Corporate Payout Policies Under Stress: Evidence from the GFC and COVID-19

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Abstract (*English version*)

Title: Corporate Payout Policies Under Stress: Evidence from the GFC and COVID-19

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This thesis examines how U.S. firms adjusted dividend policies during the Global Financial Crisis (2008–2009) and the COVID-19 pandemic (2020–2021). Dividend event data from CRSP were linked to Compustat fundamentals, and three models were estimated: a logit regression for dividend cuts, a linear fixed-effects model for payout intensity, and a difference-in-differences approach to test leverage heterogeneity. The results show that dividend cuts were significantly more likely during the GFC, consistent with credit distress, while COVID generated a weaker and more heterogeneous effect. Firm fundamentals remained decisive: leverage increased both the probability of cuts and the retention ratio, while larger firms displayed resilience. Profitability showed mixed results, positively linked to cuts in the logit model but negatively related to payout in the linear model, suggesting reinvestment motives alongside distributional choices. The analysis also revisits dividend signaling. In the GFC, maintaining payouts was costly and thus highly informative, while cuts were interpreted as strong negative signals. During COVID, widespread suspensions diluted informational content, and stability or increases became the true signals of resilience.

Resumo (Português)

Título: Políticas de Dividendos em Situações de Stress: Evidência da GFC e da COVID-19

Palavras-chave: Política de dividendos; Sinalização; Crise Financeira Global; COVID-19

Esta dissertação analisa como as empresas norte-americanas ajustaram as suas políticas de dividendos durante a Crise Financeira Global (2008–2009) e a pandemia de COVID-19 (2020–2021). Os eventos de dividendos da CRSP foram ligados aos fundamentos contabilísticos da Compustat, e três modelos foram estimados: uma regressão logit para cortes, um modelo linear com efeitos fixos para intensidade das distribuições e uma abordagem de diferenças-em-diferenças para testar a heterogeneidade do endividamento.

Os resultados mostram que os cortes foram significativamente mais prováveis durante a GFC, refletindo dificuldades de crédito, enquanto a COVID gerou um efeito mais frágil e heterogéneo. Os fundamentos revelaram-se determinantes: o endividamento aumentou a probabilidade de cortes e a retenção, enquanto empresas maiores mostraram resiliência. A rentabilidade apresentou efeitos mistos, positiva nos cortes mas negativa na intensidade da distribuição, sugerindo escolhas entre reinvestimento e pagamento.

A análise também revê a função de sinalização dos dividendos. Na GFC, manter dividendos foi dispendioso e altamente informativo, enquanto os cortes funcionaram como sinais negativos fortes. Na COVID, as suspensões generalizadas diluíram o conteúdo informativo, e apenas a estabilidade ou aumentos sinalizaram resiliência. Assim, os dividendos mantêm-se como instrumento de ajustamento e sinalização, mas o seu significado depende da natureza da crise.

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1. Introduction

Dividend policy has long been a central topic in corporate finance, given its role in remunerating shareholders while signaling firm stability and prospects. Yet payout decisions are not taken in a vacuum: they are shaped by macroeconomic conditions, firm fundamentals, and investor expectations. In particular, periods of systemic crisis place firms under acute pressure to reassess payout strategies, making them an ideal setting for studying the drivers and consequences of dividend policies.

This thesis aims to compare two profound crises that challenged firms in diverse ways: the Global Financial Crisis (GFC), and the COVID-19 pandemic. The GFC originated in the collapse of the U.S. housing market and the subprime mortgage sector, culminating in the bankruptcy of Lehman Brothers. It represented a financial-system-driven shock, in which frozen credit markets, liquidity shortages, and deleveraging constrained firms' ability to finance operations. Its effects were persistent and systemic, foremost with banks and capital-intensive industries particularly affected. In contrast, the COVID-19 crisis was triggered by an exogenous public health shock that resulted in disrupting the global supply and demand. Lockdowns and travel restrictions impacted service-oriented sectors such as hospitality, retail, and transport. However, unlike the GFC, credit markets remained relatively functional due to monetary and fiscal interventions, and the economic recovery was faster though uneven across industries. These differences underscore how crisis origins and transmission mechanisms condition firms' payout responses.

Despite a rich and growing body of research on dividend behavior in single crises, comparative evidence remains scarce. Prior studies often examine either the GFC or COVID-19 in isolation, neglecting the opportunity to identify whether payout dynamics are crisis-specific or reflect more fundamental determinants. Moreover, much of the literature focuses either on market reactions to dividend announcements or on payout levels alone, leaving not explored the integrated view of discrete dividend cuts, continuous adjustments in retention, and heterogeneous responses across firms with differing leverages.

The guiding research questions that I aim to answer are:

1. **Crisis effect on cuts:** Are dividend cuts more likely during crises compared to neutral periods, and do their magnitudes differ between the GFC and COVID?

2. **Role of fundamentals:** How do profitability, liquidity, leverage, and size shape payout policies, particularly through firms' retention ratios?
3. **Heterogeneity by leverage:** Do highly leveraged firms adjust payout policies more strongly than low-leverage firms when crises hit?
4. **Signaling function:** Are dividends still used as signals of firm strength in crises, and does their signaling role differ between a financial crisis (GFC) and an exogenous shock (COVID)?

By aligning two crises of distinct origin and nature within the same empirical framework, this thesis seeks to clarify whether payout adjustments reflect the macroeconomic context or are primarily driven by firm fundamentals, and whether dividends retain their informational value as signals during systemic stress.

2. Literature Review

2.1 Dividend Signaling Hypothesis

In Corporate Finance, the *dividend signaling hypothesis* has been a point of discussion for decades. This theory was first introduced in a seminal study, where Lintner (1956) interviewed 28 well-established listed companies to understand what were the crucial factors that affected dividend policy. What he discovered was that most of the managers believed that stockholders prefer a reasonably stable rate, and that the market trades the companies that follow this rate at a premium. Thus, conservatism was the answer. Further conclusions were that the level of dividends was tied to sustainable long-term earnings, and the management would rather smoothly adjust dividends toward a long-term payout ratio. The study's qualitative analysis and reliance on managerial interviews set the tone for future research.

The second main piece of the literature is Modigliani & Miller (1961). This study broadly documented how the market reacted to a dividend announcement in the same direction as the change, meaning that an increase in the level of dividends would have been seen as an appreciation of the expected earnings, and vice versa. Consistently with this theory we find Bhattacharya (1979) whose paper examines the role of the dividend. Even despite the tax disadvantage of the latter, the author finds that firms may decide to pay dividends as they better function as a signal of future expected cash flows. In this model, managers have greater knowledge about the expected firm's cash flow, and they use dividends precisely because they represent an expensive signal. This concept of costly signaling became a foundational idea in literature.

Under the concept of asymmetrical model, Rock (1985) showed that firms with higher projected earnings are more likely to pay higher dividends. Sustaining a high dividend is costly if future earnings are weak, thus paying a high dividend today "commits" the firm to keep that payout ratio. Good firms will not have problems doing so, whereas "bad" firms will have troubles, and need to reduce dividends in the future. Therefore, a dividend increase works as a credible signal of financial strength, while a cut is seen as negative news about future financial performance. During a second survey made by Brav, Graham, Harvey & Michaely (2005) almost 400 financial executives were interviewed, along with an additional 23 in-depth interviews, to understand the factors that influenced payout and buyback decisions. Their methodology combined qualitative insights with quantitative survey analysis, allowing them to evaluate managerial reasoning behind payout policies. Their findings demonstrated that keeping the dividend level constant was one of the main targets. As in Lintner (1956), perceived stability of future earnings was still affecting dividend policies, even though with a weaker link between dividends and earnings. Thus, this study reinforced the idea of dividends as a strategic and costly signal.

Another notable contribution comes from DeAngelo, DeAngelo, and Skinner (1999), who investigated the historical decline in the use of special dividends and what that implied for the signaling hypothesis. They analyzed over 10,000 special dividend payments by NYSE firms from 1926 to 1995, and found that, most of these, were issued by firms that paid specials repeatedly and predictably, often in over 90% of years between their first and last special dividend. This repetitive behavior diluted the unique informational content of specials, leading investors to treat them as substitutes for regular dividends. Their findings suggest that for dividends to be effective signals, they must convey *distinct* and *unexpected* information. Firms gradually abandoned special dividends in favor of regular increases, simplifying their payout structures. Importantly, when special dividends disappeared, firms tended to preserve the earnings-to-dividend relation by shifting toward more frequent regular dividend hikes. This shift reflects an evolution in signaling practice, where clarity and simplicity in dividend policy were prioritized to maintain credibility with investors.

Next, I looked for more recent studies supporting the signal role of dividend.

Baker, M., Mendel, B., & Wurgler, J. (2016) showed that a dividend signal approach is needed for managers to signal firm strength to investors. In particular, the latter are loss averse to dividend reductions relative to the reference point set by prior dividends. Hence managers with strong (cash) earnings differentiate themselves by giving strong dividends and, at the same time, retaining enough earnings not to fall short of the same level in the next period. Soltes & Skinner (2011) investigated the informative power of dividends about the quality of earnings. By confirming and expanding DeAngelo et al. (1992), firms reporting losses seldom pay dividends and the ones that paid dividends were unlikely to report losses in the future, especially if considering the quality of the earnings. Specifically, adjusting the earnings for special elements, they found that dividend payers report losses only 5% of the time. These results perfectly fit with the theory which states that managers are reluctant to reduce dividends and pay them only if they are confident to be consistent over time. By estimating regressions that predict future earnings on current earnings, conditioning on payout policies, they found that dividend-payers have higher quality earnings. Overall, they demonstrated that dividends are informative about earnings quality.

More recently, Ham, Kaplan, and Leary (2020) revisited the predictive value of dividend announcements using enhanced methodologies. Their study, published in the Journal of Financial Economics, examined whether dividends convey information about future earnings by carefully designing their event window to avoid capturing earnings already known at the time of the announcement. They employed multiple measures of future profitability, including gross profit and adjusted net income, and controlled for non-linearity in the size of dividend changes. Their findings indicate that dividend increases are associated with significant increases in future earnings up to three years after the announcement, with the strongest effects in the first year. The study also found that analysts revise their forecasts in the direction of dividend news, reinforcing the market's interpretation of such announcements as informative. These results challenge earlier literature that found little support for dividend-based signaling and underscore the importance of methodological precision when evaluating informational content. Further expanding on the signaling theory, Harford (2000) conducted a comparative study of dividend increases and share repurchases to assess their relative information content regarding the permanence of cash flows. Their research, published in the Journal of Financial Economics, employed regression analyses across firms that used either method of payout. They concluded that dividend increases are associated with more permanent improvements in cash flows than repurchases, strengthening the claim that dividends serve as more credible signals of long-term financial health.

In a more theoretical and empirical blend, Fuller (2003) explored how the presence of informed trading affects the credibility of dividend signals. Published in the Journal of Corporate Finance, this study showed that when informed traders are active in the market, the ability of dividends to credibly signal private information weakens. This could suggest that dividend signals are most effective in markets with lower levels of information asymmetry or where other signaling mechanisms are absent.

Karpavičius (2014) offered a nuanced discussion on the rigidity and relevance of dividends in signaling. He argued that consistent dividend payment, especially when adjusted gradually, help build managerial credibility and signal earnings stability. His findings suggest that dividend smoothing is not just a by-product of managerial conservatism, but a purposeful signaling mechanism designed to communicate reliable performance to investors. In contrast to the Modigliani-Miller theory, firm value does depend on payout policy.

Li and Lie (2006) extended Baker and Wurgler's catering theory, adding an important behavioral angle to the discussion, and that is the increasing and decreasing of existing dividends scenario. Their study found that dividend changes often reflect managers' attempts to meet shifting investor preferences rather than purely signaling fundamentals. This finding does not reject the signaling hypothesis but qualifies it, indicating that dividends may sometimes serve as a response to demand-side pressures.

