Norwegian School of Economics
Bergen, Autumn 2023

The Frequency Factor: Unraveling the Impact of Dividend Payout Frequency on Stock Valuation and Institutional Ownership

An Empirical Study of Dividend Policy Dynamics in the U.S. Market

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Master thesis, Economics and Business Administration

Major: Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgements

This master's thesis was written as part of our master's degrees in Financial Economics at the Norwegian School of Economics (NHH) and corresponds to one semester of full-time studies.

We would like to extend our sincere gratitude to our supervisor, Darya Yuferova, whose insightful guidance and expert knowledge were pivotal in shaping our research. Through engaging and constructive discussions she particularly enriched our understanding and helped ensure the robustness of our methods and assumptions. Lastly, we would like to thank the Norwegian School of Economics for providing an engaging and insightful master's program.

Norwegian School of Economics

Bergen, December 2023

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Abstract

By conducting event studies, we demonstrate a significant positive market reaction to increases in dividend payout frequency in the short-term $(-1+1)$ day and $(-3+3)$ days event windows. Conversely, decreases in payout frequency do not uniformly trigger a negative market reaction, suggesting a nuanced interpretation by investors.

Through logistic regression, and by adopting both a conventional two-way fixed effect setup and the difference-in-difference method proposed by Callaway and Sant'Anna (2021), we establish a novel and causal link between payout frequency and institutional holdings. Specifically, an increase in dividend frequency leads to an average 6.1 percentage points increase in institutional holdings, peaking at 9.9 percentage points three years post-change, equivalent to 2.3 times the median standard deviation in institutional holdings within a firm.

These insights may prove crucial for decision makers, and highlight dividend payout frequency as a strategic tool for shaping the share of institutional investors. Consequently, this thesis contributes to understanding dividend policy design and its influence on investor composition, opening new avenues for further exploration in corporate finance.

Keywords – Dividend Payout Frequency, U.S. Stock Market, Stock Valuation, Institutional Investors, Corporate Strategy, Event Study, Logistic Regression, Difference-in-Difference Estimation

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1 Introduction

Payout policy is one of the most important financial decisions a firm makes (Michaely & Moin, 2022). As of August 2023, about 80% of the firms listed on the S&P500 pay dividends (Krantz, 2023). Despite the extensive utilization, little unanimity exists within empirical research on dividend policy design (Baker & Wurgler, 2004b; Miller & Modigliani, 1961; Rozeff, 1982). To quote the Nobel prize-winning economist Fischer Black "The harder we look at the dividend picture, the more it seems like a puzzle, with pieces that just don't fit together" (Black, 1976). The payout frequency of dividends is an aspect of dividend policy research that remains largely overlooked. Our study fills the research gap by examining the impact of dividend payout frequency on stock valuation and the share of institutional holdings in U.S. firms.

The frequency at which dividend is distributed to the shareholders may seem like a trivial consideration compared to the yield or distribution channel. However, distributing dividends limits financial flexibility, incurs transaction costs, and requires great discipline and coordination by management (Rapp et al., 2014) – implications that become increasingly pronounced with higher payout frequencies. One could then wonder why firms would employ a more frequent payout schedule at all. Empirical studies suggest positive information signaling, mitigation of agency problems, and investor composition as potential explanations for the observed corporate behavior (Chen, 2022; Easterbrook, 1984; Miller & Rock, 1985). The shareholders also have their preferences for the distribution frequency and may assign a premium to stocks that align with their preferences (Barberis & Huang, 2001; Kahneman & Tversky, 1979; Lee, 2011). Hence, the frequency of dividend payouts should play an important role in dividend policy design.

This thesis investigates the nuanced role of dividend payout frequency in corporate finance. The most notable contribution prior to this thesis is Ferris et al. (2010), who find a significant positive effect of dividend frequency on stock valuation in an international study. We extend on previous research by narrowing our focus to the U.S. market as well as by employing a more sophisticated Fama-French Five Factor market model that better reflects the analyzed sample. Inspired by their findings, our first hypothesis posits a positive (negative) relationship between dividend payout frequency increases (decreases) and stock price. In particular, we conduct an event study to analyze the abnormal returns observed surrounding a decrease or increase in dividend payout frequency.

Our findings reveal significant positive abnormal returns for the $(-1+1)$ day and $(-3+3)$ days event windows following dividend payout frequency increases, supporting theories that emphasize the influence of dividend policies on stock valuation. These theories, including the bird-in-hand fallacy, prospect theory, and mental accounting, suggest investors prioritize regular income streams and value the reliability of dividend payouts over the uncertainty of potential capital gains. Additionally, there is abundant non-behavioral empirical literature that provides a rationale for the valuation implications of different payout frequencies (S. Bhattacharya, 1979; Easterbrook, 1984).

Conversely, and in contrast to Ferris et al. (2010), our analysis does not show significant negative abnormal returns following decreases in dividend payout frequency. Interestingly, the absence of a uniform negative market response to such decreases suggests that they are sometimes perceived as strategic financial management decisions rather than a direct indicator of a firm's deteriorating financial health.

The second hypothesis of our study investigates the relationship between dividend payout frequency and factors suspected to be crucial determinants. Specifically, we conduct multivariate logistic regression models to ascertain whether there is a significant positive correlation between institutional holdings and the frequency of dividend payouts. Extending on the model employed by Ferris et al. (2010), we introduce measures for institutional holdings, leverage ratio, and dividend yield. Additionally, our sample is confined to U.S. firms exclusively, thereby ensuring homogeneity in financial reporting, a consistent regulatory environment, as well as higher institutional and investor uniformity.

The results from the logistic regression model prove partially consistent with Ferries et al. (2010). In particular, we identify similar positive effects of size, earnings, and earnings volatility, while we find inverse results to their positive association of return on assets. Furthermore, the three novel variables – institutional holdings, dividend yield, and leverage – exhibit a significant positive effect on dividend payout frequency. The applications of the identified relationships include speculation of stock price projections as well as integration of dividend payout frequency considerations to manage the timing and magnitude of cash in-flows in portfolio construction.

The third hypothesis, and the most novel aspect of our research, considers the causality of dividend frequency changes on the share of institutional investors. More precisely, we test whether increasing (decreasing) the frequency of dividend payouts is followed by an increase (decrease) in the share of institutional investors. We adopt both the conventional two-way fixed effect setup and a robust difference-in-difference approach, utilizing the method proposed by Callaway and Sant'Anna (2021) to account for multiple time periods, varying treatment timing, and staggered adoption of treatment.

Our findings confirm a significant and positive causal relationship between increased dividend payout frequency and a higher share of institutional holdings. Specifically, we observe that, on average, an increase in payout frequency leads to a 6.1 percentage points increase in institutional holdings. This effect represents a relative increase in the sample mean institutional holdings of 8.5%, and an impact equivalent to 1 standard deviation change at the sample average, and 1.4 standard deviation change for the median. Further, as is possible to prove with the Callaway and Sant'Anna (2021) method, the effect amplifies over time, peaking at 9.9 percentage points three years post-treatment, which is 1.6 times the average standard deviation and 2.3 times the median standard deviation. These numbers underscore the considerable economic magnitude of our findings. Conversely, we find a negative, though non-significant, effect of dividend payout frequency decreases on institutional holdings. The magnitude of the estimate, at -6.6 percentage points, equals a 1.1 standard deviation change at the sample average, and a 1.5 standard deviation change for the median.

We highlight that the impact of increased or decreased institutional holdings varies across sectors. Sectors with lower baseline levels of institutional ownership, such as real estate, financials, and consumer staples, are likely to experience more significant relative changes in institutional holdings by changing dividend payout frequency. In contrast, for sectors like health care where institutional ownership is already high, the relative impact may be less marked.

For corporate managers, these insights carry profound implications and highlight the strategic value of dividend payout frequency as a strategic tool to shape its share of institutional ownership. Increasing dividend frequencies attract institutional investors, known for their positive influence on firm performance, financialization processes, and governance (Alexiou et al., 2018; McConnel & Servaes, 1990). Yet, this also means welcoming more rigorous oversight and potentially reduced managerial autonomy. Hence, any decision to alter dividend payout frequency should be carefully weighed against the tangible costs and benefits entailed by such a change, particularly in regard to the resultant shift in the composition of institutional holdings. For investors, particularly retail investors, the presence of institutional investors in a firm can serve as a quality signal, albeit with an inherent information asymmetry risk.

The thesis begins by reviewing relevant literature related to dividend frequency, then proceeds to outline the data gathering-process and methodology applied in the analysis. The main sections of our paper, Section 5 and 6, are devoted to empirical analysis of the proposed hypotheses and a detailed discussion of the resulting implications and applications in an economic and corporate strategy context. In the end, we summarize the main insights of our paper and present intriguing opportunities for further research.

2 Literature Review

This section provides a comprehensive summary of existing literature and research on relevant topics, addressing both general dividend theories and specific studies on dividend policy design. Initially, we present foundational theories about the role of dividends, considering how these theories might apply to the significance of payout frequency. Then, Section 2.2 covers modern research on investor behavior and how investors may derive different levels of utility from specific payout frequencies. Followingly, Section 2.3 presents how dividend payout frequency and investor behavior affect investor composition and the share of institutional holdings. The literature review concludes with Section 2.4, which discusses the approach and results of the, to date, only significant study of payout frequency – "The more, the Merrier" – and how our analysis contributes to and extends on their findings. The final subsection, Section 2.5, is dedicated to the three hypothesises our paper delves into.

2.1 Dividend Relevance Theories

The literature on dividend policies dates all the way back to the 1950s with John Lintner's observations of corporate behavior (Lintner, 1956). Most prominent is the irrelevance theorem by Modigliani and Miller (1961), suggesting that under certainty, no transaction costs, no tax, no information asymmetries, and perfect capital markets, the method in which the firm chooses to distribute its earnings is irrelevant to its value (Miller & Modigliani, 1961). That is, whether the firm chooses to retain its earnings and invest in projects rather than distributing dividends, does not affect the intrinsic value of the firm.

There are however opposing views due to the employed assumptions and its real-world applicability. Myron Gordon and John Lintner are among those who have proposed alternative theories, most notably their bird-in-hand fallacy (Gordon, 1962; Lintner, 1956). Their theory explains how investors may prefer the certainty and immediacy of dividend payments over the uncertainty of capital gains, and consequently assign a dividend premium. The empirical evidence for the fallacy is however differing (Black & Scholes, 1974; Karpavičius & Yu, 2018). We propose that a higher payout frequency ensures a larger fraction of the dividends become certain earlier, which investors prefer and may assign a higher valuation to.

Miller and Rock (1985) suggest that dividend payouts signal management's confidence in the firm's financial health and future prospects. That is, dividend increases are perceived as a positive signal, while dividend cuts are viewed negatively (S. Bhattacharya, 1979). The findings of Capstaff et al. (2004) support this rationale by identifying significant positive abnormal returns around the announcement of dividend changes for firms listed on the Oslo stock exchange. The effect was proven most pronounced for large and positive dividend announcements. Similarly, an increase in dividend frequency could be interpreted as a positive signal by investors as it implies manager confidence in their ability to distribute more consistently, perhaps from greater or more stable earnings. Additionally, the negative market response to dividend cuts, which leads to managerial hesitance in reducing dividends as noted by Brav et al. (2005) and Guttman (2010), could similarly influence decisions regarding the frequency of dividend payouts.

Easterbrook (1984) discusses how managers' incentives are not necessarily aligned with shareholders' best interest and how dividend payouts mitigate agency costs like managerial entrenchment and sub-optimal investing by reducing the free cash flow available. Jensen (1986) finds similar results and introduces the positive relationship between excess free cash flow and empire building. Further, a comprehensive literature review of 66 relevant papers on corporate governance and dividend policy identified that the majority of research finds a positive relationship between better corporate practices and higher dividend payouts (Das Mohapatra & Panda, 2022). That is, dividends serve as an additional monitoring mechanism imposed on managers to ensure shareholder interests are pursued, which may produce a positive market reaction. In a similar way, a higher dividend payout frequency may also be accompanied by lower agency costs as more frequent payouts require more disciplined cash management. Consequently, changing the frequency at which dividends are paid out may produce abnormal returns.

In summary, dividend relevance theories suggest that investors may value a company higher due to the attributes of its dividends, a concept that can also apply to the frequency of distribution. The assurance of regular returns, the perception of dividends as positive indicators of a company's financial health and future prospects, as well as mitigation of agency problems in management, collectively provide a rationale for why investors might favor more frequent dividend payouts. These factors contribute to the reasoning that a higher dividend frequency could be associated with a premium in market valuation.

2.2 Behavioural Finance Theories

Prospect theory by Kahneman and Tversky (1979) posits that investors act irrationally when faced with uncertainty and risk. In line with mental accounting by Thaler (1980), the resulting implications are that investors perceive utility over a concave utility function when assessing gains and a convex function over the domain of losses (Kahneman & Tversky, 1979). A concave utility function provides investors with higher utility from smaller, discrete payments rather than a single aggregate payment. That is, investors would derive higher utility from four payments of $1 than a single payment of $4. Consequently, to the extent that dividends are viewed as gains, prospect theory suggests that higher frequency of dividend payouts is associated with higher stock valuation

Barberis and Huang (2001) supplement the prospect theory by examining how recent stock performance affects the perceived risk of future returns. Their results show that at a cross-sectional level, stocks with low price-to-dividend ratios have higher average returns than stocks with high price-to-dividend ratios (Barberis & Huang, 2001). In line with the bird-in-hand fallacy, they explain that investors perceive future cash flows as less risky if they have already realized gains, leading them to apply a lower discount rate to future cash flows (Barberis & Huang, 2001). In this context, a more frequent dividend payout schedule would theoretically result in higher stock valuations, as a larger portion of the dividends is perceived as more certain. This phenomenon aligns with the concept of hyperbolic discounting, a behavioral bias indicating time-inconsistent discounting, wherein rewards occurring later are discounted more heavily, with the discount factor increasing the longer the delay (Green & Myerson, 2004).

Baker and Wurgler (2004b) suggest that dividend policies are catered to the prevailing market sentiment-driven demand for dividends. The dividend premium thus varies depending on the current market demand; dividends tend to disappear during booms and considerable market growth, while reappear during recessions (Baker & Wurgler, 2004a). Ferris et al. (2009) find that dividend policies in the period 1995-2004 are subject to catering and that the effect is stronger for common law countries like the U.S.. Hoberg and Prabhala (2008), however, find catering insignificant when accounting for risk during the reduction in dividend-paying firms between 1978 and 1999. Baker and Wurgler (2004b) attribute the dividend demand to investor sentiment, hence considering a sufficiently large data sample and time fixed-effects are essential to mitigate biased results when investigating the determinants for dividend payout frequency.

Jointly, prospect theory, mental accounting, and hyperbolic discounting suggest that the frequency at which dividends are paid influences investors' perception of the utility received, and may in turn materialize in stock valuation. The catering theory contributes further to investor behavior toward dividends by suggesting that the demand for dividends fluctuates, which firm's dividend policies adapt to. Consequently, we anticipate that an increase (decrease) in the frequency of dividend payouts result in a positive (negative) and abnormal response from the market. We investigate this hypothesis in detail using an event study approach in Section 5.1.

2.3 Investor Composition

Investor behavior and the composition of a company's shareholders are pivotal in understanding the dynamics of firm performance and governance. The clientele effect, as discussed by Chen et al. (2022), suggests that investors gravitate towards firms whose characteristics align with their financial goals and risk profiles. Notably, firms offering more aggressive dividend payout policies attract investor clienteles with a preference for regular cash flow rather than capital gains, thus shaping the firm's shareholder composition (Black & Scholes, 1974; Kalay, 1982). In the same way, Allen et al. (2000) find that the share of institutional investors increases after positive dividend announcements, in line with additional studies that prove institutional investor's preference for dividend-paying firms (Graham & Kumar, 2006; Grinstein & Michaely, 2005).

Keasey et al. (2002) present additional motivation for institutions like pension funds and insurance companies to demand higher dividends, beyond a constant stream of cash in-flows to meet their liabilities. In this regard, the paper points to the agency perspective, saying that institutions may demand higher or more frequent dividend payouts in order to force companies to distribute excess cash and obtain external financing, and therefore be subject to monitoring by the external market, such as creditors (Keasey et al., 2002).

However, both Keasey et al. (2002) and Han et al. (1999) suggest that investor appetite for dividends should be more pronounced in the UK, where they conducted their studies, than in the U.S. due to differences in investor and dividend taxation. In the U.S., companies are subject to a uniform corporate tax rate on their earnings, while shareholders incur personal income tax on the dividends they receive, calculated based on their individual income tax brackets. Consequently, dividends undergo a double layer of taxation: initially as corporate tax on the company's profits, and subsequently as income tax when these profits are distributed as dividends to shareholders. Still, as dividends are certain and investors are risk-averse, there are incentives for U.S. institutional investors to prefer dividends (Karpavičius & Yu, 2018).

