ASSESSING STOCK PRICE VOLATILITY STUDY OF G-7 AND WEST EUROPEAN MARKETS WITH EXTREME MEASURES

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A Thesis

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Abstract

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An alternative approach to examine stock market volatility based on the percentages of extreme days, weeks, and months out of a year period is applied to the G-7 group of seven countries and three other western European countries. Compared with the traditional standard deviation method, we find a similar volatility pattern for both measures. In addition, the extreme measure has three benefits: dividing volatility into positive and negative parts; classifying volatility as different levels and allowing researchers evidently to recognize the length of the volatile period for each level during a specified period; and having flexibility to self define extreme measures depending on various research requirements. When we apply the extreme-day measure to examine investor behaviors in Canada, the U.S. and the U.K., we find that the extreme-day measure more efficiently explains Canadian investor behavior than the standard deviation does.

I. Introduction

A traditional measure of stock market volatility is the standard deviation of stock returns. However, this measure has its limitations. First of all, daily stock market returns are not normally distributed, but leptokurtic, skewed, and are nonstationary with observed positive and negative autocorrelation over time. In addition, Benartzi and Thaler (1995) argue that the standard deviation metric is problematic for loss averse investors whose utility responses to stock price change are asymmetric.[1]

An alternative approach is based on extreme value theory and applies the extreme measure of volatility using the frequency of large percentage changes in daily, weekly and monthly stock price changes within annual periods (see e.g. Jones, Walker and Wilson (2004)). This approach focuses on large price changes, and, unlike the standard deviation, has a loss function that distinguishes between positive and negative components.

In this paper, we use extreme measures to study historical stock volatility in the G-7 group of seven industrialized countries: the U.S., the U.K., Germany, Canada, France, Japan, and Italy as well as three other western European countries, Switzerland, Spain,

[1] i.e., for a given stock price change in the amount x, the utility loss associated with a price decline of x exceeds the utility gain from a price increase of x.

and Netherlands, over the 20th century. These ten countries account for 84.1%[2] of the capitalization of the world stock market in the year 2000.

Our approach is to examine the distribution of the logarithmic percentage changes of daily, weekly, and monthly stock prices for each market; we classify the mild outliers as the extreme values, and calculate the percentage of extreme days, weeks, and months over a year to measure stock market volatility. Furthermore, we compare the volatility measured by the annualized geometric standard deviation of the logarithmic percentage change with the volatility proxied by the extreme measure and rank the both volatilities by a descending order. We will also relate our measures of volatility to special economic events during the past century for some markets, such as the Great Depression during 1929 to 1939, the OPEC oil shock in 1973, and the stock market crashes of 1987 and 1989, as well as the September 11, 2001 periods. In addition, for the U.K., for which we have the longest data series, we can examine volatility over the past three centuries. Finally, we apply the extreme-day measure to examine investor behavior proxied by net flows of equity mutual funds. We find that for Canada and the U.K., the extreme-day measure more efficiently explains investor behavior than the standard deviation measure does; for the U.S., investors are more concerned about the negative changes of stock

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[2] Source: Dimson, E., Marsh P., and Staunton M., 2002, *Triumph of the optimists: 101 years of global investment returns* (Princeton University Press)

price than the positive changes, while Canadian investors pay closer attention to the positive changes than the negative changes.

The paper serves to contribute to the literature on stock market volatility in a number of ways. First, we test whether or not risk inferences using the traditional standard deviation proxy are consistent with extreme measures, which offer more information about investor responses to stock price shocks, and have been subject to increased attention by academics and practitioners.

Furthermore, most of the previous literature on historical stock market volatility concentrates on either on the U.S. stocks or the U.K. stocks. Very few studies have appeared on other major industrialized or developed countries in the world. Our research will be the first to provide a detailed look at several other markets, providing a global view of market behaviour over long period. Studying the early historical records of stock price of such markets can be useful for academic researchers, as well as for analysts and investors.

The remainder of this paper is organized as follows: Section II provides a brief review of the relevant literature; Section III describes the data; summary statistics and the calculation methods of extreme measures are explained in Section IV; Section V continues with the volatility comparison between these two measures: the annualized geometric standard deviation and the percentage of extreme logarithmic changes; The application of the extreme measures for investor behavior is described in Section VI; The paper concludes with a summary in Section VII.

II. Applications of Extreme Value Theory

Measuring stock market volatility with the standard deviation of stock returns is the most common approach in the literature. This method is appropriate for return distributions that are symmetric. For example, for a normal distribution, two times the standard deviation will contain approximately 95% of the stock returns observed in a period.

However, financial analysts and investors are often concerned the remaining 5% of the distribution in the area of the tails, when performing risk analyses, such as Value at Risk (VAR). Furthermore, the standard deviation does not capture the risk to the investor when the distribution is non symmetric. Therefore, the demand for studying the distribution in the tail area results in the development of the extreme value theory. A succinct description of the extreme value theory is given by Hill (1975). In practice, Hill's estimator is the most widely used method in application of the extreme value theory.

Extreme measures not only can be divided into positive and negative components but can also efficiently utilize data. Parkinson (1980) demonstrates that, for a given accuracy in stock market volatility, using extreme measures is more efficient than using the traditional method. The extreme value method needs about 20% the data required by the traditional standard deviation to reach a specified level of accuracy. Kunitomo (1992) refines Parkinson's method and notes that the efficiency of the extreme estimator is about ten times, instead of about five times of Parkinson, in comparison with the classical estimation method when the number of observation is large.

A few major articles in the literature employ extreme value theory to study financial market volatility. Longin (1996) specifies the lowest or highest logarithmic daily return of an index of the most traded stocks on the New York Stock Exchange as the extreme values to examine the extreme price movements over the time period from 1885 through 1990. He suggests that to measure stock market volatility the extreme value method concerning the tails of the distribution may be better than the traditional standard deviation method.

Bali (2003) uses extreme value theory to analyze the volatility of extreme changes in short-term interest rates and to estimate VAR. He examines the U.S. Treasury Bills with different maturity periods from the mid 1950s through the end of 1998 and finds that the method of employing the tails of extreme value distribution is more efficient than the standard deviation approach.

Jones, Walker and Wilson (2004) use the frequency of large percentage changes in daily stock price changes within annual period to measure the volatility of two U.S. stock index series, S&P 500 and Dow Jones Industrial Average, from February 1885 through December 2002. Compared with the annualized geometric standard deviation of returns, they conclude that their extreme-day measure might be a better measure of stock market risk insofar as explaining investor behavior. In this paper, we will re-examine this conclusion using a longest data series

III. Data Description

This study collects long series of stock return from various sources. For Canada, we collect the daily and weekly closing prices of The Composite Index of the Montreal Stock Index[3] from *The Montreal Stock Exchange, Monthly Review* and *The Financial Post* beginning at March 1935 and ending at December 31, 1963. The data series of the Industrial Index of Toronto Stock Exchange are collected from *The Toronto Exchange Review* and *The Financial Post* and continue until December 31, 1976. The prices of the TSE Composite 300 Index, which we retrieved from the database of the Canadian Financial Markets Research Center (CFMRC), continue to December 31, 2004. This data series to out knowledge is the longest daily and weekly series data for Canada. Furthermore, the monthly data for Canada consisting of the return series since 1900[4] are provided by Lorne Switzer.

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[3] The Composite Index of Montreal Stock Exchange was combined by 1/3 weight of the utility stocks and 2/3 weight of the industrials.

[4] See Dimson, E., Marsh P., and Staunton M., 2002, *Triumph of the optimists: 101 years of global investment returns* (Princeton University Press), monthly data provided by Lorne Switzer.

For the U.S., we use the Dow Jones Industrial Average Index, which was obtained from the website of the Dow Jones Indices[5], was applied for the U.S. market and covered from May 26, 1896 through December 31, 2004.

All data sets of the other eight countries were provided by Global Financial Data Inc. The indices[6] and the number of observations for each country are shown in Table 1. Each market has three series of data, based on daily price, weekly price, and monthly price. The daily data have the same study period as the weekly data have for all markets except Switzerland and the U.K. having longer period of weekly data than that of their daily data. Among the three groups of data, the monthly data cover the longest period of time.

The U.K. has the earliest record starting from January 1693, already 300 years from now. The U.S., France, and Germany have their monthly records from the late of the 1800s. The data sets of other countries begin in the early 1900s.

IV. Summary Statistics and Calculation Method

A. Summary Statistics

To use the extreme measure as a proxy of stock market volatility, most researchers define the extreme value as the lowest or the highest daily return of a stock

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[5] The link of the website is: http://www.djindexes.com/mdsidx/index.cfm?event=showAverages

[6] For the detail description of these indices, please refer to the website of Global Financial Data Inc. : http://www.globalfindata.com

market index observed over a given period, for example, Longin (1996). We follow Jones, Walker and Wilson (2004) using the logarithmic percentage change (*L%*) of stock index closing price to measure the movement of stock price. The equation is as follows:

$$L\% = 100 \times \ln[P(t)/P(t-1)]. \tag{1}$$

This logarithmic measure divides volatility into two components: positive and negative. In contrast to Jones, Walker and Wilson (2004), we apply this measure not only to daily prices but also to weekly and monthly prices. The percentage of extreme days, weeks or months during a given annual period will represent the stock market volatility. We report the summary statistics of logarithmic percentage changes for each country in Table 2, where Panel A, B, and C present the statistics for daily data, weekly data, and monthly data separately. The data series used in Table 2 cover different periods for each country.

The statistics of daily data show that Netherlands has the highest arithmetic means of the logarithmic percentage returns, 0.035 *L%*, and Germany has the least one, 0.0168 *L%* during their study periods. Expressed in the annualized geometric mean based on 252 trading days, those logarithmic returns present the average annual return of 9.22% and 4.32% respectively. The equation transferring the arithmetic mean to the annualized geometric mean is:

$$AnnualizedGeoMean = \left\{ \left[EXP\left(\frac{1}{T} \sum_{t=1}^{T} L_t \right) \right]^{T} - 1 \right\} \times 100\% = \left[\frac{P_T}{P_1} - 1 \right] \times 100\% \tag{2}$$

The equation indicates that the annualized daily geometric mean is equal to the total percentage change in index prices for the year. All the markets are negatively skewed and leptokurtic, especially for Canada and the U.S., who have the largest and the second largest kurtosis, 29.8358 and 20.9110; in other words, the distribution of logarithmic changes of Canada and the U.S. have fatter tails and are less evenly distributed around the mean.

For the weekly data, each market has a lower kurtosis compared with that of the daily data except for the U.K., whose kurtosis is 8.9983, instead of 7.9952 for the daily data. The possible reason for lower kurtosis is that less of the variance of the logarithmic changes of weekly closing prices is due to infrequent extreme deviations, and it causes not so wide tails as the daily data have.

Since the monthly data cover a longer period of time than the daily and weekly data, the statistics for monthly data show a different distribution from the daily and the weekly. Canada, Netherlands, Spain, Switzerland, the U.K., and the U.S. are still left-skewed, but France, Germany, Italy, and Japan become right-skewed. The U.K. has the highest kurtosis of 55.9397, since the monthly data of the U.K. cover more than 300 years and reflect many significant events in the history with the extreme changes of stock price. From the point of statistical view, the distribution of the stock price change of the U.K. has more extreme values that result in fatter tails during the past 300 years. The country with the second largest kurtosis of 24.0047 is Germany, and the third largest is

France with the kurtosis of 14.7917. The kurtosis values of Canada and the U.S. shrink a lot from the daily data and are reduced to 4.4481 and 7.1134 respectively.

In addition to reporting the first, second, and third moments, we also use Jarque-Bera normality test to examine whether the distribution of the logarithmic change of stock price is normally distributed. The large values of Jarque-Bera and zero of p-values for all three series are reported in Table 2, and we reject the null hypothesis of normal distribution at the 5% level.

Since the statistics in Table 2 are based on the data series covering various time periods, the results may reduce the comparability among the markets. Thus, we also report the statistics based on the data series covering the same time periods in Table 3, 4, 5, 6, and 7. Table 3 compares the statistics of the daily and weekly data staring from March 1st, 1935 between Canada and the U.S. For either the daily or weekly data, the U.S. has a higher mean than Canada, and it suggests that the stock market return of the U.S. is higher than that of Canada. The higher values of the standard deviation of the U.S. also show the U.S. stock market more volatile. Table 3 also shows that the U.S. market is more negatively skewed and leptokurtic than Canadian market.

Table 4 compares the statistics of the daily and weekly data beginning at January 2nd, 1970 for the G-7 countries. For daily data, the U.K. has the highest logarithmic return and Germany has the least one. Italy has the largest value of the standard deviation among the G-7 countries, but Canada has the least one. The statistics of the weekly data shows the same natures as the daily statistics. Furthermore, all markets are left-skewed and leptokurtic.

Table 5 compares the statistics of the monthly data beginning at January 1st, 1900 for Canada, France, Germany, the U.K., and the U.S. France has the largest log return, but Germany has the least return. For the standard deviation, Germany has the largest value, but Canada has the least value. Finally, we compare the statistics of the monthly data beginning at February 2nd, 1914 for the G-7 countries in Table 7. The same conclusion as Table 6 is drawn: Germany has the least return but has the largest value of the standard deviation; France has the largest return, and Canada has the least value of the standard deviation.

In summary, all the tables above show that some common properties of the percentage logarithmic changes of stock prices are very apparent. The distribution is not normally distributed and tends to skewed and leptokurtic. In addition, the distribution has very long tails resulting from extremely large positive or negative logarithmic changes of stock price. When the study period is extended, the distributions of some markets exhibit more leptokurtic with higher kurtosis.

B. GARCH Test

In addition to report the regular statistics, we also test the daily, weekly, and monthly data for GARCH effects on the 1st, 4th, and 10th lagged values of the squared residuals. We report the values of the Chi-square for all the GARCH (1), GARCH (4), and GARCH (10) in Table 7, 8, 9, 10, and 11 by country and time period. Moreover, we use the GJR GARCH (Glosten, et. al. (1993)) model to test for the asymmetric behavior of the logarithmic returns. For a GARCH (1, 1), the GJR variance model is:

$$h_t = a + bu_{t-1}^2 + ch_{t-1} + du_{t-1}^2 I_{u>0}(u_{t-1}) \tag{3}$$

where I is an indicator function, in this case, for $u>0$. If d is negative, we can conclude that negative residuals tend to increase the variance more than positive residuals; in another words, asymmetric effects are observed.

In Table 7, we can observe GARCH effects at a statistical significance level of 5% on all these three series of data due to the large chi-square values. For the coefficient of asymmetric term, d, all countries show asymmetric behaviours for the daily data. Italy has a positive coefficient of term d for both the weekly and monthly data and does not show asymmetric effects. In addition, Canada, Spain, and the U.K. also do not have asymmetric effects on the monthly data.

In table 8, we report GARCH results for Canada and the U.S. on the daily and weekly data beginning at March 1st, 1935. We can easily recognize GARCH and asymmetric effects for these data series. Further, GARCH results listed in Table 9 for the G-7 countries with the daily and weekly data starting from January 2nd, 1970 are similar to other tables, except for France, which has zero value of term d.

Table 10 reports GARCH results for Canada, France, Germany, the U.K., and the U.S. with the monthly data beginning at January 1st, 1900. In addition to that we observe

GARCH effects for all these five countries, we does not find asymmetric effects for Canada and Germany. Finally, Table 11 reports GARCH results for all the G-7 countries with the monthly data beginning at February 2^{nd}, 1914. They all have GARCH effects, but only Canada, Japan, and the U.S. show asymmetric effects; amongst, the result of Canada is significant at a 5% level.

In sum, we find GARCH effects on all three series of data for all these ten countries. Most of data series show asymmetric behaviours, but we do not find asymmetric effects for some countries when we use weekly or monthly data.

C. Classifying Extremes

Unlike Jones, Walker and Wilson (2004) who referred to the statistical distribution of logarithmic percentage changes and arbitrarily assigned the distribution percentiles 5% and 95% as the cutoff points to distinguish extreme values, we use outliers that are far away from the rest of the data as the extreme values. There are two types of outlier in statistics. One is the mild outlier, the observations of which are less than the difference between the lower quartile (Q1) and the value of 1.5 times the interquartile range (IQR), known as the lower inner fence, or greater than the sum of the upper quartile (Q3) and the value of 1.5 times of the interquartile range (IQR), known as the upper inner fence. Expressed with equation, it is:

$$\textit{The Mid Outlier} < Q1 - 1.5 \times IQR, \text{ or } \textit{The Mid Outlier} > Q3 + 1.5 \times IQR \qquad (4)$$

where IQR is the difference between the higher quartile and the lower quartile, expressed in equation: Q3 - Q1.

The other is the extreme outlier, whose observations are less than the difference between the lower quartile (Q1) and the value of 3 times of the interquartile range (IQR), known as the lower outer fence, or greater than the sum of the upper quartile (Q3) and the value of 3 times of the interquartile range (IQR), known as the upper outer fence. The equation is:

$$\textit{The Extreme Outlier} < Q1 - 3 \times IQR, \textit{ or The Extreme Outlier} > Q3 + 3 \times IQR \qquad (5)$$

The percentage of outliers during a given annual period presents the volatility for that year. The volatility function is:

$$\textit{Percentage of Extremes} = \textit{No. of Outliers / Annual Trading Days (Weeks or Months)} \qquad (6)$$

Using the daily data of the U.S. as an example, we can see the difference of employing the mild outlier and the extreme outlier to classify extreme logarithmic changes. Figure 1 and Figure 2 illustrate the whole percentage of extreme days within a year with the classifying method of mild outliers and extreme outliers respectively. Figure 3 and Figure 4 illustrate the divided positive and negative percentage with the both methods.

The extreme values in Figure 3 are same as the values in Figure 1; as a result, the bars that present the extreme values in these two figures for a specific year have the equal length. The difference is merely the pattern that the whole percentage of extreme days in Figure 1 is divided into the percentage of positive extreme days and the percentage of negative extreme days in Figure 3. The same holds for Figure 2 and Figure 4. Compared with Figure 1 and 3, Figure 2 and 4 keep these extreme outliers but filter out the mild outliers and other observations. Therefore, the method of the mild outlier contains more information for us than that of the extreme outlier does. Since both classification methods illustrate the same trend, we use inner fences to classify extreme values in the following part.

D. Annualizing Geometric Standard Deviations

To measure the volatility of stock markets with standard deviation, we employ the annualized geometric standard deviations of the logarithmic percent changes over the study period for each index. The annualized geometric standard deviation is calculated by measuring the arithmetic standard deviation of the logarithmic changes, transforming to the annualized standard deviation from daily, weekly or monthly measure, and exponentiating for conversion into geometric standard deviation. The equation is below:

$$AnnualizedGeoStd = EXP[\sigma(L\%) \times \sqrt{T}\,] - 1 \qquad (7)$$

where T is the number of effective trading days (about 252 days), weeks (about 52 weeks), or months (12 months) during a year period.

Figure 5 shows the annualized geometric standard deviation of the U.S. daily logarithmic percentage change. The horizontal lines in the figure are drawn for reference at the median value of 15.7688% and the lower and upper quartile values of 11.7173% and 20.7264%, respectively.

V. Comparing Volatilities

In this section, we compare the volatility as measured by the annualized geometric standard deviation and the volatility as measured by the percentage of extreme days, weeks, or months by country. Meanwhile, we can also examine the different patterns of the volatility using extreme measures with various series of stock prices: daily, weekly, and monthly. In addition, the volatility comparison of each stock market over the 20^{th} century can be shown in either the standard deviation measure or the extreme measure.

A. Canada (1900-2004)

Figure 8 and Figure 9 provide the comparisons between the volatility measured by the annualized standard deviations and the volatility measured by the percentage of extremes using the daily and weekly data of Canada from 1935 to 2004, respectively. Figure 10 provides the comparison using the monthly data from 1900 to 2004. Moreover, we select the highest 25 years of volatility for both measures, rank them in descending order, and report the rankings of daily data on the left side of Table 12, weekly data in the middle of the table, and monthly data on the right side of the table.

For daily data, the similar patterns for Figure 8(a) and 6(b) give support for the extreme measure is an alternative approach to analyze the volatility of stock market. Figure 8(a) graphs the largest and the second largest values of the standard deviation in 1940 at 35.5315% and in 1938 at 33.2183% around the period of the Great Depression (1929-1939) and its aftermath. The year 2000, when the technology bubble burst, occupies the next position at 30.4339%, and 1937 ranks 4th with a value of 28.4642%. The fifth largest value is 26.9211% in 1987, when global stock markets crashed. Then, the year 1998 ranks 7th with a value of 21.7819%, 2001 ranks 8th, and 2002 ranks 11th. In the years of 1980, 1981, and 1982, when the world's major economies were recovered, the values of volatility for these years are 20.5743%, 15.8276%, and 18.8640% and take the 9th, 14th, and 10th position, respectively. The year 1974, in which the stock market was influenced by the OPEC oil crisis, ranks 12th with a value of 16.4605%.

A little different from the rank of the standard deviation measure, the year 2000 has the largest percentage of extreme days of 32.6693%, which presents 82 extreme days out of 251 trading days, 43 negative and 39 positive, instead of the third rank position provided by the standard deviation measure. The year 1938 takes the second position with 21.1921% of extreme days, same as the rank position using the standard deviation. The ranking for 1940 with the extreme measure is 14th instead of the first with the other measure. Applying the percentage of extreme days, 1998 ranks 4th, 2001 ranks 6th, 2002 ranks 9th, and 1987 ranks 11th, compare with the rankings of 7th, 8th, 11th, and 5th, respectively, when employing the traditional measure. The Spearman rank correlation coefficients are given in Table 13. The Spearman coefficient of the daily data of Canada is 0.9256, which shows a higher rank correlation between these two measures.

In addition to using the daily data of Canada to compare the two approaches for the market volatility, we also apply the weekly data and the monthly data. Figure 9(a) reports a time series of the annualized geometric standard deviation of weekly data. The year 1940 still keep the first position of the ranking with the value of 33.0241%, but 2000 becomes the second instead of the third in the rank of daily data. The rankings for 1998, 1987, 1982, and 1974 are 5th, 6th, 8th, and 9th, respectively, relative to the rankings of 7th, 5th, 10th, and 12th using the daily data. Although the rankings of the weekly data are different from that of the daily data in some years, both Figure 8(a) and Figure 9(a) apparently depict all those volatile periods mentioned above and come to an agreement on the volatility rank order from high to low for the following historical events: the period of 1937 to 1940 (the Great Depression), 1998 to 2000 (the Dot-com bubble), 1987 (the stock market panic), 1980 to 1982 (major economies recovery), and 1974 (the OPEC oil shock).

