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Abstract

Since the 1970s, electronics and associated electrical equipment (henceforth "electronics") has been one of the most dominant industries in the developed countries, with its geographical centre firmly rooted in the USA. The overall presence of electronics patents in the USA is considerable, with the share of electronics reaching 31% of all US patents in 1996 and total electronics patents reaching close to 170,000 in 1997. For the empirical analysis, the time-varying nature of volatility in the electronics patent share, namely the ratio of US electronics patents to total US patents, is examined using monthly data from January 1975 to December 1997. As negative and positive movements in the patent share may have different impacts on innovative activity, and hence on volatility, both symmetric and asymmetric models of volatility are estimated. The estimated models are the symmetric AR(1)-GARCH(1,1), the asymmetric AR(1)-GJR(1,1), and asymmetric AR(1)-EGARCH(1,1). Of these, the asymmetric AR(1)-GJR(1,1) model is found to be suitable for modelling the electronics patent share in the USA.

Keywords: Electronics patents, patent share, innovation, trends, volatility, GARCH, GJR, EGARCH, asymmetry, shocks.

1. Introduction

The pervasiveness of electronics is demonstrated not only with the application of electronic and electrical devices across all sectors of the economy and human life, but also with its implications for the rise of the information age and the knowledge economy. 'New industries' (chemicals, motor vehicles and electricity) that were established in the late 19th Century gave way to electronics, which was partly inspired by the demands of the military and space agencies [44]. Since the early 1970s, with the invention of the memory chip and the microprocessor, electronics has been an area of intensive research, development and innovation. This has resulted in a constant improvement of performance levels, functional qualities and variety of technology, while drastically reducing unit costs. Electronics has attracted large amounts of new investments and created the majority of new jobs [16].

In the USA the electronics industry, and consequently the information sector, grew at twice the rate of the economy as a whole in the 1980s [39]. The European production of consumer electronics was valued at 40 billion ecu in 1991, and directly employed tens of thousands of workers [32]. Japan invested heavily in semiconductors, computer hardware and communication equipment, as well as in colour televisions, videocassette recorders and compact disc players, and strategically targeted foreign markets [41]. The modern telecommunications of the 1990s made up "the nervous system of global capitalism" ([43], p. 3). Such a dominance of electronics within the industrialised economies led to these technologies being widely recognised within the field of innovation (see, for example, [15], [20] and [28]) as the current Kondratieff wave[1].

The last century also witnessed a shift in the geography of economic power and innovation from Europe to North America ([12], [34]). California's Silicon Valley, for example, "became the world's number one address in high technology" [42], which was followed by Route 128 in Greater Boston and Orange County in Southern California. New centres of production emerged in states such as Colorado, Oregon and Utah. The USA not only generated new technologies, including electronics and electrical equipment (henceforth "electronics") at an unprecedented rate, but also became the major market for innovations developed elsewhere. Among others, the attractiveness of the US market is demonstrated

[1] At the beginning of the 20th Century, the Russian economist Kondratieff stressed the cyclical pattern of development in capitalist economies [3], and pioneered the long waves concept. This idea was later endorsed by the Austrian economist Schumpeter, who explained the waves with the clustering of particular technological innovation. The technologies associated with the first three Kondratieff waves, which finished around the mid-1990s, are cotton, textiles, iron and steam power (first wave), railroads (second wave), and electricity, automobiles and chemicals (third wave). For further discussion see, for example, [29].

in the large number of foreign patent applications, which is greater by far than in any other country [2]. The broadly defined "high technology" industry of electronics attracted inventors and companies interested in commercialising their technologies, particularly from Japan [31]. Asian import penetration of the North American market was substantial in semiconductors, as well as in consumer electronics. Consequently, the protection of intellectual property became crucial in this "war of supremacy" ([11], p. 311) in the youngest, but the most far-reaching, technological sector. The overall presence of electronics in patents registered in the USA has subsequently become considerable.

In this paper we examine the trends and volatility in patenting in the USA of new technologies related to electronics between 1975 and 1997. The following section describes the patent data used in the empirical analysis, and outlines the general trends in US patenting in the electronics industry. Section 3 discusses the economic and finance-related motivation for examining the GARCH, GJR and EGARCH volatility models. These models are estimated for the US electronics patent share in Section 4. The empirical results are analysed, and concluding comments are presented in Section 5.

2. General Trends in Electronics Patenting in the USA

The US Patent and Trademark Office (PTO) provides reliable information on registered patents, and this has been the main source of data for our analysis. Nevertheless, the classification systems used by the PTO, namely the Current US Classification and the International Patent Classification, do not provide a direct link between patent class and industry application. This issue has been reported by a number of previous researchers (see, for example, [18], [19], [30] and [37]). In order to deal with the problem, patent classes need to be allocated to certain industries [1]. It was decided to use the Current US Classification, in which the electronics industry is broadly covered by 68 classes[2]. The patent data actually used refer to the date of patent application, which is a more accurate measure of patent activity than the date of issue as it is not influenced by administrative delays in the US PTO related to the processing of the applications[3]. The time period covered in this analysis is from 1975 to 1997 as the

[2] The classes associated with electronic and electrical equipment are as follows: 109, 174, 200, 218, 219, 236, 257, 307, 310, 313, 314, 315, 318, 320, 322, 323, 324, 326, 327, 329, 330, 331, 332, 333, 344, 335, 336, 337, 338, 341, 345, 346, 349, 360, 361, 362, 364, 365, 368, 369, 371, 372, 373, 374, 375, 377, 378, 381, 382, 385, 386, 388, 392, 395, 438, 439, 445, 477, 505, 701, 702, 704, 705, 706, 707, 711, 901 and 902. The PTO has established a concordance between the US and the international patent classes, which can be accessed on its web site.

