An Econometric Analysis of Asymmetric Volatility: Theory and Application to Patents

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Abstract: The purpose in registering patents is to protect the intellectual property of the rightful owners. Deterministic and stochastic trends in registered patents can be used to describe a country's technological capabilities and act as a proxy for innovation. This paper presents an econometric analysis of the symmetric and asymmetric volatility of the patent share, which is based on the number of registered patents for the top 12 foreign patenting countries in the USA. International rankings based on the number of foreign US patents, patent intensity (or patents per capita), patent share, the rate of assigned patents for commercial exploitation, and average rank scores, are given for the top 12 foreign countries. Monthly time series data from the United States Patent and Trademark Office for January 1975 to December 1998 are used to estimate symmetric and asymmetric models of the time-varying volatility of the patent share, namely US patents registered by each of the top 12 foreign countries relative to total US patents. A weak sufficient condition for the consistency and asymptotic normality of the quasi-maximum likelihood estimator (QMLE) of the univariate GJR(1,1) model is established under non-normality of the conditional shocks. The empirical results provide a diagnostic validation of the regularity conditions underlying the GJR(1,1) model, specifically the log-moment condition for consistency and asymptotic normality of the QMLE, and the computationally more straightforward but stronger second and fourth moment conditions. Of the symmetric and asymmetric models estimated, AR(1)-EGARCH(1,1) is found to be suitable for most countries, while AR(1)-GARCH(1,1) and AR(1)-GJR(1,1) also provide useful insights. Non-nested procedures are developed to test AR(1)-GARCH(1,1) versus AR(1)-EGARCH(1,1), and AR(1)-GJR(1,1) versus AR(1)-EGARCH(1,1).

***Keywords*:** Patents, patent shares, trends, volatility, GARCH, GJR, EGARCH, asymmetry, regularity conditions, asymptotic theory, international rankings, non-nested tests.

1. INTRODUCTION

Deterministic and stochastic trends in patent registrations have frequently been used to describe a country's technological capabilities and intellectual property, and have acted as a proxy for innovation (see, for example, Pavitt, 1988; Patel and Pavitt, 1995; Griliches, 1986; and Marinova, 2001). Having the world's largest economic market, the USA has consistently been a destination for registering patents by innovative US and foreign companies, as well as by individuals with intentions to commercialise new technologies. Consequently, patents registered at the US Patent and Trademark Office (PTO) represent an excellent source of information regarding research and development (R&D), technological strengths, intellectual property and market ambitions.

Most of the research on patents registered in the USA has examined snapshot images representing patent activities for a particular time period, based on a single year or on an aggregated annual information base. For example, patent data have been used in econometric models to analyse the factors affecting decisions by companies to patent innovations (Duguet and Kabla, 2000). Auction models have also been used to analyse the processes of patent acquisition and/or patent renewal (Waterson and Ireland, 2000; Crampes and Langinier, 2000). Patent numbers have been used as a measure of R&D output in several production function studies (Goel, 1999). Cross-country correlations using patents data are also very common (see, for example, Pianta, 1998). When time series data have been analysed, simple methods of estimation have been used, and tests of stationarity have typically not been reported (see, for example, Archibugi and Pianta, 1998).

Volatility in patent registrations has not previously been analysed in the literature. Patents are the most widely used indicator of industrial intellectual property. The most common variation analysed empirically is the patent share, namely patents registered at the US PTO by each of the top 12 foreign countries relative to total US patents. Variations in the patent share are of interest because the patent share is a leading indicator of technical innovation. Moreover, knowledge of the stochastic process underlying variations in the patent share provides crucial information regarding the riskiness associated with innovative activity over time. For example, futures contracts and options, and other derivatives, are used widely to design optimal hedging strategies against price risk in commodity markets. Sensible strategies for hedging, and for pricing options and other derivatives, require knowledge of the volatility of the underlying series. As volatility is generally unknown, it must be estimated. These estimated volatilities are fundamental to risk management in financial models that evaluate risk spillovers and describe the risk-return trade-off, such as in portfolio selection models, pricing of primary and secondary derivatives, valuation of warrants and options, and modelling the premium in futures prices.

Where markets for such commodities do not yet exist, such as options and futures prices on intellectual property, the estimation of volatilities associated with patent shares for different countries would seem to be a crucial first step in this direction. Thus, a primary aim of this paper is to present an econometric analysis of the symmetric and asymmetric volatility in the patent shares of the top 12 foreign countries in the USA using monthly time series data from January 1975 to December 1998.

The plan of the paper is as follows. Section 2 describes the trends and volatility in the data used, presents the Innovation Strengths Model, and provides international rankings based on the number of foreign US patents, patent intensity (or patents per capita), patent share, the rate of assigned patents for commercial exploitation, and average rank scores for the top 12 foreign countries. Section 3 discusses the structural and asymptotic properties of the time-varying AR(1)-GARCH(1,1), AR(1)-GJR(1,1) and AR(1)-EGARCH(1,1) models, and uses non-nested testing procedures to test GARCH against EGARCH, and EGARCH against GJR. A weak sufficient condition for the consistency and asymptotic normality of the quasi-maximum likelihood estimator (QMLE) of the univariate GJR(1,1) model is established under non-normality of the conditional shocks. Empirical results for the volatilities in the patent share for the top 12 foreign countries, the empirical validation of the regularity conditions underlying the models, and the outcomes of the non-nested tests, are discussed in Section 4. Some concluding remarks are given in Section 5.

2. TRENDS AND VOLATILITIES IN PATENTS DATA

2.1 Data

For over two centuries, the USA has firmly adopted the patents system as a mechanism for protection of intellectual property and stimulation of innovative activities. According to Goel (1999), the patents system is supported by government as a tool to correct market imperfections, thereby allowing imitating firms to benefit from costly technologies developed elsewhere. The system assures appropriability of returns to inventors[1], and benefits society by making the revealed

[1]A patent in the USA confers to the inventor a 17-year monopoly over the technical idea(s) covered. However, a large number of patented inventions can remain dormant without ever reaching the innovation stage (Oi, 1995).

information public knowledge after the expiry of the patent.[2]

Patent laws were introduced in the USA in the 1780s. The US patents system has steadily attracted international companies and individuals interested in developing technologies and establishing trade links. In absolute numbers, the US PTO receives by far the largest number of foreign applications (Archibugi, 1992). Not surprisingly, around 40% of all patents in the USA are granted to residents and companies of 12 foreign countries (Griliches, 1990; Goel, 1999) (see Table 1 below).

There are, however, large variations between firms and countries in terms of what costs they can afford (such as patenting fees) to protect their inventions or to purchase patents rights originating elsewhere. This paper examines trends and volatility in the patent share, or US patents of the top 12 foreign countries relative to total US patents (see Table 1). The foreign country with the largest number of US patents is Japan, followed distantly by Germany and then France. Of these 12 countries, the country with the highest patent intensity (or patents per capita) is Switzerland, followed by Japan, Sweden and Germany.[3] France and Italy have numerous patents but relatively low patent intensities, whereas Switzerland and Sweden have relatively few patents but high patent intensities.

The sample period selected for the empirical analysis covers all granted patents with dates of lodged applications between January 1975 and December 1998 (inclusive), with the data extracted on 4 April and 30 May, 2002. Patent data have been obtained from the official Internet webpage of the US PTO using the search engine available on the site (http://164.195.100.11/netahtml/search-adv.htm), and population figures were obtained from (http://www.census.gov/ipc/www/idbprint.html). The date of lodgement of granted applications for the time series is used instead of the date of issue of patents to avoid organisational delays associated with the complicated process of issuing a patent (which includes procedures such as examination, expert review, and appeals). Consequently, the data on patents by date of application represent more accurately the process of commercial protection for intellectual property and innovative outcomes from R&D.

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[2] Being an invention of the neoclassical economic model, the patents system also incorporates a number of deficiencies. For example, it has been used to establish monopoly positions in industries, such as aluminum or shoe manufacturing (Mansfield, 1993, 1995). Patent fees can also be highly prohibitive, which can discriminate against potential applicants. The patents system cannot accommodate a number of ethical and economic issues newly emerging from the scientific and technological advances in the fields of biotechnology, pharmaceutical or information technologies. Scotchmer (1991, p.40) describes the patents system as "a very blunt instrument trying to solve a very delicate problem."

[3] The small economies of Liechtenstein and Monaco have higher patent intensities than that of Switzerland (Marinova, 2001), but are not included in the analysis as their total patent numbers are very small.

Although data prior to 1975 are also available, the US PTO search algorithm does not provide consistency with the data after 1975. In addition, previous studies have indicated that, during the 1980s and 1990s, the number of patents by foreign countries in the USA surged at an unprecedented rate (see, for example, Patel and Pavitt, 1995; Kortum and Lerner, 1999; Arundel and Kabla, 1998). The US PTO updates the information on patents granted on a fortnightly basis. However, the time from application to the granting of a patent can be very long. In 1997, the US PTO estimated that it takes 22.9 months on average between a patent application being lodged and a decision (issue or rejection) being made (US PTO, 1997). Thus, any data on granted patents with application dates in 1999 and 2000 will be incomplete for purposes of estimating volatilities and conducting statistical tests. For this reason, data from 1975 to 1998 are used in this paper.

