The Impact of Stock Index Futures Trading on Daily Returns Seasonality: A Multicountry Study

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Abstract

In this paper we investigate the potential impact of the introduction of stock index futures trading on the daily returns seasonality of the underlying index for seven national markets. This daily seasonality testing is performed with respect to (a) mean returns; (b) return autocorrelations; and (c) return volatilities using a modified GARCH model. It has been previously argued that the introduction of futures trading should lead to reduced seasonality of mean returns and generally our results support this conclusion. This is particularly the case with regard to the general weakening of the Monday effect in mean returns for the US; Germany; and Switzerland, and to a lesser extent for the UK. Similarly for Japan and to a lesser extent for Australia, the Tuesday effect in mean returns is no longer in evidence. While we detect daily seasonality in return autocorrelations and volatilities that is largely related to Monday and Tuesday observations, this seasonality does not seem to be affected by the introduction of index futures contracts.

Key Words: Day-of-the-Week Effect; Stock Index Futures; Seasonality; GARCH Modeling.

JEL Reference: G12; G15.

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I. INTRODUCTION

Futures contracts provide investors with a relatively low cost way of trading on new information and for hedging against adverse price movements. The price of futures contracts is fundamentally determined by the price of the underlying asset on which the futures contract is based. Thus, the introduction of futures trading may impact on the market for the underlying asset and a body of literature has evolved which attempts to empirically validate the nature of this relationship.

One major area of this literature has considered the impact of futures trading on the volatility of the underlying asset. For example, in the case of financial futures this literature is well represented by Figlewski (1981); Moriarty and Tosini (1985); and Edwards (1988a); while for commodity futures see Working (1960); Powers (1970) and Cox (1976). Further, in the case of stock index futures the literature includes Stoll and Whaley (1987); Edwards (1988a and 1988b); Harris (1989); Damodaran (1990); Hodgson and Nicholls (1991); Bessembinder and Seguin (1992); Kamara, Miller and Siegel (1992); Lee and Ohk (1992); Robinson (1994); Antoniou and Holmes (1995); Kamara (1997); Hiraki, Maberly and Taube (1998); and Antoniou, Holmes and Priestley (1998).[1] In general, this literature provides mixed evidence as to the volatility impact of futures trading.

This empirical ambiguity is not all that surprising since the theoretical literature proposes both a "destabilizing forces" hypothesis which predicts increased volatility and a "market completion" hypothesis in which decreased volatility is predicted. For the former hypothesis, it is argued that the inflow and existence of speculators in futures markets may produce destabilizing forces, which among other things create undesirable "bubbles".[2] However, the contrary view is that the introduction of futures trading leads to more complete markets, enhancing information flows and thus improving investment choices facing investors.[3] Moreover, futures may bring more (private) information to the market and allow for a quicker dissemination of

[1] A parallel literature also exists for the case of the impact of option listing on the underlying stock's return behavior. See, for example, Conrad (1989); Skinner (1989); Damodaran and Lim (1991); and Kumar, Sarin and Shastri (1998).
[2] See, for example, Harris (1989); Edwards (1988a & 1988b); and Stein (1987 & 1989)).
[3] See, for example, Ross (1977); Hakansson (1978); Breeden and Litzenberger (1978) and Arditti and John (1980)).

information. Further, speculative activity may be transferred from the spot to the futures market which can dampen spot market volatility.

The principal aim of the current study is to extend the segment of this literature which has investigated the impact of index futures introduction. While the vast majority of these studies have focussed on US markets [see for example, Harris (1989) and Kamara, Miller and Siegel (1992)], only a limited amount of work has been directed toward other markets [for example, in the case of the UK see Robinson (1994), Antoniou and Holmes (1995), and Antoniou, Holmes and Priestley (1998); in the case of Australia see Hodgson and Nicholls (1991); and in the case of Japan see Hiraki, Maberly and Taube (1998)]. Accordingly, the general argument of Leamer (1983) regarding the concern about data snooping and that of Lo and MacKinlay (1990) in the context of finance research, oblige us to investigate alternative datasets in order to assess the robustness of these findings.[4] In the current paper this is achieved by analysing seven separate markets in which index futures have been introduced.

Stock market index futures typically have a face value of a given multiple (e.g. 100) times the value of a predetermined national stock market index. Thus, the value of these futures contracts fluctuates as the value of the underlying index changes reflecting the machinations of the overall market. It is commonly hypothesized that the introduction of such stock index futures may have an impact on the return characteristics of the index itself. While much of the relevant literature has solely focused on the (unconditional) volatility impact of such an event, other related but under-researched areas of interest have recently been identified. Of particular relevance to the current paper, is the potential impact that the introduction of index futures trading has on the daily seasonality of the underlying index returns.

[4] A similar 'data-snooping' justification has been used elsewhere to examine non-US data – see for example, Jagannathan, Kubota and Takehara (1998) who use Japanese data to test a labor-income based CAPM [of Jagannathan and Wang (1996)] and Clare, Priestley and Thomas (1998) who use UK data to test the CAPM using a one-step procedure.

Daily seasonality in mean returns is a phenomenon that has been documented in many asset return series including numerous national stock market indices [see for example, Osborne (1962); Cross (1973); French (1980); Gibbons and Hess (1981); Jaffe, Westerfield and Ma (1989); Wilson and Jones (1993); Chang, Pinegar and Ravichandran (1993); Agrawal and Tandon (1994); Dubois and Louvet (1996); Wang, Li and Erickson (1997); Bachiller, Blasco and Espitia (1998) and Coutts and Hayes (1999)]. In most markets it is has generally been observed that to some degree a "Monday" effect is in evidence – namely, that the Monday mean return is significantly negative and less than the average return found for all other days. However, in a smaller subset of markets such as Japan and Australia, a "Tuesday" effect has been documented, in which it is the mean Tuesday return which is found to be significantly negative and less than the average return for all other days.

Although daily seasonality in return autocorrelations and return volatility has also attracted some research attention, they are far less extensively investigated than their mean returns counterpart. With regard to the daily seasonality in return autocorrelations, Bessembinder and Hertzel (1993) and Higgins and Peterson (1999) are representative of the literature. For example, Bessembinder and Hertzel (1993) examined a large set of US equity and futures markets data. Generally, they found that the return autocorrelation between Monday (Tuesday) and the previous trading day is unusually high (low) and positive (and in many cases negative) compared to other day of the week autocorrelations. With regard to the daily seasonality in return volatility, Fama (1965); Gibbons and Hess (1981) and Agrawal and Tandon (1994) are good examples of this literature. Generally, these papers have found that the Monday return variance tends to be higher than for all other days of the week.

Recently an interest has emerged in investigating whether, and to what extent, daily return seasonality is impacted by the introduction of index futures trading. Specifically, Kamara (1997) considered the impact of the introduction of an S&P 500 index futures contract on the daily mean return seasonality of the US market index return. Using data sampled over the period 1962 to 1993, the author finds evidence to suggest that the daily seasonal effect in the S&P 500 declined significantly in the post-futures trading period. The author argued that the observed decline in the daily seasonal is consistent with the fact that futures' trading greatly reduces the obstacle to arbitraging it, due to the considerable reduction in transaction costs. Further, similar analysis of this issue for the Japanese market is reported in Hiraki, Maberly and Taube (1998). In their paper, the authors found that trading of the NIKKEI 225 stock index futures had impacted on daily index returns seasonality. Specifically, while the Tuesday effect was found to disappear in the post-trading period, a Monday effect seemed to take its place. The authors argue that such effects are the result of heightened information flows which result from futures index trading.