[3] According to the US PTO, it takes an average of two years for a patent application to be approved [45]. However, in some cases it can take much longer, and delays of 7-8 years are not unknown.

data for the more recent years are still incomplete through lags between the date of application and the date of granting the patent.

Figure 1 presents the monthly US electronics patents from 1975 to 1997, while Figure 2 shows the annual figures for the same period. Some descriptive statistics are given in Table 1. The trend is clearly upward sloping, with the 1990s being a period of intensive patenting of electronics technologies. Indeed, the total number of electronics patents in the USA reached 51,898 in 1997. Total monthly (Figure 3) and annual (Figure 4) patents registered in the USA from all industries have also been increasing steadily, reaching a peak of close to 170,000 approved patents from the applications lodged in 1997. The correlation coefficient between US electronics patents and total US patents is very high at 0.983.

As the monthly patent data show some seasonality, as well as extreme observations, for both US electronics patents and total US patents (see Figures 1 and 3, respectively), the use of patent shares (see Figure 5) mitigates this problem. The annual total US patents and US electronic patents (see Figures 2 and 4, respectively) have eliminated the apparent extreme observation in 1995. However, the presence of a negative outlier in November 1997 suggests a dramatic decrease in the patent share.

A comparison of the two trends in Figures 1 and 2, on the one hand, and Figures 3 and 4, on the other, shows that US electronics patents have been growing at a faster rate than total US patents, which confirms the growing importance of this industry. The average monthly electronics patent share for 1975-1997 was over 26%, as shown in Table 1 (that is, more than 1 in 4 patents registered in the USA were related to electronics). Moreover, the monthly patent share fluctuated between the low- to mid-20% region in the 1970s, and the low- 30% range in 1997 (see Figures 5), with the highest share of 33.8% in December 1995. The largest annual electronics patent shares (see Figure 6) have been increasing in a general stable manner from 23.8% in 1975 to 30.6% in 1997, with the highest share being 31% in 1996. This is indicative of the consistent and growing inventiveness in this area. The upward trend of the electronics patent share also confirms the tremendous importance of this technology for the economic development of the industrialised world.

The Phillips and Perron (PP) test for non-stationarity [38] strongly suggests that the Electronics Patent Share (EPS) is trend stationary. Using the EViews 4 econometric software package with a wide range of lags, the choice of the truncated lag order did not seem to affect the test results. The motivation for conducting the PP test over the conventional Augmented Dickey-Fuller (ADF) test is to accommodate the possible presence of GARCH errors. While the ADF test accommodates serial correlation by specifying explicitly the structure of serial correlation in the errors, the PP test does not assume the type of serial correlation or heteroscedasticity in the disturbances [38], and can have higher power than the ADF test under a wide range of circumstances.

Due to the noticeable presence of a time trend and the non-zero autocorrelation in EPS, the volatility of EPS is estimated using the following model:

$$EPS_t = \phi_0 + \phi_1 EPS_{t-1} + \theta t + \varepsilon_t$$

from which the estimated volatility can be calculated as

$$\hat{\varepsilon}_t^2 = (EPS_t - \hat{\phi}_0 - \hat{\phi}_1 EPS_{t-1} - \hat{\theta} t)^2 .$$

The estimated volatility of the monthly EPS is given in Figure 7. There are two interesting features of this series, namely the presence of clustering and a single outlier. Clustering seems most noticeable during the periods 1980 to 1985 and 1995 to 1997, together with the presence of an outlier in November 1997. These features reflect the time-varying nature of the volatility in EPS. As the Lagrange Multiplier test of no ARCH effects clearly rejects the null hypothesis, it would seem important to accommodate the presence of time-varying volatility with an appropriate model.

3. Models of Volatility

As volatility in electronic patent registrations and patent shares have been analysed only recently (see [31] for Japanese electronics patents in the USA), the primary purpose of this section is to model the volatility in the electronics patent share (EPS) in the USA. By comparison, there has been far greater research on volatility in the areas of finance and financial econometrics, where volatility is perceived as an inherent characteristic of financial markets and the main interest is in the pricing of financial products. The undeniable impact of electronic technologies on the development of any other technologies and sectors in the economy require a better understanding of the nature of their development, particularly the market characteristics and the associated property rights. As the dominance of electronic technologies is expected to continue into the future, the analysis of the volatilities in the EPS will yield improved estimates and forecasts, and lead to more informed decision making in the private and public sectors. For further details regarding the modelling and pricing of the risks associated with patents, see [33].

