

# Is Seasonal Heteroscedasticity Real? An International Perspective

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## Abstract

This letter demonstrates that, surprisingly, there is a substantially higher number of statistically significant calendar effects in volatility than in expected returns. Using daily returns data from ten international stock indices, we document the size and statistical significance of the day of the week, month of the year, and holiday seasonal effects in both expected returns and volatility. We assess the significance of these calendar effects by conducting formal hypothesis testing using bootstrapping.

*Keywords:* Calendar Effects, Seasonal Heteroscedasticity, Hypothesis Testing, Bootstrapping.

*JEL Classification:* C12, G10.

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# 1 Introduction

There has been overwhelming evidence for decades that there are statistically significant seasonal abnormalities in expected stock returns in the form of day of the week, month of the year and holiday effects (Lakonishok and Smidt (1988)). More recently, there have also been methodological contributions in assessing the statistical significance of calendar effects, which point to the same conclusion. Specifically, Hansen and Lunde (2003) propose a new test, which verifies that many calendar effects are statistically significant in expected returns.<sup>1</sup> Furthermore, Sullivan et al. (2001) conclude that calendar trading rules have significant predictive superiority over a simple buy and hold strategy, unless we explicitly account for the distortions on statistical inference induced by data mining. Notably, there is no study to date, which provides a comprehensive analysis of the statistical significance of seasonality in volatility (seasonal heteroscedasticity).

This investigation documents the evidence on the seasonality of expected returns and volatility using daily data from ten international stock indices. More importantly, using bootstrap-based hypothesis testing, we demonstrate that overall there is considerably more seasonality in volatility than in expected returns; at least 20% more day, month and holiday effects are statistically significant in volatility compared to expected returns. Further, we find that Monday and September are the most significant effects in expected returns, whereas in volatility Monday, Friday, Holiday, and especially June (surprisingly) and October are overwhelmingly strong calendar effects. The evidence on the significance of the well-known January abnormality in expected returns is rather weak. Finally, we comparatively assess the seasonality in the two prominent US indices, the Dow Jones Industrial Average (DJIA) and the S&P 500, and show that the S&P 500 is one of the least seasonal indices, especially in expected returns. None of the bootstrapping results is driven by the October 1987 Crash or the 9/11 outliers.

The letter is organized as follows. Section 2 briefly discusses the international stock index data on which we apply the bootstrap-based hypothesis tests we present in Section 3. Section 4 discusses the results and concludes.

## 2 International Index Returns Data

In this letter, we examine the statistical significance of the seasonal periodicity of expected daily returns. More importantly, we document the seasonal heteroscedasticity of the average daily absolute returns, which are a model-free proxy to daily volatility. We use daily returns data from the 10 international stock indices presented in Tables 1 and 2. The names of the indices, the start date of the samples, and the number of observations are all shown in the

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<sup>1</sup>The Hansen and Lunde (2003) test exploits the correlation between the returns of (for example) Monday and January due to the intersection of their elements (i.e. some January days are Mondays). As we will see, our hypothesis is constructed in a way that avoids this issue.

tables. The sample size of the daily returns ranges from 53 years in the case of the Nikkei 225 and the DJIA (about 13,000 observations) to just 11 years for Italy's MIB 30 (about 2700 observations). The end date for all indices is December 31, 2003. For ease of identification, we will be referring to the indices by their country name, except for the United States for which we examine both the DJIA and the S&P 500. The source of the data is Datastream.

Let  $P_t$  denote the daily closing value of each international price index. Then, the continuously compounded percent returns are constructed simply as

$$R_t = 100 \log \frac{P_t}{P_{t-1}} \quad (2.1)$$

The three sets of calendar effects are captured by isolating the daily returns of each day (Monday to Friday), each month (January to December), and the holidays. The holiday effect is defined as the return from the pre-holiday close to the post-holiday close. In other words, the holiday returns are the daily returns for a trading weekday which follows a non-trading weekday.

### 3 Hypothesis Testing using Bootstrapping

Our key contribution is that we comparatively assess the statistical significance of the calendar effects we observe in both expected returns and volatility. Specifically, we form hypothesis tests for evaluating whether each day, month and holiday is statistically different to its complement. For example, we define the complement of the Monday expected return as the average return of all days which are not Mondays. Similarly, the complement of the January volatility is the volatility of the eleven months February to December.<sup>2</sup> This setup is motivated by a simple question: do Monday (or October) expected returns and volatility need to be modelled separately from the rest of the days (or months)? In other words, is there clear misspecification in assuming that the volatility of all days and months persists around the same mean? If indeed the answer to this question is yes, we should be modelling the seasonality in daily returns and volatility by employing a periodic specification, such as the periodic GARCH model (Bollerslev and Ghysels (1996)) or the periodic stochastic volatility model (Tsiakas (2004)).