On the other hand, many empirical studies find poor evidence of the dividend effect. For instance, DeAngelo, DeAngelo & Skinner (1996) studied the signaling effect of 145 NYSE Firms whose annual earnings declined after nine or more years of growth. The study found no support for the hypothesis that dividend decisions help predict firms with better future earnings. On the same page, Benartzi, Michaely & Thaler (1997) investigated the information power of dividend changes for future earnings and found limited support for it. They implemented an event study methodology and cross-sectional regression analysis to assess whether dividend increases predicted positive future earnings. Their results showed that although dividend increases often followed earnings increases in the previous year, they did not reliably predict further earnings growth. This suggested that dividends are more reflective of past performance than future expectations. Fama and French (2001) conducted a long-term analysis on the use of dividends and found that the proportion of firms paying dividends fell from 66.5% in 1978 to 20.8% in 1999. This was probably due to the new characteristics of the publicly traded firms, leaning more towards a smaller size, and with strong growth opportunities. Moreover, regardless of their size, they found a general shift in the payout policy: firms had become less likely to pay dividends. The dividend was no longer used as a signal.

2.2 Market Reactions to Dividend Changes

Market reactions to dividend changes are a critical test of the signaling hypothesis. If dividend announcements convey private information, they should induce price reactions. The early literature laid the foundation for this question.

One of the first research comes from Pettit (1972), published in the *Journal of Finance*. Using monthly data from a set of 625 NYSE traded firms, he selected announcement dates of dividend changes from January 1964 to June 1968. By constructing abnormal return metrics around announcement dates, he found out that stock prices systematically increased after dividend increases and declined following dividend cuts or omissions. This early piece of literature supports the idea that dividends convey new and reliable information to the market. Next, another early and influential contribution comes from Charest (1978), who published his findings in the *Journal of Financial Economics*. Using event-study methodology on NYSE-listed firms, Charest documented that dividend increases lead to significant positive abnormal returns, suggesting that dividend announcements are interpreted by the market as informative. His study supports the semi-strong form of market efficiency and demonstrates that dividend changes are rapidly integrated into prices.

Following this, Healy and Palepu (1988) in the *Journal of Financial Economics* focused specifically on dividend initiations and omissions. Their study used event-study methodology to measure market reactions over a short event window surrounding these announcements. They found out that dividend initiations led to statistically significant positive abnormal returns, while omissions triggered negative reactions. The authors also documented that dividend initiations tended to precede earnings increases, while omissions anticipated earnings decline. These results showed that investors interpreted announcements of dividend changes as a change in the management's forecasts for projected earnings.

A deeper and more comprehensive analysis came from Michaely, Thaler, and Womack (1995) in the *Journal of Finance*. They examined both the short-term announcement effects and the long-term post-event stock price behavior associated with dividend initiations and omissions. Using a large dataset of NYSE and AMEX firms from 1964 to 1988, they found significant stock price increases on initiation and decreases on omission dates. More importantly, their analysis documented a phenomenon of post-announcement drift, where the market continued to adjust to dividend news well beyond the announcement date. This pattern suggested a degree of underreaction and was interpreted as evidence that dividend changes provide lasting, informative signals about firm fundamentals.

Again, Fuller (2003) in the *Journal of Corporate Finance*, introduced a dual theoretical and empirical examination of how informed trading interacts with dividend signaling. Using a sample of dividend-paying firms from the late 1990s and employing cross-sectional regressions, Fuller demonstrated that when insider or informed trading activity is high, the market's reaction to dividend announcements diminishes. This finding implies that dividend signals are most effective in environments where alternative sources of private information are limited.

Lee and Mauck (2016) focused on dividend initiations and increases and their effect on idiosyncratic volatility. Using U.S. firm-level panel data from 1990 to 2013 and fixed effects regressions, they found that these events led to statistically significant reductions in volatility, implying that investors view dividend increases as signals of reduced uncertainty.

Nevertheless, not all empirical studies find uniformly strong effects.

Lang and Litzenberger (1989), in their *Journal of Financial Economics* paper, investigated how dividend announcements impact stock prices under different firm characteristics. Their empirical strategy involved classifying firms by investment opportunities and analyzing CARs across these subsamples. The study found that high-growth firms exhibited muted reactions to dividend increases, whereas low-growth firms (those with fewer profitable reinvestment opportunities) showed stronger positive reactions. This finding aligned more with the free cash flow hypothesis, suggesting that dividend increases might signal fewer agency problems than with signaling of higher earnings per se.

Lee and Mauck (2016) explored how dividend initiations and increases affect idiosyncratic volatility. They found that volatility decreases following such announcements, which implies greater investor consensus and supports the signaling interpretation. Gebka (2019) offered a behavioral finance perspective by analyzing asymmetric market reactions to dividend increases and decreases. He found that investors tend to overreact to dividend cuts relative to increases, often in an irrational manner, especially when payout costs are high. This finding challenges the purely rationalist view of dividend signaling and suggests a psychological asymmetry in investor interpretation. Finally, Asem (2023) contributed to the most recent wave of literature by analyzing price reactions to particularly large dividend increases. His findings, based on short-term abnormal returns, show that large increases do not always yield proportionately large positive returns, hinting at diminishing marginal signaling effects or market skepticism toward excessively large payouts.

Collectively, this rich literature demonstrates a spectrum of findings. Early empirical works provided strong support for the informational value of dividend changes. However, more recent studies offer a more nuanced picture, often emphasizing alternative interpretations like maturity signaling, earnings stability, or agency motivations. The complexity of dividend policy and its market perception underscores the need for careful contextual analysis in interpreting firm payout decisions.

2.3 Dividend Policies During Crises

The COVID-19 pandemic presented an unprecedented global economic shock, sharply disrupting firm revenues, capital markets, and macroeconomic stability. In contrast to prior financial crises, the pandemic's impact was widespread across sectors and countries, simultaneously introducing demand and supply-side shocks. This section synthesizes recent empirical evidence on how firms responded to the crisis in terms of dividend policy, particularly whether they cut or maintained payouts in response to these shocks, and whether decisions aligned with signaling or financial constraint motives.

2.3.1 Widespread Dividend Cuts and Suspensions

The early wave of the pandemic saw a significant wave of dividend suspensions and reductions. Pettenuzzo, Sabbatucci, and Timmermann (2023) conducted a large-scale empirical investigation of U.S. firms during 2020 and found that corporations saved approximately $29 billion via suspensions and $56.5 billion through reductions, far exceeding the $36.4 billion distributed through increases. Their methodology employed event-study techniques and aggregate payout analysis, concluding that firms prioritized liquidity hoarding and internal cash flow stability over distribution, with capital preservation being a dominant motive.

Similarly, Krieger, Mauck, and Pruitt (2021) reported that by mid-2020, over 800 U.S. public companies, including many in the S&P 500, had suspended or slashed dividends. This rapid response was explained through firm-level analysis, suggesting that managements reacted defensively to unprecedented earnings uncertainty. However, the authors also noted that many firms delayed cuts as long as possible, reinforcing the idea that dividends still carry reputational significance.

H. Ali (2022) extended the geographical scope by analyzing G-12 economies using a logistic regression approach on 8,889 firm-year observations. The findings confirmed that profitability, leverage, and firm size were key determinants of payout resilience. Nevertheless, even among profitable firms, the incidence of dividend cuts surged, indicating that financial constraints and macro uncertainty overrule traditional dividend signaling concerns for many firms.

Ntantamis and Zhou (2022), using panel data across G-7 countries, demonstrated that firms with low pre-crisis cash holdings were significantly more likely to reduce dividends. The authors highlighted the role of cash buffers as both liquidity tools and signaling mechanisms, showing that capital-constrained firms abandoned payout norms when external finance became scarce.

From a behavioral finance lens, Alves, Gietzmann, and Jorgensen (2021) analyzed S&P 1500 companies and found a significant correlation between dividend suspensions and voluntary CEO pay cuts. Their results suggest that CEO pay cuts were used to signal alignment with shareholders and to reduce the reputational cost of dividend reductions, an implicit recognition of the stigma still attached to payout cuts.

S. Liang et Al. (2023) with *Dividend Payouts Under a Societal Crisis* examined firms in China's A-share market and found that dividend reductions were primarily driven by liquidity constraints and elevated debt ratios, rather than any deliberate signaling strategy. Their regression models showed that constrained firms had significantly higher probability of suspending dividends, offering further evidence that capital preservation motives dominated during the pandemic.

2.3.2 Dividend Stability and Signaling Behavior

Despite the dominant trend of dividend suspensions and reductions during the COVID-19 pandemic, a subset of firms exhibited payout resilience, some of them even modestly increasing dividends. These firms were generally characterized by strong balance sheets, conservative financial policies, or ownership structures that incentivized signaling behavior.

Back to Ntantamis and Zhou (2022), they demonstrated on the other hand, that companies with substantial pre-crisis cash holdings were not only better positioned to preserve dividend policies but, in some cases, even increased payouts. Their panel data regressions revealed that liquidity served a dual purpose: enabling both financial stability and communicative signaling to investors. In particular, North American and Japanese firms were more likely to exhibit this form of payout resilience, in contrast to their European counterparts.

Complementing these macro-level findings, Gosain, Kashiramka, and Chaudhry (2024) provided firm-level evidence from India showing that promoter-owned firms, characterized by concentrated ownership, were more inclined to maintain or modestly increase dividends during the pandemic. Their results, drawn from fixed-effects regressions over crisis-year financials, suggest that such firms leveraged dividends to mitigate agency conflicts and reinforce credibility with minority shareholders. By sustaining dividend flows even when profitability weakened, these companies appeared to use payout policy as a governance mechanism to reassure external investors.

Collectively, these studies suggest that while dividend reductions dominated the global corporate landscape during COVID-19, dividends increase, albeit limited and selective, did occur. These increases were not indiscriminate, but rather reflective of firms with financial robustness, strategic signaling intent, or agency-mitigating ownership structures. This differentiated response underscores the heterogeneity in corporate dividend policy under crisis conditions, shaped by both internal firm characteristics and broader institutional contexts.

2.3.3 Role of Governance, Ownership, and Ideology

Beyond firm fundamentals, ideological and governance factors also shaped payout decisions during the pandemic. Bayat, Goergen, Koutroumpis, and Wei (2024) investigated the political ideology of CEOs and its impact on payout and labor decisions during COVID-19. Using CEO-level ideological proxies and firm outcomes, they found that right-leaning CEOs were more likely to preserve dividends while reducing labor costs, while left-leaning CEOs tended to cut dividends while maintaining employment. This heterogeneity highlights that dividend policy, particularly in crises, can reflect not only financial constraints but also managerial preferences and stakeholder priorities.

2.3.4 Summary

In contrast to the 2007–2009 financial crisis where banks were reluctant to cut dividends, the COVID-19 pandemic prompted a more rapid and widespread reduction in payouts across global firms. Liquidity constraints, macro uncertainty, and limited access to capital markets drove this shift. However, a subset of firms, especially those with high cash holdings, strong governance, or strategic signaling motives, continued paying dividends to signal resilience. Ownership structure, ideological orientation, and executive pay alignment also shaped the diversity of payout responses. Together, all of these studies underscore that dividend policy during COVID-19 was not monolithic, but instead reflected a complex balancing of financial constraints, reputational signaling, and stakeholder strategy in a uncertain environment.

2.4 Determinants of Dividend Payout Policies

The academic literature provides a comprehensive array of factors that influence firms' dividend payout decisions. These determinants can mainly be clustered into profitability, liquidity, leverage, firm size, risk, and firm maturity. This section synthesizes key empirical findings, describing each study's objectives and conclusions in a clear and structured manner.

Profitability emerges as one of the most consistent determinants of dividend payout policies. Getting back to Lintner (1956), in his seminal study emphasized the centrality of net earnings, observing that managers target stable dividends and adjust payouts gradually in response to earnings changes. This foundational finding was reinforced by Freeman et al. (1982), who used return on equity (ROE) as a proxy for profitability and confirmed its significant positive relationship with dividends. Fama and French (2001) contributed further by identifying that dividend-paying firms tend to be more profitable and larger, while companies with strong growth prospects pay fewer dividends. Aivazian et al. (2003), focusing on emerging markets, validated that profitability and ROE are positively correlated with payout ratios. This positive relationship is also evident in the study by DeAngelo, DeAngelo, and Stulz (2006), who revealed that firms with a greater proportion of earned capital are significantly more likely to issue dividends, even when controlling for size, leverage, cash reserves, and growth. Finally, according to the signaling theory (Bhattacharya, 1979; John and Williams, 1985; Miller and Rock,1985; Chang & Rhee, 1990; Ho, 2003; Aivazian et al., 2003), firms that pay dividends are the ones that want to credibly signal their strength (thus, their profitability).

