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Australian Stock Market Volatility: 1875-1987*

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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 centres upon whether the 'stylized facts' regarding returns in the US 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 US 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 1930s. 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 1980s 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 US data. Section II summarizes some initial findings on the nature of stock market returns in Australia. This evidence points to subperiods 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 US stock returns were quiescent. Section III 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 1930s, both World Wars, and for much of the past two decades.

Section IV concentrates upon the issue of whether a shock impinging upon the stock market is persistent or not. This has been a major theme of US work, and the models estimated in Section III are utilized to examine the question. As for the US research, *prima facie* it seems that shocks are not persistent before the Great Depression, but have been since that date. However, we subject that conclusion to a somewhat more intensive scrutiny than has been usual in US research, studying the sensitivity of persistence measures to variations in the data used for estimation, concluding that any

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inferences about a shift in persistence are very fragile. Finally, Section V makes some concluding remarks.

II 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.

(i) The Data

In this study the raw data is the monthly aggregate stock market price index (P_t) collected and initially analyzed by Lamberton (1958a,1958b, 1958c), 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. Lamberton sought to construct an index that

> ... intended to show what would have happened to an investor's funds, if at the beginning of 1875, he had bought all shares quoted on the Sydney Stock Exchange, allocating his purchases among the individual issues in proportion to their total monetary value, and each month by the same criterion redistributed his holdings among all quoted shares (1958c, p. 254).

Hence the series was designed to be comparable to the All Ordinaries Index; the main discrepancy arises from the introduction after 1935 of a finance and mining sector in the All Ordinaries not present in the Commercial and Industrial Index. The series used here is identical to that published by the Research Department of the Sydney Stock Exchange for 1875-1975 as the '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 the 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. Such a characteristic of returns was observed for subperiods in which we did have access to dividend data, and it was therefore felt that concentrating solely on capital appreciation would allow us to capture the volatility movements in the market. Returns (r_t) were available monthly over the period February 1875 to December 1987, but the following analysis was conducted on a return series, $\hat{e}_t$, adjusted to eliminate the influence of any movements in the conditional mean of the series. Working with 'mean-corrected' data seems justified, as the focus of this study is on the volatility or variance of returns. To effect such an adjustment we follow the procedure adopted by Pagan and Schwert (1990).

There are at least two reasons to expect some predictability of the mean value of returns from available data-calendar effects and non-synchronous trading.[1] To account for such effects we first regressed raw returns (r_t) on 12 monthly dummy variables (D_t), i.e. the underlying model of returns is,

$$r_t = D'_t c + u_t, \tag{2}$$

producing residuals $\hat{u}_t$ which are free of calendar effects. In order to examine the impact on returns of non-synchronous trading (or other effects) we considered the autocorrelations of the residuals through a regression of $\hat{u}_t$ on $\hat{u}_{t-1}, \ldots, \hat{u}_{t-12}$. In this regression, only lags 1, 2, 3 and 9 of $\hat{u}_t$ 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. These pieces of evidence support the belief that the non-synchronous trading effect can be well approximated by an AR(10), and the residuals from a regression of $\hat{u}_t$ on $\hat{u}_{t-1}, \ldots, \hat{u}_{t-10}$ will therefore be defined as the adjusted returns ($\hat{e}_t$). Because of these adjustments some observations are lost and our effective sample runs from December 1875 to December 1987, yielding 1345 observations.

[1] Calendar effects, for example the January effect, have been well documented for US returns (see, *inter alia*, Keim, 1983; and Reinganum, 1983). Non-synchronous trading (for example, not all stocks being traded at close of business at month's end) may result in serial correlation in returns, leading to some predictability of returns from their past history (see Lo and MacKinley, 1990, for an analysis of this phenomenon). Regressing raw returns on monthly dummies and subsequently accounting for the autocorrelation deals with these predictable elements.

