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Abstract

This paper investigates the volatility of monthly Australian stock returns over the period 1875–1987. There has been extensive work on this question in the United States, but little with data outside that country. Our analysis centers upon whether the "stylized facts" regarding returns in the U.S. also hold true for Australia. We find that there are both similarities and differences. There is little evidence for asymmetry in Australian returns but strong persistence of shocks into volatility. What is particularly interesting in the Australian series is the large volatility of the last two decades; an experience not matched in the U.S. data.

I. Introduction

The stock market crashes of October 1987 were traumatic events, raising fears of financial collapse and depression, and reviving the spectre of the 1930's. Little wonder then that the volatility of stock markets subsequently came under intense scrutiny by governments, market professionals and academics. Of central concern was the issue of what causes volatility; if volatility was a predictable quantity then steps might be taken to reduce it. Much of this work has been done with United States data, and the most extensive investigations are probably those of Schwert (1989a), (1989b). Later we will itemize his conclusions, but for the moment one can recite the major ones. These are that volatility in the 1980's is not unusually high by historical standards; that it increases during recessions and major financial panics; that it is lower in a bull market than in a bear market; and that shocks to returns have a persistent influence upon volatility.

In this paper we attempt to provide an analysis of the volatility of stock returns with monthly Australian data from 1875 to 1987 that is similar to those performed on U.S. data. Section 2 summarizes some initial findings on the nature of stock market returns in Australia. This evidence points to sub-periods of our sample for which volatility was markedly higher than in other periods. Moreover it is found that the Australian market sometimes exhibited volatility when U.S. stock returns were quiescent. Section 3 moves onto a characterization of the determinants of volatility. Following other work, the predictable component of volatility is taken to be the conditional variance of stock returns, and a variety of models of the conditional variance are identified and calibrated. Modelling the predictable volatility allows us to identify periods of unusual volatility. These models show that volatility was noticeably higher during various financial crises, the Depression years of the 1930's, both World Wars, and for much of the last two decades.

Section 4 concentrates upon the issue of whether a shock impinging upon the stock market is persistent or not. This has been a major theme of U.S. work, and the models estimated in section 3 are utilized to examine the question. As for the U.S. research, ***prima facie*** it seems that shocks are not persistent before the Great Depression but have been since that date. Rather than accept this conclusion blindly, we investigate its sensitivity to which data is retained for estimation, concluding that any inferences about a shift in persistence are very fragile. Finally, section 5 makes some concluding remarks.

2. Return Characteristics of the Australian Stock Market

This section examines the characteristics of returns of the Australian stock market and compares our findings to those previously documented for the United States market. We find many similarities, but there are also some noticeable differences between the two markets.

2.1 The Data

In this study the raw data is the monthly aggregate stock market price index (P_t) collected and initially analysed by Lamberton (1958a,1958b), extended with subsequently published data. From January 1875 to June 1936 the index is the Commercial and Industrial Index; from July 1936 to December 1979 the Sydney All Ordinaries Index; and from January 1980 to December 1987, the Australian Stock Exchange All Ordinaries Index. Throughout the study returns are identified solely as capital appreciation, thereby ignoring dividend income, that is:

$$r_t = (P_t - P_{t-1})/P_t \, , \tag{1}$$

where r_t is the return for month t, and P_t is the index level at the end of month t. This approach is justified as the thrust of this study is an investigation of the volatility of the market. Dividend returns tend to be relatively stable over time, and thus do not substantially add to the variance of total returns. This characteristic of returns was observed for sub–periods in which we had access to dividend data, and it was therefore felt that concentrating on capital appreciation allowed us to capture the volatility characteristics of the market. Returns (r_t) were available monthly over the period 1875 to December 1987. However, much of the following analysis was performed on returns, $\hat{e}_t$, adjusted to account for monthly and over–lapping data effects. The precise derivation of these adjusted returns is described in the next section. Because of the adjustments some observations are lost and our effective sample runs from December 1875 to December 1987, yielding 1345 observations.

2.2 Large Price Index Movements

Table 1 lists the 25 largest absolute monthly adjusted returns ($\hat{e}_t$) from December 1875 to December 1987.[1] The market crash of late 1987 stands out with the two largest negative returns (of –28.6 percent and –18.2 percent) occurring in November and October of that year. That the crash was spread over two months can be attributed to the fact that, for many stocks, the first trade after October 20, 1987 was in November, with the index calculation based on last sale prices. The next largest return occurred in November 1930, around the time of the Great Depression. This negative return followed the largest positive return, 25 percent in October 1930. In examining this table several patterns emerge. Firstly, it appears that there are many reversals in stock returns, where large falls are followed by large rises and vice versa. For example, September–October–November 1930 appear as large fall–rise–fall, while August–November 1974, March–May 1968, and February–April 1975 also exhibit both rises and falls. This grouping of large changes in returns of either sign is characteristic of an increase in stock market volatility. Furthermore, it is apparent that there are

[1]Because the sign is important later it is given in the table. However, when we refer to large and small we will generally mean the absolute value of returns.

specific sub–periods in which large returns of either sign are prevalent. The 1930's, late 1960's, 1970's and 1980's are all notable by their frequent appearance in Table 1.

These results are similar in many ways, although different in other respects, to findings in the United States. Schwert (1989c) examines the largest and smallest returns for the U.S. stock market for the period 1802–1989. He also finds patterns of reversals, and distinct sub–periods of large market movements. However, unlike the Australian findings, the last two decades do not dominate. In fact, only three of fifty entries in his table are from this period in the U.S., compared to thirty–two of fifty in Australia. Although his sample covers a longer time period, this is still a striking difference between the two markets. This indicates that in the last two decades the Australian market has behaved fundamentally differently to its U.S. counterpart, a point we will return to subsequently.

2.3 Intertemporal Market Volatility

To further examine the intertemporal pattern of market volatility, we calculated the variance of returns by half decade. Table 2 shows the variance of stock market returns for the five years ending December 1882, through to the five years ending December 1987, and Figure 1 plots these. As suspected, the five years to December 1932 and the final four half decades exhibit substantially higher variance than other sub–periods. This confirms the finding above, where these periods reveal substantially more large price changes, and thus higher volatility.

There are two other ways of gaining insight into the volatility of the market. One is to examine a plot of the ***recursive*** estimate of the variance against time (see Mandelbrot (1963)). Given our adjusted returns $\hat{e}_t$, a recursive estimate of the unconditional variance at time t is given by

$$\hat{\mu}_2(t) = t^{-1} \sum_{k=1}^{t} \hat{e}_k^2 . \tag{2}$$

Figure 2 displays the plot of $\hat{\mu}_2(t)$ against time for the period April 1876 to December 1987. The first four observations are excluded to allow the recursive variance estimate to "settle down" and not be swamped by initial large returns. Four distinct phases are apparent. Up to 1896 the estimate is quite erratic. From 1897 to 1930 the unconditional variance is relatively stable, drifting downwards, but not erratically. In 1930 the variance jumps to a much higher level. Following this, the estimate is again quite stable until 1968, where it can be seen to rise quite dramatically and continuously. Again, this can be compared to findings from the U.S. stock market. Pagan and Schwert (1990) display a plot of the recursive variance estimate for the period 1834 to 1987. They find three distinct phases, initially erratic up to 1866, relatively stable until 1930, whereupon it jumps to a much higher level, but essentially stable thereafter. This highlights the difference between the two stock markets alluded to above. The Australian market seems to exhibit much higher volatility from the late 1960's to the present; a feature which is not apparent in the United States data.

A second method is to form an estimate of **yearly** volatility from the average of ***monthly*** squared returns; Schwert (1989a) computes monthly volatility in a similar way by using daily returns. Figure 3 plots this quantity (VOL) over time, where VOL is calculated for financial years, and it forms the basis of the following outline of historical volatility patterns.

