Modelling the Asymmetric Volatility of Anti-pollution Technology Patents Registered in the USA

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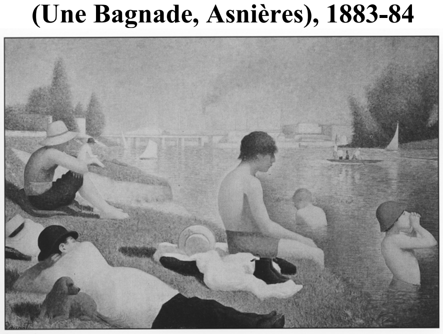
Abstract: The paper analyses the asymmetric volatility of patents related to pollution prevention and abatement (that is, anti-pollution) technologies registered in the USA. Ecological and pollution prevention technology patents have increased steadily over time, with the 1990's having been a period of intensive patenting of technologies related to the environment. The time-varying nature of the volatility of anti-pollution technology patents registered in the USA is examined using monthly data from the US Patent and Trademark Office for the period January 1975 to December 1999. Alternative symmetric and asymmetric volatility models, such as GARCH, GJR and EGARCH, are estimated and tested against each other.

Keywords: Anti-pollution patents, trends, volatility, GARCH, GJR, EGARCH, asymmetry, nested models, non-nested models.

1. INTRODUCTION

Since the Industrial Revolution in the 18th Century, technology has dominated the economic, social and environmental fabric of society. From its earliest days, industrial development was associated with pollution. For example, smoke, fumes and fog-laden air can be seen clearly in the beautiful city landscapes painted by impressionists who depicted images directly from nature. The general tones, effects and vivid colours in paintings such as Claude Monet's "The Tames at Westminster" (painted in 1871), Georges Seurat's neo-impressionist "Bathing at Asnières" (1983-84, see Figure 1) and "Entrance to the Port of Honfleur" (1886), or Camille Pissaro's "Pont Neuf – A Winter Morning" (painted near his death in 1903), show that pollution has long left its ominous mark on the ecological environment. Only in recent decades, however, has the serious environmental damage caused by pollution been recognised.

Figure 1. George Seurat: Bathing at Asnières (Une Bagnade, Asnières), 1883-84



Billions of tons of carbon and other harmful elements produced through the burning of fossil fuels are added to the earth's atmosphere each year (Dunn and Peterson, 2001), with the emission of CO_2 alone totalling more than 22.6 billions in 1996 (World Bank, 2001). This enormous pollution has caused global warming and climate change, and posed major threats to the inhabitants of the planet.

Major expectations for dealing with the impact of pollution have been imposed on both human creativity and the development of technologies which can prevent or abate the problem. For purposes of this paper, "anti-pollution technologies" incorporate the range of technical solutions to the problem of pollution. The paper examines the trends and volatilities in the patenting of anti-pollution technologies in the USA, the world's largest and technologically most advanced market, using monthly data from the US Patent and Trademark Office (PTO) from January 1975 to December 1999.

The plan of the paper is as follows. Section 2 describes the data used. Section 3 discusses various symmetric and asymmetric volatility models, including GARCH, GJR and EGARCH. The empirical results regarding trends and volatilities in anti-pollution patent registrations are presented in Section 4. Some concluding remarks are given in Section 5.

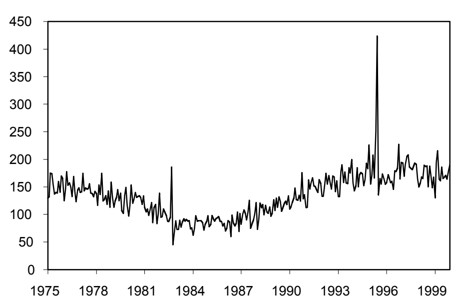
2. DATA

The US Patent and Trademark Office patent database (URL http://164.195.100.11/netahtml/search-adv.htm), which is organised according to both the US and international classifications of technologies, does not include a special class for anti-pollution technologies. Consequently, extracting empirical information is a challenging exercise which requires the development of working rules and definitions (see Marinova and McAleer (2003a) for a detailed analysis of the nanotechnology industry). In the present case, the definition implies that a registered patent falls within the category of "anti-pollution patents" if its abstract, claims or specifications include the word "pollution".

