Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Dept. of Industrial Economics and Technology Management

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Calendar Effects in the US Stock Market: Are they still present?

Master's thesis in Industrial Economics and Technology Management
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Abstract

This thesis examines the turn-of-the-month (TOM), turn-of-the-quarter (TOQ), and turn-of-the-year (TOY) effects. We employ panel regression models using four-day return windows of individual companies listed on the NYSE, AMEX, and NASDAQ between 1986 and 2021. We find that the TOM, TOQ, and TOY effects are present in the US stock market, and their magnitude is related to firm characteristics. The TOY effect is particularly substantial in small stocks with volatile prices and low momentum, supporting the hypothesis that individual investors sell their losses for tax purposes. Additionally, the results support the explanation that institutional investors sell volatile, small-cap stocks to window dress their portfolios or hedge performance. We further provide evidence that the TOM and TOY effects have resurfaced in the last decade and continue to exist. The TOQ effect is no longer significant, suggesting that portfolio pumping by mutual funds in the US stock market is diminished. Finally, we develop a trading strategy that predicts the stocks with the 20% highest returns over the TOM and TOY windows. The trading strategy generates an accumulated four-day profit of 3.7% over the TOY window. This return is significantly higher than realistic trading costs; consequently, the results can be used to develop profitable trading strategies that exploit calendar effects.

Keywords: Calendar anomalies; calendar effects; turn-of-the-month effect; turn-of-the-quarter effect; turn-of-the-year effect; the January effect

Sammendrag

Denne oppgaven undersøker kalendereffekter tilknyttet månedsskiftet (TOM), kvartalsskiftet (TOQ) og årsskiftet (TOY). Vi bruker panelregresjoner med et firedagers avkastningsvindu for individuelle selskaper notert på NYSE, AMEX og NASDAQ mellom 1986 og 2021. Vi finner at TOM-, TOQ- og TOY-effektene vedvarer i det amerikanske aksjemarkedet, og at deres påvirkningskraft er relatert til selskapsspesifikke forhold. TOY-effekten er bemerkelsesverdig i små aksjer med volatile priser og lavt momentum, noe som støtter hypotesen om at individuelle investorer selger sine tapsaksjer for skattemessige formål. I tillegg støtter resultatene forklaringen om at institusjonelle investorer selger volatile, små aksjer i et forsøk på å sminke deres porteføljer eller sikre et godt resultat. Videre har TOM- og TOY-effektene gjenoppstått det siste tiåret og forblir signifikant. TOQ-effekten er dog ikke lengre signifikant, noe som tyder på at portfølje-pumping i det amerikanske markedet har avtatt. Avslutningsvis utvikler vi en investeringsstrategi som predikerer aksjene med de 20% høyeste avkastningene over månedsskiftet og årsskiftet. Investeringsstrategien oppnår en akkumulert firedagers avkastning på 3,7% over årsskiftet. Denne avkastningen er betydelig høyere enn realistiske transaksjonskostnader; følgelig kan resultatene brukes til å utvikle lønnsomme investeringsstrategier med formål om å profittere på kalendereffektene.

Nøkkelord: Kalendereffekter; nyttårsraketter; månedsskifte-effekten; kvartalsskifte-effekten; årsskifte-effekten; Januar-effekten

Preface

This thesis concludes our Master of Science degree in Industrial Economics and Technology Management within Financial Engineering at the Norwegian University of Science and Technology (NTNU) in the spring of 2022. We study whether calendar effects are present and exploitable in the US stock market today. This thesis should interest academics, researchers, and financial market practitioners who seek to exploit calendar effects for hedging, transaction scheduling, and portfolio management.

We thank our supervisor, Peter Molnár, Associate Professor at the Norwegian University of Science and Technology and the University of Stavanger. His advice, exceptional guidance, and constructive feedback have been invaluable resources throughout the project. We also thank Dr. Francesc Miralles, Dean at La Salle Campus Barcelona, Ramon Llull University. We appreciate his flexibility and availability, which have allowed us to accomplish a four-month mobility at Ramon Llull University.

Barcelona, June 17th, 2022

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1 Introduction

Calendar anomalies occur from abnormal deviations in stock returns that appear to be related to the calendar. Since the discovery of the January effect by Wachtel (1942), various calendar anomalies have intrigued financial professionals and academics in attempting to explain these phenomena. Most prominent is the turn-of-the-month effect (Ariel, 1987; Lakonishok & Smidt, 1988), the turn-of-the-quarter effect (Carhart et al., 2002), the turn-of-the-year effect, also known as the January effect (Reinganum, 1983; Roll, 1983; Keim, 1983; Haug & Hirschey, 2006), the day-of-the-week effect (Berument & Kiymaz, 2001), the Holiday effect, and the Halloween effect, showing mixed evidence in finance literature. Market practitioners regard these anomalies as some of the most bizarre examples of market inefficiency, persistent mispricings, and seemingly consistent profit opportunities. Calendar anomalies are crucial to financial academia because their exploitation undermines the efficient market hypothesis (Fama, 1970). According to behavioral finance, calendar anomalies are induced by investors who base their decisions on psychological reasons. On the other hand, proponents of the efficient market hypothesis assert that several calendar anomalies are not persistent over time, rendering trading strategies based on calendar anomalies worthless. To this day, the origin of calendar anomalies and whether they can be exploited for profit continue to be a subject of intense debate and speculation in the financial world.

The finance literature attributes calendar effects to various explanations, including tax-loss selling at the year-end, mutual fund portfolio disclosures at the quarter-end, and investor's increased liquidity at the month-end. Nonetheless, conclusive evidence for what is causing these anomalies is still missing. Because calendar anomalies appear relatively easy to exploit, their sustained existence seems incomprehensible. The question remains why these effects, which literature has recognized for years, have not been arbitraged away. Transaction costs impede exploiting calendar anomalies, and some market researchers argue that modern markets work too efficiently for calendar anomalies to impact trading significantly. Thus, it is necessary to determine whether calendar anomalies still prevail today, how they have evolved, and what factors drive them. The study of calendar effects is relevant for financial managers, market professionals, and investors who seek to predict future market movements for speculative purposes, hedging, scheduling trades, and portfolio management.

The primary purpose of this study is to investigate the contentious subject of calendar anomalies, focusing on the turn-of-the-month (TOM) effect, the turn-of-the-quarter (TOQ) effect, and the turn-of-the-year (TOY) effect, also known as the January effect. To establish whether these three calendar effects persist over time, we first explore historical stock returns of 15 000 companies listed on the three major US stock exchanges, NYSE, AMEX, and NASDAQ, over the past 35 years. Second, we study whether the calendar effects are comprehensive phenomena affecting the entire market or if they are more prominent in companies with particular firm characteristics. Third, we include a measure of attention to determine whether calendar anomalies can be attributed to the attention given to a specific company. Finally, we implement a trading strategy to investigate whether investors can profit from exploiting calendar anomalies. We aim to answer two research questions: (1) whether the TOM, TOQ, and TOY effects are present across the US stock market at the firm level and (2) which types of companies are strongest influenced by these effects, i.e., the impact of firm characteristics on calendar anomalies.

Our contribution to the existing literature is fivefold. First, we find all three calendar effects, TOM, TOQ, and TOY, to be present across the three major stock exchanges, NYSE, AMEX, and NASDAQ updating evidence with data from 1986 to 2021. Second, the TOY effect is particularly substantial in small stocks with volatile prices and low momentum, supporting the hypothesis that individual investors sell their losses for tax purposes. The result also supports the idea that institutional investors sell volatile small-cap stocks to window dress their portfolio or hedge performance. Third, we find that calendar effects have evolved dramatically over the decades. We provide evidence that the TOM and TOY effects have resurfaced in the last decade and continue to exist. The TOQ effect is no longer significant, supporting literature that argues how increased disclosure regulations have reduced portfolio pumping in the US. Fourth, we discover that all three calendar effects are significantly stronger for companies with low Google search volumes. Finally, we demonstrate that our proposed trading strategy generates profit opportunities. Over the four-day TOY window, the model yields an accumulated profit of 3.7%. Considering that many investors face much lower transaction costs, our findings are of great importance to financial market practitioners.

The remainder of the thesis is organized as follows. Chapter 2 reviews related literature and contextualizes our study. Chapter 3 presents the data sources used and summary statistics. The econometric methodology and the empirical results are presented in Chapter 4. Chapter 5 discusses the results in relation to the literature. Chapter 6 demonstrates a trading strategy. Finally, in Chapter 7, we conclude.

2 Literature Review

This chapter contextualizes our study and discusses its contribution to current research. First, we review the literature concerning calendar effects and their impact on the US stock market. We examine evidence and explanations for calendar effects that occur at the turn-of-the-month (TOM), the turn-of-the-quarter (TOQ), and the turn-of-the-year (TOY). Investors may view specific phases of the yearly cycle as especially important and behave accordingly. Researchers have suggested that human behavior may offer reasonable explanations for calendar effects (Jacobs & Levy, 1988; Vasileiou, 2015). Since one of our contributions is how calendar anomalies relate to public attention, we review the literature on measuring attention using Google search volumes in the last section.

2.1 The turn-of-the-year effect

Since its discovery by Wachtel (1942), the TOY effect, also known as the January effect, has been one of the most debated topics in financial academics, and numerous studies have attempted to explain its persistence. In essence, the effect amounts to stocks in January performing exceptionally well compared to other months of the year (Rozeff & Kinney, 1976; McEnally, 1976; Dyl, 1977; Branch, 1977; Clark & Ziemba, 1987; Haugen & Jorion, 1996). As with all anomalies, any evidence of the TOY effect would contradict the efficient market hypothesis, as an efficient market would immediately correct the anomaly once recognized (Fama, 1970). Multiple researchers show that the TOY effect persists, indicating that it violates the efficient market hypothesis and behavioral explanations are essential to explaining the effect (Blocher et al., 2011; Haugen & Jorion, 1996; Haug & Hirschey, 2006).

The tax-loss selling hypothesis is arguably the most prevalent explanation for the January effect in the US stock market (Brown & Marsh, 1983). According to the researchers, investors sell small, underperforming stocks to declare a capital loss before the year-end. Following the year-end, investors reinvest their profits, which explains why stock prices spike in January. This hypothesis has long been proposed as a plausible explanation for the TOY effect, but its persistence since the Tax Reform Act of 1986 weakens it. Since the tax reform, capital losses incurred in the last two months of a calendar year are carried forward to the subsequent tax year (Auerbach & Slemrod, 1997). According to Haug & Hirschey (2006), since the TOY effect is observed only for a few days around year-ends, institutional investors selling losses for tax purposes do not cause the short-term TOY effect. The TOY effect generally impacts small companies more than large ones

(Reinganum, 1983; Keim, 1983; Roll, 1983). Individual investors are more sensitive to income taxes and will likely sell small, volatile stocks before the year-end to gain a tax benefit, according to Pietranico (2004). Consistent with this theory, D'Mello et al. (2003) report that individual investors exert abnormal selling pressure on underperforming stocks before the year-end. On the other hand, Gultekin & Gultekin (1983) study the TOY effect in 16 worldwide stock markets with varying tax calendars and concludes that the effect is evident in 15 of the 16 countries studied, suggesting that the effect may have alternative explanations. Additionally, several researchers demonstrate a decreasing trend or lack of evidence for the TOY effect after 1986 (Gu, 2003; Mehdian & Perry, 2002).

Literature provides a second explanation for the TOY effect: window dressing by institutional investors seeking to portray positive results, as evident by Haugen & Lakonishok (1988). According to this hypothesis, portfolio managers rebalance their portfolios before year-end reporting by selling underperforming stocks. The performance hedging hypothesis is a third explanation for the TOY effect offered by the literature. The hypothesis posits that institutional investors, averse to holding stocks that may adversely impact performance, periodically sell volatile, small stocks and invest their assets in an index. After year-end performance evaluations and bonus collections, fund managers reinvest in small companies to outperform their benchmark (Lee et al., 1998).

Undoubtedly, the literature offers no unified explanation for the TOY effect after 1986. Our study will add to the literature by examining the TOY effect for the entire period between 1986 and 2021, and in relation to firm characteristics.