Our methodology is based on bootstrapping. The tools described below can be applied to the investigation of seasonality in both expected returns (by focusing on average daily returns) and volatility (by analyzing average daily absolute returns). Our formal hypotheses are all one-sided. Since we can determine whether each calendar effect is higher or lower than its complement, we wish to test the statistical significance of that difference only in the direction it is actually observed.

We test the one-sided hypothesis

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<sup>2</sup>Our hypothesis test assesses the significance of each calendar effect separately and thus avoids the issues discussed in Hansen and Lunde (2003). See also footnote 1.

$$\begin{aligned}
H_0 &: \theta_1 = \theta_2 & \text{or} & & \theta_1 - \theta_2 = 0 \\
H_1 &: \theta_1 < \theta_2 & \text{or} & & \theta_1 - \theta_2 < 0
\end{aligned} \tag{3.1}$$

at size  $\alpha$ . We construct the test statistic

$$T = \frac{\widehat{\theta}_1 - \widehat{\theta}_2}{s(\widehat{\theta}_1 - \widehat{\theta}_2)} \tag{3.2}$$

and reject in favour of  $H_1$  if  $T < c$ . The standard error in testing for the difference between two sample means for unequal sample sizes ( $N_1$  and  $N_2$ ), different population variances ( $\sigma_1$  and  $\sigma_2$ ), and independent groups is computed as

$$s(\widehat{\theta}_1 - \widehat{\theta}_2) = \sqrt{\frac{\widehat{\sigma}_1^2}{N_1 - 1} + \frac{\widehat{\sigma}_2^2}{N_2 - 1}} \tag{3.3}$$

The critical value  $c$  is selected so that  $\Pr(T < c) = \alpha$  or  $c = q_\alpha$ , where  $q_\alpha$  is the quantile of the empirical distribution of the test statistic  $T$  at the significance level  $\alpha$ . Since  $q_\alpha$  is unknown, a bootstrap test replaces it with the bootstrap estimate  $q_\alpha^B$  and the test rejects if  $T < q_\alpha^B$ . Similarly, if the alternative is  $H_1 : \theta_1 > \theta_2$  or  $\theta_1 - \theta_2 > 0$ , the bootstrap test rejects if  $T > q_{1-\alpha}^B$ .

Computationally, the critical value can be estimated from a bootstrap simulation by sorting the bootstrap  $t$ -statistics

$$T = \frac{(\widehat{\theta}_{1,b}^* - \widehat{\theta}_{2,b}^*) - (\widehat{\theta}_1 - \widehat{\theta}_2)}{s(\widehat{\theta}_1^* - \widehat{\theta}_2^*)} \tag{3.4}$$

where  $\widehat{\theta}_{1,b}^*$  is the sample mean of  $\theta_1$  in the  $b$ 'th of a total of  $B$  bootstrap samples. It is important to note that the bootstrap test statistic is centered at the estimate  $\widehat{\theta}_1 - \widehat{\theta}_2$ , and the standard error  $s(\widehat{\theta}_1^* - \widehat{\theta}_2^*)$  is calculated on the bootstrap samples as

$$s(\widehat{\theta}_1^* - \widehat{\theta}_2^*) = \sqrt{\frac{1}{B} \sum_{b=1}^B \left\{ (\widehat{\theta}_{1,b}^* - \widehat{\theta}_{2,b}^*) - (\overline{\widehat{\theta}_1^*} - \overline{\widehat{\theta}_2^*}) \right\}^2} \tag{3.5}$$

where  $\overline{\widehat{\theta}_1^*}$  is the average of the bootstrap means across all the  $B$  bootstrap samples. Note that even though we generate the same number of bootstrap samples  $B$  for both variables,  $\widehat{\theta}_1$  and  $\widehat{\theta}_2$  (and hence  $\widehat{\theta}_{1,b}^* - \widehat{\theta}_{2,b}^*$ ) are constructed using different original sample sizes ( $N_1 \neq N_2$ ). We set  $B = 10,000$  bootstrap samples. These  $t$ -statistics are then sorted to find the estimated quantiles  $q_\alpha^B$  or  $q_{1-\alpha}^B$ .<sup>3</sup>

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<sup>3</sup>For more details on hypothesis testing using bootstrapping see Hansen (2004).