As noted above there have been several sub–periods in which volatility increased noticeably over the years 1875 to 1987. The first of these appears around March 1879. The last six months of 1878 and the first several months of 1879 saw the market fall quite substantially in percentage terms. This fall, following an equally substantial rise in early 1878, resulted in the market displaying noticeably higher volatility over this period. The next outstanding increase in volatility appeared in late 1887. This occurred during the market surge commensurate with a speculative urban property boom. After reaching a peak in late 1888, the market fell for the next five years, which included the financial panic and bank closures of the early 1890's. These years witnessed increased market volatility, although dampened by the market's decline being spread over several years.

Around the time of Federation and the Boer War the market experienced a languid period, subsequently falling before a sharp recovery, all of which lead to several more periods of high volatility in 1902 and 1904. A quiet period then ensured until just prior to World War I. During the War, war priorities and the shortage of inputs restricted industrial activity, in consequence of which the market declined substantially until 1916, whereupon it once more reversed direction. Accordingly, these factors validated substantial volatility throughout the war years.

Low volatility in the twenties was rudely interrupted in the 1930's by the (prolonged) market crash of 1929–1930, the subsequent rebound, and immediate "re–crash". Volatility surged in late 1930, remained high for over a year following this, and again experienced high levels in late 1932; as apparent from Figure 3 this episode was the most volatile period in Australian share market history. By the late 1930's volatility had subsided and it was only the onset of World War II which changed this state of affairs; most noticeably the entry of the U.S. into the war following Pearl Harbor resulted once again in increased volatility, as the market reacted to these events and their economic implications. The introduction of share price controls in 1942 (until 1946) dampened market movements, and it was not until 1951/52 that volatility once again increased. The stock market surged on the back of wool price increases until early 1952, but then fell dramatically when wool prices collapsed and the economy experienced a severe, if brief, inflation.

One of the most spectacular increases in volatility over the sample period occurred in the late 1960's, following the resource boom and bust. Stocks such as Poseidon and Tasminex and others experienced extreme rises and falls, dragging the market along with them, and dramatically increasing volatility. This episode was merely a pre–cursor to a period of much higher volatility and for a longer duration than had been previously experienced. In very short order the market suffered from a hangover from the mining boom/bust of the late 1960's, the industrial and property boom of 1972–3, the OPEC oil crisis in 1973–4, and the start of a commodity price recovery from the mid–1970's. These all contributed to large swings in the market, and resulted in the very persistent increase in volatility displayed in Figure 3 during this period. The late 1970's provided some respite from these wild swings, but it wasn't to last as the new decade issued in more large market movements. During the early 1980's, many resource stocks experienced large price rises and falls, as commodity prices fluctuated over these years. As in the late 1960's and mid 1970's, the importance of this sector in the Australian economy created large general market movements. Interestingly enough, on a yearly basis volatility in 1987 was not particularly striking; the years 1982–1984 all saw larger average monthly movements in returns.

2.4 Market Asymmetry

A recurring finding of studies of the U.S. stock market is an asymmetric effect, in that negative shocks to returns lead to larger stock volatility than equivalent positive shocks. For example, Black (1976) found changes in stock returns and stock return volatility to be negatively correlated, implying that a decrease in returns is likely to be accompanied by an increase in volatility and vice versa. These results have been confirmed by, amongst others, Christie (1982), French, Schwert and Stambaugh (1987), Nelson (1989a) and Schwert (1989a). As a check on this phenomenon in the Australian market, we divided returns into those that were higher than the previous month by an amount x, and those that were lower by this amount, thereafter calculating the variance of these two sub–groups. We repeated this procedure for different values of x of 1, 3, 5, and 7 percent. If there is the conventional asymmetry, the variance of data when returns decline by more than x should exceed that for observations increasing by more than x.

Table 3 shows the results of this procedure for both the full sample and two sub–samples composed of 1875 to 1925 and 1926 to 1987. There is much weaker evidence for this asymmetric effect in Australian data than in the U.S. data. The full sample and the second sub–sample weakly support the hypothesis, revealing higher variances following falls in returns, although the differences are not substantial. Against this the data from 1875–1925 shows exactly the reverse, with high variances following rises in returns.

Various explanations have been advanced for this effect, including a leverage argument (see Black (1976) and Christie (1982)). This might be consistent with the comparisons just given, as leverage has presumably increased substantially since the 1930's. However, empirical evidence from the U.S. suggests that the leverage effect does not fully account for the negative relationship between stock returns and volatility (see French, Schwert and Stambaugh (1987)). Recently, Campbell and Hentschel (1990) have proposed and estimated a model that attempts to explain the observed asymmetry. Any shock to returns results in a persistent increase in volatility that reduces the current stock price. If the original shock was positive, the positive impact on prices is dampened by the increased volatility. If the news was negative, the volatility effect exacerbates the price decline. Hence the asymmetric effect discussed above. Campbell and Hentschel claim the data supports their model, although more work is undoubtably required before this effect is fully understood. Clearly a central feature of their model is that shocks are persistent, and this necessary condition needs to be carefully investigated.

2.5 Volatility and the Economy

Schwert (1989a,b) has shown that, in the U.S., stock market volatility is higher on average during recessions. He also documents that volatility increases following major banking/financial panics. It is of interest then to determine if the Australian market has a similar relationship with overall economic conditions. In doing so, we concentrate on the annual volatility series, VOL, which averaged squared monthly returns within financial years. Figure 3 gave a plot of this series.

A formal test relating volatility to economic conditions was performed by regressing VOL against itself lagged once and the yearly growth rate of real GDP over the period 1877 to 1987. A negative relation was found between volatility and GDP growth, but the t–statistic was only 1.5, and this shrank to just under unity after heteroskedasticity adjustments. Inspection of the data indicated that most of the effect was due to 1931, where a sharp jump in volatility was coincident with a 9.8% contraction in output. Eliminating the effect of this observation by a dummy variable gave a small **positive** coefficient for the growth rate term and a very large negative effect for 1931. An alternative approach, closer to Schwert's methodology, was to compare the mean of VOL in recession and non–recession years. Schwert used NBER reference cycle results to date recession years. There is no analogous information for Australia prior to WW2, so we designated a recession year as one experiencing negative growth. After WW2 the dating methods in Boehm and Moore (1984) were employed. As might be expected however, there was no evidence of any effect; the dummy variable used to represent recessions having a t value of only 0.2.

3. Modelling the Conditional Variance

Our objective is to examine volatility in the Australian stock market, and, in particular, periods of unusual volatility. To this end it is useful to model "normal" volatility, so unusual periods may be identified. This section presents several models that attempt to accomplish this. The first two models of conditional variance (or predictable volatility) examined are those of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) introduced by Bollerslev (1986) and Exponential GARCH (EGARCH) introduced by Nelson (1989a). Both these models are generalizations of the ARCH model of Engle (1982), and have been extensively applied to many financial and economic time series. Estimation of the model parameters involves joint Maximum Likelihood estimation of the return process and the conditional variance. The third model considered here is an iterative two step autoregressive filter for the conditional standard deviation. All three models identify periods in which volatility is unusual.

The first step in estimating any of the models just described is to adjust returns for any influences upon their conditional mean. In doing so we follow the procedure adopted by Pagan and Schwert (1990). There are two reasons to expect some predictability of the mean value of returns from available data — calender effects and non–synchronous trading. To account for such effects, we first regressed raw returns (r_t) on twelve monthly dummy variables (D_t) and examined the autocorrelations of the residuals, $\hat{u}_t$, i.e.

$$r_t = D_t'\beta + u_t \; . \tag{3}$$

Subsequently we regressed the residuals $\hat{u}_t$ on their twelve lagged values $\hat{u}_{t-1}...\hat{u}_{t-12}$, in order to eliminate the impact of non–synchronous trading. In this latter regression lags 1, 2, 3 and 9 were significant. The point estimates for the first four lags were 0.21, –0.08, 0.06 and –0.03, suggesting an MA(1) pattern with parameter approximately equal to 0.2. This effect was approximated by an AR(10), so that adjusted returns ($\hat{e}_t$) were the residuals from $\hat{u}_t$ regressed on $\hat{u}_{t-1}...\hat{u}_{t-10}$.