The US PTO database permits searches of patents by the country of origin of the inventor(s). However, the information available in the actual patent description for inventors residing in the USA generally includes only the name of the State[4]. Consequently, the only way to extract data on US patents held by US residents is by undertaking separate searches by State. It is not possible to include all States in a simultaneous search, as there is a limit of 35 States in the US PTO search engine. Conducting separate searches leads to double counting of patents that have inventors from more than one US State[5]. Avoiding double counting of patents for inventors residing in the USA would require checks of individual patents. Given the approximately 1.5 million patents registered by US residents for the period 1975-98, this would be an incredibly time consuming exercise. Data on foreign patents registered in the USA do not suffer from this immediate double counting problem.

2.2 Innovation Strengths Model

Numerous studies in the innovation literature have supported a direct link between patents and innovation at both the national and international levels, as well as for specific industries, companies and technologies. Some recent examples in the innovation literature include: the innovative capacity of OECD countries (Furman et al., 2002); the internationalisation of technology (Guellec and van

[4] Between January 1975 and December 1998, there are only two patents which list USA as the country of origin of the inventor. This situation has most likely resulted from a deviation from the standard data entry principle. The two patents do not list the State of the US inventors.

[5] For example, for the period 1975-98, a search of the US PTO database for the top 6 patenting States in the USA returns 240,102 entries for patents whose inventors reside in California, 127,670 for New York, 94,640 for New Jersey, 90,610 for Texas, 85,592 for Illinois, and 82974 for Pennsylvania. A combined search for the 6 States simultaneously returns 689,822 entries, which is 31,766 patents fewer that the sum of the individual searches. The greater the number of separate searches that are conducted, the greater will be the double counting of patents.

Pottelsberghe de la Potterie, 2001); the effectiveness of patents versus secrets in innovation (Arundel, 2001); overseas innovations by Japanese firms (Belderbos, 2001); the Canadian biotechnology industry (Hall and Bagchi-Sen, 2002); and the analysis of Canon’s printers and Sanyo’s photovaltaics (Watanabe et al., 2001).

Innovation is commonly defined as the commercial application of new inventions. By their nature, patents represent new technological inventions, so that patent statistics could reasonably be expected to provide a good approximation for innovation.

An Innovation Strengths Model (ISM) based on patent statistics should be able to capture the two major aspects of the innovation process, namely novelty and commercialisation. The following two statistical indicators are useful indicators in an ISM for purposes of assessing specific innovation strengths.

(1) *Patent share* (*PS*): This ratio indicates a country’s contribution to new technologies globally, and hence is a measure of innovation *novelty* strength. The patent share (PS) is given by Patel and Pavitt [1991] as:

$$PS_j = \frac{P_j}{\sum_j P_j} \quad , \qquad 0 \le PS_j \le 1,$$

where PS_j denotes the patent share of country *j*, namely the number of patents of country *j* relative to total patents in the USA, $\sum_j P_j$. The larger is PS_j, the higher is the innovation strength of a country.

(2) *Rate of assigned patents* (*RAP*): At the time of issue, the ownership of the patent can be assigned to one or more individuals and/or companies for commercial exploitation. Not all patents are commercially transformed into innovations (for example, Tsuji (2002) discusses the decoy and defence functions of patenting). However, when a patent has been assigned, the legally-protected prototype is clearly intended for *commercialisation*. Although an unassigned patent can still be exploited commercially, assigning a patent indicates an explicit intention to use it for commercial purposes. The rate of assigned patents (RAP) is given by Marinova (1999) as:

$$RAP_j = \frac{AP_j}{P_j} \ ,$$

where AP_j is the number of patents assigned to residents of country *j*. The rate equals 0 when there are no assigned patents, and equals 1 when the number of patents assigned to residents of country j equals the number of patents invented by residents of country *j*. Although unlikely, RAP_j can exceed 1 when $AP_j > P_j$, that is, when patents invented by residents outside country *j* are assigned to country *j*.

Table 2 presents the values of PS and RAP and the rankings of the twelve countries according to the two indicators, which are calculated using data from the US PTO for the period 1975 to 1998. The data on assigned patents were extracted on 30 May 2002**.**

The top performing country for the patent share is Japan, which has 16.31% of the total US patents, followed by Germany with 6.49% and France with 2.76%. Japan is also the strongest performer for the commercialisation of patents, with a rate of assigned patents of 0.969, followed by Korea with 0.914 and Germany with 0.817. A combined ranking based on the average of both indicators shows that Japan is ranked first, followed by Germany and France. Of the top twelve foreign patenting countries in the USA, the country with the least innovation strength is Australia, with a patent share of 0.48% and a rate of assigned patents of 0.57. Although the low patent share should not be surprising in view of Australia's relatively small population, the rate of assigned patents is considerably lower than the mean rate of 0.71.

The Innovation Strengths Model is based on time series data. Some countries may establish their innovation strength through a consistent effort over an extended period of time, whereas other countries may achieve similar innovation strength through a concentrated effort over a shorter period. In the remainder of this paper, the volatility of the monthly patent shares of the top 12 foreign countries in the USA are analysed to examine their patenting behaviour over time.

2.3 Trends in Patents Data

Figures 1-4 show the trends based on monthly data in US patents held by the top 12 foreign countries and in total US patents. Japan and Germany have far more US patents than the remaining ten countries. All countries exhibit positive linear or exponential trends. However, the top 12 foreign performers can be divided into two groups. Group A includes Japan, France, Canada, Taiwan, (South) Korea and UK, all of which have much higher rates of increase in patenting than those in Group B (given below). Taiwan, Korea and the UK (and to a lesser extent, Canada) had high rates of increase in the 1990s. Of particular interest are the two East Asian countries, which have started to close the technology gap with the West. According to Patel and Pavitt (1998, p.59), "technology in Taiwan and South Korea is now attaining world best practice levels in an increasing number of fields – a striking example of technological catch up compared with the advanced countries."

Group B consists of Germany, Switzerland, Italy, The Netherlands, Sweden and Australia. These countries have demonstrated a stable upward trend over the 23-year period, which is generally consistent with the increase in the overall number of total US patents.

In Figures 5-7 are given the patent shares for each of the top 12 foreign countries. Each of the series is trend stationary, with the exceptions of Japan and the UK. The patent shares for Japan show a generally increasing trend with a slight reduction at the end of the sample, whereas the reverse is true for Germany, which has a generally decreasing trend. Of the remaining group A countries, France and Canada display substantial volatility, whereas Taiwan, Korea and the UK show milder volatility around increasing deterministic trends. Apart from Germany in the Group B countries, Italy, The Netherlands and Australia have substantial volatility with no deterministic trend, whereas Switzerland has substantial volatility around a uniformly decreasing trend. Sweden displays a similar trend pattern to that of Germany, but with greater volatility.

Not surprisingly, the correlations of US patents for the top 12 countries and total US patents are very high, in general, and are given in Tables 3 and 4. As shown in Table 4, Canada is ranked first with a correlation coefficient of 0.979, follow closely by France and Japan with 0.922 and 0.916, respectively. Furthermore, correlations within the top 12 countries are also high, in general, as shown in Table 3. US patent registrations from Taiwan and UK have the highest correlation of 0.957, followed by Taiwan and Korea with 0.926. Canada and France are ranked third with a correlation coefficient of 0.903. Interestingly, five of the six countries from Group A, namely Canada, France, UK, Korea and Taiwan, are highly correlated among themselves.

2.4 Volatilities in Patent Shares

The volatilities in the patent shares can be found in Figures 8-10. Countries such as The Netherlands and Sweden are extremely volatile, especially in the late 70s and early 80s. Asian countries such as Taiwan and Korea have low volatilities during the early periods, but both become volatile in the 90s, which can be viewed as a reflection of technological catch up (as suggested in Patel and Pavitt (1998, p.59)). Volatility clustering, as commonly found in financial data, also appears to be a common feature in the patent shares data, particularly for Italy, Germany, The Netherlands, and Switzerland. Some countries, such as Australia, Korea, Taiwan and Japan also appear to have outliers in the volatilities, which is a common feature of financial time series data. Undoubtedly, these graphs provide strong support for the time-varying nature of volatilities in patent shares, which justifies the need for modelling conditional variances.

3. GARCH, GJR AND EGARCH: THEORETICAL RESULTS

The primary purpose of the empirical analysis in this paper is to obtain an optimal model of the volatility of the patent share, namely the ratio of registered US patents for the top 12 foreign countries relative to total US patents. This approach is based on Engle’s (1982) path-breaking idea of capturing time-varying volatility (or risk) using the autoregressive conditional heteroskedasticity (ARCH) model, and subsequent developments forming the ARCH family of models (see, for example, the surveys of Bollerslev, Chou and Kroner, 1992; Bollerslev, Engle and Nelson, 1994; and Li, Ling and McAleer, 2002). Of these developments, the most popular has been the generalised ARCH (GARCH) model of Bollerslev (1986), especially for the analysis of financial data. In order to accommodate asymmetric behaviour between negative and positive shocks (or movements in the time series), Glosten, Jagannathan and Runkle (1992) proposed the GJR model. Some further theoretical developments have been suggested by Wong and Li (1997), He and Teräsvirta (1999), and Ling and McAleer (2002a, b, c).