Accordingly, the specific purpose of the current paper is to supplement and enhance the literature which considers the impact of the introduction of a stock index futures contract on the daily returns seasonality of the underlying aggregate national stock market index. In contrast to the previous work which has confined its scope for analysis to a single national index, this study will empirically scrutinize a wide range of markets. Specifically, in addition to the US and Japan cases which were the subject of analysis in Kamara (1997) and Hiraki *et al* (1998) respectively, we present evidence on the effect of stock index futures trading on daily returns seasonality for the Australian, German, Spanish, Swiss and UK markets. The use of a broad range of countries for analysis has distinct advantages. For example, it allows the experiences of each country to be compared and any common pattern to be uncovered, thus helping to alleviate the data snooping concern discussed above. Further, the inclusion of the US and Japan cases allows comparisons to be made between the new methodology applied in this paper and the results of the earlier literature.

As pre-empted in the preceding paragraph, the current paper employs a different (and arguably superior) testing methodology compared to previous studies that have investigated the impact of futures trading. Specifically, as far as we are aware our methodology for the first time uniquely brings together three major elements, namely: (a) the impact of futures trading; (b) the incidence of daily seasonality; and (c) the GARCH modeling framework.[5] Accordingly, within this framework we make two major contributions to the existing literature. First, the use

[5] Interestingly, while (to our knowledge) these three features have not ever before been combined together in one unified analysis, it is true that each pairwise combination has been previously explored. In the case of (a) GARCH modeling and the impact of futures introduction, see for example, Antoniou and Holmes (1995); and Antoniou, Holmes and Priestley (1998); (b) the impact of futures introduction and daily seasonality, see for example, Kamara (1997) and Hiraki *et al* (1998); and (c) GARCH modeling and daily seasonality, see for example, Connolly (1989) and Easton and Faff (1994).

of a GARCH model allows us to provide new insights as we may simultaneously consider the impact of stock index futures trading on daily returns seasonality in both the mean and volatility dimensions.[6] Specifically, daily seasonality testing is performed with respect to (a) mean returns; (b) return autocorrelations; and (c) return volatilities. Second, as mentioned earlier we present a unified package of evidence spanning a number of national boundaries that will help to counter the concern of data snooping bias. Existing evidence (and then for mean returns seasonality only) pertaining to this general area is currently only available for two markets, namely, the US and Japan. Our investigation extends the coverage to seven markets.

A brief summary of our major findings is as follows. In general, our results suggest that the introduction of futures trading has been associated with reduced seasonality of mean returns. This is particularly the case with regard to the general weakening of the Monday effect in mean returns for the US; Germany; and Switzerland, and to a lesser extent for the UK. Similarly for Japan and to a lesser extent for Australia, the Tuesday effect in mean returns no longer is in evidence. This finding supports the arguments presented by Kamara (1997) and Hiraki *et al.* (1998) that, for example, futures trading lowers transaction costs of traders who may be looking to arbitrage any profitable opportunities, including daily seasonals. Furthermore, while we detect daily seasonality in return autocorrelations and volatilities that is largely related to Monday and Tuesday observations, this seasonality does not seem to be affected by the introduction of index futures contracts. With reference to the previous literature, these results provide an important international extension of the evidence of seasonality in return volatility such as that found in Fama (1965), Gibbons and Hess (1981) and Agrawal and Tandon (1994) and seasonality in return autocorrelations as reported in Bessembinder and Hertzel (1993).

The rest of this paper proceeds as follows. Section II details the basic testing methodology which is employed in this paper. Section III discusses details of the seven national stock indices on which futures contracts are traded. Further, the estimation results are presented and discussed. Finally, Section IV presents some concluding comments.

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[6] Recently, this general issue has been found to be important in the case of futures (see Antoniou, Holmes and Priestley (1998)).

II. RESEARCH METHOD

A. Daily Seasonality Modified GARCH Model Framework

Our basic model comprises an Auto-Regressive (AR) mean equation augmented by dummy variables to capture the day-of-the-week (DOW) seasonality.[7, 8] The inclusion of autoregressive terms follows Bessembinder and Hertzel (1993), Higgins and Peterson (1999) and Hiraki *et al.* (1998). The latter authors argue that:

> "[f]ailure to adjust for the short-term pricing dynamics in returns may introduce bias in the estimates of the DOW coefficients since the coefficient estimates will attempt to capture some of the effects associated with the missing model components". (p.498)

Specifically, the mean equation takes the form:

$$R_t = \varphi_{Mon} D_{Mon} + \varphi_{ODW} D_{ODW} + \lambda_{Mon} D_{Mon} R_{t-1} + \lambda_{ODW} D_{ODW} R_{t-1} + \varepsilon_t \qquad (1)$$

where R_t is the return to the stock market index; D_{Mon} is a dummy variable which takes the value unity if the day is a Monday and zero otherwise; D_{ODW} is a dummy variable for the "other days of the week" (ODW) which takes a value of unity if the day is a Tuesday, Wednesday, Thursday or Friday and zero otherwise; and φ_{Mon}, φ_{ODW}, λ_{Mon} and λ_{ODW} are coefficients to be estimated. It should be noted that for Australia and Japan in which a Tuesday effect has been documented in the literature, the role of the Monday dummy in the above specification is supplanted by a Tuesday dummy (D_{Tue}) and so the ODW dummy in this case captures Monday, Wednesday, Thursday and Friday.

The stochastic error term, ε_t in Equation (1), is modeled as a GARCH process whereby the variance of the error term is attributed with dynamic (autoregressive) properties. Specifically, we adopt the GARCH (1,1) specification of Bollerslev (1986), which has been widely applied in the literature. As with the mean equation,

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[7] A version of the model was investigated in which a dummy variable was included for the stock market crash of October 1987. As the results are robust to this variation they are not reported in order to conserve space.

[8] In earlier versions of this paper, higher order autoregressive terms were also employed. In order to keep the specification manageable, only first order terms are reported here. Importantly, the outcome of the hypothesis testing is robust to this variation.

the GARCH specification of the conditional variance equation is also augmented to include a matching set of day-of-the-week dummy variables to capture the potential for daily seasonality in market volatility. Thus, the conditional variance equation is specified as:

$$h_t = \alpha_{0Mon} D_{Mon} + \alpha_{0ODW} D_{ODW} + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{2}$$

where h_t is the conditional variance of the stochastic error term (ε_t) in the mean equation, α_1 (ARCH term), β_1 (GARCH term), α_{0Mon} and α_{0ODW} are coefficients to be estimated. As was the case for the mean equation, in those markets in which a Tuesday effect has been documented in the literature (Australia and Japan), the role of the Monday dummy in the above specification is supplanted by a Tuesday dummy (D_{Tue}) and the ODW dummy captures Monday, Wednesday, Thursday and Friday.[9]

B. Daily Seasonality and Pre/Post Index Futures Trading Modified GARCH Model Framework

To determine the impact of the introduction of (and, hence, trading in) an aggregate stock market futures contract on the daily returns seasonality of the underlying index, the basic model as specified above, requires modification. Specifically, the day-of-the-week dummy variables of Equations (1) and (2) may be split into a pre-futures trading period and a post-futures trading period. Thus, each dummy variable in the pre-trading era D_i (i = PreMon and PreODW) will take on a value of unity on the day(s)-of-the-week to which it is assigned and zero otherwise. In the post-trading period however, they will take on a value of zero regardless. The converse case is

[9] Our focus in this specification of the variance equation is on the intercept term. In principle, the ARCH and GARCH terms can also be allowed to vary according to daily seasonality, however the interpretation of any changes found is not straightforward. Furthermore, we encountered considerable computation problems when extending the specification of our model to allow for such shifts in the ARCH and GARCH terms – indeed the model typically failed to converge in these cases. Interestingly, in the few cases in which versions of these models did successfully estimate, the ARCH and GARCH parameters seemed remarkably similar – clearly unable to reject basic tests of equality. Accordingly, we feel justified holding these parameters constant over the full sample period.

true for day-of-the-week dummy variables assigned to the post-trading regime, D_i (i = PostMon and PostODW). Accordingly, the fully specified mean and variance equations become:

$$R_t = \sum_{i=PreMon}^{PreODW} \varphi_i D_i + \sum_{i=PostMon}^{PostODW} \varphi_i D_i + \sum_{i=PreMon}^{PreODW} \lambda_i D_i R_{t-1} + \sum_{i=PostMon}^{PostODW} \lambda_i D_i R_{t-1} + \varepsilon_t \qquad (3)$$

$$h_t = \sum_{i=PreMon}^{PreODW} \alpha_{0i} D_i + \sum_{i=PostMon}^{PostODW} \alpha_{0i} D_i + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (4)$$

In this specification, all coefficients with a PreMon (PostMon) subscript measure the Monday value for that feature in the pre-futures (post-futures) period. For example, φ_{PreMon} measures the mean Monday return in the pre-futures period. Similarly, all coefficients with a PreODW (PostODW) subscript measure the "other days of the week" value for that feature in the pre-futures (post-futures) period. For example, $\varphi_{PostODW}$ measures the mean return for all other days (namely, Tuesday, Wednesday, Thursday and Friday) in the post-futures period. Furthermore, as was the case for the basic model represented by Equations (1) and (2), for Australia and Japan, the role of the Monday dummy in the above specification is supplanted by a Tuesday dummy (D_{Tue}) and the ODW dummy captures Monday, Wednesday, Thursday and Friday.