2.2 The turn-of-the-quarter effect

The literature documents systematic patterns in returns around quarter-ends, and several theories are put forward to explain these abnormal levels of stock returns. At the end of the quarter, many firms, analysts, and government agencies release critical new financial data. Moreover, mutual fund portfolios are disclosed to the general market each quarter, reinforcing the perception that quarter-ends are meaningful events. Portfolio disclosure has been shown to incentives fund managers to execute trades to conceal their actual performance (Wermers, 2001; Musto, 1997; Agarwal et al., 2014). Bernhardt & Davies (2005) demonstrate that returns on disclosure days are higher than at the beginning of a quarter, linking this phenomenon to the behavior of strategic fund managers and the growing presence of mutual funds in the market. Gormley et al. (2021) also demonstrate that disclosure requirements generate a dynamic pattern of fund trading.

Since institutions disclose their portfolio around the quarter-end, not only year-end, the window dressing hypothesis is a plausible explanation for these return anomalies (Haugen

& Lakonishok, 1988; Ritter, 1994). According to the window dressing hypothesis, managers sell stocks with low momentum before the quarter-end to present promising results at the time of disclosure, thus causing abnormally high stock returns around quarter-ends. Meier & Schaumburg (2004) provide strong evidence for a peak in trading activity and return at the TOQ, consistent with window dressing. Another explanation for abnormal returns around quarter-ends put forth in the literature is portfolio pumping. According to Carhart et al. (2002), a surge of trading in the quarter's last minutes coincides with a rise in equity prices, and they suggest that portfolio pumping by mutual funds is the reason for quarter-end rallies. According to Gallagher et al. (2009), active managers tend to buy illiquid stocks in which they own overweight positions on the last day of a quarter. However, Duong & Meschke (2020) suggest that increased regulatory attention in the previous decades has led to reduced portfolio pumping by US mutual funds. As part of our contribution to the literature, we examine returns around quarter-ends over the previous four decades to see if regulations have reduced portfolio pumping.

2.3 The turn-of-the-month effect

The financial literature has identified and analyzed considerable anomalies in stock returns at the end of the month. Ariel (1987) first documented that returns on the month's last and the first four trading days are higher than on other days. Lakonishok & Smidt (1988) reported that cumulative returns in four days around the month-end exceeded those over the entire month. Explanations in the literature for the TOM effect focus on individual investors, including payment standardization, macroeconomic news, and earnings announcements.

The TOM effect has been linked to increased liquidity among individual investors at the end of the month (Ogden, 1990; Clark & Ziemba, 1987). To explain the TOM effect, according to Ogden (1990), the payment of wages, interest, and dividends at the end of the month increases investors' liquidity, which increases demand for stocks. McConnell & Xu (2008) name the explanation the payday hypothesis. Additionally, literature relates abnormal returns around month-ends to a change in investor expectations resulting from earnings announcements (Ball & Kothari, 1991). Also, Nikkinen et al. (2007) suggests that the TOM effect arises from macroeconomic news released at the end of the month.

2.4 Measure of attention

The calendar cycle affects investor sentiment, and their behavioral change influences market performance and calendar anomalies (Vasileiou, 2015). Contrary to the extant literature, which exclusively focuses on financial factors as explanations for abnormal seasonality, this study also examines whether calendar anomalies are related to the level of attention companies receive during the calendar.

The literature emphasizes the importance of combining behavioral data with financial markets. De Long et al. (1990) first recognized investor sentiment as an essential factor for financial markets. Following this, Baker & Wurgler (2007) began asking how to quantify its impact. Da et al. (2014) use daily internet search volume to reveal the market-level sentiment. Several studies have demonstrated that Google searches for individual companies significantly explain stock returns (Baker & Wurgler, 2006; Da et al., 2014; Bijl et al., 2016). Some studies show that high levels of investor sentiment reduce stock returns (Tetlock, 2007; Yu & Yuan, 2011; Joseph et al., 2011). On the other hand, Kim et al. (2019) find that Google searches neither correlate nor predict abnormal returns. Preis et al. (2010) further emphasizes the value of combining extensive behavioral data to understand financial market fluctuations. Their research suggests that Google searches during periods of increased market activity provide a unique insight into the behavior of market participants.

To our knowledge, there is no evidence in the literature of calendar anomalies being related to the public attention given to a particular company. We contribute to the field of study by using Google search volumes as a proxy for public attention and investigating how it relates to return over the TOM, TOQ, and TOY.

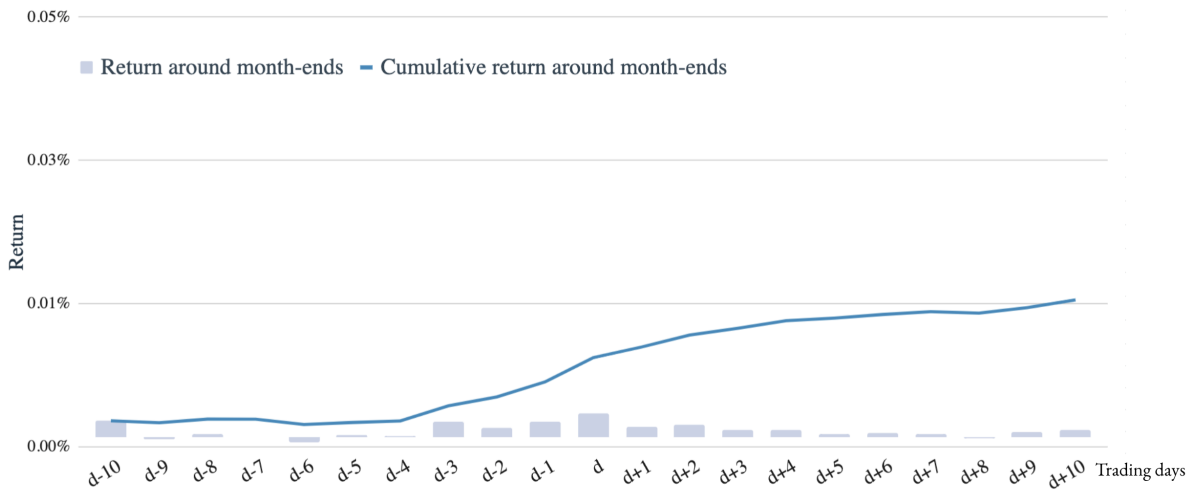
3 Data

This chapter elaborates on the data sources and processing methods we apply to the data. We obtain our data from Compustat and The Center for Research in Security Prices (CRSP) through Wharton Research Data Services (WRDS). We compute four-day stock return windows over the last trading day of every month, quarter, and year, as well as over ordinary trading days. Then, we construct three independent variables that flag windows capturing the turn-of-the-month (TOM), the turn-of-the-quarter (TOQ), and the turn-of-the-year (TOY). Further, we use nine explanatory firm characteristics in our analysis. We also construct one variable from Google search volumes, representing public attention to individual companies. Our data consists of time series, with the sample period spanning from Jan 1986 until Dec 2021 (35 years). Table 3 provides an overview of all variables and their associated definitions.

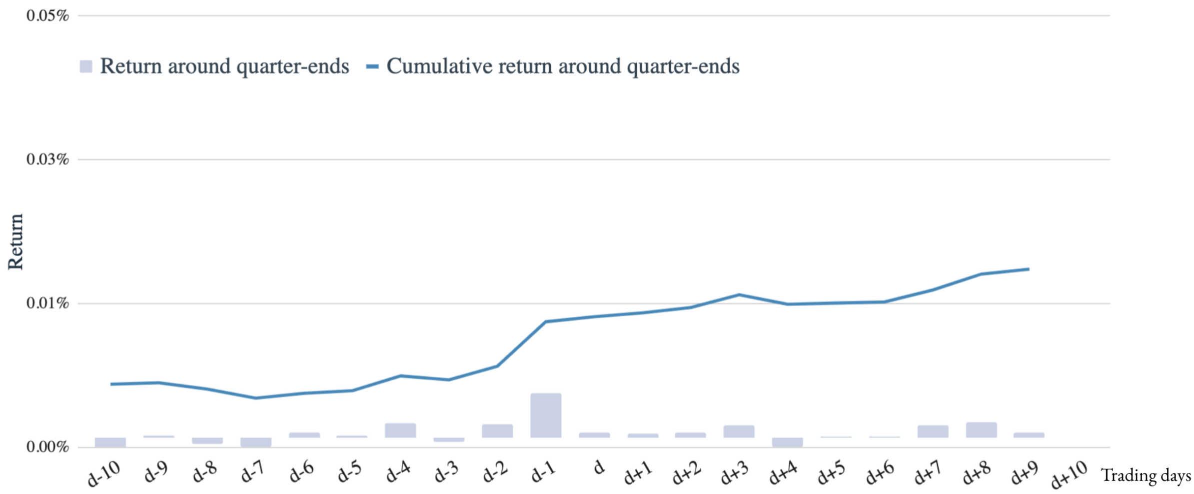
3.1 Stock market data

To select our company sample, we utilize the same criteria as Verma (2021). Therefore, we restrict the sample to common shares (i.e., share codes 10 and 11) that trade on NYSE, AMEX, or NASDAQ (i.e., exchange codes 1, 2, and 3) and have a prior month-end market capitalization of minimum $10 million. All companies must have the following price factors: book-to-market ratio, gross profitability, market value of equity, standardized unexpected earnings, volatility, volume, 3 and 12-month momentum, and dividend yield, consistent with how they are defined in Green et al. (2017). Similarly to Da et al. (2014), we examine all stocks listed on the three exchanges during our sample period to eliminate survivorship bias. The data is unbalanced, with the number of companies ranging from 2 290 to 4 801. Moreover, Lakonishok & Smidt (1988) proposes that long and new data series are the most effective means against data snooping, noise, and selection bias to confirm anomalies. Since we collect stock market data for the past 35 years, the data consists of long time series. Table 12 in Appendix A provides a complete overview of the number of companies at each year-end.

We determine an appropriate time window over the turns of the calendar to examine calendar effects. The literature demonstrates that calendar anomalies arise before and persist beyond turns of the calendar (Carhart et al., 2002). Hence, we select a four-day window from $d-1$ to $d+2$, similar to the window used by Lakonishok & Smidt (1988). A longer window may be subject to much noise, whereas a smaller window may not capture the calendar effect.



(a) Cumulative and actual return over month-ends.



(b) Cumulative and actual return over quarter-ends.

(c) Cumulative and actual return over year-ends.

Figure 1: Cumulative and actual stock return 20 days relative to the last trading day of the month, quarter and year, averaged for all companies. Sample period is Jan 1986 to Dec 2021.

We denote d as the last trading day of a month, quarter, or year, while the x-axis denote the days relative to d.

We divide the time into four-day windows, and compute four-day stock return over the last trading day of every month, quarter, and year, as well as over ordinary trading days. Hence, we can compare the return of holding a stock over turns of the calendar to the return of holding a stock over ordinary trading days. We calculate cumulative stock returns over each four-day window for each company using the Equation 3.1.

$$ret_t = 100 * [(1 + ret_{d-1})(1 + ret_d)(1 + ret_{d+1})(1 + ret_{d+2}) - 1] \tag{3.1}$$

where ret_d is the daily stock return on day d, whereas ret_t denote the return over four-day windows. To convert the cumulative return to a percentage, we multiply the result by 100.

3.2 Indicators of the turn of calendar periods

We construct three independent variables, TOM, TOQ, and TOY, that flag four-day windows capturing turns of the calendar. The windows denote four trading days; non-trading days are excluded from the sample.

The first indicator, TOY, indicates the four-day window over each year-end, i.e. the shift from the December to January (Equation 3.2).

$$TOY_t = \begin{cases} 1, & \text{if the four-day period coincides with the turn-of-the-year.} \\ 0, & \text{otherwise} \end{cases} \tag{3.2}$$

Similarly, the TOQ indicates the four-day window over each quarter-end in a calendar year, i.e., the shift from March to April, June to July, September to October, and December to January. The TOM indicator represents the four-day window over each month-end in a calendar year, i.e., the shift from January to December. To illustrate, the four-day TOM window in November 2021 corresponds to November 29, November 30, December 1, and December 2, with each day being a trading day. In sum, we define the TOM, TOQ, and TOY as the four-day window around the last trading day d in each period: $d-1$, d, $d+1$, and $d+2$. Figure 2 depicts the notation used to indicate the turns of the calendar.