3.1 Regularity Conditions and Asymptotic Theory

Consider the stationary AR(1)-GARCH(1,1) model for the patent share, y_t:

$$y_t = \phi_1 + \phi_2 y_{t-1} + \varepsilon_t, \qquad |\phi_2| < 1 \tag{1}$$

for $t = 1,...,n$, where the shocks (or movements in the patent share) are given by:

$$\begin{aligned} \varepsilon_t &= \eta_t \sqrt{h_t}, \quad \eta_t \sim iid(0,1) \\ h_t &= \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}, \end{aligned} \tag{2}$$

and $\omega > 0, \alpha \geq 0, \beta \geq 0$ are sufficient conditions to ensure that the conditional variance $h_t > 0$. In (2), the ARCH (or α) effect indicates the short run persistence of shocks, while the GARCH (or β)

effect indicates the contribution of shocks to long run persistence (namely, $\alpha+\beta$). The stationary AR(1)-GARCH(1,1) model can be modified to incorporate a non-stationary ARMA(*p*,*q*) conditional mean and a stationary GARCH(*r*,*s*) conditional variance, as in Ling and McAleer (2002d).

In equations (1) and (2), the parameters are typically estimated by the maximum likelihood method to obtain Quasi-Maximum Likelihood Estimators (QMLE) in the absence of normality of η_t. The QMLE is efficient only if η_t is normal, in which case it is the MLE. When η_t is not normal, adaptive estimation can be used to obtain efficient estimators. Ling and McAleer (2002d) investigate the properties of adaptive estimators for univariate non-stationary ARMA models with GARCH(*r*,*s*) errors.

The conditional log-likelihood function is given as follows:

$$\sum_{t=1}^{n} l_t = -\frac{1}{2}\sum_{t=1}^{n}\left(\log h_t + \frac{\varepsilon_t^2}{h_t}\right).$$

Ling and Li (1997) showed that the GARCH(p,q) model is strictly stationary and ergodic if the second moment is finite, that is, $E(\varepsilon_t^2)<\infty$. Ling and McAleer (2002c) showed that the QMLE for GARCH(p,q) is consistent if the second moment is finite. For GARCH(p,q), Ling and Li (1997) demonstrated that the local QMLE is asymptotically normal if the fourth moment is finite, that is, $E(\varepsilon_t^4)<\infty$, while Ling and McAleer (2002c) proved that the global QMLE is asymptotically normal if the sixth moment is finite, that is, $E(\varepsilon_t^6)<\infty$. Using results from Ling and Li (1997) and Ling and McAleer (2002a, b) (see also Bollerslev (1986), Nelson (1990) and He and Teräsvirta (1999)), the necessary and sufficient condition for the existence of the second moment of ε_t for GARCH(1,1) is $\alpha+\beta<1$ and, under normality, the necessary and sufficient condition for the existence of the fourth moment is $(\alpha+\beta)^2+2\alpha^2<1$.

For the univariate GARCH(p,q) model, Bougerol and Picard (1992) derived the necessary and sufficient condition, namely the log-moment condition or the negativity of a Lyapunov exponent, for strict stationarity and ergodicity (see also Nelson (1990)). Using the log-moment condition, Elie and Jeantheau (1995) and Jeantheau (1998) established it was sufficient for consistency of the QMLE of GARCH(p,q) (see Lee and Hansen (1994) for the proof in the case of GARCH(1,1)), and

Boussama (2000) showed that it was sufficient for asymptotic normality. Based on these theoretical developments, a sufficient condition for the QMLE of GARCH(1,1) to be consistent and asymptotically normal is given by the log-moment condition, namely

$$E(\log(\alpha\eta_t^2 + \beta)) < 0\,. \tag{3}$$

However, this condition is not straightforward to check in practice, even for the GARCH(1,1) model, as it involves the expectation of a function of a random variable and unknown parameters. Although the sufficient moment conditions for consistency and asymptotic normality of the QMLE for the univariate GARCH(*p*,*q*) model given in Ling and Li (1997) and Ling and McAleer (2002a, b), and for the multivariate GARCH(*p*,*q*) model in Ling and McAleer (2002c), are stronger than their log-moment counterparts (where they exist), the second and fourth moment conditions are far more straightforward to check in practice.

The extension of the log-moment condition to multivariate GARCH(*p*,*q*) models has not yet been shown to exist, although Jeantheau (1998) showed that the multivariate log-moment condition could be verified under the additional assumption that the determinant of the unconditional variance of ε_t in (1) is finite. Jeantheau (1998) assumed a multivariate log-moment condition to prove consistency of the QMLE of the multivariate GARCH(*p*,*q*) model. An extension of Boussama's (2000) log-moment condition to prove the asymptotic normality of the QMLE of the multivariate GARCH(*p*,*q*) process is not yet available.

The effects of positive shocks (or upward movements in the patent share) on the conditional variance, h_t, are assumed to be the same as the negative shocks (or downward movements in the patent share) in the symmetric GARCH model. In order to accommodate asymmetric behaviour, Glosten, Jagannathan and Runkle (1992) proposed the GJR model, for which GJR(1,1) is defined as follows:

$$h_t = \omega + (\alpha + \gamma I(\eta_{t-1}))\varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{4}$$

where $\omega > 0, \alpha \geq 0, \alpha + \gamma \geq 0, \beta \geq 0$ are sufficient conditions for $h_t > 0,$ and $I(\eta_t)$ is an indicator variable defined by:

$$I(\eta_t) = \begin{cases} 1, & \varepsilon_t < 0 \\ 0, & \varepsilon_t \geq 0 \end{cases}$$

as η_t has the same sign as ε_t. The indicator variable differentiates between positive and negative shocks, so that asymmetric effects in the data are captured by the coefficient γ, with $\gamma \geq 0$. The asymmetric effect, γ, measures the contribution of shocks to both short run persistence, $\alpha + \frac{\gamma}{2}$, and to long run persistence, $\alpha + \beta + \frac{\gamma}{2}$.

Ling and McAleer (2002b) derived the unique strictly stationary and ergodic solution of a family of GARCH processes, which includes GJR(1,1) as a special case, a simple sufficient condition for the existence of the solution, and the necessary and sufficient condition for the existence of the moments. For the special case of GJR(1,1), Ling and McAleer (2002b) showed that the regularity condition for the existence of the second moment under symmetry of η_t is

$$\alpha + \beta + \frac{1}{2}\gamma < 1, \tag{5}$$

and the condition for the existence of the fourth moment under normality of η_t is

$$\beta^2 + 2\alpha\beta + 3\alpha^2 + \beta\gamma + 3\alpha\gamma + \frac{3}{2}\gamma^2 < 1. \tag{6}$$

Although the regularity conditions for the existence of moments for the GJR model are now well known, no theoretical results have yet been established regarding the statistical properties of the model.

A weak sufficient condition for the consistency and asymptotic normality of the QMLE of the GJR(1,1) model in (4) will be established under non-normality of η_t. Let

$$c(\eta_t) = (\alpha + \gamma I(\eta_t))\eta_t^2 + \beta. \tag{7}$$

Conditions relating to $c(\eta_t)$ lead to the following proposition.

Proposition 1. *If* $E[c(\eta_t)]^\lambda < 1$ *for some* $\lambda \in (0,1]$, *then there exists a unique, strictly stationary and ergodic solution to (4), with the following causal expansion:*

$$h_t = \omega\left[1 + \sum_{k=0}^{\infty}\prod_{j=0}^{k} c(\eta_{t-1-j})\right] \tag{8}$$

where the infinite sum converges almost surely.

Proof: Define $\Phi(\lambda) = E[c(\eta_t)]^{\lambda}$, with $\Phi(0) = 1$. Since η_t has a finite second moment, $\Phi(\lambda)$ is a twice differentiable function with

$$\Phi'(\lambda) = E[\ln[c(\eta_t)]c(\eta_t)^{\lambda}]$$

and $\Phi''(\lambda) > 0$. The function $\Phi(\lambda)$ is convex and, under the assumptions of the Proposition, $\Phi'(0) < 0$. Therefore, there exists $\lambda \in (0,1]$ such that $E[c(\eta_t)]^{\lambda} < 1$. Applying Theorem 2.1 in Ling and McAleer (2002b) yields the result. ■

Remark 1. The Proposition makes it clear that the GJR model started infinitely many periods ago, and is a consequence of the existence of the unique stationary solution.

The condition in Proposition 1 yields the following log-moment condition for the GJR(1,1) model.

