

Challenging the Substitutional View: Evidence of the Complementary Informational Role of Dividends and Earnings in Sweden

Johanna Lilliehöök Fäldt (26069) and Gabriel Rudebeck (26053)

Abstract: Whether dividends substitute for or complement the information in earnings announcements remains an open question outside the U.S. context. We address this gap by examining Swedish listed firms from 2005 to 2024, evaluating three mechanisms through which dividends could reduce the informational role of earnings: stock-price reactions, earnings-forecast value, and investor attention at the announcement. We estimate multivariate regressions across several matching and weighting methods to account for differences between dividend-paying and non-paying firms. Across all tests, we fail to find evidence that dividends weaken the informational content of earnings. Market reactions to earnings news are generally stronger for dividend-paying firms, earnings surprises remain at least as informative about future performance, and investor attention does not vary with payout status. While significance levels are modest, the directional patterns are consistent. Overall, we find weak evidence that dividends and earnings serve complementary rather than substituting informational roles in the Swedish setting.

Keywords: Dividend policy, Earnings announcements, Earnings response coefficients, Information environment, Investor attention

Supervisor: Hao Ma, Assistant Professor

Acknowledgements: We would like to extend our sincerest gratitude to Hao Ma for her advice and guidance through the writing process.

Table of Contents

1. Introduction	3
1.1. Background	3
1.2. Purpose and Research Question	4
2. Literature Review	5
2.1. Overview	5
2.2. Theoretical Background	6
2.2.1. The Dividend Irrelevance Theorem	6
2.2.2. Signalling Theory	7
2.2.3. Agency Theory	7
2.2.4. Attention-Based and Behavioural Perspectives	8
2.3. Empirical Evidence	8
2.3.1. Dividends as Information Complements	8
2.3.2. Dividends as Information Substitutes	9
2.4. The Swedish Market	10
2.5. Hypothesis Development	11
3. Research Method	12
3.1. Research Design	12
3.2. Model Specification	12
3.2.1. H1: Earnings Response Coefficient Model	12
3.2.2. H2: Earnings Persistence Model	13
3.2.3. H3: Investor Attention Model	14
3.3. Variable Definitions	15
3.3.1. Dependent Variables	15
3.3.2. Variables of Interest	16
3.3.3. Control Variables	17
3.4. Statistical Considerations	18
3.5. Sample Selection and Treatment of Data	19
3.5.1. Sample Selection	19
3.5.2. Alternative Sample Constructions	20
3.5.3. Quarterly Analysis	22
4. Results	22
4.1. Summary Statistics	22
4.2. Dividends and Their Effect on Earnings Response Coefficients (H1)	28
4.3. Dividend Payers and the Persistence of Earnings Surprises (H2)	30
4.4. Dividends and the Attention to Earnings (H3)	32
5. Discussion	33
5.1. Dividends and Their Effect on Earnings Response Coefficients (H1)	33
5.2. Dividend Payers and the Persistence of Earnings Surprises (H2)	35
5.3. Dividends and the Attention to Earnings (H3)	37
5.4. Integrated Interpretation of Results	38
6. Conclusion	39
6.1. Summary and Contribution	39
6.2. Limitations	40
6.3. Suggestions for Further Research	41
7. References	42
A. Appendix	46
A.1. Additional Tables	46
A.2. AI-disclosure	50

1. Introduction

1.1. Background

“Does it pay a dividend?” is one of the most common questions posed when collecting information about a company you are looking to invest in. However, another question that researchers have pondered for decades is what information the dividend itself contains about the firm and its future performance.

Prior research shows that dividend announcements trigger immediate stock-price reactions across markets, with both dividend initiations and omissions generating strong and consistent abnormal returns (Asquith and Mullins, 1983; Healy and Palepu, 1988). Dividend forecast revisions and dividend surprises are also significantly priced by investors (Bilinski et al., 2022). These patterns indicate that investors pay close attention to dividends and may rely on such signals when interpreting other fundamental information, including earnings. This raises the broader question of how dividends interact with other types of public information, such as earnings announcements (EAs). If dividends capture disproportionate attention from investors, they may influence how earnings information is processed and incorporated into share prices.

