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Could the global financial crisis improve the performance of the G7 stocks markets?

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Abstract

Financial crises are normally associated with negative effects on financial markets. In this paper, we investigate whether the most recent Global Financial Crisis (GFC) had any positive impact on the G7 (Canada, France, Germany, Italy, Japan, the United Kingdom and the United States) indices. We carry out our investigation by employing mean-variance (MV) analysis, CAPM statistics, a runs test, a multiple variation ratio test, and stochastic dominance (SD) tests. Our MV and CAPM results conclude that most of the G7 stock indices are significantly less volatile and have a higher beta, higher Sharpe ratios and a higher Treynor's index after the GFC. Run tests and multiple variation ratio results confirm that efficiency improved in the post-GFC period. Finally, SD results conclude that there is no arbitrage opportunity and the markets are efficient due to the GFC, and, in general, investors prefer investing in the indices after the GFC. Overall, we conclude that the GFC led to markets that are more efficient and mature, confirming that crises can also have positive impacts on stock markets.

Keywords: Market Performance; the Global Financial Crisis; Randomness; Market Efficiency; Stochastic Dominance

JEL Classifications: G14; G15

I. Introduction

The goal of putting money into the stock market is to generate a return on the capital invested. Many investors try not only to make a profitable return but also to outperform, or beat, the market. However, market efficiency, championed in the efficient market hypothesis (EMH) formulated by Eugene Fama in 1970, suggests that at any given time, prices fully reflect all available information on a particular stock and/or market. In other words, it is impossible for investors to consistently earn excess or abnormal returns using information from the market.

The most recent Global Financial Crisis (GFC) is considered by many economists to have been the worst financial crisis since the Great Depression of the 1930s. And in general, most of the literature focuses on the negative impact of the GFC. For instance, Furceri and Mourougane (2012) suggest that the occurrence of a financial crisis negatively and permanently affects potential output. Also, financial crises can lead to an increase in the structural unemployment rate for economies with rigid labor market institutions (Bassanini and Duval, 2009). In the aftermath of the financial crisis, GDP has declined by 5.2% on average in the G7 countries from the first quarter of 2008 to the second quarter of 2009 and the unemployment rate has increased by 1.67 percentage points on average in the G7 countries. Most of the literature conveys the message that financial crises have negative impacts on the economy and stock markets. In this paper, we investigate whether this statement is true, and we also check whether the GFC had any positive impact on the stock markets.

We examine these issues by seeking answers for the following questions: Did the GFC generate any arbitrage opportunities? Did market efficiency increase during the most recent global financial crisis? Do the markets perform better in the post-GFC period than in the pre-GFC period? What is the preference of investors in the period before and after the GFC? To look for answers to the above questions, we investigate the GFC's impact on the G7 stock exchanges in terms of performance, randomness, arbitrage opportunity, market efficiency, and investors' preferences. To conduct the analysis, we first apply the mean-variance (MV) criterion and the CAPM statistics to examine the performance of the G7 stock markets before and after the GFC. We then apply the runs and multiple variation ratio tests to examine whether the markets improve their randomness after the GFC. Last, we apply stochastic dominance tests to examine investors' preferences for the markets before and after the GFC and check whether there is any arbitrage opportunity in these markets and whether these markets are efficient.

Using the MV approach, our results confirm that most of the G7 stock indices are significantly less volatile in the post-GFC period than in the pre-GFC period, and all of their mean excess returns are higher (though not significantly higher), except for the UK, in the pre-GFC period than in the post-GFC period. Thus, in general, investors prefer to invest in the G7 indices after the GFC. On the other hand, our results show that the beta is higher in the post-GFC period than in the pre-GFC period for all of the G7 stock indices except Japan and the US, while both the Sharpe ratios and Treynor's index are higher in the post-GFC period than in the pre-GFC period for all of the G7 stock indices. Thus, our CAPM analysis concludes that, in general, all of the G7 stock indices perform better after the GFC. Moreover, our results from the run test and multiple variation ratio tests conclude that although the G7 markets are still not efficient, their efficiency improved after the GFC. Moreover, our SD results conclude that there is no arbitrage opportunity and the markets are efficient due to the GFC. In addition, investors are indifferent between the pre- and post-GFC periods or prefer investing in the indices after the GFC to maximize their expected utility, but not their expected wealth. Thus, overall, we conclude that in general the G7 markets perform better and become more efficient and mature after the GFC and investors prefer investing in the indices after the GFC. To the best of our knowledge, this is the first paper to find any positive impacts from financial crises on global stock markets.

The paper is organized as follows. The next section summarizes the relevant literature review and Section III describes the data and Section IV presents the methodology of the different statistics. Section V outlines the empirical methodology used and section VI concludes.

II. Literature Review

Since 1970 the efficient market theory has been a major topic in the financial literature. The validity of the EMH has important implications for financial theories and investment strategies, and so academicians, investors and regulatory authorities are interested in this issue.

Testing of the random walk model, a requirement of the weak-form efficient market hypothesis, has been a subject of much attention in the empirical finance literature since the seminal work of Fama (1970). Several studies, for example, Fama and French (1988), Poterba and Summers (1988) and Lo and MacKinlay (1988), have shown that stock price returns do not follow random walks. Following the earlier studies, some researchers have developed alternative tests for a random walk hypothesis and challenged the findings of the earlier studies. For example, Lo and MacKinlay (1988) developed the variance ratio test to test the random walk hypothesis. Recently, Ito *et al.* (2014) develop a non-Bayesian methodology to analyse the time-varying structure of international linkages and market efficiency in G7 countries. The empirical results provide a new perspective that the international linkages and market efficiency change over time and that their behaviours correspond well to historical events of the international financial system. Lean and Smyth (2015) apply a recently developed GARCH unit root test with multiple structural breaks to crude palm oil spot and futures prices and find much more evidence against weak-form efficiency than with tests that fail to allow for conditional heteroskedasticity.

