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Abstract: This paper studies tests of calendar effects in equity returns. It is necessary to control for all possible calendar effects to avoid spurious results. The authors contribute to the calendar effects literature and its significance with a test for calendar-specific anomalies that conditions on the nuisance of possible calendar effects. Thus, their approach to test for calendar effects produces robust data-mining results. Unfortunately, attempts to control for a large number of possible calendar effects have the downside of diminishing the power of the test, making it more difficult to detect actual anomalies. The authors show that our test achieves good power properties because it exploits the correlation structure of (excess) returns specific to the calendar effect being studied. We implement the test with bootstrap methods and apply it to stock indices from Denmark, France, Germany, Hong Kong, Italy, Japan, Norway, Sweden, the United Kingdom, and the United States. Bootstrap *p*-values reveal that calendar effects are significant for returns in most of these equity markets, but end-of-the-year effects are predominant. It also appears that, beginning in the late 1980s, calendar effects have diminished except in small-cap stock indices.

JEL classification: C12, C22, G14

Key words: calendar effects, data mining, significance test

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1. Introduction

Calendar effects are anomalies in stock returns that relate to the calendar, such as the day-of-the-week, the month-of-the-year, or holidays. Two leading examples are the Monday effect and the January effect. Economically small calendar specific anomalies need not violate no-arbitrage conditions, but the reason for their existence, if they are indeed real, is intriguing.

Much effort continues to be devoted to research on calendar effects. Yet, the literature remains open about the significance of these effects for asset markets. One reason is that the discovery of specific calendar effects could be a result of data mining. Even if there are no calendar anomalies, an extensive search – or data mining – exercise across a large number of possible calendar effects can yield significant results of an "anomaly" by pure chance.[1] Another reason data mining is a plausible explanation is that theoretical explanations have been suggested only subsequent to the empirical "discovery" of the anomalies.

The universe of possible calendar effects is not given *ex ante* from economic theory. Rather, the number of different calendar effects that potentially could be analyzed is only bounded by the creativity of interested researchers. Since an extensive empirical analysis of calendar effects is likely to suffer from data mining problems, it is therefore surprising that there is little work that aims to limit the problem. The reason might be that an explicit control for data mining is costly because it is less likely that a true anomaly will be found to be significant. The best remedy for preserving the ability to detect true anomalies, is to employ a test for calendar effects that is as powerful as possible. A robust test for a specific calendar effect needs to condition on the nuisance of all conceivable effects, unless one is willing to violate basic principles for inference.

We construct a powerful test to evaluate the significance of calendar effects in this paper. This test combines and incorporates the information from all calendar anomalies to achieve good power properties without compromising test size by exploiting the correlation structure that is specific to this testing problem. The new test is asymptotically F-distributed. However, we implement a bootstrap version of the test that diminishes possible small sample problems.

Our new test of calendar effects can be interpreted as a generalized-F test. It is related to some recent methods for comparing forecasting models that have been proposed by White (2000) and Hansen (2001), who builds on results of Diebold & Mariano (1995) and West (1996). These tests exploit indirectly the sample information about the dependence across forecasting models, which are being compared. This is analogous to our generalized-F test because it depends on the covariance of returns given the calendar effects being studied.

Our test is also closely related to a test West & Cho (1995) develop to compare the predictive ability

[1] Evidence for calendar effects tests is subject to the criticism that "the data has been tortured until it confessed". Merton (1987), Lo & MacKinlay (1990), and Fama (1991) contain useful discussions about data mining. Schwert (2003) gives a recent survey on the subject in relation to anomalies in returns, including the calendar specific anomalies.

of volatility models. Their test applies to series with the same length (same number of observations), so it is not directly applicable to our problem, where we have an unequal number of observations for the different calendar effects. A major difference between our generalized-F test and West & Cho's is that we employ bootstrap methods to evaluate the significance of the statistics, whereas they invoke asymptotic distributional results.

An alternative method to control for the universe of possible effects is a Bonferroni bound type test. The Bonferroni bound ignores the correlation structure among the objects, which results in a more conservative, and therefore less powerful test. Our test dominates Bonferroni bound methods in terms of power because it accounts for dependence across calendar effects. This avoids conservative approximations.

Alternatively, one can control for data mining by confronting anomalies found in one data set, with a different data sets. This approach has been suggested by several authors, for example Schwert (2003). However, there are two reasons this approach cannot entirely remove data mining bias: (1) if the two data sets were totally independent, then it remains possible to *mine* the two data sets simultaneously to find calendar effects that appear to be significant in both samples; and (2) if the data sets overlap in time, the data sets are likely to be dependent. The returns on the Dow-Jones index and the S&P 500 index are clearly correlated, as are indices across countries. Therefore, evaluating results found in one equity index on a different equity index cannot be viewed as an independent experiment.

Extensive references to the vast calendar effects literature can be found in Dimson (1988), Keim & Ziemba (2000), and Sullivan, Timmermann & White (2001) (STW).[2] Most papers that address the issue of data mining apply Bonferroni bound methods or cross country studies to evaluate the significance of calendar effects. An exception is STW because they apply the *reality check* of White (2000) in their analysis. Although the paper by STW is closely related to our paper, our analysis differs from STW in three important ways.

First, we define the null hypothesis that returns are identical across all calendar dating schemes (e.g., no calendar anomalies of any kind) and test it using either expected returns or standardized returns. In contrast, STW analyze the ability of a collection of calendar-based trading rules to yield higher returns than a buy-and-hold strategy. Since their set of trading rules consist of short, neutral, or long trading strategies based on calendar-based rules, our approach is better suited to test jointly the significance of calendar effects. For example, the *January effect* implies expected returns are higher in January than the rest of the year. The January effect does not imply that excess returns are possible by taking a long position in January and a short or neutral position the rest of the year. Rather, a January effect test needs to compare the daily average return to the daily average return of the specific calendar effect under consideration.

Another feature that distinguishes our calendar effects test from STW is the dimension of the "ob-

[2]The interested reader should see these papers for additional references. Section 2 of this paper also contains further references.

jects" that are being compared. Compared to the 9,452 calendar effects-based trading rules STW examine, most studies of calendar effects in stock returns analyze far fewer and fail to condition on the universe of calendar effects. Our empirical exercise includes 181 calendar effects that is most, if not all, of the relevant ones. Our full universe of calendar effects covers almost all the anomalies STW use to define their 9,452 calendar-based equity trading rules. Thus, our generalized-F test enjoys a power advantage relative to STW because an increase in the dimension of the nuisance anomalies reduces the power of calendar effects tests which makes it harder to detect actual anomalies.

The third difference between our approach and STW is the choice of statistical test. The hypothesis that there are no calendar specific anomalies is a two-sided hypothesis of multiple equalities. Our test is designed for this hypothesis. STW apply the reality check of White (2000), a test that is designed to test one-sided hypotheses of multiple inequalities, to select the most profitable calendar effects-based trading strategy. Testing multiple inequalities involves complications discussed in Hansen (2001). Most importantly, Hansen (2003) points out that if there are non-binding inequalities, the reality check is known to be conservative and lack power. Thus, a poor trading rule can distort the reality check and erode its power. Interestingly, Sullivan et al. (2001, Figure 2) show that the reality check's p-value jumps from about 0.33 to about 0.52 at a point where the worse performing models are included in the analysis (around model 8,300). Since the large jump in the p-value is most likely caused by the distortion that poor models have on this test, the correct p-value is likely to be smaller than the 0.554 STW obtain from the full sample. See Hansen & Lunde (2004) for an empirical application that accentuate the reality check's power problems.

We apply our generalized-F test to evaluate the significance of calendar effects to returns on stock indices from ten countries. These countries are: Denmark, France, Germany, Hong Kong, Italy, Japan, Norway, Sweden, Japan, the UK, and the US. Our study covers three indices of each country, except for Denmark, Hong Kong, and Sweden, where one, one, and two indices are examined, respectively. An analysis of the significance of calendar effects involves a subjective choice of the universe of calendar effects to be reviewed. Different choices can lead to different results, e.g., the January effect may be significant in a small universe, but insignificant in a larger universe. We study a total of 181 possible calendar effects, where our choices are guided by the calendar effects analyzed in the extant literature. Although it is possible there are other effects, we believe the universe considered is rich enough to include all relevant calendar effects.

Application of our generalized-F test to stock returns from ten countries provides evidence that calendar effects are statistically significant. The largest anomalies are typically produced by end-of-year effects. The evidence in favor of calendar effects is in most cases only marginally different when the analysis is based on standardized returns. The robustness of these finding is assessed in a subsample analysis. This analysis reveal that for large-cap and market indices the significance of calendar effects is not an economically important phenomenon because in most cases significant effects only occurred in a short interval of time. In contrast, the significance of calendar effects in small-cap stock indices appears to be more robust across subsamples. We also examine the robustness of our test of calendar effects by shrinking the universes to include 17 and 5 calendar effects, respectively.

The rest of the paper is organized as follows. Section 2 describes calendar effects. We analyze the statistical properties of the problem and derive the generalized-F test in section 3. Section 4 describes the data. Empirical results are presented in Section 5. Section 6 concludes. The appendix contains technical background and a few proofs.

2. Calendar Effects

This section presents the universe of possible calendar effects that we consider in our analysis. We often write "calendar effect" as short for "possible calendar effect". Hence, "calendar effect" need not imply that there is an anomaly associated with the "possible calendar effect", only the alternative hypothesis that it may exist.

Day-of-the-week: This effect states that expected return, or standardized return, are not the same for all weekdays. This effect was first documented by Osborne (1962), and subsequently analyzed by Cross (1973), French (1980), Gibbons & Hess (1981), Lakonishok & Levi (1980), Smirlock & Starks (1983), Keim & Stambaugh (1983), Rogalski (1984) and Jaffe & Westerfield (1985). In our universe, we include the five day-of-the-week calendar effects: Monday, Tuesday, Wednesday, Thursday, and Friday. The Friday effect considers the return from the preceding trading day's closing price (typically a Thursday) to Friday's closing price, and similarly for the other days. The returns on Mondays are found to be negative in many studies, which is commonly referred to as the weekend-effect.

Month-of-the-year: This includes the January effect that was first reported in Wachtel (1942). The January effect is perhaps the most famous calendar effects. Haugen & Lakonishok (1988) devote their book to the study of the January effect. We study all 12 month-of-the-year effects.

Weekday-of-the-month: We interact day-of-the-week with month-of-the-year, (Mondays in December, Wednesdays in June, etc.) to add 60 ($= 5 \times 12$) calendar effects to our universe.

Week-of-the-month: We use the STW definition of the week-of-the-month effect. *Weeks* are constructed such that the first trading day of the month defines the first day of the first week. If the first trading day is a Thursday, the first week consists of two days (a Thursday and a Friday). The last week-of-the-month is defined similarly, which means there will often be fewer than five days in a week. Week-of-the-month effects are discussed in Ariel (1987), Lakonishok & Smidt (1988), and Wang, Li & Erickson (1997). This adds 65 ($= 5 + 5 \times 12$) effects to our universe.

Semi-month: Our definition of semi-months follows that of Lakonishok & Smidt (1988).[3] The trading days are partitioned into two sets. The first set consists of trading days for which the date is 15 or less, and the other set contains dates that are 16 or higher. By interacting these two semi-month-of-the-year effects with month-of-the-year effects we obtain another 24 semi-months that adds another 26 ($= 2 + 2 \times 12$) effects to our universe.

Turn-of-the-month: We add eight effects that relate to turn-of-the-month to our universe: one for each of the last four trading days of the month and one for each of the first four trading days of the month. This type of calendar effects is discussed in Ariel (1987), Lakonishok & Smidt (1988), and Hensel & Ziemba (1996).

