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ORIGINAL RESEARCH

Calendar anomalies and dividend announcements effects on the stock markets returns

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Abstract

In this study, we extend the existing literature around dividend signaling theory and calendar anomalies by addressing the question of whether calendar anomalies, including Halloween, Turn-of-the-Month (TOM), January, Monday, and Friday effects, have any influence on the relationship between stock returns and dividend announcements. Previous studies have primarily focused on demonstrating the impact of calendar anomalies on overall stock market returns. Our main aim is to investigate whether the Cumulative Abnormal Returns (CARs) associated with dividend announcements made by firms listed in the FTSE 350 index exhibit deviations from the norm due to these calendar anomalies. Our findings reveal a notable asymmetry in the reactions to dividend increase and decrease announcements. Specifically, the timing of dividend increase announcements appears to have no significant effect on their associated CARs. However, dividend decrease announcements made during periods characterized by seasonality exhibit CARs that differ significantly from those observed during normal times. Importantly, these findings remain robust across various alternative economic model specifications, including interaction models, binary models, and GMM estimations. Consequently, our results suggest that calendar anomalies, such as Halloween, January, and Friday effects, play a key role in shaping the association between stock returns and dividend announcements.

Keywords CAR · Stock markets · Calendar anomalies · Dividend signaling theory · GMM

JEL Classification G35 · G39 · G41

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1 Introduction

This research investigates several stock market anomalies that have previously been found to significantly influence stock returns. These stock market irregularities are commonly referred to as calendar anomalies, with Wachtel (1942) being the first to describe them. Notable calendar anomalies, including the Monday effect, Friday effect, Halloween effect (commonly known as "Sell in May and go away"), TOM impact, and January effect, are explored in this study. These anomalies pose challenges to the Efficient Market Hypothesis (EMH) (Urquhart and McGroarty 2014), as the EMH posits that stock prices consistently reflect all available information in the market. Additionally, according to the EMH investors cannot gain any advantage if they anticipate future earnings using market-related information (weak form).

However, previous literature shows a positive relationship between stock returns and dividend change announcements (Boubaker et al. 2024; Hasan 2022, 2024; Hasan and Al-Najjar 2024). Pettit (1972) provides early proof that favorable (unfavorable) dividend changes lead to favorable (unfavorable) abnormal returns. Easton and Harris (1991) discovers, based on Australian data, that dividend announcements and earnings fluctuations interact to affect stock returns, indicating that the interchange of signals influences investor selling and buying decisions. According to Nissim and Ziv (2001) dividend increases (decreases) have a positive (negative) impact on future earnings changes. However, other researchers have found little or no relationship between dividend changes and future earnings or profitability changes (Alhalabi et al. 2023; Grullon et al. 2005; Choi et al. 2011; Hasan 2021a, 2021b).

The main aim of this paper is to examine if calendar anomalies have any impact on the association between stock returns and dividend announcements. To do so, we analyze whether calendar anomalies affect the cumulative abnormal returns (CARs) associated with dividend announcements made by firms listed in the FTSE 350 index. We employ an extensive dataset spanning from January 1990 to December 2021 and focus on the announcement CAR within the event window $[-1,+1]$. Our two models are (1) linear interaction model and (2) linear binary model. The second specification serves as a robustness test. Furthermore, we use GMM estimation, as an endogeneity test, to validate our findings. In alignment with existing literature, we incorporate five well-known calendar anomalies: Halloween, TOM, January, Monday, and Friday effects.

This study offers several significant contributions to the existing literature. Firstly, it pioneers the examination of how calendar or seasonal irregularities influence the stock market's reactions to dividend announcements. This investigation sheds light on a previously unexplored dimension of market behavior, enriching our understanding of the interplay between temporal anomalies and financial markets. Secondly, this research introduces an innovative model specification, referred to as the binary model. This novel approach enhances our analytical approach and opens new avenues for comprehending the complexities of stock market dynamics in response to dividend announcements. The inclusion of this model contributes to the methodological diversity in our field. Thirdly, our study employs an extensive dataset to provide a more robust foundation for our analysis, enhancing the reliability and generalizability of our findings. Lastly, our findings make a distinctive contribution to the broader literature on calendar or seasonal effects and the dividend signaling theory. By demonstrating the intricate relationship between calendar anomalies and stock market reactions to dividend announcements, we offer fresh insights into the dynamics of financial markets. Our research extends research work in this field, enriching the theoretical framework underpinning dividend signaling and its interaction with temporal irregularities."

Despite the dominance of the Efficient Market Theory, stock market seasonality has a long history (Fama 1970, 1991). According to Bakar et al. (2014) Monday effect is an old and effective stock market anomaly. This phenomenon, characterized by negative or significantly lower returns on Mondays compared to other days of the week, was initially observed in the US market in the 1950s and 1970s by French (1980). Subsequent investigations by Tong (2000), Condoyanni et al. (1987), and Jaffe and Westerfield (1985) have validated the presence of the Monday effect across various markets. Based on previous literature, the January effect is connected to accounting earnings and prospects for the future earnings in a way that is compatible with both economic and accounting theory (see Easterday and Sen 2016). It is observed that returns are often higher in January compared to other months (Easterday and Sen 2016). While some studies (Gu 2003; Hasan and Islam 2022; He and He 2011) suggest that the January effect may be diminishing, others (Ziemba 2011; Ciccone 2011; Anderson et al. 2007) demonstrate its persistence in contemporary US markets, albeit not consistently (Easterday and Sen 2016). The Halloween effect, also known as "Sell in May and go away," was initially identified by Bouman and Jacobsen (2002). This phenomenon is based on the adage that stock returns have a tendency to be lower from May through October compared to other months. Although the exact origin of this adage remains uncertain, Jacobsen and Zhang (2010) trace its documented reference back to the Financial Times in 1935. Additionally, we examine the TOM effect, first noted by Ariel (1987), which continues to be a subject of interest in the realm of seasonal anomalies. The TOM effect refers to the tendency for stock returns to rise between the end of one month and the beginning of the next. Lastly, the Friday effect, as found in previous research (Dubois and Louvet 1996; Brusa et al. 2003), indicates that the market typically responds more favorably on Fridays compared to Mondays and other weekdays.

While previous research has investigated the association between stock market performance and calendar anomalies using various calendar or seasonal anomalies, the impact of calendar anomalies on the association between stock market performance and dividend announcements remains unexplored. This paper fills that gap. To conduct this research, we employ data from FTSE-350 (LSE) companies, as efforts to fully explain calendar anomalies' impact on stock markets, especially the distinct weekend effect observed in the UK stock market, have proven challenging. The weekend effect is less pronounced and shorter-lived in the UK compared to other countries, becoming more evident during market downturns (Steeley 2001). Furthermore, the UK's calendar anomalies effect is more pronounced in larger-capitalized companies than in smaller ones, suggesting a disconnect from explanations based on size-based anomalies, unlike many other equity markets. Additionally, this effect appears to be somewhat more closely related to settlement practices than in other markets, although this relationship remains only partially explained. The unique combination of characteristics necessitates exploring unconventional explanations for the UK calendar anomalies effect.

Our findings suggest that calendar or seasonal irregularities significantly influence the stock market's response to dividend announcements. We observe a notable asymmetry in the stock market's reaction to dividend announcements on calendar anomalies. Specifically, CARs for dividend increases declared on calendar anomalies show no significant change. In contrast, there are distinct results for dividend reduction announcements. Announcing a dividend reduction between November and April, as opposed to May and October, results in a substantially less negative market reaction (Halloween effect). However, there is a slight negative impact for the TOM effect when companies announce a dividend cut.

Additionally, the stock market reacts negatively to news of dividend reductions made in January. Notably, there are no substantial differences in how the stock market responds to Monday announcements of dividend increases or decreases. However, there is some evidence that the stock market responds less favorably to announcements of dividend reductions on Fridays. Similar results, for dividend reductions, are obtained for all calendar anomalies when GMM estimator is applied, aligning with previous research (French 1980; Rogalski 1984; Smirlock and Starks 1986). In sum, the results concerning dividend reductions deviate from both the literature on calendar anomalies and the dividend signaling theory.

The rest of this paper is structured as follows: the next section investigates calendar irregularities and develops hypotheses based on prior literature. Section 3 discusses methodology and data collection techniques, while Sect. 4 presents empirical findings and robustness testing. Conclusions are presented in Sect. 5.

2 Literature review and hypotheses development

Bouman and Jacobsen (2002) was first to document the Halloween effect, and they identified a market adage suggesting that "*selling in May and going away but buying back on St. Leger Day*" yielded positive results in 36 out of 37 equity markets analyzed. Bouman and Jacobsen (2002) explore various factors in an attempt to explain this anomaly, including risk, cross-correlations within markets, the January effect, data mining, shifts in interest rates, alterations in trading volume and the seasonality of news provision. Bouman and Jacobsen's (2002) research shows that not a single of these variables appeared to offer a convincing clarification.

The Halloween impact, initially described by Bouman and Jacobsen (2002) based on the US stock market, is revisited by Maberly and Pierce (2004). In their investigation, they report that the significant Halloween effect initially reported by Bouman and Jacobsen (2002) appears to be influenced by the presence of two distinct outliers. Notably, one of these outliers pertains to the "crash" observed in the global equity market in October 1987, while the other is attributed to the August 1998 failure of the Long-term Capital Management hedge fund. Upon the adjustment of these outliers, Maberly and Pierce (2004) observe a notable alteration in their findings, leading to the disappearance of the Halloween effect within the US market. However, Witte (2010) contends that Maberly and Pierce (2004) identify these two outliers without adhering to formalized criteria and address them in a manner that is deemed unsatisfactory. In distinction to the assertions made by Maberly and Pierce (2004), Witte (2010) employs robust regression analysis, the results of which suggest that the outliers identified do not exert a substantial influence on the outcomes originally presented by Bouman and Jacobsen (2002). Based on this discussion, our hypothesis:

H_{a1} The stock market responds to dividend announcements differently during the Halloween season (November–April) than it does the rest of the year (May–October).

The TOM effect, which is known as an upward tendency in returns through the first trading days of every month, has been studied in the past (Sharma and Narayan 2014). Numerous studies have been conducted on this well-known phenomenon (Lakonishok and Smidt 1988; McConnell and Xu 2008; Holden et al. 2005). Ariel (1987) was the first to recognize the TOM effect in the American stock market. Ariel (1987) in his seminal study examines equally weighted and value-weighted daily returns using NYSE data from 1963 to 1981 and documents that at the beginning of every month the mean value of daily stock returns is continuously positive, these positive mean values stay first half of the month and then disappears. The first three trading days and the final trading day of each month saw the biggest returns, according to Lakonishok and Smidt's (1988) analysis of the DJIA from 1897 to 1986.

