ASSESSING STOCK PRICE RISK IN DEVELOPED MARKETS USING EXTREME MEASURES

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ABSTRACT

This paper examines the volatility characteristics of ten developed markets over long time horizons, focusing on the percentages of extreme days, weeks, and months over of a year as an alternative to the traditional standard deviation metric. The use of the standard deviation as a risk measure for these markets is problematic for loss averse investors, since returns for these markets are demonstrably not normally distributed, but leptokurtic, skewed, and are non-stationary. While many commonalities in the attribution of high risk by both measures are observed, many differences are also found, particularly over shorter frequencies. The extreme-day measure captures the behavior of loss averse investors in the US and Canada better than the traditional standard deviation measure. The evidence for the other countries of the study is mixed.

JEL codes: G11, G12, G15

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I. Introduction

The traditional measure of stock market volatility is the standard deviation of stock returns, which is predicated by the assumptions of ***normality of returns*** **and** ***risk averse investors***. However, daily stock market returns are not normally distributed, but leptokurtic, skewed, and are non-stationary with observed positive and negative autocorrelation over time. In addition, Benartzi and Thaler (1995), Barberis et al (2008), and Veld and Veld-Merkoulova (2008)) demonstrate that the standard deviation metric is problematic for ***loss averse*** investors whose utility responses to stock price change are asymmetric.[1]

An alternative approach to capturing volatility is based on extreme value theory and applies extreme metrics, such as the distribution around the tail of returns, or the frequency of large percentage changes in daily, weekly as well as monthly stock price changes (see e.g. Jones, Walker and Wilson (2004), and Burnie and De Ritter (2009)). The latter 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 ten developed markets: the G-7 group of seven industrialized countries: U.S., Canada, Japan, U.K., France, Germany, and Italy as well as three other western European countries, including the Netherlands, Spain, and Switzerland over long horizons. These ten countries represent a

[1] 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.

sizable share of the global market [2] and have commonalities and differences in terms of their experiences across business cycles and major political events over the past century.

We examine the distributions of the logarithmic percentage changes of daily, weekly, and monthly stock prices, 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 volatility measured by the annualized geometric standard deviation of the logarithmic percentage change with an extreme volatility variable. The results show that the extreme measures do not always cohere with the classical standard deviation measure of risk for the countries considered. For example if we wished to pinpoint the timing of drastic economic crises such as the Great Depression, and the Great Recession, based on extreme statistics vs. the classical volatility measures, the results would be not coincide. For example, based on daily stock returns over the period 1896-2013, the year 1929 of the Crash that signaled the onset of the Great Depression in the US ranked higher (4^{th}) in terms of standard deviation than the Global Financial Crisis (5^{th}) of 2008; on the other hand, based on the percentage of Extreme Days, the 2008 Global Financial Crisis ranked higher (4^{th} vs. 8^{th}).

Finally, we test whether or not extreme-day measures are better determinants of investor behavior as proxied by net flows to equity mutual funds. We find mixed results. For both the US and Canada, the extreme risk variable explains outflows better than the standard deviation

[2] As a group, they represent about 65% of the capitalization of world stock market according to the World Bank in 2012 See http://databank.worldbank.org/data/views/reports/tableview.aspx

measure, including the effects of the financial crisis. Higher risk is associated with outflows from equity mutual funds, consistent with “flight to (perceived) safety” behavior. For the UK and Italy, increased risk as captured both through the extreme measure and through the standard deviation measure cause funds to flow **into** equity mutual funds (flight to risk). For France, Germany, and Japan neither measure of risk affects mutual fund flows.

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 U.S. equities. 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 both a more global view of market behaviour over a longer time frame.

The remainder of the article 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. Previous Work

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. T he standard deviation of returns is also an essential component of the traditional value-at-risk (VaR) measure, Such risk has been the focus of regulators in seeking to establish how much financial institutions should put aside to guard against the types of financial and operational risks banks (and the whole economy) face.[3] Since the standard deviation does not capture the risk to the investor when the distribution is non symmetric, the traditional methods of calculating traditional value-at-risk (VaR) measures that are based on a normal distribution are problematic. Alternative approaches that focus on the distribution around the tail fall under the rubric of extreme value theory. The Hill (1975) method is one of the most widely used approaches based on extreme value theory. Parkinson (1980 provides a method

[3] The most recent accords of the Basel Committee on Banking Regulation, Basel II, 2.5, and II, different primary measure of market risk in global banking regulation: traditional value-at-risk (VaR), which focuses on two times the standard deviation (to identify the 5% tail risk), stressed VaR, and expected shortfall (see e.g. Bank for International Settlements (2013) . A crude method permitted in the Basel accords and used for estimating tail risk is to use an multiply the traditional estimate by a number such as 3. Stressed VAR, which is an approach advocated, since the financial crisis subjects conventional VaR, tested at the 99 percent confidence level (1–a, where a = .01) and with a ten-day holding period, to a one year historic dataset that encompasses "a continuous 12-month period of significant financial stress." Basel III seeks to replace VaR with an alternative, mathematically related measure of risk, expected shortfall. is defined as the average of all losses which are greater or equal than VaR, i.e. the average loss in the worst (1-p)% cases, where p is the confidence level. Hence, the expected shortfall provides the expected value of an investment in the worst q% of the cases

that economizes on data: it requires about 20% the number of observations relative to the traditional standard deviation to reach a given level of accuracy. Kunitomo (1992) provides a further improvement on the Parkinson (1980) method.

A few articles have appeared that provide empirical applications of extreme value theory to portfolio analysis. Longin (1996) focuses on the lowest or highest logarithmic daily return of an index of the most traded stocks on the New York Stock Exchange to identify extreme price movements over the time period from 1885 through 1990. He shows that measuring the tails of the distribution using the extreme value method is superior to the traditional standard deviation estimates. Longin and Solnik (2001) develop a bivariate extreme value theory model to study stock market indexes in developed markets: U.S., U.K., France, Germany and Japan and reject bivariate normality for the left-tail of the distribution and conclude that correlation across markets increases markedly during bear markets. These results should also be consistent with commonalities in the identification of periods of volatility risk across countries. Bali (2003) applies of extreme value theory to analyze the volatility of extreme changes in short-term interest rates and to estimate value at risk. He studies US 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. Hyung and De Vries (2005) show that further benefits of including assets with fat-tails in the distribution: idiosyncratic risk (and in turn total risk) will decreases more quickly as such assets are added.to a portfolio. More recently, DiTragliaa and Gerlach (2012) develop a model that suggests that lower tail dependence produces a sizable risk premium in the market that reflects compensation for holding assets that will collapse in value during economic disasters. They conclude that lower tail risk may be useful as a complement to traditional risk measures.

Insofar as how volatility affects investor behavior, Jones, Walker, and Wilson (2004) use the frequency of large percentage changes in daily stock prices within annual periods 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. They find that an extreme-day measure of volatility more accurately explains investor behavior relative to the geometric standard deviation, using annual and semi-annual equity mutual funds from 1984-2004. Furthermore, they show that large negative changes in prices appear to influence investor behavior more than large positive changes. In contrast, Burnie and De Ritter (2009) show that for Sweden, over the period 2000-2007, neither the standard deviation measure of risk nor the extreme risk measures help to predict quarterly flows into equity mutual funds. On the other hand, extreme negative returns have a positive and significant impact on flows into bond mutual funds, consistent with "flight to quality" effects.