End-of-Year: We group the days at the end of December into three calendar effect, which follows Lakonishok & Smidt (1988):

1. Pre-Christmas from mid-December: the trading days from mid December up to, but no including, the last trading day before Christmas, (e.g.,December 15th – 23rd).
2. Between Christmas and New Year: from the first trading day after Christmas up to, but not including, the last trading day before New Year's Day.
3. Pre-Christmas and New Year: the last trading day before Christmas, and the last trading day before New Year's Day.

Holiday-effects: We classify the pre- and post-holiday effect as in STW. Pre-holidays are those trading days which directly precede a day where the market is closed, but would normally be open for trading. Post-holidays are those trading days that follow pre-holidays. This adds two calendar effects to our universe.

Table 1 gives a summary of these calendar effects and their mnemonics.

TABLE 1 ABOUT HERE

3. Statistical Analysis of Calendar Effects

This section describes the notation and constructs the test for calendar specific anomalies. Let $r_t \equiv \log P_t - \log P_{t-1}$ be the continuously compounded returns on a stock index, where P_t denote the closing price of the index on day t, (dividends are assumed to be accumulated in P_t). The expected return and the variance of r_t are denoted by $\mu_t \equiv E(r_t)$ and $\sigma_t^2 \equiv \text{var}(r_t)$, respectively, $t = 1, \ldots, n$, and throughout we assume that the sequence of returns are uncorrelated between dates t and s, $s \neq t$, i.e., $\text{cov}(r_s, r_t) = 0$.

[3] The definition of semi-months of Lakonishok & Smidt (1988, p.407-8) differs slightly from that of Ariel (1987).

3.1. Calendar Sets

It is convenient to attach each calender effect with a set, $\mathcal{S}_{(k)}$, where the subscripts in parentheses refer to different calendar effects, $k = 0, 1, \ldots, m$, and subscripts without parentheses refer to time, $t = 1, \ldots, n$. The number of calendar effects that are being considered is m and the number of elements in $\mathcal{S}_{(k)}$ is denoted by $n_{(k)}$. For example, $k = 1$ corresponds to the Monday effect in our analysis, so $\mathcal{S}_{(1)}$ contains all the ts that are Mondays, and $n_{(1)}$ is the number of Mondays in the sample. The full sample is associated with the set $\mathcal{S}_{(0)} \equiv \{1, \ldots, n\}$.

The average return of calendar effect k, is given by $\bar{r}_{(k)} \equiv n_{(k)}^{-1} \sum_{t \in \mathcal{S}_{(k)}} r_t$, and its expected value is denoted by $\xi_{(k)} \equiv E(\bar{r}_{(k)}) = n_{(k)}^{-1} \sum_{t \in \mathcal{S}_{(k)}} \mu_t$. Similarly, the average variance of calendar effect, k, is given by $\bar{\omega}^2_{(k),n} \equiv n_{(k)}^{-1} \sum_{t \in \mathcal{S}_{(k)}} \sigma_t^2$, and the expected standardized return is defined by $\rho_{(k)} \equiv \xi_{(k)}/\bar{\omega}_{(k),n}$, $k = 1, \ldots, m$.

3.2. Hypotheses of Interest

We consider two hypotheses. The first hypothesis is that there are *no calendar specific anomalies in returns*, which can be formulated parametrically as,

$$H_0 : \xi_{(0)} = \cdots = \xi_{(m)}.$$

The hypothesis, H_0, may not be supported by the data if, for example, there is a risk-premium from holding assets from Friday to Monday. Therefore, we also consider the hypothesis that there are *no calendar specific anomalies in standardized returns*, which can be expressed as

$$H_0' : \rho_{(0)} = \cdots = \rho_{(m)}.$$

3.3. Covariance Structure and Asymptotic Results

Define the covariance matrix of the vector $\bar{\mathbf{r}} = (\bar{r}_{(0)}, \bar{r}_{(1)}, \ldots, \bar{r}_{(m)})'$ of average returns for the m calendar effects to be $\mathbf{\Sigma}_n$, such that the $(k+1, l+1)$ element of $\mathbf{\Sigma}_n$ is given by $\text{cov}(\bar{r}_{(k)}, \bar{r}_{(l)})$, $k, l = 0, \ldots, m$. Utilizing that $\{r_t\}$ is assumed to be uncorrelated, and $\text{cov}(r_t, r_s) = \sigma_t^2$ if $t = s$, and zero otherwise, it is straight forward to provide an expression for the elements of $\mathbf{\Sigma}_n$. We formulate this in the following lemma:

Lemma 1 *The elements of $\mathbf{\Sigma}_n$ are given by*

$$\text{cov}(\bar{r}_{(k)}, \bar{r}_{(l)}) = n_{(k)}^{-1} n_{(l)}^{-1} \sum_{t \in \mathcal{S}_{(k)} \cap \mathcal{S}_{(l)}} \sigma_t^2, \qquad \textit{for } k, l = 0, \ldots, m.$$

Note that $\mathbf{\Sigma}_n$ needs to be multiplied by n in order to converge to a nontrivial limit, and that the diagonal elements of $\mathbf{\Sigma}_n$ (those for which $k = l$) are simply given by

$$\text{var}(\bar{r}_{(k)}) = n_{(k)}^{-2} \sum_{t \in \mathcal{S}_{(k)}} \sigma_t^2, \qquad \text{for } k = 0, \ldots, m.$$

Primitive assumptions (Assumption A.1 in appendix) ensure that a law of large numbers and a central limit theorem apply (Theorem A.1 in appendix), such that we have

$$\bar{\mathbf{r}} \overset{p}{\to} \boldsymbol{\xi}$$
$$\sqrt{n}\,(\bar{\mathbf{r}} - \boldsymbol{\xi}) \overset{d}{\to} N_{m+1}(\mathbf{0}, n\boldsymbol{\Sigma}_n),$$

where $\boldsymbol{\xi} = (\xi_{(0)}, \xi_{(1)}, \ldots, \xi_{(m)})'$.

Our new test for calendar anomalies is a simple χ^2-test. The only complication that arises is that $\boldsymbol{\Sigma}_n$ may be singular. The solution to the potential singularity is given in the following well-known result.

Lemma 2 *Let* $\mathbf{X}$ *be a normally distributed vector with mean* $\boldsymbol{\lambda}$ *and covariance matrix* $\boldsymbol{\Omega}$. *If* $\boldsymbol{\lambda} = \mathbf{B}\boldsymbol{\theta}$, *where* $\mathbf{B}$ *is a known matrix with full column rank and* $\boldsymbol{\theta}$ *a vector with proper dimension, then*

$$T = \mathbf{X}'\mathbf{B}_\perp(\mathbf{B}_\perp'\boldsymbol{\Omega}\mathbf{B}_\perp)^+\mathbf{B}_\perp'\mathbf{X}, \tag{1}$$

is χ^2*-distributed with* $f = \mathrm{rank}(\mathbf{B}_\perp'\boldsymbol{\Omega}\mathbf{B}_\perp)$ *degrees of freedom, where* $\mathbf{B}_\perp$ *is the orthogonal matrix to* $\mathbf{B}$ *and where* $(\mathbf{B}_\perp'\boldsymbol{\Omega}\mathbf{B}_\perp)^+$ *is the Moore-Penrose inverse of* $\mathbf{B}_\perp'\boldsymbol{\Omega}\mathbf{B}_\perp$.[4]

The joint hypotheses of no calendar effects is $H_0 : \boldsymbol{\xi} = \boldsymbol{\iota}\theta_{\boldsymbol{\xi}}$ and $H_0' : \boldsymbol{\rho} = \boldsymbol{\iota}\theta_{\boldsymbol{\rho}}$, where $\boldsymbol{\iota}$ is a vector with $m + 1$ ones, and where $\theta_{\boldsymbol{\xi}}$ and $\theta_{\boldsymbol{\rho}}$ are unknown scalar parameters. Equation (1) can be used to construct test statistics for the hypotheses H_0 and H_0', where the relevant covariance matrix (to use in place of $\boldsymbol{\Omega}$ in (1)) is $\boldsymbol{\Sigma}_n$ under the hypothesis H_0, and $\boldsymbol{\Omega}_n = \boldsymbol{\Lambda}_n^{-1}\boldsymbol{\Sigma}_n\boldsymbol{\Lambda}_n^{-1}$ under the hypothesis, H_0', where $\boldsymbol{\Lambda}_n = \mathrm{diag}(\bar{\omega}_{(0),n}, \ldots, \bar{\omega}_{(m),n})$. Note that Λ_n is the matrix with standard deviations that define the expected standardized returns ($\boldsymbol{\rho} = \boldsymbol{\Lambda}_n^{-1}\boldsymbol{\xi}$).

3.4. *Estimation and F-Tests for Calendar Specific Anomalies*

The parameters can be estimated by

$$\hat{\xi}_{(k)} = \bar{r}_{(k)}, \qquad \hat{\omega}^2_{(k),n} = n_{(k)}^{-1}\sum_{t=\mathcal{S}_{(k)}}(r_t - \bar{r}_{(k)})^2, \qquad \text{and} \qquad \hat{\rho}_{(k)} = \hat{\xi}_{(k)}/\hat{\omega}_{(k),n}$$

for $k = 0, \ldots, m$.

The common value for expected returns is estimated by $\hat{\theta}_{\boldsymbol{\xi}} = (\boldsymbol{\iota}'\boldsymbol{\Sigma}_{\mathbf{n}}^+\boldsymbol{\iota})^{-1}\boldsymbol{\iota}'\boldsymbol{\Sigma}_n^+\bar{\mathbf{r}}$, (this number actually equals the sample average of returns $\bar{r}_{(0)}$), and the common value for standardized expected returns is estimated by $\hat{\theta}_{\boldsymbol{\rho}} = (\boldsymbol{\iota}'\boldsymbol{\Omega}_{\mathbf{n}}^+\boldsymbol{\iota})^{-1}\boldsymbol{\iota}'\boldsymbol{\Omega}_n^+\hat{\boldsymbol{\rho}}$, where $\hat{\rho}_{(k)} = \bar{r}_{(k)}/\omega_{(k)}$, $k = 0, \ldots, m$.

The estimation of the covariance matrices, $\boldsymbol{\Sigma}_n$ and $\boldsymbol{\Omega}_n$, is also relatively simple. First we define the $n \times (m + 1)$ matrix $\mathbf{A}$, with elements

$$A_{t,(k)} = \begin{cases} n_{(k)}^{-1} & \text{if } t \in \mathcal{S}_{(k)} \\ 0 & \text{otherwise,} \end{cases} \qquad t = 1, \ldots, n, \quad k = 0, \ldots, m,$$

[4]The orthogonal matrix, $\mathbf{B}_\perp$, to a matrix, $\mathbf{B}$, with full column rank, satisfies $\mathbf{B}_\perp'\mathbf{B} = \mathbf{0}$ and $(\mathbf{B}, \mathbf{B}_\perp)$ is a squared full rank matrix. The Moore-Penrose inverse, $\mathbf{A}^+$, of a symmetric matrix, $\mathbf{A}$, is defined by the identities: $\mathbf{A}\mathbf{A}^+\mathbf{A} = \mathbf{A}$ and $\mathbf{A}^+\mathbf{A} = (\mathbf{A}^+\mathbf{A})'$.