Subsequently, McConnell and Xu (2008) extend the findings of Lakonishok and Smidt (1988) using data from 1897 to 2005 and assert the existence of the TOM effect in 31 out of the 35 countries they investigated. Utilizing FT-30 stock market returns from July 1935 to March 2009 and employing a range of -1 to $+3$ days Atanasova and Hudson (2010) added extra evidence in support of the TOM effect. Liu (2013) have identified the TOM effect in the broader U.S. equities market, analyzing data from January 2001 to December 2011.Building upon these insights, we formulate the hypothesis that:

H_{a2} The stock market responds to announcements of dividend increases (decreases) differently early in the month $[-1, +3]$ compared to later in the month.

Ever since Rozeff and Kinney (1976) first brought attention to the phenomenon known as the January effect, it has remained a topic of intense debate within finance literature. The January effect posits that the month of January tends to yield larger returns compared to other months throughout the year. Normally, investors realize disproportionately higher returns on small-cap shares at the onset of the calendar year when they acquire stocks in smaller or underperforming companies towards the end of the preceding year and subsequently sell them as their prices rise in January (Klock and Bacon 2014). Using data from the NYSE spanning the years 1904–1974, Rozeff and Kinney (1976) report an average return of 3.48% for the month of January compared to 0.42% for other months. Using NYSE data from 1963 to 1979 Keim (1983) finds that abnormal returns in January constitute around 50% of the average risk premium associated with small enterprises relative to big enterprises, based on NYSE data from 1963 to 1979. Keim (1983) also reports that the abnormal returns during the first week of the year account for 50% of the January premium. These conclusions pertaining to small businesses, particularly those with lower stock prices, are corroborated by Roll (1983) and Reinganum (1983). However, Kohers and Kohli (1991) contend that the January effect is not related to small enterprises. Lakonishok and Smidt (1988), when analyzing DJIA market data, did not uncover any compelling evidence supporting the presence of the January effect.

Furthermore, a growing body of research indicates that the January effect is diminishing in significance (Gu 2003; He and He 2011; Hensel and Ziemba 2000). Kato and Schallheim (1985) explore excess return using data from the Tokyo Stock Exchange and found evidence of excessive returns, along with a significant correlation between returns and firm size. Easterday and Sen (2016) identify a connection between the January effect and accounting outcomes, as well as expectations regarding future profitability. Their findings build upon arguments raised by Henkeer and Debapriya (2012), who challenged the "irrational noise trader" theory of the January effect. Drawing from these insights, we formulate the hypothesis that:

H_{a3} The stock market reacts differently in January than it does in other months of the year when a dividend increases, or decline is announced.

The phenomenon known as the Monday effect has long been a subject of scrutiny, elucidating how Mondays often coincide with suboptimal asset returns. This phenomenon has been explored extensively by both scholars and industry experts. A seminal three-year statistical study conducted by Kelly (1930) underscored that Monday was notably the least favorable day for purchasing stocks. Remarkably, practitioners had already discerned the presence of the Monday effect as early as the 1920s, as revealed by Maberly (1995). The persistently negative returns on Mondays have exhibited robustness across different time periods and various markets (cf. Jaffe and Westerfield 1985; Keim and Stambaugh 1984). Pioneering research by French during the 1950s and 1970s in the U.S. market provides some of the earliest evidence of anomalous price movements during weekends (1980).

Cross (1973) stands as the first researcher to employ S&P 500 data from 1953 to 1970 to demonstrate the existence of the Monday effect. Over this period, Cross (1973) observes that 62% of Fridays witnessed an increase in the index, with a mean return of + 0.12%, while only 39.5% of Mondays recorded an index increase, with a mean return of −0.18%. It is noteworthy that Friday returns from the previous week formed the basis for Monday returns in Cross's analysis.

Lakonishok and Smidt (1988) have further contributed to the literature, reporting consistently negative Monday returns spanning the entire sample period from 1897 to 1986. They have noted that nearly all their subsamples exhibited statistical significance. Rogalski (1984) delved into the negative average Monday return during the non-trading interval between Friday's close and Mondays open. Subsequently, Damodaran (1989) sheds light on the propensity of companies to disseminate unfavorable news on Fridays, suggesting that this delayed disclosure of adverse information might contribute to the observed weak Monday returns. In light of these empirical observations, we formulate the following hypothesis:

H_{a4} When dividends are announced on Mondays, the stock market reacts differently than it does the rest of the week.

Previous research shows that the weekend effect (also known as the Friday effect) continues to exist in the Tokyo Stock Exchange, the London Stock Exchange, the Toronto Stock Exchange, the Belgian and Swiss Stock Exchanges, the US Stock Exchange, the Tokyo Stock Exchange (Jaffe and Westerfield 1985), the London Stock Exchange (Theobald and Price 1984), and the London Stock Exchange (Brusa et al. 2003).

Using the FTSE-100 index in London Stock Exchange Steeley (2001) find that negative Friday return for the period 1991–1998. On the other hand, using Dow Jones Industrial Average Index, Brusa et al. (2003) find that stock market reacts positively on Fridays, and Carlucci et al. (2014) find no statistically significant difference between each weekday for the period on 2004–2012, when they used Brazil, Mexico and U.S. Stock Exchange data. Based on above argument we established following hypothesis:

H_{a5} On Fridays, the stock market reacts differently to dividend news than it does the rest of the week.

3 Methodology and data

3.1 Methodology and model specifications

We employ standard event research techniques and regression analysis to examine the hypotheses. CAR [− 1, + 1] is the event window for us. We employ two alternative linear model specifications to carry out the hypothesis testing. The first and second model specifications, respectively, are a linear binary model and a linear interaction model. Two explanatory variables in our linear interaction model both exhibit interaction effects, which are (1) dividend increase dummy and (2) DPD dividend decrease dummy. In contrast, the only explanatory factors in our linear binary model are the dummy variables DPI and DPD.

We have chosen five of the most well-known anomalies in terms of calendar impacts, and for each of the anomaly we created distinctive dummy variables. According to Bouman and Jacobsen (2002) Halloween dummy takes 1 if time period from November to April, otherwise 0. Atanasova and Hudson (2010) assert that the TOM variable takes value 1 for the TOM impact from the final trading day of one month through the third trading day of the following month [− 1 to + 3] and a value of 0 in all other circumstances. If the month of January is present, the January dummy for the January effect has a value of 1, otherwise it has a value of 0. Similar to this, the Monday dummy accounts for the Monday effect by taking value 1 on Mondays and 0 otherwise. For the Friday effect, the Friday dummy has a value of 1 on Fridays and 0 otherwise. Returns are measured as:

$$R_{i,t} = \ln\left(P_{i,t}\right) - \ln\left(P_{i,t-1}\right) \tag{1}$$

For the abnormal returns, we employ the difference between the expected returns and the actual returns. Sharpe's (1963) market model is used to predict the expected returns (Campbell and Vuolteenaho 2004):

$$\widehat{R}_{i,t} = \alpha_i + \gamma_i R_{mkt,t} \tag{2}$$

where α_i is the regression line's intercept and γ_i is its slope, the estimated return is $\widehat{R}_{i,t}$ and the benchmark is the market index ($R_{mkt,t}$). In this study, the FTSE-350 Index was used as the benchmark market to determine anticipated returns.

An estimation window from t-200 days to t-20 days before to the announcement date was utilised to calculate γ_i, which measures the correlation between the stock and the market index. Since information might be available, we consider different event windows' lengths- before and after-the announcements. The abnormal return is reported as:

$$AR_{i,t} = R_{i,t} - \left(\hat{\alpha}_i + \hat{\gamma}_i F_t\right) \tag{3}$$

The average abnormal return ($\overline{AR}_t$) on day t is measured as:

$$\overline{AR}_t = \frac{1}{n}\sum_{i=1}^{n} AR_{i,t} \tag{4}$$

The average abnormal returns for all day's t in the event window are added to determine the CAR for each stock i, which is calculated as $CAR_{i,(\tau_1,\tau_2)}$:

$$CAR_{i,(\tau_1,\tau_2)} = \sum_{t=\tau_1}^{\tau_2} AR_{i,t} \tag{5}$$

The mean CAR in the event windows ($\left(\overline{CAR\left(\tau_1,\tau_2\right)}\right)$) is measured as:

$$\overline{CAR\left(\tau_1,\tau_2\right)} = \frac{1}{n}\sum_{i=1}^{n} CAR_{i,(\tau_1,\tau_2)} \tag{6}$$

(1) Linear interaction model

There is an asymmetrical association between dividend changes and stock returns for both dividend increases and declines. We form the ensuing interaction model as a result. This model allows for asymmetric responses to dividend increases and cuts while taking momentum in stock returns and uniform mean reversion into consideration. In model 7, we included two interaction terms related to the positive dividend-change group and the negative changes in dividends.

Model a: Halloween effect

$$\begin{aligned} CAR_{it} = {} & \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * HALL_t \\ & + \lambda_4 R\Delta DIV_{it} * DPD_{it} * HALL_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} \\ & + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVYIELD_{it} + \lambda_9 Shock_{it} \\ & + \vartheta_1 DOW\ DUMMY + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS \\ & + \varepsilon_{it} \end{aligned} \tag{7}$$

where CAR_{it} is cumulative abnormal return. $R\Delta DIV_{it}$ is the percent change in the dividend payment made by firm *i*. If the dividend change is positive, the DPI_{it} takes value 1, otherwise it takes value 0. If the dividend change is negative, DPD_{it} takes value 1, else it takes value 0. Its $SIZE_{it}$ is the natural logarithm of the market capitalization of the company. Using cumulative stock returns from the preceding month (in percentage terms), $REVERSAL_{it}$ is a measurement. Measures of $MOMENTUM_{it}$ are based on the total monthly stock returns from months *t*-12 to *t*-2. $DIVIDEND_{YIELD_{it}}$ represents the annual dividend over the price one day prior to the dividend announcement. We created a dummy variable if data falls between the 1995–2001 (the Dot-com Bubble), 2008–2009 (the Global Financial Crisis), and 2020–2021 (COVID-19), shock, a dummy variable, takes value 1; otherwise, it takes value 0. DOW stands for day-of-the-week dummy. On the appropriate day of the week, they each have a value of 1, and 0 otherwise. The reference day is Tuesday. Year dummies are fixed effect dummies with a year starting in 1990 and ending in 2021. Either industry fixed effects dummies or company fixed effects dummies are *FIXED EFFECTS*. The 17 industry classes created by Fama and French provide the foundation for the industry fixed effect dummies. In terms of the firm fixed effects, our data sample contains 231 firms.