In the domain of corporate governance and firm performance, the composition of a company's shareholders, particularly the proportion of institutional investors, garners significant interest due to its implications on financial outcomes. Alexiou et al. (2018) establish that institutional holdings positively influence the financialization of firms within the UK, underscoring that companies with substantial institutional investment tend to outperform their industry and size-matched counterparts. The study utilizes various indices to gauge financialization, assessing market depth, access to financial services, and the efficiency of financial institutions. Again, we note the difference in the investor environment, where UK investors have more controlling power in their portfolio companies than their U.S. counterparts. For instance, UK shareholders can initiate a change in the company memorandum and the articles of association if they reach a majority at a shareholders meeting. In the U.S., however, only the board can initiate any change to the corporate charter and the state of incorporation, whereas shareholders only have the power of veto (Alexiou et al., 2018).

The monitoring hypothesis posits that institutional ownership bolsters firm performance due to the investors' capacity for effective oversight and the meticulous research underpinning their investments. Empirical support for this hypothesis is extensive. McConnel and Servaes (1990) discern a positive correlation between institutional ownership and Tobin's Q, suggesting that firms with higher institutional investment are projected to yield future earnings surpassing their asset replacement costs. This relationship signals market confidence in the influence of institutional investors to steer firms toward superior performance.

Further supporting evidence is found in the U.S. manufacturing sector, where Chaganti and Damanpour (1991) link elevated institutional ownership with increased return on equity. Likewise, Bhattacharya and Graham (2009), in Finland, corroborate the beneficial impact of institutional ownership on firm performance, emphasizing the significance of institutional investors' voting power in positively influencing corporate decisions, with Tobin's Q once again serving as a key performance metric.

Based on this literature we posit that an increase in the frequency of dividend payouts correlates positively with the share of institutional holdings. Our methodology employs two difference-in-differences approaches in order to estimate the influence of dividend payout frequency on institutional ownership and ensure the robustness of our results. The discussion in Section 6 contextualizes our findings within the scope of the clientele effect and monitoring hypothesis, considering implications for firms, managers, and investors.

2.4 Prior Dividend Payout Frequency Research

The existing research on what dividend payout frequencies firms should employ is scarce. A notable study by Ferris and colleagues (2010) stands out as one of the few to delve into how the frequency of dividend payouts affects firm value. In their global sample from 1995 to 2007, they identify that changes in distribution frequency lead to significant abnormal stock returns and highlight how the legal regime of the country in which the firm operates is a crucial determinant for payout frequency (Ferris et al., 2010). Their research is based on the notion that investors derive higher utility from smaller and more frequent income streams as implied by prospect theory and mental accounting (Kahneman & Tversky, 1979; Thaler, 1980). However, the previously described literature such as the bird-in-hand fallacy, agency theory, and signaling theory, suggests that other factors might influence the outcomes as well. Our paper therefore investigates the significance of payout frequency in the U.S. market during 1980-2022 and employs alternative covariates to identify determinants. Additionally, our research introduces a novel angle to dividend studies by examining the causal relationship between dividend payout frequency and the share of institutional investors.

2.5 Hypotheses

Based on the contemporary empirical literature, there is a gap in regard to the frequency at which dividend is paid out. Still, dividends relevance theories such as the signaling effect (S. Bhattacharya, 1979; Capstaff et al., 2004; Miller & Rock, 1985), bird-in-hand fallacy (Gordon, 1962; Lintner, 1956), and agency costs (Das Mohapatra & Panda, 2022; Easterbrook, 1984; Jensen, 1986), give reason to expect benefits from employing a higher dividend frequency. Further, behavioral studies suggest that investors have a preference for receiving dividends at a more frequent schedule. Inspired by Ferris et al. (2010), we test the significance of abnormal returns around the date when firms announce a change in their distribution frequency. We, however, consider a larger sample period, have identified a larger number of events, and focus on the U.S. market. The first hypothesis is therefore:

Dividend payout frequency increases (decreases) have a significant positive (negative) effect on the stock price of U.S. firms surrounding frequency change events.

Following the results of the event study, we aim to identify the determinants of the observed distribution frequencies. We apply a similar approach as Ferris et al. (2010) by using logistic regression. However, we utilize a distinct set of covariates where the variable of particular interest is the share of institutional investors. Hence, we hypothesize that:

The share of institutional holdings has a significant and positive relationship to the frequency at which a firm distributes its dividends.

The identified relationship between dividend frequency and institutional ownership serves as the foundation for investigating a novel aspect: the causality of dividend frequency on the share of institutional investors. Employing difference-in-difference estimations, we aim to validate our final hypothesis:

An increase (decrease) in dividend payout frequency causes a significant increase (decrease) in the share of institutional holdings.

These hypotheses are examined sequentially, starting with the event study, followed by the analysis of dividend frequency determinants, and concluding with the difference-in-difference estimation on institutional ownership.

3 Data and Sample Construction

The financial and firm-specific data in this study is sourced from the Bloomberg Terminal. First, we extract dividend data from all firms listed on the NYSE and NASDAQ in the U.S. that have or have had a history of paying dividends to their shareholders. We deem a sample period of 1980 to 2023 to be sufficient in order to ensure that an adequate number of events is present in the data. For each firm, and each dividend payment that has been made in this period, we gather information such as declared date, ex-date, dividend amount, dividend type and the dividend frequency. We apply the declared date as the main date variable, as it reflects when the information of the dividend is released to the market.

In our data, dividend payout frequencies vary from monthly to irregular, where the latter signifies an absence of a consistent payout schedule. We identify changes in dividend payout frequency by tracking alterations in this variable, while also considering the duration between such changes. For example, if a firm initially disbursed quarterly dividends, ceased payouts for a period, and then resumed with annual dividends, this scenario is not classified as a relevant event for our study. From a market perspective, such a resumption is essentially a re-initiation of dividends after a period of absence, potentially triggering a market response that could skew our findings. In this regard, the maximum length between dividend frequency payouts is set to one year and three months, to allow for some variability in timing year on year. Further, we choose to focus on cash dividends, and exclude dividend types such as "spinoff", "split-off" and "poison pill rights", which were present in the original data.

We also compile key financial indicators for the pertinent companies, which encompass daily market statistics like share price, trading volume, and volatility, alongside financial ratios and metrics such as return on assets, dividend yield, and price-to-book ratio. Additionally, we consider fundamental financial data including revenues, earnings, free cash flow, and debt levels. To accommodate the non-daily nature of updates for some financial figures like earnings, we carry the latest available data forward until a new update occurs in our data. Furthermore, because Bloomberg retroactively aligns their historical earnings release data to the acquisition date rather than the public announcement date, we adjust our data to reflect the actual market announcement dates. This adjustment ensures our analysis accurately captures the market's response to new financial information.

To construct our market model, we source daily market data on the risk free rate, excess market return, and the four additional factors in the Fama-French Five Factor model from the Kenneth R. French library (Fama & French, 2015). After merging the dividend data with the market and financial data, we are left with a daily data-set containing 1,812 unique U.S. tickers.

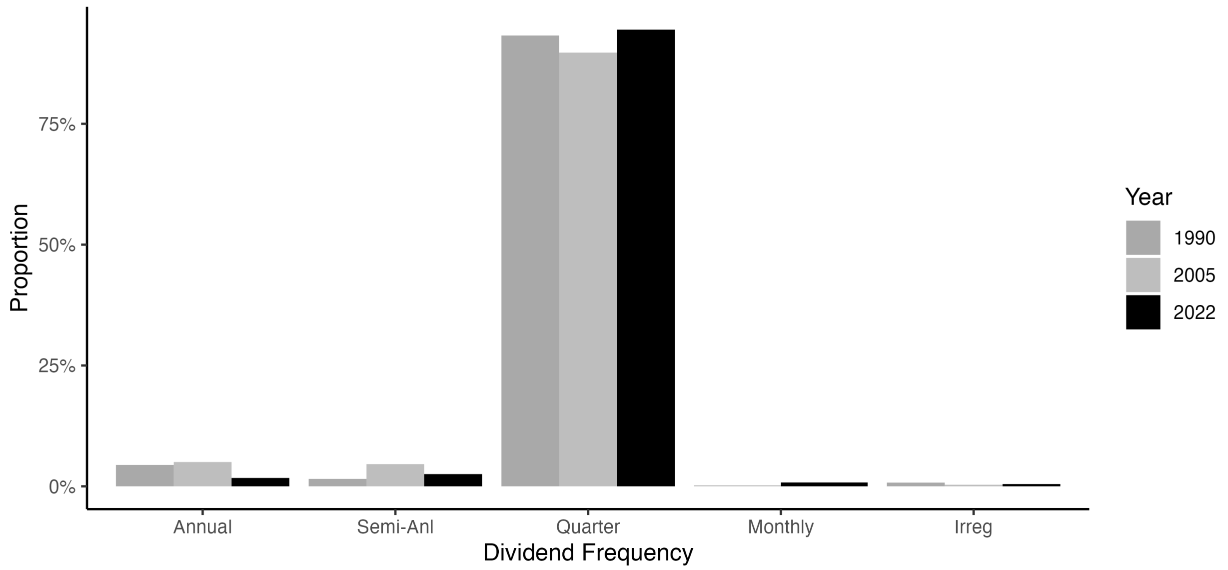
As we hypothesize an increase and decrease in dividend payout frequency to have a distinctly differing effect on the variables investigated in this paper, we separate the relevant event dates into two different data frames. Then, we utilize these tickers, and their respective event dates, to gather the relevant data for the estimation-, hold out- and event period. This leaves us with two unique data sets; one for dividend frequency increases and one for dividend frequency decreases,

Lastly, we Winsorize financial data with very large or unreasonable outliers. By Winsorizing, we strengthen the robustness of the data-set by capping the outliers at a certain level determined by the percentiles, rather than simply discarding them and potentially loose data points. For this purpose, we apply the 5th and 95th percentiles.

3.1 Distribution of Dividend Payout Frequency and Frequency Changes

In Figure 3.1 we present the percentage distribution of the dividend paying frequencies in our sample as of 1990, 2005, and 2022. First, we observe that the majority of U.S. listed firms pay dividends on a quarterly basis, and that the distribution holds relatively firm throughout our sample. Overall, the share of firms paying dividends on a quarterly basis has increased from 93.3% in 1990 to 94.5% in 2022, with a small dip in 2005 (89.7%). Second, we find that our sample distribution aligns well with the findings of Ferris et al. (2010), which found that 87% of their U.S. sample (1995-2007) paid dividends on a quarterly basis.

Figure 3.1: Distribution of Dividend Frequencies



The figure shows the distribution of dividend payout frequencies in the sample. The observed payout frequencies are Annual, Semi-annual, Quarterly, Monthly, and Irregular. Irregular considers the firms who do not follow an established payout schedule but distributes dividends with inconsistent intervals. Additionally, each frequency displays the adaptation in there distinct years, 1990, 2005, and 2022, to visualize development across different time periods.

In Table 3.1, we present the distribution of dividend frequency changes by sector. In our sample, financials, industrials, and consumer discretionary are the sectors with the most changes, both in terms of increases and decreases. Financials have had the largest share of dividend payout increases, while communication services and real estate have seen the largest share of dividend payout decreases.

In Table 3.2 we present the distribution of relevant events over time by 5-year intervals. The number of events increases noticeably from the start of our sample and until the 1995 – 1999 period. Afterwards, the number of events remain stable in the 60 – 100 events per five-year interval range. Since 1990, there has steadily been an overweight of number of dividend payout increases compared to decreases.

Table 3.1: Summary of Dividend Frequency Changes by Sector

Sector	Count	Increases	Decreases	% Increases	% Decreases
Communication Services	17	10	7	58.8%	41.2%
Consumer Discretionary	70	54	16	77.1%	22.9%
Consumer Staples	33	24	9	72.7%	27.3%
Energy	37	26	11	70.3%	29.7%
Financials	211	174	37	82.5%	17.5%
Health Care	28	18	10	64.3%	35.7%
Industrials	96	71	25	74.0%	26.0%
Information Technology	40	29	11	72.5%	27.5%
Materials	47	36	11	76.6%	23.4%
Real Estate	14	8	6	57.1%	42.9%
Utilities	12	9	3	75.0%	25.0%
Total	605	459	146	75.9%	24.1%

The table reports summary statistics for dividend payout frequency changes across the 11 sectors in the sample. The table includes the total number of identified changes and separate between cases of frequency increases and decreases. Further, the table presents the sector percentage share of dividend frequency increases and decreases. The sample period is 1980 to 2023.

Table 3.2: Summary of Dividend Frequency Changes by 5-Year Intervals

Year Group	Count	Increases	Decreases	% Increases	% Decreases
1980-1984	3	1	2	33.3%	66.7%
1985-1989	27	11	16	40.7%	59.3%
1990-1994	39	30	9	76.9%	23.1%
1995-1999	160	121	39	75.6%	24.4%
2000-2004	82	53	29	64.6%	35.4%
2005-2009	67	59	8	88.1%	11.9%
2010-2014	97	81	16	83.5%	16.5%
2015-2019	62	48	14	77.4%	22.6%
2020-2023	68	55	13	80.9%	19.1%
Total	605	459	146	75.9%	24.1%

The table reports summary statistics for dividend payout frequency changes across the sample period, grouped into years of five. The table includes the total number of identified changes and separate between cases of frequency increases and decreases. Further, the table presents the respective percentage share of total frequency changes assigned to each five-year period. The sample period is 1980 to 2023.

In total, 75.9% of our relevant events are dividend increases. This aligns with theories on dividend's signaling effect where managers are reluctant to reduce dividends in fear of a negative market reaction, while an increase in dividend payments often is followed by a positive market reaction (Brav et al., 2005).

In Table 3.3, we detail the summary statistics for firms that have increased their dividend payout frequency in comparison to those that have decreased it, based on financial data at the time of these changes. This comparison reveals noteworthy distinctions between these two groups of firms.

Significantly, firms that have increased their dividend payout frequency demonstrate a larger EBIT-to-interest payments ratio. This metric indicates that their operational results cover their current interest payments more times than those firms that have decreased their dividend frequency. This suggests that firms increasing their dividend frequency might be in a stronger financial position to sustain higher interest or more frequent dividend payouts.

Additionally, while not statistically significant within our sample, some trends are observable. Firms that have increased their dividend frequency tend to be larger in terms of market capitalization and possess a higher cash ratio, indicating a greater proportion of liquid assets relative to short-term liabilities. They also exhibit a higher price-to-book value, suggesting a greater market valuation relative to their book value. Conversely, these firms have a lower price-to-earnings ratio, which may imply that they are priced more conservatively in terms of their earnings. Dividend yield seem to, on average, be fairly similar across firms that increase or decrease their payout frequency.

Table 3.3: Summary Statistics with Comparable Measures for Frequency Changes

Characteristic	Increases	Decreases	P-value[1]
Log Market Capitalization			0.700
Mean	5.84	5.81	
Median	5.55	5.27	
Interest Coverage Ratio			0.018
Mean	60	57	
Median	9	5	
Dividend Yield			0.090
Mean	0.03	0.04	
Median	0.01	0.01	
Cash Ratio			0.300
Mean	1.33	1.00	
Median	0.56	0.48	
Price-to-Book			0.400
Mean	3.07	2.23	
Median	1.74	1.69	
Price-to-Earnings			0.120
Mean	28	42	
Median	15	17	
Count	459	146	

[1]Wilcoxon rank sum test

The table reports summary statistics for cases of dividend payout frequency increases and decreases, along with the estimated P-value for the difference. The firm characteristics included are Logarithm of Market Capitalization, Interest Coverage Ratio, Dividend Yield, Cash Ratio, Price-to-Book, and Price-to-Earnings. Mean and median values are provided for each characteristic.

3.2 Summary Statistics for Determinants of Dividend Payout Frequency

In Table 3.4, we present summary statistics for the determinants analyzed in Section 5.2, reflecting the sample as of 2022. This summary reveals notable differences between firms with a high dividend payout frequency (DPF = 1, indicating quarterly or more frequent distributions) and those with a lower frequency (DPF = 0, indicating less frequent than quarterly distributions).

Most importantly, there are significant differences in the average share of institutional holdings, with firms that distribute dividends more frequently having a higher proportion of institutional ownership. These firms also tend to be larger in terms of market capitalization, exhibit higher dividend yields, carry more debt relative to their market capitalization, and report higher earnings. We note, however, that the correlation between higher earnings and larger firm size might limit the comparability of this measure. Nevertheless, this variable is included to provide a comprehensive view of the sample and the variables investigated in Section 5.2.

Other metrics, such as return on assets, earnings volatility, and capital expenditure as a percentage of EBIT, show no significant differences between the two groups. The constructed variables for earnings volatility and capital reinvestment aim to capture the financial stability and investment priorities of the firms, respectively.

