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Price and Volume Distributions in International Equity Markets

Margaret Lynch

A Dissertation Presented

in

Fulfilment of Requirements for the Degree

of

Doctor of Philosophy

in

Business Studies

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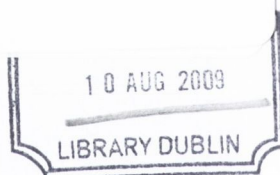
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Summary

This thesis examines asymmetry in international equity market returns, in associated trading volume distributions and in returns to funds of hedge funds. The method used in all three of the four empirical chapters is non-parametric, comprising three distribution-free tests, namely the Wilcoxon rank sum, the Siegel-Tukey and the binomial distribution. I conducted an original Monte Carlo study of the small sample behaviour of two distribution free tests, the Wilcoxon rank sum and the binomial distribution test. In the fourth empirical chapter I investigated the relationship between returns and volumes in 11 international equity markets using panel regressions and VAR models. I used a detrending technique involving the regression of logged volume on a time trend to counteract the well known positive drift associated with trading volumes distributions. In the econometric analysis I used variance decompositions to estimate the ordering of the variables in the VAR. In my impulse response analysis I used the generalised impulse response technique of Pesaran and Shin (1999).

Overall, my analysis of return asymmetry showed negative excess returns dominated positives numerically in the extremes of the distributions, but positives are dominant, at statistically significant levels in a number of alternative intervals. Turnover distributions were positively skewed in all countries except Switzerland. I established a strong and significant correlation between the first and second moments of trading volumes. I found that the first and third moments of trading volumes are significant determinants of subsequent market return skewness. There are substantial, hitherto unrecognised, interactions between all three moments of trading volumes, and these interactions play an important role in driving the volume-skewness relation. I found significant evidence of the volume-skewness relation – that higher trading volumes trigger subsequent greater negative market return skewness.

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Chapter 1

Introduction and Overview

1.1 Introduction

Recent research has focused on whether trading volume levels can explain negative equity return skewness. The results of this research have been ambiguous. Firm-level data for the US suggests that there is no role for trading volume levels to explain market skewness. However, more recent results contradict these findings. This thesis investigates whether levels, standard deviations and skewness of trading volumes can impact the skewness of market returns in international equity markets.

Finance literature has recognized for many decades that the empirical distributions of daily equity market returns have higher peaks and fatter tails than the standard normal distribution (see Mandelbrot (1963), Fama (1965) for early work on this issue), and leptokurtosis is now a universally recognized property of short horizon equity market returns. With regard to the third moment of equity market returns, however, there is less agreement about the nature, extent and implications of skewness. Simkowitz and Beedles (1980), using updated data from Fama (1965), found evidence that the returns on individual securities are positively skewed. Subsequent work by Singleton and Wingender (1986), Aggarwal, Rao and Hiraki (1989), Alles and Kling (1994), Peiró (1994, 1999, 2002), Aggarwal and Schatzberg (1997), Cont (2001) and Jondeau and Rockinger (2003) found varying degrees of positive and negative skewness in national and international equity markets. Others have investigated the implications of asymmetry in equity markets. In this vein, asset-pricing models incorporating a preference for positive skewness have been advanced by Kraus and Litzenberger (1976, 1983), Friend and Westerfield (1980), Lim (1989), Harvey and Siddique (1999, 2000), Chen, Hong and Stein (2001) and Barone-Adesi (2003). The implications of skewness for portfolio selection have been investigated by Conine and Tamarkin (1981), Lai (1991), Chunhachinda et al (1997), Ait-Sahalia and Brandt (2001), Engle and Patton (2001), Ang and Chen (2002), Prakash, Chang and Pactwa (2003), Sun and Yan (2003) and Patton (2004).

Most of these studies use the sample skewness statistic, the third moment of returns divided by the standard deviation cubed, to decide the shape of the distribution. The asymptotic distribution of this statistic is based on the clear assumption of normality in the underlying series distribution. Yet there is ample evidence that the returns to financial assets are not normally distributed, with higher peaks and fatter tails than would be congruent with a normal distribution. In addition, the sensitivity of the sample skewness statistic to the presence of outliers in the data can lead to inconsistent conclusions concerning the skewness of returns.

The strong and positive relation between the level of trading volumes and the volatility of stock markets is well-documented, (see, for example, Epps and Epps (1976), Karpoff (1987), Tauchen and Pitts (1983)). This thesis examines, through the application of both single-equation regression analysis and the VAR modelling methodology, the extent to which this relation persists when the dynamics in the third moments of both equity returns and trading volumes are permitted to interact. The generalized impulse response technique of Pesaran and Shin (1999) is employed in the impulse response analysis. Panel data regression analysis is used to examine the dynamic influence of trading volume levels, variance and skewness as determinants of return skewness, using return data and volume data from 11 international equity markets. A detrending technique involving the regression of logged volume on a time trend is used to counteract the well known positive drift associated with trading volumes distributions.

The practice of hedging against downside risk is now commonly observed in fund management, although the risk and returns to hedge funds are not well understood. The number of funds of hedge funds (henceforth FOHFs) increased from 550 in 2001 to approximately 780 in mid-2003, comprising almost one-third of the \$650 billion invested in hedge funds (The Economist, 18th September, 2003). At the same time, FOHFs continue to become available to a greater range of potential investors. While most direct investment in hedge funds is restricted to institutions and high net-worth individuals, recent changes to regulations in various jurisdictions have opened investment in FOHFs to retail investors.

Indeed, one of the claimed benefits of FOHFs is that moderately wealthy investors are now able to participate in hedge fund investment. FOHFs are portfolios of hedge funds and should therefore be less risky than individual hedge funds. While this may be true, the risk and return characteristics of FOHFs are not well understood. Accordingly I apply a non parametric analysis to the distributions of a number of FOHFs in Chapter 6.

In this chapter I will first provide a short overview of the closely related literature and describe the fundamental research question. In Section 1.3 I present the motivation for my work in this dissertation as it relates to the fundamental research question. In Section 1.4 I outline the structure of the thesis and in Section 1.5 I summarise my main novel findings.

1.2 The fundamental research questions

This thesis investigates the presence of asymmetry in equity market returns (Chapter 4), in trading volume distributions (Chapter 5) and in fund of hedge fund returns (Chapter 6). The method of testing for the presence of asymmetry in equity returns is motivated by Harvey and Siddique (1999) who, in their opening paragraph define asymmetry, negative skewness, as ‘the phenomenon’ whereby the probability of obtaining a negative excess return ‘of a given magnitude’ is higher than that of obtaining a positive excess return of the same magnitude. Two main explanations have been advanced to explain this asymmetry and these are described in detail in section 7.1 (*page 155*). In brief, representative investor theories explain return asymmetries by leverage effects, by volatility feedback mechanisms and by stochastic bubble models in which the asymmetry is caused by the bursting of the bubble. An alternative explanation is to be found in the investor heterogeneity theory of Hong and Stein (2003), who suggest that high trading volumes lead to greater negatively skewed returns because some investors are short sales constrained so that previously hidden information comes out during market declines. This follows the volume-volatility literature, which is reviewed in Chapter 2, in which the level of trading volumes proxies for the extent of heterogeneity of investor opinions concerning the fundamental values of stocks (Clark, 1973; Epps and Epps, 1976; Tauchen and Pitts, 1983; Harris and Raviv, 1993; Shalen 1993).

The decision to examine the asymmetry in distribution of equity trading volume distributions (Chapter 5) using the same non-parametric approach is motivated by the absence of prior documented studies of asymmetry in the trading volume literature. The study of asymmetry in fund of hedge fund returns (Chapter 6) finds that funds of hedge funds are both positively and negatively skewed in roughly equal proportions. This demonstrates the difference in patterns of asymmetry among diverse asset classes. The question of whether differences of opinion about the future value of stock returns, associated with rising trading volumes, lead to greater skewness in returns is investigated in Chapter 7.

The relation between trading volumes and the third moment of price changes, skewness, has only recently become the focus of attention in the finance literature. Chen, Hong and Stein (2001) (hereafter CHS), Hong and Stein (2003), Hueng and Brooks (2003), Charoenrook and Daouk (2004) and Hueng and McDonald (2005) have examined whether differences of opinion about the future value of stock returns, associated with rising trading volumes, lead to greater skewness in returns. Using firm-level data for the United States from July 1962 to December 1998, CHS show that stocks with higher than average returns and volumes tend to be associated with future negative skewness. When they examine market data, however, the relation between volume and skewness disappears. Contrary to CHS, Hueng and Brooks (2003) find that although lagged returns and volumes are significant determinants of future skewness, the coefficients are rarely negative, implying that higher volumes are not generally associated with future negative skewness. Charoenrook and Daouk (2004) estimate individual country and pooled cross-section time series models, and report weak evidence that lagged trend-adjusted volumes lead to more negative skewness. More recently, Hueng and McDonald (2005) using an autoregressive conditional density model with a skewed t-distribution on daily AMEX and NYSE data from 1962 to 2000 show that the negative relation between trading volumes and return skewness found by Hong and Stein (2003) in their cross section study is not supported by the time series evidence. Overall, the existing studies provide mixed evidence in favour of the investor heterogeneity theory, but they also suggest that the volume-skewness relation

might be more complex than has been implicitly assumed in the literature to date, involving a possibly wider set of variables and more sophisticated dynamics.

1.3 Motivation for studying volumes and skewness

The recognition in the finance literature that the unconditional distribution of short period returns is not adequately represented by the normal distribution has motivated the quest for alternative distributions that could adequately account for leptokurtosis, the main departure from normality. However, the symmetry or asymmetry of the unconditional distribution of returns has not received the same level of attention in the literature, despite the fact that the study of the symmetry/asymmetry of the distribution of returns has relevance in a number of financial applications including portfolio theory, the assumptions underpinning the Capital Asset Pricing Model (CAPM) and option pricing theory.

Traditionally, the symmetry of a returns distribution was measured using the third moment normalised by the standard deviation cubed, commonly known as 'relative skewness'. The asymptotic distribution of this statistic is valid only in the case that the underlying distribution is normal and, given the general agreement that returns are not normally distributed, a rejection of symmetry may in fact be a rejection of normality in an otherwise perfectly symmetric distribution. While the central focus of this thesis is whether trading volumes have a role to play in determining equity market skewness, the analysis of asymmetry in returns to equity markets (Chapter 4) has been extended to include an analysis of volume distributions (Chapter 5) and funds-of-funds markets (Chapter 6).

1.4 Thesis outline

In Chapter 2, I review the literature, both historical and current, on skewness in financial asset returns. I describe the well documented positive relation between volume and volatility and explore the emerging relationship between trading volume and market skewness. In Chapter 3, I describe the data used for all my empirical analyses. In Chapter 4, I examine the extent of asymmetry in six international equity markets from 1978-2002

using a distribution-free approach and report the findings of an original Monte Carlo study into the behaviour of two of the distribution free tests, the Binomial distribution and the Wilcoxon rank sum test in the presence of a time-varying mean.

In Chapter 5, I extend the work of Chapter 4 by investigating return and volume asymmetry in 12 international equity markets, the main focus being on the distribution of volume (turnover). I have included the analysis of return distributions in conjunction with volume because this is the dataset that I use in the econometric tests of Chapter 7. The view that more can be learned about speculative prices by studying them in conjunction with volume is also a motivating factor in including price distribution in Chapter 5. In Chapter 6, I apply a similar approach to the analysis of FOHF return distributions. The work in this chapter demonstrates that a non parametric approach to asymmetry is easily applied to other financial asset classes, such as hedge funds. In Chapter 7, I investigate the role of trading volume as a determinant of future negative skewness in 11 of the 12 equity markets whose distributions I analysed in Chapter 5. The investigation includes both single equation panel regressions and VAR models. I use the generalised impulse response analysis of Pesaran and Shin (1998). In Chapter 8, I provide a summary of the main work of the thesis, I draw together the novel findings, and I outline the limitations of the study, as well as indicating the direction of future work.

1.5 Novel findings

In Chapter 4, I conduct a Monte Carlo test of the small sample behaviour of the Wilcoxon Rank Sum test and the Binomial distribution test by imposing a time-dependency in the mean and drawing the error terms from a known symmetric distribution, the standard normal, $N \sim (0, 1)$. I find that the two tests are not compromised because neither test rejects the null of symmetry too often. This study has not been reported elsewhere in the literature and as such makes an original, empirical contribution.

In Chapter 5, I describe an empirical study of price/volume/volatility in the 11 equity markets that I use in the econometric tests of Chapter 7. In Chapter 6, I examine the return

distributions of 332 FOHFs and associated indexes. In Chapter 7, I provide new evidence in favour of the investor heterogeneity theory of the relation between trading volumes and return asymmetry. I report that the level and variability of trading volumes are strongly positively correlated in all markets in my sample. This finding supports the investor heterogeneity theory of return asymmetry but has not, so far, been investigated in the volume/skewness literature. By making allowance for indirect effects that have not been incorporated in previous research, I find considerable interaction between trading volumes and return skewness in all international markets, including the US.

Publications

E. Hutson, C. Kearney and M. Lynch (2008), 'Volume and Skewness in International Equity Markets', *Journal of Banking and Finance*, 32, 7, 1255-1268.

Kearney, C. and M. Lynch (2007), 'Are International Equity Markets Really Asymmetric?' *Applied Financial Economics*, 17, 5, 399-411.

E. Hutson, M. Lynch and M. Stevenson (2006), 'Distributional Characteristics of funds of hedge funds returns' in G. Gregoriou (ed.) *Funds of Hedge Funds: Performance, Assessment, Diversification and Statistical Properties* (Elsevier Press, Quantitative Finance Series), Chapter 14, 213-238.

Conference Papers

E. Hutson, M. Lynch and M. Stevenson (2004) 'Are Funds of Hedge Fund Returns Asymmetric?' presented to the 12th Global Finance Conference, Dublin, June 2005.

C. Kearney and M. Lynch (2004) 'Are International Equity Markets Really Skewed?' presented to the 12th Global Finance Conference, Dublin, June 2005.

E. Hutson, C. Kearney and M. Lynch (2005) 'Volume and Skewness in International Equity Markets' presented to the Annual SNDE Conference (Society for Nonlinear Dynamics and Econometrics) in London, March 2005; the 12th Global Finance Conference, Dublin, June 2005 and the 2004 Annual Conference of the Southern Finance Association, Naples, Florida.

C. Kearney and M. Lynch (2002) 'Skewness and Trading Volumes' presented to the 2002 Irish Economic Association Conference, Mullingar.

1.6 Summary and Conclusions

In the introduction to this chapter I have referred to the well researched relation between price and quantity in the asset pricing literature. One of the fundamental principles of this literature is that stock markets respond asymmetrically to good and bad news. This asymmetric response has been the focus of a substantial body of literature and is still of interest to both academics and practitioners. Trading volumes are long understood to have a role to play in determining speculative prices, and there is a well documented positive relationship between the level of trading volumes and the volatility of returns to speculative assets.

Chapter 2

Literature Review

Introduction

In this chapter I start in Section 2.1 by examining the historical treatment of the third moment of asset returns from several perspectives, beginning with the traditional mean-variance approach to portfolio asset construction of Markowitz (1952). Mandelbrot (1963) noted that there are larger numbers of abrupt changes in the economic variables that determine equilibrium prices in speculative markets than would be the case under a Gaussian hypothesis and proposed an alternative distribution, the Stable Paretian. The question of how to handle sudden, steep price changes is raised by Mandelbrot and several other contributors to the literature.

Some of the shortcomings of the Capital Asset Pricing Model (CAPM) that were thought to have arisen from restrictions imposed by the model on riskless borrowing, or divergent borrowing and lending rates, may in fact have been related to the omission of systemic skewness. Another application of skewness, discussed below, relies upon parallels drawn between the activities of bettors at a racetrack and investors in the stock market. The fact that bettors are willing to place bets on low return, high variance bets is because these bets offer higher skewness than high return low variance bets, which would suggest that bettors have a preference for positive skewness. The analogy of a stock market investor is developed in Harvey and Siddique (2000) who argue that the willingness to hold a portfolio when the expected return is negative is rational if there is positive skewness, i.e., a high probability of a large positive return at some future time.

In Section 2.2. I examine the literature on market microstructure because this is closely related to the trading volume literature. This section covers the role of the dealer or market-maker, the bid-ask spread, the effect of open versus closed markets, the number of dealers in a stock and the role of liquidity traders in a stock. In Section 2.3 I review the literature on the Mixture of Distributions Hypothesis (MDH). I map chronologically the evolution of the daily price change in financial asset returns from the pioneering work of Osborne (1959)

and Clark (1973) to the investor heterogeneity theory of Chen, Hong, Stein (2001). I describe the theoretical basis of rational expectations models and draw on Karpoff's (1987) excellent critique of the Copeland (1976) sequential arrival of information model and the Shalen (1993) model that explains a number of stylized facts in the volume volatility relation in terms of the dispersion between past and current beliefs. I review work that examines the implications for the joint distribution of prices and volumes in several alternative markets such as commodity futures and emerging markets in central and eastern European countries.

The literature on the volume-volatility relation is extensive and, in Section 2.4, I examine the chief developments in the literature that track this relation. The main axis of this literature is the strongly positive relation between the level of trading volume and the volatility of returns. The potential for the second moment of trading volume to have an impact on expected returns had not been studied extensively prior to the seminal work of Chordia, Subrahmanyam and Anshuman (2001) (henceforth CSA) who, following Amihud and Mendelson (1986), used trading volume as a proxy for liquidity. CSA hypothesised that since it was established that liquidity was priced in asset returns, fluctuations in liquidity, proxied by the second moment of volume, should be of concern to investors.

I have shown in this introduction how I have structured the literature review to cover the historical treatment of the skewness statistic in the literature, the market microstructure and the MDH, together with the volume volatility relation and the volume skewness relation. The areas that are most relevant and most germane to the empirical work of the thesis are the MDH in section 2.3, the volume volatility literature in section 2.4 and the volume skewness literature in section 2.5.

2.1 Historical Treatment of Third Moment of Equity Returns

2.1.1 Introduction

Early literature examining the third moment of equity returns focused on issues concerning the distributions of prices. One such issue related to the arguments for and against the inclusion of skewness in portfolio analysis and asset valuation models. A second issue was the number of outliers, corresponding to abrupt price changes, in the tails of equity distributions and the vexed question of how to handle these outliers. The abrupt price changes then, as now, reflected real dynamics in underlying economic conditions and as such, should not be dismissed as being merely inconvenient. The Kraus and Litzenberger (1976) introduction of a 3-moment Capital Asset Pricing Model (CAPM) arose from the intuition that investors valued positive skewness. One of the enduring puzzles of investor behaviour is the low level of investor diversification. Conine and Tamarkin (1981) contended that it was rational for investors to hold a limited number of stocks if both risk aversion and skewness preference were of concern, because fully diversified portfolios have lower levels of skewness.

The implications of a normal distribution are that skewness and excess kurtosis are both zero. When skewness and excess kurtosis are both non zero, the null hypothesis of normality is rejected. The evidence of non normality in individual stock and aggregate market returns raises questions concerning the validity of relying solely on the skewness coefficient to decide the symmetry of the distribution. The coefficient of skewness is not reliable if the underlying distribution is not normal, indicating the necessity of a distribution-free approach. Several papers are included because they highlight other issues that were of concern in the early literature, such as the length of the interval over which skewness is measured, the initial date of the study and the derivation of the skewness coefficient (the raw third moment divided by the standard deviation cubed).

2.1.2 Markowitz's (1952) Mean-Variance Principle

As justification for using the return-variance principle in constructing an investment portfolio, Markowitz (1952) associated the third moment with a propensity to gamble. In a

seminal paper entitled 'The Utility of Wealth', he contended that the method of placing a bet during a series of games could influence the overall dispersion of wins and losses. Markowitz (1952) argued that the mind-set of the bettor in the context of horse and dog racing and the investor in the context of the stock market can influence the shape of the distribution of the final outcome. He suggested that if a person placed bets with equal generosity at each game, regardless of previous wins or losses, then the frequency distribution of final wins and losses would be symmetric. The effect of playing conservatively when losing and liberally when winning is to make the frequency distribution of final outcomes skewed to the right. Markowitz (1952) showed a clear preference for investment strategies that avoid any taint of gambling, asserting that yield is a good thing, risk a bad thing and a propensity to gamble is not a prudent investment strategy. Golec and Tamarkin (1998) drew a similar analogy between the behaviour of bettors at a race track and investors in a stock market. Golec and Tamarkin (1998) set out to explain the anomaly whereby long shots have greater, and favourites smaller, subjective than objective probabilities. The authors stated that bettors willingly select low-return, high-variance bets, because these bets offer higher skewness than high-return, low-variance bets. Harvey and Siddique (1999) applied the same thinking in holding the view that if there is a high probability of large positive return investors may hold a portfolio even if its expected return is negative. This is because it is reasonable to assume that investors do in fact have a preference for skewness, given the statistical evidence of skewness in returns.

2.1.3 Mandelbrot (1963) Stable Paretian Hypothesis

In 1963, Mandelbrot introduced a new model of price behaviour in speculative markets known as Stable Paretian, exploiting the fact that the theory of 'Brownian motion' could not account for the empirical distributions of price changes being too peaked to be Gaussian. While agreeing that the histograms of price changes are indeed unimodal and that their central bells are similar to the Gaussian ogive, Mandelbrot (1963) argued that there are typically so many outliers that cumulative probability curves fitted to the mean square of price changes are much lower and flatter than the distribution of the data themselves. One of the consequences of these tails is that the second moment does not seem to tend to any limit even though the sample size is large by economic standards. The infinite variance

assumption of the Stable Paretian model and the implications that this assumption holds for the role of the sample variance as a measure of dispersion was commented upon by Fama (1963). It follows that other statistical tools (e.g. least squares regressions), that are based on the assumption of a finite variance, cannot then be relied upon to yield reliable inference.

In relation to the excessive numbers of large price changes usually observed in the data, Mandelbrot (1963) proposed that one should look for well-determined causes, since a priori, large price changes are usually traceable to causes that are clearly identifiable; therefore, these price changes should be eliminated before applying a stochastic model to the remainder. The argument against this, however, is that if one succeeded in eliminating all large changes in this way, one would have a Gaussian-like remainder from which one could infer very little useful information. This raises the issue of the appropriate treatment of one or more of these exceptionally large, but correct, holding period returns. These outliers can result in skews as much as four standard deviations above average. Beedles and Simkowitz (1978) argued that since these exceptionally large returns are in some way unrepresentative of the returns generating process as a whole, eliminating them might provide better insights into the behaviour of equity values. This approach would mean that researchers using higher moments should decide, a priori, and on a case by case basis, whether an analysis is more meaningful with or without legitimate outliers. Kim and White (2004) examined daily returns on the S&P 500 from January 1982 to June 2001 in a study that set out to demonstrate that the conventional measure of skewness is extremely biased in the presence of a single or small number of outliers. The skewness statistic for the series is -2.39 , indicative of extreme left skewness. When the large negative return associated with the stock market crash of 1987 is removed, the statistic falls to -0.26 , still negatively skewed but small compared with -2.39 .

The Geometric Brownian Motion (GBM) model of Black and Scholes (1973) is still the pre-eminent asset pricing model for equity and currency markets; nevertheless there are well documented shortcomings in the model in a number of financial markets. Under GBM the returns, $Z(h)$ are presumed to be distributed normally,

$$Z(h) \sim N[\mu h, \sigma^2 h] \quad (2.1)$$

where the mean μ and variance σ^2 are linear functions of (dependent on) the length of the holding period h . While the mean and variance are dependent on the length of the holding period, skewness and kurtosis are independent of h . In any normal distribution, skewness and excess kurtosis are both zero, but in a number of financial markets these presumptions are commonly violated. Non-zero unconditional skewness has been reported in many financial markets, together with positive excess kurtosis in returns distributions. In addition, far from being independent of the length of the holding period, h , many studies cited by Das and Sundaram (1997) found significant changes in excess kurtosis levels and skewness patterns when changing from weekly to monthly levels in currencies, equities and options markets.

Kon (1984) proposed a discrete mixture of normal distributions to explain the significant positive skewness in the distribution of daily returns for three indexes, the S&P, the CRSP value-weighted and the CRSP equal-weighted over an 18¹/₂ year time series from July 1962 to December 1980. The evidence provided by Blattberg and Gonedes (1974) suggested that the distribution of monthly returns could be classified as normal, but increasingly researchers were turning to daily data for event studies such as those related to information and to provide larger estimation samples to facilitate hypothesis testing in asset pricing models. The parameters of the price change process do in practice fluctuate due to changes in investment decisions, capital structure changes, leverage effects, earnings disclosures, exogenous macro information and institutional trading restrictions.

2.1.4 Levy theory of utility functions

Levy (1969) set out to show that a utility function which is a linear combination of the first three moments is inconsistent with the assumption that $U''(x) < 0$, i.e. that the investor dislikes a large variance, or that marginal utility decreases with increasing wealth. Risk aversion implies that the second derivative of the utility function with respect to wealth is negative. This may be explained in terms of rejecting a fair gamble. An example of a fair

gamble is a utility function that either doubles the investor's money or gives him/her nothing, with equal probability. Assume that in order to participate, an investor must pay \$1. Since the probability is $\frac{1}{2}$, the option to invest has an expected value of $\{(1/2)(2) + (1/2)(0)\} = 1$. The alternative is not to invest, thus enjoying the certainty of \$1 gained in the sense of \$1 not being lost. In this scenario a risk averse investor will choose not to participate because the expected value of the investment is equivalent to the amount he would have to pay to take part in the investment. Levy's view is that unless the utility function is restricted to a special form, the higher moments must be taken into account. The importance of Levy's contribution is that he argued against the neglect of the higher moments and specified only two conditions under which the higher moments could be ignored:

- (a) If all higher moments tend to zero, *or*
- (b) If it is assumed that the utility function is cubic. In this case every derivative higher than the third vanishes.

2.1.5 Investor preference for positive skewness

Arditti (1967, 1971) conducted two separate studies to evaluate whether investors consider skewness when making their investment decisions. Arditti (1967) used annual data from the Standard and Poor's (S&P) Composite Index from 1946-1963, and concluded that investors like positive skewness. Arditti (1971) used Sharpe's annual data for 34 mutual funds from 1954-1963 and found the third moment was significant in investors' decision making. An attempt to disprove the validity of Arditti's (1971) findings was made by Francis (1975). Using mutual fund data, Francis ran a series of regressions using quarterly returns in preference to Arditti's annual returns, in order to increase the sample size, on the basis that small sampling distributions tend to yield large sampling errors. This is particularly so in the case of the third moment as the skewness statistic is sensitive to extreme observations or outliers in the data.

To investigate the importance of skewness in an investor's decision making process, Francis (1975) estimated a simple regression using skewness as the independent variable and then estimated a multiple regression with both skewness and the standard deviation as independent variables. While the t statistics for the skewness coefficients in both equations

were statistically significant, they were contrary to the theory that investors weigh the value of skewness in their decision making process. One possible explanation for the discrepancy in findings between Arditti (1971) and Francis (1975) is the different intervals used. Since the average of annual returns is larger than the average of quarterly returns, the raw third moments of quarterly and annual returns will reflect this difference. This problem of scale is addressed by normalizing the raw third moment by the standard deviation cubed, and using the result, defined as 'skewness', to compare monthly, quarterly and annual returns. Francis (1975) found that even using the normalised raw third moment, the annual funds were still more positively skewed than their quarterly returns, and in turn, the quarterly returns were more positively skewed than monthly returns. The skewness statistics, therefore, appear to be nonstationary across different intervals. Having rerun all the regressions three ways, using monthly, quarterly and annual returns, Francis (1975) concluded that skewness statistics are sample dependent.

2.1.6 Systemic skewness in CAPM

In the 1970s, the notion that asset returns, within an equilibrium framework, are subject to systemic skewness as well as systemic risk grew out of tests of the two parameter CAPM. Simonson (1972) and Kraus and Litzenberger (1976) proposed a three parameter asset pricing model that incorporated systemic skewness alongside systemic risk. Beedles (1979), in discussing the two studies, drew attention to the divergence in the empirical results; the former, using logs of the quarterly S&P Composite for 1961 to 1970, found the market to be negatively skewed. Kraus and Litzenberger (1976) found positive skewness for a sample of monthly excess deflated returns from 1936 to 1970. Within the asset pricing framework proposed by Simonson (1972) and Kraus and Litzenberger (1976), the *sign* of ex ante skewness was an instrument used to price assets using the following reasoning. Investors should be rewarded by gaining additional expected returns for willingness to hold a portfolio of assets with high systemic skewness, if the market is (ex ante) negatively skewed. Conversely, if the market is positively skewed, which is a desirable state, assets with large values should be priced so as to return less.

In the two parameter models discussed earlier, the utility function was constrained to be quadratic and the returns were assumed to be normally distributed. The economic

importance of the third moment, skewness, is recognised by Arditti and Levy (1975) in a study that investigated the relationship between the first three moments of an asset's single period return and the first three moments of its multiperiod returns. Using mathematical expansions analysis, Arditti and Levy (1975) showed that the coefficient of skewness can be zero for one period returns, but this does not lead to the conclusion that multi-period skewness will also be zero. The implication of this is that skewness is dependent upon the investment horizon, and this in turn, is subject to individual choice. For investors with short investment horizons, skewness of portfolio returns can be ignored since existing empirical evidence indicates that these distributions are symmetric. For longer horizons however the skewness coefficient is not necessarily zero, and therefore skewness should be considered as a relevant variable in the decision making process.

Fama (1971) placed the Sharpe (1964) and Lintner (1965) CAPM in the context of the earlier portfolio models and extended these earlier models in a number of directions. Fama (1971) derived the characteristics of equilibrium in the capital market by showing that the market risk-return relations as determined in the two-parameter models are straightforward generalizations of the risk measures and expected risk-return relationships that characterize optimal consumption-investment decisions. The assumptions underlying the earlier models were based on a market of risk-averse consumers who could make their investment decisions on the means and standard deviations of one period portfolio returns, implicitly assuming that these standard deviations exist. In the light of other empirical studies, this assumption was questionable. Distributions of common stocks were considered to conform well to non-normal members of the stable Paretian class of distributions, and the standard deviations of these distributions do not exist. Jean (1971) set out to establish an equilibrium relation between the first and third moments of investors' returns using a generalization of the Sharpe-Lintner mean-variance model for price determination under uncertainty. The problem with Jean's (1971) approach, as argued by Arditti and Levy (1972), was the absence of good economic grounds on which this model could be based, unlike the mean-variance equilibrium model of price determination under uncertainty of Sharpe (1964) and Lintner (1975), which made good economic sense. Jean (1971) found a positive premium for skewness; the higher the skewness, the higher the required expected return will be. The

conclusion arrived at in Jean (1971) was that the correct way to deal with skewness is to find an equilibrium relation that incorporates the first three moments simultaneously.

The role of the third moment in asset valuation was examined by Kraus and Litzenberger (1976) in an extension of the two-parameter CAPM of Sharpe (1964) and Lintner (1975) that incorporated the effect of including skewness on valuation. They found that alongside an aversion to variance, investors favour positive skewness. This skewness preference has implications for the practical application of a quadratic utility function as a basis for positive valuation theory; therefore prior negative results that were thought to have arisen from restrictions imposed by the CAPM on riskless borrowing or divergent borrowing and lending rates, might instead have been attributable to misspecification of the model due to the omission of systemic skewness.

2.1.7 Skewness and diversification

Simkowitz and Beedles (1978) contended that investors who hold less than fully diversified portfolios, despite regular advice to the contrary, exhibit a preference for positive skewness. Given the theory that investors like skewness, and recognising that a fully diversified portfolio is one that has reduced levels of skewness, a rational investor with a preference for skewness will hold a less than fully diversified portfolio. The authors suggested that even in a frictionless market, the number of assets held is a function of each individual's skewness/variance awareness level. An investor who is more concerned with skewness should hold fewer assets and one who is concerned with variance should hold relatively more.

Portfolios of different numbers of stocks were created and the following findings reported. As the degree of diversification increases, skewness levels decrease, and as the number of assets held increases, skewness is diversified away rapidly. In the context of a quadratic utility function, the coefficient of skewness has traditionally been set to zero, which is effectively assuming a symmetric returns distribution. Simkowitz and Beedles (1978), by allowing for some level of investor concern for skewness, challenged the then prevailing view that the typical investor's utility function could be described adequately by a quadratic function, and that return distributions are symmetric.

Scott and Horvath (1980) contributed to the debate on the use of higher moments in portfolio analysis by demonstrating that investors, on the whole, exhibit a positive preference for odd central moments and a negative preference for even central moments. Their paper explicitly associates the preference for positive skewness with risk aversion. Earlier studies argued for diversification as rational investment behaviour for the risk-averse investor, suggesting that by adding randomly selected and equally weighted risky assets, one could reduce total risk without affecting return. The concept of investor preference for positive skewness is a reason for a rational investor to hold an optimal limited number of homogeneous risk assets in an investment portfolio, according to Conine and Tamarkin (1981). Homogeneous in this context refers to the assumption that all risk assets have identical means, identical variances and identical skewness; and that all joint product moments, i.e. all combinations of risk assets, have identical curvilinear relationships.

The assumption of homogeneity is used to demonstrate that low levels of diversification are consistent with rational investor behaviour in perfect market conditions. Prior studies had relaxed some of the assumptions of the CAPM including that of homogeneous expectations, thus implying theoretically that anti-diversification can be explained only in the context of imperfect markets. Other market imperfections such as transactions costs, regarded as having an inhibiting effect on diversification in prior studies, could no longer be seen to have the same impact. This was due to the elimination of fixed commissions in May 1975 and a dramatic increase in the popularity of no-load mutual funds in the U.S. These are funds in which shares are sold without a commission or sales charge. This is because the shares are distributed directly without going through a broker or financial planner. This is the opposite of a load fund which charges a commission at the time of the fund's purchase, at the time of its sale or as a 'level load' for as long as the investor holds the fund.

2.1.8 Log versus simple returns

A key observation of Beedles (1979) is that there is less measured asymmetry when log rather than simple returns are used. Beedles (1979) examined an empirical study by Fogler

and Radcliffe (1974) which found that skewness measures are sensitive to the size of the differencing interval and to the initialization point. Beedles (1979) used monthly data from January 1927 to December 1976 to estimate the relative skewness of both simple and log returns of equal and value weighted indices from Chicago's Centre for Research in Securities Prices (CRSP) for various sub periods. His paper supported the Fogler–Radcliffe (1974) study of the importance of the initialisation point; a researcher with 10 years of data beginning in January 1957, using logs of the equally weighted index, could reject the null hypothesis of a Gaussian distribution at the 1% level given a negative skewness measure of (-0.51). However, the same researcher using 20 years of data could also reject the null hypothesis of a Gaussian distribution on the basis of the magnitude of the positive skewness (0.25). In his summary Beedles (1979) concluded that when log returns are used there is less measured asymmetry than when simple returns are used. This method, the accuracy of which has been widely accepted in the finance literature, is used to calculate returns in the original work of this thesis.

Summary of Section 2.1

Under Geometric Brownian Motion, the mean and standard deviation of an asset's return distribution both depend on the length of the holding period, h . The third and fourth moments (skewness and excess kurtosis) are both zero and independent of h . These assumptions are routinely violated in practice, with non zero skewness and excess kurtosis frequently observed, and significant changes in excess kurtosis levels and skewness patterns have been reported when changing from weekly to monthly levels in currencies, equities and options markets. This raises questions concerning the validity of relying solely on the skewness coefficient to decide the symmetry of the distribution. The coefficient of skewness is not reliable if the underlying distribution is not normal, indicating the necessity of a distribution-free approach.

In the early literature there was a divergence of opinion concerning the inclusion of skewness in portfolio analysis and asset valuation models. The two moment mean/variance approach to portfolio construction was justified in one case by associating the third moment with gambling. Other academics argued in favour of higher moments and presented clear

indications of when higher moments could safely be neglected, as when for example, the utility function was cubic and all derivatives higher than the third vanished.

In relation to the excessive numbers of large price changes usually observed in the data, one suggestion proposed that large price changes should first be eliminated before one applied a stochastic model to the remainder. Others reinforced this argument by stating that eliminating exceptionally large price changes might provide better insights into the behaviour of equity values. The question of how to handle these exceptionally large but correct returns has not as yet been definitively answered, and it is now accepted that the conventional measure of skewness is extremely biased in the presence of a single or small number of outliers.

In the 1970s the extent to which investors considered skewness when making their investment decisions became the focus of attention in the literature. The economic importance of skewness and the consequences of not factoring in a preference for skewness in capital asset pricing models led to the 3-moment CAPM. The notion that investors favoured positive skewness was advanced as a possible explanation for poor levels of diversification in portfolio construction. Holding a limited number of stocks was perceived to be a perfectly rational strategy for a risk-averse investor who favoured positive skewness. Having surveyed the early literature on skewness in financial markets, I now turn to examine the market microstructure literature in Section 2.2.

2.2 Market Microstructure

2.2.1 Introduction

One of the fundamental research questions posed in this thesis is whether differences of opinion about the future value of stock returns, associated with rising trading volumes, lead to greater skewness in returns. In Chapter 5 I examine the distributions of equity trading volumes using a series of non-parametric tests and differentiate between positive excess trading and negative excess trading by identifying the former as ‘overtrading’ and the latter as ‘undertrading’. In Chapter 7, I investigate whether trading volumes influence equity

return skewness in any or all of the first three moments of volumes. In order to substantiate the theory that return asymmetry or negative skewness arises from a difference of opinion concerning future price direction, I now undertake a substantial review of the theory of microstructure, because it is important, in the overall context of the thesis, to highlight the complex nature of trading volume activity. This is especially relevant in the discussion of the findings in Chapter 7, section 7.5, where I argue that trading that is generated by liquidity and noise traders during 'light volume' periods has little impact on the volatility of volumes. These volumes will consequently have minimal effects on returns.

In this section, I review the market microstructure literature and outline what it is that constitutes normal trading activity, typical trader profiles and motivation to trade. Much of normal trading volume activity does not impact the index price enough to stimulate higher than normal volatility. Higher than normal trading volume levels can issue from trading that is related to liquidity, dividend payouts, portfolio rebalancing, profit warnings and other trading related activities. Investors trade for complex reasons; informed traders interpret and assess signals related to shifts in fundamental values of stocks while liquidity traders engage in trading activity that may have little or no bearing on fundamental values. The role of the market maker is described in detail because without the market maker no trading activity would take place. The bid-ask spread is included because it provides information. Individual stocks are constituents of total market indexes; the number of dealers in a stock and the number of analysts following the stock are variables that are important in evaluating the importance of movement in that stock. This section explains why there are periods of relatively large trading volumes and yet little price movements.

2.2.2 The role of the Dealer or Market-Maker

The transaction costs on the New York Stock Exchange (NYSE) and the importance of the role of the specialist in managing orders and assuming risk is analysed in a seminal paper by Demsetz (1968). The specialist has a valuable role in keeping trade active by trading on his own account when the bid-ask quotations by outsiders are too far apart to maintain trading activity without wide jumps in price. The specialist or dealer can increase the pace of trading by offering a smaller spread than the current gap between ask and bid prices.

This willingness to assume risk provides a valuable service to the exchange as a whole in maintaining a momentum of trading, and it must therefore be appropriately rewarded.

While the willingness to invest his own resources in buying now and selling later is common to other inventory holders such as retailers and wholesalers, the specialist is different, in that he is obligated to make a market in the securities in which he specialises. Other members of the exchange have a vested interest in the maintenance of narrow spreads, because this increases the volume of business and the size of their commissions. One of the stated guidelines from the NYSE, for example, is for specialists to keep spreads narrow and close to the last transaction price. Other reasons for maintaining a small spread pertain to the fact that many securities are listed on more than one exchange and trading unlisted securities can be done on many exchanges.

2.2.3 Bid-Ask spread

The policy issues involved in supplying dealer services in securities markets are discussed in Stoll (1978a). Put simply, in order to be able to trade, investors need to find other investors who are willing to trade with them. In the absence of other such investors, dealers are willing to trade for their own account as principals, thus providing a service of immediacy to the general trading public. The costs of providing immediacy include the price risk and the opportunity cost of holding securities, the costs associated with arranging trades and clearing transactions, and the costs incurred when traders with whom they are transacting have superior information. In organized markets, the dealer quotes a bid price at which he is willing to buy and an ask price at which he is willing to sell. Even if the dealer is privy to inside information such as that provided by knowledge of the book of limit orders, for example, this information is reflected in his bid-ask spread, but he is still exposed to losses from informed traders. Therefore, since he cannot distinguish informed traders from uninformed, he has to set his bid-ask spread wide enough to recover from liquidity traders his potential losses from informed traders.

The perception of the bid-ask spread as a trade off between expected losses to informed traders and expected gains from liquidity traders is likened to a combination of put and call options in Copeland and Galai (1983). One of the key assumptions of this model is that

asset markets are anonymous, in that the dealer does not know, *ex ante*, whether the trader with whom he is transacting is in possession of superior information. The imposition of the condition of asset market anonymity arises from the recognition that traders known to possess superior knowledge would be easily identifiable and other traders would be unwilling to trade with them. It follows that one of the functions of the broker is to maintain the anonymity of the person who initiates the trade. The greater the proportion and the higher the quality of the superior information, the more the specialist or dealer will have to make on the bid-ask spread and the higher the bid-ask spread must be. The bid-ask spread is shown to be a function of increased volatility in the underlying asset, a higher asset price level and a lower trading volume (thinly traded stocks). In the presence of a trader with superior information it is likely that the short run price movements will not favour the dealer, even though he may have gained on the bid-ask spread. The less liquid the security the greater the bid-ask spread is likely to be. This is particularly true in the bond market where bonds with low liquidity are likely to have very large bid-ask spreads.

2.2.4 Number of dealers in a stock

Stoll (1978b) raised the importance of the role of the dealer in providing immediacy to the general public who want to trade. Using Over the Counter (OTC) market data, Stoll examined the factors that determine the dealer's costs and the number of dealers willing to make a market in a particular stock. The study comprised closing bid and ask prices and trading volumes for each NASDAQ stock over six consecutive trading days in 1973. Information trading is measured by turnover (volume of shares traded/shares outstanding) on the basis that the number of shares traded is high relative to the total number of shares outstanding when investors have information that they believe is not shared by other traders and the dealers in the stock.

The turnover variable was found to have a large and significantly positive effect on spread. Increased competition through the presence of greater numbers of dealers also reduces spreads. Stoll also found that the number of dealers in a stock is significantly related to the characteristics of the stock, which has implications for arbitrarily reducing the number of dealers. This relationship implies an optimum number of dealers in a particular stock, with each dealer at an optimum level of activity. Interfering with this by reducing the number of

dealers would force dealers to work at a non optimal level, thus incurring more cost for the investor. Stoll demonstrated that trading is quite expensive for a significant number of NASDAQ stocks from the evidence of their spreads. He explicitly linked the prohibitive trading costs to low volume and high risk stocks, comparing them to financial stocks where volume is greater and risk is less.

2.2.5 Liquidity traders in the domestic market

If a security is traded on more than one exchange, liquidity traders will perform their transactions with the exchange that has the lowest cost according to Barclay, Litzenberger, Warner (1990). For stocks that have an international listing, this is commonly the domestic market. Following earlier work by Kyle (1985) and Admati and Pfleiderer (1988) who showed that private information revealed through trading activity causes variance, the authors confirm a role for discretionary liquidity traders in rational trading models. Discretionary liquidity traders have no private information, but unlike random liquidity traders can exercise some 'discretion' over the timing of their trades. In common with informed traders they also tend to cluster their trades and to trade when the market is 'thick'. It is this clustering of trades that causes variance to be highest when trading is most active. Another implication of clustering is related to cost. The domestic market is by definition less costly for discretionary liquidity traders to whom it is assumed cost matters. Since informed traders only come to the market when the liquidity traders are present, the level of trading volume will be lower on foreign exchanges, thereby reducing the impact on the stock return variance. Specifically, Barclay, Litzenberger and Warner (1990) find that secondary listing of U.S. stocks on the Tokyo exchange does not increase the overall level of variance, nor does it affect its overnight pattern, despite a substantial increase in trading hours.

Summary of Section 2.2

Much of normal trading volume activity does not impact the index price enough to stimulate volatility above normal levels. The specialist or market maker is required to make a market in the securities in which he specialises. In order to do this he trades on his own account when the bid-ask quotations are too far apart to maintain trading activity without wide jumps in price. The costs of providing immediacy include the price risk and the

opportunity cost of holding securities, the costs associated with arranging trades and clearing transactions, and the costs incurred when traders with whom they are transacting have superior information.

The bid-ask spread may be perceived as a trade off between expected losses to informed traders and expected gains from liquidity traders. The bid-ask spread is shown to be a function of increased volatility in the underlying asset, a higher asset price level and a lower trading volume (thinly traded stocks). When investors have information that they believe is not shared by other traders and the dealers in the stock, the number of shares traded is high relative to the total number of shares outstanding. The turnover variable therefore was found to have a large and significantly positive effect on spread. Increased competition through the presence of greater numbers of dealers also reduces spreads. Prohibitive trading costs are linked to low volume, high risk stocks, compared with financial stocks where volume is greater and risk is less. Discretionary liquidity traders in common with informed traders tend to trade when the market is 'thick'. It is this clustering of trades that causes variance to be highest when trading is most active.

2.3 Mixture of Distributions Hypothesis

2.3.1 Introduction

The Mixture of Distributions Hypothesis (MDH), first proposed by Clark (1973) and developed by Epps and Epps (1976), Tauchen and Pitts (1983) and Andersen (1996), is based upon the theory that information drives volatility and trading volume. The main proposition of the MDH is that daily price changes and trading volumes are subordinated to the same underlying information flow variable. The arrival of unexpected good news increases the stock price while bad news results in a price decrease. Both of these events are accompanied by higher than average levels of trading activity. Under the MDH therefore, both the daily stock return r_t and the daily trading volume V_t are the sum of a random number of individual price increments and volumes. The random number is dependent upon the rate of information arrival during the day. Each time information arrives to the market, traders adjust their equilibrium prices and trading volumes rise as the

market adjusts to its new equilibrium. If each intraday return is assumed to be independent and identically distributed (i.i.d.) with mean zero and variance σ^2 , the joint distribution of daily returns and trading volume is a bivariate normal conditional on the daily number of information arrivals, I_t .

$$r_t \mid I_t \sim N(0, \sigma^2 I_t) \quad (2.2)$$

$$V_t \mid I_t \sim N(a + bI_t, c I_t) \quad (2.3)$$

The two expressions above show that the volatility of returns and the mean and volatility of trading volume are both dependent on the behaviour of I_t .

Other versions of the MDH hypothesise that the daily price change is the sum of a random number, n , of within-day price changes. For a given value of n , the Central Limit Theorem implies that the change in price, Δp , is approximately normal with variance proportional to n . If the random variable n is not fixed, however, the distribution of Δp is subordinate to the distribution of n . Karpoff (1987) suggests that it is intuitively appealing to interpret the number of within-day price changes, n , as the number of within-day information arrivals. It follows that the conditional variance of Δp is related to the intensity of information flow and the ensuing $(V, \mid \Delta p \mid)$ correlation occurs because volume is an increasing function of the number of intra-day price changes. Harris (1986) allows the variation in n to vary across securities and derives inferences that sample measures of price change kurtosis, volume skewness and the correlation of squared price change with volume should all be positively correlated.

The most significant development of the early Osborne (1959) paper was to allow the interval of time between transactions to vary. This modelling approach featured in Clark (1973), Tauchen and Pitts (1983) and Harris (1986). The Tauchen and Pitts (1983) model hypothesised that the correlation between the volume and the absolute price change was an increasing function of the variance of the daily information flow. An increase in the number of traders entering the market causes an increase in the trading volume, but a decrease in the variance of the price change.

The Epps and Epps (1976) model explained the change in the market price on each intra day transaction as the average of all the changes in the traders' reservation prices. This implies that there exists a positive relation between the extent to which traders disagree as they revise their reservation prices and the absolute value of the change in the market price. It follows that an increase in the extent to which traders disagree could indicate a larger absolute price change, and it is from this hypothesis that the $(V, |\Delta p|)$ correlation occurs. The disagreement among traders in speculative models arises from heterogeneity in traders' expectations concerning the value of new information, either because they have private information or they disagree about the implications of public information for the future price path of the asset.

The cross-sectional implications of the MDH for the joint distribution of daily price changes and volumes on all common stocks continuously traded on the New York or American Stock Exchanges between January 1, 1976 and December 31, 1977, for which the number of shares outstanding did not change by more than 5 per cent, are examined in Harris (1986). The 5 per cent stipulation was to ensure that volume changes were not the result of stock splits, dividends or other microstructural issues. Likewise, the requirement that the stocks be continuously traded was because of the assumption that active trading grows from large numbers of information arrivals each day, a necessary condition for the derivation of the MDH. Harris (1986) assumed that the distribution of the directing variable, interpreted as the daily rate of information flow, is not uniform across all securities. It follows that predictable cross security differences in the joint distribution of returns and volume can be attributed to changes in this mixing variable, and that prices are the outcome of information events evolving at different rates.