We define model 1a for Halloween effect without *DOW* dummy, year dummy, industry fixed effect and without clustered by company ID (company name) and date. Model 2a for Halloween effect without *DOW* dummy but with year dummy, industry fixed effect and with clustered by company ID and date. Model 3a for Halloween effect with *DOW* dummy, year dummy, industry fixed effect and with clustered by company ID and date. Model 4a for Halloween effect with *DOW* dummy, year dummy, firm fixed effects and with clustered by company ID and date. Model 1b for TOM effect without *DOW* dummy, year dummy, industry fixed effect and without clustered by company ID and date.

Model b: TOM effect

$$\begin{aligned} CAR_{it} = {} & \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} \\ & * DPI_{it} * TOM_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * TOM_t + \lambda_5 SIZE_{it} \\ & + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIV\ YIELD_{it} \\ & + \lambda_9 Shock_{it} + \vartheta_1 DOW\ DUMMY + \vartheta_2 YEAR\ DUMMIES \\ & + \vartheta_3 FIXED\ EFFECS + \varepsilon_{it} \end{aligned} \tag{8}$$

where TOM_t takes value 1 if t belongs to the TOM interval, i.e. which is defined as the third trading day of one month to the last trading day of the following month $[-1, +3]$, and 0 otherwise. We define model 2b for TOM effect without *DOW* dummy but with year dummy, industry fixed effect and with clustered by company ID and date. Model 3b for TOM effect with *DOW* dummy, year dummy, industry fixed effects and with clustered by company ID and date. Model 4b for TOM effect with *DOW* dummy, year dummy, firm fixed effect and with clustered by company ID and date.

Model c: January effect

$$\begin{aligned} CAR_{it} = {} & \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} \\ & * Jan_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * Jan_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} \\ & + \lambda_7 MOMENTUM_{it} + \lambda_8 DIV\ YIELD_{it} + \lambda_9 Shock_{it} + \vartheta_1 DOWDUMMY \\ & + \vartheta_2 YEAR\ DUMMYIES + \vartheta_3 FIXED\ EFFECTS + \varepsilon_{it} \end{aligned} \tag{9}$$

where Jan_t takes value 1 if t belongs to the month of January, and 0 otherwise. Model 1c for January effect without *DOW* dummy, year dummy, industry fixed effect and without clustered by company ID and date. Model 2c for January effect without *DOW* dummy but with year dummy, industry fixed effects and with clustered by company ID and date. Model 3c for January effect with *DOW* dummy, year dummy, industry fixed effect and with clustered by company ID and date. Model 4c for January effect with *DOW* dummy, year dummy, firm fixed effect and with clustered by company ID and date.

Model d: Monday effect

$$\begin{aligned} CAR_{it} = {} & \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} \\ & * Mon_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * Mon_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} \\ & + \lambda_7 MOMENTUM_{it} + \lambda_8 DIV\ YIELD_{it} + \lambda_9 Shock_{it} + \vartheta_1 DOWDUMMY \\ & + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \varepsilon_{it} \end{aligned} \tag{10}$$

where Mon_t takes value 1 on Mondays, and 0 otherwise. Model 1d for Monday effect without *DOW* effect, year dummy, industry fixed effect and without clustered by company ID and date. Model 2d for Monday effect without *DOW* dummy but with year dummy, industry fixed effect and with clustered by company ID and date. Model 3d for Monday effect without *DOW* dummy, but with year dummy, industry fixed effects, firm fixed effects and with clustered by company ID and date. Model 4d for Monday effect with year dummy, firm fixed effect and with clustered by company ID and date.

Model e: Friday effect

$$\begin{aligned} CAR_{it} = {} & \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} \\ & * Fri_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * Fri_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} \\ & + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVYIELD_{it} + \lambda_9 Shock_{it} + \vartheta_1 DOWDUMMY \\ & + \vartheta_2 YEARDUMMIES + \vartheta_3 FIXEDEFFECTS + \varepsilon_{it} \end{aligned} \tag{11}$$

where Fri_t takes value 1 on Fridays, and 0 otherwise. Model 1e for Friday effect without *DOW* dummy, year dummy, industry fixed effect and without clustered by company ID and date. Model 2e for Friday effect without *DOW* dummy but with year dummy, industry fixed effects and with clustered by company ID and date. Model 3e for Friday effect with year dummy, industry fixed effect, firm fixed effects and with clustered by company ID and date. Model 4e for Friday effect with year dummy, firm fixed effect and with clustered by company ID and date.

(2) Linear binary model.

The binary model, in contrast to the linear interaction model, only considers the direction of the dividend changes, independent of the size of the changes, and ignores the size of the dividend changes entirely. The specification of the linear interaction model is complemented by linear binary specification because it has the potential to reduce the effects of outliers on the outcomes.

Model a: Halloween effect

$$\begin{aligned} CAR_{it} = {} & \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * HALL_t + \lambda_4 DPD_{it} * HALL_t \\ & + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} \\ & + \lambda_8 DIV\ YIELD_{it} + \lambda_9 Shock_{it} + \vartheta_1 DOW\ DUMMY \\ & + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \varepsilon_{it} \end{aligned} \tag{12}$$

Model b: TOM effect

$$\begin{aligned} CAR_{it} = {} & \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * TOM_t + \lambda_4 DPD_{it} * TOM_t \\ & + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} \\ & + \lambda_8 DIV\ YIELD_{it} + \lambda_9 Shock_{it} + \vartheta_1 DOW\ DUMMY \\ & + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \varepsilon_{it} \end{aligned} \tag{13}$$

Model c: January effect

$$\begin{aligned} CAR_{it} = \lambda_0 &+ \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * Jan_t + \lambda_4 DPD_{it} \\ &* Jan_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} \\ &+ \lambda_8 DIV\ YIELD_{it} + \lambda_9 Shock_{it} + \vartheta_1 DOW\ DUMMY \\ &+ \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \varepsilon_{it} \end{aligned} \tag{14}$$

Model d: Monday effect

$$\begin{aligned} CAR_{it} = \lambda_0 &+ \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * Mon_t + \lambda_4 DPD_{it} \\ &* Mon_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} \\ &+ \lambda_8 DIV\ YIELD_{it} + \lambda_9 Shock_{it} + \vartheta_1 DOW\ DUMMY \\ &+ \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \varepsilon_{it} \end{aligned} \tag{15}$$

Model e: Friday effect

$$\begin{aligned} CAR_{it} = \lambda_0 &+ \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * Fri_t + \lambda_4 DPD_{it} \\ &* Fri_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} \\ &+ \lambda_8 DIV\ YIELD_{i} + \lambda_9 Shock_{it} + \vartheta_1 DOW\ DUMMY \\ &+ \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \varepsilon_{it} \end{aligned} \tag{16}$$

3.2 Data

This paper employs data from a subset of companies listed in the FTSE-350 index, spanning from January 1990 to December 2021. It's worth noting that the composition of the FTSE-350 index is subject to change over time (as of June 2022). To assess each of the five hypotheses, we utilized the event window known as Cumulative Abnormal Returns (CAR) within the interval $[-1,+1]$. In this context, Day 0 corresponds to the date of the dividend announcement, Day -1 refers to the day preceding the announcement, and Day + 1 signifies the day following the announcement. The estimation window, comprising a total of 181 estimating days, spans from t-200 to t-20. Descriptive statistics of those five calendar anomalies based on dividend announcements are present in Table 1.

Table 1 illustrates the distribution of observations among the various calendar anomalies. Notably, Halloween boasts the highest number of observations, totaling 2335 cases.

Table 1 Details of firm dividend changes observations by calendar anomalies

Variables	Number of obs	Dividend increase	Dividend decrease	Unchanged dividend
Halloween	2335	1908	138	289
TOM	438	367	23	48
January	61	50	4	7
Monday	476	419	25	32
Friday	237	201	10	26

This table showing the details of firm's dividend changes event window by calendar anomalies variables

Within this category, there were 1,908 instances of dividend increases, 138 instances of dividend decrease, and 289 instances where dividends remained unchanged. Conversely, January recorded the lowest number of observations, with only 61 cases in total. Among these, there were 50 instances of dividend increases, 4 instances of dividend decrease, and 7 instances where dividends remained unchanged.

Table 2 provides an overview of the dataset, demonstrating that each of the six variables under consideration encompasses a total of 4021 observations. We winsorized our data set at 2.5%. It is noteworthy that the mean values for all six variables are positive. While variables like momentum, CAR, and percentage dividend changes exhibit negative skewness values, it is worth noting that all six variables exhibit positive kurtosis. While Table 3 displays a correlation matrix for each explanatory factor and dependent factor. Only the dividend yield displays a negative association with dividend changes, reversal, and momentum, according to all five panels in Table 3. All other factors and the TOM impact have a favorable correlation. Halloween and dividend changes and yield are inversely correlated, while dividend changes and reversal and January impact are positively correlated. Size, dividend yield, and CAR all exhibit poor Monday effect correlations.

4 Empirical results

4.1 Linear interaction model

Five of our hypotheses are based on the context of calendar irregularities. To scrutinize these hypotheses comprehensively, we employ a 3-day event window to calculate Cumulative Abnormal Returns (CAR), denoted as CAR $[-1,+1]$. We have generated four distinct tables to investigate the impact of each of these calendar anomalies. Table 4 delineates the particulars of our interaction model specification. We consider four alternative model iterations for each of the calendar anomalies, as outlined in Table 4. Specifically, model 1 lacks DOW, year, industry, and firm fixed effects, and clustered standard errors. In contrast, model 2 introduces DOW and firm fixed effects, while omitting industry fixed effects. Model 3 incorporates clustered standard errors, industry, and year fixed effects, but excludes firm fixed effects. Lastly, model 4 includes four fixed effects, and clustered standard errors, yet excludes industry fixed effects.

Our analysis shows that the average return for stocks stands at 0.01619%. A closer examination of Table 4 elucidates statistically significant results across all four models for both RΔDIV •DPI and RΔDIV •DPD. These findings align with the tenets of dividend signaling theory, as corroborated by prior research (Grullon et al. 2005; Choi et al. 2011; Hasan 2021a).

Table 4 further reveals that when dividend increase interacts with the calendar anomalies, the results do not attain statistical significance across all four models. These outcomes imply limited evidence suggesting that calendar irregularities exert an influence on how the stock market responds to dividend increase announcements.