Table 3.4: Summary Statistics with Comparable Measures for DPF

Characteristic	Low DPF	High DPF	P-value[1]
Institutional Holdings			0.004
Mean	0.66	0.78	
Median	0.65	0.86	
Log Market Capitalization			0.001
Mean	6.98	7.86	
Median	6.90	7.83	
ROA			0.700
Mean	0.05	0.06	
Median	0.04	0.04	
Dividend Yield			0.001
Mean	0.021	0.027	
Median	0.014	0.022	
Debt-to-Market Capitalization			<0.001
Mean	0.020	0.42	
Median	0.010	0.18	
Relative Earnings Volatility			0.700
Mean	0.72	0.77	
Median	0.42	0.34	
CAPEX-to-EBIT			0.300
Mean	0.17	0.82	
Median	0.22	0.28	
Earnings			0.028
Mean	787	918	
Median	45	105	
Count	72	1,432	

[1]Wilcoxon rank sum test

The table reports summary statistics for firms who utilize a less than quarterly payout frequency (DPF=0) and those who utilize a quarterly or higher payout frequency (DPF=1). Variables included are Institutional holdings, Log Market Capitalization, Return on Assets, Dividend Yield, Debt-to-Market Capitalization, Relative Earnings Volatility, CAPEX-to-EBIT, and Earnings. All variables are present in the multivariate logistic regressions presented in Table 5.3.

3.3 Summary Statistics for Institutional Holdings

In Table 3.5 we present summary statistics for institutional holdings by sector for the sample period applied in the difference-in-difference analysis in Section 5.3. We find that the average share of institutional holdings for our sample is 71.9%, and that the average standard deviation for institutional holdings within individual tickers are 6.1%. Additionally, we establish notable differences between different sectors. The health care sector stands out with both the highest average institutional holdings at 80.0% and the lowest average standard deviation of 4.9%. This sector's defensive nature, characterized by steady demand irrespective of economic fluctuations, combined with intensive research and developments activities and its heavy regulatory environment, may necessitate sophisticated investor expertise, thus attracting substantial institutional investment.

Table 3.5: Summary of Institutional Holdings by Sector

Sector	Mean	Q25	Q75	Avg. SD	Median SD	Count
Communication Services	77.2%	60.5%	98.1%	6.4%	4.2%	411
Consumer Discretionary	79.1%	69.5%	100%	6.0%	4.1%	1,041
Consumer Staples	67.9%	47.6%	88.6%	6.1%	3.6%	509
Energy	75.2%	58.0%	96.4%	8.8%	6.5%	781
Financials	62.2%	39.2%	84.7%	6.4%	4.9%	3,606
Health Care	80.8%	75.1%	99.1%	4.9%	3.3%	513
Industrials	78.6%	71.4%	99.6%	5.2%	3.4%	2,097
Information Technology	73.3%	51.7%	98.7%	5.1%	3.6%	764
Materials	78.4%	71.1%	98.8%	5.5%	3.9%	839
Real Estate	54.8%	16.1%	93.6%	5.5%	2.8%	127
Utilities	76.5%	65.9%	89.6%	6.2%	4.5%	498
Total Sample	71.9%	53.6%	98.3%	6.1%	4.3%	11,186

This table presents summary statistics for institutional holdings across the 11 different sectors included in our sample. The reported statistics are the Mean, First Quartile, Third Quartile, Average and Median Standard Deviation of institutional holdings for firms within the respective sector, and number of observations. The values are reported on a yearly basis and matches the sample period applied in the analysis in Section 5.3 (2016-2022).

In contrast, the real estate sector, which tend to be more sensitive to economic cycles and interest rate fluctuations, exhibits the lowest level of institutional ownership (54.8%). Furthermore, the energy sector demonstrates the highest variability in institutional holdings, as indicated by the average standard deviation of 8.8%. This can likely be attributed to the sector's sensitivity to external factors such as oil and energy prices, leading to heightened volatility in its investor composition. Recent trends in institutional investors actively managing their portfolios with an emphasis on reducing indirect emissions and divesting from fossil fuels may also contribute to the higher variability in this sector's institutional holdings.

4 Methodology

4.1 Event Study

4.1.1 Model and Variable Selection

To evaluate whether investors have clear preferences for the frequency of dividend payouts, we conduct an event study with the identified dividend frequency increases and decreases as events. Event study is a widely employed and accepted statistical method to estimate the effect of dividend policy changes on firm value (Brown & Warner, 1985; Ferris et al., 2010). By estimating the abnormal returns during the event window, we are able to identify the effect of the event (a dividend frequency change) on a firm's stock price.

The event date is set to the announcement date of when the new distribution frequency is publicly revealed to the market, often via a press release. We further apply a 250-day estimation window, a 6-day holdout period, and test for three different event windows. A 250-day estimation window ensures that the estimation of the expected returns in the absence of the event are based on a sufficient number of observations, and enables us to estimate abnormal returns with accuracy. The outline of the event study is consistent with what Ferris et al. (2010) utilized in their analysis of global distribution frequencies.

To control for possible confounding events during the event window, we conduct multivariate panel regressions on three different event windows; $(-1, +1)$ day, $(-3, +3)$ days, and $(-5, +5)$ days, with the corresponding CAR as the dependent variable. Our main independent variable is the frequency change variable, constructed by calculating the change in yearly dividend payouts. That is, a firm converting from quarterly to annual dividend payouts would have decreased the number of payouts per year from four to one, an effective change in dividend payout frequency of three.

To ascertain which factors drive the abnormal returns, we incorporate controls for additional variables that might influence the CAR. Consequently, we isolate the effect of the change in dividend payout frequency on the abnormal returns, which is the variable of interest. Naturally, changes in financial measures such as debt per share, return on assets, and earning per share shape the market's perception of the stock during financial report releases. In addition, changes in dividend yields may significantly affect the market reaction as it directly affects the total return of a stock. Lastly, we incorporate a measure for the stock volatility to account for the possibility that the fluctuations are a result of the nature of the firm. Hence, we end up with three regressions, one for each event window, with CAR as the dependent variable, the frequency change variable as the main explanatory variable, and six control variables. The coefficient and significance level of the frequency change variable allow us to determine if a change in distribution frequency is significantly related to the observed abnormal returns.

4.1.2 Abnormal Return Estimation

We adopt a return-generating process (RGP) based on the Fama-French Five Factor Model (FF5) as our market proxy and basis for computing abnormal returns. The FF5 market model estimates the excess return ($R_{i,t}$) above the risk free rate ($R_{f,t}$) for company i at time t using the following equation:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{mkt}(R_{m,t} - R_{f,t}) + \beta_{SMB} SMB_t + \beta_{HML} HML_t \\ + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \epsilon_{i,t} \end{aligned}$$

The α is the intercept or abnormal returns not explained by the model. Then, the first factor, $(R_{m,t} - R_{f,t})$ captures the market risk premium, that is, the excess return of the broad market portfolio, in this case, the S&P500 index, over the risk-free rate. The second and third factor, SMB (Small Minus Big) and HML (High Minus Low) represent the size and value premiums, respectively. SMB measures the additional return investors expect from investing in companies with smaller market capitalization. HML quantifies the additional return from investing in stocks with high book-to-market values, often considered value stocks. The fourth and fifth factors, RMW (Robust Minus Weak) and CMA (Conservative Minus Aggressive), are the profitability and investment factors respectively. RMW captures the difference in returns between firms with robust and weak operating profitability. CMA measures the difference in returns between firms that invest conservatively and those that invest aggressively. Finally, $\epsilon_{i,t}$ represents the error term, capturing the idiosyncratic risk.

The estimated market returns by the FF5 model are then applied to the calculation of abnormal returns (AR) using the equation below. The $R_{i,t}$ denotes the actual daily return of a unit, while $E(R_{i,t}|X_t)$ represents the expected daily returns predicted by the return generating process. That is, the abnormal returns are the difference between the observed returns and the predicted returns absent of the event.

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|X_t)$$

After constructing the RGP and calculating the abnormal returns for the days surrounding the event, we are able to compute the CAR defined as abnormal return accumulated between day K, first day of the event window, and day L, last day of the event window.

$$CAR(K,L)_i = \sum_{t=K}^{L} AR_{i,t}$$

We index the date of abnormal returns to its relative position to a corresponding event, hence accommodating for events occurring at different times throughout the sample period. Then, as we have several events, we are able to compute an average abnormal return (AAR) for each relative day and the cumulative aggregate abnormal returns (CAAR) for the event window. AAR for the relative day, t, is calculated using the following equation, where N denotes the number of stocks.

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{i,t}$$

The CAAR is determined over a period from day t_1 to t_2, and is denoted as

$$CAAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AAR_t$$

We employ a t-test to determine the significance of the abnormal returns for all three event windows. Consistent with our hypothesis, we expect significant positive abnormal returns and CAAR for dividend frequency increases and negative for decreases. Further, we aim to prove that the change in dividend payout frequency significantly explains the observed abnormal returns for the event window.

4.2 Multivariate Logistic Analysis

4.2.1 Model and Variable Selection

In the second part of our analysis, we employ a multivariate logistic regression model to investigate the determinants of dividend payout frequency (DPF) among firms in the U.S.. Our binary dependent variable, DPF, equals 1 when the firm distributes dividends quarterly or more frequently, and 0 otherwise. Using a binary dependent variable allows us to predict how certain variables influence the propensity of a firm having a high dividend distribution frequency. The logistic model also provides intuitive results in terms of the size and direction of the effect.

Further, the consensus in empirical literature when identifying determinants of dividend policy is to utilize binary dependent variable regression; Fama and French (2001) employ logistic models for their identification of characteristics significant for dividend-paying firms; Ferris et al. (2010) also utilize logistic regression to identify global determinants of dividend payout frequency.

The independent variables selected for this analysis are grounded in both theoretical foundations and empirical precedents. Fama and French (2001) find that the size, return on investment, profitability, and debt-levels are firm characteristics that significantly affect the propensity of firms paying dividends at a higher frequency. We incorporate these results and anticipate that larger and more mature firms are better positioned to provide shareholders with frequent cash outflows. Firm size is measured by the firm's market capitalization.

Profitability, gauged through the return on assets, serves as an indicator of a firm's operational efficiency and capacity to generate returns on their assets. Following the results of Denis and Osobov (2008), we investigate the notion that firms with high returns on assets prefer retaining earnings rather than distributing them. More specifically, we test whether firms with higher return on assets distribute at a less frequent schedule to maintain greater control over when to invest and when to pay dividends.

Further, debt-to-market capitalization is a measure intended to account for the proportion of debt in a firm's capital structure. Leverage is included to examine its impact on dividend decisions, particularly in the context of financial constraints and agency costs as implied by Florackis et al. (2015).

The CAPEX-to-EBIT ratio measures the proportion of operational earnings directed towards capital expenditures, thereby indicating the percentage of EBIT reinvested in the company. As the residual earnings after reinvestment proxies excess earnings available for dividend distribution, we anticipate an inverse relationship between this ratio and the frequency of dividend payouts.

To account for differences in the ability to maintain certain dividend policies, we also include the standard deviation of earnings relative to its mean earnings. Signaling theory suggests that dividend cuts are met with negative market reactions, hence managers should be reluctant to commit to a payout schedule not aligned with the nature of their earnings (Kalay, 1980). Consequently, we expect firms with higher volatility in earnings to opt for less frequent dividend policies as it is easier to attain and maintain.

Dividend yield is included based on the theoretical intuition that firms with higher dividend yields prefer to do so through regular and smaller installments, and to account for investors' preferences for immediacy outlined by the bird-in-hand fallacy. We therefore expect that higher dividend yields are related to more frequent payouts.

In our study, the proportion of institutional investors is the pivotal variable. Allen et al. (2000) propose that institutional investors generally prefer companies that pay dividends, a concept that might extend to their preference for specific payout frequencies. Furthermore, certain types of institutional investors, such as pension funds and insurance companies, have cash outflow requirements that must be met, to which dividend payouts help fund their liabilities (Short et al., 2002). Another perspective considers the significant ownership stake and persistence of institutional investors in many companies, granting them considerable influence (Jory et al., 2017). Their influence might be used to sway managerial decisions towards preferred dividend payout frequencies, benefiting from the associated reduction in agency costs and the positive signals such payouts send to the market.

We incorporate fixed effects across entities (sectors) and time (year) to account for unobserved non-time-varying effects like sector norms or culture, mentioned as potential noise by Ferris et al. (2010), as well as time-varying effects like economic conditions or dividend catering (Baker & Wurgler, 2004b; Ferris et al., 2009). Considering fixed effects involves including a dummy variable for each sector and year. By including fixed effects we correct for potential unobserved heterogeneity in the sample, enabling us to estimate more precise coefficients and better understand the causal relationship between payout frequency and the parameters.

4.2.2 The Logistic Model

The logistic model predicts the probability of DPF equaling 1 using a logistic cumulative distribution function, unlike linear regression which expresses a numeric value. The logistic function is denoted in the below equation, where X denotes all the parameters included and x_i specifically variable i. A fundamental assumption of logistic regression is the linearity between the logit of the outcome and the independent variables. Essentially, log-odds of the outcome should exhibit a linear relationship to the predictors. Additionally, logistic regression assumes no multicollinearity, no endogeneity, homoscedasticity, no significant outliers, as well as a sufficiently large sample size to ensure validity.

$$Prob(y = 1|X) = G(a + \beta_1 x_1 + ... + \beta_2 x_i) = G(z) = \frac{e^z}{1 + e^z}$$

The parameters of the function are commonly estimated using maximum-likelihood estimation (MLE). MLE maximizes the likelihood function such that the observed data is the most probable given the assumed statistical model. This entails finding the value of the beta coefficients (β) that maximizes the $L(\beta)$. The first equation visualizes how the likelihood is estimated, with i refering to specific observations and where n denotes the number of observations. To account for minuscule values that the likelihood function may produce, it is common to estimate log-likelihood.

$$L(\beta) = \Pi_{i=1}^{n}[P(y_i = 1|X_i)]^{y_i} \cdot [1 - P(y_i = 1|X_i)]^{1-y_i}$$

$$ln(\beta) = \Pi_{i=1}^{n}[y_i \cdot ln(P(y_i = 1|X_i)) + (1 - y_i) \cdot ln(1 - P(y_i = 1|X_i))]$$

The estimated coefficients of the logistic model are expressed as log-odds, such that the effect on the dependent variable is interpreted as log-odds change for a unit change in the explanatory variable, keeping everything else constant. For easier and better contextual relevance, the marginal effects are reported in the analysis. The marginal effects can be understood as the change in percentage points in the propensity of being a high frequency distributor. Marginal effects amount to the product of the derivative of the logistic regression and the respective variable coefficient. The mathematical computation is shown below, where X denotes all parameters in the model and x_i variable i.

$$ME(x_i) = \beta_i \cdot [P(y = 1|X)] \cdot [1 - P(y_i = 1|X)]$$

Further, the logistic functional form is non-linear causing the marginal probabilities to be dependent on the x-value. To compare results across models one must either calculate the marginal effect at the mean (MEM) or the average marginal effect (AME). Given the skewed distribution of dividend payout frequencies toward quarterly, as depicted in Figure 3.1, we use AME to determine the marginal effects.

Lastly, in order to evaluate the economic magnitude of our marginal effects, we convert the intercept coefficient to reflect the baseline probability of a firm adopting a higher dividend payout frequency. This baseline probability is the likelihood of the event occurring when all explanatory variables are at their reference levels and can be denoted as

$$BaselineProbability = \frac{e^{\beta_0}}{1 + e^{\beta_0}}$$

4.3 Difference in Difference Analysis

4.3.1 Constructing a Control Group

The full sample comprises 1,812 tickers, which includes all U.S. stocks with a history of paying dividends. As presented in Table 3.1, we observe, for instance, that the financial sector accounts for a significant proportion of the identified events. Given that different sectors exhibit unique characteristics that may influence our dependent variable beyond the scope of factors we control for, it is imperative to construct a relevant control group. This is essential to mitigate biased results and uphold the parallel trends assumption, which posits that, in the absence of treatment, the difference between the treatment and control groups would remain constant over time.

In this analysis, we focus on recent events from 2016 to 2022 to ensure our results are timely and relevant. This period selection also allows us to maintain a balanced panel where each ticker is represented for each year, ensuring consistency and comparability in our sample. In order to construct a control group that satisfies the parallel trend assumption, we identify relevant controls by propensity score matching. In essence, we apply a logit model, explained in Section 4.2.2, to predict the probability of a firm being treated based on firm characteristics. Then, we select controls for each treated firm that have a similar predicted probability of being treated.

More specifically, the control group is matched based on factors deemed as key determinants of a firm's dividend payout frequency and attractiveness to institutional shareholders. These determinants include market capitalization, return on assets, the sector it operates in, dividend yield, and earnings level. Furthermore, we implement a matching ratio of 5:1, meaning that we find five control firms for each treated firm. We choose this ratio to ensure a control group that is sufficiently large while also being limited to firms most likely to satisfy the parallel trends assumption.

In determining the value of these controls, we use the sample means for each ticker, introducing a degree of look-ahead bias. This occurs as we utilize levels of the characteristic that may not be known before the sample period. However, we find that, for example, 20 firms that underwent a dividend payout increase during the 2016-2022 period lack data for 2015, indicating that these firms are relatively new to the stock market and may still be establishing their dividend strategies. Given the high value of keeping these observations in our analysis, and that the potential look-ahead bias is not a primary concern for our results and its interpretation, we choose to acknowledge and accept this limitation, bearing it in mind as we interpret the findings. Overall, as presented in Section 5.3.1, we successfully construct control groups that validate the parallel trends assumption.