In sum, most of the previous literature that compares traditional measures of stock market volatility vs. extreme measures concentrates on U.S. equities. Our research will be the first to provide a detailed look at several other markets, providing both a more global view of markets and the response of investors to differential measures of risk over a longer time frame.

III. Data Description

We chose one major stock index with the longest history for each country.

For Canada, used data from the Financial Post, the Toronto Stock Exchange Review, and the Canadian Financial Markets Research Center (CFMRC) to create a daily and weekly series that extends from March 1935 to December 2013. The monthly Canadian Index combines the S&P/TSX Index with the Switzer Canadian Century Index, as reported in Dimson et al. (2002), and start from December 1899. The Dow Jones Industrial Average Index, is[4] used for the U.S. covers the period May 26, 1896 through December 31, 2013. The equity prices for the other eight countries were provided by Global Financial Data Inc. and the Thomson Reuters DataStream.[5] The mutual fund data were obtained from Thomson Reuters DataStream and IFIC.

The stock market indices and the number of observations for each country for daily, weekly and monthly frequencies are shown in Table 1.

[Please insert Table 1 about here]

Canada and the US have the longest data series on a daily and weekly basis. The U.K. has the longest record of monthly data, starting from January 1693. The U.S., France, Germany and

[4] See http://www.djindexes.com/mdsidx/index.cfm?event=showAverages
[5] For a detailed description of these indices, please refer to the website of Global Financial Data Inc. : http://www.globalfindata.com.

Canada have monthly records that extend from the late 19th century.

IV. Computation of Market Volatility Estimates

A. Summary Statistics

Most researchers define the extreme value as the lowest or the highest daily return of a stock market index observed over a given period (e.g. Longin (1996)). As in Jones, Walker and Wilson (2004) we use the logarithmic percentage change (*L%*) of the stock index closing price:

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

We estimate (1) both on a daily, weekly, and monthly basis. The extreme measure of volatility is obtained as the percentage of extreme days, weeks or months during a given annual period. Summary statistics of logarithmic percentage changes for each country in are shown in Table 2. Panel A, B, and C provide the statistics for daily data, weekly data, and monthly data, respectively.

[Please insert Table 2 about here]

The arithmetic mean of each series is transformed to an annualized geometric mean using:

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

For all countries, significant departures from normality are observed for all data frequencies, based on the Jarque-Bera statistics. At daily and weekly frequencies, for all countries, the markets show negative skewness and leptokurtosis. On a monthly basis, all countries show negative skewness, with the exception of France, Italy, Japan, and Spain.

B. Classifying Extremes

Jones, Walker and Wilson (2004) use the statistical distribution of logarithmic percentage changes to arbitrarily assign the distribution percentiles of 5% and 95% as cutoff points to distinguish extreme values. In this paper, we define the extreme dates as outliers, defined as observations of which are less than the difference between the lower quartile (Q1) and the value of 1.5 times of 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:

$$\textit{Extreme Observation/Outlier} < Q1 - 1.5 \times IQR, \text{ or } \textit{Extreme Observation/Outlier} > Q3 + 1.5 \times IQR \qquad (3)$$

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

The extreme volatility measure for a given year is determined as the percentage of outliers during a given interval over that year. This volatility is expressed as:

$$\textit{Percentage of Extremes} = \textit{No. of Outliers / Annual Trading Days (Weeks or Months)} \qquad (4)$$

C. Annualizing Geometric Standard Deviations

The traditional measure of volatility that we also use is determined as the annualized geometric standard deviation of the logarithmic percent changes:

$$AnnualizedGeoStd = EXP[\sigma(L\%) \times \sqrt{T}\,] - 1 \qquad (5)$$

where T is the number of effective trading days (about 252 days), during the year.

V. Standard Deviation vs. Extreme Measures of Volatility.

In Tables 3 through 9 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. Figure 1 plots the behavior of the extreme volatility measure for the US, as per equation (5) for the period 1896-2014.

[Please insert Figure 1 about here].

As is shown therein, some upward trend in the frequency of volatility spikes is observed since the 1973 Opec oil crisis. The magnitude of these spikes is considerably lower than that observed during the period of the Great Depression in the 1930's, however.

Table 3 and 4 shows the rankings of volatility as measured by the standard deviation and the percentage of extreme days for the US and Canada. These countries have the longest available daily data series across the sample. We note that the extreme measures of risk do not always cohere with the classical standard deviation measure of risk for the countries considered. In addition, country specific extreme events also are present that differ from significant risky events identified usuing the standard deviation metric for individual countries. In general, if we wish to pinpoint the timing of major global economic crises such as the Great Depression, and the Great Recession, based on extreme statistics vs. the classical volatility measures, the results would be coincide. For example, the year 1929 of the Crash that signaled the onset of the Great Depression in the US ranked higher (4th) in terms of standard deviation than the Global Financial Crisis of 2008 (5th); on the other hand, based on the percentage of Extreme Days, the 2008 Global Financial Crisis ranked higher (4th vs. 8th). For Canada, the Financial Crisis Year of 2008 shows up as the riskiest year both in terms of the extreme measure and the standard deviation of returns.

[Please insert Tables 3 and 4 about here]

From Table 1, we note that the only other countries in the sample with a fairly long history of daily data are Italy and Japan. For these two countries, who have daily data extending to the late 1950's, we perform the analyses for the most volatile 15 years.

[Please insert Table 5 about here]

It is interesting to note that the stock market crash year of 1987 shows up as a volatile year in terms of standard deviation, but not in terms of percentage of extreme days. It is evident that the global financial crisis year of 2008 was reflected in a markedly higher percentage of extreme days in Japan (31.3%) vs. Italy (14.2%). Not surprisingly, the Asian crisis year of 1997 was more felt in Japan (21.6% extreme days) vs. Italy (7.6% extreme days).

Tables 6-10 show the volatility rankings based on the percentage of Extreme Months for the countries with fairly limited daily series, but long monthly series.

The country with the longest monthly history is the UK. Table 6 juxtaposes UK volatility measures, based on data from 1693-2013 with those of France, whose data extend from 1898-2013. For the UK, many years that are in the top 25 rankings in terms of volatility do not appear as extreme days, and vice versa. More than one-half of the extreme months have occurred since the last century. For France, the most volatile period extends from the period of the Great Depression to the end of World War II.

[Please insert Table 6 about here]

Table 7 gives a longer perspective on volatility measurement using the UK's extensive history. As is shown therein, over this long period, with the exception of the decade 1800-1809, there is some convergence between the standard deviation of risk and the percentage of extreme months.

[Please insert Table 7 about here]

Table 8 shows the rankings of Volatility as measured by the Standard Deviation and by the Percentage of Extreme Months for the Most Volatile 25 Years for Germany (1870-2013) and Italy (1905-2013).

[Please insert Table 8 about here]

In the case of Germany, both the standard deviation and the extreme measure of risk reflect the unusual surge of volatility that extends from 1922 through 1924, and reflects the hyperinflation experience which followed World War I. The period around the end of World War to the establishment of the punitive Reparations Commission by the victorious allies to 1921, exhibits the particularly high volatility. Another surge in volatility occurred during the aftermath of World War II from 1948 to 1949. Unlike Italy, neither the OPEC crisis, nor the recent financial crisis appear as particularly volatile for Germany.

Table 9 shows the rankings of Japan and Spain. Japan faced the most volatile period during the end of World War II subsequent years from 1946 through 1950. A sharp increase in volatility occurred in 1990, when the Japanese economic bubble burst, with a banking crisis coinciding with a stock market crashs caused stock prices crash. With the exception of 1932, equity risk was not particularly high over the Great Depression. For Spain, as shown in Table 9, the last three decades have been particularly troublesome, and the volatility measures reflect the limited recovery from the global financial crisis through 2012.