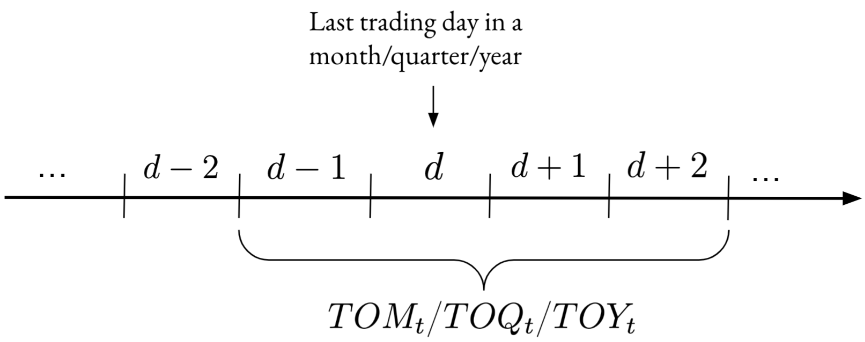


Figure 2: Illustration of how four-day windows around the turns of the calendar is indicated.

3.3 Firm characteristics

Research show that a large number of observable firm characteristics can predict the cross-section of stock returns (Fama & French, 1995; Nagel, 2012; McLean & Pontiff, 2016). Following this, we obtain nine firm characteristics to explore their relationship with the calendar anomalies. These are book-to-market ratio, gross profitability, market value of equity, standardized unexpected earnings, volatility, volume, 3 and 12-month momentum, and dividend yield. We obtain values from CRSP and Compustat in order to compute the firm characteristics described in Green et al. (2017). Certain values are only updated every month, quarter, or fiscal year. In such situations, the most recent observation for each four-day window is utilized.

The use of the book-to-market ratio is motivated by the findings of Fama & French (1995). Book-to-market ratios enables us to differentiate between value stocks relative to growth stocks. Following Green et al. (2017), we define the book-to-market ratio as the book value of equity, bve, divided by market capitalization, mve (Equation 3.3).

$$bm_t = \frac{bve_t}{mve_t} \tag{3.3}$$

where t denotes the four-day window in all following equations.

Gross profitability explains most earnings related anomalies according to (Novy-Marx, 2013). We calculate gross profitability as revenues minus the cost of goods sold divided by total assets, as shown in Equation 3.4.

$$gp_t = \frac{Revenues_t - COGS_t}{TotalAssets_t} \tag{3.4}$$

We include a measure of firm size, as the natural log of market capitalization as shown in Equation 3.5.

$$mve_t = log(SharesOutstanding_t * Price_t) \tag{3.5}$$

We obtain standardized unexpected earnings, sue_t, from Compustat quarterly file.

We include volatility as a parameter in the model due to the relationship between volatility and future returns (Banerjee et al., 2007). We obtain volatility directly from WRDS in the Beta Suite database, which computes volatility as the volatility of realized returns using a 3-month estimation window.

Previous research finds evidence of a high-volume return premium, indicating that trading volume has an effect on future stock price fluctuations (Chordia & Swaminathan, 2000; Barber & Odean, 2008). Therefore, we include the trading volume and standardize it relatively to the past six months' observations (Equation 3.6).

$$volume_t = log(vol_m) - log(Median(vol_{m-1}, vol_{m-2}, ..., vol_{m-6})) \tag{3.6}$$

where vol denotes volume and m denotes the month to the first trading day in the window t.

In order to distinguish between stocks that have performed well or poorly in the past, we include 3-month and 12-month momentum. We calculate 3-month momentum, $mom3m$, as the 3-month cumulative returns ending one month before the four-day window t. Further, we calculate 12-month momentum, $mom12m$, as 12-month cumulative returns ending one month before the window t as defined in Equations 3.7 and 3.8.

$$mom3m_t = (ret_{m-1} + 1)(ret_{m-2} + 1)(ret_{m-3} + 1) - 1 \tag{3.7}$$

$$mom12m_t = (ret_{m-1} + 1)(ret_{m-2} + 1)...(ret_{m-12} + 1) - 1 \tag{3.8}$$

where m denotes the month to the first trading day in the window t.

We include dividend yield to test whether the TOY effect is more substantial for companies with capital gains and, on the contrary, weaker for companies that pay high dividends. According to Naranjo et al. (1998), using quarterly dividends rather than the previous year's post-yield may better reflect the anticipated dividend yield for the upcoming year.

As a result, we calculate dividend yield similarly to Naranjo et al. (1998), by dividing the quarterly dividend by the stock price, as defined in Equation 3.9.

$$dy_t = \frac{4 * D_t}{Price_t} \tag{3.9}$$

where D_t is the dividend and dy denotes the dividend yield.

3.4 Google Trends data

We obtain Google search volumes from the Google Trends website to construct a measure of attention. Google Trends provides largely unfiltered samples of actual search queries made to Google (Google, 2022). The Google Trends tool allows users to compare the popularity of search phrases across time. Accordingly, Google Trends scales the data from 0 to 100, where 100 symbolizes the most popularity. Google Trends divides each data point by the total searches within the specified time and geographical area to remove time effects from the data. Hence, Google Trends outputs a time series showing the search volume index (SVI) given a specified category, country, time frame, and several other parameters. We use a Python Google Trends API (pytrends) to obtain the SVIs from Google Trends.

Google Trends lets us delimit queries geographically to consider search volumes in defined regions. Preis et al. (2013) find that US data predicts US stock market movements better than global data. Following this, we exclusively retrieve US search volumes. This is reasonable since many investors trading on the NYSE, AMEX, and NASDAQ are based in the US, and investors searching for US companies are not likely to be interested in an alternate meaning of the word in other languages. Therefore, geographically restricting SVIs to the US is a more suitable indicator of investor attention to each company.

When measuring company attention using Google search volume, an essential factor is the search term to gauge. Using company names and tickers to measure attention is common in the literature. Both approaches are well-supported; however, they serve somewhat different purposes. Da et al. (2014) conclude that searches for tickers capture people's attention for financial information about a given stock. According to Joseph et al. (2011) , only an investor seriously considering an investment decision would search for tickers. On the other hand, Vlastakis & Markellos (2012) use company names as search keywords because it indicates attention associated with a company rather than a stock in particular. Accordingly, we only consider search volumes on company names instead of tickers to measure public attention to individual companies.

We use official company names as search terms but remove standard abbreviations to fit a more practical purpose. For example, ".inc" and "corp." are removed. In addition, "Apple," "Ambient," and "CNS" are also excluded as they have generic meanings. Such terms can potentially have abnormally high search volumes unrelated to the attention paid to the company. To avoid this bias, we manually review all 7730 companies in NYSE, AMEX, and NASDAQ from the period of Jan 2004 to Dec 2021 and exclude those with these "noisy" search terms. Our data comprise 5854 valid company names. If a company was listed or delisted during the sample period, we only include data from the listing period. Re-branding companies during crises or in response to a change of focus has been a popular strategy for decades. Therefore, we include all companies' previous and current names that have changed during the sample period. To illustrate, we include the search term "FACEBOOK" in conjunction with "META PLATFORMS" to capture complete attention towards the company "Meta Platforms Inc.". Consequently, by including former company names, we capture attention before and after re-branding or image concerns.

We compute the time series for abnormal search volumes (ASVI) for each company, as given by Equation 3.10.

$$ASVI_t = log(SVI_m) - log(Median(SVI_{m-1}, SVI_{m-2}, ..., SVI_{m-6})) \quad (3.10)$$

where m denotes the month to the first trading day in the window t.

3.5 Summary statistics and variable summary

We observe some extreme values in the following variables: *sue*, *bm*, *gp*, *mom3m*, and *mom12m*. To reduce the presence of outliers, we remove the observations at the 1% and 99% levels. Ultimately, we use the Augmented Dickey-Fuller test to check for stationarity, and the results confirm that all variables are stationary. Tables 1 and 2 present correlation coefficients between all variables used in our models for the periods of 1986 to 2021 and 2004 to 2021, respectively. We follow the same approach for calculating correlations as Da et al. (2014). We first calculate correlations individually for each company and then average the results for all companies.

Table 1 reports a certain degree of correlation among the firm characteristics. To exemplify, the correlation coefficient of -0.623 between *bm* and *mve*, implies a moderate negative correlation. However, Green et al. (2017) concludes that firm characteristics, evident from average US monthly returns from 1980 to 2014, cannot be considered independent. We there find it is reasonable that the firm characteristics are correlated to a certain degree.

Table 1: Correlation matrix for all the variables in the data sample period from 1986 to 2021.

	ret	*bm*	*gp*	*mve*	*sue*	*volatility*	*volume*	*mom3m*	*mom12m*	*dy*
ret	1.000	0.043	0.002	-0.056	0.017	0.002	0.004	-0.007	-0.014	-0.000
bm		1.000	-0.154	-0.623	-0.171	0.016	-0.076	-0.258	-0.476	0.047
gp			1.000	0.066	0.069	-0.036	0.009	-0.012	0.098	-0.019
mve				1.000	0.058	-0.046	0.060	0.209	0.382	0.002
sue					1.000	-0.022	0.026	0.075	0.199	-0.022
volatility						1.000	0.159	0.171	0.007	0.004
volume							1.000	0.184	0.088	0.039
mom3m								1.000	0.327	0.009
mom12m									1.000	-0.032
dy										1.000

There are low correlations between $ASVI$ and all the firm characteristics, as shown in Table 2. For example, the events leading to changes in firm characteristics may include earnings releases, company news, central bank announcements or interest rate changes (Brooks & Byrne, 2008). On the contrary, ASVI spikes are possibly caused by hypes in social media, campaigns, changes in advertising exposures, and more. Therefore, the $ASVI$ could provide information not captured by the firm characteristics. Both correlation matrices show that we have no issue with highly correlated variables.

Table 2: Correlation matrix for all the variables in the data sample period from 2004 to 2021.

	ret	*ASVI*	*bm*	*gp*	*mve*	*sue*	*volatility*	*volume*	*mom3m*	*mom12m*	*dy*
ret	1.000	-0.004	0.047	-0.001	-0.058	0.016	0.002	0.001	-0.004	-0.014	-0.002
ASVI		1.000	-0.034	0.006	0.034	0.009	0.032	0.146	0.049	0.036	0.002
bm			1.000	-0.182	-0.642	-0.162	0.057	-0.063	-0.261	-0.459	0.046
gp				1.000	0.076	0.070	-0.047	0.013	-0.034	0.077	-0.027
mve					1.000	0.068	-0.081	0.049	0.222	0.388	0.002
sue						1.000	-0.034	0.018	0.074	0.194	-0.024
volatility							1.000	0.177	0.150	-0.025	0.013
volume								1.000	0.095	0.061	0.045
mom3m									1.000	0.319	0.008
mom12m										1.000	-0.034
dy											1.000

Table 3 provides an overview of all variables and their associated definitions.

Table 3: A complete overview of all variables and their associated definitions.

Variable	**Definition**	**Data source**
ret	Stock market return	CRSP
TOY	Indicator of the four-day window over each year-end, i.e., the shift from December to January.	
TOQ	Indicator of the four-day window over each quarter-end, i.e., the shift from March to April, June to July, September to October, and December to January.	
TOM	Indicator of the four-day window over each month-end, i.e., the shift from every month to the subsequent month.	
bm	Book-to-market calculated as book value of equity divided by market capitalization.	Compustat
gp	Gross profitability calculated as revenues minus cost of goods sold divided by total assets.	Compustat
mve	Market value of equity calculated as the natural log of market capitalization, where market capitalization is computed as the share price multiplied by number of shares outstanding.	CRSP
sue	Standardized unexpected earnings.	Compustat
$volatility$	Volatility calculated as the volatility of the realized returns of the underlying security using a 3-month rolling window.	WRDS - Beta Suite
$volume$	Scaled trading volume calculated as the monthly trading volume subtracted by the median of the previous six months trading volume.	CRSP
$mom3m$	Prior 3-month cumulative return.	CRSP
$mom12m$	Prior 12-month cumulative return.	CRSP
dy	Dividend yield computed as dividend by stock price.	CRSP
$ASVI$	Abnormal search volume index constructed by Googles search volumes for company names. Scaled by subtracting the median $ASVI$ of the previous six months.	Google Trends

4 Results

In this chapter, we describe the methodology we use for empirical analysis and the results produced. We present panel regression models employed to the panel data of 15 000 companies traded on the NYSE, AMEX, and NASDAQ between 1986 and 2021. We present the corresponding results for each model. First, we evaluate the existence of the turn-of-the-month (TOM), turn-of-the-quarter (TOQ), and turn-of-the-year (TOY) effects across the US stock market. Second, we investigate the impact of firm characteristics on calendar effects. To evaluate the evolution of the calendar effects, we divide our sample into decades. We also include a measure of Google search volumes to assess the relationship between abnormal levels of attention in a company and the TOM, TOQ, and TOY windows. Finally, we test the robustness of our results.