The purpose of this section is to select the optimal model for the volatility of the EPS in the USA using the Autoregressive Conditional Heteroscedasticity (ARCH) model [14], as well as subsequent developments (see, for example, [6], [7] and [22]). The most widely used variation in the case of symmetric shocks is the generalised ARCH (GARCH) model of [5]. In the presence of asymmetric behaviour between negative and positive shocks, the GJR model is also widely used [17]. Further theoretical developments have recently been suggested by [25], [26] and [27].

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

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

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

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

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.

The conditional log-likelihood function is given as follows:

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

It has been shown that the QMLE for GARCH(*p,q*) is consistent if the second moment is finite [27], that is, $E(\varepsilon_t^2) < \infty$, the local QMLE is asymptotically normal if the fourth moment is finite [23], that is, $E(\varepsilon_t^4) < \infty$, and the global QMLE is asymptotically normal if the sixth moment is finite [27], 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, the log-moment condition was shown to be sufficient for consistency of the QMLE for the univariate GARCH(*p,q*) model [13], [21], and also sufficient for asymptotic normality [9]. 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

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

However, this condition is not straightforward to check in practice as it involves 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 counterparts (where they exist), the moment conditions are far more straightforward to check in practice.

The effects of positive shocks (or upward movements in the EPS) on the conditional variance, h_t, are assumed to be the same as the negative shocks (or downward movements in the EPS) in the symmetric GARCH model. Asymmetric behaviour is accommodated in the GJR model, for which GJR(1,1) is defined as follows:

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

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 to long run persistence, $\alpha + \beta + \frac{\gamma}{2}$.

The regularity condition for the existence of the second moment of GJR(1,1) under symmetry of η_t [26] 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 [26] is

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

Using a weak novel condition, the log-moment condition for GJR(1,1), namely

$$E(\ln[(\alpha + \gamma I(\eta_t))\eta_t^2 + \beta]) < 0, \tag{7}$$

is sufficient for consistency and asymptotic normality of the QMLE [33].

An alternative model to capture asymmetric behaviour in the conditional variance is the Exponential GARCH (EGARCH(1,1)) model [35], namely:

$$\log h_t = \omega + \alpha \,|\, \eta_{t-1} \,| + \gamma\eta_{t-1} + \beta \log h_{t-1}, \quad |\, \beta \,| < 1. \tag{8}$$

There are some distinct differences between EGARCH, on the one hand, and GARCH and GJR, on the other, 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) $|\beta| < 1$ ensures stationarity and ergodicity for EGARCH(1,1) [35]; (iii) $|\beta| < 1$ is likely to be a sufficient condition for consistency of QMLE for EGARCH(1,1) [40]; (iv) as the conditional (or standardized) shocks appear in equation (4), $|\beta| < 1$ is likely to be a sufficient condition for the existence of moments [33]; (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) [33].

As GARCH is nested within GJR, based on the theoretical results in [33], 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 to test GARCH versus EGARCH, in which the test statistic is asymptotically N(0,1) under the null hypothesis [24]. Following a similar approach, a non-nested procedure for testing EGARCH versus GJR was derived, in which the test statistic is asymptotically N(0,1) under the null hypothesis [33].

4. Empirical Results

This section models the volatility of EPS using GARCH(1,1), GJR(1,1) and EGARCH(1,1), as defined in (2), (4), (8), respectively. The sample is from January 1975 to December 1997, with a total of 276 observations. In order to accommodate the presence of a deterministic time trend, all three volatility models have the following specification for the conditional mean:

$$y_t = \phi_0 + \phi_1 y_{t-1} + \theta t + \varepsilon_t .$$

Estimates of the parameters of the models are given in Table 2. Descriptive statistics of the rolling estimates with window size 200 can be found in Table 4, and their dynamic paths in Figures 8-10.

In order to facilitate the selection of the optimal model, the results of the non-nested tests of GARCH versus EGARCH, and of GJR versus EGARCH, are given in Table 3.

Unless otherwise stated, the Brendt-Hall-Hall-Hausman [4] (BHHH) algorithm implemented in EViews 4 is used to obtained estimates for the parameters of the models. Both the asymptotic t-ratios and the Bollerslev-Wooldridge robust t-ratios [8] are computed numerically by EViews 4.

Full Sample Estimates

Estimates of the conditional mean and conditional variance for the three models using the whole sample are given in Table 2. It is worth noting that the estimates in the conditional mean for each of the three models do not differ substantially. The AR estimates range from 0.189 to 0.205, and are significant in all three cases, based on both the asymptotic and robust t-ratios. A similar comment applies for the time trend coefficients, which range from 0.000217 to 0.000218 and are highly significant in all three cases.

It is also interesting to note that the log-moment conditions are satisfied for both GARCH and GJR, suggesting that the QMLE are consistent and asymptotically normal. However, neither the second nor the fourth moment condition is satisfied for GARCH, although both conditions are satisfied for GJR. The β estimate for EGARCH is less than one, which implies that all the moments exist and that the QMLE are likely to be consistent and asymptotically normal.