3.1 A GARCH Model

Writing the series to be modelled as $\hat{e}_t = \mu + \epsilon_t$, where μ is the unconditional mean of $\hat{e}_t$ and ϵ_t is a normally distributed error term with zero mean and conditional variance σ_t^2, Bollerslev (1986) proposed the GARCH(p,q) model of the conditional variance

$$\sigma_t^2 = \sigma^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{k=1}^{q} \gamma_k \epsilon_{t-k}^2 . \tag{4}$$

Following French, Schwert and Stambaugh (1987) and Pagan and Schwert (1990) a GARCH(1,2) model was estimated[2] giving (t–values in parentheses)

$$\hat{e}_t = \underset{(0.813)}{0.00047} + \hat{\epsilon}_t \tag{5}$$

$$\hat{\sigma}_t^2 = \underset{(4.064)}{0.00002} + \underset{(42.234)}{0.8803}\, \hat{\sigma}_{t-1}^2 + \underset{(8.978)}{0.3132}\, \hat{\epsilon}_{t-1}^2 - \underset{(-5.300)}{0.2085}\, \hat{\epsilon}_{t-2}^2 . \tag{6}$$

The log likelihood for this model was 2961.23. Table 4 presents the results of a diagnostic test suggested by Pagan and Sabau (1987) for checking the adequacy of this model; it involves the regression of $\hat{\epsilon}_t^2$ against a constant and $\hat{\sigma}_t^2$, the estimated conditional variance from the GARCH model. The slope coefficient of such a regression should be unity, and the intercept zero. The t–statistic of –.31 implies the hypothesis that the slope being unity cannot be rejected; the intercept is also within one standard deviation of its hypothesized value.[3] The coefficient of determination in Table 4 indicates how well the estimated conditional variance predicts the actual variance, which can be used to compare each of the models. The Box–Pierce statistic tests for

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[2]French et al. allow for an MA(1) in ϵ_t, but as we have purged the returns of this effect we ignore that variation here. In fact if the MA parameter is estimated its estimate is .0259 and the t–value if –.931.

[3]Pagan and Hong (1990) found that the model in French et al. (1987) could be rejected with this test.

(twelfth order) serial autocorrelation in the errors. The insignificant Q(12) statistic indicates the GARCH model captures much of the persistence in actual volatility.

As a check on the criterion function used to compare the different models, we also regressed $\ln \hat{e}_t^2$ on a constant and $\ln \hat{\sigma}_t^2$, with the coefficient of determination reported as "R^2 for logs". This is inspired by the idea of a proportional loss function rather than the quadratic one implicit in the linear regression. Again, this statistic can be used to compare the different models estimated. What is striking about the results in Table 4 is that the degree of predictability is much higher than in the U.S. data (see Pagan and Schwert (1990, Table 1)).

3.3 An EGARCH Model

Nelson (1989a) has argued that the GARCH specification is too restrictive as it imposes a quadratic mapping between σ_t^2 and the past history of ϵ_t, and that negative coefficients on the quadratic terms may lead to a negative conditional variance. To eliminate this latter possibility, and to allow σ_t^2 to be an asymmetric function of the past data, Nelson specifies the conditional variance as

$$\ln \sigma_t^2 = \sigma^2 + \sum_{j=1}^{p} \beta_j \ln \sigma_{t-j}^2 + \sum_{k=1}^{q} \alpha_k [\theta \varphi_{t-k} + \eta(|\varphi_{t-k}| - (2/\pi)^{0.5})], \tag{7}$$

where $\varphi_t = \epsilon_t/\sigma_t$, and (7) forms his Exponential GARCH(p,q) model. In estimation η is set equal to one to identify the parameters. As discussed above, there is some weak evidence in our data that σ_t^2 may indeed be an asymmetric function of past data, in which case the EGARCH model for conditional volatility may be more appropriate. As in Pagan and Schwert (1990) we estimated an EGARCH(1,2) model

$$\hat{e}_t = \underset{(-0.029\ )}{-.00002} + \hat{\epsilon}_t \tag{8}$$

$$\ln \hat{\sigma}_t^2 = \underset{(-3.503)}{-0.1637} + \underset{(150.602)}{0.9760} \ln \hat{\sigma}_{t-1}^2 + \underset{(11.341)}{0.4666}\, \hat{z}_{t-1} - \underset{(-5.572)}{0.2600}\, \hat{z}_{t-2}$$

$$\hat{z}_{t-k} = [\underset{(-3.772)}{-0.1857}\,\hat{\varphi}_{t-k} + |\hat{\varphi}_{t-k}| - (2/\pi)^{0.5}] . \quad (9)$$

The log likelihood for this model was 2970.19 suggesting the EGARCH model is superior to the GARCH model for this data set. Given the results on asymmetry earlier, the margin of preference is surprisingly large, hinting that it is the non–linear transform induced by logs that is making EGARCH superior. To investigate this further we fitted a model like (7) but with ϵ_{t-1}^2 and ϵ_{t-2}^2 as the forcing variables in place of z_{t-1} and z_{t-2}. This produced a log likelihood of 2938. So there is something else in the structure of an EGARCH model that accounts for its superiority. What is interesting however is that, when fitted to the data up to 1926, this new model had a log likelihood of 1422.0, dominating the 1416.5 and 1413.9 of EGARCH and GARCH respectively. Thus it may pay researchers to experiment with a variety of functional forms. The results in Table 4 again indicate that the null hypothesis $\hat{\sigma}_t^2 = E(e_t^2)$ cannot be rejected. The R^2 of .196 indicates the EGARCH model is superior to the GARCH model in explaining squared returns.[4] The Box–Pierce test again shows no evidence of residual correlation.

Figure 4 is a plot of the conditional variance from the EGARCH model against time. There are several outstanding features. Most suprising is the extremely large conditional variance in January 1897. This result is attributable to a large –11.2 percent return for December 1896, which occurred along with a very small conditional variance in the same month. The specification of the EGARCH model, with lagged residual returns in the numerator and lagged conditional variances in the denominator of the z_{t-k} term, results in this abberant finding. Other months with large negative returns rarely result in such large subsequent conditional variances as their effect is

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[4]The log–likelihood is for the returns $\hat{e}_t$, while the R^2 pertains to squared returns $\hat{e}_t^2$. Thus the two are not comparable, although they point in the same direction.

tempered by large contemporaneous conditional variances. This result must be viewed as detrimental to the EGARCH model. Apart from this extraordinary finding, Figure 4 is consistent with previously discussed evidence on volatility in the Australian stock market. There are particular sub-periods in which the volatility of the market increased, sometimes dramatically. The Great Depression years of the 1930's stand out, as do the last two decades of the sample.

3.3 An Autoregressive Model for the Conditional Standard Deviation

The ARCH class of models has had a brief if spectacular history of modelling the conditional variances of financial series. Of course, much research had been conducted on this problem before Engle's (1982) contribution. For example, Officer (1973), Fama (1976), Merton (1980) and others employ a 12-month rolling standard deviation estimator. It is thus of interest to estimate such a model and to compare it to the GARCH and EGARCH models above, firstly to see the improvement, if any, of such models in predicting volatility, and secondly to verify the findings on volatility patterns in the Australian market.

The model employed here is an iterative two-step procedure which is a generalization of the rolling 12-month models mentioned above. This model has been estimated for the U.S. by Schwert (1989a,1989b).