4.3.2 Ordinary Two-way Fixed Effects Panel Regression

The conventional two-way fixed effects (TWFE) approach is widely known and applied in a difference-in-difference context. The approach builds on the two-group and two-period approach that estimates the coefficient of the interaction of a treatment dummy group ($TREAT$) and a post-treatment period dummy ($POST$) in the following regression

(Goodman-Bacon, 2021) :

$$Y_{it} = \gamma + \gamma_i TREAT_i + \gamma_t POST_t + \beta^{2x2} TREAT_i * POSTt + \epsilon_{it}$$

However, this $2x2$ setup often does not align with real-world applications where treatment occurs at different points in time (Goodman-Bacon, 2021). In such cases, we can estimate the effect on the dependent variable by being treated by:

$$Y_{it} = \alpha + \beta T_{it} + \gamma X_{it} + \lambda_t + \mu_i + \epsilon_{it}$$

Where Y_{it} is the outcome variable (in this case the institutional share of holdings) for unit i at time t. T_{it} is the treatment indicator that equals 1 if unit i is treated at time t and 0 otherwise. Then, β becomes the coefficient of interest, as it represents the average treatment effect on the treated. X_{it} represent the covariates for unit i at time t. λ is the time-fixed effect (in our case year) capturing common shocks affecting all units at time t, while μ is the entity fixed effect (ticker), capturing unobserved characteristics of unit i that are constant over time. Lastly, α is the intercept, γ is a vector of coefficients associated with the control variables, and ϵ is the error term for unit i at time t .

However, recent literature, particularly Goodman-Bacon (2021), has highlighted several limitations of the TWFE approach under varying treatment timing. Notably, the approach's comparison of mean outcomes across groups is not well-defined, and the interpretation of the treatment effect parameter is ambiguous. This ambiguity extends to our understanding of how alternative model specifications might influence these estimates.

Goodman-Bacon (2021) demonstrates that the TWFE difference-in-difference estimator is essentially a weighted average of all possible $2x2$ comparisons across different timing groups. The weights, based on both timing group sizes and the variance of the treatment indicator, disproportionately influence units treated in the middle of the panel. While stable treatment effects yield positive weights in this variance-weighted average, fluctuating treatment effects introduce negative weights, particularly when already-treated units serve as controls.

Furthermore, the paper discusses potential biases in the crucial "common trends" assumption and the complexities introduced by time-varying controls, which, while mitigating bias, also change the source of identification in the estimator.

These insights underscore the limitations of the TWFE difference-in-difference estimator in interpreting treatment effects, especially when treatment timing varies. This motivates our adoption of more nuanced and flexible estimators, such as those proposed by Callaway and Sant'Anna (2021). We apply both methods not only as a robustness check but also to compare and discuss differences or similarities in our results with those obtained using the conventional TWFE approach.

4.3.3 Difference-in-Difference With Multiple Time Periods

The difference-in-difference approach proposed by Brantly Callaway and Pedro Sant'Anna (2021) facilitates the assessment of average treatment effects in difference-in-difference analyses encompassing multiple time periods. Particularly pertinent to our study is its focus on staggered adoption, where units, once treated, continue as such in subsequent periods. This aspect aligns well with the nature of a dividend payout frequency change. Further, Callaway and Sant'Anna's method is advantageous for its capacity to estimate and interpret causal parameters, acknowledging potential treatment effect heterogeneity, and dynamic effects. According to the authors, this approach mitigates the interpretational challenges with conventional TWFE regressions discussed in Section 4.3.2, and thereby offers a significant methodological advantage for our purpose.

In particular, we consider aggregated treatment effect parameters with similarities to the average treatment effect for the treated subpopulation (ATT) in a two-period setup. More precisely, we utilize the average treatment effect for units that are members of a particular group, g, at a particular time, t, denoted by:

$$ATT(g,t) = E[T_t(g) - Y_t(0)|G = 1]$$

Where units are assigned to groups based on the time period they were first treated, and G_g is a binary variable that is equal to 1 if a unit is first treated in period g.

To assess the results' significance, the method applies simultaneous confidence bands for the group-time average treatment effects. These confidence bands cover the entire path of the group-time average treatment effects with fixed probability and take into account the dependency across different group-time average treatment effect estimators (Callaway & Sant'Anna, 2021). We adopt a 5% significance level for our analysis.

In addition to staggered adoption, the approach builds on several assumptions. We assume that each unit is randomly drawn from a large population of interest, meaning our sample is independent and identically distributed (iid). Thirdly, we assume limited treatment anticipation, meaning that it is not a priori known when and if a unit is going to be treated. Next, is the parallel trends assumption that, depending on covariates, the average outcomes for the group treated in a period, and for the 'never-treated' group, would have followed parallel paths in the absence of treatment (Callaway & Sant'Anna, 2021). This is particularly important in our application as differences in observed characteristics can potentially create non-parallel outcome dynamics between groups. In our setup, we introduce market capitalization, return on assets, dividend yield, earnings, price-to-book value, debt, cash ratio, and the sector in which a firm operates, as such conditional covariates. This can be denoted as:

$$\begin{aligned}\Delta Y_{it}(0) =& (\theta_t - \theta_{t-1}) + \beta_{1t}(\text{log\_market\_cap}_{it} - \text{log\_market\_cap}_{i,t-1}) \\ & + \beta_{2t}(\text{roa}_{it} - \text{roa}_{i,t-1}) + \beta_{3t}(\text{dividend\_yield}_{it} - \text{dividend\_yield}_{i,t-1}) \\ & + \beta_{4t}(\text{earnings}_{it} - \text{earnings}_{i,t-1}) + \beta_{5t}(\text{price\_to\_book}_{it} - \text{price\_to\_book}_{i,t-1}) \\ & + \beta_{6t}(\text{debt}_{it} - \text{debt}_{i,t-1}) + \beta_{7t}(\text{cash\_ratio}_{it} - \text{cash\_ratio}_{i,t-1}) \\ & + \sum_j \beta_{8jt}(\text{sector}_{ijt} - \text{sector}_{ij,t-1}) + \Delta\epsilon_{it}\end{aligned}$$

The change in potential outcomes for untreated units, $\Delta Y_{it}(0)$, is modeled as a function of the change in covariates, each interacting with their respective coefficients, adjusted for time effects and unobserved individual heterogeneity. This modeling captures the underlying trends that would have persisted in the absence of treatment, thereby allowing for an accurate assessment of the treatment's true impact.

Building upon this foundation, our analysis extends to evaluate how the magnitude and significance of treatment effects may vary depending on the duration of exposure and the specific timing of treatment across different groups. Such an evaluation is crucial for understanding not only the presence of a treatment effect of changes in dividend frequency on institutional holdings, but also its evolution and stability over time.

To aggregate the $ATT(g,t)$ values, highlighting treatment effect heterogeneity relative to the elapsed time since treatment (e), we use the formula:

$$\theta_e s(e) = \sum 1\{g + e < \tau\} P(G = g | G + e \leq \tau) ATT(g, g + e)$$

This formula captures the average effect of participating in treatment e periods post-adoption, considering all groups observed to have participated in the treatment for exactly e periods. This advanced aggregation method is a key strength of Callaway and Sant'Anna's approach, offering deeper insights into the impact of the timing of treatment (Callaway & Sant'Anna, 2021).

5 Analysis

This section constitutes the main analysis of our paper and answers to the hypotheses introduced in Section 2.5. Each subsection is dedicated to its individual hypothesis, and is presented in the outlined order. Initially, in Section 5.1, we conduct an event study to assess the significance of the estimated abnormal returns surrounding announcements of a dividend payout frequency change. Second, in Section 5.2, we investigate the determinants of dividend frequency using logistic regression. Lastly, Section 5.3 examines the reaction in institutional investor ownership following a change in dividend payout frequency. For each section, we provide a brief explanation of background, motivation, methodology applied, before the empirical results are presented. The subsequent discussion, Section 6, will contextualize these empirical results within the broader spectrum of dividend policy research and discuss its practical implications for financial decision makers.

5.1 The Market's Reaction to Changes in Dividend Payout Frequency

To test the significance of dividend payout frequency on stock valuation and answer our first hypothesis, we perform an event study on the market reaction following announcements of dividend payout frequency changes. To ensure that the event of interest, a change in payout frequency, is significantly related to the observed abnormal returns, we run regressions on the cumulated abnormal returns, controlling for covariates that may be alternative sources to the abnormal returns. In this way, we are able to investigate whether a change in dividend payout frequency has a significant relationship to the abnormal returns, even after controlling for such covariates. The abnormal returns surrounding the event date is presented in Table 5.1, while the regression results are laid out in Table 5.2. The results are consistent with our hypothesis that an increase in dividend payout frequency has a positive and significant effect on the stock price. However, we do not observe significant results for dividend payout frequency decreases.

5.1.1 Dividend Increases versus Combined Dividend and Payout Frequency Increases

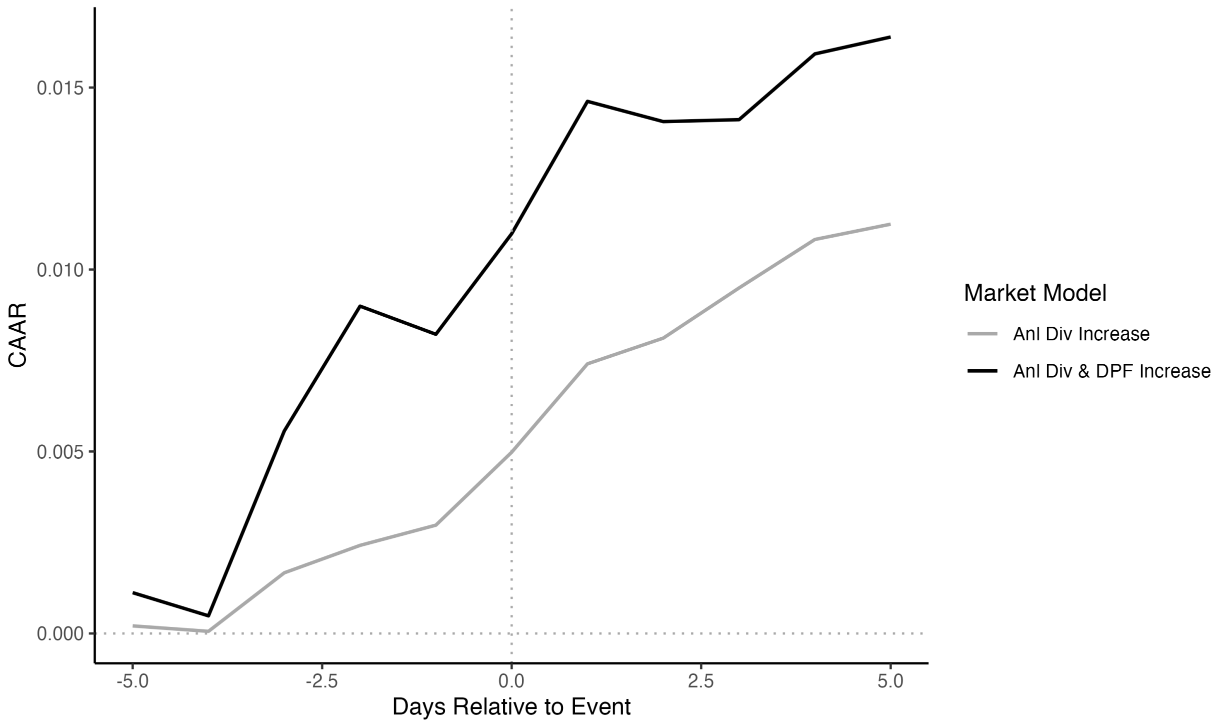
First, to provide evidence that an increase in dividend payout frequency confers additional value to investors beyond the well-documented positive effect of an increase in dividend amount alone, we conduct an initial event study separating between events where firms increase their dividends and where firms increase both dividends and dividend payout frequency. Recognizing that many firms tie their dividend payouts to variable metrics like earnings and free cash flow — for example adhering to a policy that specifies a percentage of free cash flow as dividends — we narrow our scope to those events where firms have maintained consistent annualized dividend payouts in the preceding year. This approach ensures that our identified dividend increase events are based on a stable dividend history, providing investors with definite expectations prior to any announced increment.

Consequently, we have two distinct event types: those characterized by a definitive increase in the annualized dividend amount and those accompanied by simultaneous increases in both the dividend amount and payout frequency. We identify 55 events that meet the criteria for both an increase in the dividend amount and payout frequency, in contrast to 255 events that solely satisfy the criteria for a dividend amount increase without a concurrent change in payout frequency.

The outcomes of this analysis are presented in Figure 5.1, and compellingly illustrates that the cumulative average abnormal returns (CAAR) are markedly higher for events entailing a rise in both the annualized dividend amount and payout frequency, as opposed to an increase in the annualized dividend amount alone.

This observation motivates our subsequent analysis of how dividend payout frequencies impact stock returns. Further, it affirms our hypothesis that a dividend payout frequency increase (decrease) has a significant positive (negative) effect on the stock price. Crucially, Figure 5.1 implies that this relationship holds even after accounting for concurrent changes in dividend yield, suggesting that the frequency of payouts is an independent driver of stock valuation.

Figure 5.1: Dividend Increase With and Without DPF Increase



The figure illustrates the CAAR for two event types: those characterized by a definitive increase in the annualized dividend amount and those accompanied by simultaneous increases in both the dividend amount and payout frequency. The CAAR is shown on the Y-axis and the days relative to the event date on the X-axis. The grey line depicts development of CAAR for events with only an increase in annualized dividend amount, while the black line represents the CAAR for simultaneous increases in annualized dividend amount and the payout frequency.

5.1.2 Abnormal Returns - Full Sample

Table 5.1 presents the average abnormal returns on and around the event day when companies announce a change in their dividend payout frequency. Specifically, for dividend frequency increases, we note a significant CAAR at the 1% level for the $(-1+1)$ event window, at the 5% level for the $(-3+3)$ event window, and an insignificant CAAR for the broader $(-5+5)$ window. These findings are partially consistent with those of Ferris et al. (2010), who report significant CAARs at the 1% level across all three event windows, albeit with notably higher absolute values than those observed in our study. For instance, whereas we record a 0.568% CAAR for the smallest event window $(-1+1)$, Ferris et al. (2010) document a 2.3% market reaction.

The instant positive response to a dividend payout frequency increase aligns with signaling theory, suggesting that the market views such changes as indicators of strong financial health or confidence by management (S. Bhattacharya, 1979; Capstaff et al., 2004; Miller & Rock, 1985). However, the diminishing significance as the event window widens may be attributed to various factors. Initially, investors might react favorably to the announcement, driven by the signal it sends, however, over time, they may shift their focus back to a broader analysis of firm fundamentals and prevailing market conditions. Furthermore, questions regarding the long-term viability of the new dividend policy might arise, potentially tempering the initial enthusiasm. Other contributing factors could include market overreactions or activities by short-term traders seeking to capitalize on the announcement. Such dynamics could drive up prices temporarily, with adjustments occurring as the market stabilizes post-announcement.

In the case of dividend frequency decreases, our analysis indicates a negative but non-significant CAAR for the $(-3+3)$ and $(-5+5)$ event windows, diverging from the significant negative reaction across all event windows reported by Ferris et al. (2010). Notably, we observe an increasingly negative CAAR as the event window widens, a trend inverse to that found by Ferris et al. (2010). Additionally, we find small but positive, average abnormal returns on the event day, possibly reflecting that the market view a dividend payout frequency decrease as a necessary and prudent measure from management in order to gain better control over their cash balance and finances.

The divergence in abnormal returns between our study and that of Ferris et al.(2010) can be attributed to several factors. Their international scope encompasses diverse markets with distinct characteristics compared to the U.S. market. Additionally, our larger sample size may contribute to the variance in results. Our sample of dividend frequency increases applied in the event study, 325, is notably larger than their sample of 45. Moreover, Ferris et al. (2010) base their abnormal return estimates on two CRSP indexes that are reflective of the U.S. market (Curry & Fried, 2021). The use of U.S. indexes as the market proxy in an international study raises natural concerns, as it is likely to overlook significant local market trends, potentially leading to abnormal returns greater than what would be warranted when benchmarked against a more appropriate home market index.

Further, the period of their sample (1995-2007) coincides with a period of relatively higher returns in U.S. markets compared to the rest of the world (as proved by investigating relevant indexes on the Bloomberg Terminal), adding to the risk of overestimated abnormal returns. The effect is also larger for firms in countries that constitute a small share of the sample. We can see this effect as the absolute value of abnormal returns from the value-weighted index are larger than for the equally-weighted index (Ferris et al., 2010). In contrast, our study's focus on U.S. stocks from 1980 to late 2023 and the adoption of the FF5 market model, which uses U.S. market excess returns and factors based on the U.S. market, is likely to yield more precise and robust results. Consequently, some of the reason behind the more modest abnormal returns found in our analysis is likely attributed to the enhanced accuracy of our market model and return-generating process (RGP).