As regards dividend decrease, for the Halloween-themed impact, as evidenced in Table 4, our findings attain statistical significance at the 1% level across all four models, all bearing a negative sign. It is noteworthy that despite only 60 of the 198 dividend reduction announcements in our dataset occurring between November and April, these results economic value is around 22 times higher compared to the average stock return. These findings suggest that the stock market reacts with less negativity to dividend

Table 2 Descriptive statistics for dividend event observations

Variables	N	Mean	Std. Dev	Mini	Max	5%	25%	75%	95%	Skewness	Kurtosis
R ΔDIV (%)	4,021	9.787	13.101	−50.00	50.00	−2.522	4.098	15.347	31.034	−0.820	8.135
Size (£ billion	4,021	7.080	1.453	0.386	12.061	4.891	6.078	8.014	9.708	0.253	3.201
Reversal (%)	4,021	0.055	0.435	−4.039	7.490	−0.618	−0.157	0.281	0.693	0.869	29.924
Momentum (%)	4,021	0.303	1.503	−9.598	6.279	−2.354	−0.507	1.232	2.509	−0.631	5.282
DIV Yield (%)	4,021	2.035	1.328	0.004	17.248	0.004	1.268	2.639	4.211	2.086	16.467
CAR[−1, +1] (%)	4,021	1.256	5.945	−40.881	51.255	−7.294	−1.732	4.224	10.469	−0.034	9.873

This table reports the firm's characteristics for the sample firms. *R ΔDIV* is the annual changes of the dividend payment in percentage terms. *Size* is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the *Size* values are in billions. *Reversal* is measured using cumulative stock returns over the previous month, it also representing in percentage. *Momentum* is cumulated monthly stock returns from month *t*-12 to *t*-2. *DIV Yield* calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. And finally CAR is representing Cumulative Abnormal Return, estimated using the abnormal returns around the dividend announcement date. The sample period is from January 1990 to December 2021

Table 3 Correlation matrix for four calendar anomalies

Variables	R ΔDIV	Size	Reversal	Momentum	DIV Yield	CAR	Halloween
Panel A: Halloween effect							
R ΔDIV	1.000						
Size	0.048	1.000					
Reversal	0.028	0.007	1.000				
Momentum	0.241	0.068	−0.040	1.000			
DIV Yield	−0.222	−0.168	−0.137	−0.356	1.000		
CAR	0.097	−0.131	−0.063	−0.034	0.064	1.000	
Halloween effect	−0.003	0.001	0.059	0.005	−0.075	0.037	1.000
Variables	R ΔDIV	Size	Reversal	Momentum	DIV Yield	CAR	TOM
Panel B: TOM effect							
R ΔDIV	1.000						
Size	0.048	1.000					
Reversal	0.028	0.007	1.000				
Momentum	0.241	0.068	−0.041	1.000			
DIV Yield	−0.222	−0.168	−0.137	−0.356	1.000		
CAR	0.097	−0.131	−0.063	−0.034	0.064	1.000	
TOM effect	0.002	0.037	0.015	0.031	0.026	0.002	1.000
Variables	R ΔDIV	Size	Reversal	Momentum	DIV Yield	CAR	January
Panel C: January effect							
R ΔDIV	1.000						
Size	0.048	1.000					
Reversal	0.028	0.007	1.000				
Momentum	0.241	0.068	−0.041	1.000			
DIV Yield	−0.222	−0.168	−0.137	−0.356	1.000		
CAR	0.097	−0.130	−0.063	−0.034	0.064	1.000	
January effect	−0.004	0.049	0.014	−0.011	−0.038	−0.022	1.000
Variables	R ΔDIV	Size	Reversal	Momentum	DIV Yield	CAR	Monday
Panel D: Monday effect							
R ΔDIV	1.000						
Size	0.048	1.000					
Reversal	0.028	0.007	1.000				
Momentum	0.241	0.068	−0.041	1.000			
DIV Yield	−0.222	−0.168	−0.137	−0.356	1.000		
CAR	0.097	−0.131	−0.063	−0.034	0.064	1.000	
Monday effect	0.041	−0.093	0.021	0.039	−0.089	−0.021	1.000
Variables	R ΔDIV	Size	Reversal	Momentum	DIV Yield	CAR	Friday
Panel E: Friday effect							
R ΔDIV	1.000						
Size	0.047	1.000					
Reversal	0.003	0.007	1.000				
Momentum	0.251	0.068	−0.074	1.000			

Table 3 (continued)

Variables	R ΔDIV	Size	Reversal	Momentum	DIV Yield	CAR	Friday
DIV Yield	−0.209	−0.168	−0.119	−0.344	1.000		
CAR	0.087	−0.131	−0.050	−0.044	0.068	1.000	
Friday effect	0.009	−0.001	0.008	−0.001	−0.011	−0.048	1.000

This table reports the firm's characteristics for the sample firms. *R ΔDIV* is the annual changes of the dividend payment in percentage terms. Size represents the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the *Size* values are in billions. *Reversal* is measured using cumulative stock returns over the previous month, it also representing in percentage. *Momentum* is cumulated monthly stock returns from month *t*-12 to *t*-2. *DIV Yield* calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. And finally, *CAR* is representing Cumulative Abnormal Return, estimated using the abnormal returns around the dividend announcement date. The sample period is from January 1990 to December 2021

reduction announcements made during the period from November to April compared to the other months. We have computed the partial impact of a dividend cut announcement on CAR when it takes place between November and April.

$$\begin{aligned}
&\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}} | DPD_{it} = 1\right) = \lambda_2 DPD_{it} + \lambda_4 DPD_{it} * HALL_t \\
&=> \left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}} | DPD_{it} = 1\right) = \widehat{\lambda_2} + \widehat{\lambda_4} * HALL \\
&= \widehat{\lambda_2} + \widehat{\lambda_4} * \mathbf{1}
\end{aligned} \tag{17}$$

where **1** is an indicator function that takes the value 1 if *t* belongs to the period between November and April, and 0 otherwise.

The presence of firm fixed effects in Table 4 emerges as statistically significant, as indicated by the joint significant test results pertaining to the Halloween effect presented in Table 5. Consequently, model 4 is designated as our preferred model, although we have duly considered the alternatives. As per Eq. (17) in Table 5, a 10% reduction in dividends leads to a decline in stock returns of 0.11% (as per Model 4) if it transpires between November and April. However, if the same reduction occurs between May and October, the impact is substantially more pronounced, resulting in a decrease of 2.03% (as per Model 4). Comparable outcomes are observed across the other models as well. These findings imply that the stock market responds with less negativity to news of dividend reductions between November and April in contrast to other periods throughout the year (Maberly and Pierce 2004; Bouman and Jacobsen 2002). These results indicate that this anomaly does not suffer from Murphy's law, which is documented by Dimson and Marsh (1999). This indicates that, in contrast to many other anomalies, this one does not, at least not yet appear to vanish or reverse itself upon detection; rather, it persists despite the possibility that investors have become aware of it. This specific calendar anomaly has significant economic implications as well.

In addition, TOM effect is statistically significant across two models (models 1 and 3) when it interacts with dividend decreases dummy. Holding all other factors constant partial effects shows that:

Table 4 Regression analysis of calendar anomalies effect on dividend announcement dates using interaction specification

Variables	Halloween				TOM				January			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
Constant	0.040[a]	0.031[a]	0.033[a]	0.056[a]	0.041[a]	0.038[b]	0.036[b]	0.066[a]	0.041[a]	0.031[a]	0.029[a]	0.065[a]
	(0.005)	(0.011)	(0.011)	0.019	(0.005)	(0.017)	(0.017)	(0.022)	(0.005)	(0.011)	(0.012)	(0.019)
$R\Delta DIV \cdot$ DPI	0.047[a]	0.054[a]	0.055[a]	0.074[a]	0.055[a]	0.062[a]	0.063[a]	0.075[a]	0.055[a]	0.062[a]	0.064[a]	0.073[a]
	(0.014)	(0.014)	(0.014)	0.023	(0.011)	(0.012)	(0.012)	(0.014)	(0.011)	(0.011)	(0.011)	(0.014)
$R\Delta DIV \cdot$ DPD	0.187[a]	0.193[a]	0.190[a]	0.203[a]	0.097[a]	0.099[b]	0.086[b]	0.091[b]	0.066[a]	0.095[a]	0.095[b]	0.062[b]
	(0.026)	(0.057)	(0.057)	0.057	(0.016)	(0.030)	(0.029)	(0.031)	(0.016)	(0.026)	(0.026)	(0.028)
$R\Delta DIV \cdot$ DPI · HALL/TOM/Jan/Mon/Fri	0.011	0.011	0.012	−0.001	−0.011	−0.009	−0.007	−0.021	−0.077	−0.062	−0.063	−0.071
	(0.014)	(0.014)	(0.014)	0.027	(0.021)	(0.019)	(0.019)	(0.021)	(0.053)	(0.026)	(0.029)	(0.042)
$R\Delta DIV \cdot$ DPD · HALL/TOM/Jan/Mon/Fri	−0.177[a]	−0.192[a]	−0.186[a]	−0.192[a]	−0.156[b]	−0.103	−0.112[b]	−0.109	0.427[a]	0.396[b]	0.375[b]	0.392[a]
	(0.031)	(0.062)	(0.061)	0.062	(0.046)	(0.042)	(0.042)	(0.041)	(0.093)	(0.135)	(0.128)	(0.129)
SIZE	−0.005[a]	−0.004[a]	−0.005[a]	−0.013[a]	−0.005[a]	−0.004[a]	−0.005[a]	−0.013[a]	−0.005[a]	−0.004[a]	−0.004[a]	−0.013[a]
	(0.001)	(0.001)	(0.001)	0.002	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
REVERSAL	−0.861[a]	−0.994[a]	0.988[a]	−1.032[a]	−0.853[a]	−0.986[a]	−0.981[a]	−1.0502[a]	−0.894[a]	−1.026[a]	−1.019[a]	−1.104[a]
	(0.239)	(0.365)	(0.363)	0.387	(0.241)	(0.365)	(0.363)	(0.381)	(0.242)	(0.357)	(0.355)	(0.372)
MOMENTUM	−0.152[b]	−0.195[c]	−0.199[c]	−0.175	−0.171[b]	−0.209[c]	−0.214[c]	−0.191[c]	−0.168[b]	−0.206[c]	−0.211[c]	−0.189[c]
	(0.073)	(0.111)	(0.111)	0.114	(0.073)	(0.112)	(0.112)	(0.114)	(0.073)	(0.112)	(0.111)	(0.114)
DIV Yield	0.234[a]	0.196[c]	0.170	0.132	0.207[b]	0.171	0.143	0.122	0.199[b]	0.173	0.145	0.122
	(0.087)	(0.116)	(0.116)	0.237	(0.088)	(0.115)	(0.115)	(0.234)	(0.087)	(0.114)	(0.115)	(0.235)
Shock	−0.248[b]	−0.235[b]	−0.267[b]	−0.247[b]	−0.125[b]	−0.199[b]	−0.152[b]	−0.099[b]	−0.257[b]	−0.298[b]	−0.245[b]	−0.275[b]
	(0.534)	(0.635)	(0.256)	(0.258)	(0.314)	(0.365)	(0.348)	(0.299)	(0.365)	(0.396)	(0.389)	(0.354)
DOW dummy	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Year Dummy	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
FF (17) Industry dummy	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No
Firm dummy	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes

Table 4 (continued)