(i) Estimate a 12-th order autoregression for the (raw) returns, r_t, including monthly dummy variables,

$$r_t = \sum_{i=1}^{12} \alpha_i r_{t-i} + \sum_{j=1}^{12} \beta_j D_{jt} + e_t . \qquad (10a)$$

(ii) Estimate a 12-th order autoregression for the absolute values of the residuals from (10a), including monthly dummy variables to allow for different average monthly standard deviations,

$$|\hat{e}_t| = \sum_{i=1}^{12} \rho_i |\hat{e}_{t-i}| + \sum_{j=1}^{12} \gamma_j D_{jt} + \epsilon_t. \tag{10b}$$

The absolute errors $|\hat{e}_t|$ are multiplied by the constant $(2/\pi)^{-.5}$, as the expected value of the absolute error is less than the standard deviation from a Normal distribution, $E|\hat{e}_t| = \sigma_t(2/\pi)^{.5}$. The fitted values from (10b) estimate the conditional standard deviation of r_t, given that $\sigma_t = \sum_{i=1}^{12} \rho_j |e_{t-i}| + \sum_{j=1}^{12} \gamma_j D_{jt}$. In this model the (absolute value) standard deviation is used, not the variance (σ_t^2) as it has been argued (see Davidian and Carrol (1987)) that the standard deviation specification is more robust than variance based estimates. As in Schwert (1989a,b) we iterate twice between (10a) and (10b) using predictions from (10b) as the weights for a Weighted Least Squares regression on (10a). Further iterations revealed only negligible changes in the parameter estimates and standard errors.

The estimated parameters of (10a) and (10b) appear in Table 5, with Table 4 containing the result of the same diagnostic test as performed on the GARCH and EGARCH models. Here again we cannot reject the null hypothesis that the slope coefficient in the regression is unity and the intercept is zero. The R^2 statistic reveals that this estimation procedure performs better than the GARCH model, but not as well as the EGARCH model. Residual correlation again does not seem to be a problem.

Figure 5 plots the squared standard deviation estimates from (10b). This plot confirms previous findings of distinct sub–periods in which volatility has noticeably increased. It is interesting to compare once again these findings with those from the U.S. Schwert (1989b) displays a plot of conditional standard deviations from a model identical to (10b) for the period 1836 to 1987. He too finds markedly higher volatility during the Great Depression years. However for the U.S., there is no dramatic increase in volatility over the past twenty years, except for a slight surge around the OPEC oil crisis of 1973–4.

3.5 Summary

The overall picture of volatility in Australian stock markets is similar to that in the U.S. There is some predictability from the past history of returns and some weak evidence that volatility is larger in a bear than a bull market. However, there are also differences to the U.S. The asymmetric reaction just mentioned is very strong in U.S. data and volatility of stocks during the Great Depression just dominates any other period in U.S. history. In fact, it has even been concluded that the late 80's volatility is not unusual by historical standards (see Schwert (1989c)). Transference of these conclusions to the Australian context must be regarded as suspect. In the last two decades volatility was very high in Australian stock markets, even by historical standards. Of course the U.S. has not had the resource boom–bust cycle that Australia witnessed at the end of the 1960's and the early 1980's, but this fact should caution one in blindly applying methods successful in the study of one economy to that of another. Certainly, the Australian experience of the 70's and 80's is a challenging one for researchers, and deserves a fuller study elsewhere.

4. Persistence of Shocks

Of interest in stock market studies is how persistent are shocks to the volatility process, that is, once volatility increases, does it remain high for many subsequent periods. Persistence or lack thereof has implications for the parameter values of the various models presented above. In terms of the GARCH and EGARCH models, we are interested in whether they can be described as Integrated GARCH and EGARCH (IGARCH and IEGARCH respectively). The definition of an IGARCH model is $\sum_j \alpha_j + \sum_i \beta_i = 1$,[5] and for an IEGARCH model, $\sum_i \beta_i = 1$. In both cases, the

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[5]Nelson (1989b) provides a comprehensive discussion of the conditions required for an IGARCH model. Provided there is a constant term in (4), shocks will be persistent if this condition holds. Without a constant term σ_t^2 is a degenerate random variable as $t \to \infty$.

estimated parameter values sum close to unity, indicating strong persistence of shocks. Similarly the sum of the coefficients in (10b) is .764. Unfortunately, there is no test statistic available for assessing whether the point estimates deviate significantly from unity. Hong (1988) has argued that the IGARCH process yields MLE estimators that are asymptotically normal, but it seems unlikely that this would be true for IEGARCH. Nevertheless, the fact the point estimates are so close to unity hints that the degree of persistence is very high even if shocks are not permanently incorporated into volatility. Thus, all models indicate that once volatility increases, it is likely to remain high for many future periods.

This conclusion is in line with findings in the U.S. stock market. French, Schwert and Stambaugh (1987) find high persistence using a GARCH model for the period 1928 to 1984. Using the same data set, Nelson (1989a) finds a similar result from an EGARCH model. For the period 1836 to 1987 Schwert (1989) also finds a high degree of persistence from an autoregressive model. However, if estimation is restricted to data from 1835 to 1925, Pagan and Schwert (1990) do not find such persistence. We thus investigated the degree of persistence in volatility shocks for the Australian market for sub–periods 1876–1925, and 1926–1987. For the first sub–period, the sum of the coefficients for a GARCH model is 0.5265, while the estimate of the autoregressive parameter in the EGARCH model is 0.6528. For the 2 step model the coefficients in (10b) were estimated to sum to .289. For the second sub–period, the results are reversed. The GARCH parameters sum to 0.9851, the EGARCH autoregressive parameter is .976, and the (10b) parameters to 0.773 with a standard error of 0.079. It thus appears that, in this respect at least, the Australian stock market is in accord with its U.S. counterpart, displaying marked persistence since the mid to late 1920's, but rather less before.

Some objections might be raised to accepting this conclusion too hastily. Findings of "unit roots" in series have been criticized as stemming from only a few observations such as the Great Depression or structural change, e.g., Perron (1989) and Lamoureux and Lastrapes (1990). Alternatively, it might be argued that only large shocks are persistent and that small ones are not. To assess how robust our conclusion is to these objections, we performed the following experiment: estimate the GARCH model over a number of sub–periods omitting observations on returns whose ***absolute*** value exceeded x%, where x = 20, 15, 10, 7.5, 5, 3 and 1%. Trimming the data symmetrically before estimation is our way of considering if persistence is different for small and large changes. We do the trimming symmetrically in an attempt to avoid bias being introduced into an estimator from the omission of observations. Suppose that the persistence parameter has the same value θ_o regardless of return magnitude. For large samples, the MLE of θ using all observations is that value of θ (θ^*) which sets the expectation of the scores to zero, i.e., θ^* solves $\int_{-\infty}^{\infty} \frac{\partial L}{\partial \theta} (\theta^*) f(y)dy = 0$, where L is the log likelihood for earnings and f(y) is their density. If the model is correctly specified, $\theta^* = \theta_o$. When the density f(y) is symmetric, performing symmetrically trimmed maximum likelihood does not modify this conclusion since the expectation of the scores under trimming is $\int_{-x}^{x} \frac{\partial L}{\partial \theta} f(y)dy$ and hence it equals zero when $\theta = \theta^* = \theta_o$. However, if volatility persistence differs between large and small returns, the solution for θ from setting the limits of integration to $\pm \infty$ and $\pm$ x will differ. Note that it is important to trim symmetrically, otherwise one will observe the standard "censored regression bias".

Before considering the outcome of trimming and sample variation experiments, it is necessary to check if returns are symmetrically distributed. A necessary condition is that the third moment of returns standardized by the conditional standard deviation be zero. Testing if the population third moment is zero with the sample third moment, easily leads to acceptance of the null hypothesis: the largest t–statistic under all types of trimming is only .5.

