215	0.0437**	0.0176	0.0478***	0.0177	0.1743***	0.0126	0.2646***	0.0001
μ_1	−0.1394***	0.0240						–			−0.0744***	0.0126
ϕ_{10}	−0.0022	0.0226	−0.0265	0.0227	−0.0347*	0.0187	−0.0372**	0.0182	−0.0576***	0.0075	0.0148***	0.0000
ϕ_{11}	−0.0900**	0.0418									−0.1589***	0.0213
v_1	0.0233***	0.0000										
ω	0.0000	0.0558	0.0107**	0.0047	0.4414**	0.0872	0.0186***	0.0024	0.0000	0.0558	1.0717***	0.2965
α	0.0849***	0.0062	0.0795***	0.0140	0.0209***	0.0027	0.0772**	0.0034	0.0790***	0.0014	0.1094***	0.0145
β	0.8608***	0.0121	0.9150***	0.0148	0.9762***	0.0036	0.9030***	0.0024	0.8848***	0.0063	0.8515***	0.0172
ρ	0.9932***	0.0013			0.9364**	0.0228			0.9951***	0.0012	1.0000***	0.0000
ϕ	0.0086**	0.0021			0.0933***	0.0147			0.0108***	0.0001	0.0280***	0.0012
θ	−0.8056***	0.0456					−3.3365***	0.8431	−0.7535***	0.0715	−0.5852***	0.0001
δ	0.1915**	0.0739					1.8788***	0.6852	0.5155***	0.0224	0.0000**	0.0000
λ_0	0.0130***	0.0015					0.0068**	0.0000	0.1101***	0.0062	0.2631***	0.0126
ρ_1	0.9628***	0.0044							0.4606***	0.0152	0.1944***	0.0379
γ_1	0.0852***	0.0289							0.4447***	0.0225	0.5582***	0.0022
Log L	−3262.1331		−3304.8791		−3295.8603		−3271.4754		−3269.6633		−3258.6476	
H_0: GARCH			85.4920***									
H_0: Component-GARCH					67.4544***							
H_0: GARCH-Jump							18.6652***					
H_0: ARJI-Trend (no breaks)									15.0604***			
H_0: ($\rho=1$)											−6.9710	

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

Table 3. Parameter estimates of the GARCH-type model for S&P 500 floor-traded index futures.

	ARJI-Trend		GARCH(1,1)		Component GARCH		GARCH Jump		ARJI-Trend (no breaks)		ARJI-Trend (ρ=1)	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
μ_0	0.2383***	0.0166	0.0400**	0.0195	0.0435**	0.0190	0.0507***	0.0180	0.2523***	0.0208	0.0547***	0.0000
μ_1	−0.0766***	0.0206									−0.0377	0.0240
ϕ_{10}	0.0109	0.0224	−0.0268	0.0223	−0.0272	0.0233	−0.0284	0.0220	−0.1228***	0.0113	0.0507***	0.0000
ϕ_{11}	−0.0427	0.0399									−0.0288	0.0432
v_1	−0.0518***	0.0222										
v_2	−0.0576***	0.0198										
ω	0.0000	0.0528	0.0108***	0.0035	0.4335***	0.0645	0.0176***	0.0026	0.0002	0.0003	0.0000***	0.0000
α	0.0735***	0.0066	0.0868***	0.0126	0.0210***	0.0010	0.0811***	0.0058	0.0093***	0.0066	0.0886***	0.0077
β	0.8737***	0.0117	0.9088***	0.0128	0.9764***	0.0010	0.9004***	0.0035	0.9823***	0.0093	0.8701***	0.0136
ρ	0.9937***	0.0011			0.9423**	0.0112			0.9471***	0.0179	1.0000***	0.0000
ϕ	0.0081***	0.0019			0.0959***	0.0079			0.0797***	0.0123	0.0215***	0.0052
θ	−0.6927***	0.0620					−2.7810***	0.6354	−0.6956***	0.0863	−0.5739***	0.1020
δ	0.5710***	0.0508					2.0560***	0.5792	0.4559***	0.0663	0.7909***	0.0817
λ_0	0.0246***	0.0031					0.0095***	0.0000	0.2490***	0.0729	0.0404***	0.0088
ρ_1	0.9259***	0.0099							0.2950*	0.1650	0.6872***	0.0647
γ_1	0.1939***	0.0576							0.4262***	0.1171	0.5861***	0.2261
Log L	−3303.7758		−3352.6116		−3342.5027		−3321.1007		−3303.7319		−3309.5355	
H_0: GARCH			97.6716***									
H_0: Component-GARCH					77.4538***							
H_0: GARCH-Jump							34.6498***					
H_0: ARJI-Trend (no breaks)									−0.0878			
H_0: (ρ = 1)											11.5194***	

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

Table 4. Parameter estimates of the GARCH-type model for S&P 500 E-mini index futures.