Note that each column of $\mathbf{A} = (\mathbf{a}_{(0)}, \ldots, \mathbf{a}_{(m)})$ sum to one, and that $\mathbf{a}'_{(k)}(r_1, \ldots, r_n)' = \bar{r}_{(k)}$, where $\mathbf{a}_{(k)}$ is the $(k+1)$th column of $\mathbf{A}$. From Lemma 1 we have $\boldsymbol{\Sigma}_n = \mathbf{A}'\text{diag}(\sigma_1^2, \ldots, \sigma_n^2)\mathbf{A}$, which shows that it is simple to estimate $\boldsymbol{\Sigma}_n$ given an estimate of $(\sigma_1^2, \ldots, \sigma_n^2)$. In the special case, where σ_t^2 is assumed to be constant, the expression simplifies to $\boldsymbol{\Sigma}_n = \sigma^2\mathbf{A}'\mathbf{A}$, and one can use the estimator $\hat{\sigma}^2 = \frac{1}{n-1}\sum_{t=1}^n \left(r_t - \bar{r}_{(0)}\right)^2$.

In the general case, where μ_t and σ_t^2 may depend on weekday, month, etc., the estimation of $\boldsymbol{\Sigma}_n$ is slightly more complicated. Let the sample be divided into q distinct groups, and assume that within each of these groups both μ_t and σ_t^2 are constant. Define the $n \times q$ matrix, $\mathbf{J}$, of zeros and ones where each column is associated with a group, such that $J_{t,i} = 1$ if day t is in group i (and zero otherwise). Note that each row of $\mathbf{J}$ has precisely one non-zero entry. Within each group, we estimate the mean by

$$\bar{r}^{(i)} = \frac{\sum_{t=1}^n J_{t,i} r_t}{n^{(i)}}, \qquad i = 1, \ldots, q,$$

where $n^{(i)} \equiv \sum_{t=1}^n J_{t,i}$ is the number of ts in group i, and the variance is estimated by

$$\hat{\sigma}^2(i) = \frac{\sum_{t=1}^n J_{t,i}(r_t - \bar{r}^{(i)})^2}{n^{(i)} - 1}, \qquad i = 1, \ldots, q.$$

These estimates can be mapped into the estimates $\hat{\sigma}_t^2 = \sum_{i=1}^q J_{t,i}\hat{\sigma}^2(i)$, $t = 1, \ldots, n$, which translates into the estimate of $\boldsymbol{\Sigma}_n$, $\hat{\boldsymbol{\Sigma}}_n = \mathbf{A}'\text{diag}(\hat{\sigma}_1^2, \ldots, \hat{\sigma}_n^2)\mathbf{A}$. The estimate of $\boldsymbol{\Omega}_n$ is then given by $\hat{\boldsymbol{\Omega}}_n = \hat{\boldsymbol{\Lambda}}_n^{-1}\hat{\boldsymbol{\Sigma}}_n\hat{\boldsymbol{\Lambda}}_n^{-1}$, where $\hat{\boldsymbol{\Lambda}}_n = \text{diag}(\hat{\omega}_{(0),n}, \ldots, \hat{\omega}_{(m),n})$.

This leads to the following test statistics,

$$F_{\boldsymbol{\xi}} = \hat{\boldsymbol{\xi}}'\boldsymbol{\iota}_\perp(\boldsymbol{\iota}_\perp'\hat{\boldsymbol{\Sigma}}_n\boldsymbol{\iota}_\perp)^+\boldsymbol{\iota}_\perp'\hat{\boldsymbol{\xi}}/q_\xi, \tag{2}$$

which is asymptotically $F(q_\xi, \infty)$-distributed under H_0, and

$$F_{\boldsymbol{\rho}} = \hat{\boldsymbol{\rho}}'\boldsymbol{\iota}_\perp(\boldsymbol{\iota}_\perp'\hat{\boldsymbol{\Omega}}_n\boldsymbol{\iota}_\perp)^+\boldsymbol{\iota}_\perp'\hat{\boldsymbol{\rho}}/q_\rho, \tag{3}$$

which is asymptotically $F(q_\rho, \infty)$-distributed under H_0'. The degrees-of-freedom, q_ξ and q_ρ, equals the rank of $\boldsymbol{\iota}_\perp'\hat{\boldsymbol{\Sigma}}_n\boldsymbol{\iota}_\perp$ and $\boldsymbol{\iota}_\perp'\hat{\boldsymbol{\Omega}}_n\boldsymbol{\iota}_\perp$, respectively. Here, $\boldsymbol{\iota}_\perp$ is an $(m+1) \times m$ matrix that is orthogonal to $\boldsymbol{\iota}$, (the vector of ones). This matrix is not unique, however, any choice of $\boldsymbol{\iota}_\perp$ will produce the same value of the test statistic. A particular choice of $\boldsymbol{\iota}_\perp$ is given by the matrix that has ones in, and right below, the diagonal and zeroes, elsewhere, i.e., $\iota_{\perp hh} = 1$, and $\iota_{\perp h+1,h} = -1$ for $h = 1, \ldots, m$, otherwise $\iota_{\perp h,g} = 0$.

In practice, one must make a choice for the grouping of dates, where the unconditional mean and variance is constant *within* each group. The assumption of homoskedastic returns is accommodated by selection of a single group that contains all dates. In our analysis, we use $q = 60$ groups that are the combinations of weekdays and months, e.g., one group contains all t s that are Mondays in January.[5]

[5] The Dow-Jones data contains Saturdays in the first part of the sample. So in our full sample analysis of the DJIA returns, we add an additional group that contains all the ts that are Saturdays.

When σ_t^2 is assumed to be constant, the test statistic, F_{ξ}, is identical to a standard F-statistics that can be obtained from the regression of r_t on the dummy-variables, $1_{\{t \in \mathcal{S}_{(k)}\}}$, $k = 1, \ldots, m$. The relevant F-statistic is the one that tests that all regression parameters, excluding the constant, are zero. When σ_t^2 is non-constant, the test statistic F_{ξ} can be calculated using a GLS estimator.[6]. Under the H_0', the test statistic F_{ρ} does not have a simple relation to standard regression statistics.

The F_{ξ} test statistic is closely related to one used by West & Cho (1995) to compare of the predictive ability of volatility models. The key difference between our generalized-F test and the West & Cho test is that they employ a robust estimator of $\mathbf{\Sigma}$ and invoke asymptotic theory, whereas we rely on the covariance structure that specific to Lemma 1. Moreover, we employ bootstrap methods to evaluate the significance of the calendar effect test statistics F_{ξ} and F_{ρ}. Another important difference is that West & Cho only compare series of equal length, whereas we have greater flexibility to consider series (calendar effects) that have an unequal number of observations.

3.5. Bootstrap Implementation

The bootstrap implementation of our test is relatively simple to carry out in this setting. Nonetheless, we must make a sufficiently strong assumption, such that our tests can be implemented by bootstrap methods. The assumptions depends on the relaxed (moments) conditions developed by Goncalves & de Jong (2003), stating that for $r > 2$ and $\delta > 0$ it holds that $E|r_t|^{r+\delta} < \infty$, and that r_t is α-mixing of order $-r/(r-2)$.

To generate resamples, recall that in general we have that $r_t \sim (\mu_t, \sigma_t^2)$, and the hypothesis of interest are $H_0 : \mu_t = \mu$ for all t, or $H_0' : \frac{\mu_t}{\sigma_t} = \rho$ for all t. We allow for variation in σ_t^2 according to weekday/month and obtain $\hat{\sigma}_t^2$, $t = 1, \ldots, n$ from the 'groups' $\hat{\sigma}^2(i)$, $i = 1, \ldots, q$. We would like to construct bootstrap variables, r_t^* that (approximately) satisfy

$$r_t^* \sim (\mu, \sigma_t^2) \quad \text{under } H_0 \qquad \text{and} \qquad \tilde{r}_t^* \sim (\rho\sigma_t, \sigma_t^2) \quad \text{under } H_0'.$$

These can be obtained as

$$r_t^* = \hat{\sigma}_t \tfrac{r_\tau - \bar{r}}{\hat{\sigma}_\tau} + \bar{r} \qquad \text{and} \qquad \tilde{r}_t^* = \hat{\sigma}_t \tfrac{r_\tau}{\hat{\sigma}_\tau},$$

since $r_t^*|Data \sim (\bar{r}, \hat{\sigma}_t^2)$ under H_0 and $\tilde{r}_t^*|Data \sim (\hat{\sigma}_t\rho, \hat{\sigma}_t^2)$ under H_0'.

The implementation goes through the following steps.

1. **(Bootstrap indexes for resampling)**

   (a) Choose the block-length bootstrap parameter, l. The optimal choice for l is tied to the persistence in r_t. One can use different choices for l, and verify that the result is not sensitive to the choice.

   (b) Generate B bootstrap resamples of $\{1, \ldots, n\}$. I.e., for $b = 1, \ldots, B$:

[6] Collinearity of the regressors can be a potential problem with the regression-approach to the F-test.

i. Choose $\xi_{b_1} \sim U\{1,\ldots,n\}$ and set $(\tau_{b,1},\ldots,\tau_{b,l}) = (\xi_{b_1}, \xi_{b_1}+1,\ldots,\xi_{b_1}+l-1)$, with the convention $n+i=i$ for $i \geq 1$.

ii. Choose $\xi_{b_2} \sim U\{1,\ldots,n\}$ and set $(\tau_{b,l+1},\ldots,\tau_{b,2l}) = (\xi_{b_2}, \xi_{b_2}+1,\ldots,\xi_{b_2}+l-1)$.

iii. Continue until a sample size of n, is constructed.

iv. This is repeated for all resamples $b=1,\ldots,B$, using independent draws of the ξ's.

2. **(Sample and Bootstrap Statistics)**

(a) Calculate the sample test statistics (2) or (3) using the original sample r_t, $t=1,\ldots,n$. The r_t series should also be used to compute and save $\bar{r}$ and

$$\hat{\sigma}_t = \sqrt{\sum_{i=1}^{q} \frac{J_{t,i}}{n^{(i)}-1}\left(\sum_{t=1}^{n} J_{t,i}(r_t - \bar{r}^{(i)})^2\right)}, \quad t=1,\ldots,n,$$

(b) Calculate the resampled test statistics

$$F^*_{\xi,b} = \hat{\boldsymbol{\xi}}^{*\prime}_b \boldsymbol{\iota}_\perp(\boldsymbol{\iota}'_\perp \hat{\boldsymbol{\Sigma}}^*_{n,b}\boldsymbol{\iota}_\perp)^+ \boldsymbol{\iota}'_\perp \hat{\boldsymbol{\xi}}^*_b / q_\xi \quad \text{or} \quad F^*_{\rho,b} = \hat{\boldsymbol{\rho}}^{*\prime}_b \boldsymbol{\iota}_\perp(\boldsymbol{\iota}'_\perp \hat{\boldsymbol{\Omega}}^*_{n,b}\boldsymbol{\iota}_\perp)^+ \boldsymbol{\iota}'_\perp \hat{\boldsymbol{\rho}}^*_b / q_\rho,$$

using the bootstrap samples

$$r^*_{\tau(t),b} = \hat{\sigma}_t \tfrac{r_{\tau(t),b}-\bar{r}}{\hat{\sigma}_{\tau(t),b}} + \bar{r} \quad \text{to test } H_0, \quad \text{or} \quad \tilde{r}^*_{\tau(t),b} = \hat{\sigma}_t \tfrac{r_{\tau(t),b}}{\hat{\sigma}_{\tau(t),b}} \quad \text{to test } H'_0,$$

respectively, for $t=1,\ldots,n$, and $b=1,\ldots,B$.