In contrast, Figure 9(b) shows that 1938 has the longest bar with the percentage of 26.9231%, which means there were 14 volatile weeks in 1938, 7 positive and 7 negative, out of the 52 trading weeks. The ranks from the percentage of extreme weeks for these volatile periods in a declining volatility order are: the end of period the Great Depression, the period of the technology bubble, the OPEC oil shock, the economic recovery of the early 1980s, and the stock market panic in 1987. Finally, the Spearman coefficient shown in Table 13 is 0.8896, less than the coefficient of daily data of 0.9256, and shows that the rankings using the weekly data are less correlated than the rankings using the daily data.

We notice that the lower quartile in Figure 9(b) is zero, the median is 1.9231%, which indicates exactly one week out of 52 weeks, and the upper quartile is 5.7692%, which indicates three weeks out of 52 trading weeks. Therefore, the weekly extreme chart provides more easily understood information than the standard deviation chart. We can easily recognize that there are one fourth of the 70 years from 1935 through 2004, or 17.5 years, during each of which there are three weeks or more having the extreme percentage changes of stock price. This feature can give researchers more information about how long the volatile period lasts during a specified period.

Finally, we use the monthly data to examine the applications of these two measures. Since the monthly data start from 1900 and have a longer period than either the daily or the weekly data, we can observe the volatility before 1935. Figure 10 (a) and Table 12 indicate that the most volatile period is around the Great Depression. The years 1929-1933 rank 5th, 10th, 3rd, 1st, and 2nd and have the standard deviations of 36.0705%, 25.5856%, 36.9807, 47.0987%, and 39.0402%, respectively. In addition, the year 1987 of the stock market crash ranks 4^{th}; 1998 and 2000 during the period of the dot com bubble burst rank 6^{th} and 14^{th} respectively; 1980 and 1982 during the economy recovery rank 7^{th} and 8^{th} respectively; and 1974 of the OPEC oil crisis ranks 15^{th}.

Readers may recognize that the differences of the volatility ranks also exist among the ranks of the standard deviation using various types of data. We combine the annualized geometric standard deviations from the daily, weekly, and monthly data in Figure 11 with a joint line for each time series. The bold line presents the standard deviation calculated by the daily data, and the dotted line and the non-bold line present the weekly and monthly data, respectively. The three lines have a similar trend except for a few years, for example, 1964 and 2000, and make a volatility area with a lower bound produced by the daily volatility line and an upper bound produced by the monthly volatility line. The weekly volatility line usually moves within the area, but it can be higher than the upper bound, for instance, in 1974 and 2000, and lower than the lower bound, for instance, in 2001.

The reason is that we use the logarithmic percentage changes of stock price from day to day, week to week, or month to month to calculate the annualized geometric standard deviation. Normally, the price gap from week to week is greater than the gap from day to day, and the monthly price change is greater than the other two. Thus, the annualized geometric standard deviation of monthly data has the largest value, then the weekly data, and the lowest value is for daily data. However, if the price of a stock changes a lot during the first week in a month but comes back during the following three weeks, the logarithmic percentage change of the first week will be greater than the percentage change for that month. That is why the weekly volatility line exceeds the monthly line in 1974 and 2000. The same reason fits the situation that daily volatility line can be lower than weekly volatility line.

To continue with the extreme measure of monthly data, Figure 10(b) illustrates a simpler chart than the daily and weekly charts with a zero value for both the lower quartile and the median, and Table 12 shows that there are only six volatility levels measured as the percentage of extreme months: 41.4447%, 33.3333%, 25%, 16.6667%, 8.3333%, and 0, which represent volatile periods for five months, four months, three months, two months, one month, and zero out of total 12 months a year, respectively. The extreme measure has the same result as the other measure that the most volatile period occurred during the Great Depression and indicates that there are five volatile months in each year of 1931, 1932, and 1933, four months in 1929, and three months in 1930. Different from the ranking of the standard deviation, the ranking of the extreme measure shows that the year 1982 has a larger extreme value of 33.3333% meaning four volatile months, 1974 and 2000 have the same extreme value of 25%, 1998 has a value of 16.6667%, and 1987 has an extreme value of 8.3333%. Compared with the daily and weekly extreme measures, the monthly measure classifies volatility into several levels and filters out much more noise, but the monthly logarithmic percentage also ignores those less volatile years. The Spearman coefficient is 0.7870, even less than the coefficient of the weekly data.

In summary, with 70 years of daily and weekly and 105 years of monthly stock price records of Canada, we compare not only the volatilities as measured by the annualized geometric standard deviation and by the percentage of extreme intervals but also the volatilities as represented by daily, weekly, and monthly closing prices in the both methods. The comparison shows that the daily and weekly extreme measures have a similar volatility pattern as the standard deviation measure. The higher Spearman coefficient for the daily data also shows that the volatility rankings of these two measures closely correspond. Therefore, the extreme measure of the logarithmic percentage change is an effective alternative measure to analyze volatility. Furthermore, the extreme measure provides more information about volatility, not only for the division of positive and negative components but also for the ease to distinguish the length of volatile periods during a specified time period.

B. The United States (1896-2004)

The data of the U.S. are available from May 26, 1896. In Section IV, we use the daily data as an example and report the annualized geometric standard deviation in Figure 5, the percentage of extreme days in Figure 1, and the divided components of the percentage of extreme days in Figure 3. Table 14 reports the rankings of the highest 25 years for each measure.

Figure 5 illustrates that the most volatile period is from 1929 to 1933, and the highest standard deviation is 69.8022% in 1932. The year 1987 exhibits the second-volatile period with the value of 44.1090%. The period of 2000 through 2002 stands out as the third-volatile period and is followed by the aftermath of the depression of 1893 (1896 to 1899), the banking panic in 1907, involving in World War I from 1917, and the OPEC oil shock in 1973 and 1974. In the ranking of the extreme measure, the Great Depression still retains the largest volatility position. The year 1896 ranks 4th instead of 12th in the rank of the standard deviation measure, in part because the U.S. data start from May 26, 1896. In 1896 there are only 153 daily observations, instead of about 252 observations a year and the reduced denominator causes the percentage of extreme days for this year to become larger when we do the calculation with equation (5). In addition, the year 1987 is second to 2002 and changes to 9th from 5th, and 1974 and 1907 rank 11th and 12th, respectively, instead of 14th and 11th in the rank of the standard deviation. The Spearman coefficient of the daily data is 0.9686, compared with 0.9256 of Canada.

The weekly and monthly figures of the U.S. market are showed by Figure 6 and Figure 7.

C. United Kingdom (1693-2004)

The monthly data of the U.K. cover the longest time period in our study for more than 300 years; thus, we will pay a close attention to the results from the monthly data.

Since the daily and weekly data start from January 1965 and December 1968 and cover shorter periods, we will not discuss these results.

Figure 12(a) illustrates the annualized geometric standard deviation. Since the South Sea Bubble in 1720 caused an extremely high standard deviation of 204.51% for this year, the volatility trends of other years become less evident. Therefore, we plot another graph using logarithmic scale for the vertical axis, as shown by Figure 12(b). The second largest volatile period is around 1824 and 1825 with values of 38.135% and 91.416%, known as the panic of 1825. The OPEC oil shock makes the third greatest volatile period in the U.K. history from 1974 to 1975, which rank 6th and 3rd, respectively, with values of 65.583% and 38.534%. Then, the stock market panic in 1987 takes the fourth with 48.482% of the standard deviation. The first year, 1940, after the period of the Great Depression from 1929 to 1939 occupies the next position with a value of 39.806%. After that, The first stock market boom in London stock market during the 1690s makes the years of 1701, 1696, and 1694 more volatile with standard deviations of 37.130%, 37.057%, and 36.289%, respectively. The years of 2001 and 2002, during the technology bubble burst, are not as volatile as the above events above for the U.K. market and rank 46th and 21st with values of 17.099% and 22.842, respectively.

The extreme measure shown by Figure 12(c) appears to have an advantage analyzing market volatility covering longer time periods, since the extreme graph can filter out noise and highlight those volatile years. Unlike the standard deviation measure, the year 1720 ranks second with the extreme measure with 66.6667% of extreme months out of total 12 months a year; in another words, the value means that there were eight volatile months during 1720. The year 1825 ranks first with a value of 83.333%, 10 volatile months in 1825 caused by the panic. The longest negative bar of 1825 in Figure 12(d) reflects eight months of declining stock prices. The years of 1696 and 1974 have the same extreme value of 58.333%, which means a seven-month for a volatile market. From the left side of Table 15, we can see that there are six years, in each of which there are six volatile months with a 50% of extreme value, and that there are ten years with 41.6667% of extreme value meaning four volatile months a year. The year 1693 has an extreme value of 45.4545%, which indicates five extreme months out of 11 trading months a year, we lose the first observation of January 1693 in calculating the logarithmic change of monthly stock price. The great number of monthly observations of the U.K. makes it clearer that the measure of the percentage of extreme months has an advantage of classifying volatility as various levels over a study period and a disadvantage of hiding the difference information among the years at a same volatility level; to illustratively express, the measure of percentage of extreme months transforms standard deviation from a continuous analogous variable to an intermittent digital variable.

An alternative implementation method of monthly data for extreme measure is to use the percentage of extreme months out of 120 months, a decade, instead of the percentage of extreme months out of 12 months, a year. Meanwhile, the annualized geometric standard deviation is also transformed to the geometric standard deviation for a decade. Figure 13 shows the comparison of these decade measures, and Table 16 reports the ranking for the decades from the 1700s to 1990s. By the standard deviation measure, the 1720s has the highest volatility with a value of 210.227%. The 1970s, 1820s, and 1980s come in second, third, and fourth, respectively, with standard deviations of 138.133%, 121.720%, and 84.825%. Furthermore, the 1700s ranks 5th with 64.862%, and the 1940s, 1930s, and 1990s rank 6th, 7th, and 8th, respectively. In additions, the 1693-1699 has a standard deviation of 103.131% for these seven years, and the 2000-04 has a value of 40.838% for these five years.

The ranking of the extreme measure shows that the 1970s is the period of the highest volatility and has 41.6667% of extreme months, 50 months or four years and two months out of the decade. The 1720s changes from the first of the standard deviation rank to 9th, but the 1980s comes in 2nd, relative to the ranking of 4th using the standard deviation. The 1940s ranks 10th, instead of 6th using the other measure. The Spearman coefficient of 0.9596 shows an obvious improvement compared with 0.8741 for the annually percentage of extreme months.

D. France (1898-2004)

For France, the monthly data is available from Jan 1898 and much longer than both the daily and weekly data, which start from September 1968. Since the results for the following countries have similar properties on the comparison and the rankings of volatilities between two methods, we will not discuss them in detail but focus on the impact of historical events on stock market. The volatility comparison and the rankings for France are shown in Figure 14 and the left side of Table 15.

The most volatile period for France is from the Great Depression to the end of World War II, which had little immediate impact on world stock markets. France is an exception, and the market became very volatile after Germany invaded France in 1941. The Great Depression made 1936 of higher volatility just after 1941. When the war was close to the end in 1944, the market became volatile again with the third largest volatility and recovered to a normal level later. France was also not able to avoid from the global market crash in 1987, when the volatility reached the fourth highest level. The period from 1998 to 2002 is the most volatile period in French market during recent years. The OPEC oil shock did impact on French stock market, but not that much compared to other events.

E. Germany (1870-2004)

The results of the monthly data are illustrated in Figure 15 and the right side of Table 17. The extremely high volatility from 1922 through 1924 was caused by the hyperinflation, following World War I. The period around the end of World War I, from 1918 to 1921, exhibits the second-largest volatility. Another increase in volatility occurred during the aftermath of World War II from 1948 to 1949. From 1998, the volatility also increased, peaked in 2002, and remained high until 2003. The next sharp increase in volatility occurred during the Great Depression of 1931. Finally, the impact of the 1987 panic is limited for Germany stock market compared with these events above.

F. Italy (1905-2004)

We report both the daily and monthly comparison results in Figure 17 and Figure 16, respectively, the monthly ranking on the right side of Table 17, and the daily ranking on the left side of Table 18. The monthly chart of Figure 17(a) shows the very volatile period during World War I from 1941 through 1946, and the volatility remains high until 1949. The year 1981 exhibits the second-largest volatility due to the economy recovery. The next increase in volatility occurred in 1998 and then happened in 1986, instead of 1987. The 1973-1974 OPEC oil crisis made another increase in volatility; thereafter, the volatility of the post-1974 period rose at a higher average volatility level. The continuous economy growth from 1957 resulted in an increasing volatility in 1960. Finally, volatility in the pre-1915 period is very low but increases at a higher level after 1915 and remains until 1932.

G. Japan (1914-2004)

Figure 19 and Figure 18 graph the daily and monthly charts, respectively, and the daily and monthly rankings are shown on the left side of Table 18 and the right side of Table 19, individually. Japan faced the most volatile period during the end of World War II and the aftermath of the war from 1946 through 1950. The year 1920 has the second-highest volatility due to inflation and the brief slump after the boom during World War I. The next sharp increase in volatility occurred in 1990, when the economy bubble bursts caused stock prices crash and remained until 1995. During the Great Depression, another increase happened in 1932 since Japan effectively avoided the depression impact and made an economy growth. Figure 18(c) clearly shows the positive volatility bar in 1932. Finally, the stock market crash in 1987, shown by the daily charts in Figure 19, has an impact on the stock market but not very obvious compared with the crash of 1990; the OPEC oil shock influences the volatility much less.

H. Spain (1915-2004)

The monthly results of Spain are reported in Figure 20 and on the right side of Table 19. Spain experienced the most volatile period during 1987 due to the effects of both stock crash in 1987 and the economic growth from 1982 through 1986, when Spain entered into the European Economic Community. The second-greatest volatility occurred in 1998 because of the continuous economic growth from 1994 and the internet bubble. The next increase in volatility happened in 1990, when Spain implemented restrictive financial policy to solve the imbalance of the economy caused by the economic growth during the period from 1986 through 1989. Furthermore, the burst of dot com bubble made 2002 another volatile year. After the Spanish Civil War ended in 1939, the country experienced ten years of severe depression that made the volatile period from 1946 to

1949. The impact of the oil crisis from 1973 to 1974 on stock market is also reflected in Figure 20.

I. Netherlands (1919-2004)

We report the monthly results and volatility rankings in Figure 21 and the left side of Table 20, respectively. Although the Netherlands is one of the countries which has the longest history of a stock market, its stock market is influenced very much by international economic events during the modern time. The stock market of Netherlands was shocked by the technology bubble from 2002 through 2003 and had the greatest volatility in its history. The second volatile period is around 1987 due to the stock market crash. Another increase in volatility occurred from 1931 to 1932 and from 1936 to 1937 because of the global slump. The next sharp increase happened in 1997 and 1998. After the recession from 1980 through 1983, the Netherlands welcomed the next economic recovery that started from 1984 and caused an increasing volatility in 1984 and 1986. Next increase in volatility appeared during the period of the oil shock from 1973 to 1974 and also in 1975. Finally, the year 1946 after World War II is another year for higher volatility due to the economy recovery.

J. Switzerland (1921-2004)

Figure 22 and Figure 23 show the monthly and weekly charts, respectively. The rankings are reported on the right side of Table 20. The largest volatility in Swiss market occurred in 1962, when global economies started to recover from World War II and inflation began in the 1960s. The stock market hit its high in February 1962, and the high was able to be replaced until 1985. The second largest volatility happened in 1987, and the third appeared in 1998 and 2002. The next sharp increase in volatility occurred in 1931, 1932 and 1936 due to the Great Depression. The volatility also increased during the period of the oil crisis in 1974 and 1975.

J. Volatility Comparison for the G-7 Countries

By the total value of the equity market, the G-7 Countries have 79.1% of the capitalization of world stock market in 2000[7]. Therefore, we overlay the volatilities of all the G-7 group countries into one volatility chart with each measure and compare how volatile the stock market of each country was in different historical periods, how the historical events influenced stock markets, and how the both volatility measures performed for these seven countries.

Figure 24(a) and 19(b) report the standard deviation measure and the extreme measure using daily logarithmic percentage changes, respectively. The U.S. has the earliest daily data beginning from 1896, and Germany has the latest daily data from 1970. Both figures apparently show the largest volatility, represented by the U.S. in 1932, during the period of the Great Depression. Canadian market also performed volatile from 1938 through 1940. Italy met an increasing volatility in 1960 due to its economy growth

[7] Source: Dimson, E., Marsh P., and Staunton M., 2002, *Triumph of the optimists: 101 years of global investment returns* (Princeton University Press)

commencing from 1957. During the OPEC oil shock, the U.K. and Italy were impacted much more than other counties, even than the U.S. The next increase in volatility was reflected by those European countries during the global economies recoveries in the beginning of the 1980s, especially for Italy and France. Then, the stock market crash in 1987 caused all the countries to become more volatile, and the U.S. had the largest volatility during this period. Thereafter, Japan experienced its volatile period due to the economy bubble burst in the 1990s. From the period from 1990 through 1994, the markets of Japan and Italy became more volatile but other countries became less volatile. Finally, all the countries become more volatile in 1998 and even further in 2002 or 2003.

The volatility trends illustrated by the both charts are very similar. An exception is that the average value of the standard deviation is higher than that of the extreme measure since the least value of the extreme measure is zero, which is impossible for the standard deviation measure. This conclusion accords with what we noted earlier that the extreme measure can filter out some volatility noise.

Furthermore, we graph the volatilities of the seven countries with each measure using the monthly logarithmic percentage change in Figure 25(a) and 20(b) from 1870 to 2004, since more countries have monthly data over longer periods. The U.K. and France have the earliest data from 1870, and Canada has the latest data from 1935. Providing more information than Figure 24, Figure 25(a) shows that the period of World War II is more volatile than the Great Depression period, especially for France, Italy, and Japan.

Germany did not show an abnormal volatility during the war since the Nazi government controlled the stock market during the war. The higher volatility during World War I from 1918 through 1921 for Germany may give supports on that. The hyperinflation from 1922 through 1924 is the most volatile period not only for Germany but also for all other countries in the world.

Figure 25(b) shows the volatility measured as the percentage of extreme months for each country in an identical-scale chart. These charts filter out more noise than those charts of percentages of extreme days. Each bar in a chart indicates how many volatile months during a year for a given stock market. The greatest number of volatile months is nine in 1920, 1923 and 1924 for Germany, 75% of the percentage of extreme months.

In summary, the volatility comparison between the standard deviation measure and the extreme measure for the ten countries shows that the extreme measure proxied by the percentage of extreme days, weeks, or months has the similar volatility patterns as the standard deviation measure for each country. Therefore, the extreme measure provides an alternative method to analyze market volatility. Not only can the extreme measure effectively describe volatility, but also it has three advantages over the standard deviation measure. First, the extreme measure can be divided into the positive part and the negative part, which present positive volatility when stock price rises and negative volatility when stock price declines. Second, the extreme-week measure and the extreme-month measure can classify volatility as various volatility levels and give more information about how long the volatile period for each level during a specified study period. Finally, the extreme measure gives researchers more flexibility to choose the classification rule of extreme values, the extreme unit, for instance, extreme days, weeks, or months, and the base period during which the extremes occur, for example, one year, five year, one decade, or a self-definite period.

VI. Application of Extreme Volatility Measure

Since the extreme measure can be divided into positive and negative parts, it provides us a convenience means to examine the behavior of loss averse investors whose utility responses to stock price change are asymmetric; in other words, the utility of loss averse investors when stock prices decrease a certain amount is greater than the utility when stock prices increase the same amount. But, the standard deviation measure cannot be used for this test.

To proxy for investor behavior, we use net flows to equity mutual funds collected from the Investment Funds Institute of Canada (IFIC)[8] for Canada, the Investment Company Institute (ICI)[9] for the U.S., and the Investment Management Association of U.K (IMA)[10] for the U.K. The monthly net flows of Canada are available from 1994 to

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[8] The data of net flows of equity mutual fund were collected from the website of IFIC: http://www.ific.ca/eng/frames.asp?l1=Statistics

[9] The data of net flows of equity mutual fund were collected from the website of ICI: http://www.ici.org/stats/mf/arctrends/index.html#TopOfPage

[10] The data of net flows of equity mutual fund were collected from the website of IMA: http://www.investmentfunds.org.uk/statistics/default.asp

2005, the data for the U.S. from 1984 to 2005, and the data of the U.K. from 1995 to 2005. Net flows of equity mutual funds are calculated by the equation that new sales plus reinvestment of income and minus withdrawals and transfers.

The annual and semi-annual net flows of equity mutual funds are the dependent variables. To deal with the potential delayed reaction of investors to market price changes, we first regress the annual net flows against lagged annual geometric returns of stock and the lagged risk variables as measured by the standard deviation, the total percentage of extreme days, and the negative and positive components of the extreme-day measure, respectively. Then, we employ the semi-annual net flows and run the regression again. All the independent variables are calculated with the daily stock prices. The models for annual data are described as following:

$$NetFlows(t) = \alpha + \beta GeoMean(t\text{-}1) + \gamma GeoStdDev\ (t\text{-}1) + \delta Time + \varepsilon(t) \qquad \text{Model 1}$$

$$NetFlows(t) = \alpha + \beta GeoMean(t\text{-}1) + \gamma TotalExtr\ (t\text{-}1) + \delta Time + \varepsilon(t) \qquad \text{Model 2}$$

$$NetFlows(t) = \alpha + \beta GeoMean(t\text{-}1) + \gamma NegExtr\ (t\text{-}1) + \zeta PosExtr\ (t\text{-}1) + \delta Time + \varepsilon(t) \qquad \text{Model 3}$$

where the variable '*NetFlow*' represents for the annual net flows in billion, '*GeoMean*' for the annual geometric return, '*TotalExtr*' for the total percentage of annual extreme days, '*NegExtr*' and '*PosExtr*' for the percentages of negative and positive extreme days, respectively, and '*Time*' for a time trend variable.

We expect that the regression coefficients for annual returns to be positive, and for market volatility to be negative, either for the standard deviation measure or extreme-day measure. In addition, when volatility is divided into negative and positive components, the coefficient for the percentage of negative extreme days should be negative since when stock market is negatively volatile, investors tend to hold less equity, and the coefficient for the percentage of positive extreme days probably is positive.