Under dividend theory, the role of dividends is not straightforward. The Dividend Irrelevance Theorem, proposed by Miller and Modigliani (1961), states that payout policy should not affect firm value in perfect capital markets. However, due to real-world frictions such as taxes, agency conflicts, and information asymmetry, dividends may convey value-relevant information (Easterbrook, 1984; Lintner, 1956). Dividend-paying firms also tend to exhibit more persistent earnings and a lower likelihood of reporting losses (Skinner and Soltes, 2011), and dividend increases often reflect more permanent cash-flow shocks (Guay and Harford, 2000).

Behavioural perspectives add that investors have limited cognitive capacity to process information and tend to overweight salient or easily interpretable signals, potentially reducing attention to other information (Hirshleifer and Teoh, 2003). Notably, Ham et al. (2023) find that dividend-paying firms in the U.S. exhibit lower earnings response coefficients (ERCs), consistent with dividends substituting for information otherwise provided by EAs.

However, whether these mechanisms are generalisable to other markets with differing institutional environments remains unclear. Dividend policy, reporting conventions, ownership structures, and regulatory environments vary across countries, and these factors may influence how investors interpret both dividends and earnings.

1.2. Purpose and Research Question

One institutional context in which the above-described substitution effect has not yet been tested is the Swedish market. Swedish-listed firms operate under several institutional conditions that differ from the U.S. They report under IFRS rather than U.S. GAAP. They typically ratify and pay out a single annual dividend during the annual general meeting (AGM) period between March and mid-May (Carlsson and Steiner, 2025), in contrast to the quarterly dividend payments common in the U.S.

The difference in payout frequency means that dividends may be less intertwined with quarterly earnings in Sweden, potentially affecting their informational role. The seasonal concentration of dividend announcements may also affect their salience relative to earnings, potentially shaping how investors interpret quarterly information at different times of the fiscal year. These institutional differences present a clear gap in existing research and motivate our study.

We contribute to existing literature by examining the dividend substitution mechanism and evaluating whether previous empirical findings hold in the Swedish market. By examining whether the stock-price reaction to EAs differs between dividend-paying and non-paying firms, this study provides new evidence on the informational role of dividends in a distinct institutional environment outside the U.S. Thus, we consider the following research question:

Do dividends substitute for earnings information in the valuation of Swedish firms, and how does this affect investor reactions to earnings announcements?

Consistent with prior U.S. evidence, we hypothesise that dividend-paying firms exhibit patterns consistent with a substitution mechanism. We evaluate this using three testable predictions: weaker ERCs for payers (H1), lower persistence of earnings surprises for payers (H2), and reduced investor attention around payers' EAs (H3). If dividends already convey information about permanent earnings, stock-price reactions to quarterly EAs should be weaker for dividend payers than non-payers, earnings surprises should contain less information about future earnings for payers, and investors should devote less attention to the EAs of dividend-paying firms. These expectations follow from the idea that dividend announcements reveal information about permanent earnings and thus reduce the incremental value of EAs.

To answer our research question and evaluate H1 – H3, we analyse EA returns and their associated mechanisms in the Swedish equity market from 2005 to 2024. Our sample comprises 9,911 firm-quarters of Swedish listed firms on Nasdaq Stockholm, First North, Nordic Growth

Market, and Spotlight Stock Market. We estimate ERCs by regressing cumulative abnormal returns (CARs) on unexpected earnings (UEs) for payers and non-payers. We further test the relation between earnings surprises and future earnings persistence for both groups. Investor attention is proxied using trading volume and announcement-window absolute returns. This research design largely follows Ham et al. (2023). We also examine whether these relations differ by fiscal quarter, given Sweden's seasonally uniform annual dividend cycle.