Liquidity also features prominently in dividend policy literature, though findings are more nuanced. Jensen (1986) argued that firms with excess liquidity face higher agency costs, which could be mitigated by paying dividends. Alli et al. (1993) corroborated this with a factorial analysis underscoring liquidity's role in stable dividend payments. Similarly, Myers and Bacon (2001), along with Ho (2003), demonstrated that liquidity positively influences dividend policy. On the other hand, Banerjee et al. (2007) contributed with a liquidity-risk framework using turnover ratios, bid-ask spreads, and trading volumes, and found that firms with greater illiquidity actually show higher propensities to pay dividends. Bulan et al. (2007) complemented this by revealing that illiquid firms are more likely to initiate dividends, although liquidity changes themselves were not predictive. In Ahmad and Wardani (2014), although they found a positive relationship between dividends and profitability and firms' size, they introduced contrasting evidence from Indonesia, signaling a significant negative relationship between liquidity and dividend payouts.

The relationship between **leverage** and dividends remains contentious. Theoretical contributions from Modigliani and Miller (1961) suggest that debt may substitute for dividends in signaling firm quality, while the pecking order theory by Myers and Majluf (1984) indicates that highly leveraged firms prefer internal financing, thus limiting dividends. Empirical findings mirror this theoretical divide. Rozeff (1982) introduced an agency cost perspective, showing that while leverage can discipline management, it may also restrict dividend payments. Naceur et al. (2005) found that firms with high leverage levels generally exhibit lower dividend yields. Again, another conclusion of Ahmad and Wardani (2014), was reinforcing the inverse relationship, observing that Indonesian firms with higher debt levels tended to pay fewer dividends.

Firm size has repeatedly shown a positive influence on dividend payout policies. Fama and French (2001) and Aivazian et al. (2003) found that larger firms, due to reduced information asymmetry and better access to external capital, are more inclined to pay dividends. Barros et al. (2020) argue that firms with greater scale and stable growth tend to focus more on shareholder compensation. Earlier contributions from Machfoedz (1999) suggested that smaller firms, with fewer shareholders, retain profits for operational growth, whereas larger firms tend to share profits with investors by delivering dividends. Ranti (2013), focusing on Nigerian firms, found size to be a robust determinant due to greater trust and market access. Other studies, including Dickens et al. (2002), Lloyd et al. (1985), Jensen et al. (1992), Redding (1997), Holder et al. (1998), and Sawicki (2005), consistently highlight that firm size positively correlates with dividend payouts.

Finally, the **maturity** of a firm is closely tied to its dividend behavior. Fama and French (2001) found that firms with both current high profitability and low-growth rates (i.e. mature firms) tend to pay dividends. On the same page, DeAngelo et al. (2006) linked higher levels of retained earnings to firm maturity, noting that mature firms face stronger pressure to pay dividends due to declining investment opportunities and rising agency costs of cash retention. Bulan, Subramanian, and Tanlu (2007) examined dividend initiators and concluded that such firms typically exhibit characteristics of maturity, including larger size, higher profitability, and fewer growth opportunities compared to non-initiators.

In sum, the academic consensus identifies profitability, firm size, and maturity as strong positive determinants of dividend payouts. Conversely, leverage and risk act as constraints, discouraging distributions to shareholders. Liquidity, while generally seen as a facilitator, displays varying effects depending on the institutional and geographical context. Together, these studies provide a robust framework for understanding corporate dividend behavior across diverse markets and economic conditions.

3. Data and Methodology

The aim of this research is to compare the determinants of the dividend payout policies across firms and between the Global Financial Crisis and the COVID-19. To achieve this analysis, both market (dividends) and accounting information were needed. In this section I am going to show how I outlined my work, from getting the raw data, to formatting, sorting and merging them, to finally performing the regressions models.

3.1 Data Sources

For the scope of the research, I mainly focused on getting dividends information and balance sheets information as annual fundamentals and financial ratios. To get these pieces of data, I used *Wharton Research Data Services*[1] (WRDS), which gave me access to *Center for Research in Security Prices* (CRSP) and *Compustat* databases.

3.1.1. CRSP Stock Events - Dividends

CRSP Stock / Events – Dividends is a CRSP section that includes the most comprehensive distribution information available, as well as market indices and total return calculations. What were the steps to get the data? First, I selected the *Ex-Distribution Date Range* (EXDT) as 2006-12 to 2021-12, since I wanted to include both the crises as well as the "neutral period" in between. Next, I chose to search for the entire database of records as it allowed me to get the most data available. Then, for step 3, I ticked only *Dividend* as Distribution code. Finally, step 4 was choosing the query variables, and I went for the following ones:

- **(permno)** CRSP Permanent Issue Number
  - Is a unique five-digit permanent identifier assigned by CRSP to each security in the file. Unlike CUSIP, TICKER, and COMNAM, the PERMNO neither changes during an issue's trading history, nor is reassigned after an issue ceases trading.
- **(divamt)** Dividend Cash Amount
  - Is the US dollar value per share of distributions.
- **(dclrdt)** Declaration Date
  - Is the date on which the board of directors declares a distribution.
- **(rcrddt)** Record Date
  - Is the date on which the stockholder must be registered as holder of record on the transfer of records of the company, to receive a distribution directly from the company.
- **(paydt)** Payment Date
  - Is the date upon which dividend checks are mailed.

[1] https://wrds-www.wharton.upenn.edu/

3.1.2 Compustat Financial Ratios

Compustat Financial Ratios is a WRDS Suite that delivers over 70 pre-calculated financial ratios for all U.S. companies across different categories such as Valuation, Liquidity, Profitability, etc. It provides monthly time series data per company. Aligned with the first dataset I chose to get data from the end of 2006 to the end of 2021. Then, I searched for the entire database. Finally, using GVKEY as firm identifier, I decided to download the following variables:

- **(permno)** PERMNO
- **(gvkey)** Global Company Key – GVKEY
- **(public_date)** Publication Date of the ratios to the public
- **(adate)** Fiscal Year to which the information pertains
- **(qdate)** Fiscal Quarter to which the information pertains
- **(dpr)** Dividend Payout Ratio
- **(gpm)** Gross Profit Margin
- **(npm)** Net Profit Margin
- **(cfm)** Cash Flow Margin
- **(roa)** Return on Assets
- **(roe)** Return on Equity
- **(roce)** Return on Capital Employed
- **(de_ratio)** Total Debt/Equity
- **(lt_debt)** Long-term debt over total liabilities
- **(dltt_be)** Long-term debt to book equity
- **(da_ratio)** Debt to Assets ratio
- **(debt_ebitda)** Debt to EBITDA ratio
- **(curr_ratio)** Current Ratio
- **(quick_ratio)** Quick Ratio
- **(intcov_ratio)** Interest coverage ratio
- **(icapt)** Invested Capital
- **(bm)** Book-to-market ratio
- **(ptb)** Price to book ratio
- **(evm)** Enterprise value multiple

3.1.3 Compustat Fundamentals Annual

Compustat Fundamentals Annual is a Compustat section that allows to retrieve the Annual fundamentals for US, Canadian, and some foreign firms. I choose to focus only on US firms. The procedure is the same here: I selected the data range (as data year – Fiscal) from 2006-09 to 2021-12, using GVKEY as identifier, and searched for the entire database. Next, I decided to retrieve the following variables:

- **(conm)** Company Name
- **(sic)** Standard Industry Classification Code
- **(apdedate)** Actual Period End date
- **(fyear)** Data Year – Fiscal
    - It represents the fiscal year of the current fiscal year-end month. For instance, if the current fiscal year-end month falls in January through May, this item is the current calendar year minus 1 year.
- **(ni)** Net Income (Loss)
- **(at)** Assets – Total
- **(act)** Current Assets - Total
- **(dltt)** Long-Term Debt – Total
- **(lct)** Current Liabilities – Total
- **(ceq)** Common/Ordinary Equity – Total
- **(icapt)** Invested Capital – Total
- **(lt)** Liabilities - total
- **(ch)** Cash
- **(check)** Cash and Cash Equivalents
- **(revt)** Revenue – total

3.1.4 CRSP/Compustat Link History (CCM converting Table)

In order to make a final dataset, which is the result of the three above, a merge was imperative. But the issue lies within the different identifiers used between CRSP and Compustat. The first mainly uses PERMNO to track stock issues, and PERMCO to track companies, whereas the latter goes with GVKEY for companies, and a combination of GVKEY and IID to track securities. Even though the TICKER could have been a match-key for both, the problem lies with the fact that the ticker is a unique combination of letters and numbers that represents just a particular share. Very often companies issue different classes of shares (meaning multiple tickers referring to the same single firm) or they simply replace one class with another one. For this reason, using the ticker could have led to mismatching in time, and thus a different approach was needed. Fortunately, there's a CRSP product, called *CRSP/Compustat Merged Database (CCM)*, which is a database structured so that Compustat items can be accessed using CRSP's PERMNO and PERMCO identifiers in addition to Compustat's GVKEY. This linking table provides a link between CRSP stock data and Compustat fundamental data. To retrieve it, I used WRDS and simply downloaded it with the entire database. A preview of what the table looks like is attached below. This table has been a requirement to move forward with the merge.

Table 1 Extract of CCM database

GVKEY	LIID	LINKTYPE	PERMNO	PERMCO	LINKDT	LINKENDDT	conm
1000	1	LU	25881	23369	13/11/1970	30/06/1978	A & E PLASTIK PAK INC
1001	1	LU	10015	6398	20/09/1983	31/07/1986	A & M FOOD SERVICES INC
1002	1	LC	10023	22159	14/12/1972	05/06/1973	AAI CORP
1003	1	LU	10031	6672	07/12/1983	16/08/1989	A.A. IMPORTING CO INC
1004	1	LU	54594	20000	24/04/1972	E	AAR CORP
1005	1	LU	61903	11	31/01/1973	31/01/1983	A.B.A. INDUSTRIES INC

3.2 Merging to get the final data frame

In this subsection I am going to describe which final steps I followed in order to prepare the raw databases to merge into a unique one.

3.2.1 CRSP Stock Events – Dividends adjustments

Cleaning and normalizing dividends events was the first step. I dropped missing observations (NA) among these crucial variables:

- **DCLRDT** Declaration Date of the dividend by the board of directors.
- **PAYDT** Payment Date of the dividend.
- **DIVAMT** Dividend Amount. Here, I excluded DIAVMT = 0 values (which represented non-cash distributions, out of the scope of this work).

Next, I made sure that the dates variables such as DCLRDT and PAYDT were formatted correctly. Then, a sanity filter that I did was to exclude all the events with an Announcement – Payment time span greater than 11 months. Having distributions events with such big-time spans could have led to economically incoherent timing with an announcement-driven analysis. As the market reaction is tied to the announcement date, if the payment is then pushed far away in time, then the conditions' firms by the announcement date could change, and it gets difficult to understand the real determinants of the payout.

Finally, I got to attach firm IDs to the events. Using the CCM table I performed an interval join: for a given PERMNO, I matched the event's PAYDT within the CCM link window (LINKDT, LINKENDDT), and returned GVKEY, PERMCO, CONM on each event. The rationale behind this chunk of code was to get the right GVKEY used at that specific payment date. If the linking was still active (LINKENDDT = "E"), then the "E" was replaced by the actual date at that day.