[Please insert Table 9 about here]

We report the volatility rankings for the Netherlands and Switzerland in Table 10 below.

[Please insert Table 10 about here]

As shown therein, the stock market of Netherlands was shocked by the technology bubble from 2002 through 2003 as well as the global financial crisis of 2008. Other sharp volatility periods include 1987 (another crash year), as and the Great Depression. Switzerland also experienced high volatility over the Great Depression, and over the global financial crisis. The largest volatility in Swiss market occurred in 1962, when the market attained a peak and then entered into an extended bear market that persisted until 1985.

In sum, volatility as captured by the extreme measure shows similar patterns as the traditional volatility measure for the ten countries of this study for most years. . Many commonalities in the attribution of high risk by both measures are observed, consistent with Longin and Solnik (2001). However, many differences are also observed, particularly over shorter frequencies, when daily data are used in the computations, and hence are subject to larger departures from normality.

VI. Extreme Volatility Measures vs. Standard Deviation and Investor Behaviour

Since extreme measures are comprised of both positive and negative components, they may be useful for predicting the behavior of loss averse investors whose utility responses to stock price change are asymmetric; for such investors, the reduction in utility of loss when stock prices decrease a certain amount is greater than the utility gained when stock prices increase by the same amount. Simply put, the standard deviation measure cannot capture this preference function.

Our approach is to capture the behavioral response to changes in market risk conditions, through the responses of net flows to equity mutual funds to such changes. Net flows of equity mutual funds are defined as t new sales plus reinvestment of income less withdrawals and transfers. The relationship between net flows into mutual funds and extreme risk measure is shown in Figure 2 below. On first glance, it seems evident that: investors move out (into) equity mutual funds over periods of extreme (mild) volatility in the US.

[Please insert Figure 2 about here]

Assuming a delayed reaction of investors to market price changes of one period, we regress the net flows on the two lagged risk measures in separate specifications. We also include a linear time trend to account for possible secular growth in such funds, as well as a financial market crisis dummy variable. The competing models are:

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

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

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

where the variable '*NetFlow*' represents for the net flows to equity funds, '*GeoMean*' for the geometric mean return (computed with daily data), '*TotalExtr*' for the annual extreme days over the horizon, '*NegExtr*'and '*PosExtr*' represent the negative and positive extreme days, respectively, '*Time*' is time trend variable, and Crisis is a dummy variable for the global financial crisis period (2008-9).

We expect that the regression coefficients for mean returns are positive, and for market volatility are negative, using the traditional or extreme day risk measures. In addition, when volatility is divided into negative and positive components, the coefficient for the negative extreme days should be negative since when stock market is negatively volatile, loss averse investors tend to hold less equity, and the coefficient for the positive extreme days probably positive.

We test whether or not extreme-day measures are better determinants of investor behavior as proxied by net flows to equity mutual funds for the G-7 countries for which data are available.[6] The results for Canada and the US are shown below in Table 11. Panel A shows the results using annual data, while Panel B shows the results using semi-annual data. The signs of the risk variables are as expected using annual data both annual and sem-annual data. However, they are only significant when using semi-annual data for both countires, and significant only for the US using both annual data and semi-annual data. Using semi-annual data for both countries, the extreme risk variable explains net flows flows better than the standard deviation measure, accounting for the effects of the financial crisis. Higher estimated extreme risk is associated with outflows from equity mutual funds, consistent with "flight to safety" behavior.

[Please insert Table 11 about here]

For the other G-7 countries, for which only annual data are available, the results are mixed. For the UK and Italy, increased traditional risk as well as increased extreme risk cause funds to flow into equity mutual funds (flight to risk), For France, Germany, and Japan, neither measure of risk affects mutual fund flows, however.

[Please insert Tables 11-12 about here]

VII. Conclusion

Whether or not risk inferences using the traditional standard deviation proxy are

[6] Due to data unavailability, we do not perform the analyses for Spain, Switzerland or the Netherlands.

consistent with extreme measures has been of increased interest to researchers and practitioners over the two decades. Most of the empirical work to date focuses on US equities. Very few studies have appeared for other developed countries in the world. Our paper covers ten major developed markets over a long time frame. In a number of cases, we find commonalities in the identification of periods of severe market risk across countries, consistent with Longin and Solnik (2001). However, the extreme measures are not always consistent with the classical standard deviation measure of risk for the many of the countries considered, particularly using shorter frequencies, when daily data are used in the computations, and hence are subject to larger departures from normality.

When we apply the extreme-day measure to examine investor behavior and find out that the extreme-day measure more efficiently explains the behavior of loss averse investors for Canada and the U.S. investors The evidence for the other countries of the G-7 is mixed.

Given the increased prevalence of extreme volatility since the beginning of the millennium, and the potential impact of such volatility on investor behavior, forecasting extreme volatility[7] for major markets should be an important topic of research for the future.

[7] Fodor, Krieger, Mauck, and Stevenson (2013) attempt to forecast extreme volatility of individual stocks in the US.

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Figure 1 Plot of Extreme Risk Volatility Measure in the US by Year in the US, 1896-2013

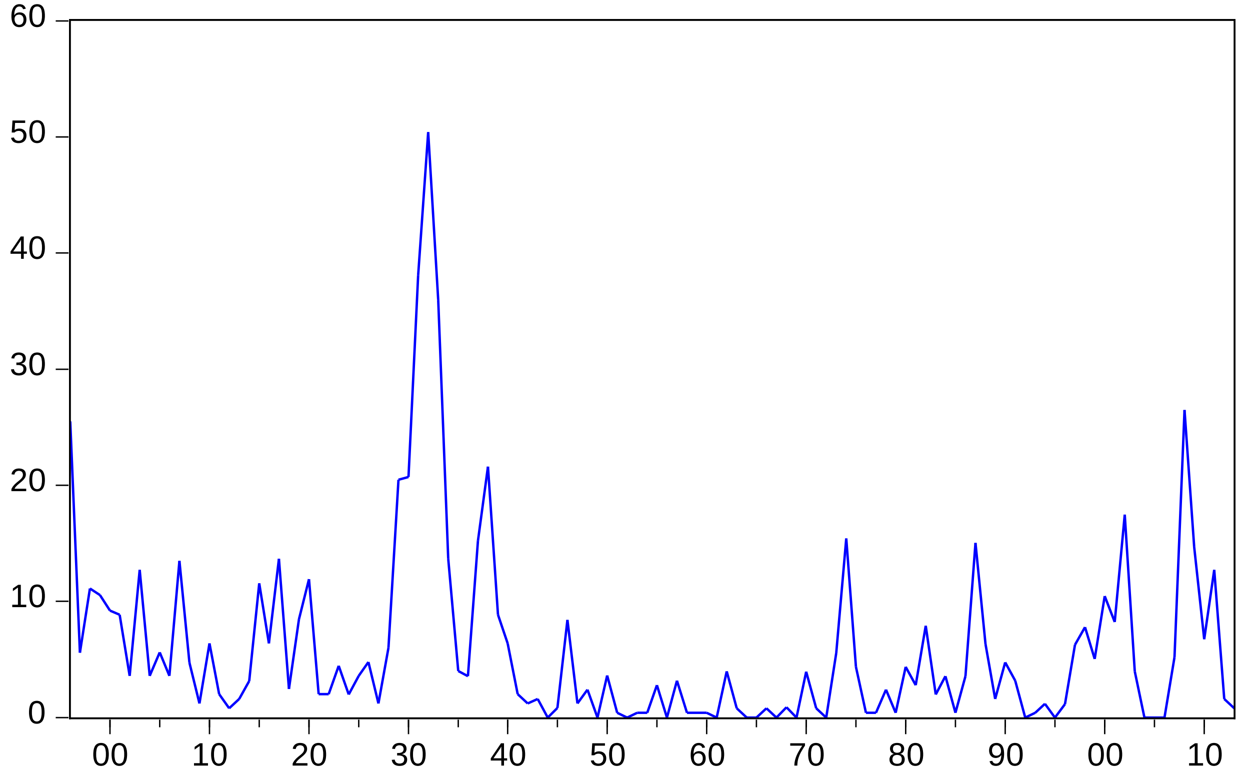

Figure 2

Net Flows (semi-annual) into Equity Mutual Funds (MUTUALA) in the US (in $100Million) vs. the Number of Extreme Days in the US (TOTALEXTR), 1984-2013