TABLE 1

The 25 Largest and Smallest Monthly Per Cent Returns, 1875-1987

	Smallest Per Cent Returns		Largest Per Cent Returns	
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

(ii) Large Price Index Movements

Table 1 lists the 25 largest absolute monthly adjusted returns ($\hat{e}_t$) from December 1875 to December 1987.[2] The market crash of late 1987 stands out with the two largest negative returns (of -28.6 per cent and -18.2 per cent) 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 20 October 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 per cent in October 1930. In examining this table several patterns emerge. First, 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 specific subperiods in which large returns of either sign are prevalent. The 1930s, late 1960s, 1970s and 1980s 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 US stock market for the period 1802-1989. He also finds patterns of reversals, and distinct subperiods of large market movements. However, unlike the Australian findings, the last two decades do not dominate. In fact, only three of 50 entries in his table are from this period in the US, compared to 32 of 50 in Australia. Although his sample covers a longer time period, this is still a striking difference

[2] 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.

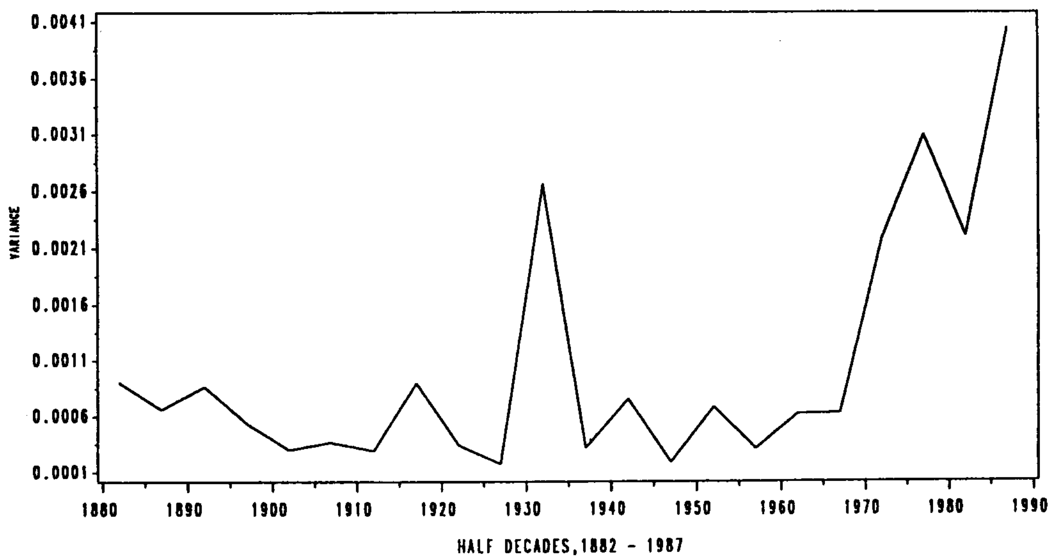

FIGURE 1

Stock Market Variance by Half Decade

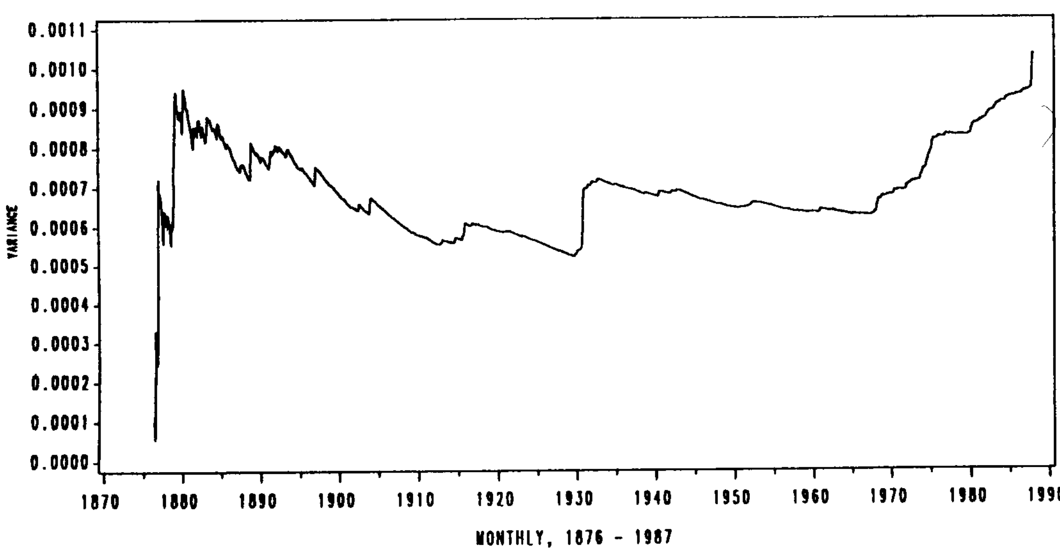

FIGURE 2

Recursive Stock Market Variance

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

between the two markets. This indicates that in the last two decades the Australian market has behaved fundamentally differently from its US counterpart, a point we will return to subsequently.