	ARJI-Trend		GARCH(1,1)		Component GARCH		GARCH Jump		ARJI-Trend (no breaks)		ARJI-Trend ($\rho=1$)	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
μ_0	0.3331***	0.0000	0.0394**	0.0194	0.0429**	0.0178	0.0500***	0.0182	0.2268***	0.0122	0.2203***	0.0280
μ_1	−0.1024***	0.0247									−0.0590*	0.0342
ϕ_{10}	−0.1270***	0.0000	−0.0290	0.0227	−0.0254	0.0221	−0.0271	0.0226	−0.0840***	0.0184	−0.0122	0.0211
ϕ_{11}	−0.0763***	0.0390									−0.0896***	0.0282
v_1	0.1030***	0.0223										
ω	0.0000***	0.0000	0.0108***	0.0041	0.4359***	0.1131	0.0175***	0.0020	0.0005***	0.0002	0.0107***	0.0011
α	0.0745***	0.0071	0.0853***	0.0132	0.0213*	0.0110	0.0821***	0.0030	0.0818***	0.0075	0.0574***	0.0196
β	0.8708***	0.0142	0.9101***	0.0133	0.9761***	0.0112	0.9001***	0.0027	0.8592***	0.0143	0.9114***	0.0287
ρ	0.9924***	0.0014			0.9411***	0.0228			0.9896***	0.0017	1.0000***	0.0000
ϕ	0.0142***	0.0036			0.0961***	0.0161			0.0143***	0.0037	0.0656***	0.0192
θ	−0.7103***	0.0470					−2.8126***	0.7682	−0.6825***	0.0481	−0.5536***	0.1004
δ	0.4752***	0.0492					2.1382***	0.6459	0.4925***	0.0503	0.4284***	0.0744
λ_0	0.1305***	0.0118					0.0083***	0.0032	0.2082***	0.0199	0.2253**	0.0913
ρ_1	0.6107***	0.0358							0.3542***	0.0603	0.2389	0.2039
γ_1	0.2233***	0.0911							0.3632***	0.1283	0.4330***	0.1465
Log L	−3302.0651		−3364.0375		−3353.7131		−3331.6032		−3314.6898		−3327.6124	
H_0: GARCH			123.9448***									
H_0: Component-GARCH					103.2960***							
H_0: GARCH-Jump							59.0762***					
H_0: ARJI-Trend (no breaks)									25.2494***			
H_0: ($\rho=1$)											51.0946***	

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

Table 5. Estimation results of the ARJI-Trend model for the S&P 500 indices.

Variable[a]	Spot index[b] Coeff.	S.E.	Floor-traded futures[b] Coeff.	S.E.	E-mini futures[b] Coeff.	S.E.
μ_0	0.3504***	0.0193	0.2383***	0.0166	0.3331***	0.0000
μ_1	−0.1394***	0.0240	−0.0766***	0.0206	−0.1024***	0.0247
ϕ_{10}	−0.0022	0.0226	0.0109	0.0224	−0.1270***	0.0000
ϕ_{11}	−0.0900**	0.0418	−0.0427	0.0399	−0.0763*	0.0390
v_1	0.0233***	0.0000	−0.0518**	0.0222	0.1030***	0.0223
v_2			−0.0576***	0.0198		
ω	0.0000	0.0558	0.0000	0.0528	0.0000***	0.0000
α	0.0849***	0.0062	0.0735***	0.0066	0.0745***	0.0071
β	0.8608***	0.0121	0.8737***	0.0117	0.8708***	0.0142
ρ	0.9932***	0.0013	0.9937***	0.0011	0.9924***	0.0014
ϕ	0.0086**	0.0021	0.0081***	0.0019	0.0142***	0.0036
θ	−0.8056***	0.0456	−0.6927***	0.0620	−0.7103***	0.0470
δ	0.1915**	0.0739	0.5710***	0.0508	0.4752***	0.0492
λ_0	0.0130***	0.0015	0.0246***	0.0031	0.1305***	0.0118
ρ_1	0.9628***	0.0044	0.9259***	0.0099	0.6107***	0.0358
γ_1	0.0852***	0.0289	0.1939***	0.0576	0.2233**	0.0911
$Q(26)$	25.6189		28.2439		29.7274	
$Q^2(26)$	22.6970		38.2480*		32.7562	
Log L	−3262.1331		−3303.7758		−3302.0651	
H_0: $\mu_1=0$ and H_0: $\phi_{11}=0$	31.0737***		14.7318***		21.1511***	