An interesting feature of the results in Table 2 is that the γ estimate for GJR is negative, which implies that the lagged negative shocks reduce current volatility. This reflects decreasing intellectual property momentum in the electronics patent share (for further details, see [33]). However, the short run effect of the positive shocks (α) is clearly larger than the short run effect of the negative shocks ($\alpha+\gamma$).

The estimates of EGARCH suggest that the sign effect (γ) is more important than the size effect (α), as it is not statistically significant. However, since none of the models under consideration is capable of accommodating extreme observations and outliers, the effects of these aberrant observations on the estimates and their respective standard errors is still an area for further research (see [10], [36] and [46] for further details).

Interestingly, given the insignificant estimate of α in EGARCH, the non-nested tests of EGARCH versus GARCH clearly reject GARCH in favour of EGARCH, as shown in Table 3. This suggests that, although the size effect is not statistically significant, the inclusion of asymmetric effects is important. The non-nested tests of EGARCH versus GJR reject both models, so that the test is unable to discriminate between these two models.

Rolling Estimates

In order to examine the impacts of each observation on the estimates of the model, rolling estimates with window size 200, and their associated moment conditions for each model, are given in Figures 8-10. The summary statistics for each of the rolling estimates are reported in Table 4.

In the case of GARCH, the α estimates exhibit an upward trend, with a mean of 0.045. Of particular interest is the period between May 1978 and July 1978, when the α estimates increase from 0.010 to 0.088, and remain high for three months, then decrease dramatically in November 1978. Interestingly, this dramatic movement has some equally dramatic counterparts in the β estimates. In May 1978, the β estimates decrease from 0.797 to -0.732, and remain low for three month, then increase dramatically to 0.895, in November 1978. Overall, the mean β estimate is 0.721, which is lower than its full sample counterpart reported in Table 2.

There are 4 rolling windows which fail to satisfy the log-moment condition, but 28 and 39 rolling windows fail to satisfy the second and fourth moment conditions, respectively. It is important to note that the 28 rolling windows which fail to satisfy the second moment condition include the 4 rolling windows that fail to satisfy the log-moment condition. Moreover, almost all the failing rolling windows occur after November 1978. The means of the log-, second and the fourth moment conditions are -0.190, 0.765 and 0.878, respectively. Interestingly, both second and fourth moment conditions are satisfied on average, even though over 30% of the rolling windows fail to satisfy either the second or fourth moment conditions.

Although movements in the α estimates in GJR(1,1) are less dramatic, with a mean of 0.056, it would appear that there is a structural change in the α estimates. Prior to September 1978, the α estimates are relatively low, with a slight upward trend, but between September 1978 and May 1979, they increase from 0.030 to 0.122, and remain high thereafter. These movements match those in the γ and β estimates, with means of -0.095 and 0.887, respectively. Specifically, the γ estimates decrease from

-0.088 to -0.139 between September 1978 and May 1979, and the β estimates increase from 0.797 to 0.876 during the same period. Furthermore, there is a substantial decrease in the β estimates in August 1977 from 0.890 to 0.737, but an increase to 0.890 in the following month. As shown in the second moment condition, the long run persistence is generally quite high, especially towards the end of the rolling sample. Movements in the log-, second and fourth moment conditions are very similar, but most importantly, all rolling windows satisfy the moment conditions. The mean log-, second and fourth moment conditions are -0.111, 0.896 and 0.814, respectively.

The α estimates of EGARCH(1,1) exhibit substantial fluctuations in the early rolling samples, ranging from 0.549 to -0.131, with a mean of 0.227, but remains steady from April 1979. Both the γ and β estimates exhibit similar patterns, with means of 0.126 and -0.121, respectively. Of particular interest are the movements in the β estimates, which fluctuate dramatically in the early rolling samples, namely from January 1975 to December 1975, then remain low until April 1979, and increase dramatically from -0.702 to 0.883. These variations explain the low mean of the β estimates, and reflect the difficulties in estimating the EGARCH model precisely.

In general, the estimates of the parameters in the conditional mean, namely ϕ_1 and δ, do not differ substantially, reflecting the block diagonal nature of the associated log-likelihood functions.

5. Concluding Remarks

This paper examined the trends and volatility in the electronics patent share, namely total electronics patents in the USA relative to total patents in the USA. Three models of volatility with the same conditional mean have been estimated. The estimates based on the full sample suggested weak asymmetric effects through GJR, but detected significant asymmetric effect through EGARCH. However, non-nested tests of EGARCH versus GARCH clearly rejected GARCH in favour of EGARCH, but failed to discriminate between EGARCH and GJR. Moreover, both GARCH and GJR satisfied the log-moment conditions for consistency and asymptotic normality of the QMLE.

The dynamic paths of the rolling estimates provided important information about the impacts of individual observations on the estimates of the models. In all cases, the estimates seemed to experience a structural change during the late 1970's, specifically during the period May 1978 to April 1979.

Overall, both GJR and EGARCH satisfied their respective moment conditions for all rolling windows, but 3, 28 and 39 rolling windows failed to satisfy the log-, second and fourth moment conditions, respectively, for GARCH.

Based on both the rolling and full sample estimates, non-nested tests and moment conditions, the AR(1)-GJR(1,1) model is the most suitable volatility model to capture the dynamics in the electronics patent share in the USA.