The mixture model has the following predictions:

- (a) The marginal distribution of daily returns is kurtotic relative to the normal distribution,
- (b) The marginal distribution of daily volume is skewed to the right,
- (c) There is price heteroscedasticity because return variance is subordinate to the variance of the mixing variable,
- (d) The marginal distribution of returns is skewed, and

(e) Returns and volumes are correlated.

These predictions of the mixture model are valid only in the case that the rate of information variable, I_t , varies through time and the greater its variation through time, the more pronounced should be these attributes of the joint distribution. A marginal probability distribution is obtained from the joint probability density by summing or integrating out the other variable. In (a), (b) and (d) above, the marginal distribution is defined with respect to only one of the two variables in the joint distribution. So for example, in part (b) the marginal probability distribution is defined with respect to the volume variable in the joint density function of daily returns and trading volumes.

Prior to Richardson and Smith (1994), most empirical studies of the MDH focussed on particular moments of price changes and trading volumes. Consequently, the implications of the MDH for the third and fourth moments of the distribution of price changes were by then well established in the literature. In tests of the model, Clark (1973), Epps and Epps (1976) and Harris (1987) all reported daily price changes to be skewed and kurtotic, relative to the normal distribution. Using daily data on the Dow Jones 30 firms from 1982-1986, Richardson and Smith (1994) estimated the parameters of the largely unobserved information flow that is proxied by trading volume in Clark (1973). They found that most of the firms in the Dow Jones 30 displayed a positively skewed information flow; thereby inferring that the flow of information for firms such as IBM is asymmetric. They related the positive skewness statistic, where the weight of the distribution is in the right tail, to the fact that, generally, only a small number of information events occurs throughout the day. On occasion, a significant information flow will happen. Of the firms in the sample that fit the data well, the coefficient of variation statistics are, for the most part, significantly less than one. The coefficient of variation is a measure of relative dispersion that is expressed as a pure number without any units. It is a ratio of the standard deviation to the mean and is particularly useful in comparing the relative dispersions of two or more distributions (as in the case study being described) where the means differ.

The coefficient of variation parameter for IBM, for example, is over 12 standard errors from one. This implies that the standard deviation of the information flow for IBM is very small relative to the average. This is not surprising given that the market regularly receives information that is both firm specific and relevant market wide, such as profit warnings, stock splits, and quarterly results. The implication, for the random variable, information flow, is that while there is some uncertainty in the flow, the *amount* of information is for the most part set. Obviously, the same cannot be said for the nature of the information. Much of the information that is relevant to individual firms is widely available to the general public and very little new information is released on a day to day basis. However, when a large piece of information is released, good or bad, relative to normal the distribution of the random variable becomes more positively skewed.

2.3.2 Noise versus information based trades in futures markets

Holmes and Tomsett (2004) explored the role of information flow in providing a link between futures volume and volatility, using Andersen's (1996) specification of the MDH. Building on the theoretical approach of Glosten and Milgrom (1985), Andersen modelled the volume movements and price changes that result from traders with varying amounts of information. In the Andersen model, a distinction is drawn between volume movements that are generated by noise traders and those movements that can be ascribed to information based trades. The study of the noise and informed components of volume as factors in driving price change in futures markets is important for the pricing of derivatives. Holmes and Tomsett (2004) is the first test of Andersen's (1996) MDH for assets other than stocks traded in the US; specifically, for three futures contracts, the FTSE 100, the Long Gilt and Brent Oil, the findings are broadly in line with the MDH of Andersen. The results confirm that the price movements and trading activity are both governed by the same underlying process, the flow of information. By decomposing the information variable into 'informed' and 'noisy' components, the authors establish that, for futures contracts, it is informed trading that generates volume. This finding has implications for regulatory behaviour that seeks to place artificial restraints on price movements or the volume of trade in these markets. The impetus behind such a desire is the perceived threat to stability posed by trading in derivative markets. By showing that trading is dominated by informed rather than

noisy activity, the authors are indicating that the imposition of greater controls in these markets is unwarranted and would have implications for market makers and ultimately investors in higher transactions costs.

2.3.3 Commodity futures markets

The mechanism by which differences in information flows and market microstructures can contribute to differences in volatility in commodity futures markets is examined in Dhillon, Lasser and Watanabe (1997). The focus of the paper is the impact of both the trading mechanism and information on return variances for gold futures contracts traded on the commodity exchanges of New York and Tokyo, and in the case of Tokyo, across a change in trading mechanisms. In 1991, the Tokyo Commodity Exchange (TOCOM) changed from a Walrasian trading system to a continuous computerized trading system, whereas the Commodity Exchange of New York (COMEX) uses a dual auction trading system throughout. Both the trading mechanism and information are shown to influence price volatility. Exchange volume conveys private information consistent with the private information based rational trading model of French and Roll (1986), and returns for the COMEX gold futures contracts have consistently higher levels of intraday variance than the comparable contracts traded on the TOCOM, attributed to the differences in trading mechanisms.

2.3.4 New market implications of MDH

The extent to which the implications of the MDH are valid for new markets, such as those of central and eastern European countries, is investigated in Bohl and Henke (2003) using daily returns and trading volumes for 20 stocks listed on the Warsaw Stock Exchange from January 4, 1999 to October 31, 2000. The authors studied the volumes issuing from two distinct trading mechanisms, auction trading and continuous trading. This facilitated a sensitivity analysis of the different volume time-series. The findings are to a large extent supportive of the results for highly liquid markets in developed countries, and the implications of the MDH can theoretically explain Polish stock market volatility.

One of the implications of the MDH is that serial correlation in volume causes conditional heteroscedasticity in stock returns; volume serving as a proxy measure of the

(unobservable) amount of information flow. This follows from the theory that the more news that is conveyed to the market about a share or shares, the greater will be the divergence of opinion among the shareholders concerning the value of this information and the greater is the incentive to trade based on divergent expectations of the future price path of the shares. Under the MDH the daily returns are normally distributed with mean zero and variance that is proportional to the intensity of information arrivals. If the arrivals process is assumed to have an autoregressive structure, this process becomes absorbed into the conditional variance equation giving rise to the typical generalised autoregressive conditional heteroscedasticity (GARCH) structure. Since news arrivals are proxied by volume, one of the implications of the MDH for volumes is that they must be serially correlated. The findings in this paper confirm that the inclusion of trading volume as an explanatory variable in the conditional variance equation results in substantial reduction of volatility persistence in daily returns for the most part, and therefore serially correlated information arrivals are a source of GARCH effects in the Polish stock market.

2.3.5 Bivariate normal mixtures model.

Tauchen and Pitts (1983) extend the earlier work of Clark (1973) and Epps and Epps (1976) by deriving a joint probability distribution function of price change and trading volume over any interval of time. Previous studies had not addressed the issue of growth in speculative markets; the empirical results suggested that variance should increase as trading volume increased. Tauchen and Pitts (1983) chose the 90-day Treasury bills (T-bills) futures market (one of the first and most popular of the then new futures markets) as, during its growth phase, the number of traders had expanded dramatically. The sources of this growth related to a gradual spread of information concerning these new markets and the relaxation of restrictions on financial institutions trading in futures markets. From the first day of trading, January 6, 1976 to June 30, 1979, the volume grew exponentially; the result shows a 0.39 per cent daily growth in the volume of trading over the period. Existing theory of speculative trading would suggest that the variance should increase with the growth in trading volume, but Tauchen and Pitts (1983) show, via a regression of the log of the daily price change on a trend, that the variance at -.04 per cent, actually declines as the volume grows. Therefore, the key difference between Epps and Epps (1976) and Tauchen and Pitts (1983) is the way in which both models connect the price change to the trading

volume; the latter uses a variance-components scheme to model the intra-day changes in traders' reservation prices. This allows them to derive the joint probability distribution function of price change and trading volume for each intra-day market clearing. Adding the random number of intra-day price changes and trading volumes provides the daily values for each variable in a bivariate normal mixtures model.

Summary of Section 2.3

The Mixture of Distributions Hypothesis (MDH) is based upon the theory that information drives volatility and trading volume. The arrival of unexpected good news increases the stock price while bad news results in a price decrease. Both of these events are accompanied by higher than average levels of trading activity. Under the MDH, disagreement among traders in speculative models arises from heterogeneity in traders' expectations concerning the value of new information, either because they have private information or they disagree about the implications of public information for the future price path of the asset. If the distribution of the daily rate of information flow is not uniform across all securities, it follows that prices are the outcome of information events evolving at different rates.

By the mid-1990s, tests of the MDH showed daily price changes to be skewed and kurtotic, relative to a normal distribution. Using daily data on the Dow Jones 30 firms from 1982-1986, Richardson and Smith (1994) showed that most of the firms in the Dow Jones 30 displayed a positively skewed information flow. This is consistent with the rate of information flow for individual firms being generally steady from day to day and fairly predictable. Only a small number of information events will occur throughout the day, but occasionally, a significant information flow will take place.

In futures contracts, the flow of information is a driving force in price movements and trading activity. Furthermore, it is informed trading that generates volume. This has implications for those who seek to impose tighter controls in these markets. The desire for greater controls emanates from the perceived threat posed to markets by unregulated trading in futures. In a rapidly growing market such as the 90-day Treasury bills (T-bills)

futures market (one of the first and most popular of the then new futures markets) the variance actually declines as the volume grows. In commodity futures markets both the trading mechanism and information are shown to influence price volatility.

2.4 Empirical Literature on Volume and Volatility

2.4.1 Introduction

Price and quantity have been described as the fundamental building blocks of any theory of economic activity, suggesting that analysis of the relation that exists between them is fundamental to a better understanding of the determinants of price change. Karpoff (1987) traced the earliest treatment of the price-volume relation to Osborne (1959), who modelled the stock price change as a process where the variance was a function of the number of transactions. By assuming that transactions are uniformly distributed through time, Osborne modelled the price change process purely in terms of time intervals and did not consider the volume-volatility relation.

Gallant, Rossi and Tauchen (1992) investigated price and volume co-movement using daily data from the S&P Composite Index and the total New York Stock Exchange (NYSE) trading volume from 1928 to 1987. While Karpoff provides an excellent review of the empirical studies prior to 1987, Gallant *et al.* (1992) describe the NYSE stock market between 1987 and 1992 as being characterized by sharp downward price movements accompanied by high volume and increased future volatility. On October 19th 1987, the S&P Composite Index fell by 22.9 per cent on the second highest volume ever (604 million shares). On October 20th 1987, the S&P 500 *rose* by 5.2 per cent on the highest volume ever (608 million shares). These figures led the authors to observe that more can be learned about stock market volatility by studying prices in conjunction with volume instead of prices alone, and that existing theory was inadequate to guide the specification of an empirical model of daily stock market data. They found the *direction* of the daily price in the stock market to be unrelated to contemporaneous volume, implying that the market is as likely to rise as fall on heavy volumes as it is on light volumes. It follows that lagged trading volumes are important as predictors, which begs one of the central questions I

address in this thesis: can lagged trading volumes and high past returns predict negative skewness at the level of the aggregate market? Therefore lagged volumes are important as predictors.

In a review of the then-existing literature on the price-volume relationship, Karpoff (1987) enumerated four reasons why the study of the price change/volume relationship is important. First, it provides a better understanding of the structure of the capital market, by examining the flow of information, the dissemination of information and the manner in which information becomes impounded in the price change. Second, in joint tests of price changes and trading volumes, price changes are interpreted as the market response to new information and the corresponding trading volumes as an indication of the extent to which traders disagree concerning the value of the information. Third, the price/volume relation is fundamental to the study of the empirical distribution of speculative prices. The fourth application of the study of the price/volume relationship relates to futures markets. Price variability has a bearing on the volume of trade in futures markets: the time to delivery impacts on the volume of trade which may in turn impact the price. Finally, the price/volume relation in futures markets can be used in the study of private versus public information in determining investor requirements. Karpoff (1987) showed that a substantial body of empirical work supports a positive volume – absolute price change correlation in market indices and individual stocks; this held true for cotton futures, Treasury bill futures, foreign currency futures and transactions data from individual stocks. Karpoff (1987) presents, in tabular format, a summary of the empirical studies from which inferences can be made about the correlation of the absolute value of the price change $|\Delta p|$ with trading volume, V . For a variety of sample periods, measured annually, and differencing intervals ranging from hourly to yearly, of aggregate market data, common stocks and futures contracts, 18 of 19 studies support a positive $(|\Delta p|, V)$ correlation.

The empirical findings reported by Karpoff (1987) are:

- The correlation is always positive, though small for some of the studies; for example, Crouch (1970) reported an average squared correlation coefficient of 0.20 for stock indices and 0.23 for individual firms.
- The correlation is present in both futures and equity markets.

- The correlation is found over all calendar intervals, though appearing weaker in transactions data.

In looking at theoretical explanations for the observed phenomenon, Karpoff's (1987) analysis is critical of some of the assumptions of the 'sequential arrival of information' model of Copeland (1976), one of which is that volume is greatest when all investors agree on the meaning of information. Extensions of this model used the sequential arrival of information process to hypothesise that trading volume will be abnormally high during the same time intervals in which the absolute value of returns are serially correlated. Other extensions allowed traders to take speculative positions, where prices might be predicted to react more quickly to new information but the effect of this on trading volumes is ambiguous. In one such case cited by Karpoff, the model implied a positive correlation between V and $|\Delta p|$ for a given investor's trade but this positive correlation becomes obscured with data sampled over time intervals as long as a day. Another explanation of the volume/volatility relation grew out of wider research into the distribution of speculative prices. Daily price changes appear to be uncorrelated with each other: they are symmetrically distributed but with a high level of kurtosis relative to a normal distribution. One reason for this characterization was that daily price changes were assumed to come from distributions that had different variances. This is the MDH described in detail in Section 2.3. In the Epps and Epps (1976) version of the MDH, the variance of the price change on a single transaction is conditional on the volume of that transaction.

2.4.2 Rational expectations models

In the rational expectations models, disagreement among traders is generated by private information. Traders are characterized as privately informed, uninformed or noise traders. Wang (1994) derives an equilibrium model of investors who are heterogeneous, both in terms of private information and investment opportunities and whose trading behaviour can be motivated by information and, equally, non-information. To hedge against the risk that is inherent in dealing with informed traders, the uninformed investors must be offered inducements to trade in the form of lower prices. Thus trading volume is always positively correlated with absolute price change and the correlation increases with information

asymmetry. The information asymmetry arises because the more uninformed the trader the greater the discount that must be offered to effect the trade. As this model makes no allowance for informed trading activity (such as institutional portfolio rebalancing), all trading activity is related to price change.

2.4.3 Difference-of-opinion theory

According to difference-of-opinion theory, traders differ in the way that they interpret common information. This model assumes that investors believe in the correctness of their own assessment of the common information. Harris and Raviv (1993) assume that investors are homogeneous in their prior assessment of the returns to a single asset. As information becomes available, the investors may re-evaluate their original assessment and revise their beliefs accordingly. In this model, the trading public is composed of two types of risk-neutral speculative investors, who could be categorised as 'bullish' and 'bearish' or 'responsive' and 'unresponsive'. When a signal is received, both types agree as to its nature, whether favourable or unfavourable, but *disagree* on the impact it will have on the future return to the asset. When cumulative past information has been favourable, bullish investors are inclined to buy while bearish investors are more inclined to sell. Conversely, when past information has been unfavourable, bullish investors tend to revise their expectations downwards and are disposed to sell while their more bearish counterparts are inclined to buy. It follows that trading activity takes place only when cumulative past information changes states from favourable to unfavourable and vice versa.

In the Hong-Stein (2003) model, when differences of opinion are large, bearish investors who may have short-sales constraints are forced to sit out the market, thus concealing information from other, more bullish investors who continue to trade. An unfavourable signal at some future time may cause these bullish investors to join their more conservative counterparts on the sidelines, at which time the bearish investors may become the marginal support buyers, thus revealing accumulated hidden information. It follows that more accumulated hidden information tends to come out during market declines; and since trading volume is a proxy for difference of opinion, it follows that markets are predicted to be more negatively skewed after periods of high trading volume.

2.4.4 Copeland model

In Copeland's (1976) sequential arrival of information model, the trading public is composed of optimists and pessimists. Information is disseminated to only one trader at a time implying a positive correlation between V and $|\Delta p|$. Each information arrival causes a fixed upward shift in each optimist's demand curve and a fixed downward shift in each pessimist's demand curve. Trading occurs upon receipt of information but the model assumes that uninformed traders are not permitted to infer anything from the actions of informed traders. In this model, short selling is prohibited and this has a knock-on effect on the volume generated by the activities of the pessimist, since the pessimist cannot short-sell upon receipt of information.

In this model, the total volume depends on the path by which the final equilibrium is reached; as such it is a random variable with an expected value equal to a weighted average of the volume generated under each possible path of information dispersion. Volume is found to be highest when all traders are optimists or all pessimists; the $|\Delta p|$ is at its lowest level when the percentage of optimists trading results in the lowest level of volume and $|\Delta p|$ rises as volume rises. Two assumptions of this model are highly questionable: first, the fact that traders cannot learn from the market price response to the actions of other traders; and second, the implication that volume is highest when all investors *agree* in their evaluation of the information. The fact that traders are forced into a binary response to information is a somewhat odd interpretation of disagreement among traders.

2.4.5 The Shalen model

Shalen (1993) hypothesised that the dispersion between past and current beliefs helps to explain a number of stylized facts in the volume/volatility relation. The liquidity demand of futures hedgers is by definition noisy, and obscures the extent of private information embedded in prices, thus preserving or maintaining the dispersion of beliefs. This dispersion of beliefs is a means of quantifying the excess levels of both volumes and volatility induced by the noise traders. The variance of price changes, the expected volume of trade, the correlations between absolute price changes and both contemporaneous and

lagged volumes are all, to some extent, influenced by dispersion of beliefs. Price variation is connected to the dispersion of price expectations through the actions of speculators who extract, from current prices, information concerning the future price path of the asset. Price variation can stem from a change in liquidity demand or can be the result of private information. Speculators, unable to identify the source of the price variation, may be over-responsive to liquidity shocks in their estimates of future price paths. This can create an excess covariance between the average estimates of future prices and liquidity demand.

Shalen (1993) modelled speculative trade as a linear combination of the dispersions of expectations in the current and preceding round of trade, the dispersions being weighted by the precision of the speculator's estimate of the next future's price and a coefficient of risk aversion. Shalen presented two limiting cases where investors' expectations are reversed. In the first case, traders have homogeneous expectations in the first round of trade, but divergent expectations in the second round. The expected volume of trade in the second round depends on the final precision weighted dispersion; precision refers to the level of accuracy in the speculator's estimate of the next futures price. If speculators differ in their estimates of the next future's price, then the expected volume of trade by a speculator will also depend on how accurate his estimate of the price is relative to the average estimate. In the second case, speculators start with dispersed expectations and end with identical expectations; in this case trading is used to close out the speculative bets in the first round, so the expected volume of trade is related to the precision-weighted dispersion of expectations.

2.4.6 Trader types

Daigler and Wiley (1999) examined the impact of trader type on the futures volatility-volume relation. Traders are categorized in accordance with the information they possess, obtained from a database that categorises futures volume by four types of traders: market makers, financial institutions trading on their own account, floor traders and the general public. Central to their analysis is the association of price with information; traders are differentiated either on the basis of the private information they possess or on the dispersion of beliefs they hold concerning the information. Proximity to the trading floor is a key element in access to information. Clearing house members can directly observe the

source of trades, the short term direction of prices and order imbalances, in addition to private information on the cash market. This implies that clearing house traders can identify more precisely the signals that indicate a change in volumes, unlike the general public who lack access to the trading floor. While clearing house traders can modify their trading behaviour to attenuate the price volatility of their own trades, the trading public, whose signals are mixed, cannot distinguish precisely between liquidity trading and shifts in fundamental value. Volatility is increased in accordance with an imprecise information signal and a greater dispersion of expectations; it is therefore the general public that drives the positive volume-volatility relation. A key finding is that large changes in volume, either positive or negative, are more significant in explaining return volatility than average levels of volume.

2.4.7. Volatility of Volume

The potential for the second moment of trading volume to have an impact on expected returns had not been studied extensively prior to the seminal work of Chordia, Subrahmanyam and Anshuman (2001) (CSA) who analysed the relation between expected equity returns and the level as well as the variation of liquidity. Building upon an earlier paper by Amihud and Mendelson (1986) which established the role of liquidity in asset returns, CSA put forward the hypothesis that investors should be concerned about fluctuations in liquidity, proxied by trading activity, since the volatility of liquidity (i.e. trading volumes) could potentially affect asset returns. Following this reasoning, and factoring in the assumption that investors are risk averse, CSA expected the volatility of liquidity to have a premium, meaning that stocks whose liquidity is volatile should command higher expected returns. In contrast to their expectations, however, the authors document a strong, negative relation between average returns and both the level and variation of trading volume. Furthermore, the evidence shows that stocks with high variation in trading volume actually command lower expected returns. Two measures of trading activity are used, dollar volume and turnover. Share turnover is a dimensionless variable and is used to triangulate the findings using dollar volume thus controlling for potentially spurious effects of using a price related variable. One possible theoretical explanation for the finding is provided by Merton (1987) who contends that lower expected

returns are inversely related to the numbers investing in the stock; the variation of trading activity could in that case be related to the heterogeneity of the clientele holding the stock.

Theoretically, a higher level of trading volatility could indicate a shift in investor behaviour, i.e., more people wanting to own the stock causing a lowering of the expected return. One way to control for the level of investor interest is to use the number of analysts following a firm or stock as a proxy; however CSA reported no change in the effect that trading volatility has on expected returns, when they take this approach. However, the statistically strong and economically significant negative relation between average returns and both the level and variation of trading volume remains significant after controlling for the size effect, the book-to-market ratio, momentum effects, and the price level and dividend yield. Building upon CSA's finding, in Chapter 7 I posit a positive relation between the level and variation of trading volumes. This relation has not so far been investigated in the literature on volume and skewness.

Summary of Section 2.4

Epps and Epps (1976) presented a version of the MDH that perceived the variance of the price change on a single transaction as conditional on the volume of the transaction. Tauchen and Pitts (1983) inferred that the correlation between absolute price change and volume was related to information flow. Harris (1986) hypothesised that price change kurtosis, volume skewness and the correlation of squared price change with volume should all be positively correlated. Karpoff (1987) showed that a substantial body of empirical work supported a positive volume–absolute price change correlation.

The mechanism by which the volume volatility relation is established is explored in a number of models beginning with the rational expectations model in which traders are risk averse and a price change always accompanies trading activity. In the difference of opinion model, bullish and bearish investors agree on the nature of the signal received but disagree on the implications for the future price of the asset. The sequential arrival of information model categorises all investors as either optimists or pessimists and finds that the volume is highest when all traders agree on the value of information. The fact that speculative investors cannot always differentiate between liquidity motivated trades and private

information based trades causes uncertainty when prices fluctuate, leading to higher levels of price volatility. Proximity to the trading floor is a key element in access to information; clearing house traders can identify more precisely the signals that indicate a change in volumes, unlike the trading public, who cannot distinguish precisely between liquidity trading and shifts in fundamental value.

2.5 Empirical Literature on Volume and Skewness

2.5.1 Introduction

While many studies have documented the nature, extent and persistence of asymmetries in stock markets, relatively little attention has been paid to the relation between trading volume and the third moment of price changes, skewness. The exceptions are Chen, Hong and Stein (2001) (CHS), Hong and Stein (2003), Hueng and Brooks (2003), Charoenrook and Daouk (2004) and Hueng and McDonald (2005). CHS examined whether differences of opinion about the future value of stock returns, associated with rising trading volumes, lead to greater skewness in returns. Using firm level data for the US from July 1962 to December 1998, they estimated cross sectional models in which the skewness estimated from daily data over a six month period is regressed on lagged returns and lagged detrended volumes. Consistent with investor heterogeneity theory, they showed that stocks with higher than average returns and volumes tend to be associated with future negative skewness. When they examined market data, however, the relation between volume and skewness disappeared. The aggregate market selected for analysis in CHS is the value-weighted NYSE-AMEX index and returns are excess relative to T-bills. As in the cross-sectional analysis, the turnover is detrended by its own moving average over the previous 18 months, and the authors used overlapping monthly observations to extract the maximum amount of statistical power from the time series analysis. While the past return terms are always positive and many are statistically significant, the coefficient on detrended turnover, although positive, is never significant.

Extending the work of CHS, Hueng and Brooks (2003) used an asymmetric generalised t -distribution approach to obtain conditional estimates of sample skewness, which enabled

them to estimate their models on non-overlapping daily time series data. In contrast to CHS, they found that while lagged returns and skewness are significant determinants of future skewness, the coefficients are rarely negative, implying that higher volumes are not generally associated with future negative skewness. Charoenruek and Daouk (2004) used daily market data for 57 countries from January 1973 to December 2002 to estimate individual country and pooled cross-section time series models, and found weak evidence that lagged trend adjusted volumes lead to more negative skewness.

Hueng and McDonald (2005) employed an autoregressive conditional density model with a skewed t -distribution on daily AMEX and NYSE data from 1962 to 2000 to show that the negative relation between trading volumes and return skewness found by Hong and Stein (2003) in their cross section study is not supported by the time series evidence. In Hueng and McDonald's (2005) model, the parameter that measures asymmetry is dependent on the daily information available on the forecasting variables. They used Hansen's (1994) skewed t to model the variation in the conditional distribution in moments higher than the variance. Using NYSE and AMEX daily data from 1962 to 2000, they found that higher prior turnover either predicts a more positively skewed distribution for future market returns or the effect is insignificant. These findings conflict with CHS.

The length of time over which information is allowed to accumulate remains open to debate, and Hueng and McDonald (2005) follow CHS (2001) in selecting the average of turnover ratios from date $t-125$ to $t-1$, as the past turnover variable. While the effects of prior turnover ratios on λ (the parameter that controls the rate of descent of the density around $v_t = 0$) are all positive, they are not statistically significant; on the other hand, the estimated coefficients of prior 36-month returns are negative and statistically significant; the latter finding is consistent with CHS (2001), who argue that their findings fit Blanchard and Watson's (1982) version of stock price bubbles.

2.5.2 Difference of Opinion Proxy

Since the turnover ratio (the ratio of the number of shares traded to the total number of shares) is a proxy for difference of opinion, the variable that actually predicts negative

skewness in the Hong-Stein model, Hueng and McDonald (2005) addressed the issue of the information accumulation period by experimenting with several alternative definitions of the 6-month average turnover ratios. They found that the effects of prior turnover on asymmetry are positive and significantly different from zero at the 5 per cent level when the prior daily, weekly, monthly and 36-month average turnover ratios are used. In recognition of the upward trend in turnover at various periods they experimented with using the *change* in turnover as a measure of trading volume activity, following Lee and Swaminathan (2000). They found the effects of prior turnover ratios on market skewness to be negative, albeit statistically insignificant, for models with changes in turnover ratios and lagged turnover ratios. Hueng and McDonald (2005) reported that higher past turnover ratios either predict (a) more positively skewed market returns or (b) have an insignificant negative effect on market returns, the latter finding being consistent with CHS. The insignificant negative finding arises from experimenting with different measures of past turnover, raising the question of whether the past turnover variables are a good proxy for the intensity of disagreement among investors. To detrend data with positive drift as is the case with trading related measures such as turnover, a more systematic approach to detrending would be to apply a filter to the volume measure. For example, in Chapter 7, I regress the log of turnover on a time trend and use the exponentials of the residuals as the volume variable. Similar to Hueng and McDonald (2005) I had earlier experimented with several moving average measures before deciding that a more systematic approach to detrending is required. I find past turnover variables to be a good proxy for the intensity of disagreement which suggests that Hueng and McDonald should have asked whether using a moving average approach to detrending turnover is adequate.

In a related study, Charoenrook and Daouk (2004) examined the role of short-sales constraints in the relation between lagged trend-adjusted turnover and skewness as proposed in the Hong-Stein (2003) model. They analysed aggregate market returns in 57 countries and reported that lagged one month returns predict conditional skewness of daily returns during the following month. When they extended the lag length to 3 months, 6 months and 12 months the results were unchanged. In examining the relation between lagged trend-adjusted turnover and skewness, they found weak statistical evidence that

returns of developed markets are more negatively skewed following high trend adjusted turnover. As a further test of the prediction in the Hong-Stein (2003) model, Charoenrook and Daouk (2004) introduced a variable that measured the existence of short selling in each country, and studied its interaction with the past turnover variable. They found that in markets where short selling is viable, the stock market returns are more negatively skewed following an increase in trend-adjusted turnover than in markets where short selling is prohibited. The turnover variable is defined as the ratio of dollar trade per month to dollar market capitalisation at the end of the month, and the detrending involves subtracting from turnover the previous six months average.

2.5.3 Lagged return as a predictor of market skewness

Charoenrook and Daouk (2004) report lagged return to be a strong predictor of market return skewness in both developed and emerging countries, with slope estimates for lagged returns reported to be between -0.66 and -0.52 and all coefficients statistically significant at less than 1%. This relation between lagged return and skewness is also shown to be economically significant, where a one standard deviation change in lagged return predicts a 0.64 change in skewness of returns. Charoenrook and Daouk (2004) reported that stock returns become more negatively skewed following a positive return month and become more positively skewed following a negative return month. In relation to the dynamics of the second moment, they reported higher volatility following a large price change in either direction and a higher increase in volatility following a price decline than a price increase.

The findings on volatility are consistent with the leverage effect and the volatility feedback effect in the theory of finance, but the findings on conditional skewness do not fit with these theories. Charoenrook and Daouk turn to another theoretical model for an economic mechanism that is most consistent with all their empirical findings, especially their findings on conditional skewness. This model describes a universe of investors composed of informed, uninformed and noise traders and an uninformed market maker. All participants are fully rational and incur heterogeneous trading costs, and a set of investors is assumed to receive a commonly informative but noisy signal concerning the valuation of a security. High trading costs prohibit some informed traders from dealing initially while others with lower trading costs participate in buying the security. The stock price rises following the

buying activity of the informed low trading cost investors, and the sidelined informed trader gets confirmation of the accuracy of his signal on the one hand, but must now pay more for the stock.

The model assumes that the market maker is uninformed, therefore the market maker can only assign a probability to the possibility that the last trade was from a liquidity trader and not a privately informed trader. The sidelined investor with a confirmed signal may then choose to trade, because the confirmation of his signal outweighs his trading costs. Charoenrook and Daouk argue that the sidelining of investors causes conditional changes in skewness as a function of past returns through the following mechanism; after an upward price trend it is likely that there are a few sidelined investors with favourable signals but a larger number of investors with adverse signals. When these investors eventually start to trade their activity will cause a major correction, thus returns become more negatively skewed following price rises, and the opposite occurs when private news is negative.

2.5.4 Turnover as a measure of trading activity

The turnover rate is used regularly in the finance literature, for example, as a proxy for liquidity in Datar, Naik and Radcliffe (1998) who test the Amihud and Mendelson (1986) theory of a liquidity premium, whereby low volume stocks earn higher returns than high volume stocks. Lo and Wang (2000) construct weekly turnover series for individual NYSE and AMEX securities from 1962 to 1996 and state on page 272 that ‘Since turnover is by definition an asymmetric measure of trading activity – it cannot be negative – its empirical distribution is *naturally skewed*.’ Since the same can be said about any volume measure, a study of the distribution of excess turnover relative to the average should be useful in identifying some stylistic features of turnover distributions. Further motivation to examine the distribution of excess turnover distributions is provided in a paper by Tkac (1999), who uses monthly trading volume data and market capitalization figures for a subset of NYSE/AMEX in CRSP between 1988 and 1991 to derive a ‘rebalancing benchmark’ that delivers a connection between trading volumes in individual stocks and market wide activity. In order to be able to characterize patterns of anomalous trading activity, it is firstly important to filter out normal trading volume activity, with an adjustment for market related activity. Tkac (1999) found that 20 per cent of the firms have trading activity

patterns of behaviour as predicted by the benchmark model, but there are systematic deviations in many of the firms. She also found average excess turnover versus the benchmark to be positively related to option availability and institutional ownership and negatively related to firm size. Inclusion in the S&P does not significantly affect firms that are already trading above the benchmark level, but it does increase trading for firms that were trading below the benchmark before inclusion in the index. Of the 807 firms sampled in the study, Tkac finds that 644 (79.8 per cent) exhibit statistically significant excess turnover at the 5 per cent level. When this is broken down further, it shows 380 firms (47 per cent of the sample) exhibit average excess turnover that is significantly negative at the 5 per cent level, while 264 firms (32.7 per cent) exhibit significantly positive average excess turnover.

The characteristic behaviour of institutional investors in their trading practices differs from that of private shareholders. Typically institutional investors account for large percentages of the trading volume on stock exchanges such as the NYSE, and they deal in large trades leading to predictable concerns about liquidity. There are examples in the literature of portfolio managers buying past winners and dumping losers and more recently there is evidence of herding behaviour among investment fund managers with the need to beat a benchmark providing the incentive to trade. This active management strategy should result in a practice of overtrading relative to some benchmark level as argued by Tkac (1999) and this 'overtrading' should be related to positive levels of average excess turnover. By a similar argument, option availability should also be related to positive average excess turnover. The issue of positive drift in turnover is addressed in Lo and Wang (2000) where it is noted that many empirical studies use some form of detrending to induce stationarity in turnover. Lo and Wang (2000) experiment with six alternative methods of detrending turnover in order to gauge the impact that different methods of detrending can have on the time series properties of turnover. They conclude that the method of detrending volume data can have a substantial impact on the time series properties of turnover.

Summary of Section 2.5

The relation between trading volume and the third moment of price changes, skewness, has received relatively little attention in the literature. Chen, Hong and Stein (2001) examined whether differences of opinion about the future value of stock returns, associated with rising trading volumes, lead to greater skewness in returns. Consistent with investor heterogeneity theory, they showed that stocks with higher than average returns and volumes tend to be associated with future negative skewness. When they examined market data, however, the relation between volume and skewness disappeared.

Hueng and Brooks (2003) used non-overlapping daily time series data. In contrast to CHS, they found that while lagged returns and skewness are significant determinants of future skewness, the coefficients are rarely negative, implying that higher volumes are not generally associated with future negative skewness. Hueng and McDonald (2005) reported that higher past turnover ratios predict either more positively skewed market returns or have an insignificant negative effect on market returns, the latter finding being consistent with CHS. As a further test of the prediction in the Hong-Stein (2003) model Charoenruek and Daouk (2004) introduced short selling in each country, and studied its interaction with the past turnover variable. They found that in markets where short selling is viable the stock market returns are more negatively skewed following an increase in trend-adjusted turnover than in markets where short selling does not occur. An active management strategy such as buying past winners and dumping losers should result in a practice of overtrading relative to some benchmark level as argued by Tkac (1999) and this 'overtrading' should be related to positive levels of average excess turnover. The issue of positive drift in turnover is addressed in Lo and Wang (2000) who show that different methods of detrending volume data can have significant effects on the time series properties of turnover.

2.6 Summary and Conclusions

In this chapter, I have surveyed the literature that is germane to the main research topic of this thesis, namely the distributional properties of both trading volumes and returns in

financial markets. One of the specific research questions that I set out to investigate asks if it is possible to predict increased levels of negative skewness in market returns by looking at unusually high trading volume levels. In looking at the treatment of skewness, I identified some particular concerns with regard to the behaviour of the skewness statistic over different time horizons and with varying start dates. I highlighted papers that showed that the skewness statistic varied depending on the data frequency, yielding different results for data sampled at quarterly, monthly, weekly, daily intervals. I showed that the skewness statistic is particularly sensitive to the presence of outliers in the data and reviewed the methods suggested in the early finance literature on how best to handle these inconvenient extreme returns. The relevance of the study of the third moment is justified by a number of papers that point to the role of skewness in the CAPM and the early empirical studies that drew a parallel between investor preference for positive skewness and poorly diversified portfolios.

Having focused on skewness I then turned to trading volumes, beginning with a survey of the market microstructure literature. I discussed the role of the market-maker and the bid-ask spread. I showed that information trading is measured by turnover because when investors have information that they believe is not shared by other traders and dealers, the number of shares traded is high relative to the total number of shares outstanding. The MDH literature was reviewed in detail because it is directly related to the work in Chapter 7 where I show that the first and second moments of trading volumes are strongly positively correlated. I have shown the evolution of the MDH model chronologically and demonstrated, via a mathematical expression, that under this model, the volatility of returns and both the mean and variance of trading volumes are linearly related to the rate of information flow. I reviewed the literature that tested the role of information flow in providing a link between volume and volatility in a derivative market, considered commodity futures and analysed the literature on the implications of the MDH for new markets.

Having examined the formative papers on the MDH, I then turned my attention to the volume-volatility literature. I traced the development of the relationship and discussed a

number of models of speculative trading and their underlying assumptions. One such model is the Hong and Stein (2003) difference-of-opinion theory, which underpins the central focus of the thesis. Having examined the main empirical studies that confirm the strength of the relation between trading volume levels and return volatility, I drew attention to new research that explores the relation between average equity returns and the first and second moments of liquidity, proxied by trading volumes. The literature on trading volume and skewness is somewhat sparse, with the important and relevant developments reviewed in Section 2.5.2. I focused on the handful of papers that have addressed the concerns in the seminal CHS (2001) paper. The importance of these papers in the context of this thesis is that the findings they report are either weakly supportive of, or flatly contradict, the CHS findings.

CHS (2001) found that individual stocks with higher than average returns and volumes can be associated with future negative skewness. CHS were forced to use overlapping data to augment the scarcity of their data sets when they examined the aggregate market. Hueng and Brooks (2003) overcame this problem by deriving a measure of conditional skewness but their results were in conflict with CHS, reporting evidence that higher trading volumes were indicative of positive skewness. Charoenrook and Daouk (2003) found only weak evidence that lagged trend adjusted volumes lead to more negative skewness.

Hueng and McDonald (2005) addressed the issue of too few data points in CHS by using a parameter that was dependent on the daily information available on the forecasting variables, then used Hansen's (1994) skewed t to model variation in moments higher than the second. The problem with this approach is that the forecasting variables are those that were chosen by CHS and there may be a question of omitted variables, whose influence might yield different results. Hueng and McDonald's (2005) results also contradict CHS, finding that higher prior turnover either predicts future positive skewness or the effect is negligible. All the papers reviewed so far used essentially the same method of detrending the turnover data, i.e. a moving average approach, and all justified the use of the detrending by demonstrating that their results were unaffected by varying the length of the detrending period. None of the papers reviewed used the CHS skewness measure, seeking instead to

design a parameter that would proxy for skewness. None of the papers looked at moments of turnover higher than the first, nor did they allow for indirect effects where the skewness of returns might be affected, directly, through the second or third moment of volumes and indirectly as a result of the potential impact of the volatility or skewness of trading volumes on the level of volumes.

I examined briefly the role of turnover as a preferred measure of trading volume in the literature and discussed in some detail a paper that is closely related to the work in Chapter 5. Tkac (1999) examined a subset of NYSE/AMEX stocks and found institutional ownership and option availability to be positively related to average excess turnover levels. 80 per cent of the firms surveyed had excess turnover that was statistically significant. Of this percentage, well over half were due to significant levels of negative excess turnover, the remainder to significant positive excess turnover. The characteristic behaviour of institutional shareholders is different to that of individual shareholders and they generally account for large trades that have a real impact on liquidity and price movements. Tkac (1999) did not examine aggregate markets and her study is confined to a subset of CRSP securities between 1988 and 1991.

In summary, while the relation between return volatility and trading volume levels is well established in the literature, the relation between return skewness and trading volumes is now the subject of a small but rapidly expanding literature. This literature is of most relevance to the empirical analysis contained in subsequent chapters. The theoretical basis of this new research is that asymmetry in returns distributions is the result of investor heterogeneity, where disagreement is proxied by trading volumes. The model of speculative trading that is germane to the empirical work of this thesis is the Hong and Stein (2003) difference-of-opinion theory, which is closely related to one of the fundamental research questions of the thesis: 'The question of whether differences of opinion about the future value of stock returns, associated with rising trading volumes, lead to greater skewness in returns'. In testing the Hong and Stein (2003) theory, CHS (2001) found that individual stocks with higher than average returns and volumes can be associated with future negative skewness. However, CHS were forced to use overlapping data to augment the scarcity of

their data sets when they examined the aggregate market. Hueng and Brooks (2003) used an asymmetric generalised t-distribution approach to obtain conditional estimates of sample skewness, which enabled them to estimate their models on non-overlapping daily time series data. In contrast to CHS, they found that while lagged returns and skewness are significant determinants of future skewness, the coefficients are rarely negative, implying that higher volumes are not generally associated with future negative skewness. Hueng and McDonald's (2005) results also contradict CHS, finding that higher prior turnover either predicts future positive skewness or the effect is negligible. Charoenrook and Daouk (2004) examined the role of short-sales constraints in the relation between lagged trend-adjusted turnover and skewness as proposed in the Hong-Stein (2003) model. Consistent with all of the above papers, Charoenrook and Daouk (2004) report lagged return to be a strong predictor of market return skewness in both developed and emerging countries, with slope estimates for lagged returns reported to be between -0.66 and -0.52 and all coefficients statistically significant at less than 1%. This literature constitutes the main papers that are relevant to one of the fundamental research questions of this thesis, which is reiterated above. In discussing the work of these authors I focused on the areas where their work diverged from mine, specifically in their methods of detrending the data and in their construction of a skewness measure or proxy. I highlighted the fact that none of these authors considered moments of volume higher than the first, nor did their models allow for indirect mechanisms of transmission.

Chapter 3

Data and Methodology

3.1 Introduction

In this chapter, I describe the data sets and the methodology used in implementing the non parametric tests in Chapters 4, 5 and 6 and the econometric models in Chapter 7. In accordance with the title of the thesis, the empirical studies in Chapters 4, 5 and 7 are based on aggregate markets and do not, therefore, examine individual securities. This is consistent with the stated aims of the thesis as stated in Chapter 1, section 1.2 (*page 11.*) In Section 3.2, I identify the sources of the raw equity, volume and FOHF data, the dates upon which the various studies begin and the numbers of observations. In Section 3.3, I present some basic mathematical equations that describe the first three moments of a distribution and I include a number of alternative skewness measures.

Having described the sources, I proceed to present a more detailed description of the data used in subsequent chapters. In Section 3.4, I provide a detailed description of a set of 6 tables and one illustrative figure that chart the evolution of the datasets that were used in the econometric models in Chapter 7. In Section 3.5, I introduce the three distribution free tests that I use in Chapters 4, 5 and 6. I begin by describing the mathematical equations that describe the Wilcoxon rank sum and the Siegel-Tukey tests followed by a description of the tables that illustrate the implementation of these two tests. I then describe the binomial distribution test together with the tables that demonstrate the method I used in implementing this test. I complete this section by describing the Monte Carlo study that I conducted in Chapter 4. In the final Section 3.7 I summarise the main features of the data and methodologies used in subsequent chapters and point to some limitations.

3.2 Data Sets used in the thesis

3.2.1 Data Description for Chapter 4

For the study of equity return asymmetry in Chapter 4 the data was obtained from *Thomson Datastream*. The indexes used in Chapter 4 were chosen primarily because they were most closely related to the indexes used by Peiró (1999) for comparative purposes. In choosing these specific indexes I was also influenced by the start date since I wanted enough observation points for meaningful inference. In the case of Italy for example, the *Milan Comit* was the most appropriate index available on Datastream at that time. I use daily log price changes from 01/01/1978 to 02/02/2002 for 6 international markets, the *Financial Times All Share* index (UK), the *DS (Datastream) Total French Market*, the *Frankfurt Faz* (Germany), the *Milan Comit* (Italy), the *Nikkei 225* (Japan) and the *New York Stock Exchange* (United States). Days on which the log price change was zero were excluded, and the number of observations varied from 6058 for France to 5898 for Germany, 6008 for Italy, 5944 for Japan, 6082 for the UK, and 5944 for the US. The data is presented in a series of figures and tables in Appendix A (page 192). Figure A.1 (page 194) shows the natural log of daily price changes for all six markets. In order to illustrate the impact of the stock market crash of October 1987 on the individual markets in the study, Figure A.2 (page 194) shows the returns for five of the six markets over a one-month period from 19/10/1987 to 18/11/1987, to be highly volatile. Italy is missing from Figure A.2 (page 194) because it was not subject to historically high levels of volatility in 1987. In Table A.1 (page 196) I present the ten largest positive and the ten largest negative price changes for each individual country over the full duration of the study.

3.2.2. Data Description for Chapter 5 and Chapter 7

The data sets used in both Chapter 5 and Chapter 7 are drawn from the *Thomson Datastream Total Market Index* of Australia, Belgium, Canada, France, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, the UK and the US. In Chapter 5, I examine asymmetry in the returns and volume distributions of these 12 indexes and in Chapter 7, I use 11 of the 12 markets in estimating single equation and VAR models. I excluded Switzerland from Chapter 7 having examined the distributions of all 12 countries in

Chapter 5. As I show in the histograms of the distributions in Chapter 5, the distribution of turnover in Switzerland is negatively skewed, in contrast with the positive skewness I found in all other individual country indexes. The start dates are dictated by the availability of two specific variables for each market studied, namely the value of the shares traded daily and the total market value which I use to construct the turnover variable. I use corresponding daily log price changes in conjunction with the turnover measure and exclude days on which the log price change is zero. These correspond to national holidays and weekends when no trading activity is observed. The dataset starts on *03/01/1984* (5303) for Australia, Belgium *02/01/1986* (4707), Britain *27/10/1986* (4580), Canada *02/01/1986* (6273), France *02/06/1988* (4151), Italy *01/07/1986* (4651), Japan *04/01/1990* (3716), Netherlands *03/02/1986* (4759), Spain *05/02/1990* (3726), Sweden *04/01/1982* (5733) Switzerland *16/01/1989* (3981), and the U.S. *02/01/1980* (6295); the numbers in parentheses are the valid observations i.e., numbers of days for which I had both returns and volume data.

In order to provide a clearer understanding of the information in the preceding paragraph, a representative set of 5 figures that illustrate graphically the distributions of daily returns and daily detrended volumes used in the single equation and VAR models in Chapter 7, is presented in the data appendix. Figure A.3 (*pages 197/8*) shows the distributions of daily returns and Figure A.4 (*pages 198/9*) the daily detrended volumes for each individual market index. As explained, the start date for each country is dictated by the availability of volume data and this is illustrated graphically in Figures A.3 (*pages 187/8*) and A.4 (*pages 189/190*). The monthly return volatilities are plotted in Figure A.5 (*pages 201/2*). The monthly skewness is not included because each variable requires two pages for clear illustration, and the monthly volume skewness is presented instead. The skewness measure illustrated is called DUVOL and is the preferred alternative used in the models in Chapter 7. The methodology of the derivation of DUVOL is described fully in Section 3.4 of this chapter. Figures A.6 (*pages 193/4*) and A.7 (*pages 195/6*) illustrate the monthly volume volatilities and monthly volume skewness respectively. The monthly return means and volume means are aggregated from the daily data as explained in Section 3.4. The first

three moments of returns and the first three moments of volumes are the variables used in the econometric tests of Chapter 7, hence their inclusion in this section on data description.

3.2.3 FOHF Data

The data for this study was obtained from Hedge Fund Research, Inc. (HFR), which is the main provider of FOHF information. It includes return data on 525 hedge funds for the period from January 1988 to May 2003. Returns are monthly and represent the change in net asset value during the month relative to net asset value at the beginning of the month. All returns are in US dollars, and are net of all fees and expenses. HFR data include both domestic (US) and offshore funds, and in order to avoid survivorship bias in returns it also includes defunct funds.

The age profile of these funds is summarised in Table 6.1 (*page 146*), which confirms the massive growth in FOHFs formation in recent years. The mean (median) fund age is 57 (45) months, and over half (53 percent) are less than 4 years old, with only 10 percent being more than 10 years old. While the data for the individual FOHFs begins in January 1988, because the hedge fund indexes are available only from January 1990, I eliminate observations before January 1990. Due to data limitations, I also remove funds that have been in existence for less than 2½ years, leaving a data set of 332 FOHFs. The attrition rate for the sample is low. Of the 525 funds in the data set, 14 had ceased reporting by March 2003. Of these, 10 had more than 30 return observations and so were retained, leaving more than 70 percent of the defunct funds in the sample, which is more than the 63 percent of the full sample that had greater than 30 observations.

Sub Index Description

HFR produces an equally weighted composite FOHF index comprising funds of various ages and asset sizes. It also produces 4 equally weighted sub-indexes: conservative, diversified, market defensive and strategic. A FOHF is classified as conservative if its constituent funds conduct market-neutral (low volatility) strategies. Diversified funds invest in hedge funds with a variety of strategies, and are designed for minimal loss in down-markets and superior returns in up-markets. Market defensive FOHFs invest in

short-biased hedge funds and are constructed to be negatively correlated with the returns on standard asset classes. Lastly, strategic funds invest in hedge funds with opportunistic strategies such as ‘emerging markets,’ and are expected to perform well in up-markets and underperform in down-markets. Seventy-four funds in my sample are classified as conservative, 153 are diversified, 34 are market defensive and 71 are strategic.

3.3 Distribution Moments

3.3.1 Measures of Central Tendency

The most important measures of central tendency in a distribution are (1) the mean, (2) the median and (3) the mode. The arithmetic mean or average of a population is represented by μ , calculated as

$$\mu = \frac{\sum X}{N} \quad (3.1)$$

Here $\sum X$ refers to the sum of all the observations and N the number of observations. The median is the value of the middle term when all the terms have been ordered in ascending or descending order, while the mode is the value that occurs most frequently in the dataset.