[a]The $Q(26)$ and $Q^2(26)$, distributed as χ^2_{26}, are the Ljung–Box Q-statistics with a lag of 26 for standardized residuals and standardized squared residuals for the purpose of examining whether linear and nonlinear dependence have been removed.
[b]Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

(ρ) in the trend equation being very close to 1 (0.9932 for spot, 0.9937 for regular futures, and 0.9924 for E-mini futures). In order to determine whether the permanent component of volatility is integrated, we carry out the statistical test by letting $\rho=1$. In the subsequent procedure, we follow Chen and Shen (2004) to re-estimate the model and calculate the restricted log likelihood function.

As shown in tables 2 to 4, the log-likelihood ratio tests are −6.9710 for spot, 11.5194 for floor-traded futures, and 36.1116 for E-mini index futures, results which reveal no rejection of the restricted ARJI-Trend model for the S&P 500 spot; that is, the permanent component of the spot volatility is a random walk, whereas those of the regular and E-mini futures are not. Furthermore, the convergence speed to long-run innovation appears to be most rapid in the E-mini futures market, with the slowest convergence speed being found for floor-traded futures.

Accordingly, this also implies that, in the spot market, almost 87.24% of the news shock on the permanent components still persists after 20 trading days, whilst 88.13% (85.85%) of the news shock persists in the open-outcry (E-mini) futures market over the same horizon.† Conversely, the respective sums of $\alpha+\beta$, which represent the continuance level of the transitory component, are 0.9457 for spot, 0.9472 for open-outcry, and 0.9453 for E-mini futures. These figures correspond to their respective half-lives of 18.5, 19 and 18 trading days. These results reveal that the trend has a high level of persistence, whereas the arrival of new information has only minor impacts on the markets. The outcome also reveals that the deviations in GARCH conditional variance from the general trend are temporary, thereby providing support for the findings of the prior studies.‡

The shock effects on the permanent and transitory components are respectively given by ϕ and α, with a comparison of the parameter estimates showing that, for the three markets, the arrival of news has a much greater influence on the transitory component than on the permanent component. However, combined with the previous results, despite the shock effect on the transitory component being stronger, as in Engle and Lee (1999) and Chen and Shen (2004), the effect is found to be short-lived. Furthermore, as the relationships between the parameters are $(\alpha+\beta)<\rho<1$, the permanent component will tend to dominate the forecasting of GARCH.

To briefly summarize, when certain information arrives into the market, the more rapid convergence speed of the permanent and transitory components of the E-mini futures indicates that the E-mini market is better at transmitting the information. Conversely, floor-traded futures appear to be the least efficient in dealing with the news. This suggests that the introduction of E-mini futures may well have led to them playing a governing role in price discovery. Indeed, since the open-outcry

†Given that the daily impact of news shocks on the permanent components for each market are 0.9932 for the spot market, 0.9937 for the open-outcry market, and 0.9924 for the E-mini market, their effects after 20 trading days are, respectively, computed as 0.9932^{20}, 0.9937^{20} and 0.9924^{20}. The resultant percentages are 87.24%, 88.13% and 85.85%.
‡See Engle and Lee (1999), Speight *et al.* (2000) and Ané (2006).