Proposition 2. *If* $E[c(\eta_t)]^{\lambda} < 1$ *for some* $\lambda \in (0,1]$, *it follows that:*

$$E(\ln[(\alpha + \gamma I(\eta_t))\eta_t^2 + \beta]) < 0 . \tag{9}$$

Proof: By Jensen's inequality, $E[c(\eta_t)]^{\lambda} < 1$ is equivalent to the log-moment condition in (9). This completes the proof. ■

The log-moment condition (9) for the GJR(1,1) model specialises to (3) when $\gamma = 0$, namely the log-moment condition for the GARCH(1,1) model.

As the log-moment condition is the expectation of a function of an unknown random variable and unknown parameters, and as $(\alpha + \gamma I(\eta_t))\eta_t^2 + \beta > 0$ may not be satisfied for all *t*, stronger conditions for the existence of the second and fourth moments, as in (5) and (6), respectively, might prove useful as diagnostic checks in practice.

In order to obtain the QMLE of the GJR(1,1) model, h_t given by (2) in the log-likelihood function is replaced by (4). This leads to the asymptotic results given in the following proposition.

Proposition 3. *Under Proposition 1, when η_t is not normal the QMLE of the GJR(1,1) model given by (1) and (4) is consistent and asymptotically normal.*

Proof: Under Proposition 2, the log-moment condition in (9) holds. In addition to (9), the GJR(1,1) model in (1) and (4) satisfies the sufficient conditions for consistency given in Elie and Jeantheau (1995) and Jeantheau (1998), and the sufficient conditions for asymptotic normality given in Boussama (2000). This completes the proof. ■

Corollary 1. Stronger, and hence less general, but more straightforward conditions than the log-moment condition for consistency and asymptotic normality can be obtained for the GJR(1,1) model in (1) and (4). The second moment condition for consistency of Ling and McAleer (2002c), namely (5), implies the log-moment condition, (9), but not the reverse. Thus, when the log-moment condition is satisfied, the second moment condition need not be satisfied. Similarly, the fourth moment condition of Ling and Li (1997) for the local QMLE to be asymptotically normal, namely (6), implies the second moment condition, but not the reverse. Thus, when the log-moment condition is satisfied, the fourth moment condition need not be satisfied. Finally, the sixth moment condition of Ling and McAleer (2002c) for the global QMLE to be asymptotically normal implies the fourth moment condition, but not the reverse.

For the reasons given in Corollary 1, it would seem sensible to compute the log-moment, second and fourth moment conditions as practical diagnostic checks of the structure of the model. As the log-moment condition is weaker than the second and fourth moment conditions, the latter two need not be examined if the log-moment condition is satisfied. Based on these theoretical results, the structure and asymptotic theory of the GJR(1,1) model is now complete.

An alternative model to capture asymmetric behaviour in the conditional variance is the Exponential GARCH (EGARCH(1,1)) model of Nelson (1991), namely:

$$\log h_t = \omega + \alpha \,|\, \eta_{t-1} \,| + \gamma \eta_{t-1} + \beta \log h_{t-1}, \quad |\, \beta \,| < 1 . \tag{10}$$

There are some distinct differences between EGARCH and the previous two GARCH models, as follows: (i) EGARCH is a model of the logarithm of the conditional variance, which implies that no restrictions on the parameters are required to ensure $h_t > 0$; (ii) Nelson (1991) showed that $|\beta| < 1$ ensures stationarity and ergodicity for EGARCH(1,1); (iii) Shephard (1996) observed that $|\beta| < 1$ is likely to be a sufficient condition for consistency of QMLE for EGARCH(1,1); (iv) as the conditional (or standardized) shocks appear in equation (4), $|\beta| < 1$ would seem to be a sufficient condition for the existence of moments; (v) in addition to being a sufficient condition for consistency, $|\beta| < 1$ is also likely to be sufficient for asymptotic normality of the QMLE of EGARCH(1,1).

Furthermore, EGARCH captures asymmetries differently from GJR. The parameters α and γ in EGARCH(1,1) represent the magnitude (or size) and sign effects of the conditional (or standardized) shocks, respectively, on the conditional variance, whereas α and $\alpha + \gamma$ represent the effects of positive and negative shocks, respectively, on the conditional variance in GJR(1,1).

3.2 Nested and Non-nested Tests

As GARCH is nested within GJR, based on the theoretical results in Section 3.1, an asymptotic t-test of $H_0 : \gamma = 0$ can be used to test GARCH against GJR. However, as EGARCH is non-nested with regard to both GARCH and GJR, non-nested procedures are required to test EGARCH versus GARCH and EGARCH versus GJR. Ling and McAleer (2000) proposed a simple non-nested procedure to test GARCH versus EGARCH. Denoting GARCH in (1) and (2) as the null hypothesis and EGARCH in (1) and (10) as the alternative, the optimal test statistic for $H_{GARCH} : \delta = 0$ in (1), (2) and (11) is given by:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \delta \hat{g}_t \tag{11}$$

where $\hat{g}_t$ is the generated one-period ahead conditional variance of EGARCH. For the reverse case, that is, denoting EGARCH as the null hypothesis and GARCH as the alternative, the optimal test statistic for $H_{EGARCH} : \delta = 0$ in (1), (10) and (12) is given by:

$$\log g_t = \omega + \alpha |\eta_{t-1}| + \gamma \eta_{t-1} + \beta \log g_{t-1} + \delta \log \hat{h}_t \tag{12}$$

where g_t denotes the conditional variance of EGARCH and $\hat{h}_t$ is the generated one-period ahead conditional variance of GARCH. Ling and McAleer (2000) showed that the QMLE of δ in both (1), (2) and (11) and (1), (10) and (12) are asymptotically normal under their respective null hypotheses, and consistent under their respective alternative hypotheses. They also derived the power functions of both test statistics under their respective local alternative hypotheses.

It is possible to develop non-nested tests to test EGARCH versus GJR using a similar approach to the above. If EGARCH in (1) and (10) is the null hypothesis and GJR in (1) and (4) is the alternative, the test statistic for $H_{EGARCH}:\delta=0$ in (1), (10) and (13) is given by:

$$\log g_t = \omega + \alpha |\eta_{t-1}| + \gamma\eta_{t-1} + \beta \log g_{t-1} + \delta \log \hat{f}_t \qquad (13)$$

where $\hat{f}_t$ is the generated one-period ahead conditional variance of GJR. Similarly, when GJR is the null hypothesis and EGARCH the alternative, the test statistic for $H_{GJR}:\delta=0$ in (1), (4) and (14) is given by:

$$f_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma I(\eta_{t-1})\varepsilon_{t-1}^2 + \beta f_{t-1} + \delta \log \hat{g}_t \qquad (14)$$

Using modifications of the results of Ling and McAleer (2000), which assumed some theoretical results established in Ling and McAleer (2002a,b), it can be shown that the QMLE of δ in both (1), (2) and (13) and (1), (2) and (14) are asymptotically normal under their respective null hypotheses, and consistent under their respective alternative hypotheses.

A weaker sufficient condition for the validity of the non-nested tests of GARCH in (11) and GJR in (14) would be an adaptation of the log-moment conditions in (3) and (9), respectively, under the respective null hypotheses

4. EMPIRICAL RESULTS

4.1 Estimation

This section models the volatility of the patent share, or US patents by the top 12 foreign countries relative to total US patents. The AR(1)-GARCH(1,1), AR(1)-GJR(1,1) and AR(1)-EGARCH(1,1) models, as defined in (1)-(2), (1)-(4) and (1)-(10), respectively, are estimated using data for the top 12 foreign countries in the USA. The estimates for the three models are given in Tables 5, 6 and 7, respectively, and the log-moment conditions are evaluated at their sample mean values for equations (3) and (9). Proposition 3 in Section 3 can be used for inferences regarding the GJR(1,1) model.

4.1.1 AR(1)-GARCH(1,1)

The estimated parameters, and hence conditional volatilities, in Table 5 vary wildly across countries. When the estimates of α and/or β are negative, this will not guarantee that the estimated volatility is positive. However, unless otherwise stated, all models which fail to satisfy the sufficient conditions for $h_t > 0$ in this paper nevertheless yield positive estimates of conditional volatility, as required.

Three countries fail to satisfy the second moment condition for GARCH(1,1), namely, France, Korea and Taiwan, although the failure is only marginal for the first two countries. Five countries fail to satisfy the fourth moment condition, namely France, Korea, Sweden, UK and Taiwan, with the result for Taiwan arising from an extremely high estimated α (or short run persistence). Interestingly, all Asian countries have high estimated α values, and relatively low estimated β values, which reflect high levels of short run persistence. The dramatic growth in registered patents in these countries is consistent with the rapid economic growth in Asian countries in the 1980s and 1990s.

Although three countries fail to satisfy the second moment condition, only France and Taiwan fail to satisfy the weaker log-moment condition. This outcome is not surprising as the estimated short run persistence, $\hat{\alpha}+\hat{\beta}$, is larger for both France and Taiwan than for Korea. Thus, although $\hat{\alpha}+\hat{\beta}>1$ for Korea, which suggests that the second moment is not finite, the QMLE is still consistent and asymptotically normal because the log-moment condition is satisfied.