(c) The p-value of H_0 and H'_0 are given by

$$\hat{p}_{H_0} \equiv \frac{1}{B}\sum_{b=1}^{B} 1_{\left\{F_\xi > F^*_{\xi,b}\right\}} \quad \text{and} \quad \hat{p}_{H'_0} \equiv \frac{1}{B}\sum_{b=1}^{B} 1_{\left\{F_\rho > F^*_{\rho,b}\right\}} \tag{4}$$

where $1_{\{\cdot\}}$ is the indicator function.

3.6. *Comparison to Bonferroni Bound Tests*

An alternative and simpler way to adjust inference for the universe of calendar effect is to evaluate the calendar effects individually while adjusting the critical values as prescribed by the Bonferroni bound. This can be done by a simple regression,

$$r_t = \beta_0 + \beta_1 1_{\{t \in \mathcal{S}_{(1)}\}} + \cdots + \beta_m 1_{\{t \in \mathcal{S}_{(m)}\}} + u_t,$$

where $1_{\{\cdot\}}$ is the indicator function. The hypothesis H_0 implies that $\beta_1 = \cdots = \beta_m = 0$, which suggests t-statistics for each of these parameters. To ensure that the overall size of the test is more than α, say 5%, one can use $\frac{\alpha}{m}$-critical values from the appropriate t-distribution. However, this leads to a conservative test as it ignores the correlation across the m different t-statistics. The new test incorporates the correlation structure, whereby it avoids the conservative nature that Bonferroni bound methods have. In the special case where r_t is assumed to be homoskedastic, our F_ξ test is the usual F-test of $H_0 : \beta_1 = \cdots = \beta_m = 0$. Thus, the new test can be viewed as a generalized-F test.

4. Data Description

We have analyzed data from Denmark, France, Germany, Hong Kong, Italy, Japan, Norway, Sweden, United Kingdom, and United States. Most data were extracted from Datastream, the two exceptions are the Danish data, which were extracted from "Børsdatabasen",[7] and the French net return series that are from the Paris Stock Exchange.

The data are daily closing prices with observations ranging back to the base date of the indices or alternatively as far back as the data were available to us. Observations are, if available, included up until 06.05.2002 (May 6, 2002). Summary statistics and the sample period are reported in Table 2.

Holidays, which are used to define some of the calendar effects, were determined using the holiday function in Datastream. In the following, we give a short description of individual series.

Denmark: The KFX is the main index for stocks in Denmark. It comprises the 20-25 most important stock. We use a version of the index that has been adjusted for dividends, this index has been constructed by Tangaard & Belter (2001).

France: We include three indices from France. The CAC 40 is the main index that is based on 40 of the largest companies in terms of market capitalization. The SBF 120 index includes an additional 80 stocks, and this index is typically used as a benchmark for index funds. The MIDCAC index tracks the performance of mid-cap stocks. This index consists of 100 stocks. The indices are available in terms of "net return" and "total return", where the latter incorporates a special "avoid fiscal" tax credit. For comparability with the series from other countries, our analysis is based on the "net return" indices.

Germany: Our analysis includes three German indices. The DAX 30 is the main indicator of the blue-chip segment and contains the 30 largest companies in terms of capitalization and turnover. The MDAX represents the mid-cap segment of the German stock market and includes the next 70 companies after those in DAX 30. DAX 100 combines the DAX 30 and the MDAX and is comparable to the French SF 120. The Deutsche Böres publishes both price indices and performance indices, where the latter are adjusted for dividends and are the indices that we use in our analysis.

Hong Kong: The Hang Seng Main (HS MAIN) includes 33 stocks and accounts for about 70 percent of total market capitalization of stocks listed on the Hong Kong Stock Exchange.

Italy: The MIBTEL is a general national index that contains almost all shares listed on the Italian stock exchange. Italian stocks are ordered according to a measure based on capitalization and transaction volume. The MIB 30 index consists of the first 30 stocks and the MIDEX index consists of the next 25 companies. The adjustment for dividends are somewhat complicated as ordinary and extraordinary dividends are treated differently.

[7] Børsdata is accessible from The Aarhus School of Business's website: www.asb.dk.

Japan: The Nikkei All Stock Index includes all stocks listed on the Tokyo, Osaka, Angola, Sappers, and Judoka exchanges, as well as Nasdaq Japan, and Mother's. The Nikkei 225 Stock Average contains 225 of the most actively traded stocks on the first section of the Tokyo Stock Exchange. The Tokyo Stock Exchange Small Cap (Tokyo SC) index contains a selection of liquid and small capitalization stocks that are traded on the Tokyo stock exchange.

Norway: The All Share (OSLO ALL) index includes all stocks listed on the Oslo Stock Exchange, and the OBX index is based on a smaller number of shares that are thought to be representative for the market. This index is comparable to the Danish KFX index. We also include a small cap index that contains companies with smaller market capitalization.

Sweden: The SAX-General (SAX-GEN) comprises a large number of companies that are traded on the Stockholm Stock Exchange.[8] OMX comprises the 30 stocks with the largest turnover on the exchange (during a certain control period). The Swedish indices do not account for dividends, and we were unable to find a small cap index with a sample that was sufficiently long for our analysis.

United Kingdom: The FTSE includes a large number of stocks that must satisfy certain criteria, see www.londonstockexchange.com for details. The FTSE 100 index is comparable to main indices for other countries, the FTSE 350 is a broader index, and the FTSE 250 mid cap index represents smaller companies.

United States: The Dow Jones Industrial Average (DJIA) comprises 30 of the largest US stocks. The stocks are selected at the discretion of the editors of The Wall Street Journal and add up to about 29% of the US market capitalization. Unlike most indices the DJIA does not weight the individual stocks by their market capitalization. The S&P 500 Index consists of 500 stocks and the S&P Midcap 400 (S&P 400) Index consists of 400 domestic stocks, where the stocks in both indices are selected according to criteria for market size, liquidity, and industry representation.

5. Empirical Results

Our core results appear in tables 3-5 and figure 1. Table 1 lists the calendar effects we examine and provides mnemonics. Summary statistics of the 25 return series are found in table 2. The columns on the far right of table 2 give the number of observations and sample period of the return series. The Norwegian OBX series has the fewest data points, 1586, given a January 3, 1995 to May 6, 2002 sample. More typical are returns on the German DAX 100 that run from December 30, 1987 to April 30, 2002 for a total of 3599 observations. The longest series is the Dow Jones Industrial Average (DJIA) that includes 29,380 observations starting with May 26, 1896 and ending on May 6, 2002. Our DJIA series contains about

[8] SAX-General comprise all companies on the A-, OCT-, and O-listen of the Stockholm Stock Exchange. Prior to 1998 in comprised companies on the A-list only.

six more years of observations (or nearly 2000 more) than available to STW. Using their shorter sample, STW report little evidence that their calendar effects-trading rules provide superior returns compared simply to a strategy that holds the DJIA market index.

5.1. The full universe of calendar effects

We assess the significance of calendar effects with the full universe of calendar effects presented in section 2 and listed in Table 1. Table 3 provides the p-values of the generalized-F test applied to the 25 return and standardized return series. Our bootstrap procedure generates p-values that contradict STW's analysis that calendar effects have few asset pricing implications, once account is made of data mining biases. The p-values of table 3 show that significant calendar effects arise in all the national stock markets we study, for at least one index using either returns or standardized returns, conditional on the full universe of 181 calendar effects. There is no evidence against the null of no calendar effects in about a quarter of the return indices, conditional on the full universe. These indices are the German-DAX 100 and -DAX 30, Italian-MIB 30, Japanese-NIKKEI 225, Norwegian-OSLO All and -OBX, and USA-S&P500.[9] Nevertheless, the p-values we report in table 3 supports the view that calendar effects matter for stock returns. We obtain this evidence using returns on ten national stock markets, examining 181 calendar effects, and accounting for the data mining biases created by studying this full universe anomalies.

5.2. Negative returns, and day-of-the-week and month-of-the-year anomalies

Our choice of anomalies for the 17-calendar effects universe is motivated by STW. They find the most important anomaly in 90 to 100 years of daily DJIA returns to be the Monday effect. Beside abnormal returns on Monday, our 17-calendar effects universe includes other day-of-the-week and month-of-the-year anomalies. Thus, our test for the significance of the Monday effect conditions on the entire set of day-of-the-week and month-of-the-year effects. This is also true of the other 16 day-of-the-week and month-of-the-year anomalies included in the 17-calendar effects universe.

Table 3 reveals the 17-calendar effects universe gives little evidence against the null which is at odds with results obtained from the full universe of calendar effects. Only eight p-values on returns and five p-values on standardized returns are less than 0.05, conditional on the 17-calendar effects universe. These markets are France-MIDCAC, Japan-Tokyo SC, Norway-OSLO SC, UK-FTSE 250, and DJIA for returns and standardized returns and only for returns: Germany-MDAX, Hong Kong-HS MAIN, and Italy-MIDEX. It also appears that small- and mid-cap indices are most affected by day-of-the-week and month-of-the-year return anomalies.

Our tests of the 17-calendar effects universe are at odds with the importance attributed to the Monday

[9] The tests for the full universe of calendar effects on standardized returns yield no rejection for the same indices plus the French-SBF120 and -CAC 40, Swedish-SAX-GEN and -OMX, and USA-S&P400.

anomaly by STW. We present tables 5 and 6 to understand this quandary. Table 5 lists the five calendar effects that had the smallest sample return for the 25 return series. Of the 125 calendar effects that generate the smallest returns, 124 are either week-of-the-month-of-the-year or week-day-of-the-month anomalies.[10] The lone exception is the third-worst performing calendar effect of the Tokyo small cap (SC) index which is associated with an end-of-the-year anomaly. Table 7 of the five worst calendar effects for standard returns reinforces this view.

STW report that the negative returns on the DJIA associated with Monday effect are important for their calendar effects-based trading rules. This is consistent with table 7 because the Monday effect is the anomaly responsible for the most negative DJIA standardized return. Otherwise, only three (end-of-the-year effects) of the 125 worst performing anomalies on standardized returns do not involve either a day, week, month, or combination anomaly. Thus, the significance of the Monday effect found by STW in the DJIA is not observed in other national stock markets (for returns or standard returns). Tables 5 and 7 also show that the anomalies that generate the five poorest returns are more complicated than those in the 17-calendar effects universe. Our analysis shows that the week-of-the-month-of-the-year and week-day-of-the-month anomalies help to produce the rejections of the null conditional on the full universe of calendar effects. These results rest on the abnormally small (e.g., negative) returns produced by the week-of-the-month-of-the-year and week-day-of-the-month anomalies.

5.3. Positive returns and end-of-the-year effects

Rejections of the null of no calendar effect appear robust to using either returns or standardized returns and across national stock markets, given we condition on the full universe of calendar effect. The previous subsection indicates the calendar anomalies that contribute to these rejections *and* yield abnormally large negative returns. Tables 4 and 6 help to identify the calendar effects that also are responsible for the rejections and generate abnormally large returns.

Table 4 and table 6 present the five calendar effects that had the largest returns and standardized returns, respectively. Unlike tables 5 and 7, there is no systematic pattern of calendar effects that produce the five largest returns or standardized returns on the ten national stock markets. For example, only 25 of the 50 best and second best returns are end-of-the-year effects. The other half are either week-of-the-month-of-the-year or week-day-of-the-month anomalies. However, we do find end-of-the-year effects generate about two-thirds of the 'Best' returns and standardized returns.[11]

The abnormally large returns end-of-the-year effects generate for many national stock markets suggests we conduct tests conditioning only on these anomalies. This is our 5-calendar effects universe, which consists of two pre- and post-holiday effects and three end-of-the-year effects. Table 3 reports that only 6 (5) of the 25 p-values of the (standardized) return series are greater than 0.05, when we condition

[10] These anomalies are not part of the 17-calendar effects universe.