We report the regression results of Canada and the U.S. on both the annual data and the semi-annual data in Panel A and Panel B of Table 21, respectively and the regression results of the U.K. on the annual data in Table 22. In Panel A, the results of Canada show the consistent signs with our expectations, but the *t*-values reported in brackets indicate a lack of statistical significance at the 0.05 level for all the coefficients. The possible reason is that we do not have enough observations for Canada. The negative coefficients for the time trend variables in all three models indicate the decrease in Canadian mutual fund assets from the period of 1994 to 2005. The adjusted *R*-square value of Model 3 is 0.3421, slightly higher than the other two but pretty low. The coefficient for the positive extreme variable slightly exceeds that for the negative extreme variable, which may suggest that Canadian investors are more likely influenced by market boom.

For the results of the U.S., in addition to that all the coefficient signs are consistent with our expectation; the adjusted *R*-square values for the three models are higher than the values of Canada since the number of observation of the U.S. is almost two times as that of Canada. However, the adjusted *R*-square value of Model 3 is less than the values of the other two models. The significance of the coefficients for annual return variables shows a positive relation between the holding volume of equity fund and equity market return. Different from Canada, the coefficient for the negative extreme variable slightly exceeds that for the positive extreme variable, which probably suggests that the U.S. investors concern more about market recession.

Little different from the models based on annual observations, we use not only the first lagged independent variables for volatility measures in the regressions on the semi-annual data but also the second lagged variables. We report only the results for the second lagged independent variables in Panel B. For Canada, the coefficients of return variables become significant. The adjusted *R*-square values are all higher than the values based on annual observations, but all the coefficients are still not significant except for time trend variable. When using the first lagged standard deviation in Model 1 and the first lagged percentage of semi-annual extreme days in Model 2, the adjusted *R*-square values are 0.4150 and 0.4160, comparing with 0.3840 and 0.3812 for the second lagged variables. It may imply that Canadian investors have less delayed reaction time for large market price changes; in another word, Canadian investors are more sensitive for market price changes. However, the second lagged volatility variables for Model 3 perform better than the first lagged variables, with the adjusted *R*-square values of 0.4310 versus 0.3855. For the U.S., the regression results of second lagged variables on semi-annual data dominate the results using the first lagged variables, but the adjusted *R*-square values are less than the values using annual observations.

For the U.K., different from the regression results of Canada and the U.S., the coefficient signs of these two extreme components for the U.K. are just opposite to Canada and U.S.: positive for the negative extreme component and negative for the positive component. These results are totally different from our expectation and may indicate that the U.K. investors have different behaviours from 1995 to 2005: holding more equities when stock market goes down and holding fewer equities when stock market goes up. Comparing with the value of 0.3529 for Model (1), the decreased R-square value of Model (2) and the increased R-square of Model (3) indicate that the less efficiency of Model (2) and more efficiency of Model (3) for the U.K.

In sum, the regression results indicate that the holding volume of equity has a positive relation with stock market returns and a negative relation with market volatility in some delay for Canada and the U.S. The extreme measures provide more information about investor behavior during negatively volatile and positively volatile period, which the standard deviation measure impossibly offers. When using the negative and positive components of the percentage of extreme days as the independent variables, we find that the extreme-day measure more efficiently explains investor behavior than the standard deviation does for Canada and the U.K. and that negative extreme-days influence the U.S.

investors in a greater degree than positive extreme days do, but negative extreme days influence in a lesser degree than positive extreme days do for Canadian investors.

VII. Conclusion

In this paper, we use an alternative measure using the percentages of extreme days, weeks, and months to examine the volatilities of the G-7 group of seven countries and three western European countries. Compared with the traditional measure of standard deviation, the new extreme measure has the same effect to describe stock market volatility as the traditional measure has.

In addition, we found out that the extreme measure has three additional benefits to analyze volatility: dividing volatility into positive and negative parts; classifying volatility as different levels and allowing researchers evidently to recognize the length of the volatile period for each level during a specified period; and having flexibility to self define extreme measures depending on various research requirements. Furthermore, we use the both methods to measure the volatilities of all the ten countries over the 20th century and examine how the historical events made impacts on stock market volatility and how large the degree of the impacts for each country.

Finally, we apply the extreme-day measure to examine investor behavior and find out that the extreme-day measure more efficiently explains investor behavior than the standard deviation measure does for Canada and the U.K. and that the U.S. investors concerned more about the negative changes of stock price than the positive changes, but Canadian investors pay closer attention to the positive changes than the negative changes. Our study suggests that the extreme measure is effective to analyze market volatility and provides more convenience and flexibility than the traditional measure for researchers.

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Table 1. Summary of the Data Sets for the Ten Countries

No.	Country	Index	Daily Data		Weekly Data		Monthly Data	
			Time Period	Obs.	Time Period	Obs.	Time Period	Obs.
1	Canada	Composite Index of Montreal Ex., Industrial Index of Toronto Ex., and TSE Composite 300 Index	Mar 1, 1935 – December 31, 2004	18,248	Mar 2, 1935 – December 31, 2004	3,645	December 31, 1899 – December 31, 2004	1,261
2	France	France SBF-250 Index	September 18, 1968 – December 31, 2004	8,984	September 20, 1968 – December 31, 2004	1,898	January 31, 1898 – December 31, 2004	1,269
3	Germany	Germany CDAX Composite Index	January 2, 1970 – December 31, 2004	9,046	January 2, 1970 – December 31, 2004	1,845	January 31, 1870 – December 31, 2004	1,613
4	Italy	Banca Commerciale Italiana Index	January 2, 1957 – December 31, 2004	11,810	January 4, 1957 – December 31, 2004	2,490	September 30, 1905 – December 31, 2004	1,186
5	Japan	Japan Nikkei 225 Stock Average	January 4, 1955 – December 30, 2004	13,886	January 8, 1955 – December 30, 2004	2,604	July 31, 1914 – December 30, 2004	1,076
6	Netherlands	Netherlands All-Share Price Index	January 2, 1980 – December 31, 2004	6,334	January 4, 1980 – December 31, 2004	1,313	January 31, 1919 – December 31, 2004	1,008
7	Spain	Madrid SE General Index	August 12, 1971 – December 30, 2004	7,582	August 13, 1971 – December 30, 2004	1,754	January 31, 1915 – December 30, 2004	1,037
8	Switzerland	Switzerland Price Index	January 3, 1969 – December 30, 2004	8,995	January 6, 1956 – December 30, 2004	2,563	January 31, 1921 – December 31, 2004	1,009
9	United Kingdom	UK FT-Actuaries All-Share Index	January 2, 1969 – December 31, 2004	9,108	January 8, 1965 – December 31, 2004	2,104	January 31, 1693 – December 31, 2004	3,739
10	United States	Dow Jones Industrial Average Index	May 26, 1896 – December 31, 2004	27,199	May 26, 1896 – December 31, 2004	5,646	May 26, 1896 – December 31, 2004	1,300

Table 2. Summary Statistics of Daily/Weekly/Monthly Logarithmic Percent Changes Covering Various Time Period

Country	Mean	Median	StdDev	Skewness	Kurtosis	Jarque-Bera	Percentile					
							1%	5%	10%	90%	95%	99%
Panel A. Daily Data												
Canada	0.0221	0.0366	0.7998	-0.6370	29.8358	677,547.00	-2.3254	-1.1147	-0.7325	0.7762	1.0813	1.9922
France	0.0310	0.0000	1.0638	-0.5661	8.8737	29,915.41	-2.9638	-1.6342	-1.1125	1.1732	1.5919	2.8025
Germany	0.0168	0.0138	0.9661	-0.4868	8.2389	25,906.67	-2.9329	-1.4470	-0.9486	0.9907	1.3781	2.5766
Italy	0.0249	0.0039	1.2414	-0.3733	6.4513	20,734.12	-3.4578	-1.8883	-1.3037	1.3923	1.9266	3.1590
Japan	0.0250	0.0527	1.0513	-0.3496	10.9659	69,794.29	-3.1028	-1.6147	-1.0767	1.0700	1.5706	2.9281
Netherlands	0.0350	0.0613	1.1690	-0.3322	7.4612	14,783.03	-3.4878	-1.7462	-1.2058	1.2299	1.6816	3.0961
Spain	0.0328	0.0110	1.1051	-0.1999	5.3301	9,009.88	-2.9231	-1.6788	-1.1708	1.2623	1.7625	3.1151
Switzerland	0.0193	0.0310	0.9370	-0.8474	10.8454	45,104.54	-2.8842	-1.3729	-0.9326	0.9626	1.3648	2.4202
U.K.	0.0289	0.0630	1.0290	-0.2953	7.9952	24,360.39	-2.8367	-1.5448	-1.1021	1.1092	1.5110	2.6516
U.S.	0.0213	0.0465	1.1398	-0.6318	20.9110	497,142.30	-3.3033	-1.6539	-1.1275	1.1399	1.6181	3.0563
Panel B. Weekly Data												
Canada	0.1106	0.2001	1.9972	-0.6849	7.2599	8,252.62	-5.9930	-2.9957	-2.0962	2.2123	2.9120	5.0697
France	0.1462	0.1897	2.4284	-0.4467	4.1371	1,406.65	-6.3107	-3.7841	-2.7398	2.9866	3.8486	5.8641
Germany	0.0811	0.1765	2.2292	-0.4359	3.0370	761.59	-6.5471	-3.6588	-2.4763	2.6327	3.3980	5.3131
Italy	0.1183	0.1391	2.9215	-0.0136	5.7543	3,418.65	-7.6804	-4.3184	-3.1749	3.3440	4.6206	7.5106
Japan	0.1334	0.2731	2.3732	-0.5405	3.9359	1,798.90	-6.6254	-3.6830	-2.6537	2.7152	3.5987	6.0165
Netherlands	0.1689	0.3512	2.4165	-0.5637	4.1770	1,014.62	-7.0037	-3.9007	-2.6118	2.7317	3.6368	5.5803
Spain	0.1417	0.1414	2.5700	-0.0378	4.2076	1,284.10	-6.3428	-3.7767	-2.7222	3.1034	4.1971	7.1251
Switzerland	0.0907	0.1463	2.0948	-0.6682	6.9796	5,366.83	-5.9152	-3.1366	-2.2700	2.3459	3.1719	5.1625
U.K.	0.1527	0.2685	2.4652	-0.3665	8.9983	7,106.66	-6.5960	-3.7417	-2.6348	2.7509	3.6361	5.9736
U.S.	0.1034	0.2562	2.5795	-1.0150	14.2317	48,502.42	-7.5134	-4.0208	-2.7115	2.7809	3.7337	6.3020

Panel C. Monthly Data												
Canada	0.3814	0.6322	4.3258	-0.7921	4.4481	1,159.79	-14.4725	-6.7481	-4.2506	4.9179	6.5251	10.9992
France	0.5877	0.0625	5.4487	1.1392	14.7917	11,734.88	-12.7839	-7.7705	-5.4402	6.7487	8.9417	14.0445
Germany	0.2942	0.2895	6.3290	0.2246	24.0047	38,464.71	-20.4371	-7.5509	-4.5321	5.4372	7.5257	14.7906
Italy	0.5197	0.0000	6.9799	0.9805	6.5550	2,289.84	-16.4328	-9.3149	-6.8636	7.6130	10.8596	23.8411
Japan	0.5782	0.5479	6.2875	0.3519	7.6350	2,605.17	-17.2021	-9.4181	-5.9133	6.7288	9.2810	19.2194
Netherlands	0.3269	0.5288	4.8151	-0.4289	2.6581	322.99	-13.3522	-7.5091	-5.3435	5.7158	7.4907	11.7171
Spain	0.4344	0.5096	4.7191	-0.3409	3.9528	686.02	-12.0416	-6.8040	-5.0137	6.1325	8.1736	12.8168
Switzerland	0.3863	0.5534	4.4385	-0.4737	5.3784	1,237.88	-12.9269	-6.8930	-4.4111	5.1172	7.0499	10.4332
U.K.	0.1167	0.1214	3.9929	-0.4986	55.9397	486,205.30	-10.8313	-5.1459	-3.3146	3.5833	5.2643	9.3741
U.S.	0.4294	0.8413	5.7131	-0.8048	7.1134	2,854.03	-18.3431	-8.9712	-5.6908	6.0972	8.3837	13.0736

Table 3. Summary Statistics of Daily/Weekly Logarithmic Percent Changes For the U.S. and Canada Beginning at Mar 1, 1935

Country	Mean	Median	StdDev	Skewness	Kurtosis	Jarque-Bera	Percentile					
							1%	5%	10%	90%	95%	99%
Panel A. Daily Data												
U.S.	0.0265	0.0389	0.9422	-1.3852	37.2459	1,021,610.00	-2.5057	-1.4043	-0.9833	1.0178	1.4076	2.4546
Canada	0.0221	0.0366	0.7998	-0.6370	29.8358	677,547.00	-2.3254	-1.1147	-0.7325	0.7762	1.0813	1.9922
Panel B. Weekly Data												
U.S.	0.1279	0.2562	2.1911	-1.0420	13.8866	298,28.72	-5.6659	-3.2933	-2.3561	2.4511	3.3340	5.1320
Canada	0.1106	0.2001	1.9972	-0.6849	7.2599	8,252.62	-5.9930	-2.9957	-2.0962	2.2123	2.9120	5.0697

Table 4. Summary Statistics of Daily/Weekly Logarithmic Percent Changes for G-7 Beginning at Jan.2, 1970

Country	Mean	Median	StdDev	Skewness	Kurtosis	Jarque-Bera	Percentile					
							1%	5%	10%	90%	95%	99%
Panel A. Daily Data												
Canada	0.0246	0.0499	0.8288	-0.8754	13.5022	68,076.08	-3.0002	-1.6509	-1.1207	1.1768	1.6010	2.8369
France	0.0291	0.0000	1.0699	-0.5993	8.8365	28,663.82	-2.9638	-1.6342	-1.1125	1.1732	1.5919	2.8025
Germany	0.0168	0.0138	0.9661	-0.4868	8.2389	25,906.67	-2.9329	-1.4470	-0.9486	0.9907	1.3781	2.5766
Italy	0.0260	0.0156	1.2859	-0.4021	5.8518	12,697.95	-3.5877	-1.9964	-1.3666	1.4595	1.9962	3.2274
Japan	0.0169	0.0478	1.1561	-0.3170	10.4646	42,882.15	-3.3668	-1.8633	-1.2089	1.1664	1.7297	3.2642
U.K.	0.0316	0.0634	1.0323	-0.2975	8.0882	24,233.07	-2.8464	-1.5448	-1.1011	1.1209	1.5282	2.6864
U.S.	0.0293	0.0273	1.0336	-1.7617	46.8914	816,759.30	-2.4773	-1.5396	-1.0942	1.1503	1.5968	2.6499
Panel B. Weekly Data												
Canada	0.1210	0.2190	2.1126	-0.6831	4.5502	1,706.18	-6.2139	-3.1883	-2.3241	2.4186	3.1790	5.2592
France	0.1379	0.1828	2.4423	-0.4637	4.1564	1,372.70	-6.3107	-3.8554	-2.7603	2.9866	3.8516	5.7588
Germany	0.0811	0.1765	2.2292	-0.4359	3.0370	761.59	-6.5471	-3.6588	-2.4763	2.6327	3.3980	5.3131
Italy	0.1241	0.1573	3.0547	-0.1055	5.5431	2,338.30	-7.9284	-4.4287	-3.3029	3.6698	4.7836	7.5106
Japan	0.0868	0.2128	2.5119	-0.5388	3.9555	1,267.93	-7.0111	-4.0347	-2.8624	2.8144	3.7318	6.3040
U.K.	0.1517	0.2516	2.5521	-0.3629	8.8348	5,993.72	-7.1170	-3.8304	-2.6808	2.8438	3.7019	6.2992
U.S.	0.1430	0.2309	2.3590	-1.2072	17.8247	24,436.93	-5.6986	-3.5445	-2.5735	2.6975	3.6154	5.4129

Table 5. Summary Statistics of Monthly Logarithmic Percent Changes for Canada, France, Germany, U.K., and U.S. Beginning at January 1, 1900

Country	Mean	Median	StdDev	Skewness	Kurtosis	Jarque-Bera	Percentile					
							1%	5%	10%	90%	95%	99%
Canada	0.3814	0.6322	4.3258	-0.7921	4.4481	1,159.79	-14.4725	-6.7481	-4.2506	4.9179	6.5251	10.9992
France	0.5886	0.2020	5.4925	1.1323	14.5624	11,170.36	-12.7839	-7.8113	-5.5636	6.8179	8.9978	1.0445
Germany	0.3307	0.2505	6.9588	0.2213	20.7369	22,253.61	-23.6511	-8.3239	-5.0222	6.0220	8.4616	18.0545
U.K.	0.3312	0.4508	4.3401	-0.0450	11.5710	6,940.51	-11.8450	-6.7463	-4.5135	4.7968	6.3580	10.4172
U.S.	0.4110	0.8406	5.6200	-0.8484	7.7098	3,232.45	-17.7677	-8.9098	-5.5137	59790	8.3233	12.5910

Table 6. Summary Statistics of Monthly Logarithmic Percent Changes for G-7 Beginning at February 2, 1914

Country	Mean	Median	StdDev	Skewness	Kurtosis	Jarque-Bera	Percentile					
							1%	5%	10%	90%	95%	99%
Canada	0.4044	0.6341	4.5687	-0.7796	3.9034	794.59	-15.5685	-7.2235	-4.7846	5.3012	6.7352	11.1824
France	0.6611	0.4759	5.8404	1.0624	12.8214	7,497.01	-14.8427	-8.4052	-5.9781	7.0826	9.6942	14.6604
Germany	0.3810	0.3173	7.4514	0.1900	17.8821	14,294.29	-25.4044	-9.2731	-5.6788	6.4284	9.7822	21.5792
Italy	0.5961	0.0000	7.2593	0.9235	5.8787	1,698.88	-17.4875	-9.9133	-7.0740	7.8677	11.1704	25.4612
Japan	0.5782	0.5479	6.2875	0.3519	7.6350	2,605.17	-17.2021	-9.4181	-5.9133	6.7288	9.2810	19.2194
U.K.	0.3981	0.6347	4.6227	2.3358	10.0838	4,555.13	-12.5200	-7.0749	-4.9623	5.1817	6.6678	10.6308
U.S.	0.4482	0.9205	5.6625	-0.9041	8.5471	3,421.73	-19.1686	-8.7390	-5.3190	5.9067	8.3234	12.5910

Table 7. GARCH Test for Daily/Weekly/Monthly Logarithmic Percent Changes

Country	Value of Chi-Square			Coefficient of
	GARCH (1)	GARCH (4)	GARCH (10)	Asymmetric Term (*d*)
Panel A: Daily Data				
Canada	2,817.6278 (0.0000)	2,970.7331 (0.0000)	3,078.1322 (0.0000)	-0.0742 (0.0000)
France	110.3825 (0.0000)	425.3734 (0.0000)	610.9245 (0.0000)	-0.0563 (0.0000)
Germany	508.5780 (0.0000)	1,324.5105 (0.0000)	1,659.8554 (0.0000)	-0.0478 (0.0000)
Italy	902.2109 (0.0000)	1,457.0429 (0.0000)	1,584.3207 (0.0000)	-0.0103 (0.1190)
Japan	666.7083 (0.0000)	1,017.7995 (0.0000)	1,166.3031 (0.0000)	-0.1435 (0.0000)
Netherlands	723.1571 (0.0000)	1,340.1401 (0.0000)	1,491.5176 (0.0000)	-0.0597 (0.0000)
Spain	462.4639 (0.0000)	839.7812 (0.0000)	1,029.5946 (0.0000)	-0.0338 (0.0007)
Switzerland	258.4368 (0.0000)	1,383.2011 (0.0000)	1,424.4732 (0.0000)	-0.1337 (0.0000)
U.K.	1,658.5707 (0.0000)	1,970.7822 (0.0000)	2,068.3228 (0.0000)	-0.0512 (0.0000)
U.S.	1,139.9659 (0.0000)	2,182.3731 (0.0000)	2,680.4522 (0.0000)	-0.0755 (0.0000)
Panel B: Weekly Data				
Canada	148.1611 (0.0000)	220.7346 (0.0000)	313.8452 (0.0000)	-0.0818 (0.0000)
France	29.7792 (0.0000)	138.4376 (0.0000)	164.9540 (0.0000)	-0.1051 (0.0001)
Germany	184.8010 (0.0000)	310.3443 (0.0000)	332.0389 (0.0000)	-0.0599 (0.0043)
Italy	254.7726 (0.0000)	282.0769 (0.0000)	331.8538 (0.0000)	0.0088 (0.6838)
Japan	38.5789 (0.0000)	91.4035 (0.0000)	126.8448 (0.0000)	-0.1188 (0.0001)
Netherlands	88.8275 (0.0000)	211.5944 (0.0000)	221.5950 (0.0000)	-0.0789 (0.0046)
Spain	96.1240 (0.0000)	137.7068 (0.0000)	181.0407 (0.0000)	-0.0688 (0.0211)
Switzerland	143.3868 (0.0000)	209.8581 (0.0000)	233.7583 (0.0000)	-0.1515 (0.0000)
U.K.	93.2796 (0.0000)	131.5869 (0.0000)	162.4364 (0.0000)	-0.1090 (0.0000)
U.S.	119.3686 (0.0000)	299.4331 (0.0000)	349.7277 (0.0000)	-0.0832 (0.0000)

Panel C: Monthly Data				
Canada	50.2547 (0.0000)	74.7936 (0.0000)	106.5312 (0.0000)	0.0621 (0.0018)
France	13.2872 (0.0003)	16.1688 (0.0028)	19.1255 (0.0387)	-0.1045 (0.0000)
Germany	151.2892 (0.0000)	394.4534 (0.0000)	443.6932 (0.0000)	-0.0282 (0.3211)
Italy	30.8255 (0.0000)	87.5682 (0.0000)	150.8587 (0.0000)	0.0627 (0.0039)
Japan	27.5898 (0.0000)	122.3076 (0.0000)	189.1266 (0.0000)	-0.0017 (0.9635)
Netherlands	25.3619 (0.0000)	34.5796 (0.0000)	41.2557 (0.0000)	-0.0889 (0.0514)
Spain	19.7000 (0.0000)	41.0010 (0.0000)	71.3752 (0.0000)	0.0529 (0.0487)
Switzerland	26.9229 (0.0000)	33.7287 (0.0000)	38.1362 (0.0000)	-0.1005 (0.1248)
U.K.	212.7178 (0.0000)	468.4583 (0.0000)	526.4326 (0.0000)	0.0493 (0.0010)
U.S.	10.5272 (0.0012)	61.8296 (0.0000)	98.8713 (0.0000)	-0.0852 (0.0248)