It was decided to analyse the time series of patents according to the application date rather than the approval date in order to avoid artificial distortions of the data caused by organisational delays in the process of granting patents. The data were extracted on 26 January 2003.

Figure 2 shows the trends in anti-pollution patenting in the USA, based on monthly data from January 1975 to December 1999. The graph exhibits two trends, namely downward sloping from the mid-1970s to the mid-1980s, and upward sloping from the mid-1980s to the mid-1990s, followed by stabilisation in the late-1990s. It would seem that the interest in anti-pollution patents diminished in the mid-1980s after higher levels in the late-1970s, but has been resurrected slightly in the 1990s.[1]

Figure 2. Anti-pollution Patents in the USA by Date of Application, 1975(1) - 1999(12)



Note: The data were extracted on 26 January 2003.

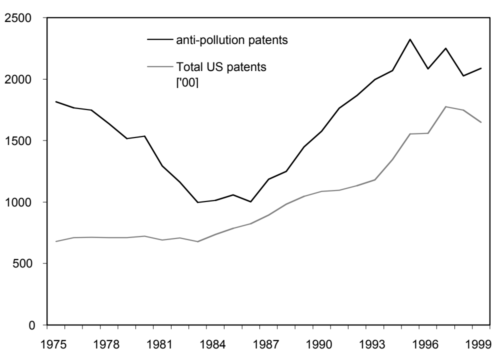
During the sample period, the largest number of anti-pollution patents awarded annually arose from applications lodged in 1995, namely 2,324 (see Figure 3), with the month of June 1995 being a period of extreme patenting activity (see Figure 2). Monthly patent data show some seasonality for both US anti-pollution and total US patents. The use of patent ratios in the empirical analysis (see Section 4 below) allows this problem to be largely eliminated (see McAleer et al. (2002) for further details).

[1] The absence of a trend between 1995 and 1999 may be artificial. As patents from more recent applications are approved, the numbers of approved patents would be expected to increase.

Figure 3 presents total annual US patents and US anti-pollution patents for the period 1975-1999. Total annual patents registered in the USA have been increasing steadily, reaching a peak of close to 180,000 approved patents from the applications lodged in 1997. In addition, the figure shows the annual trend in approved anti-pollution patents, which reached a global peak of 2,324 in 1995 and a slightly lower peak of 2,251 in 1997.

A comparison of the two trends shows very different patterns between total annual US patents, which exhibit a clear upward trend, and annual US anti-pollution patents, which have experienced two separate trends, first falling and then rising. It is interesting to note that anti-pollution patents are, in principle, a subset of ecological patents, which have tended to increase over the period 1975-1999 (for further details, see Marinova and McAleer (2003b)). Hence, pollution issues do not appear to have been of lasting importance as far as the development of new technologies have been concerned.

Figure 3. Total Patents and Anti-pollution Patents in the USA by Date of Application, 1975 - 1999

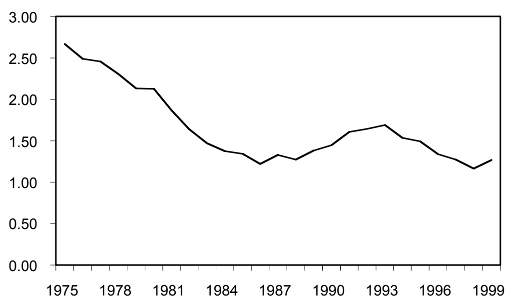


Note: The data were extracted on 26 January 2003.

Such an inference is confirmed by an analysis of the annual ratio of anti-pollution patents to total US patents (see Figure 4). The highest share of 2.7% was recorded in 1975, and has been consistently below 2% since 1981, reaching its lowest value of 1.2% in 1998. This pattern may be a warning of a lack of commitment from companies and individuals regarding the prevention and abatement of pollution. The long-term implications of ignoring the effects of pollution include adverse impacts on the natural environment, a rise in sea levels, development of extreme weather conditions, loss of biodiversity, and greater prevalence of infectious diseases, among other.