3.2.2 Compustat adjustments

The starting database *Compustat Financial Ratios* included most of the financial ratios available, but very often it was missing values. For this reason, I performed a left-join from the *Compustat Fundamentals Annual* database to get all the primitives values behind each ratio computation. For instance, if the profitability ratio Return on Assets (roa) is computed such as $roa = \frac{Net\ Income}{Total\ Assets}$, I merged net income (ni) and total assets (at) values for each row. Whatever a ratio in the first database was missed, I then would have replaced it by computing it manually by its primitives. This loop code had given me the chance of filling out missing values whenever it was possible, so that I could lose the least amount of observations possible. Next, I dropped all the rows that contained missing values at the same time between all the targeted ratios. For example, if roa = roe = npm = gpm = … = 0, then I'd get rid of that observation row.

3.2.3 Final Dataset

After having cleaned, sorted, and added the complementary ID to each database, I then proceeded to merge CRSP Stock Events – Dividends and Compustat Financial Ratios databases. The primary rule was to do a rolling join on the same GVKEY, PERMNO pair to the latest *public_date* close to the declaration date. The rationale was to get, for each dividend observation, the latest financial information of that firm available on the declaration date, with a time span of ±60 days of DCLRDT. For instance, if a dividend was declared on March the 1^{st}, I retrieved the closest financial data available within the data range [March 1^{st} – 60 days; March 1^{st} + 60 days]. With this trick it was feasible to consider the latest possible financial information available with which the board decided on the dividend policy. The final database was hence ready to be used, containing both dividends and accounting information.

3.3 Description of the final dataset

3.3.1 Variables check, creations and transformations

Once the merge was concluded, it was time to fix the database, by looking at each variable, and creating new ones when needed. Here's a quick summary of what variables I looked at, which ones I created, and which ones I transformed:

1. **Dividend Cut binary** (div_cut) is a dummy equal to 1 if the dividend amount (DIVAMT) was lower than the previous year, or 0 elsewhere.
2. **Three-level Crisis** (Crisis) is a dummy variable which identifies the time periods in the sample:
    a. **"GFC"** when the payment date (PAYDT) was in the [2008-09-01; 2009-12-31] time range. I picked this time span to consider the climax of the crisis with the bankruptcy of Lehman Brothers.
    b. **"Covid"** when PAYDT was in the [2020-01-30; 2021-12-31] time range. I decided to take into account the WHO declaration of global pandemic on March the 11th, and step 1 month back, and to conclude it at the end of the year 2021.
    c. **"Neutral"** whenever the PAYDT was different from the two conditions above. This resulted in the period in between the two crises.
3. **High leverage dummy** (high_leverage), a variable =1 if the observed leverage was within the top 25% of the sample. This variable was then later not utilized for the final regressions, but I'm going to discuss this in the next chapter (3.4.3)
4. **Debt to equity ratio** (de_ratio) adjustments. The variable was distributed such that it had negative values and outliers. One can argue that the ratio could be negative in case the net financial position was negative, but that is not how Compustat computes the ratio. According to the database, the ratio is "…calculated by dividing its fiscal year end Total Long-Term Debt by its fiscal year end Total assets minus its Fiscal Year end total debt in Current Liabilities.". Thus, negative values were to be entirely dropped. On the next page I attach a summary of the *de_ratio* variable.

Table 2 Summary of de_ratio

Summary	**Min.**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
	-456.360	0.617	1.222	2.165	2.140	1268.890
Quantiles	**1%**	**2.5%**	**5%**	**95%**	**97.5%**	**99%**
	-8.500000	0.016000	0.153000	5.528000	8.894575	18.735000

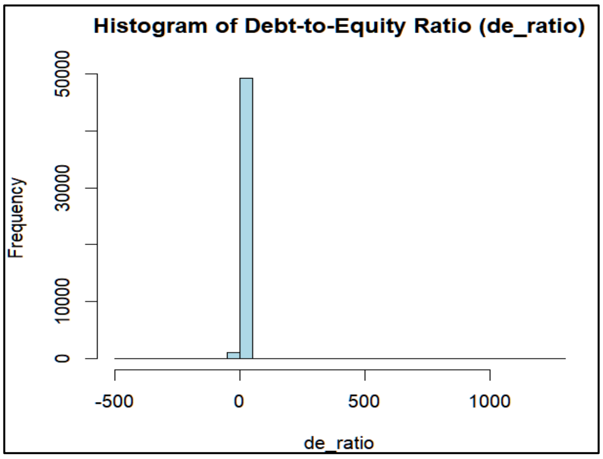

Figure 1 Histogram of de_ratio

By giving a look at this distribution, I decided to go for a winsorizing at a 2.5% level. With this technique, it was possible to not reduce the sample size, by artificially substituting extreme outliers. By winsorizing the distribution changed shape. This is what the new variable de_ratio_wins looked like after winsorizing at 2.5%.

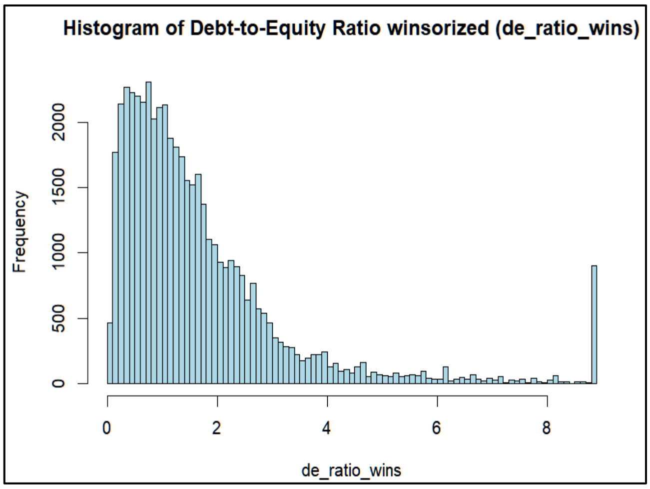

Figure 2 Histogram of de_ratio_wins

5. **Return on Assets** (roa)

   By looking at the variable distribution, the values seemed to be in a normal range, with no anomalies detected such as outliers. Thus, no change was made.

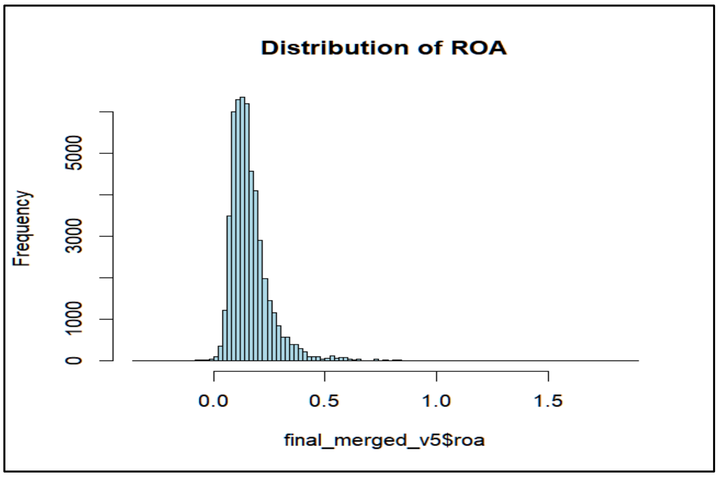

Figure 3 Distribution of roa

6. **Return on Equity** (roe)

The roe distribution looked average, except for a few outliers that needed to be dropped. Below I attach a summary table, and a quantile distribution.

Table 3 Summary of roe

Summary	**Min.**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
	-65.3636	0.0760	0.1270	0.1982	0.2040	228.4491
Quantiles	**1%**	**2.5%**	**97.5%**	**99%**		
	-0.8093	-0.0170	0.6880	1.3100		

As it's shown, the distribution interval at [1%; 99%] looked average. For this reason, I decided to trim at 1% level.

7. **Total Assets** (at)

The variable Total Assets represents the total value of assets reported on the Balance Sheet. Differently from the other variables, which are ratios, this one's unit is the million, and with such a heterogeneity in the sample, the distribution was right-skewed.

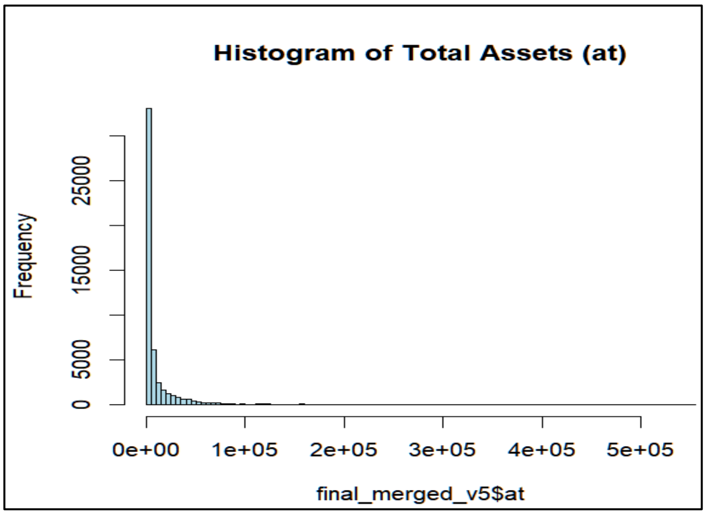

Figure 4 Histogram of at

In this case, a logarithmic transformation was applied, and it served as a metric for gauging the size and scale of a business. By applying this transformation to total assets, the impact of extreme values was mitigated, and comparisons between different companies' sizes made easier.

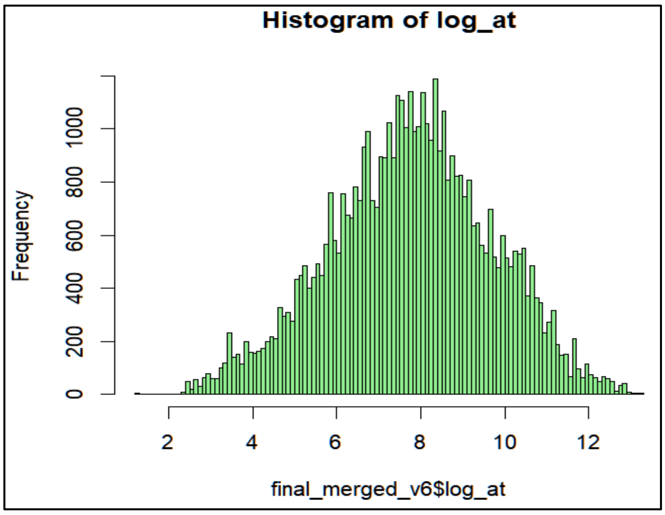

Figure 5 Histogram of log_at

8. **Quick ratio** (quick_ratio)

   The next variable is the quick ratio, computed as the sum of fiscal year end Cash and Equivalents (which represent cash and all securities readily transferable to cash) plus fiscal year end Total Receivables (which are claims against other collectible in money within one year) divided by fiscal year end Total Current Liabilities (which are liabilities due within one year). This ratio should normally range from 1 to 5 and never negative by construction. Below I attach the summary report of the variable as well as the quantile table and a boxplot, which gives a visual view of the outlier.

Table 4 Summary of quick_ratio

Summary	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
	0.093	0.872	1.281	1.756	1.931	168.366
Quantiles	**1%**	**2.5%**	**50%**	**97.5%**	**99%**	
	0.252	0.326	1.281	5.787	8.180	

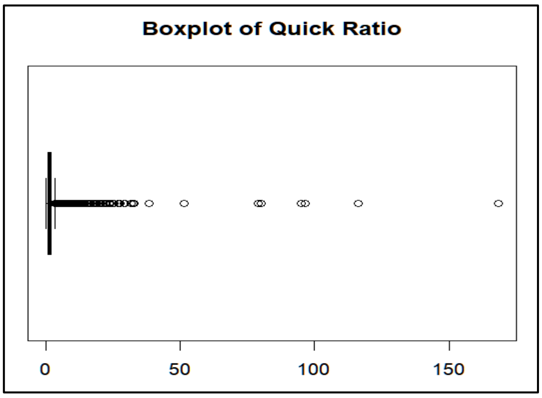

Figure 6 Boxplot of quick_ratio

For this reason, I decided to winsorize at a 0.5% level, and this is what the distribution looked like after (quick_ratio_wins).