[11] This requires counting the December semi-month-of-the-year anomaly as an end-of-the-year effect for standardized returns.

on the 5-calendar effects universe.[12] Given the abnormally large returns end-of-the-year effect generate, it is not surprising the null of no calendar effects is rejected in this case.

It is well-known that larger stock returns are most often associated with a higher variance in returns. This is as true for negative returns as it is for positive returns. Since calendar effects are abnormally large returns (in absolute value) associated with a specific seasonal event, it raises the question that some of the extant evidence about calendar effects may reflect conditional time-variation in the second moment of returns, e.g., Garch-in-mean relationships in the first two (conditional) moments of returns. The results we present in the next subsection make us suspicious of the notion that calendar effects are only generated by systematic movements in the first moment of returns.

5.4. DJIA subsample analysis

Calendar effects studies often use different market indices and sample periods to test for the significance of return anomalies. For example, Lakonishok & Smidt (1988) divide 90 years of daily DJIA returns into seven (non-overlapping) ten to 14 year subsamples. They note substantial time-variation in the mean, median, and standard deviation of DJIA returns in 90 years of daily DJIA returns divided into seven (non-overlapping) ten to 14 year subsamples.[13] This induces Lakonishok & Smidt to conduct a robustness check of calendar anomalies across these subsamples. The calendar effects that arise in 90 years of daily DJIA return also persist in the subsamples, according to Lakonishok & Smidt.

We report on the robustness of our tests for calendar effects in returns on the DJIA in figure 1. It plots dynamic p-values of the hypotheses H_0 and H_0' using the entire DJIA sample: May 26, 1896 and to May 6, 2002. The p-values are calculated using rolling subsamples with 2000 observations (approximately eight years of overlapping data in each subsample). The upper, middle, and lower panels contain dynamic p-values for H_0 and H_0', conditional on the full universe, the 17-effects universe and the 5-effects universe, respectively.

The plots of the p-values reveal long periods during which no calendar effects is significant, based on 2000 observations. Yet, there are long periods, such as the 1920s and from about 1950 to 1970, where the calendar effects in the full and the 17-calendar effects universes are significant. On the other hand, the interval from early 1970s to the late 1980 indicate there is little evidence in favor of calendar effects. However, there is a brief period around the first Gulf War and recession of the early 1990s during which there are significant calendar effects. Note that periods of significance for calendar effects in the 5-calendar effects universe is of much shorter duration than for the full and 17-calendar effects universes. Further, there is little evidence of calendar effects of any type subsequent to the second oil price shock of the late 1970s.

[12] The relevant indices for returns and standardized returns are the Hong Kong-HS Main, Japan-NIKKEI All and NIKKEI-225, and Sweden-SAX-GEN and-OMX, but the USA-S&P500 only for returns.

[13] The sample moments of DJIA returns are computed by subtracting the average return over the second-half of the month from the first.

Our study of the time-variation in the calendar effect test p-values suggests that significant calendar effects are not an economically important phenomenon in DJIA returns. This is especially true for the for recent history of DJIA return because the last instance of small p-values is short-lived. The DJIA returns show that the power of calendar effects in DJIA returns appear to be tied to specific episodes during the mid-20th century (e.g., post-World War I and II expansions), but these effects have had a smaller impact in recent years. Thus, evidence for calendar effects in DJIA returns is fragile.

The time-variation in the significance of calendar effects found in DJIA returns holds for DJIA standardized returns. Our subsample analysis also reveals that calendar effects fail to appear in the last 25 years of DJIA standardized returns across the three universes we consider. This bolsters the notion that support for anomalous seasonal behavior in the DJIA is weak.

In summary, claims for calendar effects in DJIA returns are fragile. We inspect the time-path of p-values that account for data-mining biases and find significant calendar effects arise only in specific sub-samples of DJIA returns and standardized returns during the 20th. The appearance of time-varying calendar effects suggests systematic movements tied to seasonal events are the not a key source of fluctuations in DJIA returns.

5.5. Calendar effects in small- and mid-cap indices

Table 3 shows that all but one of the small- and mid-cap return indices reject the null for one of the calendar effects universes. The exception is the Japanese-NIKKEI 225. This suggests the underlying returns generating process differs for stocks with smaller capitalized value compared to stocks with greater valuations. However, the five best and worst small- and mid-cap returns and standardized returns often exhibit the same pattern (or and lack of one) as do the broader market indices, according to tables 4-7. It seems that the behavior of returns on small- and mid-cap indices with respect to calendar effects is not that different from returns on stock indices with larger capitalizations. This result carries over to plots of the p-values of the other (than DJIA) return series.[14] These plots show that the remaining 24 indices produce time-variation in calendar effects qualitatively similar to the DJIA plot in Figure 1 (conditional on significant calendar effects).

6. Concluding Remarks

We argue that to evaluate the significance of calendar effects it is necessary to control for the full universe of these anomalies to avoid data mining biases and therefore, spurious results. A simple generalize-F test is derived for this purpose. We show our test dominates a Bonferroni bound tests because of its superior power properties. The power gain exploits the correlation structure of returns conditional on the universe of calendar effects, which a Bonferroni bound type test ignores. Thus, our test is specifically designed to evaluate significance of calendar effects that are robust to data mining.

[14] Which are available by request from the corresponding author.

This paper finds calendar effects to be statistically significant in almost all of the 25 stock indices from the ten countries we study. Some of the strongest evidence we have is for calendar effects small- and mid-cap indices. End-of-the-year, week-of-the-month-of-the-year, and week-day-of-the-month effects stand out as being responsible for the largest (in absolute value) anomalies. The Monday effect drives abnormally negative returns on the Dow-Jones Industrial Average on 106 years of daily returns, but not on the standardized returns of this index or on any other index we consider.

A subsample analysis shows that the significance of calendar effects is not an economically important phenomenon because in many cases the last instance of significant calendar effects occurred in the late 1980s and early 1990s. Subsequent to this period, we find no evidence of significant calendar effects in any of 25 stock return (or standardized return) indices. This suggests there is an element of time-variation in calendar effects that is not consistent with systematic seasonal variation in stock returns. An interesting task for future research is to examine the connection between measured calendar effects and conditional time-variation in the second moment of returns associated with Garch-in-mean return generating functions.

Appendix: Technical Assumptions and Proofs

In this appendix we present some assumptions and the proofs of the Lemmas and the Theorem applied in the paper.

Proof of Lemma 1. The results follow from first principles, as $\{r_t\}$ is assumed to be uncorrelated, and $\text{cov}(r_t, r_s) = \sigma_t^2$ if $t = s$, and zero otherwise. ■

Proof of Lemma 2. We have $\mathbf{X} \sim N(\mathbf{B}\boldsymbol{\theta}, \boldsymbol{\Omega})$ such that $\mathbf{B}_\perp' \mathbf{X} \sim N(\mathbf{0}, \mathbf{B}_\perp' \boldsymbol{\Omega} \mathbf{B}_\perp)$. Since $\mathbf{B}_\perp' \boldsymbol{\Omega} \mathbf{B}_\perp$ is symmetric and positive semi-definite, we can write $\mathbf{B}_\perp' \boldsymbol{\Omega} \mathbf{B}_\perp = \mathbf{Q} \boldsymbol{\Lambda} \mathbf{Q}'$ where $\boldsymbol{\Lambda}$ is a diagonal matrix with non-negative elements, $\boldsymbol{\Lambda} = \text{diag}(\lambda_1, \ldots, \lambda_q)$, and $\mathbf{Q}$ orthonormal, i.e., $\mathbf{Q}'\mathbf{Q} = \mathbf{I}$. Let the elements of $\boldsymbol{\Lambda}$ be ordered, such that $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_r > \lambda_{r+1} = \cdots 0$, then clearly $r = \text{rank}(\mathbf{B}_\perp' \boldsymbol{\Omega} \mathbf{B}_\perp)$. Next, define the $q \times q$ diagonal matrix $\mathbf{D} = \text{diag}(d_1, \ldots, d_r, 0, \ldots, 0)$, where $d_i = 1/\sqrt{\lambda_i}$ for $i = 1, \ldots, r$. It then follows that $(\mathbf{B}_\perp' \boldsymbol{\Omega} \mathbf{B}_\perp)^+ = \mathbf{QDDQ}'$ and that $\mathbf{DQ}'\mathbf{B}_\perp' \mathbf{X}$ is a vector of independent and normally distributed variables, with mean zero and where the first r elements, $u_1, \ldots, u_r$ say, have unit variance and the last $q - r$ elements have zero variance (equals zero with probability one). Finally, it follows that

$$T = \mathbf{X}'\mathbf{B}_\perp (\mathbf{B}_\perp' \boldsymbol{\Omega} \mathbf{B}_\perp)^+ \mathbf{B}_\perp' \mathbf{X} = \mathbf{X}'\mathbf{B}_\perp \mathbf{QDDQ}' \mathbf{B}_\perp' \mathbf{X} = \sum_{i=1}^{r} u_i^2,$$

which is $\chi^2(r)$ distributed. ■

The assumption below, (Assumption A.1), provides conditions that are similar to those needed for a central limit theorem for martingale difference sequences, (see, e.g., Davidson, 2000, p. 124). The difference is that we have formulated it in terms of the sets, $\mathcal{S}_{(k)}$, $k = 1, \ldots, m$, and the formulations is for all sets simultaneously.

Define the σ-algebra $\mathcal{F}_t = \sigma(r_t, r_{t-1}, \ldots)$, and recall that $n_{(k)}$ is the number of elements in $\mathcal{S}_{(k)}$, and recall the definitions $\bar{r}_{(k)} \equiv n_{(k)}^{-1} \sum_{t \in \mathcal{S}_{(k)}} r_t$, $\xi_{(k)} \equiv E(\bar{r}_{(k)})$, and $\bar{\omega}^2_{(k),n} \equiv n_{(k)}^{-1} \sum_{t \in \mathcal{S}_{(k)}} \sigma_t^2$, $k = 0, 1, \ldots, m$, and the definition of $A_{(k),t}$ (equal to $n_{(k)}^{-1}$ if $t \in \mathcal{S}_{(k)}$, zero otherwise).

Assumption A.1 *The process, $\{r_t - \mu_t, \mathcal{F}_t\}$ is a martingale difference sequence, and*

(*i*) $\bar{\omega}^2_{(k),n} - n_{(k)}^{-1} \sum_{t \in S_{(k)}} (r_t - \mu_t)^2 \xrightarrow{p} 0$, *where* $\bar{\omega}^2_{(k),n} \equiv n_{(k)}^{-1} \sum_{t \in S_{(k)}} \sigma_t^2$, *and*

(*ii*) *For some* $\delta > 0$ *and some* $C > 0$, *it holds that* $\max_{t \in S_{(k)}} [E \left| r_t - \mu_t \right|^{2+\delta} / \bar{\omega}^2_{(k),n}] \leq C < \infty$ *for all* $n \geq 1$.

From Davidson (2000) it follows directly that

$$n_{(k)}^{1/2} \frac{\bar{r}_{(k)} - \xi_{(k)}}{\bar{\omega}_{(k),n}} \xrightarrow{d} N(0,1).$$

The multivariate theorem, which is needed for the analysis of calendar effects, is the following.