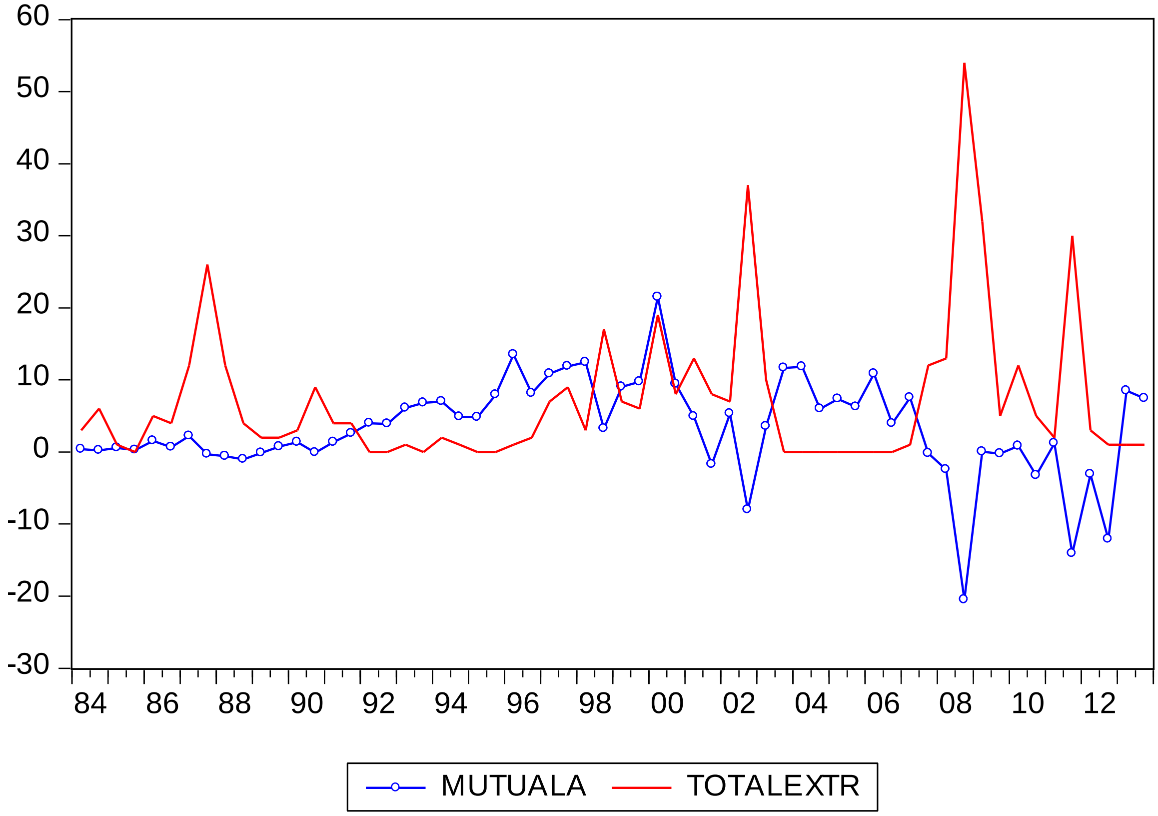

Table 1. Summary of the Data Sets or the Ten Countries

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	March 1,1935-December 31,2013	20508	March 2,1935-December 31,2013	4115	December 31,1899-December 31,2013	1367
2	France	France SBF-250 Index	September 18, 1968-December 31,2013	11289	September 20, 1968-December 31,2013	2367	January 31, 1898-December 31,2013	1377
3	Germany	Germany CDAX Composite Index	January 2, 1970-December 31,2013	11337	January 2, 1970-December 31,2013	2314	January 31, 1870-December 31,2013	1721
4	Italy	Banca Commerciale Italiana Index	January 2, 1957-December 31,2013	14098	January 4, 1957-December 31,2013	2959	September 30, 1905-December 31,2013	1294
5	Japan	Japan Nikkei 225 Stock Average	January 4, 1955-December 31,2013	16213	January 8, 1955-December 31,2013	3073	July 31,1914-December 31,2013	1184
6	Netherlands	Netherlands All-Share Price Index	January 2,1980-December 31,2013	8638	January 4,1980-December 31,2013	1782	January 31,1919-December 31,2013	1116
7	Spain	Madrid SE General Index	August 12,1971-December 31,2013	9876	August 13,1971-December 31,2013	2223	January 31,1915-December 31,2013	1146
8	Switzerland	Switzerland Price Index	January 3,1969-December 31,2013	11259	January 6,1956-December 31,2013	3031	January 31, 1921-December 31,2013	1185
9	United Kingdom	UK FT-Actuaries All-Share Index	January 2,1969-December 31,2013	11384	January 8,1965-December 31,2013	2573	January 31, 1693-December 31,2013	3847
10	United States	Dow Jones Industrial Average Index	May 26, 1896-December 31,2013	29464	May 26, 1896-December 31,2013	6114	May 26, 1896-December 31,2013	1384