Two countries, namely Australia and Italy, have negative estimates of β, indicating that GARCH may not be an appropriate model. It is interesting to note that the LM test proposed in Engle (1982) and Bollerslev (1986) did not reject the null hypothesis of the absence of GARCH effects, but the results reported in Section 4.1.2 below will show that Australia has a significant asymmetric GARCH effect.

Italy also has a negative estimate of β. Thus, even though Australia and Italy satisfy the second and fourth moment conditions, the GARCH model does not seem to be appropriate as it is possible to obtain negative conditional variances. Another interesting feature is that the α and β estimates for other European countries, such as France, Germany, UK, The Netherlands and Sweden, are reasonably similar in magnitude to those using financial time series data.

4.1.2 AR(1)-GJR(1,1)

The number of countries failing to satisfy the second moment condition for GJR(1,1) in Table 6 has decreased to three, namely UK, The Netherlands and Taiwan, with only Taiwan being extreme, arising from an excessively high estimated short run persistence in shocks (that is, $\hat{\alpha}$).

Unlike the case of AR(1)-GARCH(1,1), only The Netherlands and Taiwan fail to satisfy the log-moment condition. Interestingly, the log-moment conditions for Taiwan are similar for both GARCH and GJR. Although $\hat{\alpha}+\hat{\beta}>1$ for the UK, the log-moment condition is satisfied, so that the QMLE are consistent and asymptotically normal.

As mentioned previously, the LM test failed to reject the null hypothesis of the absence of GARCH effects for Australia. However, the asymptotic t-ratio for the γ estimate for Australia is highly significant. Furthermore, the β estimate is now positive, though insignificant, and the α estimate is also insignificant. These results for GJR suggest that only negative shocks have a significant impact on volatility, whereas the impact of positive shocks is negligible. A similar result holds for The Netherlands. Although the estimates of the GARCH model for The Netherlands satisfy the second and fourth moment conditions, as well as the log-moment condition, the estimates for the more general GJR model fail to satisfy any of these sufficient conditions. Moreover, the γ estimate is much larger than the α estimate, which suggests that negative shocks have a more significant impact on the conditional variance than positive shocks.

Furthermore, four countries have negative estimates of γ, namely, France, Italy, Japan and Korea, with the estimates for Italy and Korea being significant. Only France and Italy fail to satisfy the condition that $\alpha+\gamma>0$, which implies that the positivity of the conditional variances associated with negative shocks is not guaranteed.

The β estimate for Italy arising from GJR is now positive, as compared with the negative estimate for GARCH, which implies that the sign of the estimates arising from these models can provide important information regarding model misspecification. This is an interesting area for future research.

4.1.3 AR(1)-EGARCH(1,1)

As shown in Table 7, all the β estimates from EGARCH(1,1) for all countries are less than one in absolute value, which suggests that all moments exist, with the estimates likely to be consistent and asymptotically normal. There is no parametric restriction for conditional volatility to be positive, as EGARCH is a model of the logarithm of the conditional variances.

Overall, the size effects have positive impacts on the conditional variances except in two cases, namely France and Italy. Furthermore, the γ estimates of these two countries, along with Korea, are higher than for the corresponding α estimates. This indicates that the sign effects have larger impacts than size effects on the conditional variances.

It is also important to note that none of the three models is adequate for the UK. Apart from failing to satisfy the fourth moment condition for GARCH(1,1), as well as the second and fourth moment conditions for GJR(1,1), EGARCH(1,1) does not seem to be identifiable for the UK as the α and γ estimates are not statistically significant. As Engle's (1982) LM test does not reject the null hypothesis of the absence of an ARCH effect for the UK, one possible explanation is that there is no ARCH or GARCH effect in the series.

4.2 Non-nested Tests

Non-nested tests of GARCH(1,1) versus EGARCH(1,1) and GJR(1,1) versus EGARCH(1,1) can be calculated using the testing procedures proposed in Ling and McAleer (2000), and further developed in Section 3 above. Table 8 shows the results of two sets of non-nested tests, namely GARCH versus EGARCH and GJR versus EGARCH.

As shown in Table 8, the test fails to discriminate between GARCH and EGARCH for six countries, namely, France, The Netherlands, Sweden, Switzerland, Taiwan and the UK, rejecting both models in all cases. Except for Germany, which favours GARCH over EGARCH, EGARCH is favoured over GARCH for the remaining five countries. Moreover, in testing EGARCH versus GJR, EGARCH is favoured for five countries, namely Canada, France, Germany, Japan, and The Netherlands. The non-nested tests, however, fail to discriminate between EGARCH and GJR for the remaining seven countries, rejecting both models in six cases and failing to reject either model in the case of Australia. It is interesting to note that the non-nested tests do not provide strong support for GJR against EGARCH for any of the 12 countries.

It would seem that the best model for both Canada and Japan is EGARCH. However, the non-nested tests do not provide a definitive conclusion for the remaining ten countries, which may arise, in part, from the presence of outliers in the series. It is important to note that none of the three models was designed to accommodate extreme observations and/or outliers. It is well known that these observations have significant impacts on the QMLE (see for example, Verhoeven and McAleer (1999)), which can subsequently affect the performance of the non-nested tests. Therefore, appropriate methods of accommodating these observations are important in order to apply these tests more efficaciously.

5. CONCLUDING REMARKS

This paper analysed the trends and volatilities in registered US patents for the top 12 foreign patenting countries in the USA from 1975 to 1998. The time-varying volatility of the patent share, namely US patents lodged by each of the top 12 foreign countries relative to total US patents, was examined using monthly data for 1975 - 1998 from the US PTO.

A weak sufficient condition for the consistency and asymptotic normality of the quasi-maximum likelihood estimator (QMLE) of the univariate GJR(1,1) model was established under non-normality of the conditional shocks. Therefore, the structure and asymptotic theory of the GJR(1,1) model is now complete.

Based on the moment conditions, log-moment condition, significance of the estimates and non-nested tests, the asymmetric AR(1)-GJR(1,1) model was found to be suitable for Australia, while the best model for Switzerland and The Netherlands was the symmetric AR(1)-GARCH(1,1). An alternative asymmetric model, AR(1)-EGARCH(1,1), was found to be suitable for Canada, France, Germany, Italy, Japan, Korea, Sweden and Taiwan.

Future research will focus on the effects of extreme observations and outliers on the estimates and diagnostic tests of these models. Appropriate methods to accommodate such abberrant observations would be helpful in modelling these time series data more accurately and efficiently.

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Table 1. US Patents and Patent Intensity for Selected Countries, 1975(1) –1998(2)

Country	US Patents	US Patents Ranking	Patent Intensity*	Patent Intensity Ranking
Japan	429,228	1	3,405	2
Germany	170,875	2	2,076	4
France	72,595	3	1,233	8
Canada	52,354	4	1,709	5
Switzerland	34,684	5	4,800	1
Italy	30,302	6	527	10
Taiwan (China)	28,647	7	1,313	7
Netherlands	24,461	8	1,558	6
Sweden	22,960	9	2,589	3
United Kingdom	22,052	10	373	12
Korea	20,159	11	433	11
Australia	12,734	12	678	9
US Patents by Top 12 Foreign Countries	921,051		1,589	
Total US patents	2,397,490			
US Patents by Top 12 Relative to Total US Patents	38.4%			

Notes: 1. The patent data were extracted on 4 April 2002.

2. Patent intensity denotes US patents per million of 1998 population

3. Sources of data: http://164.195.100.11/netahtml/search-adv.htm and http://www.census.gov/ipc/www/idbprint.html

Table 2. Patent Shares (PS), Rate of Assigned Patents (RAP) and Rankings, 1975-1998

Country	**PS (%)**	**RAP**	**PS rank**	**RAP rank**	**Average rank score**	**Ranking of average rank score**
Japan	16.31	0.969	1	1	1	1
Germany	6.49	0.817	2	3	2.5	2
France	2.76	0.793	3	5	4	3
Switzerland	1.32	0.794	5	4	4.5	4
Korea	0.77	0.914	11	2	6.5	5
Italy	1.15	0.727	6	7	6.5	5
Canada	1.99	0.536	4	10	7	7
Sweden	0.87	0.751	9	6	7.5	8
United Kingdom	0.84	0.605	10	8	9	9
Netherlands	0.93	0.523	8	11	9.5	10
Taiwan	1.09	0.402	7	12	9.5	10
Australia	0.48	0.570	12	9	10.5	12

Note: The data on assigned patents were extracted on 30 May 2002.