Investigating the distribution of the abnormal returns across the event windows in more detail, we refer to Panel B and Panel C of Table 5.1. Starting with the reactions to the dividend payout frequency increases in Panel B, we observe significant abnormal returns at the 10% level on the event date as well as significance comfortably below the 1% level the day after. All other days have insignificant AARs. Further, we identify negative abnormal returns five days prior to the event date, as well as two days after and outward. The small, but negative abnormal returns in the days after the $(-1+1)$ event window are what makes the $(-3+3)$ window somewhat less significant, and the $(-5+5)$ window insignificant.

Considering the cases of dividend frequency decreases in Panel C, we observe a significant negative reaction at the 10% level two days after the announcement. We also note a large insignificant negative reaction 5 days after the event date. Interestingly, we observe positive reactions, though not significant, two days prior and on the day after the announcement. These positive reactions contribute to the insignificance of the CAAR for all event window sizes. A potential rationale for the non-significant reactions may be that the market had already incorporated negative news and adjusted expectations accordingly. Hence, a reduction in distribution frequency might be viewed as a prudent management decision to regulate cash holdings in favor of operational performance.

Table 5.1: FF5 Market Model

Panel A: CAAR's and significance

	FF5 Market Model	
CAAR	Increases	Decreases
Days −1, +1	0.586%***	0.099%
Days −3, +3	0.624%**	-0.121%
Days −5, +5	0.573%	-0.410%
Note:		*p<0.1; **p<0.05; ***p<0.01

Panel B: Dividend Payout Frequency Increases

t	AAR	AAR T-value	CAAR	CAAR T-value	Count
-5	-0.119%	-0.912	-0.119%	-1.027	325
-4	0.162%	1.241	0.043%	0.262	325
-3	0.084%	0.642	0.127%	0.632	325
-2	0.080%	0.615	0.207%	0.894	325
-1	-0.045%	-0.344	0.162%	0.626	325
0	0.210%	1.612	0.372%	1.313	325
1	0.421%	3.228	0.793%	2.590	325
2	-0.042%	-0.326	0.750%	2.293	325
3	-0.083%	-0.637	0.667%	1.923	325
4	-0.071%	-0.543	0.597%	1.631	325
5	-0.024%	-0.181	0.573%	1.493	325

Panel C: Dividend Payout Frequency Decreases

t	AAR	AAR T-value	CAAR	CAAR T-value	Count
-5	0.217%	0.647	0.217%	0.700	58
-4	-0.083%	-0.246	0.135%	0.307	58
-3	-0.054%	-0.160	0.081%	0.150	58
-2	0.354%	1.054	0.434%	0.701	58
-1	-0.070%	-0.208	0.365%	0.526	58
0	-0.124%	-0.369	0.241%	0.317	58
1	0.293%	0.872	0.533%	0.650	58
2	-0.543%	-1.618	-0.010%	-0.011	58
3	0.024%	0.071	0.014%	0.015	58
4	-0.088%	-0.263	-0.074%	-0.076	58
5	-0.336%	-1.001	-0.410%	-0.399	58

Note: This table presents the average abnormal returns (AAR), estimated using Fama & French 5-factor model, as well as the respective cumulative average abnormal returns (CAAR). Panel A reports the CAAR across the three different event windows and differentiates between frequency increases and decreases. Panel B and C displays the distribution of AAR over the 11 days surrounding an event. Panel B shows the market's reaction for frequency increases, while Panel C considers frequency decreases. For both of these panels, the AAR, CAAR, their corresponding t-values, as well as number of observations are presented respective to each event day. The analysis includes 325 observations for frequency increases and 58 for decreases from a total sample of 605 events. Specifically, some firms lack comprehensive data across the event and estimation windows, while we find instances of firms making several frequency changes within the time-span of a single estimation window. These events are omitted due to concerns of data completeness and to prevent noise in our estimations.

5.1.3 Multivariate Analysis

To confirm the relationship between the changes in dividend frequency and the observed abnormal returns, we implement a multivariate OLS regression analysis. By using the CAR from the three distinct event windows as the dependent variables and regressing these on factors that potentially can influence abnormal returns, we are able to isolate the impact attributable to an increase or decrease in dividend payout frequency.

The regression outcomes, as presented in Table 5.2, prove that an increase (decrease) in dividend payout frequency has a significant and positive (negative) effect on the CAR across all examined event windows. Consistent with the results from Table 5.1, the magnitude of the frequency change coefficient diminishes as we expand the event window. This pattern, again, suggests that the immediate effect of dividend frequency changes is pronounced, but that the influence becomes smaller as the event window increases.

Additionally, our regression analysis reveals that variables such as dividend yield, return on assets, volatility of returns, and earnings per share play significant roles in explaining the CARs. Consistent with existing literature, we find that an increase in dividend yield typically is followed by a favorable market response. This correlation underscores the importance of controlling for dividend yield, particularly as announcements regarding dividend amounts may coincide with frequency changes.

However, the influence of dividend yield on CAR exhibits a diminishing pattern; it maintains significance at the 5% level within the $(-3+3)$ event window but loses significance in the extended $(-5+5)$ window. This trend suggests that the market more rapidly incorporates changes in dividend yield compared to changes in dividend payout frequency.

Furthermore, earnings per share is another covariate that is crucial to control for, as dividend announcements often occur in proximity to earnings releases. A positive association between earnings per share and abnormal returns is to be expected as positive earnings announcements and surprises often lead to a positive reaction in stock prices.

Table 5.2: Abnormal Returns Around Announcement of Change in Dividend Payout Frequency

	Dependent variable:		
		CAR	
	CAR (-1, +1)	CAR (-3, +3)	CAR (-5, +5)
Frequency Change	0.014***	0.005***	0.006***
	(0.004)	(0.0003)	(0.0003)
Dividend Yield	1.414***	0.088**	−0.020
	(0.180)	(0.041)	(0.037)
Log Market Capitalization	0.005	−0.001	−0.005***
	(0.003)	(0.002)	(0.002)
ROA	−0.886***	−0.365***	−0.422***
	(0.074)	(0.023)	(0.022)
Debt-per-Share	0.001	0.0001*	0.001***
	(0.001)	(0.0001)	(0.0001)
Return volatility	−0.098***	−0.015**	−0.021***
	(0.016)	(0.007)	(0.007)
Earnings-per-Share	0.045***	0.003***	0.005***
	(0.005)	(0.001)	(0.001)
Observations	491	1,571	2,463
Sector Fixed Effects	Yes	Yes	Yes
R^2	0.478	0.273	0.281
Adjusted R^2	0.228	0.175	0.222
F Statistic	43.362***	74.154***	127.062***
	(df = 7; 331)	(df = 7; 1384)	(df = 7; 2276)
Note:			*p<0.1; **p<0.05; ***p<0.01

This table presents the output of OLS regression across three event windows: 3-day, 7-day, and 11-day. The model estimates the relationship between the dependent variable Cumulative Abnormal Return (CAR) and the independent variables: Frequency Change, Dividend Yield, Log Market Capitalization, Return on Assets, Debt-per-Share, Return Volatility, and Earnings-per-Share. The independent variables are based on daily data sourced from Bloomberg. The dataset encompasses 325 instances of dividend frequency increases and 58 decreases, spanning from 1980 to October 2023. The table reports the estimated regression coefficients, with standard errors shown in parentheses below each coefficient. The significance of these coefficients is determined using T-values. Sector fixed effects are incorporated into all models. Additionally, the table provides the R^2, Adjusted R^2, and F Statistic for each model to evaluate their respective fits.

Stock volatility exhibits a negative correlation with abnormal returns, which is consistent with Ferris et al. (2010). This relationship can be understood through the lens of market sentiment and risk perception. High stock volatility often signals greater risk and uncertainty about a company's future prospects. When firms with volatile stocks announce changes in dividend frequency, this might increase investor concerns about the firm's stability and earnings potential. Consequently, the market might react more cautiously, leading to lower or negative abnormal returns as investors reassess the risk-return profile in light of the new dividend policy. This is particularly relevant for dividend frequency increases, which can be viewed as a commitment to higher future payouts that might not be sustainable for volatile firms.

In contrast to Ferris et al. (2010), we find a negative relationship between return on assets and the abnormal returns surrounding a dividend payout frequency increase or decrease. This can be rationalized from a market expectations perspective. Typically, a high return on assets indicates efficient use of assets to generate earnings. Then, if a firm announces changes in dividend frequency that are interpreted as a strategic move that does not align with the operational efficiency reflected in the return on assets, the change may warrant a negative market reaction. Investors may perceive such changes as a management strategy to either please shareholders despite operational challenges or to redistribute excess cash in ways that might not optimally benefit long-term growth and asset utilization. Thus, a higher return on assets does not necessarily translate into positive abnormal returns following dividend frequency changes, as the market views the implications of these changes in light of a company's operational efficiency.

We also observe that debt-per-share and market capitalization only become significant in the model encompassing the broadest ($-5+5$) event window. The key takeaway, however, is the consistent significance of changes in dividend payout frequency in explaining abnormal returns across all three event windows, thereby validating our initial hypothesis.

Overall, our results are consistent with the general trend identified by Ferris et al. (2010), albeit with a less pronounced effect size. Another notable parallel is the similarity in the adjusted R-squared values between our models and those reported by Ferris et al. (2010), suggesting a comparable level of explanatory power despite the variations in specific outcomes.

5.2 Determinants of Dividend Payout Frequency

Section 2.2 describes how behavioral financial theories imply that investors receive higher utility from a more frequent stream of payments, as well as how the rationale of economic theories like signaling and agency costs can be extended to explain the consequences of different distribution frequencies. However, there are other firm-specific factors that affect the choice of dividend payout frequency. To ascertain which characteristics significantly explain the firms' observed payout frequency, we perform multivariate logistic regression.

The binary dependent variable, DPF, takes the value of 1 if a firm pays dividends quarterly or more frequently and 0 otherwise. Hence, the marginal effects express how the propensity of being a high-frequency distributor is affected by the covariates. The explanatory variables included are the logarithmic value of a firm's market capitalization, return on assets, dividend yield, debt as a share of market capitalization, relative earnings volatility, CAPEX as a share of EBIT, earnings, and percentage share of institutional investors. In the output, we report the corresponding average marginal effects to facilitate a meaningful interpretation. To further supplement the economic intuition of the suggested relationships, we provide a comparison to baseline probability in Section 5.2.2.

We present five different model specifications with a varying number of explanatory variables. All models account for possible unobserved effects like sector-specific culture, economic conditions, and dividend catering by including fixed effects for sector and year.

5.2.1 Regression Output

Table 5.3 reports the marginal effects for the five different regression models. In Model 5 we observe that five variables are significant at the 1% confidence level: logarithmic value of market capitalization, return on assets, dividend yield, debt as a share of market capitalization, and share of institutional investors. Furthermore, earnings and the relative volatility of earnings appear significant at the 5% level, while CAPEX as a share of EBIT has an insignificant negative effect on the dividend frequency. The return on assets and volatility of earnings appear to have a negative relationship to the frequency of distribution, whereas all the other significant variables suggest a positive association across all model specifications. The interpretation then becomes that a greater market capitalization, dividend yield, leverage ratio, earnings, and share of institutional investors, increase the propensity of a firm distributing dividends quarterly or more frequently. Conversely, higher return on assets and volatility of earnings reduce the propensity of distributing at a high frequency.

We measure the Akaike Information Criterion (AIC) as a mean for relative model quality and to serve as selection criteria. AIC estimates how well the model is at explaining the observed data while accounting for overfitting, specifically, it measures the relative amount of information lost by the respective model. The AIC is however not absolute in nature but rather relative to other models, hence a lower value indicates less information loss and a higher quality model relative to the other models. We observe that Model 5 is the estimated best model with the lowest AIC-value.

To confirm our model selection, we include the McFadden R^2 to measure the improvement in log-likelihood by the respective model relative to a null model with no predictors. A higher McFadden score indicates a better predictive power and again Model 5 is favored with a McFadden R^2 value of 0.109. The discussion of variable effects in Section 5.2.2 therefore refers exclusively to model 5.

Our results are partially consistent with those of Ferris et al. (2010). In particular, the directional effects of our variables are equal except for the return on assets. In contrast to their significant positive relationship, our analysis suggests a significant negative effect on the propensity of paying dividends on a quarterly or more frequent basis. Our negative relationship could however be rationalized, as firms with high returns on their investments are likely to be better off reinvesting excess cash into the business for growth rather than distributing out the excess cash through dividend payouts.

However, without providing any measure for goodness of fit or quality of their models, comparing the overall explanatory power is futile. Moreover, due to the nature of logistic regression, we are also unable to directly compare the effect of each variable, as Ferris et al. (2010) do not provide the marginal effects for their covariates. However, we provide a comparison based on directional effects in Section 5.2.2.

Table 5.3: Determinants of Dividend Payout Frequency (Logistic Model)

	Dependent variable:				
	DPF				
	(1)	(2)	(3)	(4)	(5)
Institutional Holdings	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Market Capitalization		0.006***	0.007***	0.008***	0.006***
		(0.001)	(0.001)	(0.001)	(0.001)
ROA			−0.001***	−0.001***	−0.001***
			(0.000)	(0.000)	(0.000)
Dividend Yield				0.007***	0.007***
				(0.001)	(0.001)
Debt-to-Market Capitalization					0.016***
					(0.004)
Relative Earnings Volatility					−0.00003**
					(0.000)
CAPEX-to-EBIT					−0.0001
					(0.000)
Earnings					0.0001**
					(0.0001)
Constant	−0.045	−0.018	−0.518**	−0.850***	−0.997***
	(0.204)	(0.215)	(0.237)	(0.240)	(0.290)
Observations	16,427	16,400	15,853	15,709	10,568
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes
McFadden R^2	0.075	0.079	0.076	0.082	0.109
Akaike Inf. Crit.	7,189.911	7,137.674	6,677.797	6,314.672	4,015.855

Note: *p<0.1; **p<0.05; ***p<0.01

The table reports average marginal effects of the multivariate logistic regressions with binary dependent variable dividend payout frequency (DPF). The explanatory variables include are Percentage share of institutional holdings, Logarithm of Market Capitalization, Return On Assets, Dividend Yield, Debt-to-Market Capitalization, Relative Standard deviation of Earnings, CAPEX-to-EBIT, and Earnings. All data is gathered from the Bloomberg Terminal. Relative Earnings Volatility is calculated as the standard deviation of earnings over the mean of earnings, Debt-to-Market-Capitalization as the debt share of market capitalization, and CAPEX-to-EBIT as the CAPEX share of EBIT. Sample period is 1980-2022 and considers annual values. The decrease in observations from model 1-5 is due to instances of missing data in covariates.

5.2.2 Effect of Variables

In our analysis, we examine the marginal effects of various variables with respect to the baseline probability of a firm adopting a higher dividend payout frequency. The baseline probability is the likelihood of the event occurring when all variables are at their reference levels, which entails converting the intercept coefficient of -0.997 to a probability value using the equation detailed in Section 4.2.2. The baseline probability amounts to about 27% and represents the propensity of a firm paying dividends quarterly or more frequently.

We first observe that market capitalization has a positive marginal effect of 0.6 percentage points, suggesting larger firms are more inclined to distribute dividends more often. This effect is, in relative terms, large compared to the marginal effect of earnings amount, a mere 0.01 percentage points. These results indicate equal directional effects as those of Ferris et al. (2010). Comparing these marginal effects to the baseline propensity, we get a relative change in the propensity of 2.2% and 0.04% for a unit change in size and earnings, respectively. Both earnings and market capitalization, before converted to a logarithmic value, are stated in millions. For example, an increase in earnings of 10 million dollars would entail an increase in the propensity of being a firm paying quarterly or more frequently of 0.1 percentage points. This exemplifies that a substantial elevation in profits is necessary for it to significantly influence the probability of more frequent dividend payouts.

We further identify a negative relationship between the frequency of dividend payouts and return on assets and the volatility of earnings. The marginal effect of return on assets amounts to -0.1 percentage points, while earnings volatility is a smaller marginal effect of -0.003 percentage points. Notably, the direction of the return on assets' effect contradicts Ferris et al. (2010) who identify a positive effect.

We also notice an insignificant effect for CAPEX-to-EBIT in contrast to a similar measure by Ferris et al. (2010). Their measure dividend-to-earnings reflects the fraction of earnings allocated to dividend distribution, whereas CAPEX-to-EBIT measures the amount reinvested. Hence, the opposite directional effect we observe is consistent with their findings. Intuitively, the more of obtained earnings reinvested in the business, the less is available for payouts, hence a negative sign is economically sensible.