In discussing our results, we report on the statistical significance of a set of adjusted samples, which have excluded the daily returns data for the two full weeks encompassing the October 1987 Crash and the 9/11 attacks.<sup>4</sup> This ensures that any seasonality we uncover is not the direct effect of extreme non-seasonal outliers. Excluding these two weeks eliminates the minima for 9 out of the 10 indices and the maxima for half of them. For the average daily returns, average absolute returns, and the quantiles of both, which we present in the tables, we have used the original samples that include the outliers. We exclude the outliers only for the purpose of assessing statistical significance.

## 4 Results and Discussion

The results are summarized in Tables 1 and 2. Specifically, Table 1 displays the size and statistical significance of all day of the week, month of the year, and holiday seasonal effects in the average daily returns of the ten international stock indices. Table 2 presents the results for the daily absolute returns. This section presents four sets of results, which shed light in (i) assessing the relative strength (size and statistical significance) of seasonality in expected returns versus volatility across all indices; (ii) documenting the evidence for each individual country; (iii) analyzing the significance of each seasonal effect across all countries; and, finally, (iv) providing a comparative assessment of the seasonality in the two prominent US indices, the DJIA and the S&P 500.

First, by examining the evidence across all indices, we determine that the seasonal heteroscedasticity in volatility is substantially stronger than the seasonal periodicity of expected returns. In volatility, 54% of the day of the week effects, 45% of the month of the year effects, and 70% of the holiday effects are statistically different to their complements with at least 95% confidence. This compares very favourably to expected returns, for which only 38% of the days, 26% of the months, and 20% of the holidays are significant with the same confidence. In more detail, for the three levels of confidence of 90%, 95% and 99%, the average number of significant days in expected returns is 2.6, 1.9, and 1.3 out of the 5 days, respectively. The same numbers for volatility are 3.1, 2.7, and 1.8 days. Similarly, for the same three levels of confidence, the average number of significant months in expected returns is 4.6, 3.1, and 0.7 out of the 12 months, respectively. The same numbers for volatility are 6.8, 5.4, and 3.2 months. Finally, the number of significant holiday effects in expected returns is for 3, 2, and 0 countries, respectively. The same numbers for volatility are for 7, 7, and 3 countries.

The second set of results concerns the significance of the calendar effects for each individual country. In expected returns, Hong Kong has the highest number of statistically significant seasonal effects with 95% confidence, with the Dow Jones and Canada tied at second. The

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<sup>4</sup>With the single exception of Hong Kong, we exclude the daily returns for the dates of October 19-23, 1987 and September 10-14, 2001. For Hong Kong only, we also exclude the week of October 26-30, 1987. The Hong Kong market was closed after the Crash on Oct 20-23, 1987. In fact, the following Monday, October 26, 1987, the Hang Seng index experienced a massive 40% daily drop.

least seasonality in expected returns is observed in Italy, followed by both the S&P 500 and Japan in a tie. In volatility, Japan has the most seasonality with 95% confidence, with the Dow Jones, Hong Kong and Italy tied at second. The least seasonality in volatility is observed in Australia, the UK and the S&P 500 all in a tie.

More importantly, the third set of results focuses on the strength of each seasonal effect across all countries. In expected returns, the strongest day of the week effect is Monday, which is statistically significant in 8 countries, except in Australia (for which there is a significant Tuesday effect) and Italy. The second strongest day of the week effect is Friday, which is significant in 6 countries. The strongest month of the year effect in expected returns is by far September, being significant in 9 countries, with the single exception of Australia.<sup>5</sup> Surprisingly, the much discussed January effect is significant in the expected returns of only half of the ten countries.

In volatility, there is a substantially higher number of significant effects. The strongest day of the week effect is still Monday, which is statistically significant in 9 countries, all with 99% confidence. The only exception to the Monday volatility effect is Canada. The second strongest day of the week effect is still Friday, which is significant in 8 countries, all with at least 95% confidence. The two exceptions to the Friday volatility effect are the UK and the S&P 500. Interestingly, even though Australia has a Tuesday effect in expected returns, it still has a Monday effect in volatility. Among the month of the year volatility effects, October (as expected) and June (quite surprisingly) are significant in all 10 countries. The holiday volatility effect is significant in 7 of the 10 countries. It is important to recall that the strong September mean effect and the even stronger October volatility effect cannot be the product of the outliers due to the 9/11 attacks and the October 1987 Crash, respectively, since in assessing statistical significance we have excluded the two relevant weeks of data.