**p-values are reported in brackets.*

Table 8. GARCH Test for Daily/Weekly Logarithmic Percent Changes for U.S. and Canada Beginning at Mar 1, 1935

Country	Value of Chi-Square			Coefficient of Asymmetric Term (*d*)
	GARCH (1)	GARCH (4)	GARCH (10)	
Panel A: Daily Data				
Canada	2,817.6278 (0.0000)	2,970.7331 (0.0000)	3,078.1322 (0.0000)	-0.0742 (0.0000)
U.S.	170.0320 (0.0000)	579.6478 (0.0000)	789.2103 (0.0000)	-0.0717 (0.0000)
Panel C: Weekly Data				
Canada	148.1611 (0.0000)	220.7346 (0.0000)	313.8452 (0.0000)	-0.0818 (0.0000)
U.S.	22.7379 (0.0000)	38.8846 (0.0000)	63.0937 (0.0000)	-0.1230 (0.0000)

**p-values are reported in brackets.*

Table 9. GARCH Test for Daily/Weekly Logarithmic Percent Changes for G-7 Beginning at January 2, 1970

Country	Value of Chi-Square			Coefficient of Asymmetric Term (*d*)
	GARCH(1)	GARCH(4)	GARCH(10)	
Panel A: Daily Data				
Canada	685.8560 (0.0000)	1,189.1050 (0.0000)	1,367.6445 (0.0000)	-0.0524 (0.0000)
France	107.0387 (0.0000)	417.1248 (0.0000)	598.8096 (0.0000)	0.0000 (1.0000)
Germany	508.5780 (0.0000)	1,324.5105 (0.0000)	1,659.8554 (0.0000)	-0.0478 (0.0000)
Italy	691.8214 (0.0000)	1,154.6875 (0.0000)	1,241.5328 (0.0000)	-0.0148 (0.0641)
Japan	427.4919 (0.0000)	650.1009 (0.0000)	741.1460 (0.0000)	-0.1463 (0.0000)
U.K.	1,628.3282 (0.0000)	1,932.9322 (0.0000)	2,027.3788 (0.0000)	-0.0522 (0.0000)
U.S.	76.4084 (0.0000)	268.8211 (0.0000)	365.9106 (0.0000)	-0.0735 (0.0000)
Panel B: Weekly Data				
Canada	88.5833 (0.0000)	111.0255 (0.0000)	136.7867 (0.0000)	-0.0697 (0.0008)
France	28.8959 (0.0000)	134.1763 (0.0000)	159.8765 (0.0000)	-0.1093 (0.0002)
Germany	184.8010 (0.0000)	310.3443 (0.0000)	332.0389 (0.0000)	-0.0599 (0.0043)
Italy	191.1317 (0.0000)	212.4293 (0.0000)	247.0199 (0.0000)	-0.0026 (0.9074)
Japan	25.7764 (0.0000)	59.1528 (0.0000)	83.6306 (0.0000)	-0.0685 (0.0420)
U.K.	79.9840 (0.0000)	111.9309 (0.0000)	138.2475 (0.0000)	-0.1159 (0.0000)
U.S.	1.1899 (0.2754)	5.5588 (0.2346)	13.3141 (0.2066)	-0.1503 (0.0001)

**p-values are reported in brackets.*

Table 10. GARCH Test for Monthly Logarithmic Percent Changes for Canada, France, Germany, U.K., and U.S. Beginning at January 1, 1900

Country	Value of Chi-Square			Coefficient of
	GARCH (1)	GARCH (4)	GARCH (10)	Asymmetric Term (*d*)
Canada	50.2547 (0.0000)	74.7936 (0.0000)	106.5312 (0.0000)	0.0621 (0.0018)
France	12.8482 (0.0003)	15.5706 (0.0037)	18.3545 (0.0493)	-0.0924 (0.0000)
Germany	114.8566 (0.0000)	302.2915 (0.0000)	339.8001 (0.0000)	0.0001 (0.0000)
U.K.	51.0063 (0.0000)	83.8704 (0.0000)	128.7444 (0.0000)	-0.0001 (0.9785)
U.S.	11.3193 (0.0000)	63.2497 (0.0000)	99.1454 (0.0000)	-0.0953 (0.0221)

**p-values are reported in brackets.*

Table 11. GARCH Test for Monthly Logarithmic Percent Changes for G-7 Beginning at February 2, 1914

Country	Value of Chi-Square			Coefficient of
	GARCH (1)	GARCH (4)	GARCH (10)	Asymmetric Term (*d*)
Canada	38.9723 (0.0000)	56.7996 (0.0000)	81.6875 (0.0000)	-0.0001 (0.0000)
France	9.8407 (0.0017)	11.6169 (0.0204)	13.2207 (0.2116)	0.0001 (0.0000)
Germany	96.8853 (0.0000)	256.9803 (0.0000)	289.1689 (0.0000)	0.0001 (0.2360)
Italy	25.6883 (0.0000)	74.5356 (0.0000)	138.8410 (0.0000)	0.0111 (0.0000)
Japan	27.5898 (0.0000)	122.3076 (0.0000)	189.1266 (0.0000)	-0.0017 (0.9635)
U.K.	40.9198 (0.0000)	67.2237 (0.0000)	105.1536 (0.0000)	0.0000 (0.0000)
U.S.	10.1012 (0.0015)	58.3729 (0.0000)	122.9693 (0.0000)	-0.0268 (0.4507)

**p-values are reported in brackets.*

Table 12. Rankings of Volatility as Measured by the Standard Deviation and by the Percentage of Extreme Days, Weeks, or Months for the Highest 25 Years, Canada (1900-2004)

Rank	Daily Data (1935-2004)				Rank	Weekly Data (1935-2004)				Rank	Monthly Data (1900-2004)			
	Geometric Standard Deviation		Percentage of Extreme Days			Geometric Standard Deviation		Percentage of Extreme Weeks			Geometric Standard Deviation		Percentage of Extreme Months	
	Year	StdDev%	Year	L %		Year	StdDev	Year	L %		Year	StdDev	Year	L %
1	1940	35.5315	2000	32.6693	1	1940	33.0241	1938	26.9231	1	1932	47.0987	1931	41.6667
2	1938	33.2183	1938	21.1921	2	2000	32.6450	2000	25.0000	2	1933	39.0402	1932	41.6667
3	2000	30.4339	1939	20.6667	3	1938	32.5933	1937	21.1538	3	1931	36.9807	1933	41.6667
4	1937	28.4642	1998	20.2381	4	1937	30.5616	1939	19.2308	4	1987	36.8209	1929	33.3333
5	1987	26.9211	1937	19.3980	5	1998	30.1127	1974	19.2308	5	1929	36.0705	1982	33.3333
6	1939	26.1365	2001	17.5299	6	1987	28.3342	1998	19.2308	6	1998	32.9512	1930	25.0000
7	1998	21.7819	1982	17.4603	7	1939	27.9698	1982	17.3077	7	1980	32.5999	1940	25.0000
8	2001	21.4765	1980	16.2055	8	1982	25.8140	1940	15.3846	8	1982	29.7981	1974	25.0000
9	1980	20.5743	2002	15.8730	9	1974	24.8209	1980	13.2075	9	1940	28.4901	2000	25.0000
10	1982	18.8640	1974	13.4921	10	1980	22.2150	2002	11.5385	10	1930	25.5856	1937	16.6667
11	2002	17.9521	1987	13.0435	11	2002	19.2445	1950	9.6154	11	2001	24.5509	1946	16.6667
12	1974	16.4605	1999	12.3016	12	2001	18.2672	1987	9.6154	12	1953	24.3738	1953	16.6667
13	1999	15.8561	1981	11.1111	13	1997	17.8294	1979	7.6923	13	1937	24.1336	1970	16.6667
14	1981	15.8276	1940	9.9010	14	1999	17.1371	1997	7.6923	14	2000	24.0604	1971	16.6667
15	1950	15.2753	1983	8.7649	15	1981	16.3954	1936	7.5472	15	1974	23.3527	1980	16.6667
16	1946	14.7714	1973	7.9365	16	1950	16.3250	1941	5.7692	16	1981	22.5478	1998	16.6667
17	1997	14.1652	1946	7.2000	17	1983	16.0051	1951	5.7692	17	1975	21.9464	1935	8.3333
18	1973	13.7303	1997	7.1429	18	1973	15.7585	1969	5.7692	18	1979	20.0887	1938	8.3333
19	1936	13.5176	1970	7.1146	19	1951	15.7199	1973	5.7692	19	1970	19.5426	1943	8.3333
20	1970	13.4586	1950	7.0671	20	1979	15.3153	1983	5.7692	20	1938	19.4802	1957	8.3333
21	1983	13.1280	1979	6.7460	21	1941	15.0147	1999	5.7692	21	1956	19.0559	1962	8.3333
22	1979	12.9414	1957	5.9055	22	1936	14.8236	2001	5.6604	22	1946	18.8603	1969	8.3333
23	1951	12.7744	1969	5.5556	23	1946	14.5664	1935	4.6512	23	1957	18.6816	1973	8.3333
24	1955	11.8813	1951	5.3004	24	1969	14.5016	1962	4.0000	24	1976	18.1586	1975	8.3333
25	2004	11.8639	1941	4.9505	25	1970	14.4682	1946	3.8462	25	1969	18.0872	1976	8.3333

Table 13. Summary of the Spearman Rank Correlation Coefficient

Country	Daily Data		Weekly Data		Monthly Data	
	No. of Obs.	Spearman Coefficient	No. of Obs.	Spearman Coefficient	No. of Obs.	Spearman Coefficient
Canada	70	0.9256	70	0.8896	105	0.7870
France	37	0.9412	37	0.8902	107	0.7010
Germany	35	0.9782	35	0.8579	135	0.8618
Italy	48	0.9521	48	0.8624	100	0.7893
Japan	50	0.9728	50	0.8961	91	0.7425
Netherlands	25	0.9679	25	0.9459	85	0.6991
Spain	34	0.9040	34	0.7613	87	0.7478
Switzerland	36	0.9654	49	0.9150	84	0.7860
U.K.	36	0.9418	40	0.8606	312	0.8741
U.S.	109	0.9686	109	0.8694	109	0.7885

Table 14. Rankings of Volatility as Measured by the Standard Deviation and by the Percentage of Extreme Days for the Highest 25 Years, U.S. (1896-2004)

Geometric Standard Deviation			Percentage of Extreme Days		
Rank	Year	GeoStdDev (%)	Year	L (%)	Rank
1	1932	69.8022	1932	50.8000	1
2	1931	55.9104	1931	38.0952	2
3	1933	52.8461	1933	35.9504	3
4	1929	48.4666	1896	25.4902	4
5	1987	44.1090	1929	20.8835	5
6	1930	33.9944	1938	20.8000	6
7	1938	30.3935	1930	20.3187	7
8	1937	30.0120	2002	17.4603	8
9	2002	28.9879	1987	15.0198	9
10	1899	28.3073	1937	14.8000	10
11	1907	27.8139	1974	14.6245	11
12	1896	27.0148	1907	13.4921	12
13	1917	25.4291	1917	13.2530	13
14	1974	25.3854	1934	13.2530	14
15	1934	24.6540	1903	12.6984	15
16	1898	24.2261	1920	11.9048	16
17	1920	24.0517	1915	11.1554	17
18	1903	23.8780	1898	10.7143	18
19	2001	23.6955	1899	10.5263	19
20	1901	23.5966	2000	10.0775	20
21	1915	23.4601	1900	9.6000	21
22	2000	23.1573	1901	8.8353	22
23	1939	23.0865	1919	8.4677	23
24	1919	22.5254	1946	8.4000	24
25	1998	22.0062	2001	8.2353	25

Table 15. Rankings of Volatility as Measured by the Standard Deviation and by the Percentage of Extreme Months for the Highest 25 Years, U.K. (1693-2004) and France (1898 -2004)

	United Kingdom				France				
	Geometric Standard Deviation		Percentage of Extreme Months		Geometric Standard Deviation		Percentage of Extreme Months		
Rank	Year	GeoStd Dev (%)	Year	L (%)	Year	GeoStd Dev (%)	Year	L (%)	Rank
1	1720	204.508	1825	83.3333	1941	84.5253	1932	25.0000	1
2	1825	91.416	1720	66.6667	1936	44.5381	1945	25.0000	2
3	1975	65.583	1696	58.3333	1944	37.3919	1946	25.0000	3
4	1987	48.482	1974	58.3333	1987	36.1048	1940	20.0000	4
5	1940	39.806	1701	50.0000	1932	34.4600	1941	20.0000	5
6	1974	38.534	1826	50.0000	2002	33.5640	1936	16.6667	6
7	1824	38.135	1938	50.0000	1945	33.1356	1937	16.6667	7
8	1701	37.130	1975	50.0000	1988	32.2368	1938	16.6667	8
9	1696	37.057	1976	50.0000	1947	31.6500	1944	16.6667	9
10	1694	36.289	1987	50.0000	1978	31.1056	1978	16.6667	10
11	1721	34.800	1693	45.4545	1998	30.9190	1990	16.6667	11
12	1697	32.513	1694	41.6667	1937	30.0572	1998	16.6667	12
13	1976	31.449	1698	41.6667	1939	29.8420	2002	16.6667	13
14	1695	30.748	1700	41.6667	1981	29.4010	1912	8.3333	14
15	1981	28.137	1931	41.6667	1920	27.3250	1916	8.3333	15
16	1698	28.005	1940	41.6667	1948	27.3166	1917	8.3333	16
17	1693	25.460	1972	41.6667	2001	27.1028	1918	8.3333	17
18	1699	25.318	1979	41.6667	1974	27.0917	1926	8.3333	18
19	1931	24.344	1984	41.6667	1946	26.6661	1931	8.3333	19
20	1826	23.381	1986	41.6667	1986	26.3114	1939	8.3333	20
21	2002	22.842	2002	41.6667	1940	24.8473	1942	8.3333	21
22	1979	22.147	1695	33.3333	1975	24.2311	1943	8.3333	22
23	1938	21.974	1710	33.3333	1938	23.7396	1947	8.3333	23
24	1700	21.948	1721	33.3333	1997	23.4787	1948	8.3333	24
25	1992	21.869	1939	33.3333	1926	22.7686	1955	8.3333	25

Table 16. Rankings of Volatility as Measured by the Standard Deviation per Decade and by the Percentage of Extreme Months per Decade for the Highest 15 Decades, U.K. (1700s-1990s)

Geometric Standard Deviation			Percentage of Extreme Months		
Rank	Year	GeoStdDev (%)	Year	L (%)	Rank
1	1720-1729	210.227	1970-1979	41.6667	1
2	1970-1979	138.133	1980-1989	30.0000	2
3	1820-1829	121.720	1700-1709	22.5000	3
4	1980-1989	84.825	1820-1829	20.0000	4
5	1700-1709	64.862	1930-1939	20.0000	5
6	1940-1949	58.371	1950-1959	20.0000	6
7	1930-1939	57.911	1990-1999	19.1667	7
8	1990-1999	56.397	1960-1969	15.0000	8
9	1950-1959	54.582	1720-1729	11.6667	9
10	1960-1969	52.180	1940-1949	11.6667	10
11	1710-1719	42.136	1710-1719	8.3333	11
12	1790-1799	38.618	1790-1799	8.3333	12
13	1830-1839	34.016	1830-1839	6.6667	13
14	1800-1809	32.391	1860-1869	5.0000	14
15	1840-1849	31.403	1760-1769	4.1667	15

Table 17. Rankings of Volatility as Measured by the Standard Deviation and by the Percentage of Extreme Months for the Highest 25 Years, Germany (1870-2004) and Italy (1905 -2004)

	Germany				Italy				
Rank	Geometric Standard Deviation		Percentage of Extreme Months		Geometric Standard Deviation		Percentage of Extreme Months		Rank
	Year	GeoStd Dev (%)	Year	L (%)	Year	GeoStd Dev (%)	Year	L (%)	
1	1923	192.001	1920	75.0000	1947	92.9623	1946	66.6667	1
2	1922	154.851	1923	75.0000	1943	83.8374	1944	58.3333	2
3	1924	107.594	1924	75.0000	1946	82.2093	1947	50.0000	3
4	1920	70.783	1922	66.6667	1944	77.4118	1945	36.3636	4
5	1919	47.966	1919	58.3333	1948	74.4617	1943	25.0000	5
6	1949	46.154	1949	41.6667	1981	54.4417	1948	25.0000	6
7	2002	44.526	1925	33.3333	1945	50.3701	1960	25.0000	7
8	1931	43.737	1926	33.3333	1998	46.4129	1981	25.0000	8
9	1918	43.392	1927	33.3333	1986	43.4252	1998	25.0000	9
10	1987	36.854	2002	33.3333	1949	43.0522	1932	16.6667	10
11	1927	33.539	1918	25.0000	1973	38.6122	1974	16.6667	11
12	1990	33.310	1921	25.0000	1960	38.3265	1986	16.6667	12
13	1921	31.773	1931	25.0000	1932	37.6682	1992	16.6667	13
14	1925	31.454	1959	25.0000	1941	37.3602	1915	8.3333	14
15	2003	29.684	1962	25.0000	1915	35.4430	1916	8.3333	15
16	2001	29.240	1973	25.0000	1980	34.6353	1917	8.3333	16
17	1998	29.012	1987	25.0000	1992	32.3434	1923	8.3333	17
18	1914	27.249	1990	25.0000	1927	32.1516	1924	8.3333	18
19	1997	25.990	1997	25.0000	1974	31.5364	1926	8.3333	19
20	1986	25.269	1932	22.2222	1917	29.5809	1927	8.3333	20
21	1948	23.224	1948	18.1818	2002	29.4891	1941	8.3333	21
22	1973	23.220	1875	16.6667	1997	29.2506	1942	8.3333	22
23	1959	22.853	1891	16.6667	1942	29.1755	1949	8.3333	23
24	2000	22.186	1914	16.6667	1925	28.2687	1964	8.3333	24
25	1999	21.605	1951	16.6667	1993	28.1820	1973	8.3333	25

Table 18. Rankings of Volatility as Measured by the Standard Deviation and by the Percentage of Extreme Days for the Highest 15 Years, Italy (1957-2004) and Japan (1955 -2004)

	Italy				Japan				
Rank	Geometric Standard Deviation		Percentage of Extreme Days		Geometric Standard Deviation		Percentage of Extreme Days		Rank
	Year	GeoStd Dev (%)	Year	L (%)	Year	GeoStd Dev (%)	Year	L (%)	
1	1981	45.1299	1981	20.7171	1990	37.9695	1992	28.3401	1
2	1960	40.1353	1960	19.4805	1992	34.5270	1990	26.8293	2
3	1986	38.4050	1998	18.9300	2001	33.6051	2001	24.7967	3
4	1998	34.8382	1986	15.6000	1997	31.6977	2002	23.5772	4
5	1973	29.0388	2002	9.1633	1987	30.9633	1998	23.0769	5
6	1980	28.7807	1980	9.0909	1998	30.8211	1997	22.8571	6
7	1987	25.3378	1974	9.0164	2002	29.1157	2003	17.1429	7
8	1994	25.0843	1973	8.5366	2003	25.4955	2000	16.1290	8
9	1974	24.9648	1997	8.0000	1995	25.2816	1995	14.4578	9
10	1997	24.9198	2001	7.9681	2000	25.2641	1991	13.0081	10
11	2001	24.8725	1976	7.6000	1991	23.2624	1999	11.4286	11
12	2002	24.7656	1964	7.5949	1973	22.5817	1973	9.7561	12
13	1992	24.4630	1987	7.4803	1993	22.4313	1993	9.3496	13
14	1964	23.7080	1994	7.0866	1999	22.3911	1987	8.3942	14
15	1993	22.3465	1992	7.0588	1971	21.1352	2004	7.7236	15

Table 19. Rankings of Volatility as Measured by the Standard Deviation and by the Percentage of Extreme Months for the Highest 25 Years, Japan (1914-2004) and Spain (1915 -2004)

	Japan				Spain				
Rank	Geometric Standard Deviation		Percentage of Extreme Months		Geometric Standard Deviation		Percentage of Extreme Months		Rank
	Year	GeoStd Dev (%)	Year	L (%)	Year	GeoStd Dev (%)	Year	L (%)	
1	1949	101.864	1948	58.3333	1987	58.0452	1986	33.3333	1
2	1948	89.586	1949	58.3333	1998	40.5223	1987	33.3333	2
3	1946	59.295	1946	50.0000	1990	35.1841	1998	33.3333	3
4	1953	57.210	1990	33.3333	1986	35.0494	2002	33.3333	4
5	1920	56.273	1932	25.0000	2002	31.4373	1948	25.0000	5
6	1990	49.959	1947	25.0000	1948	31.3824	1951	16.6667	6
7	1947	45.796	1950	25.0000	1974	25.5937	1969	16.6667	7
8	1950	45.127	1952	25.0000	1947	25.4911	1977	16.6667	8
9	1932	40.635	1953	25.0000	1957	25.3316	1985	16.6667	9
10	1993	31.061	1920	16.6667	1997	25.1541	1990	16.6667	10
11	1916	29.994	1915	8.3333	2001	23.9695	1930	8.3333	11
12	1992	29.712	1916	8.3333	2000	22.7448	1947	8.3333	12
13	1995	29.215	1917	8.3333	1973	22.5427	1957	8.3333	13
14	1971	27.542	1937	8.3333	1981	22.3346	1973	8.3333	14
15	1991	27.135	1941	8.3333	1992	22.2989	1974	8.3333	15
16	2000	26.862	1957	8.3333	1951	21.8262	1975	8.3333	16
17	1998	26.390	1961	8.3333	1959	21.6617	1976	8.3333	17
18	1917	26.212	1962	8.3333	1991	21.2543	1981	8.3333	18
19	1952	26.162	1963	8.3333	1977	21.1906	1991	8.3333	19
20	1961	25.904	1970	8.3333	1976	21.0567	1992	8.3333	20
21	1954	23.449	1971	8.3333	1985	20.9220	1993	8.3333	21
22	1970	23.352	1973	8.3333	1941	20.9193	1994	8.3333	22
23	2002	23.091	1986	8.3333	1994	20.4346	1997	8.3333	23
24	1965	23.012	1992	8.3333	1949	20.0530	2000	8.3333	24
25	1962	22.905	1993	8.3333	1993	19.7281	2001	8.3333	25