The remainder of the paper examines the volatility in anti-pollution patents in the USA. Reasons for analysing this group of patents are very similar to that for any patent volatility (for further explanations, see McAleer et al. (2002)). In the absence of explicit and active markets for commodities such as ecological and/or anti-pollution innovations and intellectual property, the estimation of volatilities associated with such patents is fundamental to risk management in financial and other models that describe the risk-return trade-off. The econometric modelling of volatility would seem to be a useful first step in establishing such markets, and will also lead to more informed business and policy decisions.

Figure 4. Ratio of Anti-pollution Patents to Total Patents in the USA by Date of Application, 1975 - 1999



Note: The data were extracted on 26 January 2003

3. MODEL SPECIFICATIONS

The primary purpose of the following sections is to model the volatility of the ratio of the number of anti-pollution patents registered in the USA to the total number of patents registered in the USA (henceforth, the "patent share"). This approach is based on Engle's (1982) path-breaking idea of capturing time-varying volatility (or uncertainty) using the autoregressive conditional heteroskedasticity (ARCH) model, and subsequent developments forming the ARCH family of models. Of these models, 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, and Nelson (1991) proposed the Exponential GARCH (EGARCH) model.

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

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

where the shocks, or movements in the patent share, are given by:

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

and $\omega > 0, \alpha \geq 0, \beta \geq 0$ are sufficient conditions to ensure that the conditional variance $h_t > 0$. 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, $\alpha + \beta$). 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.

Ling and McAleer (2002a) established the necessary and sufficient moment conditions for the univariate GARCH(p,q) model. Ling and McAleer (2003) showed that the QMLE for GARCH(*p,q*) is consistent if the second moment is finite, that is, $E(\varepsilon_t^2) < \infty$, Ling and Li (1997) showed that the local QMLE is asymptotically normal if the fourth moment is finite, that is, $E(\varepsilon_t^4) < \infty$, and Ling and McAleer (2003) showed that the global QMLE is asymptotically normal if the sixth moment is finite, that is, $E(\varepsilon_t^6) < \infty$. 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 $(\alpha + \beta)^2 + 2\alpha^2 < 1$.

Using a weaker condition, Elie and Jeantheau (1995) and Jeantheau (1998) showed that the log-moment condition is sufficient for consistency of the QMLE for the univariate GARCH(*p,q*) model, and Boussama (2000) showed that it is also sufficient for asymptotic normality. Based on these theoretical developments, the sufficient log-moment condition for the QMLE of GARCH(1,1) to be consistent and asymptotically normal is given by

$$E(\log(\alpha\eta_t^2 + \beta)) < 0. \qquad (3)$$

However, this condition is not straightforward to check in practice as it involves a function of an unknown random variable and unknown parameters. Although the sufficient moment conditions for consistency and asymptotic normality of the QMLE for the GARCH(*p,q*) model are stronger than their log-moment counterpart, the moment conditions are far more straightforward to check in practice.

The effects of positive shocks (or upward movements in the patents 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. Asymmetric behaviour is accommodated in the GJR model, for which GJR(1,1) is defined as follows:

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

where $\omega > 0, \alpha + \gamma \geq 0, \beta \geq 0$ 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. Such an indicator variable differentiates between positive and negative shocks, so that asymmetric effects in the data are captured by the coefficient γ, with $\gamma > 0$. In the GJR model, the asymmetric effect, γ, measures the contribution of shocks to both short run persistence, $\alpha + \frac{\gamma}{2}$, and long run persistence, $\alpha + \beta + \frac{\gamma}{2}$.

Ling and McAleer (2002b) showed that the regularity condition for the existence of the second moment of GJR(1,1) under symmetry of η_t is $\alpha + \beta + \frac{1}{2}\gamma < 1,$ and the condition for the existence of the fourth moment under normality of η_t is $\beta^2 + 2\alpha\beta + 3\alpha^2 + \beta\gamma + 3\alpha\gamma + \frac{3}{2}\gamma^2 < 1$. Using a weak novel condition, McAleer et al. (2002) showed that the log-moment condition for GJR(1,1), namely $E(\ln[(\alpha + \gamma I(\eta_t))\eta_t^2 + \beta]) < 0$, is sufficient for consistency and asymptotic normality of the QMLE.