C. Test of Main Hypotheses: Daily Seasonality Effects

C.1 Daily Seasonality Effects in the Mean Return

Following Kamara (1997), our primary tests relate to the basic seasonal effect – that is, for Spain, Germany, Switzerland, the UK and the US; we perform a test of whether Monday returns are significantly lower than the average return on other weekdays. The analogous test of whether Tuesday returns are significantly lower than the average return on other weekdays is applicable for Australia and Japan. Hence, in the pre-trading case the test is formalized as (note that the Tuesday version of the hypothesis is presented in parentheses to avoid confusion):

$$H1: \varphi_{PreMon} = \varphi_{PreODW} \qquad (H1: \varphi_{PreTue} = \varphi_{PreODW})$$

Similarly, the post-trading counterpart of the above test may be specified as:

$$H2: \varphi_{PostMon} = \varphi_{PostODW} \qquad (H2: \varphi_{PostTue} = \varphi_{PostODW})$$

C.2 Daily Seasonality Effects in the Return Autocorrelation[10]

An analogous set of hypothesis tests is performed for the return autocorrelations, following Bessembinder and Hertzel (1993). That is, in the case of Spain; Germany; Switzerland; the UK; and the US (Australia and Japan in parentheses) the hypothesis tested in the pre-trading period is:

$$H3: \lambda_{PreMon} = \lambda_{PreODW} \qquad (H3: \lambda_{PreTue} = \lambda_{PreODW})$$

Similarly, the counterpart autocorrelation hypotheses for the post-trading period are:

$$H4: \lambda_{PostMon} = \lambda_{PostODW} \qquad (H4: \lambda_{PostTue} = \lambda_{PostODW})$$

C.3 Daily Seasonality Effects in the Return Volatility

Following Fama (1965); Gibbons and Hess (1981) and Agrawal and Tandon (1994) which identifies a seasonal effect in variances, an analogous set of tests is performed for the variance equation intercepts. Specifically, for the pre-trading period we have:

$$H5: \alpha_{0PreMon} = \alpha_{0PreODW} \qquad (H5: \alpha_{0PreTue} = \alpha_{0PreODW})$$

While for the post-trading period we have:

$$H6: \alpha_{0PostMon} = \alpha_{0PostODW} \qquad (H6: \alpha_{0PostTue} = \alpha_{0PostODW})$$

[10] We thank an anonymous referee for suggesting the modeling of seasonality in the autocorrelations.

D. Tests of Supplementary Day of the Week Hypotheses

In addition to the hypotheses outlined above, some further tests can be performed on a variation of the model represented by Equations (3) and (4) in which individual day of the week dummies are incorporated. Thus, we define five separate day-of-the-week dummy variables in the pre-trading era (PreMon, PreTue, PreWed, PreThu, PreFri) which each take on a value of unity on the day-of-the-week to which they are assigned and zero otherwise. In the post-trading period however, they take on a value of zero regardless. The converse case is true for day-of-the-week dummy variables assigned to the post-trading regime, (PostMon, PostTue, PostWed, PostThu, PostFri). Accordingly, the fully specified mean and variance equations in this case become:

$$R_t = \sum_{i=PreMon}^{PreFri} \varphi_i D_i + \sum_{i=PostMon}^{PostFri} \varphi_i D_i + \sum_{i=PreMon}^{PreFri} \lambda_i D_i R_{t-1} + \sum_{i=PostMon}^{PostFri} \lambda_i D_i R_{t-1} + \varepsilon_t \qquad (5)$$

$$h_t = \sum_{i=PreMon}^{PreFri} \alpha_{0i} D_i + \sum_{i=PostMon}^{PostFri} \alpha_{0i} D_i + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (6)$$

This specification allows us to compare the pre-trading and post-trading day-of-the-week effects by testing some null hypotheses framed in terms of equality restrictions.[11]

Specifically, in the pre-trading (post-trading) period we consider whether the joint hypothesis of equality of the day-of-the-week impacts has any empirical support. In the case of the mean returns this is formalized as:

H7: $\varphi_{PreMon} = \varphi_{PreTue} = \varphi_{PreWed} = \varphi_{PreThu} = \varphi_{PreFri}$

and

H8: $\varphi_{PostMon} = \varphi_{PostTue} = \varphi_{PostWed} = \varphi_{PostThu} = \varphi_{PostFri}$

Similarly, in the case of the return autocorrelations we may test:

H9: $\lambda_{PreMon} = \lambda_{PreTue} = \lambda_{PreWed} = \lambda_{PreThu} = \lambda_{PreFri}$

and

H10: $\lambda_{PostMon} = \lambda_{PostTue} = \lambda_{PostWed} = \lambda_{PostThu} = \lambda_{PostFri}$

Finally, in the case of the variance equation we have a similar pair of tests relating to the pre-trading and post-trading periods, respectively:[12]

H11: $\alpha_{0PreMon} = \alpha_{0PreTue} = \alpha_{0PreWed} = \alpha_{0PreThu} = \alpha_{0PreFri}$

and

H12: $\alpha_{0PostMon} = \alpha_{0PostTue} = \alpha_{0PostWed} = \alpha_{0PostThu} = \alpha_{0PostFri}$

III. RESULTS

A. Data

In the current paper, the impact of the introduction of stock index futures trading on seven national stock market indices is investigated. Specifically, the markets analysed are Australia; Spain; Germany; Japan; Switzerland; the UK and the US. Daily stock market index data were collected from the Datastream database from the earliest available date to the end of January 1999. The longest sample period involved the US S&P 500 index for which the initial observation occurs in January 1969.[13] Accumulated indexes were chosen for analysis except for Japan, Switzerland and the US – for these countries a price index series was employed to allow a longer period to be analyzed.[14] Details of the stock indexes used, the date on which the futures contracts began trading as well as the beginning of each sample period are presented in Table 1.

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[11] Estimation results of the model represented by Equations (5) and (6) will not be reported – only the outcome of the hypotheses outlined in this section will be reported to conserve space. The full set of estimation results is available from the authors upon request.

[12] A series of further hypotheses were tested with regard to the equality of individual day of the week measures (mean, autocorrelation and volatility) in the pre- and post-futures trading period. These results do not greatly enhance those discussed in the text and, hence, are not reported in order to conserve space.

[13] As is common in studies that model conditional heteroskedasticity, we use long sample periods [for example, see Jones, Lamont and Lumsdaine (1998, p. 319)].

[14] In the case of the countries in which both price and accumulation are available, we checked the sensitivity of our results, with regard to whether the type of index matters. While not reported here, we find that the basic thrust of our conclusions is robust to this variation in data. The details are available from the authors upon request.

[TABLE 1 ABOUT HERE]

The returns for each index were estimated as the log price relative and some basic descriptive statistics are reported in Table 2. It can be seen that the average daily returns vary between 0.015% for Japan (capital returns only) to 0.064% for Spain. Further, while all market returns reveal some degree of negative skewness, as expected in daily data there is strong evidence of leptokurtosis, particularly for Australia and the US.