Many of the results in the literature are based on the seasonal behaviour of the DJIA because there is a larger sample of daily data available for this index (Lakonishok and Smidt (1988)). In addition, Tsiakas (2004) has found that there is very little seasonality in the expected returns of the S&P 500. It would, therefore, be interesting to conclude with the fourth set of results, which provides a comparative assessment of the seasonality in these two US indices. Not surprisingly, in expected returns, the Dow Jones has almost three times as many significant seasonal effects (11) compared to the S&P 500 (4). In volatility, the Dow Jones has 13 significant seasonal effects as opposed to 8 for the S&P 500. In short, all the calendar effects that are significant in the S&P 500 are also significant in the Dow Jones, but not vice versa.

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<sup>5</sup>This is not surprising as Australia is in the southern hemisphere.

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Table 1  
Seasonality in Expected Returns

	<i>Australia</i> (ASX all ord.)	<i>Canada</i> (TSX Comp)	<i>France</i> (CAC 40)	<i>Germany</i> (DAX 30)	<i>Hong Kong</i> (Hang Seng)	<i>Italy</i> (MIB 30)	<i>Japan</i> (Nikkei 225)	<i>UK</i> (FTSE 100)	<i>USA</i> (DJIA)	<i>USA</i> (S&P 500)
<i>Start</i>	1/1/1980	1/1/1969	1/1/1988	1/1/1965	1/1/1970	1/1/1993	1/1/1951	1/1/1984	1/1/1951	1/1/1969
<i>Obs</i> ( <i>T</i> )	6043	9131	4014	9746	8424	2761	13149	5040	13272	8816
<i>ALL</i>	0.031 (.011, .051)	0.023 (.008, .038)	0.031 (-.003, .067)	0.022 (.002, .042)	0.052 (.017, .087)	0.036 (-.012, .083)	0.035 (.019, .051)	0.030 (.005, .055)	0.028 (.015, .042)	0.027 (.009, .044)
<i>MON</i>	0.009 (-.041, .057)	-0.061*** (-.098, -.024)	-0.065** (-.154, .023)	-0.092*** (-.144, -.040)	-0.120*** (-.225, -.019)	-0.004 (-.129, .120)	0.001* (-.043, .043)	-0.048** (-.111, .014)	-0.061*** (-.098, -.026)	-0.052*** (-.101, -.004)
<i>TUE</i>	-0.041*** (-.099, .012)	-0.016** (-.051, .017)	0.058 (-.018, .132)	0.003 (-.039, .045)	0.004* (-.065, .074)	0.092 (-.016, .198)	0.003* (-.031, .037)	0.038 (-.020, .094)	0.038 (.009, .066)	0.036 (-.002, .074)
<i>WED</i>	0.058 (.018, .099)	0.060** (.027, .093)	0.012 (-.063, .088)	0.049 (.007, .093)	0.149*** (.077, .221)	0.023 (-.121, .075)	0.083*** (.048, .118)	0.032 (-.020, .083)	0.068*** (.041, .095)	0.077** (.040, .114)
<i>THU</i>	0.067 (.028, .108)	0.051* (.018, .084)	0.091* (.010, .172)	0.054* (.010, .097)	0.026 (-.046, .097)	0.066 (-.037, .167)	0.058 (.024, .093)	0.029 (-.026, .082)	0.027 (.001, .054)	0.017 (-.020, .055)
<i>FRI</i>	0.061* (.022, .100)	0.075*** (.044, .107)	0.057 (-.017, .131)	0.093*** (.050, .135)	0.193*** (.122, .264)	0.047 (-.054, .147)	0.031 (-.002, .064)	0.093** (.042, .145)	0.067*** (.040, .095)	0.051 (.013, .089)
<i>JAN</i>	0.075 (.010, .141)	0.076* (.022, .130)	0.026 (-.097, .149)	0.095** (.023, .167)	0.187** (.071, .303)	0.216** (.045, .386)	0.180*** (.121, .239)	0.066 (-.014, .146)	0.060 (.016, .104)	0.069 (.007, .134)