Table 3. Correlation Coefficients of US Patents Among the Top 12 Foreign Countries, 1975(1)-1998(12)

Country	Australia	Canada	France	Germany	Italy	Japan	Korea	Netherlands	Sweden	Switzerland	Taiwan	UK
Australia	1.000	0.826	0.775	0.715	0.769	0.801	0.739	0.738	0.661	0.525	0.783	0.784
Canada	0.826	1.000	0.903	0.741	0.844	0.890	0.841	0.877	0.758	0.615	0.887	0.893
France	0.775	0.903	1.000	0.727	0.897	0.851	0.761	0.859	0.718	0.629	0.774	0.788
Germany	0.715	0.741	0.727	1.000	0.747	0.877	0.625	0.722	0.835	0.415	0.685	0.691
Italy	0.769	0.844	0.897	0.747	1.000	0.857	0.694	0.818	0.672	0.527	0.744	0.744
Japan	0.801	0.890	0.851	0.877	0.857	1.000	0.775	0.848	0.750	0.452	0.831	0.806
Korea	0.739	0.841	0.761	0.625	0.694	0.775	1.000	0.785	0.739	0.423	0.926	0.899
Netherlands	0.738	0.877	0.859	0.722	0.818	0.848	0.785	1.000	0.730	0.561	0.789	0.813
Sweden	0.661	0.758	0.718	0.835	0.672	0.750	0.739	0.730	1.000	0.466	0.741	0.787
Switzerland	0.525	0.615	0.629	0.415	0.527	0.452	0.423	0.561	0.466	1.000	0.419	0.492
Taiwan	0.783	0.887	0.774	0.685	0.744	0.831	0.926	0.789	0.741	0.419	1.000	0.957
UK	0.784	0.893	0.788	0.691	0.744	0.806	0.899	0.813	0.787	0.492	0.957	1.000

Note: The patent data were extracted on April 2002.

Table 4. Correlation Coefficients of US Patents by the Top 12 Foreign Countries with Total US Patents, 1975(1) – 1998(12)

Country	Total	Rank
Australia	0.839	9
Canada	0.979	1
France	0.922	2
Germany	0.762	11
Italy	0.863	8
Japan	0.916	3
Korea	0.864	7
Netherlands	0.887	6
Sweden	0.770	10
Switzerland	0.634	12
Taiwan	0.899	4
UK	0.898	5

Note: The patent data were extracted on 4 April 2002.

Table 5. GARCH(1,1) Estimates of US Patent Shares for the Top 12 Foreign Countries, 1975(1) - 1998(12) (asymptotic t-ratios in parentheses)

	Parameters			Moments		
Country	ω	α	β	Log	Second	Fourth
Australia	2.13E-06 (1.857)	0.065 (0.803)	-0.384 (-0.587)	-1.167	-0.319	0.110
Canada	7.62E-07 (0.810)	0.052 (1.18)	0.790 (3.641)	-0.176	0.842	0.714
France	-1.63E-07 (-4.043)	0.028 (6.20)	0.981 (14.776)	0.009	1.008	1.018
Germany	1.50E-06 (0.429)	0.052 (0.50)	0.923 (6.025)	-0.028	0.975	0.956
Italy	1.00E-05 (11.162)	0.128 (4.76)	-0.906 (-20.949)	N.C.	-0.778	0.638
Japan	0.000112 (1.818)	0.332 (2.362)	0.445 (2.110)	-0.493	0.776	0.822
Korea	2.37E-07 (0.873)	0.313 (1.632)	0.691 (4.798)	-0.109	1.004	1.205
Netherlands	1.01E-08 (0.255)	0.051 (1.96)	0.944 (29.613)	-0.006	0.995	0.996
Sweden	1.02E-07 (0.431)	0.119 (0.783)	0.868 (5.405)	-0.033	0.986	1.001
Switzerland	2.95E-08 (0.737)	0.052 (3.06)	0.937 (44.033)	-0.013	0.990	0.985
Taiwan	2.73E-09 (2.139)	0.758 (5.79)	0.526 (9.067)	0.006	1.284	2.795
UK	2.59E-08 (0.748)	0.146 (1.096)	0.849 (7.073)	-0.014	0.995	1.034

Notes: 1. The log-moment, second moment and fourth moment conditions for the GARCH(1,1) model are given in (3), (5) for $\gamma = 0$, and (6) for $\gamma = 0$, respectively.

2. N.C. denotes that the mean log-moment was “not calculated” as the log-moment for one observation could not be calculated.

3. The patent data were extracted on 4 April 2002.

Table 6. GJR(1,1) Estimates of US Patent Shares for the Top 12 Foreign Countries, 1975(1) – 1998(12) (asymptotic t-ratios in parentheses)

	Parameters				Moments		
Country	ω	α	γ	β	Log	Second	Fourth
Australia	1.31E-06 (3.359)	0.001 (0.0122)	0.408 (2.323)	0.035 (0.171)	-2.435	0.240	0.141
Canada	1.76E-06 (2.881)	-0.084 (-5.700)	0.269 (2.636)	0.594 (3.808)	-0.508	0.644	0.420
France	1.31E-06 (1.555)	0.086 (1.328)	-0.140 (-1.739)	0.869 (11.157)	-0.136	0.884	0.783
Germany	3.415E-05 (0.496)	0.146 (0.424)	0.034 (0.0619)	0.623 (0.918)	-0.363	0.785	0.669
Italy	6.36E-07 (2.152)	0.097 (2.160)	-0.183 (-3.130)	0.862 (13.985)	-0.160	0.868	0.754
Japan	1.51E-05 (1.677)	0.265 (3.385)	-0.064 (-0.668)	0.698 (8.561)	-0.120	0.932	0.976
Korea	1.04E-07 (3.237)	0.394 (5.271)	-0.574 (-6.063)	0.843 (27.670)	-0.111	0.951	0.927
Netherlands	-3.98E-08 (-3.743)	0.001 (0.601)	0.032 (4.174)	0.999 (40.774)	0.014	1.015	1.031
Sweden	5.14E-08 (0.349)	0.0920 (0.640)	0.0008 (0.005)	0.901 (7.381)	-0.017	0.993	1.003
Switzerland	1.49E-08 (0.349)	0.030 (1.270)	0.037 (1.171)	0.947 (39.758)	-0.008	0.996	0.996
Taiwan	2.76E-09 (2.147)	0.735 (3.766)	0.040 (0.155)	0.527 (9.011)	0.006	1.282	2.785
UK	1.399E-08 (0.587)	0.173 (0.128)	0.099 (0.278)	0.822 (6.429)	-0.002	1.044	1.187

Notes: 1. The log-moment, second moment and fourth moment conditions for the GJR(1,1) model are given in (9), (5) and (6), respectively.

2. The patent data were extracted on 4 April 2002.

Table 7. EGARCH(1,1) Estimates of US Patent Shares for the Top 12 Foreign Countries, 1975(1) – 1998(12)
(asymptotic t-ratios in parentheses)

Country	ω	α	γ	β
Australia	-4.316	0.128	-0.048	0.684
	(-0.647)	(0.852)	(-0.859)	(1.381)
Canada	-22.291	0.194	-0.052	-0.806
	(-14.509)	(2.014)	(-0.857)	(-6.172)
France	-6.651	-0.105	0.273	0.406
	(-2.825)	(-0.810)	(3.387)	(1.946)
Germany	-15.644	0.526	-0.010	-0.546
	(-10.553)	(3.059)	(-0.191)	(-3.517)
Italy	-3.155	-0.203	0.373	0.731
	(-4.049)	(-2.277)	(4.819)	(10.735)
Japan	-2.627	0.584	0.081	0.754
	(-3.114)	(6.241)	(1.272)	(7.990)
Korea	-8.719	0.0252	0.0976	0.2817
	(-22.383)	(2.205)	(9.947)	(7.926)
Netherlands	-0.353	0.107	0.021	0.979
	(-0.796)	(1.849)	(0.509)	(29.281)
Sweden	-5.027	0.478	0.237	0.632
	(-2.487)	(2.940)	(2.492)	(4.040)
Switzerland	-6.454	0.410	-0.232	0.514
	(-2.538)	(3.362)	(-2.652)	(2.554)
Taiwan	-3.871	1.140	-0.078	0.768
	(-11.004)	(8.354)	(-0.727)	(27.183)
UK	-8.301	0.103	0.006	0.363
	(-2.090)	(1.864)	(0.806)	(59.412)

Note: The patent data were extracted on 4 April 2002.

Table 8. Non-nested Tests of GARCH versus EGARCH and GJR versus EGARCH for US Patent Shares, 1975(1) – 1998(12)

Country	H_0 : GARCH H_A : EGARCH	H_0 : EGARCH H_A : GARCH	H_0 : EGARCH H_A : GJR	H_0 : GJR H_A : EGARCH
Australia	2.4658	0.3068	0.5797	1.8668
Canada	8.3346	0.0686	0.4668	5.5633
France	2.8839	3.2900	0.7849	8.6868
Germany	0.6332	3.8912	1.7944	13.3718
Italy	6.1631	0.2263	2.5292	5.6725
Japan	5.8698	0.1864	0.0861	3.6386
Korea	2.9693	0.5817	2.3410	3.5734
Netherlands	2.1601	2.4631	1.9274	2.2969
Sweden	4.2916	2.3712	2.5406	5.0537
Switzerland	2.0703	5.3307	5.6900	11.4745
Taiwan	5.9372	3.3539	3.6908	7.7450
UK	4.1017	13.1239	10.9485	9.2034

Notes: 1. Entries in columns 2-5 are the calculated asymptotic non-nested t-ratios from equations (11)-(14), respectively.