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Table 1: Descriptive Statistics for Total Patents, Electronics Patents and Electronics Patent Shares

	Total	Electronics	EPS
Mean	8039.261	2154.630	0.261
Median	6976	1817	0.259
Maximum	26987	7073	0.338
Minimum	3133	869	0.209
Standard Deviation	2846.864	966.211	0.027
Skewness	1.813	1.458	0.475
Kurtosis	9.499	5.444	3.003

Table 2: Full Sample Estimates of GARCH, GJR and EGARCH

	ϕ_1	θ	ω	α	γ	β	Log-moment	Second Moment	Fourth moment
GARCH	0.195	2.17E-04	1.94E-06	0.091		0.909	-0.008	1.000	1.016
	3.040	10.837	0.591	2.282		19.302			
	3.717	14.060	0.317	2.231		14.879			
GJR	0.205	2.17E-04	8.95E-06	0.123	-0.131	0.882	-0.067	0.940	0.903
	3.276	11.788	1.302	2.226	-1.279	14.478			
	3.549	11.753	1.029	2.029	-1.767	11.277			
EGARCH	0.189	2.18-E04	-0.558	0.151	0.078	0.950			
	2.928	11.678	-2.430	1.820	1.885	38.141			
	1.687	12.238	-2.767	1.006	2.079	13.062			

Note: The three entries for each parameter are their respective estimate, the asymptotic t-ratio and the Bollerslev-Wooldridge robust t-ratio [8].

Table 3: Non-nested Tests

Test Statistics	$H_0 : GARCH$ $H_A : EGARCH$	$H_0 : EGARCH$ $H_A : GARCH$	$H_0 : GJR$ $H_A : EGARCH$	$H_0 : EGARCH$ $H_A : GJR$
$t(\hat{\theta})$	4.205	0.008	4.078	4.844

Note: The non-nested tests are given in [24] and [33].

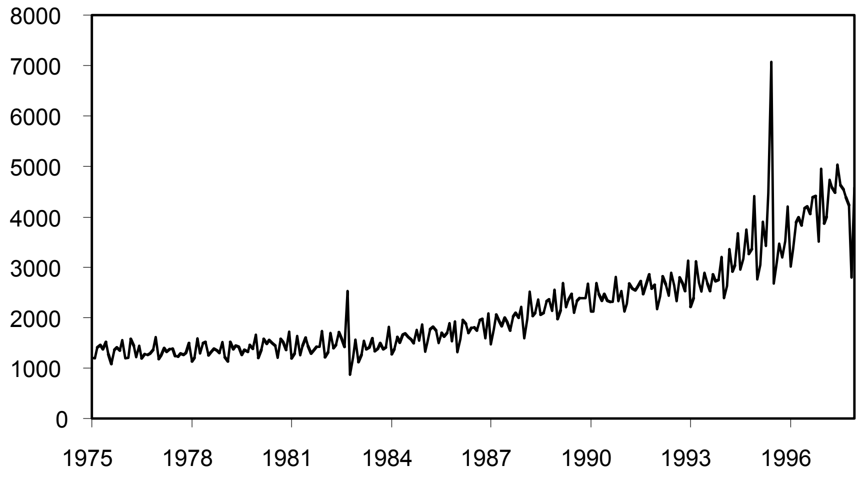
Table 4: Descriptive Statistics for the Rolling Estimates

GARCH	ϕ_1	θ	α	β	Log-moment	Second Moment	Fourth moment
Mean	0.085	2.38E-04	0.045	0.721	-0.190	0.765	0.878
Median	0.074	2.40E-04	0.032	0.892	-0.054	0.951	0.972
Maximum	0.209	2.69E-04	0.116	1.017	0.008	1.009	1.228
Minimum	-0.014	2.02E-04	-0.027	-0.749	-2.012	-0.708	0.077
Standard Deviation	0.053	1.71E-05	0.037	0.460	0.352	0.454	0.276
Skewness	0.716	-0.154	0.065	-2.536	-3.258	-2.488	-1.267
Kurtosis	2.735	1.914	1.728	8.132	14.331	7.912	3.941

GJR	ϕ_1	θ	α	γ	β	Log-moment	Second Moment	Fourth moment
Mean	0.082	2.40E-04	0.056	-0.095	0.887	-0.111	0.896	0.814
Median	0.067	2.49E-04	0.042	-0.082	0.897	-0.096	0.909	0.831
Maximum	0.221	2.73E-04	0.129	-0.051	0.937	-0.041	0.961	0.938
Minimum	0.024	1.96E-04	0.004	-0.158	0.737	-0.303	0.739	0.552
Standard Deviation	0.054	2.32E-05	0.038	0.029	0.037	0.055	0.048	0.086
Skewness	1.055	-0.354	0.461	-0.498	-1.616	-1.134	-1.002	-0.772
Kurtosis	3.062	1.733	1.775	1.894	5.912	4.013	3.598	3.022