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

$$\log h_t = \omega + \alpha \mid \eta_{t-1} \mid + \gamma\eta_{t-1} + \beta \log h_{t-1}, \quad \mid \beta \mid < 1. \qquad (5)$$

The distinct differences between EGARCH, on the one hand, and GARCH and GJR, on the other, include the following: (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 $\mid \beta \mid < 1$ ensures stationarity and ergodicity for EGARCH(1,1); (iii) Shephard (1996) noted that $\mid \beta \mid < 1$ 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), McAleer et al. (2002) observed that $\mid \beta \mid < 1$ is likely to be a sufficient condition for the existence of moments; (v) in addition to being a sufficient condition for consistency, $\mid \beta \mid < 1$ is also likely to be sufficient for asymptotic normality of the QMLE of EGARCH(1,1).

As GARCH is nested within GJR, based on the theoretical results in McAleer et al. (2002), 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. A simple non-nested procedure was proposed by Ling and McAleer (2000) to test GARCH versus EGARCH, in which the test statistic is asymptotically N(0,1) under the null hypothesis. Following a similar approach, McAleer et al. (2002) derived a non-nested procedure for testing EGARCH versus GJR, in which the test statistic is asymptotically N(0,1) under the null hypothesis.

In the next section, the volatilities of the anti-pollution patent ratio will be modelled by estimating the GARCH, GJR and EGARCH models through the use of rolling windows with size 240. The dynamic paths of the estimates, second moments and log-moments will provide insightful information regarding the short and long run persistence over time, as well as the stability and performance of each model.

4. EMPIRICAL RESULTS

All the models in this paper were estimated by EViews 4. The dynamic paths of all estimates for each model are available on request.

4.1 GARCH(1,1)

Varied movements in the α estimates reflect the instability of the short run persistence in GARCH(1,1) for the anti-pollution patent share. For the total of 62 rolling samples, the values of $\hat{\alpha}$ vary from 0.125 to –0.110 with a mean of –0.009 and standard deviation of 0.042. In particular, $\hat{\alpha}$ increases from –0.043 to 0.125 in December 1975, and then decreases to 0.068 in January 1976. Such wide fluctuations are not uncommon throughout the remaining rolling samples. The other two samples for such behaviour occur in April 1977, when $\hat{\alpha}$ increases from –0.005 to 0.096, then declines to 0.037 in the following month, and in February 1979, when $\hat{\alpha}$ increases from –0.008 to 0.102, then declines to –0.017 in March 1979. Furthermore, the α estimates are negative in 49 of 62 rolling samples, which violate the sufficient condition for the conditional variance to be positive.

Movements in $\hat{\beta}$ correspond to the movements in $\hat{\alpha}$ for GARCH(1,1): $\hat{\beta}$ decreases from 1.000 to 0.787 in December 1975, then increases slowly to 1.005 in the following five months. In April 1977, $\hat{\beta}$ decreases from 1.007 to 0.824, and gradually increases to 1.000 in August 1977. Moreover, $\hat{\beta}$ decreases from 1.001 to 0.751 in March 1979 and then increases immediately to 1.020 in April 1980. It is interesting to note that, while most of the α estimates are negative, the β estimates are greater than one in 32 rolling samples. Overall, the mean β estimate is 0.980, varying between 1.030 and 0.751.

Interestingly, all of the rolling samples satisfy the second moment condition, except in March 1979, when the second moment is 1.003. Furthermore, the second moment, or long run persistence, seems unstable throughout the rolling samples. This is not particularly surprising since the second moment is the sum of the α and β estimates in a GARCH(1,1) model. Overall, the mean second moment is 0.972 varying between 1.003 and 0.853. All of the rolling samples satisfy the log-moment condition. This is surprising since most of the α estimates are negative, and it is possible for the negativity of the α estimate to lead to a failure in evaluating the log-moment condition for a particular rolling sample. Furthermore, the dynamic path of the log-moment condition exhibits a downward trend, but no such trend can be observed in either the α or β estimates. Overall, the mean log-moment is –1.114, varying between –0.932 and –1.264. However, the satisfaction of the log-moment condition in all rolling samples means that the QMLE is consistent and asymptotically normal.