Our results fail to find evidence of the substitution mechanism documented by Ham et al. (2023). Instead of reducing the information content of earnings, dividends appear to complement EAs in the Swedish market. Dividend-payers do not exhibit weaker ERCs (H1). The estimated association between UE and stock-price reactions is positive for payers in all models. The pattern is most pronounced in Q2, where the estimates are positive across all samples and reach statistical significance in several cases. Moreover, earnings surprises for dividend-paying firms are at least as informative about next year's earnings as those for non-payers, contradicting the idea that dividends reveal the permanent component of earnings in advance (H2). Finally, investors do not allocate less attention to the EAs of dividend-paying firms, as trading activity and return magnitudes are broadly similar across both groups (H3).

The remainder of this thesis is structured as follows. Section 2 reviews the relevant literature on various frameworks for the role of dividends, empirical evidence, and the Swedish institutional setting, and develops the hypotheses. Section 3 outlines our research method, variable descriptions, and sample selection. Section 4 presents our results, Section 5 discusses them, and Section 6 concludes.

2. Literature Review

2.1. Overview

Dividends are among the most established and debated topics in financial accounting, and researchers have long examined why firms pay dividends and how investors interpret them. By definition, dividends are a way for corporations to return capital to their shareholder by distributing a specific monetary amount, typically on a repeated basis.

Dividends can be viewed as indicators of firms' underlying strength and tend to signal more permanent performance improvements (Guay and Harford, 2000). Lintner (1956) documents that managers typically increase payouts only when they believe higher earnings levels are permanent. Brav et al. (2005) later show that managers are also reluctant to reduce dividends.

These observations support the view that dividends serve as a means of communicating information to investors.

Although dividend policy has been examined for decades, recent reviews conclude that the underlying motives remain unclear and the dividend puzzle persists (Ed-Dafali et al., 2023). This has led to the development of several competing theoretical perspectives. Some theories argue that dividends should not affect firm value, whereas others suggest they convey information or influence the interpretation of other signals, such as earnings. Empirical evidence mirrors this divide: some studies view dividends and earnings as complementary forms of information, while others argue that dividends may substitute for earnings by conveying overlapping insights about long-run profitability. The following sections review these theoretical perspectives and the empirical findings related to each mechanism.

2.2. Theoretical Background

2.2.1. The Dividend Irrelevance Theorem

The starting point for modern dividend theory is the Dividend Irrelevance Theorem, proposed by Miller and Modigliani (1961). This framework stipulates that, under perfect capital markets with no taxes, transaction costs, or information asymmetry, firm value depends solely on its investment policy, not on how earnings are distributed. According to this view, investors can adjust their portfolios to create whatever cash-flow pattern they prefer. This classical view implies that dividends do not convey incremental information about firm value.

This logic is reflected in the accounting-based valuation framework of Feltham and Ohlson (1995), which shows that under clean-surplus accounting, firm value is determined entirely by current book value and the present value of expected future abnormal earnings. In their framework, dividends themselves provide little incremental information for valuing a going-concern firm because their informational content is already incorporated into expected future earnings and book values. This implies that dividend announcements should not generate stock-price reactions, which stands in contrast to the strong market responses documented empirically (Asquith and Mullins, 1983; Healy and Palepu, 1988).

However, real-world frictions such as taxes, transaction costs, agency problems, and information asymmetries challenge the assumptions underlying the irrelevance theorem, creating environments in which dividend decisions may matter. Taxes can distort preferences between dividends and capital gains by treating them differently. Booth and Zhou (2017) note

that such frictions create heterogeneous investor preferences, giving rise to different dividend clienteles and scope for behavioural responses to payout decisions. Information asymmetry and agency conflicts further introduce room for dividends to convey information or discipline managers. These frictions motivated the development of signalling and agency theories, which seek to explain why dividends may matter and to suggest certain conditions under which dividends may convey information or influence investor behaviour.

2.2.2. Signalling Theory

Signalling theory argues that dividends convey information about a firm's prospects because they are costly to change and maintain. Managers avoid cutting dividends, instead preferring gradual, stable adjustments that reflect sustainable earnings capacity, and thus raise dividends only when they believe future earnings will support them (Lintner, 1956). Brav et al. (2005) provide evidence of this behaviour, documenting that managers prioritise maintaining dividends, often preferring to raise external financing or adjust investment plans rather than reduce payouts. This is because managers expect dividend cuts to send a negative signal about the firm's prospects and trigger negative market reactions. These findings reinforce the view that dividends communicate management's private information about expected performance.