Table 2. Summary Statistics of Daily/Weekly/Monthly Logarithmatic Percent change

Country	Mean	Median	StdDev	Skewness	Kurtosis	Jarque-Bera	Percentile					
							1%	5%	10%	90%	95%	99%
Panel A. Daily Data												
Canada	0.0225	0.0411	0.8636	-0.5562	25.9360	450577	-3.3068	-1.6342	-1.0537	1.0768	1.5113	2.7690
France	0.0266	0.0123	1.1472	-0.3660	8.6428	15229.1609	-3.2699	-1.7832	-1.1897	1.2353	1.7226	2.9730
Germany	0.0181	0.0248	1.0625	-0.3204	8.4585	14268.3796	-3.3068	-1.6342	-1.0537	1.0768	1.5113	2.7690
Italy	0.0184	0.0205	1.2410	-0.3853	6.2480	6545.6854	-3.5559	-1.9441	-1.3195	1.3644	1.9050	3.1794
Japan	0.0235	0.0474	1.1396	-0.4618	11.8255	53190.5884	-3.2974	-1.7397	-1.1624	1.1624	1.7121	3.0479
Netherlands	0.0277	0.0627	1.2204	-0.3164	8.2311	9991.8236	-3.6512	-1.8416	-1.2544	1.2645	0.0627	3.1736
Spain	0.0257	0.0247	1.2235	-0.0425	7.1113	6085.5913	-3.3922	-1.8574	-1.2989	1.3383	1.9095	3.2931
Switzerland	0.0186	0.0371	0.9755	-0.6355	10.0547	24105.8694	-2.9630	-1.4520	-0.9841	1.0017	1.3948	2.5150
U.K.	0.0266	0.0615	1.0705	-0.2723	8.0551	12127.1314	-2.9466	-1.6073	-1.1276	1.1415	1.5749	2.8160
U.S.	0.0204	0.0472	1.1541	-0.8351	24.6526	579000	-3.3617	-1.6680	-1.1346	1.1428	1.6236	3.0757
Panel B. Weekly Data												
Canada	0.1122	0.2147	2.0625	-0.7042	7.5631	3910.2220	-6.8803	-3.9383	-2.6041	2.7483	3.5973	5.5469
France	0.1261	0.2196	2.5757	-0.7944	6.7946	1669.0539	-6.4489	-4.0675	-2.8750	3.0306	3.9609	5.9392
Germany	0.0887	0.2319	2.4464	-0.8099	7.1539	1916.6536	-6.8803	-3.9383	-2.6041	2.7483	3.5973	5.5469
Italy	0.0867	0.1496	2.9482	-0.2570	6.0610	1187.3650	-7.9884	-4.3941	-3.2259	3.3831	4.5869	7.3991
Japan	0.1229	0.2813	2.5161	-0.9101	7.9258	3529.7750	-6.8684	-3.8948	-2.8029	2.8813	3.7537	6.1819
Netherlands	0.1349	0.3366	2.6017	-1.1023	9.8291	3821.4657	-7.5754	-4.0892	-2.7590	2.7933	3.7839	6.1231
Spain	0.1142	0.1783	2.7798	-0.4801	5.5849	564.2801	-6.9715	-4.3385	-2.9985	3.1921	4.3053	7.1578
Switzerland	0.0886	0.1625	2.1746	-0.9867	10.7743	8124.7687	-5.9446	-3.2342	-2.3314	2.3574	3.1750	5.2145
U.K.	0.1400	0.2572	2.4969	-0.6037	10.0914	6534.9537	-6.8775	-3.7591	-2.6308	2.7340	3.6240	5.9782
U.S.	0.0981	0.2562	2.5925	-1.1531	15.0978	38639.1826	-7.3759	-4.0544	-2.7059	2.7688	3.7096	6.3137

Panel C. Monthly Data												
Canada	0.3953	0.6839	4.4658	-0.9791	5.8476	856.4225	-8.8352	-4.7157	-3.1033	3.4951	4.9783	7.3534
France	0.5572	0.2209	5.4161	1.0230	14.0375	7230.0101	-5.9459	-3.5726	-2.5141	2.8635	3.7099	5.2595
Germany	0.1291	0.2151	2.9535	-0.5212	2.9667	77.9959	-8.8352	-4.7157	-3.1033	3.4951	4.9783	7.3534
Italy	0.4493	0.0000	6.8968	0.9162	6.4088	807.5481	-15.8807	-9.6090	-6.9162	7.2306	10.5919	23.1428
Japan	0.5550	0.5457	6.2697	0.2388	7.2605	906.7547	-16.6522	-9.4114	-6.1321	6.7874	9.2119	18.7830
Netherlands	0.3104	0.6059	4.8836	-0.5599	2.7803	60.4920	-13.8713	-7.8190	-5.3602	5.6728	7.5825	11.4629
Spain	0.4682	0.5360	5.4131	2.5463	43.6680	78041.4666	-12.5326	-7.1579	-5.3173	6.1798	8.3914	13.2404
Switzerland	0.3750	0.6076	4.3754	-0.4974	5.2082	289.6279	-12.5493	-6.7670	-4.4593	4.9363	6.8767	10.1108
U.K.	0.1239	0.1431	3.9987	-0.5083	54.0876	128916.863	-10.8721	-5.2041	-3.3532	3.6199	5.3965	9.3410
U.S.	0.4337	0.8413	5.6621	-0.6784	5.8351	569.6663	-18.0132	-9.0277	-5.6920	6.1390	8.3836	12.7418

Table 3. Rankings of Volatility as Measured by the Standard Deviation and by the Percentage of Extreme Days for the Highest 25 Years, U.S. (1896-2013)

Geometric Standard Deviation			Percentage of Extreme Days		
Rank	Year	GeoStdDev (%)	Year	L (%)	Rank
1	1932	69.8022	1932	50.4000	1
2	1931	55.9104	1931	38.0952	2
3	1933	52.8461	1933	35.9504	3
4	1929	48.4666	2008	26.4822	4
5	2008	46.0386	1896	25.4902	5
6	1987	44.1090	1938	21.6000	6
7	1930	33.9944	1930	20.7171	7
8	1938	30.3935	1929	20.4819	8
9	1937	30.0120	2002	17.4603	9
10	1914	29.1282	1974	15.4150	10
11	2002	28.9879	1937	15.2000	11
12	1899	28.3073	1987	15.0198	12
13	1907	27.8139	2009	14.6825	13
14	2009	27.3733	1917	13.6546	14
15	1896	27.0148	1934	13.6546	15
16	1917	25.4291	1907	13.4921	16
17	1974	25.3854	1903	12.6984	17
18	1934	24.6540	2011	12.6984	18
19	1898	24.2261	1920	11.9048	19
20	1920	24.0517	1915	11.5538	20
21	1903	23.8780	1898	11.1111	21
22	2001	23.6955	1899	10.5263	22
23	1901	23.5966	2000	10.4651	23
24	2011	23.4730	1900	9.2000	24
25	1915	23.4601	1991	8.8353	25

Table 4. 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 (1900-2013)

Daily Data (1935-2013)					Weekly Data (1935-2013)					Monthly Data (1900-2013)				
Rank	Geometric Standard Deviation		Percentage of Extreme Days		Rank	Geometric Standard Deviation		Percentage of Extreme Weeks		Rank	Geometric Standard Deviation		Percentage of Extreme Months	
	Year	StdDev%	Year	L %		Year	StdDev	Year	L %		Year	StdDev	Year	L %
1	2008	48.2595	2008	38.8889	1	2008	36.8432	2000	25.0000	1	1932	47.0987	1931	41.6667
2	1940	35.5315	2009	34.2629	2	1940	33.0241	2009	25.0000	2	1933	39.0402	1932	41.6667
3	1938	33.2183	2000	31.0757	3	2000	32.6450	2008	24.5283	3	1931	36.9807	1933	33.3333
4	2000	30.4339	1938	20.1987	4	1938	32.5933	1938	21.1538	4	1987	36.8209	1929	33.3333
5	2009	29.8108	1939	18.9369	5	1937	30.5616	1937	21.1538	5	1929	36.0705	1982	33.3333
6	1937	28.4642	2011	18.8000	6	1998	30.1127	1974	19.6078	6	1939	33.8204	1938	25.0000
7	1987	27.0106	1937	18.0602	7	1987	28.3342	1998	19.2308	7	1998	32.9512	1939	25.0000
8	1939	26.1366	1998	17.0635	8	1939	27.9698	1939	19.2308	8	1980	32.5997	1930	25.0000
9	1998	21.7819	2001	15.5378	9	2009	27.2372	1982	15.3846	9	1982	29.7979	1974	25.0000
10	2001	21.4765	1980	15.4150	10	1982	25.8140	1940	13.4615	10	2008	29.3378	1998	16.6667
11	1980	20.5743	1982	14.6825	11	1974	24.5538	1980	13.2075	11	1940	28.4901	1980	16.6667
12	2011	20.1228	2002	14.2857	12	1980	22.2150	2002	11.5385	12	1937	28.4840	2008	16.6667
13	1982	18.8640	1987	13.3858	13	2002	19.2445	1987	9.6154	13	1930	25.5856	1937	16.6667
14	2002	17.9521	1974	13.0952	14	2011	18.8458	1962	7.8431	14	2001	24.5509	2000	16.6667
15	1974	16.4605	2007	11.5079	15	2001	18.2672	2011	7.6923	15	2000	24.0623	1976	16.6667
16	1999	15.8561	1999	10.7143	16	1962	17.8460	1997	7.6923	16	1981	22.5477	1940	8.3333
17	1981	15.8276	1981	9.9206	17	1997	17.8294	1950	7.6923	17	1974	22.0211	1987	8.3333
18	1962	15.5235	1940	9.9010	18	1999	17.1371	1936	7.5472	18	1979	20.0851	2001	8.3333
19	1950	15.2753	2010	9.5618	19	1981	16.3954	1983	5.7692	19	1975	19.9711	1981	8.3333
20	2007	15.1459	1983	7.5697	20	1950	16.3250	1979	5.7692	20	2009	19.5536	1979	8.3333
21	1997	14.1652	1973	7.5397	21	1983	16.0051	2006	5.7692	21	1938	19.4082	1975	8.3333
22	2006	13.9387	2006	7.1713	22	1973	15.9207	1969	5.7692	22	1951	19.1021	2009	8.3333
23	1964	13.8214	1979	6.3492	23	1951	15.7199	2001	5.6604	23	1976	19.0625	1951	8.3333
24	2010	13.7704	2012	6.3492	24	1979	15.3153	1973	5.6604	24	1970	18.5199	1970	8.3333
25	1973	13.7303	1970	6.3241	25	1941	15.0147	1935	4.6512	25	1936	18.2197	1936	8.3333