In addition, many studies investigate the efficiency of individual markets and regional markets. For example, Lee *et al*. (2010) find evidence that the random walk hypothesis cannot be rejected for France. Loc *et al.* (2010) review developments in the Stock Trading Centre (STC) in Vietnam since its start in 2000. They apply the autocorrelation test, the runs test and the variance ratio test to examine whether the market is weak-form efficient and find that the stock market in Vietnam is not efficient in the weak form. Areal and Armada (2002) apply regression analysis to investigate Portuguese stock market data from 1983 to 1996 and conclude that the weak-form market efficiency hypothesis is not rejected. In addition, using monthly stock index prices from France, Germany, the UK, Greece, Portugal, and Spain from 1993 to 2007, Borges (2010) finds that stock prices follow random walks in all six of these countries. Nevertheless, when using daily prices, they document that only France, Germany, the UK, and Spain meet most of the criteria for random walk behavior, while the random walk hypothesis was rejected for Greece and Portugal because of significantly positive autocorrelation. Liu *et al.* (1997) using the cointegration and causality test to examine the efficiency of Shanghai and Shenzhen

Stock Exchanges in China. The statistical evidence shows that both the Shanghai and Shenzhen indexes can be best characterized as random walk processes and therefore the markets are efficient individually. But, using the Engle-Granger two-stage cointegration analysis and the Johansen procedure imply that the stock markets are collectively inefficient.

Some studies investigate the impact of a financial crisis on the degree of efficiency of financial markets. For instance, applying the rolling bi-correlation test statistics, Lim *et al*. (2008) show that the eight Asian stock markets are not efficient during 1997 financial crisis; however, most of these markets become more efficient in the post-1997-crisis period. In addition, Lim (2008) shows that the Asian crisis had a negative impact on the Malaysian stock market in seven out of its eight economic sectors. Kim and Shamsuddin (2008) employ a multiple variance ratio test to demonstrate that the stock markets in Hong Kong, Japan, Korea, and Taiwan are efficient in the weak form, while the markets of Indonesia, Malaysia, and the Philippines are not efficient. They also find that both the Singapore and the Thai markets become efficient after the 1997 Asian crisis.

Market efficiency can be examined by the SD rule as follows. If non-satiated investors can increase their expected wealth by switching their choice of assets, then market inefficiency is implied. This means that market efficiency can be rejected if FSD exists. For example, using the SD approach, Lean *et al*. (2010) find that the spot and futures oil markets are efficient and rational. Qiao and Wong (2015) apply the SD approach and find that the housing market in Hong Kong is efficient.

III. Data

Our data are daily closing values of stock market indices for the G7 (Canada, France, Germany, Italy, Japan, the United Kingdom and the United States), including the S&P/TSX, CAC 40, DAX, FTSE MIB, NIKKEI 225, FTSE 100 and Dow Jones Index, respectively. In addition, we use the MSCI World Index to represent the regional market index. The MSCI World Index captures large and mid-cap representations from markets in 23 developed countries. With 1611 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in each country. All data from 1 January, 1999 to 31 December 2013 are obtained from Bloomberg.

In the period we study in this paper, the markets are very volatile, as shown in Fig. 1. From the figure, we can see that there is a significant breakpoint at the end of 2008 due to the global financial crisis. Thus, to compare the stock market returns before and after the breakpoint, we use 1 January, 2009 as a cut-off point. We denote the period before the breakpoint as the "pre-GFC period" and the period after the breakpoint as the "post-GFC period." That is, the pre-GFC period is from 1 January, 1999 to 31 December, 2008 and the post-GFC period is from 1 January, 2009 to 31 December, 2013. We compare the stock returns between the pre- and post-GFC periods. Since returns could be affected by the market return, we deduct each of the return series by the return of the MSCI World Index to obtain their excess returns in order to eliminate the influence of the global economy. In other words, we compare the excess returns between the pre-GFC period and the post-GFC period for the G7 stock market indices.

< Fig.1 here >

IV. Methodology

In this paper, we adopt several tests, including the MV criterion, CAPM statistics, runs test, multiple variation ratio test and SD test, to investigate whether the GFC had a positive impact on the efficiency of the markets we are analyzing. Our methodology consists of three parts. The first part is used to measure the performance of indices before and after the GFC using a MV approach and CAPM statistics; the second part is used to test whether the GFC had an impact on the randomness of the indices movement using runs and multiple variation ratio tests; and in the third part we apply the SD approach to examine investors' preferences between the pre-GFC and post-GFC periods.

Performance

We will use the MV approach and the CAPM statistics to compare the performance of indices before and after the GFC.

The Mean-Variance Criterion. For any two investments of returns X and Y with means μ_X and μ_Y and standard deviations σ_X and σ_Y, respectively, Y is said to dominate X by the MV criterion for risk averters if $\mu_Y \geq \mu_X$ and $\sigma_Y \leq \sigma_X$ with at least one inequality holds (Markowitz, 1952). Thus, the MV rule for risk averters is to check whether $\mu_Y \geq \mu_X$ and $\sigma_Y \leq \sigma_X$. If both are not rejected with at least one strictly inequality relationship, then we conclude that Y dominates X significantly by the MV rule. Wong (2007) has proved that if both X and Y belong to the same location-scale family or the same linear combination of location-scale families, and if Y dominates X by the MV criterion for risk averters, then risk averters will attain higher expected utility by holding Y than X. The theory can be extended to non-differentiable utilities, see Wong and Ma (2008) for details.

The CAPM Statistics. We next apply the CAPM[1] analysis, including a beta component, Sharpe ratio,[2] Treynor's index and Jensen's index (alpha), to measure the performance of stock indices. The beta of the portfolio measures the marginal contribution of a portfolio to the total market portfolio and the sensitivity of its return to the movement of market portfolio returns. The estimation requires fitting the following CAPM equation for the return $R_{i,t}$ of index *i* at time *t*:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i \left(R_{m,t} - R_{f,t} \right) + \varepsilon_{i,t} \tag{1}$$

where $\varepsilon_{i,t}$ is the residual assumed to be i.i.d., $R_{m,t}$ is the return of the market portfolio, and $R_{f,t}$ is the return of the risk-free asset at time *t*. In our paper, we use the return of the MSCI World Index to represent the $R_{m,t}$ and the return of the 3-month Treasury bill as the $R_{f,t}$. From Equation 1, three performance indices — the Sharpe ratio (S_i), Treynor's index (T_i), and Jensen's index (J_i) — are then computed using the following formula:

$$S_i = \frac{\bar{R}_i - \bar{R}_f}{\hat{\sigma}_i}, \; T_i = \frac{\bar{R}_i - \bar{R}_f}{\hat{\beta}_i} \text{ and } J_i = \hat{\alpha}_i = (\bar{R}_i - \bar{R}_f) - \hat{\beta}_i(\bar{R}_m - \bar{R}_f) . \tag{2}$$

where $\hat{\sigma}_i$ is the estimated standard deviation, and $\bar{R}_i$, $\bar{R}_m$ and $\bar{R}_f$ are the expected return of index *i*, the market portfolio and the risk-free asset, respectively.