3.3.2 Measures of Dispersion

Dispersion refers to the variability or spread in the data. The population variance, σ^2 is given by the formula

$$\sigma^2 = \frac{\sum (X - \mu)^2}{N} \quad (3.2)$$

The most widely used measure of absolute dispersion is the standard deviation σ , given as

$$\sigma = \sqrt{\frac{\sum (X - \mu)^2}{N}} \quad (3.3)$$

3.3.3 Measures of Skewness

The two moments that define the shape of a distribution are the third moment, (skewness), and the fourth moment, (kurtosis). A distribution that is symmetrical about its mean has zero skewness and its mean, median and mode are equal. A distribution is described as 'negatively skewed' if the left tail is elongated; in this case the mode > median > mean. If the right tail is longer, the distribution is positively skewed and the mean > median > mode.

The probability density function of daily financial returns is symmetric about μ , if (for any k)

$$f(\mu + k) = f(\mu - k) \quad (3.4)$$

where f is the density function of the returns, see Greene (1997). If this equation holds, then μ is the mean of the distribution and coincides with the median. The traditional test for the skewness of returns on a financial asset, i , is based on the coefficient of sample skewness given in equation (3.5)

$$SK^i = \frac{\sum_{t=1}^N (R_t^i)^3 / N}{(\sigma^i)^3} \quad (3.5)$$

Here, SK^i is the skewness of asset i , R_t^i is asset i 's excess return at time t , σ^i is the sample standard deviation, and N is the number of observations in the series. Under the assumption of normality, the asymptotic distribution of SK^i is given by

$$SK^i \sim N(0, 6/N) \quad (3.6)$$

The Pearson coefficient uses the median as well as the mean and is used in Chapter 5 to provide an alternative measure of the degree of skewness present in the sample.

The Pearson coefficient of skewness is defined as:

$$SK^i = \frac{3(\mu - med)}{\sigma} \quad (3.7)$$

Here μ is the mean, med is the median, σ is the standard deviation and SK^i is as above.

$SK^i = 0$ when the distribution is symmetric.

Following the approach of Chen, Hong and Stein (2001), I employ two alternative measures of skewness, namely, SKW^i and DU^i described in equations (3.8) and (3.9) below.

$$SKW_t^i = - \frac{N(N-1)^{3/2} \sum_{i=1}^n R_t^{i^3}}{(N-1)(N-2) \left(\sum_{i=1}^n R_t^{i^2} \right)^{3/2}} \quad (3.8)$$

$$DU_t^i = \log \left[\frac{(N_u - 1) \sum_{i=1}^n R_{down}^{i^2}}{(N_d - 1) \sum_{i=1}^n R_{up}^{i^2}} \right] \quad (3.9)$$

Equation (3.8) is a derivative of the standard coefficient of skewness presented in (3.5). It is derived by calculating the negative of the third moment of daily returns, divided by the cubed standard deviation. Scaling by the cubed standard deviation has the desired effect of standardising the measure of skewness for differences in variance across different markets. The negative is taken of this measure of skewness because of the convention that a higher value corresponds to a more negatively skewed distribution. Equation (3.9) provides an

alternative description of the degree of skewness, which is used because it is less influenced by extreme outliers. This is the measure that I use in calculating the skewness of both market return and trading volume and its derivation is fully described in Section 3.4.1. This measure is effectively a ratio of the standard deviation of the ‘down’ days to the ‘up’ and, therefore, since it is not so sensitive to the presence of outliers in the data, I had no occasion to delete any observation point. A recent paper by Premaratne and Bera (2005) proposes a simple test of symmetry in the presence of high levels of leptokurtosis and reports encouraging results in individual stock return data. This has not, however been tested on aggregate markets, as are used in this thesis. In order to avoid a potential problem with bias, one example of which is the behaviour of the traditional skewness statistic in the presence of leptokurtosis, I used Equation 3.9, because it is not sensitive to the presence of extreme outliers in the data.

3.4 Data Manipulation and Methodology

In this section, I describe the work of constructing the data set that is used in the single equation, panel and VAR models of Chapter 7. This data set is composed of monthly observations on the first three moments of the distributions of return and volume for a total of 11 international equity markets from 1980 to 2004. For clarity I have provided a series of 6 tables that chart the evolution of the data set for Belgium. Belgium will serve as an example of the approach I adopt towards data manipulation and construction in this and the equity markets of Australia, Canada, France, Italy, Japan, Netherlands, Spain, Sweden, the UK and the US.

3.4.1 Description of data tables

Table 3.1 (*page 71*) presents an extract from the Belgium daily price index and volume data, comprising value of shares traded and total market value, as obtained from Datastream. PI represents price index, LNPI the natural log of the price change, VA refers to the value of shares traded and MV stands for total market value. The data selected runs from 30/03/1999 to 20/05/1999. The complete dataset for each of the 11 countries

commences on the first date in the time series for which both price and volume data are available; each country has, therefore, a different start date. Thus the dataset from which this extract is selected commences on the 02/01/1986. In constructing the turnover variable I eliminate from the dataset days on which no trading occurs; in the column headed VA this corresponds to days for which the value of shares traded is denoted by #N/A. The return variable LNPI is included in this table to illustrate that days on which no trading activity occurs have corresponding zero entries in logarithmic return.

In Table 3.2 (*page 72*) the price index and volume data of Table 3.1 (*page 71*) are manipulated to construct a set of daily returns and daily raw turnover. The number of observations is now three less than Table 3.1 (*page 71*) corresponding to the deletion of the dates 02/04/1999, 05/04/1999 and 13/05/1999 because no trading activity occurred on those days. The value of shares traded (VA) is reported in thousands, and the total market value (MV) is quoted in millions. The turnover measure, VA/MV is calculated by dividing the value of shares traded on any given day by the total market value for that day. In Table 3.3 (*page 74*), I demonstrate the method of detrending the volume data used in the models in Chapter 7. There is general agreement in the finance literature that volume data should be systematically detrended in light of the positive drift associated with trading related measures such as turnover, see Lo and Wang (2000) and Datar, Naik and Radcliffe (1998). So using logs, I perform the following regression:

$$\text{Log}(V_t) = \alpha + \beta t + \mu_t \quad (3.10)$$

Denoting the estimates by $\hat{\alpha}, \hat{\beta}, \hat{\mu}$, the detrended volume is given by $\hat{V}_t$ where

$$\hat{V}_t = \frac{V_t}{\exp(\hat{\alpha} + \hat{\beta}t)} = \exp(\hat{\mu}_t) \quad (3.11)$$

Table 3.1 Belgium Price and Volume Data

Date	PI	LNPI	VA	MV
30/03/1999	916.92	-0.0039	93611	148378
31/03/1999	916.99	0.0001	132966	148389
01/04/1999	920.65	0.0040	79731	148982
02/04/1999	920.65	0	#N/A	148982
05/04/1999	920.65	0	#N/A	148982
06/04/1999	928.1	0.0081	122423	150188
07/04/1999	939.65	0.0124	115311	152057
08/04/1999	940.46	0.0009	95633	152188
09/04/1999	943.83	0.0036	113885	152734
12/04/1999	939.21	-0.0049	78877	151987
13/04/1999	938.58	-0.0007	128117	151886
14/04/1999	936.76	-0.0019	81995	151592
15/04/1999	939.76	0.0032	110562	152076
16/04/1999	928.14	-0.0124	224355	150197
19/04/1999	935.7	0.0081	157812	151420
20/04/1999	916.88	-0.0203	187132	148374
21/04/1999	926.74	0.0107	156926	149970
22/04/1999	925.31	-0.0015	153654	149741
23/04/1999	916.59	-0.0095	97525	148043
26/04/1999	915.32	-0.0014	112904	147837
27/04/1999	922.29	0.0076	116575	149115
28/04/1999	912.51	-0.0107	107693	147533
29/04/1999	908.37	-0.0045	110149	146864
30/04/1999	908.64	0.0003	126216	146908
03/05/1999	918.69	0.0110	82800	148533
04/05/1999	915.04	-0.0040	118693	147944
05/05/1999	911.94	-0.0034	79016	147442
06/05/1999	907.94	-0.0044	144184	146796
07/05/1999	903.93	-0.0044	120985	146250
10/05/1999	910.26	0.0070	73337	147341
11/05/1999	916.4	0.0067	70576	148366
12/05/1999	914.96	-0.0016	85173	148133
13/05/1999	914.96	0	#N/A	148133
14/05/1999	906.11	-0.0097	53992	146700
17/05/1999	890.25	-0.0177	77113	144133
18/05/1999	888.06	-0.0025	73694	143778
19/05/1999	897.07	0.0101	121898	145237
20/05/1999	903.9	0.0076	92482	146343

Note: PI is price index, VA is value of shares traded and MV is total market value. LNPI is the natural log of price change.

Table 3.2 Belgium Price and Turnover Variable

Date	PI	LNPI	VA	MV	VA/MV
30/03/1999	916.92	-0.0039	93611	148378	0.0006
31/03/1999	916.99	0.0001	132966	148389	0.0009
01/04/1999	920.65	0.0040	79731	148982	0.0005
06/04/1999	928.1	0.0081	122423	150188	0.0008
07/04/1999	939.65	0.0124	115311	152057	0.0008
08/04/1999	940.46	0.0009	95633	152188	0.0006
09/04/1999	943.83	0.0036	113885	152734	0.0007
12/04/1999	939.21	-0.0049	78877	151987	0.0005
13/04/1999	938.58	-0.0007	128117	151886	0.0008
14/04/1999	936.76	-0.0019	81995	151592	0.0005
15/04/1999	939.76	0.0032	110562	152076	0.0007
16/04/1999	928.14	-0.0124	224355	150197	0.0015
19/04/1999	935.7	0.0081	157812	151420	0.0010
20/04/1999	916.88	-0.0203	187132	148374	0.0013
21/04/1999	926.74	0.0107	156926	149970	0.0010
22/04/1999	925.31	-0.0015	153654	149741	0.0010
23/04/1999	916.59	-0.0095	97525	148043	0.0007
26/04/1999	915.32	-0.0014	112904	147837	0.0008
27/04/1999	922.29	0.0076	116575	149115	0.0008
28/04/1999	912.51	-0.0107	107693	147533	0.0007
29/04/1999	908.37	-0.0045	110149	146864	0.0008
30/04/1999	908.64	0.0003	126216	146908	0.0009
03/05/1999	918.69	0.0110	82800	148533	0.0006
04/05/1999	915.04	-0.0040	118693	147944	0.0008
05/05/1999	911.94	-0.0034	79016	147442	0.0005
06/05/1999	907.94	-0.0044	144184	146796	0.0010
07/05/1999	903.93	-0.0044	120985	146250	0.0008
10/05/1999	910.26	0.0070	73337	147341	0.0005
11/05/1999	916.4	0.0067	70576	148366	0.0005
12/05/1999	914.96	-0.0016	85173	148133	0.0006
14/05/1999	906.11	-0.0097	53992	146700	0.0004
17/05/1999	890.25	-0.0177	77113	144133	0.0005
18/05/1999	888.06	-0.0025	73694	143778	0.0005
19/05/1999	897.07	0.0101	121898	145237	0.0008
20/05/1999	903.9	0.0076	92482	146343	0.0006

Note: PI is price index, LNPI is natural log of price change, VA is value of shares traded, MV is total market value and VA/MV is turnover.

Using ordinary least squares I regress Log (VA/MV) on N (a set of natural numbers) and obtain the set of residuals (RESID). I then calculate the exponentials of the residuals (EXP), and use this column as the volume variable in estimating the means, standard deviations and skewness statistics used in the generalized single equation and VAR models of Chapter 7. Table 3.3 (*page 74*) and Figure 3.1 (*page 75*) illustrate the effect that this method of detrending has on the raw turnover data. The trend that is clearly visible in the upper picture is reduced in the bottom graph without removing the information required for analysis.

The method of aggregating the daily returns and daily detrended turnover into monthly means, standard deviations and skewness is shown in Table 3.4 (*page 77*). The monthly means, standard deviations and skewness of returns (LNPI) and volume (EXP), are estimated on the first day of each calendar month and cover the period from the first day to the last, inclusive, representing each month as a discrete unit in time. The first three entries under the headings, MEAN , STD and SKEW are the mean, standard deviation and skewness respectively of the detrended volume variable EXP , from 02/01/1986 to 31/01/1986 inclusive. Similarly, the next three entries are from 03/02/1986 to 28/02/2008 inclusive. Although not shown in the table, the method is the same for calculating the first three moments of returns. I use two alternative skewness measures, NSKEW and DUVOL in the single equation and VAR models of Chapter 7 which, for clarity, are not presented in Table 3.4 (*page 77*). The variable NSKEW is derived by taking the negative of SKEW . The second alternative skewness measure and the one that is used in all of the modelling exercises in Chapter 7 is termed DUVOL , the ratio of down to up volatility.

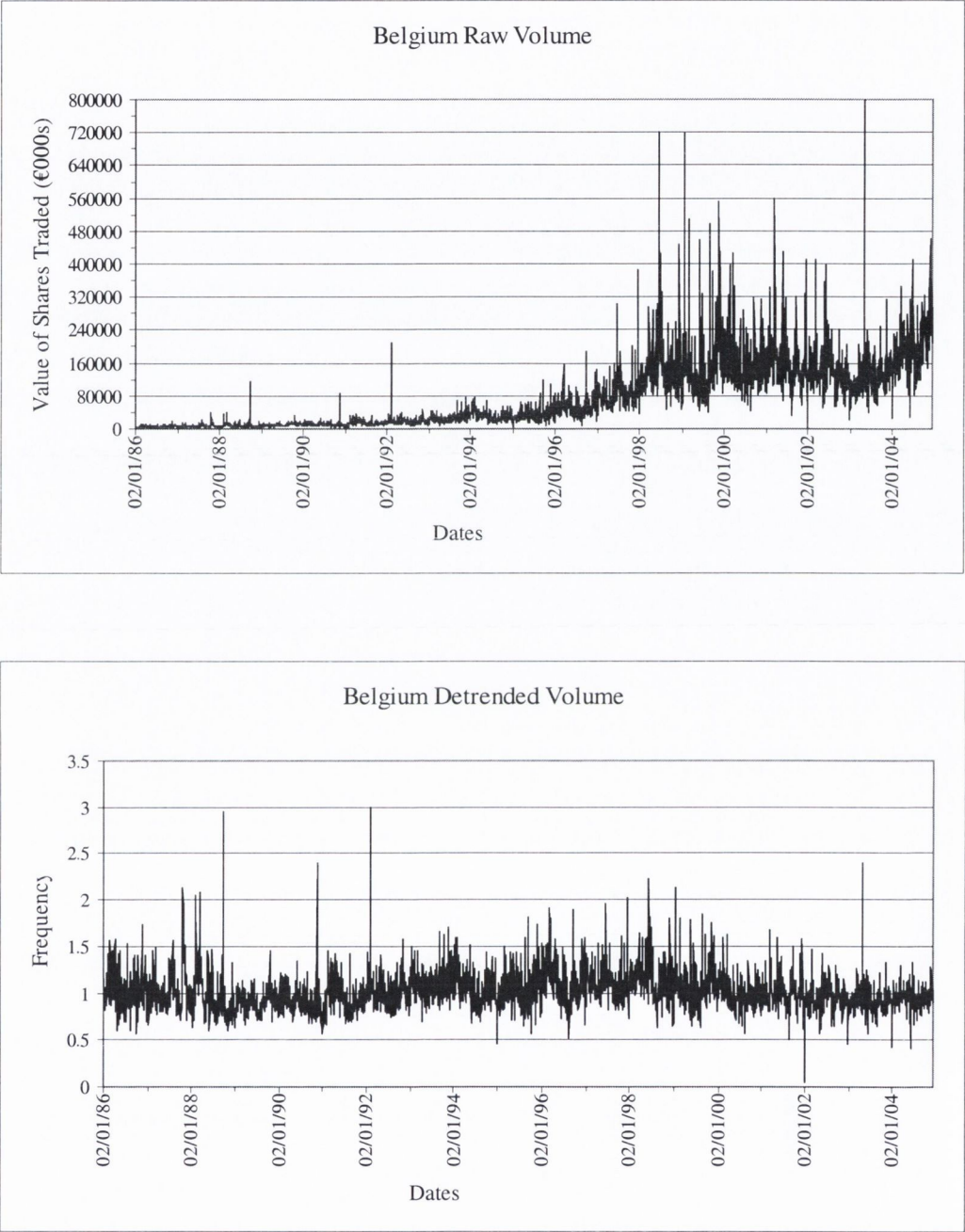
Table 3.5 (*page 78*) demonstrates how DUVOL is derived using the volume variable, EXP . Although not shown here, the method is exactly the same when calculating DUVOL for the return variable LNPI . Each month I divide the exponentials into two discrete subsets, one subset under the heading $\{\geq\}$ contains entries that are greater than or equal to the monthly average for that month, while the other, headed $\{<\}$, contains entries that are below the average. The standard deviation of each subset is then calculated separately and shown under the heading $\{\text{STD} \geq\}$ or $\{\text{STD} <\}$.

Table 3.3 Belgium Detrended Turnover

Date	VA/MV	Log(VA/MV)	N	Residuals	EXP
02/01/1986	0.0002	-3.7231	1	-0.1160	0.8905
03/01/1986	0.0003	-3.5218	2	0.0852	1.0889
06/01/1986	0.0003	-3.4707	3	0.1361	1.1458
07/01/1986	0.0002	-3.6454	4	-0.0387	0.9620
08/01/1986	0.0002	-3.7676	5	-0.1611	0.8512
09/01/1986	0.0002	-3.7179	6	-0.1116	0.8944
10/01/1986	0.0002	-3.6553	7	-0.0491	0.9521
13/01/1986	0.0002	-3.7957	8	-0.1897	0.8272
14/01/1986	0.0002	-3.7731	9	-0.1673	0.8459
16/01/1986	0.0002	-3.7727	10	-0.1670	0.8462
17/01/1986	0.0003	-3.5573	11	0.0482	1.0494
20/01/1986	0.0002	-3.6701	12	-0.0648	0.9373
21/01/1986	0.0004	-3.4094	13	0.1958	1.2163
22/01/1986	0.0003	-3.5897	14	0.0153	1.0154
23/01/1986	0.0003	-3.5201	15	0.0848	1.0885
24/01/1986	0.0003	-3.5370	16	0.0677	1.0700
27/01/1986	0.0002	-3.6598	17	-0.0552	0.9463
28/01/1986	0.0002	-3.7033	18	-0.0989	0.9058
29/01/1986	0.0003	-3.5276	19	0.0766	1.0796
30/01/1986	0.0002	-3.7485	20	-0.1444	0.8655
31/01/1986	0.0002	-3.6956	21	-0.0917	0.9124
03/02/1986	0.0003	-3.5351	22	0.0686	1.0711
04/02/1986	0.0002	-3.6112	23	-0.0076	0.9924
05/02/1986	0.0003	-3.4719	24	0.1315	1.1406
06/02/1986	0.0004	-3.3841	25	0.2192	1.2451
07/02/1986	0.0006	-3.2527	26	0.3504	1.4196
10/02/1986	0.0005	-3.2825	27	0.3204	1.3777
11/02/1986	0.0003	-3.5343	28	0.0685	1.0709
12/02/1986	0.0003	-3.4564	29	0.1462	1.1575
13/02/1986	0.0003	-3.4925	30	0.1100	1.1163
14/02/1986	0.0002	-3.7198	31	-0.1175	0.8892
17/02/1986	0.0002	-3.6613	32	-0.0591	0.9426
18/02/1986	0.0004	-3.3979	33	0.2041	1.2265
19/02/1986	0.0006	-3.2486	34	0.3532	1.4236
20/02/1986	0.0007	-3.1532	35	0.4485	1.5660
21/02/1986	0.0007	-3.1723	36	0.4292	1.5361
24/02/1986	0.0004	-3.3946	37	0.2067	1.2297

Note: VA/MV is turnover, N a set of natural numbers, the residuals are obtained by regressing Log(VA/MV) on N. EXP is the exponential of the residuals.

Figure 3.1 Belgium Sample Data



Note: The upper chart is the raw turnover distribution with the value of shares denominated in (€000s). The lower chart shows the effect of detrending using the log linear method described in the text.

The first entries in the latter two columns in Table 3.5 (*page 78*) inserted on the same line as the initial date 02/01/1986, are the standard deviations of the above average and below average entries for the dates between 02/01/1986 and 31/01/1986 inclusive. Similarly the second and third entries in the same two columns cover the periods 03/02/1986 to 28/02/1986 and 03/03/1986 to 31/03/1986 (both inclusive). The variable DUVOL is obtained by dividing each entry from the column headed {STD <}, by its counterpart from the column {STD ≥} and then calculating the log of this ratio. This estimate of skewness is used in the single equation and VAR models in Chapter 7 because it is less sensitive to the presence of outliers in the data, and because a higher value of DUVOL, by construction, admits to a more negatively skewed distribution.

Table 3.6 (*page 80*) is an extract from a comprehensive data set that is a cross section of the monthly means, standard deviations and skewness of 11 international equity markets, comprising up to 286 observations on each individual market. The three variables, P1BE, P2BE and P3BE represent the first three moments of Belgium return and V1BE, V2BE, V3BE are the first three moments of Belgium volume. The additional variables P4BE and P5BE are NSKEW and DUVOL, alternative measures of return skewness and V4BE and V5BE represent the same alternative measures of volume skewness. The former is simply the negative of the coefficient of skewness and the latter is as described in the preceding paragraphs.

3.5 Distribution Free tests

3.5.1 Excess Returns

The distribution-free tests that I use in the examination of asymmetry in equity, FOHFs and volume distributions are the Binomial Distribution test, (in all three) and the Wilcoxon Rank Sum test and the Siegel –Tukey test in the equity and volume studies. Before the specific tests are applied the data sets are divided into two subsets, positive and negative excess returns, denoted $|R^+|$ and $|R^-|$ respectively. Following Peiró (1999) these two distributions can be said to be symmetric if both of the following conditions apply; first, if the probability of a positive excess return is equal to the probability of a negative excess return (after the elimination of zero excess returns) and second, if the statistical

Table 3.4 Belgium Volume Estimates

Date	LNPI	EXP	Mean	STD	Skew
02/01/1986	-0.0255	0.8905	0.9710	0.1113	0.5981
03/01/1986	-0.0153	1.0889			
06/01/1986	0.0037	1.1458			
07/01/1986	-0.0065	0.9620			
08/01/1986	-0.0012	0.8512			
09/01/1986	-0.0028	0.8944			
10/01/1986	-0.0014	0.9521			
13/01/1986	-0.0072	0.8272			
14/01/1986	0.0011	0.8459			
16/01/1986	0.0027	0.8462			
17/01/1986	0.0043	1.0494			
20/01/1986	-0.0036	0.9373			
21/01/1986	0.0008	1.2163			
22/01/1986	-0.0029	1.0154			
23/01/1986	-0.0164	1.0885			
24/01/1986	0.0030	1.0700			
27/01/1986	0.0044	0.9463			
28/01/1986	0.0039	0.9058			
29/01/1986	0.0030	1.0796			
30/01/1986	0.0049	0.8655			
31/01/1986	0.0007	0.9124			
03/02/1986	0.0078	1.0711	1.2298	0.2000	0.2151
04/02/1986	0.0088	0.9924			
05/02/1986	0.0135	1.1406			
06/02/1986	0.0140	1.2451			
07/02/1986	0.0243	1.4196			
10/02/1986	-0.0023	1.3777			
11/02/1986	-0.0015	1.0709			
12/02/1986	-0.0036	1.1575			
13/02/1986	0.0079	1.1163			
14/02/1986	0.0056	0.8892			
17/02/1986	0.0103	0.9426			
18/02/1986	0.0122	1.2265			
19/02/1986	0.0154	1.4236			
20/02/1986	0.0197	1.5660			
21/02/1986	0.0049	1.5361			
24/02/1986	0.0010	1.2297			
25/02/1986	-0.0002	1.5478			
26/02/1986	-0.0172	1.3414			
27/02/1986	0.0041	1.1409			
28/02/1986	0.0146	1.1616			

Note: LNPI refers to natural log of price change; EXP the exponentials of a set of residuals. The Mean, STD and Skew figures are the monthly observations on the first three moments of volume.

Table 3.5 Derivation of DUVOL Estimates for Belgium

Date	LNPI	EXP	{ $\geq$ }	{<}	{STD $\geq$ }	{STD <}
02/01/1986	-0.0255	0.8905		0.8905	0.0617	0.0454
03/01/1986	-0.0153	1.0889	1.0889			
06/01/1986	0.0037	1.1458	1.1458			
07/01/1986	-0.0065	0.9620		0.9620		
08/01/1986	-0.0012	0.8512		0.8512		
09/01/1986	-0.0028	0.8944		0.8944		
10/01/1986	-0.0014	0.9521		0.9521		
13/01/1986	-0.0072	0.8272		0.8272		
14/01/1986	0.0011	0.8459		0.8459		
16/01/1986	0.0027	0.8462		0.8462		
17/01/1986	0.0043	1.0494	1.0494			
20/01/1986	-0.0036	0.9373		0.9373		
21/01/1986	0.0008	1.2163	1.2163			
22/01/1986	-0.0029	1.0154	1.0154			
23/01/1986	-0.0164	1.0885	1.0885			
24/01/1986	0.0030	1.0700	1.0700			
27/01/1986	0.0044	0.9463		0.9463		
28/01/1986	0.0039	0.9058		0.9058		
29/01/1986	0.0030	1.0796	1.0796			
30/01/1986	0.0049	0.8655		0.8655		
31/01/1986	0.0007	0.9124		0.9124		
03/02/1986	0.0078	1.0711		1.0711	0.1125	0.1069
04/02/1986	0.0088	0.9924		0.9924		
05/02/1986	0.0135	1.1406		1.1406		
06/02/1986	0.0140	1.2451	1.2451			
07/02/1986	0.0243	1.4196	1.4196			
10/02/1986	-0.0023	1.3777	1.3777			
11/02/1986	-0.0015	1.0709		1.0709		
12/02/1986	-0.0036	1.1575		1.1575		
13/02/1986	0.0079	1.1163		1.1163		
14/02/1986	0.0056	0.8892		0.8892		
17/02/1986	0.0103	0.9426		0.9426		
18/02/1986	0.0122	1.2265		1.2265		
19/02/1986	0.0154	1.4236	1.4236			
20/02/1986	0.0197	1.5660	1.5660			
21/02/1986	0.0049	1.5361	1.5361			
24/02/1986	0.0010	1.2297		1.2297		
25/02/1986	-0.0002	1.5478	1.5478			
26/02/1986	-0.0172	1.3414	1.3414			
27/02/1986	0.0041	1.1409		1.1409		
28/02/1986	0.0146	1.1616		1.1616		
03/03/1986	0.0087	1.1590	1.1590		0.1213	0.0772
4/03/1986	0.0078	1.3855	1.3855			
06/03/1986	-0.0085	0.8608		0.8608		

Notes: LNPI refers to the natural log of price change; EXP is the detrended volume variable; $\{\geq\}$ refers to entries that are greater than or equal to the average monthly entry; $\{<\}$ denotes less than average monthly entry; STD $\{\geq\}$ is the STD of the above average monthly volume.

distribution of the absolute values of the negative excess returns is equal to the distribution of the positive excess returns.

3.5.2 Wilcoxon rank sum description

The Wilcoxon Rank Sum test, analogous to the usual t test statistic for the equality of means, is a standardized two-sample test in which the null hypothesis establishes the equality of the populations underlying the two sample distributions. The Wilcoxon test is especially appropriate in detecting differences in location between two different distributions, and can be considered a test for symmetry if the only assumption made is that the random sample is drawn from a continuous distribution, (see Gibbons (1971)). In this test, the absolute values of positive and negative excess returns are combined into one ordered sample. The test statistic is the sum of the ranks of the absolute values of the negative excess returns in the combined ordered sample. The Wilcoxon test statistic is:

$$W_N = \sum_{i=1}^N iZ_i \tag{3.13}$$

where the Z_i are indicator random variables defined as follows. Let

$$Z_i = (Z_1, Z_2, \dots, Z_N) \tag{3.14}$$

where $Z_i = 1$ if the i th random variable in the combined ordered sample is from the set of negative excess returns and $Z_i = 0$ otherwise. Under the null hypothesis of equal distributions the exact mean and variance of W_N are

$$E(W_N) = \frac{m(N+1)}{2} \qquad \text{var}(W_N) = \frac{mn(N+1)}{12} \tag{3.15}$$

where m is the number of negative excess returns and n is the number of positive excess returns, and $m + n = N$

Table 3.6 Belgium Monthly Return and Volume Data

Time	P1BE	P2BE	P3BE	P4BE	P5BE	V1BE	V2BE	V3BE	V4BE	V5BE
Jan-86	-0.0024	0.0080	-1.6651	1.6651	0.7374	0.9710	0.1113	0.5981	-0.5981	-0.1329
Feb-86	0.0070	0.0094	-0.5708	0.5708	0.0483	1.2298	0.2000	0.2151	-0.2151	-0.0221
Mar-86	0.0027	0.0058	-0.2027	0.2027	-0.0893	1.1217	0.1727	0.4588	-0.4588	-0.1961
Apr-86	0.0016	0.0090	-0.3786	0.3786	0.0659	1.1167	0.2126	-0.2758	0.2758	0.0777
May-86	0.0004	0.0063	0.2552	-0.2552	-0.0560	1.1145	0.2116	-0.4667	0.4667	0.1135
Jun-86	0.0008	0.0045	0.2118	-0.2118	-0.1166	0.9758	0.1224	-0.6053	0.6053	0.2294
Jul-86	-0.0008	0.0052	0.8452	-0.8452	-0.1074	0.9748	0.1897	1.2567	-1.2567	-0.3543
Aug-86	0.0033	0.0052	1.1492	-1.1492	-0.1530	0.9560	0.1639	-0.2322	0.2322	0.0720
Sep-86	-0.0002	0.0114	-0.5795	0.5795	0.1382	1.0452	0.1999	0.0326	-0.0326	-0.0004
Oct-86	0.0012	0.0077	0.9307	-0.9307	-0.1998	0.9483	0.1749	0.4158	-0.4158	-0.0689
Nov-86	0.0018	0.0083	0.6488	-0.6488	-0.0966	1.1448	0.2744	0.9019	-0.9019	-0.2707
Dec-86	0.0007	0.0050	0.2740	-0.2740	-0.1487	1.0875	0.1733	-0.6235	0.6235	0.1448
Jan-87	-0.0003	0.0062	-1.5853	1.5853	0.4100	0.9207	0.1257	0.1427	-0.1427	-0.0552
Feb-87	0.0015	0.0048	0.0308	-0.0308	-0.2033	1.0517	0.1517	0.6150	-0.6150	-0.1911
Mar-87	0.0016	0.0094	0.2800	-0.2800	-0.1084	1.0353	0.1858	1.0703	-1.0703	-0.3655
Apr-87	0.0027	0.0065	0.1302	-0.1302	-0.0365	0.9603	0.0870	-0.5857	0.5857	0.1972
May-87	-0.0009	0.0074	0.0461	-0.0461	0.0640	0.9699	0.1020	0.4240	-0.4240	-0.1399
Jun-87	0.0031	0.0043	0.5835	-0.5835	-0.4124	0.8911	0.0748	-0.0525	0.0525	0.0376
Jul-87	0.0052	0.0121	0.1333	-0.1333	-0.1374	1.1925	0.1868	-0.1039	0.1039	0.0357
Aug-87	0.0008	0.0068	0.7417	-0.7417	-0.3298	1.0320	0.1491	0.5405	-0.5405	-0.2095
Sep-87	-0.0012	0.0101	-0.4041	0.4041	0.0644	0.9357	0.1269	-0.1349	0.1349	0.0351
Oct-87	-0.0126	0.0394	-0.9934	0.9934	0.1131	1.2395	0.4600	0.4593	-0.4593	-0.2739
Nov-87	-0.0041	0.0196	-0.1274	0.1274	0.0594	1.0721	0.2318	0.2693	-0.2693	-0.1591
Dec-87	-0.0008	0.0143	-0.1149	0.1149	0.0635	0.9291	0.0950	0.0989	-0.0989	-0.0704
Jan-88	0.0036	0.0188	-0.1472	0.1472	0.0388	0.9078	0.1680	0.0233	-0.0233	0.0183
Feb-88	0.0076	0.0178	-1.0321	1.0321	0.2393	1.2735	0.3403	1.3134	-1.3134	-0.3678
Mar-88	0.0001	0.0120	-0.1513	0.1513	0.0323	1.3276	0.2702	1.6169	-1.6169	-0.4325
Apr-88	0.0008	0.0061	-1.4829	1.4829	0.3308	0.8556	0.1244	0.6678	-0.6678	-0.2425
May-88	0.0004	0.0064	-1.7282	1.7282	0.3337	0.9458	0.2322	0.8639	-0.8639	-0.2926
Jun-88	0.0041	0.0065	-0.3384	0.3384	-0.0875	1.0540	0.1580	0.6346	-0.6346	-0.1302
Jul-88	-0.0014	0.0042	-0.7050	0.7050	0.3570	0.8002	0.1187	1.3394	-1.3394	-0.3777
Aug-88	0.0007	0.0065	-0.6658	0.6658	0.1641	0.8970	0.1524	0.7298	-0.7298	-0.2046
Sep-88	0.0035	0.0105	0.2924	-0.2924	-0.0406	1.1718	0.5097	2.3880	-2.3880	-0.6744

Notes: P1BE, P2BE and P3BE are the first three moments of return; P4BE and P5BE are alternative skewness measures. V1BE, V2BE and V3BE are the first three moments of volume; V4BE and V5BE are alternative volume skewness measures.

3.5.3 Siegel-Tukey test Description

The Siegel-Tukey test, analogous to the F test statistic for the equality of variances is especially suited to detecting differences in dispersion (see Gibbons and Chakraborti (1992)). In the Siegel-Tukey test, the absolute values of positive and negative excess returns are also combined in one ordered sample. Like the Wilcoxon rank sum test, the Siegel-Tukey belongs to a class of statistics called the linear rank statistic. The weights are constructed so that the higher weights are assigned to the middle of the combined sample and the smaller weights to the extremes. The Siegel-Tukey statistic is

$$S_N = \sum_{i=1}^N \alpha_i Z_i \quad (3.16)$$

where Z_i are the indicator random variables as defined in Equation (3.11)

and α_i is defined as

$$\begin{aligned} \alpha_i &= \begin{cases} 2i & \text{for } i \text{ even, } 1 < i \leq \frac{N}{2} \\ 2i - 1 & \text{for } i \text{ odd, } 1 \leq i \leq \frac{N}{2} \\ 2(N - i) + 2 & \text{for } i \text{ even, } \frac{N}{2} < i \leq N \\ 2(N - i) + 1 & \text{for } i \text{ odd, } \frac{N}{2} < i \leq N \end{cases} \end{aligned}$$

Under the null hypothesis of equal distributions, the asymptotic distribution of S_N is the same as W_N .

$$S_N \rightarrow N \left(\frac{m(N+1)}{2}, \frac{mn(N+1)}{12} \right) \quad (3.17)$$

If N is odd, the middle observation is dropped and these weights are then applied to the remaining number of observations. The non-parametric tests, the Wilcoxon rank sum, the

Siegel-Tukey and the Binomial distribution test are all essentially joint tests of the i.i.d. assumption in the data and the symmetry of the underlying series. Therefore a rejection of the null hypothesis of symmetry might in fact be a rejection of independence in a perfectly symmetric distribution. To examine the power of these tests I used a quadratic function to simulate a returns distribution that was perfectly symmetric and found that the Wilcoxon rank sum test rejected the null of symmetry very frequently, despite the inherently symmetric shape of the distribution. This confirmed that the test was, in fact, rejecting the independence of the data. I then used a Monte Carlo simulation, described in section 3.5.6 (page 86), and found that the test rejected the null of symmetry much less frequently.

3.5.4 Description of tables in Wilcoxon and Siegel-Tukey tests

Table 3.7 (page 85) describes the methodology used to calculate two test statistics, the Siegel-Tukey and the Wilcoxon rank sum. In each case the standardized statistic is calculated using a small sample of 45 observations from a sample dataset of 2000 daily logarithmic returns. There are 9 columns in Table 3.7 (page 85) comprising the excess returns in the first column, the negative excess returns in column 2 and the negative signs only in column 3 followed by the absolute excess returns in column 4. The sorted excess returns prefixed by the original negative sign are presented in columns 5 and 6. The observation numbers in the sequence of 2000 that correspond to the selected sample are presented in column 7. The final two columns in the table contain the weights derived from the formulae used to calculate the Siegel-Tukey and the Wilcoxon rank sum test.

The section of the full dataset that is presented in Table 3.7 (page 85) is drawn from the lower end of the 2000 observations, beginning at 1916 and ending at 1960. While the asymptotic distribution of the two tests is identical there are distinct differences in their weighting systems. The Siegel-Tukey test is constructed so that the smallest weights, assigned to the extremes of the distribution, increase systematically as the distribution tends towards the centre, and decrease systematically as the distribution moves away from the centre. In the column headed Siegel-Tukey test the weights are seen to decrease as the observation number increases; the formula that generates the weights is programmed to

respond when an entry in the combined ordered sample is prefixed by a negative sign. The programme uses 4 ‘IF’ functions that differentiate between even and odd numbered observations, two distinct functions for entries below the median and two for entries above. By contrast the weights in the Wilcoxon rank sum tests are simply the corresponding observations in the combined ordered sample, as evident in the table.

Table 3.8 (page 86) is included to illustrate the method by which the weights are programmed to increase as they approach the median (the mid point of the frequency), in this example, 1000. Table 3.8 (page 86) goes from observation 985 to 1016 and the weights are seen to increase steadily up to observation 1001 when they reach their maximum value of 2002, decreasing systematically thereafter.

Panel B is a further sample from the same dataset which illustrates that in intervals of the distribution to the right of the median the positive excess returns dominate substantially the negative excess returns. The Siegel-Tukey test in Table 3.8 (page 86) clearly demonstrates that the distribution of positive and negative excess returns around the measure of central tendency, the median in this test, is influential in determining the asymmetry of the distribution as a whole. Because this test assigns little or no weight to the extreme observations, either positive or negative, the heaviest weights are clustered around the median; Panel A shows that the weights are roughly symmetric about this measure of central tendency. I use the sum of the weights of the negative excess returns as the test statistic in both the Wilcoxon rank sum and the Siegel-Tukey tests, in calculating the standardized statistic. A variable is standardized if the mean value of the variable is subtracted from its individual value and the difference is divided by the standard deviation of the variable. Thus in the following formula

$$\frac{x - \mu}{\sigma} \tag{3.18}$$

x is the test statistic, in this case the sum of the weights attached to the negative excess returns, μ is the asymptotic mean from the formula above and σ is the square root of the asymptotic variance, again from above. Having calculated the standardized normal variable, the function NORMSDIST in Excel, which can be used in place of a table of

standard normal curve areas, returns the standard normal cumulative distribution function. This distribution has a mean of zero and a standard deviation of one.

3.5.5 Description of Binomial distribution test

Table 3.9 (*page 90*) describes the application of the Binomial Distribution test to a small sample of positive and negative excess returns taken from two intervals equidistant from the mean. The null hypothesis of the Binomial Distribution test, as applied here, is that the probability, (denoted p^*), of obtaining a positive excess return is equal to the probability of obtaining a negative return. The hypothesis takes the form of a two-tailed test:

$$H_0: P = \frac{1}{2} \text{ and } H_1: P \neq \frac{1}{2}$$

Table 3.7 Siegel-Tukey and Wilcoxon rank sum tests.

1	2	3	4	5	6	7	8	9
Excess Returns	Negative Excess Returns	Negative Sign	Absolute Excess Returns	Sorted Absolute Excess Returns with Original Negative Sign		Series Observation No.	Siegel-Tukey	Wilcoxon Rank Sum
0.00192			0.00192	-	0.01806	1916	171	1916
0.00221			0.00221	-	0.01810	1917	170	1917
-0.01305	-0.01305	-	0.01305	-	0.01822	1918	167	1918
-0.00774	-0.00774	-	0.00774		0.01829	1919		
0.00317			0.00317		0.01834	1920		
-0.00047	-0.00047	-	0.00047		0.01857	1921		
0.00093			0.00093		0.01891	1922		
0.00280			0.00280	-	0.01919	1923	158	1923
0.00023			0.00023	-	0.01925	1924	155	1924
0.01069			0.01069		0.01926	1925		
0.00323			0.00323		0.01931	1926		
-0.00367	-0.00367	-	0.00367		0.01953	1927		
-0.01114	-0.01114	-	0.01114	-	0.01974	1928	147	1928
0.00495			0.00495	-	0.01993	1929	146	1929
-0.00396	-0.00396	-	0.00396	-	0.02015	1930	143	1930
0.00870			0.00870		0.02023	1931		
-0.00079	-0.00079	-	0.00079	-	0.02028	1932	139	1932
-0.00315	-0.00315	-	0.00315	-	0.02037	1933	138	1933
0.00086			0.00086		0.02039	1934		
0.00772			0.00772		0.02039	1935		
0.00297			0.00297	-	0.02046	1936	131	1936
0.00892			0.00892	-	0.02094	1937	130	1937
0.01074			0.01074	-	0.02150	1938	127	1938
-0.00567	-0.00567	-	0.00567		0.02153	1939		
0.00046			0.00046	-	0.02166	1940	123	1940
0.00051			0.00051		0.02169	1941		
0.00113			0.00113		0.02172	1942		
0.00148			0.00148	-	0.02195	1943	118	1943
-0.00137	-0.00137	-	0.00137		0.02211	1944		
-0.00047	-0.00047	-	0.00047	-	0.02251	1945	114	1945
-0.00255	-0.00255	-	0.00255		0.02300	1946		
-0.00382	-0.00382	-	0.00382	-	0.02304	1947	110	1947
0.00106			0.00106		0.02317	1948		
0.00560			0.00560	-	0.02376	1949	106	1949
0.00427			0.00427	-	0.02377	1950	103	1950
0.00737			0.00737	-	0.02377	1951	102	1951
0.00486			0.00486	-	0.02381	1952	99	1952
0.00647			0.00647		0.02392	1953		
-0.00235	-0.00235	-	0.00235	-	0.02397	1954	95	1954
0.00344			0.00344	-	0.02401	1955	94	1955
0.00168			0.00168		0.02403	1956		
-0.00181	-0.00181	-	0.00181		0.02423	1957		
0.00648			0.00648		0.02450	1958		

Notes: The negative sign in the 3rd column identifies the negative entries in the original set of excess returns. The weights in columns 8 and 9 are derived using the observation numbers in column 7.

Table 3.8 Siegel-Tukey tests

Panel A			Panel B		
Negative Sign	Series Obs. No.	Siegel-Tukey Test	Negative Sign	Series Obs. No.	Siegel-Tukey Test
-	985	1968		1345	
	986		-	1346	1311
-	987	1972		1347	
	988			1348	
	989		-	1349	1306
	990			1350	
-	991	1980	-	1351	1302
	992			1352	
	993			1353	
	994			1354	
	995			1355	
-	996	1989		1356	
	997			1357	
	998		-	1358	1287
	999		-	1359	1286
-	1000	1997	-	1360	1283
-	1001	2002		1361	
	1002		-	1362	1279
	1003			1363	
	1004			1364	
	1005			1365	
	1006		-	1366	1271
	1007		-	1367	1270
	1008			1368	
	1009			1369	
	1010			1370	
-	1011	1982		1371	
-	1012	1979		1372	
	1013			1373	
-	1014	1975	-	1374	1255
	1015			1375	
-	1016	1971		1376	

Notes: The last column in each table is the Siegel-Tukey weight, derived using the corresponding observation number in the middle column. Only the numbers with a corresponding negative sign are used.

The last two entries in column 4, Table 3.9 (*page 90*) are the lower and upper critical values for rejection of the null hypothesis at 5 per cent significance level. Both numbers are obtained using the formulas in the adjacent cells in column 3. In looking for the critical values for a 5 per cent rejection, I use the following formula, replacing z_q with (1.96) and (-1.96), since these values are the appropriate quantiles of a standard normal random variable.

$$Xq = n.p^* + z_q \sqrt{n.p^*(1-p^*)} \quad (3.12)$$

The rejection region of desired size α (5%) corresponds to the two tails of the null distribution of T , where both the lower tail denoted α_1 , and the upper tail denoted α_2 , are approximately half the size of the target α . As in the case of the Wilcoxon rank sum test and the Siegel-Tukey, the standardised statistic is used to test the null hypothesis. The formulas in column 6, which differ only in the sign of p^* (± 0.5), are calculated and the results obtained are the Binomial distribution standardised statistics. The NORMSDIST function in EXCEL returns the two *rho* (ρ) values which appear in column 7.

The first of these is α_1 which is approximately half the size of the target α and is therefore doubled and the second α_2 is first calculated as $1-\alpha_2$ and then multiplied by 2. The minimum of these two results is then taken as the ρ -value of the test, see Conover (1999) and Brown and Hollander (1977).

3.5.6 Description of Tables in Monte Carlo Study

I demonstrate in Tables 3.10 (*page 92*) and 3.11 (*page 93*) how I generated the data sets that were used in the Monte Carlo simulations in Chapter 4. My objective was to examine the behaviour of two of the distribution free tests used by Peiró (1999), the Wilcoxon rank sum test and the binomial distribution test. Both these tests can reject symmetry due to time-variation in the mean even if returns are symmetric. Therefore a rejection of the null hypothesis of symmetry might in fact be a rejection of the null hypothesis of independence in the mean of the time series.

Using Ordinary Least Squares (OLS), I regressed a dataset of 296 monthly average returns for Canada on its own one-month lagged return thereby inducing a strong time dependency in the mean equation:

$$Y_t = \alpha + \beta y_{t-1} + \varepsilon_t \quad (3.19)$$

From the regression I obtained the parameters α and β and used these fixed values to generate a new series of returns with the error terms selected from a normal (symmetric) distribution. I created 2000 such artificial datasets with 295 observations per dataset each time holding the parameters fixed and using a new set of errors drawn from the same symmetric distribution. I estimated the Wilcoxon rank sum statistic and the Binomial distribution statistic for each of the 2000 simulations.

Table 3.10 (*page 92*) shows a portion of the output of this regression, namely the predicted Y values and a corresponding set of residuals, identified by a set of consecutive integers. In the Monte Carlo test I retain the predicted Y values but replace the residuals by 2000 random draws from a known symmetric distribution. The methodology of generating the randomly drawn sets of numbers proxying for residuals is explained in Table 3.11 (*page 93*). For pragmatic reasons the data in Table 3.11 (*page 93*) is merely representative of the actual numbers in the original study; there were over 2000 randomly generated numbers from which repeated draws of 295 observations were made. These numbers appear in Table 3.11 (*page 93*) as 36 and 20 respectively. Column 1 Table 3.11 (*page 93*) shows a set of consecutive integers from 1 to 36 and column 2 a randomly generated set of 36 real numbers, obtained using the $\{\text{RAND}()*(b-a)+a\}$ function in Excel. Columns 3 and 5 each contain 20 random draws from column 1 obtained using the $\{\text{RANDBETWEEN}()\}$ function in EXCEL. The entries in column 4 are obtained using a $\{\text{VLOOKUP}()\}$ function, which reads the number in column 3 (a random number between 1 and 36), identifies this number in column 1 and returns the adjacent number from column 2. The entries in column 6 are obtained in exactly the same way. This process is repeated 2000 times. Each of these newly generated sets is added to the set of 295 predicted Y values

from the original regression and thus 2000 datasets that have the same predicted Y values, differing only in the residual part, are made

Table 3.9 Binomial Distribution Test

1	2	3	4	5	6	7
Pos(P)	38	$\sqrt{np^*(1-p^*)}$	3.57	$\rho(a)$	$\frac{((N - np^*) + p^*)}{\sqrt{np^*(1-p^*)}}$	0.0004
Neg(N)	13	$\sqrt{np^*(1-p^*)} * (-1.96)$	-7.00	$\rho(b)$	$\frac{((N - np^*) - p^*)}{\sqrt{np^*(1-p^*)}}$	0.0001
Total(n)	51	$\sqrt{np^*(1-p^*)} * (1.96)$	7.00			
p^*	0.5			$\rho(a)*2$		0.00
np^*	25.5	$np^* + \sqrt{np^*(1-p^*)} * (-1.96)$	18.50	$(1-\rho(b))*2$		2.00
$np^*(1-p^*)$	12.75	$np^* + \sqrt{np^*(1-p^*)} * (1.96)$	32.50	Minimum		0.00

Notes: p^* refers to probability; the test statistic is the number of negative excess returns; the mean is np^* and the variance is $np^*(1-p^*)$. The test is two-tailed hence the minimum value of $\rho(a)*2$ and $\rho(b)*2$ is taken as the probability. The two critical values for rejection of the null hypothesis are 18.5 and 32.5

available for testing the small sample behaviour of two distribution free tests, the Wilcoxon rank sum and the binomial distribution test. A limitation of the Monte Carlo simulation is that the level of dependency imposed in the mean equation is arbitrary and subjective. I imposed a strong time dependency by making the mean a function of its own one-month lagged return.