(iii) A History of Australian Stock 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 subperiods. 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

$$\hat{\mu}_2(t) = t^{-1} \sum_{k=1}^{t} \hat{e}_k^2. \tag{3}$$

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, due to there being relatively few observations included, the estimate jumps around somewhat. Even so, it is possible to identify occasions, such as 1888, where the variance noticeably increases. From 1897 to 1930 the unconditional variance is relatively stable, drifting downwards, but not exhibiting large (discrete) jumps. In 1930 the variance increases 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 US 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; an (small t) erratic period up to 1866, a relatively stable period until 1930, and then a jump to a much higher level, which essentially remains 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 1960s to the present, a feature which is not apparent in the United States data.

A second method of describing volatility patterns 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. A major use of this second measure is to provide a description of historical volatility patterns, which can not be easily gleaned from $\hat{\mu}_2(t)$. The account that follows is therefore a summary of the salient features of Figure 3.

As noted above there have been several subperiods in which volatility increased noticeably over the years 1875 to 1987.[3] The first of these appears around March 1879. The last six months of 1878 and the first few 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

[3] To gain some idea of the significance of the peaks in VOL apparent in Figure 3, we calculated the standard deviation of VOL up to 1929. This turned out to be 0.0005. As can be seen, many of the high points in VOL are significantly different from the preceding values.