[1] Ostermark (1991) uses the capital asset pricing model to analyse two Scandinavian stock markets and finds that the standard CAPM is unable to exhaustively represent the economic forces of capital asset pricing, especially in Sweden.

[2] Agudo and Marzal (2004) apply the Sharpe ratio to analyse the performance of Spanish investment funds.

Randomness

Runs Test. The runs test (Bradley, 1968) is a nonparametric test to determine whether successive price changes are independent. It is based on the signs of deviations from the median observation. It does not require returns to be normally distributed.

If $y_1, \dots y_N$ is a time series of N returns and y_m is their median, the series of signs of residuals, sign u_1,..., sign u_N are considered where $u_i = y_i - y_m$ and $i = 1, \dots, N$. That is, a positive change *"+"* is assigned to each return y_i that is greater than the median, a negative change *"–"* is assigned when the return is less than the median, and the return is omitted when it equals the median. A run is the number of sequences of like signs. For example, the series of signs + + – + – – – + – + – + – – gives 10 runs.

To perform this test, we let n_+ and n_- be the number of runs of *"+"* and *"–"*, respectively and let *U* be the observed number of runs. Too many or too few runs in the sequence are the result of negative and positive autocorrelation, respectively. Under the null hypothesis of randomness or independence, by comparing the observed number of runs (*U*) with the expected number of runs (μ_U), the test of the randomness hypothesis can be constructed. It has been shown that, for large sample sizes where both n_+ and n_- are greater than twenty, the standardized test statistic is

$$Z = \frac{U - \mu_U}{\sigma_U} \ , \tag{3}$$

where $\mu_U = \frac{2n_+ n_-}{n} + 1$, $\sigma_U = \sqrt{\frac{2n_+ n_- \left(2n_+ n_- - n\right)}{n^2 \left(n-1\right)}}$ and $n = n_+ + n_-$.

We note that *Z* is approximately normally distributed under the null hypothesis of randomness or independence. If $Z < -Z_{1-\alpha/2}$ ($Z > Z_{1-\alpha/2}$), we reject the null hypothesis and conclude that Y_i is not random and not independent, and thus, we can conclude that Y_i is negatively (positively) auto-correlated.

Multiple Variation Ratio Test. Variance ratio tests have been widely used and are particularly useful for examining the behavior of stock prices or indices in which returns are frequently not normally distributed. Suppose we have the time series $\{X_t\} = (X_0, X_1, X_2, ..., X_T)$ satisfying

$$\Delta X_t = \mu + \varepsilon_t , \tag{4}$$

where X_t is the stock index and μ is an arbitrary drift parameter. The residual ε_t satisfies $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_{t-j}) = 0$ when $j \neq 0$ for all *t*. Lo and MacKinlay (1988) provide tests of the null hypothesis of randomness. Variance ratio tests focus on the property that under a random walk with uncorrelated increments in X_t, the variance of these increments increases linearly in the observation intervals such that $Var(X_t - X_{t-q}) = qVar(X_t - X_{t-1})$ for any positive integer *q*. The variance ratio is then given by

$$VR(q) = \frac{\frac{1}{q} Var(X_t - X_{t-q})}{Var(X_t - X_{t-1})} = \frac{\sigma^2(q)}{\sigma^2(1)} . \tag{5}$$

Under the null hypothesis that $\{X_t\}$ follows the random walk model stated in Equation 4, we have $\mathrm{VR}(q) = 1$.

Lo and MacKinlay (1988) generate the asymptotic distribution of the estimated variance ratios and provide two test statistics, $Z_1(q)$ and $Z_2(q)$,[3] both of which have

[3] Readers may refer to Lo and MacKinlay (1988) for the formula.

asymptotic standard normal distributions under the null hypothesis. $Z_1(q)$ is derived under the assumption that the disturbances of Equation 4 are homoscedastic, while $Z_2(q)$ treats them as heteroscedastic. The latter test statistic is not only sensitive to the changes in stock prices but is also robust to many general forms of heteroscedasticity and non-normality.

The random walk hypothesis implies that $VR(q)=1$ for any integer *q*. To improve the work of Lo and MacKinlay (1988), Chow and Denning (1993) show how controlling test size facilitates the multiple variance ratio tests. For a single variance ratio test, under the null hypothesis that $M_r(q)=VR(q)-1=0$, we follow Chow and Denning (1993) to consider a set of *m* tests $\{M_r(q_i)|i=1,2,\cdots,m\}$ associated with the set of aggregation intervals $\{q_i|i=1,2,\cdots,m\}$. Under the null hypothesis of a random walk, there are multiple sub-hypotheses:

$$\begin{aligned} &H_{0i}: M_r(q_i)=0 \text{ for all } i=1,2,\cdots,m; \\ &H_{1i}: M_r(q_i)\neq 0 \text{ there exists any } i=1,2,\cdots,m. \end{aligned} \tag{6}$$

Rejection of at least one H_{0i} for $i=1,2,\cdots,m$ implies rejection of the random walk. For the homoscedastic situation, we use the test statistics $\{Z_1(q_i)|i=1,2,\cdots,m\}$,whereas, for the heteroscedastic situation, we adopt the test statistics $\{Z_2(q_i)|i=1,2,\cdots,m\}$. Since the random walk hypothesis is rejected if any of the $\hat{VR}(q_i)$ is significantly different from one, we only consider the $Z_1^*(q)$ and $Z_2^*(q)$, where

$$Z_i^*(q)=\max\left(|Z_i(q_1)|,\cdots,|Z_i(q_m)|\right),\ \ i=1,2. \tag{7}$$

The decision rules are:

If $Z_1^*(q)$ ($Z_2^*(q)$) is greater than the SMM (*α*, *m*, *N*), then the random walk hypothesis is rejected under the homoscedastic (heteroscedastic) assumption, where SMM is the upper *α* point of the studentized maximum modulus distribution (Richmond, 1982) with parameter *m* and *N* (sample size) degrees of freedom.