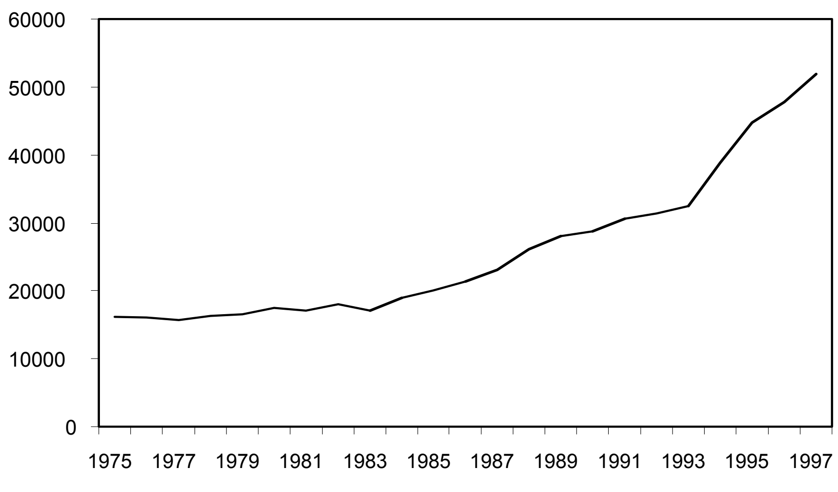
EGARCH	ϕ_1	θ	α	γ	β
Mean	0.082	2.39E-04	0.227	0.126	-0.121
Median	0.062	2.49E-04	0.175	0.132	-0.699
Maximum	0.206	2.79E-04	0.549	0.199	0.957
Minimum	-0.002	1.76E-04	-0.131	0.032	-0.980
Standard Deviation	0.056	2.81E-05	0.188	0.032	0.825
Skewness	0.727	-0.533	0.051	-0.127	0.427
Kurtosis	2.510	1.950	1.559	3.401	1.225

Figure 1: Monthly US Electronics Patents by Date of Application, 1975(1) – 1997(12)



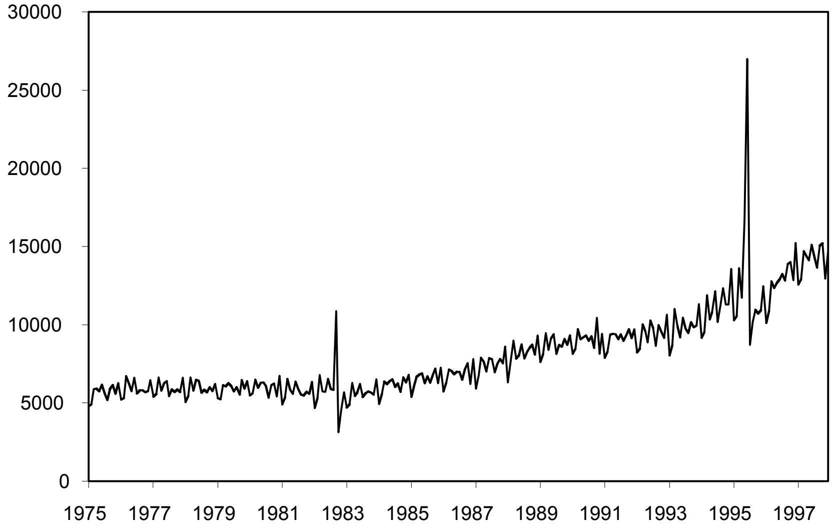
Note: The patent data were extracted on 30 May 2001.

Figure 2: Annual US Electronics Patents by Date of Application, 1975 – 1997



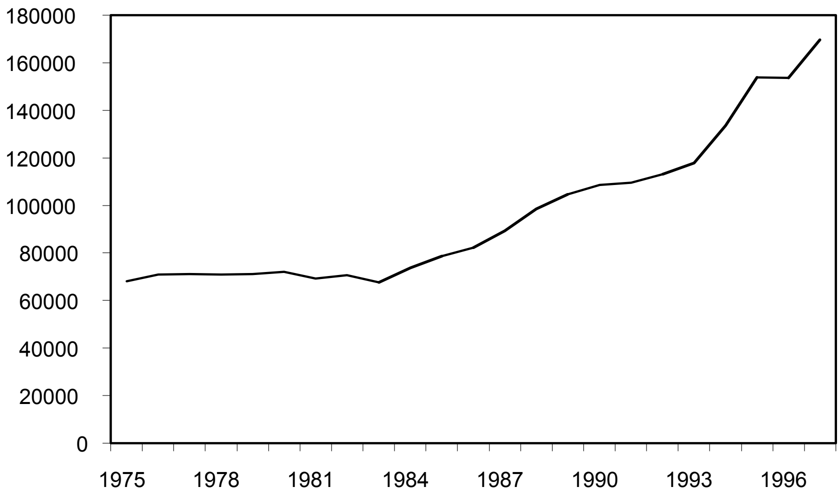
Note: The patent data were extracted on 30 May 2001.