Easterbrook (1984) formalises this mechanism by arguing that dividends function as a costly signalling tool because they reduce free cash flow under managerial discretion. This forces firms to access external capital markets to finance new investments, where managers are subject to greater monitoring by investors. As this is costly, managers commit to dividend payouts only when they expect future cash flows to support them, making dividend policies credible signals of future performance.

Signalling theory further suggests that dividends can reinforce the credibility of a firm's reported earnings. Booth and Zhou (2017) argue that dividends communicate management's confidence in expected future profitability, particularly because maintaining a stable payout requires managers to be convinced that future cash flows can sustain it. They emphasise that investors often interpret dividend stability as an indication of strong underlying fundamentals and reduced uncertainty. This can strengthen the credibility of other disclosures, such as earnings. Under this perspective, dividends and EAs act as complements.

2.2.3. Agency Theory

A closely related framework to the signalling perspective is agency theory, which offers another

explanation for why dividend policy may matter. Managers may have incentives to retain excess cash for private benefits or inefficient investments. Regular dividend payments help mitigate these conflicts of interest by reducing the free cash flow available for discretionary use (Easterbrook, 1984; Jensen, 1986; Rozeff, 2005). By committing to regular payouts, managers reduce the resources under their control, thereby constraining opportunistic behaviour.

Consistent with agency-based explanations, Denis and Osobov (2008) show that dividend-paying firms tend to be larger, more profitable, and characterised by higher retained earnings. This pattern aligns with the view that dividends help limit managerial discretion and reduce free cash flow problems. By mitigating these agency frictions, dividends can complement other disclosures, such as earnings, by increasing investor confidence in a firm's financial discipline and in the ability to assess firm value.

2.2.4. Attention-Based and Behavioural Perspectives

While signalling and agency theories emphasise dividends as mechanisms that reinforce earnings information, behavioural perspectives highlight circumstances in which dividends may substitute for earnings. The limited attention framework proposes that investors have limited cognitive capacity to process information (Hirshleifer and Teoh, 2003). Consequently, they may focus on the most salient or easily interpretable signals, while paying less attention to other, more complex disclosures. As a result, if dividend announcements are viewed as more salient, they may attract disproportionate attention. Under this perspective, dividend announcements may therefore reduce the incremental informational contribution of earnings.

2.3. Empirical Evidence

2.3.1. Dividends as Information Complements

A large body of empirical research supports the agency- and signalling-based view that dividends complement other financial information. Regular dividend payments have been shown to mitigate agency problems by reducing free cash flow available for discretionary use, limiting managerial discretion and lowering the risk of inefficient investments (Easterbrook, 1984; Jensen, 1986; Rozeff, 2005).

Empirical evidence also shows that firms that commit to or maintain dividends are perceived as financially stronger and less risky. Grullon and Michaely (2002) document that firms increasing dividends experience a significant decline in systematic risk and positive

announcement-period abnormal returns. This suggests that the market interprets dividend increases as indicators of reduced uncertainty and greater financial stability. Similarly, Dempsey and Sheng (2023) find that increases in dividend payouts are followed by decreases in firms' implied cost of equity, and vice versa.

By signalling financial strength and reduced uncertainty, a stable dividend policy can increase investors' trust and confidence in reported earnings. Under this interpretation, dividends and earnings act as complements, making earnings surprises of dividend-payers more informative to the market.

2.3.2. Dividends as Information Substitutes

A contrasting stream of research supports the view that dividends substitute for earnings. Fama and French (1998) infer that dividends proxy for permanent earnings, capturing information about expected profitability that is missed by current accounting measures. Guay and Harford (2000) show that dividends contain information about earnings persistence. They find that firms increasing their dividend payouts experience more permanent cash-flow shocks than those who repurchases stock, makes smaller dividend increases, as well as compared to the control group. These findings suggest that investors can use the payout policy to infer information about a firm's long-term profitability, and by extension, rely less on EAs.