4.2 GJR(1,1)

Movements in $\hat{\alpha}$ for GJR(1,1) show substantial improvement in stability over their GARCH counterparts. In particular, the number of negative $\hat{\alpha}$ values is now reduced to 22, with most of them occurring toward the end of the rolling samples. In fact, the mean $\hat{\alpha}$ is 0.034 for GJR(1,1) varying between 0.119 and –0.077. For the first 6 rolling samples, the α estimates remain low and vary around 0, but increase dramatically to 0.115 in July 1975. It remains high around 0.08 before June 1977, and then decreases dramatically to 0.007. The α estimates then show greater fluctuations in the remaining rolling samples.

For GJR(1,1), the γ estimates exhibit similar patterns to the α estimates. However, the $\hat{\gamma}$ values are generally greater than their $\hat{\alpha}$ counterparts. This is reflected in the fact that the mean $\hat{\gamma}$ is 0.078, varying between 0.413 and –0.0347. Interestingly, $\hat{\gamma}$ is less than zero for the first six rolling samples, but increases dramatically to 0.413 in July 1975. However, the estimate declines immediately to 0.380 and 0.145 in August 1975 and October 1975, respectively, stays at around 0.15 until June 1977, then decreases to –0.023 and remains mostly negative in the rest of the rolling samples. This suggests the presence of asymmetric and time-varying behaviour in the volatilities of the anti-pollution patent shares.

The β estimates also exhibit a great improvement over their GARCH counterparts. First, the number of $\hat{\beta}$ values greater than one is now reduced to 5, with mean $\hat{\beta}$ of 0.838, which is lower than its GARCH counterpart. Contrary to the movements in $\hat{\alpha}$ and $\hat{\gamma}$, $\hat{\beta}$ is generally high and varies around 0.95 in the first six rolling samples, then decreases dramatically from 0.982 to 0.454 in July 1975, but bounces back almost immediately to 0.773 in September 1975. It remains around 0.650 until June 1977, with a dramatic increase from 0.655 to 0.984, then remains close to one in most of the remaining samples.

All of the rolling samples satisfy the second moment condition, which suggests that the QMLE are consistent and asymptotically normal. The mean second moment is 0.910, varying between 0.991 and 0.762. Furthermore, all the rolling samples satisfy the log-moment conditions with the mean of –2.477 varying between –2.327 and –2.811.

4.3 EGARCH(1,1)

In general, the estimates for EGARCH are disappointing. The dynamic paths of $\hat{\alpha}$, $\hat{\gamma}$ and $\hat{\beta}$ exhibit periodic behaviour. These suggest that the QMLE are extremely sensitive to the samples, so that the estimates are less likely to be reliable. Although $\hat{\beta}$ is less than one in all the rolling samples, the mean $\hat{\beta}$ is 0.249, varying between 0.995 and –0.665. This is not particularly satisfactory, considering the variability in the estimates. Similar conclusions can be found for both $\hat{\alpha}$ and $\hat{\gamma}$, where the mean $\hat{\alpha}$ is 0.318, varying between 0.605 and –0.079, and the mean $\hat{\gamma}$ is –0.056, varying between 0.0466 and –0.139.

5. CONCLUSION

This paper analysed the trends and volatility in anti-pollution patents registered in the USA using monthly US PTO data for the period January 1975 to December 1999. The volatilities of anti-pollution patent shares, namely the ratio of the number of anti-pollution patents registered in the USA to the total number of patents registered in the USA, was analysed using three time-varying volatility models, namely GARCH, GJR and EGARCH. In particular, GJR and EGARCH are intended to capture the presence of asymmetric effects in the volatilities of the anti-pollution patent shares. It was found through the use of rolling windows that the asymmetric effects were significant, but varied over time. The use of threshold models for both the conditional mean and conditional variance may provide a more accurate description of the dynamics in the data. Overall, based on the variability and robustness of the rolling estimates, GJR was superior to both GARCH and EGARCH in modelling the volatilities of anti-pollution patent shares.

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