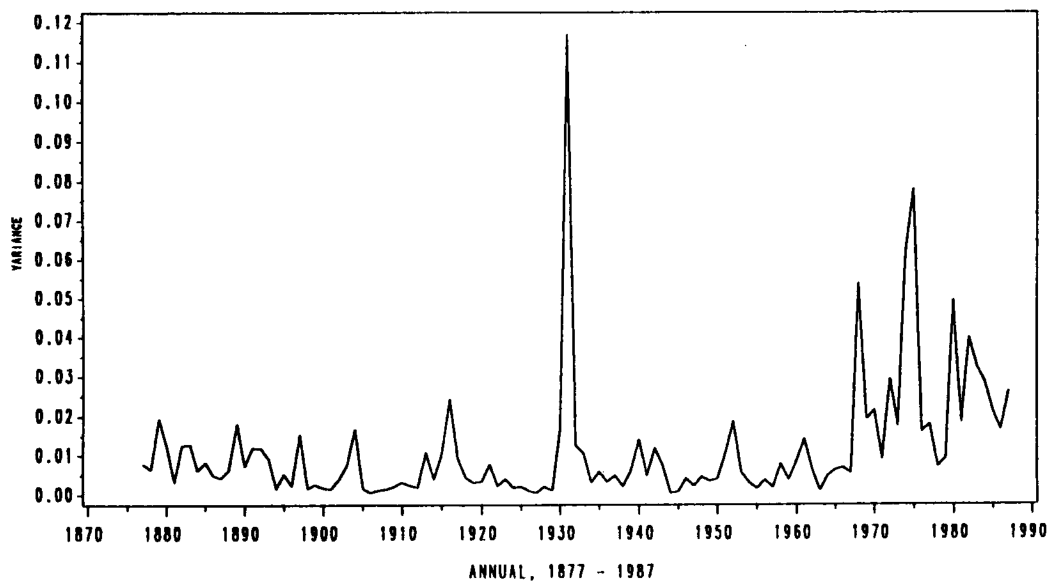

FIGURE 3

Annual Stock Market Variance

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 1890s. 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 led to several more periods of high volatility in 1902 and 1904. A quiet period then ensued 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 1930s 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 1930s 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 US 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 1960s, 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 1960s, the industrial and property boom of 1972-73, the OPEC oil crisis in 1973-74, and the start of a commodity price recovery from the mid-1970s. 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 1970s 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 1980s, many resource stocks experienced large price rises and falls, as commodity prices fluctuated over these years. As in the late 1960s and mid 1970s, the importance of this sector in the Australian economy created large general market movements. Noticeably absent from Figure 3 is a large value of VOL in 1987, which is due to our use of financial rather than calendar years. In fact, if VOL is calculated on a calendar year basis, the resulting value exceeds even that of 1930, demonstrating the significance of this episode of stock market history.

(iv) Volatility and the Economy

Schwert (1989a,b) has shown that, in the US, 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 per cent 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, would be 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 World War II, so we designated a recession year as one experiencing negative growth. After World War II 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.

(v) Market Asymmetry

A recurring theme of studies of the US stock market is that of an asymmetric effect of market activity upon volatility, 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 (1991) 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 subgroups. We repeated this procedure for different values of x of 1, 3, 5 and 7 per cent. 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 an asymmetric effect in Australian data than in the US 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 show exactly the reverse, with high variances following rises in returns.[4]

[4] If we make the plainly inappropriate assumption of independent normal distributions, we can test for the equality of the population variances of the two groups. Doing so, there is some evidence of statistically different variances, especially for smaller initial values (x). However, not too much should be made of this outcome, due to the required assumptions failing to hold with stock market data. Devising an appropriate test runs into the difficulty that many of the models which provide a good fit to the data in Section III would actually indicate that the variances do not exist and any comparison is meaningless.

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	0.000574	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

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 1930s. However, empirical evidence from the US 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. In their account, 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 support 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, a question to which we turn in Section III.

III 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 (1991). The GARCH model is a generalization of the ARCH model of Engle (1982), while EGARCH, although not a generalization in the strict sense (as an ARCH model cannot be derived by restricting an EGARCH model), is again inspired by Engle's ARCH. Both these models have been extensively applied to many financial and economic time series.

In all these cases, the conditional variance (or the volatility predicted to prevail next period given currently available information) is related to current and past returns and past conditional variances, although, as will be clear below, the mapping is different for the different models. In this sense, the models are analogous to ARMA models for the conditional mean. Of course, it is possible to formulate models specifying alternative functional forms (such as the VGARCH and NGARCH suggested by Engle and Ng, 1991), or to condition on a wider data set (as in Hodrick, 1989). In regard to the first it seems unlikely that any general conclusions relating to volatility movements would be modified much by departing

TABLE 4

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

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

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) heteroskedastic consistent covariance matrix are in parentheses, and t statistics for $\alpha = 0$, $\beta = 1$ in brackets. R^2 is the coefficient of determination. $Q(12)$ is the heteroskedastic 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 heteroskedastic variance. The statistic should be distributed as a $\chi^2(12)$. The 5 per cent critical value for a $\chi^2(12)$ is 21.03. The R^2 for logs shows the R^2 from a regression of $ln\,\hat{\epsilon}_t^2$ on $ln\,\hat{\sigma}_t^2$.

from the 'standard' models adopted in this paper, and, as our emphasis is upon broad movements, it does not seem worthwhile to undertake a detailed study of the best relationship between the conditional variance and the past history of returns. When considering the possibility of conditioning upon information apart from past returns, one is constrained by the availability of monthly data over this long time period. Furthermore, as for ARMA models of the conditional mean, it has usually been found that relating the conditional variance to past returns performs as well, if not better, than more 'structural' models.