4.1 Impact of calendar effects on stock returns

In this section, we examine whether calendar effects exist and are comprehensive phenomena affecting the entire market over the sample period. Therefore, we construct Pooled OLS regression models to compare the average stock return over the TOM, TOQ, and TOY windows with the average return over ordinary trading day windows. In Equation 4.1, we first evaluate the average stock return over the entire sample. Subsequently, we individually evaluate the average stock return over the TOM, TOQ, and TOY windows in the models presented in Equations 4.2, 4.3, and 4.4.

$$ret_{i,t} = \alpha + \epsilon_{i,t} \tag{4.1}$$

$$ret_{i,t} = \alpha + \beta TOM_t + \epsilon_{i,t} \tag{4.2}$$

$$ret_{i,t} = \alpha + \beta TOQ_t + \epsilon_{i,t} \tag{4.3}$$

$$ret_{i,t} = \alpha + \beta TOY_t + \epsilon_{i,t} \tag{4.4}$$

where t denotes the four-day window and i denotes the company. Henceforth, we use these same notations in all the equations that follow.

Lastly, we concurrently include the TOM, TOQ, and TOY in Equation 4.5.

$$ret_{i,t} = \alpha + \beta_1 TOM_t + \beta_2 TOQ_t + \beta_3 TOY_t + \epsilon_{i,t} \tag{4.5}$$

We present the fitted coefficients from the above regression models in Table 4. Model 1 includes only the constant, reporting the average return over the sample period. Models 2 to 4 separately report the effect of the TOM, TOQ, and TOY on stock returns. To exclusively capture the unique effects for each specific turn of the calendar, we simultaneously include the TOM, TOQ, and TOY indicators in Model 5.

Table 4: Pooled OLS regression results for all companies' stock returns over four-day return windows. Model 1 reports the relationship on average. Models 2 to 4 reports the relationship over the turn-of-the-year (TOY), turn-of-the-quarter (TOQ), and turn-of-the-month (TOM) separately. Model 5 includes the TOM, TOQ, and TOY concurrently. The TOM, TOQ, and TOY are defined as the four-day windows over the last trading day d of the respective period: $d-1$, d, $d+1$, and $d+2$. The sample period is from Jan 1986 to Dec 2021.

	Dependent variable: ret_t				
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
TOM_t				0.499***	0.471***
				(0.009)	(0.010)
TOQ_t			0.440***		−0.265***
			(0.001)		(0.014)
TOY_t		1.503***			1.423***
		(0.027)			(0.030)
Constant	0.277***	0.236***	0.229***	0.111***	0.111***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Company fixed effects	No	No	No	No	No
Observations	4,339,506	4,339,506	4,339,506	4,339,506	4,339,506
R^2	0.000	0.001	0.0004	0.001	0.002
Adjusted R^2	-0.001	-0.001	-0.001	0.000	0.001

Note: Driscoll & Kraay (1998) robust standard errors are reported in parenthesis. *,**,*** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 4 shows that the TOM, TOQ, and TOY effects are related to abnormally high stock returns in the US stock market, with widespread significance at the 1% rejection level. The significantly positive constant in Model 1 indicates a positive average stock return over the entire sample. The positive TOM, TOQ, and TOY coefficients in Models 2 to 4 show that stock returns around the turns of the calendar are abnormally high relative to ordinary trading day windows. All coefficients are significant at the 1% level in Model 5, suggesting the presence of all three effects, with the TOY effect being the most pronounced. The TOM and TOY effects positively affect return, whereas the TOQ effect negatively affects return. Nonetheless, the returns are abnormally positive across all three turns of the calendar, as depicted in Figure 3.

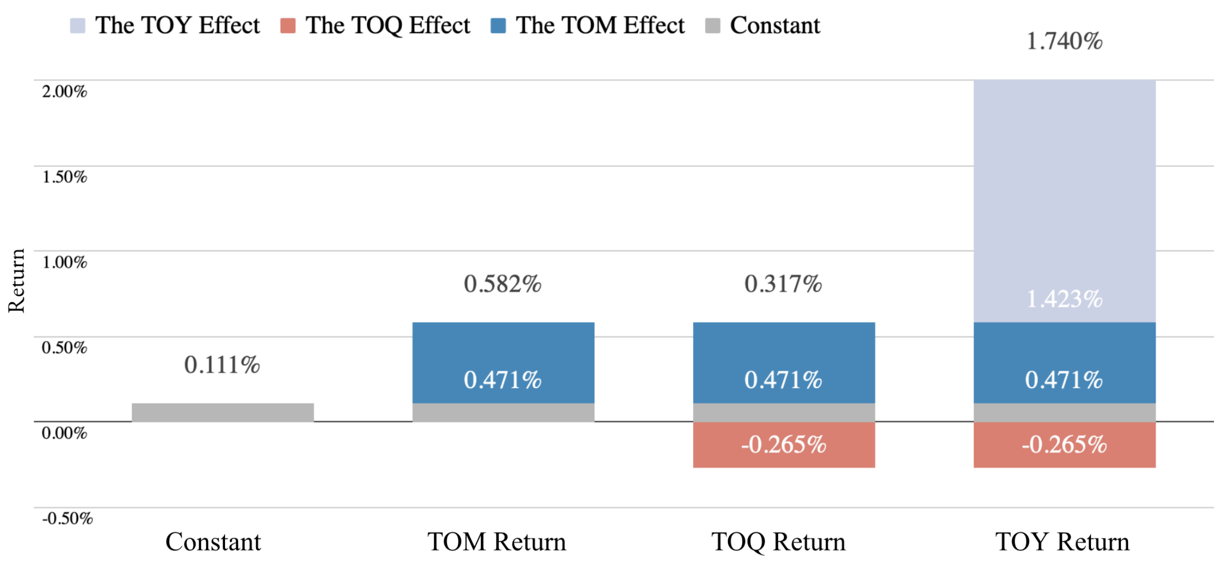


Figure 3: The figure shows the total average return over the TOM, TOQ, and TOY windows, and illustrates the separate impact made by each calendar effect.

Figure 3 illustrates how each calendar effect separately impacts return over the TOM, TOQ, and TOY windows. The average return over a four-day window on ordinary trading day windows is 0.11%. If the window is a TOM, the return is increased by 0.47%, and if it is also a TOQ, the return is further decreased by 0.27%. If the window is a TOY as well, the return is increased by 1.4%. To exemplify, the last four-day window in December 2020, including December 30, December 31, January 4, and January 5, corresponds to a TOM, TOQ, and TOY simultaneously. Overall, Table 4 confirms our assumption that the US stock market generally experiences abnormally high stock returns over the TOM, TOQ, and TOY. The TOM and TOY effects positively impact the return, whereas the TOQ effect negatively impacts the return. The results indicate that the TOY effect is the most substantial calendar effect.

4.2 Impact of firm characteristics on calendar effects

This section evaluates which type of companies are most influenced by calendar effects by exploring the relationship between stock return over the turns of the calendar and nine firm characteristics. First, we relate the TOM, TOQ, and TOY indicators to book-to-market ratio, gross profitability, market value of equity, standardized unexpected earnings, volatility, volume, 3- and 12-month momentum, and dividend yield. Secondly, we split our sample by decade and repeat the analysis to investigate how the calendar effects have evolved. Lastly, we analyze a subset of the data from 2004 to 2021 and include a measure of public attention given to companies through Google searches.

In the preceding section, we employed Pooled OLS regression models to evaluate the magnitude of each calendar effect. Moving forward, we are primarily interested in assessing the time-varying impact of firm characteristics. Based on Torres-Reyna (2007), we determine that Fixed effects regression models are more appropriate for this purpose than Pooled OLS. Given that our data contains information on 15 000 companies spanning 35 years, the time dimension is sufficiently large. In addition, we perform the Lagrange Multiplier test and the F-test for individual effects (Breusch & Pagan, 1980). Based on the results, we conclude statistically that fixed effects are present in our data and should be incorporated into the empirical analysis. There are two sorts of fixed effects; entity fixed and time-fixed effects (Torres-Reyna, 2007). We are interested in analyzing the common movement of the stock returns of all companies over the turns of the calendar. In light of this, we only include company fixed effects as the time-fixed effects would control for the effect we aim to analyze. Based on the intended analysis and statistical tests, panel regressions with company fixed effects are the most appropriate models for the remainder of the thesis.

We use Driscoll & Kraay (1998) robust standard errors, as described by Hoechle (2007), to calculate more conservative and unbiased standard error coefficients robust to cross-sectional dependency. The Breusch & Pagan (1979) and White (1980) tests both indicate heteroscedasticity in the data, whereas the Wooldridge (2010) test reveals serial correlation. The Driscoll & Kraay (1998) standard errors are robust to heteroscedasticity, autocorrelation, and cross-sectional dependence.

4.2.1 Calendar effects and firm characteristics

We examine the general relationship between firm characteristics and stock returns using Equation 4.6.

$$ret_{i,t} = \alpha + \sum_{j=1}^{9} \theta_j FC_{i,t} + \mu_i + \epsilon_{i,t} \tag{4.6}$$

where FC represents firm characteristics, μ_i denotes company fixed effects for company i and ϵ is the error term. Hereafter, we use this same notation for all following equations.

Next, we assess how specific firm characteristics affect returns over the turns of the calendar given by Equations 4.7, 4.8, and 4.9. In particular, we separately relate the TOM, TOQ, and TOY indicators to the following firm characteristics: book-to-market ratio, gross profitability, market value of equity, standardized unexpected earnings, volatility, volume, 3- and 12-month momentum, and dividend yield.

$$ret_{i,t} = \alpha + \beta_1 TOM_t + \sum_{j=1}^{9} \theta_j FC_{i,t} + \sum_{m=1}^{9} \gamma_m FC_{i,t} TOM_t + \mu_i + \epsilon_{i,t} \tag{4.7}$$

$$ret_{i,t} = \alpha + \beta_2 TOQ_t + \sum_{j=1}^{9} \theta_j FC_{i,t} + \sum_{k=1}^{9} \delta_k FC_{i,t} TOQ_t + \mu_i + \epsilon_{i,t} \tag{4.8}$$

$$ret_{i,t} = \alpha + \beta_3 TOY_t + \sum_{j=1}^{9} \theta_j FC_{i,t} + \sum_{n=1}^{9} \rho_n FC_{i,t} TOY_t + \mu_i + \epsilon_{i,t} \tag{4.9}$$

Lastly, we examine each calendar effect while controlling for the two remaining effects. Therefore, we simultaneously include the TOM, TOQ, and TOY indicators, and interact them with the firm characteristics, as shown in Equation 4.10.

$$\begin{aligned} ret_{i,t} = \alpha &+ \beta_1 TOM_t + \beta_2 TOQ_t + \beta_3 TOY_t \\ &+ \sum_{j=1}^{9} \theta_j FC_{i,t} + \sum_{m=1}^{9} \gamma_m FC_{i,t} TOM_t \\ &+ \sum_{k=1}^{9} \delta_k FC_{i,t} TOQ_t + \sum_{n=1}^{9} \rho_n FC_{i,t} TOY_t + \mu_i + \epsilon_{i,t} \end{aligned} \tag{4.10}$$

We present the fitted coefficients from the above regression models in Table 5. Note that $Calendar$ is a placeholder for TOM, TOQ, or TOY in all following models. In Model 1, we examine how each firm characteristic generally relates to return on ordinary trading day windows. Moreover, Models 2 to 4 report the relationship between firm characteristics and return separately over the TOM, TOQ, and TOY windows. To capture the unique impact of the calendar effects, we simultaneously incorporate and interact them with each firm characteristic in Model 5. We underline that Model 5 is organized in three columns, each reporting the relationship between the firm characteristics and return over the TOM, TOQ, and TOY, respectively. The relationship between firm characteristics and return on ordinary trading day windows unaffected by calendar effects is reported below.