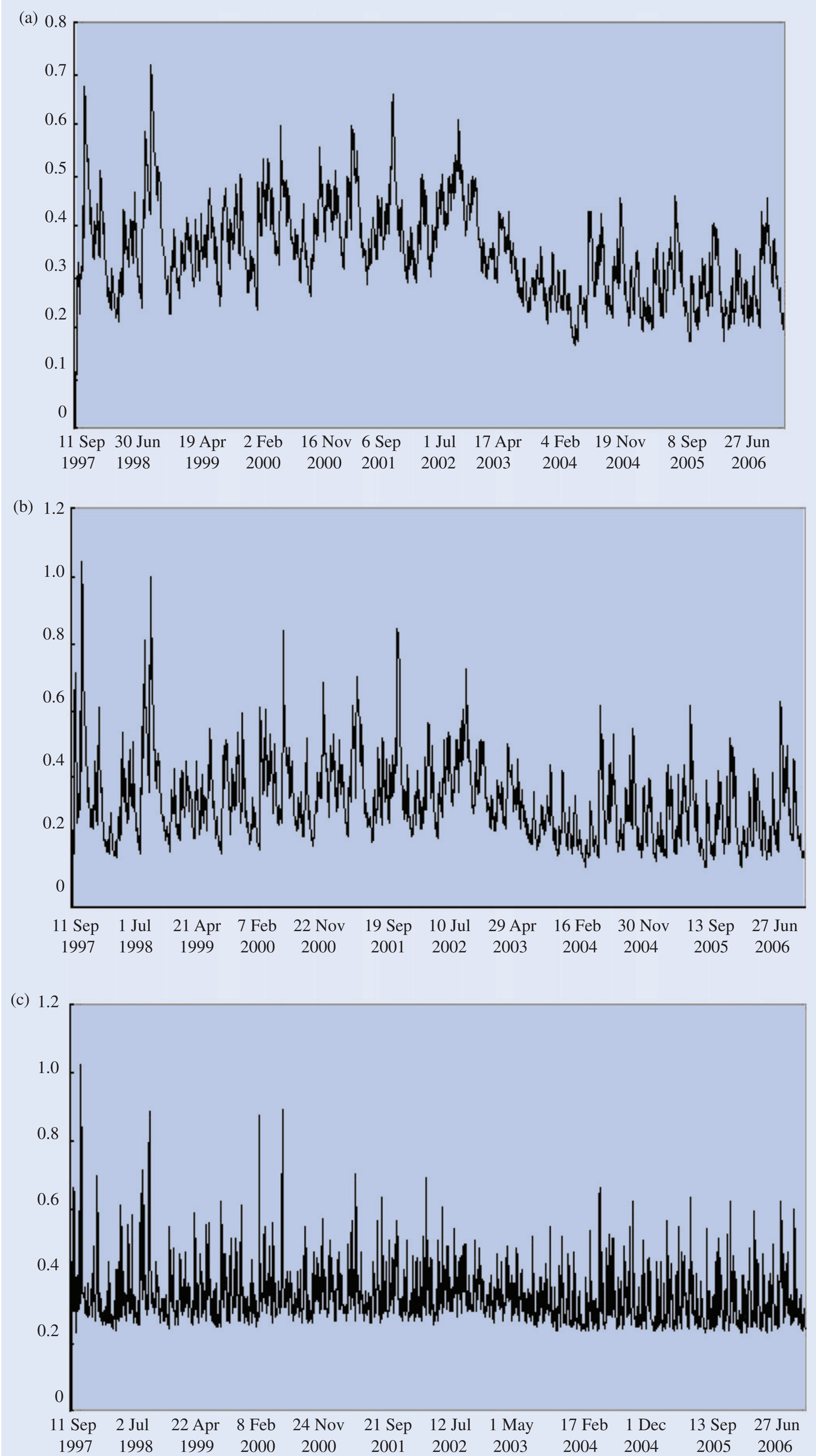

Figure 2. Conditional time-varying jump intensity on the S&P500 (a) spot index, (b) index futures, and (c) E-mini futures, September 1997 to August 2006.

Table 6. Basic statistics for the total conditional variance combination.

Variance combination	Value	%	Value	%	Value	%
GARCH conditional variance						
Transitory component	0.712	48.50	0.693	47.40	0.655	53.50
Permanent component	0.411	28.00	0.444	30.37	0.489	39.95
Jump conditional variance	0.344	23.43	0.326	22.30	0.081	6.62
Total conditional variance	1.468	100.00	1.463	100.00	1.224	100.00

trading mechanism involves greater human participation within the overall trading process (Christie *et al.* 1994), this is likely to result in a reduction in information efficiency within the market.