[TABLE 2 ABOUT HERE]

B. Daily Seasonality and the Pre/Post Index Futures Trading Modified GARCH Model: Mean Equation Results

The modified GARCH (1,1) model represented by Equations (3) and (4) was fitted to the stock market index returns data for each of the seven countries in our sample and the mean equation results are presented in Table 3.[15] According to Panel A of the table, with respect to the pre-trading period, as expected (given the existing literature), a Tuesday effect is in evidence in both Australia and Japan. Specifically, we see that the Tuesday mean return is negative and lower than the mean return of all other days for these two cases. Of the remaining countries, Germany, Switzerland, and the US reveal a Monday effect – that is, a significant negative return (at the 5 % level) on Monday that is lower than the mean return for all other days of the week. Further, the UK reveals a significantly negative mean Monday return at the 10 % level. In addition, it can be seen that during the pre-trading period, average returns on all other days of the week are positive and highly significant in all cases (except Spain). This again is generally consistent with previous evidence documenting daily seasonality across international markets [see for example, Dubois and Louvet (1996)].

[15] It should be noted, consistent with the arguments of Nelson (1990a, 1990b) and others, that the thrust of our mean equation results is robust to the specification of the variance equation. Indeed, the conclusions we draw based on the mean equation results are valid even (a) in the case where the variance equation contains no daily seasonal dummy variables and (b) in the case where the variance equation is omitted altogether. Further details are available from the authors upon request.

[TABLE 3 ABOUT HERE]

The post-futures trading period average day-of the-week returns are also reported in Panel A of Table 3. The most notable finding here is that the significant negative Monday and Tuesday returns documented in the pre-trading period analysis have disappeared. Specifically, consistent with the findings of Dubois and Louvet (1996); Kamara (1997) and Hiraki *et al*. (1998); the US Monday effect and the Japanese Tuesday effect, respectively, are no longer in evidence. In the case of the US the average pre-trading Monday return was –0.18 % (with a t-statistic of –5.80), compared to its average post-trading period counterpart of 0.03 % (with a t-statistic of 1.35). Similarly, for Japan the average pre-trading Tuesday return was –0.08 % (with a t-statistic of –2.90), compared to its average post-trading period counterpart of 0.09 % (with a t-statistic of 2.45). Interestingly, the unreported estimation results for Equations (5) and (6) which allow individual estimates of each day of the week separately, reveals that the average pre-trading period Monday return is 0.14 % (with a t-statistic of 3.03), compared to its post-trading period counterpart of –0.03 %. This supports the suggestion of Hiraki *et al.* (1998), that the Tuesday effect in Japan has changed to a Monday effect in the post-trading period. Thus, the existing findings in the literature [Kamara (1997) and Hiraki *et al.* (1998)] are strongly confirmed in the context of our more general experimental design based on a modified GARCH model framework.

Our findings however, extend much further than simply confirming known outcomes for the US and Japanese markets. Specifically, we find that a similar disappearance of the daily seasonal effect in mean returns is in evidence for Australia (where the previously documented Tuesday effect is now absent in the post-trading period analysis); and for Germany, the UK and Switzerland (where the previously documented Monday effect is now absent in the post-trading period). For example, in the case of Germany the average pre-trading Monday return was –0.12 % (with a t-statistic of –4.07), compared to its average post-trading period counterpart of -0.02 % (with a t-statistic of –0.50). Finally, as was the case for the pre-trading period, it is evident that average "other day of the week" returns for the post-trading period are positive and significant across all countries.

Evidence as to the seasonality of return autocorrelation is presented in Panel B of Table 3 and several major features are evident. First, across the five relevant countries there is a high and positive return autocorrelation between Monday equity returns and those of the prior trading day. For example, in the case of Spain the pre-trading period Monday coefficient is 0.6788 as compared to a value of 0.0549 for all other days in the pre-trading period. This is consistent with the findings of Bessembinder and Hertzel (1993) who examined US equity and futures markets data.

Second, the finding of daily seasonality in return autocorrelations discussed above, is also evident in the post-trading period across these five countries, although to a lesser extent than for the pre-trading period. For example, reconsider Spain in the post-trading period in which the Monday autocorrelation coefficient has fallen to 0.3061 as compared to a value of 0.1011 for all other days in the post-trading period.

Third, in the case of Japan and Australia, there is a tendency for the return autocorrelation to be low between Tuesday equity returns and those for the prior trading day – in both the pre-trading and post-trading periods. For example, in the case of Japan in the pre-trading period, the Tuesday return autocorrelation is –0.054 as compared to a value of 0.1238 for the counterpart all other days case. This finding is also consistent with the Bessembinder and Hertzel (1993) results.

In summary, in terms of the estimated return autocorrelations reported in Table 3, while daily seasonality is generally observed, there is not a strong pattern indicating any particular effect associated with the introduction of futures trading in index futures contracts.

C. Daily Seasonality and the Pre/Post Index Futures Trading Modified GARCH Model: Variance Equation Results

Table 4 presents the estimated coefficients for the GARCH model variance equation [Equation (4)]. It can be seen from the table that the ARCH and GARCH terms are all positive, statistically significant and sum to be less than unity, which indicates that shocks to the model are not permanent. With regard to both the pre-trading and post-trading periods the predominant pattern revealed in this set of results is that the Monday volatility coefficients (for Spain, Germany, Switzerland, the UK and the US) are all significantly positive and predominantly larger in magnitude compared to their other day of the week (ODW) counterparts. This suggests that the volatility impact on all other days of the week is lower than the Monday volatility – a form of daily seasonality in return volatility that is consistent with the previous literature [see, for example, Agrawal and Tandon (1994)]. Interestingly, for the two markets (Australia and Japan) in which Tuesday is isolated from other days of the week, the reverse volatility effect is apparent. That is, in these markets the point estimate of the volatility impact tends to be larger in the all other days case relative to Tuesday.

[TABLE 4 ABOUT HERE]

D. An Extended Analysis of the US Case

Following Kamara (1997) we extend the analysis of the US market to incorporate two pre-trading subperiods. Specifically, May 1, 1975 is identified as a potential point for a structural break relating to the move from non-negotiable to competitive commissions on the NYSE. To the extent that the existence of the daily seasonal relates to transaction costs, reduced brokerage costs in this “post-nonnegotiable commissions” period would suggest a greater ability of traders to arbitrage any Monday seasonal. Hence, we have three subperiods (broken at May 1, 1975 and April 21, 1982) and Kamara (1997) argues (and finds) that as we move through these subperiods, we expect to observe a weakening of the Monday seasonal.

Accordingly, the three subperiods are: (a) the “non-negotiable commissions” period covering the interval January 1969 to April 30, 1975 (“Pre1”); (b) the “post-nonnegotiable commissions” period covering the interval May 1, 1975 to April 20, 1982 (“Pre2”); and (c) the “post-S&P 500 futures” period covering the interval April 21, 1982 to 31 January, 1999 (“Post”). The outcome of this extended analysis in the context of our modified GARCH model is reported in Table 5. The table is partitioned into three panels – Panel A reports the estimation results for the mean returns, Panel B reports the return autocorrelation estimates, while Panel C reports the estimated coefficients for the variance equation.

[TABLE 5 ABOUT HERE]

In Panel A we observe that the average Monday return in the "non-negotiable commissions" period of –0.25 % (with a t-statistic of -6.23) is significant, negative and lower than the average returns recorded for all other days of the week in that period. In the second pre-futures trading subperiod ("post-nonnegotiable commissions"), the average Monday return of –0.09 % is significant, negative and estimated to be lower than the average return for all other days of the week. Further, in the third subperiod (which heralds post-futures trading activity), the average Monday return (0.03 %) is now positive (although insignificant) and is no longer the lowest across all days of the week (in unreported results the average Thursday return is now lowest). Hence, this finding of a general weakening in the Monday effect over time strongly confirms the analysis of Kamara (1997) in the more comprehensive setting of the GARCH framework employed in the current paper. This confirmation is important as it serves to show that the Kamara (1997) results have not been induced by neglecting to model time-varying volatility effects in the data or by the omission of the dynamics captured by return autocorrelations in the mean equation.