Based on Table 5, the TOM, TOQ, and TOY effects are generally more pronounced for smaller companies, companies with low trading volume, and companies with volatile stock prices. In other words, these companies see greater returns during the TOM and TOY windows but lower returns during the TOQ windows. Furthermore, the TOY effect is more prominent in firms with low momentum, whereas the TOM effect is stronger in firms with

Table 5: Company fixed effects regression results for all companies' stock returns over four-day return windows. Model 1 reports the general relationship between return and firm characteristics. Models 2 to 4 report the relationship over the turn-of-the-month (TOM), turn-of-the-quarter (TOQ), and turn-of-the-year (TOY) separately. Model 5 includes the TOM, TOQ, and TOY concurrently. The firm characteristics are book-to-market ratio, gross profitability, market value of equity, standardized unexpected earnings, volatility, volume, 3- and 12-month momentum, and dividend yield. The TOM, TOQ, and TOY are defined as the four-day windows over the last trading day d of the respective period: $d-1$, d, $d+1$, and $d+2$. The sample period is from Jan 1986 to Dec 2021.

	Dependent variable: ret_t						
	Model (1)	Model (2)	Model (3)	Model (4)		Model (5)	
		TOM	TOQ	TOY	TOM	TOQ	TOY
$Calendar_t$		0.712^{***}	0.885^{***}	2.850^{***}	0.555^{***}	-0.115^{*}	2.568^{***}
		(0.039)	(0.059)	(0.129)	(0.046)	(0.074)	(0.142)
$Calendar_t$*bm		0.047^{**}	0.123^{***}	0.351^{***}	0.012	-0.043	0.384^{***}
		(0.019)	(0.028)	(0.060)	(0.022)	(0.034)	(0.066)
$Calendar_t$*gp_t		-0.042	-0.208^{***}	-0.295^{***}	0.036	-0.198^{***}	-0.136
		(0.027)	(0.039)	(0.081)	(0.031)	(0.049)	(0.089)
$Calendar_t$*mve_t		-0.060^{***}	-0.088^{***}	-0.397^{***}	-0.044^{***}	0.043^{***}	-0.409^{***}
		(0.004)	(0.006)	(0.013)	(0.005)	(0.007)	(0.015)
$Calendar_t$*sue_t		-0.019^{***}	-0.003	-0.026^{*}	-0.023^{***}	0.013	-0.020
		(0.005)	(0.007)	(0.012)	(0.005)	(0.008)	(0.015)
$Calendar_t$*$volatility_t$		0.906^{***}	0.454^{**}	9.486^{***}	1.028^{***}	-3.525^{***}	12.029^{***}
		(0.124)	(0.191)	(0.399)	(0.139)	(0.235)	(0.451)
$Calendar_t$*$volume_t$		-0.139^{***}	0.025	-0.231^{***}	-0.197^{***}	0.206^{***}	-0.278^{***}
		(0.014)	(0.019)	(0.042)	(0.016)	(0.024)	(0.047)
$Calendar_t$*$mom3m_t$		-0.286^{***}	-1.435^{***}	-5.231^{***}	0.309^{***}	-0.001	-5.456^{***}
		(0.057)	(0.085)	(0.158)	(0.067)	(0.105)	(0.174)
$Calendar_t$*$mom12m_t$		0.206^{***}	0.304^{***}	-0.744^{***}	0.126^{***}	0.475^{***}	-1.278^{***}
		(0.022)	(0.032)	(0.069)	(0.025)	(0.039)	(0.074)
$Calendar_t$*dy_t		0.003^{*}	0.003	-0.006^{*}	0.003	0.001	-0.008^{**}
		(0.002)	(0.002)	(0.048)	(0.002)	(0.003)	(0.004)
bm_t	0.252^{***}	0.236^{***}	0.239^{***}	0.234^{***}		0.231^{***}	
	(0.015)	(0.016)	(0.015)	(0.015)		(0.016)	
gp_t	0.141^{***}	0.153^{***}	0.169^{***}	0.152^{***}		0.153^{***}	
	(0.026)	(0.028)	(0.027)	(0.026)		(0.027)	
mve_t	-0.229^{***}	-0.209^{***}	-0.219^{***}	-0.216^{***}		-0.206^{***}	
	(0.007)	(0.007)	(0.007)	(0.007)		(0.007)	
sue_t	0.068^{***}	0.074^{***}	0.068^{***}	0.068^{***}		0.074^{***}	
	(0.002)	(0.003)	(0.003)	(0.002)		(0.003)	
$volatility_t$	-0.0112	-0.320^{***}	-0.055	-0.277^{***}		-0.323^{***}	
	(0.041)	(0.074)	(0.065)	(0.062)		(0.074)	
$volume_t$	0.0853^{***}	0.129^{***}	0.086^{***}	0.092^{***}		0.129^{***}	
	(0.006)	(0.008)	(0.007)	(0.006)		(0.007)	
$mom3m_t$	0.054^{**}	0.148^{***}	0.212^{***}	0.230^{***}		0.147^{***}	
	(0.020)	(0.032)	(0.028)	(0.026)		(0.032)	
$mom12m_t$	0.181^{***}	0.114^{***}	0.144^{***}	0.193^{***}		0.112^{***}	
	(0.008)	(0.013)	(0.012)	(0.011)		(0.013)	
dy_t	-0.003^{***}	-0.003^{***}	-0.003^{***}	-0.003^{***}		-0.003^{***}	
	(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	
Constant	1.361^{***}	1.127^{***}	1.261^{***}	1.275^{***}		1.102^{***}	
	(0.047)	(0.049)	(0.048)	(0.048)		(0.049)	
Company fixed effects	Yes	Yes	Yes	Yes		Yes	
Observations	4,339,506	4,339,506	4,339,506	4,339,506		4,339,506	
R^2	0.003	0.003	0.002	0.005		0.006	
Adjusted R^2	-0.001	-0.001	-0.001	0.001		0.003	

Note: Driscoll & Kraay (1998) robust standard errors are reported in parenthesis. *,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

high momentum. We conclude that all calendar effects significantly impact small, volatile stocks. According to our findings, the TOY effect is the most robust calendar effect, with the greatest impact on stock returns.

4.2.2 Calendar effects' evolution over time

Since our sample spans the entire period from 1986 to 2021, the calendar effects have likely evolved through time. To examine the evolution of calendar effects, we divide our sample by decade and repeat the analysis (Equation 4.10). We only report the coefficients of firm characteristics interacted with TOM, TOQ, and TOY, for brevity. Table 6 shows the regression results for the following decades: 1986-1990, 1991-2000, 2001-2010 and 2010-2021.

Table 6 reveals a dramatic evolution in the calendar effects from 1986 to 2021. The results show a significantly positive TOY effect from 1986 to 2000, which turns significantly negative between 2001 and 2010. Despite this, the TOY effect resurfaces between 2011 and 2021, indicating that the effect is still in force. In the past decade, the TOY effect has been strongest for small companies, those with volatile stock prices, and those with low momentum, consistent with the overall market pattern already observed in Section 4.2.1. From 1986 to 1990 and 2001 to 2010, the TOM effect is statistically significant and positive at the 1% level. In contrast, the TOM effect is slightly negative and significant at the 10% level from 2011 to 2021. Thus, the TOM effect influences return less and in the opposite direction than the TOY effect, suggesting that distinct factors drive these two effects. Moreover, our findings show a negative relationship between TOQ and stock returns in the late 1990s, a positive relationship between 2001 and 2010, and no significance between 2011 and 2021. This finding indicates that the effect is no longer evident in the US stock market.

Table 6: Company fixed effects regression results for all companies' stock returns over four-day return windows with firm characteristics for the following periods: 1986-1990, 1991-2000, 2001-2010, and 2010-2021. Each model reports the relationship between firm characteristics and their interaction with TOM, TOQ, and TOY concurrently. The table does not report firm characteristics coefficients, for brevity. The TOM, TOQ, and TOY are defined as the four-day windows over the last trading day d of the respective period: $d-1$, d, $d+1$, and $d+2$.

	Dependent variable: ret_t											
		1986-1990			1991-2000			2001-2010			2011-2021	
	TOM	TOQ	TOY	TOM	TOQ	TOY	TOM	TOQ	TOY	TOM	TOQ	TOY
$Calendar_t$	0.970***	−1.058***	3.758***	−0.098	0.075	3.806***	0.477***	1.031***	−0.768***	−0.156*	0.208	2.880***
	(0.105)	(0.164)	(0.322)	(0.088)	(0.139)	(0.267)	(0.082)	(0.135)	(0.246)	(0.086)	(0.153)	(0.289)
$Calendar_t*bm_t$	−0.204***	0.150*	0.031	0.152***	−0.136***	0.261***	0.013	−0.270***	0.816***	0.040	0.087	0.296*
	(0.054)	(0.082)	(0.161)	(0.044)	(0.068)	(0.141)	(0.040)	(0.064)	(0.113)	(0.038)	(0.063)	(0.121)
$Calendar_t*gp_t$	−0.054	0.095	−0.258	−0.030	−0.169**	0.194	−0.086*	−0.180**	−0.149	−0.052	0.096	−1.012***
	(0.074)	(0.112)	(0.221)	(0.056)	(0.088)	(0.162)	(0.052)	(0.086)	(0.149)	(0.058)	(0.099)	(0.164)
$Calendar_t*mve_t$	0.066***	0.041**	−0.326***	0.079***	−0.020	−0.552***	−0.007	−0.133***	−0.068***	−0.009	0.048***	−0.407***
	(0.011)	(0.017)	(0.032)	(0.010)	(0.015)	(0.028)	(0.009)	(0.014)	(0.025)	(0.008)	(0.014)	(0.026)
$Calendar_t*sue_t$	−0.064***	0.054**	−0.039	−0.034***	0.058***	−0.112***	−0.017*	−0.002	−0.019	−0.017*	−0.021	0.116***
	(0.014)	(0.021)	(0.038)	(0.010)	(0.016)	(0.029)	(0.010)	(0.016)	(0.028)	(0.009)	(0.014)	(0.026)
$Calendar_t*volatility_t$	−1.117***	3.040***	1.700**	2.073***	−4.751***	12.921***	1.168***	−5.953***	16.983***	0.354	0.035	6.608***
	(0.356)	(0.636)	(1.140)	(0.254)	(0.388)	(0.799)	(0.229)	(0.390)	(0.756)	(0.274)	(0.440)	(0.892)
$Calendar_t*volume_t$	−0.465***	0.367***	0.172*	−0.175***	−0.003	−0.242***	−0.002	2.215***	−0.647***	−0.318***	0.390***	0.003
	(0.034)	(0.053)	(0.095)	(0.026)	(0.042)	(0.080)	(0.029)	(0.048)	(0.087)	(0.035)	(0.058)	(0.117)
$Calendar_t*mom3m_t$	0.963***	−1.919***	−6.574***	−0.153***	1.601***	−6.087***	0.394***	−0.962***	−4.103***	0.435***	0.078	−4.834***
	(0.167)	(0.261)	(0.423)	(0.120)	(0.186)	(0.355)	(0.118)	(0.183)	(0.308)	(0.130)	(0.211)	(0.348)
$Calendar_t*mom12m_t$	0.160***	0.634***	−0.554***	0.454***	−0.223***	−1.659***	−0.171***	1.078***	−1.76***	−0.092**	0.597***	−1.020***
	(0.069)	(0.102)	(0.190)	(0.046)	(0.074)	(0.138)	(0.045)	(0.070)	(0.118)	(0.045)	(0.074)	(0.146)
$Calendar_t*dy_t$	0.001	−0.002	−0.008	0.003	0.003	−0.027**	−0.001	0.004	0.007	−0.004	0.003	−0.010
	(0.004)	(0.004)	(0.006)	(0.003)	(0.005)	(0.008)	(0.004)	(0.007)	(0.09)	(0.004)	(0.005)	(0.006)
Company fixed effects		Yes			Yes			Yes			Yes	
Firm characteristics		Yes			Yes			Yes			Yes	
Observations		544,532			1,427,615			1,272,572			1,094,811	
R^2		0.020			0.009			0.008			0.005	
Adjusted R^2		0.010			0.002			0.002			0.0001	

Note: Driscoll & Kraay (1998) robust standard errors are reported in parenthesis.
*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.2.3 Calendar effects and public attention

In this part, we explore the relationship between public attention received by a company and the stock return during turns of the calendar. Turns of the calendar are critical periods when information about firms and their financial performance is available. Consequently, we hypothesize that investors appear to be more uncertain throughout these periods and use Google to seek out information regarding companies. We present a variable, $ASVI$, which measures the public attention in a company based on abnormal levels of Google searches. We analyze the impact of Google searches on returns over the TOM, TOQ, and TOY windows by extending Equations 4.6, 4.7, 4.8, 4.9, and 4.10 with the $ASVI$ variable as an independent variable. Since Google search volume data is only accessible from 2004, we examine a subset of the data from 2004 to 2021.