3.7 Summary and Conclusions

In this chapter I described the equity return and volume data used in the analysis of return asymmetry in Chapter 4 and volume asymmetry in Chapter 5. I described the evolution of the dataset used in the single equation, panel regression and VAR models in Chapter 7 and I described the FOHF data used in Chapter 6. I provided the mathematical equations that describe the first three distribution moments used in this thesis. I described the distribution free tests theoretically and presented some practical examples of the implementation of these tests. I described the Monte Carlo study and showed via a series of tables the methodology used. In a data appendix I provided a set of figurative and tabular examples of the actual data used in three chapters of the thesis. I alluded to a limitation of the Monte Carlo study being the subjective and arbitrary nature of this method of testing the small sample behaviour of a test statistic.

Table 3.10 OLS Regression Output

<i>Obs. No.</i>	<i>Predicted Y</i>	<i>Residuals</i>
1	0.00046	0.00365
2	-0.00012	0.00336
3	0.00033	-0.00833
4	0.00039	0.00032
5	0.00039	0.00151
6	0.00039	0.00159
7	0.00027	0.00159
8	0.00033	-0.00080
9	0.00029	0.00048
10	0.00049	-0.00055
11	0.00017	0.00382
12	0.00026	-0.00269
13	0.00022	-0.00077
14	0.00045	-0.00188
15	0.00027	0.00289
16	0.00032	-0.00071
17	0.00020	0.00039
18	0.00020	-0.00201
19	0.00020	-0.00201
20	-0.00001	-0.00175
21	0.00025	-0.00608
22	0.00048	-0.00138
23	0.00023	0.00354
24	0.00009	-0.00125
25	0.00020	-0.00418
26	0.00020	-0.00194
27	0.00024	-0.00196
28	0.00028	-0.00135
29	0.00011	-0.00040
30	0.00040	-0.00390
31	0.00064	0.00158
32	0.00025	0.00656
33	0.00058	-0.00132
34	0.00036	0.00527
35	0.00046	0.00095
36	0.00032	0.00298
37	0.00050	0.00011
38	0.00027	0.00389
39	0.00052	-0.00087
40	0.00035	0.00404

Notes: Predicted Y is the output of regressing a set of monthly returns on a one-month lag; residuals in Column.3

Table 3.11 Random number generators

1	2	3	4	5	6
1	0.63388	19	0.26285	24	-0.33444
2	0.99001	33	-0.53426	6	0.688692
3	-0.51238	11	-0.04996	17	-0.1416
4	0.81974	24	-0.33444	20	-0.48485
5	-0.81124	8	0.87559	36	-0.92309
6	0.68869	11	-0.04996	32	0.031081
7	0.19263	28	-0.08385	10	-0.68165
8	0.87559	4	0.81974	28	-0.08385
9	-0.95092	13	-0.34926	34	-0.60854
10	-0.68165	16	-0.54013	14	-0.89653
11	-0.04996	10	-0.68165	32	0.031081
12	0.19162	7	0.19263	2	0.990013
13	-0.34926	2	0.99001	13	-0.34926
14	-0.89653	22	-0.47958	20	-0.48485
15	0.14519	17	-0.14160	33	-0.53426
16	-0.54013	31	-0.43128	26	-0.3128
17	-0.14160	22	-0.47958	28	-0.08385
18	-0.36414	35	-0.38336	20	-0.48485
19	0.26285	19	0.26285	35	-0.38336
20	-0.48485	25	0.56274	35	-0.38336
21	-0.82483				
22	-0.47958				
23	0.56242				
24	-0.33444				
25	0.56274				
26	-0.31280				
27	0.90901				
28	-0.08385				
29	-0.14327				
30	0.22626				
31	-0.43128				
32	0.03108				
33	-0.53426				
34	-0.60854				
35	-0.38336				
36	-0.92309				

Notes: Column 2 is a set of pure random numbers; cols.3 and 5 are random numbers between 1 and 36; cols.4 and 6 are matching draws from column 2

Chapter 4

Asymmetry in International Equity Market Indices

4.1 Introduction

In this chapter I examine the unconditional distributions of returns to six international equity markets from January 1978 to February 2002. I first address the question of the normality of the returns distributions using a methodology similar to that used by Fama (1965) in his analysis of the returns to the 30 stocks in the Dow Jones Industrial Average Index over a five-year period from 1957 to 1962. I confirm Fama's results for individual stocks in identifying leptokurtosis as a regular feature in the daily returns to a cross section of international equity indexes. In the empirical distributions, I demonstrate that there is a consistent deficiency of relative frequency within two to five standard deviations of the mean, implying that there is too much relative frequency beyond these intervals. This excess of relative frequency is commonly referred to as long tails. In Section 4.2, I provide evidence of the extent to which the numbers of observations in the tails deviate from normality, by relating the actual numbers of observations within given standard deviations of the mean, to what those numbers should be if the distribution were Gaussian. While the Fama approach is useful in typically describing the nature of the departures from normality in the returns distributions, it says nothing concerning the symmetry or asymmetry of the distributions.

The incentive to examine the symmetry of the distributions in greater detail is encouraged by the observation that many authors have remarked that returns to daily financial assets are negatively skewed. Engle and Patton (2001), for example, find daily close price data on the Dow Jones Industrial Index from 1988 to 2001 to be "substantially negatively skewed; a common feature of equity returns." In a similar vein, Cont (2001) observes "large drawdowns in stock prices and stock index values but not equally large upward movements." Chen, Hong and Stein (2001) remark upon a "striking empirical asymmetry – the fact that big price changes are more likely to be decreases than increases. In other words, stock markets melt down, but they don't melt up." They observe that of the ten biggest one-day movements in the S&P 500 since 1947, nine were declines. Other authors,

Ang and Chen (2002) for example, motivate their paper on asymmetric correlations by showing that, with the exception of a large negative return for the October 1987 crash, the ten largest weekly moves in absolute magnitude, from July 1963 to December 1998, are approximately equal for both positives and negatives. As Peiró (1999, 2002) pointed out, two distribution free tests, the Wilcoxon rank sum and the Siegel-Tukey test are particularly appropriate for detecting differences between two distributions, since neither requires an assumption concerning the distributional characteristics of the underlying series. The Wilcoxon rank sum test is especially appropriate for detecting differences in location and the Siegel-Tukey test is used to examine the dispersion of returns about their means.

The remainder of this chapter is structured as follows. In Section 4.2 I first subject the returns from the six international stock markets to tests of normality. In Section 4.3 I apply a series of distribution free tests that are particularly suited to detecting asymmetry in location and dispersion. I examine the nature of the asymmetry in Section 4.4. and describe the Monte Carlo study that has been demonstrated in Section 3.5.6, Chapter 3. In the final section I summarise the chapter and draw together my conclusions.

4.2 Testing for Normality

As explained in Section 3.2 of Chapter 3, I use daily log price changes from 1 January 1978 to 2 February 2002 from 6 international markets, the Financial Times All Share index (Britain), the DS Total French Market, the Frankfurt Faz (Germany), the Milan Comit (Italy), the Nikkei 225 (Japan), and the New York Stock Exchange (United States). Descriptive statistics in Table 4.1 (*page 96*) indicate a clear rejection of the normality of the daily returns for all markets. The returns are leptokurtic, confirming the findings of other researchers using daily data. The absence of normality is also shown in the Jarque-Bera (JB) test results. This is a simple test of normality based on the fact that a normal probability density function has skewness = 0 and kurtosis = 3. Under the null hypothesis of normality, the JB statistic is distributed as a χ^2 statistic with 2 degrees of freedom. The Studentised range statistics also clearly reject normality. To further examine the distribution of log price changes, I construct frequency distribution tables using the methodology of Fama (1965). For each market, the proportions of price

Table 4.1 Descriptive Statistics

	Britain	France	Germany	Italy	Japan	US
Observations	6082	6058	5898	6008	5944	5944
Mean	0.0004	0.0005	0.0003	0.0006	0.0001	0.0004
Standard deviation	0.009	0.0114	0.0118	0.0137	0.0124	0.0101
Student range	19.66	15.986	18.677	18.447	23.114	35.677
Skewness	-0.896	-0.502	-0.857	-0.66	-0.171	-1.496
Kurtosis	11.02	6.16	9.797	8.208	10.682	54.607
Jarque-Bera	170658	2776	11353	7227	14645	661817

Note: This table provides basic statistics for the log price changes of the market indices of the six countries indicated at the head of the columns. The skewness statistic is measured as m_3 / s^3 , and the kurtosis statistic is m_4 / s^4 . The Jarque-Bera statistic is $T (\text{Skewness}^2 / 6 + (\text{Kurtosis}-3)^2 / 24)$, where m_k is the central moment of order k , and s^2 is the sample variance. $\bar{R}$ is the sample mean of returns and T is the number of observations.

changes within given standard deviations of the mean are computed and compared with what would be expected if the distributions were standard normal. In Panel A of Table 4.2 (page 98), the first column on the left divides the distributions into 8 intervals containing observations within 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 4.0 and 5.0 standard deviations of the mean. The second column gives the proportions of observations that would appear in each interval for the standard normal distribution. In the next 6 columns, each market has 2 numbers in each interval; the top number is the proportion of observations in the interval, and the bottom number is these proportions minus the standard normal proportions. For example, the bottom entry in interval 0.5S for Japan, 0.160, is computed by subtracting 0.383 (the unit normal entry) from 0.543. A positive number in the bottom entry for each country indicates an excess of relative frequency in the empirical distribution over what would be expected for the interval if the distribution were normal.

It is clear from the column on the right of Table 4.2 (page 98) that the empirical distributions contain, on average, over 11 percent more frequency within a half standard deviation from the mean than would be expected if they were normal. These figures vary from just under 5 percent for Britain to 16 percent for Japan, and they indicate a significant degree of leptokurtosis in all markets in the sample. This pattern is continued in the 1.0S and 1.5S intervals with an average excess of relative frequency of 9 and 2.8 percent respectively. Indeed, all entries for each market in the first three intervals up to 1.5 standard deviations from the mean are positive. A negative number in an interval implies a scarcity of relative frequency. For example, the entry in the 2.5S interval for Britain (-0.035) implies that we observe 3.5 per cent less relative frequency within 2.5 standard deviations of the mean than would be expected under the standard normal. From interval 2.0S to 5.0S inclusive, all entries are negative except for two very small positive entries in interval 2.0S for France and the United States, indicating a general deficiency of relative frequency within any of the intervals from 2 to 5 standard deviations from the mean. This means that there is a general excess of relative frequency beyond these points. In particular there is an excess of relative frequency greater than five standard deviations from the mean, which is commonly referred to as long tails.

Panel B of Table 4.2 (page 98) compares the expected numbers of observations greater

Table 4.2 Interval Analysis of Asymmetry in International Equity Returns

Intervals	Unit Normal	UK	France	Germany	Italy	Japan	US	Average
		<i>Panel A: Proportions of observations</i>						
0.5	0.383	0.431	0.485	0.496	0.494	0.543	0.534	0.114
		0.048	0.102	0.113	0.111	0.16	0.151	
1	0.683	0.726	0.768	0.789	0.764	0.789	0.798	0.09
		0.044	0.086	0.106	0.081	0.107	0.115	
1.5	0.866	0.877	0.901	0.9	0.882	0.892	0.914	0.028
		0.011	0.035	0.033	0.016	0.026	0.048	
2	0.955	0.928	0.956	0.95	0.937	0.943	0.966	-0.088
		-0.026	0.001	-0.004	-0.018	-0.011	0.011	
2.5	0.988	0.952	0.976	0.973	0.957	0.969	0.984	-0.019
		-0.035	-0.011	-0.014	-0.03	-0.019	-0.004	
3	0.997	0.96	0.987	0.984	0.968	0.985	0.99	-0.018
		-0.037	-0.01	-0.014	-0.029	-0.013	-0.008	
4	1	0.966	0.995	0.993	0.975	0.994	0.994	-0.014
		-0.034	-0.005	-0.007	-0.025	-0.006	-0.006	
5	1	0.968	0.996	0.997	0.979	0.998	0.996	-0.011
		-0.032	-0.004	-0.003	-0.021	-0.002	-0.004	
		<i>Panel B: Numbers of observations</i>						
2	274	275	263	289	375	333	199	289
3	16	58	73	93	187	87	57	93
4	0	22	28	35	149	32	30	49
5	0	9	16	16	124	10	19	32

Note: Panel A provides proportions of all equity return observations within intervals of the distributions. Panel B converts these proportions to numbers of observations. Interval 0.5S refers to observations within one half standard deviation of the mean. The Unit Normal column gives the percentages of total observations that would be found if the distributions were normal. In the columns for each market, the top number is the proportion of observations within 0.5, 1, 1.5, 2, 2.5, 3, 4 and 5 standard deviations of the mean, and the bottom number is calculated by subtracting the corresponding unit normal entry from the top number. The averages column on the right of the Table gives the average proportion of observations in all markets relative to the standard normal distribution.

than 2, 3, 4 and 5 standard deviations from their means, when sampled from a normal distribution, with the actual numbers observed in the empirical distributions. The results are consistent in recording departures from normality for all markets. Beyond 3 standard deviations, there should be on average about 16 observations for each market. The actual numbers range from a minimum of 57 for the United States to a maximum of 187 for Italy. Beyond 4 standard deviations, there should be no observations in a normal distribution given the sample sizes. The actual numbers, however, range from a minimum of 22 for Britain to a maximum of 149 for Italy. The actual numbers of observations more than 5 standard deviations from their means range from a minimum of 9 for Britain to a maximum of 124 for Italy.

4.3 Distribution- Free Tests

The symmetry or asymmetry of equity return distributions is very often established by using the skewness coefficient in (4.1).

$$\alpha = \frac{\sum_{t=1}^T (R_t - \bar{R})^3 / T}{\sigma^3} \quad (4.1)$$

This is a re-statement of equation (3.5), Chapter 3. As explained in Section 3.3, the asymptotic distribution of this statistic is tied to the assumption of normality in the underlying series, and Peiró (1999) demonstrated that its behaviour can be different under alternative distributions in the parent series. It may therefore be misleading to make inferences concerning the asymmetry of equity returns on the basis of results obtained using this statistic. I have shown that the null hypothesis of normality is clearly rejected for the 6 international equity markets, and will therefore look to other methods of testing for differences in location and dispersion of returns in the distributions of negative and positive excess returns. Distribution free tests are appropriate here, and I employ the binomial, Wilcoxon rank sum and the Siegel-Tukey tests to the distributions of returns above and below the mean.

4.3.1 Binomial Distribution Tests

The binomial distribution test is applied to formally examine the probabilities of obtaining negative versus positive excess returns in all intervals of the distributions. Following Peiró (1999, 2002), logarithmic returns are considered to be symmetric if two conditions hold: first, if the probability of obtaining a positive excess return equals the probability of obtaining a negative excess return after zero excess returns have been excluded, and second, if the distribution of negative excess returns in absolute value is equal to the distribution of positive excess returns. If the probability of a negative excess return is the same as the probability of a positive excess return, the returns can be considered to follow a binomial distribution with parameters n equal to the number of observations and $p = 0.5$. The test statistic T is the number of negative excess returns for each series. The null distribution of T is the binomial distribution with parameters $p = p^* (0.5)$ and $n =$ number of observations. Because the values of n are large, the normal approximation is used. A full description of the binomial distribution test is provided in Section 3.5.5, Chapter 3.

The binomial distribution test results for the whole sample and for the 10 percent highest absolute excess returns are shown in Table 4.3 (*page 102*). Looking first at the whole sample, we can see in the first two columns that all countries except Italy have a higher proportion of positive excess returns. The null hypothesis of equal probability of obtaining a positive or a negative excess return is rejected for Britain, France, Germany and Japan. France records the highest percentage of positive returns at 53 percent and the lowest percentage of negative returns at 47 percent. We cannot reject the null hypothesis for Italy and the United States at the 5 percent level of significance. Looking now at the results for the largest 10 percent returns, Italy is the only country that has a higher percentage of negative returns, both in the whole sample and in the 10 percent highest excess returns. All other countries, except France, have more negative than positive excess returns in the 10 percent extremes. There is a statistically significant difference in the probability of obtaining a negative versus a positive return for Britain (at the 6 percent level), Germany (at the 1 percent level) and Japan (at the 2 percent level) in the 10 percent tails of the distributions, but not for any other country. While there are differences in the numbers of

positive and negative excess returns at these extreme levels, the differences are not statistically significant for 3 of the 6 markets sampled.

Table 4.3 Binomial Tests on the Whole Sample and on the 10 Percent Largest Excess Returns

	Percent positive	Percent negative	rho value		Percent positive	Percent negative	rho value
	Whole sample				10% highest excess returns		
<i>Britain</i>	51.69	48.31	0.01		46.22	53.78	0.06
<i>France</i>	53.03	46.97	0		51.15	48.85	0.6
<i>Germany</i>	51.29	48.71	0.05		44.24	55.76	0.01
<i>Italy</i>	49.83	50.17	0.61		48.17	51.83	0.39
<i>Japan</i>	51.58	48.42	0.02		44.95	55.05	0.02
<i>US</i>	50.98	49.02	0.14		47.81	52.19	0.31

Note: The rho value confirms that the null hypothesis of equality in the Binomial test cannot be rejected for Britain, France, Germany and Japan in the full sample and for Britain, Germany and Japan in the 10% highest excess returns.

Table 4.4 (*page 104*) presents the positive and negative excess returns for all markets using the same intervals as those used by Peiró (1999). For Britain, there is a statistically significant difference in the intervals 0-0.5 per cent, 0.5-1.5 per cent and 2.5-3.5 percent; for Germany in the 0.5-1.5 percent, 2.5-3.5 percent and >5.5 percent intervals; for Italy in the 0-0.5 percent, 1.5-2.5 percent and >5.5 percent intervals; and for Japan in the 0.5-1.5 per cent interval. Consistent with Table 4.3 (*page 102*), there is no interval in which there is a statistically significant difference in the probability of getting a negative or a positive return for the United States market. Overall, the most interesting result is that only 2 of the 6 markets, Germany and Italy, record differences in the probability of negative versus positive returns at greater than 5.5 per cent. Only one third of the countries in the sample exhibits asymmetry in the tails of the distributions.

In the intervals containing observations between 3.5-4.5 per cent and 4.5-5.5 per cent, Table 4.4 (*page 104*) shows that for all 6 countries, the numbers of positive and negative excess returns are very close. Beyond this interval, (4.5-5.5 per cent) the numbers of negative returns dominate the numbers of positive returns, but not consistently at statistically significant levels. In the case of France, for example, there is exactly the same number of positive and negative excess returns within the 4.5-5.5 per cent interval, and in the case of Japan, the number is almost identical. In the case of Britain, there are 2 negative returns and 1 positive return in the interval between 4.5-5.5 per cent and there are 4 negative and 2 positive returns in the interval greater than 5.5 per cent. But given that we are looking at a total of 3 observations out of 6,082 in one interval, and a total of 6 observations out of 6,082 in the second interval, it does not offer clear justification for concluding that the whole distribution is negatively skewed. Furthermore, the formal binomial test does not reject the equal probability of obtaining a negative or a positive return in either of these two intervals.

Consistent with my findings from the normality tests in Section 4.2, there are differences in the probability of obtaining negative and positive excess returns in the interval 0.5-1.5 per cent in four of the six markets. These differences are statistically significant at the 1 percent level in Germany and Japan, at the 5 percent level in Britain and at the 10 percent level

Table 4.4 Binomial Test on Intervals of the Distributions

		0-0.5	0.5-1.5	1.5-2.5	2.5-3.5	3.5-4.5	4.5-5.5	>5.5
Britain	Neg. returns	1409	1279	198	37	9	2	4
	Pos. returns	1538	1397	179	20	7	1	2
	p-value	0.02	0.02	0.35	0.80	1	1	0.68
France	Neg. returns	1309	1277	312	75	27	5	11
	Pos. returns	1247	1376	327	67	15	5	5
	p-value	0.23	0.06	0.58	0.56	0.09	1	0.21
Germany	Neg. returns	1281	1173	277	187	27	13	15
	Pos. returns	1291	1344	280	69	29	7	5
	p-value	0.86	0.00*	0.93	0.00*	0.89	0.26	0.04
Italy	Neg. returns	1207	1250	369	105	39	15	29
	Pos. returns	1104	1281	435	117	37	9	11
	p-value	0.03	0.55	0.02	0.46	0.91	0.31	0.01
Japan	Neg. returns	1337	1053	316	116	35	13	8
	Pos. returns	1425	1209	282	93	34	12	11
	p-value	0.1	0.00*	0.18	0.13	1	1	0.65
US	Neg. returns	1555	1088	215	31	8	5	11
	Pos. returns	1609	1170	210	24	10	2	5
	p-value	0.35	0.09	0.85	0.42	0.81	0.45	0.21

Note: The Table provides the numbers of positive and negative excess returns in each interval of the distributions for the 6 markets in the sample, along with the binomial test of difference in their number. The '*' indicates statistical significance at the 1 percent level.

in the United States, the latter being the nearest I come to any evidence of asymmetry in any interval of the excess returns distribution for the United States. This asymmetry occurs because the number of positive excess returns exceeds, in all cases, the number of negative excess returns in this interval. In the case of Italy the difference is small and statistically insignificant. Furthermore, the total percentages of all returns, both positives and negatives, in this one interval are 45 percent for Britain, 41 percent for Germany, and 38 percent for both Japan and the United States. This illustrates a general point about the shortcomings implicit in tests for asymmetry that conclude that stock market returns are negatively skewed because there are more negative than positive excess returns in the tails, and because the biggest observable changes are negative. By failing to examine alternative intervals of the distribution, these tests are based on intervals within which the numbers of positive and negative returns can be in single digits and almost negligible as a percentage of the entire distribution.

4.3.2. Wilcoxon rank sum and Siegel-Tukey Tests

The Wilcoxon rank sum and the Siegel-Tukey test are described in Chapter 3, Section 3.5. The results of these tests are shown in Table 4.5 (*page 106*). The equality of the distributions of the negative and positive excess returns cannot be rejected at the 5 percent level using either the Wilcoxon test or the Siegel-Tukey test on the whole sample distribution and on the 10 percent largest excess returns for the United States. This is consistent with Peiró (1999) who sampled the S&P500 and the Dow Jones Industrial Average index of the NYSE for a shorter time period and could not reject the null of equal distributions at the 5 percent level for either of these indexes. Looking at the results for the whole sample, the Wilcoxon test rejects the equality of the distributions for France and Italy, and the Siegel-Tukey test does likewise for Britain, Germany and Japan. Looking next at the results for the 10 percent largest returns, the null of equal distribution of positive and negative returns is rejected only in Italy using the Siegel-Tukey test. It seems, therefore, that the whole sample findings of asymmetry in both the Wilcoxon rank sum (France and Italy) and the Siegel-Tukey test (Britain, Germany and Japan) are not due mainly to asymmetries in the tails of the distributions.

Table 4.5 Distribution Free tests for Asymmetry

	W	W*	p-value	ST	ST*	p-value
<i>Whole sample</i>						
Britain	9014637	1.15	0.13	8742443	-2.828	0
France	8440961	-2.684	0	8569520	-0.793	0.21
Germany	8425043	-0.748	0.23	8068392	-1.953	0.03
Italy	8866264	-2.816	0	8977512	-1.161	0.12
Japan	8640132	-1.538	0.1	8270158	-4.306	0
US	8670647	0.133	0.45	8631193	-0.464	0.32
<i>10 percent largest returns</i>						
Britain	102777	1.484	0.93	97725	-0.855	0.2
France	95065	2.138	0.98	88521	-0.885	0.19
Germany	99118	0.923	0.82	97046	-0.084	0.47
Italy	96402	1.389	0.92	88996	-2.102	0.02
Japan	94207	-1.478	0.07	97711	0.206	0.58
US	93986	0.843	0.8	90954	-0.608	0.27

Notes. *W* is the Wilcoxon rank sum statistic. *ST* is the Siegel-Tukey statistic. *W** is the standardized Wilcoxon rank sum statistic and *ST** is the standardized Siegel-Tukey statistic. The *p*-values are marginal significance levels.

4.4 Analysis of Asymmetry

A possible weakness of distribution free tests is that they may lack power when examining the symmetry of entire distributions with large numbers of observations and no assumptions about the underlying probability distribution function. In the absence of normality, which I have clearly demonstrated to be the case in this study, I cannot say with certainty what the shape of the underlying distribution is. Therefore, when asymmetry is found, I cannot be sure where the source of the asymmetry is located. By segmenting the distribution I am able to show that the source of asymmetry identified in the whole density function may be located at the centre of the distribution and not in the extremes. My interpretation of asymmetry is based on the definition of negative skewness in the opening paragraph of Harvey and Siddique (1999) 'Asymmetry is a phenomenon whereby there exists a higher probability of obtaining a negative excess return of a given magnitude than a positive excess return of the same magnitude'.

It is therefore of considerable interest to conduct these same tests over different intervals to see whether they can reject the hypothesis of symmetry in any of the intervals, and if so, whether this tends to occur near the mean or further out in the tails. Table 4.6 (*page 108*) provides the results. Britain shows very weak evidence of asymmetry, with only the Siegel-Tukey test rejecting symmetry in the 0.5-1.5 percent interval and the Wilcoxon test rejecting symmetry in the 4.5-5.5 percent interval. France is the only market that rejects symmetry in any interval on the basis of both the Wilcoxon and the Siegel-Tukey tests, and it does this in the 0.5-1.5 per cent interval. Germany shows evidence of asymmetry in the 3.5-4.5 per cent interval according to the Siegel-Tukey test (although it should be noted that the 29 positive excess returns exceed the 27 negatives). Italy rejects the hypothesis of symmetry using the Wilcoxon test in the 0.0-0.5 per cent interval. I find no asymmetry for any interval in the distributions for Japan or the United States at less than 5 per cent.

Overall, Table 4.6 (*page 108*) reports 72 distribution free tests of symmetry using the Wilcoxon and the Siegel-Tukey tests for 6 markets divided into 6 intervals. I have been able to reject symmetry at the 5 percent level in only 6 of these cases, (and at the 10 percent level in a further 4 cases), and only 2 of the former are in the two intervals closest to the

Table 4.6 Distribution Free Interval Tests

	<i>Intervals</i>	<i>0.0-0.5</i>	<i>0.5-1.5</i>	<i>1.5-2.5</i>	<i>2.5-3.5</i>	<i>3.5-4.5</i>	<i>4.5-5.5</i>
Britain	Negative returns	1409	1279	198	37	9	2
	Positive returns	1538	1397	179	20	7	1
	W*	-1.386	1.173	0.197	0.752	-0.159	-2.449
	p-value	0.08	0.88	0.58	0.77	0.44	0.01
	ST*	-0.869	-1.812	-0.606	-1.254	-0.794	1.225
	p-value	0.19	0.04	0.27	0.11	0.21	0.89
France	Negative returns	1309	1277	312	75	27	5
	Positive returns	1247	1376	327	67	15	5
	W*	-1.228	-1.943	1.679	0.676	0.328	0.731
	p-value	0.11	0.03	0.95	0.75	0.63	0.77
	ST*	-0.609	-2.298	-0.724	-0.607	0.853	-0.104
	p-value	0.27	0.01	0.24	0.27	0.8	0.46
Germany	Negative returns	1281	1173	277	87	27	13
	Positive returns	1291	1344	280	69	29	7
	W*	-0.493	-1.096	2.752	1.029	-0.664	0.04
	p-value	0.31	0.14	1	0.85	0.25	0.52
	ST*	0.183	-0.351	-0.646	-0.512	-1.812	-0.436
	p-value	0.36	0.36	0.26	0.3	0.04	0.33
Italy	Negative returns	1207	1250	369	105	39	15
	Positive returns	1104	1281	435	117	37	9
	W*	-1.731	-0.584	1.421	0.918	-0.348	-0.468
	p-value	0.04	0.28	0.92	0.82	0.36	0.32
	ST*	0.636	1.196	-1.564	0.738	1.065	-0.351
	p-value	0.74	0.88	0.06	0.77	0.86	0.36
Japan	Negative returns	1337	1053	316	116	35	13
	Positive returns	1425	1209	282	93	34	12
	W*	-1.418	2.831	1.42	-0.382	-0.084	1.088
	p-value	0.08	1	0.92	0.35	0.47	0.86
	ST*	-0.932	-0.276	0.487	-0.552	0.468	-0.326
	p-value	0.18	0.39	0.69	0.29	0.68	0.37
US	Negative returns	1555	1089	215	31	8	5
	Positive returns	1609	1170	210	24	10	2
	W*	0.059	-0.26	0.605	0.187	-0.8	0.387
	p-value	0.72	0.4	0.73	0.57	0.21	0.65
	ST*	1.633	-0.408	0.398	0.56	1.155	-0.387
	p-value	0.95	0.34	0.66	0.71	0.88	0.08

Note: W* is the standardized Wilcoxon rank sum statistic and ST* is the standardized Siegel-Tukey statistic. The p-values are marginal significance levels.

tails of the distributions. The remaining 4 cases are in the two intervals closest to the means. To the extent that asymmetry as defined in the opening paragraph of Harvey and Siddique (1999) occurs in the markets in my sample, it is somewhat more likely to occur towards the centre of the distributions rather than further out in the tails and is more likely the reverse of the Harvey and Siddique prediction.

4.4.1 Siegel-Tukey test statistic

In this section, I discuss the inference that I draw from the sign of the standardized statistic in the Siegel-Tukey test, since my interpretation differs from Peiró (1999) and contributes to the wider debate on asymmetry. Both Peiró's (1999) original paper and my results here reach similar conclusions for the most part, but our analysis diverges on the significance of a negative standardized statistic in the Siegel-Tukey test. There are three countries in my study, Britain, Germany and Japan where two tests, the binomial distribution and the Siegel-Tukey, identify asymmetry in the full sample distributions. The binomial test shows a higher proportion of positive versus negative excess returns in the full sample although the Siegel-Tukey standardized statistics are, in all three cases, negative. When I examined the 10 percent extremes I found the same three countries showing significantly higher proportions of negative excess returns in the binomial distribution test. However, the Siegel-Tukey test did not reject the null of symmetry in any one of these three markets in the 10 percent extremes. The Siegel-Tukey test detected asymmetry in the full sample of returns but could detect no asymmetry in the extremes; the binomial distribution test detected asymmetry in both the full sample of returns and in the 10 percent extremes. However, in the full sample the asymmetry arose because of significantly higher proportions of positive over negative excess returns and in the 10 percent extremes the reverse was the case. In his paper, Peiró (1999) draws attention to the negative standardized statistics in the Siegel-Tukey tests by pointing out that the statistics are below their expected values, in other words that the sum of the weights attached to the negative excess returns is less than it should be. He therefore ascribes the differences in variance to higher numbers of negative excess returns located in the extremes, since, by construction in the Siegel-Tukey test, the extremes are where the lowest weights are to be found. The question is, is the asymmetry detected in the Siegel-Tukey whole sample test due to a disproportionate portion of negative excess returns in the extremes (as suggested by Peiró)

or is it due to a disproportionate number of positive excess returns in an alternative interval of the distributions? I favour the latter inference.

In my study, the binomial distribution test, Table 4.4 (*page 104*) identifies one interval, 0.5-1.5 per cent, where there is a significantly higher probability of obtaining a positive versus a negative excess return for Britain, Germany and Japan, the precise markets identified in the Siegel- Tukey test. This suggests that the negative standardized statistic in my Siegel-Tukey test is related to a smaller proportion of negative returns in the middle of the distribution than a larger proportion of negative returns in the 10 percent tails. Given that the Siegel-Tukey test, by construction, assigns the largest weights to the centre of the distribution, or close to the median, it confirms that the asymmetry identified in my tests is located in one or possibly two intervals closer to the mean.

4.4.2. Monte Carlo Study

Peiró (1999) assumes explicitly that the returns to the equity and foreign exchange markets in his study are independent and identically distributed (i.i.d.), because without this assumption an investigation of symmetry would be virtually impossible. In looking at 9 different time series subject to unknown and varying patterns of dependence and mindful of increasing levels of international integration, the i.i.d. assumption was critical in Peiró's view. Regulez and Zarraga (2002) raise the question of relying on a non-parametric approach to the investigation of asymmetry when the i.i.d. assumption may not be appropriate. Both the Wilcoxon rank sum and the binomial distribution test are essentially joint tests of the returns being i.i.d. and symmetric. Either test therefore could reject symmetry due to time-variation in the mean, even if returns are symmetric. To test the small sample properties of these two distribution free tests, I constructed a returns generating process with a strong time dependency in the mean equation, and generated 2000 artificial datasets that differed from each other only in the residuals which were random draws from a known symmetric distribution, the standard normal. In the binomial distribution test I recorded 22 out of 2000, the equivalent of 1.10 per cent, rejections of the null hypothesis of symmetry at the 5 per cent significance level and 5 out of 2000, the equivalent of 0.25 per cent rejections at the 1 per cent level of significance. In the Wilcoxon

rank sum test there were 81 out of 2000 rejections of the null hypothesis, or 4.5 per cent of the total at a significance level of 1 per cent, and 278 out of 2000, or 13.9 per cent of the total rejections of the null hypothesis of symmetry at 5 per cent test. The Monte Carlo study is described fully in Section 3.5.6, Chapter 3.

4.4.3. Discussion of Peiró (1999)

In this section I compare my results with the results obtained by Peiró (1999) and highlight the important differences in findings. The first obvious difference is that I have a much larger data set with 6082 observations for Britain, compared to Peiró's 3469, and 5944 for Japan where Peiró has 3389.

I found higher percentages of positive excess returns, four at statistically significant levels, in all countries. Consistent with Peiró this trend was reversed in the 10 percent highest excess returns where all markets, except France, reported higher percentages of negative excess returns, Britain, Germany and Japan at significant levels. In the full sample of returns distributions I found that the Siegel-Tukey test rejected the equality of distributions for Britain, Germany and Japan. The Wilcoxon rank sum test did not reject the null hypothesis of equality in the distributions of these markets so I calculated the percentages of positive and negative excess returns in the whole sample of returns to each market. Unlike Peiró, I did find significant differences in proportions of positive and negative excess returns for Britain, Germany (at 5 percent) and Japan. In all three cases, however, the proportion was higher for positive excess returns, although the standardized statistics were, in all three cases, negative in the Siegel-Tukey tests.

Because Peiró (1999) did not find significant differences in proportions of negative and positive excess returns in his whole sample, he turned his attention to the 10 per cent extremes. He found significant differences in probability in these extremes, in the same markets where the Siegel-Tukey tests had detected asymmetry. He attributed the rejection of equality in the Siegel-Tukey tests to the unequal dispersion of positive and negative extreme excess returns. To confirm that the rejections in his study were caused by the 10 per cent extreme excess returns, Peiró ran the tests again excluding these extreme values.

This time he found that he could not reject the null hypothesis of equal distributions of positive and negative excess returns. Peiró concluded with the statement that ‘it seems reasonable to attribute the rejection of equality in these markets to the different dispersion caused by extreme excess returns, more frequent in $|R|^-$ than $|R|^+$ ’.

I ran these tests again, having excluded the 10 per cent highest excess returns. I found that the Siegel-Tukey test still rejected the null of equality of the underlying distributions for both Britain and Japan. In both cases, the standardized statistic in the Siegel-Tukey test was negative, but the proportion of positive excess returns exceeded the proportion of negative excess returns. Since I now had evidence of asymmetry for Britain and Japan in the whole sample, in the 10 percent highest excess returns, and in the remainder of the returns after I had excluded the top 10 percent, I could not isolate the source of this asymmetry as Peiró (1999) did.

In order to substantiate the theory that skewness (asymmetry) is influenced by the differencing interval, see Fogler and Radcliffe (1976), I conducted a series of nonparametric tests on my data in the time period from 3/1/1980 to 27/9/1993 as these dates correspond exactly to Peiró’s (1999) dates. I extracted from the Peiró study those markets that corresponded most accurately with my markets with some adjustments. Peiró (1999) used two indexes, the Dow Jones and the Standard and Poor’s 500, whereas I used the NYSE, and Peiró (1999) used the FTSE 100 whereas I used the Financial Times All Share Index. I chose the FT All Share Index in preference to the FTSE 100 in light of survivorship bias in the FTSE 100. In the Wilcoxon rank sum tests our results are almost identical, for example, I find a significant rejection of the null hypothesis of equal distributions for Italy at a marginal level of 0.2% and Peiró’s result is very close at a marginal level of 0.3%

When it comes to the Siegel–Tukey test results, both studies find rejection of the null hypothesis of equal distributions for two markets, the British and Japanese. To verify that the asymmetry identified in these markets is largely attributable to extreme returns, Peiró (1999) reruns the Siegel–Tukey tests excluding these higher returns and finds that it is no

longer possible to reject the null of equality for the remainder of the sample. I also rerun the tests on the remainder of my excess returns, having excluded the 10 per cent highest excess returns, but still find that the returns for Britain reject the null hypothesis of equal distributions at the 5 per cent level of significance (p-value 0.038). I find in looking at the percentages of negative and positive excess returns that a negative standardized statistic is not necessarily an indicator of a higher percentage of negative excess returns, in this case. In my sample, excluding the 10 per cent highest excess returns, the percentage of negative excess returns for the FT All Share market is 47.8 per cent despite the negative standardized statistic in the Siegel-Tukey test.

4.5 Summary and Conclusions

Financial researchers have recognised for some time that the extreme tails of the distributions of equity returns tend to exhibit more negative than positive returns (for recent examples, see Harvey and Siddique (2000), Chen, Hong and Stein (2001), Cont (2001) and Engle and Patton (2001)). The literature, however, remains unclear about how pervasive asymmetry is in returns across the entire distribution, and very few studies to date have conducted a rigorous and systematic analysis of this question. A notable recent exception to this is the work of Peiró (1999, 2002) who finds little evidence of skewness in 9 developed international equity markets in Europe, Japan and the United States. I have contributed to this research question by analysing daily returns in 6 international stock markets from Britain, France, Germany, Italy, Japan and the US from January 1978 to February 2002. I established that returns are not normally distributed using the approach of Fama (1965) and applied a broadly similar methodology to the analysis of asymmetry.

A novel contribution of this chapter is the Monte Carlo study that tested the behaviour of two of the distribution free tests, the Wilcoxon rank sum and the binomial distribution test, since both are essentially joint tests of returns being both *i.i.d.*, and symmetric. It follows that a rejection of symmetry might in fact be a rejection of normality in an otherwise perfectly symmetric distribution. The findings show that the tests were not compromised, in that neither test rejected the null of symmetry too often, despite the very high level of time dependency imposed in the mean. The findings also validate the use of a non-parametric

approach to the study of asymmetry of volumes in Chapter 5 and FOHFs in Chapter 6 in this thesis.

I first examined excess kurtosis levels, Studentised- range and Jarque-Bera statistics, and established that international equity returns do not follow a normal probability distribution. Having established non-normality in all international equity markets in my sample, I then examined the behaviour of excess returns. I conducted binomial tests on the whole distributions, the 10 per cent tails and the individual intervals of the distributions. I used three distribution free tests, the Wilcoxon rank sum, the Siegel-Tukey and the binomial distribution test on the entire samples, on the 10 percent highest excess returns, and on the individual intervals of the distributions.

I found that while there are more negative than positive returns in the extreme tails of the distributions in 5 of the 6 countries studied, the differences are generally not statistically significant. Distribution-free tests show no statistically significant evidence of asymmetry in most intervals of the distributions. My findings call into question some perceptions about the asymmetry of daily stock market returns. More specifically, my analysis demonstrates that asymmetry is not a statistically significant stylistic feature of stock returns. I do not find that there is a consistently higher probability of obtaining a negative rather than a positive excess return of the same magnitude in the returns to the stock markets in my study. When I do find asymmetry, it is more likely to be related to the higher probability of obtaining a positive rather than a negative excess return of the same magnitude.

Peiró (1999) infers that a negative standardized statistic in the Siegel-Tukey test *may* be related to a preponderance of negative excess returns in the extremes of the distributions. I submit that while this is a reasonable assumption, it is not the full story. I show that a negative standardized statistic in the Siegel-Tukey test may just as reasonably infer a scarcity of negative excess returns closer to the mean.

If asymmetry is to be considered as a stylised fact or characteristic of equity market distributions generally, it is based on a false premise to argue that the asymmetry is present because there is a higher frequency of negative excess returns in the extremes of the distributions. I show clearly that, in many intervals of the distributions, even in the tails, the numbers are frequently approximately equivalent. The work in this chapter, therefore, is a first step in looking, not just at the tails, but also at the entire distributions of returns to equity markets. I have contributed to the literature by exploring the extent to which daily returns could be described as ‘substantially negatively skewed, ((Engle and Patton, (2001)) and Cont (2001). I have shown that the definition of asymmetry in Harvey and Siddique (1999) is not valid for all intervals of the distribution of equity returns. I built upon the work of Peiró (1999) by verifying the validity of his approach to the use of non-parametric methods in the analysis of asymmetry. This is a novel contribution to the literature on equity return asymmetry.

Chapter 5

Asymmetry in Trading Volumes

5.1 Introduction

In this chapter I examine the distributions of turnover in 12 international equity markets using the same approach as described in Chapter 4. The aim of the chapter is to investigate the extent and nature of asymmetry in the distributions of raw trading volumes. These two chapters therefore provide a detailed analysis of the distributional characteristics of the two variables, returns and volumes, which are central to the econometric analysis in Chapter 7. The methodological approach adopted in this chapter differentiates between positive excess turnover (overtrading) and negative excess turnover (undertrading). This approach is closely related to the work of Tkac (1999), who uses monthly trading volume data and market capitalization figures for a subset of NYSE/AMEX in CRSP between 1988 and 1991 to derive a rebalancing benchmark that delivers a connection between trading volumes in individual stocks and market wide activity. Although Tkac (1999) considers individual stocks and I work with aggregate markets, her approach can be generalised to the aggregate market context. In order to be able to characterize patterns of anomalous trading activity, it is firstly important to filter out normal trading volume activity, with an adjustment for market related activity. Tkac (1999) identified institutional ownership, size and options availability as factors that contribute to either overtrading (institutional ownership and options availability) or undertrading (size). Overtrading is defined as significantly positive average excess turnover and analogously undertrading is associated with significantly negative average excess turnover.

In addition to the study of the distribution of turnover in these equity markets from 1980 to 2004, I include also a set of summary statistics of the associated returns. Although the inclusion of return distributions appears initially to be a replication of the work of Chapter 4, it is provided in order to facilitate a direct comparison between equity index returns and associated volume distributions. The chapter is structured as follows. In Section 5.2, I present the derivation of the turnover ratio used in the analysis of asymmetry in this

chapter. In Section 5.3, I test the normality of the volume distributions using the methodology of Chapter 4. In Section 5.4, I apply the distribution free tests of Chapter 4, the binomial distribution, the Wilcoxon rank sum and the Siegel Tukey tests. I have a comprehensive dataset of high frequency equity and associated trading volume data, so in Section 5.5, I describe an empirical study of the 10 highest absolute price changes and turnover ratios for all 12 country market indexes. I cross-reference the relevant dates against the monthly volatility data for the same markets and discuss the degree to which the theoretical relationships between absolute price changes, high trading volume and volatility are confirmed or absent. Section 5.6 provides a summary of the chapter and draws together the conclusions.

5.2 Derivation of turnover ratio

I begin this section by motivating the use of the turnover ratio I use in the distributional analysis of this chapter. It is useful to note that in this chapter, I use raw or undetrended volumes. These volumes will be detrended in Chapter 7. I use raw volumes in order to study, more closely, the distributional properties of volumes. The previous literature which relates volumes to other variables in a time series framework has used detrended volumes in order to provide unbiased estimates of the model coefficients. This is not relevant in Chapter 5.

As described in Section 3.2.2, Chapter 3, the dataset used in this chapter is based on daily returns and turnover of 12 stock market indexes: the total market index of Australia, Belgium, Canada, France, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, the UK and the US. The market returns at time t are calculated as $R_t = (\ln(p_t) - \ln(p_{t-1}))$. In order to apply a non-parametric analysis to the distribution of turnover similar to that used in the analysis of returns in Chapter 4, I use a scaling factor c , calculated as the inverse of the mean. The purpose of introducing this scaling factor is to allow the series of daily turnover rates to have a scale similar to the return series R_t . The advantage of choosing the inverse of the mean as a scaling factor is that it enables me to standardize the approach across all countries in the study. Some of the markets I examine are among the most capitalised in the world with approx 1000 constituent firms, while others are small with less than 100 listed companies. Table 5.1 (page 119) shows the method of implementing the scaling factor to

derive the turnover ratio, using a small sample of value of shares traded and total market value for the Belgian market. Column 1 presents a sample of 29 observations on value of shares traded (denominated in thousands of Euro) and column 2 contains the total market value (denominated in millions of Euro). In the third column I calculate the percentage of total market value traded on each day. I calculate the average of the entries in column 3 and enter each deviation from this average in column 4. On the right of the table I normalise each entry in column 4 by the mean and use this column as the turnover ratio in all the subsequent work in this chapter.

Table 5.1 Sample: Derivation of Turnover Ratio using Belgium Data

VA (000's €)	MV (m)	%	Deviation from Average	Normalised Deviation
2573	13601	0.018918	-0.00856	-0.311481
4028	13393	0.030075	0.002599	0.094608
4548	13443	0.033832	0.006356	0.231321
3022	13356	0.022627	-0.00485	-0.176497
2278	13339	0.017078	-0.0104	-0.378448
2547	13302	0.019147	-0.00833	-0.303118
2938	13284	0.022117	-0.00536	-0.195048
2111	13189	0.016006	-0.01147	-0.417463
2226	13203	0.01686	-0.01062	-0.38638
2239	13265	0.016879	-0.0106	-0.385681
3692	13323	0.027711	0.000236	0.0085715
2837	13274	0.021373	-0.0061	-0.222134
5176	13285	0.038961	0.011485	0.4180114
3407	13247	0.025719	-0.00176	-0.063944
3934	13030	0.030192	0.002716	0.0988463
3795	13069	0.029038	0.001562	0.0568575
2873	13126	0.021888	-0.00559	-0.203382
2609	13177	0.0198	-0.00768	-0.279383
3922	13217	0.029674	0.002198	0.079995
2370	13282	0.017844	-0.00963	-0.350571
2679	13292	0.020155	-0.00732	-0.266451
3907	13396	0.029165	0.001689	0.0614885
3310	13523	0.024477	-0.003	-0.109155
4624	13707	0.033735	0.006259	0.2277853
5741	13901	0.041299	0.013823	0.5031023
7959	14243	0.05588	0.028404	1.0337804
7414	14210	0.052175	0.024699	0.898915
4146	14189	0.02922	0.001744	0.0634683
4943	14139	0.03496	0.007484	0.2723862

Notes: VA refers to value of shares traded; MV is total market value. Column 3 is VA expressed as a Percentage of MV. Each entry in column 4 is the corresponding entry in column 3 minus the average of the ratios in column 3. The final column shows the normalised values of column 4.

In Table 5.2 (*page 121*), I present a set of summary statistics for returns and turnover in 12 international equity markets. The upper part of the table presents the return statistics while the turnover statistics are shown in the bottom half. Looking first at the return statistics we note that the means are all zero while the maximum and minimum figures indicate the range around this mean. Return skewness is negative in all countries except Japan (0.091) and excess kurtosis is evident in all countries, consistent with prior research into daily returns. The lower part of Table 5.2 (*page 121*) shows that the turnover ratio is positively skewed in all 12 countries and the standard deviation of the turnover ratio is significantly higher than return standard deviation in all countries. There is a much greater range around the mean with Australia, Canada and Japan all showing maximum values in excess of 15. The Jarque-Bera test shows very high levels of non-normality and Pearson's coefficient of skewness, which is derived using both the mean and median, also confirms the positive skewness in the turnover distributions, albeit at much lower levels than those obtained using the traditional coefficient of skewness.

5.3. Normality Tests

Figure 5.1 (*page 123*) describes the histograms of trading volume distributions for each country index in the study. The base of the histogram is divided into 16 equally spaced discrete intervals. The first interval, 1, denotes observations strictly less than -5 $\{-5\}$ standard deviations from the mean; interval 2, denoted by $\{\geq -5, < -4\}$, contains observations that are greater than or equal to -5 and strictly less than -4 standard deviations. The following intervals contain observations as follows: 3 $\{\geq -4, < -3\}$; 4 $\{\geq -3, < -2\}$; 5 $\{\geq -2, < -1.5\}$; 6 $\{\geq -1.5, < -1\}$; 7 $\{\geq -1, < -0.5\}$; 8 $\{\geq -0.5, < 0\}$; 9 $\{\geq 0, < 0.5\}$; 10 $\{\geq 0.5, < 1\}$; 11 $\{\geq 1, < 1.5\}$; 12 $\{\geq 1.5, < 2\}$; 13 $\{\geq 2, < 3\}$; 14 $\{\geq 3, < 4\}$; 15 $\{\geq 4, \leq 5\}$; 16 $\{> 5\}$.