Variables	Halloween				TOM				January			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
Clustered by Company ID and Date	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
R^2	4.53%	5.85%	6.13%	13.83%	3.85%	5.16%	5.42%	13.21%	4.10%	5.38%	5.64%	13.43%
N	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021

Variables	Monday				Friday			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
Constant	0.042^{a}	0.038^{b}	0.036^{b}	0.067^{a}	0.041^{a}	0.038^{b}	0.035^{b}	0.037^{b}
	(0.005)	(0.018)	(0.018)	(0.021)	(0.005)	(0.179)	(0.017)	(0.020)
$R\Delta DIV \cdot$ DPI	0.057^{a}	0.064^{a}	0.064^{a}	0.074^{a}	$0.\ 055^{a}$	0.062^{a}	0.063^{a}	0.068^{a}
	(0.011)	(0.012)	(0.012)	(0.014)	(0.011)	(0.012)	(0.012)	(0.019)
$R\Delta DIV \cdot$ DPD	0.082^{a}	0.089^{b}	0.043^{b}	0.069^{b}	0.088^{a}	0.088^{b}	0.078^{b}	0.087^{a}
	(0.016)	(0.025)	(0.025)	(0.026)	(0.016)	(0.027)	(0.027)	(0.024)
$R\Delta DIV \cdot$ DPI · HALL/TOM/Jan/Mon/Fri	−0.032	−0.026	−0.029	−0.015	−0.021	−0.024	−0.009	−0.009
	(0.019)	(0.016)	(0.027)	(0.031)	(0.026)	(0.022)	(0.037)	(0.042)
$R\Delta DIV \cdot$ DPD · HALL/TOM/Jan/Mon/Fri	0.107^{c}	0.102	0.104	0.086	0.109^{c}	0.127^{c}	0.099^{c}	0.093^{c}
	(0.048)	(0.119)	(0.123)	(0.132)	(0.063)	(0.132)	(0.137)	(0.066)
SIZE	-0.005^{a}	-0.004^{a}	-0.005^{a}	-0.013^{a}	-0.005^{a}	-0.004^{a}	-0.004^{a}	-0.004^{a}
	(0.001)	(0.005)	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
REVERSAL	-0.859^{a}	-0.988^{a}	-0.985^{a}	-1.056^{a}	-0.872^{a}	-1.001^{b}	-1.001^{a}	-1.001^{a}
	(0.241)	(0.364)	(0.362)	(0.382)	(0.241)	(0.358)	(0.357)	(0.249)
MOMENTUM	-0.164^{b}	-0.203^{c}	-0.209^{c}	−0.187	-0.167^{b}	-0.203^{c}	-0.208^{b}	-0.229^{b}
	(0.073)	(0.112)	(0.112)	(0.115)	(0.073)	(0.112)	(0.113)	(0.082)

Table 4 (continued)

Variables	Monday				Friday			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
DIV Yield	0.199^{b}	0.164	0.147	0.126	0.216^{b}	0.176	0.150	0.150
	(0.088)	(0.115)	(0.115)	(0.235)	(0.088)	(0.115)	(0.115)	(0.092)
Shock	-0.269^{b}	-0.256^{b}	-0.299^{b}	-0.189^{b}	-0.193^{a}	-0.235^{a}	-0.239^{a}	-0.246^{a}
	(0.364)	(0.123)	(0.238)	(0.298)	(0.301)	(0.304)	(0.315)	(0.396)
DOW dummy	No	No	No	No	No	No	No	No
Year dummy	No	Yes	Yes	Yes	No	Yes	Yes	Yes
FF (17) Industry dummy	No	Yes	Yes	No	No	Yes	Yes	No
Firm dummy	No	No	Yes	Yes	No	No	Yes	Yes
Clustered by Company ID and Date	No	Yes	Yes	Yes	No	Yes	Yes	Yes
R^2	3.87%	5.17%	5.37%	13.11%	3.79%	6.47%	11.95%	13.53%
N	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021

The standardized coefficient values and dependent variable is CAR $[-1,+1]$. $R\Delta DIV_0$ is annual dividend changes percentage. *DPI* and *DPD* are two dummy variables. If the dividend changes percentage increase, then $DPI=1$, otherwise 0, and if the dividend changes percentage decrease, then $DPD=1$, otherwise 0. *HALL* equals to 1 if *t* belongs to month November to April, and 0 otherwise. TOM takes value 1 if *t* belongs to the interval of $[-1,+3]$, and 0 otherwise. *Jan* takes value 1 if *t* belongs to month of January, and 0 otherwise. *Mon* takes value 1 if *t* is a Monday, and 0 otherwise. *Fri* takes value 1 if *t* is a Friday, and 0 otherwise. *Size* is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the *Size* values are in billions. *Reversal* is measured using cumulative stock returns over the previous month, it also representing in percentage. *Momentum* is cumulated monthly stock returns from month *t*-12 to *t*-2. *DIV Yield* calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. *DOW* is a day-of-the-week dummy, where M_d, W_d, $T_d andF_d$ are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. We also use year dummies, Fama and French (FF) 17 industry and firm dummies. The sample period is from January 1990 to December 2021.Significant coefficients are highlighted, and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively

Table 5 Partial derivatives for dividend decrease announcements with calendar anomalies using interaction specification

Variable	Model (1)					Model (2)					Model (3)					Model (4)				
	Halloween	TOM	January	Monday	Fri day	Hal low een	TOM	Janu ary	Mon day	Fri day	Halloween	TOM	Janu ary	Monday	Fri day	Hal low een	TOM	Janu ary	Monday	Friday
$\widehat{\lambda}_2 + \widehat{\lambda}_4 \cdot 1$	0.010					0.001					0.004					0.011				
$\widehat{\lambda}_2 + \widehat{\lambda}_4 \cdot 1$		−0.059					−0.004					−0.026					−0.018			
$\widehat{\lambda}_2 + \widehat{\lambda}_4 \cdot 1$			0.493					0.491					0.470					0.454		
$\widehat{\lambda}_2 + \widehat{\lambda}_4 \cdot 1$				0.189					–					–					–	
$\widehat{\lambda}_2 + \widehat{\lambda}_4 \cdot 1$					0.197					0.215					0.177					0.180

This tables reports the partial effect of a dividend decrease announcements on the CAR with joint consideration of a calendar anomaly. The dummy variables $DPD = 1$ if the dividend changes percentage decrease, otherwise $0.Z_t$ is a calendar anomaly that includes Halloween, TOM, January, Monday and Friday. *HALL* is equal to 1 if t belongs to month November to April, and 0 otherwise. TOM takes value 1 if t belongs to the interval of $[-1, +3]$, and 0 otherwise. *Jan* takes value 1 if t belongs to month of January, and 0 otherwise. *Mon* takes value 1 if t belongs Monday, and 0 otherwise. *Fri* takes value 1 if t belongs to Friday, and 0 otherwise. From Eqs. (7) to (11) the partial derivatives are calculated as $\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}} | DPD_{it} = 1\right) = \lambda_2 DPD_{it} + \lambda_4 DPD_{it} * Z_t$. The sample period is from January 1990 to December 2021

$$\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}}|DPD_{it}=1\right)=\lambda_2 DPD_{it}+\lambda_4 DPD_{it}*TOM_t$$
$$=>\left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}}|DPD_{it}=1\right)=\widehat{\lambda}_2+\widehat{\lambda}_4*TOM_t \tag{18}$$
$$=\widehat{\lambda}_2+\widehat{\lambda}_4*\mathbf{1}$$

where **1** is an indicator function that takes the value 1 if t belongs to the TOM interval, i.e. $[-1,+3]$, and 0 otherwise.

We also examined our other three models, but joint significant test results for TOM in Table 5 suggest that the firm fixed effects in Table 4 are significant, hence model 4 is our top choice. Equation (18) demonstrates that a 10% dividend cut increases model 4 stock returns if it occurs at the beginning of the month but decreases model 4 stock returns if it happens over the remainder of the month by 0.91%. The rest of the three models also display the same outcomes. This shows that announcements of dividend reductions affect the stock market less negatively (positively) if they are issued at the beginning of the month as compared to the middle of the month, these findings are in line with our hypothesis and previous studies (Lakonishok and Smidt 1988; McConnell and Xu 2008; Holden et al 2005; Liu 2013). These findings demonstrate that a statistically and economically substantial fraction of the returns for the TOM period may be explained by changes in predicted volatility from the end of the previous month to the first day of the current month. These findings support a narrative in which "liquid funds" generated by dividend income are diverted from equity assets during times of elevated information risk and then reinvested in stocks once these periods conclude and information uncertainty is cleared.

January effect demonstrates that our results are statistically significant at 1% in models 1 and 4 and at 5% in models 2 and 3 when dividend decrease interacts with the January effect. Our findings are highly significant from an economic perspective though our sample has only four dividend announcements during January. January announcements partial impact:

$$\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}}|DPD_{it}=1\right)=\lambda_2 DPD_{it}+\lambda_4 DPD_{it}*Jan_t$$
$$=>\left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}}|DPD_{it}=1\right)=\widehat{\lambda}_2+\widehat{\lambda}_4*Jan_t \tag{19}$$
$$=\widehat{\lambda}_2+\widehat{\lambda}_4*\mathbf{1}$$

where **1** is an indicator function that takes the value 1 if t belongs to the month of January, and 0 otherwise.

The firm fixed effects in Table 4 are statistically significant, according to the joint significant test results for the January effect, hence model 4 is our recommended model. Table 5 shows that according to Eq. (19), a 10% dividend cut will reduce model 4 stock returns by 4.54% if it occurs in January, but only by 0.62% if it occurs in any other month of the year (see Table 4). The outcomes from the other three models are also comparable. These findings suggest that announcements of dividend reductions have a stronger (i.e. more negative) impact on the stock market if they happen in January as opposed to the rest of the year. This conclusion is quite weak because our sample only includes four announcements of dividend reductions that occurred in January. This means that still stock market has January effect but weak, these results are consistent with Previous researchers (Gu 2003; He & He 2011; Hensel & Ziemba 2000). Our evidence confirms that asset returns exhibit recurrence based on one dividend announcements across congruent-mood months (January), which is in line with Hirshleifer et al. (2020) findings.

Regarding Monday effect, our results show that only Model 1 is statistically significant when dividend decrease interacts with the Monday effect. These findings imply that there is only tenuous evidence that the stock market reacts differently on Mondays than it does on other days of the week to announcements of dividend reductions. In the table below, we estimate the impact of a dividend cut announcement, assuming it occurs on a Monday.

$$\begin{aligned}&\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}}|DPD_{it}=1\right)=\lambda_2 DPD_{it}+\lambda_4 DPD_{it}*Mon_t\\&=>\left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}}|DPD_{it}=1\right)=\hat{\lambda}_2+\hat{\lambda}_4*Mon_t\\&=\hat{\lambda}_2+\hat{\lambda}_4*\mathbf{1}\end{aligned}\tag{20}$$

where **1** is an indicator function that takes the value 1 on Mondays, and 0 otherwise.