Table 7 presents the results. Model 1 shows how firm characteristics and ASVI generally relate to stock return. Models 2 to 4 display results from separately regressing returns over the TOM, TOQ, and TOY windows on firm characteristics and ASVI. Lastly, Model 5 includes the TOM, TOQ, and TOY indicators simultaneously. All three calendar effects are significantly stronger for companies with low ASVI (Table 7). In addition, Model 1 shows no significant relationship between ASVI and stock return. The ASVI is significantly related to the TOM, TOQ, and TOY indicators (Model 5). In sum, the results indicate that attention, as measured by the ASVI, impacts return significantly over the TOM, TOQ, and TOY windows, but not generally.

Table 7: Company fixed effects regression results on return. Model 1 reports the relationship between return and both firm characteristics and ASVI. Models 2 to 4 report the relationship over the turn-of-the-month (TOM), turn-of-the-quarter (TOQ), and turn-of-the-year (TOY) separately. Model 5 includes the TOM, TOQ, and TOY concurrently. The TOM, TOQ, and TOY are defined as the four-day windows over the last trading day d of the respective period: $d-1$, d, $d+1$, and $d+2$. The sample period is from Jan 2004 to Dec 2021.

	Dependent variable: ret_t						
	Model (1)	Model (2)	Model (3)	Model (4)		Model (5)	
		TOM	TOQ	TOY	TOM	TOQ	TOY
$Calendar_t$		0.404***	0.638***	1.308***	0.221***	0.270**	0.909***
		(0.058)	(0.071)	(0.137)	(0.066)	(0.108)	(0.213)
$Calendar_t$*$ASVI$		−0.024	0.050***	−0.049	−0.053***	0.140***	−0.140***
		(0.014)	(0.021)	(0.039)	(0.016)	(0.027)	(0.046)
$Calendar_t$*bm_t		0.005	0.111***	0.623***	−0.041	−0.044	0.695***
		(0.020)	(0.031)	(0.058)	(0.031)	(0.049)	(0.093)
$Calendar_t$*gp_t		−0.070**	−0.270***	−0.805***	0.026	−0.099	−0.731***
		(0.032)	(0.053)	(0.094)	(0.043)	(0.061)	(0.126)
$Calendar_t$*mve_t		−0.047***	−0.070***	−0.235***	−0.028***	0.007	−0.225***
		(0.005)	(0.008)	(0.015)	(0.007)	(0.010)	(0.020)
$Calendar_t$* sue_t		−0.006	−0.003	0.049***	−0.005	−0.020*	0.071***
		(0.006)	(0.009)	(0.018)	(0.007)	(0.011)	(0.021)
$Calendar_t$*$volatility_t$		1.451***	1.101***	9.061***	1.499***	−2.258***	10.399***
		(0.119)	(0.182)	(0.352)	(0.217)	(0.338)	(0.687)
$Calendar_t$*$volume_t$		−0.0578***	0.077**	−0.111***	−0.019*	0.238***	−0.365***
		(0.010)	(0.033)	(0.073)	(0.025)	(0.040)	(0.035)
$Calendar_t$*$mom3m_t$		−0.882***	−3.110***	−5.825***	0.349***	−2.148***	−4.129***
		(0.062)	(0.120)	(0.170)	(0.096)	(0.165)	(0.246)
$Calendar_t$*$mom12m_t$		0.133***	0.678***	−0.376***	−0.158***	1.09***	−1.253***
		(0.030)	(0.036)	(0.073)	(0.035)	(0.041)	(0.103)
$Calendar_t$*dy_t		−0.001	0.003	0.005***	−0.003	0.005	0.0004
		(0.003)	(0.004)	(0.007)	(0.005)	(0.005)	(0.006)
$ASVI$	−0.001	0.007	−0.007	0.002		0.006	
	(0.007)	(0.008)	(0.007)	(0.007)		(0.008)	
bm_t	0.127***	0.125***	0.116***	0.104***		0.123***	
	(0.016)	(0.017)	(0.023)	(0.016)		(0.025)	
gp_t	−0.008	0.015	0.026	0.017		0.021	
	(0.034)	(0.036)	(0.046)	(0.034)		(0.048)	
mve_t	−0.373***	−0.357***	−0.362***	−0.364***		−0.353***	
	(0.009)	(0.009)	(0.009)	(0.011)		(0.013)	
sue_t	0.058***	0.060***	0.059***	0.057***		0.060***	
	(0.003)	(0.003)	(0.003)	(0.003)		(0.004)	
$volatility$	−0.036	−0.532***	−0.144	−0.262**		−0.519***	
	(0.063)	(0.075)	(0.066)	(0.063)		(0.111)	
$volume_t$	−0.032***	0.046***	−0.020*	0.034***		−0.046***	
	(0.011)	(0.014)	(0.012)	(0.011)		(0.012)	
$mom3m_t$	0.326***	0.623***	0.702***	0.514***		0.621***	
	(0.029)	(0.045)	(0.043)	(0.043)		(0.048)	
$mom12m_t$	0.195***	0.149***	0.110***	0.201***		0.147***	
	(0.016)	(0.019)	(0.017)	(0.016)		(0.019)	
dy_t	−0.004***	−0.004**	−0.004***	−0.004***		−0.004**	
	(0.001)	(0.002)	(0.001)	(0.001)		(0.002)	
$Constant$	2.493***	2.361***	2.332***	2.439***		2.339***	
	(0.101)	(0.102)	(0.101)	(0.099)		(0.101)	
Company fixed effects	Yes	Yes	Yes	Yes		Yes	
Observations	1,954,949	1,954,949	1,954,949	1,954,949		1,954,949	
R^2	0.002	0.002	0.003	0.004		0.005	
Adjusted R^2	-0.002	-0.002	-0.001	-0.0002		0.001	

Note: Driscoll & Kraay (1998) robust standard errors are reported in parenthesis. *,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.3 Robustness test: alternative return windows

In previous parts of this thesis, we analyzed cumulative returns over four-day windows, which we select in line with prior research. To assess the robustness of our findings, we now consider also shorter (four-day) and longer (six-day) window lengths. This not only provides robustness check for our results, but also provides insights into how long lasting these effects are.

We compare two-day, four-day, and six-day window lengths. Using Equations 4.11 and 4.12, we calculate the two-day and six-day cumulative stock return, respectively. Then, we re-estimate the model specified in Equation 4.5. Furthermore, we use the two-day, four-day, and six-day windows to study the relationship between firm characteristics and return over the TOM, TOQ, and TOY windows (Equation 4.10).

$$ret_t = 100 * [(1 + ret_d)(1 + ret_{d+1}) - 1] \tag{4.11}$$

$$ret_t = 100 * [(1+ret_{d-2})(1+ret_{d-1})(1+ret_d)(1+ret_{d+1})(1+ret_{d+2})(1+ret_{d+3}) - 1] \tag{4.12}$$

The results of the Pooled OLS regression with two-day, four-day, and six-day window returns as dependent variables are shown in Table 8.

Table 8: Pooled OLS regression results for all companies' stock returns over two-day, four-day, and six-day return windows. All models includes the TOM, TOQ, and TOY concurrently. The sample period is from Jan 1986 to Dec 2021.

	Dependent variable: ret_t		
	two-day window	four-day window	six-day window
TOM_t	0.256***	0.471***	0.671***
	(0.007)	(0.010)	(0.013)
TOQ_t	0.004	-0.265***	-0.505***
	(0.010)	(0.014)	(0.017)
TOY_t	0.749***	1.423***	1.717***
	(0.021)	(0.030)	(0.038)
Constant	0.042***	0.111***	0.110***
	(0.002)	(0.004)	(0.008)
Company fixed effects	No	No	No
Observations	8,202,108	4,339,506	2,685,568
R^2	0.001	0.002	0.003
Adjusted R^2	-0.001	-0.001	0.000

Note: Driscoll & Kraay (1998) robust standard errors are reported in parenthesis. *,**,*** denote statistical significance at 10%, 5%, and 1% levels, respectively.

The coefficients in Table 8 for two-day and six-day return windows demonstrate a similar trend as the coefficient for the four-day return window. Moreover, all three calendar effects increase in magnitude with the window length. This means that these anomalies last several days. In terms of trading, it indicates that investors may earn higher profits by holding stocks during a longer time window.

Table 9 presents the relationship between firm characteristics and return over the TOM, TOQ, and TOY with two-day, four-day, and six-day windows. The results show that the window length does not impact the relationship between firm characteristics and the calendar effects. Again, the pattern is similar to the one with four-day windows, and the coefficients increase in magnitude with increasing window length. In conclusion, the results of the robustness analysis confirm that our conclusions remain unaffected by the choice of the time window.

Table 9: Company fixed effects regression results for two-day, four-day, and six-day return over the TOM, TOQ, and TOY with firm characteristics. Each model reports the relationship between firm characteristics and their interaction with TOM, TOQ and TOY concurrently. The table does not report control variables coefficients, for brevity. The sample period is from Jan 1986 to Dec 2021.

	Dependent variable: ret_t								
	two-day window			four-day window			six-day window		
	TOM	TOQ	TOY	TOM	TOQ	TOY	TOM	TOQ	TOY
$Calendar_t$	0.438***	−0.191***	2.040***	0.555***	−0.115*	2.568***	0.458***	−0.066***	2.840***
	(0.031)	(0.053)	(0.108)	(0.046)	(0.074)	(0.142)	(0.081)	(0.089)	(0.171)
$Calendar_t{*}bm_t$	−0.051***	0.025	0.342***	0.012	−0.043	0.384***	0.157***	−0.137***	0.551***
	(0.016)	(0.026)	(0.050)	(0.022)	(0.034)	(0.066)	(0.030)	(0.042)	(0.081)
$Calendar_t{*}gp_t$	0.011	−0.118***	−0.197***	0.036	−0.198***	−0.136	0.090*	−0.253***	−0.102
	(0.021)	(0.035)	(0.067)	(0.031)	(0.049)	(0.089)	(0.042)	(0.060)	(0.110)
$Calendar_t{*}mve_t$	−0.043***	0.050***	−0.314***	−0.044***	0.043***	−0.409***	−0.031***	0.034***	−0.475***
	(0.003)	(0.005)	(0.011)	(0.005)	(0.007)	(0.015)	(0.006)	(0.009)	(0.018)
$Calendar_t{*}sue_t$	−0.010***	−0.001	−0.008	−0.023***	0.013	−0.020	−0.027***	−0.002	−0.052***
	(0.004)	(0.006)	(0.011)	(0.005)	(0.008)	(0.015)	(0.007)	(0.010)	(0.019)
$Calendar_t{*}volatility_t$	0.570***	−0.850***	5.321***	1.028***	−3.525***	12.029***	2.228***	−5.244***	14.837***
	(0.092)	(0.164)	(0.305)	(0.139)	(0.235)	(0.451)	(0.194)	(0.289)	(0.554)
$Calendar_t{*}volume_t$	−0.154***	0.079***	−0.035	−0.197***	0.206***	−0.278***	−0.271***	0.121***	−0.191***
	(0.011)	(0.019)	(0.035)	(0.016)	(0.024)	(0.047)	(0.022)	(0.031)	(0.072)
$Calendar_t{*}mom3m_t$	0.551***	−0.015	−3.738***	0.309***	−0.001	−5.456***	0.008	1.204***	−5.574***
	(0.045)	(0.075)	(0.133)	(0.067)	(0.105)	(0.174)	(0.092)	(0.127)	(0.218)
$Calendar_t{*}mom12m_t$	0.226***	0.098***	−0.964***	0.126***	0.475***	−1.278***	0.168***	0.542***	−1.310***
	(0.017)	(0.029)	(0.055)	(0.025)	(0.039)	(0.074)	(0.036)	(0.049)	(0.092)
$Calendar_t{*}dy_t$	0.001	0.001	−0.004	0.003	0.001	−0.008**	0.002	0.002	−0.017***
	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)
Company fixed effects		Yes			Yes			Yes	
Firm characteristics		Yes			Yes			Yes	
Observations		8,202,108			4,339,506			2,685,568	
R^2		0.003			0.006			0.009	
Adjusted R^2		0.001			0.002			0.003	

Note: Driscoll & Kraay (1998) robust standard errors are reported in parenthesis.
*,**,*** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5 Discussion

This chapter discusses explanations for the identified calendar effects and relates them to the existing literature. We have provided evidence that the turn-of-the-month (TOM), turn-of-the-quarter (TOQ), and turn-of-the-year (TOY) effects are present in the US stock market from 1986 to 2021. Moreover, the TOY effect is the most robust of the calendar effects. Therefore, we will discuss potential explanations for the TOY effect first, followed by the TOQ and TOM effects.