Table 5. Rankings of Volatility as Measured by the Standard Deviation and by the Percentage of Extreme Days for the Highest 15 Years, Italy (1957-2013) and Japan (1955-2013)

	Italy				Japan				
Rank	Geometric Standard Deviation		Percentage of Extreme Days		Geometric Standard Deviation		Percentage of Extreme Days		Rank
	Year	StdDev%	Year	L%	Year	StdDev%	Year	L%	
1	1981	45.1299	1981	21.1155	2008	58.1735	2008	31.2977	1
2	1960	40.1334	1960	19.9134	1990	37.9695	1992	26.3158	2
3	1986	38.4050	1998	18.9300	1992	34.5270	1990	24.7967	3
4	2008	36.2505	1986	15.6000	2001	33.6051	2001	23.9837	4
5	1998	34.8382	2008	14.2857	1997	31.6977	1998	22.2672	5
6	1973	29.0388	2011	11.3281	2009	31.4845	1997	21.6327	6
7	2011	28.8555	2009	11.0236	1987	30.9633	2013	20.0000	7
8	1980	28.7807	1974	9.4262	1998	30.8211	2009	19.9234	8
9	2009	27.5281	2002	9.1633	2013	30.5745	2002	19.5122	9
10	1987	25.3378	1980	9.0909	2002	29.1157	2003	15.9184	10
11	1994	25.0844	1973	8.5366	2011	26.4391	2000	13.7097	11
12	1974	24.9648	2001	8.3665	2003	25.4955	1995	13.2530	12
13	1997	24.9198	1964	8.0169	1995	25.2816	2010	12.2605	13
14	2001	24.8725	1987	7.8740	2000	25.2641	1991	11.7886	14
15	2002	24.7656	1997	7.6000	1991	23.2624	1999	9.7959	15

Table 6. Rankings of Volatility as Measured by the Standard Deviation and by the Percentage of Extreme Months for the Highest 25 Years, U.K. (1693-2013) and France (1898 -2013)

	United Kingdom				France				
Rank	Geometric Standard Deviation		Percentage of Extreme Days		Geometric Standard Deviation		Percentage of Extreme Days		Rank
	Year	StdDev%	Year	L%	Year	StdDev%	Year	L%	
1	1720	204.5078	1825	75.0000	1941	84.5253	1945	25.0000	1
2	1825	91.4160	1720	66.6667	1936	44.5381	1940	20.0000	2
3	1975	65.5832	1974	58.3333	1944	37.3919	1936	16.6667	3
4	1987	48.4821	1826	50.0000	1987	36.1048	1944	16.6667	4
5	1940	39.8057	1938	50.0000	1932	34.4600	1932	16.6667	5
6	1974	38.5340	1693	45.4545	2002	33.5640	2002	16.6667	6
7	1824	38.1347	1975	41.6667	1945	33.1356	1978	16.6667	7
8	1701	37.1296	1987	41.6667	1988	32.2368	1998	16.6667	8
9	1696	37.0575	1940	41.6667	1947	31.6500	2008	16.6667	9
10	1694	36.2887	1701	41.6667	1978	31.1056	1946	16.6667	10
11	1721	34.8004	1696	41.6667	1998	30.9190	1938	16.6667	11
12	1697	32.5129	1694	41.6667	1937	30.0572	1990	16.6667	12
13	1976	31.4493	1976	41.6667	1939	29.8420	1941	10.0000	13
14	1695	30.7479	1931	41.6667	1981	29.4010	1987	8.3333	14
15	1981	28.1366	2002	41.6667	2008	27.5247	1988	8.3333	15
16	1698	28.0054	1979	41.6667	1920	27.3250	1937	8.3333	16
17	2008	25.5666	2010	41.6667	1948	27.3166	1939	8.3333	17
18	1693	25.4603	1986	41.6667	2001	27.1028	1981	8.3333	18
19	1699	25.3184	1695	33.3333	1974	27.0917	1948	8.3333	19
20	1931	24.3439	1698	33.3333	1946	26.6661	2001	8.3333	20
21	1826	23.3811	2008	33.3333	1986	26.3114	1974	8.3333	21
22	2002	22.8420	1700	33.3333	2009	26.2211	1986	8.3333	22
23	1979	22.1472	1992	33.3333	1940	24.8473	2009	8.3333	23
24	1938	21.9738	1970	33.3333	1975	24.2311	1926	8.3333	24
25	1700	21.9480	1990	33.3333	1938	23.7396	2011	8.3333	25

Table 7. 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-2010s)

Rank	Geometric Standard Deviation		Percentage of Extreme Days		Rank
	Year	StdDev%	Year	L%	
1	1720-1729	210.2270	2010-2019	45.4545	1
2	1970-1979	138.1328	1970-1979	40.0000	2
3	1820-1829	121.7203	1980-1989	25.0000	3
4	1980-1989	84.8249	1820-1829	20.0000	4
5	2000-2009	63.1843	1700-1709	19.3277	5
6	1700-1709	62.1779	2000-2009	19.1667	6
7	1940-1949	58.3709	1930-1939	19.1667	7
8	1930-1939	57.9114	1950-1959	19.1667	8
9	1990-1999	56.3969	1990-1999	17.5000	9
10	1950-1959	54.5823	1960-1969	12.5000	10
11	1960-1969	52.1801	1720-1729	11.6667	11
12	1710-1719	42.1364	1940-1949	10.8333	12
13	1790-1799	38.6175	1710-1719	8.3333	13
14	1830-1839	34.0158	1790-1799	8.3333	14
15	1800-1809	32.3909	1830-1839	6.6667	15

Table 8. Rankings of Volatility as Measured by the Standard Deviation and by the Percentage of Extreme Months for the Highest 25 Years, Germany (1870-2013) and Italy (1905-2013)