<i>FEB</i>	-0.036** (-.105, .031)	0.034 (-.014, .081)	0.108 (-.006, .221)	0.046 (-.019, .112)	0.189** (.062, .318)	-0.004 (-.162, .148)	0.027 (-.021, .074)	0.041 (-.036, .118)	0.004 (-.038, .045)	-0.001 (-.055, .055)
<i>MAR</i>	0.021 (-.045, .084)	0.022 (-.027, .069)	0.056 (-.064, .178)	0.049 (-.016, .114)	-0.092** (-.207, .025)	0.021 (-.146, .192)	0.029 (-.031, .089)	0.046 (-.039, .133)	0.044 (.003, .086)	0.045 (-.012, .101)
<i>APR</i>	0.170*** (.102, .237)	0.005 (-.042, .053)	0.152** (.042, .266)	0.047 (-.013, .106)	0.054 (-.070, .177)	0.245** (.066, .422)	0.067 (.007, .125)	0.086 (.008, .164)	0.086** (.043, .129)	0.049 (-.011, .109)
<i>MAY</i>	0.035 (-.021, .092)	0.033 (-.015, .082)	0.015 (-.092, .121)	-0.030* (-.093, .033)	0.110 (.004, .215)	-0.071* (-.211, .070)	0.013 (-.035, .060)	0.002 (-.074, .079)	-0.004* (-.046, .039)	0.023 (-.033, .079)
<i>JUNE</i>	-0.023** (-.075, .030)	-0.018** (-.057, .023)	-0.026 (-.129, .079)	0.007 (-.052, .065)	0.041 (-.077, .155)	-0.053 (-.189, .082)	0.055 (.003, .105)	-0.034** (-.104, .038)	-0.002* (-.040, .037)	0.019 (-.030, .067)
<i>JULY</i>	0.090* (.032, .147)	0.033 (-.015, .082)	-0.004 (-.125, .122)	0.058 (-.004, .121)	0.090 (-.011, .193)	0.028 (-.120, .174)	-0.009* (-.060, .042)	0.025 (-.062, .112)	0.049 (.008, .091)	-0.005 (-.063, .053)
<i>AUG</i>	0.050 (-.009, .108)	0.016 (-.033, .064)	-0.099** (-.236, .039)	-0.010 (-.080, -.060)	-0.080** (-.190, .027)	-0.048 (-.196, .101)	0.008 (-.048, .063)	0.025 (-.060, .111)	-0.011* (-.054, .033)	0.008 (-.054, .069)
<i>SEP</i>	-0.009 (-.069, .051)	-0.084*** (-.139, -.030)	-0.171** (-.317, -.027)	0.132*** (-.205, -.060)	-0.101** (-.216, .015)	0.190* (-.406, .021)	-0.029** (-.088, .030)	-0.082** (-.177, .013)	-0.063*** (-.112, -.013)	-0.062*** (-.128, .002)
<i>OCT</i>	-0.072 (-.208, .046)	-0.029 (-.106, .049)	0.144* (-.003, .288)	0.034 (-.055, .122)	0.121** (-.058, .284)	0.014 (-.205, .175)	0.009 (-.057, .075)	0.022 (-.101, .142)	0.021 (-.047, .085)	0.038 (-.051, .126)
<i>NOV</i>	0.003 (-.065, .072)	0.070* (.018, .120)	0.088 (-.024, .201)	0.042 (-.030, .112)	0.064** (-.187, .059)	0.154* (.006, .304)	0.040 (-.019, .098)	0.051 (-.027, .131)	0.076** (.030, .123)	0.058 (-.001, .119)
<i>DEC</i>	0.086* (.029, .144)	0.122*** (.076, .169)	0.100 (-.007, .205)	0.056 (-.012, .124)	0.196** (.086, .309)	0.180* (.013, .340)	0.049 (-.008, .106)	0.115** (.037, .189)	0.080** (.040, .120)	0.077* (.022, .131)
<i>HOL</i>	0.157** (.044, .270)	0.051 (-.041, .145)	0.146 (-.069, .360)	0.152** (.027, .280)	0.079 (-.237, .358)	0.261 (-.072, .595)	0.110 (.003, .217)	-0.036 (-.251, .156)	0.092* (.022, .163)	0.022 (-.086, .129)

The entries are the means of the daily percent returns  $R_t$ . The numbers in parenthesis are the 5% and 95% quantiles for the means generated by 10,000 bootstrap samples. The superscripts \*, \*\*, and \*\*\* indicate that the relevant one-sided null hypothesis is rejected at significance level  $\alpha = 10\%$ ,  $\alpha = 5\%$ , and  $\alpha = 1\%$ , respectively. The end date for all indices is December 31, 2003.