Theorem A.1 *Under Assumption A.1 it holds that*

$$\sqrt{n} \begin{pmatrix} \bar{r}_{(0)} - \xi_{(0)} \\ \vdots \\ \bar{r}_{(m)} - \xi_{(m)} \end{pmatrix} \xrightarrow{d} N_{m+1}(0, n\boldsymbol{\Sigma}_n), \quad \textit{where} \quad \Sigma_n = \left[n_{(k)}^{-1} n_{(k')}^{-1} \sum_{t \in S_{(k)} \cap S_{(k')}} \sigma_t^2 \right]_{k,k'=0,\ldots,m}.$$

Proof. The theorem is proven by employing a Cramer-Wold device. Let $\boldsymbol{\lambda} \in \mathbb{R}^{l+1}$, where $\boldsymbol{\lambda}'\boldsymbol{\lambda} = 1$ and consider the linear combination

$$\sum_{k=0}^{m} \lambda_{(k)} \bar{r}_{(k)} = \sum_{k=0}^{m} \lambda_{(k)} \sum_{t=1}^{n} A_{(k),t} r_t = \sum_{t=1}^{n} b_{n,t} r_t,$$

where $b_{n,t} = \sum_{k=0}^{m} \lambda_{(k)} A_{(k),t}$. The sequence $\{b_{n,t}\}$ satisfies $\lim_n \sup_{1 \leq t \leq n} b_{n,t} = 0$, such that

$$\frac{\sum_{t=1}^{n} b_{n,t}(r_t - \mu_\lambda)}{\omega_n} \xrightarrow{d} N(0,1),$$

where $\omega_n^2 = \boldsymbol{\lambda}' \boldsymbol{\Sigma}_n \boldsymbol{\lambda}$, and where $\mu_\lambda = \sum_{k=0}^{m} \lambda_{(k)} \mu_{(k)} = E(\sum_{k=0}^{m} \lambda_{(k)} \bar{r}_{(k)})$.

Since

$$\left(\sum_{k=0}^{m} \lambda_{(k)} A_{(k),t} \right)^2 = \left(\sum_{k=0}^{m} \sum_{k'=0}^{m} \lambda_{(k)} \lambda_{(k')} A_{(k),t} A_{(k'),t} \right),$$

it holds that

$$\text{var}(\sum_{k=0}^{m} \lambda_k \bar{r}_{(k)}) = \sum_{t=1}^{n} b_{n,t}^2 \text{var}(r_t) = \sum_{t=1}^{n} \left(\sum_{k=0}^{m} \sum_{k'=0}^{m} \lambda_{(k)} \lambda_{(k')} A_{(k),t} A_{(k'),t} \right) \sigma_t^2$$

which equals

$$\boldsymbol{\lambda}' \boldsymbol{\Sigma}_n \boldsymbol{\lambda} = \sum_{k=0}^{m} \sum_{k'=0}^{m} \lambda_{(k)} \lambda_{(k')} n_{(k)}^{-1} n_{(k')}^{-1} \sum_{t \in S_{(k)} \cap S_{(k')}} \sigma_t^2.$$

This completes the proof. ■

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Appendix: Tables and Figures

Table 1: Summary of calendar effects.

Name of Effect	# Effect	Individual Effect Names/Apprehensions
Day-of-the-week	5	`monday`, ⋯, `friday`
Month-of-the-year	12	`january`, ⋯, `december`
End-of-December	3	`pre.xmas`, `pre.xm.ny`, `inter.xm.ny`
Turn-of-the-month	8	`mo.first.4`, ⋯, `mo.first.1`, `mo.last.1`, ⋯, `mo.last.4`
Holiday-effects	2	`preholiday`, `postholiday`
Semi-month	2	`mo.1.half`, `mo.2.half`
Semi-month-of-the-year	24	`mo.1.jan`, ⋯, `mo.1.dec`, `mo.2.jan`, ⋯, `mo.2.dec`
Week-of-the-month	5	`week1`, ⋯, `week5`
Week-of-the-month-of-the-year	60	`week1.jan`, ⋯, `week1.dec`, `week2.jan`, ⋯, `week4.dec`, ⋯, `week5.dec`
Week-day-of-the-month	60	`mon.jan`, ⋯, `mon.dec`, `tue.jan`, ⋯, `thu.dec`, `fri.jan`, ⋯, `fri.dec`

This table summarizes the calendar effects investigated in the paper. The first column gives the effect name, the second gives number of individual effects, and the last gives the individual effect mnemonics employed in the text and tables.

Table 2: Summary Statistics for Index Returns

Series	Mean	Med.	Min	Max	Std.	Skew.	Kurt.	#Obs.	Sample Period
DENMARK									
KFX	0.05	0.06	-10.91	7.21	1.01	-0.69	12.04	3861	03.06.1985-30.10.2000
FRANCE									
SBF 120	0.05	0.05	-7.69	6.20	1.16	-0.26	5.98	2839	28.12.1990-30.04.2002
CAC 40	0.05	0.06	-7.68	6.81	1.25	-0.21	5.36	3586	31.12.1987-30.04.2002
MIDCAC*	0.03	0.05	-7.71	5.90	0.84	-0.98	15.09	2839	28.12.1990-30.04.2002
GERMANY									
DAX 100	0.04	0.09	-14.05	6.65	1.24	-0.81	12.17	3599	30.12.1987-06.05.2002
DAX 30	0.03	0.08	-13.71	7.29	1.37	-0.68	10.07	4095	02.01.1986-06.05.2002
MDAX*	0.04	0.07	-15.16	8.12	0.89	-2.14	36.86	3599	30.12.1987-06.05.2002
HONG KONG									
HS MAIN	0.05	0.08	-40.54	17.25	1.85	-3.36	74.56	4036	01.01.1986-06.05.2002
ITALY									
MIBTEL	0.04	0.05	-7.71	6.83	1.38	-0.20	5.24	2222	16.07.1993-06.05.2002
MIB 30	0.04	0.02	-8.11	7.77	1.52	-0.12	5.15	1903	17.10.1994-06.05.2002
MIDEX*	0.06	0.05	-7.71	4.99	1.18	-0.45	7.33	1851	02.01.1995-06.05.2002
JAPAN									
NIKKEI ALL	-0.01	-0.05	-6.51	7.13	1.23	0.17	6.24	2793	01.01.1990-06.05.2002
NIKKEI 225	$-3*10^{-3}$	0.02	-16.14	12.43	1.45	-0.10	10.65	4024	01.01.1986-06.05.2002
TOKYO SC*	-0.01	0.02	-11.95	5.49	1.01	-0.82	12.63	4024	01.01.1986-06.05.2002
NORWAY									
ALL SHARE	0.03	0.07	-6.34	5.64	1.14	-0.60	6.83	1588	29.12.1995-06.05.2002
OBX	0.03	0.04	-7.24	6.34	1.31	-0.44	6.59	1586	03.01.1995-06.05.2002
OSLO SC*	0.05	0.08	-7.28	5.54	0.89	-0.81	10.69	1588	29.12.1995-06.05.2002
SWEDEN									
SAX-GEN	0.05	0.08	-8.07	9.88	1.40	0.06	6.88	1839	02.01.1995-06.05.2002
OMX	0.05	0.07	-8.53	11.02	1.58	0.04	5.83	1839	02.01.1995-06.05.2002
UK									
FTSE 350	0.03	0.07	-11.98	5.81	0.95	-1.09	16.01	4129	01.01.1986-06.05.2002
FTSE 100	0.03	0.06	-13.03	7.60	1.02	-0.97	15.77	4129	01.01.1986-06.05.2002
FTSE 250*	0.04	0.09	-11.28	7.25	0.79	-2.03	32.17	4129	01.01.1986-06.05.2002
USA									
DJIA	0.02	0.04	-27.96	14.27	1.09	-1.17	39.31	29380	26.05.1896-06.05.2002
S&P 500	0.03	0.03	-22.83	8.71	1.01	-1.69	42.05	7409	01.01.1973-06.05.2002
S&P 400*	0.05	0.08	-7.33	5.97	1.03	-0.30	7.24	2748	12.06.1991-06.05.2002

This table reports summary statistics for the 25 stock indexes investigated in the paper. Mid- and small-cap indices are marked with an asterix.

Table 3: p-values from tests for calendar effects.

Series	#Obs.	p-value return			p-value std. return		
		Full	17	5	Full	17	5
DENMARK							
KFX	3861	**0.0312**	0.1016	**0.0078**	**0.0492**	0.2394	**0.0084**
FRANCE							
SBF 120	2839	**0.0376**	0.5374	**0.0088**	0.0572	0.5874	**0.0050**
CAC 40	3586	**0.0436**	0.4242	**0.0122**	0.0606	0.4424	**0.0078**
MIDCAC*	2839	<**.0001**	<**.0001**	<**.0001**	<**.0001**	<**.0001**	<**.0001**
GERMANY							
DAX 100	3599	0.0510	0.1814	**0.0014**	0.0686	0.2574	**0.0010**
DAX 30	4095	0.0816	0.3250	**0.0068**	0.1072	0.3574	**0.0064**
MDAX*	3599	**0.0004**	**0.0470**	**0.0118**	**0.0026**	0.0990	**0.0106**
HONG KONG							
HS MAIN	4036	**0.0354**	**0.0308**	0.1696	**0.0358**	0.1144	0.1386
ITALY							
MIBTEL	2222	**0.0078**	0.0980	<**.0001**	**0.0114**	0.1686	**0.0006**
MIB 30	1903	0.3158	0.4714	**0.0038**	0.3622	0.5522	**0.0030**
MIDEX*	1851	**0.0046**	**0.0392**	**0.0004**	**0.0086**	0.1144	**0.0002**
JAPAN							
NIKKEI ALL	2793	**0.0394**	0.7298	0.1034	**0.0496**	0.7828	0.1200
NIKKEI 225	4024	0.1224	0.3400	0.3078	0.1182	0.4046	0.3108
TOKYO SC*	4024	<**.0001**	**0.0002**	**0.0364**	<**.0001**	<**.0001**	**0.0426**
NORWAY							
OSLO ALL	1588	0.1528	0.3580	**0.0002**	0.2082	0.4732	<**.0001**
OBX	1586	0.2070	0.6204	**0.0004**	0.2658	0.6618	**0.0002**
OSLO SC*	1588	<**.0001**	<**.0001**	<**.0001**	**0.0010**	**0.0018**	<**.0001**
SWEDEN							
SAX-GEN	1839	**0.0402**	0.2300	0.1346	0.0530	0.3050	0.1280
OMX	1839	**0.0430**	0.3230	0.2068	0.0578	0.4250	0.2046
UK							
FTSE 350	4129	**0.0094**	0.3230	**0.0162**	**0.0144**	0.4590	**0.0166**
FTSE 100	4129	**0.0134**	0.4266	**0.0308**	**0.0198**	0.5302	**0.0250**
FTSE 250*	4129	<**.0001**	<**.0001**	**0.0056**	<**.0001**	**0.0076**	**0.0032**
USA							
DJIA	28899	<**.0001**	<**.0001**	<**.0001**	<**.0001**	<**.0001**	<**.0001**
S&P 500	7409	0.3104	0.3966	0.0518	0.3584	0.4186	**0.0344**
S&P 400*	2748	**0.0262**	0.6242	<**.0001**	0.0528	0.6744	**0.0004**

This table reports bootstrap p-values for the F test. In columns 3-5 test are performed on returns, and it is performed on standardized returns in columns 6-8. "Full" denotes the complete universe of effects, "17" denotes the universe with day-of-the-week and month-of-the-year effects, and "5" is the xmas, new year and holiday effects. Mid- and small-cap indices are marked with an asterix.

Table 4: Performance of Calendar Effects: The Best five in terms of Returns.