Table 6 records what happens to the sum of the GARCH parameters as the sample period and the amount of trimming varies. Apart from the 1875–1925 period it is hard to escape the conclusion that shocks to volatility seem equally persistent for both large and small returns. Even for 1875–1925 this would be the conclusion if only data with absolute returns less than or equal to 10% was retained for estimation purposes, leading us to a closer examination of the source of the much smaller persistence when absolute returns above 10% are included in the sample. Inspection of the data shows that only 3 absolute returns exceed 10% in the 1875–1925 period, so that the .5 estimate of persistence is being determined solely by these three observations. Such sensitivity of the point estimate of the sum of the GARCH coefficients to a few observations must make any inference about persistence extremely fragile — to use Leamer's (1983) description. Accordingly, we feel it safe to conclude that there is persistence of shocks in volatility, and that this persistence is as true of small shocks as it is of large ones. Moreover, there is no evidence that the persistence is due to structural change; over long periods it has remained remarkably constant.

5. Conclusion

This study has documented the pattern of volatility for the Australian stock market over more than a century. The summary statistics of Section 2 and the models of Section 3 all point to various times during which volatility was substantially higher than for the remainder of the sample. A major finding of this study is that there are differences between the Australian and U.S. markets. Many of the features of the U.S. market, such as asymmetry in responses, sensitivity to economic conditions etc. are either not present in the Australian context or are present to a lesser degree. Moreover, particularly in the last two decades, there seem to be fundamentally quite different volatility patterns in the two markets. From the late 60's onward high volatility is apparent in Australian data largely independent of recessions, banking crises and so on. Perhaps, as is suggested above, this is attributable to the Australian market's relative dependence on commodity prices, which the more diversified U.S. market does not share. Rationalization of this high volatility based on these or other explanations is a fruitful topic for future research.

REFERENCES

Black and Fischer (1976) "Studies of Stock Price Volatility Changes", ***Proceedings of the 1976 Meetings of the Business and Economics Statistics Section***, American Statistical Association, 177–181.

Boehm and Moore (1984) "New Economic Indicators for Australia, 1949–84", ***Australian Economic Review***, 4184, 34–56.

Bollerslev, T. (1986) "Generalized Autoregressive Conditional Heteroskedasticity", ***Journal of Econometrics***, 31, 307–328.

Campbell, J. and L. Hentschel (1990) "No News is Good News: An Asymmetric Model of Changing Volatility in Stock Returns" (mimeo, Princeton University).

Christie, A. A. (1982) "The Stochastic Behaviour of Common Stock Variances: Value, Leverage and Interest Rate Effects", ***Journal of Financial Economics***, 10, 407–432.

Davidian, M. and R. J. Carroll (1987) "Variance Function Estimation", ***Journal of the American Statistical Association***, 82, 1079–1091.

Engle, R. F. (1982) "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation", ***Econometrica***, 50, 987–1007.

Fama, E. F. (1976) "Inflation Uncertainty and Expected Returns on Treasury Bills", ***Journal of Political Economy***, 84, 427–428.

French, K. R., G. W. Schwert and R. F. Stambaugh (1987) "Expected Stock Returns and Volatility", ***Journal of Financial Economics***, 19, 3–29.

Hong, C. H. (1988) "The Integrated Generalized Autoregressive Conditional Heteroskedastic Model: The Process, Estimation and Monte Carlo Experiment" (mimeo, University of California at San Diego).

Lamberton, D. Mc (1958a) "Economic Growth and Stock Prices: The Australian Experience, ***Journal of Business***, 31, 200–212.

Lamberton, D. Mc. (1958b) "Appendix I of ***Share Price Indices in Australia***, Law Book Company of Australasia, Sydney.

Lamoureux and Lastrapes (1990) "Persistence in Variance, Structural Change and the GARCH Model", ***Journal of Business and Economics***, 225–234.

Leamer, E. E. (1983) "Lets Take the Con Out of Econometrics", ***American Economic Review***, 73, 31–44.

Mandlebrot, Benoit (1963) "The Variation of Certain Speculative Prices", ***Journal of Business***, 36, 394–419.

Merton, R. C. (1980) "On Estimating the Expected Return on the Market: An Exploratory Investigation", ***Journal of Financial Economics***, 8, 323–361.

Nelson, D. B. (1989a) "Conditional Heteroskedasticity in Asset Returns: A New Approach", Working Paper in Economics and Econometrics, No. 89–73, University of Chicago.

Nelson, D. B (1989b), "Stationarity and Persistence in the Garch(1,1) Model", Working Paper No. 88–68, Graduate School of Business, University of Chicago.

Officer, R. R. (1973) "The Variability of the Market Factor of the New York Stock Exchange, ***Journal of Business***, 46, 434–453.

Pagan, A. R. and H. Sabau (1987) "Consistency Tests for Heteroskedastic and Risk Models", Unpublished manuscript, University of Rochester.

Pagan, A. R. and Y–S. Hong (1990) "Nonparametric Estimation and the Risk Premium", in W. Barnett, J. Powell and G. Tauchen, eds, ***Semiparametric and Nonparametric Methods in Econometrics and Statistics***, Cambridge University Press, Cambridge (forthcoming).

Pagan, A. R. and G. W. Schwert (1990) "Alternative Models for Conditional Stock Volatility", ***Journal of Econometrics***, 45, 267–290.

Perron, P. (1989) "The Great Crash, the Oil Price Shock and the Unit Root Hypothesis", ***Econometrica***, 57, 1381–1401.

Schwert, G. W. (1989a) "Why Does Stock Market Volatility Change Over Time?", ***Journal of Finance***, 44, 1115–1153.

Schwert, G. W. (1989b) "Business Cycles, Financial Crises and Stock Volatility", ***Carnegie–Rochester Conference Series on Public Policy***, 31, 83–125.

Schwert, G. W. (1989c) "Stock Market Volatility", MERC Working Paper, 89–24, University of Rochester.

White, H. (1980) "A Heteroskedasticity–Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity", ***Econometrica***, 48, 817–838.

Table 1

The 25 Largest and Smallest Monthly Percent Returns, 1875–1987

	Smallest Percent Returns		Largest Percent Return	
1	November 1987	–28.62	October 1930	24.99
2	October 1987	–18.24	February 1876	24.84
3	November 1930	–16.41	February 1975	15.44
4	June 1974	–12.23	October 1888	12.08
5	January 1876	–11.65	January 1980	12.03
6	August 1974	–11.50	December 1903	11.41
7	March 1968	–11.45	December 1971	11.40
8	March 1980	–11.43	January 1974	10.70
9	September 1973	–11.24	November 1974	10.59
10	December 1896	–11.12	April 1983	9.51
11	November 1915	–9.85	February 1968	9.36
12	June 1940	–9.79	January 1983	8.99
13	September 1930	–9.20	May 1968	8.73
14	January 1982	–9.12	April 1968	8.71
15	May 1970	–9.11	November 1931	8.47
16	March 1982	–8.96	July 1902	8.07
17	November 1960	–8.79	August 1984	8.04
18	April 1975	–8.62	October 1986	7.91
19	December 1878	–8.55	June 1980	7.87
20	July 1986	–8.35	March 1972	7.80
21	June 1931	–8.32	October 1973	7.49
22	August 1914	–8.12	September 1982	7.26
23	October 1976	–7.94	February 1980	7.21
24	January 1930	–7.58	August 1932	7.18
25	June 1984	–7.83	July 1987	7.12

Table 2

Stock Market Variance by Half Decade

5 Years Ending	Variance (x 10^{-3})
December 1882	0.9037
1887	0.6637
1892	0.8664
1897	0.5391
1902	0.3007
1907	0.3678
1912	0.2964
1917	0.8977
1922	0.3467
1927	0.1805
1932	2.6564
1937	0.3159
1942	0.7557
1947	0.1924
1952	0.6857
1957	0.3095
1962	0.6203
1967	0.6287
1972	2.1744
1977	3.0903
1982	2.2007
1987	4.0413