**Table 2**  
**Seasonality in Volatility**

	<i>Australia</i> (ASX all ord.)	<i>Canada</i> (TSX Comp)	<i>France</i> (CAC 40)	<i>Germany</i> (DAX 30)	<i>Hong Kong</i> (Hang Seng)	<i>Italy</i> (MIB 30)	<i>Japan</i> (Nikkei 225)	<i>UK</i> (FTSE 100)	<i>USA</i> (DJIA)	<i>USA</i> (S&P 500)
<i>Start</i>	1/1/1980	1/1/1969	1/1/1988	1/1/1965	1/1/1970	1/1/1993	1/1/1951	1/1/1984	1/1/1951	1/1/1969
<i>Obs</i> ( <i>T</i> )	6043	9131	4014	9746	8424	2761	13149	5040	13272	8816
<i>ALL</i>	0.652 (.638, .668)	0.579 (.568, .590)	1.002 (.978, 1.025)	0.848 (.834, .862)	1.276 (1.250, 1.302)	1.153 (1.122, 1.184)	0.779 (.767, .790)	0.775 (.758, .792)	0.646 (.637, .656)	0.711 (.698, .723)
<i>MON</i>	0.717*** (.683, .752)	0.599 (.571, .627)	1.093*** (1.032, 1.156)	0.922*** (.884, .961)	1.559*** (1.479, 1.641)	1.327*** (1.246, 1.408)	0.942*** (.911, .973)	0.830*** (.785, .876)	0.709*** (.682, .738)	0.774*** (.737, .812)
<i>TUE</i>	0.649 (.607, .700)	0.596 (.571, .620)	0.953** (.902, 1.006)	0.844 (.814, .874)	1.197*** (1.147, 1.249)	1.133 (1.065, 1.204)	0.730*** (.706, .755)	0.769 (.730, .811)	0.652 (.632, .671)	0.723 (.697, .750)
<i>WED</i>	0.649 (.622, .677)	0.581 (.556, .605)	1.090 (.932, 1.029)	0.852 (.823, .880)	1.206** (1.154, 1.260)	1.096* (1.033, 1.160)	0.766 (.741, .791)	0.744** (.711, .779)	0.632* (.612, .652)	0.679*** (.654, .705)
<i>THU</i>	0.632 (.605, .659)	0.576 (.552, .599)	1.039* (.984, 1.095)	0.815** (.784, .847)	1.235* (1.185, 1.285)	1.127 (1.060, 1.195)	0.747** (.722, .773)	0.768 (.731, .804)	0.620*** (.601, .640)	0.684** (.658, .710)
<i>FRI</i>	0.617*** (.590, .644)	0.545*** (.522, .569)	0.947** (.899, .997)	0.808*** (.778, .838)	1.199*** (1.149, 1.252)	1.086** (1.021, 1.155)	0.711*** (.688, .735)	0.770 (.735, .806)	0.621** (.602, .641)	0.696 (.670, .722)
<i>JAN</i>	0.677* (.637, .719)	0.638*** (.600, .678)	1.073* (.997, 1.154)	0.907** (.858, .959)	1.295 (1.213, 1.381)	1.228 (1.122, 1.140)	0.812* (.770, .855)	0.779 (.729, .831)	0.667* (.636, .698)	0.739 (.696, .783)
<i>FEB</i>	0.690** (.648, .733)	0.538** (.504, .572)	1.016 (.951, 1.082)	0.844 (.802, .887)	1.319 (1.228, 1.414)	1.130 (1.040, 1.226)	0.683*** (.650, .712)	0.732 (.683, .781)	0.619* (.593, .646)	0.681 (.646, .717)
<i>MAR</i>	0.671 (.628, .715)	0.555 (.521, .592)	1.016 (.936, 1.099)	0.825 (.780, .870)	1.326 (1.243, 1.412)	1.261** (1.159, 1.366)	0.826** (.783, .873)	0.803 (.748, .860)	0.623 (.594, .653)	0.680 (.642, .719)
<i>APR</i>	0.663 (.618, .711)	0.521*** (.487, .557)	0.945 (.873, 1.019)	0.747*** (.708, .789)	1.255 (1.167, 1.346)	1.221 (1.104, 1.338)	0.804 (.762, .847)	0.713** (.664, .765)	0.632 (.602, .661)	0.706 (.666, .747)
<i>MAY</i>	0.607** (.572, .644)	0.569 (.534, .605)	0.878*** (.808, .948)	0.790** (.749, .833)	1.186** (1.108, 1.267)	0.987*** (.895, 1.083)	0.696*** (.663, .730)	0.714** (.666, .764)	0.627 (.598, .656)	0.682 (.645, .720)