Table 20. Rankings of Volatility as Measured by the Standard Deviation and by the Percentage of Extreme Months for the Highest 25 Years, Netherlands (1919-2004) and Switzerland (1921 -2004)

	Netherlands				Switzerland				
Rank	Geometric Standard Deviation		Percentage of Extreme Months		Geometric Standard Deviation		Percentage of Extreme Months		Rank
	Year	GeoStd Dev (%)	Year	L (%)	Year	GeoStd Dev (%)	Year	L (%)	
1	2002	40.5646	1931	25.0000	1962	38.4076	1962	33.3333	1
2	1987	39.3247	1932	25.0000	1987	37.7453	2002	33.3333	2
3	1932	34.5564	2002	25.0000	1998	37.0460	1931	25.0000	3
4	1998	29.0359	1936	16.6667	1931	35.2568	1932	25.0000	4
5	1931	28.1565	1974	16.6667	1932	33.0553	1974	25.0000	5
6	1936	27.5818	1984	16.6667	1936	32.3623	1990	25.0000	6
7	1984	27.4684	1987	16.6667	1974	26.0634	1998	25.0000	7
8	1937	25.8977	1997	16.6667	1990	25.7024	1938	16.6667	8
9	1997	25.2540	1998	16.6667	1975	24.4800	1959	16.6667	9
10	1975	24.9638	1940	12.5000	2002	23.7947	1965	16.6667	10
11	2003	23.8624	1946	12.5000	1959	23.0037	1969	16.6667	11
12	1946	23.1608	1920	8.3333	1938	21.7337	1973	16.6667	12
13	1957	22.3584	1921	8.3333	1997	21.6839	1987	16.6667	13
14	1956	22.3149	1929	8.3333	1969	20.8868	1997	16.6667	14
15	1920	22.0096	1937	8.3333	1972	20.0210	1921	8.3333	15
16	2001	21.6449	1947	8.3333	1961	19.6915	1936	8.3333	16
17	1962	21.1706	1956	8.3333	1986	19.4654	1957	8.3333	17
18	1966	21.0365	1962	8.3333	1957	19.4014	1961	8.3333	18
19	1981	20.6393	1966	8.3333	1921	19.2069	1967	8.3333	19
20	1970	20.5302	1970	8.3333	1965	18.6412	1970	8.3333	20
21	1922	20.3004	1973	8.3333	1973	18.3881	1972	8.3333	21
22	1924	20.0840	1975	8.3333	1967	18.3725	1975	8.3333	22
23	1941	18.8797	1981	8.3333	1971	18.3101	1980	8.3333	23
24	1955	18.6997	1983	8.3333	2003	16.8239	1986	8.3333	24
25	1973	18.6613	2001	8.3333	2001	16.7691	2001	8.3333	25

Table 21. Regression Results of Equity Mutual Fund Net Flows on Risk Measures for Canada (1994-2005) and U.S. (1984-2005)

	Canada			U.S.		
	Model (1)	Model (2)	Model (3)	Model (1)	Model (2)	Model (3)
Panel A: Annual Observation (Canada: n=12; U.S.: n=22)						
Constant	10.0292 (1.75)	9.3403 (2.28)	13.4779 (2.41)	-16.5027 (-0.31)	-43.6032 (-1.09)	-54.6057 (-1.24)
GeoMean(t-1)	0.1750 (1.40)	0.1807 (1.51)	0.0692 (0.44)	2.7508 (2.48)	2.84139 (2.32)	2.8891 (2.32)
GeoStdDev(t-1)	-0.0633 (-0.21)			-1.8333 (-0.93)		
TotalExtr (t-1)		-0.0397 (-0.14)			-1.8761 (-0.51)	
NegExtr(t-1)			-2.1223 (-1.08)			-10.8054 (-0.74)
PosExtr(t-1)			2.1813 (1.05)			9.1384 (0.51)
Time	-0.8449 (-1.69)	-0.8614 (-1.77)	-0.9585 (-1.95)	9.7513 (4.43)	9.9426 (4.40)	10.70612 (4.12)
Adjusted R^2	0.3311	0.3292	0.3421	0.5219	0.5062	0.4891
Panel B: Semiannual Observation (Canada: n=23; U.S.: n=43)						
Constant	5.7713 (3.46)	5.3833 (4.22)	5.7602 (4.63)	7.5974 (0.40)	-10.0477 (-0.65)	-16.6352 (-1.00)
GeoMean(t-1)	0.1274 (2.00)	0.1393 (2.12)	0.1429 (2.27)	1.6183 (2.33)	1.5883 (2.23)	1.6928 (2.35)
GeoStdDev(t-2)	-0.0464 (-0.32)			1.1260 (-1.64)		
TotalExtr (t-2)		0.0117 (0.12)			-0.9183 (-0.75)	
NegExtr(t-2)			-0.4271 (-1.50)			-6.1149 (-1.16)
PosExtr(t-2)			0.5725 (1.61)			5.2940 (0.84)
Time	-0.2593 (-2.66)	-0.2769 (-2.97)	-0.2820 (-3.15)	2.4289 (4.45)	2.4213 (4.24)	2.6686 (4.29)
Adjusted R^2	0.3840	0.3812	0.4310	0.3351	0.2992	0.2996

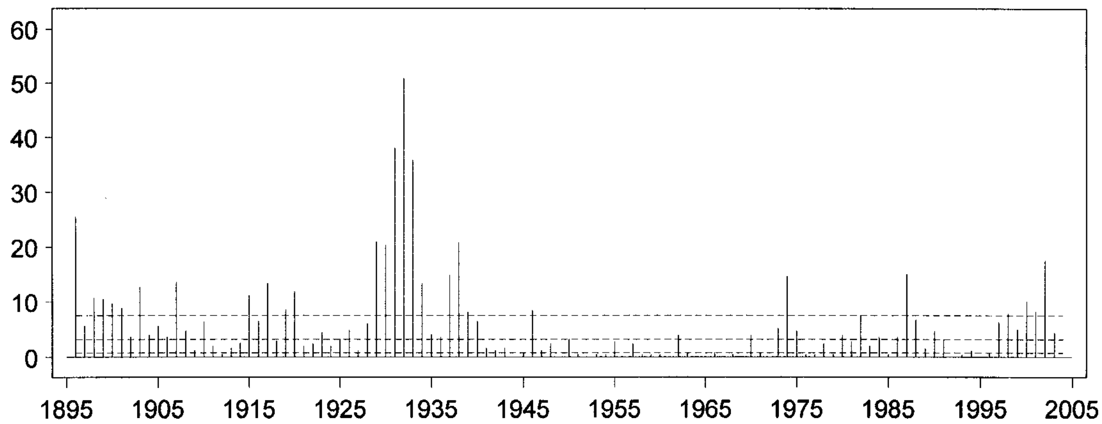
* *t-values are reported in brackets.*

Table 22. Regression Results of Equity Mutual Fund Net Flows on Risk Measures for U.K. (1995-2005)

	U.K.		
	Model (1)	Model (2)	Model (3)
Annual Observation (U.K.: n=11)			
Constant	3.2372 (0.93)	7.7905 (3.22)	6.6545 (3.47)
GeoMean(t-1)	0.1736 (2.27)	0.1490 (1.70)	0.1584 (2.34)
GeoStdDev(t-1)	0.4124 (1.84)		
TotalExtr (t-1)		0.3469 (1.08)	
NegExtr(t-1)			2.0009 (2.75)
PosExtr(t-1)			-1.2407 (-1.77)
Time	-0.7304 (-2.10)	-0.6343 (-1.59)	-0.6348 (-2.07)
Adjusted R^2	0.3529	0.1780	0.5140

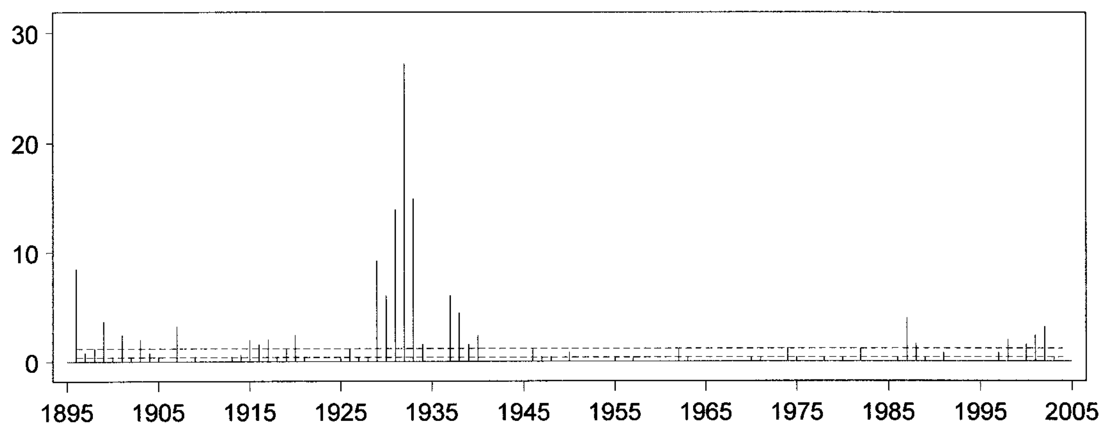
* *t-values are reported in brackets.*

Figure 1. Percentage of Extreme Days by Year with Mild Outliers, U.S. : 1896-2004



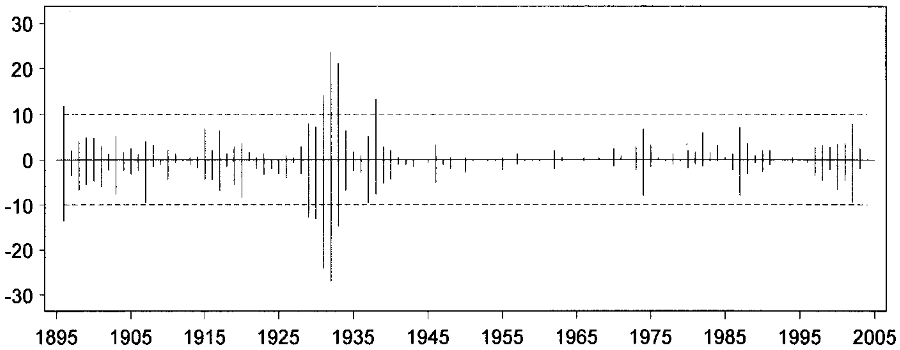
Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=0.7905%; median=3.2129%; upper quartile=7.5099%.

Figure 2. Percentage of Extreme Days by Year with Extreme Outliers, U.S.: 1896-2004



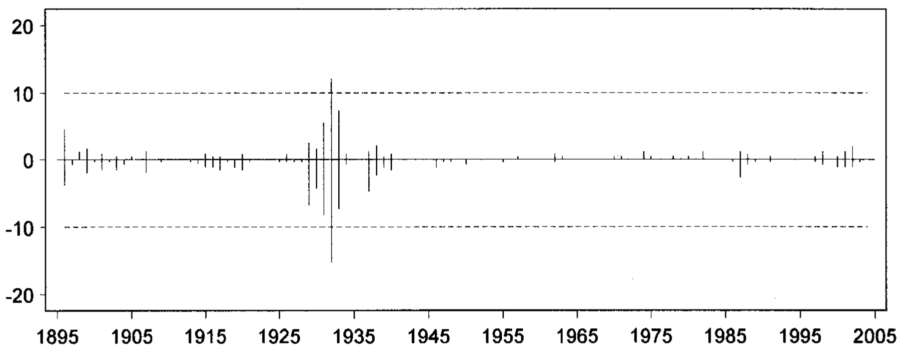
Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=0%; median=0.3968%; upper quartile=1.1952%.

Figure 3. The Percentage of Extreme Days beyond the Inner Fences, U.S.: 1896-2004



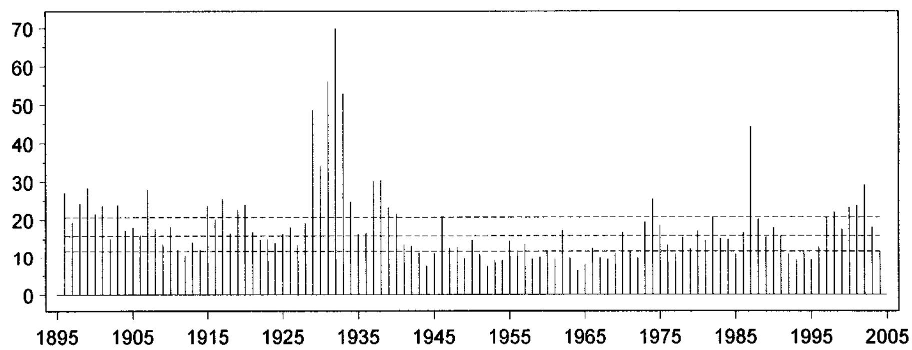
Note: The part above the zero line presents the percentage of positive extreme trading days, and the part below the zero line presents the percentage of negative extreme trading days. Horizontal Dot lines indicate ±10% of the trading days.

Figure 4. The Percentage of Extreme Days beyond the Outer Fences, U.S.: 1896-2004



Note: The part above the zero line presents the percentage of positive extreme trading days, and the part below the zero line presents the percentage of negative extreme trading days. Horizontal Dot lines indicate ±10% of the trading days.

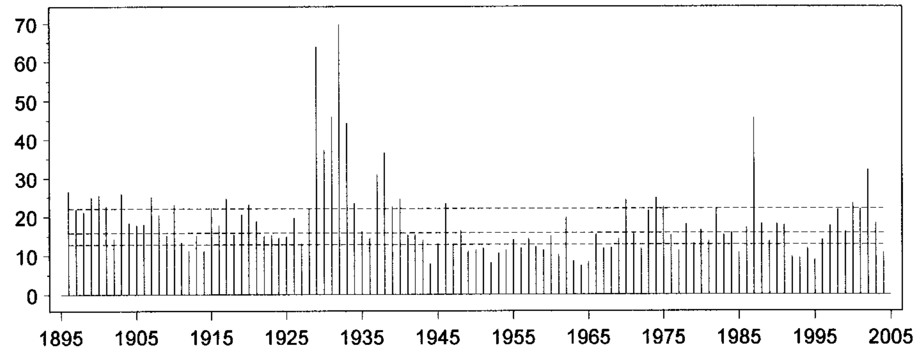
Figure 5. Annualized Geometric Standard Deviation for Daily Data, U.S.: 1896-2004



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=11.7173%; median=15.7688%; upper quartile=20.7264%.

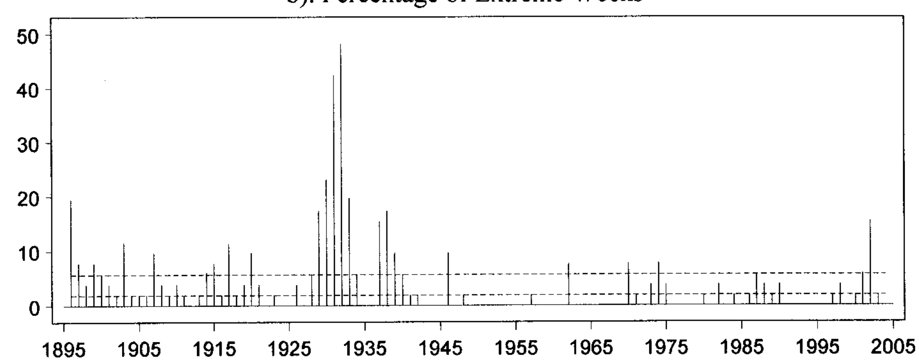
Figure 6. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Weekly Data of U.S., 1896-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=12.8464%; median=15.8343%; upper quartile=22.0546%.

b). Percentage of Extreme Weeks



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=0%; median=1,9231%; upper quartile=5.6604%.

c). Positive and Negative Components of Extreme Measures

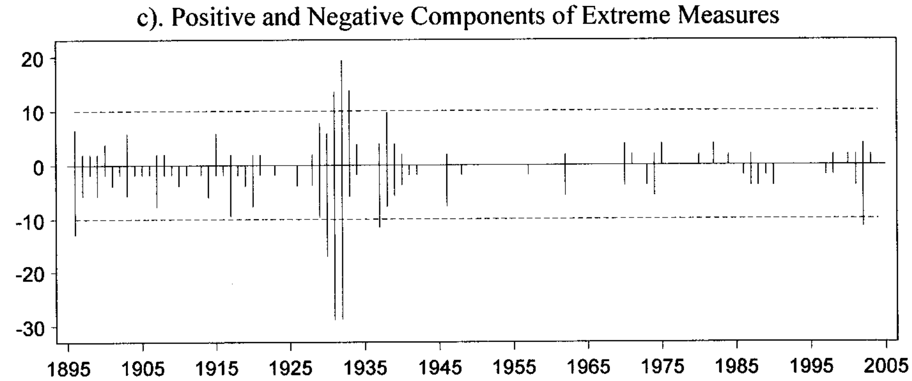
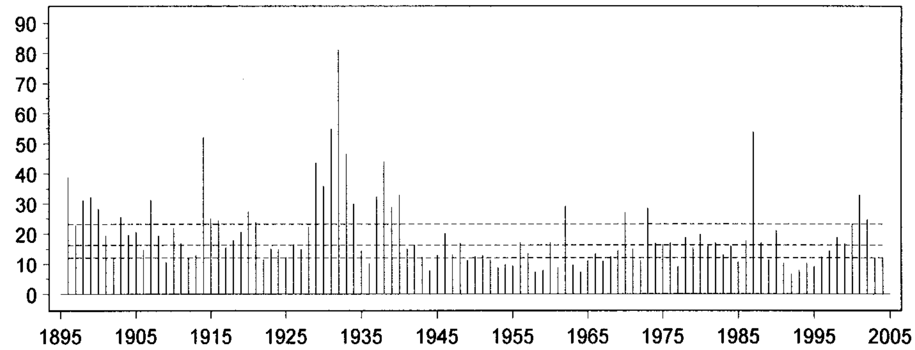


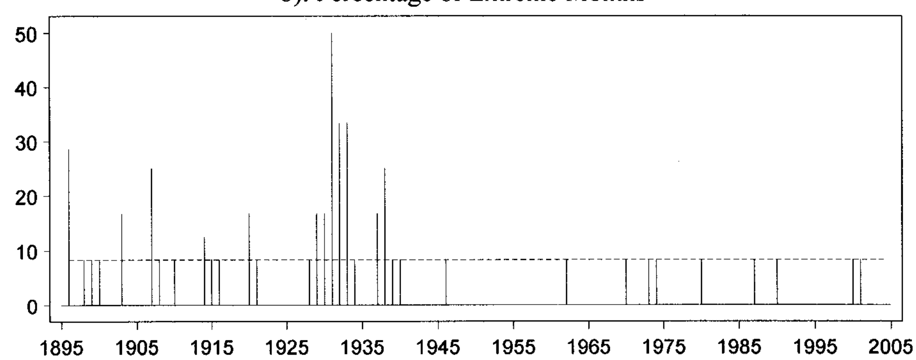
Figure 7. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Monthly Data of U.S., 1896-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=12.0438%; median=16.2481%; upper quartile=23.1352%.

b). Percentage of Extreme Months



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=0%; median=0%; upper quartile=8.3333%.

c). Positive and Negative Components of Extreme Measures

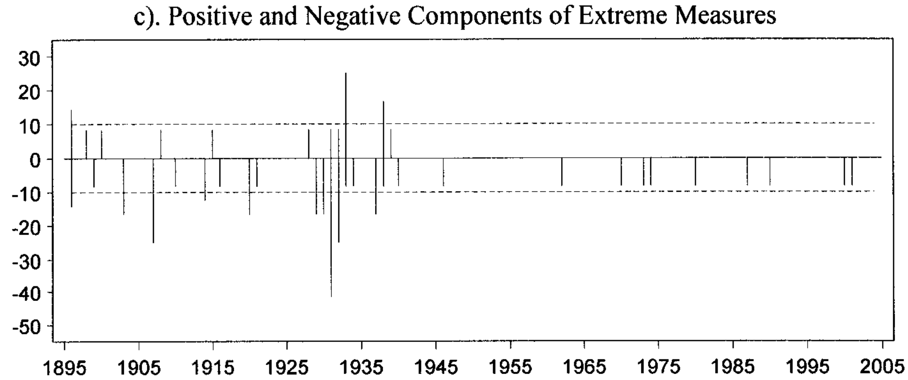
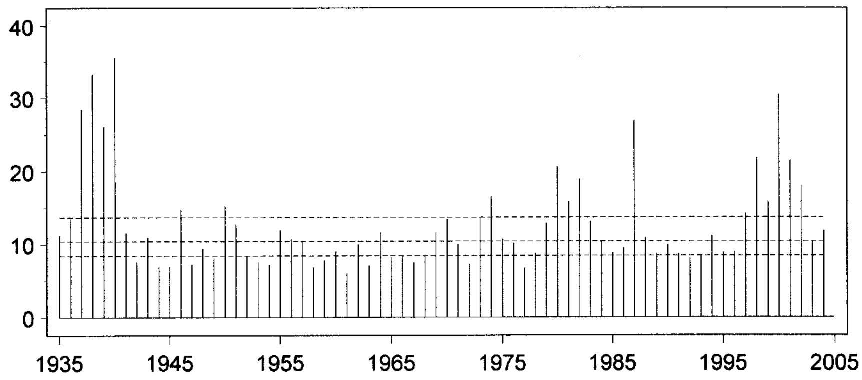


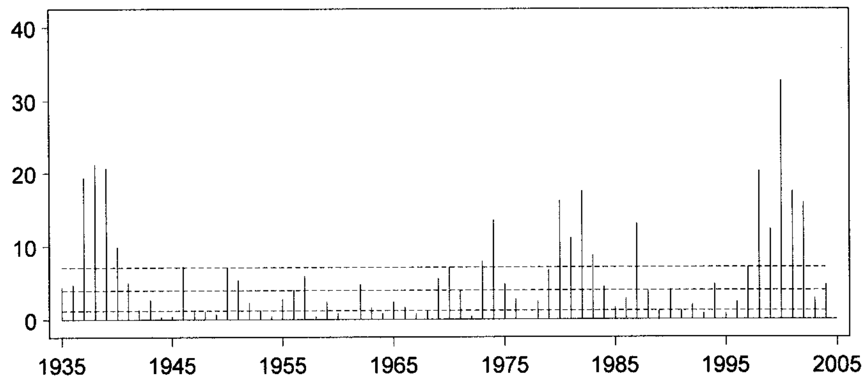
Figure 8. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Daily Data of Canada, 1935-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=8.4152%; median=10.4022%; upper quartile=13.7303%.