	Germany				Italy				
Rank	Geometric Standard Deviation		Percentage of Extreme Days		Geometric Standard Deviation		Percentage of Extreme Days		Rank
	Year	StdDev%	Year	L%	Year	StdDev%	Year	L%	
1	1923	192.0015	1920	75.0000	1947	92.9721	1946	58.3333	1
2	1922	154.8513	1922	75.0000	1943	83.8068	1944	58.3333	2
3	1924	107.5944	1923	75.0000	1946	82.2548	1947	50.0000	3
4	1920	70.7834	1919	66.6667	1944	77.3820	1945	27.2727	4
5	1919	47.9661	1924	66.6667	1948	74.4416	1943	25.0000	5
6	1949	46.1544	1927	41.6667	1981	54.4417	1948	25.0000	6
7	1931	43.7366	1949	41.6667	1945	50.3982	1998	25.0000	7
8	1918	43.3924	1931	37.5000	1998	46.4129	1960	25.0000	8
9	1927	33.5390	1925	33.3333	1986	43.4252	1981	16.6667	9
10	1921	31.7729	1926	33.3333	1949	43.0403	1986	16.6667	10
11	1925	31.4538	1951	33.3333	1973	38.6123	1932	16.6667	11
12	1914	27.2493	1962	33.3333	1960	38.3277	2009	16.6667	12
13	1959	22.8526	1875	25.0000	1932	38.1364	1974	16.6667	13
14	1962	21.4893	1918	25.0000	1941	37.1321	2008	16.6667	14
15	1932	21.0610	1948	25.0000	1915	35.3283	1973	8.3333	15
16	1960	20.7224	1959	25.0000	1980	34.6353	1941	8.3333	16
17	1952	20.4261	1873	16.6667	1992	32.3434	1980	8.3333	17
18	1926	20.3174	1877	16.6667	1927	32.1831	1992	8.3333	18
19	1878	20.2152	1879	16.6667	2009	32.1200	2002	8.3333	19
20	1933	20.0629	1891	16.6667	1974	31.5364	1990	8.3333	20
21	1891	19.6263	1914	16.6667	1917	29.7898	2001	8.3333	21
22	1875	19.5188	1921	16.6667	2002	29.4891	1987	8.3333	22
23	1873	19.3389	1930	16.6667	1997	29.2506	1924	8.3333	23
24	1877	17.2878	1933	16.6667	1942	28.9138	2011	8.3333	24
25	1955	17.0232	1955	16.6667	2008	28.6837	1964	8.3333	25

Table 9. Rankings of Volatility as Measured by the Standard Deviation and by the Percentage of Extreme Months for the Highest 25 Years, Japan (1914-2013) and Spain (1915-2013)

	Japan				Spain				
Rank	Geometric Standard Deviation		Percentage of Extreme Days		Geometric Standard Deviation		Percentage of Extreme Days		Rank
	Year	StdDev%	Year	L%	Year	StdDev%	Year	L%	
1	1949	101.8638	1949	50.0000	1987	58.0452	1998	33.3333	1
2	1948	89.5858	1948	50.0000	1998	40.5223	1986	33.3333	2
3	1946	59.2952	1990	41.6667	1990	35.1841	1987	25.0000	3
4	1953	57.2104	1946	33.3333	1986	35.0494	2012	25.0000	4
5	1920	56.2727	1947	25.0000	2012	33.6409	2010	25.0000	5
6	1990	49.9595	1953	16.6667	2010	32.3498	2002	25.0000	6
7	1947	45.7957	1920	16.6667	2002	31.4373	1948	25.0000	7
8	1950	45.1271	1950	16.6667	1948	31.3824	2009	25.0000	8
9	2008	41.3368	2008	16.6667	2009	26.8183	1990	16.6667	9
10	1932	40.6353	1932	16.6667	2008	26.6381	2008	16.6667	10
11	1993	31.0612	1952	16.6667	1974	25.5937	1951	16.6667	11
12	1916	29.9943	1993	8.3333	1947	25.4911	1977	16.6667	12
13	1992	29.7118	1916	8.3333	1957	25.3316	1974	8.3333	13
14	1995	29.2150	1992	8.3333	1997	25.1541	1947	8.3333	14
15	1971	27.5417	1995	8.3333	2001	23.9695	1957	8.3333	15
16	2009	27.3088	1971	8.3333	2000	22.7448	1997	8.3333	16
17	1991	27.1355	2000	8.3333	1973	22.5427	2001	8.3333	17
18	2000	26.8615	1998	8.3333	1981	22.3346	2000	8.3333	18
19	1998	26.3895	1917	8.3333	1992	22.2989	1973	8.3333	19
20	1917	26.2119	1961	8.3333	1951	21.8262	1981	8.3333	20
21	1952	26.1623	2010	8.3333	1959	21.6617	1991	8.3333	21
22	1961	25.9040	1970	8.3333	1991	21.2543	1976	8.3333	22
23	2010	24.2836	1962	8.3333	1977	21.1906	1985	8.3333	23
24	2012	23.5659	1986	8.3333	2013	21.107	2011	8.3333	24
25	1954	23.4492	1957	8.3333	1976	21.0567	1993	8.3333	25

Table 10. Rankings of Volatility as Measured by the Standard Deviation and by the Percentage of Extreme Months for the Highest 25 Years, Netherlands (1919-2013) and Switzerland (1921-2013)

	Netherlands				Switzerland				
Rank	Geometric Standard Deviation		Percentage of Extreme Days		Geometric Standard Deviation		Percentage of Extreme Days		Rank
	Year	StdDev%	Year	L%	Year	StdDev%	Year	L%	
1	2002	40.5646	2002	25.0000	1962	38.4076	1962	33.3333	1
2	1987	39.3247	2008	25.0000	1987	37.7453	2002	33.3333	2
3	2008	38.9279	1932	25.0000	1998	37.0460	1998	25.0000	3
4	1932	34.5564	1931	25.0000	1931	35.2568	1931	25.0000	4
5	1998	29.0359	1987	16.6667	1932	33.0553	1932	25.0000	5
6	1931	28.1565	1998	16.6667	1936	32.3623	1974	25.0000	6
7	1936	27.5818	1936	16.6667	1974	26.0634	1990	25.0000	7
8	1984	27.4684	1997	16.6667	1990	25.7024	1987	16.6667	8
9	1937	25.8977	1974	16.6667	1975	24.4800	1959	16.6667	9
10	1997	25.2540	1940	12.5000	2002	23.7947	1938	16.6667	10
11	1975	24.9638	1984	8.3333	1959	23.0037	1997	16.6667	11
12	2009	24.5260	1937	8.3333	1938	21.7337	1969	16.6667	12
13	2003	23.8624	2009	8.3333	1997	21.6839	1965	16.6667	13
14	1946	23.1608	1956	8.3333	1969	20.8868	2008	16.6667	14
15	1957	22.3584	1920	8.3333	2009	20.7465	1973	16.6667	15
16	1956	22.3149	2001	8.3333	1972	20.0210	1921	9.0909	16
17	1920	22.0096	1962	8.3333	1961	19.6915	1936	8.3333	17
18	2001	21.6449	1966	8.3333	1986	19.4654	2009	8.3333	18
19	1962	21.1706	1981	8.3333	1957	19.4014	1972	8.3333	19
20	1966	21.0365	1970	8.3333	1965	18.6412	1961	8.3333	20
21	1981	20.6393	2011	8.3333	2008	18.6006	1986	8.3333	21
22	1970	20.5302	1973	8.3333	1973	18.3881	1957	8.3333	22
23	1922	20.3004	1983	8.3333	1967	18.3725	1967	8.3333	23
24	1924	20.0840	1921	8.3333	1971	18.3101	2003	8.3333	24
25	2011	19.7896	1929	8.3333	2003	16.8239	2001	8.3333	25