Figure 3: Monthly Total US Patents by Date of Application, 1975(1) – 1997(12)



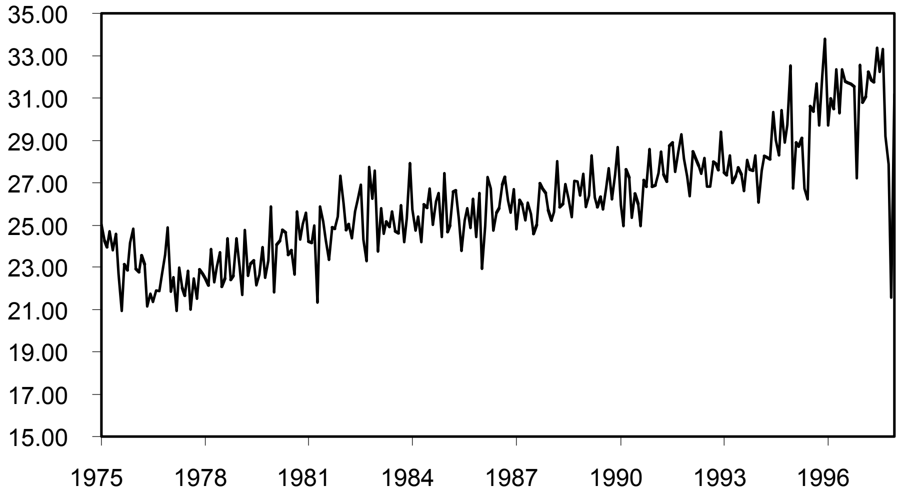
Note: The patent data were extracted on 30 May 2001.

Figure 4: Annual Total US Patents by Date of Application, 1975 – 1997



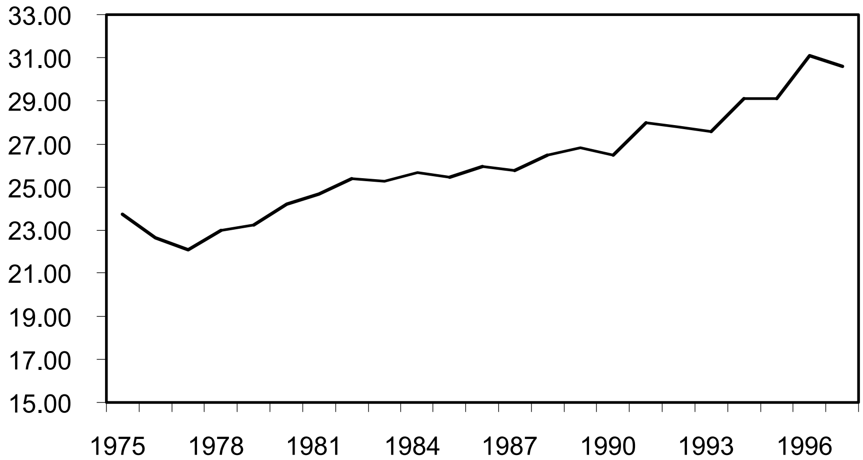
Note: The patent data were extracted on 30 May 2001.

Figure 5: Monthly Electronics Patent Share (%) by Date of Application, 1975 – 1997



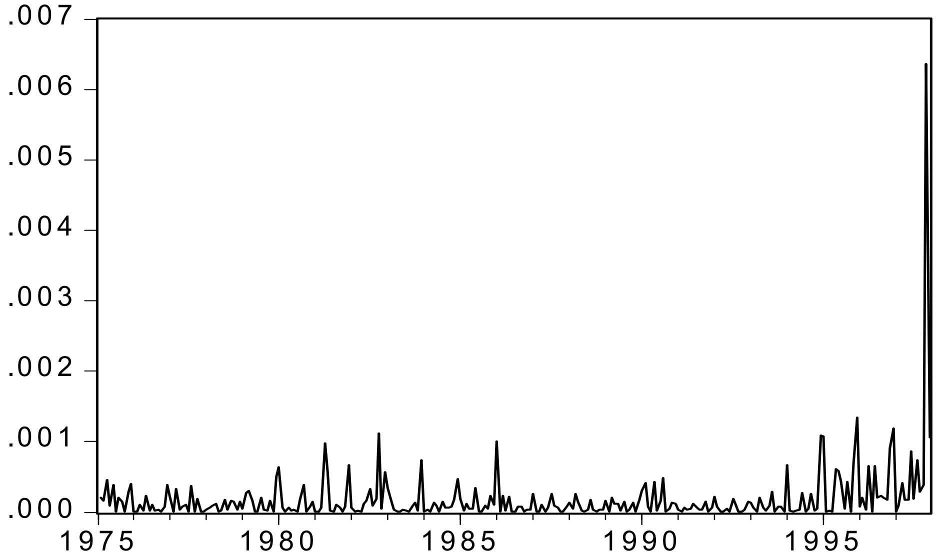
Note: The patent data were extracted on 30 May 2001.

Figure 6: Annual Electronics Patent Share (%) by Date of Application, 1975 – 1997



Note: The patent data were extracted on 30 May 2001.

Figure 7: Volatility of the Monthly Electronics Patent Share (EPS)
by Date of Application, 1975 – 1997



Note: The patent data were extracted on 30 May 2001.