2. The patent data were extracted on 4 April 2002.

Figure 1. Total US Patents by Date of Application, 1975(1)-1998(12)

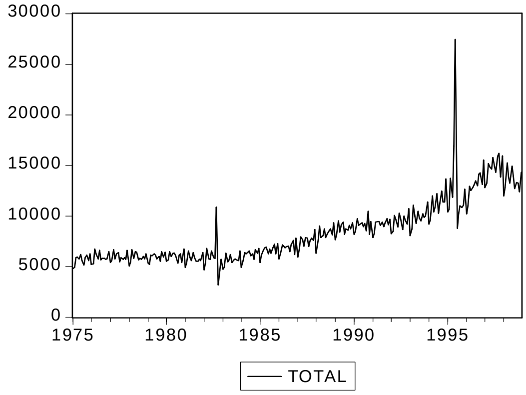

Figure 2. US Patents held by Japan and Germany,
by Date of Application, 1975(1)-1998(12)

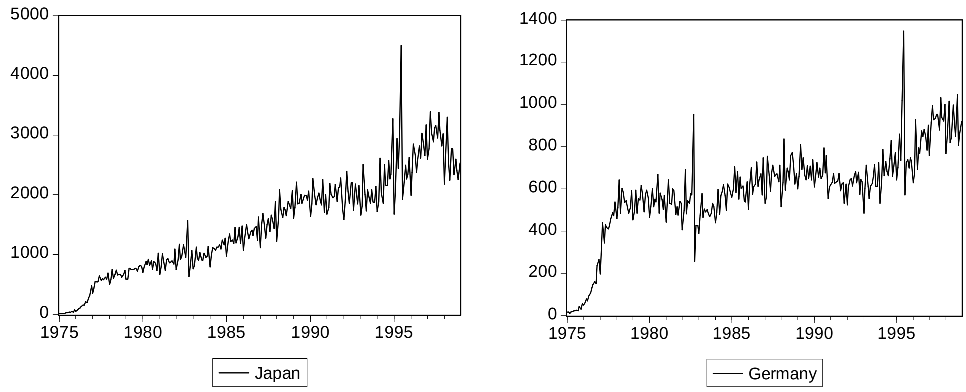

Figure 3. US Patents held by France, Canada, Switzerland, Italy and Taiwan,
by Date of Application, 1975(1)-1998(12)

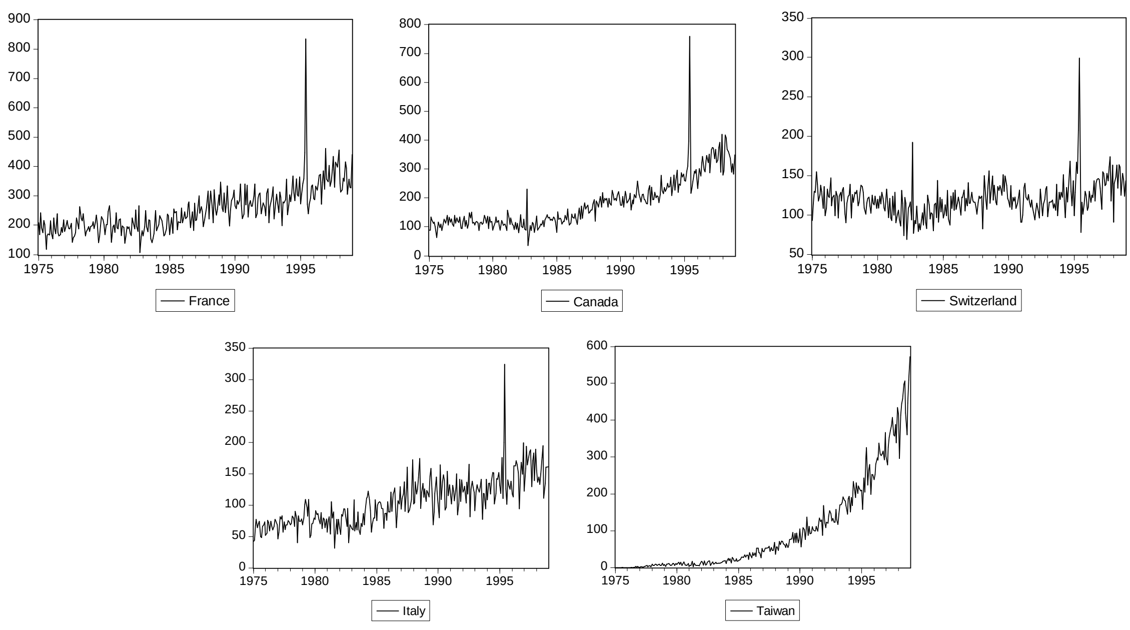

Figure 4. US Patents held by The Netherlands, Sweden, UK, Korea and Australia, by Date of Application, 1975(1)-1998(12)

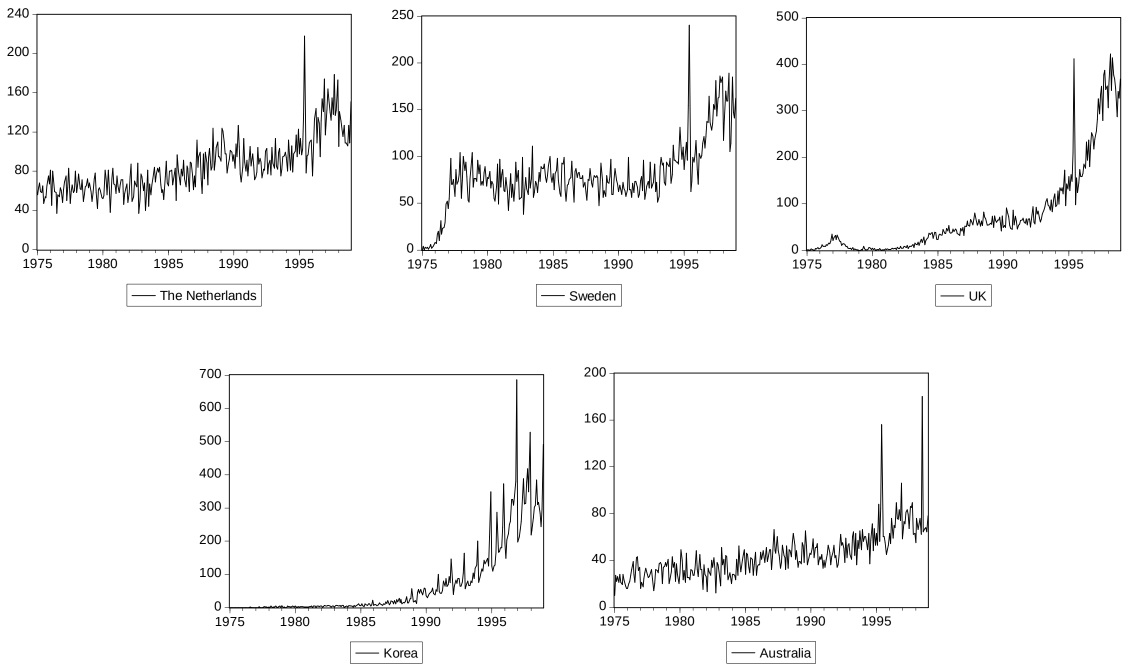

Figure 5. US Patent Shares for Japan and Germany, by Date of Application, 1975(1)-1998(12)

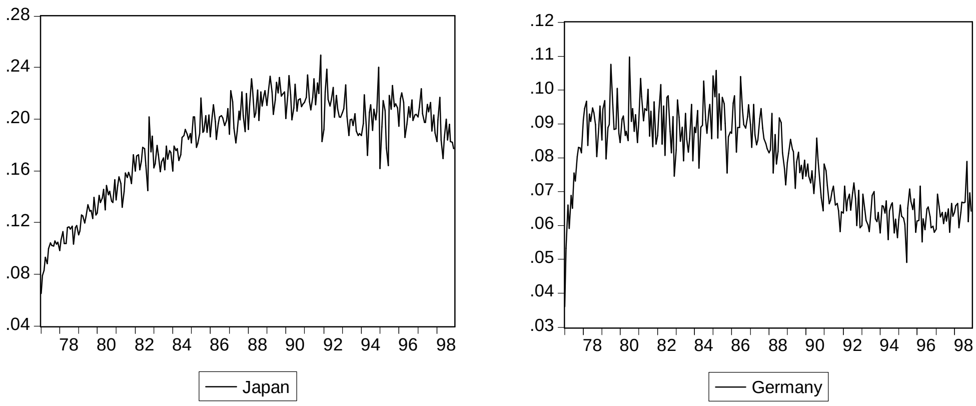

Figure 6. US Patent Shares for France, Canada, Switzerland, Italy and Taiwan, by Date of Application, 1975(1)-1998(12)