Stochastic Dominance Test

The stochastic dominance (SD) theory developed by Hanoch and Levy (1969) and others is a utility-based framework for evaluating investment prospects under uncertainty. Hadar and Russell (1974) survey the use of SD in decision making under uncertainty. SD rules offer superior criteria for prospective investment decisions, since it uses information on the entire return distributions, rather than the first two moments, as in the MV and CAPM.

Let *X* and *Y* represent two series of excess return that have a common support of $\Omega = [a,b]$, where $a < b$ with their cumulative distribution functions (CDFs), *F* and *G*, and their corresponding probability density functions (PDFs), *f* and *g*, respectively. Define[4]

$$H_0 = h,\ H_j(x) = \int_a^x H_{j-1}(t)dt \text{ for } h = f, g;\ H = F, G; \text{ and } j = 1,2,3. \qquad (8)$$

We call the integral H_j the *j*-order cumulative distribution function (CDF), for *j* = 1, 2 and 3 and for $H = F$ and G.

The most commonly used SD rules corresponding to the three broadly defined utility functions are first-, second- and third-order ascending SD,[5] denoted FSD, SSD, and TSD, respectively. All investors are assumed to have non-satiation (more is preferred to less) under FSD, non-satiation and risk aversion under SSD, and non-

[4] See Wong and Li (1999) and Li and Wong (1999) for further discussion.
[5] We call it ascending SD since its integrals are counted from the worst return ascending to the best return.

satiation, risk aversion, and decreasing absolute risk aversion (DARA) under TSD. We define the SD rules as follows (see Quirk and Saposnik, 1962; Fishburn, 1964; Hanoch and Levy, 1969):

X dominates Y by FSD (SSD, TSD), denoted by $X \succ_1 Y$ ($X \succ_2 Y$, $X \succ_3 Y$) if and only if $F_1\left(x\right) \le G_1\left(x\right)$ ($F_2\left(x\right) \le G_2\left(x\right)$, $F_3\left(x\right) \le G_3\left(x\right)$) for all possible returns x, and the strict inequality holds for at least one value of x.

The theory of SD is important since it is related to utility maximization (see Quirk and Saposnik 1962; Hanoch and Levy, 1969). The theory can be extended to non-differentiable utility (see Wong and Ma (2008) for further details). The existence of SD implies that investors always obtain higher expected utility when holding the dominant asset than when holding the dominated asset, so that the dominated asset would never be chosen. We note that a hierarchical relationship exists in SD: FSD implies SSD, which, in turn, implies TSD. However, the converse is not true: the existence of SSD does not imply the existence of FSD. Likewise, a finding of the existence of TSD does not imply the existence of SSD or FSD. Thus, only the lowest dominance order of SD is reported.

Let $\{(f_i, g_i)\}$ $(i = 1,...,n)$ be pairs of observations drawn from the random variables X and Y, with distribution functions *F* and *G*, respectively, and with their integrals $F_j\left(x\right)$ and $G_j\left(x\right)$ defined in Equation 8 for $j = 1,2,3$. For a grid of pre-selected points x_1, x_2, ..., x_k, Bai *et al*. (2015) modify the statistic developed by Davidson and Duclos (2000) to obtain the following *j*-order DD test statistic, T_j is:

$$T_j(x) = \frac{\hat{F}_j(x) - \hat{G}_j(x)}{\sqrt{\hat{V}_j(x)}} \qquad (9)$$

where

$$\hat{V}_j(x) = \hat{V}_{F_j}(x) + \hat{V}_{G_j}(x) - 2\hat{V}_{FG_j}(x);$$
$$\hat{H}_j(x) = \frac{1}{N(j-1)!}\sum_{i=1}^{N}(x-z_i)_+^{j-1},$$
$$\hat{V}_{H_j}(x) = \frac{1}{N}\left[\frac{1}{N((j-1)!)^2}\sum_{i=1}^{N}(x-z_i)_+^{2(j-1)} - \hat{H}_j(x)^2\right], H = F, G; z = f, g;$$
$$\hat{V}_{FG_j}(x) = \frac{1}{N}\left[\frac{1}{N((j-1)!)^2}\sum_{i=1}^{N}(x-f_i)_+^{j-1}\left(x-g_i\right)_+^{j-1} - \hat{F}_j(x)\hat{G}_j(x)\right].$$

It is not possible to test empirically the null hypothesis for the full support of the distributions. Thus, Bishop *et al*. (1992) propose to test the null hypothesis for a pre-designed finite numbers of values *x*. Specifically, for all $i = 1, 2, ..., k;$ the following hypotheses are tested:

$$\begin{aligned} &H_0: F_j(x_i) = G_j(x_i)\ , \text{ for all } x_i; \\ &H_A: F_j(x_i) \neq G_j(x_i) \text{ for some } x_i; \\ &H_{A1}: F_j\left(x_i\right) \leq G_j\left(x_i\right) \text{ for all } x_i, F_j\left(x_i\right) < G_j\left(x_i\right) \text{ for some } x_i; \\ &H_{A2}: F_j\left(x_i\right) \geq G_j\left(x_i\right) \text{ for all } x_i, F_j\left(x_i\right) > G_j\left(x_i\right) \text{ for some } x_i. \end{aligned} \tag{10}$$

We note that in the above hypotheses, H_A is set to be exclusive of both H_{A1} and H_{A2}. This means that if the test does not reject H_{A1} or H_{A2}, it will not be classified as H_A. Therefore, Bai *et al*. (2011) modify the decision rules to be:

$$\begin{aligned} &\max_{1\leq k\leq K}|T_j(x_k)| < M_\alpha^j, \text{ accept } H_0: X =_j Y \\ &\max_{1\leq k\leq K} T_j(x_k) > M_\alpha^j \text{ and } \min_{1\leq k\leq K} T_j(x_k) < -M_\alpha^j, \text{ accept } H_A: X \neq_j Y \\ &\max_{1\leq k\leq K} T_j(x_k) < M_\alpha^j \text{ and } \min_{1\leq k\leq K} T_j(x_k) < -M_\alpha^j, \text{ accept } H_{A1}: X \succeq_j Y \\ &\max_{1\leq k\leq K} T_j(x_k) > M_\alpha^j \text{ and } \min_{1\leq k\leq K} T_j(x_k) > -M_\alpha^j, \text{ accept } H_{A2}: Y \succeq_j X \end{aligned} \tag{11}$$

where M_{α}^{j} is the bootstrapped critical value of *j*-order DD statistics. The test statistics are compared with M_{α}^{j} at each point of the combined sample.[6] However, it is empirically difficult to do so when the sample size is very large. In order to ease the computation, we specify K equal-interval grid points $\{x_k, k = 1, 2, ..., K\}$ that cover the common support of random samples $\{X_i\}$ and $\{Y_i\}$. Simulations show that the performance of the modified DD statistics is not sensitive to the number of grid points. Thus, in practice, we follow Fong *et al*. (2005) and Gasbarro *et al*. (2007), among others, and choose $K = 100$.