3.3.2. Jump intensity. The jump-size mean θ is found to be significant at the 1% level for all three indices, ranging from −0.8056 to −0.6927, with such significance implying that there is abnormal information resulting in a discontinuous jump in the index spot and futures market which, in the long run, will be significantly different from zero. The jump parameters λ_0 are also found to be significant at the 1% level, thereby implying the existence of jump behavior for the S&P 500 index spot and futures whenever there is abnormal information flowing into the markets.

Furthermore, the parameters ρ_1 and γ_1 are also found to be significant at the 1% level, thereby indicating that the probability of jumps incited by abnormal information would change over time, leading to clustering, as noted by Maheu and McCurdy (2004). The unconditional jump intensity is 0.3495 for spot, 0.3320 for regular futures, and 0.3352 for E-mini index futures, which suggests that jumps to returns will occur, on average, once every 1.537, 1.497 and 1.504 business days for the corresponding markets.† Thus, the abnormal innovations occurring in the S&P 500 index markets are frequent; however, since the jumps will almost completely decay in about 4–5 trading days in all three markets, their impacts will rapidly disappear.

The conditional jump intensities for the S&P 500 spot, open-outcry and E-mini index futures markets are illustrated in figures 2(a)–(c), which clearly reveal that jump intensity is time-varying. Thus, although some studies (such as Chen and Shen (2004)) hypothesize that jump intensity is constant, it will vary when different events occur over various time spans.

3.3.3. Comparison of the three features of total conditional variance (risk). Total conditional variance comprises the permanent and transitory components, along with jump variance; however, an interesting point from the results shown in table 6 is that volatility arises mainly from the transitory component (48.50% for the spot market, 47.40% for floor-traded futures, and 53.50% for E-mini futures). Although GARCH variance provides the main contribution to total variance (about 83%), jump-induced variance similarly explains about 17% of the volatility for the three index markets.

The results indicate that jump behavior is important, and must therefore be taken into account when considering investing in the S&P 500 index. However, responses to events seem to be less dramatic in the US, as compared to the Taiwan index market (Chiu *et al.* 2008). Furthermore, since the total variance is greatest in the spot index (1.468), followed by the floor-traded index futures (1.462), and the E-mini index futures being the smallest (1.224), this suggests that trading is riskier in the spot and regular index futures markets than in the E-mini futures market.

The permanent and transitory components and the jump variance for the three markets are illustrated in figures 3(a)–(c), which show that the permanent component moves in a rather even manner, whilst the transitory component is driven up and down by news arrivals. Furthermore, despite the permanent component lasting for a longer period, it is not found to be particularly large. Overall, the transitory component is found to be far greater than either the permanent component or the jump-induced variance.

For investors, although the effects of transitory and jump components are significant, they are merely temporary. Conversely, despite the more prolonged impacts of permanent components, in the long run, these are relatively smooth. From a perspective of long-term investment, the investment risks appear to be under control, essentially because the market will ultimately return to its long-run state; however, what such investors do need to be aware of is fundamental risk (economics, politics, and so on). Conversely, speculators in the market can make use of the sizable temporary and jump component to engage in arbitrage activities.

3.4. Out-of-sample analysis

For our evaluation of the out-of-sample one-period-ahead variance forecasting ability of the GARCH(1,1) and ARJI-Trend models, we select the first nine years as our in-sample period, and set the final year as our out-of-sample period. The loss functions, mean absolute error (MAE) and root mean square error (RMSE) are considered as the criteria for assessing the forecasting

†When the ARJI specification is stationary ($|\rho| < 1$), then the unconditional jump intensity will be equal to $E[\lambda_t] = \lambda_0/(1-\rho_1)$.