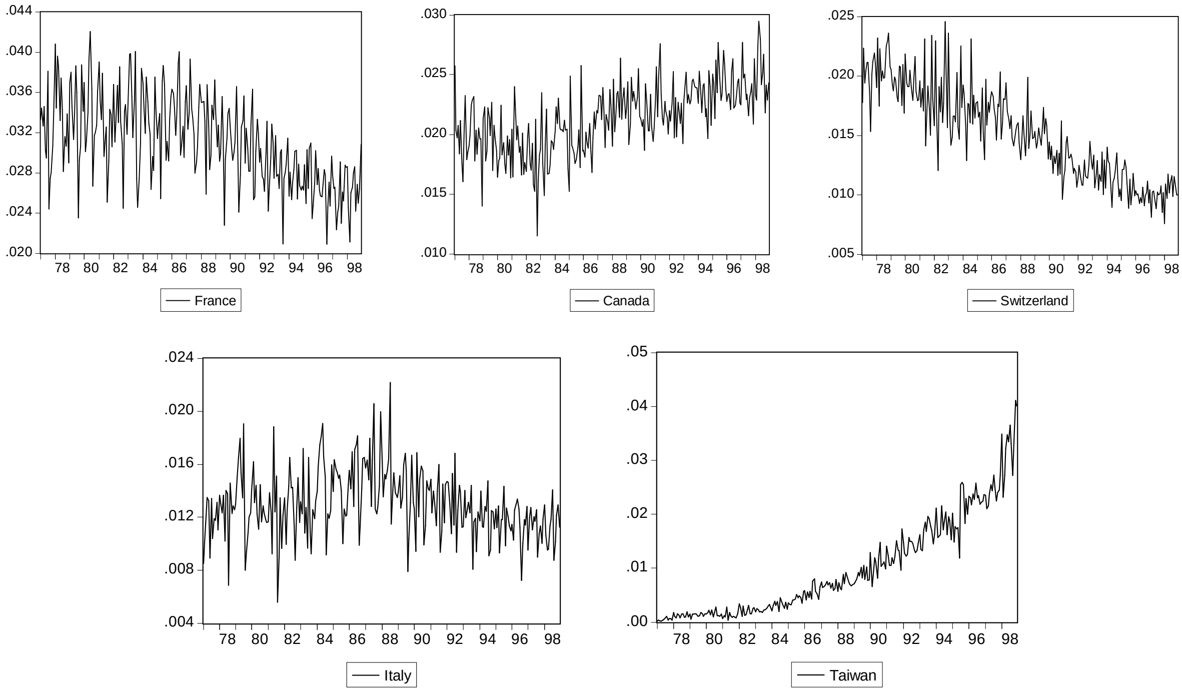

Figure 7. US Patent Shares for The Netherlands, Sweden, UK, Korea and Australia, by Date of Application, 1975(1)-1998(12)

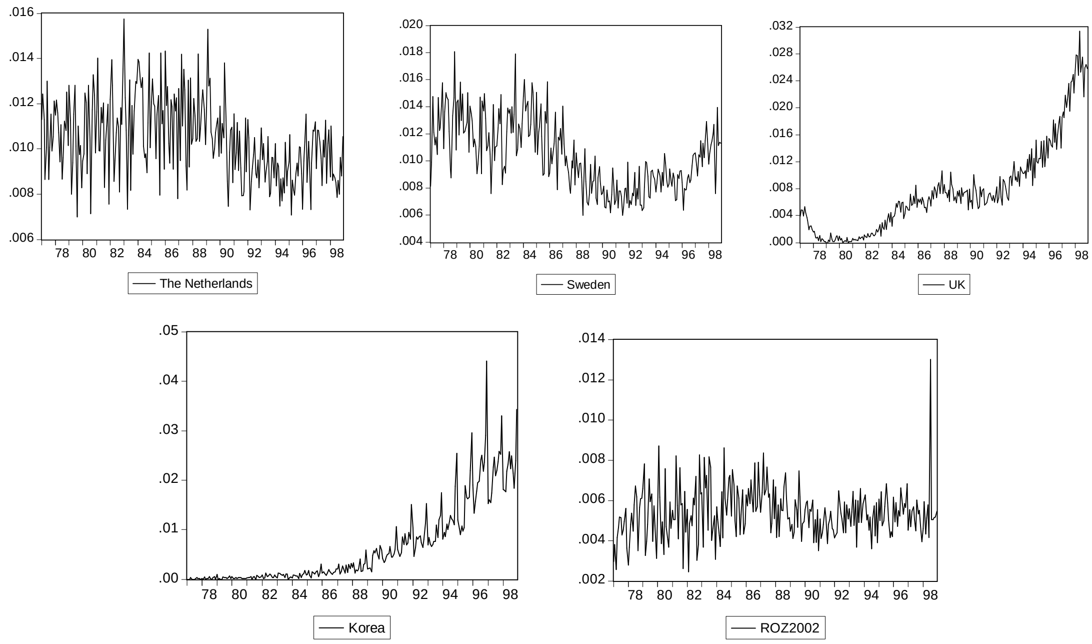

Figure 8. Volatility of US Patent Shares of Japan and Germany, by Date of Application, 1975(1)-1998(12)

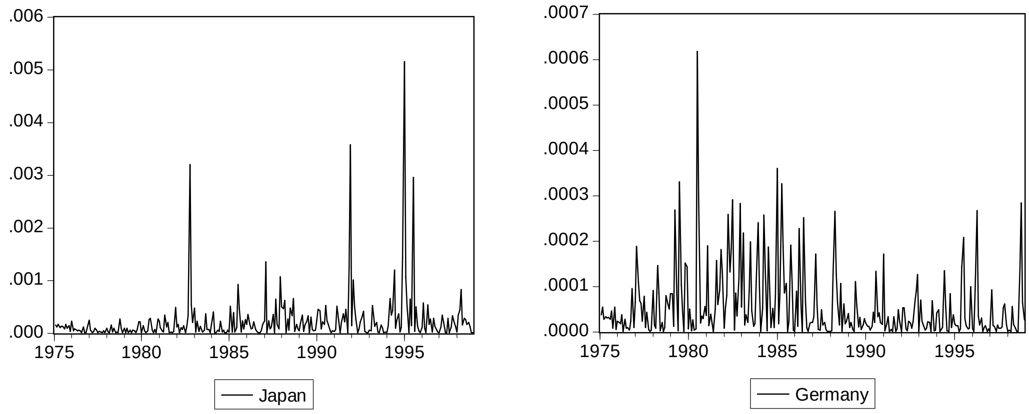

Figure 9. Volatility of US Patent Shares of France, Canada, Switzerland, Italy and Taiwan, by Date of Application, 1975(1)-1998(12)

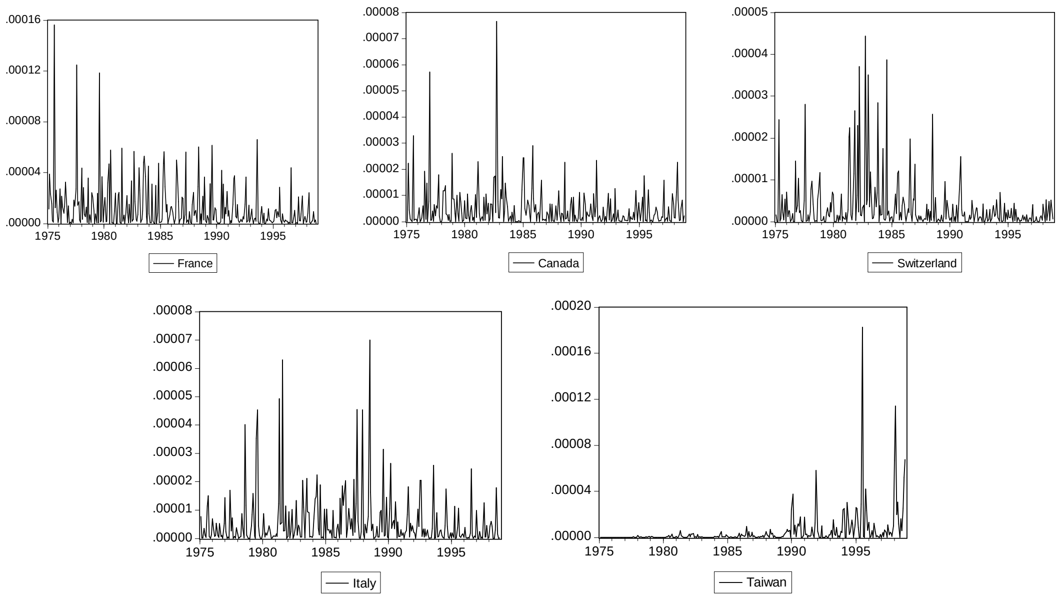

Figure 10. Volatility of US Patent Shares of The Netherlands, Sweden, UK, Korea and Australia, by Date of Application, 1975(1)-1998(12)