V. Empirical Results

We analyse the impact of the GFC on the G7 stock markets in three aspects: the first part discusses the performance of the G7 stock markets before and after the GFC, the second part studies whether the GFC improved the randomness of the markets, and the third part examines the investors' preferences in the markets before and after the GFC.

Performance

We use the MV approach and the CAPM statistics to compare the performance of indices before and after the GFC.

Mean-Variance Criterion. In order to carry out this analysis, we present the descriptive statistics of the daily excess returns for each of the G7 stock indices in Table 1. From the table, we find that the daily mean excess returns of all of the stock

[6] Refer to Bai *et al*. (2011) for the construction of the bootstrapped critical value M_{α}^{j}.

market indices except the UK are higher in the pre-GFC period than in the post-GFC period. However, the t statistic shows that the mean returns of all of the stock indices are not statistically significant in the periods before and after the GFC, not even at the 10% significance level. On the other hand, we find that the standard deviations of all of the stock market indices except Italy are smaller in the post-GFC period than in the pre-GFC period. Among them, the values of all of the F-statistics except France are significant. These results indicate that all of the stock indices except France and Italy become significantly less volatile after the GFC. Thus, if one employs the MV criterion for investors to compare their preferences before and after the GFC, one will conclude that the GFC has a very good impact on the G7 stock markets. And, in general, investors prefer to invest in the G7 stock indices in the post-GFC period because all of the mean excess returns are higher (though not significantly higher) except the UK in the pre-GFC period than in the post-GFC period, while most of the stock indices are significantly less volatile in the post-GFC period.

< Table 1 here >

CAPM Statistics. We turn to using the CAPM statistics reported in Table 2 to evaluate the influence of the GFC on the G7 stock markets and, thus, investigate whether the GFC could have any impact on the performance of the G7 stock markets. We first consider the Sharpe ratios for the G7 stock markets. This ratio, developed by Sharpe (1964), is the most commonly used statistic employed in stock evaluation. It measures the excess return per unit of risk determined by the standard deviation. The higher the value of the Sharpe ratio, the better the portfolio's return relative to its risk, or the larger the excess return per unit of risk in a portfolio. From Table 2, we find that the Sharpe ratios are higher in the post-GFC period than in the pre-GFC period for all of the G7 stock indices, implying that in terms of the portfolio's returns relative to its risk, all G7 indices perform better in the post-GFC period. The Treynor index, invented by Treynor (1965), measures the relationship of excess return with the beta lies along the security market line. It takes into account the systematic risk or market volatility as its measure of risk instead of using the standard deviation as in the Sharpe ratio. From Table 2, we find that all of the values of the Treynor index are higher in the post-GFC period than in the pre-GFC period. This suggests that all of the G7 stock market indices perform better in the post-GFC period.

Jensen’s index, on the other hand, gives some mixed results. Jensen's index, developed by Jensen (1968), is a measurement used to determine how well an asset or portfolio performs relative to its expected return as predicted by the CAPM model. Jensen’s index can be positive, negative, or zero. In efficient markets, Jensen’s index is assumed to be zero. It is commonly believed that if it is negative, the portfolio is underperforming the market, and thus, a higher Jensen’s index is more desirable. In the post-GFC period, the US and Japan achieve the returns with lower volatility, and, therefore, with lower market risk in the pre- and post-GFC periods. For the other five indices, in the post-GFC period, Jensen's index is negative and smaller than those in the pre-GFC period. Nevertheless, a stock with a smaller Jensen index and a higher beta might be preferred to another stock with a higher Jensen index and a smaller beta when return is high. This is exactly what we find in our results: all indices with a smaller Jensen index have a higher beta in the post-GFC period. Thus, they might perform better when return is high even with a smaller Jensen index.

< Table 2 here >

In short, our results using the mean-variance approach show that most of the stock indices are significantly less volatile in the post-GFC period, while all of the mean excess returns are higher (though not significantly higher) except the UK in the pre-GFC period than in the post-GFC period, and thus, risk-averse investors prefer to invest in the post-GFC period than in the pre-GFC period. On the other hand, the Sharpe ratios and the Treynor's index for all indices are higher in the post-GFC period than in the pre-GFC period for all of the G7 stock indices, while the beta attains higher values for most of the indices in the post-GFC period. Thus, in general, our MV and the CAPM statistics suggest that the G7 stock market indices perform better in the post-GFC period and investors prefer to invest in the G7 stock indices in the post-GFC period than in the pre-GFC period.

Randomness Tests

Runs Test. The results of the runs test for daily excess returns, which do not depend on the normality of returns, are presented in Table 3. From the table, we find that all of the values of the Z test are statistically significant at the 1% level in both the pre- and the post-GFC periods except Canada. The results imply that the random walk hypothesis is rejected in both the pre- and the post-GFC periods for France, Germany, Italy, Japan, the UK, and the US but not for Canada. However, we find that the values of the Z test for all countries except Japan are much smaller in the post-GFC period. This implies that the randomness of all of the indices except Japan is improved in the post-GFC period.

< Table 3 here >

Variation Ratio Test. Table 4 presents the results of the multiple variance ratio test (Chow and Denning, 1993) for stock market indices prices. In order to draw a better picture of the comparison, we adopt the common practice and select lags 2, 4, 8, and 16 in the testing procedure. From the table, we notice that the values of both $Z_1^*(q)$ and $Z_2^*(q)$ of all of the G7 stock market indices are significant at the 1% level for both the pre- and the post-GFC periods. These results reject the random walk hypothesis under both homoscedastic and heteroscedastic situations. Nevertheless, we also notice that the values of the Z statistics $(Z_1^*(q), Z_2^*(q))$ of all of the G7 countries become smaller in the post-GFC period, showing the tendency toward a random walk. Under the efficient market hypothesis, the evidence of a random walk suggests that a market could be efficient. Overall, we conclude from the run test and the multiple variation ratio tests that although the G7 markets are still not efficient, their efficiency (in terms of the randomness) has improved in the post-GFC period.