Series	Bench.	Best	2th Best	3th Best	4th Best	5th Best
DENMARK						
KFX	0.046	0.497[p.xm.ny]	0.496[i.xm.ny]	0.419[w5.dec]	0.377[w4.dec]	0.371[w3.jan]
FRANCE						
SBF 120	0.047	0.625[p.xm.ny]	0.561[w4.dec]	0.493[tue.oct]	0.472[w5.apr]	0.456[w5.feb]
CAC 40	0.049	0.662[p.xm.ny]	0.628[w1.feb]	0.543[w4.dec]	0.503[w5.apr]	0.476[w5.feb]
MIDCAC*	0.033	0.674[p.xm.ny]	0.572[w5.dec]	0.488[i.xm.ny]	0.482[w5.feb]	0.410[w4.feb]
GERMANY						
DAX 100	0.044	0.965[p.xm.ny]	0.560[w4.dec]	0.550[w5.dec]	0.464[w1.feb]	0.454[i.xm.ny]
DAX 30	0.031	0.935[p.xm.ny]	0.580[w4.dec]	0.465[thu.nov]	0.397[w3.nov]	0.389[tue.oct]
MDAX*	0.035	0.458[p.xm.ny]	0.446[w1.feb]	0.318[tue.oct]	0.299[w4.dec]	0.294[w5.dec]
HONG KONG						
HS MAIN	0.047	0.700[fri.oct]	0.610[p.xm.ny]	0.602[w1.oct]	0.533[w1.jul]	0.524[w4.dec]
ITALY						
MIBTEL	0.041	0.626[fri.jan]	0.617[mon.dec]	0.578[w4.dec]	0.577[p.xm.ny]	0.555[p.xmas]
MIB 30	0.040	0.700[fri.jan]	0.700[p.xm.ny]	0.637[preholi]	0.610[mon.sep]	0.606[i.xm.ny]
MIDEX*	0.058	0.864[i.xm.ny]	0.815[w5.dec]	0.733[w1.feb]	0.633[mon.dec]	0.628[w3.jan]
JAPAN						
NIKKEI ALL	-0.014	0.715[w5.jan]	0.644[w1.may]	0.355[w5.dec]	0.351[i.xm.ny]	0.344[mo.l.1]
NIKKEI 225	-0.003	0.504[w1.may]	0.471[w5.jan]	0.407[wed.apr]	0.405[wed.dec]	0.373[thu.jul]
TOKYO SC*	-0.008	0.656[w1.may]	0.550[w5.jan]	0.411[w5.mar]	0.336[fri.apr]	0.302[mo.1.may]
NORWAY						
OSLO ALL	0.033	1.241[p.xm.ny]	1.070[i.xm.ny]	0.975[w5.dec]	0.749[postholi]	0.704[w1.jan]
OBX	0.028	1.220[p.xm.ny]	1.096[i.xm.ny]	0.964[w5.dec]	0.829[postholi]	0.663[mo.2.dec]
OSLO SC*	0.046	1.375[p.xm.ny]	1.028[w5.dec]	0.896[i.xm.ny]	0.785[w1.jan]	0.617[preholi]
SWEDEN						
GENERAL	0.048	0.848[i.xm.ny]	0.839[p.xm.ny]	0.780[w5.dec]	0.777[w3.nov]	0.647[thu.jan]
OMX	0.048	0.882[w3.nov]	0.877[i.xm.ny]	0.794[w5.dec]	0.778[p.xm.ny]	0.717[mon.sep]
UK						
FTSE 350	0.032	0.444[i.xm.ny]	0.357[w5.jan]	0.309[w4.dec]	0.296[w1.jul]	0.294[w1.mar]
FTSE 100	0.031	0.463[i.xm.ny]	0.371[w5.jan]	0.313[w1.jul]	0.300[w4.dec]	0.298[w1.mar]
FTSE 250*	0.036	0.418[w1.jan]	0.345[i.xm.ny]	0.321[w4.dec]	0.319[w1.mar]	0.283[mo.2.dec]
USA						
DJIA	0.019	0.250[p.xm.ny]	0.239[preholi]	0.233[w5.dec]	0.222[w1.jul]	0.215[i.xm.ny]
SP 500	0.029	0.278[w5.jan]	0.230[fri.dec]	0.223[w1.jun]	0.220[i.xm.ny]	0.207[w3.apr]
SP 400*	0.053	0.627[p.xm.ny]	0.598[w5.dec]	0.587[i.xm.ny]	0.469[w4.dec]	0.457[mo.2.dec]

This table reports the returns (effects names are given in brackets) of the five best performing calendar effects in terms of returns. Mid- and small-cap indices are marked with an asterix. See Table 1 and Section 2 for an explanation of the effect mnemonics.

Table 5: Performance of Calendar Effects: The Worst five in terms of Returns.

Series	Bench.	Worst	2th Worst	3th Worst	4th Worst	5th Worst
DENMARK						
KFX	0.046	-0.236[mon.apr]	-0.209[w5.aug]	-0.199[w4.feb]	-0.198[w2.aug]	-0.192[fri.aug]
FRANCE						
SBF 120	0.047	-0.450[w5.nov]	-0.395[thu.sep]	-0.384[thu.aug]	-0.360[w2.sep]	-0.321[mon.aug]
CAC 40	0.049	-0.421[mon.aug]	-0.377[thu.aug]	-0.328[thu.sep]	-0.327[mon.nov]	-0.311[w5.nov]
MIDCAC*	0.033	-0.369[fri.sep]	-0.364[w5.nov]	-0.354[w2.sep]	-0.325[thu.sep]	-0.282[w3.sep]
GERMANY						
DAX 100	0.044	-0.507[thu.sep]	-0.318[mon.aug]	-0.314[tue.sep]	-0.272[w3.sep]	-0.255[fri.sep]
DAX 30	0.031	-0.520[thu.sep]	-0.293[thu.oct]	-0.284[fri.sep]	-0.251[w3.sep]	-0.249[tue.sep]
MDAX*	0.035	-0.420[w3.sep]	-0.354[mon.aug]	-0.301[thu.sep]	-0.264[w4.aug]	-0.238[fri.sep]
HONG KONG						
HS MAIN	0.047	-0.992[w5.oct]	-0.931[mon.oct]	-0.531[mon.jun]	-0.475[mon.aug]	-0.409[mon.apr]
ITALY						
MIBTEL	0.041	-0.625[thu.sep]	-0.625[w2.sep]	-0.591[wed.may]	-0.565[w1.oct]	-0.522[mon.jun]
MIB 30	0.040	-0.874[thu.sep]	-0.576[wed.may]	-0.529[w2.sep]	-0.458[w5.aug]	-0.454[w1.oct]
MIDEX*	0.058	-0.557[thu.sep]	-0.405[mon.jun]	-0.390[mon.oct]	-0.389[w3.sep]	-0.384[w2.sep]
JAPAN						
NIKKEI ALL	-0.014	-0.453[w1.jan]	-0.397[w4.jul]	-0.345[w3.jun]	-0.302[tue.jan]	-0.295[mon.aug]
NIKKEI 225	-0.003	-0.422[mon.apr]	-0.371[mon.jun]	-0.341[wed.sep]	-0.322[w4.jul]	-0.319[fri.aug]
TOKYO SC*	-0.008	-0.433[w4.jul]	-0.345[wed.sep]	-0.328[p.xmas]	-0.314[w4.sep]	-0.310[mon.aug]
NORWAY						
OSLO ALL	0.033	-0.603[w3.sep]	-0.571[thu.sep]	-0.444[w3.mar]	-0.359[w2.oct]	-0.343[mo.2.sep]
OBX	0.028	-0.774[w3.sep]	-0.656[thu.sep]	-0.532[w2.oct]	-0.492[w3.mar]	-0.430[fri.sep]
OSLO SC*	0.046	-0.528[p.xmas]	-0.412[thu.sep]	-0.394[w3.dec]	-0.392[w3.sep]	-0.320[tue.sep]
SWEDEN						
GENERAL	0.048	-0.511[wed.mar]	-0.493[thu.sep]	-0.453[thu.aug]	-0.450[w3.mar]	-0.444[wed.may]
OMX	0.048	-0.559[thu.sep]	-0.559[wed.mar]	-0.529[thu.aug]	-0.521[wed.may]	-0.515[w5.aug]
UK						
FTSE 350	0.032	-0.355[mon.oct]	-0.338[w4.oct]	-0.272[w2.sep]	-0.261[tue.sep]	-0.229[w4.jul]
FTSE 100	0.031	-0.345[mon.oct]	-0.340[w4.oct]	-0.290[w2.sep]	-0.258[tue.sep]	-0.232[w4.jul]
FTSE 250*	0.036	-0.390[mon.oct]	-0.352[w4.oct]	-0.285[w3.sep]	-0.263[tue.sep]	-0.255[mon.aug]
USA						
DJIA	0.019	-0.244[mon.sep]	-0.188[mon.oct]	-0.162[mon.may]	-0.152[mon.jun]	-0.136[thu.sep]
SP 500	0.029	-0.171[w4.oct]	-0.150[mon.oct]	-0.147[thu.dec]	-0.122[thu.aug]	-0.116[thu.sep]
SP 400*	0.053	-0.352[fri.feb]	-0.250[w1.oct]	-0.238[mon.apr]	-0.226[w4.jul]	-0.221[w1.jan]

This table reports the returns (effect names are given in brackets) of the five worst performing calendar effects in terms of returns. Mid- and small-cap indices are marked with an asterix. See Table 1 and Section 2 for an explanation of the effect mnemonics.

Table 6: Performance of Calendar Effects: The Best five in terms of Standardized Returns.