Panel B of Table 5 reports the outcome for the return autocorrelations. As was the case above there is a strong tendency for the autocorrelation to be high and positive between Monday and the previous trading day equity returns. While this feature appears to have weakened over time, the post-trading period in the US still reveals a relatively high return autocorrelation for the Monday case (0.2242) as compared to all other days of the week (0.0012).

Perhaps even more importantly, the modified GARCH framework permits us to detect whether there is some sort of related daily seasonal effect in the volatility equation. Accordingly, we now turn our attention to Panel C of Table 5. Similar to the preceding analysis, we observe that the estimated Monday volatility coefficient in the first pre-trading period (Pre1Mon) is higher than the estimated average volatility in all other cases with the exception of the Monday volatility coefficient in the second pre-trading period (Pre2Mon). A Wald test of equality between the Pre1Mon and Pre2Mon volatility coefficients produces a p-value of 0.7017 which suggests that these two coefficients are statistically indistinguishable from each other.

In sum, the preceding analysis of mean and volatility suggests a paradox - higher average returns tend to be associated with lower return volatility. The decline in volatility may simply reflect a decline in noise however, both of which could be consistent with an improvement in efficiency. Furthermore, unless information arrival varies by day of the week, a seasonal in volatility may reflect a seasonal in noise (especially for the Tuesday seasonal since it does not follow the non-trading weekend). Moreover, even if information arrival is different on Monday than on other weekdays, unless this has changed by the introduction of futures, a change in the volatility seasonal following futures inception may reflect a change in the seasonal in noise.[16]

E. Tests of Main Hypotheses – Daily Seasonal Effects: Mean Equation Results

The above analysis indicates that a certain degree of variation is observed when comparing daily seasonality in the mean and variance equation in pre-trading and post-trading (of share index futures) subperiods. To further investigate the statistical significance of these seasonalities, we investigate our main set of hypotheses as outlined in Section II C, by applying a series of Wald tests. Specifically, for (a) mean returns; (b) return autocorrelations; and (c) return volatilities; we formally test whether Monday (Tuesday) values are statistically different from the average values on all other days. The results are presented in Panels A, B and C of Table 6, respectively.

The first set of analysis presented in this table consists of testing the basic "seasonality" hypothesis as applied to the mean returns case. This is represented by Hypotheses H1 and H2 outlined previously. H1: $\varphi_{PreMon} = \varphi_{PreODW}$ represents the null hypothesis that average pre-trading period Monday returns equal the average return on other pre-trading period weekdays. The alternative hypothesis of interest here is whether average Monday returns are significantly lower than the average return on other weekdays. As revealed in Panel A of Table 6, the Monday version of hypothesis H1 is resoundingly rejected for all countries – although note that Spain presents a perverse case since the average Monday return is significantly positive (refer back to Table 3). Likewise, H1: $\varphi_{PreTue} = \varphi_{PreODW}$ – the Tuesday counterpart for the pre-trading period is strongly rejected for both countries involved – Australia and Japan. Interestingly, when we consider the post-trading versions of these two tests we find

[16] The authors are most grateful to an anonymous referee for suggesting this interpretation.

only Australia (H2: $\varphi_{PostTue} = \varphi_{PostODW}$); and Spain and the UK (H2: $\varphi_{PostMon} = \varphi_{PostODW}$) provide a rejection of the relevant hypothesis. Notably, in each case the rejection is much less convincing than that found for each pre-trading period counterpart.

[TABLE 6 ABOUT HERE]

Overall, the results discussed thus far suggest that the introduction of share index futures has at least coincided with a general change in the daily seasonality in mean returns. Moreover, our evidence largely confirms the findings of Kamara (1997) and Hiraki *et al.* (1998) for the US and Japanese markets, and importantly suggests similar effects have occurred in other markets such as Germany, Switzerland and the UK.

Further analysis consists of testing the basic "seasonality" hypothesis as applied to the return autocorrelations case. This is represented by Hypotheses H3 and H4 outlined previously and the results are shown in Panel B of Table 6. For H3: $\lambda_{PreMon} = \lambda_{PreODW}$, in all cases except the UK this hypothesis is rejected. This therefore supports the earlier conclusion that the Monday autocorrelation is significantly higher than its counterpart taken for all other days during the pre-trading period. In the case of Australia and Japan, H3: $\lambda_{PreTue} = \lambda_{PreODW}$ shows rejection only for Japan – in this case driven by a lower Tuesday return autocorrelation. Furthermore, the counterpart autocorrelation hypotheses for the post-trading period (H4: $\lambda_{PostMon} = \lambda_{PostODW}$ and $\lambda_{PostTue} = \lambda_{PostODW}$) reveal similarly strong rejections. Generally, these findings confirm the belief that the introduction of futures trading has not been associated with any major change to the return dynamics as reflected by daily seasonality in return autocorrelations.

F. Tests of Main Hypotheses – Daily Seasonal Effects: Variance Equation Results

Panel C of Table 6 presents the outcome of the set of Wald tests of the analogous "seasonality" hypothesis in the variance equation. This is represented by Hypotheses H5 and H6 outlined previously. Generally, it can be seen in the table that the basic seasonality hypothesis for volatility only fails to be rejected twice out of 14 occasions. Of note is the case of Australia in which the daily seasonal in volatility, while being strong in the post-trading period, was non-existent in the pre-trading period. However, the US reveals the opposite change – namely, an extremely strong rejection of the main volatility seasonal hypothesis in the pre-trading period, has become starkly insignificant in the post-trading period. This latter finding is consistent with the earlier extended analysis reported for the US. Given that the volatility equality hypothesis is only rejected for Australia and the US – and then in opposing ways, suggests that this is unlikely to be driven by the introduction of index futures trading. A more plausible conclusion relates to noise, as outlined earlier.

G. Tests of Supplementary Day of the Week Hypotheses

Finally, for (a) mean returns; (b) return autocorrelations; and (c) return volatilities; we perform an additional set of joint tests as outlined in Section II D – namely, the joint equality of (a) the five pre-trading period day-of-the-week coefficients and (b) the five post-trading period day-of-the-week coefficients, for each country. These tests are conducted in the context of the expanded version of the model outlined in Equations (5) and (6) earlier and the results are reported in Table 7.

[TABLE 7 ABOUT HERE]

Consulting Panel A of the table with respect to the mean returns version of this hypothesis in the pre-trading period (H7), except in the case of Spain, the day-of-the-week coefficients are statistically different from each other. With regard to the counterpart joint tests applied to the post-trading period (H8), only Australia, Japan and the UK reject the null hypothesis. However, in the case of Japan and the UK the strength of the rejection is much weaker in the post-trading period (particularly for Japan). While these results vary slightly from the main tests reported above, they confirm that in the case of Germany, Switzerland and the US, a significant change in the day of the week effect in mean returns coincided with the introduction of index futures contracts.

Panel B of Table 7 reveals the outcome of the supplementary equality tests applied to the return autocorrelations. Specifically, it can be seen that in the pre-trading period (H9) all countries (with the exception of Australia) reject the equality of day of the week return autocorrelations coefficients. In the post-trading period (H10) it is Germany that presents the only case of a non-rejection of this hypothesis. These outcomes are largely consistent with the results of the main hypothesis testing reported in the previous table.

Finally, Panel C of Table 7 reports the results for testing the equality hypothesis as applied to the day of the week volatilities. In both the pre-trading period (H11) and the post-trading period (H12) an overwhelming rejection of the equality hypothesis is revealed.

Generally, the outcome of the secondary tests reported in this subsection reinforce the earlier conclusion that while index futures trading has coincided with a change in the mean return daily seasonality, similar changes in either the return autocorrelation or volatility seasonality have not been evident.