Figure 8: Rolling GARCH(1,1) Estimates

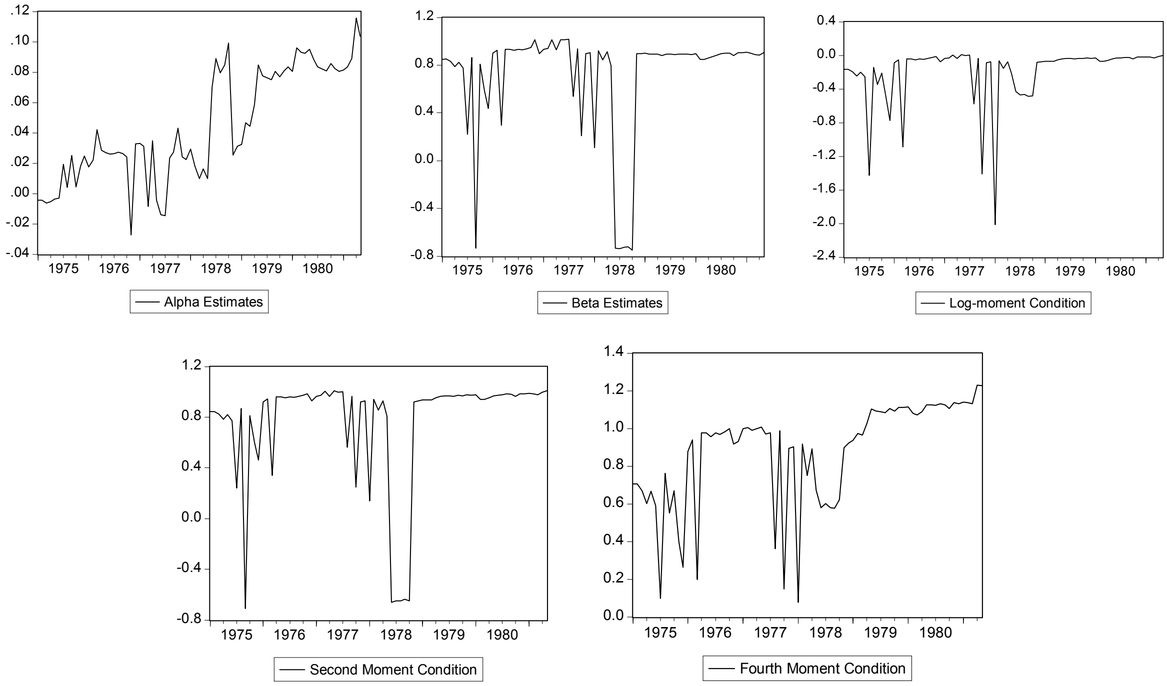


Figure 9: Rolling GJR(1,1) Estimates

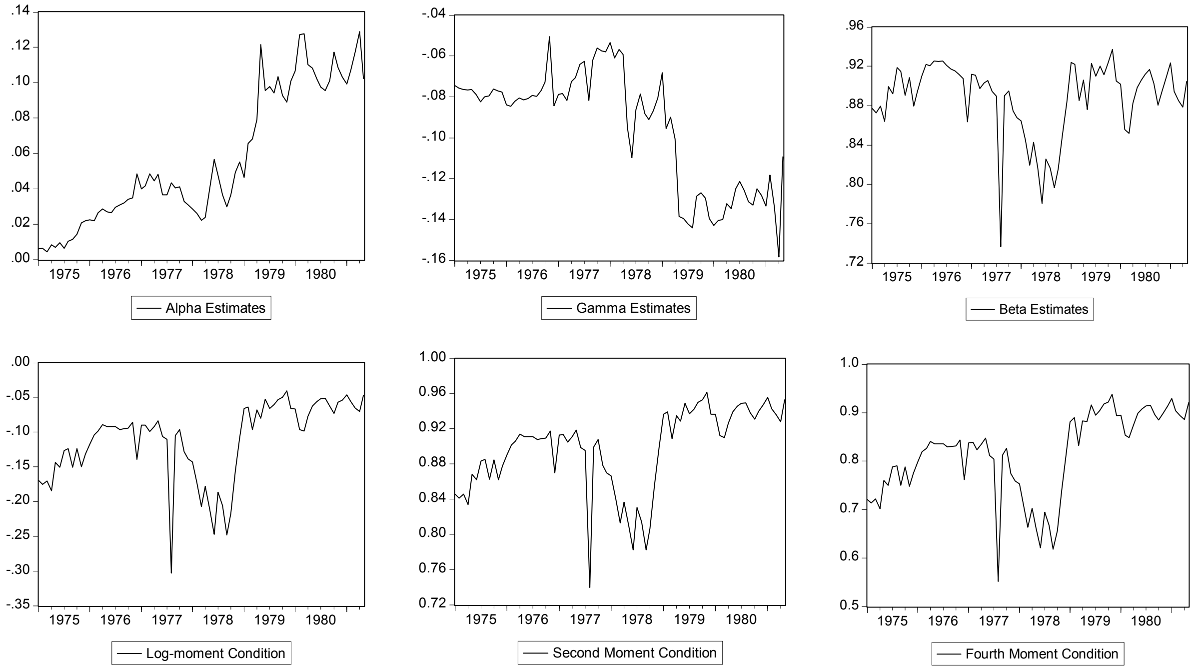


Figure 10: Rolling EGARCH(1,1) Estimates