Table 3

Return Asymmetry

	1875–1987		1875–1925		1926–1987	
	Number	Variance	Number	Variance	Number	Variance
Higher by 0%	669	0.001036	306	0.000647	352	0.001271
Lower by 0%	675	0.001139	294	0.00574	380	0.001520
Higher by 1%	485	0.001312	213	0.000859	258	0.001595
Lower by 1%	496	0.001467	195	0.000796	287	0.001898
Higher by 3%	233	0.002236	78	0.00185	151	0.002409
Lower by 3%	239	0.002573	83	0.00150	153	0.003052
Higher by 5%	120	0.003430	28	0.00361	83	0.003537
Lower by 5%	110	0.004163	32	0.00257	77	0.004716
Higher by 7%	64	0.005418	12	0.00670	44	0.005138
Lower by 7%	55	0.006467	16	0.00390	44	0.006742

Table 4

Comparison of Predictive Power for the Conditional Variance of Stock Returns, 1875 – 1987

$$\hat{e}_t = \alpha + \beta\, \hat{\sigma}_t^2 + \eta_t$$

Model	α	β	R^2	Q(12)	R^2 for logs
1. GARCH	0.00013 (.0003) [.3943]	0.88191 (.3760) [-.314]	0.1317	12.1	0.1138
2. EGARCH	-0.00042 (.00050) [-.8429]	1.49182 (.5590) [.8644]	0.1959	8.5	0.1205
3. Iterative 2–Step	-0.00006 (.00028) [-.2143]	1.17610 (.3735) [.4716]	0.1604	17.6	0.1189

Standard errors using White's (1980) heteroscedastic consistent covariance matrix are in parentheses, and t–statistics for α=0, β=1 in brackets. R^2 is the coefficient of determination. Q(12) is the heteroscedastic corrected Box–Pierce statistic for 12 lags of the residual autocorrelation. The corrected Box–Pierce statistic is calculated by summing the squared autocorrelation estimates, each divided by White's heteroscedastic variance. The statistic should be distributed as a $\chi^2(12)$. The 5% critical value for a $\chi^2(12)$ is 21.03. The R^2 for logs shows the R^2 from a regression of $\ln \hat{e}_t^2$ on $\ln \hat{\sigma}_t^2$.

Table 5

Estimate of the Autoregressive Model of Conditional Volatility (10b)

	Monthly Data, 1875 – 1987		
Parameter	Estimate	Std Error	t–Statistic
ρ_1	0.2556	0.0692	3.6949
ρ_2	0.0600	0.0463	1.2949
ρ_3	0.1693	0.0367	4.6099
ρ_4	–0.0120	0.0387	–.3102
ρ_5	0.0371	0.0346	1.0712
ρ_6	0.0187	0.0382	0.4889
ρ_7	0.0880	0.0355	2.4792
ρ_8	0.0571	0.0390	1.4624
ρ_9	0.0451	0.0428	1.0536
ρ_{10}	0.0162	0.0336	0.4828
ρ_{11}	0.0272	0.0351	0.7743
ρ_{12}	0.0014	0.0344	0.0407

Table 6

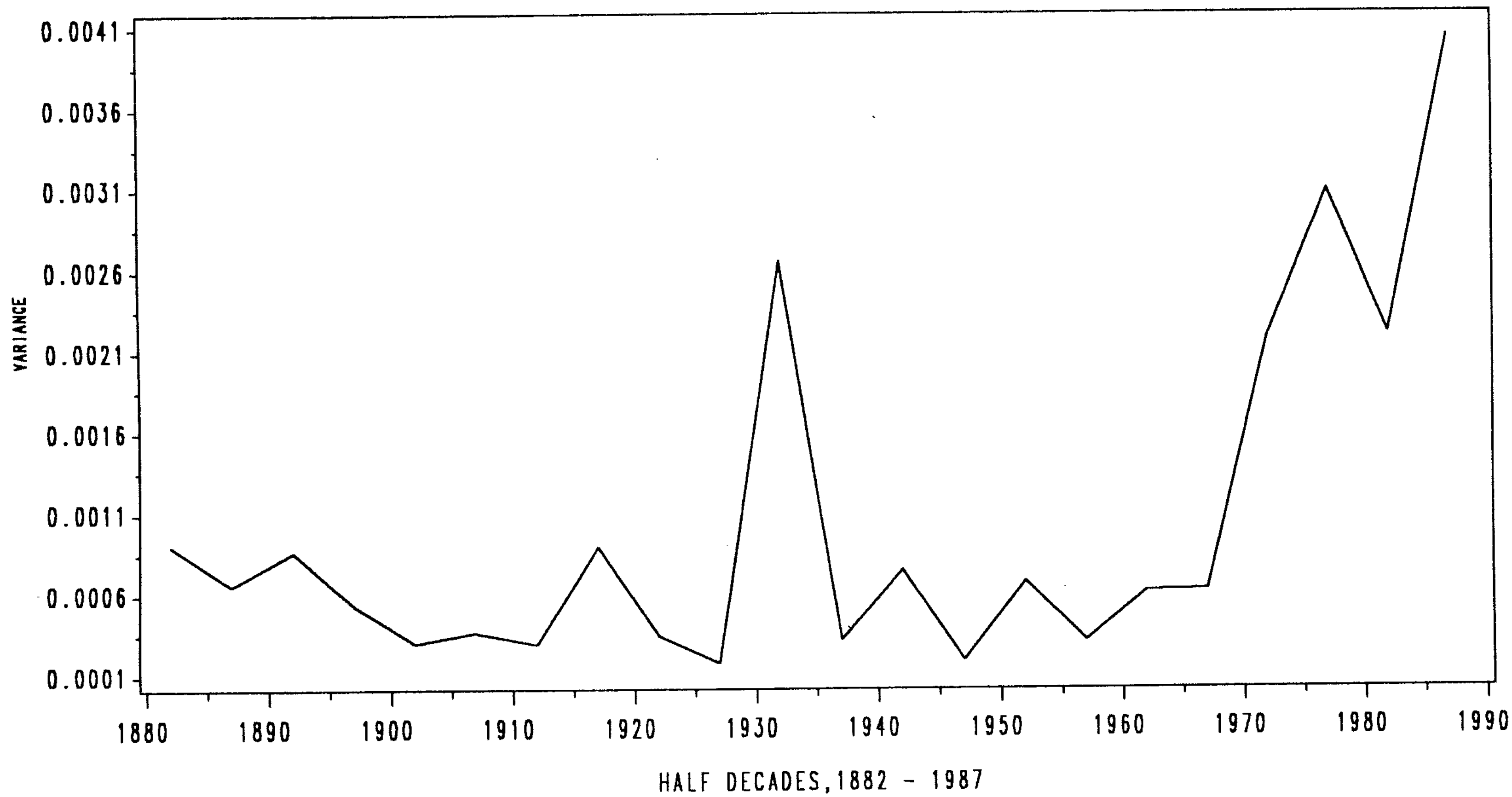
Estimates of the Degree of Persistence with Varying

Degrees of Trimming and Sample Periods

Sample	∞	20	15	10	7.5	5	3	1
1875–1925	.51	.51	.51	.97	.97	.97	.97	.97
1875–1935	.97	.96	.96	.96	.96	.96	.94	.96
1875–1987	.99	.98	.98	.97	.95	.93	.92	.97