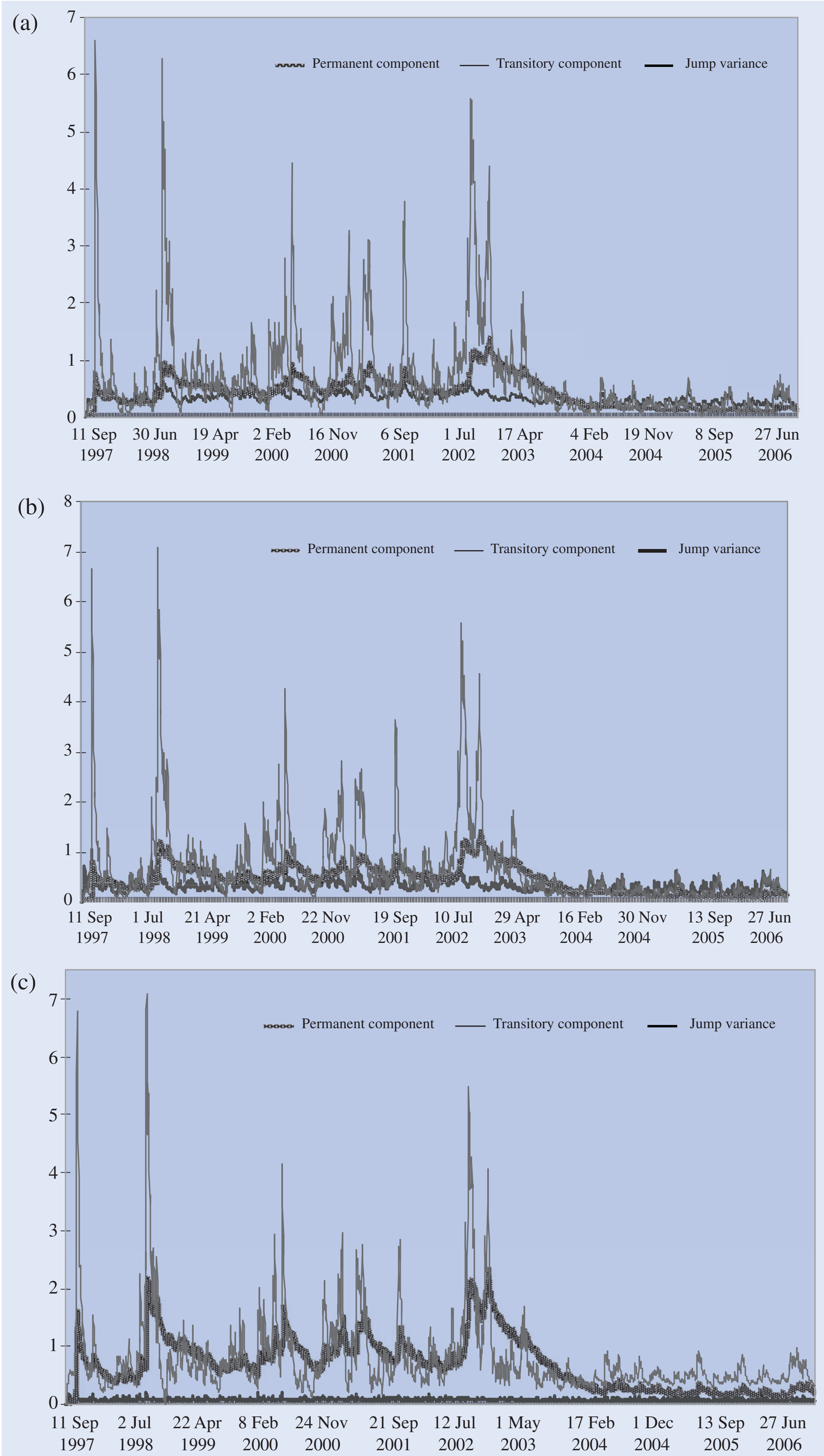

Figure 3. Jump variance and permanent and transitory components for the S&P 500 (a) spot index, (b) index futures, and (c) E-mini index futures, September 1997 to August 2006.

Table 7. Out-of-sample forecasting performance of conditional volatility for S&P 500 spot, floor-traded and E-mini index futures.

	GARCH(1,1)		ARJI-trend		DM statistics[a,b]	
Index market	MAE	RMSE	MAE	RMSE	MAE	RMSE
Spot	1.3847	3.3517	1.3826	3.3516	−6.8586***	−2.7203***
Futures	1.4559	3.6901	1.5131	4.0618	1.6234	1.2487
E-mini	1.4516	3.6692	1.4803	3.7406	1.9153	1.4194

[a]DM refers to the Diebold and Mariano (1995) t-statistics. The null hypothesis of the DM-test is of equal predictive ability for the two models, whereas a significantly negative t-statistic would indicate that the GARCH(1,1) model was dominated by the ARJI-Trend model.
[b]Significant at the 1% level.

performance of the ARJI-Trend model relative to that of the GARCH(1,1) model.† The formulae for computing the MAE and RMSE are as follows:

$$MAE = \frac{\sum_{t=1}^{T} |Y_t - \hat{Y}_t|}{T}, \quad RMSE = \sqrt{\frac{\sum_{t=1}^{T} \left(Y_t - \hat{Y}_t\right)^2}{T}},$$

where Y_t is the observed value, and $\hat{Y}_t$ is the estimator of the estimated parameter Y. The forecasting performance will be better with a smaller value of MAE or RMSE.