Table 5.2 Stock Index Returns and Turnover Ratios

	Australia	Belgium	Canada	France	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
Returns												
Mean	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.001	0.000	0.000	0.000
Standard Deviation	0.010	0.009	0.009	0.012	0.013	0.013	0.011	0.012	0.014	0.010	0.010	0.010
Skewness	-5.208	-0.529	-0.844	-0.212	-0.234	0.091	-0.459	-0.284	-0.024	-0.604	-0.911	-1.433
Kurtosis	146.608	13.634	15.074	3.225	2.931	3.484	7.123	3.303	4.639	6.705	11.730	29.901
Minimum	-0.294	-0.130	-0.116	-0.074	-0.078	-0.072	-0.110	-0.082	-0.085	-0.093	-0.130	-0.207
Maximum	0.061	0.075	0.088	0.062	0.069	0.094	0.070	0.063	0.109	0.064	0.065	0.083
Count	5303	4707	6273	4151	4651	3716	4759	3726	5733	3981	4580	6295
Jarque-Bera test	4572225	22399	38847	40	43	41	3537	64	642	2519	15177	191939
Studentised Range	35.544	21.549	23.678	11.570	11.490	13.046	16.355	12.130	13.986	15.246	19.791	28.086
Turnover Ratio												
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	0.591	0.651	0.761	0.652	0.893	0.747	0.539	0.524	0.837	0.471	0.502	0.515
Skewness	5.242	2.754	4.553	0.372	0.741	4.289	1.502	0.541	1.477	0.334	1.298	0.996
Kurtosis	99.554	27.071	65.790	0.418	0.015	61.744	4.121	0.124	2.953	1.114	1.750	0.670
Minimum	-0.940	-0.998	-0.999	-0.999	-0.998	-1.000	-0.996	-0.992	-0.996	-0.998	-0.921	-0.999
Maximum	15.380	11.406	15.421	3.963	5.158	15.311	4.834	2.806	5.782	2.705	3.274	2.842
Observations	5303	4707	6273	4151	4651	3716	4759	3726	5733	3981	4580	6295
Jarque-Bera test	2084193	119587	1052172	1249	2152	545691	2039	1466	2085	664	1584	2466
Studentised Range	27.631	19.065	21.582	7.606	6.893	21.836	10.810	7.244	8.093	7.865	8.353	7.457
Pearson's Coefficient of Skewness	0.568	0.429	0.863	0.055	0.488	0.643	0.654	0.251	0.894	-0.153	0.924	0.908

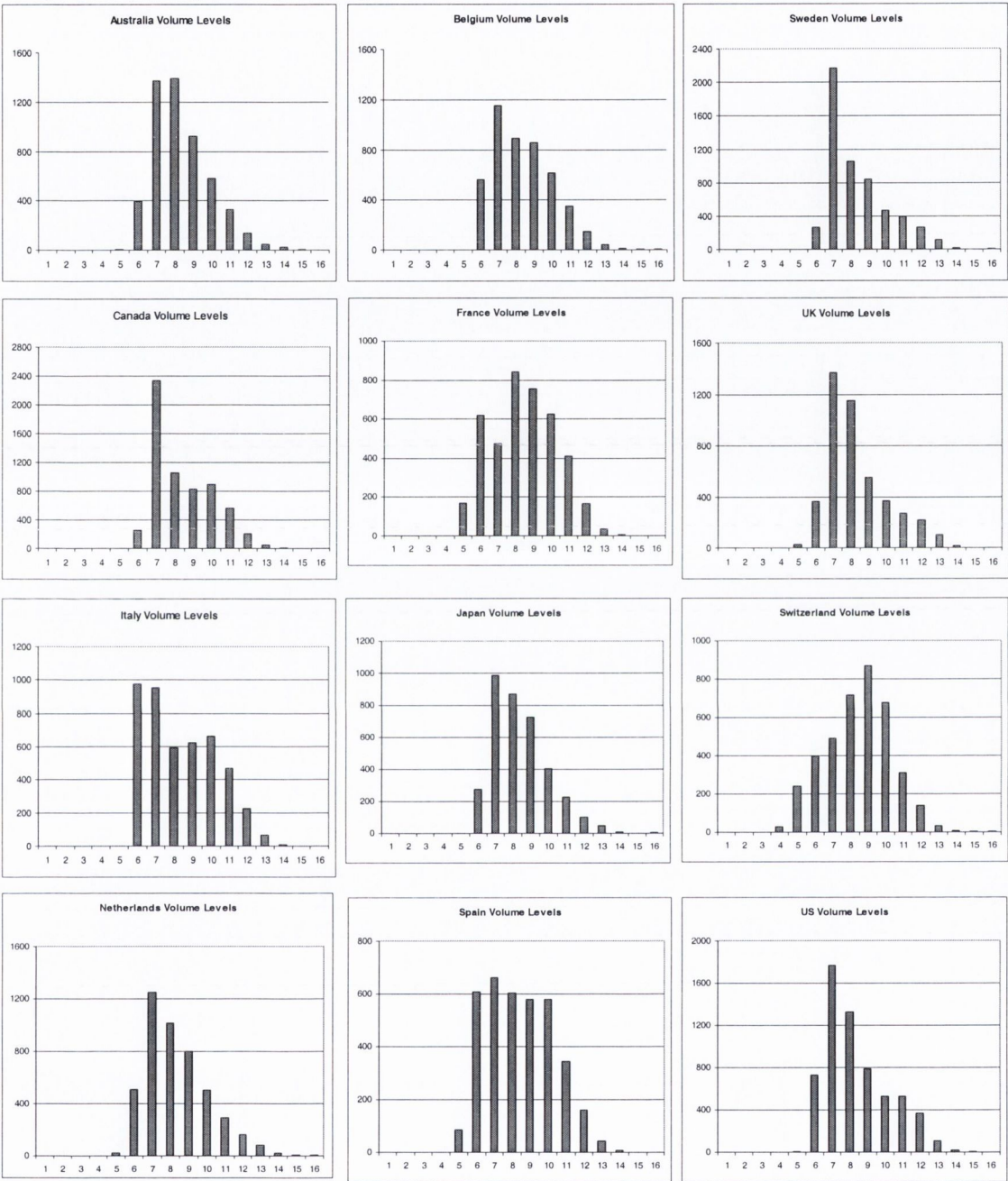
Note: Turnover ratio is the value of shares traded each day divided by the total market value. Return at time t is defined as: $R_t = \ln(r_t) - \ln(r_{t-1})$. The Pearson coefficient of skewness is $3(\mu - \text{med})/\sigma$. Jarque-Bera is a joint test for the absence of skewness and kurtosis. The Jarque-Bera follows a $\chi^2(2)$ distribution with the 5% critical value being 5.99

Visually, the mean can be interpreted to lie between intervals 8 and 9. In 10 of the 12 histograms, there is a clear absence of symmetry with higher frequencies of negative excess turnover ratios to the left of the mean and a long tail to the right of the mean, the exceptions being Switzerland and France. Switzerland has a distribution that is negatively skewed and France is almost symmetric. This graphic impression of symmetry is borne out in the summary statistics for Switzerland and France. In 8 of the 12 countries, the modal interval, is 7, $\{\geq -1, < -0.5\}$. This is true for Belgium, Canada, Japan, Netherlands, Spain, Sweden, the UK and the U.S., the exceptions being Australia, France, Italy and Switzerland. However it should be noted that in the case of both Italy and Japan the modal interval 6, $\{\geq -1.5, < -1\}$ is adjacent. This means that for 10 of the 12 markets the two intervals that contain observations between -1.5 and -0.5 standard deviations of the mean, $\{\geq -1.5, < -0.5\}$ contain the highest frequencies of observations. This implies that the average rate of average excess turnover for all markets, regardless of capitalisation, is -1 per cent.

5.3.1 Fama Normality Tests

Table 5.3 (*page 125*) analyses the distributions of excess turnover ratios relative to the standard normal distribution. For each market, the proportions of turnover ratios within given standard deviations of the mean are computed and compared with what would be expected if the distributions were standard normal. The first column on the left divides the distributions into 7 intervals containing observations within 0.5, 1.0, 1.5, 2.0, 3.0, 4.0 and 5.0 standard deviations from the mean. The second column gives the proportions of observations that would appear in each interval for the standard normal distribution. In the next 12 columns, each market has two numbers in each interval; the top number is the proportion of observations in the interval, and the bottom number is these proportions minus the standard normal proportions. For example, the bottom entry in interval 0.5S for Australia, 0.053, is computed by subtracting 0.383 (the unit normal entry) from 0.436. A positive number in the bottom entry for each country indicates an excess of relative frequency in the empirical distribution over what would be expected for the interval if the distribution were normal. The most striking feature of Table 5.3 (*page 125*) is an average deficiency of 2.3 per cent of relative frequency within one half standard deviation of the

Figure 5.1 Histograms of Trading Volume Distributions



Notes: This figure shows the distributions of trading volume turnover in 12 international equity markets. The base of each histogram is composed of 16 equally spaced intervals as described in the text. The mean can be interpreted to lie between intervals 8 and 9.

mean. This deficiency has implications for levels of kurtosis in turnover distributions. It is clear from the column on the right of the table that the empirical distributions contain, on average, almost 5 per cent more frequency in the intervals within 1 and 1.5 standard deviations of the mean than would be the case if the distributions were normal. A negative number in an interval indicates a general deficiency of relative frequency within the interval, with a corresponding excess of relative frequency beyond this point. For example, the entry in the 2.0S interval for the UK (-0.010) implies that we observe 1 per cent less relative frequency within 2 standard deviations of the mean than would be expected under the standard normal. While the Fama approach is very useful in giving an intuitive feel for asymmetry in the distributions, it only deals with the absolute number of observations within a given standard deviation of the mean relative to what would be expected if the distribution were from a standard normal.

5.4 Distribution Free Tests

5.4.1 Binomial distribution results

The binomial distribution test is described in Chapter 3, Section 3.5.5. The results of the binomial distribution test are presented in Table 5.4 (*page 127*). Between 0.5 and one standard deviation of the mean, Table 5.4 (*page 127*) shows the numbers of negative excess turnover ratios dominate the positive excess ratios in multiples of between 2 and 4. Sweden has 5 times as many, UK has 4 times as many negatives, the US has over 3 times the number of negatives and in Canada the ratio is almost three to one. In the case of Australia and Netherlands there are twice as many negatives as positives and Belgium has almost twice as many. For 10 of the 12 countries in the study, the exceptions being France and Switzerland, the average proportion of negative excess turnover is 65.7 per cent. There is a statistically significant probability of obtaining a negative versus a positive excess turnover ratio in this interval for Italy and Spain also at 5 per cent or better. Between 1.0 and 1.5 standard deviations, negative turnover ratios dominate positives in 10 markets; Australia, Belgium, France, Italy, Japan, Netherlands, Spain, Switzerland, UK and US, although

Table 5.3 Interval Analysis of Turnover Distributions in International Equity Markets

Proportions of observations														
Intervals	Unit Normal	Australia	Belgium	Canada	France	Italy	Japan	NL	Switzerland	Sweden	Spain	UK	US	Average
0.5S	0.383	0.436	0.372	0.299	0.385	0.261	0.429	0.381	0.398	0.33	0.317	0.372	0.336	-0.023
		0.053	-0.011	-0.084	0.002	-0.122	0.046	-0.002	0.015	-0.053	-0.066	-0.011	-0.047	
1S	0.683	0.804	0.747	0.816	0.65	0.608	0.804	0.749	0.691	0.791	0.65	0.752	0.699	0.047
		0.121	0.064	0.133	-0.033	-0.075	0.121	0.066	0.008	0.108	-0.033	0.069	0.016	
1.5S	0.866	0.941	0.94	0.946	0.899	0.919	0.938	0.916	0.868	0.905	0.905	0.89	0.899	0.048
		0.075	0.074	0.08	0.033	0.053	0.072	0.05	0.002	0.039	0.039	0.024	0.033	
2S	0.955	0.968	0.971	0.979	0.979	0.967	0.966	0.954	0.963	0.951	0.971	0.945	0.958	0.009
		0.013	0.016	0.024	0.024	0.012	0.011	-0.001	0.008	-0.004	0.016	-0.01	0.003	
3S	0.997	0.987	0.99	0.994	0.996	0.995	0.992	0.987	0.995	0.99	0.995	0.991	0.992	-0.005
		-0.01	-0.007	-0.003	-0.001	-0.002	-0.005	-0.01	-0.002	-0.007	-0.002	-0.006	-0.005	
4S	1	0.995	0.994	0.998	0.999	0.999	0.997	0.996	0.998	0.997	0.999	0.999	0.999	-0.003
		-0.01	-0.006	-0.002	-0.001	-0.001	-0.003	-0.004	-0.002	-0.003	-0.001	-0.001	-0.001	
5S	1	0.998	0.997	0.998	0.999	1	0.998	0.998	0.999	0.998	1	0.999	1	-0.001
		-0	-0.003	-0.002	-0.001	0	-0.002	-0.002	-0.001	-0.002	0	-0.001	0	

Notes: Table 5.3 provides proportions of all observations within intervals of the distributions. Interval 0.5S refers to observations within one half standard deviation of the mean. The Unit Normal column gives the percentages of total observations that would be found if the distributions were normal. In the columns for each market, the top number is the proportion of observations within 0.5, 1, 1.5, 2, 2.5, 3, 4 and 5 standard deviations of the mean, and the bottom number is calculated by subtracting the corresponding unit normal entry from the top number. The averages column on the right of the Table gives the average proportion of observations in all markets relative to the standard normal distribution.

clearly not at the levels in the adjacent interval. This is a segment of the distribution that should be examined more closely, since it implies that much of the trading volume activity that happens at a daily frequency is below average, and the 'abnormally' high trading volumes are relatively rare. In the interval that contains observations between 1.5 and 2.0 standard deviations from the mean, I find that in 4 of the 12 markets, there are no negative entries in this interval; another 5 markets have less than 30 negatives and the remaining two, France and Switzerland are the only two that have more negatives than positives in this interval. In the next interval that contains ratios between 2 and 3 standard deviations from the mean, there are zero negative entries in 11 of the 12 markets, Switzerland being the exception. No country shows any negative entry greater than 3 standard deviations from the mean, but all markets have positive entries in all intervals up to and beyond 5 standard deviations from the mean.

The right hand column in Table 5.4 (*page 127*) gives the numbers of turnover ratios greater than 5 standard deviations from their means. It is worth noting here that all markets have one or more entries in this column, and that all entries are positive; this illustrates that there are some abnormally high ratios in the turnover distributions. In some cases, the numbers of these outliers are in single digits. For Italy, Spain and US for instance, there is only one observation greater than 5 standard deviations from the mean. From this one could extrapolate that looking to the extreme tails of the turnover distributions for explanations of trading volume behaviour may not be a useful exercise, since there are simply not enough observations in these tails for meaningful inference. However, Table 5.4 (*page 127*) shows that there are other intervals that can provide useful insights into how trading volume distributions are different to return distributions. For 10 of the 12 markets presented in Table 5.4 (*page 127*) there are wide ranging differences between the positive and negative excess turnover levels in Column 4, (1.5-2.0) and Column 5, (2.0-3.0), with the positive average excess turnover dominating the negative in these intervals. This could be construed to infer that dynamics in intervals of the distribution of turnover other than the extreme tails may have a role to play in explaining volume skewness.

Table 5.4 Binomial Distribution Test

		0-0.5S	0.5 - 1.0S	1.0 - 1.5S	1.5 - 2.0S	2.0 - 3.0S	3.0 - 4.0S	4.0 - 5.0S	>5.0s
Australia	Pos	924	580	327	139	101	46	12	12
	Neg	1389	1372	398	3	0	0	0	0
	p-value	0	0	0.01	0	0	0	0	0
Belgium	Pos	859	614	347	146	87	21	14	13
	Neg	892	1151	562	1	0	0	0	0
	p-value	0.44	0	0	0	0	0	0	0
Canada	Pos	826	896	561	208	97	20	5	10
	Neg	1052	2342	256	0	0	0	0	0
	p-value	0	0	0	0	0	0	0.07	0
France	Pos	755	627	411	164	72	11	3	3
	Neg	842	476	619	168	0	0	0	0
	p-value	0.03	0	0	0.87	0	0	0.25	0.25
Italy	Pos	624	660	467	223	133	16	4	1
	Neg	591	955	977	0	0	0	0	0
	p-value	0.36	0	0	0	0	0	0.13	1
Japan	Pos	724	405	226	102	98	19	3	7
	Neg	871	986	275	0	0	0	0	0
	p-value	0	0	0.03	0	0	0	0.25	0.02
Netherlands	Pos	800	501	289	159	157	46	10	8
	Neg	1012	1252	505	20	0	0	0	0
	p-value	0	0	0	0	0	0	0	0.01
Spain	Pos	578	579	344	161	88	16	2	1
	Neg	603	661	608	85	0	0	0	0
	p-value	0.48	0.02	0	0	0	0	0.48	1
Sweden	Pos	842	473	392	265	223	41	7	10
	Neg	1051	2167	262	0	0	0	0	0
	p-value	0	0	0	0	0	0	0.02	0
Switzerland	Pos	868	675	310	138	69	12	5	4
	Neg	716	490	398	239	57	0	0	0
	p-value	0	0	0	0	0.33	0	0.07	0.13
UK	Pos	552	369	273	221	211	37	3	3
	Neg	1153	1369	361	28	0	0	0	0
	p-value	0	0	0	0	0	0	0.25	0.25
US	Pos	787	526	524	365	215	40	7	1
	Neg	1326	1764	730	10	0	0	0	0
	p-value	0	0	0	0	0	0	0.02	1

Notes: The table provides the numbers of positive and negative excess turnover in each interval of the distributions of the 12 markets, along with the binomial test of difference in their number.

5.4.2. Wilcoxon Rank Sum and Siegel-Tukey Results

In both the Wilcoxon rank sum and the Siegel-Tukey test, the test statistic is the sum of the ranks of the negative excess turnover ratios. This is the test statistic that I used in Chapter 4 and continue to use in this chapter. I begin the analysis with a discussion of the Wilcoxon rank sum test and in the following paragraph I examine the Siegel-Tukey results. Recall from Table 3.7 (*page 85*) in Chapter 3 that the weights in the Wilcoxon rank sum test are concentrated in the tails and, as explained, the test statistic used is the sum of the ranks of the negative excess turnover ratios. This implies that if, as in this case, there is a scarcity of negative observations in the tails, the sums of the ranks of the negative excess turnover ratios will be below their expected values. The results of both the Wilcoxon rank sum tests and the Siegel-Tukey tests are presented in Table 5.5 (*page 130*). The Wilcoxon test rejects the equality of the distributions for 8 of the 12 markets, at 1 per cent for Australia, Canada, Italy, Netherlands, Sweden, the UK and the US and at 5 per cent for Japan. The Wilcoxon rank sum standardized statistics are negative, or below their expected values, for 10 of the 12 markets surveyed, the exceptions being Switzerland and France. In the case of the latter two markets the Wilcoxon rank sum test fails to reject the null hypothesis of symmetry. This is consistent with the visual evidence in the histograms in Figure 5.1 (*page 123*) and the two alternative skewness measures reported in the bottom half of Table 5.2 (*page 121*). The skewness coefficients for France (0.372) and Switzerland (0.334) are the lowest for all 12 countries and this pattern is repeated in the Pearson's coefficient of skewness statistics in Table 5.2 (*page 121*), (0.055) for France and (-0.153) for Switzerland. In addition the binomial distribution test results discussed in the preceding section and presented in Table 5.4 (*page 127*), show that France and Switzerland have cumulatively significantly fewer observations than all other markets in intervals greater than 2 standard deviations from the mean.

By contrast, Table 5.5 (*page 130*), shows that the Siegel-Tukey test statistics are positive for all markets except France and well above their expected values; the null hypothesis of equality in the dispersions of the distributions is not rejected in 11 of the 12 markets due to the higher concentrations of negative excess turnover ratios in the middle of the distribution, where the weights in the Siegel-Tukey test are located by construction. As in

the previous paragraph, the test statistic is the sum of the ranks of the negative excess turnover ratios. The Siegel-Tukey result for France is consistent with the histogram in Figure 5.1 (*page 123*) and the two skewness statistics in the lower half of Table 5.2 (*page 121*).

The foregoing discussion of the summary statistics, Fama normality tests, histograms and distribution-free tests has illustrated the nature of applying a multi-faceted approach to the analysis of the distributions of turnover ratios. While the summary statistics by definition provide a general picture of the overall distribution of turnover and the histograms provide a graphic image, the non-parametric tests refine the analysis by identifying either specific intervals where asymmetry occurs (the binomial test) or differences in location (Wilcoxon) or dispersion (Siegel-Tukey).

5.5 Returns and Volume Discussion

Karpoff (1987) argued that more could be learned about the capital market by studying prices in conjunction with volumes than by focusing on prices alone. I have daily price changes and corresponding daily turnover data for 12 international equity markets from 1980 to 2004. In this section, I examine the ten highest price changes together with the ten highest turnover ratios and the ten highest monthly volatilities, for all markets, ranked 1 to 10. I find that historically, the month of October 1987 still ranks highly in price changes and volatility figures for most countries. The impact of September 11 2001 is evident in a number of countries in a significantly negative price change on that day in some cases, in others, a price drop occurs a day or two later. The countries where the impact was immediate were France, Italy, Sweden, Switzerland, and the UK. The impact was felt in Japan a day later and in the Netherlands three days later. The US market ceased to trade on that day and remained closed for a further four days.

5.5.1 Individual Country Analysis

The analysis which follows is motivated by Karpoff's (1987) suggestion that more could be learned about the capital market by studying prices in conjunction with volume than by focusing on prices alone. The country by country analysis makes use of price, volume and

Table 5.5 Wilcoxon and Siegel-Tukey test Results

	<i>W*</i>	<i>p-value</i>	<i>ST*</i>	<i>p-value</i>	<i>Obs</i>
Australia	-6.44	0	16.12	1	5303
Belgium	-0.39	0.35	13.41	1	4707
Canada	-5.35	0	30.92	1	6273
France	0.69	0.75	-4.88	0	4151
Italy	-3.12	0	23.69	1	4651
Japan	-1.74	0.04	15.17	1	3716
Netherlands	-4.87	0	4.18	1	4759
Spain	-0.6	0.28	5.02	1	3726
Sweden	-10.39	0	32.66	1	5733
Switzerland	18.82	1	1.1	0.86	3981
UK	-14.85	0	25.33	1	4580
US	-17.07	0	27.41	1	6295

Notes: W is the standardized Wilcoxon rank sum statistic and ST* is the standardized Siegel-Tukey statistic. The p-values are marginal sig. levels.*

volatility data and seeks to relate theory to practice. Unquestionably the month of October 1987 had a strong and significant impact on price in the countries for which I had volume data that preceded that date. The method of extracting the 10 top price changes and 10 top turnover rates may be a blunt instrument in the analysis of price and volume dynamics, but it does provide for a surprising amount of confirmation of basic financial theory. The fact that a number of countries in the study were in the process of currency change while others were not allowed for some speculation in relation to very high volume levels, not accompanied by associated price change or volatility.

Table 5.6 (*pages 138/9*) presents the ten greatest price changes together with the ten highest volume levels, ranked 1 to 10 in order of magnitude, for each individual market. The information in Table 5.6 (*pages 138/9*) is presented graphically in Figure 5.2 (*page 141*) in which the price change and turnover ratio are plotted on the same axis. The information in Figure 5.2 (*page 141*) is available as a result of normalising the excess turnover ratio by the mean as explained in Section 5.2 above. In discussing the price changes and volume levels, I refer where appropriate to the information on monthly volatility contained in Table 5.7 (*page 140*). My objective is to investigate the extent to which extreme price changes coincide with high trading volume levels and/or higher volatility. The study for Australia begins in January 1984. The single largest price change, a 29.44 per cent drop in price, occurred on 20/10/1987, and in fact 8 of the top 10 price changes were recorded in 1987, 5 of the 8 being negative. Looking at the volume data for the corresponding time period, I find that in the top 10 turnover levels there is one entry for October 1987, 27/10/1987, exactly one week after the largest drop in relative price changes in the Australian stock market. Table 5.7 (*page 140*) shows that the Australian stock market was very volatile during the month of October 1987; in my study of all markets for which I had volume data, Australia had the highest volatility for the month of October 1987, with a standard deviation of 0.07. Clearly trading volume and volatility were positively related in Australia 1987 supporting the theory that says that volatility is always accompanied by contemporaneous high trading volumes but high trading volumes are not always accompanied by volatility.

The year 1987 features again in examining high price changes, trading volume levels and volatility in Belgium. Table 5.6 (*pages 138/9*) shows that the largest price change, a drop of 13 per cent occurred on the 19/10/1987, one of 4 for that year alone in the top 10. Table 5.7 (*page 140*) shows the month of October 1987 to be the most volatile month and November 1987 ranked in the top 10 also. There are four positive price changes in 2002 and 2003, two of these occurring on consecutive days in March 2003. In terms of volatility Table 5.7 (*page 140*) records 4 consecutive months in 2002, July, August, September, and October when volatility levels were within the top 10. The highest level of turnover, 11.4, is recorded in April 2003; it seems likely that the volumes recorded in 2003 are a response to the high price changes and volatility in 2002. Of the top 10 price changes for Belgium in Table 5.6 (*pages 138/9*) it is worth noting that 2 were negative and 8 were positive.

The data for Canada starts on 02/01/1980. The top three absolute price changes are all recorded in October 1987, the largest on 14/10/1987, second largest on 16/10/1987 followed by the third largest on 21/10/1987. Since the largest price change is negatively signed and the second largest recorded two days later is positively signed it appears that the Canadian stock market as a whole was somewhat volatile in the days preceding the stock market crash of 1987. This is confirmed in Table 5.7 (*page 140*) which shows the highest historical volatility level occurring in October 1987. Table 5.6 (*pages 138/9*) shows 8 dates in the first quarter of 1982 when the highest turnover rates for Canada are recorded, 4 in the month of January alone. The month of November 1982 has 2 consecutive price changes ranked in the top 10, a negative on 4/11/1982 followed by a positive on 5/11/1982. Table 5.7 (*page 140*) shows the volatility for November 1982 ranked second in the top 10. Financial theory states that in equity markets, large movements in volumes are positively related to price changes *per se*, and not just to the magnitude of the price changes, $|\Delta p|$.

For France, Table 5.6 (*pages 138/9*) shows four dates in 1982 when historically high price changes occurred. October and November saw the sign of the price change oscillate between positive and negative while the highest turnover ratio, 3.96, occurred on 27/11/2002. This convergence of high fluctuating price changes and historically high

turnover is confirmed in looking at the volatility figures in Table 5.7 (*page 140*). The highest monthly volatility is July 2002 and within the top 10 there are 5 in the latter half of 2002. This is again supportive of the financial theory that finds a high price change is accompanied by a high trading volume as well as the well- documented link between volume and volatility. The highest turnover figure on 27/11/2002 is clearly a response to the volatility of the previous three months and affirms the positive volume/ volatility relation. The impact of September 11, 2001 is evident in that the largest price change, a decline of 7.36 per cent is recorded on that date.

The Italy price and volume data starts on 01/07/1986. Similar to France, Table 5.6 (*pages 138/9*), shows the largest price change, a drop of 7.79 per cent occurred on 11/09/2001 and two dates in 1997, 20/6/1997 and 19/9/1997 when record numbers of volumes were traded. The year 1997 also features in the ten most extreme price changes, showing a drop of 6.47 per cent on 28/10/1997. The highest volatility for Italy, as shown in Table 5.7 (*page 140*), occurred in September 2001 and is clearly related to the negative price change on the same date. There are three months in 1998 when record levels of volatility are evident in Italy, April, September and October, related most likely to the two extreme price changes for April and October in 1998. October 1997 also features in Table 5.6 (*pages 138/9*) as one of the top 10 recorded levels of volatility. It seems clear that there is a definite empirical relationship between the volatility and volume levels in Italy in 1998. Looking at Table 5.6 (*pages 138/9*) there are three dates in 2002, two in 2003 and one in 2004 when record numbers of volumes were traded. However, the volume levels traded in Italy in 2003 and 2004 do not seem to be price related, certainly not to the same extent as in 1998. There are two months in 2002 when volatility levels for Italy were in the top 10, July and September, consistent with the very high trading volume levels for 2002. The reason for this anomaly may be related to the impact of the Euro changeover on Italian investing behaviour. As was the case with other countries within the Euro zone, Italian investors could now look outside Italy without incurring a foreign currency risk. In order for instance to have equity to rebalance investment portfolios, fund managers would have been constrained to liquidate existing stocks listed on the Italian stock exchange, leading to large levels of trading volumes not accompanied by large price changes, *per se*. The time lag between the

introduction of the Euro and the ‘anomalous’ volume behaviour is not surprising given that the changeover took place over a number of years, and other factors unique to Italy itself such as political instability, for example, would also have contributed.

There are 5 entries in Japan, three on consecutive dates at the end of October and two in early November 1993, when record volumes were traded in the Japanese market. Table 5.6 (*pages 138/9*) shows this pattern of very high trading extending into the early part of 1994 with record trading activity on 31/1/1994 and 1/2/1994. In the top price changes there is one date 31/1/1994 when a price rise of 6.64 per cent is recorded. Financial theory states that a large volume is accompanied by either a large increase or a large decrease in price; in this case it does seem possible to conclude that the volumes are driving up the price. Table 5.6 (*pages 138/9*) shows three extreme price changes for 1990, one positive and two negative. Table 5.7 (*page 140*) confirms this with four months, March, April, August and October when volatility levels were historically high.

The highest recorded turnover ratio for the Netherlands, 4.83, occurred on 30/06/1987. The largest price change, a drop of 11 per cent occurred on 19/10/1987, and the second largest, also a negative price change of 7 per cent is reported a week later on 26/10/1987. On two consecutive days in November 1987, 11/11/1987 and the 12/11/1987, Table 5.6 (*pages 138/9*) shows a strong recovery in the Netherlands market. The impact of September 11, 2001 is evident in price change, turnover and volatility levels. Table 5.6 (*pages 138/9*) shows four days 12/9/2001, 20/9/2001, 21/9/2001 and 25/9/2001 when historically high volumes were traded. The impact on price is also evident in two entries for September, a decline of 6.21 per cent on 14/9/2001 and a rise of 5.87 per cent on 24/9/2001. In terms of volatility, September 2001 is ranked third in the top 10. Table 5.7 (*page 140*) shows four months in 2002, July, August, September and October when the volatility for the Netherlands was at record levels. This is borne out in Table 5.6 (*pages 138/9*) with two price changes in July, a drop of 6.66 per cent on 22/7/2002 and a rise of 5.81 per cent a week later. It is possible that the volatility in 2002 is a response to the historically high trading volumes in the latter half of 2001, as evident in Table 5.6 (*pages 138/9*).

For Spain Table 5.6 (*pages 138/9*) shows the second largest volumes traded on 28/10/1997 and a day later a price rise of 5.6 per cent. In terms of extreme price changes 7 of the top 10 occurred in the years between 1997 and 1999, three positive and four negative. By contrast the highest trading volumes occur predominantly within the years 2000-2004. Consistent with the fluctuating price changes in Table 5.6 (*pages 138/9*), Table 5.7 (*page 140*) shows August, September and October 1998 to be highly volatile and October 1997 features within the top 10 months when volatility was at historically high levels.

The impact of September 11, 2001 is again evident in the Swedish stock market, with a drop of 8.5 per cent in price on that day shown in Table 5.6 (*pages 138/9*). The volatility for September 2001 is ranked 5th in the top 10 historically high volatility levels, as shown in Table 5.7 (*page 140*). There are two consecutive dates in October 1987, 29/10/1987 and 30/10/1987 when a price decline of 8.1 per cent was followed by a rise of 7.4 per cent. This is borne out in Table 5.7 (*page 140*) which shows very high volatility in Sweden for October and November 1987.

The impact of September 11, 2001 on Switzerland is evident in Table 5.6 (*pages 138/9*) in a price decline of 6.9 per cent on 11/9/2001 and a further drop in price of 5.04 per cent on 21/9/2001. On the same date, the third highest turnover ratio of 2.47 is recorded. Three days later, Table 5.6 (*pages 138/9*) shows a price increase of 5.64 per cent, indicating a high level of volatility. This is borne out in Table 5.7 (*page 140*) which shows the month of September 2001 to be the most volatile of all months for Switzerland. The year 2002 also features strongly in Table 5.7 (*page 140*) with four consecutive months, July, August, September and October returning historically high volatility figures. The volatility in 2002 is consistent with the price change data in Table 5.6 (*pages 138/9*), where on two dates 19/7/2002 and 25/7/2002 a drop of 5.05 and 5.17 per cent respectively were recorded.

Table 5.6 (*pages 138/9*) shows five dates, four of them consecutive, during the month of October 1987 when record price changes are shown for the U.K. On only one of those dates, 21/10/1987, was the price change positive. Consistent with the price declines in October 1987, the months of September and October 1987 feature in the top 10 historically

high volatility levels, as evident in Table 5.7 (*page 140*). The highest turnover ratio for the U.K. (3.27) is reported on 20/9/2002 which is followed by a historically high price rise of 4.62 per cent on 15/10/2002.

The concentration of record levels of volumes in 2004 is not reflected in volatility. When I look for trend in the raw price data I find an upwardly trending market, particularly in the latter half of 2004. The correlation between price change and volume level for 2004 is recorded as -0.09. This finding of record levels of trading volumes in an upwardly trending market does not support the hypothesis of an asymmetric volume /price change relationship of Karpoff (1987), and Gerlach et al (2005). However in the second half of 2004, the US dollar was losing value due in part to a monetary policy on the part of the Federal Reserve; it is plausible to assume that investors who were selling dollars were buying Sterling. Traditionally too, the stock markets of US and UK are closely associated with significant degrees of integration and co movement.

For the US market the largest price change was a drop of 21 per cent recorded on 19/10/1987, followed two days later by an increase of 8.3 per cent, and one week later on 26/10/1987, a fall of 8.4 per cent. Looking at the volatility levels in Table 5.7 (*page 140*), I find October 1987 to be the most volatile month in the US. Although there were two dates in October 1987, 20/10/1987 and 21/10/1987 when record levels of volumes were traded (not shown in Table 5.6 (*pages 138/9*) because they were not ranked in the top 10), Table 5.6 (*pages 138/9*) shows that the 10 historically highest trading volumes all occurred since the year 2000. The highest turnover ratio (2.84) is recorded on 3/1/01, corresponding exactly with a historically high price rise of 5.33 per cent. The second highest turnover ratio (2.44) corresponds exactly with a price rise of 5.37 on 24/7/02. There are two dates in April 2000, the 4/4/2000 and the 17/4/2000 when record volumes were traded in the US market, (2.44 and 2.21 respectively). Between these two dates Table 5.6 (*pages 138/9*) shows a price drop of 6.8 per cent on 14/4/2000. Consistent with the high trading volumes, preceding and succeeding a sharp fall in price, Table 5.7 (*page 140*), shows April 2000 ranked third in US volatility levels. April 2001 shows a historically high turnover ratio

(2.31) on 18/4/2001 match by a historically high volatility level, as shown on Table 5.7 (*page 140*). This confirms the positive volume volatility relation of Karpoff (1987).

In summary, the foregoing analysis could be regarded as being in the same vein as the Gallant, Tauchen and Rossi (1992) analysis, as reviewed in Chapter 2. The main limitation of the study is the requirement to limit the analysis to the ten greatest price changes, turnover ratios and volatility levels. The stock market crash of 1987 and the catastrophic events of September 2001 are both prominent in almost all countries surveyed. The observation that prices are as likely to rise as fall on high contemporaneous trading volumes is corroborated in a number of instances, implying that the first moment of trading volume is not a reliable indicator of future negatively skewed returns. This provides a good motivation to incorporate higher moments of trading volumes as I do in Chapter 7.

Table 5.6 Ten Greatest Price Changes and Volume Levels

		1	2	3	4	5	6	7	8	9	10
Australia	Price changes	-29.44	-8.57	-7.97	-6.99	-6.67	-6.34	-6.29	6.14	6.07	5.77
	Date	20/10/87	29/10/87	16/10/89	28/10/97	26/10/87	23/10/87	4/11/87	13/11/87	28/10/87	2/11/87
	Volume	15.38	8.87	5.56	3.62	3.24	3.20	3.07	3.07	3.07	3.03
	Date	10/4/86	22/6/98	28/6/90	28/6/02	31/7/95	27/9/89	27/10/87	31/3/03	22/5/86	29/10/04
Belgium	Price Changes	-12.99	7.48	-6.91	6.38	5.76	5.71	5.43	5.42	5.34	5.32
	Date	19/10/87	13/3/03	28/10/87	14/3/03	15/10/02	30/10/87	17/1/91	21/10/87	16/3/00	29/7/02
	Volume	11.41	6.48	5.65	5.35	4.88	4.35	4.11	3.90	3.56	3.50
	Date	24/4/03	11/2/92	12/6/98	15/1/99	7/2/92	21/9/88	19/12/97	20/8/99	20/6/97	14/3/01
Canada	Price Changes	-11.65	8.76	-8.03	-7.53	-7.33	-7.25	7.08	-6.16	-6.03	-5.58
	Date	14/10/87	16/10/87	21/10/87	4/11/82	15/10/87	20/10/00	5/11/82	22/10/97	24/8/98	11/4/00
	Volume	15.42	13.18	12.23	11.90	8.27	7.48	6.93	5.00	3.97	3.96
	Date	6/1/82	11/2/82	14/4/82	5/1/82	25/1/82	29/3/82	12/2/82	12/1/82	16/5/97	27/4/00
France	Price Changes	-7.36	-6.78	-6.24	6.17	6.02	5.98	5.85	5.73	5.39	-5.35
	Date	11/9/01	19/8/91	16/10/89	14/3/03	29/10/97	15/10/02	29/7/02	17/1/91	26/9/02	30/9/02
	Volume	3.96	3.52	3.41	2.94	2.86	2.70	2.42	2.34	2.31	2.30
	Date	27/11/02	26/2/03	28/11/03	30/9/04	21/4/04	18/6/04	21/9/01	23/6/04	11/3/04	24/7/02
Italy	Price Changes	-7.79	-7.60	-7.23	6.90	-6.62	-6.58	-6.47	6.43	-6.39	5.91
	Date	11/9/01	19/8/91	16/10/89	24/9/01	14/9/01	27/4/98	28/10/97	12/10/98	19/10/87	30/1/96
	Volume	5.16	4.17	3.98	3.82	3.77	3.35	3.33	3.25	3.24	3.18
	Date	18/6/04	19/9/97	20/6/97	20/12/02	21/9/01	20/6/03	21/6/02	25/6/03	6/5/94	20/9/02
Japan	Price Changes	9.39	-7.21	7.12	-6.52	6.52	6.46	-6.45	6.38	6.06	-5.96
	Date	2/10/90	2/4/90	21/8/92	17/4/00	10/4/92	31/1/94	12/9/01	17/11/97	21/3/01	23/8/90
	Volume	15.31	10.21	7.05	6.88	4.78	4.37	4.19	3.12	3.04	3.04
	Date	27/10/93	28/10/93	2/4/01	29/10/93	31/1/94	2/11/93	1/2/94	12/3/04	10/11/93	8/3/02

Table 5.6 Ten Greatest Price Changes and Volume Levels (continued)

		1	2	3	4	5	6	7	8	9	10
Netherlands	Price Changes	-11.03	-7.13	7.00	-6.66	6.21	-6.21	6.19	5.87	5.84	5.81
	Date	19/10/87	26/10/87	13/3/03	22/7/02	12/11/87	14/9/01	11/11/87	24/9/01	15/10/02	29/7/02
	Volume	4.83	3.57	3.42	3.25	3.15	2.74	2.73	2.70	2.45	2.42
	Date	30/6/87	19/2/96	21/9/01	4/1/01	19/1/01	1/3/01	20/9/01	12/9/01	25/9/01	13/5/93
Spain	Price Changes	-8.22	-6.64	-6.57	-6.51	6.33	-6.11	-5.97	5.67	5.61	5.30
	Date	19/8/91	13/1/99	10/9/98	1/10/98	17/1/91	6/8/90	27/8/98	29/10/97	4/1/99	23/9/98
	Volume	2.81	2.33	2.27	2.08	2.04	1.95	1.89	1.86	1.84	1.81
	Date	15/3/04	28/10/97	13/1/00	21/9/01	19/9/03	16/3/04	7/1/00	21/3/03	13/1/99	7/1/04
Sweden	Price Changes	10.86	10.19	-8.50	-8.10	7.75	7.65	-7.55	-7.54	7.44	-7.38
	Date	12/10/98	20/11/92	11/9/01	29/10/87	29/7/02	17/1/91	5/10/92	16/10/89	30/10/87	12/3/01
	Volume	5.78	5.73	5.66	5.23	4.47	4.42	4.40	4.32	4.23	4.23
	Date	6/2/04	5/3/04	26/10/01	20/10/00	11/3/04	29/4/03	26/1/01	22/10/99	8/1/04	25/4/02
Switzerland	Price Changes	-9.30	-7.41	-6.90	6.43	-6.12	5.64	-5.39	-5.17	-5.05	-5.04
	Date	16/10/89	19/8/91	11/9/01	6/10/98	6/8/90	24/9/01	22/3/01	25/7/02	19/7/02	21/9/01
	Volume	2.70	2.66	2.47	2.37	2.25	2.16	2.14	2.11	1.91	1.86
	Date	28/10/97	21/3/03	21/9/01	20/6/03	17/3/00	18/6/04	19/3/04	31/7/96	28/8/98	22/1/97
UK	Price Changes	-13.01	-9.29	-7.09	6.49	5.41	-5.37	-5.27	-5.14	5.08	4.62
	Date	20/10/87	19/10/87	26/10/87	21/10/87	10/4/92	11/9/01	22/10/87	15/7/02	13/3/03	15/10/02
	Volume	3.27	2.96	2.67	2.35	2.26	2.16	1.97	1.96	1.92	1.90
	Date	20/9/02	11/2/00	12/1/01	17/2/04	11/3/04	21/9/01	5/5/04	17/7/02	18/2/04	8/2/00
US	Price Changes	-20.71	-8.41	8.35	-7.03	-6.80	-6.80	-6.40	-6.00	5.37	5.33
	Date	19/10/87	26/10/87	21/10/87	31/8/98	14/4/00	27/10/97	8/1/88	13/10/89	24/7/02	3/1/01
	Volume	2.84	2.44	2.44	2.31	2.24	2.21	2.20	2.11	2.01	1.97
	Date	3/1/01	24/7/02	4/4/00	18/4/01	4/1/01	17/4/00	15/12/00	26/10/00	16/3/00	18/10/00

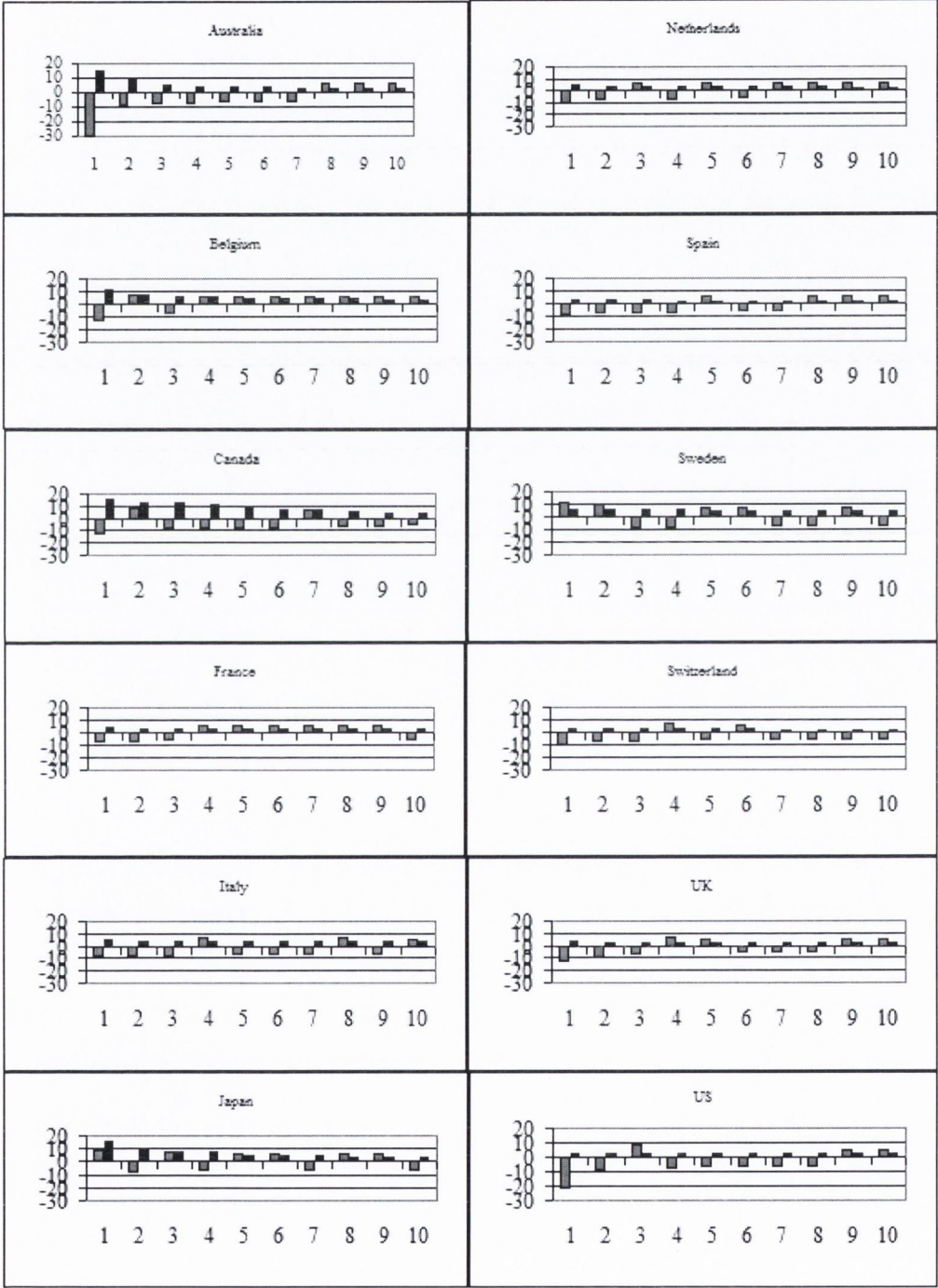
Notes: This table shows the ten greatest price changes and volume (turnover ratios) ranked 1 to 10 in 12 equity markets. The corresponding dates are located in the cells immediately below the relevant figures.

Table 5.7 Ten Greatest Monthly Volatilities

		1	2	3	4	5	6	7	8	9	10
Australia	Volatility	0.0697	0.0316	0.0221	0.0216	0.0185	0.0172	0.0170	0.0161	0.0145	0.0145
	Date	Oct-87	Nov-87	Oct-97	Oct-89	Apr-00	Sep-01	Dec-87	Mar-88	Jan-88	Oct-98
Belgium	Volatility	0.0394	0.0286	0.0281	0.0229	0.0219	0.0215	0.0215	0.0210	0.0196	0.0195
	Date	Oct-87	Mar-03	Jul-02	Sep-01	Aug-02	Oct-02	Aug-90	Sep-02	Nov-87	Oct-98
Canada	Volatility	0.0432	0.0252	0.0244	0.0240	0.0213	0.0206	0.0201	0.0191	0.0166	0.0165
	Date	Oct-87	Nov-82	Apr-00	Oct-00	Aug-98	Mar-80	Sep-98	Dec-00	May-00	Oct-97
France	Volatility	0.0298	0.0283	0.0272	0.0271	0.0269	0.0249	0.0240	0.0226	0.0213	0.0202
	Date	Jul-02	Mar-03	Oct-02	Sep-01	Sep-02	Aug-02	Oct-98	Sep-98	Jun-02	Oct-97
Italy	Volatility	0.0359	0.0299	0.0294	0.0290	0.0274	0.0234	0.0227	0.0222	0.0214	0.0204
	Date	Sep-01	Sep-98	Oct-98	Apr-98	Oct-87	Oct-97	Aug-90	Jan-99	Jul-02	Sep-02
Japan	Volatility	0.0277	0.0257	0.0257	0.0246	0.0243	0.0241	0.0237	0.0232	0.0228	0.0226
	Date	Nov-97	Aug-92	Oct-90	Sep-01	Aug-90	Apr-92	Mar-01	Apr-90	May-04	Oct-98
Netherlands	Volatility	0.0349	0.0332	0.0321	0.0309	0.0308	0.0278	0.0264	0.0258	0.0258	0.0256
	Date	Oct-87	Jul-02	Sep-01	Nov-87	Mar-03	Aug-02	Sep-02	Oct-98	Oct-02	Sep-98
Spain	Volatility	0.0299	0.0270	0.0268	0.0265	0.0259	0.0245	0.0219	0.0217	0.0213	0.0211
	Date	Sep-98	Oct-98	Jan-99	Jul-02	Aug-90	Sep-01	Aug-91	Aug-98	Oct-97	Aug-02
Sweden	Volatility	0.0388	0.0376	0.0347	0.0322	0.0299	0.0298	0.0296	0.0276	0.0272	0.0269
	Date	Oct-98	Oct-87	Nov-87	Jul-02	Sep-01	Mar-01	Sep-92	Apr-01	Oct-02	Nov-92
Switzerland	Volatility	0.0315	0.0274	0.0263	0.0261	0.0239	0.0238	0.0234	0.0217	0.0214	0.0209
	Date	Sep-01	Jul-02	Oct-98	Sep-98	Mar-03	Aug-90	Oct-89	Aug-02	Oct-02	Sep-02
UK	Volatility	0.0419	0.0286	0.0245	0.0220	0.0218	0.0215	0.0211	0.0200	0.0198	0.0172
	Date	Sep-87	Jun-02	Aug-01	Feb-03	Oct-87	Aug-02	Jul-02	Sep-02	Sep-98	Feb-01
US	Volatility	0.0564	0.0260	0.0243	0.0220	0.0219	0.0210	0.0207	0.0206	0.0205	0.0205
	Date	Oct-87	Jul-02	Apr-00	Oct-02	Sep-01	Sep-98	Jan-88	Aug-98	Aug-02	Apr-01

Notes: This table presents the 10 greatest monthly volatility figures for 12 equity markets. The corresponding month is reported directly beneath the volatility.