Finally, Friday effect is statistically at 10% significant in all four models when dividend decrease interacts with and Friday dummy. These findings imply that there is sufficient evidence to conclude that the stock market reacts differently on Fridays than it does on other days of the week to announcements of dividend decreases.

$$\begin{aligned}&\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}}|DPD_{it}=1\right)=\lambda_2 DPD_{it}+\lambda_4 DPD_{it}*Fri_t\\&=>\left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}}|DPD_{it}=1\right)=\hat{\lambda}_2+\hat{\lambda}_4*Fri_t\\&=\hat{\lambda}_2+\hat{\lambda}_4*\mathbf{1}\end{aligned}\tag{21}$$

where **1** is an indicator function that takes the value 1 on Fridays, and 0 otherwise. According to the partial derivatives results in Eq. (21), a 10% dividend cut on a Friday will reduce model 4's stock returns by 1.80%. These findings suggest that announcements of dividend reductions had a stronger (i.e. more positive) impact on the stock market on Fridays than on other days of the week. These results show the congruent mood of the investors during Fridays, which is in line with Hirshleifer et al. (2020) findings.

4.2 Linear binary model

To determine if the direction of a dividend change has any impact on stock returns, the linear binary model solely focuses on the direction of dividend changes and ignores the size of dividend changes. Technically, this means that the variable $R\Delta DIV_{it}$ is set to zero. For dividend decreases, it implies that the signs of the binary model's estimated coefficients are the opposite of the interaction model as the product $R\Delta DIV_{it}\cdot DPD$ is negative in the interaction model and the respective variable in the binary model, i.e. DPD, is always positive.

We can see that similar kind of results (without the interactions with the calendar anomalies) in Table 6 as what we reported in Table 4. However, when dividend increase dummy integrated with calendar anomalies, only the Halloween effect is significant. In addition, in Table 6 we can see those results for Halloween effect, January effect and Friday effect are

Table 6 Regression analysis of calendar anomalies effect on dividend announcement dates using binary specification

Variables	Halloween				TOM				January			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
Constant	0.038^{a}	0.031^{a}	0.031^{a}	0.059^{a}	0.039^{a}	0.042^{b}	0.038^{b}	0.067^{a}	0.039^{a}	0.029^{a}	0.029^{a}	0.063^{a}
	(0.006)	(0.012)	(0.010)	(0.019)	(0.006)	(0.018)	(0.018)	(0.019)	(0.006)	(0.068)	(0.075)	(0.019)
DPI	0.016^{a}	0.052^{b}	0.018^{a}	0.018	0.018^{a}	0.018^{a}	0.019^{a}	0.016^{a}	0.016^{a}	0.025^{a}	0.032^{a}	0.018^{a}
	(0.004)	(0.004)	(0.004)	(0.008)	(0.005)	(0.005)	(0.005)	(0.008)	(0.003)	(0.038)	(0.003)	(0.021)
DPD	-0.056^{a}	-0.067^{a}	-0.052^{a}	-0.068^{a}	-0.018^{b}	-0.019^{b}	-0.019^{c}	-0.020^{c}	-0.022^{b}	-0.031^{c}	-0.032^{c}	-0.069^{c}
	(0.010)	(0.018)	(0.028)	(0.019)	(0.015)	(0.016)	(0.016)	(0.017)	(0.015)	(0.015)	(0.018)	(0.066)
DPI · HALL/TOM/Jan/Mon/Fri	0.003^{c}	0.004^{b}	0.004^{b}	0.005	0.002	0.007	0.001	0.008	−0.013	−0.007	−0.097	−0.006
	(0.002)	(0.002)	(0.008)	(0.006)	(0.010)	(0.012)	(0.009)	(0.009)	(0.011)	(0.014)	(0.018)	(0.077)
DPD · HALL/TOM/Jan/Mon/Fri	0.072^{a}	0.087^{a}	0.069^{a}	0.078^{a}	0.028	0.026	0.026	0.025	-0.078^{a}	-0.077^{a}	-0.076^{a}	-0.082^{a}
	(0.009)	(0.015)	(0.015)	(0.016)	(0.013)	(0.016)	(0.016)	(0.019)	(0.029)	(0.026)	(0.024)	(0.023)
SIZE	-0.005^{a}	-0.005^{a}	-0.005^{a}	-0.013^{a}	-0.005^{a}	-0.005^{a}	-0.005^{a}	-0.013^{a}	-0.005^{a}	-0.005^{a}	-0.005^{a}	-0.013^{a}
	(0.002)	(0.002)	(0.001)	(0.002)	(0.007)	(0.007)	(0.006)	(0.002)	(0.001)	(0.097)	(0.097)	(0.071)
REVERSAL	-0.853^{a}	-0.971^{a}	-0.967^{a}	-1.002^{a}	-0.863^{a}	-0.974^{a}	-0.969^{a}	-1.039^{a}	-0.877^{a}	-0.987^{a}	-0.971^{a}	-1.058^{a}
	(0.241)	(0.358)	(0.356)	(0.382)	(0.241)	(0.366)	(0.359)	(0.382)	(0.241)	(0.354)	(0.376)	(0.376)
MOMENTUM	-0.123^{c}	−0.151	−0.154	−0.117	-0.139^{c}	−0.162	−0.164	−0.128	-0.142^{c}	−0.164	−0.166	−0.136
	(0.072)	(0.112)	(0.112)	(0.116)	(0.073)	(0.111)	(0.111)	(0.116)	(0.072)	(0.111)	(0.118)	(0.115)
DIV Yield	0.209^{b}	0.162	0.138	0.101	0.169^{c}	0.121	0.096	0.096	0.168^{c}	0.122	0.092	0.091
	(0.087)	(0.117)	(0.117)	(0.231)	(0.087)	(0.115)	(0.116)	(0.229)	(0.087)	(0.115)	(0.116)	(0.229)
Shock	-0.186^{b}	-0.145^{b}	-0.199^{b}	-0.204^{b}	-0.102^{b}	-0.199^{b}	-0.181^{b}	-0.147^{b}	-0.109^{b}	-0.145^{b}	-0.123^{b}	-0.145^{b}
	(0.265)	(0.278)	(0.245)	(0.305)	(0.325)	(0.299)	(0.278)	(0.244)	(0.123)	(0.235)	(0.144)	(0.158)
DOW Dummy	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Year dummy	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
FF (17) Industry dummy	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No
Firm dummy	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes

Table 6 (continued)

Variables	Halloween				TOM				January			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
Clustered by Company ID and Date	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
R^2	4.15%	5.31%	5.61%	13.17%	3.35%	4.51%	4.77%	12.40%	3.57%	4.68%	4.94%	12.58%
N	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021

Variables	Monday				Friday			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
Constant	0.045^{a}	0.044^{b}	0.038^{b}	0.068^{a}	0.039^{a}	0.040^{b}	0.035^{b}	0.038^{b}
	(0.006)	(0.018)	(0.018)	(0.019)	(0.006)	(0.018)	(0.017)	(0.018)
DPI	0.019^{a}	0.016^{a}	0.019^{a}	0.019^{a}	0.021^{a}	0.018^{a}	0.031^{a}	0.024^{a}
	(0.003)	(0.053)	(0.003)	(0.004)	(0.012)	(0.004)	(0.003)	(0.003)
DPD	-0.027^{b}	-0.032^{c}	-0.031^{c}	-0.025^{c}	-0.025^{b}	-0.035^{c}	-0.019^{c}	-0.019^{c}
	(0.014)	(0.061)	(0.016)	(0.025)	(0.012)	(0.016)	(0.028)	(0.013)
DPI · HALL/TOM/Jan/Mon/Fri	−0.005	−0.019	−0.007	−0.007	−0.006	−0.006	−0.022	−0.027
	(0.013)	(0.079)	(0.021)	(0.018)	(0.009)	(0.010)	(0.022)	(0.024)
DPD · HALL/TOM/Jan/Mon/Fri	−0.011	−0.064	−0.053	−0.043	-0.025^{b}	-0.026^{b}	-0.042^{b}	-0.042^{b}
	(0.012)	(0.025)	(0.023)	(0.024)	(0.020)	(0.029)	(0.033)	(0.042)
SIZE	-0.005^{a}	-0.023^{a}	-0.005^{a}	-0.013^{a}	-0.005^{a}	-0.007^{a}	-0.005^{a}	-0.005^{a}
	(0.071)	(0.097)	(0.007)	(0.071)	(0.007)	(0.009)	(0.001)	(0.001)
REVERSAL	-0.857^{a}	-0.967^{a}	-0.967^{a}	-1.041^{a}	-0.879^{a}	-0.994^{b}	-0.973^{a}	-0.993^{a}
	(0.277)	(0.363)	(0.358)	(0.382)	(0.240)	(0.355)	(0.354)	(0.250)
MOMENTUM	-0.137^{c}	−0.158	−0.161	−0.127	-0.136^{c}	−0.158	−0.165	-0.175^{c}
	(0.072)	(0.111)	(0.112)	(0.116)	(0.072)	(0.111)	(0.112)	(0.081)
DIV Yield	0.159^{c}	0.114	0.099	0.095	0.171^{c}	0.123	0.096	0.083
	(0.087)	(0.116)	(0.116)	(0.229)	(0.077)	(0.115)	(0.116)	(0.092)

Table 6 (continued)

Variables	Monday				Friday			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
Shock	−0.214^b	−0.147^b	−0.149^b	−0.244^b	−0.214^b	−0.193^b	−0.187^b	−0.186^b
	(0.143)	(0.244)	(0.258)	(0.259)	(0.147)	(0.201)	(0.206)	(0.214)
DOW dummy	No	No	No	No	No	No	No	No
Year dummy	No	Yes	Yes	Yes	No	Yes	Yes	Yes
FF (17) Industry dummy	No	Yes	Yes	No	No	Yes	Yes	No
Firm dummy	No	No	Yes	Yes	No	No	Yes	Yes
Clustered by Company ID and Date	No	Yes	Yes	Yes	No	Yes	Yes	Yes
R^2	3.43%	4.57%	4.77%	12.40%	3.23%	5.59%	6.98%	6.50%
N	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021

The standardized coefficient value and dependent variable is CAR [− 1, + 1]. $R\Delta DIV_0$ is annual dividend changes percentage. The dummy variables are *DPI* and *DPD*. If the dividend changes percentage increase, then *DPI* = 1, otherwise 0, and if the dividend changes percentage decrease, then *DPD* = 1, otherwise 0. *HALL* equals to 1 if *t* belongs to month November to April, and 0 otherwise. TOM takes value 1 if *t* belongs to the interval of [− 1, + 3], and 0 otherwise. *Jan* takes value 1 if *t* belongs to month of January, and 0 otherwise. *Mon* takes value 1 if *t* is a Monday, and 0 otherwise. *Fri* takes value 1 if *t* is a Friday, and 0 otherwise. *Size* is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the *Size* values are in billions. *Reversal* is measured using cumulative stock returns over previous month, it also representing in percentage. *Momentum* is cumulated monthly stock returns from month *t*-12 to *t*-2. *DIV Yield* calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. *DOW* effect, where $M_d, W_d, T_d and F_d$ are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. We also use year dummy and Fama and French 17 industry dummy. The sample period is from January 1990 to December 2021. Significant coefficients are highlighted, and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively statistically significant when dividend decrease dummy interacted with these three calendar anomalies. These results are consistent with our interaction model specifications and with previous findings. These results indicate that the stock market's response to dividend announcements is strongly influenced by calendar or seasonal irregularities.