The model parameters are initially set at the values shown in table 5; we then use a fixed-sized rolling window of 250 observations, and also adopt the Diebold and Mariano (1995) 'DM-test' (the forecast comparison test) to compute the MAE and RMSE, comparing the forecasting efficiency between the ARJI-Trend and GARCH (1,1) models during the out-of-sample period.

Although the outcomes of the DM test appear to reveal that the ARJI-Trend model performs better than the GARCH model in the S&P 500 spot index, there are only very small differences in the values of MAE (1.3847 vs. 1.3826) and RMSE (3.3517 vs. 3.3516). Therefore, the DM-test results reported in table 7 indicate that, for the two models, the out-of-sample forecasting performance is virtually the same for the S&P 500 spot, floor-traded and E-mini indices.

3.5. *News effects*

As shown in figures 2(a)–(c) and 3(a)–(c), during the event periods in our sampling span, there are increases in the permanent and temporary components, jump intensity and jump variance for all three indices. To explain this in a concise way, we simply display the jump intensity and transitory components for the related events in table 8. Both jump intensity and the transitory components are generally larger than their means during these periods; however, the degree of priority is not consistent amongst the three indices. We surmise that the different responses to news arrivals during such spans stem mainly from the divergent trading systems and clientele characteristics. These results provide some support for the dissimilarities in structural fundamentals in the index markets, as noted by both Chiu *et al*. (2006) and Chung and Chiang (2006).

To summarize, the results indicate the coexistence of time-varying jumps, as well as both permanent and transitory components in the volatility behavior of the S&P 500 spot and index futures markets. Furthermore, the diverse responses to news arrivals amongst the S&P 500 indices may be attributable to certain characteristics relating to market structure. Indeed, this also suggests that, under the new form of economic generation—within which greater uncertainty is the norm—aside from traditional GARCH volatility, jumps leading to infrequent large moves in returns must be taken into account when considering investing in the financial markets. Although the ARJI-Trend model does provide us with a heightened perception of the reaction to events and volatility behavior within the S&P 500 markets, when faced with shocks and innovations within these markets, we suggest that investors should treat them as a normal condition, since, in the long run, the impacts will ultimately disappear.

4. Conclusions

We propose a model structure, comprising a combination of time-varying continuous-state GARCH and discrete jump components, which we suggest is appropriate for describing the volatility features of the S&P 500 index markets. Our results reveal the coexistence of trend and transitory components, together with time-varying jumps, and although we find that the trend has a high level of persistency, the arrival of new information appears to have only minor impacts on the markets.

The variance in the transitory and jump components is capable of explaining about 83% of the total conditional variance in the US markets; nevertheless, such variance will decay in the long run, which suggests that following the occurrence of trading noise and events, there may be some inherent force stabilizing the market. Rational investors must therefore treat such news arrivals and noise trading as normal occurrences, since the market will eventually return to its long-run state; that is, in addition to the fundamental risk and trading noise, investors in the

†The MAE and RMSE are frequently used measures for determining the differences between values predicted by a model and the values actually observed from the issue being modeled or estimated.

Table 8. Conditional jump intensity and transitory components of the S&P 500 spot, floor-traded and E-mini index futures during specific events.