Figure 5.2 Ten Greatest Price Changes and Volume Levels



Notes: This figure shows the 10 greatest price changes and volume levels (turnover ratios) for each individual country. The horizontal axis is ranked 1 -10, where 1 is greatest.

■ Volume levels ■ Price changes

5.6 Summary and Conclusions

In this chapter I have examined the distribution of trading volume turnover in 12 international equity markets. In Section 5.2, I explained the motivation and method used in normalising the volume data. The summary statistics in Table 5.2 (*page 121*) show return skewness is negative in all countries except Japan, while turnover skewness is mainly positive. Pearson's coefficient of skewness is negative for Switzerland. The standard deviation of turnover is significantly higher than return standard deviation. In Section 5.3, I discussed the histograms of the turnover distributions, highlighting the fact that France and Switzerland, exceptionally, are showing evidence of either negative skewness (Switzerland) or symmetry (France). I then used the Fama (1965) method to analyse the distributions of turnover relative to the standard normal. One pertinent difference between the analysis of returns in Chapter 4 and turnover in this chapter is the deficiency of relative frequency within one half standard deviation of the mean in the volume distributions and an excess of relative frequency of 11.3 per cent within this one interval in the returns distributions in Chapter 4.

In Section 5.4, I analysed the nature of the asymmetry using the binomial distribution, the Wilcoxon rank sum and the Siegel Tukey tests. The binomial distribution test identifies one interval of the volume distributions, between 0.5 and one standard deviation of the mean, where the average proportion of negative excess turnover is 65.7 per cent. This pattern of statistically significant differences in probability of obtaining a negative versus a positive excess turnover ratio is maintained in the interval between 1 and 1.5 standard deviations. In Section 5.4.2, the Wilcoxon rank sum test fails to reject the null hypothesis of symmetry for France and Switzerland, a finding that is consistent with Pearson's coefficient of skewness in Table 5.2 (*page 121*). The Siegel-Tukey test result for France is also consistent with the evidence in the histogram in Figure 5.1 (*page 123*) and the two skewness measures in Table 5.2 (*page 121*).

I performed a detailed analysis of the 10 highest absolute price changes and turnover ratios for all 12 country market indexes. I cross-referenced the relevant dates against the monthly

volatility data for the same markets and discussed the degree to which the theoretical relationships between absolute price changes, high trading volume and volatility are confirmed or absent. October 1987 accounts for the highest price declines and the highest levels of associated trading volumes and volatility levels in those countries whose dates preceded 1987. I find very high levels of trading volume, not correlated with steep price movements or volatility in a number of European countries in the early years of this century. This would appear to be related to the Euro currency changeover.

Having examined the asymmetry in the distributions of returns in six international equity markets in Chapter 4 and the asymmetry of trading volume turnover in twelve international equity markets in Chapter 5, I now highlight some salient differences in the distributions. Firstly, returns distributions are characterised by negative skewness whereas trading volume turnover distributions are clearly positively skewed. This is clearly shown in the summary statistics in Table 5.2 (*page 121*). Secondly, in returns distributions, both positives and negatives are observed in all intervals equidistant from the mean, but this is not the case in the volume distributions. The binomial distribution tests in this chapter show clearly that in intervals in excess of 5 standard deviations above the mean, every country has one or more entries, but there are no negative entries observed in any interval in excess of 3 standard deviations below the mean. Thirdly, in Chapter 4, it is the Siegel-Tukey test, which detects differences in dispersion that identifies asymmetry in three equity markets. By contrast, it is the Wilcoxon rank sum test, which detects differences in location that identifies asymmetry in the volumes distributions. Fourthly, the Fama normality tests of returns identify over 11 per cent excess frequency within one half standard deviation of the mean relative to a normal distribution, as demonstrated in Chapter 4. The same test identifies a deficiency of relative frequency of 2.3 per cent within half standard deviation of the mean in the volumes distributions. Thus far I have shown that the distributions of equity returns and volumes are different. Having discussed the main differences in equity market returns and volumes distributions as demonstrated in Chapters 4 and 5, I now apply a similar analysis to the distributions of FOHF returns.

Chapter 6

Asymmetry in Fund of Hedge Funds Returns

6.1. Introduction

Previous researchers investigating the distributional characteristics of asset returns have usually relied on parametric tests of asymmetry, and this is no different in hedge fund research. Most of the early studies of hedge fund and FOHF performance used assessment techniques such as the Sharpe ratio or Jensen's alpha; for example, Agarwal and Naik (2001), Amin and Kat (2003), Fung and Hsieh (1999) and Lo (2001). The key assumption of these performance measures is that returns are normally distributed and investors focus only on the expected return and the standard deviation of returns. Prior studies of hedge fund performance that have included an analysis of asymmetry, such as Brooks and Kat (2001), Kat and Lu (2002) and Lamm (2003) use the skewness statistic, and generally find that hedge funds and hedge fund indexes are either not significantly skewed or negatively skewed. With strong evidence of non-normality, the mean and standard deviation are not sufficient to describe the return distribution, and higher moments need to be considered. Brooks and Kat (2001) show that although hedge funds offer high mean returns and low standard deviations, the returns also exhibit third and fourth moment attributes (skewness and kurtosis) that are precisely the opposite of those that investors desire. They find that high Sharpe ratios tend to go together with negative skewness and high kurtosis, and this suggests that the relatively high means and low standard deviations offered by hedge funds and FOHFs are very much a partial picture of return outcomes.

In this chapter, I extend the analysis of asymmetry to a dataset of 332 FOHFs and associated indexes, for example, the Standard and Poor's 500. I have elected to examine FOHF asymmetry in preference to hedge fund index data because FOHFs do not suffer from the data conditioning biases that are well understood to affect hedge fund returns data, Fung and Hsieh (2002). The chapter is structured as follows. In Section 6.2, I describe my approach to the investigation of asymmetry in FOHFs distributions, using the binomial distribution test described fully in Section 3.5.5, Chapter 3. The distributional characteristics of the FOHFs are identified in Section 6.3 and in Section 6.4 I compare the

Binomial distribution tests results for the S&P 500, the hedge fund index I use, the FOHF index and four sub strategy indexes. In the final section, I present a summary and conclusions.

6.2 Non Parametric Tests

Of the 332 FOHFs in the sample, 74 are classified as conservative, 153 are diversified, 34 are market defensive and 71 are strategic. I use a non parametric approach initially to test the asymmetry of the returns, beginning with the binomial distribution test which is described fully in Chapter 3. Using the binomial test I calculate the probability of obtaining a negative versus a positive excess return within $\frac{1}{2}$, $\frac{1}{2} - 1$, $1 - 1\frac{1}{2}$, and $1\frac{1}{2} - 2$ standard deviations of the mean, and in the tails between 2 and 3, 3 and 4, and 4 and 5 standard deviations either side of the mean. The results show little evidence of significant asymmetry in FOHF returns. While it is generally assumed that hedge fund skewness is due to observations in the left tail of the return distribution (because the nature of many hedge fund strategies means that occasional large negative returns would be a feature of the expected payoff), when I do find evidence of asymmetry using the binomial distribution test in the intervals above, it is close to the mean rather than in the tails. I also show that for FOHFs the skewness coefficient can lead to incorrect inferences about the nature of return distributions.

The age profile of these funds is summarised in Table 6.1 (*page 146*) which confirms the massive growth in FOHF formation in recent years. The mean (median) fund age is 57 (45) months, and over half (53 percent) are less than 4 years old, with only 10 percent being more than 10 years old. While the data for the individual FOHFs begins in January 1988, because the hedge fund indexes are available only from January 1990, I eliminate observations before January 1990. Due to data limitations, I also remove funds that have been in existence for less than $2\frac{1}{2}$ years, leaving a data set of 332 FOHFs. The attrition rate for the sample is low. Of the 525 funds in the data set, 14 had ceased reporting by March 2003. Of these, 10 had more than 30 return observations and so were retained, leaving more than 70 percent of the defunct funds in the sample, which is more than the 63 percent of the full sample that had greater than 30 observations.

Table 6.1 FOHF age

Age	Count	Cumulative count	Proportion of Sample (%)	Cumulative proportion (%)
< 6 months	26		5	
6 – 12 months	32	58	6.1	11.1
12 – 18 months	61	119	11.6	22.7
18 – 24 months	38	157	7.2	29.9
24 – 30 months	36	193	6.9	36.8
30 – 36 months	26	219	5	41.8
3 – 4 years	60	279	11.4	53.2
4 – 5 years	50	329	9.5	62.7
5 – 7 years	64	393	12.2	74.9
7 – 10 years	76	469	14.5	89.4
> 10 years	56	525	10.6	100

Notes: The first column gives the age of the FOHF. The figure in Row 2(6-12) months, includes 6 but < 12. The first entry in Column 3 is the sum of the first two entries in Column 2.The first entry in Column 5 is the sum of the first two entries in Column 4.

Table 6.2 (*page 148*) presents descriptive statistics for the indexes and for the S&P 500 for the period January 1990 to May 2003. Consistent with prior studies of hedge fund performance, the hedge fund index appears to generate higher returns (13.9 percent versus 10.9 percent) and lower volatility (a standard deviation of 7.22 percent compared with 15.25 percent) than the S&P 500 over the same period. All of the FOHFs indexes show lower annual average returns than the hedge fund index, but these lower returns are offset by lower standard deviations for all of the sub-indexes except for the strategic index (which is to be expected given that strategic FOHFs specialise in hedge funds with aggressive strategies). Also consistent with its construction, the conservative index has both the lowest return and the lowest standard deviation of all the FOHFs indexes. It appears that the funds' diversification benefits are outweighed by the double fee structure inherent in FOHFs. The most visible FOHF fees are management fees which are usually set at 1 per cent of the total of assets under management, and performance fees, which are usually set at 10 per cent of return. This is on top of standard hedge fund fees of typically 2 per cent of assets under management and 20 per cent of return (Jaffer, 2003).

6.3 FOHF distributional features

The last column of Table 6.2 (*page 148*) reports the results of the Jarque-Bera test for normality. For all the FOHFs indexes, the null hypothesis of normality is rejected at the 1 percent level, whereas for the S&P 500, normality is rejected only at the 10 percent level. In all cases, the index return distributions show significant excess kurtosis, but the findings for skewness are not as consistent. Interestingly, while the hedge fund index is significantly left-skewed, the FOHFs composite is negatively skewed but not significantly so. This is consistent with Brooks and Kat (2001) who found that all but one of the FOHFs indexes in their sample were not significantly skewed. The conservative and strategic sub-indexes are significantly negatively skewed, but there is no significant skewness for the market defensive and diversified sub-indexes. While investing in FOHFs on the face of it looks like an inferior risk-return trade-off relative to the hedge fund index, the skewness statistics give some indication that this may be offset by a distribution of returns with fewer small or negative values.

Table 6.2 Descriptive statistics for FOHF indexes

	Average Annual Return	Annual standard deviation	Skewness	Kurtosis	JB
S&P 500	10.88	15.25	-0.43*	3.37*	5.69 -0.06
Hedge fund	13.94	7.22	-0.62*	5.50*	49.62 0
FOF composite	9.93	5.86	-0.27	6.79*	94.22 0
Conservative	8.78	3.36	-0.54*	6.45*	83.98 0
Diversified	9.19	6.3	-0.1	6.69*	87.63 0
Market defensive	10.3	6.08	0.16	4.26*	10.42 -0.01
Strategic index	13.19	9.51	-0.38*	6.06*	63.37 0

Notes. This table shows the average annualised return, the annualised standard deviation, skewness and kurtosis statistics for the various fund and market indexes (these kurtosis statistics have been standardised such that the kurtosis of the normal distribution is zero). An asterisk denotes significant difference from zero at the 5% level. The last column reports the Jarque-Bera statistic and, in parentheses, the p-value for the test that the returns distribution is normal against the alternate hypothesis that it is non-normal

Table 6.3 (*page 150*) presents the summary statistics and performance measures for the 332 FOHFs. The table presents the mean for the average and standard deviation of returns and mean values for skewness and kurtosis. The lower part of Table 6.3 (*page 150*) presents the summary statistics for the four sub-strategy categories. The average returns and standard deviations for the conservative, diversified and market defensive sub-strategies are comparable to the statistics for the equivalent indexes, as shown in Table 6.2 (*page 148*). For the strategic sub-strategy, however, the average return is much lower than the strategic sub-index and the standard deviation much higher.

For the individual FOHFs, more than two-thirds (229/332 cases or 69 percent) have non-normal return distributions according to the Jarque-Bera statistic (at the 5 percent level of significance or better). This is a smaller proportion than reported for hedge funds by Amin and Kat (2003), who found that 86 percent of their sample of 77 hedge funds had significantly non-normal return distributions. The authors state that their sample is highly skewed but do not report skewness statistics. Table 6.3 (*page 150*) shows the mean and median skewness and kurtosis for the full sample. The sample overall appears to show excess kurtosis rather than skewness. The mean (median) kurtosis is rather high at 7.03 (5.19) but the skewness is small at an average (median) of -0.12 (0.01). This is very close to the mean skewness statistic of -0.16 calculated for FOHFs by Kat and Lu (2002) using the TASS database. TASS is a research unit of Tremont Data.

Almost all of the FOHFs (331/332) have return distributions with significant excess kurtosis. Skewness, however, is not only rarer, but is equally positive and negative. In only half of the sample (177 or 53 percent) does the skewness statistic show significant levels of asymmetry. In contrast with the apparent negative skewness of hedge fund returns, Table 6.2 (*page 148*) these significantly skewed FOHFs exhibit both positive and negative skewness in almost equal measure. 91 (51 percent) are negatively skewed and 86 (49 percent) are positively skewed. For the individual funds, between 46 and 58 percent of significantly skewed cases are negatively skewed. Of these significantly skewed cases (not reported in the table), the conservative FOHFs appear to be the most negatively skewed (36 out of 43 or 84 percent). However, as we will see in the next section, the case of the

Table 6.3 Summary statistics for FOHFs

	Annualised average return	Annualised standard deviation	skewness	kurtosis
Full sample	9.48	7.76	-0.12	7.03
			(-53%)	(-100%)
Sub-strategies				
Conservative (n = 74)	8.47	3.5	-0.96	9.64
			(-58%)	(-100%)
Diversified (n = 153)	10.11	7.15	0.11	6.68
			(-56%)	(-99%)
Market defensive (n = 34)	12.18	9.06	0.17	6.52
			(-47%)	(-100%)
Strategic (n =71)	8.05	12.88	0.11	5.32
			-46%	-100%

Notes. This table shows the mean values for the sample's average annualised return, annualised standard deviation, skewness and kurtosis. In brackets under the values for skewness and kurtosis is the proportion of the sample or sub-sample where the parameter is significantly different from zero (or in the case of kurtosis, significantly more than 3) at the 5 percent level.

Table 6.4 Distribution characteristics of indexes: binomial test of intervals

		$\pm 1/2\sigma$	$1/2\sigma - 1\sigma$	$1\sigma - 1 1/2\sigma$	$1 1/2\sigma - 2\sigma$	$> 2\sigma$
S&P 500	negative	22	26	10	8	5
	positive	39	25	16	7	3
	p-value	0.04*	1	0.33	1	
Hedge fund	negative	28	23	12	7	3
	positive	40	28	14	4	1
	p-value	0.18	0.58	0.85	0.55	
FOF composite	negative	39	23	13	5	2
	positive	36	24	9	3	6
	p-value	0.82	1	0.52	0.72	
Conservative	negative	36	16	11	6	5
	positive	40	32	9	1	5
	p-value	0.73	0.03*	0.82	0.13	1
Diversified	negative	44	22	12	4	3
	positive	36	20	9	6	5
	p-value	0.83	0.88	0.66	0.75	
Market defensive	negative	38	25	14	6	2
	positive	33	19	13	7	4
	p-value	0.63	0.45	1	1	
Strategic index	negative	31	22	15	4	3
	positive	41	25	11	3	6
	p-value	0.29	0.77	0.56	1	

Notes. This table gives the proportion of the sample between the mean and $1/2$, $1/2-1$, $1-1 1/2$, and $1 1/2-2$, and beyond 2 standard deviations either side of the mean. For each index, the negative and positive counts and in brackets the proportions of the sample in that category, and the p-value for the test that the distributions of the absolute value of the excess returns are equal. An asterisk denotes significance at the 5 percent level.

conservative FOHFs illustrates very well the danger of making strong inferences about the shape of the underlying distribution simply from the skewness statistic.

6.4 Binomial test results

Table 6.4 (*page 150*) presents the results for the binomial tests of the S&P 500, the hedge fund index, the FOHFs index, and the four sub-strategy indexes. There are two significant findings in the table. For the S&P 500, there are significantly more positive excess returns than negative excess returns within half a standard deviation of the mean. This finding is consistent with the results reported in Chapter 4, Section 4.3.1, where the asymmetry arises from significantly higher levels of positive excess returns in intervals close to the mean. The only other significant finding is for the conservative FOHF index. Between $\frac{1}{2}$ and 1 standard deviation either side of the mean, positive excess returns significantly outnumber negative excess returns. Also of interest are the positives outnumbering the negatives close to the mean (by about 25 percent) for the hedge fund index and the FOHFs strategic index, although these differences are not significant using the binomial test.

Table 6.5 (*page 154*) presents the findings on the binomial tests for the 332 FOHFs. Panel A summarises the cases in which significant asymmetry was found in any interval of the distribution, and Panel B separates these results into three regions within the distribution: $\frac{1}{2}$, $\frac{1}{2}$ to 1, and 1 to $1\frac{1}{2}$ standard deviations either side of the mean. No results are presented for further out in the distributions because I found very little significant asymmetry in the tails. As can be seen in the first row of Panel A, between 18 and 22 percent of the FOHFs in each sub-strategy are significantly asymmetric. However, there are vast differences between the sub-strategies when the asymmetrical cases are separated into negative and positive asymmetries. For the diversified, market defensive and strategic sub-strategies, most of the asymmetry is negative; this is particularly so for the market defensive sub-strategy where all cases of significant skewness are negative. Of particular interest is the conservative sub-strategy: 16 percent of these FOHFs have significantly positive asymmetry. This positive asymmetry was not picked up in the standard summary statistics. In fact, Table 6.3 (*page 150*) shows that the mean skewness value for the conservative FOHFs was -0.96 , and that 58 percent of conservative FOHFs demonstrated significant skewness. Most of these are negatively skewed, so that over 50 percent of the sample

ended up being significantly negatively skewed according to the standard skewness statistic. However, our binomial testing finds only 1 conservative case of significant negative asymmetry.

Delineation of the asymmetry by distribution interval (Panel B) gives further insights into the distributional characteristics of the FOHFs. Most of the asymmetry occurs within one standard deviation of the mean, and the major part of this asymmetry is negative. This bunching of negative observations just below the mean in approximately 12 percent of FOHFs is consistent with the argument that the double fee structure of FOHFs reduces month-to-month returns. But this is a very small proportion of the sample; it must be remembered that most FOHFs show no significant asymmetry either way. The main differences between fund of hedge funds and equities have been discussed in Chapter 3, section 3.3.2. In particular the sub-index description demonstrates that hedge funds and funds of hedge funds are created to respond to market conditions and operate under quite different strategies. They are not, therefore subject to the same constraints as markets. Not surprisingly their risk /return profiles are fundamentally different to equity markets.

6.5 Summary and Conclusions

In this chapter, using data for 332 FOHFs for the period from January 1990 to May 2003, I have examined the return distribution of 332 funds of hedge funds. Over half the sample is significantly skewed according to the skewness statistic and these significantly skewed cases are split 50/50 positive and negative. Almost all exhibit excess kurtosis. Using the binomial test of asymmetry in various intervals of the distribution, I find no evidence of significant asymmetry in the FOHFs composite index, or in the indexes for the diversified, market defensive and strategic sub-strategies. However, I find evidence of positive asymmetry in the interval $\frac{1}{2}$ to 1 standard deviation either side of the mean for the conservative index.

For the individual FOHFs, I find evidence of asymmetry using the binomial test in about 20 percent of cases. Most of this asymmetry occurs within half a standard deviation of the mean, and in most cases the asymmetry is negative.

I have now examined the distributional properties of international equity index returns (Chapter 4), trading volumes for equity indexes (Chapter 5) and FOHF returns (in this chapter). Overall I find that equity returns are negatively skewed, equity trading volumes are positively skewed and that while half of the FOHFs are significantly skewed, these are

Table 6.5 Distribution characteristics of FOHFs: significant cases of asymmetry using the Binomial test

Panel A: Cases of significant asymmetry anywhere in the distribution						
		conservative	diversified	market defensive	strategic	Total
	count	13	33	7	13	66
		18%	22%	21%	18%	20%
	negative	1	26	7	11	45
		1%	17%	21%	15%	14%
	positive	12	7	0	2	21
		17%	5%	0%	3%	6%
Panel B: Asymmetry in different intervals either side of the mean						
		conservative	diversified	market defensive	strategic	Total
$\pm\frac{1}{2}\sigma$	count	3	18	4	8	33
	negative	1	16	4	6	27
	positive	2	2	0	2	6
$\frac{1}{2}\sigma-1\sigma$	count	7	12	3	4	26
	negative	0	8	3	4	15
	positive	7	4	0	0	11
$1\sigma-1\frac{1}{2}\sigma$	count	3	3	0	1	7
	negative	0	2	0	1	3
	positive	3	1	0	0	4

Notes: The cells in this table show the count of cases where significant asymmetry was found using the Binomial test. Panel A summarises the cases where asymmetry was found anywhere in the distribution and in brackets underneath the count is the proportion of cases in each listed sub-strategy found significant. Panel B separates the significant cases into locational categories: $\frac{1}{2}$ standard deviation, $\frac{1}{2}$ to 1 standard deviation, and 1 to $1\frac{1}{2}$ standard deviations either side of the mean. No significant asymmetry was found further out toward the tails than $1\frac{1}{2}$ standard deviations from the mean. Four cases appear twice; 1 each of strategic, conservative and diversified were found significant in both the $\frac{1}{2}$ to 1σ and the $1-1\frac{1}{2}\sigma$ regions, and 1 diversified case was found significant in both the $\pm\frac{1}{2}\sigma$ and $1-1\frac{1}{2}\sigma$ regions.

fifty per cent positive and negative. Using the binomial test of asymmetry in various intervals of the distribution, I find no evidence of significant asymmetry in the FOHFs composite index, or in the indexes for the diversified, market defensive and strategic sub-strategies. However, I find evidence of positive asymmetry in the interval $\frac{1}{2}$ to 1 standard deviation either side of the mean for the conservative index.

Having analysed equity return and trading volume distributions and the distributions of FOHFs, I now turn to model the relation between the first three moments of equity returns and the first three moments of trading volumes. I have shown in Chapter 5 that empirical studies can identify periods of high trading volumes that have in the words of Karpoff (1987), 'shifted prices'. However the role of trading volumes in price determination has not been solidified in the literature to date. Chapter 4 and Chapter 5 have shown that the distributions of returns and associated trading volumes are quite different and I have already clarified those differences. The MDH as discussed in Section 2.3, Chapter 2, proposed that the distributions of returns and associated trading volumes were each subordinate to a common directing variable, the rate of information flow. In Chapter 7 I model the relation between the first three moments of trading volumes and the first three moments of returns and report original and hitherto unrecognised channels of influence between the variables. In Chapter 7, I answer the fundamental research question posed in Section 1.2, Chapter 1.

Chapter 7

Volume and Skewness in International Equity Markets

7.1 Introduction

In Chapter 4, I investigated returns distributions in 6 international aggregate equity markets and found evidence of asymmetry consistent with the perception in theoretical and empirical finance that the returns to individual stocks and aggregate equity markets exhibit asymmetric behaviour. Two main explanations have been advanced to explain this asymmetry. Representative investor theories explain return asymmetries by leverage effects, whereby a decline in price leads to volatility in subsequent returns because of increased operating and financial leverage (Black, 1976; Christie, 1982); by volatility feedback mechanisms whereby volatility raises the risk premium and reduces the impact of good news relative to bad (French, Schwert and Stambaugh, 1987; Campbell and Hentschel, 1992); and by stochastic bubble models in which the asymmetry is caused by the bursting of the bubble (Blanchard and Watson, 1982). An alternative explanation is to be found in the investor heterogeneity theory of Hong and Stein (2003), who suggest that high trading volumes lead to greater negatively skewed returns because some investors are short sales constrained so that previously hidden information comes out during market declines. This follows the volume-volatility literature, which is reviewed in Chapter 2, in which the level of trading volumes proxies for the extent of heterogeneity of investor opinions concerning the fundamental values of stocks (Clark, 1973; Epps and Epps, 1976; Tauchen and Pitts, 1983; Harris and Raviv, 1993; Shalen 1993).

Although studies have investigated the nature and extent of return asymmetries (Harvey and Siddique, 1999, 2000) and the relation between trading volumes and price volatility (Fong, 2003), little attention has been paid to the relation between trading volumes and the third moment of price changes, that is, to skewness. As discussed in Chapter 2, the exceptions are Chen, Hong and Stein (2001) (hereafter CHS), Hueng and Brooks (2003), Charoenrook and Daouk (2004) and Hueng and McDonald (2005). CHS test the theory of Hong and Stein (2003) by examining whether increases in trading volumes lead to greater

negative skewness in returns. Using firm-level data for the United States from July 1962 to December 1998, they estimate cross-sectional models in which the skewness estimated from daily data over 6-month periods is regressed on lagged returns and lagged detrended volumes. Consistent with the prediction of Hong and Stein (2003), they show that increased volumes tend to be associated with future negative skewness at the individual stock level. When CHS examine market-level data, however, the relation between volume and skewness disappears. Building on the work of CHS, Hueng and Brooks (2003) use an asymmetric generalised t-distribution approach to obtain conditional estimates of sample skewness. Contrary to CHS, they find that although lagged returns and volumes are significant determinants of future skewness, the coefficients are rarely negative, implying that higher volumes are not generally associated with future negative skewness. Charoenrook and Daouk (2004) use daily market data for 57 markets from January 1973 to December 2002 to estimate individual market and pooled cross-section time-series models, and they find weak evidence that lagged volumes lead to greater negative skewness. More recently, Hueng and McDonald (2005) use an autoregressive conditional density model with a skewed t-distribution on daily AMEX and NYSE data from 1962 to 2000 to show that the negative relation between trading volumes and return skewness found by CHS in their cross-sectional study is not supported by the time-series evidence from the United States stock market. Overall, the existing studies provide mixed cross-section and time-series evidence of the relation between volumes and skewness that is incompletely supportive of the investor heterogeneity explanation of asymmetric market returns.

In this chapter, I add to the literature on the relation between trading volumes and market return skewness by showing that it is more complex than has previously been recognised. I generalise prior specifications in three ways: by including a wider set of variables in my models, by allowing more interactions between them, and by allowing more sophisticated adjustment dynamics to explain the evolution of market return skewness in response to variations in trading volumes. Using daily data from January 1980 to August 2004, I construct unconditional monthly measures of the first, second and third moments of market returns and trading volumes for 11 international stock markets. The construction of these measures is described in Section 3.4, Chapter 3. I present single equation estimates, panel

estimates and vector autoregressive (VAR) estimates of the interactions between the three moments of returns and volumes that are supportive of Hong and Stein's (2003) investor heterogeneity explanation of asymmetric market returns, and that are consistent with CHS's (2001) firm-level findings that higher trading volumes lead to subsequently greater negative return skewness.

My expansion of the set of explanatory variables is motivated by the work of Chordia, Subrahmanyam and Anshuman (2001) (hereafter CSA) who were first to examine the impact of the variability in trading activity on expected returns. Interpreting the level of trading volumes as a measure of market liquidity and the variability of trading volumes as the risk associated with fluctuations in liquidity, CSA hypothesised that higher levels of trading volumes should lead to lower expected returns (because investors require a smaller liquidity premium), and that higher variability of trading volumes should lead to higher expected returns (because investors require a higher liquidity risk premium). Contrary to their priors, however, CSA found a strong statistically and economically significant negative relation between average returns and both the level and variability of trading volumes, and this remains significant after controlling for the size effect, the book-to-market ratio, momentum effects, and the price level and dividend yield. In seeking an explanation for their apparently anomalous finding that the variability of trading volumes is negatively related to expected returns, CSA suggest that volatile trading volumes might reflect a more heterogeneous group of investors who trade the stock. They test and dismiss this explanation using the number of analysts and the proportion of institutional shareholdings as proxies for the heterogeneity of the clientele. I build upon CSA's finding that average returns are negatively related to the level and the variability of trading volumes by inferring that the latter two variables may be positively related. If this is the case, an alternative explanation for CSA's finding can be found in the theories of heterogeneity of investor opinion, rather than in the heterogeneity of investor clienteles. Although this relation has not previously been examined in the literature on volume and skewness, I show that the level of trading volumes is strongly positively correlated with the volatility of volumes in all 11 markets in my sample. I also show that there are strong interactions between the first three moments of trading volumes in my VAR models, and that these

interactions drive the volume-skewness relation in a way that has not been previously recognised.

The remainder of the chapter is organised as follows. I begin in Section 7.2 by describing the data set and discussing my measures of trading volume and market return skewness. In Section 7.3, I present my single equation specifications. I first replicate CHS's and Charoenrook and Daouk's (2004) models for each of my 11 markets. Consistent with CHS' market-level findings and with Charoenrook and Daouk (2004), I find little evidence that higher trading volumes lead to greater subsequent negative skewness. When I estimate my generalised single equation model as a panel on all markets in my sample, however, I find that trading volumes do impact significantly on subsequent return skewness. In order to allow for the possibility of different trading norms and market structures, I then estimate my generalised single equation model separately for each market. I find that lagged trading volumes influence future return skewness in 8 of the 11 markets. This includes the United States, for which I find that all three moments of trading volumes impact upon subsequent return skewness. I thus provide stronger evidence that trading volumes are associated with subsequent market return skewness than Charoenrook and Daouk (2004) and Hueng and McDonald (2005). My VAR analysis is presented in Section 7.4. Allowing for the full set of interactions between the first three moments of trading volumes and return skewness, my impulse response functions (IRFs) show that following an initial reduction in negative skewness in most markets, higher trading volumes lead to subsequently greater negative skewness in all markets in my sample. In Section 7.5, I summarise the main findings and draw together my conclusions.

7.2 Data and Descriptive Statistics

The data used in this chapter is described in Section 3.2.2, Chapter 3. Trading volume is measured as turnover; that is, the value of shares traded each day as a proportion of the total value of outstanding shares. The methodology of constructing the data sets used in the models is explained in Section 3.4, Chapter 3 and likewise the skewness measure, DUVOL, that I use in all the models. Table 7.1 (*pages 163/4*) provides summary information. The

data period spans January 1980 to August 2004, but for all markets except Canada and the United States, it begins later due to restricted availability of volume data. The start dates are detailed in the first row of Table 7.1 (*pages163/4*).

Panel A of Table 7.1 (*pages163/4*) presents basic statistics on within-month daily returns, standard deviations and skewness using the DUi measure from equation (3.9). The mean returns are broadly similar, ranging from a high of 0.052 percent for Sweden to -0.023 percent for Japan. The most volatile stock markets based on the mean of the within-month standard deviations are Sweden, Japan and Italy, and the least volatile is Canada. The mean within-month skewness figures tend to be close to zero, although there are significant variations over time as can be seen by the minimum and maximum monthly skewness figures. Panel B presents the summary statistics on trading volumes, and Panel C does similarly for detrended volumes. As the turnover data are characterised by substantial positive drift, I detrend volumes by regressing the log of volumes on a time trend, and I use the detrended volumes in all my estimations. The detrending method is described in Chapter 3, Section 3.4.1. The raw trading volumes in Panel B vary considerably for each market. The Netherlands is the most heavily traded market, in the sense that it has the highest turnover ratios on average, closely followed by the United States. The Belgian stock market has the lowest level of trading volume. The negative sign on the mean of the within-month skewness of volumes indicates that trading volumes are on average right-skewed, but the minimums and maximums show that, as with the market returns, there is a considerable range around this mean. As expected, average skewness figures for the detrended volumes are much lower than for the raw volumes.

Panel D of Table 7.1 (*pages163/4*) first reports a simple test of the volume-volatility relation – the correlation between the level of trading volume, $V1$, and the absolute change in market prices, $|\Delta P|$. Consistent with the discussion on Karpoff (1987) in Chapter 2, these correlations are positive in all markets, and are consistent with his magnitudes. In the next row, I provide the correlations between the levels of trading volumes, $V1$, and their volatilities, $V2$. As anticipated – given CSA’s finding that both the level and the volatility of turnover are negatively related to expected return – these correlations are all strongly

positive. Interestingly, this relation tends to hold across the markets. Figure 7.1 (page 165) which plots the means and volatilities of the trading volumes in each market (ranked left to right on the level of volume), shows that the markets with high trading volumes also exhibit high volatility of volumes.

7.3 Single equation models

7.3.1 Replicating CHS and Charoenrook and Daouk (2004)

I begin my empirical analysis by replicating the specifications of Charoenrook and Daouk (2004) and CHS – in equations (7.1) and (7.2) respectively – for each of the 11 markets in my data set.

$$R3_t^i = \beta_0^i + \beta_1^i RI_{t-1}^i + \phi_1^i VI_{t-1}^i + e_t^i \tag{7.1}$$

$$R3_t^i = \alpha_0^i + \alpha_1^i R3_{t-1}^i + \alpha_2^i R2_{t-1}^i + \sum_{j=1}^5 \delta_j^i RI_{t-j}^i + \phi_1^i VI_{t-1}^i + \varepsilon_t^i \tag{7.2}$$

My nomenclature uses ‘R’ to denote monthly market returns; ‘V’ denotes monthly trading volumes, and ‘1’, ‘2’ and ‘3’ denotes the first, second and third moments, respectively. Thus RI , $R2$ and $R3$ denote respectively the market returns, the volatility of returns and the skewness of returns. Analogously, VI denotes the level of trading volumes, $V2$ the volatility of volumes, and $V3$ the skewness of volumes. The models in (7.1) and (7.2) describe the evolution of return skewness in market i , $R3_t^i$, in response to lagged values of various moments of returns and the level of trading volumes. Charoenrook and Daouk (2004) (equation 7.1) include one lag of the first moment of returns, RI_t^i , and the level of trading volumes, VI_t^i . CHS (equation 7.2) include these variables as well as the first lag of the dependent variable, $R3_t^i$, the first lag of return volatility, $R2_t^i$, and 5 lags of the level of market returns, RI_t^i . I have followed each paper closely in adopting their particular technique for detrending the turnover data. The models are estimated using OLS with Newey-West standard errors to account for serial correlation and/or heteroscedasticity.

Panel A of Table 7.2 (*pages 167/8*) presents my estimates of the CHS model (equation 7.2), and Panel B presents my estimates of the Charoenrook and Daouk model (equation 7.1). While the R^2 s are low, this is not of primary concern, because they are consistent with results from related studies. In the CHS replication (Panel A), none of the explanatory variables is significant in 5 markets – Australia, Canada, Italy, Spain and the United States.

Table 7.1 Summary statistics

	Australia	Belgium	Britain	Canada	France	Italy	Japan	Netherlands	Spain	Sweden	US
Data start date	Jan-84	Jan-86	Nov-86	Jan-80	Jul-91	Jul-86	Jan-90	Feb-86	Feb-90	Jan-82	Jan-80
Panel A: Returns											
Return											
Mean	0.034	0.033	0.025	0.03	0.032	0.013	-0.023	0.029	0.031	0.052	0.039
Minimum	-2.352	-1.259	-1.361	-1.313	-0.863	-0.84	-1.199	-1.243	-1.024	-1.175	-1.07
Maximum	0.599	0.759	0.648	0.844	0.568	0.959	0.804	0.514	0.66	1.212	0.585
SD of returns											
Mean	0.855	0.794	0.873	0.74	1.064	1.172	1.187	0.939	1.095	1.237	0.921
Minimum	0.296	0.245	0.352	0.257	0.415	0.431	0.48	0.267	0.42	0.392	0.295
Maximum	6.967	3.937	4.186	4.319	2.977	3.59	2.766	3.489	2.994	3.877	5.635
Skewness of returns											
Mean	-0.002	0	0.005	0.002	-0.013	-0.016	-0.023	0.007	-0.023	-0.006	-0.023
Minimum	-0.507	-0.636	-0.563	-0.743	-0.581	-1.007	-0.531	-0.573	-0.719	-2.143	-0.709
Maximum	0.655	0.737	0.487	0.652	0.532	0.556	0.487	0.47	0.569	2.636	0.54
Panel B: Turnover											
Volume											
Mean	0.184	0.07	0.287	0.148	0.218	0.221	0.164	0.353	0.267	0.217	0.346
Minimum	0.053	0.019	0.135	0.026	0.001	0.01	0	0.148	0.05	0.035	0.107
Maximum	0.339	0.161	0.683	0.451	0.468	0.612	0.447	1.035	0.506	0.726	0.849
SD of volume											
Mean	0.072	0.025	0.063	0.045	0.061	0.06	0.046	0.092	0.07	0.067	0.057
Minimum	0.016	0.003	0.018	0.009	0	0.003	0	0.026	0.012	0.009	0.014
Maximum	0.642	0.175	0.208	0.688	0.181	0.211	0.705	0.392	0.172	0.243	0.192
Skewness of volume											
Mean	-0.43	-0.279	-0.106	-0.152	-0.247	-0.221	-0.235	-0.162	-0.158	-0.219	-0.097
Minimum	-1.679	-1.401	-0.868	-1.593	-0.923	-0.938	-1.322	-1.133	-0.805	-1.103	-0.587
Maximum	0.11	0.386	0.454	0.49	0.419	0.465	0.721	0.385	0.398	0.284	1.013

Table 7.1 Summary statistics (continued)

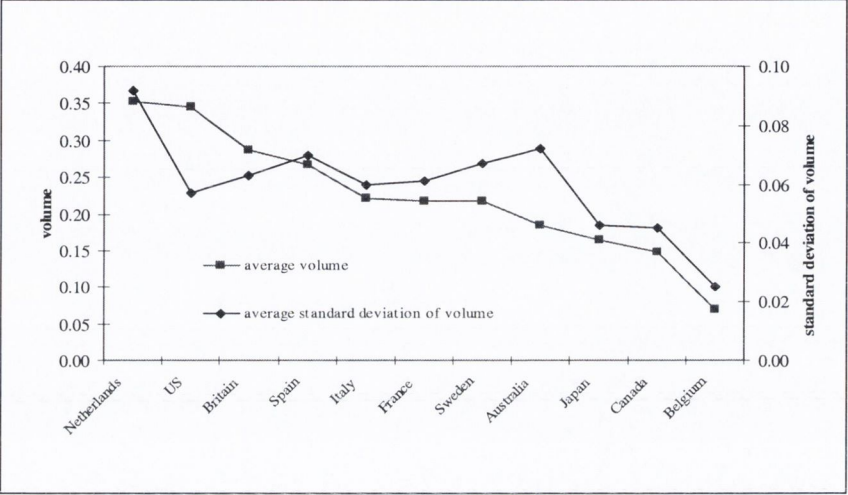
	Australia	Belgium	Britain	Canada	France	Italy	Japan	Netherlands	Spain	Sweden	US
Data start date	Jan-84	Jan-86	Nov-86	Jan-80	Jul-91	Jul-86	Jan-90	Feb-86	Feb-90	Jan-82	Jan-80
Panel C: Detrended turnover											
Volume											
Mean	1.02	1.02	1.01	1.02	1.01	1.04	1.09	1.02	1.02	1.03	1.01
Maximum	1.32	1.35	1.45	2.09	1.2	2.12	2.42	1.43	1.26	1.66	1.33
Minimum	0.78	0.77	0.81	0.73	0.8	0.51	0.11	0.78	0.74	0.6	0.82
SD of volume											
Mean	0.16	0.15	0.1	0.14	0.12	0.14	0.15	0.12	0.13	0.15	0.08
Maximum	0.76	0.56	0.3	1.4	0.22	0.37	1.16	0.39	0.28	0.36	0.21
Minimum	0.08	0.06	0.04	0.04	0.05	0.05	0.02	0.05	0.06	0.06	0.03
Skewness of volume											
Mean	-0.25	-0.13	-0.01	-0.01	-0.12	0.09	-0.08	-0.04	-0.03	-0.09	-0.02
Maximum	0.39	1.27	0.62	0.79	0.56	0.57	0.63	0.55	0.59	0.4	1.14
Minimum	-1.07	-0.97	-0.63	-1.23	-0.64	-0.7	-0.99	-0.78	-0.67	-0.63	-0.59
Panel D: Correlations											
Level of volume and $ \Delta P $	0.07	0.26	0.23	0.19	0.27	0.16	0.1	0.35	0.29	0.26	0.3
Level of volume and volatility of volume	0.45	0.66	0.64	0.48	0.82	0.85	0.44	0.67	0.74	0.88	0.72

Note: This table presents the summary information for my sample of 11 markets. The daily index and volume data are from Datastream. The sample period runs from January 1980 to August 2004, although for all markets except the United States and Canada the period starts later due to restrictions on the availability of volume data, and these start dates appear in the first row. Panels A, B and C present summary statistics for returns, raw turnover and detrended turnover. Turnover is detrended performing the following regression: $\log(V_t^i) = \alpha^i + \beta^i TIME + u_t^i$, where V_t^i is the daily volume for market

i. Thus for each market, detrended volume is estimated as $(V_t^i) = \frac{V_t^i}{(\exp(\alpha^i + \beta^i TIME))} = \exp(u_t^i)$. I first calculate the within-month mean, standard

deviation and skewness (DU^i from equation 3.9), and in this table I report the overall mean, maximum and minimum for these. By construction and consistent with convention, positive values for DU^i imply negative skewness. In Panel D I report correlations between the level of volume and the absolute value of the monthly return ($|\Delta P|$), and between the first and second moments of volume.

Figure 7.1 The level and variability of trading volumes in international stock markets



Note: This figure depicts the mean of the level of volume, which is the overall mean of the within-month daily trading volume, and the volatility of volume, which is the mean of the within-month daily standard deviation of trading volume. (The figures appear in Panel B of Table 1). The markets are sorted from left to right on the level of volume.

Belgium is the only market for which more than one independent variable is significant. Consistent with CHS's findings at the market level, the lagged volume terms are largely insignificant and the model performs poorly in all markets, including the United States.

Charoenrook and Daouk (2004) find no significant volume effects at the 5 percent level or better in their sample of developed countries (although turnover is significant at the 10 percent level in Spain and Sweden). The results of my replication of Charoenrook and Daouk (Panel B of Table 7.2) (*pages 167/8*) are largely consistent with their findings; I find that neither of the explanatory variables – lagged returns and lagged volumes – is significant in Australia, Canada, France, Italy, Spain and the United States. I do, however, find significant volume effects for Britain and Japan. In my replications of both CHS and Charoenrook and Daouk (2004), where I find significant volume effects (only 3 cases in all), the coefficients have positive signs. This is consistent with Hong and Stein's (2003) prediction that increases in trading volumes lead to greater subsequent negative return skewness.

As argued in my introduction, it is possible that these relatively simple model specifications are not sufficiently sophisticated to capture the richness of the relation between trading volumes and market return skewness. To address this possibility, I propose a more general single equation specification as follows:

$$\begin{aligned}
 R3 = & \phi_0^i + \sum_{j=1}^4 \phi_j^i R3_{t-j}^i + \sum_{j=1}^4 \gamma_j^i R2_{t-j}^i + \sum_{j=1}^4 \lambda_j^i R1_{t-j}^i \\
 & + \sum_{j=1}^4 \kappa_j^i V1_{t-j}^i + \sum_{j=1}^4 \varpi_j^i V2_{t-j}^i + \sum_{j=1}^4 \sigma_j^i V3_{t-j}^i + \xi_t^i
 \end{aligned} \tag{7.3}$$

This model describes the evolution of return skewness in market i , $R3^i$, in response to variations in return volatility, $R2^i$, the level of returns, $R1^i$, the level of detrended trading volumes, $V1^i$, the standard deviation of detrended volumes, $V2^i$, and the skewness of

Table 7.2 Replications of prior single equation models
Panel A: Replicating Chen, Hong and Stein (2001)

		Australia	Belgium	Britain	Canada	France	Italy	Japan	Netherlands	Spain	Sweden	US
R-sq		0.06	0.18	0.13	0.07	0.10	0.05	0.13	0.09	0.07	0.09	0.06
SEE		0.20	0.21	0.20	0.21	0.19	0.22	0.21	0.19	0.21	0.20	0.21
DW		1.99	2.07	2.01	2.00	2.02	2.01	2.03	2.00	1.98	1.99	2.02
constant		-0.053	-0.119	-0.113	-0.06	-0.071	-0.033	-0.057	-0.046	-0.021	-0.073	-0.152
		(1.05)	(2.77)	(1.66)	(1.11)	(1.24)	(0.53)	(0.75)	(0.76)	(0.31)	(1.40)	(2.70)
Skewness	lag 1	-0.100	-0.170	-0.082	0.099	-0.017	0.061	-0.024	0.036	-0.040	0.047	0.031
		(1.38)	(2.78)	(1.04)	(1.21)	(0.29)	(0.86)	(0.30)	(0.43)	(0.49)	(0.70)	(0.40)
Volatility	lag 1	0.664	4.926	3.461	1.452	2.669	2.86	5.392	0.336	-2.141	1.622	1.141
		(0.19)	(1.95)	(1.05)	(0.55)	(0.64)	(0.96)	(1.74)	(0.13)	(0.41)	(0.73)	(0.46)
Return	lag 1	5.780	8.799	0.858	3.476	1.337	3.848	4.407	10.416	0.632	11.410	4.717
		(0.85)	(1.52)	(0.19)	(0.71)	(0.26)	(0.80)	(0.66)	(1.61)	(0.11)	(3.47)	(0.66)
	lag 2	7.046	17.140	15.124	5.582	5.259	2.706	12.443	1.560	-0.606	5.603	3.554
		(1.13)	(2.80)	(2.00)	(0.91)	(1.07)	(0.70)	(2.15)	(0.27)	(0.24)	(1.73)	(0.58)
	lag 3	2.734	8.185	9.010	-5.359	-4.209	1.082	1.821	-1.131	0.757	2.011	-2.766
		(0.45)	(2.65)	(1.41)	(0.82)	(0.74)	(0.28)	(0.41)	(0.23)	(0.15)	(0.52)	(0.71)
	lag 4	0.609	-9.036	3.355	7.525	7.529	-0.533	-0.030	-5.662	-0.946	0.082	7.464
		(0.23)	(1.60)	(0.48)	(1.57)	(1.61)	(0.10)	(0.00)	(1.45)	(0.14)	(0.02)	(1.41)
	lag 5	-0.183	12.375	10.801	1.433	0.032	-6.066	-7.952	-3.029	4.905	-3.155	-6.617
		(0.04)	(2.03)	(1.73)	(0.25)	(0.00)	(1.29)	(1.15)	(0.72)	(0.64)	(0.75)	(0.98)
Volume	lag 1	142.072	26.612	-83.454	-14.042	68.904	-16.961	72.444	33.149	-31.600	6.000	8.201
		(1.47)	(0.16)	(1.55)	(0.15)	(1.18)	(0.39)	(1.39)	(2.36)	(0.53)	(0.15)	(0.20)

Table 7.2 Replications of prior single equation models
Panel B: Replicating Charoenrook and Daouk (2004)

		Australia	Belgium	Britain	Canada	France	Italy	Japan	Netherlands	Spain	Sweden	US
R-sq		0.03	0.09	0.08	0.06	0.07	0.04	0.08	0.07	0.06	0.08	0.04
SEE		0.20	0.21	0.20	0.21	0.19	0.22	0.21	0.19	0.21	0.20	0.21
DW		2.15	2.24	2.06	1.82	1.99	1.92	1.98	1.88	2.06	1.90	1.96
constant		-0.046	-0.074	-0.08	-0.034	-0.031	-0.003	-0.006	-0.035	-0.049	-0.062	-0.134
		(1.09)	(1.97)	(1.50)	(0.86)	(0.67)	(0.06)	(0.11)	(0.59)	(0.94)	(1.35)	(2.54)
Return	lag 1	7.347	14.187	3.922	0.210	1.818	0.723	2.657	10.894	3.257	9.412	4.012
		(1.70)	(2.19)	(0.94)	(0.05)	(0.42)	(0.19)	(0.38)	(2.77)	(0.80)	(2.99)	(0.69)
Volume	lag 1	-19.193	-118.908	69.346	30.451	3.081	- 15.236	59.699	3.704	-40.219	22.651	- 21.293
		(0.49)	(1.59)	(2.65)	(1.20)	(0.08)	(0.94)	(3.35)	(0.23)	(1.08)	(0.91)	(0.89)

Note: In this table I report results for my replications of Chen, Hong and Stein (2001) (equation 7.2) in Panel A and Charoenrook and Daouk (2004) (equation 7.1) in Panel B. In brackets underneath each coefficient is the *t*-statistic.

detrended volumes, $V3^i$. Consistent with CHS and Charoenrook and Daouk (2004), my generalised model in (7.3) includes lagged returns and volumes, and my estimation is conducted using Newey-West standard errors to correct for autocorrelation and heteroscedasticity. There are, however, two important differences between my specification in (7.3) and those of Charoenrook and Daouk (2004) and CHS in their equations (7.1) and (7.2) respectively. First, I include two additional variables: the second and third moments of trading volumes. Second, in contrast to the specifications in (7.1) and (7.2), which incorporate only one lag of the right-hand-side variables (except for returns in the CHS model for which five lags are included), my model in (7.3) is estimated using the general-to-specific dynamic estimation strategy, starting with 4 lags on each variable and sequentially restricting until the parsimonious model is obtained for each market, see Krolzig and Hendry (2001) for a fuller discussion. This allows a richer set of possible adjustment dynamics. I first estimate my model as a panel, and then separately for each market.