The largest marginal effects are observed for dividend yield and debt amount, at 0.7 percentage points and 1.6 percentage points respectively. These variables are not included by Ferris et al. (2010) or any other literature to our knowledge. The introduction of these relationships is supported by agency cost theory as higher dividend payouts and higher leverage reduce the potential of managerial agency problems with excess cash (Easterbrook, 1984; Jensen, 1986). Additionally, signaling theory provides the rationale that higher yield or leverage may signal to the market that the managers have confidence in future prospects in terms of meeting these payout requirements (Miller & Rock, 1985). In the case of leverage, an argument may also be made for managers issuing debt to cover short-term fluctuations in earnings to ensure stable dividend payouts, as dividend cuts incur considerable negative market reactions (Brav et al., 2005; Guttman et al., 2010).

Again, to asses the economic magnitude, we view the marginal effects in relation to the baseline probability of 27%. For instance, a 1% increase in the annual dividend yield and the respective 0.7 percentage points increase in propensity, translates to a 2.6% relative change in propensity. A unit change in the debt-to-market capitalization is however unrealistic, as one unit increase corresponds to issuing debt equal to the firm's market capitalization. The median debt-to-market capitalization ratio for the sample amounts to 0.18, which makes it more relevant to asses a 0.1 units increase and the accompanying 0.59% relative increase in the propensity of being a frequent distributor.

The key finding that guides our subsequent analysis is the significant positive relationship between frequent dividend payouts and the share of institutional investors. A marginal effect of 0.1 percentage points suggests that a larger institutional shareholder base increases the propensity of the firm utilizing a more frequent payout schedule. However, the causal relationship remains ambiguous, particularly whether higher institutional ownership promotes more frequent payouts or if frequent dividend payouts attract investors (Alexiou et al., 2018). This notion serves as a foundation for the analysis in Section 5.3, where we specifically examine the reaction of institutional investors after announcements of changes in payout frequency. The relative change in propensity proves considerably small at 0.37% and is subject to further analysis in Section 5.3.

Lastly, Table A.1 presented in the appendix shows the marginal effects of the 11 different sectors identified in our sample. We observe that all sectors are significantly and positively related to the dividend frequency variable, except the real estate sector, which appears negative and insignificant. We note that the sectors with the largest marginal effects are utilities, financials, and consumer discretionary at 5.9, 5.4, and 5.0 percentage points, respectively.

5.3 Dividend Payout Frequency and Institutional Holdings

In this section, we present our results in relation to our hypothesis that institutional investors with required cash flows, such as pension funds, insurance companies, and endowment funds, prefer a constant stream of dividend payments. To investigate, we employ a difference-in-differences approach allowing for multiple time periods and variation in the timing of treatment. We define 'treated' firms as those that have either increased or decreased their dividend frequency, aiming to discern the impact of such changes on institutional investment behavior. In order to isolate the effects of frequency increases and decreases, we keep the related results separate.

As laid out in Section 4.3.2 and 4.3.3, we adopt both the conventional two-way fixed effects (TWFE) difference-in-difference estimator and more flexible estimators, as proposed by (Callaway & Sant'Anna, 2021). By applying the latter, we avoid the interpretational issues of TWFE regressions as discussed in more detail in Section 4.3.2 and 4.3.3. Adopting both approaches allows us to both test the robustness of our results, as well as to contribute to the discussion on how and if results are significantly affected by the choice of method. We start by presenting the results obtained by the conventional two-way fixed effects approach. Followingly, we present the corresponding results from the Callaway and Sant'Anna (2021) proposed method and discuss the coefficients, as well as their statistical and economic significance. In this analysis, we focus on recent events from 2016 to 2022 to ensure our results are timely and relevant.

5.3.1 Presentation of Relevant Control Group

As laid out in Section 4.3.1, we adopt a propensity score approach to construct a control group of relevant firms that, based on firm characteristics, have the same probability of being treated as our treated firms. These characteristics are market capitalization, return on assets, the sector it operates in, dividend yield, and earnings. By matching on a ratio of 5:1, we obtain a control group that is sufficiently large, while also ensuring a control group that is comprised of the most likely firms to satisfy the parallel trends assumption.

In Table 5.4 and Table 5.5 we compare the sector distribution and summary statistics for the treated and untreated sample for dividend payout frequency increases and decreases, respectively. In line with the overview of the event sample presented in Table 3.1, companies in the financial sector account for a large part of our dividend payout frequency increases in Table 5.4, Panel A, making up 36.1% of the sample. Followingly, industrials (18.0%) and consumer staples (13.1%) are the second and third most represented sectors. Looking at the corresponding control group, this distribution is closely aligned as financials, industrials, and consumer staples constitutes 32.1%, 16.7%, and 13.2% of the control sample, respectively.

Looking at the summary statistics (Table 5.4, Panel B) we find no significant differences in the market capitalization, dividend yield, return on assets, or earnings. The only exception is the price-to-book value, which is significant at a 10% level. These results support our claim of a relevant control group that can be assumed to satisfy the parallel trends assumption.

Table 5.4: Control Group vs Treated Sample - DPF Increases

Panel A: Distribution of Firms by Sector

Sector	Untreated	Treated
Consumer Discretionary	4.31%	4.92%
Consumer Staples	13.2%	13.1%
Energy	10.2%	8.20%
Financials	32.1%	36.1%
Health Care	5.12%	3.28%
Industrials	16.7%	18.0%
Information Technology	9.70%	6.56%
Materials	7.01%	6.56%
Real Estate	1.35%	3.28%
Communication Services	-%	-%
Utilities	0.03%	-%
Total Count	371	61

Panel B: Summary Statistics for Control Group and Treated

Characteristics	Untreated	Treated	P-value[1]
Log Market Capitalization			0.600
Median	6.27	6.30	
Mean	6.32	6.40	
Dividend Yield			0.800
Median	0.02	0.01	
Mean	0.02	0.03	
ROA			0.500
Median	0.04	0.03	
Mean	0.05	0.07	
Price-to-Book			0.066
Median	1.70	1.60	
Mean	3.1	2.9	
Earnings			0.300
Median	9	7	
Mean	77	86	

[1]Wilcoxon rank sum test

This table constitutes of two panels, A and B. Panel A displays the distribution across sectors for the control group (Untreated) and the group experiencing a frequency increase (Treated). We note that the control group and treatment group exhibit similar representation for each sector, facilitating validation of the parallel trend assumption. Additionally, the total number of firms is included. Panel B reports the mean and median of the five firm characteristics divided by control and treated group. The P-values of the difference between the two groups are also reported. The sample considers annual data from 2016 to 2022.

Largely, the same conclusion holds true for the control group to our sample of dividend payout decreases (Table 5.5, Panel A). However, the firms that have decreased their payout frequency are more evenly distributed over the different sectors. Energy and financials have the most treated firms in this context, with both accounting for 20.8% of the sample. Information technology and materials are the second biggest sectors, with 12.5%. Again, the distribution is closely replicated in the control group, where 25.9% are in the energy sector, 20.3% in the financial sector, and 12.6% are in the information technology and materials sectors.

In terms of comparable measures, in Table 5.5 Panel B, the dividend yield has significant differences between the treated and untreated sample at the lowest 1% level. However, these differences are relatively modest in magnitude: the median dividend yield is 2% for treated firms compared to 1% for untreated firms. The treated sample's mean dividend yield of 4% suggests the presence of some larger outliers, compared to the 2% mean for the untreated sample. Further, earnings and the logarithm of market capitalization show variations at the 5% and 10% significance levels, respectively. However, these discrepancies are subdued in absolute terms. Particularly for earnings, the mean appears to be influenced by some outliers. Ultimately, these findings lead us to conclude that our control group is appropriately matched and relevant to the treated sample.

Table 5.5: Control Group vs Treated Sample - DPF Decreases

Panel A: Summary Statistics for Control Group and Treated

Sector	Untreated	Treated
Consumer Discretionary	-%	-%
Consumer Staples	5.59%	4.17%
Energy	25.9%	20.80%
Financials	20.3%	20.80%
Health Care	3.50%	4.17%
Industrials	5.59%	8.33%
Information Technology	12.6%	12.50%
Materials	12.6%	12.50%
Real Estate	5.59%	8.33%
Communication Services	8.39%	8.33%
Utilities	-%	-%
Total Count	143	24

Panel B: Summary Statistics for Control Group and Treated

Treated	Untreated	Treated	p-value[1]
Log Market Capitalization			0.056
Median	6.14	5.36	
Mean	5.98	5.72	
Dividend Yield			<0.001
Median	0.01	0.02	
Mean	0.02	0.04	
ROA			0.600
Median	0.01	0.01	
Mean	0.01	0.02	
Price-to-Book			0.200
Median	1.32	1.12	
Mean	1.99	2.08	
Earnings			0.015
Median	2	0	
Mean	23	11	

Wilcoxon rank sum test[1]

This table constitutes of two panels, A and B. Panel A displays the distribution across sectors for the control group (Untreated) and the group experiencing a frequency decrease (Treated). We note that the control group and treatment group exhibit similar representation for each sector, facilitating validation of the parallel trend assumption. Additionally, the total number of firms is included. Panel B reports the mean and median of five firm characteristics divided by control and treated group. The P-values of the difference between the two groups are also reported. The sample considers annual data from 2016 to 2022.

5.3.2 Effect of Treatment by the Two-way Fixed Effects Estimator

In this subsection, we present the results from our TWFE analysis, which investigates the proposed positive (negative) relationship between an increase (decrease) in dividend payout frequency and an increase (decrease) in institutional share of holdings. The estimated effect of being treated is captured by the treatment variable that intersects two key factors: being treated (which takes the value 1 if a firm undergoes treatment at any time) and the post-treatment period (assigned a value of 1 from the point a firm first receives treatment, continuing thereafter). In our staggered treatment setup, the treatment variable effectively mirrors the post-treatment indicator.

The results for dividend payout frequency increases, detailed in Table 5.6, reveal a statistically significant positive association for instances of increased dividend frequency, substantiating our hypothesis at a 1% significance level. This result holds true across all model specifications that account for firm-specific covariates. The lone exception is the most naive model without any covariate controls; here, the treatment effect remains positive but is significant at a 5% level.

The incorporation of covariates - namely, dividend yield, return on assets, cash ratio, and price-to-book value - enables us to control for firm attributes potentially impacting the outcome variable. The persistent statistical significance of dividend yield and return on assets emphasizes their suggested relevance when explaining the proportion of institutional holdings, while the influence of cash ratio and price-to-book value is comparatively subdued. As explained in detail in Section 4.3.2, our TWFE model integrates both entity and time-fixed effects, by ticker and year respectively, thereby accounting for latent firm-level heterogeneity and uniform temporal fluctuations.

The results support our hypothesis that increasing dividend payout frequency is related to an increase in the share of institutional holdings. Further, this is consistent with the findings of Keasey et.al (2002) and Han et al. (1999), presented in the literature review (Section 2.3), which find evidence that institutional owners have a significant preference for firms with a more aggressive dividend payout policy.

Table 5.6: TWFE Treatment Effect on Institutional Share of Holdings - DPF Increases

	Dependent variable:				
	Institutional Holdings				
	(1)	(2)	(3)	(4)	(5)
Treatment	0.040**	0.050***	0.054***	0.062***	0.060***
	(0.017)	(0.016)	(0.017)	(0.020)	(0.020)
Dividend Yield		−0.241***	−0.233***	−0.175*	−0.175*
		(0.069)	(0.070)	(0.092)	(0.093)
ROA			0.118***	0.120***	0.115***
			(0.020)	(0.022)	(0.023)
Cash Ratio				−0.0005	−0.001
				(0.001)	(0.001)
Price-to-Book					−0.00003
					(0.00004)
Observations	2,453	2,401	2,344	1,667	1,611
Ticker Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.807	0.825	0.819	0.766	0.754
Adjusted R^2	0.732	0.756	0.747	0.672	0.654
F Statistic	23.880*** (df = 309; 1769)	26.763*** (df = 303; 1723)	25.943*** (df = 292; 1679)	24.159*** (df = 161; 1189)	22.767*** (df = 154; 1143)

Note: *p<0.1; **p<0.05; ***p<0.01

The table reports the output of five panel regression models for cases of dividend frequency increases. The percentage share of Institutional Holdings is used as dependent variable with Treatment, Dividend Yield, Return on Assets (ROA), Cash ratio, and Price-to-Book as explanatory variables. Treatment is a dummy variable that captures the effect of being treated by taking the value of 1 when a firm undergoes a dividend frequency increase, and continues thereafter. Else, the variable takes the value of 0. Each model incorporate fixed effects for ticker and year. The table presents R^2, Adjusted R^2, and F statistic as measure of fit. The decrease in observations from model 1-5 is attributed to instances of missing data in covariates.

The TWFE treatment effect estimator for dividend payout frequency decreases is presented in Table 5.7. Here, we are not able to prove a statistically significant relationship between a decrease in dividend payout frequency and changes in the share of institutional shareholders. However, the sign of the treatment coefficient is negative for all model specifications, and in line with the hypothesized negative relationship between a decrease in dividend payout frequency and institutional holdings.

We will compare the TWFE results to the Callaway and Sant'Anna (2021) approach in the subsequent Section 5.3.3. Here, we will also go into more detail on the economic magnitude of the size of the coefficients. Further, the broader implications of our findings, in particular for managers and investors, are contextualized in the Discussion, Section 6.3.

Table 5.7: TWFE Treatment Effect on Institutional Share of Holdings - DPF Decreases

	Dependent variable:				
	Institutional holdings				
	(1)	(2)	(3)	(4)	(5)
Treatment	−0.024	−0.025	−0.017	−0.023	−0.027
	(0.024)	(0.024)	(0.024)	(0.028)	(0.026)
Dividend yield		-0.309^{***}	-0.234^{**}	-0.253^{*}	−0.157
		(0.118)	(0.118)	(0.135)	(0.128)
ROA			0.034	0.041	0.152^{***}
			(0.040)	(0.042)	(0.045)
Cash Ratio				0.001	0.0005
				(0.001)	(0.001)
Price-to-Book					-0.00000^{***}
					(0.00000)
Observations	946	915	891	681	643
Entity FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
R^2	0.743	0.769	0.780	0.767	0.791
Adjusted R^2	0.655	0.687	0.700	0.677	0.708
F Statistic	21.862^{***} (df = 93; 704)	24.152^{***} (df = 93; 673)	25.751^{***} (df = 90; 653)	25.627^{***} (df = 63; 491)	29.954^{***} (df = 58; 459)

Note: *p<0.1; **p<0.05; ***p<0.01

The table reports the output of five panel regression models for cases of dividend frequency decreases. The percentage share of Institutional Holdings is used as dependent variable with Treatment, Dividend Yield, Return on Assets (ROA), Cash ratio, and Price-to-Book as explanatory variables. Treatment is a dummy variable that captures the effect of being treated by taking the value of 1 when a firm undergoes a dividend frequency decrease, and continues thereafter. Else, the variable takes the value of 0. Each model incorporate fixed effects for ticker and year. The table presents R^2, Adjusted R^2, and F statistic as measure of fit. The decrease in observations from model 1-5 is attributed to instances of missing data in covariates.

5.3.3 Effect of Treatment and Length of Exposure

The adoption of the difference-in-difference methodology for scenarios with multiple treatment and time periods, as articulated by Callaway and Sant'Anna (2021), enables us to not only test the robustness of our findings but also leverage the latest advancements in empirical research. This approach is particularly critical given the staggered nature of dividend payout changes across firms and over time.

As detailed in the Methodology, Section 4.3.3, this approach allows us to evaluate the overall average treatment effect (ATT) as well as the treatment effect by length of exposure. In Table 5.8 we prove that the overall ATT of dividend payout increases have a positive and significant effect on the share of institutional holdings, applying our 5% confidence bands. More specifically, we find that, on average, an increase in dividend payout frequency leads to a significant 6.1 percentage points increase in institutional holdings. Further, we find that the effect is significant in the first year after treatment, with an increase of 5.9 percentage points, and the estimated effect continues to grow to 6.4 percentage points in the second year and 9.9 percentage points in the third year after treatment. The estimator also remains significant for this period.

The results further validate that we have constructed a control group that is likely to satisfy the parallel trend assumption, as suggested in Section 5.3.1, which is a critical aspect of the difference-in-difference methodology. This is highlighted by the lack of significant pre-treatment trends in institutional holdings, where the pre-treatment estimates consistently remain around zero (Figure 5.2). This pattern signals no divergent trends between the treated and control groups prior to the introduction of a dividend payout increase. Such comparability between the control and treatment groups before the treatment is integral to the validity of our results. Aligning with the parallel trends assumption not only ensures the reliability of our findings but also the credibility of the conclusions and implications we will later draw from them.