		Spot market		Floor-traded futures		E-mini futures	
Event	Date	Jump intensity	Transitory component	Jump intensity	Transitory component	Jump intensity	Transitory component
Southeast Asian financial crisis hampers	3 August 1998	0.4723	1.0389	0.5779	0.9805	0.4697	0.7906
both the economic growth and	4 August 1998	0.4758	0.9665	0.5523	0.8653	0.4233	0.7013
profitability of US industries, leading to	5 August 1998	0.5854	2.2185	0.8100	2.1023	0.7157	1.8967
economic decay	6 August 1998	0.5616	1.8989	0.7254	1.8476	0.5111	1.6650
The Fed reduces interest rates by 0.25%,	1 October 1998	0.4873	2.4006	0.4262	2.5474	0.3979	1.8455
lower than expected, leading to general	2 October 1998	0.5166	3.0905	0.4722	2.9974	0.4393	2.3386
disappointment in the financial markets	9 November 2000	0.4032	0.7789	0.3830	0.9357	0.4551	0.6777
Dell announces lower than expected sales	10 November 2000	0.4079	0.7127	0.3899	0.8637	0.4187	0.5975
growth for the coming year	13 November 2000	0.4715	1.2598	0.4842	1.2228	0.5051	0.9368
The Fed reduces interest rates by only	21 March 2001	0.5726	2.4824	0.6212	2.2789	0.3988	1.8306
0.5%, again not in line with the	22 March 2001	0.5802	2.4685	0.6299	2.2618	0.4051	1.8129
expectations of investors	18 September 2001	0.6422	3.4222	0.8429	3.3676	0.5657	1.9141
The '911' terrorist attacks on the World	19 September 2001	0.6312	2.9404	0.7861	2.9423	0.4631	1.5960
Trade Centre in New York	20 September 2001	0.6326	2.7944	0.7956	3.0785	0.4687	1.7498
	21 September 2001	0.6561	3.3968	0.8313	3.6244	0.5181	2.3882
Fall in Boeing stock prices leads to concern	30 October 2001	0.4244	0.9519	0.4071	1.0315	0.5076	0.7630
amongst investors of an economic	31 October 2001	0.4502	1.1398	0.4315	1.0529	0.4834	0.7946
downturn	19 July 2002	0.5377	2.2893	0.6008	2.6014	0.4407	2.0848
US Congress passes the industrial refor-	22 July 2002	0.5832	3.5011	0.6703	3.3989	0.4962	2.8976
mation law (Sarbanes–Oxley Act)	23 July 2002	0.6024	4.0996	0.7012	3.8201	0.4918	3.2848
	24 July 2002	0.6089	4.1282	0.7221	4.1515	0.4757	3.4864
Period of structural change	13 August 2002	0.4482	3.0241				
	14 August 2002	0.4589	3.0588				
	30 September 2002			0.5054	1.9901	0.4279	1.5786
	1 October 2002			0.5062	1.8341	0.4116	1.4499
Concerns amongst investors over the	22 January 2003	0.3539	0.8240	0.3639	0.7071	0.4541	0.7722
possible outbreak of war between the US	23 January 2003	0.3667	0.8276	0.3983	0.7835	0.4546	0.7593
and Iraq	27 January 2003	0.4088	1.3862	0.4717	1.1304	0.4837	0.6364
	28 January 2003	0.4270	1.5218	0.4964	1.1813	0.4798	0.7411
Sample average		0.3471	0.7002	0.3272	0.6913	0.3363	0.4545

S&P 500 markets must also take into account the potential occurrence of such events when considering engaging in short-run investment activities. In the long run, however, what investors need to do is to allocate assets within their portfolios to earn better returns.

The out-of-sample forecast performance evaluated by the DM-test reveals that the ARJI-Trend model has superior performance in the S&P 500 spot market, a result which is consistent with the finding of Chan and Maheu (2002), that the ARJI-Trend model adequately captures the time variation in the conditional jump intensity and improves both the in-sample fit and out-of-sample forecasting in the S&P 500 spot market.

Of the three indices, the mini-sized index futures market exhibits more rapid convergence to normality, as well as less trading noise, implying that this market deals with information more efficiently. This result concurs with the findings of Hasbrouck (2003) and Kurov and Lasser (2004), that the introduction of E-mini futures has led to these instruments playing a dominant role in price discovery within the index markets. Furthermore, as noted by Chiu *et al.* (2006) and Chung and Chiang (2006), the different responses to news arrivals in the S&P 500 indices may stem from market-specific characteristics associated with the market microstructure.

In conclusion, with the coexistence of trend, transitory and jump components in the volatility behavior of the S&P 500 index markets, we suggest that governments should strive to gain a firm understanding of the overall effects of changes in trading systems and policies. This would undoubtedly lead to improvements in information efficiency, thereby enabling such governments to better manage both the financial markets, and market risk. Failure to take these issues into consideration may well result in mistakes or the likelihood of erroneous decision making.

Acknowledgements

The authors would like to take this opportunity to express our sincere appreciation for the financial support provided by the National Science Council. Huimin Chung would like to gratefully acknowledge the financial support provided by the MoE ATU Plan of the National Chiao Tung University.

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