(i) 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 a conditional variance

$$\sigma_t^2 = \sigma^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{k=1}^{q} \alpha_k \epsilon_{t-k}^2 \qquad (4)$$

Following French, Schwert and Stambaugh (1987) and Pagan and Schwert (1990) a GARCH(1,2) model was estimated[5] giving (t values in parentheses)

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

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

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

[5] 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 with a t value of -.931. Alternatively, we could estimate a GARCH(1,2)-MA(1) model with data that have simply been deseasonalized, $\hat{u}_t$. Doing so resulted in parameters estimates very similar to those in (5) and (6) (this was the case as well for the EGARCH model below).

slope is unity cannot be rejected; the intercept is also within one standard deviation of its hypothesized value.[6] 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 (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 $ln\ \hat{\epsilon}_t^2$ 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 US data (see Pagan and Schwert, 1990, Table 1), although there is no doubt still room for improvement.

(ii) An EGARCH Model

Nelson (1991) 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

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

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

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

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

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

The log likelihood for this model was 2970.19 suggesting the EGARCH model is superior to the GARCH model for this data set.[7] 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 makes 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.[8] 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 surprising is the extremely large conditional variance in January 1897. This result is attributable to a large -11.2 per cent 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

[6] Pagan and Hong (1991) found that the model in French *et al.* (1987) could be rejected with this test.

[7] The GARCH and EGARCH models were also calibrated with the lag structure (p,q) = (1,3). In both cases the coefficient of the third driving variable was insignificant, suggesting that (p,q) = (1,2) is adequate for capturing the dynamics of the conditional variance. Various information criteria (such as AIC) indicate the EGARCH specification is the superior model. The Likelihood Dominance Criteria suggested by Pollak and Wales (1991) dictates the choice of EGARCH over GARCH if the former's likelihood exceeds the latter by 1.08, while GARCH is preferred if the increase is less than 0.75 (at the 5 per cent level). Clearly, this technique also selects the EGARCH model.

[8] 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.