Series	Bench.	Best	2th Best	3th Best	4th Best	5th Best
DENMARK						
KFX	0.045	4.873[mo.f.2]	4.455[mo.1.jul]	4.317[i.xm.ny]	3.795[w1.jul]	3.383[w5.dec]
FRANCE						
SBF 120	0.041	3.815[mo.2.dec]	3.606[w4.dec]	3.517[p.xm.ny]	3.392[mo.l.1]	3.008[preholi]
CAC 40	0.039	3.730[w1.feb]	3.649[w4.dec]	3.552[mo.2.dec]	3.504[p.xm.ny]	3.220[preholi]
MIDCAC*	0.039	5.852[w5.dec]	5.669[feb.]	4.790[i.xm.ny]	4.757[mo.l.1]	4.725[jan.]
GERMANY						
DAX 100	0.035	4.370[mo.1.jul]	4.287[preholi]	3.971[mo.2.dec]	3.654[w1.jun]	3.570[p.xm.ny]
DAX 30	0.023	3.923[preholi]	3.907[mo.1.jul]	3.696[p.xm.ny]	3.611[w4.dec]	3.267[mo.2.dec]
MDAX*	0.040	5.056[w1.feb]	5.038[mo.l.1]	4.792[preholi]	4.764[p.xm.ny]	4.704[week1]
HONG KONG						
HS MAIN	0.025	3.466[p.xm.ny]	3.410[mo.f.2]	3.370[w4.dec]	3.174[friday]	3.144[mo.l.1]
ITALY						
MIBTEL	0.030	3.814[mo.2.dec]	3.627[preholi]	3.079[p.xm.ny]	3.019[thu.nov]	2.932[p.xmas]
MIB 30	0.026	4.078[preholi]	3.063[mo.2.dec]	3.052[p.xm.ny]	2.882[thu.nov]	2.643[w3.nov]
MIDEX*	0.049	5.958[p.xm.ny]	4.836[preholi]	4.369[mo.l.1]	3.905[w1.feb]	3.705[w5.dec]
JAPAN						
NIKKEI ALL	-0.011	3.419[mo.l.1]	2.526[w1.may]	2.143[mo.l.4]	1.968[i.xm.ny]	1.962[thu.feb]
NIKKEI 225	-0.002	2.634[thu.jul]	2.479[wed.dec]	2.432[thu.feb]	2.421[wed.apr]	2.249[w1.may]
TOKYO SC*	-0.008	5.056[w1.may]	4.532[mo.1.may]	3.712[may]	3.676[mo.l.1]	3.662[fri.apr]
NORWAY						
OSLO ALL	0.029	5.029[p.xm.ny]	3.679[postholi]	3.670[preholi]	3.045[w2.mar]	2.989[fri.mar]
OBX	0.021	4.147[p.xm.ny]	3.609[postholi]	3.163[w1.jul]	3.141[mo.2.dec]	2.969[w2.mar]
OSLO SC*	0.051	4.984[p.xm.ny]	4.768[preholi]	4.573[mo.l.1]	4.539[w4.jan]	4.365[i.xm.ny]
SWEDEN						
GENERAL	0.034	3.839[i.xm.ny]	3.794[w3.nov]	3.660[w5.dec]	3.075[w1.feb]	2.942[mo.l.1]
OMX	0.030	3.811[w3.nov]	2.826[mon.sep]	2.742[i.xm.ny]	2.674[w1.feb]	2.556[w5.dec]
UK						
FTSE 350	0.033	3.929[mo.2.dec]	3.563[w4.dec]	3.283[mo.1.jul]	3.239[w5.jan]	2.962[december]
FTSE 100	0.031	3.613[mo.2.dec]	3.167[w4.dec]	3.145[mo.1.jul]	3.049[w5.jan]	2.794[december]
FTSE 250*	0.045	5.664[w4.dec]	5.428[mo.2.dec]	4.381[w1.jan]	4.177[week1]	4.163[w1.mar]
USA						
DJIA	0.017	7.601[preholi]	6.551[week1]	5.044[p.xm.ny]	4.906[mo.f.2]	4.797[w5.dec]
SP 500	0.029	3.697[mo.2.dec]	3.015[fri.dec]	2.889[w5.jan]	2.799[w1.jun]	2.732[wedn.day]
SP 400*	0.051	4.876[mo.2.dec]	4.222[i.xm.ny]	3.822[w5.dec]	3.508[mo.l.2]	3.475[p.xm.ny]

This table reports the returns (effect names are given in brackets) of the five best performing calendar effects in terms of standardized returns. Mid- and small-cap indices are marked with an asterix. See Table 1 and Section 2 for an explanation of the effect mnemonics.

Table 7: Performance of Calendar Effects: The Worst five in terms of Standardized Returns.

Series	Bench.	Worst	2th Worst	3th Worst	4th Worst	5th Worst
DENMARK						
KFX	0.045	-2.303[w5.aug]	-1.960[august]	-1.933[w4.feb]	-1.768[w4.jul]	-1.727[mo.1.aug]
FRANCE						
SBF 120	0.041	-2.442[thu.aug]	-2.192[w5.nov]	-1.933[w5.aug]	-1.832[w3.jun]	-1.814[mo.2.sep]
CAC 40	0.039	-2.471[thu.aug]	-1.881[w3.jun]	-1.823[w5.nov]	-1.800[mo.2.sep]	-1.775[mon.aug]
MIDCAC*	0.039	-3.358[w5.nov]	-2.977[w3.jun]	-2.672[wed.jul]	-2.590[sept.]	-2.500[w3.dec]
GERMANY						
DAX 100	0.035	-2.744[thu.sep]	-2.197[sept.]	-1.954[mo.2.sep]	-1.717[w4.jul]	-1.712[w3.aug]
DAX 30	0.023	-2.930[thu.sep]	-2.417[sept.]	-2.105[mo.2.sep]	-1.672[fri.sep]	-1.578[w3.aug]
MDAX*	0.040	-3.017[w3.sep]	-2.311[sept.]	-2.230[thu.sep]	-2.094[mo.2.sep]	-1.977[w3.jun]
HONG KONG						
HS MAIN	0.025	-2.184[mo.l.2]	-2.182[w3.sep]	-2.066[w4.jul]	-1.940[thu.mar]	-1.797[w5.nov]
ITALY						
MIBTEL	0.030	-3.015[wed.may]	-2.554[mon.jun]	-2.372[w5.aug]	-2.125[thu.sep]	-2.055[w2.sep]
MIB 30	0.026	-2.499[w5.aug]	-2.472[wed.may]	-2.187[thu.sep]	-2.053[w2.dec]	-1.785[mo.2.aug]
MIDEX*	0.049	-2.486[w2.dec]	-2.302[mon.jun]	-2.202[thu.sep]	-2.036[w5.aug]	-1.771[mo.1.jun]
JAPAN						
NIKKEI ALL	-0.011	-2.607[w4.jul]	-2.562[mo.f.4]	-2.403[monday]	-2.382[w3.jun]	-2.155[mo.2.jul]
NIKKEI 225	-0.002	-2.481[mon.jun]	-2.224[monday]	-2.070[w3.jun]	-1.947[mo.f.4]	-1.930[week4]
TOKYO SC*	-0.008	-4.768[w4.jul]	-4.245[mo.2.jul]	-3.316[sept.]	-3.086[p.xmas]	-2.898[week4]
NORWAY						
OSLO ALL	0.029	-2.338[w3.mar]	-1.924[w3.sep]	-1.828[w3.jun]	-1.770[w5.aug]	-1.720[mo.2.sep]
OBX	0.021	-2.500[w3.mar]	-1.869[w3.sep]	-1.767[wed.may]	-1.740[w2.oct]	-1.555[thu.jun]
OSLO SC*	0.051	-2.945[w3.jun]	-2.937[p.xmas]	-2.630[sept.]	-2.555[w3.dec]	-2.318[w4.jun]
SWEDEN						
GENERAL	0.034	-2.369[w5.aug]	-2.143[wed.mar]	-2.135[wed.may]	-1.892[w3.jun]	-1.891[thu.aug]
OMX	0.030	-3.053[w5.aug]	-2.155[wed.may]	-2.094[wed.mar]	-2.028[thu.aug]	-1.868[thu.sep]
UK						
FTSE 350	0.033	-2.633[w4.jul]	-2.145[w2.sep]	-2.123[tue.sep]	-2.030[mo.2.jun]	-1.795[thu.aug]
FTSE 100	0.031	-2.506[w4.jul]	-2.136[w2.sep]	-1.986[thu.aug]	-1.961[tue.sep]	-1.868[mo.2.jun]
FTSE 250*	0.045	-2.679[tue.sep]	-2.470[w4.jul]	-2.365[sept.]	-2.342[mon.aug]	-2.227[w4.jun]
USA						
DJIA	0.017	-6.021[monday]	-3.571[mon.sep]	-3.148[mon.may]	-2.673[mon.jun]	-2.566[sept.]
SP 500	0.029	-1.948[thu.dec]	-1.498[thu.aug]	-1.442[w4.jul]	-1.331[w4.sep]	-1.331[tue.jul]
SP 400*	0.051	-2.610[fri.feb]	-1.835[w4.jul]	-1.570[w2.jun]	-1.566[postholi]	-1.373[w1.oct]

This table reports the returns (effect names are given in brackets) of the five worst performing calendar effects in terms of standardized returns. Mid- and small-cap indices are marked with an asterix. See Table 1 and Section 2 for an explanation of the effect mnemonics.

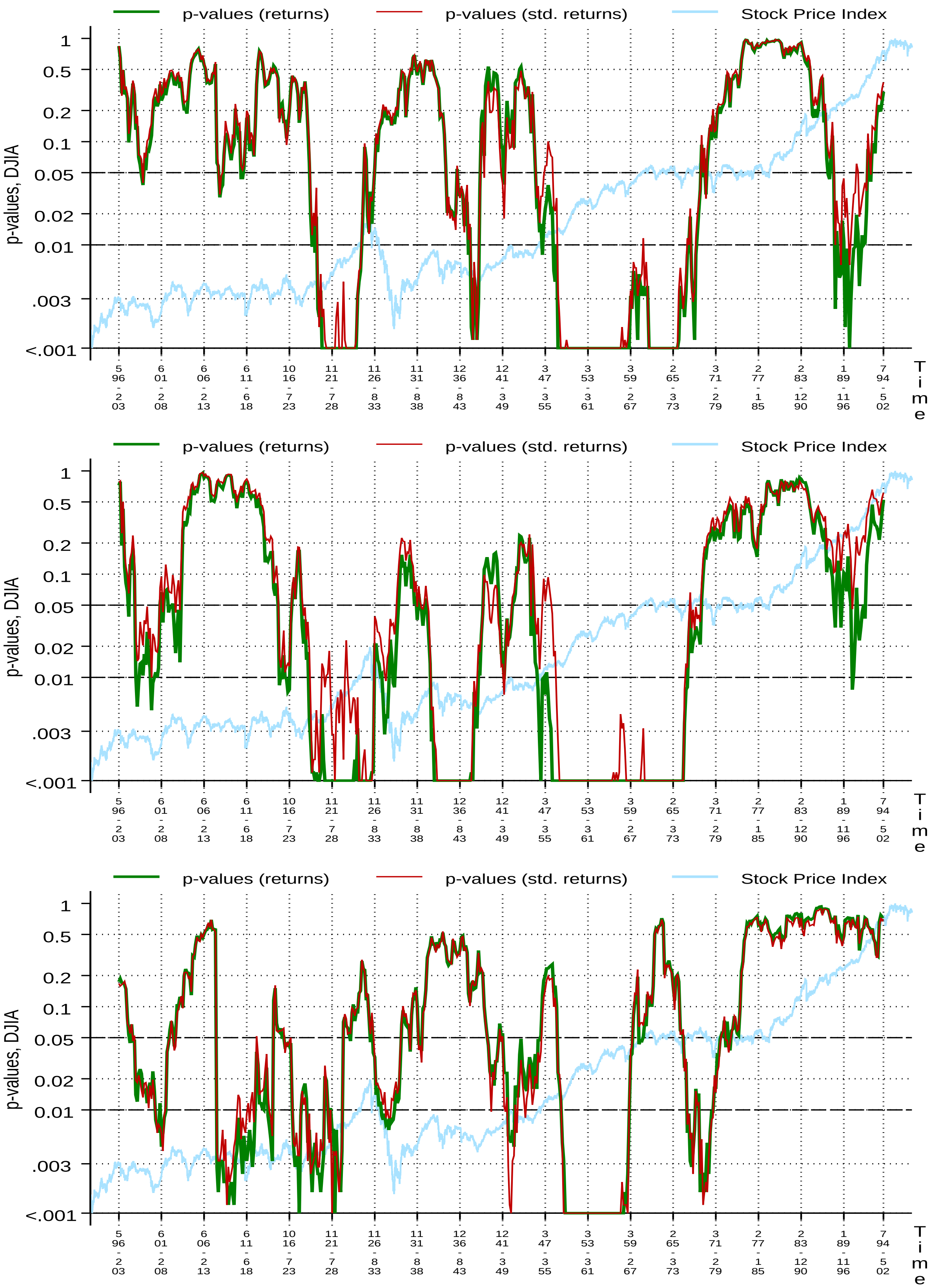

Figure 1 This figure present rolling-sample p-values for DJIA. Each p-value is based on 2000 daily returns, and calculated in step of 50 observations. The top window contains the full universe of effects, the middle window is for the 17-effects universe (day-of-the-week and month-of-the-year), and the 5-effects universe (xmas, new year, and holiday) appears in the bottom window.