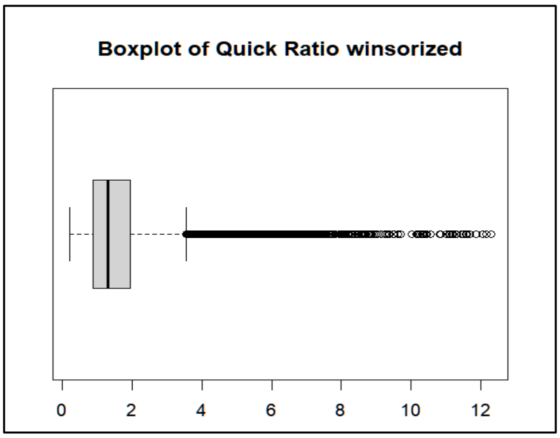

Figure 7 Boxplot of quick_ratio_wins

9. **Current ratio** (curr_ratio)

   This variable follows the same logic as the quick ratio, but it slightly differs as it is computed this way: "This concept is fiscal year end Current Assets - Total (which represents cash and other assets that in the next 12 months are expected to be realized or used in the production of revenue) divided by fiscal year end Current Liabilities - Total, which represents liabilities due within one year, including the current portion of long-term debt."

Table 5 Summary of curr_ratio

Summary	**Min.**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
	0.167	1.201	1.791	2.333	2.664	168.366
Quantiles	**1%**	**2.5%**	**50%**	**97.5%**	**99%**	
	0.4280	0.5477	1.7910	7.2570	10.2820	

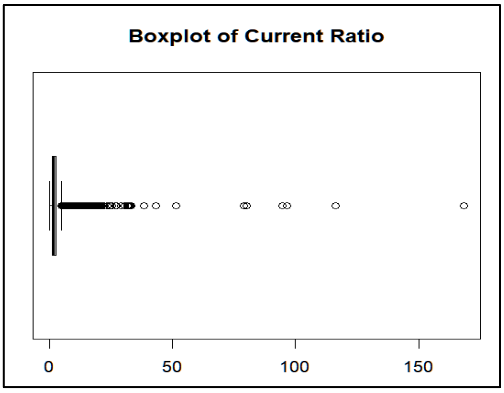

Figure 8 Boxplot of curr_ratio

On the same page, I decided to winsorize at a 0.5% level, and this is what the distribution looked like after (curr_ratio_wins).

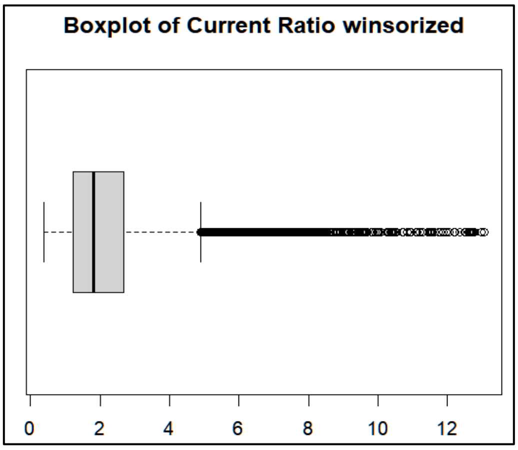

Figure 9 Boxplot of curr_ratio_wins

10. Dividend payout ratio (dpr)

This variable conveys information about the dividend payout, based on the amount of paid dividends and the net income. Complying with this logic, the dpr should be on the range [0;1], but sometimes a firm can pay dividends by using reserves and thus exceeding the amount of net income. Even if this is not something that happens often in real times, we can consider acceptable values slightly bigger than 1. Below I attach a summary table of what the variable looked like.

Table 6 Summary of dpr

Summary	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
	-1.0330	0.1940	0.3510	0.9443	0.6180	662.9010
Quantiles	**1%**	**2.5%**	**50%**	**97.5%**	**99%**	
	0.000	0.000	0.351	2.967	6.111	

I then decided to force the distribution to have a lower bound of 0 and an upper bound of 1, by creating a new variable *dpr_capped*. Below I attach the final boxplot of the new variable.

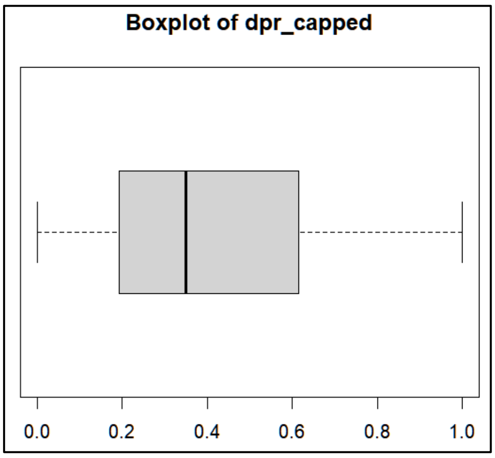

Figure 10 Boxplot of dpr_capped

11. Retention ratio (retention_ratio).

To adjust this variable, I used the new *dpr_capped* and forced it to be computed as $retention\_ratio = 1 - dpr\_capped$

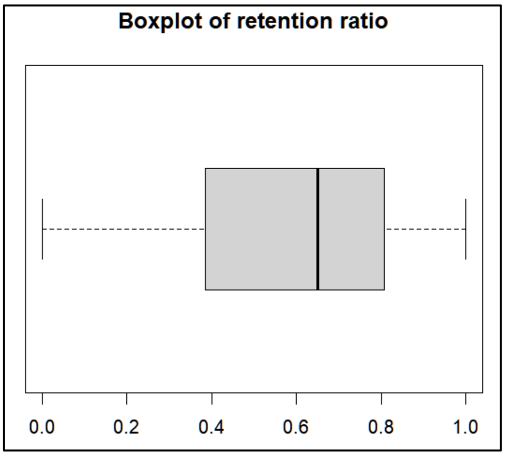

Figure 11 Boxplot of retention_ratio

12. Debt to Assets ratio (da_ratio)

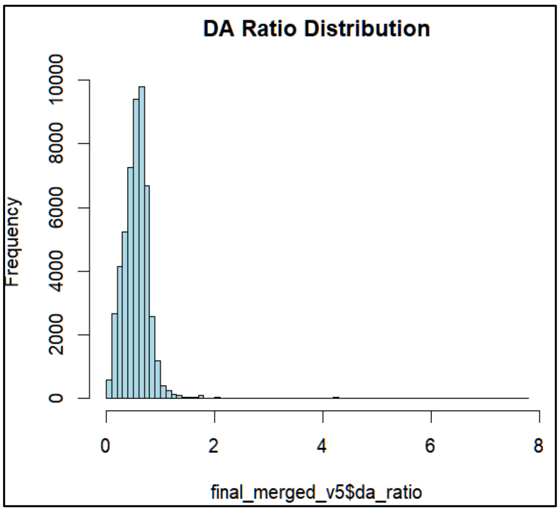

Figure 12 Distribution of da_ratio

An alternative to *de_ratio*, which is still a proxy for the leverage, is the debt to assets ratio, computed as the ratio between total liabilities (lt) and total assets (at). Below I attach the histogram and boxplot of this variable.

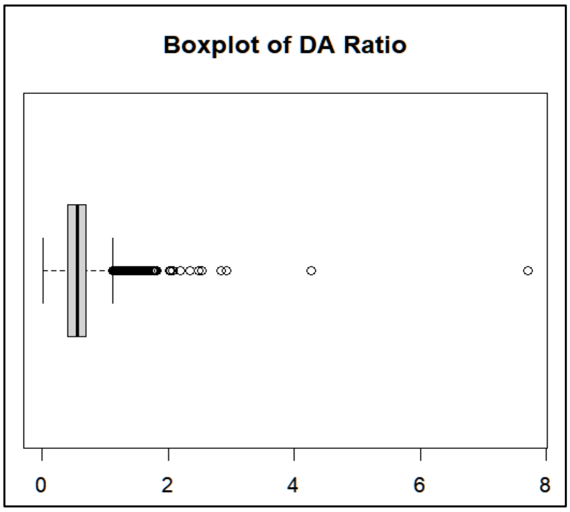

Figure 13 Boxplot of da_ratio

Having a ratio of debt over assets, values lower than 0 and greater than 1 made no sense and thus needed to be cut off. I proceeded to count how many observations I'd adjust. Given the number, I winsorized at a 0.5% level. Below I attach the boxplot of the winsorized variable.

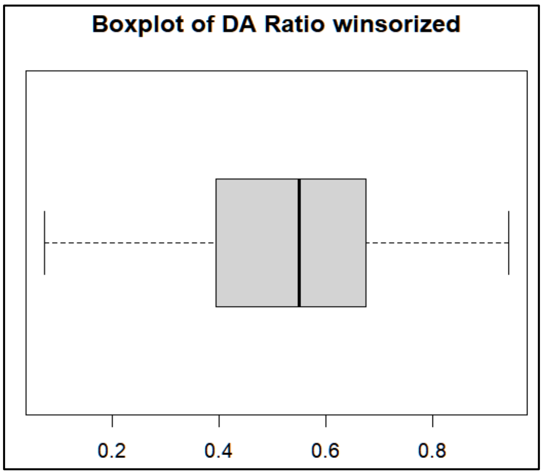

Figure 14 Boxplot of da_ratio_wins

3.3.2 Dataset dictionary

Finally, in this subsection I am attaching the dictionary of the final version of the database, containing all the transformed variables. It shows the variable name, its label, its source, a notes section and the units value.

Table 7 Dataset dictionary

Variable	Description	Source	Notes	Units
conm	Company name	Compustat	-	
GVKEY	Unique firm ID (Compustat)	Compustat	-	
PERMNO	Security ID (CRSP)	CRSP	-	
PERMCO	Company ID (CRSP)	CRSP	Can map to multiple PERMNOs	
apdedate	Actual period end date	Compustat	May differ from month-end	
qdate	Fiscal quarter end date	Compustat	-	

Variable	Description	Source	Notes	Units
public_date	Financial Ratios publication date	Compustat	-	
fyear	Fiscal year	Compustat	Fiscal year rules vary by end month	
sic	Standard Industry Classification code	Compustat	Used for industry matching	
DCLRDT	Dividend declaration date	CRSP Stock Events	Set to 0 if unavailable	
EXDT	Ex-distribution date	CRSP Stock Events	-	
RCRDDT	Record date	CRSP Stock Events	Date stockholder must be registered	
PAYDT	Dividend payment date	CRSP Stock Events	Set to last price date if missing	
DISTCD	CRSP Distribution Code	CRSP	Type of distribution	
DIVAMT	Dividend Cash amount (per share)	CRSP Stock Events	-	USD/share
at	Total assets	Compustat	Balance sheet	Millions
ch	Cash	Compustat	-	Millions

Variable	Description	Source	Notes	Units
dltt	Long-term debt	Compustat	-	Millions
lct	Current liabilities	Compustat	-	Millions
dvc	Cash dividends paid on common stock	Compustat	Declared dividends	Millions
ni	Net income	Compustat	Income statement	Millions
revt	Revenue (total)	Compustat	-	Millions
dvpsp_c	Dividends per share (Calendar pay date)	Compustat	Per share version of dvc	Units
dvpsp_f	Dividends per share (Fiscal pay date)	Compustat	-	Units
act	Current assets	Compustat	-	Millions
ceq	Common equity	Compustat	-	Millions
icapt	Invested capital	Compustat Ratios	US GAAP / IFRS definition	Millions
lt	Total liabilities	Compustat	-	Millions
bm	Book-to-market ratio	Derived (Calc)	CEQ / Market Cap	
evm	Enterprise value multiple	Derived (Calc)	-	
pe_op_basic	P/E ratio (price/operating	Compustat Ratios	-	