IV. CONCLUSION

The trading of futures contracts often has an impact on the underlying asset on which its value is based. In this paper, the potential impact of the introduction of stock index futures on the daily seasonality of the underlying share index was examined for a group of seven countries – Australia, Germany, Japan, Spain, Switzerland, the UK and the US. This daily seasonality testing is performed with respect to (a) mean returns; (b) return autocorrelations; and (c) return volatilities. Each country's index return is modeled using a GARCH model augmented by day-of-the-week dummy variables in both the mean and variance equation. A variety of Wald tests were performed to assess whether the daily seasonality in the pre-futures trading period was different to that of the post-futures trading period.

In this paper two major contributions to the existing literature are made. First, the use of a GARCH model allows us to provide new insights as we may simultaneously consider the impact of stock index futures trading on daily returns seasonality in both the mean and volatility dimensions. Second, we present a unified package of evidence spanning a number of national boundaries that will help to counter the concern of a data snooping bias. Existing evidence pertaining to this general area is currently only available for two markets, namely, the US and Japan – but then only in terms of mean return effects. Our investigation extends the coverage to seven markets.

Our major findings are as follows. In general, our results suggest that the introduction of futures trading has been associated with reduced seasonality of mean returns. This is particularly the case with regard to the general weakening of the Monday effect in mean returns for the US; Germany; and Switzerland, and to a lesser extent for the UK. Similarly for Japan and to a lesser extent for Australia, the Tuesday effect in mean returns no longer is in evidence. This finding supports the arguments presented by Kamara (1997) and Hiraki *et al*. (1998) that, for example, futures trading lowers transaction costs of traders who may be looking to arbitrage any profitable opportunities, including daily seasonals. Furthermore, while we detect daily seasonality in return autocorrelations and volatilities that is largely related to Monday and Tuesday observations, this seasonality does not seem to be affected by the introduction of index futures contracts. Notably however, the general confirmation (across our sample of seven countries) of seasonality in (a) return volatility provides an important international extension of the findings of Fama (1965); Gibbons and Hess (1981) and Agrawal and Tandon (1994); and (b) return autocorrelations, provides an important international extension of the findings of Bessembinder and Hertzel (1993).

As such, our analysis suggests that a finding of a weakening in daily seasonals that coincides with index futures introduction, is not as simple as first thought. While we agree with the conclusion of Hiraki *et al.* (1998, p. 505)

> "...that return seasonality in itself is a dynamic process and that previously documented returns patterns are likely to change whenever there is a major structural change in financial markets",

our work suggests focusing solely on mean returns may only partially capture this evolution. That is, the interplay between changes occurring in the first and second moments of returns presents additional challenges for empirical researchers. Accordingly, we commend this as a focus for future research in this area.

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TABLE 1 Stock Market Index and Date of Introduction of Share Index Futures Contract

Country	Market Index	Index Type	Futures Introduction Date	Sample Start Date
Australia	All Ordinaries	Accumulated	16 February, 1983	January, 1980
Spain	IBEX 35	Accumulated	20 April, 1992	March, 1987
Germany	DAX 100	Accumulated	23 November, 1990	January, 1973
Japan	NIKKEI 225	Price	3 September, 1986	January, 1980
Switzerland	SWISS MI	Price	9 November, 1990	July, 1988
UK *	FTSE 100	Accumulated	3 May, 1984	January, 1969
US	S&P 500	Price	21 April, 1982	January, 1969

NOTE. – Since the FTSE 100 index was introduced to support the futures contact at the time of its introduction, the FTALL index was used for testing purposes.

TABLE 2 Descriptive Statistics for National Stock Market Index Returns

Country	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera (P-value)
Australia	0.00051	0.009	-5.309	149.071	0.000
Spain	0.00064	0.012	-0.400	10.041	0.000
Germany	0.00039	0.010	-0.795	14.604	0.000
Japan	0.00015	0.012	-0.139	16.114	0.000
Switzerland	0.00056	0.010	-0.825	13.248	0.000
UK	0.00053	0.009	-0.274	12.860	0.000
US	0.00032	0.009	-1.962	53.354	0.000

NOTE. – The Jacque-Bera test is a test of the null hypothesis of normality in which the skewness and kurtosis of the series is compared to the normal distribution.

TABLE 3 Estimation of Seasonality Modified GARCH Model allowing for the Potential Impact of Stock Index Futures Trading: Mean Equation Results

$$R_t = \sum_{i=PreMon}^{PreODW} \varphi_i D_i + \sum_{i=PostMon}^{PostODW} \varphi_i D_i + \sum_{i=PreMon}^{PreODW} \lambda_i D_i R_{t-1} + \sum_{i=PostMon}^{PostODW} \lambda_i D_i R_{t-1} + \varepsilon_t$$

$$h_t = \sum_{i=PreMon}^{PreODW} \alpha_{0i} D_i + \sum_{i=PostMon}^{PostODW} \alpha_{0i} D_i + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$

Coefficient	Australia	Spain	Germany	Japan	Switzerland	UK	US
Panel A: Mean Return Coefficients							
φ_{PreMon}	-	0.0031 * (4.63)	-0.0012 * (4.07)	-	-0.0048 * (3.60)	-0.0005 (1.67)	-0.0018 * (5.80)
φ_{PreTue}	-0.0017 * (2.96)	-	-	-0.0008 * (2.90)	-	-	-
φ_{PreODW}	0.0007 * (2.32)	-0.0001 (0.49)	0.0008 * (6.89)	0.0011 * (7.53)	0.0014 * (2.47)	0.0004 * (3.57)	0.0004 * (4.37)
$\varphi_{PostMon}$	-	0.0001 (0.12)	-0.0002 (0.50)	-	0.0003 (0.72)	0.0001 (0.59)	0.0003 (1.35)
$\varphi_{PostTue}$	0.0001 (0.27)	-	-	0.0009 * (2.45)	-	-	-
$\varphi_{PostODW}$	0.0007 * (5.66)	0.0013 * (6.04)	0.0005 * (3.20)	0.0006 * (3.41)	0.0009 * (5.78)	0.0009 * (7.21)	0.0007 * (5.24)
Panel B: Return Autocorrelation Coefficients							
λ_{PreMon}	-	0.6788 * (8.61)	0.2500 * (6.45)	-	0.3802 * (3.12)	0.2540 * (6.50)	0.3258 * (7.33)
λ_{PreTue}	0.2562 * (3.16)	-	-	-0.054 (0.84)	-	-	-
λ_{PreODW}	0.3403 * (8.65)	0.0549 * (2.12)	0.0352 (1.93)	0.1238 * (4.16)	-0.0294 (0.41)	0.2153 * (12.50)	0.1483 * (8.58)
$\lambda_{PostMon}$	-	0.3061 * (4.75)	0.0854 (1.16)	-	0.3511 * (5.51)	0.2319 * (5.08)	0.2934 * (7.81)
$\lambda_{PostTue}$	0.0829 * (2.33)	-	-	-0.0721 (1.68)	-	-	-
$\lambda_{PostODW}$	0.1954 * (9.94)	0.1011 * (4.09)	0.0194 (0.74)	0.0458 * (2.01)	0.0178 (0.73)	0.0936 * (4.55)	-0.0234 (1.20)

NOTE. – In the case of Australia and Japan the model distinguishes Tuesdays from other days of the week. R_t is the daily returns measured for a given stock market index. D_{PreMon} (D_{PreTue}) is a dummy variable which takes the value unity if the day is a Monday (Tuesday) in the pre-futures trading period and zero otherwise. $D_{PostMon}$ ($D_{PostTue}$) is a dummy variable which takes the value unity if the day is a Monday (Tuesday) in the post-futures trading period and zero otherwise. In the case of Spain, Germany, Switzerland, the UK and the US, D_{PreODW} ($D_{PostODW}$) is a dummy variable for the "other days of the week" which takes a value of unity if the day is a Tuesday, Wednesday,Thursday or Friday in the pre-futures (post-futures) trading period and zero otherwise. In the case of Australia and Japan, D_{PreODW} ($D_{PostODW}$) is a dummy variable for the "other days of the week" which takes a value of unity if the day is a Monday, Wednesday, Thursday or Friday in the pre-futures (post-futures) trading period and zero otherwise. The absolute value of t-statistics are presented in parentheses below each parameter estimate. An asterisk (*) denotes statistical significance at the 5% level.