b). Percentage of Extreme Days



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=1.1952%; median=3.9526%; upper quartile=7.1429%.

c). Positive and Negative Components of Extreme Measures

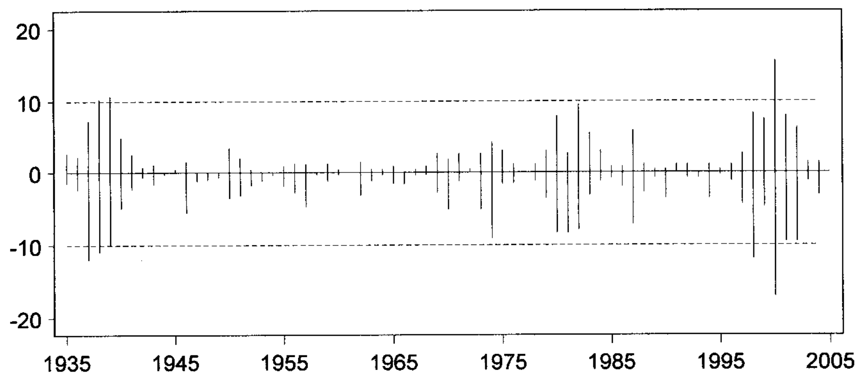
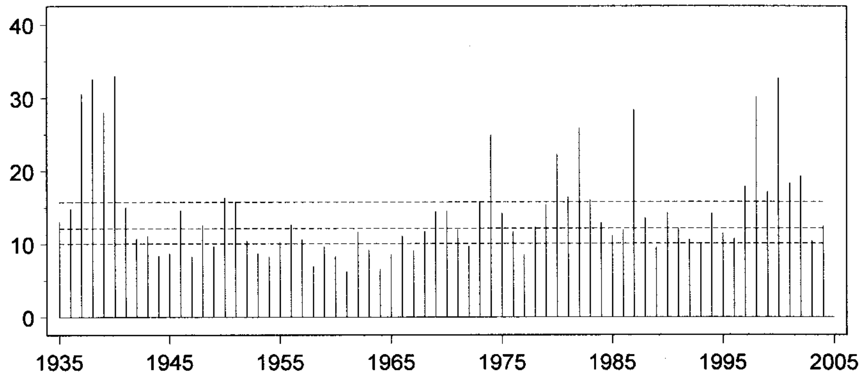


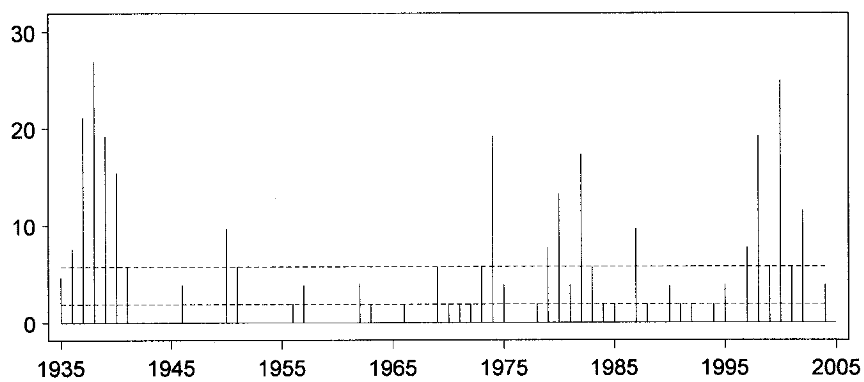
Figure 9. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Weekly Data of Canada, 1935-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=10.0550%; median=12.1481%; upper quartile=15.7585%.

b). Percentage of Extreme Weeks



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=0%; median=1.9231%; upper quartile=5.7692%.

c). Positive and Negative Components of Extreme Measures

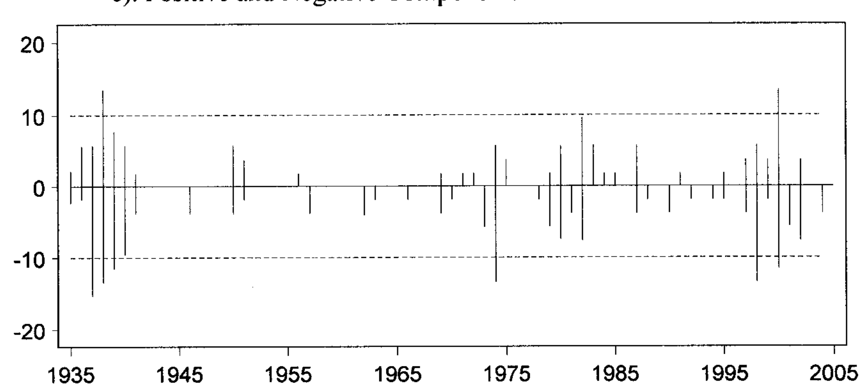
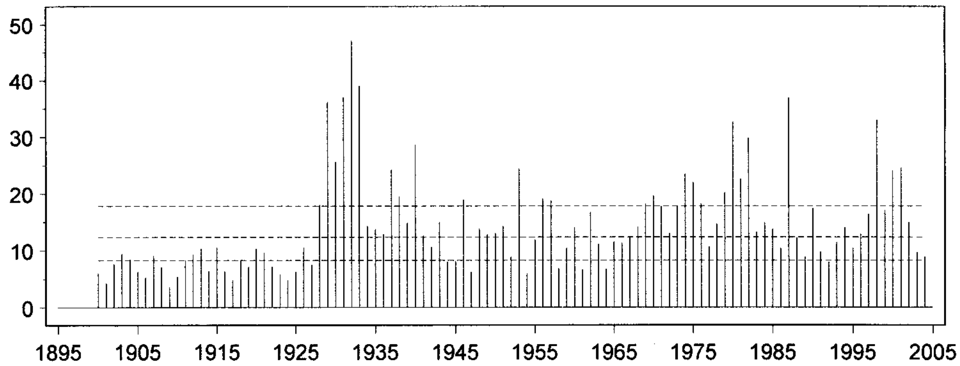


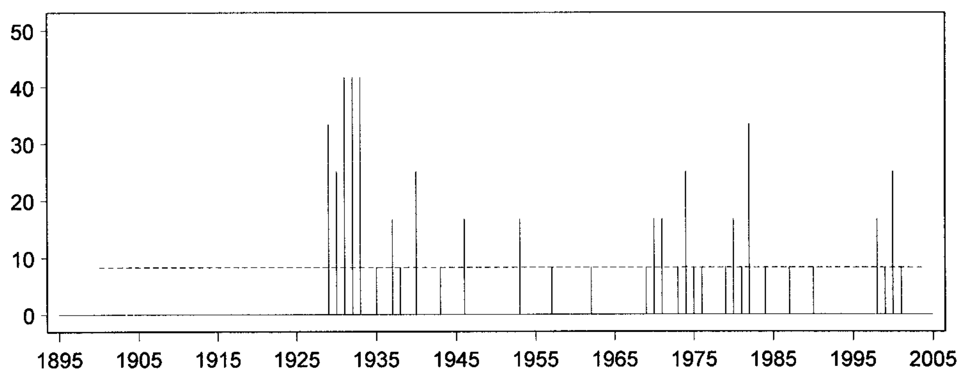
Figure 10. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Monthly Data of Canada, 1900-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal Dot lines indicate the quartiles and the median. Lower quartile=8.2977%; median=12.3928%; upper quartile=17.7909%.

b). Percentage of Extreme Months



Note: Horizontal Dot lines indicate the quartiles and the median. Lower quartile=0%; median=0%; upper quartile=8.3333%.

c). Positive and Negative Components of Extreme Measures

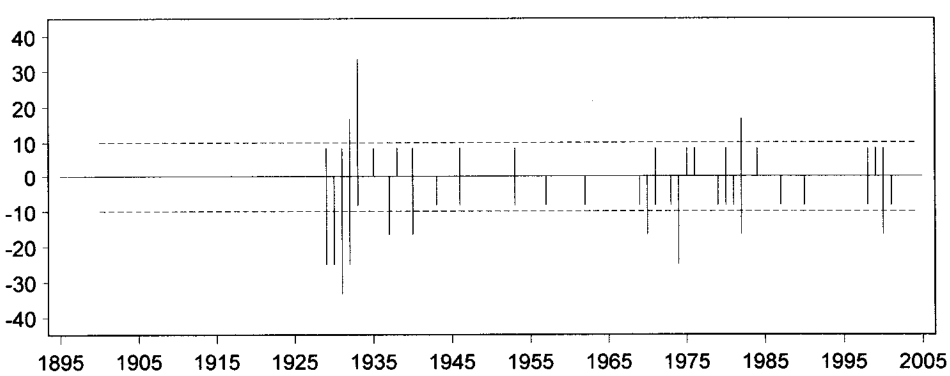


Figure 11. Comparison of Annualized Geometric Standard Deviations Using Daily, Weekly, and Monthly Data

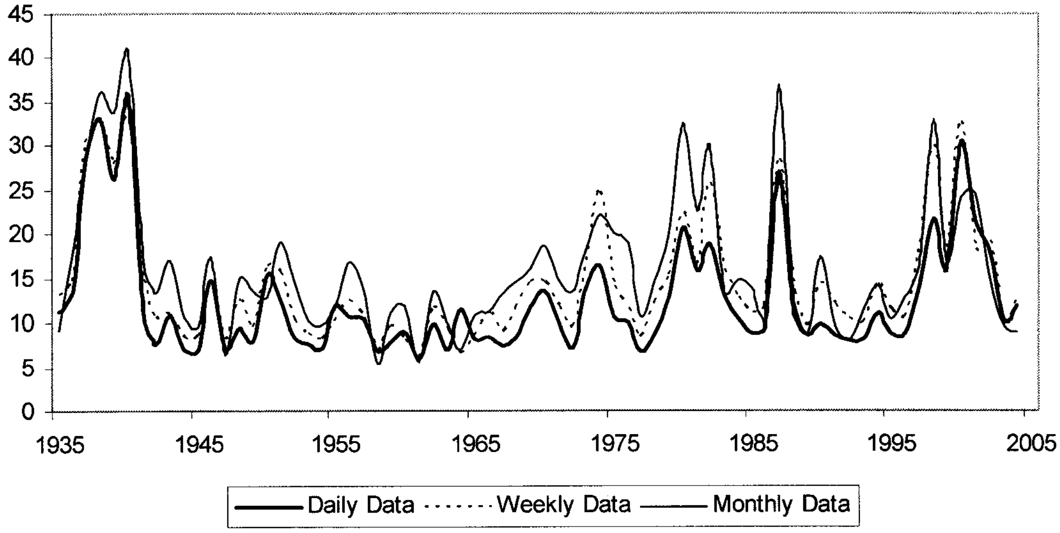
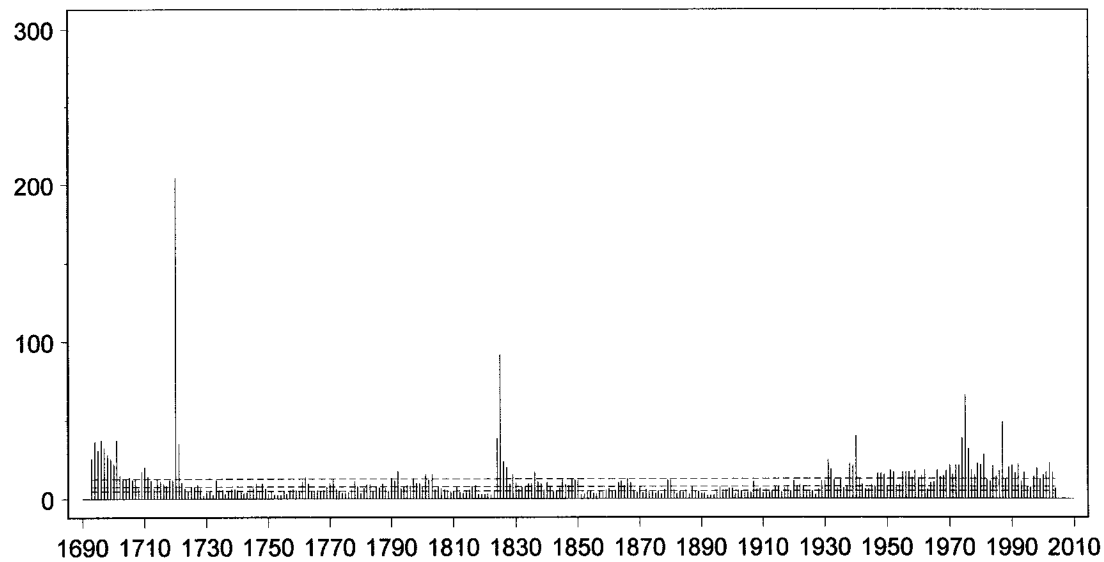


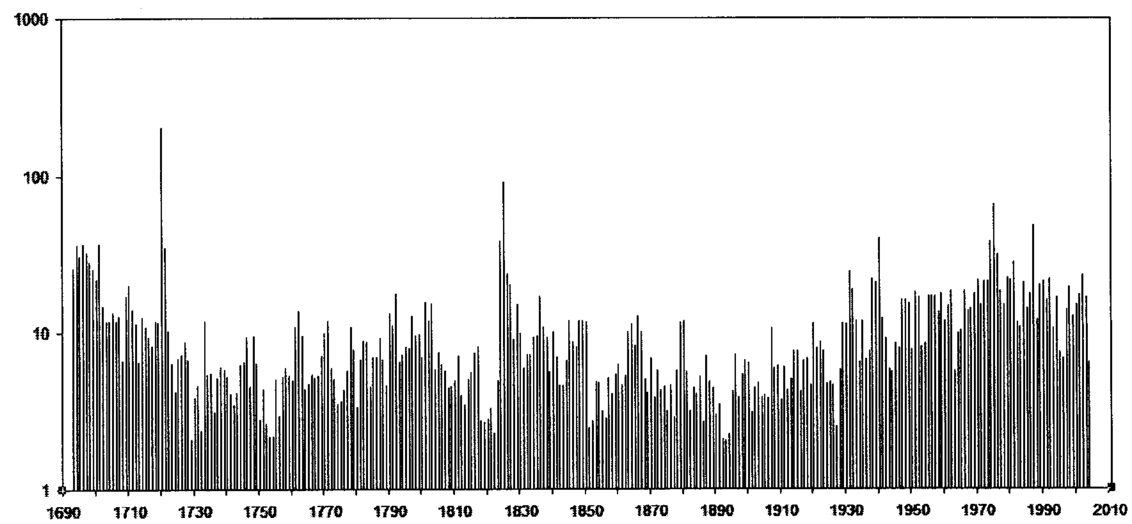
Figure 12. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Monthly Data of U.K., 1693-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=4.9436%; median=7.5071%; upper quartile=12.5582%.

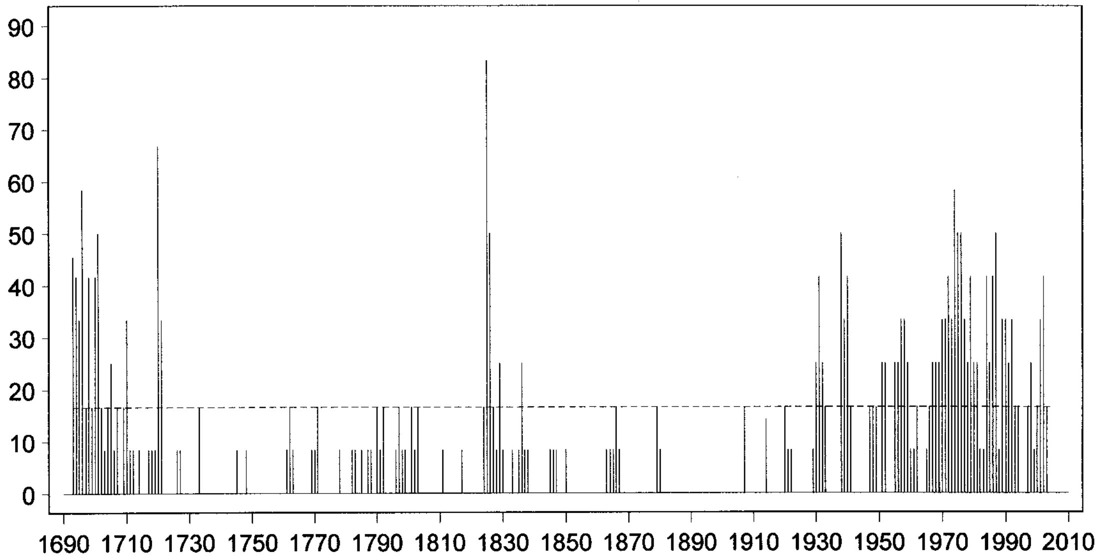
b). Annualized Geometric Standard Deviation Using Logarithmic Scale



Note: The axis Y uses logarithmic scale.

Figure 12. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Monthly Data of U.K., 1693-2004 (Continued)

c). Percentage of Extreme Months



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=0%; median=0%; upper quartile=16.6667%.

d). Positive and Negative Components of Extreme Measures

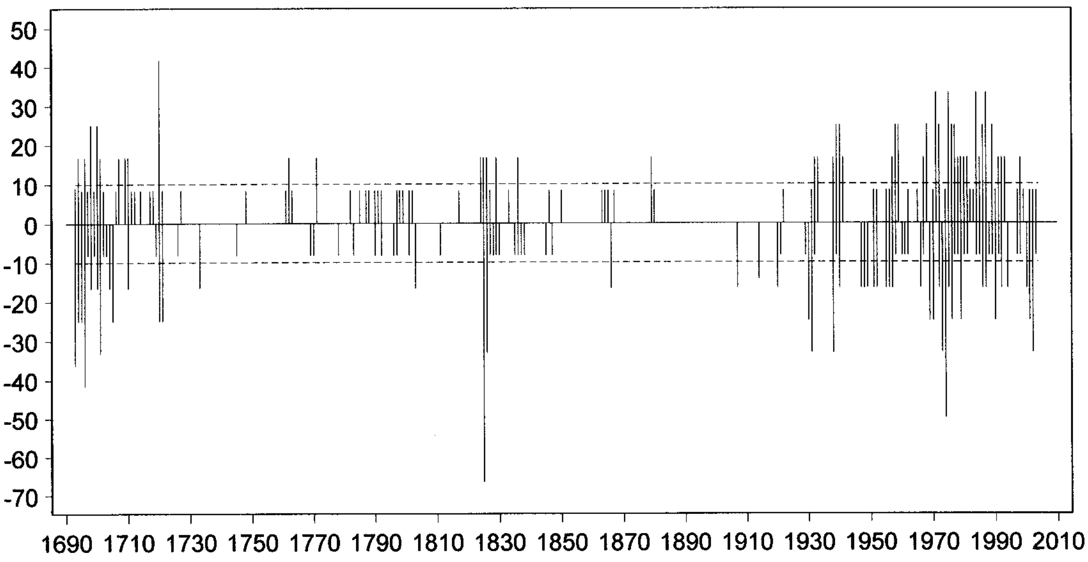
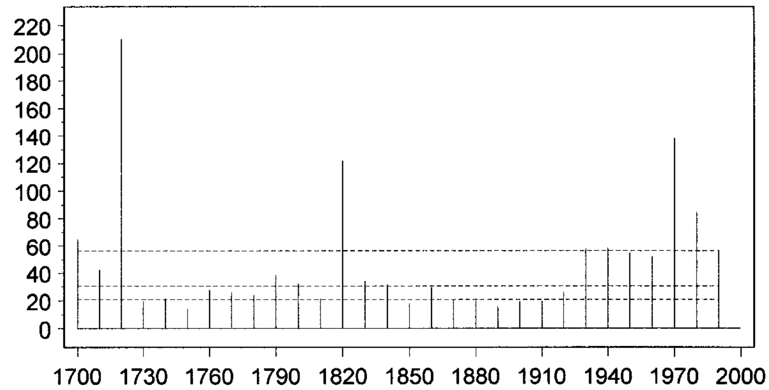


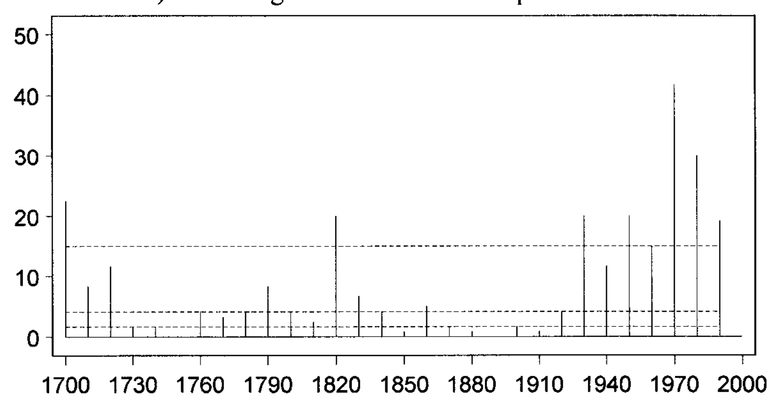
Figure 13. Volatility Measured as the Geometric Standard Deviation per Decade and Percentage of Extremes during a Decade, Monthly Data of U.K., 1700s-1990s

a). The Geometric Standard Deviation per Decade



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=20.9451%; median=30.4906%; upper quartile=56.3969%.

b). Percentage of Extreme Months per Decade



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=1.6667%; median=4.1667%; upper quartile=15.0000%.