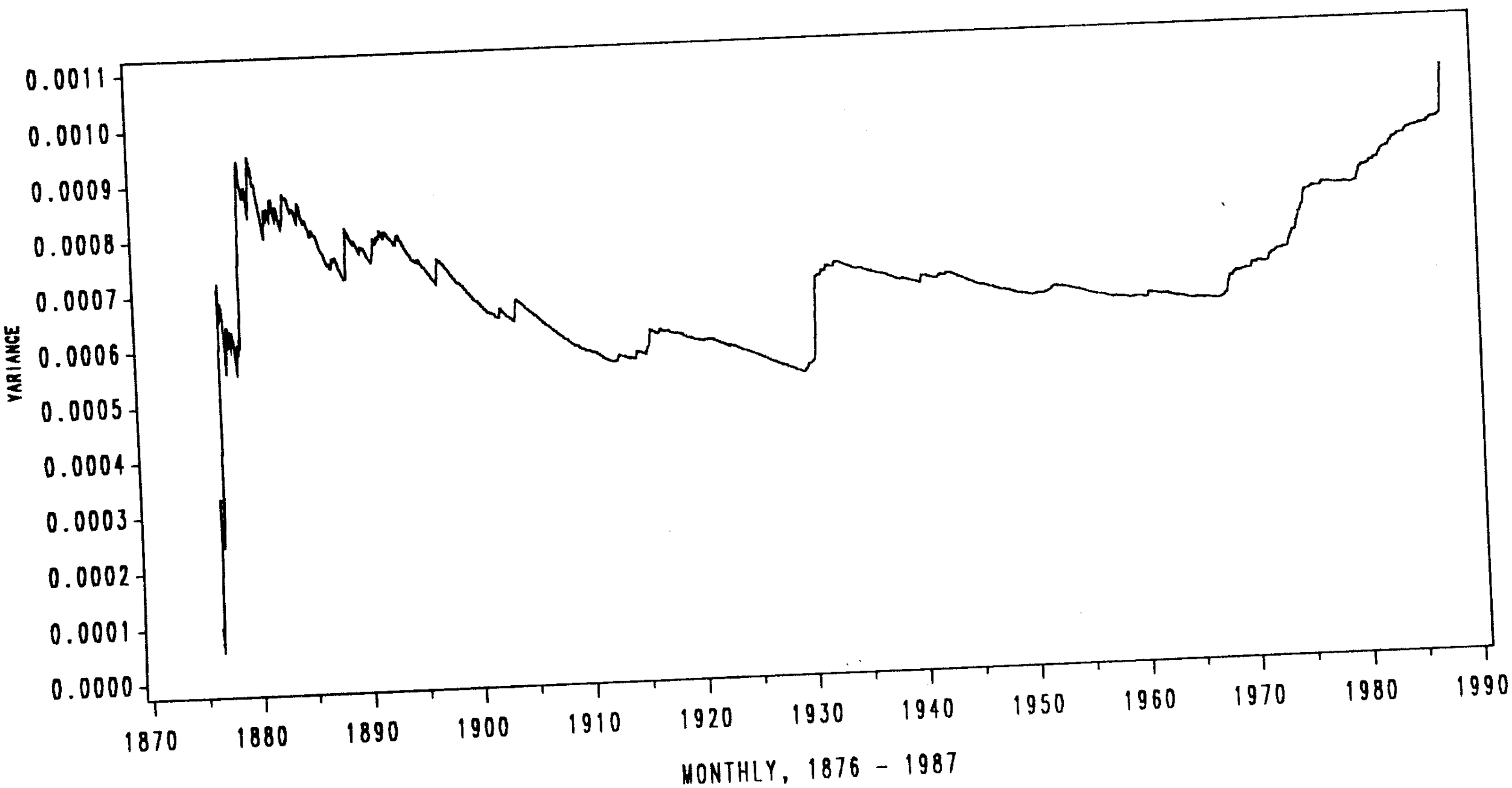
The numbers represent the sum of the GARCH parameters from a fitted GARCH(1,2) model. ∞ represents no trimming. Otherwise the top row indicates the percentage return above which observations are deleted from the sample.