Table 11. Regression Results of Equity Mutual Fund Net Flows on Risk Measures for Canada (1994-2013) and U.S. (1984-2013)

	Canada			US		
	Model (1)	Model (2)	Model (3)	Model (1)	Model (2)	Model (3)
Annual Observation (Canada: n=22; U.S.: n=29)						
Constant	**19.0449**	**17.0972**	**16.6586**	99.6032	75.1771	57.5424
	(4.08)	**(3.95)**	**(3.66)**	(1.16)	(1.26)	(0.99)
GeoMean(t-1)	0.0522	0.0366	0.1485	4.8975	4.1361	7.2916
	(0.18)	(0.13)	(0.38)	(1.08)	(0.87)	(1.50)
GeoStdDev(t-1)	-0.2423			-2.5793		
	(0.93)			(0.86)		
TotalExtr(t-1)		-0.0987			-1.8849	
		(1.10)			(1.01)	
NegExtr(t-1)			0.1565			15.5149
			(0.26)			(1.57)
PosExtr(t-1)			-0.3378			-22.3671
			(0.60)			(1.93)
Time	-0.7115	-0.6577	-0.7132	0.6988	1.0666	0.6602
	(1.71)	(1.57)	(1.59)	(0.25)	(0.39)	(0.25)
Financial Crisis Dummy	-5.4164	-5.4792	-7.0500	-90.0402	-80.7697	-94.0054
	(0.91)	(0.94)	(1.01)	(1.27)	(1.11)	(1.34)
Adjusted R Square	0.3088	0.3220	0.2879	0.1687	0.1779	0.2471
Panel B: Semi-Annual Observation (Canada: n=46; U.S.: n=60)						
Constant	**9.2888**	**7.9388**	**7.9391**	**76.0764**	**48.6883**	**50.2145**
	(5.38)	**(4.83)**	**(4.77)**	**(2.67)**	**(2.56)**	**(2.65)**
GeoMean(t-1)	0.0434	0.0366	0.0363	0.4214	0.2362	0.6275
	(0.69)	(0.60)	(0.58)	(0.33)	(0.20)	(0.52)
GeoStdDev(t-1)	-0.2180			**-3.5347**		
	(1.64)			**(2.37)**		
TotalExtr(t-1)		**-0.2584**			**-3.0152**	
		(2.02)			**(3.13)**	
NegExtr(t-1)			-0.0191			2.3702
			(0.09)			(0.50)
PosExtr(t-1)			-0.2398			-9.3139
			(1.00)			(1.70)
Time	**-0.1478**	-0.1272	-0.1256	0.1383	0.2934	0.1647
	(2.01)	(1.72)	(1.63)	(0.27)	(0.60)	(0.33)
Financial Crisis Dummy	-3.6033	-4.2744	-4.2754	-44.8609	-36.1836	-37.6076
	(1.55)	(1.81)	(1.79)	(1.67)	(1.37)	(1.43)
Adjusted R Square	0.2807	0.3029	0.2856	0.1995	0.2514	0.2562

Table 12. Regression Results of Equity Mutual Fund Net Flows on Risk Measures for Other G7 Countries

	France (1996-2013)			Germany(1994-2013)		
	Model (1)	Model (2)	Model (3)	Model (1)	Model (2)	Model (3)
Annual Observation with Financial Crisis Dummy Variable(France: n=17; Germany: n=19)						
Constant	107.2781	**91.0527**	**92.1502**	34.3683	**51.8676**	**55.3021**
	(-1.73)	**(-2.15)**	**(1.98)**	(1.18)	**(2.39)**	**(2.13)**
GeoMean(t-1)	-0.5086	0.0586	-0.4212	0.8628	0.7074	0.5231
	(-0.22)	(-0.16)	(-0.16)	(0.76)	(0.65)	(0.39)
GeoStdDev(t-1)	-1.2513			1.5755		
	(-0.51)			(1.23)		
TotalExtr(t-1)		-0.5280			0.5812	
		(-0.42)			(1.19)	
NegExtr(t-1)			-0.8602			-0.1191
			(-0.18)			(-0.04)
PosExtr(t-1)			-0.1902			1.2638
			(-0.13)			(0.64)
Time	-2.6697	-2.7405	-2.7121	-0.0779	-0.1436	0.4802
	(-0.70)	(-0.72)	(-0.68)	(-0.03)	(-0.06)	(-0.06)
Dummy Variable	-37.7594	-40.2510	-39.8909	**-69.2765**	**-65.8364**	**-66.0089**
	(-0.91)	(-0.97)	(-0.92)	**(-2.72)**	**(-2.56)**	**(-2.48)**
Adjusted R Square	-0.0065	-0.0136	-0.1052	0.2572	0.2531	0.4222

Table 12	**Cont'd**						
	Italy(1995-2013)				Japan (1994-2013)		
	Model (1)	Model (2)	Model (3)		Model (1)	Model (2)	Model (3)
Panel A: Annual Observation with Financial Crisis Dummy Variable(Italy: n=18; Japan: n=19)							
Constant	-48.9218	25.8771	22.3674		-6.3290	-3.6419	-3.6734
	(-1.15)	(0.90)	(0.78)		(-1.14)	(-0.95)	(-0.93)
GeoMean(t-1)	**2.6772**	2.0411	1.7203		0.5072	0.4662	0.4963
	(2.24)	(1.70)	(1.42)		(2.52)	(2.50)	(2.47)
GeoStdDev(t-1)	**4.7951**				0.2202		
	(3.2)				(1.07)		
TotalExtr(t-1)		**2.5548**				0.0814	
		(2.90)				(0.93)	
NegExtr(t-1)			-0.6910				0.2896
			(-0.24)				(0.67)
PosExtr(t-1)			7.334503975				-0.1523
			(1.78)				(-0.31)
Time	-3.0911	-4.2285	-4.0107		**0.5606**	**0.5771**	0.5292
	(-1.22)	(-1.60)	(-1.54)		**(2.08)**	**(2.12)**	(1.79)
Dummy Variable	-35.4134	-34.6124	-30.4944		-1.3942	-0.9491	-1.1883
	(-1.19)	(-1.10)	(-0.98)		(-0.36)	(-0.25)	(-0.30)
Adjusted R Square	0.5392	0.4891	0.5049		0.3142	0.3015	0.2619

Table 12, Cont'd.

	UK (1994-2013)		
	Model (1)	Model (2)	Model (3)
Panel A: Annual Observation with Financial Crisis Dummy Variable(UK: n=20)			
Constant	-13.4729	-0.6385	-1.9594
	(-1.91)	(-0.15)	(-0.49)
GeoMean(t-1)	1.0677	0.9698	1.1297
	(2.51)	(2.46)	(3.04)
GeoStdDev(t-1)	**1.1816**		
	(2.95)		
TotalExtr(t-1)		**0.6669**	
		(3.02)	
NegExtr(t-1)			**2.3952**
			(2.64)
PosExtr(t-1)			-1.4130
			(-1.30)
Time	0.3723	0.3540	0.2387
	(0.96)	(0.92)	(0.67)
Dummy Variable	-6.8766	-7.0087	-9.2359
	(-1.21)	(-1.25)	(-1.75)
Adjusted R Square	0.3466	0.3585	0.4603