< Table 4 here >

Stochastic Dominance Tests

From Table 1, we notice that the estimates of skewness, kurtosis, and the Jarque-Bera test show that the distributions of excess returns for all G7 indices are not normally distributed. Thus, the findings based on the MV approach and the CAPM statistics may be misleading. To circumvent this limitation, academics recommend applying the SD test. The advantages of employing the SD test are that it enables us to examine whether there is any arbitrage opportunity and whether the market is efficient due to the GFC and to analyse investors' preferences for the indices in the pre- and post-GFC periods. Thus, we adopt the modified DD statistics T_j defined in Equation 9 for j = 1, 2 and 3, letting F and G be the CDFs of the excess returns in the pre- and post-GFC periods, respectively. We exhibit the SD results in Table 5 and summarize the SD results in Table 6. To better illustrate our results, we plot in Fig. 2 the results of the SD test T_j for the US index in the pre- and post-GFC periods together with their corresponding CDFs, F and G, for j=1,2, and 3, and we skip reporting the plots of other indices for simplicity. Before we conduct the SD test formally, we look at the plots in Fig. 2 and other unreported figures to examine the following hypotheses: (1) whether there is any arbitrage opportunity, (2) whether the markets are efficient and (3) whether investors are indifferent between the pre- and post-GFC periods. Fig. 2 shows that, for the US, the CDF of G (post-GFC) lies below that of F (pre-GFC) in downside risk, while the CDF of F lies below that of G on upside profit. In addition, the values of T_1 in Fig. 2 move from positive to negative along the distribution of the excess returns. This indicates that there is no FSD between the two periods and that the CDF in the post-GFC period first-order dominates that in the pre-GFC period on the downside risk, while the dominance relationship is reversed in the upside profit.

Thereafter, we conduct the SD statistics to test our hypotheses formally. We present the DD statistics in Table 5. From the table, we find that for the US index, 1% of T_1 is significantly positive and 4% of T_1 is significantly negative. In addition, the DD statistics, T_2 and T_3, in Fig. 2 are positive over the entire range of the return distribution, with 21% of T_2 (28% of T_3) being significantly positive and no T_2 (T_3) being significantly negative. Thus, together with Fig. 2, we conclude that the Dow Jones index in the post-GFC period first-order dominates that in the pre-GFC period on the downside risk, while the dominance relationship is reversed in the upside profit, there is no arbitrage opportunity in the US market and the market is efficient due to the GFC. It is well known (Jarrow, 1986; Falk and Levy, 1989;

Wong and Ma 2008) that, under certain conditions, if FSD exists, arbitrage opportunity exists, and investors will increase their expected wealth and expected utility if they shift from holding the dominated asset to holding the dominant asset. In this situation, since one is able to earn abnormal returns, the market is considered to be inefficient (Chan, *et al.*, 2012). Since our analysis leads us to conclude that there is no FSD between the pre- and post-GFC excess returns for the Dow Jones index, we conclude that investors will not increase their expected wealth by switching their investment from the Dow Jones index in the pre-GFC period to the post-GFC period, or vice versa; there is no arbitrage opportunity in the US market; and the market is efficient due to the GFC. In addition, we conclude that the Dow Jones index in the post-GFC period dominates that in the pre-GFC period in the sense of both SSD and TSD and investors prefer investing in the Dow Jones index in the post-GFC period than in the pre-GFC period to maximize their expected utility but not their expected wealth.

< Table 5 $ Fig.2 here >

We conduct the same analysis for the indices of the other countries studied in this paper and summarize the results in Table 6. From the table, we conclude that there is no first-order SD for all of the G7 stock markets in the pre- and post-GFC periods, there is no arbitrage opportunity in the G7 stock markets, and all of the G7 markets are efficient due to the GFC. In addition, we draw the following three conclusions for the G7 stock indices: (1) for Canada, the UK, and the US, the indices in the post-GFC period stochastically dominate those in the pre-GFC period in the sense of SSD and TSD; (2) for Italy, the dominance relationship is reversed; and (3) there is no dominance for the indices in the post- and pre-GFC periods for France, Germany and Japan. Since we have a finding of 3 (post-GFC is better), 1 (pre-GFC is better), and 3 (no dominance), we conclude that, in general, the stock indices are either no different in the pre- and post-GFC periods or the indices in the post-GFC period dominate those in the pre-GFC period in the sense of both SSD and TSD and investors would prefer investing in the indices in the post-GFC period than in the pre-GFC period to maximize their expected utility but not their expected wealth. Overall, our results from the SD test lead us conclude that in general the G7 markets perform better after the GFC and investors prefer investing in the post-GFC period than in the pre-GFC period.

< Table 6 here >

VI. Conclusion

In this paper we examine whether the most recent global financial crisis (GFC) has a positive impact on the stock indices of the G7 (Canada, France, Germany, Italy, Japan, the United Kingdom and the United States) so that the markets perform better after the GFC. We investigate market performance by applying the mean-variance analysis and the CAPM statistics to investigate whether the indices perform better after the GFC. We then employ the runs and multiple variation ratio tests to examine whether the markets improve their randomness after the GFC. Last, we apply the stochastic dominance tests to examine investors' preferences pre- and post-GFC and test whether there is any arbitrage opportunity and whether markets are efficient due to the GFC.

Our results using the mean-variance approach confirm that most of the stock indices are significantly less volatile in the post-GFC period than in the pre-GFC period, while all of the mean excess returns are higher (though not significantly higher) except the UK in the pre-GFC period than in the post-GFC period, and thus, in general, investors prefer to invest in the G7 indices after the GFC. On the other hand, our results show that the beta is higher in the post-GFC period than in the pre-GFC period for all of the G7 stock indices except Japan and the US, while both the Sharpe ratios and the Treynor's index are higher in the post-GFC period than in the pre-GFC period for all of the G7 stock indices. Thus, our CAPM analysis concludes that, in general, all the G7 stock indices perform better after the GFC. Moreover, our results from the runs test and the multiple variation ratio tests conclude that although the G7 markets are still not efficient, their efficiency has improved after the GFC.

Some investors believe that financial crises might create an arbitrage opportunity and the existence of crises might imply that the market is inefficient. Nevertheless, our SD results conclude that there is no arbitrage opportunity and the markets are efficient due to the GFC. In addition, our SD results imply that, in general, investors are indifferent between the pre- and post-GFC periods and they prefer investing in the indices after the GFC to maximize their expected utility. Thus, overall, we conclude that in general the G7 markets perform better and become more efficient and mature after the GFC and investors prefer investing in the indices after the GFC.