<i>JUNE</i>	0.544*** (.511, .578)	0.491*** (.464, .517)	0.897* (.833, .961)	0.767*** (.730, .806)	1.155*** (1.071, 1.249)	0.982*** (.899, 1.070)	0.735** (.701, .770)	0.694*** (.652, .738)	0.596*** (.571, .621)	0.629*** (.597, .660)
<i>JULY</i>	0.616* (.581, .653)	0.554 (.519, .589)	0.980 (.897, 1.069)	0.830 (.787, .874)	1.148*** (1.075, 1.224)	1.045** (.951, 1.143)	0.738** (.703, .773)	0.790 (.731, .854)	0.612** (.584, .640)	0.687 (.648, .727)
<i>AUG</i>	0.616* (.577, .655)	0.543* (.508, .581)	1.080* (.986, 1.182)	0.835 (.785, .887)	1.198* (1.122, 1.276)	1.056* (.960, 1.154)	0.767 (.726, .809)	0.763 (.706, .823)	0.635 (.604, .667)	0.715 (.672, .761)
<i>SEP</i>	0.644 (.603, .685)	0.600 (.561, .641)	1.112* (1.011, 1.219)	0.883 (.831, .937)	1.315 (1.230, 1.402)	1.413*** (1.267, 1.568)	0.792 (.751, .835)	0.851* (.784, .920)	0.683** (.648, .719)	0.742* (.696, .789)
<i>OCT</i>	0.844*** (.743, .968)	0.750*** (.690, .813)	1.191*** (1.092, 1.296)	1.013*** (.946, 1.085)	1.498** (1.366, 1.647)	1.133*** (1.204, 1.464)	0.876*** (.827, .928)	0.994*** (.903, 1.089)	0.772*** (.720, .831)	0.864*** (.795, .942)
<i>NOV</i>	0.662 (.612, .714)	0.634*** (.599, .670)	0.907** (.829, 0.983)	0.880 (.830, .929)	1.370** (1.281, 1.461)	1.046** (.951, 1.142)	0.828** (.787, .871)	0.730 (.679, .783)	0.695*** (.664, .728)	0.730 (.691, .772)
<i>DEC</i>	0.586*** (.549, .624)	0.550 (.517, .583)	0.896*** (.828, .965)	0.829 (.783, .875)	1.253 (1.174, 1.336)	1.124 (1.019, 1.229)	0.785 (.744, .826)	0.715** (.667, .765)	0.592*** (.564, .620)	0.664** (.629, .702)
<i>HOL</i>	0.682 (.610, .755)	0.748*** (.683, .818)	1.021 (.873, 1.180)	0.944** (.852, 1.040)	1.755*** (1.527, 2.033)	1.423** (1.210, 1.646)	0.976*** (.901, 1.053)	0.861 (.713, 1.036)	0.703** (.655, .755)	0.814** (.741, .889)

The entries are the means of the daily absolute percent returns  $|R_t|$ . The numbers in parenthesis are the 5% and 95% quantiles for the means generated by 10,000 bootstrap samples. The superscripts \*, \*\*, and \*\*\* indicate that the relevant one-sided null hypothesis is rejected at significance level  $\alpha = 10\%$ ,  $\alpha = 5\%$ , and  $\alpha = 1\%$ , respectively. The end date for all indices is December 31, 2003.

**List of other working papers:**

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14. Basel Awartani, Valentina Corradi and Walter Distaso, Testing and Modelling Market Microstructure Effects with an Application to the Dow Jones Industrial Average, WP04-06
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19. Abhay Abhayankar, Lucio Sarno and Giorgio Valente, Exchange Rates and Fundamentals: Evidence on the Economic Value of Predictability, WP04-01

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