Similarly, Skinner and Soltes (2011) find that dividend-paying firms exhibit higher earnings quality than non-payers. Specifically, current earnings for dividend payers are more predictive of future earnings, indicating greater earnings persistence. Dividend-paying firms are also less likely to report losses, and when they occur, they are often transitory or driven by special items rather than indicative of deteriorating performance. This suggests that dividends are associated with firms whose earnings already contain more information about long-run profitability, which may already be priced by investors. This implies that subsequent EAs potentially provide less incremental information to investors.

Prior research shows that stock-price reactions to EAs depend on the extent to which these revises expectations about future performance. Easton and Zmijewski (1989) measures these reactions by ERCs and show that they increase when current earnings provide more information about future earnings. When earnings information is already incorporated into prices before the announcement, a greater share of the announcement is transitory, and transitory earnings generate weaker price reactions (Ali and Zarowin, 1992). More recently, Ham et al. (2023)

provides direct evidence of substitution by showing that dividend-paying U.S. firms exhibit lower ERCs than non-payers. This suggests that the market reacts less strongly to their EAs because dividend policy already conveys forward-looking information. They further show that this effect strengthens when dividends serve as a clearer signal of permanent earnings. For example, when the dividend is funded from current earnings rather than cash reserves, when payouts are larger, or when the dividend is less likely to be cut.

Ham et al. (2020) further show that dividend changes contain information about firms' future profitability. They find that these changes can predict future economic earnings over a horizon of at least three years, particularly when the income measures capture permanent earnings more clearly. Taken together, these findings suggest that dividend policy provides investors with a signal about a firm's permanent earnings, reducing the informational role of subsequent EAs.

2.4. The Swedish Market

A large portion of dividend research is based on the U.S. and its capital markets. Whether the described mechanisms operate similarly in Sweden remains an open question. The Swedish market provides a distinct institutional environment that differs from the U.S. context examined by Ham et al. (2023), which may affect how investors weigh dividends relative to earnings.

One key distinction concerns payout practice. In Sweden, dividend decisions are ratified at the AGM (Swedish Companies Act 2005:551, Ch. 18 §1), and most firms pay a single annual dividend distributed during the AGM season, typically from March to mid-May (Carlsson and Steiner, 2025), rather than quarterly, as is common in the U.S. An important institutional feature behind this seasonal pattern is that the AGM must be held within six months after the fiscal year-end (Swedish Companies Act 2005:551, Ch. 7 §10). As most Swedish firms have fiscal years ending on 31 December, dividend announcements cluster naturally in March–May, resulting in little variation in payout timing. This concentrated announcement window, combined with the longer interval between dividends and quarterly EAs, may affect the salience of the dividend event and influence the investor interpretation of it relative to quarterly EAs.

Financial reporting practices also differ with Swedish firms applying IFRS, while U.S. firms report under U.S. GAAP. These frameworks differ in areas such as recognition, measurement, and presentation (KPMG, 2024). Differences may affect the persistence and informativeness of earnings, potentially influencing how investors interpret them relative to dividends. Broader institutional factors also shape earnings quality, with cross-country evidence indicating that

earnings quality varies across institutional environments. Leuz et al. (2003) document that countries with stronger investor protection and effective legal enforcement exhibit lower earnings management and higher-quality, more informative earnings. Countries with weaker institutions show more opaque reporting practices. These cross-country institutional differences may affect how much investors rely on earnings reports relative to other signals, such as dividends.

Taken together, Sweden's distinct payout structure, reporting regime, and institutional environment suggest that U.S.-based findings may not directly generalise to the Swedish market. The contextual differences motivate examining whether dividends act as substitutes for, or complements to, earnings information in Sweden's institutional setting.