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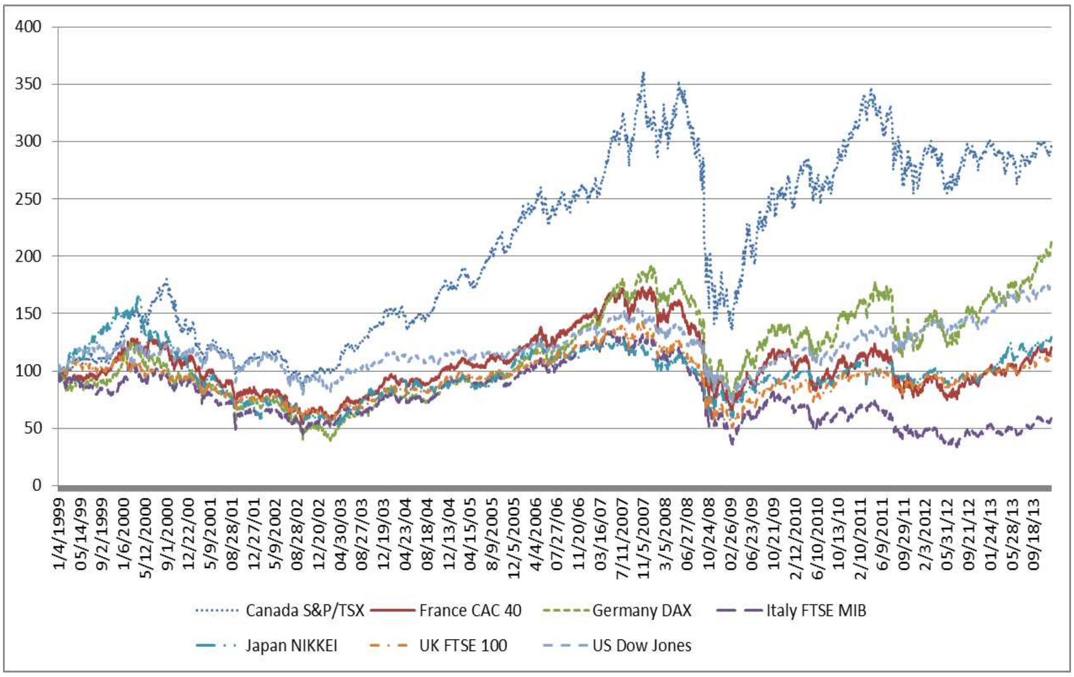

Fig. 1. G7 stock market indices – closing prices – in the period 1999 to 2013

Notes: For an easier comparison, we fix all values at the same basis of 100 on January 1, 1999.

Table 1. Descriptive Statistics

Variable		Mean (%)	SD (%)	Skewness	Kurtosis	Jarque-Bera	*t*-test *F*-test
Canada	Pre	35.54%	0.99%	-0.4938***	8.9590***	7 243.81***	1.0911
	Post	-2.47%	0.79%	0.4663***	3.8807***	708.85***	1.5894***
France	Pre	7.51%	1.09%	-0.0204	7.0709***	4 458.23***	0.95
	Post	-30.93%	1.07%	-0.1177	2.0792***	194.85***	1.0374
Germany	Pre	15.27%	1.13%	-0.3184***	3.8911***	1 386.18***	0.2112
	Post	6.67%	1.00%	-0.2273***	1.7012***	137.99***	1.2776***
Italy	Pre	-11.52%	1.11%	0.0972	13.3707***	15 944.2***	1.033
	Post	-59.96%	1.50%	-0.3102***	2.4846***	291.84***	0.5480***
Japan	Pre	1.65%	1.71%	-0.0996	3.1923***	912.22***	0.2266
	Post	-12.58%	1.61%	-0.015	1.6823***	125.98***	1.1212**
UK	Pre	-9.07%	0.98%	-0.2215***	10.8471***	10 508.78***	-0.1867
	Post	-2.74%	0.73%	-0.0164	4.0018***	712.68***	1.7878***
US	Pre	8.40%	0.71%	0.4931***	6.4108***	3 751.26***	0.1439
	Post	4.84%	0.53%	-0.1848***	2.0545***	193.91***	1.7905***

Notes: The excess return is computed by deducting the return of the MSCI World from each of the return series. *, **, and *** denote the significance at the 10%, 5% and 1% levels, respectively.

Table 2. CAPM Statistics

Variable		Beta	Sharpe Ratio (%)	Treynor's Index (%)	Jensen's Index (%)
Canada	Pre	1.0759	0.97%	14.72%	37.03%
	Post	1.1219	3.35%	46.99%	-9.20%
France	Pre	1.1509	-0.69%	-10.59%	10.49%
	Post	1.4511	1.22%	16.72%	-55.83%
Germany	Pre	1.228	-0.24%	-3.61%	19.77%
	Post	1.3807	3.25%	44.81%	-14.34%
Italy	Pre	1.0422	-1.86%	-29.96%	-10.69%
	Post	1.6096	-0.20%	-2.96%	-93.61%
Japan	Pre	0.5854	-1.01%	-30.84%	-6.52%
	Post	0.3822	2.84%	111.50%	21.52%
UK	Pre	0.9813	-1.87%	-29.33%	-9.44%
	Post	1.126	3.38%	46.59%	-9.69%
US	Pre	0.9589	-0.83%	-11.79%	7.59%
	Post	0.8768	5.05%	68.47%	11.64%

Notes: We use the return of the MSCI World Index as the return of market portfolio $R_{m,t}$ and the return of the 3-Month Treasury bill as the return of the risk-free asset $R_{f,t}$. Readers may refer to the Equations 2 for the formula of the Sharpe ratio, Treynor index, and Jensen index.