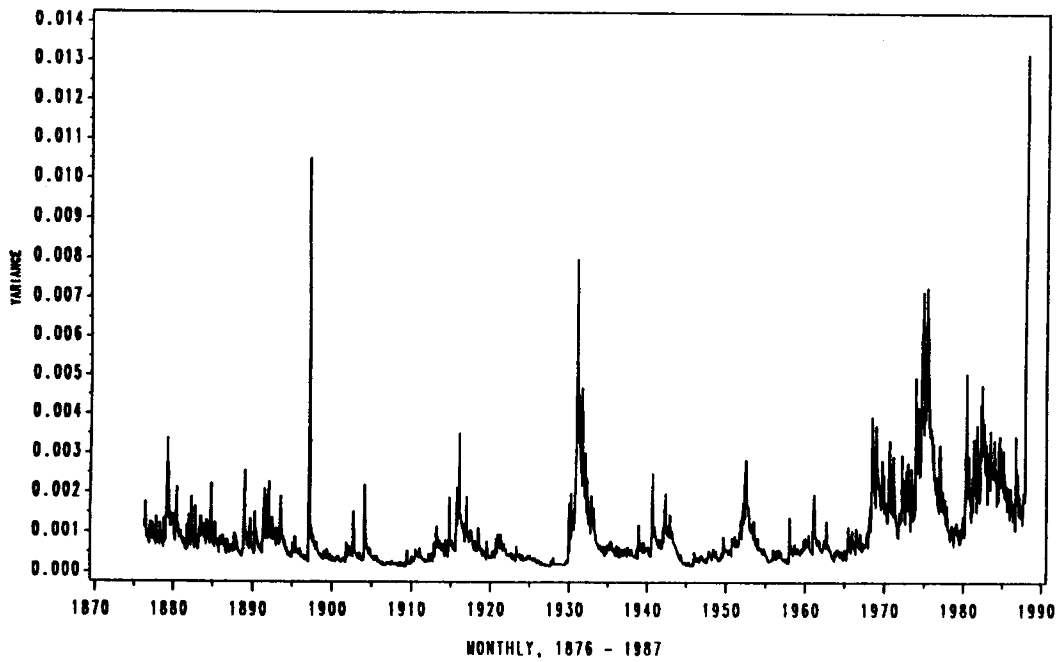

FIGURE 4

EGARCH Conditional Variance

denominator of the z_{t-k} term, results in this aberrant finding. Other months with large negative returns rarely result in such large subsequent conditional variances as their effect is 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 subperiods in which the volatility of the market increased, sometimes dramatically. The Great Depression years of the 1930s stand out, as do the last two decades of the sample.

(iii) 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 US by Schwert (1989a, 1989b), and involves:

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

TABLE 5

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

Parameter	Monthly Data, 1875 - 1987 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

different average monthly standard deviations,

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

The absolute errors $|\hat{e}_t|$ are multiplied by the constant $(2/\pi)^{.5}$, as the expected value of the absolute error is $(2/\pi)^{.5}$ times the standard deviation if $\hat{e}_t$ was normally distributed, i.e. $E|\hat{e}_t| = \sigma_t(2/\pi)^{.5}$. 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 Carroll, 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 subperiods in which volatility has noticeably increased. It is interesting to compare once again these findings with those from the US. 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 US, there is no dramatic increase in volatility over the past 20 years, except for a slight surge around the OPEC oil crisis of 1973-74.

(iv) Summary

The overall picture of volatility in Australian stock markets is similar to that in the US. 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 US. The asymmetric reaction just mentioned is very strong in US data and volatility of stocks during the Great Depression dominate any other period in US history. In fact, it has even been concluded that the late 1980s 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 past two decades volatility was very high in Australian stock markets, even by historical standards. Of course the US has not had the resource boom-bust cycle that Australia witnessed at the end of the 1960s and the early 1980s, but