FIGURE 1 STOCK MARKET VARIANCE BY HALF DECADE



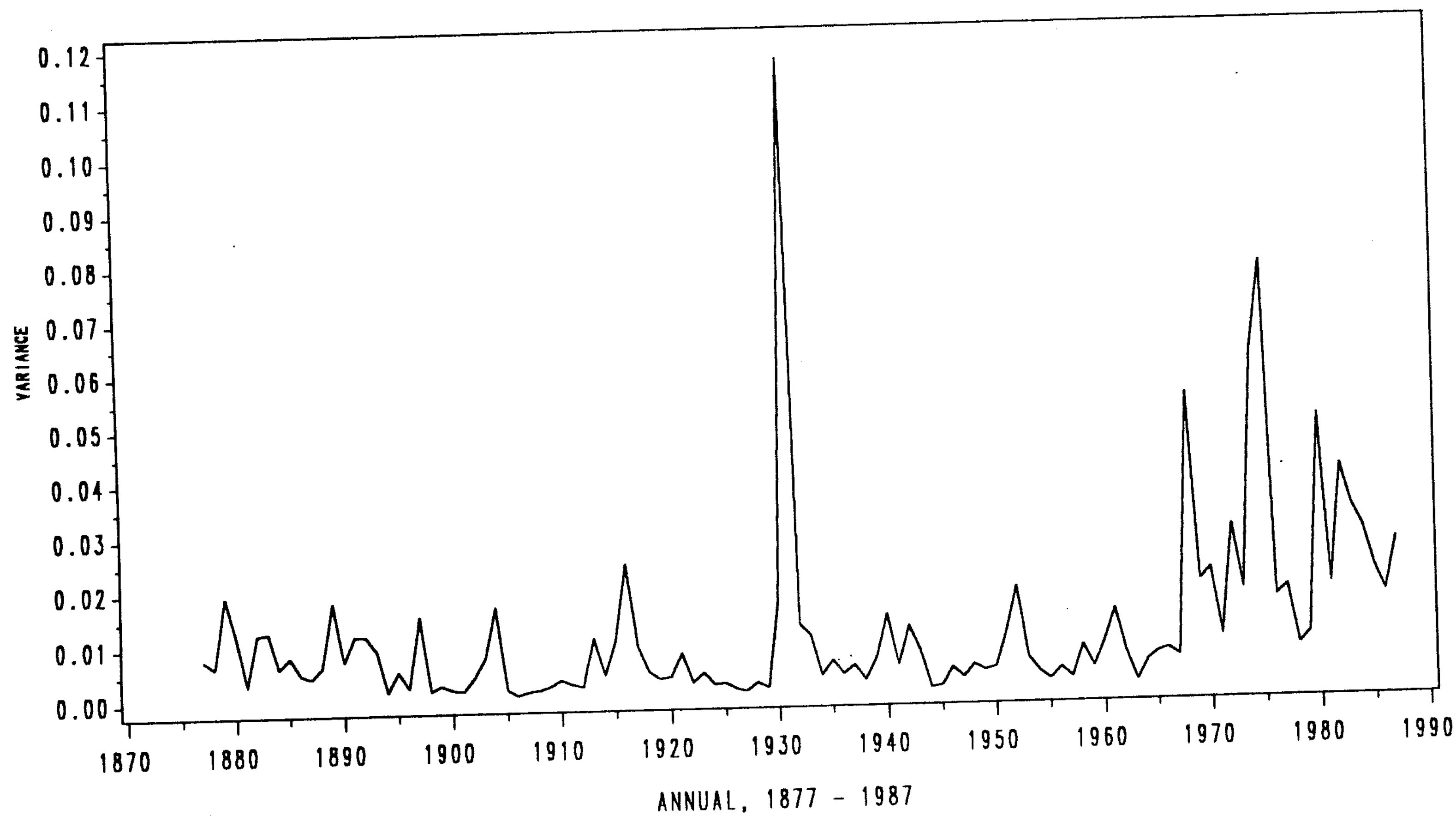
STOCK MARKET VARIANCES FOR FIVE YEAR PERIODS
FROM 1882 TO 1987

FIGURE 2 RECURSIVE STOCK MARKET VARIANCE



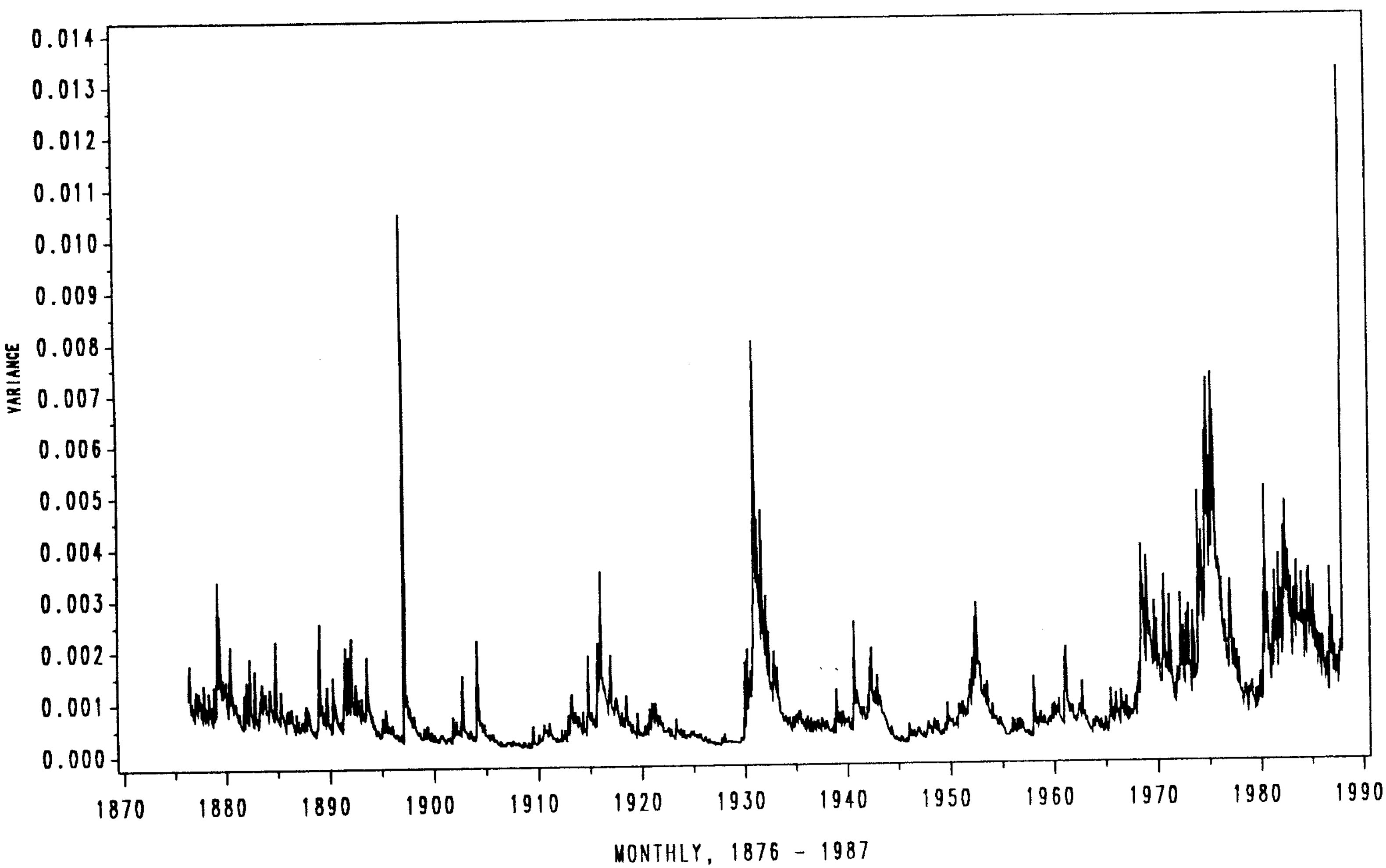
ESTIMATED RECURSIVE UNCONDITIONAL VARIANCE
1876 TO 1987

FIGURE 3 ANNUAL STOCK MARKET VARIANCE



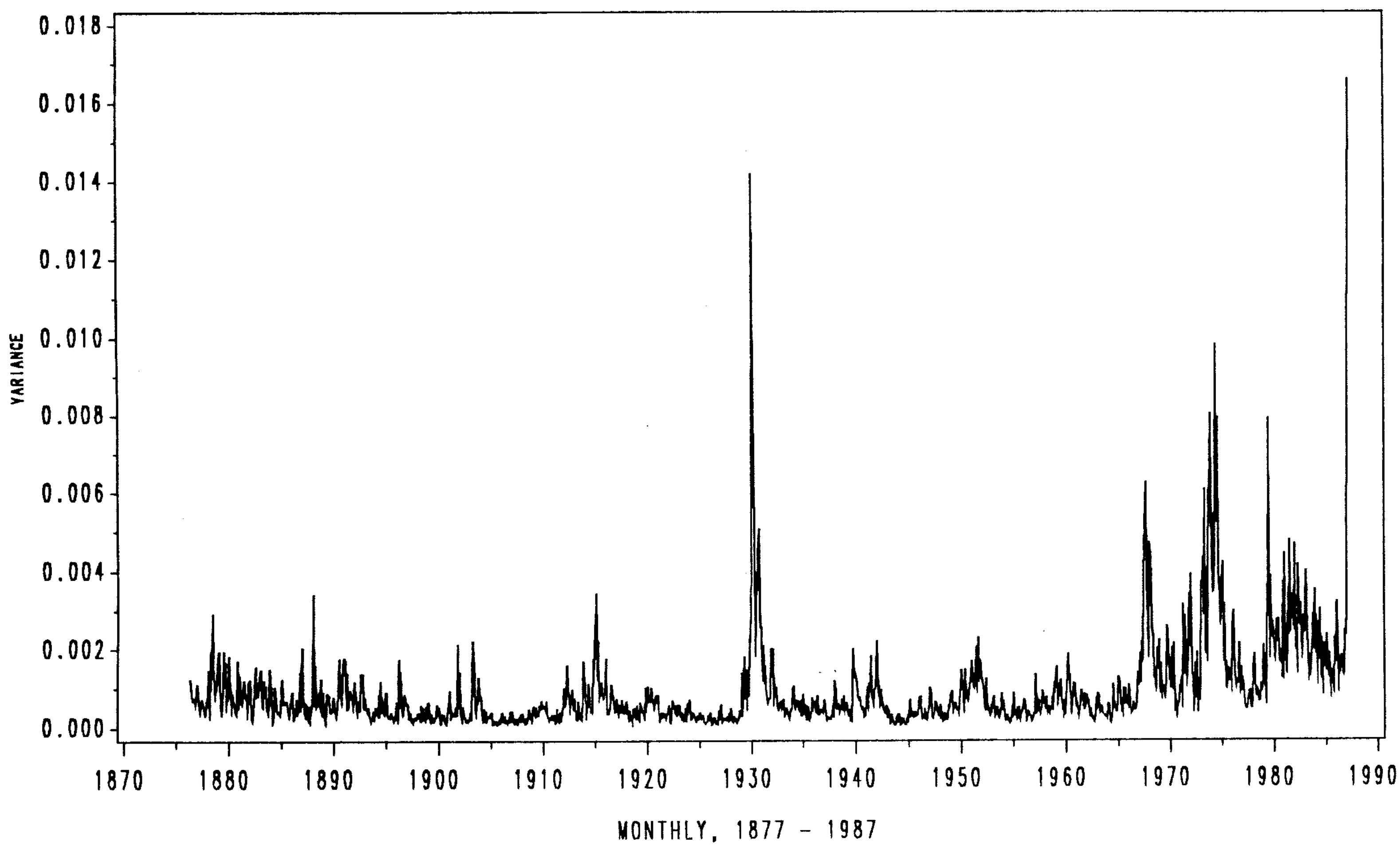
ANNUAL STOCK MARKET VARIANCE FROM SQUARED
MONTHLY RETURNS, 1877 TO 1987

FIGURE 4 EGARCH CONDITIONAL VARIANCE



MONTHLY CONDITIONAL VARIANCE ESTIMATED BY AN EGARCH(1,2) MODEL, 1876 TO 1987

FIGURE 5 AUTOREGRESSIVE CONDITIONAL VARIANCE



MONTHLY CONDITIONAL VARIANCE ESTIMATED BY A
TWO STEP ITERATIVE LINEAR FILTER, 1877 TO 1987