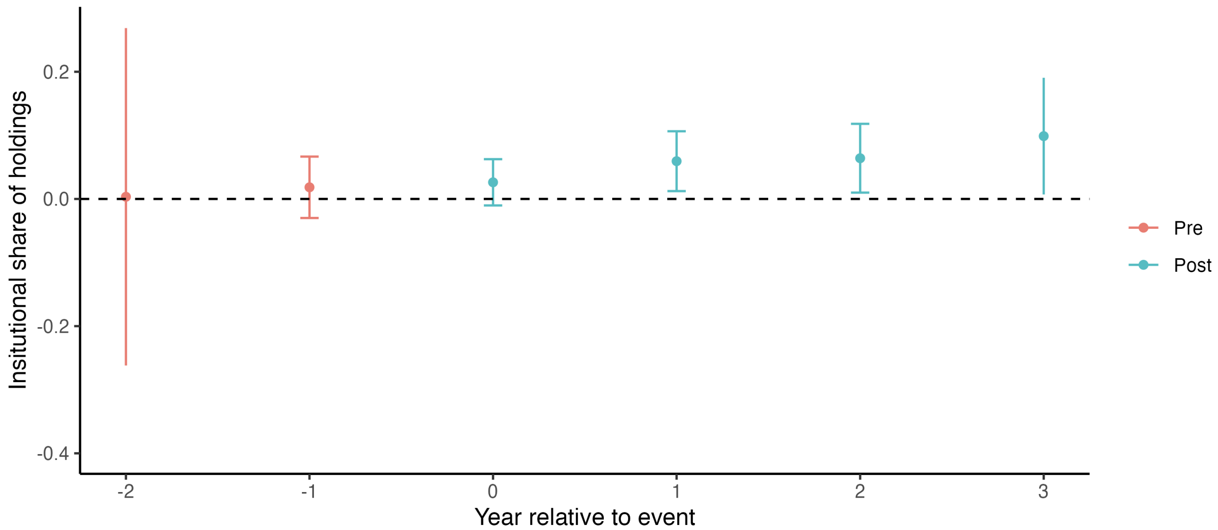
Table 5.8: Average Effect of Dividend Payout Frequency Increase on Institutional Share of Holdings

Event time	Estimate	Std. Error	[95% Simult. Conf. Band]
-3	-0.1154	0.1188	-0.4051, 0.1762
-2	0.0034	0.1110	-0.2681, 0.2749
-1	0.0183	0.0185	-0.0269, 0.0635
0	0.0262	0.0143	-0.0087, 0.0610
1	0.0594	0.0195	0.0117, 0.1070*
2	0.0640	0.0246	0.0038, 0.1242*
3	0.0988	0.0404	0.0000, 0.1975*
Overall summary of ATT's based on event-study/dynamic aggregation:			
ATT	0.0611	0.0266	[0.0089, 0.1133] *

Signif. codes: '*' confidence band does not cover 0 at 5% level

The table presents the average change in share of institutional holdings over time, relative to a dividend payout frequency increase event. For each relative point in time, we report the estimated coefficient, standard error, and resulting 95% confidence interval band. Instances where the 95% confidence band do not cover zero are denoted with ∗. The table shows that all three event periods after the announcement of payout frequency increase contain an estimated coefficient that differ significantly from zero at the 5% significance-level. Additionally, the overall average treatment effect of the treated (ATT) is included at the bottom, and prove a positive and significant average treatment effect.

Figure 5.2: Average Effect on Institutional Holdings by Length of Exposure - DPF Increases



The figure visualizes the estimated change in institutional holdings and the respective 95%-confidence intervals surrounding a payout frequency increase. The plot considers change in institutional holdings pre-treatment (Red) and post-treatment (Blue). The figure indicates that frequency increases are followed by a significant change in institutional holdings the subsequent three years after treatment.

Similar to the observations in Section 5.3.2, the results from our analysis align with the hypothesized positive relationship between an increase in dividend payout frequency and a rise in the share of institutional holdings. Notably, there is a remarkable similarity between the treatment effect estimated using the two-way fixed effects (TWFE) approach (6.0 percentage points) and the Average Treatment Effect (ATT) derived from the difference-in-difference methodology that accounts for varying treatment timing and staggered adoption (6.1 percentage points). This similarity in findings suggests that the potential limitations of the TWFE approach, as discussed by Goodman-Bacon (2021) and Callaway and Sant'Anna (2021), are negligible in our context. Consequently, the two approaches' similarity in results is another argument for the reliability of our findings, providing a robust foundation for further discussions and conclusions.

In terms of economic magnitude, it is helpful to refer back to Table 3.5, explaining the institutional holding's distribution across sectors. The overall average treatment effect (ATT), estimated at 6.1 percentage points in Table 5.6, closely approximates the sample average standard deviation of 6.1%, signifying a 1 standard deviation change. This effect size is notable, especially in sectors such as health care (4.9%), information technology (5.1%), and industrials (5.2%), where it by some margin surpasses the sector-specific average standard deviation. When compared to the median standard deviation of the full sample (4.3%), the average treatment effect is 1.4 times greater, and exceeds the median standard deviation for all sectors except energy. Three years post-treatment, where we find the largest treatment estimate (9.9 percentage points), the effect is 1.6 times the sample mean standard deviation and 2.3 times the sample median standard deviation. As such, we conclude that the treatment effect is considerable.

However, we also have to consider the relative impact of our treatment estimate. At the sample's mean institutional holdings of 71.9%, a 6.1 percentage points increase signifies an 8.5% relative change in institutional holdings. Comparatively, at the first quartile of the full sample (53.6%), the relative increase is 11.3%, while at the third quartile (98.3%), the relative increase is 1.7% due to the maximum shareholder percentage cap of 100%. Consequently, sectors with lower baseline institutional holdings, such as real estate (54.8%), financials (62.2%), and consumer staples (67.9%), are likely to experience a more substantial relative increase, indicating a larger effect in attracting new institutional investors. Three years after treatment, the relative increase in institutional holdings compared to the sample mean is approximately 13.7%, and 18.4% relative to the first quartile. These findings suggest that the results carry relevant economic magnitude, particularly for firms with institutional holdings around or below the sample mean.

It's important to note that our sample is narrowed to firms with a history of dividend payments, which we posit have higher baseline institutional holdings. Hence, the relative effects observed could be even more pronounced in a broader sample that includes non-dividend paying firms. This presents an intriguing direction for future research, particularly focused on the transition from a non-dividend to a dividend-paying status.

Conversely, for decreases in dividend payout frequency, we find a notable negative effect on institutional share of holdings becoming apparent in the first period after treatment. However, as for the TWFE approach, we are not able to prove a statistically significant relationship. Here, we suspect that our limited sample of recent dividend decreases in the U.S. is an important reason for the non-significant results. Further, as found by Ali et al. (Ali et al., 2017), the firms that are most likely to make negative adjustments to their dividend payout policy are often smaller firms and firms that are in a negative profitability trend. These are characteristics that hold institutional investors, which perform constant monitoring and due diligence, at a distance in the first place. Therefore, we suspect that some of the effect is subdued due to institutional investors having already moved away, or have never been interested, in several of these stocks.

As for the dividend payout frequency increases sample, the results in Table 5.9 and Figure 5.3 suggest that we have created a satisfactory control group. However, for the dividend frequency decreases, we find a larger disparity between the results of the TWFE and the difference-in-difference approach allowing for varied treatment timing and staggered adoption. Specifically, the latter approach finds an overall average treatment effect of -6.6 percentage points, while the TWFE approach estimates a treatment effect of -2.7 percentage points. This divergence suggests that the biases or inherent limitations associated with the TWFE approach might have a more significant impact in setups involving decreases in dividend payout frequency, underscoring the importance of methodological selection in empirical analyses.

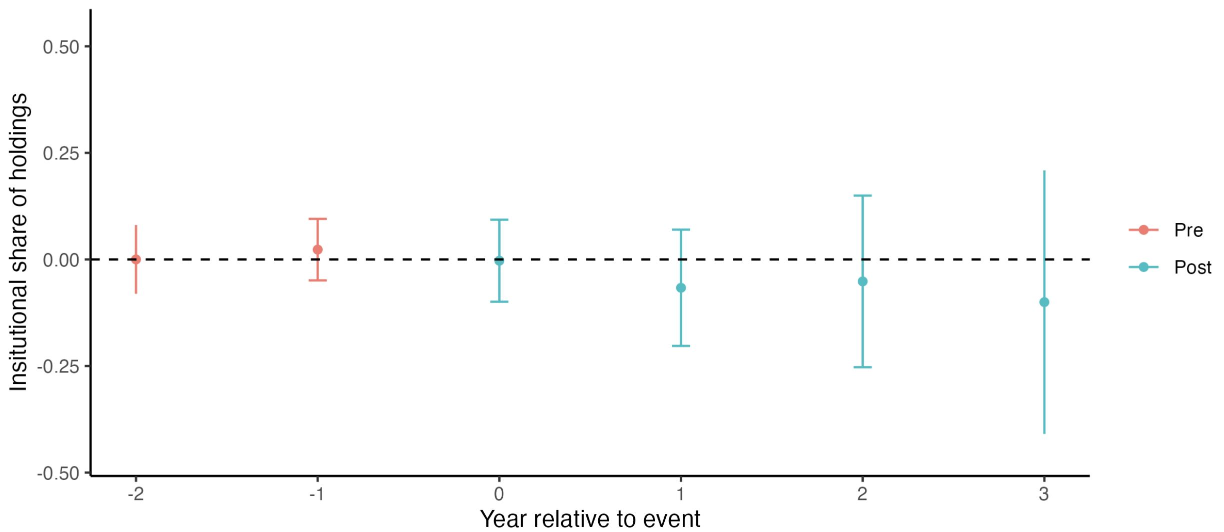
Table 5.9: Average Effect of Dividend Payout Frequency Decrease on Institutional Share of Holdings

Event time	Estimate	Std. Error	[95% Simult. Conf. Band]
-3	0.0142	0.0501	-0.1004, 0.1288
-2	0.0000	0.0352	-0.0806, 0.0806
-1	0.0230	0.0315	-0.0491, 0.0952
0	-0.0030	0.0420	-0.0992, 0.0932
1	-0.0665	0.0596	-0.2528, 0.0699
2	-0.0515	0.0880	-0.2528, 0.1498
3	-0.1001	0.1351	-0.4093, 0.2090
Overall summary of ATT's based on event-study/dynamic aggregation:			
ATT	-0.0658	0.0776	[-0.2180, 0.0864]

Signif. codes: '*' confidence band does not cover 0 at 5% level

The table presents the average change in share of institutional holdings over time, relative to a dividend payout frequency decrease event. For each relative point in time, we report the estimated coefficient, standard error, and resulting 95% confidence interval band. Instances where the 95% confidence band do not cover zero are denoted with ∗. Additionally, the average treatment effect of the treated (ATT) is included at the bottom, which find a negative but non-significant average treatment effect.

Figure 5.3: Average Effect on Institutional Holdings by Length of Exposure - DPF Decreases



The figure visualizes the estimated change in institutional holdings and the respective 95%-confidence intervals surrounding a payout frequency decrease. The plot considers change in institutional holdings pre-treatment (Red) and post-treatment (Blue). The figure indicates that the frequency decrease is followed by an insignificant change in the share of institutional holdings.

Further, though we do not find a significant effect, we consider the economic magnitude of our results. The average treatment effect of a dividend payout decrease, estimated at -6.6 percentage points, is approximately equal to 1.1 times the sample average standard deviation. Further, the estimated effect exceeds the median standard deviation for all sectors and covers the full sample median 1.5 times. Similar to dividend payout increases, we find the largest estimated treatment effect three years post-treatment (-10.0 percentage points), which covers the sample mean and median standard deviation 1.6 and 2.3 times, respectively. Therefore, we conclude that the size of the estimated coefficients carry economic significance.

Lastly, in terms of relative impact, the ATT signifies a relative decrease of -9.2% at the sample's mean institutional holdings, a relative decrease of -12.3% at the first quartile, and a relative decrease of -6.7% at the third quartile. Again, this implies that sectors with lower baseline institutional holdings are likely to experience a more substantial relative decrease and likely more pronounced effect of losing additional shares of institutional holdings.

Overall, we are able to prove that dividend frequency increases have a significant positive effect on institutional holdings, an effect that is persistent and increases in the three years after treatment. After this period, the average institutional holdings remain notably higher than before treatment. For dividend payout decreases, the direction of our treatment estimator is in line with the hypothesized link between dividend payout decreases and a decrease in institutional share of holdings. The implications of these findings, particularly the economic implications for managers and investors, are discussed in Section 6.3.

6 Discussion

In this section we integrate and interpret the findings of our analysis, revisiting the hypotheses presented in Section 2.5 and examine them in light of the empirical evidence obtained. Through the discussion we aim to not only highlight the key insights from our analysis, but also situate them within the broader context of existing literature, thereby adding depth to our understanding of dividend payout frequencies and their impact on investor behavior.

6.1 Significance of Dividend Payout Frequency

6.1.1 Market Reaction to Dividend Frequency Changes

The event study results in Section 5.1 align with our hypotheses, substantiating theories from the literature review. The significant positive market reaction to increases in dividend frequency corroborates the prospect theory's implication that investors value regular income streams (Kahneman & Tversky, 1979). This finding is also consistent with the bird-in-hand fallacy (Gordon, 1962), suggesting that investors prefer the certainty of dividends over uncertain capital gains. Additionally, an increase in dividend frequency could signal management confidence in the firm's financial health (S. Bhattacharya, 1979; Capstaff et al., 2004; Miller & Rock, 1985), and the reduction in cash-flow uncertainty might lead to a lower discount rate and higher stock valuation (Barberis & Huang, 2001). The relationship between frequent dividend payouts and corporate governance is also highlighted, as such payouts can mitigate agency costs and are associated with better corporate practices (Das Mohapatra & Panda, 2022; Easterbrook, 1984; Jensen, 1986).

6.1.2 Intepreting Increases vs. Decreases in Dividend Frequency

The contrast in market reactions to increases versus decreases in dividend frequency highlights the nuanced perceptions of market participants. The lack of a uniform negative reaction to dividend frequency decreases in the $(-1+1)$ event window suggests that such actions is interpreted in varying ways. For example, a decrease in dividend frequency might be viewed as a strategic decision to manage financial resources more effectively, rather than a direct indicator of poor financial health.

For dividend frequency increases we find a significant and positive relation to abnormal returns that support theories that argue for the relevance of dividend policies in firm valuation. Our findings suggest that stable and more frequent dividend payouts, which contribute to increased predictability and stability of total stock returns, are valued by investors and can influence stock prices. However, the results from the multivariate regression, where we find a negative relationship between return on assets and abnormal returns, indicate that dividend frequency changes are evaluated in light of a firm's operational efficiency. Therefore, if a firm with a high return on assets announces a dividend frequency increase, it might be perceived as a strategy that is not in line with its demonstrated operational efficiency. This observation indicates that while dividend frequency increases are generally viewed positively, their impact on stock valuation is also dependent on the perceived alignment with the company's operating capabilities and environment.

6.2 Determinants of Payout Frequency

Using the results from Section 5.2, we provide a link to the literature presented in Section 2 as well as an answer to the hypothesis "The share of institutional holdings has a significant and positive relationship to the frequency at which a firm distributes its dividends". The discussion primarily centers on the novel effects of leverage, dividend yield, and institutional holdings, however, the effect of the various sectors are also discussed due to their significance and lack of mention in Ferris et al. (2010). Lastly, the applicability of the results in regard to speculation and dividend portfolio construction is detailed.

6.2.1 Effect of Variables

From the results presented in Table 5.3 we note that the significant positive effects of size, earnings, and earnings volatility are similar to those of Ferris et al. (2010). The observed relationships is also consistent with other research on the determinants of dividend policy. Specifically, the size effect is consistent with the findings of Denis and Osobov (2008), who examined dividend payouts in the context of agency and life-cycle theories, while impact of earnings aligns with the work of Fama and French (2001). Additionally, as most recently proved by Brav et al. (2005), heightened earnings volatility tends to make firms cautious about committing to unsustainable payout policies in order to limit the possibility of future dividend cuts.

However, we also find some contradicting results to those of Ferris et al. (2010). Specifically, our model suggests a negative relationship between the frequency of dividend payouts and the firm's return on assets, contrary to their suggested positive relationship. Though differing, the negative relationship is easily rationalized; Firms with high operational efficiency, and their shareholders, are likely to be better off reinvesting excess cash back into the business compared to distributing it out as dividends. The observed effect is however discrete, which may imply that return on assets is better at determining whether to pay dividends than at which frequency to distribute.

Further, our research identifies a positive link between dividend yield and payout frequency. The relationship may be attributed to agency cost theory; firms that distribute substantial portions of their earnings through dividends, continuously accumulate cash holdings needed for the payouts. When dividends are paid less frequently, these cash reserves can grow significantly in size, possibly leading managers to make sub-optimal investment decisions. An alternative rationale is that firms may utilize frequent payouts to satisfy shareholders' preference for certainty and immediacy as suggested by the bird-in-hand fallacy (Gordon, 1962; Lintner, 1956). The immediacy associated with quarterly dividends is greater compared to less frequent payouts like annual. This view aligns with prospect theory by Kahneman and Tversky (1979), which proposes that shareholders derive greater satisfaction from receiving smaller, more frequent payments.