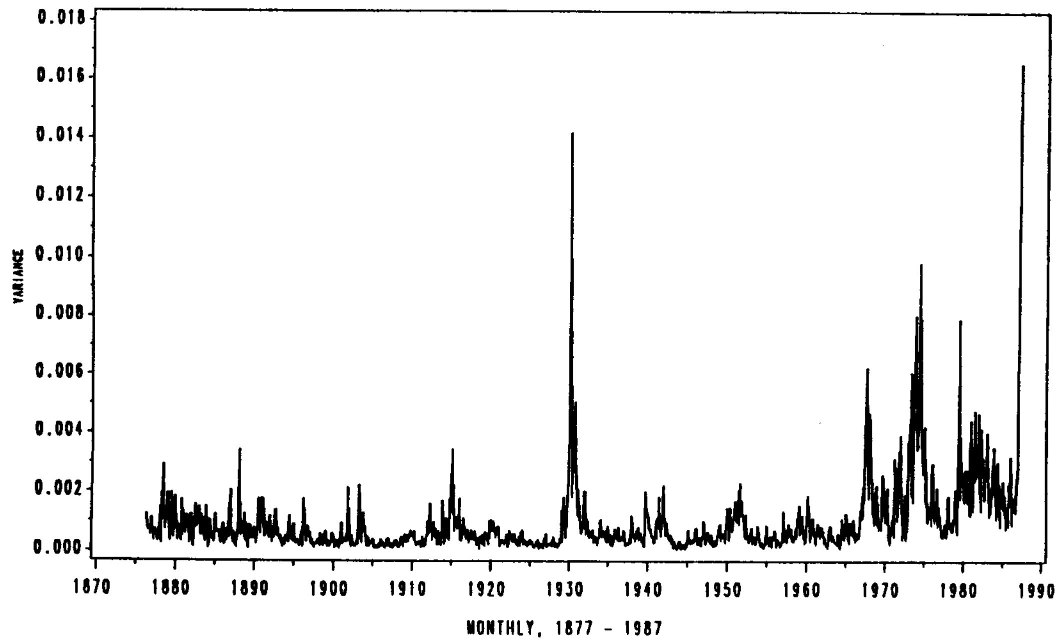

FIGURE 5

Autogressive Conditional Variance

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 70s and 80s is a challenging one for researchers, and deserves a fuller study elsewhere.

IV 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 $\sum_j \alpha_j + \sum_i \beta_i = 1$,[9] and for an IEGARCH model, $\sum_i \beta_i = 1$. In both cases, the estimated parameter values sum close to unity, indicating strong persistence of shocks. Similarly the sum of the coefficients in (10b) is .764. Lumsdaine (1990) and Lee and Hansen (1991) have shown that the asymptotic distribution of $\hat{\alpha}_j$, $\hat{\beta}_j$ is normal when the process is IGARCH, allowing a t value to be computed for the hypothesis that $\sum_j \alpha_j + \sum_i \beta_i$ is unity. This has value -2.54. Because the sample size is very large, one has to be careful when selecting a significance level for the test; Leamer (1979) argues for the model to be chosen with the Schwartz criterion, as this produces a trade-off between Type I and Type II error as the sample size grows. If a t value of 2 is selected as the critical value when the sample size is 100 the comparable figure for a sample of 1000 is 2.63 and this would indicate acceptance of the null hypothesis. For IEGARCH processes however, $\hat{\beta}_i$ would not be asymptotically normal and no such simple test is available. 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.

[9] Nelson (1990) provides a comprehensive discussion of the properties of 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 $t \to \infty$.

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 US 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 (1991) finds a similar result from an EGARCH model. For the period 1836 to 1987 Schwert (1989b) 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 subperiods 1876-1925, and 1926-1987. For the first subperiod, 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 subperiod, the results are reversed. The GARCH parameters sum to 0.9851, the EGARCH autoregressive parameter is .976, and the (10b) parameters sum 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 US counterpart, displaying marked persistence since the mid to late 1920s, 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, as in Friedman and Laibson (1989), 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 subperiods omitting observations on returns whose *absolute* value exceeded x per cent, where x = 20, 15, 10, 7.5, 5, 3 and 1 per cent. Trimming the data symmetrically 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_0 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 returns and $f(y)$ is their density. If the model is correctly specified, $\theta^* = \theta_0$. 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 $\int_{-x}^{x} \frac{\partial L}{\partial \theta} f(y)dy$, which equals zero when $\theta = \theta^* = \theta$. 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.'[10]

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 using 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 per cent were retained for estimation purposes, leading us to a closer examination of the source of the much smaller persistence when absolute returns above 10 per cent are included in the sample. Inspection of the data shows that only 3 absolute returns exceed 10 per cent 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 for the sum of the GARCH coefficients to a few observations must make any inference about persistence extremely fragile—to use Leamer's

[10] In estimating this model the strategy adopted was to use the whole sample in constructing the log likelihood but to set to zero the contribution to it of any return exceeding x. This allowed easy modification of existing programs that perform MLE on GARCH models and to maintain the original ordering of the data. The alternative of simply omitting those observations exceeding x would not maintain this ordering and may affect the resulting estimates of persistence.

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
1926-1987	.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.

(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.

V Conclusion

This study has documented the pattern of volatility for the Australian stock market over more than a century. The summary statistics of Section II and the models of Section III 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 US markets. Many of the features of the US 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 60s 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 US market does not share. Rationalization of this high volatility based on these or other explanations is a fruitful topic for future research.

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