c). Positive and Negative Components of Extreme Measures

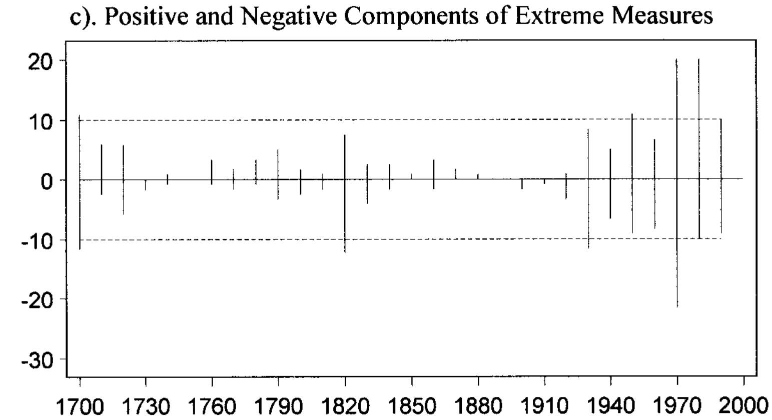
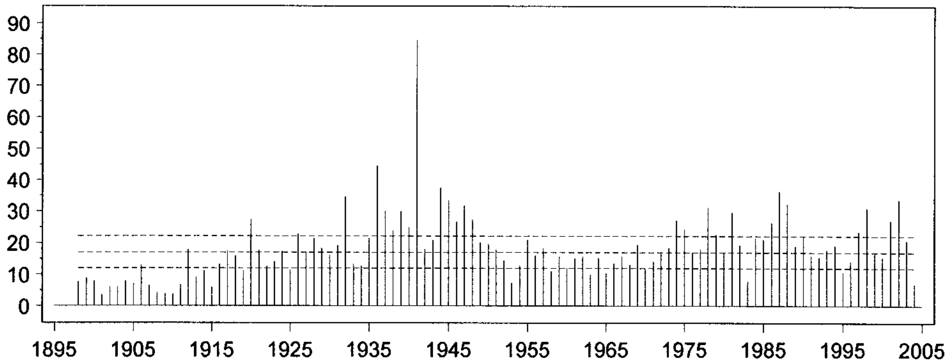


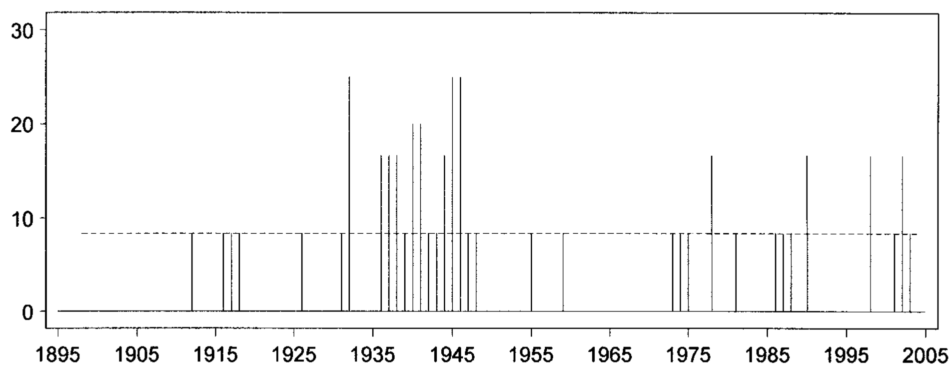
Figure 14. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Monthly Data of France, 1898-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=11.9263%; median=16.9654%; upper quartile=22.0561%.

b). Percentage of Extreme Months



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=0%; median=0%; upper quartile=8.3333%.

c). Positive and Negative Components of Extreme Measures

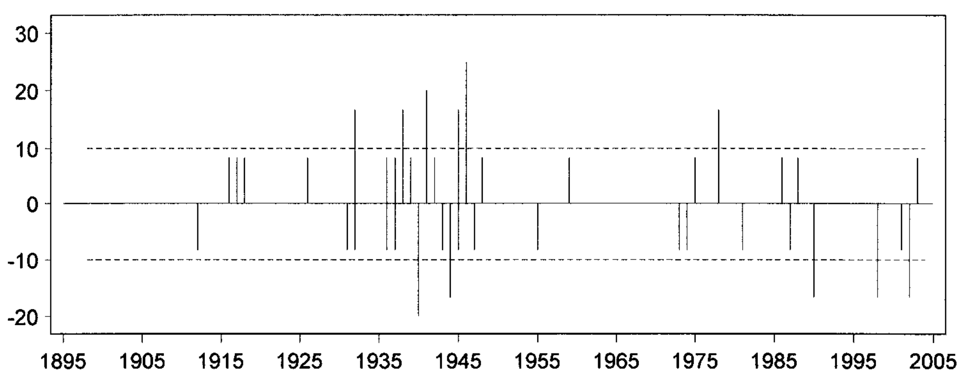
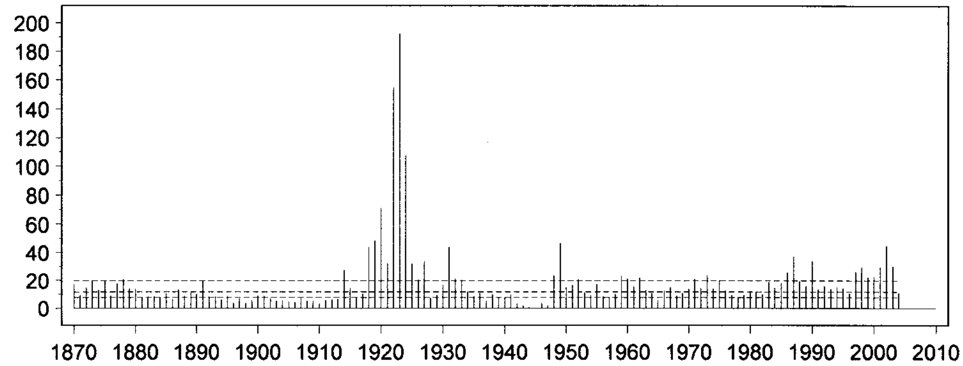


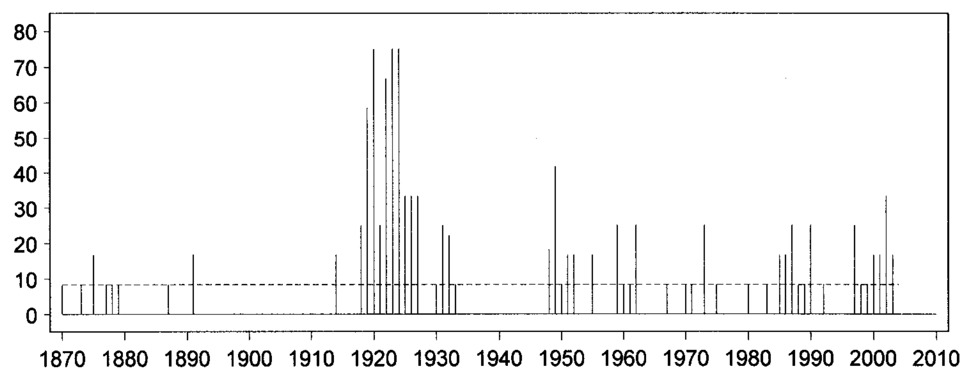
Figure 15. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Monthly Data of Germany, 1870-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=7.5060%; median=11.5812%; upper quartile=19.6263%.

b). Percentage of Extreme Months



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=0%; median=0%; upper quartile=8.3333%.

c). Positive and Negative Components of Extreme Measures

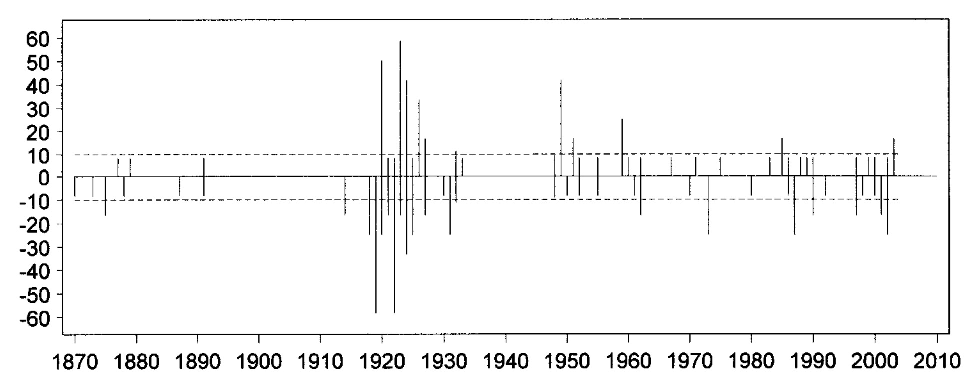
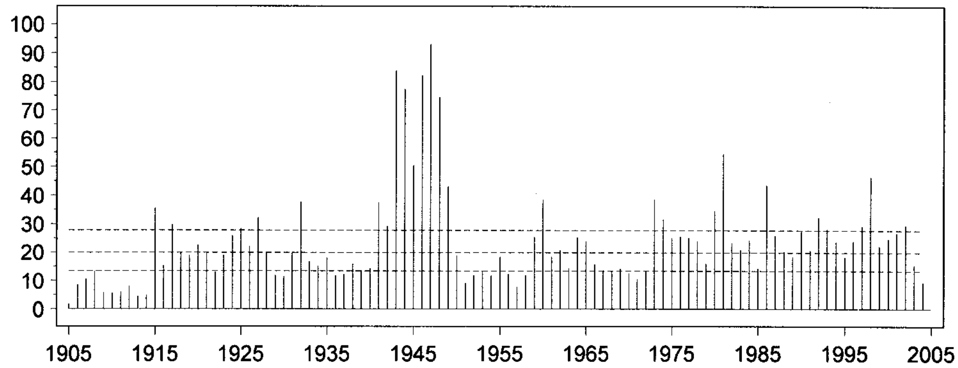


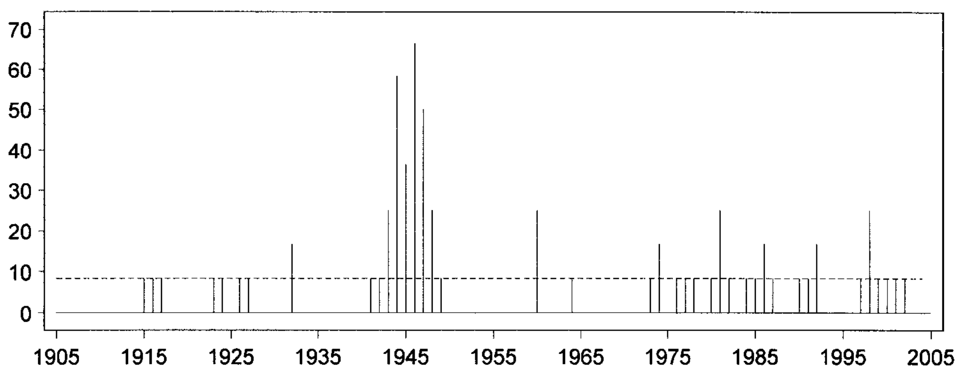
Figure 16. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Monthly Data of Italy, 1905-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=13.3124%; median=19.8159%; upper quartile=27.7969%.

b). Percentage of Extreme Months



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=0%; median=0%; upper quartile=8.3333%.

c). Positive and Negative Components of Extreme Measures

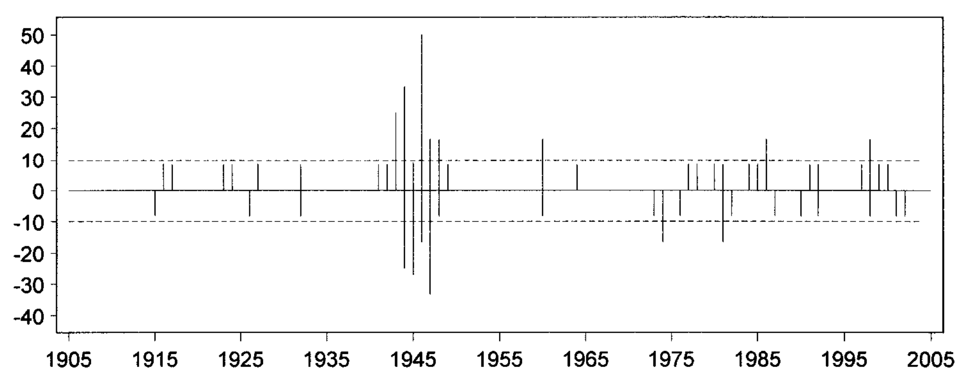
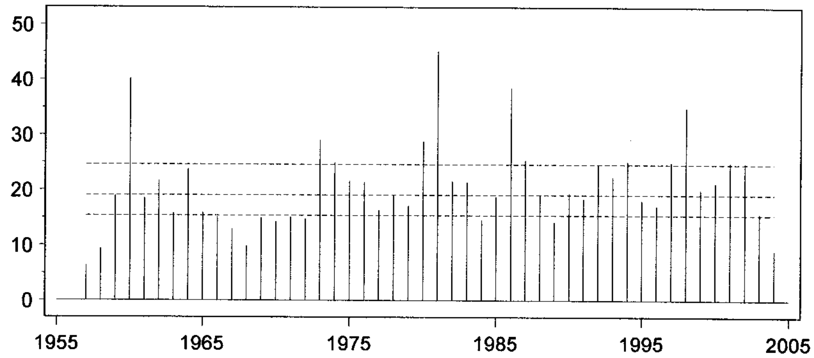


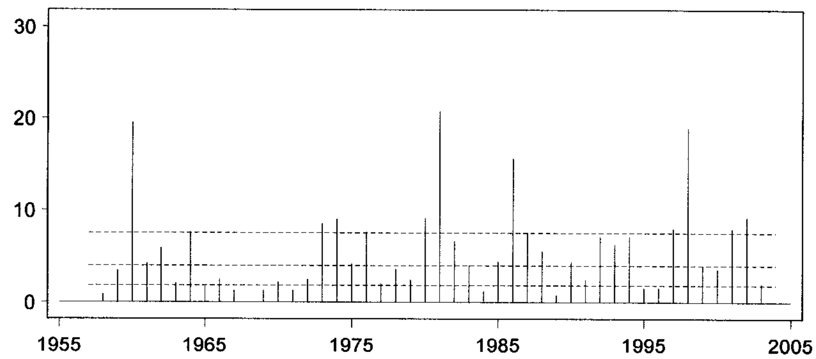
Figure 17. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Daily Data of Italy, 1956-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=15.3632%; median=19.0530%; upper quartile=24.6163%.

b). Percentage of Extreme Months



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=1.8360%; median=3.9526%; upper quartile=7.5376%.

c). Positive and Negative Components of Extreme Measures

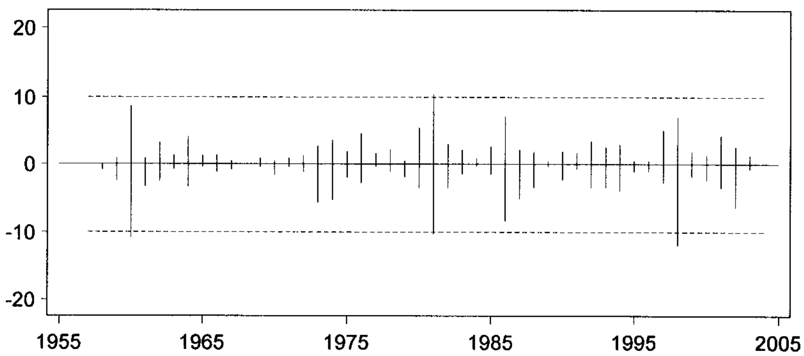
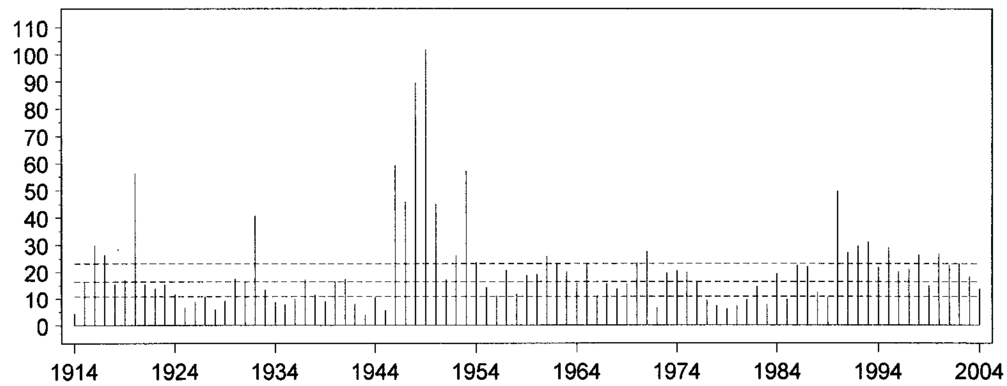


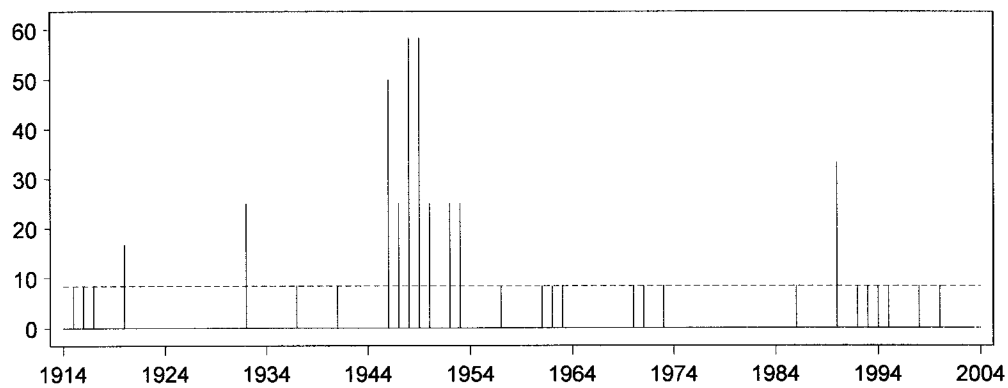
Figure 18. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Monthly Data of Japan, 1914-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=10.8258%; median=16.2962%; upper quartile=23.0911%.

b). Percentage of Extreme Months



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=0%; median=0%; upper quartile=8.3333%.

c). Positive and Negative Components of Extreme Measures

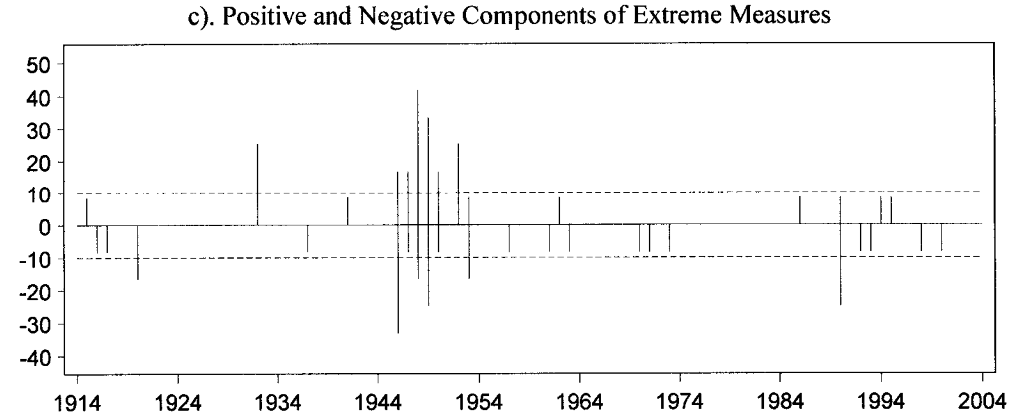
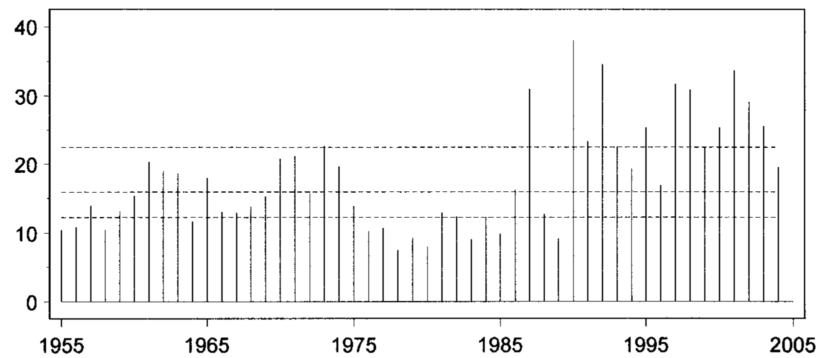


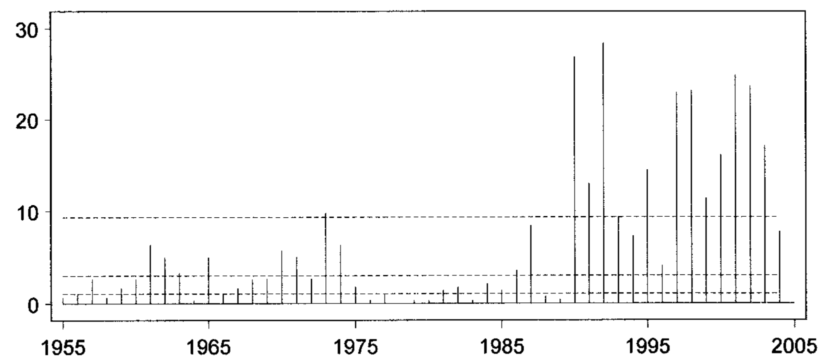
Figure 19. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Daily Data of Japan, 1955-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=12.2020%; median=15.9277%; upper quartile=22.4313%.

b). Percentage of Extreme Days



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=1.0490%; median=3.0024%; upper quartile=9.3496%.

c). Positive and Negative Components of Extreme Measures

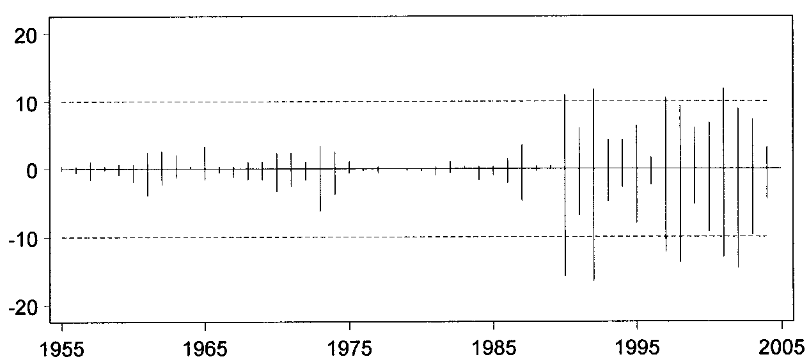
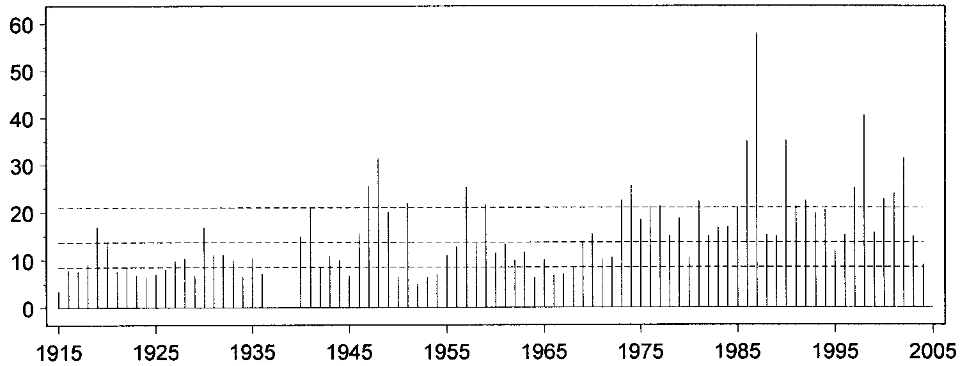