TABLE 4 Estimation of Seasonality Modified GARCH Model allowing for the Potential Impact of Stock Index Futures Trading: Variance Equation Results

$$R_t = \sum_{i=PreMon}^{PreODW} \varphi_i D_i + \sum_{i=PostMon}^{PostODW} \varphi_i D_i + \sum_{i=PreMon}^{PreODW} \lambda_i D_i R_{t-1} + \sum_{i=PostMon}^{PostODW} \lambda_i D_i R_{t-1} + \varepsilon_t$$

$$h_t = \sum_{i=PreMon}^{PreODW} \alpha_{0i} D_i + \sum_{i=PostMon}^{PostODW} \alpha_{0i} D_i + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$

Coefficient	Australia	Spain	Germany	Japan	Switzerland	UK	US
$\alpha_{0PreMon}$	-	10.80 *	2.95 *	-	5.50 *	2.68 *	3.83 *
		(14.9)	(9.63)		(8.58)	(7.29)	(9.57)
$\alpha_{0PreTue}$	1.00	-	-	-0.21	-	-	-
	(1.36)			(1.48)			
$\alpha_{0PreODW}$	1.40 *	-0.30	0.89 *	0.28 *	1.31 *	0.52 *	0.45 *
	(5.02)	(1.05)	(8.62)	(5.90)	(4.78)	(4.77)	(4.20)
$\alpha_{0PostMon}$	-	4.71 *	9.36 *	-	6.62 *	2.25 *	1.40 *
		(11.0)	(29.5)		(19.2)	(11.9)	(5.21)
$\alpha_{0PostTue}$	0.66 *	-	-	-0.59	-	-	-
	(2.90)			(1.74)			
$\alpha_{0PostODW}$	1.27 *	1.40 *	0.01	0.75 *	-0.03	0.38 *	1.52 *
	(10.8)	(7.17)	(0.14)	(8.43)	(0.17)	(5.12)	(14.35)
α_1	0.1842 *	0.1700 *	0.1885 *	0.1664 *	0.1622 *	0.1648 *	0.1629 *
	(51.4)	(15.2)	(20.1)	(28.7)	(10.5)	(20.8)	(25.7)
β_1	0.6552 *	0.6276 *	0.6460 *	0.8249 *	0.7003 *	0.7239 *	0.6366 *
	(35.2)	(39.8)	(46.7)	(147.5)	(28.6)	(69.3)	(50.5)
Adjusted R^2	0.011	0.040	0.004	0.001	0.014	0.034	0.025
DW	2.11	1.99	2.01	2.05	2.01	2.00	1.99

NOTE. – In the case of Australia and Japan the model distinguishes Tuesdays from other days of the week. R_t is the daily returns measured for a given stock market index. D_{PreMon} (D_{PreTue}) is a dummy variable which takes the value unity if the day is a Monday (Tuesday) in the pre-futures trading period and zero otherwise. $D_{PostMon}$ ($D_{PostTue}$) is a dummy variable which takes the value unity if the day is a Monday (Tuesday) in the post-futures trading period and zero otherwise. In the case of Spain, Germany, Switzerland, the UK and the US, D_{PreODW} ($D_{PostODW}$) is a dummy variable for the "other days of the week" which takes a value of unity if the day is a Tuesday, Wednesday,Thursday or Friday in the pre-futures (post-futures) trading period and zero otherwise. In the case of Australia and Japan, D_{PreODW} ($D_{PostODW}$) is a dummy variable for the "other days of the week" which takes a value of unity if the day is a Monday, Wednesday, Thursday or Friday in the pre-futures (post-futures) trading period and zero otherwise. The absolute value of t-statistics are presented in parentheses below each parameter estimate. An asterisk (*) denotes statistical significance at the 5% level. All variance equation parameters except the ARCH (α_1) and GARCH (β_1) coefficients are multiplied by 10^5. DW stands for the Durbin-Watson statistic.

TABLE 5 **Estimation of Seasonality Modified GARCH Model allowing for the Potential Impact of Stock Index Futures Trading in the US Market: An Extended Analysis**

$$R_t = \sum_{\substack{i=Pre1Mon,Pre1ODW,\\Pre2Mon,Pre2ODW}} \varphi_i D_i + \sum_{\substack{i=PostMon,\\PostODW}} \varphi_i D_i + \sum_{\substack{i=Pre1Mon,Pre1ODW,\\Pre2Mon,Pre2ODW}} \lambda_i D_i R_{t-1} + \sum_{\substack{i=PostMon,\\PostODW}} \lambda_i D_i R_{t-1} + \varepsilon_t$$

$$h_t = \sum_{\substack{i=Pre1Mon,Pre1ODW,\\Pre2Mon,Pre2ODW}} \alpha_{0i} D_i + \sum_{\substack{i=PostMon,\\PostODW}} \alpha_{0i} D_i + \alpha_1 \varepsilon^2_{t-1} + \beta_1 h_{t-1}$$

Panel A: Mean Equation – Mean Returns						
Coefficient	$\varphi_{Pre1Mon}$	$\varphi_{Pre1ODW}$	$\varphi_{Pre2Mon}$	$\varphi_{Pre2ODW}$	$\varphi_{PostMon}$	$\varphi_{PostODW}$
	-0.0025 *	0.0006 *	-0.0009 *	0.0003 *	0.0003	0.0008 *
	(6.23)	(3.57)	(2.20)	(2.05)	(1.31)	(6.62)
Panel B: Mean Equation – Return Autocorrelations						
Coefficient	$\lambda_{Pre1Mon}$	$\lambda_{Pre1ODW}$	$\lambda_{Pre2Mon}$	$\lambda_{Pre2ODW}$	$\lambda_{PostMon}$	$\lambda_{PostODW}$
	0.4386 *	0.2224 *	0.3890 *	0.1121 *	0.2242 *	0.0012
	(7.83)	(9.21)	(5.94)	(3.74)	(5.95)	(0.06)
Panel C: Variance Equation						
Coefficient	$\alpha_{0Pre1Mon}$	$\alpha_{0Pre1ODW}$	$\alpha_{0Pre2Mon}$	$\alpha_{0Pre2ODW}$	$\alpha_{0PostMon}$	$\alpha_{0PostODW}$
	2.19 *	0.20 *	2.39 *	0.40 *	0.36	1.07 *
	(7.03)	(3.00)	(5.23)	(3.18)	(1.60)	(15.16)
Coefficient	α_1	β_1				
	0.1506 *	0.7361 *				
	(24.9)	(70.3)				
Adjusted R^2	0.024					
DW	2.03					

NOTE. – R_t is the daily returns measured for the S&P 500 index. Following Kamara (1997), the pre-futures trading period has been partitioned into two subperiods to capture the possible effects of US regime changes. The first pre-futures trading subperiod (Pre1) starts at January 1, 1969 and ends April 30, 1975. The second pre-futures trading subperiod (Pre2) begins May 1, 1975 and ends on April 20, 1982. The post-trading subperiod (Post) begins April 21, 1982 and ends on January 31, 1999. Accordingly, $D_{Pre1Mon}$ ($D_{Pre2Mon}$) is a dummy variable which takes the value unity if the day is a Monday in the first (second) pre-futures trading period and zero otherwise. $D_{PostMon}$ is a dummy variable which takes the value unity if the day is a Monday in the post-futures trading period and zero otherwise. $D_{Pre1ODW}$, $D_{Pre2ODW}$ and $D_{PostODW}$ are dummy variables for the "other days of the week" which take a value of unity if the day is a Tuesday, Wednesday, Thursday or Friday in, respectively, the first pre-futures, second pre-futures or post-futures trading periods and zero otherwise. The absolute value of t-statistics are presented in parentheses below each parameter estimate. An asterisk (*) denotes statistical significance at the 5% level. All variance equation parameters except the ARCH (α_1) and GARCH (β_1) coefficients are multiplied by 10^5. DW stands for the Durbin-Watson statistic.