4.3 GMM estimation

This section displays the GMM method-based outcomes we obtained. According to Assongu et al. (2018), the GMM technique is effective when a panel data set has a short cross-sectional dimension (N = 4,021) and a small-time dimension (T = 32) that are both consistent with the panel data structure. The reverse causality might the base of many further issues, such as unobserved heterogeneity, endogeneity, and omitted variable bias. The GMM addresses these difficulties (Alam et al. 2019; Hasan et al. 2022, 2023; Mthanti and Ojah 2017).

Table 7 reports the further robustness test based on GMM estimation. In Table 7 we used the whole data sample. To do the GMM estimation we use only year fixed effect and FF (17) industry fixed effect. In Table 7 we documented our both model specifications (linear interaction model and linear binary model). Our GMM estimation shows that Halloween, TOM, January and Friday calendar anomalies are statistically significant when these four calendar anomalies interact with dividend decrease dummy. On the other hand, our results are not statistically significant when all five calendar anomalies interact with dividend increase dummy. These results are in line with Tables 4 and 6, and with our hypotheses.

5 Conclusion

Arbitrage mechanisms should theoretically eliminate the notion that psychological or institutional variables consistently influence asset values, thereby prompting analysts to interpret calendar anomalies as potential indicators of market inefficiency. The present study endeavors to ascertain whether calendar irregularities exert any discernible impact on the stock market's reactions to dividend announcements. This inquiry assumes a distinctive stance, as prior research predominantly sought to establish the mere existence and influence of calendar anomalies on overall stock market returns.

Our dataset spans from 1990 to 2021, sourced from the London Stock Exchange, and constitutes the bedrock of our analysis. We meticulously examined five prominent calendar anomalies: the Halloween effect, TOM effect, January effect, Monday effect, and Friday effect. The selection of these specific calendar irregularities was grounded in their historical prominence and well-documented prevalence within existing literature.

Our analytical framework encompassed two distinct model specifications, each designed to shed light on the potential impact of calendar irregularities on the stock market's receptivity to dividend announcements. In one model, we judiciously considered both the magnitude and direction of dividend adjustments, whereas the other model primarily concentrated on the directional aspect, relegating the magnitude of dividend changes to a secondary role. Noteworthy findings emerged from both model specifications. Our empirical insights reveal that the stock market, when confronted with announcements of dividend reductions, manifests a heightened propensity for more adverse reactions during the month of January and on Fridays, relative to other temporal segments throughout the year

Table 7 GMM estimation of calendar anomalies effect on dividend announcement dates for interaction and binary specification

Variables	Halloween		TOM		January		Monday		Friday	
	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
Panel A: Interaction specification										
Constant	0.040[a]	0.040[b]	0.041[a]	0.040[b]	0.041[a]	0.042[b]	0.043[a]	0.041[b]	0.041[a]	0.040[b]
	(0.006)	(0.018)	(0.006)	(0.018)	(0.006)	(0.017)	(0.007)	(0.018)	(0.006)	(0.018)
$R\Delta DIV \cdot DPI$	0.047[a]	0.056[a]	0.055[a]	0.064[a]	0.055[a]	0.063[a]	0.058[a]	0.065[a]	0.056[a]	0.064[a]
	(0.014)	(0.014)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
$R\Delta DIV \cdot DPD$	0.178[a]	0.178[a]	0.078[b]	0.076[b]	0.056[b]	0.055[b]	0.056[b]	0.055[b]	0.059[b]	0.058[b]
	(0.057)	(0.057)	(0.030)	(0.030)	(0.027)	(0.026)	(0.026)	(0.026)	(0.027)	(0.027)
$R\Delta DIV \cdot DPI \cdot$ HALL/TOM/Jan/Mon/*Fri*	0.011	0.011	−0.010	−0.009	−0.077	−0.066	−0.033	−0.026	−0.021	−0.025
	(0.013)	(0.014)	(0.018)	(0.018)	(0.029)	(0.031)	(0.016)	(0.016)	(0.023)	(0.023)
$R\Delta DIV \cdot DPD \cdot$ HALL/TOM/Jan/Mon/Fri	−0.171[a]	−0.173[a]	−0.105[b]	−0.099[b]	0.323[b]	0.322[c]	0.087	0.089	0.099[b]	0.105[a]
	(0.062)	(0.061)	(0.042)	(0.042)	(0.163)	(0.169)	(0.115)	(0.118)	(0.134)	(0.131)
SIZE	−0.005[a]	−0.005[a]	−0.005[a]	−0.004[a]	−0.005[a]	−0.004[a]	−0.005[a]	−0.004[a]	−0.005[a]	−0.004[a]
	(0.001)	(0.002)	(0.001)	(0.002)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.009)
REVERSAL	−0.861[b]	−0.991[a]	−0.853[b]	−0.982[a]	−0.894[a]	−1.025[a]	−0.859[b]	−0.985[a]	−0.873[b]	−1.005[a]
	(0.355)	(0.356)	(0.355)	(0.355)	(0.345)	(0.345)	(0.353)	(0.354)	(0.349)	(0.348)
MOMENTUM	−0.152	−0.194[c]	−0.170[c]	−0.211[b]	−0.168[c]	−0.206[c]	−0.165[c]	−0.205[c]	−0.162[c]	−0.205[c]
	(0.096)	(0.105)	(0.097)	(0.106)	(0.097)	(0.105)	(0.097)	(0.106)	(0.097)	(0.106)
DIV Yield	0.235[c]	0.194	0.208[c]	0.169	0.200	0.171	0.199	0.163	0.216[c]	0.176
	(0.126)	(0.101)	(0.126)	(0.131)	(0.125)	(0.131)	(0.126)	(0.131)	(0.126)	(0.101)
Shock	−0.256[b]	−0.245[b]	−0.198[b]	−0.201[b]	−0.214[b]	−0.204[b]	−0.189[b]	−0.205[b]	−0.187[b]	−0.178[b]
	(0.127)	(0.104)	(0.099)	(0.102)	(0.127)	(0.119)	(0.097)	(0.113)	(0.104)	(0.123)
Year Dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 7 (continued)

Variables	Halloween		TOM		January		Monday		Friday	
	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
FF (17) Industry Dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021
Panel B: Binary specification										
Constant	0.038[a]	0.043[b]	0.040[a]	0.041[b]	0.039[a]	0.041[b]	0.042[a]	0.042[b]	0.040[a]	0.041[b]
	(0.007)	(0.018)	(0.007)	(0.018)	(0.007)	(0.018)	(0.007)	(0.018)	(0.008)	(0.017)
DPI	0.010[b]	0.009[b]	0.012[a]	0.012[a]	0.011[a]	0.012[a]	0.013[a]	0.013[a]	0.012[a]	0.015[a]
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
DPD	−0.046[a]	−0.047[a]	−0.013c	−0.013[c]	−0.011	−0.010	−0.011	−0.012	−0.011	−0.011
	(0.014)	(0.014)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.004)	(0.007)	(0.006)
DPI · HALL/TOM/Jan/Mon/Fri	0.004	0.004	0.001	0.008	−0.010	−0.008	−0.005	−0.004	−0.007	−0.007
	(0.002)	(0.002)	(0.003)	(0.004)	(0.007)	(0.007)	(0.003)	(0.003)	(0.004)	(0.004)
DPD · HALL/TOM/Jan/Mon/Fri	0.049[a]	0.049[a]	0.008[b]	0.007[c]	−0.078[b]	−0.077[b]	−0.011	−0.011	−0.026[a]	−0.027[a]
	(0.015)	(0.015)	(0.016)	(0.017)	(0.061)	(0.062)	(0.020)	(0.021)	(0.033)	(0.033)
SIZE	−0.005[a]	−0.005[a]	−0.005[a]	−0.005[a]	−0.005[a]	−0.006[a]	−0.005[a]	−0.005[a]	−0.005[a]	−0.005[a]
	(0.007)	(0.008)	(0.001)	(0.002)	(0.007)	(0.009)	(0.007)	(0.009)	(0.006)	(0.008)
REVERSAL	−0.853[b]	−0.972[a]	−0.863[b]	−0.973[a]	−0.878[b]	−0.988[a]	−0.857[b]	−0.966[a]	−0.869[b]	−0.983[a]
	(0.353)	(0.354)	(0.353)	(0.354)	(0.346)	(0.346)	(0.353)	(0.354)	(0.348)	(0.349)
MOMENTUM	−0.123	−0.148	−0.139	−0.160	−0.142	−0.160	−0.138	−0.159	−0.136	−0.158
	(0.096)	(0.104)	(0.096)	(0.105)	(0.096)	(0.104)	(0.096)	(0.105)	(0.096)	(0.105)
DIV Yield	0.210[c]	0.161	0.169	0.121	0.160	0.121	0.159	0.114	0.171	0.122
	(0.124)	(0.129)	(0.123)	(0.129)	(0.122)	(0.129)	(0.123)	(0.129)	(0.122)	(0.128)
Shock	−0.189[b]	−0.216[b]	−0.187[b]	−0.165[b]	−0.169[b]	−0.187[b]	−0.203[b]	−0.198[b]	−0.205[b]	−0.234[b]

Table 7 (continued)

Variables	Halloween		TOM		January		Monday		Friday	
	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
	(0.126)	(0.167)	(0.125)	(0.109)	(0.124)	(0.110)	(0.135)	(0.124)	(0.134)	(0.145)
Year dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
FF (17) industry dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021

The standardized coefficient values and dependent variable is CAR $[-1,+1]$. $R\Delta DIV_0$ is annual dividend changes percentage. *DPI* and *DPD* are two dummy variables. If the dividend changes percentage increase, then $DPI=1$, otherwise 0, and if the dividend changes percentage decrease, then $DPD=1$, otherwise 0. *HALL* equals to 1 if *t* belongs to month November to April, and 0 otherwise. TOM takes value 1 if *t* belongs to the interval of $[-1,+3]$, and 0 otherwise. *Jan* takes value 1 if *t* belongs to month of January, and 0 otherwise. *Mon* takes value 1 if *t* is a Monday, and 0 otherwise. *Fri* takes value 1 if *t* is a Friday, and 0 otherwise. *Size* is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the *Size* values are in billions. *Reversal* is measured using cumulative stock returns over previous month, it also representing in percentage. *Momentum* is cumulated monthly stock returns from month *t*-12 to *t*-2. *DIV Yield* calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. We use year dummies and Fama and French (FF) 17 industry effect. The sample period is from January 1990 to December 2021.Significant coefficients are highlighted, and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively or week. Conversely, the market appeared to adopt a more positive stance, evincing a positive response during the November–April period, as opposed to the May–October interval. Significantly, this observed divergence in market sentiment remained consistent regardless of the size and direction of the dividend adjustments. Furthermore, our findings hinted at a subdued negative market response on Mondays, when compared with other weekdays, and during the TOM period concerning reports of dividend contractions.