We also contribute to dividend policy literature by identifying a significant and positive relationship between leverage and distribution frequency. At first, the positive relation may seem contradictory as higher interest payments reduce the cash available for distribution. However, firms may issue debt to subject the managers to external debt-holder monitoring (Florackis et al., 2015). A further rationale is found in firms taking on external financing in order to uphold the dividend schedule they have committed to, as managers are reluctant to make any downward adjustment to dividends, and may issue debt to cover any short-term deficits (Fama & French, 2002; Lintner, 1956). Further, through the sample overview in Section 3, we find that larger firms tend to have a higher payout frequency. Consequently, these are often firms with a large book value to lend against and generate stable earnings, making them well-equipped to operate with leverage.

The marginal effects of 0.1 percentage points from institutional ownership on the propensity of employing quarterly or more frequent distribution schedule confirms our hypothesis of a positive relationship between payout frequency and institutional holdings. A potential rationale for the observed investor behavior is the fact that certain institutional investors, like insurance companies and pension funds, have ongoing cash outflow requirements, to which frequent dividend payouts provide a steady income to fulfill these obligations.

As mentioned in Section 5.2.2, an alternative explanation may be that a large share of institutional investors enables them to exert influence on corporate decisions to align with their financial goals and preferences (Chen, 2022). Institutional investor might therefore advocate for higher dividend frequencies as it reduces their monitoring costs of managers, impose greater market discipline and capital allocation management, as well as potentially reduce agency costs of retained earnings.

6.2.2 Sector Effects

The sectors incorporated in the regression model include consumer discretionaries, consumer staples, energy, financials, health care, industrials, information technology, materials, and utilities. These are all sectors historically known for high dividend yields, which arise from the nature of their businesses (John, 2017). That is, they provide essential services that have inelastic demand, often called defensive stocks, thus they generate consistent and predictable earnings (Borzykowski, 2014). Examples of large distributors within these sectors are AT&T, Exxon mobil, Johnson&Johnson, and Coca-cola. The high yield itself may explain the positive effect on payout frequency, using the explanation provided earlier in this section. The positive relationship might also be attributed to the stable earnings the firms in these sectors experience. Our results from Table 5.3 indicate a negative relationship between earnings volatility and distribution frequency. An interesting finding, however, is that consumer stables appear insignificant in all models except one. The significance that results from including volatility of returns, CAPEX-to-EBIT, earnings, and share of institutional investors, which may suggest endogeneity problems from omitted variables in Model 4.

The real estate sector is the only sector not shown to have a significant effect on payout frequency. This result is surprising, considering the historically high dividend yields within the sector and the effect we have found between yield and frequency. However, the large investment requirements that are essential to their operation might make real estate companies opt for keeping cash available for longer periods of time in case an attractive investment opportunity arises. In addition, U.S. Real estate income trusts (REITs) are lawfully required to distribute a minimum of 90% of their net income to shareholders annually. The negative coefficient, though insignificant, suggests that operating in real estate decreases the propensity of having a higher distribution frequency. Contrary to consumer staples, the real estate sector appears to have a significant effect on DPF in models 1, 2, and 4 but turns insignificant in model 5. Again, the results indicate biased estimates of coefficients in model 4 due to omitted variables.

6.2.3 Applications

The obvious implication of our predicted relationships is to exploit stock behavior through speculation. That is, considering the results when monitoring changes in firm fundamentals, may contribute to more accurate price projections. For example, the significant positive stock reaction from dividend payout frequency increases shown in Section 5.1 should influence the investor investment decision to consider larger dividend paying-firms with greater potential for issuing debt, high yields, and currently employ a low payout frequency as potential.

However, the most prominent argument for the novelty of our results is the contribution to portfolio construction. Possessing knowledge of dividend-paying firms' behavior in relation to its firm fundamentals should supplement stock picking such that the cash flows align better with the investors' preferences. For instance, if a firm with annual payouts issues additional debt aimed at supporting cash distribution, our results suggest that the firm becomes more likely to increase its payout frequency. This could in turn alter the timing of cash flows from the portfolio in a way that affects the investor. This may not be a trivial consideration, particularly for investors who rely on portfolio income to meet liabilities. If several firms in the portfolio alter their dividend payout frequency, it could significantly impact the timing and amount of cash flows. Such a shift might lead to scenarios where the investor either faces default due to insufficient income or ends up with excessive cash holdings that could be more productively invested. Consequently, investors may benefit from strategically balancing their portfolio, taking into account each firm's likelihood of distributing dividends at a higher or lower frequency, to better align with their cash flow needs and investment objectives.

Based on our identified effects on the propensity of higher payout frequency in certain sectors, such as utilities or consumer staples, sector considerations should also be incorporated in dividend portfolio construction. For instance, a firm operating within one of these sectors with annual dividend payouts has a greater propensity for changing to a more frequent distribution frequency. Aware of the identified relationship, the investor may then engage in speculation by predicting a stock price increase from the potential frequency increase, or balance his portfolio to account for potential changes in the frequency and magnitude of cash outflows. This is even without considering the possibility that firms conform to investors' expectations for dividend policy for the relevant sector (Dempsey et al., 1993).

6.3 Institutional Holdings

With the results of our difference-in-differences analyses, we confront the hypothesis that institutional investors with fixed cash flow requirements, such as pension funds and insurance companies, exhibit a preference for firms with consistent dividend disbursements. Our analysis utilizes a difference-in-difference approach, focusing on firms that have altered their dividend frequency. The results confirm the hypothesized relationship, proving that changes in dividend frequency significantly influence institutional investment behavior.

Our results, derived using both the traditional TWFE and the advanced estimators of Callaway and Sant'Anna (2021), underscore the strength of the observed effects and the value of methodological selection. We primarily focus on the latter due to its relevance to our context of varying treatment timing and staggered adoption, as well as its foundation in recent methodological advancements. Nevertheless, incorporating both methods in our thesis enhances the robustness of our analysis.

The TWFE results, detailed in Section 5.3.2, confirm a significant and positive treatment effect of increased dividend frequency on institutional ownership, corroborating the preferences documented by Keasey et al. (2002) and Han et al. (1999). This positive association persists even after controlling for firm-specific covariates, reinforcing the notion that regular dividends are a key determinant of institutional investment strategies.

However, the relationship between decreased dividend frequency and institutional holdings is less clear, with our results not reaching statistical significance. The tendency of smaller firms, or those in negative financial trends, to reduce dividend payments could potentially preclude significant institutional investment initially, possibly explaining this absence of a significant reaction.

The Callaway and Sant'Anna (2021) estimator further elucidates the dynamics of treatment effects over time, as examined in Section 5.3.3. The observed positive and significant overall average treatment effects underscore the economic value that increased dividend frequency offers to institutional investors. Notably, we find a significant positive effect one year post-treatment, at 5.9 percentage points, which increases over time and peaks three years after treatment, at 9.9 percentage points. Further, as detailed in Section 5.3.3, we find that the average treatment effect (6.1 percentage points) equals 1 and 1.4 standard deviation change at the full sample mean and median, respectively. Three years post-treatment, these numbers are 1.6 times the average standard deviation and 2.3 times the median standard deviation. These results imply that the events are relevant, also in terms of economic magnitude.

However, the relative increase in institutional holdings due to an increase in dividend payout frequency — reflected in the estimated overall average treatment effect (ATT) — varies significantly across sectors. For instance, real estate exhibit a relative increase of 11.3% compared to the sector mean institutional holdings, while health care shows a 7.6% increase, demonstrating the context-specific nature of 6.1 percentage points higher institutional holdings. Thus, our findings are particularly pertinent for sectors with lower baseline institutional holdings, such as real estate, financials, and consumer staples. In these sectors, attracting a larger share of institutional investors is likely to have a more pronounced effect. This sectoral variation underlines the necessity of considering the unique financial and operational contexts when interpreting the impact of dividend frequency changes.

6.3.1 Implications for Managers

Our study's results suggest that managers face a nuanced decision-making landscape when considering changes to dividend frequency. On one hand, increasing dividend payout frequency attracts a larger proportion of institutional investors, who have been shown to contribute positively to the financialization process of firms (Alexiou et al., 2018). This investor cohort's active role in corporate governance can drive financial performance improvements, potentially enhancing firm value in line with the efficient monitoring hypothesis.

However, this benefit comes with the caveat of increased oversight and engagement from these shareholders. Institutional investors are known for their rigorous monitoring and active participation in voting, which can lead to greater scrutiny of managerial decisions. While this can foster transparency and align management with shareholder interests, thereby reducing agency costs, it may also limit managers' operational autonomy and strategic flexibility. For executives reticent to external intervention, the prospect of intensified monitoring might be an argument against frequent dividend payouts and the consequent increased attractiveness to institutional shareholders.

Additionally, as commented in Section 3.3, we find that the sectors that have the lowest baseline of institutional holdings tend to be more volatile and sensitive to economic cycles. Further, as discussed in Section 5.3.3, these are the sectors that are likely to see the highest relative increase in institutional holdings, and therefore the biggest effect, of a dividend frequency increase. Again, these results highlight a decision with trade-offs, as a commitment to a more frequent dividend payout schedule may put significant constraints on a firm with volatile earnings. Therefore, it is essential to view the decision of increasing payout frequency and share of institutional holdings, in comparison to both operational costs of less flexibility and potential transaction costs.

In conclusion, while our study establishes a causal relationship between changes in dividend payout frequency and institutional holdings, quantifying the direct and indirect financial implications of these changes remains a topic for further research. Understanding the tangible benefits and costs associated with different levels of relative shifts in institutional holdings will be instrumental in guiding the strategic decision making, and in order to recognize and leverage the full potential of our findings.

6.3.2 Implications for Private Investors

The presence of institutional investors can serve as a signal of firm quality to smaller investors, who may lack the resources to perform extensive due diligence. The theory holds that institutional investors, through their informed and active investment strategies, can shepherd companies towards better performance and higher market valuations. Further, institutions are able to perform constant monitoring and due diligence at a much lower relative cost than small investors (Nashier & Gupa, 2016). In this way, by mirroring the entries and exits of these entities, smaller investors are indirectly able to react to the same information.

However, smaller investors should be wary of the potential information asymmetry and the risk of being the least informed party in the firm. By simply mirroring the better informed party, smaller investors always become the last to entry and exit, and may therefore be at risk of acting too late. Followingly, the advantages institutional investors bring to the table may be counterbalanced by the challenges that retail investors face in such an environment, including potentially reduced influence and the risk of being adversely affected by decisions primarily tailored to institutional interests.

6.3.3 Establishing Causality

A key question in the relationship between dividend policies and institutional ownership is the direction of causality. While some literature suggests that increased institutional holdings may lead firms to raise their dividends, our application of the Callaway and Sant'Anna (2021) approach lends support to the inverse — that an increase in dividend frequency indeed leads to a rise in institutional ownership. Our findings show no significant pre-trend before the treatment, negating the possibility that institutional investors anticipate the dividend increase. Instead, the significant positive effect emerges post-treatment, suggesting that firms may strategically adjust dividend frequencies to attract institutional investors, rather than responding to their presence.

The implications of this causality are significant for corporate policy. If dividend increases serve as a mechanism to court institutional investors, managers may need to weigh the merits of this strategy against the potential for increased scrutiny and the demands it may place on the firm's financial planning and flexibility.

In closing, our discussion reflects on the delicate balance that firms must strike in their dividend policies to attract the right mix of investors. While the presence of institutional investors appears to be beneficial for firm performance, it necessitates careful consideration of the broader implications for corporate governance and minority shareholder interests. In this context, our most important finding, namely that increased dividend payout frequency leads to an increase in institutional share of holdings, becomes a highly relevant tool in corporate strategy. In other words, by demonstrating the significant and enduring impact of dividend frequency changes on institutional holdings, this study enriches the understanding of the interplay between firm policy decisions and investor behavior and proposes direct actions firms may take in order to increase their share of institutional owners in order to reap the rewards of improved performance, better financialization and robust governance.

7 Conclusion

This thesis has investigated the nuanced role of dividend payout frequency in corporate strategy and stock valuation, a subject that has garnered limited empirical explorations but may have profound implications. Our study contributes to the existing body of knowledge by focusing on the U.S. market, employing a sophisticated market model in calculating abnormal returns, and is the first - to our knowledge - to assess the impact of dividend payout frequency in the context of institutional holdings.

Our findings confirm our first hypothesis that an increase in dividend payout frequency is followed by a significant and positive market reaction. This provides support to theories suggesting investor preference for regular income streams and underscores the role of dividend frequency in reducing investment uncertainty. In terms of dividend frequency decreases, we do not find a significant uniform negative reaction, indicating that this action is viewed in context of a firm's financial environment and that there likely are instances where a decrease in frequency is viewed as a prudent action from management to enhance control over its financials and cash holdings.

Second, we find a positive and significant relationship between higher dividend payout frequency and the share of institutional ownership. Thirdly, and most notably, our research establishes a directional causality where an increase in dividend payout frequency significantly increases the share of institutional investors, and that this effect remains significant three years after the change, marking a novel contribution to dividend policy literature.

These findings are highly relevant to corporate strategy and real-life applications. We establish increasing dividend frequency as a direct tool for managers to increase its attractiveness to institutional investors, which is proven to improve performance, the financialization process, and corporate governance. On the other hand, managers must weigh these benefits against enhanced scrutiny and reduced managerial discretion. Notably, our study does not directly quantify the tangible financial benefits and costs of changing payout frequency and the associated change in institutional ownership. We highly suggest this topic for further research, as it will be essential to fully take advantage of the relationship we have uncovered and make qualified strategic decisions.

For investors, particularly retail ones, the presence of institutional investors in a firm could be a quality signal as they perform extensive due diligence not attainable for private investors. However, it also introduces the risk of information asymmetry.

Overall, this thesis underscores the importance of dividend payout frequency as a strategic tool in corporate finance. By demonstrating how this aspect of dividend policy influences market valuation and investor composition, we provide valuable insights for both corporate decision-makers and investors. The study bridges a significant gap in the literature and sets the stage for further exploration into the intricate landscape of dividend policies and their broader implications in the financial world.

7.1 Limitations and Further Research

As we conclude, it's essential to note that while our results are compelling, they are bound by the scope of our data and the specific context of the U.S. market. In particular, our focus on the U.S. market enhances model precision but may also limit the applicability of our findings to markets with differing dividend practices and tax regimes.

Further, as mentioned in Section 4.3.1, we introduce some degree of look-ahead bias in the construction of our difference-in-difference control groups by estimating the matching covariates on the ticker means from the analyzed sample period. However, in the context of our study, the implications are limited, and we prove in Section 5.3.3 that we successfully construct control groups that satisfy the parallel trends assumption.

For future research, we recommend exploring the distinctions between various types of institutional investors. Specifically, it would be valuable to differentiate between investors with regular cash outflows, like pension funds and insurance companies, and those with longer-term investment focus, such as sovereign wealth funds, and to assess their respective preferences for dividends and payout frequencies.

Additionally, investigating whether the impact of increasing dividend payout frequency diminishes when the starting frequency is already high could be enlightening. Exploring the long-term effects of changes in dividend payout frequency on firm performance and governance, and whether such changes can predict future firm performance, would also be worthwhile avenues for further research.

Lastly, and most importantly to fully utilize the implications of our results, is to quantify the tangible costs and benefits associated with a higher (lower) dividend payout frequency, and the accompanying higher (lower) institutional share of holdings, and, in particular, how these costs and benefits may vary compared to a firm's baseline payout frequency and institutional holdings composition.

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Appendices

A Determinants of Dividend Frequency

Table A.1: Determinants of Dividend Payment Frequency (Logit Model)

	Dependent variable:				
	DPF				
	(1)	(2)	(3)	(4)	(5)
Consumer Discretionary	0.050***	0.047***	0.048***	0.049***	0.050***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.0.005)
Consumer Staples	0.012	0.008	0.012	0.014	0.023***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)
Energy	0.036***	0.031***	0.026***	0.024***	0.026***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Financials	0.068***	0.060***	0.055***	0.059***	0.054***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.005)
Health Care	0.037***	0.033***	0.037***	1.098***	0.039***
	(0.006)	(0.007)	(0.006)	(0.038)	(0.005)
Industrials	0.030***	0.027***	0.029***	0.030***	0.039***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Information Technology	0.010	0.014	0.023***	0.027***	0.033***
	(0.008)	(0.008)	(0.007)	(0.006)	(0.006)
Materials	0.026***	0.023***	0.024***	0.024***	0.031***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Real Estate	−0.069***	−0.045**	−0.031	−0.040*	−0.028
	(0.007)	(0.027)	(0.025)	(0.027)	(0.024)
Utilities	0.066***	0.062***	0.058***	0.058***	0.059***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	−0.045	−0.018	−0.518**	−0.850***	−0.997***
	(0.204)	(0.215)	(0.237)	(0.240)	(0.294)
Observations	16,427	16,400	15,853	15,709	10,568
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Entity Fixed Effects	Yes	Yes	Yes	Yes	Yes
McFadden	0.075	0.079	0.076	0.082	0.109
Akaike Inf. Crit.	7,189.911	7,137.674	6,677.797	6,314.672	4,015.855
Note:					*p<0.1; **p<0.05; ***p<0.01