TABLE 6 Test of Main Daily Seasonality Hypotheses

$$R_t = \sum_{i=PreMon}^{PreODW} \varphi_i D_i + \sum_{i=PostMon}^{PostODW} \varphi_i D_i + \sum_{i=PreMon}^{PreODW} \lambda_i D_i R_{t-1} + \sum_{i=PostMon}^{PostODW} \lambda_i D_i R_{t-1} + \varepsilon_t$$

$$h_t = \sum_{i=PreMon}^{PreODW} \alpha_{0i} D_i + \sum_{i=PostMon}^{PostODW} \alpha_{0i} D_i + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$

Hypothesis	Australia	Spain	Germany	Japan	Switzerland	UK	US
Panel A: Mean Return Seasonality Hypotheses							
H1: $\varphi_{PreMon} = \varphi_{PreODW}$	-	20.340 * (0.000)	43.638 * (0.000)	-	19.237 * (0.000)	9.409 * (0.002)	48.135 * (0.000)
$\varphi_{PreTue} = \varphi_{PreODW}$	14.619 * (0.000)	-	-	35.017 * (0.000)	-	-	-
H2: $\varphi_{PostMon} = \varphi_{PostODW}$	-	5.621 * (0.017)	2.226 (0.135)	-	1.386 (0.239)	5.037 * (0.024)	1.631 (0.201)
$\varphi_{PostTue} = \varphi_{PostODW}$	6.116 * (0.013)	-	-	0.399 (0.527)	-	-	-
Panel B: Return Autocorrelation Seasonality Hypotheses							
H3: $\lambda_{PreMon} = \lambda_{PreODW}$	-	53.267 * (0.000)	24.778 * (0.000)	-	9.777 * (0.001)	0.839 (0.359)	13.960 * (0.000)
$\lambda_{PreTue} = \lambda_{PreODW}$	0.868 (0.351)	-	-	6.686 * (0.009)	-	-	-
H4: $\lambda_{PostMon} = \lambda_{PostODW}$	-	8.963 * (0.002)	0.695 (0.404)	-	24.063 * (0.000)	7.753 * (0.005)	62.100 * (0.000)
$\lambda_{PostTue} = \lambda_{PostODW}$	7.504 * (0.006)	-	-	5.580 * (0.018)	-	-	-
Panel C: Return Volatility Seasonality Hypotheses							
H5: $\alpha_{0PreMon} = \alpha_{0PreODW}$	-	124.187 * (0.000)	38.514 * (0.000)	-	34.601 * (0.000)	24.465 * (0.000)	55.689 * (0.000)
$\alpha_{0PreTue} = \alpha_{0PreODW}$	0.193 (0.660)	-	-	6.995 * (0.008)	-	-	-
H6: $\alpha_{0PostMon} = \alpha_{0PostODW}$	-	39.121 * (0.000)	602.925 * (0.000)	-	179.448 * (0.000)	61.925 * (0.000)	0.170 (0.679)
$\alpha_{0PostTue} = \alpha_{0PostODW}$	6.176 * (0.012)	-	-	10.497 * (0.001)	-	-	-

NOTE. – In the case of Australia and Japan the model distinguishes Tuesdays from other days of the week. R_t is the daily returns measured for a given stock market index. D_{PreMon} (D_{PreTue}) is a dummy variable which takes the value unity if the day is a Monday (Tuesday) in the pre-futures trading period and zero otherwise. $D_{PostMon}$ ($D_{PostTue}$) is a dummy variable which takes the value unity if the day is a Monday (Tuesday) in the post-futures trading period and zero otherwise. In the case of Spain, Germany, Switzerland, the UK and the US, D_{PreODW} ($D_{PostODW}$) is a dummy variable for the “other days of the week” which takes a value of unity if the day is a Tuesday, Wednesday, Thursday or Friday in the pre-futures (post-futures) trading period and zero otherwise. In the case of Australia and Japan, D_{PreODW} ($D_{PostODW}$) is a dummy variable for the “other days of the week” which takes a value of unity if the day is a Monday, Wednesday, Thursday or Friday in the pre-futures (post-futures) trading period and zero otherwise. The p-values associated with each hypothesis are presented in parentheses below the Wald test statistic. An asterisk (*) denotes statistical significance at the 5% level.

TABLE 7 Test of Supplementary Day of the Week Hypotheses

$$R_t = \sum_{i=PreMon}^{PreFri} \varphi_i D_i + \sum_{i=PostMon}^{PostFri} \varphi_i D_i + \sum_{i=PreMon}^{PreFri} \lambda_i D_i R_{t-1} + \sum_{i=PostMon}^{PostFri} \lambda_i D_i R_{t-1} + \varepsilon_t$$

$$h_t = \sum_{i=PreMon}^{PreFri} \alpha_{0i} D_i + \sum_{i=PostMon}^{PostFri} \alpha_{0i} D_i + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$

Hypothesis	Australia	Spain	Germany	Japan	Switzerland	UK	US
Panel A: Mean Return Hypotheses							
H7: $\varphi_{PreMon} = \varphi_{PreTue} = \varphi_{PreWed}$	3.013 *	1.005	8.729 *	32.150 *	3.030 *	5.623 *	11.029 *
$= \varphi_{PreThu} = \varphi_{PreFri}$	(0.017)	(0.403)	(0.000)	(0.000)	(0.016)	(0.000)	(0.000)
H8: $\varphi_{PostMon} = \varphi_{PostTue} =$	5.258 *	1.849	1.651	2.499 *	1.059	2.638 *	1.804
$\varphi_{PostWed} = \varphi_{PostThu} = \varphi_{PostFri}$	(0.000)	(0.116)	(0.158)	(0.040)	(0.375)	(0.032)	(0.125)
Panel B: Return Autocorrelation Hypotheses							
H9: $\lambda_{PreMon} = \lambda_{PreTue} = \lambda_{PreWed} =$	1.418	15.534 *	8.981 *	4.864 *	5.606 *	4.882 *	5.940 *
$\lambda_{PreThu} = \lambda_{PreFri}$	(0.225)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
H10: $\lambda_{PostMon} = \lambda_{PostTue} =$	9.758 *	2.963 *	1.428	4.556 *	3.715 *	5.103 *	16.256 *
$\lambda_{PostWed} = \lambda_{PostThu} = \lambda_{PostFri}$	(0.000)	(0.018)	(0.221)	(0.001)	(0.005)	(0.000)	(0.000)
Panel C: Return Volatility Hypotheses							
H11: $\alpha_{0PreMon} = \alpha_{0PreTue} =$	8.273 *	145.480 *	20.182 *	418.405 *	82.452 *	11.314 *	18.049 *
$\alpha_{0PreWed} = \alpha_{0PreThu} = \alpha_{0PreFri}$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
H12: $\alpha_{0PostMon} = \alpha_{0PostTue} = \alpha_{0PostWed}$	45.473 *	9.207 *	180.723 *	42.302 *	38.307 *	29.524 *	24.025 *
$= \alpha_{0PostThu} = \alpha_{0PostFri}$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

NOTE. – R_t is the daily returns measured for a given stock market index. Five separate day-of-the-week dummy variables are defined in the pre-trading era D_i (i = PreMon, PreTue, PreWed, PreThu, PreFri) which each take on a value of unity on the day-of-the-week to which they are assigned and zero otherwise. In the post-trading period however, they take on a value of zero regardless. The converse case is true for day-of-the-week dummy variables assigned to the post-trading regime, D_i (i = PostMon, PostTue, PostWed, PostThu, PostFri). The p-values associated with each hypothesis are presented in parentheses below the Wald test statistic. An asterisk (*) denotes statistical significance at the 5% level.