When we focus solely on the direction of dividend changes, examining various calendar anomalies reveals a consistent pattern. Importantly, our thorough analysis found no significant bias related to sample selection within the scope of this study.

In summation, our empirical findings provide substantive validation for the fundamental premises underpinning the dividend-signaling theory. Furthermore, they lend credence to the notion that calendar, or seasonal irregularities might wield discernible influence over the stock market's nuanced responses to dividend disclosures. This study underscores the imperative for future research endeavors to delve deeper into the intricacies of this phenomenon, with the aim of elucidating the underlying mechanisms that imbue calendar inconsistencies with their formative influence on the stock market's behavioral dynamics in the context of dividend-related information dissemination.

References

Alam A, Uddin M, Yazdifar H (2019) Institutional determinants of R&D investment: evidence from emerging markets. Technol Forecast Soc Changes 138:34–44

Alhalabi T, Castro V, Wood J (2023) Bank dividend payout policy and debt seniority: evidence from US Banks. Financ Mark Inst Instrum (in press).

Anderson LR, Gerach JR, DiTraglia FJ (2007) Yes, Wall Street, there is a January effect! Evidence from laboratory auctions. J Behav Finance 8(1):1–8

Ariel R (1987) A monthly effect in stock returns. J Financ Econ 18:161–174

Atanasova CV, Hudson RS (2010) Technical trading rules and calendar anomalies: are they the same phenomena? Econ Lett 106(2):128–130

Bakar AA, Siganos N, Vagenas-Nanos E (2014) Does mood explain the Monday effect? J Forcast 33:409–418

Boubaker S, Choudhury T, Hasan F, Nguyen DK (2024) Firm's carbon risk exposure, stock returns and dividend payment. J Econ Behav Organ 221(5):248–276

Bouman S, Jacobsen B (2002) The Halloween indicator, "sell in May and go away": another puzzle. Am Econ Rev 92(5):1618–1635

Brusa, J., Pu, L., & Craig, S. (2003). The "reverse" weekend effect: the U.S. market versus international markets. *International Review of Financial Analysis*, 12(3), 267–286.

Campbell JY, Vuolteenaho T (2004) Inflation illusion and stock prices. Am Econ Rev 94:19–23

Carlucci FV, Júnior TP, Lima FG, Gaio LE (2014) The "Week-Day Effect" anomaly in the behavior of stock index returns of Brazil, Mexico and the USA. Bus Manag Rev 3(9):31–38

Choi YM, Ju HK, Park YK (2011) Do dividend changes predict the future profitability of firms? Acc Finance 51:869–891

Ciccone SJ (2011) Investor optimism, false hopes and the January effect. J Behav Financ 12(3):158–168

Condoyanni L, O'Hanlon J, Ward CWR (1987) Day of the week effects on stock returns: international evidence. J Bus Financ Acc 14(2):159–174

Cross F (1973) The behavior of stock prices on Fridays and Mondays. Financ Anal J 29(6):67–69
Damodaran A (1989) The weekend effect in information releases: a study of earnings and dividend announcements. Rev Financ Stud 2(4):607–623
Dimson E, Marsh P (1999) Murphy's law and market anomalies. J Portf Manag 25(2):53–69
Dubois M, Louvet P (1996) The day-of-the-week effect: the international evidence. J Bank Finance 20(9):1463–1484
Easterday KE, Sen PK (2016) Is the January effect rational? Insights from the accounting valuation model. Q Rev Econ Finance 59:168–185
Easton PD, Harris TS (1991) Earnings as an explanatory variable for returns. J Account Res 29(1):19–36
Fama E (1970) Efficient capital markets: a review of theory and empirical work. J Finance 25:383–417
Fama E (1991) Efficient capital markets II. J Finance 46(5):1575–1617
French KR (1980) Stock returns and the weekend effect. J Financ Econ 8:55–69
Grullon G, Michaely R, Benartzi S, Thaler RH (2005) Dividend changes do not signal changes in future profitability. J Bus 78(5):1659–1682
Gu AY (2003) The declining January effect: evidence from the US equity markets. Q Rev Econ Finance 43(2):395–404
Hasan F (2021a) Dividend changes as predictors of future profitability. J Predict Mark 15(1):37–66
Hasan F (2021b) Relationship between orthodox finance and dividend policy: a literature review. Indian-Pac J Acc Finance 5(1):13–40
Hasan F (2022) Using UK data to study the effects of dividends announcements on stock market returns. J Predict Mark 16(2):47–75
Hasan F (2024) The impact of climate change on dividend policy in the UK Stock Market. Int J Manag Financ Account 16(1):119–137
Hasan F, Islam MR (2022) The relationship between behavioural finance and dividend policy: a literature review. Acad Acc Financ Stud J 26(5):1–11
Hasan F, Shafique S, Das BC, Shome R (2022) R&D intensity and the effect of dividend announcements on stock return: an even study analysis. J Appl Acc Res 23(4):846–862
Hasan F, Kayani UN, Choudhury T (2023) Behavioral risk preferences and dividend changes: exploring the linkages with prospect theory through empirical analysis. Glob J Flex Syst Manag 24(4):517–535
Hasan F, Al-Najjar B (2024) Exploring the connections: dividend announcements, Stock market returns, and major sporting events. Rev Quant Finance Acc (in Press)
He LT, He SC (2011) Has the November effect replaced the January effect in stock markets? Manag Decis Econ 32(7):481–486
Henkeer J, Debapriya JP (2012) Retail investors exonerated: the case of the January effect. Acc Finance 52(4):1083–1099
Hensel CR, Ziemba WT (2000) Anticipation of the January small firm effect in the US futures markets. In: Keim DB, Ziemba WT (eds) Security market imperfections in world wide equity markets. Cambridge University Press, New York, pp 179–202
Hirshleifer D, Jiang D, DiGiovanni YM (2020) Mood beta and seasonalities in stock returns. J Financ Econ 137(1):272–295
Holden K, Thompson J, Ruangrit Y (2005) The Asian crisis and calendar effects on stock returns in Thailand. Eur J Oper Res 163:242–252
Jacobsen, B, & Zhang, C. (2010). Are monthly seasonal real? A three-century perspective. *Working Paper*, Massey University.
Jaffe J, Westerfield R (1985) The week-end effect in common stock returns: the international evidence. J Financ 40(2):433–454
Kato K, Schallheim JS (1985) Seasonal and size anomalies in the Japanese stock market. J Financ Quant Anal 20(2):243–260
Keim DB (1983) Size- related anomalies and stock returns seasonality: further empirical evidence. J Financ Econ 12:13–32
Keim DB, Stambaugh RF (1984) A further investigation of the weekend effect in stock returns. J Finance 39:819–840
Kelly F (1930) Why you win or lose: psychology of speculation. Houghton Mifflin, Boston
Klock SA, Bacon FW (2014) The January effect: a test of market efficiency. J Bus Behav Sci 26(3):32–42
Kohers T, Kohli RK (1991) The anomalous stock market behaviour of large firms in January: the evidence from the S & P composite and component indexes. Q J Bus Econ 30(3):14–32
Lakonishok J, Smidt S (1988) Are seasonal anomalies real? A ninety-year perspective. Rev Financ Stud 1:403–425
Liu L (2013) The turn-of-the-month effect in the S & P 500 (2001–2011). J Bus Econ Res 11(6):269–275

Maberly ED (1995) Eureka! Eureka! Discovery of the Monday effect belongs to the ancient scribes. Financ Anal J 51(5):10–11
Maberly ED, Pierce RM (2004) Stock market efficiency withstands another challenge: Solving the “sell in May/buy after Halloween” puzzle. Econ J Watch 1(1):29
McConnell JJ, Xu W (2008) Equity returns at the turn of the month. Financ Anal J 64(2):49–64
Mthanti T, Ojah P (2017) Entrepreneurial orientation (EO): measurement and policy implications of entrepreneurship at the macroeconomic level. Res Policy 46(4):724–739
Nissim D, Ziv A (2001) Dividend changes and future profitability. J Financ 56(6):2111–2133
Pettit RR (1972) Dividend announcements, security performance, and capital market efficiency. J Financ 27:993–1007
Reinganum MR (1983) The anomalous stock market behaviour of small firms in January: empirical test for tax-loss selling effects. J Financ Econ 12(1):89–104
Rogalski RJ (1984) New finds regarding day-of-the-week returns over trading and non-trading periods: a note. J Financ 39:1603–1614
Roll RW (1983) Vas ist das? The turn-of-the-year effect and the risk premia of small firms. J Financ Econ 3:18–28
Rozeff MS, Kinney WR (1976) Capital market seasonality: the case of stock returns. J Financ Econ 3(4):379–402
Sharma SS, Narayan PK (2014) New evidence on turn-of-the-month effects. J Int Finan Mark Inst Money 29:92–108
Sharpe WF (1963) A simplified model for portfolio analysis. Manag Sci 9(2):277–293
Smirlock M, Starks L (1986) Day of the week and intra-day effects in stock returns. J Financ Econ 16:197–210
Steeley JM (2001) A note on information seasonality and the disappearance of the weekend effect in the UK stock market. J Bank Finance 25:1941–1956
Theobald M, Price V (1984) Seasonality estimation in thin markets. Journal of Finance 39:377–392
Tong W (2000) International evidence on weekend anomalies. J Financ Res 23:495–522
Urquhart A, McGroarty F (2014) Calendar effects, market conditions and the adaptive market hypothesis: evidence from long-run U.S. data. Int Rev Financ Anal 35:154–166
Wachtel SB (1942) Certain observation on seasonal movement in stock prices. J Bus 15:184–193
Witte DH (2010) Outliers and the halloween effect: comment on maberly and pierce. Econ J Watch 7(1):91–98
Ziemba WT (2011) Investing in the turn-of-the-year effect. Fin Markets Portfolio Mgmt 25(4):455–472