5.1 The turn-of-the-year effect

Despite its long-standing recognition, our results provide evidence that the TOY effect is still a robust market-wide phenomenon. Thus, our results confirm and extend existing literature (Brown & Marsh, 1983; Haugen & Jorion, 1996; Haug & Hirschey, 2006; Blocher et al., 2011). Based on the efficient market hypothesis, the TOY effect should have disappeared because an efficient market would correct a recognized anomaly (Fama, 1970). Consequently, the present TOY effect contradicts the efficient market hypothesis. Our results conclude that the TOY effect strongly impacts small companies with volatile prices, low dividend yield, low trading volume, and low momentum, lending credence to the literature arguing that the TOY effect is a small-cap phenomenon (Reinganum, 1983; Keim, 1983; Roll, 1983; Thaler, 1987; Asness et al., 2015).

Finance literature has long recognized tax-loss selling by institutional and individual investors as a possible explanation for the TOY effect (Brown & Marsh, 1983). Specifically, investors sell stocks at the end of the year to claim capital losses which tend to increase returns in January. The tax-loss selling hypothesis seems compatible with the positive TOY effect we observe. However, capital losses incurred by mutual funds in the last two months of a calendar year are carried over to the following year under the Tax Reform Act of 1986 (Auerbach & Slemrod, 1997). Accordingly, any anomaly associated with tax-loss selling by institutional investors should occur well before the end of the calendar year. Similar to Haug & Hirschey (2006), we find that the TOY effect has been remarkably consistent since 1986; the Tax Reform Act appears not to have affected it. This indicates that institutional investors selling their tax losses cannot explain the TOY effect. Important to note is that the wash-sale rule prohibits individual investors from selling at a loss and repurchasing the same investment within a 30-day window to claim a tax benefit (U.S. Securities and Exchange Commission, 2022). Still, the wash-sale rule does not contradict the idea that individual investors perform tax-loss selling; it only implies that the same investors do not immediately repurchase the losses. Suppose tax-induced sales before the end of the year result in stock price plunges. The low prices might attract additional investors, leading to a possible price spike in January. Another possible explanation for the positive and robust TOY effect is individual investors' liquidity and sentiment. Zhang & Jacobsen (2012) speculates that Christmas may affect investors' moods. According to the author, investors use year-end cash bonuses to purchase investments in January, resulting in increased trading activity. Hence, the positive TOY effect may be related to such a holiday spirit, causing stock market rallies over the TOY. In conclusion, tax-loss selling by individual investors and investor sentiment remain credible explanations for the TOY effect.

Institutional investors' behavior may nonetheless explain the TOY effect. Under the window dressing hypothesis, institutional investors conceal poor performance during yearly disclosures by selling small stocks showing losses at the end of the year (Haugen & Lakonishok, 1988; Haug & Hirschey, 2006). The performance hedging hypothesis implies that institutional investors sell risky equities regularly to avoid holding stocks that may negatively influence performance, then reinvest in small, risky firms following performance evaluations at the year-end (Lee et al., 1998). Both hypotheses are consistent with our results, which show that the TOY effect is more substantial for small, volatile, low-momentum stocks.

Furthermore, the results show a dramatic evolution in the TOY effect. Consistent with the findings of Asness et al. (2015), we note that the TOY effect faded significantly from 1986 to 2000, though it appears to have resurfaced more recently from 2011 to 2021. Also, our results contradict those of Swinkels & van Vliet (2012). The authors argue that the TOY effect is an example of the market generally rallying around the TOM. Contrary to this, we show that this cannot be accurate since the TOY effect is much stronger than the TOM effect, which indicates that distinct factors drive the two calendar effects. Our results partly complement those of Haugen & Jorion (1996). Similar to them, we show that the TOY effect persists decades after its discovery. However, the authors also report that the magnitude of the effect has not changed significantly, and there is no indication that it will disappear. In contrast, we show that the TOY effect varies in direction and magnitude over time.

5.2 The turn-of-the-quarter effect

The TOQ effect is the weakest of the documented calendar effects, possibly because its magnitude and direction change the most over time. The results show a strong negative correlation between the TOQ and stock returns until 1990. This result is consistent with the findings of Carhart et al. (2002), who suggests that funds engage in portfolio pumping. They provide evidence until 2000 indicating that funds artificially inflate portfolio performance by purchasing stocks in existing positions before quarter-ends, driving the price up, and then selling the stocks immediately after, thereby lowering the price. In contrast, the TOQ effect is no longer negative after 1990. Thus, our results are in line with those of Duong & Meschke (2020), who conclude that increased regulatory attention has reduced portfolio pumping by US mutual funds in the last decades. Furthermore, between 2001 and 2010, we observe a positive TOQ effect. Quarterly portfolio disclosures make the window-dressing hypothesis plausible for both the TOY and TOQ effects, which may explain the positive TOQ effect in this period.

5.3 The turn-of-the-month effect

The results show that the TOM effect has a positive and significant relationship with stock returns, in line with prior studies (Ariel, 1987; Lakonishok & Smidt, 1988; Ogden, 1990). According to the payday hypothesis, stock demand increases when the liquidity of individual investors rises. Individual investors receive salaries, dividends, and interest payments at the end of each month, which increases their liquidity at this time (Ogden, 1990). Consequently, the positive TOM effect is consistent with the payday hypothesis. In addition, our findings indicate that the TOM effect appears to be more robust for companies with positive momentum, providing additional support for behavioral explanations of the TOM effect. When their liquidity improves, it seems reasonable for individual investors to purchase stocks that have performed well.

5.4 Impact of public attention on calendar effects

Results show that stocks that have received low attention, measured by Google search volumes, are more susceptible to calendar effects. In accordance with Kim et al. (2019), we find that Google search volumes cannot explain stock returns during ordinary return windows. However, we find that the ASVI is significant over the TOM, TOQ, and TOY windows. In this regard, the ASVI appears to have greater explanatory power over the turns of the calendar. Preis et al. (2010) argue that Google searches during times with increased market activity offer unique insights into market participants' behavior, which matches our results. The fact that the TOM, TOQ, and TOY effects are stronger for companies with low Google search volumes is in line with previous research stating that high Google search volumes negatively impact returns (Bijl et al., 2016).

In light of the tax-loss selling hypothesis, it seems plausible for individual investors to sell stocks with little attention before the end of the year if such stocks result in capital losses. Furthermore, consistent with the negative and significant ASVI, institutional investors may sell stocks with low attention before disclosure dates to accommodate investor preferences. As a result, the window dressing hypothesis is further supported as an explanation for the TOY effect. Performance hedging remains also a plausible explanation because institutional investors may avoid holding stocks with low attention if they negatively impact performance.

It is beyond the scope of this thesis to investigate why the ASVI is only significant over the TOM, TOQ, and TOY, and not over ordinary trading day windows. However, we recommend further investigation regarding whether ASVI can explain stock returns over special calendar periods, but not in general. Also, it could be of interest to investigate whether ASVI is significant for other events, such as earnings announcements or financial news releases.

6 Trading Strategy

In this chapter, we test the economic significance of our results by implementing a trading strategy. Prior regression results indicate that the TOQ negatively correlates with stock returns. Therefore, it is unreasonable to employ the proposed trading strategy over the TOQ windows, and we will solely examine trading strategies for the TOY and TOM windows. First, we document whether the returns over the turns of the calendar are sufficiently large in magnitude for investors to gain a profit. We compare holding a portfolio exclusively during the TOY or TOM windows to holding it during windows undisturbed by calendar effects. Second, we develop a trading strategy to determine whether investors can increase their profits by trading the stocks predicted by our model to have the highest returns over the TOY and TOM windows. Our model uses firm characteristics to predict the stocks with the highest return.

6.1 Portfolio selection procedure

We separately evaluate the possibility of profiting from the TOY and TOM effects by employing the trading strategy for each effect. To avoid the TOQ effect interfering with the TOM effect in the trading strategy, we consider non-overlapping TOM. Therefore, the last windows of March, June, September, and December are excluded as a TOM. We only hold a portfolio over one four-day window at a time, implying that we buy at the close price on the day before the window, $d-2$, and sell at the close price on the last day of the window, $d+2$. We expect the market, on average, to exhibit abnormally high returns around the turns of the calendar. In this regard, we assume that shorting is not a reasonable component of our strategy. Furthermore, we only consider equally weighted portfolios. Because trading costs differ among investors, our model assumes they are zero. Hence, investors can compare the trading strategy's profitability to their own trading costs.

To see whether holding all stocks exclusively during the TOY windows yields a positive profit, we create the all-stocks TOY portfolio. Similarly, for the TOM windows, we create the all-stocks TOM portfolio. We compare these portfolios to holding all stocks during ordinary windows undisturbed by calendar effects, referred to as the all-stocks ordinary windows portfolios. To make the portfolios comparable, we calculate the rolling average return over ordinary windows using a moving window of either a year or a month, depending on the studied calendar effect.

In the next step, we employ a trading strategy with two-year rolling regressions to determine if investors can increase profits by trading only selected stocks. A complete overview of the trading strategy is presented in Table 10. We use all four-day windows from the previous two years to train the model, and then we predict the return over the TOY or TOM windows. We predict returns using panel regressions with fixed effects, including all firm characteristics and their interactions with the TOM, TOQ, and TOY indicators (Equation 4.10). We sort the stocks into five quintiles based on the predicted returns for the upcoming turn of the calendar window, resulting in five equally sized portfolios. The first portfolio consists of stocks with the 20% lowest predicted return by our model, followed by stocks with the 20% second-lowest predicted return, and so forth until the portfolio of stocks with the 20% highest predicted return. We simulate holding the five portfolios over every TOY or TOM window during the sample period. Explicitly, we buy all stocks in each portfolio at the close price on day $d-2$ and sell all stocks in each portfolio at the close price on day $d+2$. The portfolio prediction procedure is presented in Algorithm 1. We repeat Algorithm 1 for each of the TOY and TOM windows from 1988 to 2021 in two distinct trading strategies.

Table 10: Summary of all components in the trading strategy.

Component	Strategy
Training period	2-year rolling window.
Predict	Return over the four-day windows in TOY and non-overlapping TOM.
Model	Panel regression with fixed effects including firm characteristics and their interaction with the TOM, TOQ, and TOY indicators (Equation 4.10).
Portfolios	Five portfolios sorted based on the predicted return over a TOY, or TOM window: P1: Stocks with the 20% lowest predicted return. P2: Stocks with the 20% second-lowest predicted return. P3: Stocks with the 20% intermediate predicted return. P4: Stocks with the 20% second-highest predicted return. P5: Stocks with the 20% highest predicted return.
Buy	Buy at the close price on day $d-2$ before a TOY or TOM window.
Sell	Sell at the close price on day $d+2$ on the last day of a TOY or TOM window.
Shorting	No shorting.
Weighing	Portfolios are equally weighted.
Trading cost	No trading cost.