Variable	Description	Source	Notes	Units
	earnings excl. EI)			
ps	Price-to-sales ratio	Compustat Ratios	-	
npm	Net profit margin	Compustat Ratios	NI / Revenue	
cfm	Cash flow margin	Compustat Ratios	CFO / Revenue	
roce	Return on capital employed	Compustat Ratios	EBIT / Capital employed	
int_debt	Interest/Average Long-Term Debt	Derived	-	
int_totdebt	Interest/Average Total Debt	Derived	LT debt + ST debt	
cash_lt	Cash Balance over total liabilities	Derived	CH / LT	
debt_ebitda	Debt to EBITDA ratio	Compustat Ratios	Leverage indicator	
lt_debt	Long-term debt over total liabilities	Compustat Ratios	-	
lt_ppent	Total liabilities/Total Tangible Assets	Compustat Ratios	-	

Variable	Description	Source	Notes	Units
dltt_be	Long-term debt to book equity	Compustat Ratios	-	
intcov_ratio	Interest coverage ratio	Compustat Ratios	EBIT / Interest Expense	
quick_ratio	Quick ratio	Compustat Ratios	(CA - Inventories) / CL	
ptb	Price to book ratio	Compustat Ratios	Market Cap / CEQ	
dpr	Dividend payout ratio	Compustat Ratios	Dividends / Net Income	
gpm	Gross profit margin	Compustat Ratios	(Revenue - COGS) / Revenue	
roa	Return on assets	Compustat Ratios	NI / AT	
roe	Return on equity	Compustat Ratios	NI / CEQ	
de_ratio	Debt to equity ratio	Compustat Ratios	Total Debt / Equity	
curr_ratio	Current ratio	Compustat Ratios	CA / CL	
rect	Receivables total	Compustat	-	
chech	Cash and Cash Equivalents	Derived	CH / CEQ	

Variable	Description	Source	Notes	Units
da_ratio	Debt to assets ratio	Compustat Ratios	Total Debt / AT	
start_date	Start of CRSP–Compustat link	CCM link table	Sometimes duplicated	
end_date	End of CRSP–Compustat link	CCM link table	Sometimes duplicated	
i.start_date	Possibly duplicated from merging link table	CCM link table	-	
i.end_date	Possibly duplicated from merging link table	CCM link table	-	

3.4 Regression models

The empirical strategy of this study is built around two core econometric models, each addressing a specific dimension of corporate payout behavior during financial crises. These models explore different dependent variables and theoretical perspectives while maintaining consistency in the set of explanatory variables. The purpose of this approach is to test the resilience and strategic logic of dividend decisions under stress scenarios like the Global Financial Crisis (GFC) and the COVID-19 pandemic. On the next paragraphs, I am going to describe in detail why and how I structured a model, what issues I encountered in the process, what I did to address them, and what final conclusions I could take from that model.

3.4.1 Logit model

The first model aims to investigate the odds of a firm reducing its dividends in response to financial distress during crisis periods, by controlling for firms individual variables as discussed in 2.4. The dependent variable, div_cut, is a binary indicator equal to 1 if a firm paid a lower total annual dividend per share compared to the previous year, and 0 otherwise. Given the binary nature of the dependent variable, a logistic regression was the natural methodological choice.

The main explanatory variable of interest is the three-level factor Crisis, capturing whether the dividend payment occurred during the Global Financial Crisis (GFC), COVID-19 crisis, or outside any crisis period (Neutral). By setting the reference level as the Neutral period, it was possible to better visualize the effects of the crisis within the div_cut variable with respect to the "normal" periods.

The selection of control variables followed a stepwise approach aimed at balancing statistical robustness and economic interpretability. I ran several logit models and each one was evaluated according to three primary criteria: (i) the overall statistical significance of the model, assessed through the likelihood ratio test; (ii) the Akaike Information Criterion (AIC), used to measure model fit and penalize overfitting; and (iii) the individual significance of each regressor, with particular attention paid to the consistency and strength of coefficients across different models.

In addition to these statistical benchmarks, I adopted a conceptual framework that ensured coverage across key categories of firm-level financial indicators. Specifically, I sought to include at least one variable from each of the following groups: profitability ratios (e.g., return on assets or return on equity), liquidity ratios (e.g., current or quick ratio), leverage metrics (e.g., debt-to-equity or debt-to-EBITDA), and firm size (e.g., total assets). This ensured that the final model captured a broad spectrum of firm characteristics relevant to dividend policy decisions, without introducing excessive multicollinearity or redundant information. Below I attach the results of the models that I tested:

1. **M1**

$$\log\left(\frac{p(div\_cut=1)}{p(div\_cut=0)}\right)_{it} = \mathbf{-0.80 - 0.23} * Crisis_{covid_{it}} + \mathbf{0.36} * Crisis_{GFC_{it}} - \mathbf{0.31} * da\_ratio\_wins_{it} - \mathbf{0.14} * log(at)_{it} + \mathbf{0.43} * roa_{it} + \mathbf{0.82} * cfm_{it} + \mathbf{0.50} * Crisis_{covid_{it}} * da_{ratio_{wins_{it}}} - \mathbf{0.25} * Crisis_{GFC_{it}} * da\_ratio\_wins_{it}$$

(1) - M1 regression

2. **M2**

$$\log\left(\frac{p(div\_cut = 1)}{p(div\_cut = 0)}\right)_{it} = \mathbf{-0.87 + 0.03} * Crisis_{covid_{it}} + \mathbf{0.23} * Crisis_{GFC_{it}} + \mathbf{0.52} * roa_{it} + \mathbf{0.87} * cfm_{it} - \mathbf{0.16} * \log(at)_{it}$$

(2) - M2 regression

3. **M3**

$$\log\left(\frac{p(div\_cut = 1)}{p(div\_cut = 0)}\right)_{it} = \mathbf{-1.03 + 0.03} * Crisis_{covid_{it}} + \mathbf{0.24} * Crisis_{GFC_{it}} + \mathbf{0.85} * roa_{it} + \mathbf{0.03} * curr\_ratio\_wins_{it} + \mathbf{0.03} * debt\_ebitda_{it} - \mathbf{0.14} * log(at)_{it}$$

(3) - M3 regression

4. **M4**

$$\log\left(\frac{p(div\_cut = 1)}{p(div\_cut = 0)}\right)_{it} = \mathbf{-1.06 + 0.28} * Crisis\_adj_{covid_{it}} + \mathbf{0.06} * Crisis\_adj_{covid_{it}} + \mathbf{0.83} * roa_{it} + \mathbf{0.03} * curr\_ratio\_wins_{it} + \mathbf{0.03} * debt\_ebitda_{it} - \mathbf{0.14} * log(at)_{it}$$

(4) - M4 regression

Below I am attaching a summary table to confront all these models.

Table 8 Logit Models Comparison

Comparison of Logit Model Specifications

	M1	**M2**	**M3**	**M4**
(Intercept)	-0.80***	-0.87***	-1.03***	-1.06***
	(0.07)	(0.07)	(0.08)	(0.08)
Crisis[T.COVID (Jan 30 2020 – Dec 2021)]	-0.23	0.03	0.03	
	(0.13)	(0.04)	(0.05)	
Crisis[T.GFC (Sep 2008 – Dec 2009)]	0.36**	0.24***	0.24***	
	(0.12)	(0.05)	(0.05)	
da_ratio_wins	-0.31***			

Comparison of Logit Model Specifications

	M1	M2	M3	M4
	(0.09)			
log_at	-0.14^{***}	-0.16^{***}	-0.14^{***}	-0.14^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
roa	0.43^{**}	0.52^{***}	0.85^{***}	0.83^{***}
	(0.15)	(0.15)	(0.16)	(0.16)
cfm	0.82^{***}	0.87^{***}		
	(0.11)	(0.11)		
Crisis[T.COVID (Jan 30 2020 – Dec 2021)]:da_ratio_wins	0.50^{*}			
	(0.23)			
Crisis[T.GFC (Sep 2008 – Dec 2009)]:da_ratio_wins	-0.25			
	(0.23)			
curr_ratio_wins			0.03^{***}	0.03^{***}
			(0.01)	(0.01)
debt_ebitda			0.03^{***}	0.03^{***}
			(0.01)	(0.01)
Crisis_adj[T.GFC]				0.28^{***}
				(0.04)
Crisis_adj[T.COVID]				0.06
				(0.05)
AIC	34997.77	35009.76	34988.09	34964.83
BIC	35075.99	35061.91	35048.91	35025.66
Log Likelihood	-17489.89	-17498.88	-17487.04	-17475.42
Deviance	34979.77	34997.76	34974.09	34950.83
Num. obs.	43952	43952	43891	43891