7.3.2 Panel estimation

To conduct my panel regressions using OLS, I estimate equation (7.3) by combining the data for all 11 markets to form a single stacked matrix with 1,672 observations over the period 1992(1) to 2004(8). This encompasses the period for which data are available for all countries. The results are presented in Panel A of Table 7.3 (*page 171*). I find substantial lagged return effects: lags 1 and 2 of $R1$ are positive and significant, indicating that higher returns tend to be followed by greater negative skewness. This is consistent with the findings of Charoenrook and Daouk's (2004) developed countries panel. I also find that return volatility, $R2$, is significant at lag 4. In contrast to Charoenrook and Daouk's (2004) panel results, I find significant volume effects. The level of volumes, $V1$, is significantly negative at lag 2, but this is offset by the significant and slightly greater positive volume coefficient at lag 4. The skewness of volumes, $V3$, is also significant and positive at lag 4.

In Panel B of Table 7.3 (*page 171*) I report a series of diagnostic tests. My first test is for the joint significance of the lagged returns, and this is strongly confirmed with an F-statistic of 15.15 ($p = 00$). I then test that the lagged levels of volumes (lags 2 and 4) are jointly

significant, and this is also confirmed at the 10 percent level in test 2 with an F-statistic of 2.43 ($p = .08$). Given that the coefficient on the second lag of the level of volumes is similar in size but opposite in sign to its coefficient at lag 4, I test the restriction that the sum of these coefficients is equal to zero; the F-statistic in test 3 of 0.04 ($p = .87$) confirms that they are statistically equal but opposite in sign. This finding may explain why prior researchers have obtained mixed results when examining whether higher trading volumes lead to greater negative market return skewness. My results show that higher trading volumes lead initially to less negative skewness, but this effect is soon reversed. I will examine this more fully when I conduct my VAR estimates in Section 7.4. Lastly, the fourth test is a joint exclusion test for all volume effects, including two lags of the level of volumes and the third lag of the skewness of volumes. The F-statistic for this test is 3.13, with a marginal significance level of 0.03. As with the lagged returns exclusion test, this confirms that the first and third moments of trading volumes are jointly significant determinants of subsequent market return skewness.

7.3.3 Individual market estimates

Although the panel regression approach is useful in that it enlarges the data set and uncovers relationships that are common across markets, it is possible that different trading norms and market structures diminish its usefulness in modelling the relation between trading volumes and market return skewness. The results from estimating my generalised single equation specification in (7.3) for each market are presented in Table 7.4 (*page 173*). I find significant first moment volume effects in 6 markets: Australia, Belgium, Italy, the Netherlands, Spain and the United States. This contrasts with Charoenrook and Daouk (2004), who find no significant lagged trend-adjusted volume effects for any of these countries. I also find significant higher order volume effects – either the volatility or the skewness of volumes (or both) – for five markets: Britain, Canada, Italy, Spain and the United States. In most markets, therefore, trading volume is significant in at least one of its moments. This is a noteworthy finding, given that prior research has generally found little relation between trading volumes and market return skewness.

My findings for the United States are of particular interest, because neither CHS nor Charoenrook and Daouk (2004) found significant volume effects using the first lag of

Table 7.3 Panel regression of Volume Skewness Relation
Panel A: results

	lag	coefficient	t-stat
R1	1	9.36	3.87
	2	8.92	3.70
R2	4	-3.06	2.60
V1	2	-0.12	1.97
	4	0.13	2.10
V3	3	0.06	2.45

Panel B: Additional diagnostics

1.	$R1(-1)$ and $R1(-2) = 0$	$F = 15.15$ ($p = 0.00$)
2.	$V1(-2)$ and $V1(-4) = 0$	$F = 2.43$ ($p = 0.08$)
3.	$V1(-2) + V1(-4) = 0$	$F = 0.04$ ($p = 0.87$)
4.	$V1(-2)$ and $V1(-4)$ and $V3(-3) = 0$	$F = 3.13$ ($p = 0.03$)

Note: This table contains my estimates of equation (7.3) on a panel data set of all 11 markets using the general-to-specific estimation strategy. The *t*-statistics are Newey-West adjusted. *R1*, *R2*, *R3* denote the level of returns, return volatility and return skewness. *V1*, *V2*, *V3* denote the level of detrended trading volumes, the STD of detrended volumes and the skewness of detrended volumes. In Panel A I report significant (at the 5 percent level or better) coefficients only. Panel B reports the results of exclusion tests that lagged returns are jointly zero (test 1), that lagged levels of volumes are jointly zero (test 2), that the second and fourth lags of the levels of volumes are equal and opposite in sign (test 3), and that the two lags of the level and lag 4 of the skewness of volumes are jointly zero (test 4).

Sample period	1992(1) to 2004(8)
Total pool observations	1672
Adjusted R-squared	0.02
Mean of the dependent variable	-0.01
SE of regression	0.25
DW	2.05
F-statistic	7.22 ($p = 0.00$)

turnover. I find significant effects in all three moments of volume. The level of volumes is significant at the first and second lags, and the volatility of volumes is significant at the third and fourth. The skewness of volumes is significant at lags 1, 3 and 4. My more general specification with richer dynamics seems to be necessary to pick up the volume-skewness relation in the United States market. In contrast to both CHS and Charoenrook and Daouk (2004) who found a significant relation between returns and their subsequent skewness, I find no such effects. Given that my replications of these studies are also characterised by an absence of return effects for the United States, this is more likely due to their use of 6-monthly aggregations (instead of the monthly aggregations I use), rather than to their simpler adjustment dynamics.

7.4 VAR models of the volume–skewness relation

VAR modelling, which does not impose any restrictions from theoretical models on the parameters, is most appropriate to examine the time series relation between the variables under consideration. More specifically, a VAR approach to modelling the volume-skewness relation allows me to examine whether more complex transmission mechanisms are involved. The level of trading volumes may, for example, first influence market return volatility (the volume-volatility relation) which could, in turn, affect the skewness of returns. More generally, trading volumes could impact on the skewness of market returns indirectly by first affecting one or more of the other moments of returns or volumes. CHS alluded to this possibility: ‘Recall that the central issue here is whether (trading volume) is really forecasting (skewness) directly, or whether it is instead forecasting (the standard deviation of returns), and showing up in the regression only because (the standard deviation of returns) is correlated with (skewness).’ (CHS, p. 362; parentheses added). To shed light on this, CHS introduce further dynamics by including two lags of return standard deviations, and dividing them into positive and negative deviations. They also replace the actual standard deviations with their predicted values to mimic an instrumental variables approach. None of these measures adds to the significance of trading volumes in their modelling.

Table 7.4 Single equation estimates

	Australia	Belgium	Britain	Canada	France	Italy	Japan	Netherlands	Spain	Sweden	US
R-sq	0.07	0.08	0.02	0.04		0.03	0.06	0.05	0.15	0.02	0.09
SEE	0.18	0.18	0.17	0.21		0.19	0.16	0.16	0.15	0.63	0.2
DW	2	2.15	2.15	1.8		2	2.13	1.98	2.07	1.83	2.08
Skewness R_3	-0.14 {1} (2.51)								0.13 {3} (2.28)		
	-0.11 {2} (1.89)								0.16 {4} (2.93)		
Volatility R_2	10.58 {3} (3.85)	6.53 {1} (2.25)	-4.98 {4} (2.09)	-6.36 {2} (2.21) 6.50 {3} (2.26)			6.47 {3} (2.82) -8.08 {4} (3.51)		-9.63 {1} (3.92)		6.64 {3} (2.50)
Return R_1	16.13 {3} (2.94)	16.99 {1} (3.07) 16.53 {2} (3.04)					10.36 {2} (2.51) 7.98 {3} (1.93)	11.61 {1} (2.53)		27.53 {1} (2.45)	
Volume V_1	0.17 {1} (1.93) -0.27 {3} (2.85)	-0.45 {1} (4.12) 0.38 {2} (3.76)				0.08 {4} (2.30)		-0.24 {3} (2.65) 0.25 {4} (2.69)	0.35 {2} (2.89) -0.58 {3} (3.95) 0.40 {4} (3.49)		-0.41 {1} (2.05) 0.48 {2} (2.38)
Volatility of volume V_2			0.50 {3} (2.35)			-0.63 {3} (2.43)			-0.68 {2} (2.56)		-1.02 {3} (2.32) -0.91 {4} (2.15)
Skewness of volume V_3			0.11 {4} (1.99)	0.12 {4} (2.91)		0.11 {1} (1.91)			-0.13 {1} (2.72) -0.09 {2} (1.96)		-0.09 {1} (2.00) 0.09 {3} (2.01) 0.12 {4} (2.68)

Note: This table reports the results for estimate of equation (7.3) using the general-to-specific modelling strategy for each market. Reported are the variables significant at the 5% level or better. Each coefficient is followed by the lag length in braces {}, and in brackets underneath is the *t*-statistic. I found no significant effects for France.

My VAR model is written as follows:

$$A(L)x_t + By_t = u_t \quad (7.4)$$

with

$$A(L) = 1 - A_1L - A_2L^2 - \dots - A_pL^p,$$

$$E(u_t) = 0, \quad E(u_t u'_t) = \Sigma, \quad E(u_t u'_s) = 0, \text{ for } t \neq s, \quad E(x_t u_t) = 0,$$

$$x_t = (V2_t, V3_t, R2_t, R3_t, V1_t),$$

and

$$y_t = (Const, R1_t)$$

This is a standard VAR representation in which x is a $(1 \times n)$ vector of variables, A is an $(n \times n)$ matrix of coefficients, u is an $(n \times 1)$ vector of white noise disturbance terms, and L denotes the lag operator (for example, $L^i x_t = x_{t-i}$). The variables appearing in the x vector of endogenous variables are the standard deviation of trading volumes, $V2$, the skewness of trading volumes, $V3$, the standard deviation of market returns, $R2$, the skewness of market returns, $R3$, and the level of trading volumes, $V1$. The y vector of exogenous variables contains the constant term, $Const$ and the level of market returns, $R1$.

A convenient feature of the VAR representation in (7.4) is that it can be estimated by ordinary least squares, which yields consistent and asymptotically efficient estimates of the A matrix because the right-hand-side variables are predetermined and are the same in each equation of the model. I start with 4 lags for each variable, and I restrict the models sequentially to obtain my parsimonious VAR structures. I next examine the variance decompositions which inform the appropriate ordering of the variables in my IRF analysis. Examination of the 20-month ahead variance decompositions, chosen to allow sufficient time for the decompositions to stabilize, shows that the market returns explain on average almost 92 percent of their own forecast errors. This is consistent with market efficiency, and it is reflected in my models by including the market returns, $R1$, in the y vector of exogenous variables. Market return volatility, $R2$, and skewness, $R3$, explain on average 68

percent and 75 percent respectively of their own forecast errors, and $V1$, $V2$ and $V3$ explain on average 77 percent, 40 percent and 65 percent of their own forecast errors. Overall, the most endogenous variable is $V2$, and this is followed by $V3$, $R2$, $R3$ and $V1$, with $R1$ being exogenous. This explains the ordering of these variables in equation (7.4).

Table 7.5 (*pages 177/8*) presents my results from estimating (7.4) for each market. The explanatory power of the models as described by the R^2 s is quite good for this kind of modelling, the standard errors of the estimates are respectively small and the Ljung-Box Q statistics all indicate the absence of higher order autocorrelation in the equation residuals. The most interesting aspect of the models concerns the extent of causality between the trading volumes and the return variables. This is captured in the table by the F-statistics (with their marginal significance levels in brackets) for the joint exclusion of all lags of each variable in each of the equations. In discussing these results, recall that the absence of a significant F-statistic does not indicate the absence of interaction between the variables in the system, because the relation may indirectly involve one or more other variables. I will refer to *direct* relations as occurring between two variables in the models, and *indirect* relations as involving transmission mechanisms that operate through one or more additional variables.

The main significant interaction effects in Table 7.5 (*pages 177/8*) are summarised in Table 7.6 (*pages 179/180*) for ease of interpretation. I record in Table 7.6 (*pages 179/180*) any interaction that is significant at the 10 percent level or better. Panel A of Table 7.6 (*pages 179/180*) shows the effects of trading volumes on returns, Panel B the 'feedback' effects of returns on volumes, and Panel C the interactions between the first, second and third moments of volumes. I find three interesting sets of interactions. *First*, there are strong interactions between all three moments of trading volumes. Table 7.5 (*pages 177/8*) shows that the level of volumes impacts directly on the volatility of volumes in 6 markets, and the volatility of volumes affects the level of volumes in 4 markets. As discussed in the introduction, and as shown in Panel D of Table 7.1 (*pages 163/4*), this is consistent with my interpretation of CSA's finding of the same sign on both the level and the volatility of turnover in their expected return equation. The strongest set of interactions is between the

third moment of volumes and the level of volumes; $V3$ directly affects $V1$ in 8 markets, and the reverse relation is significant in 3 markets. In most markets, shocks to higher moments of volumes affect the level of volumes. Even when there is no significant direct interaction between any of the moments of volumes, as in Spain, the volumes are indirectly connected through the volatility of returns, $R2$.

Second, I find strong evidence of the volume-volatility relation. This relation is direct and statistically significant in 4 markets, and there is also ‘feedback’ from return volatility to volumes in 6 markets. This result is not surprising given the extensive prior evidence on this relation, together with my more general specification that encompasses prior specifications while allowing for a richer set of explanatory variables, interactions, and adjustment dynamics. In fact, as can be seen in Panels A and B of Table 7.6 (*pages 179/180*), the volume-volatility relation is more commonly an indirect relation than a direct one. *Third*, I find significant evidence of the volume-skewness relation. There are statistically significant direct effects of the level of volume on return skewness in 3 markets, Canada, Japan and Spain, but there are many more cases in which there is an indirect relation operating mainly through the higher moments of volumes and via the volatility of returns. In addition, as Panels A and B of Table 7.6 (*pages 179/180*) show, there are statistically significant direct effects from the higher moments of trading volumes to market return skewness, and there are also significant feedback effects from return skewness to volumes.

Table 7.5 (a) Significance tests in the VAR model

			R2				R3			
	obs	lags	R3	V1	V2	V3	R2	V1	V2	V3
Australia	248	1	2.18	2.72	0.15	0.39	1.61	2.49	0.04	0.02
			(0.14)	(0.10)	(0.70)	(0.53)	(0.20)	(0.11)	(0.84)	(0.96)
Belgium	224	4	7.50	7.87	2.40	2.56	2.47	7.22	6.71	1.96
			(0.11)	(0.10)	(0.66)	(0.63)	(0.65)	(0.12)	(0.15)	(0.74)
Britain	214	3	0.21	2.08	0.56	1.87	5.64	6.70	1.32	1.56
			(0.98)	(0.56)	(0.91)	(0.60)	(0.13)	(0.08)	(0.73)	(0.67)
Canada	294	2	3.11	7.26	2.98	4.18	2.56	10.6	14.2	0.56
			(0.21)	(0.03)	(0.22)	(0.12)	(0.28)	0.00	0.00	(0.76)
France	195	2	2.96	9.16	9.8	1.23	1.2	7.03	3.46	6.21
			(0.23)	(0.01)	(0.01)	(0.54)	(0.55)	(0.03)	(0.18)	(0.04)
Italy	218	3	2.21	3.85	4.85	4.92	1.51	2.12	4.49	3.42
			(0.53)	(0.28)	(0.18)	(0.18)	(0.68)	(0.55)	(0.21)	(0.33)

Table 7.5 (b) Significance tests in the VAR model

			V1				V2				V3			
	obs	lags	R2	R3	V2	V3	R2	R3	V1	V3	R2	R3	V1	V2
Australia	248	1	1.05	0.3	2.85	5.47	0.28	0.04	5.16	4.57	0.97	0.1	0.34	1.59
			(0.31)	(0.58)	(0.09)	(0.02)	(0.60)	(0.83)	(0.02)	(0.03)	(0.32)	(0.75)	(0.56)	(0.44)
Belgium	224	4	7.15	4.28	4.56	9.81	1.44	2.21	13.63	4.77	4.66	2.68	2.97	0.98
			(0.13)	(0.37)	(0.34)	(0.04)	(0.84)	(0.70)	(0.01)	(0.31)	(0.32)	(0.61)	(0.56)	(0.91)
Britain	214	3	33.87	3.75	19.70	19.00	39.92	2.50	22.41	12.99	10.43	3.73	0.90	6.95
			0.00	(0.29)	0.00	0.00	0.00	(0.47)	0.00	0.00	(0.02)	(0.29)	(0.83)	(0.07)
Canada	294	2	0.54	3.17	2.41	5.57	3.6	3.07	7.00	4.83	3.78	0.97	1.92	17.9
			(0.76)	(0.20)	(0.30)	(0.06)	(0.17)	(0.22)	(0.03)	(0.09)	(0.15)	(0.62)	(0.38)	0.00
France	195	2	6.05	0.06	5.77	4.13	9.4	0.46	13.4	2.58	5.39	2.28	1.76	3.77
			(0.05)	(0.97)	(0.06)	(0.13)	(0.01)	(0.97)	0.00	(0.28)	(0.07)	(0.32)	(0.41)	(0.15)
Italy	218	3	8.26	1.8	2.11	1.43	3.76	2.15	8.86	6.28	5.56	6.77	0.34	3.09
			(0.04)	(0.61)	(0.55)	(0.70)	(0.29)	(0.54)	(0.03)	(0.10)	(0.13)	(0.08)	(0.95)	(0.38)

Table 7.5 (c) Significance tests in the VAR model

			R2				R3			
	obs	lags	R3	V1	V2	V3	R2	V1	V2	V3
Japan	176	3	1.37	5.36	2.7	6.94	7.86	7.4	2.04	0.79
			(0.71)	(0.15)	(0.44)	(0.07)	(0.05)	(0.06)	(0.56)	(0.85)
Netherlands	223	4	2.82	8.1	10.2	2.94	3.46	8.48	4.39	3.84
			(0.59)	(0.09)	(0.04)	(0.57)	(0.48)	(0.08)	(0.36)	(0.43)
Spain	175	2	3.40	3.28	8.46	0.05	7.04	5.30	0.60	10.10
			(0.18)	(0.19)	(0.01)	(0.97)	(0.03)	(0.07)	(0.74)	(0.01)
Sweden	272	4	3.03	2.3	2.46	0.48	10.8	7.46	2.69	7.3
			(0.55)	(0.68)	(0.65)	(0.97)	(0.03)	(0.11)	(0.61)	(0.12)
US	292	4	1.57	17.1	4.89	1.26	8.08	3.7	7.49	7.12
			(0.81)	0.00	(0.30)	(0.87)	(0.09)	(0.45)	(0.11)	(0.13)

Table 7.5 (d) Significance tests in the VAR model

			V1				V2				V3			
	obs	lags	R2	R3	V2	V3	R2	R3	V1	V3	R2	R3	V1	V2
Japan	176	3	2.85	0.68	5.26	6.2	3.34	0.75	6.25	11	4.48	4.11	6.48	19.7
			(0.42)	(0.88)	(0.15)	(0.10)	(0.34)	(0.86)	(0.10)	(0.01)	(0.21)	(0.25)	(0.09)	0.00
Netherlands	223	4	7.91	2.54	2.86	1.9	8.64	3.77	15.5	5.06	3.03	4.67	7.96	0.95
			(0.09)	(0.64)	(0.58)	(0.75)	(0.07)	(0.44)	0.00	(0.28)	(0.55)	(0.32)	(0.09)	(0.92)
Spain	175	2	2.01	1.16	1.96	2.85	3.01	0.01	0.27	1.17	4.63	0.71	0.89	0.05
			(0.37)	(0.56)	(0.38)	(0.24)	(0.22)	(0.99)	(0.87)	(0.56)	(0.10)	(0.70)	(0.64)	(0.97)
Sweden	272	4	10.1	1.23	108	8.33	4.26	0.9	173	10.1	1.22	4.82	40.5	30.6
			(0.04)	(0.87)	0.00	(0.08)	(0.37)	(0.92)	0.00	(0.04)	(0.87)	(0.31)	0.00	0.00
US	292	4	18.2	15.3	10.8	9.74	4.46	1.52	8.87	28.8	11.8	2.29	15.4	7.09
			0.00	0.00	(0.03)	(0.05)	(0.35)	(0.82)	(0.06)	0.00	(0.02)	(0.68)	0.00	(0.13)

Note: This table presents the results of estimating the VAR model in equation (7.4), focusing on the F-statistics (with their marginal significance levels in brackets). The column headed 'obs' provides the number of observations in each market, and the column headed 'lags' gives the number of lags in the parsimonious VAR model for each market. The five columns headed R2, R3, V1, V2 and V3 denote the dependent variable in the x vector of endogenous variables in (7.4), and the four columns beneath these headings are the explanatory variables in these equations. The F-statistics with their marginal significance levels indicate the joint significance of all lags of each explanatory variable in each equation. For example, the 4 columns under V1 indicate the joint significance of R2, R3, V2 and V3 in the V1 equation. Looking at the V2 equation, we can see that the level of volumes is jointly significant in the volatility of

Table 7.6 Return–volume interactions in international equity markets

Panel A: The influence of volumes on returns

Australia	$V1 \rightarrow R2$; $V3 \rightarrow V1 \rightarrow R2$
Belgium	$V1 \rightarrow V2 \rightarrow R3$
Britain	None
Canada	$V1 \rightarrow R3$; $V2 \rightarrow V1 \rightarrow R3$; $V3 \rightarrow V1 \rightarrow R3$
France	None
Italy	$V1 \rightarrow R2$; $V1 \rightarrow V2 \rightarrow R2$; $V1 \rightarrow R2 \rightarrow R3$
Japan	$V1 \rightarrow R3$;
Netherlands	$V1 \rightarrow V2 \rightarrow R2$; $V3 \rightarrow V2 \rightarrow R2$
Spain	$V1 \rightarrow R2$; $V1 \rightarrow R3$; $V2 \rightarrow R2$; $V2 \rightarrow R2 \rightarrow R3$
Sweden	$V1 \rightarrow V2 \rightarrow R2$; $V3 \rightarrow V2 \rightarrow R2$; $V1 \rightarrow V2 \rightarrow R2 \rightarrow R3$
United States	$V1 \rightarrow R2$; $V1 \rightarrow R2 \rightarrow R3$; $V1 \rightarrow V2 \rightarrow R2$; $V1 \rightarrow V2 \rightarrow R2 \rightarrow R3$; $V3 \rightarrow R3$; $V2 \rightarrow R3$

Panel B: The influence of returns on volumes

Australia	None
Belgium	$R2 \rightarrow V3$
Britain	$R2 \rightarrow V1$; $R2 \rightarrow V2$; $R2 \rightarrow V3$; $R3 \rightarrow V1$
Canada	$R2 \rightarrow V1$; $R2 \rightarrow V1 \rightarrow V2$; $R2 \rightarrow V1 \rightarrow V2 \rightarrow V3$
France	$R2 \rightarrow V1$
Italy	$R2 \rightarrow V1$; $R2 \rightarrow V2$; $R2 \rightarrow V1 \rightarrow V2$; $R2 \rightarrow V3$; $R2 \rightarrow V1 \rightarrow V3$
Japan	$R2 \rightarrow V3$; $R2 \rightarrow V3 \rightarrow V2$
Netherlands	$R2 \rightarrow V1$; $R2 \rightarrow V1 \rightarrow V2$; $R2 \rightarrow V3$; $R3 \rightarrow V3$
Spain	$R2 \rightarrow V2$
Sweden	$R2 \rightarrow V2$
United States	$R2 \rightarrow V1$; $R2 \rightarrow V2$; $R2 \rightarrow V1 \rightarrow V3$; $R2 \rightarrow V2 \rightarrow V1$; $R2 \rightarrow V2 \rightarrow V1 \rightarrow V3$

Table 7.6 Return–volume interactions in international equity markets
Panel C: Direct interactions between volume moments

Australia	V1→V2; V3→V2, V3→V1
Belgium	V3→V2, V3→V1
Britain	V2→V1; V3→V2; V3→V1
Canada	V1→V2; V2→V1; V2→V3; V3→V1
France	V2→V1; V3→V2; V3→V1
Italy	V1→V2, V1→V3
Japan	V1→V3; V2→V3; V3→V2
Netherlands	V1→V2; V3→V2
Spain	None
Sweden	V1→V2; V3→V2, V3→V1
United States	V1→V2; V1→V3; V2→V1; V3→V1; V3→V2

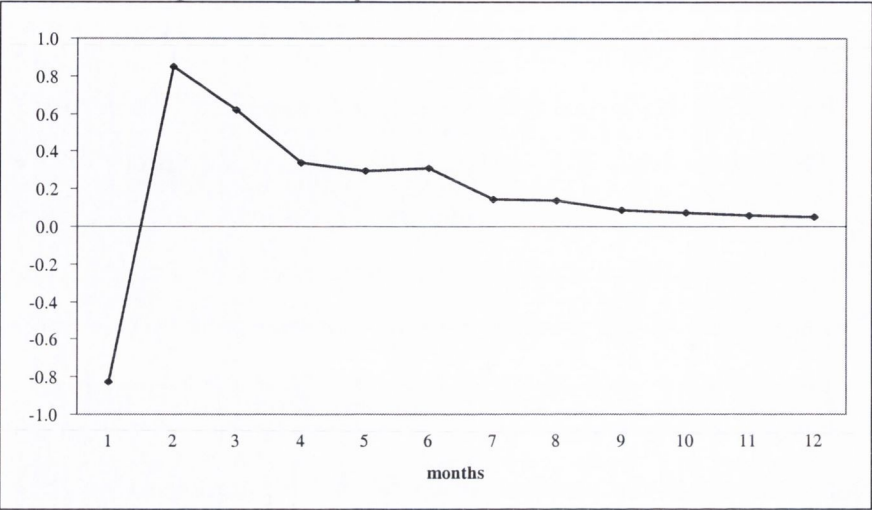
Note: This table summarises the significant (at the 10 percent level or better) interactions from the VAR model of equation (7.4) and Table 7.5. $R2$ and $R3$ are the standard deviations of returns and skewness of returns, and $V1$, $V2$ and $V3$ are the volumes, standard deviations of volumes, and skewness of volumes. Panels A and B include both direct and indirect interactions, whereas Panel C includes only direct interactions between the three moments of volumes.

7.4.1 Impulse response function analysis

Impulse response function (IRF) analysis allows me to examine the impact of a shock to one variable in the VAR system while incorporating all the direct as well as the indirect mechanisms that link all the variables through their dynamic lag structures. I use Pesaran and Shin's (1998) generalised IRF technique to simulate the effect of a one standard deviation increase in the level of trading volumes, VI , on market return skewness, $R3$. This technique differs from the traditional orthogonalised impulse response which employs a Cholesky decomposition of the positive definite covariance matrix of the shocks. This restriction forces a shock to one series to have no contemporaneous effect on the other series. The generalised version that I use does not impose this restriction and thus is not sensitive to the ordering of the variables in the VAR. Figure 7.2 (*page 182*) presents the results. Panel A of the figure depicts the average IRFs for all 11 markets in my sample, and Panel B presents the IRFs for each market. Consistent with convention, an increase (decrease) in skewness in Figure 2 implies greater (less) negative skewness.

Panel A of Figure 7.2 (*page 182*) shows that the initial effect of a one standard deviation rise in the level of volumes on return skewness is downward; that is, skewness becomes less negative. This is followed in month 2 by an increase in negative skewness of the same magnitude on average. Thereafter, the average IRF adjusts monotonically back towards its initial level, with half of the adjustment occurring within 4 months. In Panel B of Figure 7.2 (*page 182*) it can be seen that most of the markets follow this pattern. The initial reduction in negative skewness in month 1 (negative values for the IRFs) is common to 9 of the 11 markets, and this is reversed (with the IRFs becoming positive) in month 2 for all but one market. The exception is the United States, where an initial reduction is followed in month 2 by an even greater decline in negative skewness, before negative skewness increases in month 3. Overall, my IRF analysis shows that higher trading volumes lead initially to less negative return skewness, followed by a sustained rise in negative skewness that dissipates after 6 to 9 months. This pattern of adjustment is consistent with the stationarity of my VAR models.

Figure 7.2 Impulse responses of market skewness to higher trading volumes
 Panel A Average skewness response



Panel B Impulse responses by market

	1	2	3	4	5	6	7	8	9	10	11	12
Australia	-0.32	0.61	0.10	0.05	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Belgium	0.39	1.13	0.44	0.33	0.21	0.15	0.10	0.07	0.05	0.03	0.02	0.02
Britain	-0.09	1.14	1.63	-1.43	0.36	0.33	0.11	0.10	0.05	0.12	0.09	0.07
Canada	-2.33	1.86	3.18	1.26	1.14	0.82	0.66	0.51	0.41	0.33	0.27	0.22
France	0.28	0.76	0.17	0.05	-0.01	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	0.00
Italy	-1.26	0.53	0.13	0.06	0.04	0.03	0.03	0.03	0.02	0.02	0.02	0.02
Japan	-1.37	1.40	-1.92	1.90	0.83	1.31	0.39	0.40	0.17	0.10	0.02	0.04
Netherlands	-0.26	0.91	0.37	0.29	0.21	0.16	0.12	0.09	0.07	0.05	0.04	0.03
Spain	-2.18	3.16	1.63	0.88	0.44	0.21	0.09	0.04	0.01	0.00	-0.01	-0.01
Sweden	-1.34	0.23	0.31	0.26	0.22	0.19	0.16	0.14	0.11	0.10	0.08	0.07
US	-0.58	-2.41	0.73	0.12	-0.22	0.18	-0.04	0.11	0.07	0.07	0.09	0.09
Average	-0.82	0.85	0.62	0.34	0.30	0.31	0.15	0.13	0.09	0.07	0.06	0.05

Note: Panel B of this table shows the individual market IRFs of market return skewness to a 1-standard deviation increase in the level of trading volumes for my 11 sample markets, obtained from the VAR model of equation (7.4) using the technique of Pesaran and Shin (1998). The responses are multiplied by 100 for ease of exposition. The average IRF in Panel B is plotted in Panel A. Consistent with convention, an increase in the skewness figure implies greater negative skewness.

7.5 Discussion

The VAR analysis has shown that, consistent with Hong and Stein's (2003) investor heterogeneity theory of equity market asymmetry, and also with CHS's firm-level cross sectional test of this theory, more negatively skewed market returns follow a rise in trading volumes. I noted in my introduction that subsequent tests of the volume-skewness relation at the market level by Hueng and Brooks (2003), Charoenrook and Daouk (2004) and Hueng and McDonald (2005) found contradictory results. My analysis suggests that the inconsistent findings of these prior studies can be explained by their inclusion of different but incomplete subsets of explanatory variables. My more general specification – that includes a wider set of variables, more interactions between them, and more sophisticated adjustment dynamics – confirms that higher trading volumes do indeed trigger greater subsequent negative skewness in market returns. But there is a sting in the tail. This greater negative skewness is preceded by a movement in the opposite direction, and thereafter it persists for approximately 6 months before returning to its original level.

In the course of my analysis of the volume-skewness relation, I have shown that the higher moments of trading volumes play an important role in explaining the evolution of the higher moments of returns in a way that is consistent with investor heterogeneity theory. Recall that the second and third moments of trading volumes are linked to the level of trading volumes. Figure 7.1 (*page 165*) depicts a strong correlation between the average within-month daily trading volumes and the average within-month daily standard deviations of trading volumes. In other words, the level of trading volumes is positively correlated with the volatility of volumes across markets. I also demonstrated in Panel D of Table 7.1 (*pages 163/4*), that within the markets in my sample, the level of trading volumes is strongly positively correlated with the volatility of volumes, averaging 0.67 across all 11 markets. Even in markets with relatively light trading, therefore, periods of active (inactive) trading tend to be associated with periods of greater (lesser) volatility in volumes. By incorporating these hitherto neglected interactions into my analysis of investor heterogeneity theory, I can think of trading being generated by liquidity and noise traders during 'light volume' periods that have little impact on the volatility of volumes. These volumes will consequently have minimal effects on returns. When significant news hits the

market, however, the higher moments of volumes and returns come into play. Informed traders become active and volumes rise in proportion to the degree of heterogeneity of investors' interpretation of the news and its implications for future expected returns. The greater trading volumes induce more volatility in volumes depending on the degree of heterogeneity of beliefs, and in this way the level and higher moments of trading volumes drive market returns to their new equilibrium levels, impacting upon the higher moments of returns along the way. This finding that the level of trading volumes is strongly positively correlated with the volatility of volumes in all 11 markets is consistent with the MDH theory of Epps and Epps (1976), Tauchen and Pitts (1983) and Andersen (1996), described in section 2.3.1(*page 34*) which shows both the level and volatility of trading volume to be linear functions of the rate of information, i.e. they are both dependent on another parameter, I_t .

The most significant research question posed in Chapter 1, section 1.2 (*page 11*) asks whether differences of opinion about the future value of stock returns, associated with rising trading volumes can lead to increasing levels of negative skewness in equity returns. This means that the asymmetry in equity returns distributions investigated in Chapter 4 may arise from the investor heterogeneity theory of Hong and Stein (2003). This is but one of four alternative explanations of equity market asymmetry, all of which are referred to in section 7.1 (*page 155*). CHS (2001) found support for the investor heterogeneity theory using firm level data but could not substantiate it at the level of the aggregate market. The literature that sets out to test this theory is extensively reviewed in this thesis in sections 2.5.1, 2.5.2 and 2.5.3 (*page 50-54*). The findings of Hueng and Brooks (2003), Charoenrook and Daouk (2004) and Hueng and McDonald (2005) are either weakly supportive of, or flatly contradict the findings of CHS. I have demonstrated in section 7.3.1 (*page 160*) that the model used in Charoenrook and Daouk (2004) is not adequate to capture the richness of the return skewness/trading volume relation. In relation to the other two papers I have argued in sections 2.5.1 and 2.5.2 that experimenting with different measures of past turnover as a method of detrending the data is not sufficient in handling deterministic drift. As explained in section 2.6 (*page 58*), Hueng and McDonald (2005) addressed the issue of too few data points in CHS by using a parameter that was dependent on the daily

information available on the forecasting variables. In this situation the issue of omitted variables, which might influence results, arises. My results show that there is a role for trading volumes to explain equity return skewness at the level of the aggregate market. This is supportive of the investor heterogeneity theory of return asymmetry as proposed by Hong and Stein (2003).

7.6 Summary and Conclusions

My objective in this chapter has been to provide new evidence on the extent to which investor heterogeneity theory explains the relation between trading volumes and the skewness of equity returns at the market level. My motivation for this work stems from prior research by CHS who tested the prediction of Hong and Stein (2003) that higher trading volumes should lead to greater future negative return skewness. Using US data, CHS confirmed this relation at the level of the firm but not for the overall market. Subsequent work by Hueng and Brooks (2003), Charoenrook and Daouk (2004) and Hueng and McDonald (2005) tends to confirm the investor heterogeneity explanation of the volume-skewness relation at the firm level, but not at the level of the market.

Using daily data for 11 international stock market indexes for which daily trading volumes and market return data are available over the period from January 1980 to August 2004, I constructed up to 286 monthly unconditional estimates of the first three moments of trading volumes and market returns. I began my analysis by confirming that, consistent with the investor heterogeneity explanation of the volume-volatility literature, the level of trading volumes is positively correlated with the absolute change in market prices in all 11 markets. I also confirmed my inference from Chordia, Subrahmanyam and Anshuman (2001) that the levels of trading volumes and their volatilities are positively correlated in all 11 markets in our sample. I then presented a series of single equation, panel and VAR estimates that generalise previous specifications by including these features of my data along with a wider set of variables, a wider set of interactions between them, and a richer set of adjustment dynamics to explain how market return skewness evolves over time in response to variations in trading volumes.

In the single equation analysis, my replication of CHS and Charoenrook and Daouk (2004) for each of my 11 markets confirmed that, using their specifications, there is little evidence that higher trading volumes are associated with greater subsequent negative skewness. When I estimated my more general single equation model, however, I found that lagged trading volumes influence future return skewness in 8 of my 11 markets. This includes the US, for which I found that all three moments of trading volumes affect market return skewness. I thus provide stronger evidence that trading volumes are associated with future negative skewness than is reported by CHS, Charoenrook and Daouk (2004) and Hueng and McDonald (2005). When I estimated my generalised model on all markets in a panel regression, I found that the first and third moments of trading volumes are significant determinants of subsequent market return skewness. Finally, my VAR modelling for each market yielded three main results. First, there are substantial hitherto unrecognised interactions between all three moments of trading volumes, and these interactions play an important role in driving the volume-skewness relation. Second, I find strong evidence of the volume-volatility relation that is consistent with investor heterogeneity theory and is encompassed within my model. Third, I find significant evidence of the volume-skewness relation – that higher trading volumes trigger subsequent greater negative market return skewness. Overall, my market-level findings are consistent with the firm-level analysis of CHS that supports the investor heterogeneity explanation of return asymmetry.

Chapter 8

Conclusions, Implications and Future Work

8.1 Introduction and Overview

The research question that I address in this thesis is whether higher than average trading volumes can predict greater levels of negative skewness in market returns. The question, as outlined in Section 1.2, Chapter 1, is a response to the work of Chen, Hong and Stein (2001), (CHS) who tested the investor heterogeneity theory of Hong, Stein (2003). The Hong and Stein (2003) theory proposed that increased trading volumes reflected the level of investor disagreement concerning the implications of new information for the future price of a stock. CHS verified their theory at firm level for the US but failed to substantiate it at the level of the US aggregate market. Prior to the work of CHS, there was no literature that addressed the issue of a relation between equity return skewness and trading volume levels, much less the higher moments of trading volumes. Of the few papers that tested the theory of CHS in aggregate markets, the results were either weakly supportive of the negative skewness prediction of CHS or flatly contradictory.

My initial approach to the fundamental research question was to examine the treatment of the skewness statistic in the literature, since both CHS and Peiró (1999) had proposed alternative measures in recognition of the non-normality in equity returns distributions. In relation to volume distributions there were additional issues to be considered. Lo and Wang (2000) undertook an analysis of the range of alternative measures used in the volume literature, and tested a number of methods of detrending the volume data. Peiró (1999), assuming explicitly that returns were i.i.d., used a series of distribution free tests, analogous to the usual t test for differences in means and F test for differences in variance, in his analysis of asymmetry. Regulez and Zarraga (2002) argued in favour of the analysis of volumes distributions but queried the wisdom of using non-parametric tests that were joint tests of the i.i.d. assumption and the symmetry of the distribution. My contribution to this debate was to conduct a Monte Carlo study of the tests in the presence of a heavily dependent mean.

In Chapter 5 I conducted an empirical study of the ten greatest daily price changes and the ten greatest daily turnover ratios, cross referenced against the ten highest monthly volatilities, following Karpoff's (1987) idea that more can be learned about the capital market by studying prices in association with trading volumes than prices alone. While this is undoubtedly true, it does not provide the answer to the fundamental research question posed in Chapter 1. In chapter 6, I examined the return distribution of 332 funds of hedge funds. In chapter 7, I adopted a generalised approach to explain the evolution of equity market skewness in response to higher trading volumes. I supported Hong and Stein's (2003) investor heterogeneity theory of return asymmetry in single equation, panel and vector autoregressive (VAR) estimates of the interactions between the first three moments of returns and trading volumes. The rest of this chapter is organised as follows. In Section 8.2 I present a summary discussion of each chapter, emphasising the main findings. In Section 8.3, I discuss the main limitations. In section 8.4 I discuss the implications and direction of future research and section 8.5 is the conclusion.

8.2 Discussion of each chapter

In Chapter 2 I discussed the treatment of skewness, historical and current, in the literature. Some of the concerns in the early literature concerned the efforts to classify the returns distributions since the normality assumption was found to be inappropriate. The abrupt changes in the tails of the distributions of price changes had implications for the skewness measures. The second part of the review examines the treatment of the price/ volume and volume /volatility relation and the third part examines the growing literature on the skewness/ volume relation, where this thesis makes a novel contribution.

In Chapter 4, I applied the Fama (1965) normality tests to the distributions identifying departures from normality in all markets and confirming prior research that returns distributions are leptokurtic. I then applied a series of distribution free tests and found asymmetry in dispersion of positive and negative excess returns in three markets of the six. In all three cases, it resulted from higher frequencies of positive versus negative excess returns of the same magnitude. In a Monte Carlo simulation of the behaviour of two of the distribution free tests I found that the tests were not compromised in the presence of

imposed time dependence in the mean. Overall, my analysis of return asymmetry showed negative excess returns dominated positives numerically in the extremes of the distributions, but positives are dominant, at statistically significant levels in a number of alternative intervals.

In Chapter 5 I applied a similar analysis to an expanded dataset of turnover in twelve international equity markets. I presented a set of summary statistics of daily returns and associated daily turnover which facilitated a direct comparison between the variance, skewness, maximum and minimum points and other descriptive statistics. I found turnover to be positively skewed in all countries, the exception being Switzerland as shown in Pearson's coefficient of skewness. I found turnover standard deviation to be significantly higher than return standard deviation. In the distribution free tests, the Wilcoxon rank sum and the Siegel-Tukey tests, I found the asymmetry in Chapter 4 is related to differences in dispersion, whereas the asymmetry in Chapter 5 is related to differences in location. In the last part of Chapter 5 I examined the 10 greatest extremes in return, trading volume and volatility levels for all countries. I found October 1987 and September 2001 to be very influential in price change volatility and trading volume levels.

In Chapter 6 I examined the distributions of 332 FOHF returns divided into four sub-categories, conservative, diversified, market defensive and strategic. I found that almost all of the individual funds have significant excess kurtosis, but only half show significant levels of asymmetry. In contrast with equity returns distributions in Chapter 4 and turnover distributions in Chapter 5, the skewness in FOHFs is both positive and negative in almost equal measure.

In Chapter 7 I generalised the CHS model to the analysis of 11 international equity markets incorporating extra variables and extending the lag lengths. I established a strong and significant correlation between the first and second moments of trading volumes. Although this finding is consistent with the theory of investor heterogeneity, it has not, so far, been tested in the literature. I replicated the model specifications used in CHS and Charoenrook and Daouk's models and confirmed their findings using their models. I used single

equation, panel regression and VAR analysis to investigate whether trading volume dynamics generally influence return skewness. I used the generalised impulse response function of Pesaran and Shin (1998) in my impulse response analysis.

My approach to the question differed from the other responses in a number of ways. Firstly, I used a more systematic detrending method that involved regressing the log of volume on a time trend and using the exponentials of the residuals as my volume measure. Secondly, as demonstrated in Chapter 3 I used the exact same skewness measure as CHS, estimated at a monthly frequency in preference to the CHS 6 month measure, resulting in a sufficient number of observations for meaningful inference. I found that the first two moments of volumes are highly correlated. This finding is in response to the proposition of CSA who found that the first moment of returns was negatively correlated to both the first and second moment of volumes.

In Chapter 2, under the Mixture of Distributions Hypothesis, both the mean and variance of volume are shown to be linearly dependent on the rate of information flow. The high correlation that I have identified between the first and second moments may be the outcome of their joint dependence on the flow of information. It seems reasonable to infer that the strength of this correlation would be augmented in times of increased information flow, and therefore in falling markets one should expect to find a higher correlation. The difference of opinion theory of Chen, Hong and Stein (2001) and Hong and Stein (2003) posits that there is an asymmetric relation between the rate of information and market direction. In other words, it is in falling markets that the rate of information disclosure increases. Thus it is only when markets are falling that more and more is revealed about private signals.

In summary, the asymmetry found in Chapter 4 is detected using a range of non-parametric tests that are especially suited to detecting differences in means and variances between alternative distributions. This follows the work of Peiró (1999) reviewed in Chapter 2 and Chapter 3. The Monte Carlo simulation described in Chapter 3 reinforces the robustness of these results. The methodology used is applicable to any time series. Similarly the analysis of volume distributions in Chapter 5 and Fund of Hedge Funds in Chapter 6 could be

replicated to test asymmetry in any time series. The overall finding of negative asymmetry in equity returns and positive asymmetry in turnover is consistent with prior literature. The issue of different time periods is mainly relevant for Chapter 7 which estimates model parameters that could vary over time. In relation to different markets, I have added the suggestion that other markets could be examined in future research in section 8.4 (*page 191*).

8.3 Limitations of the Study

One of the limitations of the Monte Carlo study in Chapter 4 is the subjective nature of deciding upon the level of dependency in the mean equation. I chose to simulate a returns generating process where the mean was dependent on its previous one month lag. As explained in Chapter 4, the tests statistics did not reject the null hypothesis of symmetry too often, thus obviating the need to examine other patterns of dependence. A second limitation of the work occurs in Chapter 5. Isolating the ten highest price changes, trading volume levels and volatilities, restricts the parameters of the analysis somewhat. The choice of the ten highest was dictated by the necessity of presenting tables and figures that could provide more meaningful information and enhance the text.

8.4 Future Direction of this Research

The investor heterogeneity theory of return asymmetry as proposed in Chen, Hong, Stein (2001) explicitly states that more privately held information is revealed in falling markets, thereby creating the conditions for increased levels of negative skewness. The concept of asymmetric information could be applied to the recent sub prime mortgage debacle that originated in the US and resulted in sharp declines in equity markets worldwide. The extent of the exposure to the sub primes has had disastrous consequences for some of the world's largest banks and financial services providers. Asymmetric information in this context means that some banks were close to failure when the extent of their exposure to the sub prime mortgage business became generally known. The widespread negative impact of the banks' risk taking has had serious consequences for volatility levels in the world's major markets. The asymmetric information is present, the negative skewness is present. As a first

step in the direction of this research, it would be interesting to examine equity markets' returns for 2007/8 benchmarked against the 1987 figures. It would also be a potentially very rich source of research if one were to look at individual securities, in particular the financials, and different markets, given the present state of the global economy.

In this thesis I have shown that the higher moments of trading volumes play an important role in explaining the evolution of the higher moments of returns in a way that is consistent with investor heterogeneity theory. Within the markets in my sample, the level of trading volumes is strongly positively correlated with the volatility of volumes, averaging 0.67 across all 11 markets. The implication of this finding is that for all markets, periods of active trading tend to be associated with increased levels of volatility in volumes. Similarly when trading is light there will be smaller levels of volume volatility. When significant news hits the market, the higher moments of volumes and returns come into play. Informed traders become active and volumes rise in proportion to the degree of heterogeneity of investors' interpretation of the news and its implications for future expected returns.

Appendix A

Sample Data: Table and Figures

The first three figures in this Appendix are samples of the data used in Chapter 4. Figure A.1 (*page 194*) shows the returns to six international equity indexes from 1978-2002. The indexes are described in Section 3.2.1, Chapter 3. Figure A.2 (*page 195*) illustrates the impact of the stock market crash of 1987 on volatility levels in France, Germany, Japan, the UK and the US. Over a one-month period from 19/10/1987 to 18/11/1987 the stock markets in all five countries showed prices to be very volatile and a substantial amount of synchronised movement. Table A.1 (*page 196*) shows the ten largest positive and the ten largest negative price changes for the same markets with the corresponding date in the cell beneath. Italy was omitted from Figure A.2 (*page 195*) because Table A.1 (*page 196*) shows that 1987 did not feature in the historically high price movements, positive or negative in Italy.

Figures A.3 (*pages 197/8*) and A.4 (*pages 199/200*) represent the daily returns and daily detrended volume data for Chapter 5 and Chapter 7, described in Section 3.2.2, Chapter 3. The aggregation of these data sets into monthly return volatility is illustrated in Figure A.5 (*pages 201/2*). The monthly volume volatility and volume skewness are shown in Figure A.6 (*pages 203/4*) and Figure A.7 (*pages 205/6*) respectively. The manipulation of the daily data and daily detrended trading volume into the monthly estimates in these figures is described in Section 3.4.1, Chapter 3. Canada and the US are the only two countries whose return and volume data starts on 1/1/1980; for all other countries the graphs show the individual start date, dictated by the availability of both return and volume data.