Algorithm 1: Portfolio prediction procedure

```
Input  : data, window
Result: [P1, P2, P3, P4, P5]
Function Portfolio prediction procedure(data,window):
    /* Train model and estimate return over the four-day window           */
    train = regression(data, start= window - 2 years, end = previous window) ;
    prediction = predict(train, window) ;
    /* Divide stocks into five portfolios based on predicted quintiles    */
    P1 = prediction(percentile rank <= 0.20) ;
    P2 = prediction(percentile rank > 0.20 & percentile rank <= 0.40) ;
    P3 = prediction(percentile rank > 0.40 & percentile rank <= 0.60) ;
    P4 = prediction(percentile rank > 0.60 & percentile rank <= 0.80) ;
    P5 = prediction(percentile rank > 0.80) ;
    /* hold all stocks in each portfolio over the four-day window         */
    for each portfolio in [P1, P2, P3, P4, P5] do
        portfolio = trade(portfolio, buy at close price d-2, sell at close price d+2) ;
    end for
    return [P1, P2, P3, P4, P5]
```

6.2 Trading performance

In the following analysis, we examine results from buying and selling stocks according to the trading strategy outlined in Table 10. Table 11 presents the average return for all portfolios. The trading strategy is conducted individually for the TOY and TOM windows.

Table 11: Average return for all portfolios during the period from 1988 to 2021.

Portfolio:	P1	P2	P3	P4	P5	All-stocks TOM	All-stocks TOY	All-stocks ordinary windows
Average return over each TOY	0.491%	0.735%	1.081%	1.906%	3.724%		1.588%	0.107%
Average return over each TOM	0.624%	0.640%	0.476%	0.428%	0.564%	0.546%		0.155%

Figure 4 illustrates the cumulative returns from trading the all-stocks TOY portfolio, the all-stocks ordinary windows portfolio, and five portfolios selected by the trading strategy. First, we note that the all-stocks TOY portfolio generates a substantially higher average return than the all-stocks ordinary windows portfolio. Specifically, the average return obtained by holding all stocks over only the four-day TOY window is 1.6% each year, as opposed to 0.11% for holding all stocks only over windows unaffected by calendar effects. This finding implies that investors may benefit from trading exclusively on the TOY window. Furthermore, the portfolio with the 20% stocks with the highest predicted return (P5) outperforms the all-stocks TOY portfolio significantly. In particular, P5 yields an impressive average return of 3.7% over the four-day TOY window each year, which is more than twice the return of the all-stocks TOY portfolio of 1.6% (Table 11).

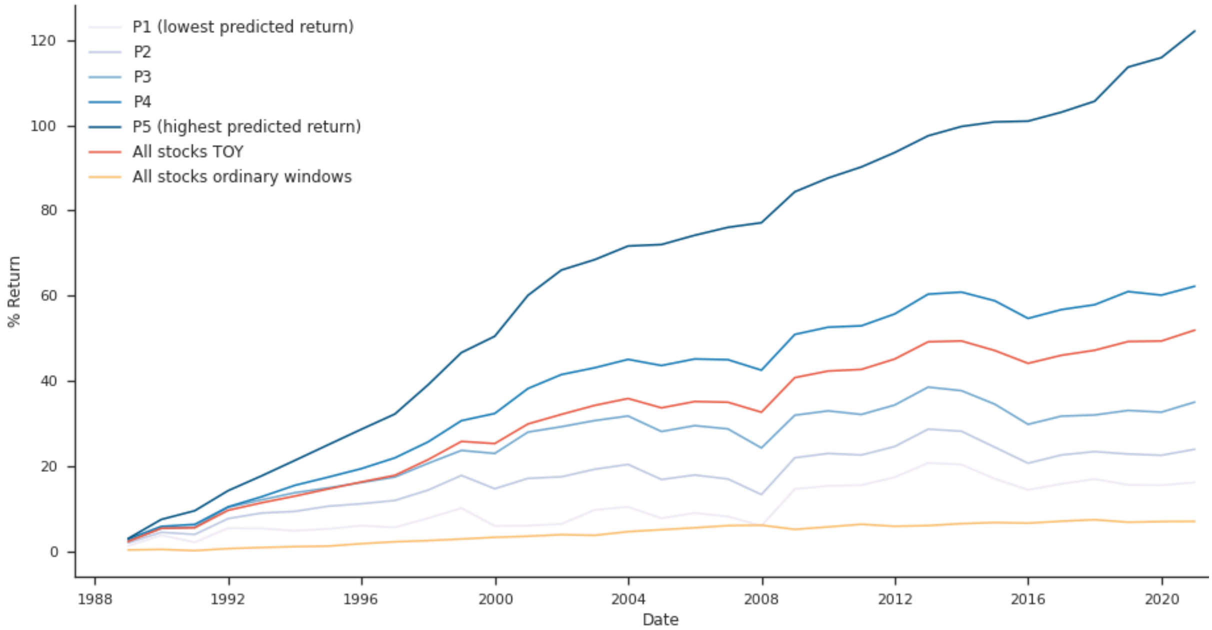


Figure 4: Trading performance of five portfolios predicted by the trading strategy, the all-stocks TOY portfolio and the all-stocks ordinary windows portfolio. Except for the final portfolio, all portfolios are held only over the TOY.

From Figure 5, we observe that the all-stocks TOM portfolio outperforms the all-stocks ordinary window portfolio by a substantial margin, indicating that investors may benefit from trading systematically over each TOM window. Specifically, the all-stocks TOM portfolio returns 0.55% on average over each four-day TOM window, while the all-stocks ordinary window portfolio returns 0.16%. However, the all-stocks TOM portfolio performs worse than the all-stocks TOY portfolio, indicating that trading over the TOM window induces greater risk for investors. Moreover, the five portfolios the trading strategy predicts to hold over the TOM windows perform rather inconsistently. The two portfolios that our model predicts will perform the worst actually perform the best (P1 and P2). From a practical perspective, the additional benefit of using the trading strategy to select specific companies to hold over the TOM windows is small. Additionally, trading costs can be relatively high, making the investment unsustainable.

Figure 5: Trading performance of five portfolios predicted by the trading strategy, the all-stocks TOM portfolio and the all-stocks ordinary windows portfolio. Except for the final portfolio, all portfolios are held only over the TOM.

In conclusion, we demonstrate how investors can exploit abnormally high returns over the four-day TOY and TOM windows. The all-stocks portfolios yield an average profit of 1.6% per TOY window and 0.55% per TOM window. Selecting specific companies following the trading strategy increases profits to an average of 3.7% over the TOY window. The findings suggest that firm characteristics can help predict which stocks will exhibit the greatest TOY effect and, thus, which stocks are the most profitable to trade over the four-day TOY window. The findings suggest that firm characteristics can help predict which stocks for which the TOY effect is the strongest and, therefore, which stocks will be most profitable to trade during the four-day TOY windows. Using the trading strategy to select companies does not result in higher profits over the TOM windows. For the practical significance of the findings, trading costs must be considered.

6.3 Trading costs

From a practical perspective, it is natural to ask whether calendar effects can be exploited for profit. This section discusses whether the profit from exploiting calendar anomalies is high enough to offset trading costs. Small firms' low trading volume and extensive bid-ask spread may prevent investors from making large profits. The profit in the proposed trading strategy might disappear once trading costs are considered. Nevertheless, this does not render calendar anomalies uninteresting, as some investors face minimal trading costs.

Due to limitations in our data, we rely on estimates from the existing literature to determine reasonable trading costs, including transaction fees and bid-ask spread. We assume a substantial capital investment and that institutional brokerage rates are available. Therefore, it is reasonable to assume that the transaction fee is almost negligible, though we set a conservative measure of 0.04%. Using data from Morgan Stanley, Robert et al. (2012) estimate execution cost and risk for NASDAQ and NYSE, resulting in a bid-ask spread of 0.20%. Additionally, Ball & Chordia (2001) report a quoted spread of approximately 0.20%. Following that, we consider total trading costs of 0.24%. We note that computing bid-ask spread directly from the data could give a more accurate measure of trading costs and profitability.

The proposed trading strategy yields an average return of 3.7% over the TOY window each year, whereas it provides small benefits over the TOM window each month. Using our conservative trading cost estimate of 0.24%, the trading strategy over the TOY window implies a significant profit for institutional investors. Because of the relatively high return, individual investors may also benefit from selecting stocks using the trading strategy. Additionally, the all-stocks TOY portfolio yields an average profit of 1.6%, while the all-stocks TOM portfolio yields 0.55%. Thus, the trading exclusively over the TOM window implies higher risk. From a practical perspective, we therefore recommend investors buy index futures or low-cost ETFs and hold them systematically over each four-day TOM window.

We stress that holding stocks for a longer period may increase profit, as indicated by the robustness test (Section 4.3). This chapter theoretically documents that the magnitude of calendar effects is sufficiently significant to be exploited. For practical purposes, we recommend that future research develop trading strategies with optimized time windows. We further recommend that the model be evaluated regarding both expected return and risk to determine whether the high profits are due to abnormal returns or risk factors by, for example employing a Fama-French or CAPM model.

7 Conclusion

Calendar anomalies, abnormal trends in stock returns related to the calendar, have captivated financial professionals and academics for decades. Some argue that calendar anomalies are invalid, while others see them as examples of market inefficiency and profit opportunities. In any case, explanations for calendar effects and whether they can be profitably exploited continue to be a subject of intense debate in the financial world. Therefore, we study whether the turn-of-the-month (TOM), turn-of-the-quarter (TOQ), and turn-of-the-year (TOY) effects are present in the US stock market from 1986 to 2021. In addition, we investigate how these calendar effects depend on firm characteristics and demonstrate a trading strategy that exploits calendar effects.

This thesis presents several valuable findings. The TOM, TOQ, and TOY effects are all present in the US stock market, with the TOY effect being the most substantial. Second, the TOY effect remains primarily confined to small stocks with volatile prices, strengthening the hypothesis that individual investors sell their losses for tax purposes before the year-end. Additionally, the TOY effect is stronger in stocks with with low momentum, which reinforces the idea that institutional investors sell stocks that negatively influence performance. These results suggest that the TOY effect can be explained by both the practice of window dressing and performance hedging by institutional investors. Third, we find that the calendar effects have evolved considerably over time. In recent decades, the TOM and TOY effects have resurfaced and continue to exist. The absence of a significant TOQ effect in the past decade suggests that increased disclosure regulations have reduced portfolio pumping in the US stock market. Fourth, companies with low Google search volumes are significantly more affected by all three effects.

To assess the economic significance of our findings, we develop a trading strategy. We show that the TOY and TOM effects can be profitably exploited. Every four-day TOY window yields an average profit of 1.66% when all stocks are held exclusively over the TOY windows. An average profit of 0.55% is generated every four-day TOM window, by exclusively holding all stocks over the TOM windows. Following the trading strategy, selecting particular companies based on firm characteristics increases profits to an average of 3.7% over every four-day TOY window. A 3.7% profit opportunity is significantly higher than realistic trading costs; consequently, our findings can be used to develop profitable trading strategies. The results are relevant for financial practitioners who seek to exploit calendar anomalies for hedging, scheduling trades, and portfolio management.

We note that some of the choices made can be revisited and further researched. The first possibility would be to investigate other calendar effects or other stock markets. Second, we propose investigating whether Google search volumes is only explanatory during certain periods of the calendar and other events, such as earnings announcements and financial news releases. Third, for practical purposes, we recommend that investors develop trading strategies with optimized time windows to fully exploit the TOY effect. We also recommend to test whether the high profits over the TOY window are due to abnormal returns or risk factors. We recommend that further research include these considerations.

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A | Appendix

Table 12: Number of firms considered at each year-end

Date	Number of firms
1986-12-31	2992
1987-12-31	2443
1988-12-30	3019
1989-12-29	2986
1990-12-31	2749
1991-12-31	2845
1992-12-31	3097
1993-12-31	3536
1994-12-30	3796
1995-12-29	4423
1996-12-31	4626
1997-12-31	4801
1998-12-31	4493
1999-12-31	4230
2000-12-29	3531
2001-12-31	3733
2002-12-31	3623
2003-12-31	3736
2004-12-31	3846
2005-12-30	3719
2006-12-29	3691
2007-12-31	3508
2008-12-31	2290
2009-12-31	3117
2010-12-31	3178
2011-12-30	2998
2012-12-31	2952
2013-12-31	2883
2014-12-31	2856
2015-12-31	2777
2016-12-30	2726
2017-12-29	2657
2018-12-31	2627
2019-12-31	2604
2020-12-31	2548
2021-12-31	2768

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