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Model M3 was favored due to its superior performance in terms of AIC (lowest among alternatives) as well as the strong global significance of the model as verified by the Likelihood Ratio Test (attached below).

```
Analysis of Deviance Table

Model 1: div_cut ~ 1
Model 2: div_cut ~ Crisis + roa + curr_ratio_wins + debt_ebitda + log_at
  Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
1     43890      35513
2     43884      34974  6   539.04 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Table 9 Analysis of Deviance - LRT M3

Let’s now break the model down by explaining what the coefficients mean.

The logistic regression model estimates the log-odds of a firm cutting its dividend (*div_cut = 1*) based on various financial characteristics and crisis-period indicators. To facilitate interpretation, we convert the estimated coefficients into **odds ratios changes** by exponentiating them: $\Delta(\frac{p_{(div_{cut}=1)}}{p_{(div_{cut}=0)}}) = e^{\beta_i}$

Here's a table summarizing the coefficients:

Table 10 M3 coefficients explanation

Variable	Coefficient	Exp Odds Ratio	Interpretation
Intercept	-1.030121	0.357	(baseline odds of cutting div when all vars = 0)
Crisis (GFC)	+0.244694	**1.277**	Firms were **27.7% more likely** to cut dividends during the GFC than in Neutral periods, holding other factors constant.
Crisis (COVID)	+0.036868	1.038	Not statistically significant. Suggests a 3.8% increase in odds of cutting dividends. It's economically small and statistically weak.
ROA	+0.848906	**2.337**	A 1-unit increase in ROA **more than doubles** the odds of a dividend cut.
Current Ratio (wins)	+0.032412	**1.033**	Each unit increase in current ratio raises the odds of a cut by 3.3%. It may suggest firms with unusually high liquidity are hoarding cash.
Debt/EBITDA	+0.029921	**1.030**	A 1-unit increase in the debt/EBITDA ratio raises odds of a cut by 3%.
Log(Assets)	-0.142548	**0.867**	A 1-unit increase in log(assets) reduces the odds of a cut by **13.3%**, suggesting larger firms are more stable in dividend policy.

The results of the logistic regression model offer a mixed picture regarding the determinants of dividend cuts during crisis periods. The dummy for the Global Financial Crisis (GFC) is positive and statistically significant, indicating that, ceteris paribus, firms were significantly more likely to cut dividends during the GFC than in neutral periods. In contrast, the COVID-19 crisis dummy is not statistically significant, suggesting that dividend policy responses were more heterogeneous or muted during this more recent crisis. This difference may reflect variations in macroeconomic conditions, regulatory interventions, or the nature of the crises themselves.

Among firm-specific characteristics, the results show that higher profitability (ROA) is associated with a greater probability of dividend cuts, which runs counter to common expectations and existing literature. According to the main pieces of literature cited in section 2, more profitable firms are expected to sustain or increase dividend payments, not reduce them. This surprising finding may be driven by the presence of extreme ROA values in the data or by firms experiencing temporary profit spikes that are not matched by long-term payout commitments. I'd personally add the theory, aligned with Fama and French (2001), that firms with higher ROA might have better growth opportunities, and decide to rather internally invest their resources than distribute them to shareholders.

In contrast, the effects of leverage and liquidity align more closely with established theory. Firms with higher debt levels (measured by the debt-to-EBITDA ratio) are more likely to reduce dividends, which is consistent with the idea that financial constraints lead firms to preserve cash. A positive relationship between the current ratio and the probability of a cut suggests that even liquid firms may behave conservatively during uncertain periods.

Lastly, firm size, proxied by the logarithm of total assets, is negatively associated with the probability of a dividend cut, implying that larger firms are generally more resilient in maintaining dividend policies, and this perfectly resonates with the literature as in Fama and French (2001) and Barros et al. (2020).

Overall, the model confirms that both macroeconomic context and firm-specific fundamentals contribute to dividend policy decisions, but it also highlights exceptions that call for further investigation. While the positive effects of leverage and firm size are in line with conventional payout theory, the unexpected behavior of the profitability variable warrants caution and suggests the need for deeper robustness checks or alternative model specifications.

3.4.2 Linear model

The second model in this study is a linear fixed-effects regression, aiming to analyze the determinants of the dividend payout ratio (*dpr_capped*), with a particular focus on firm-specific characteristics, again across crisis and non-crisis periods.

The rationale for using a linear model comes from the continuous nature of the dependent variable and the objective to capture variation in payout intensity rather than a binary dividend cut. The inclusion of firm fixed effects (via the *PERMNO* identifier) allows the model to isolate within-firm changes over time, thus enhancing the interpretability of the crisis effects and accounting variables.

To build this model, I initially experimented with different combinations of profitability, liquidity, leverage, and size variables. I then retained the specification that maximized model fit (this time based on *adj* R^2 and *within* R^2), ensured a balance across categories, and avoided multicollinearity.

The final set of independent variables includes one profitability measure (roe), one liquidity ratio (current ratio), one leverage ratio (debt-to-equity), and the total assets as a proxy for firm size. As in the logit model, Crisis periods are captured through the Crisis factor variable, with the "Neutral" period set as the baseline. Robust standard errors clustered at the firm level were employed to account for within-firm serial correlation. Here below I attach the equation of the chosen model as well as a summary of it.

$$dpr_{capped_{it}} = \beta_0 + \beta_1 * Crisis_{GFC_{it}} + \beta_2 * Crisis_{covid_{it}} + \beta_3 * roe_{it} + \beta_4 * curr\_ratio_{it} + \beta_5 * de\_ratio_{it} + \beta_6 * at_{it} + \varepsilon_{it}$$

(5) - Final Linear Regression model

Table 11 Linear Regression model summary

Statistical model

	Model 1
Crisis::COVID (Jan 30 2020 - Dec 2021)	0.0524***
	(0.0071)
Crisis::GFC (Sep 2008 - Dec 2009)	-0.0327***
	(0.0060)
roe	-0.7417***
	(0.0555)

Statistical model

	Model 1
curr_ratio	-0.0027^{**}
	(0.0009)
de_ratio	0.0047^{**}
	(0.0015)
at	0.0000^{***}
	(0.0000)
Num. obs.	48928
Num. groups: PERMNO	1722
R^2 (full model)	0.6314
R^2 (proj model)	0.1406
Adj. R^2 (full model)	0.6180
Adj. R^2 (proj model)	0.1405

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

The coefficient associated with the Covid Crisis period shows an average dividend payout ratio greater than the Neutral period by 5.24%, whereas during GFC the payout ratio shows a decrease in value by about 3.27% with respect to the baseline period. Both coefficients are significative at a 0.1% level. This result indicates that during GFC crisis, dividends were, on average, decreased, whereas during Covid, on the other hand, they increased. The GFC response perfectly resonates with the logit model, while the Covid one is in contrast with it.

The biggest effect comes with the ROE coefficient, which translates with a decrease of a 0.7417% in the payout ratio, for each 1% increase in the ROE. This means that higher profitability companies were associated with a lower payout ratio. Again, as in the logit model, I'd personally add that it could be since better performer firms prefer to internally invest their resources, instead of rewarding shareholders. The current ratio also exhibits a negative and significant relationship with dividend payout, indicating that firms with more liquidity tend to distribute less, possibly due to caution or investment needs. Similarly, debt-to-equity and total assets are both negatively associated with payout and significant, in line with the expectation that more leveraged or larger firms may retain earnings to preserve financial flexibility.

Overall, the model explains a substantial portion of the variation in payout behavior (Adj R^2 = 0.62), and the fixed effects absorb unobservable firm-specific characteristics. These results confirm that payout policies are sensitive to firm fundamentals and macroeconomic shocks, though the direction of response may vary between different crises.

3.4.3 Difference in Differences (DiD) Design Attempt

To further explore the effect of crisis periods on firms' dividend payout behavior, I attempted to implement a *Difference-in-Differences* (DiD) strategy. The idea was to compare high leverage firms before the crisis ("treated") to less constrained firms ("control") over time, focusing on changes during the GFC and COVID periods.

I defined the treatment group based on pre-crisis financial fragility, by identifying firms in the top quartile of debt-to-equity ratio in the year preceding the crisis. The Post variable was defined as =1 during Crisis, =0 elsewhere. Below I attach the R script used for computing the variables.

```
# Reprogram Treatment based on de_ratio (top 25% in t-1)
    final_merged_v6 <- final_merged_v6 %>%
      mutate(year = lubridate::year(public_date),
             year_lag = year - 1) %>%
      group_by(year_lag) %>%
      mutate(
        threshold = quantile(de_ratio, 0.75, na.rm = TRUE),
        treatment = if_else(de_ratio > threshold, 1, 0, missing = NA_real_)
      ) %>%
      ungroup() %>%
      select(-threshold)  # optional: drop helper
```

Figure 15 R script: Treatment creation

```
# New: Post_GFC
final_merged_v6 <- final_merged_v6 %>%
  mutate(Post_GFC = case_when(
    year(public_date) %in% c(2008, 2009) ~ 1,
    year(public_date) %in% c(2006, 2007) ~ 0,
    TRUE ~ NA_real_
  ))

#New: Post_COVID =
final_merged_v6 <- final_merged_v6 %>%
  mutate(Post_COVID = case_when(
    public_date >= as.Date("2020-06-01") & public_date <= as.Date("2021-12-31") ~ 1,
    year(public_date) %in% c(2018, 2019) ~ 0,
    TRUE ~ NA_real_
  ))
```

Figure 16 R script: GFC and COVID Post variables creation

I've then created the DiD models for each crisis period, based on the following regression:

$$retention_{ratio_{it}} = \beta_0 + \beta_1 * Treatment_i + \beta_2 * Post_t + \beta_3 * (Treatment_i * Post_t) + \varepsilon_{it}$$

(6) DiD general equation

```r
# GFC
    gfc_data <- final_merged_v6 %>%
      filter(!is.na(Post_GFC))

    did_gfc <- feols(
      retention_ratio ~ treatment * Post_GFC + roa + log_at + debt_ebitda |
        PERMNO,
      data = gfc_data,
      cluster = ~PERMNO
    )
    summary(did_gfc)

# COVID
    covid_data <- final_merged_v6 %>%
      filter(!is.na(Post_COVID))

    did_covid <- feols(
      retention_ratio ~ treatment * Post_COVID + roa + log_at + debt_ebitda |
        PERMNO,
      data = covid_data,
      cluster = ~PERMNO
    )
    summary(did_covid)
```

Figure 17 R script: DiD models creation

DiD Regression: GFC vs. COVID

	GFC	**COVID**
treatment	-0.046	-0.053*
	(0.025)	(0.023)
Post_GFC	-0.034***	
	(0.008)	
roa	1.155***	1.544***
	(0.182)	(0.155)
log_at	0.107*	0.100**

DiD Regression: GFC vs. COVID

	GFC	COVID
	(0.043)	(0.030)
debt_ebitda	-0.007^{***}	-0.021^{***}
	(0.001)	(0.006)
treatment:Post_GFC	0.021	
	(0.013)	
Post_COVID		-0.029^{***}
		(0.008)
treatment:Post_COVID		0.011
		(0.016)
Num. obs.	10042	10196
Num. groups: PERMNO	1068	1017
R^2 (full model)	0.848	0.813
R^2 (proj model)	0.132	0.125
Adj. R^2 (full model)	0.830	0.793
Adj. R^2 (proj model)	0.132	0.124

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 12 DiD models

All the coefficients, but the interaction one (Treatment*Post), the most important, were significant. Thus, I tried different approaches, such as changing the treatment variables.

Unfortunately, this model was unsuitable for this dataset since the fundamental assumption of the DiD method, the parallel trends, did not hold. As shown in the attached figure, which plots the average retention ratio by treatment group over time, the pre-crisis trajectories of treated and control firms diverge significantly.

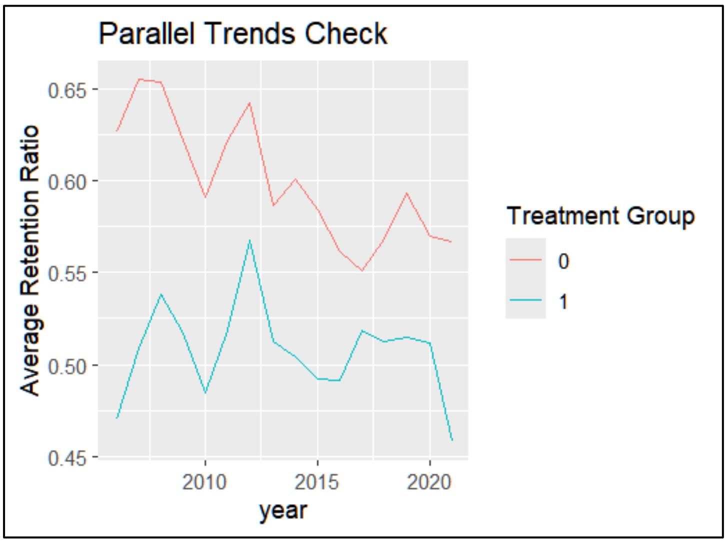

Figure 18 Parallel Trends Check

This undermines the credibility of any causal interpretation, as the differences in dividend behavior may stem from structural disparities rather than the crisis shock itself. As such, I chose not to include the DiD results in the final empirical analysis but document the attempt for completeness.

3.5 Robustness checks of the models

3.5.1 Logit model check

A logistic regression model is a statistical model that interprets the log-odds of an event as a combination of one or more independent variables. It requires the fulfillment of a few key assumptions:

1. **Dependent variables need to be binary**

   By construction, the *div_cut* variable is a dummy variable equals to 1 if the DIVAMT was lower than the year before, or to 0 elsewhere.

2. **Independent observations**

   Logistic regression requires observations to be independent from each other. Typically, this would mean that each row should not be dependent on another one. But when it comes to panel data such the one in analysis, since we're analyzing multiple observations of same firms over time, this assumption would fail. A solution to account for this kind of dependence was to cluster standard errors at the firm level, by using PERMNO code.

3. **Absence of multicollinearity**

The absence of multicollinearity among the independent variables is a required condition that was tested in the model using the *Variance Inflation Factor* (VIF). The VIF provides a summary index that measures how much the variance of an estimated coefficient increases because of collinearity, and is computed as below:

$VIF_i = \frac{1}{1-R_i^2}$ where R_2^i is the coefficient of determination for each regression that has X_i as dependent variable, and all the other predictor variable of the main regression, as independent variable. Normally, a rule of thumb is used, by setting a cutoff of 5 or 10, thus VIF values greater than cutoffs present multicollinearity issues. In this model, VIFs were tested for each variable, and did not present any issue. Below I attach the VIF report.