Figure A.1 In Daily Price Changes from 2/1/77 to 30/12/02

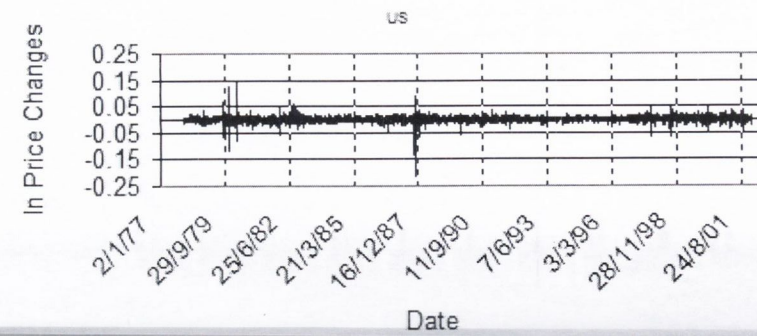
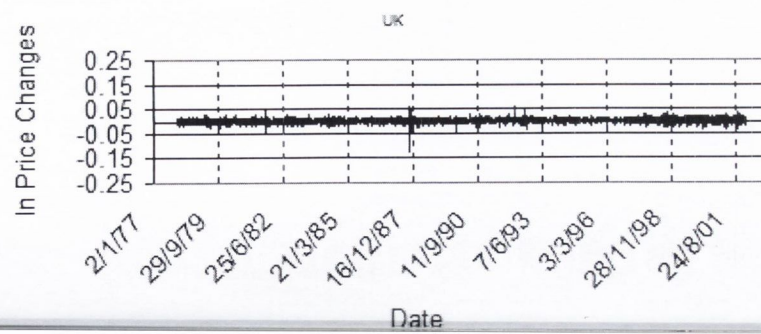
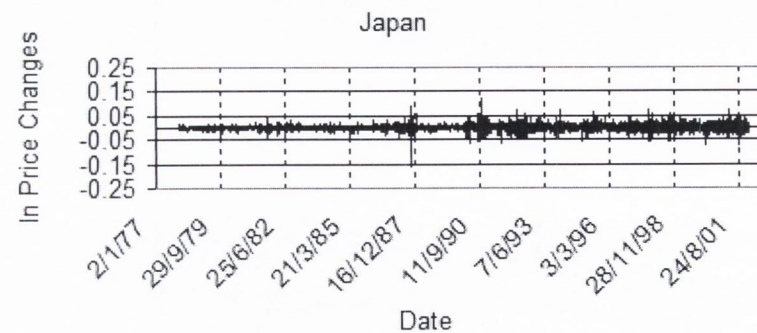
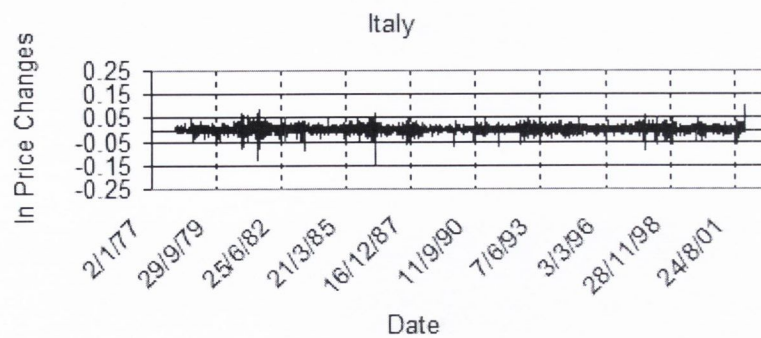
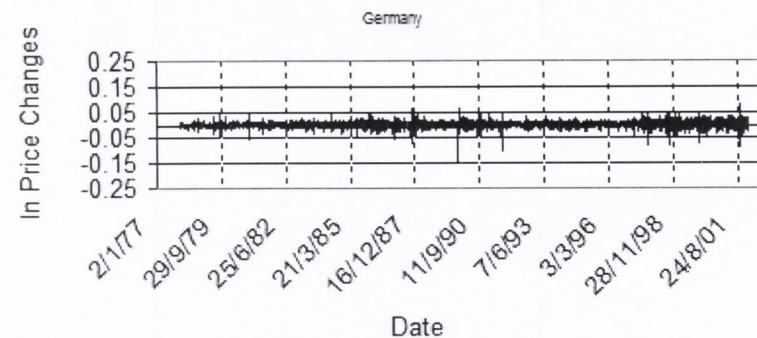
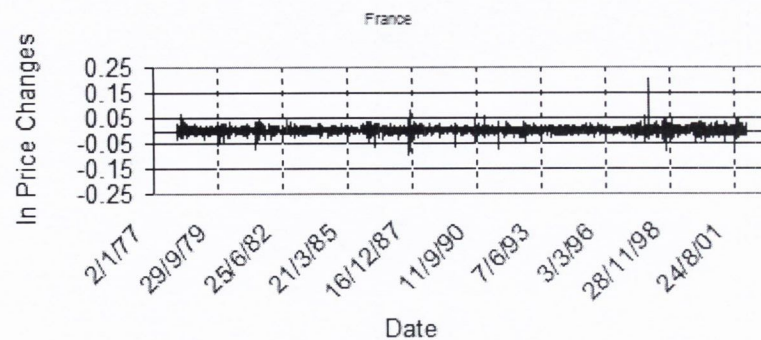


Figure A.2 1987 Volatility

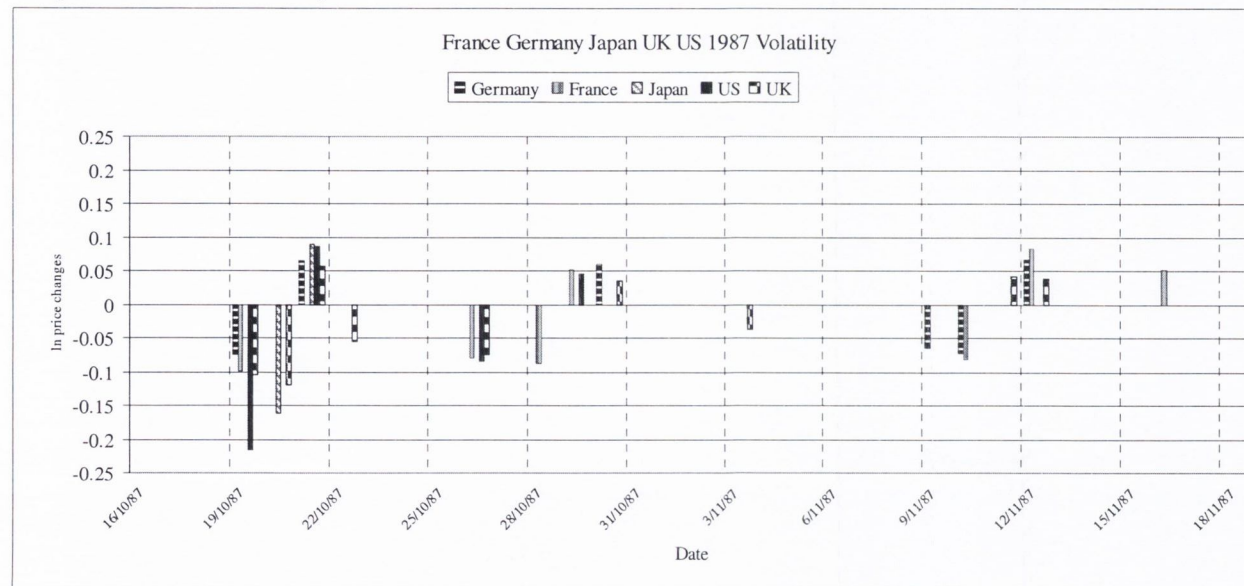


Table A.1 Ten Largest Positive and Ten Largest Negative Log Price Changes

		1	2	3	4	5	6	7	8	9	10
France	-ve ln Price Change	-0.09976	-0.08836	-0.08152	-0.08004	-0.07966	-0.07619	-0.07358	-0.0713	-0.07018	-0.06872
	Date	19/10/87	28/10/87	10/11/87	26/10/87	2/10/98	12/5/81	12/9/01	19/8/91	13/5/81	26/5/86
	+ve ln Price Change	0.207022	0.081988	0.062413	0.05991	0.058374	0.051653	0.050911	0.050506	0.045753	0.045751
	Date	2/1/98	12/11/87	13/3/78	17/1/91	29/10/97	16/11/87	29/10/87	25/9/01	12/10/98	20/3/78
Germany	-ve ln Price Change	-0.1432	-0.10521	-0.09097	-0.08125	-0.07966	-0.07408	-0.07286	-0.07229	-0.06543	-0.06495
	Date	16/10/89	19/8/91	22/9/01	28/10/97	2/10/98	19/10/87	10/11/87	4/1/00	21/9/01	9/11/87
	+ve ln Price Change	0.077503	0.066735	0.066088	0.06537	0.059774	0.05465	0.052853	0.052536	0.051737	0.051485
	Date	25/9/01	17/10/89	12/11/87	21/10/87	30/10/87	5/10/01	12/3/99	17/1/91	1/10/90	27/8/90
Italy	-ve ln Price Change	-0.14847	-0.12511	-0.09399	-0.08964	-0.0847	-0.07879	-0.07528	-0.07508	-0.07406	-0.07342
	Date	29/5/86	16/6/81	9/6/86	28/6/83	28/10/97	7/11/80	22/6/81	13/7/81	23/7/81	16/10/89
	+ve ln Price Change	0.103542	0.083033	0.075691	0.0736	0.06807	0.067347	0.064375	0.062167	0.061913	0.058524
	Date	1/2/02	27/7/81	15/7/81	24/6/81	20/10/80	30/5/86	19/11/80	29/10/97	19/1/81	28/7/81
Japan	-ve ln Price Change	-0.16135	-0.07234	-0.06864	-0.06827	-0.06135	-0.06022	-0.05957	-0.05761	-0.0543	-0.05381
	Date	20/10/87	18/4/00	13/9/01	2/4/90	19/8/91	23/8/90	8/10/98	23/1/95	19/11/97	19/12/97
	+ve ln Price Change	0.124303	0.088913	0.076605	0.075509	0.072749	0.072217	0.060787	0.060309	0.05991	0.059457
	Date	2/10/90	21/10/87	17/11/97	31/1/94	10/4/92	22/3/01	7/7/95	21/8/92	7/10/98	27/8/92
UK	-ve ln Price Change	-0.11914	-0.10399	-0.07428	-0.0551	-0.05353	-0.04781	-0.04264	-0.04147	-0.03934	-0.03705
	Date	20/10/87	19/10/87	26/10/87	22/10/87	12/9/01	28/9/81	30/11/87	16/10/89	23/3/01	3/11/87
	+ve ln Price Change	0.056976	0.056685	0.047168	0.043294	0.041213	0.037853	0.037817	0.037557	0.036588	0.035888
	Date	10/4/92	21/10/87	29/9/81	17/9/92	11/11/87	25/9/01	12/11/87	12/10/98	6/10/98	30/10/87
US	-ve ln Price Change	-0.21504	-0.11768	-0.08496	-0.08345	-0.06886	-0.06793	-0.06664	-0.06352	-0.06265	-0.05972
	Date	19/10/87	3/12/79	26/10/87	2/4/80	7/4/80	27/10/97	31/8/79	31/8/98	8/1/88	13/10/89
	+ve ln Price Change	0.144496	0.123429	0.086222	0.069852	0.057531	0.0516	0.047481	0.044796	0.044795	0.043556
	Date	8/4/80	4/12/79	21/10/87	3/9/79	23/8/82	7/10/82	17/3/00	8/9/98	29/10/87	17/8/82

Figure A3 (a) Daily Returns

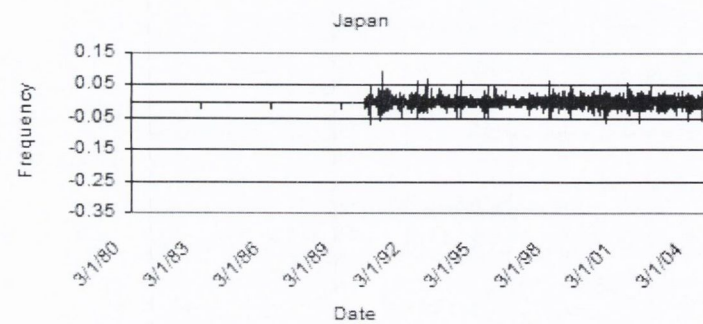
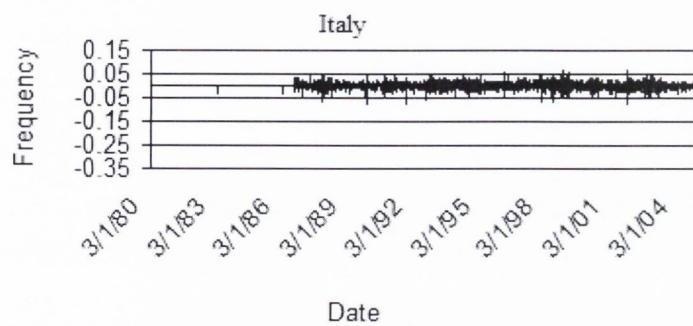
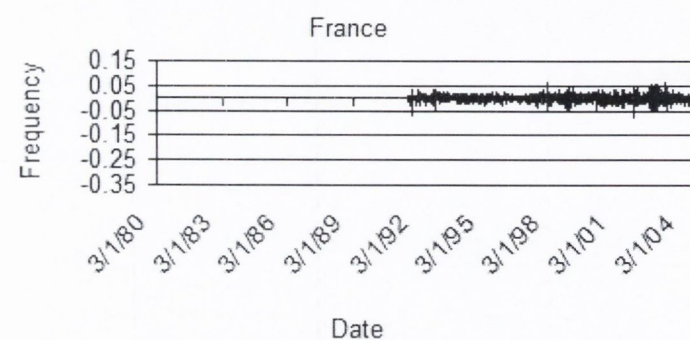
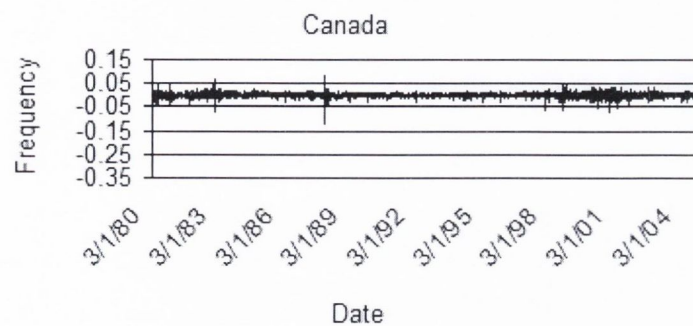
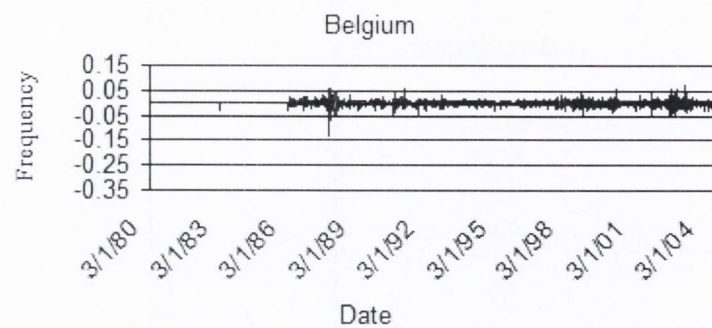
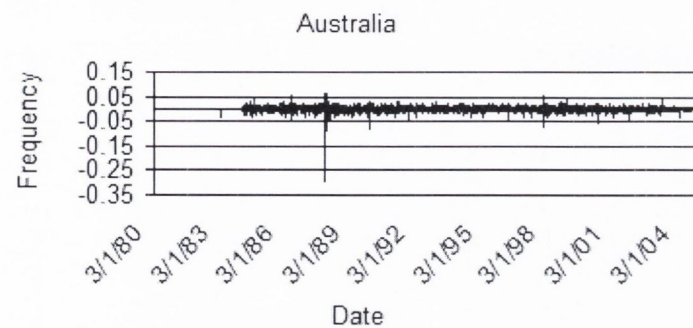


Figure A.3 (b) Daily Returns

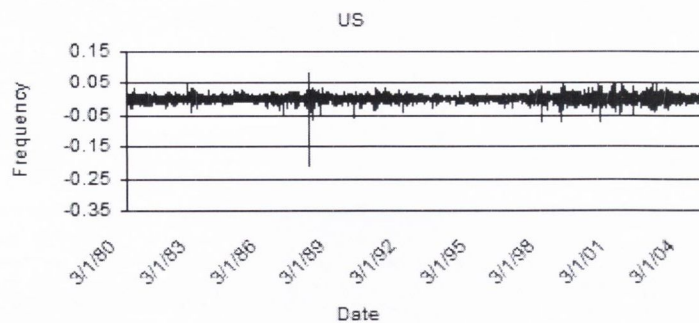
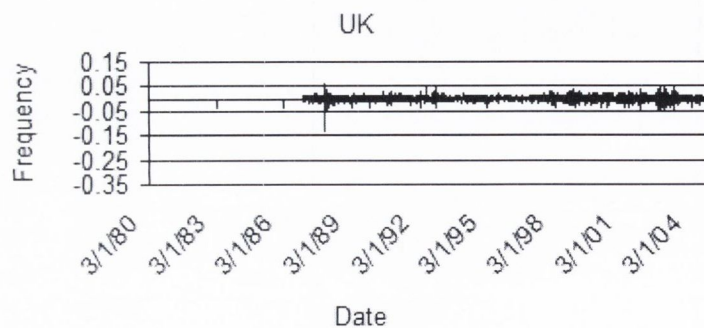
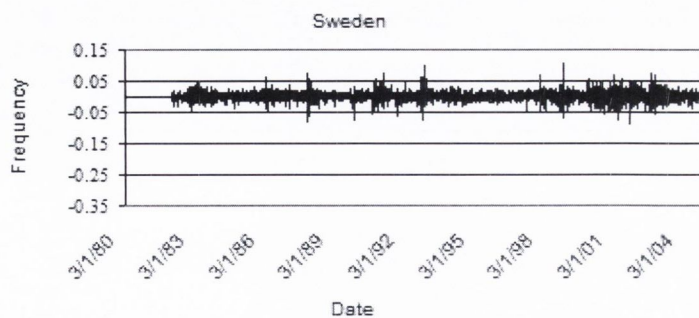
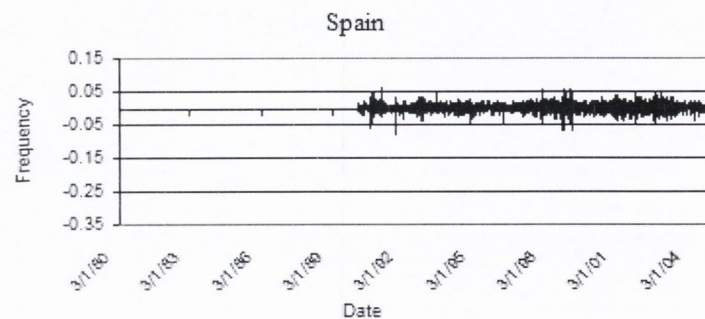
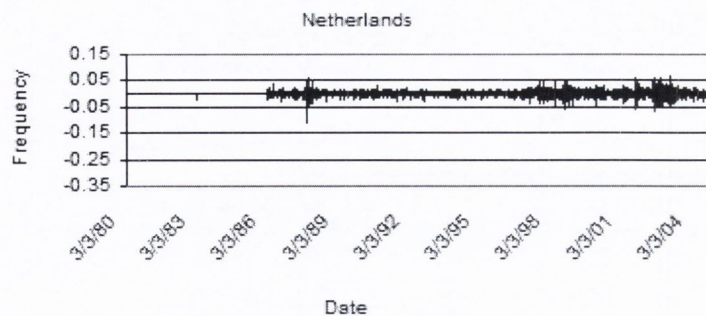


Figure A.4 (a) Daily Detrended Volumes

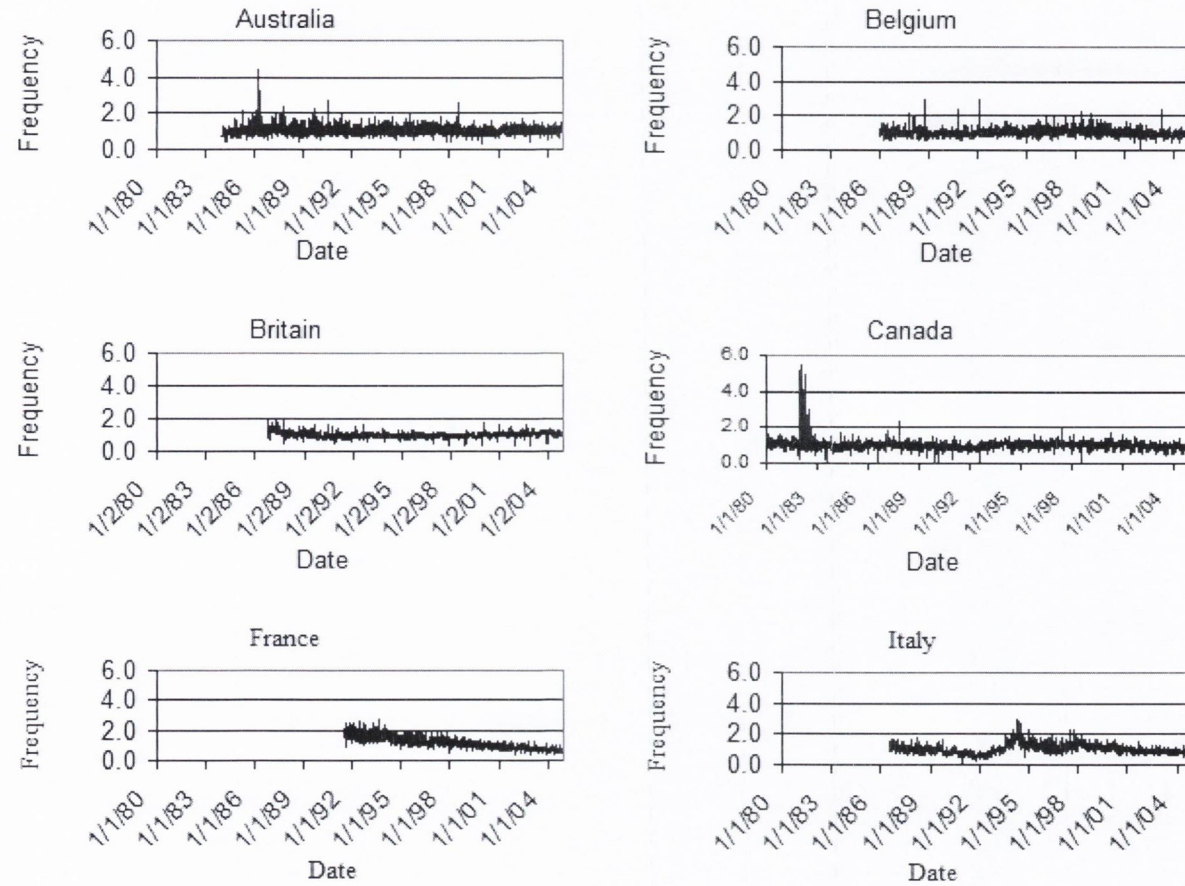


Figure A.4 (b) Daily Detrended Volumes

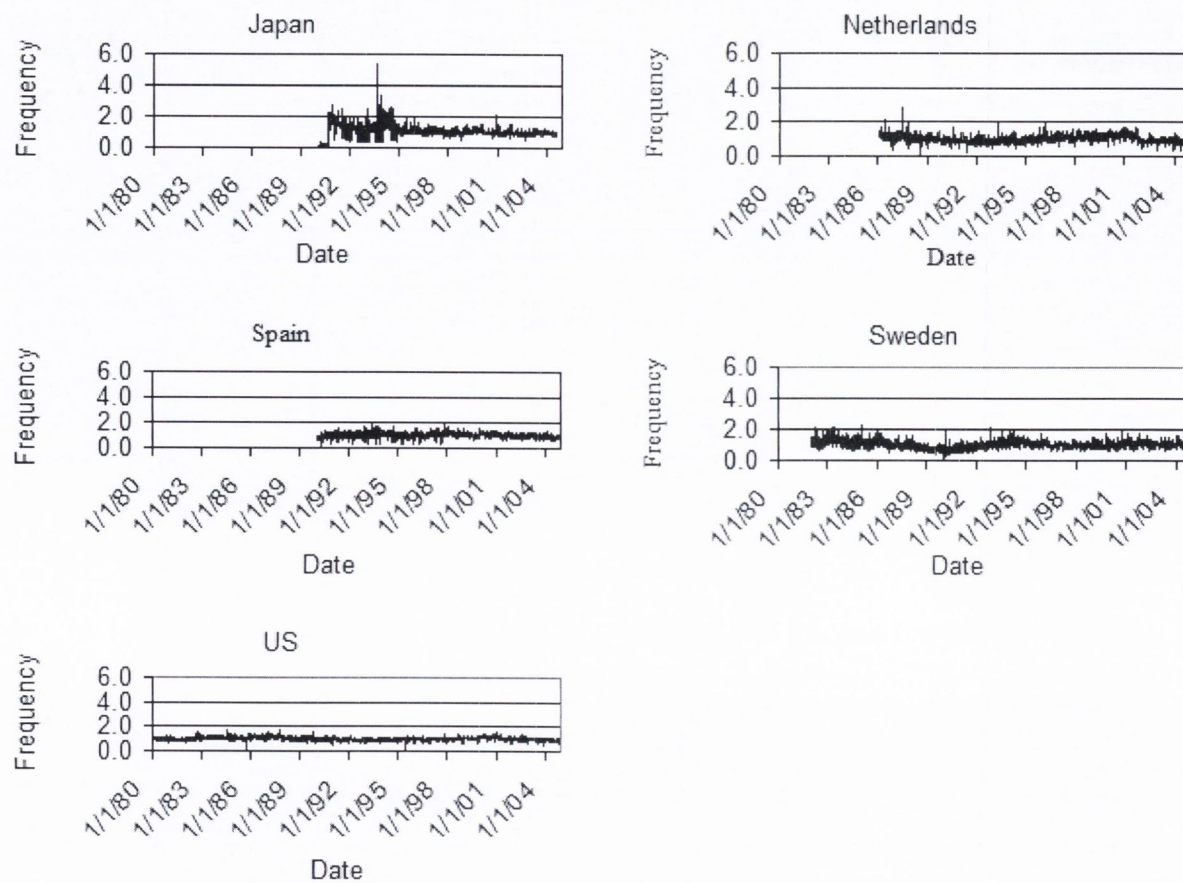


Figure A.5(a) Monthly Return Volatilities

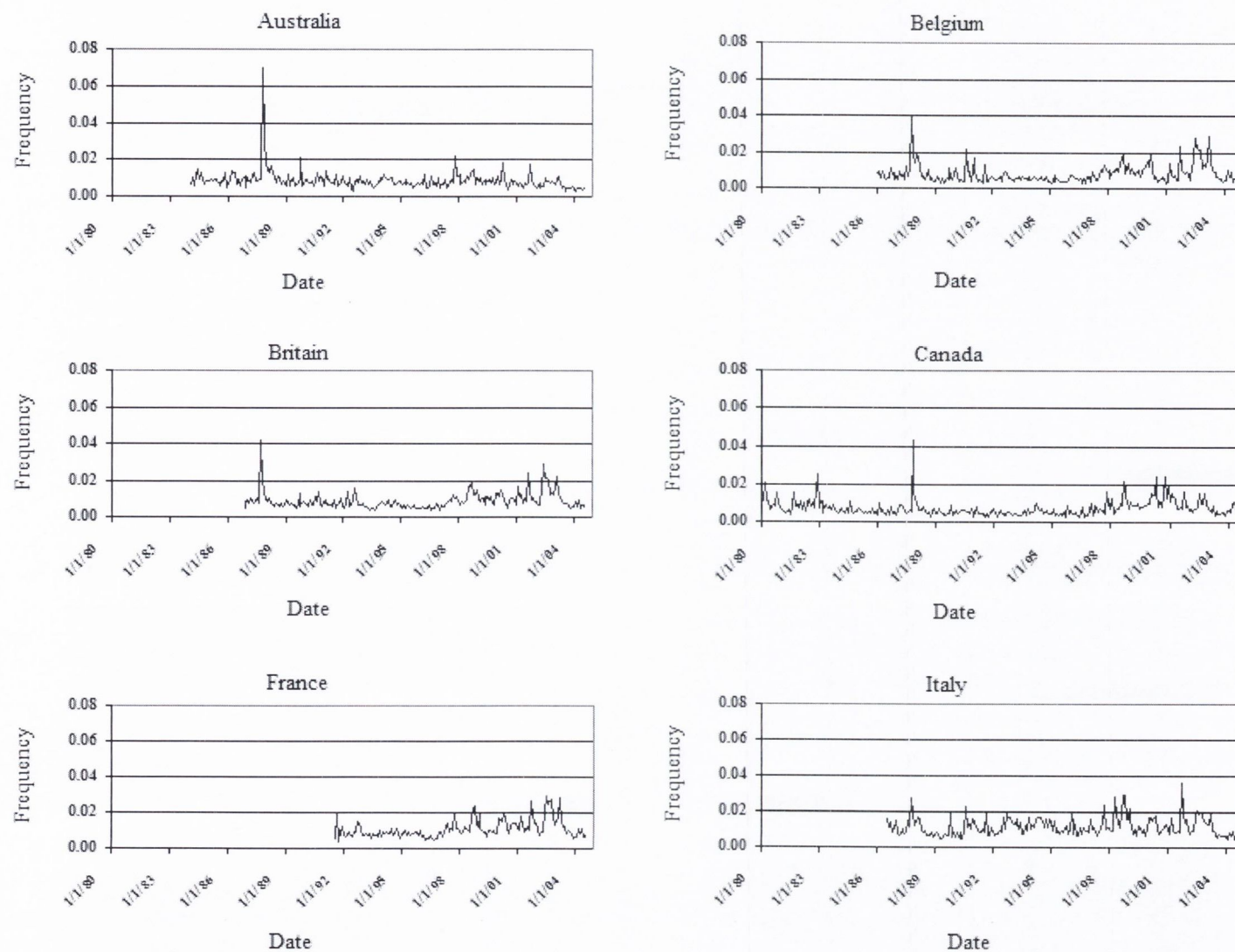


Figure A.5 (b) Monthly Return Volatilities

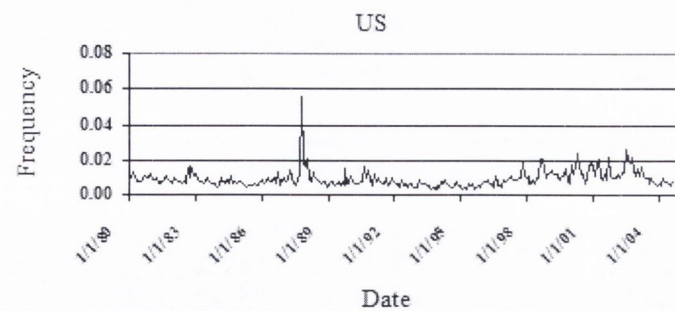
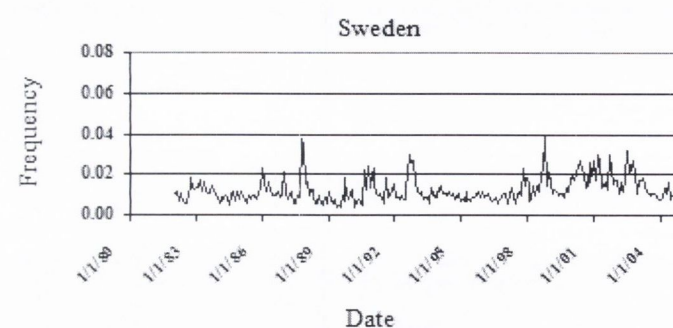
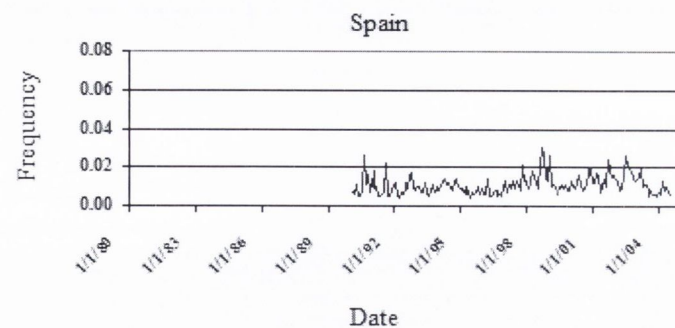
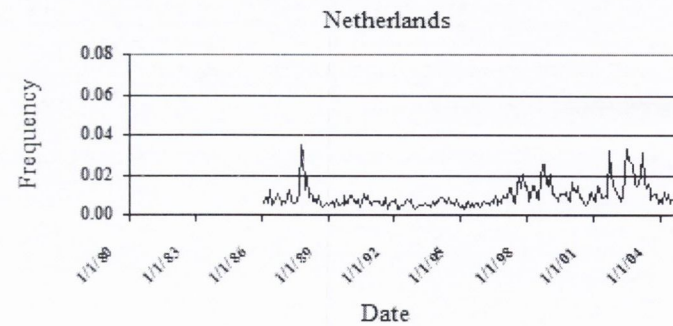
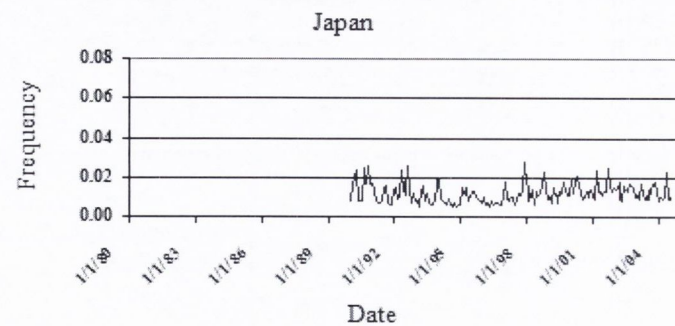


Figure A.6 (a) Volume Volatility (monthly)

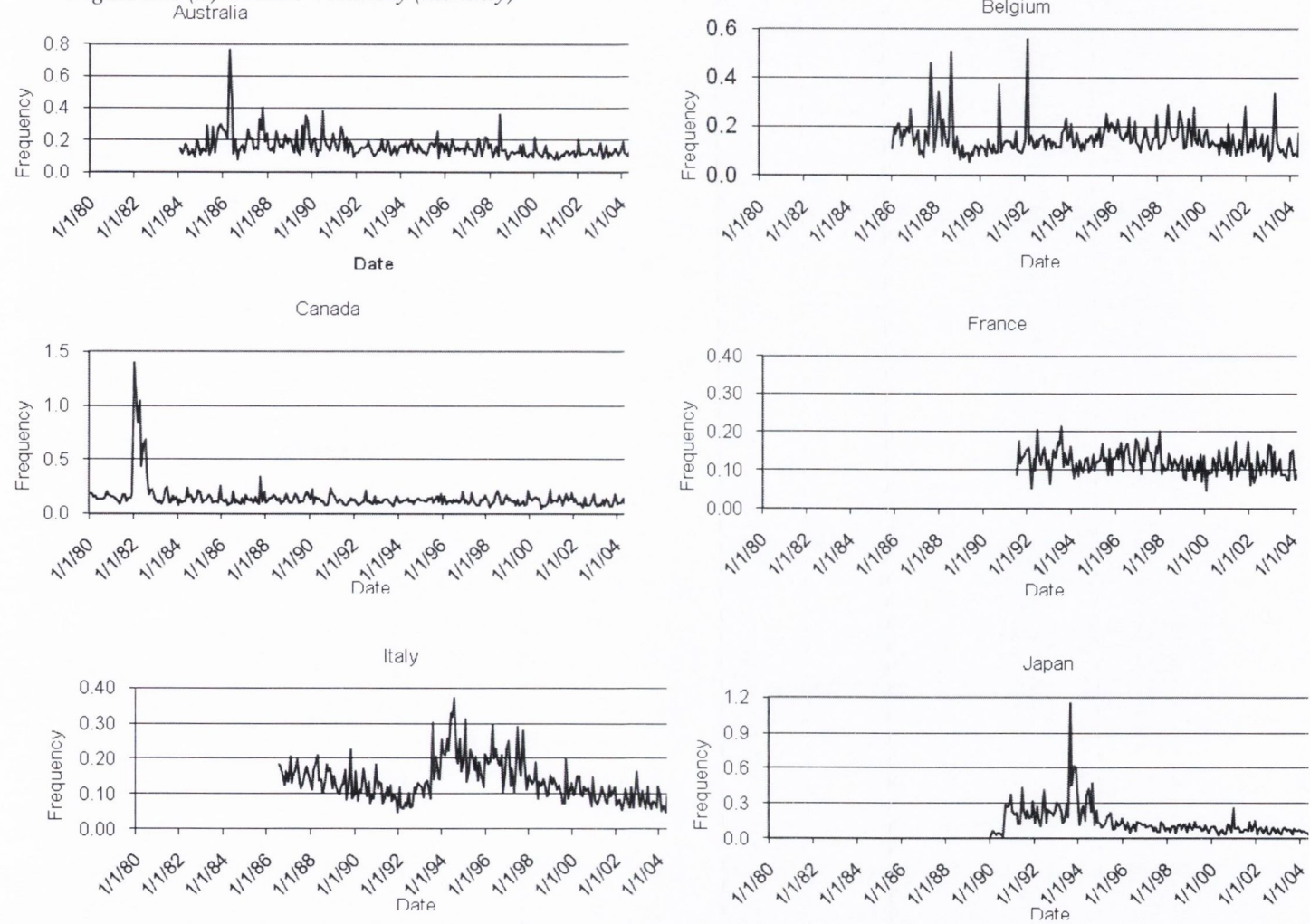


Figure A.6 (b) Volume Volatility (monthly)

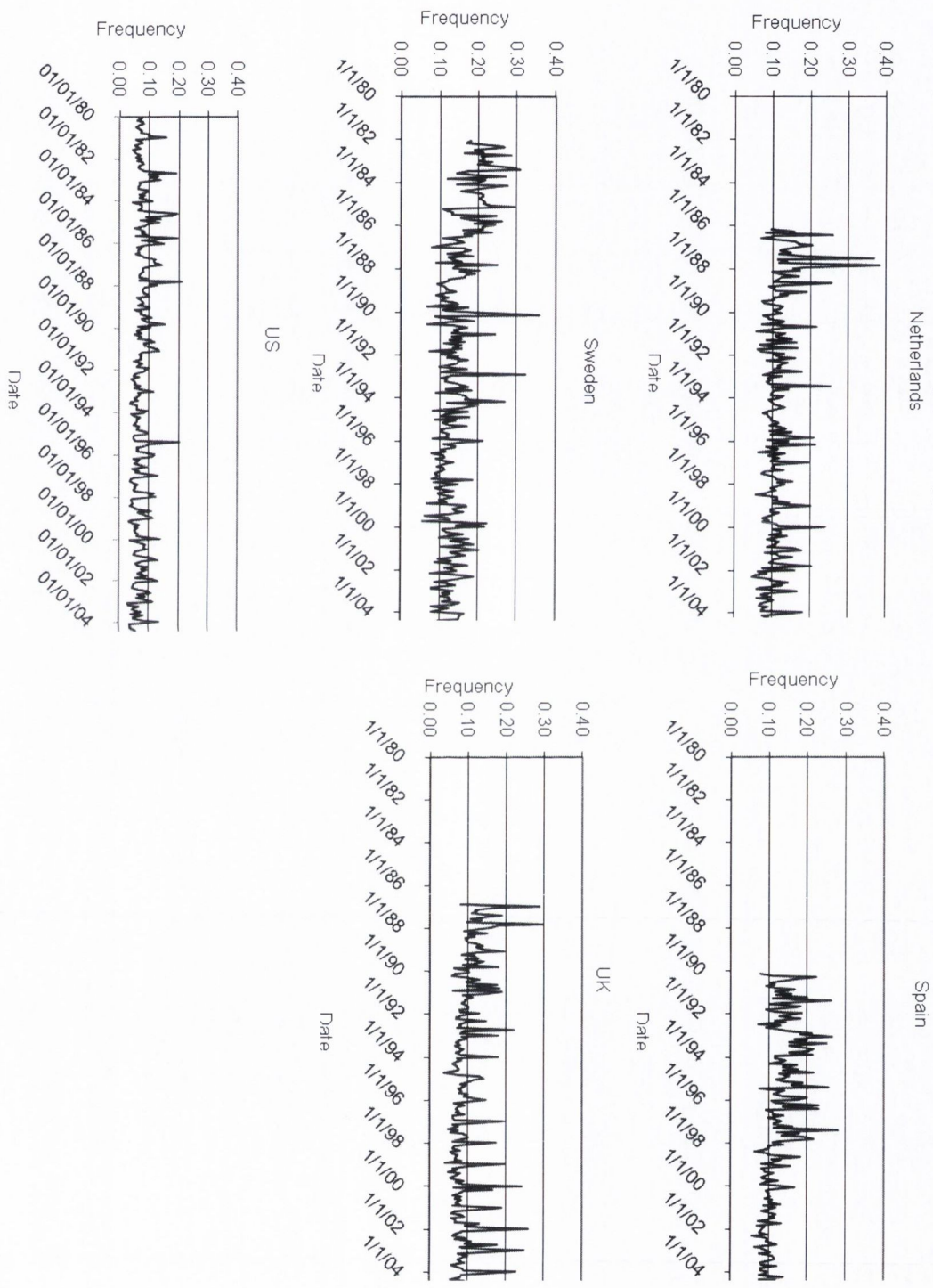


Figure A.7 (a) Monthly Volume Skewness

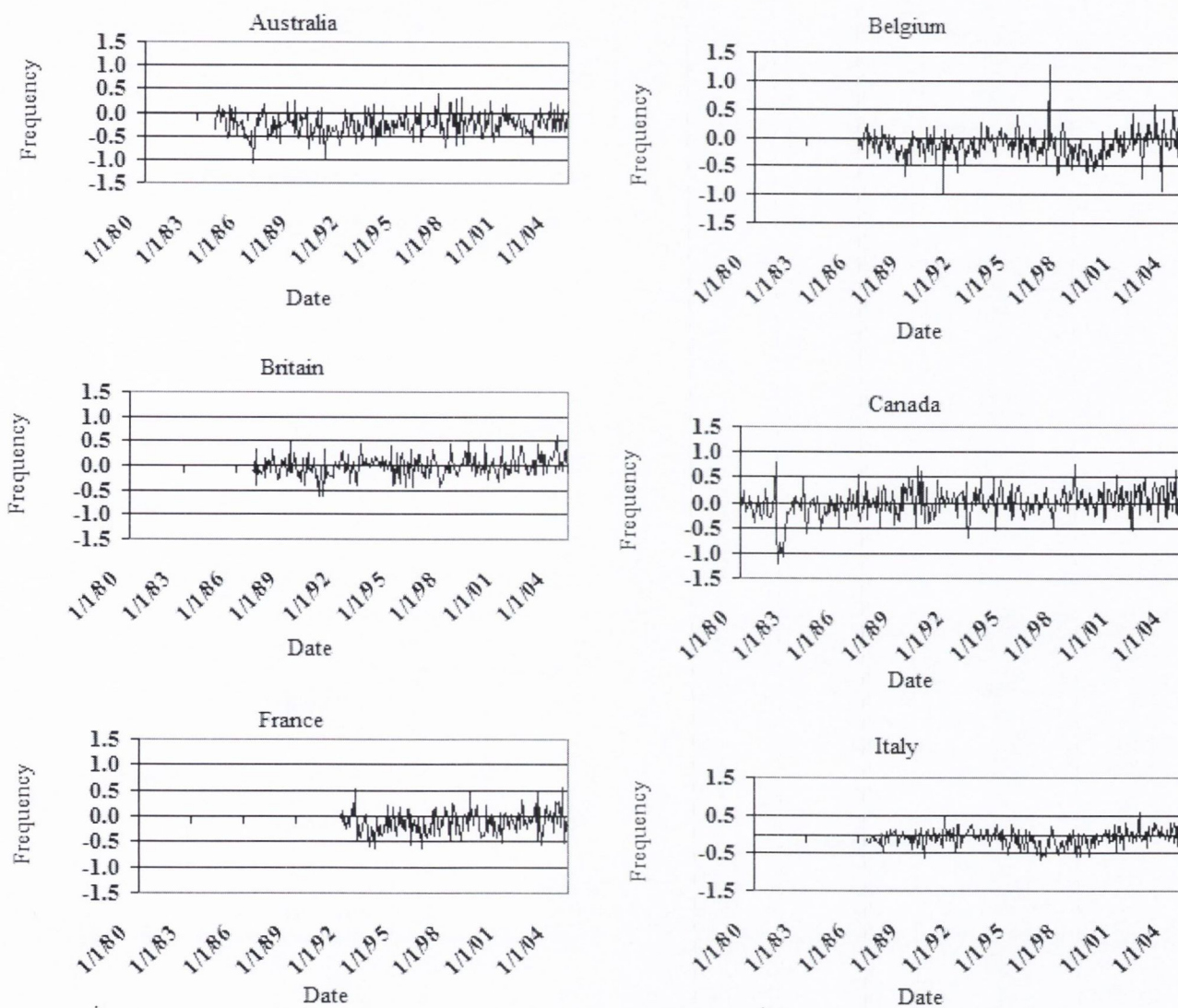
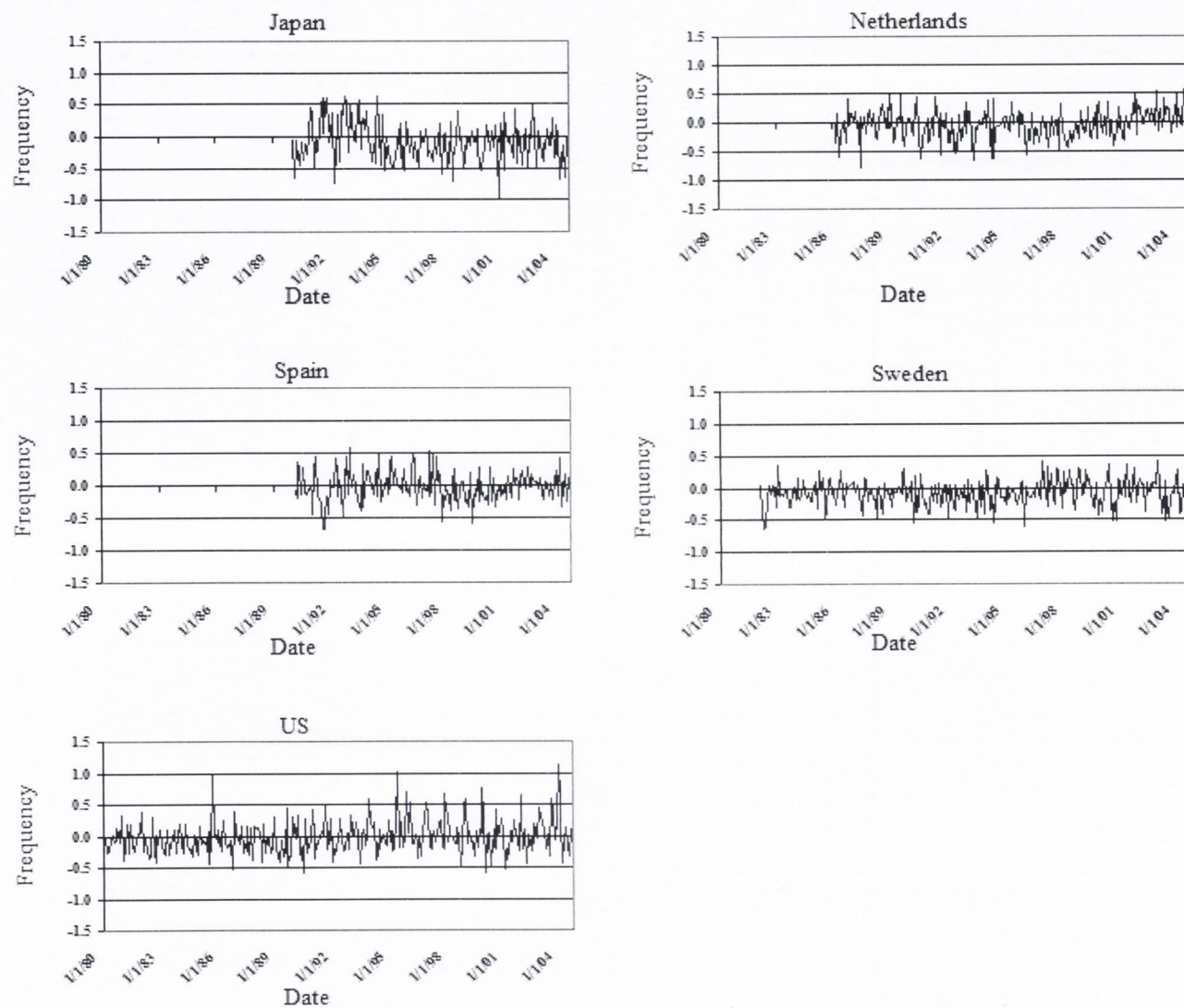


Figure A.7 (b) Monthly Volume Skewness



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