Table 3. Results of Runs Test

Variable		Total Cases (n)	Number of Runs	μ_U	σ_U	Z-statistic	p-value
Canada	Pre	2140	1095	1070.46	23.113	1.0617	0.2884
	Post	1068	537	534.393	16.3139	0.1598	0.873
France	Pre	2140	1301	1070.92	23.123	9.9501***	<.0001
	Post	1068	613	534.251	16.3095	4.8284***	<.0001
Germany	Pre	2140	1229	1070.79	23.1201	6.8430***	<.0001
	Post	1068	584	534.251	16.3095	3.0503***	0.0023
Italy	Pre	2140	1198	1070.94	23.1234	5.4949***	<.0001
	Post	1068	593	534.174	16.3072	3.6074***	0.0003
Japan	Pre	2140	1216	1070.97	23.1239	6.2720***	<.0001
	Post	1068	669	534.88	16.3288	8.2137***	<.0001
UK	Pre	2140	1244	1070.76	23.1195	7.4932***	<.0001
	Post	1068	618	534.993	16.3322	5.0824***	<.0001
US	Pre	2140	1167	1069.11	23.0837	4.2408***	<.0001
	Post	1068	587	534.773	16.3255	3.1991***	0.0014

Notes: This table presents the results of the runs test of the excess returns that are computed by deducting the return of the MSCI World Index from each of the return series. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4. The Results of the Multiple Variation Ratio Test Statistics

	Pre		Post	
Variables	$Z_1^*(q)$	$Z_2^*(q)$	$Z_1^*(q)$	$Z_2^*(q)$
Canada	156.01***	115.43***	102.82***	41.09***
France	155.93***	103.30***	102.95***	69.80***
Germany	156.41***	97.49***	102.57***	55.38***
Italy	154.50***	105.36***	106.77***	75.90***
Japan	155.44***	104.53***	102.62***	48.87***
UK	154.34***	104.81***	102.92***	45.53***
US	151.14***	88.14***	105.78***	63.34***

Notes: This table presents the results of the variance ratio test statistics $Z_1^*(q)$ and $Z_2^*(q)$ with the lag-vector (2, 4, 8, 16) assuming homoscedasticity and heteroscedasticity, respectively. The 10%, 5% and 1% critical values are 2.226268, 2.490915 and 3.022202 respectively. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 5. Davidson-Duclos Statistics

Variable		FSD		SSD		TSD	
		$T_1 > 0$	$T_1 < 0$	$T_2 > 0$	$T_2 < 0$	$T_3 > 0$	$T_3 < 0$
Canada	Positive Domain (%)	2	0	25	0	20	0
	Negative Domain (%)	0	6	0	0	0	0
France	Positive Domain (%)	0	0	0	0	0	0
	Negative Domain (%)	0	0	0	0	0	0
Germany	Positive Domain (%)	0	0	0	0	0	0
	Negative Domain (%)	0	0	0	0	0	0
Italy	Positive Domain (%)	3	0	0	0	0	0
	Negative Domain (%)	0	11	0	19	0	37
Japan	Positive Domain (%)	0	0	0	0	0	0
	Negative Domain (%)	0	0	0	0	0	0
UK	Positive Domain (%)	2	0	15	0	21	0
	Negative Domain (%)	0	2	0	0	0	0
US	Positive Domain (%)	1	0	21	0	28	0
	Negative Domain (%)	0	4	0	0	0	0

Notes: The numbers in the columns of FSD, SSD, and TSD indicate the percentages of the modified DD statistics significantly in the positive domain at the 5% level. T_j is defined in Equation 9 for $j = 1, 2$ and 3 with F and G denoting the excess return series for the pre- and post-GFC periods, respectively.

Table 6. Summary of SD Test

	stochastic dominance		
Canada	pre	$\prec_{2,3}$	post
France	pre	$=$	post
Germany	pre	$=$	post
Italy	pre	$\succ_{2,3}$	post
Japan	pre	$=$	post
UK	pre	$\prec_{2,3}$	post
US	pre	$\prec_{2,3}$	post

Notes: This table reports the stochastic dominance results to test whether the return in the pre-GFC period strictly dominates that in the post-GFC period in the sense of the *j*- order stochastic dominance for $j = 1, 2, 3$. For example, if we report pre $\succ_{2,3}$ post for Italy, this means that the return in the pre-GFC period stochastically dominates that in the post-GFC period in the sense of second and third order. When we report pre = post, this means there is no dominance in the pre- and post-GFC periods.

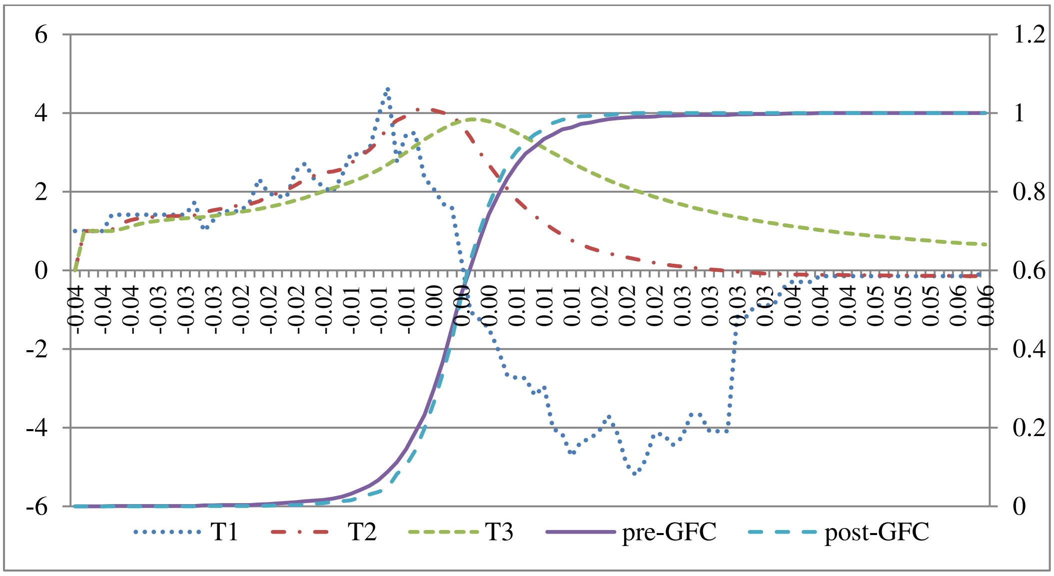

Fig. 2. CDFs and SD Statistics Pre-GFC and Post-GFC (US)

Notes: The test T_j is defined in Equation 9 with *F* and *G* denoting the excess return series for the pre- and post-GFC periods, respectively. The right-hand-side Y-axis is used for the CDF of the pre- and post-GFC excess return, whereas the left-hand-side Y-axis is used for T_j for j = 1, 2 and 3.