```
>         vif(model_log)
                    GVIF Df GVIF^(1/(2*Df))
Crisis          1.020056  2        1.004977
roa             1.184128  1        1.088177
curr_ratio_wins 1.315891  1        1.147123
debt_ebitda     1.335788  1        1.155763
log_at          1.311181  1        1.145068
```

Figure 19 VIF checks Logit model

4. **Linear relationship between the log-odds and predictors**

Logistic regression assumes linearity of independent variables and log odds of the dependent variable. This assumption can be checked by predicting the logits, saving them to the dataset, and then plotting them against each independent variable[2]. On the next page I attach the plots.

[2] https://bookdown.org/sarahwerth2024/CategoricalBook/logistic-regression-r.html

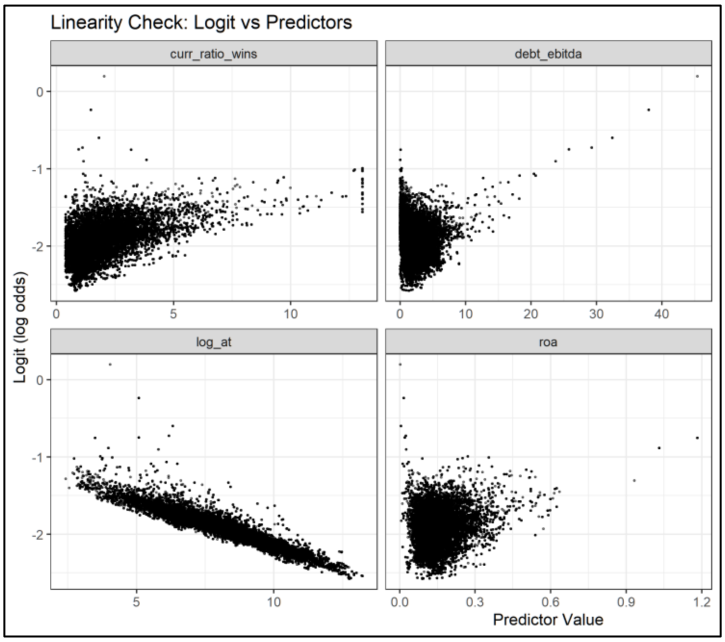

Figure 20 Linearity Assumption check - Logit model

As is shown in the picture above, the most linear variable is *log_at*, followed by *roa,* which does not show a strong linearity, but does not violate the assumption either. *Curr_ratio_wins* seems to have an upward curve at low values, and then it flats: it is not clearly linear, but not highly nonlinear either. Finally, the variable *debt_ebitda* is clearly nonlinear and violates the assumption.

3.5.2 Linear model check

The second model is a multiple linear regression, which also requires a few major assumptions to be respected. Differently from logit model, there's some extra requirements such as normality and homoscedasticity.

1. **Multicollinearity**

   As in the logit model, the linear regression needs to fulfill the absence of multicollinearity within its variables. Again, using the VIFs, I have checked whether the model fulfilled this requirement. Below I attach a summary of the VIF computed for each variable.

```
> vif(model_vif_check)
               GVIF Df GVIF^(1/(2*Df))
Crisis     1.016801  2        1.004174
roa        1.636881  1        1.279407
roe        1.678188  1        1.295449
curr_ratio 1.057133  1        1.028170
de_ratio   1.098897  1        1.048283
at         1.031815  1        1.015783
```

Figure 21 VIF checks Linear model

All the values are below the general cutoffs of 5 or 10, thus is possible to confirm that there's no multicollinearity.

2. **Normality of the errors**

The model assumes that the errors (the difference between the predicted value and the observed value) are normally distributed. This can be observed through a Q-Q plot of the residual, which I attach below.

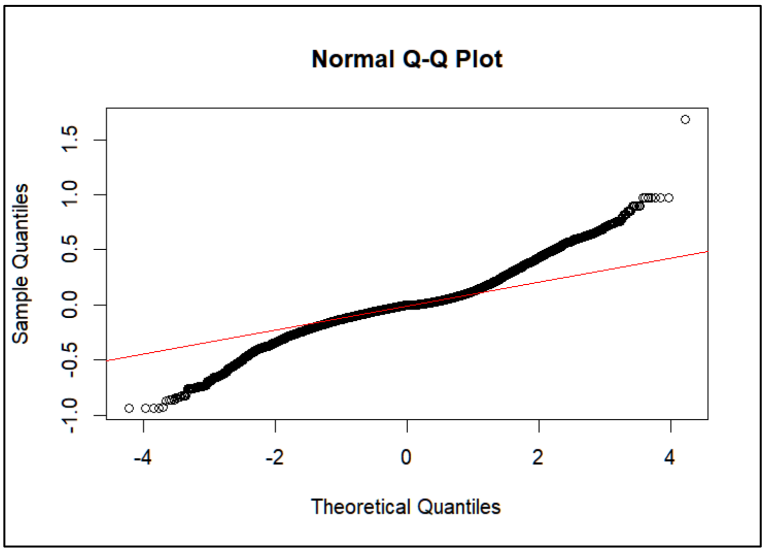

Figure 22 Q-Q plot of Linear model

The red line shows the theoretical quantiles under a normal distribution. But the actual distribution turns away from this red linear path right above the second theoretical quantile as well as the negative second one. This deviation indicates some skewness or heavier tails than normal, thus there is a mild violation of the assumption.

3. **Linearity and homoscedasticity of the errors**

If the assumptions of linearity and homoscedasticity of the errors are respected, the errors have expected value of 0 and equal variance.

A good way to test homoscedasticity is by using *Standardized Residual vs Fitted Values* plot.

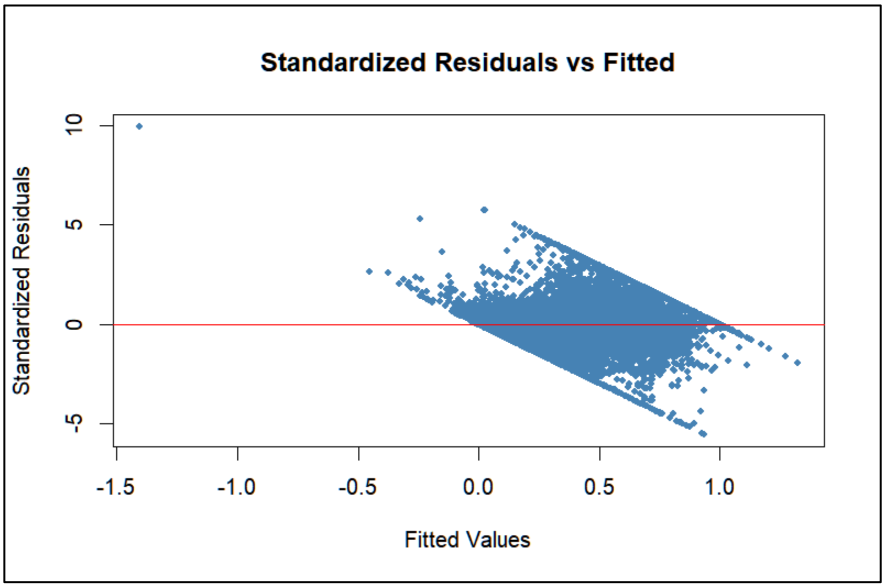

Figure 23 Standardized Residuals vs Fitted Values - Linear model

The plot indicates a distinct funnel shape, suggesting non-constant variance of the residuals, that is a violation of the homoscedasticity assumption. Although this implies heteroscedasticity, the model employed firm-level clustered standard errors, which are robust to such violations in the context of panel data.

Next, to assess the linearity assumption in the linear regression model, I plotted the residuals against each of the main continuous predictors: return on assets (ROA), current ratio, debt-to-EBITDA, and log of total assets.

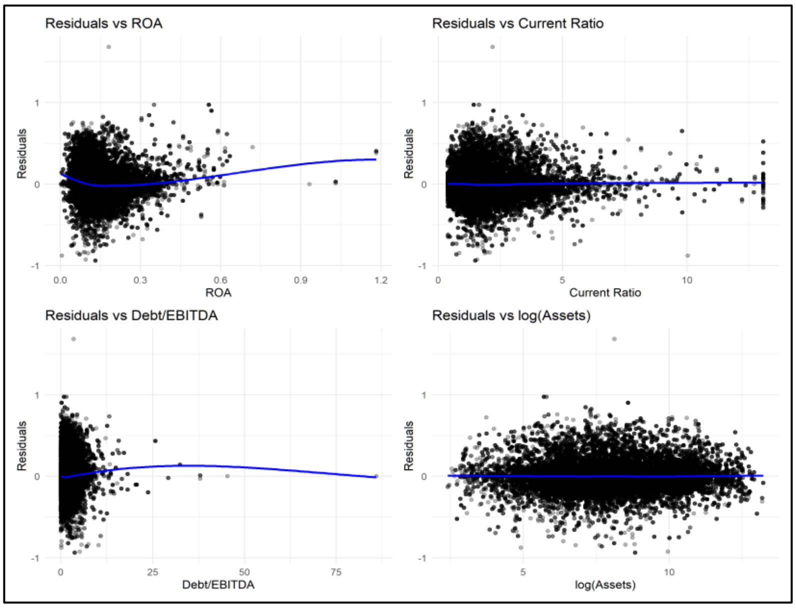

Figure 24 Residuals against each predictor - Linear model

As shown in the figure, the residuals appear randomly scattered around the horizontal axis, without strong curvature or systematic patterns, suggesting a roughly linear relationship between the independent variables and the dependent variable. The residuals vs. *roa* show a slight non-linearity in the lower range, but most of the data clusters around the center, without clear deviation from randomness. For the *current_ratio_wins* and *log(at)*, the residuals exhibit a very stable, horizontal distribution, which strongly supports the linearity assumption.

The plot for debt-to-EBITDA shows some dispersion on the left tail due to a concentration of low values, but the trend remains relatively flat overall.

Thus, while minor non-linear behavior is present for some predictors (especially ROA), the overall pattern does not indicate a major violation of the linearity assumption. The application of log transformation to total assets and prior winsorization helped to stabilize these relationships.

4. Conclusions

This thesis investigated how firms adjusted their dividend policies during two systemic crises of very different origins: the Global Financial Crisis, and the COVID-19 pandemic. By employing three econometric approaches it provided a full picture of the payout behavior of US firms under turmoil periods.

In particular, referring to the Table 10*,* both crises show a positive coefficient, meaning that the likelihood of a cut was higher during these periods with respect to the neutral one. But GFC results were stronger and significative, whereas COVID results are statistically weak and the coefficient is slightly positive, meaning that the likelihood is slightly higher than neutral period.

Firm fundamentals remain decisive. Contrary to what I found in the literature, during the logit model, profitability (roa) acted as an enhancer of cutting, whereas in the linear model profitability (roe) had the opposite effect. In both models leverage (debt_ebitda) increased the odd of a cut and the retention ratio, probably because of the need for internal cash hoarding. Larger firms display relative resilience, reflecting reputational considerations and easier capital market access, and this finding perfectly resonates with the literature.

The findings also speak directly to the signaling hypothesis. Classic theory suggests dividends convey private information about earnings prospects because maintaining payouts is costly when fundamentals are weak. This thesis, however, suggests that the signaling power of dividends weakened in both crises, though in different ways.

- During the **GFC**, banks and large industrial firms cut dividends more largely, because of the implied cost by signaling models. Dividends no longer functioned as a *credibility device*, with firms striving to preserve payout as fundamentals deteriorated. Cuts were thus interpreted by markets as negative signals of the crisis.
- During **COVID**, the exogeneity of the shock and the universality of dividend suspensions diluted their informational content. Even though the statistical weaknesses of the results, the likelihood of cuts were less spread than GFC, but still slightly higher than neutral period. Retention ratio, on the other hand, increased. In this context, signaling theory might have been held: the most profitable and liquid firms tried to maintain payouts to credibly differentiate themselves. For these firms, dividend stability acted as a positive signal of resilience, but the baseline expectation was precautionary cuts, not continuation.

Thus, the comparative evidence indicates that dividends might still be used as signals, but differently across crises: in financially driven crises (GFC), cuts were higher and highly informative of the impact of the crisis; in exogenous real-economy shocks (COVID), the cuts might sustain the signal of resilience theory.

Strengths and limitations

This thesis contributed by providing a comparative empirical lens across two structurally different crises. Nevertheless, limitations remain. The U.S. only sample restricts external validity; dividend cuts were defined relative to past payouts and may misclassify irregular payers; timing mismatches between dividends and accounting data may persist despite careful linking; and endogeneity between fundamentals and payouts is only partially mitigated by fixed effects. Finally, crisis definitions (Lehman collapse or WHO declaration) are defensible but not unique.

Overall, this thesis demonstrates that while every crisis has unique origins and propagation channels, payout policy remains a key arena where firms balance shareholder expectations with survival needs. The signaling function of dividends does not disappear in crises, but its direction might change. For investors, dividends continue to matter as signals, but they must be interpreted relative to the macro environment. Future research should expand this comparative perspective beyond the U.S., incorporate alternative payout channels such as buybacks, and explore the interaction between governance and signaling under stress. Doing so would enrich our understanding of whether dividends can remain credible signals in a world of increasingly frequent and heterogeneous crises.

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