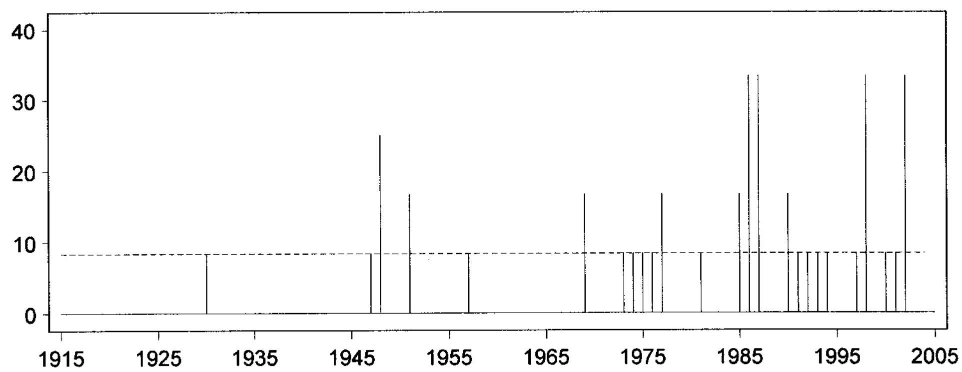
Figure 20. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Monthly Data of Spain, 1915-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=8.4639%; median=13.6462%; upper quartile=20.9193%.

b). Percentage of Extreme Months



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=0%; median=0%; upper quartile=8.3333%.

c). Positive and Negative Components of Extreme Measures

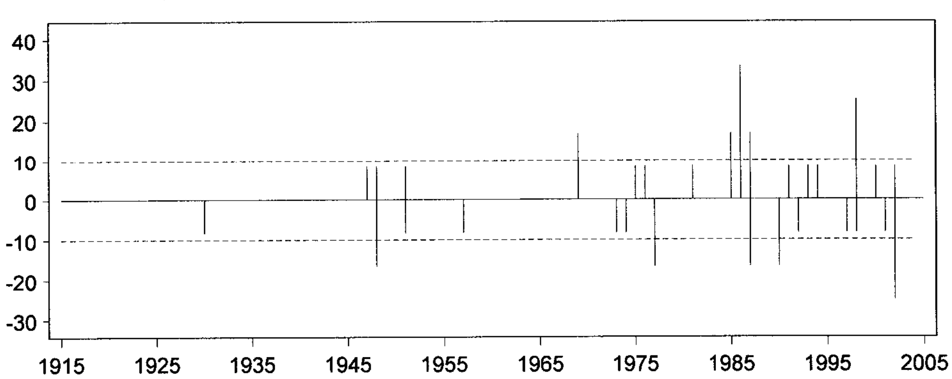
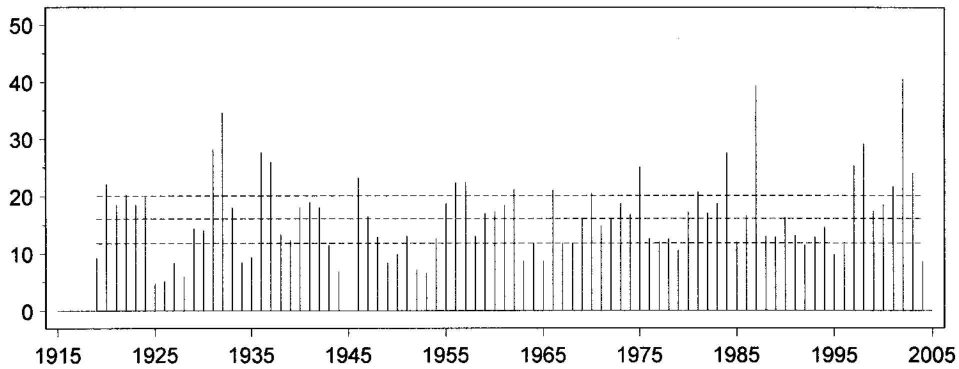


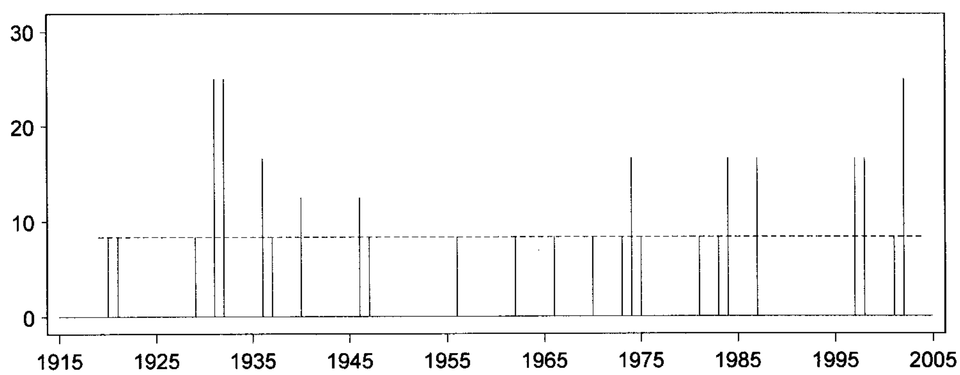
Figure 21. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Monthly Data of Netherlands, 1919-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=11.7725%; median=16.0269%; upper quartile=20.0840%.

b). Percentage of Extreme Months



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=0%; median=0%; upper quartile=8.3333%.

c). Positive and Negative Components of Extreme Measures

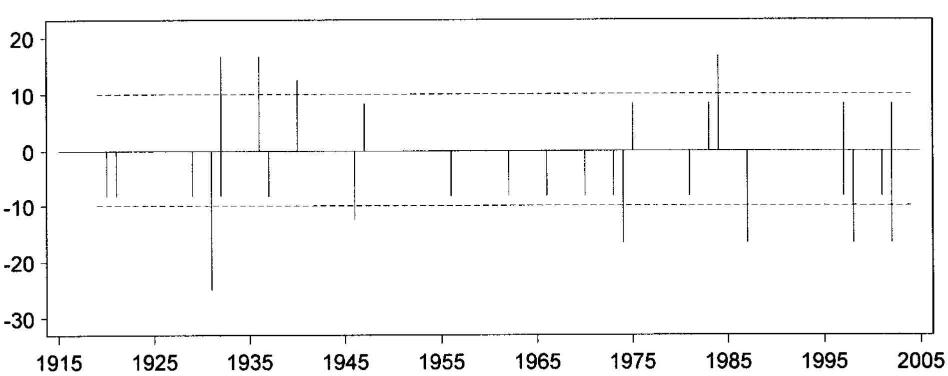
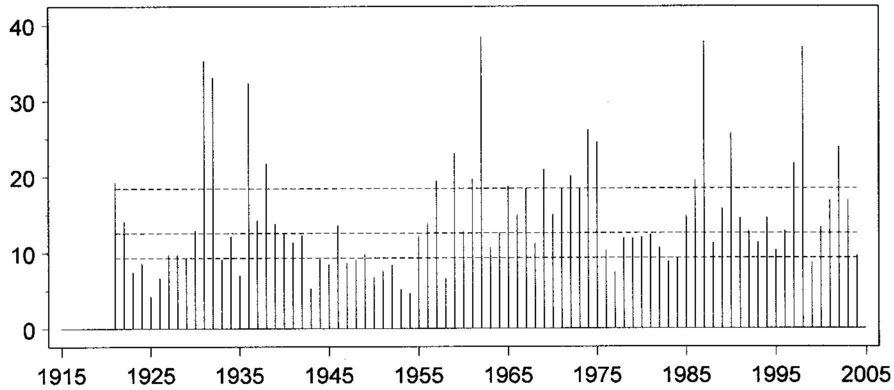


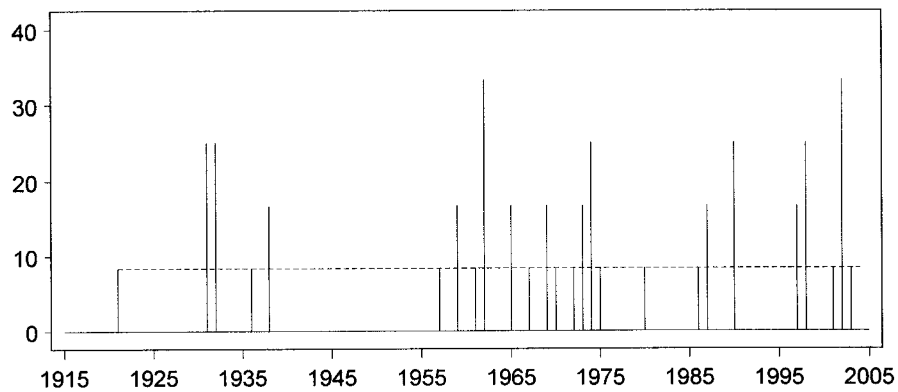
Figure 22. Volatility measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Monthly Data of Switzerland, 1921-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=9.3044%; median=12.5667%; upper quartile=18.3803%.

b). Percentage of Extreme Months



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=0%; median=0%; upper quartile=8.3333%.

c). Positive and Negative Components of Extreme Measures

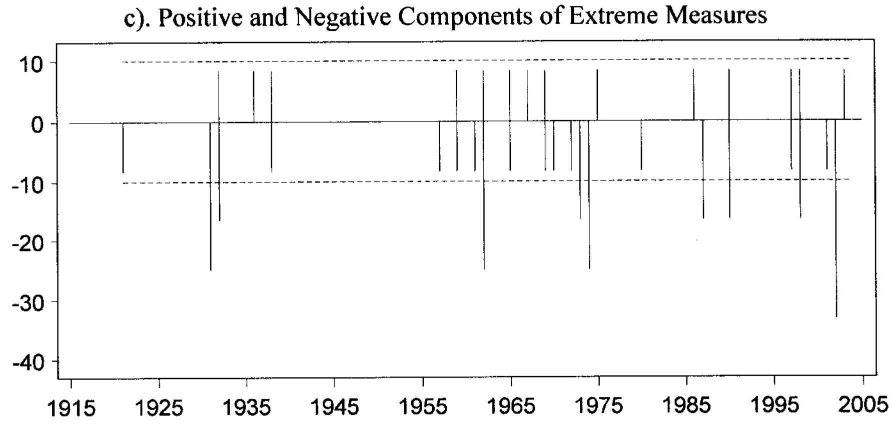
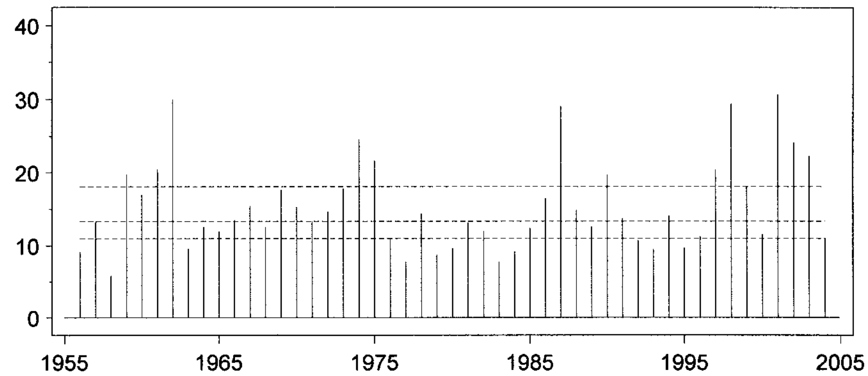


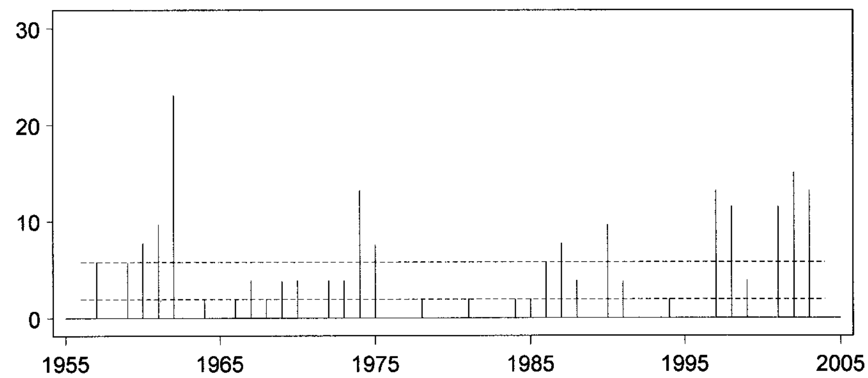
Figure 23. Volatility Measured as Annualized Geometric Standard Deviation and Percentage of Extremes, Weekly Data of Switzerland, 1956-2004

a). Annualized Geometric Standard Deviation



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=10.9376%; median=13.2725%; upper quartile=18.0472%.

b). Percentage of Extreme Months



Note: Horizontal dot lines indicate the quartiles and the median. Lower quartile=0%; median=1.9231%; upper quartile=5.7692%.

c). Positive and Negative Components of Extreme Measures

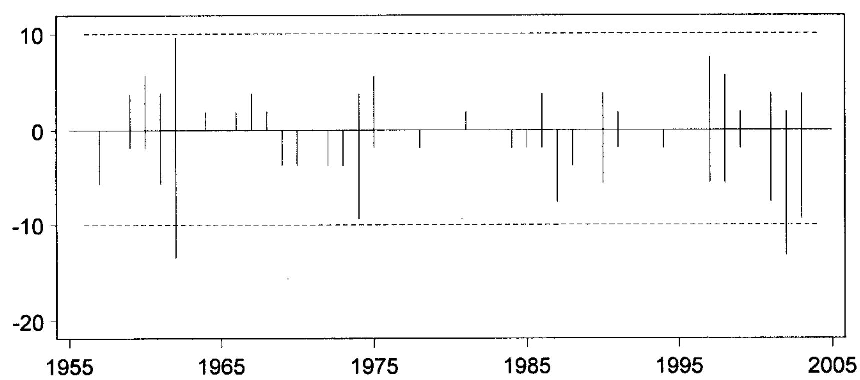


Figure 24(a). Comparison of the Volatility Measured as the Annualized Geometric Standard Deviation of Daily Logarithmic Percentage Change for the G-7 Countries

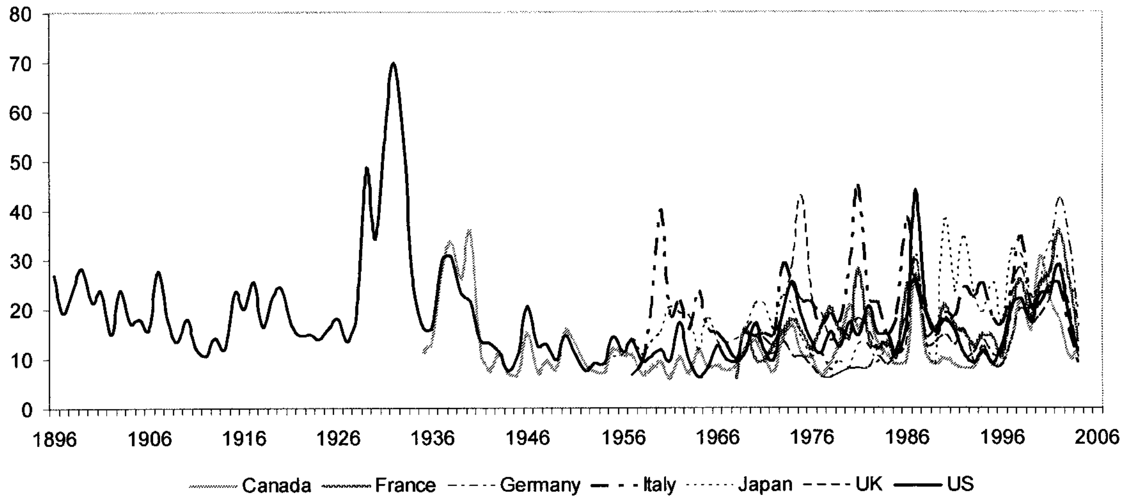


Figure 24(b). Comparison of the Volatility Measured as Percentage of Extreme Days for the G-7 Countries

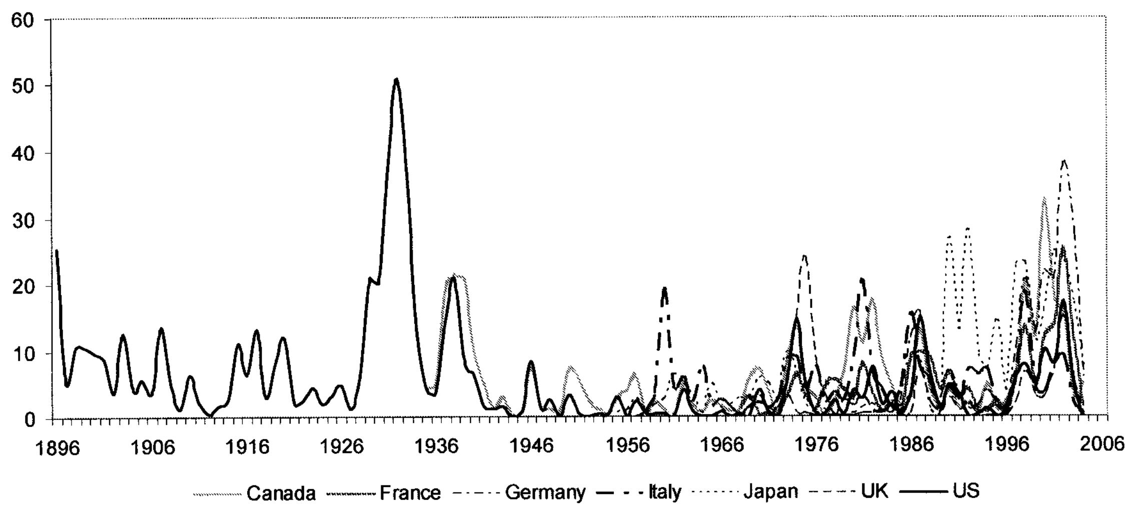


Figure 25(a). Comparison of the Volatility Measured as the Annualized Geometric Standard Deviation of Monthly Logarithmic Percentage Change for the G-7 Countries

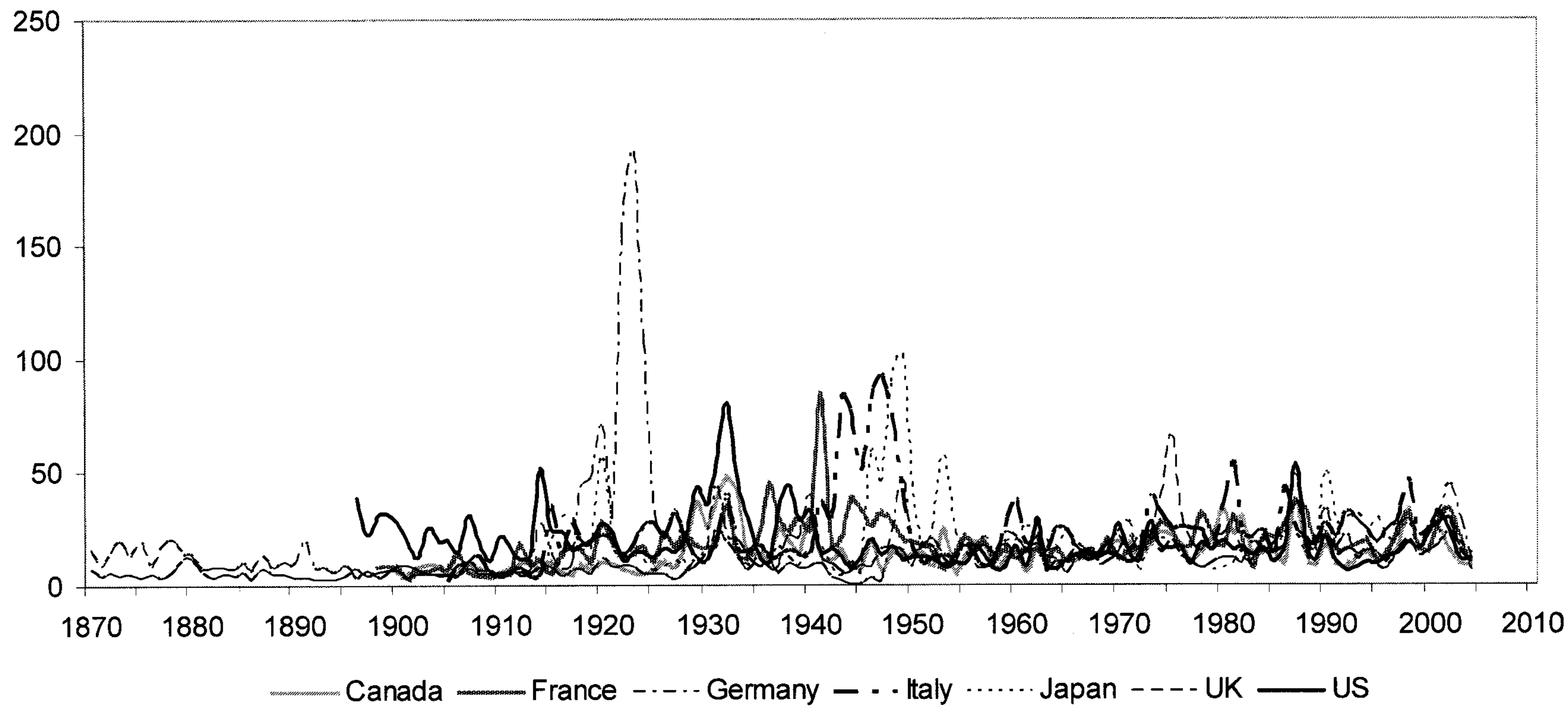


Figure 25(b). Comparison of the Volatility Measured as Percentage of Extreme Months for the G-7 Countries