2.5. Hypothesis Development

The theoretical and empirical research offers competing predictions regarding whether dividends complement or substitute for earnings information. Signalling and agency theories suggest that dividends enhance the credibility of reported earnings, reduce information asymmetry, and mitigate agency problems. This would increase the informativeness of EAs for dividend-paying firms, which thus should exhibit stronger market reactions to earnings news. In contrast, attention-based and substitution perspectives argue that dividends reveal information about long-term earnings capacity, reducing the incremental information content provided by EAs. Thus, investors should revise their expectations less upon the release of quarterly EAs, leading to weaker stock price reactions. Ham et al. (2023) document evidence consistent with substitution by showing that U.S. dividend-paying firms exhibit lower ERCs, suggesting dividends convey information about permanent earnings prior to the EA.

Whether these mechanisms operate similarly in Sweden is unclear. Because Swedish firms typically pay dividends annually, the payout decision may attract more concentrated investor attention than in markets with quarterly dividends. This might affect the informational role of dividends from that documented in the U.S., motivating an examination of whether dividends substitute for or complement earnings information in the Swedish setting.

If dividends already communicate part of the permanent component of earnings before the quarterly EA, the announcement contains less incremental information for dividend-paying firms. This motivates our first hypothesis:

H1: *Earnings announcements for dividend-paying Swedish firms have a lower earnings response coefficient than those of non-dividend-paying firms*

Earnings persistence research suggests that when dividends reflect permanent earnings, part of this information is already incorporated into stock prices prior to the EA. If so, earnings surprises should contain less information about future profitability for dividend-paying firms, as the dividend itself provides part of the relevant signal. This motivates our second hypothesis:

H2: *Earnings surprises contain less information about future earnings for Swedish dividend-paying firms than for non-dividend-paying firms*

Lastly, attention-based theories propose that investors allocate attention selectively, focusing more on salient and easily interpreted information. If dividends are perceived as more salient as well as reduce the incremental informational content of EAs, it would be expected that investors and analysts allocate less attention to these announcements for dividend-paying firms. This leads to our third hypothesis:

H3: *Swedish dividend-paying firms receive less investor attention at their earnings announcements than non-dividend-paying firms*

Together, these hypotheses allow us to examine whether dividends substitute for earnings information for Swedish firms, and to assess whether the mechanisms documented by Ham et al. (2023) extend to a market with different institutional characteristics.

3. Research Method

3.1. Research Design

We conduct a quantitative study using multivariate regression analysis to examine whether dividends substitute for earnings information in Swedish listed firms. The timeframe studied spans from January 2005 to December 2024. We divide our sample into dividend payers and non-dividend payers using a dichotomous variable and estimate three separate models corresponding to our three hypotheses, following Ham et al. (2023).

3.2. Model Specification

3.2.1. H1: Earnings Response Coefficient Model

The ERC measures how strongly a firm's stock price reacts to unexpected earnings news. A higher ERC indicates that earnings carry more information to investors. To examine whether

dividend-paying firms exhibit weaker stock-price reactions to EAs, we estimate the following multivariate linear regression model, described by Ham et al. (2023):

$$\begin{aligned} CAR_{i,q} = & \beta_0 + \beta_1 UE_{i,q} + \beta_2 DIV_{i,t-1} + \beta_3 UE_{i,q} * DIV_{i,t-1} + \gamma_k CONTROLS_{i,t-1} \\ & + \mu_k UE_{i,q} * CONTROLS_{i,t-1} + \phi_k YEAR * UE_{i,q} + \omega_k YEAR \\ & * IND_FE_{i,t-1} + \varepsilon \end{aligned} \quad (1)$$

where i represents the firm, q represents the current fiscal quarter, and $t - 1$ represents the previous fiscal year. $CAR_{i,q}$ represents the cumulative abnormal return over a three-day window surrounding the EA. Unexpected earnings ($UE_{i,q}$) is a decile-ranked variable ranging from 0 to 1, where 1 represents the decile with the most positive quarterly earnings surprise. Dividend-paying firms are identified by $DIV_{i,t-1}$, a dichotomous variable equal to one if the firm paid a dividend in the previous fiscal year and zero otherwise. The coefficient of interest is β_3 , which measures the differential ERC for dividend-paying firms. A negative estimate of β_3 would indicate that dividend-paying firms exhibit lower ERCs than non-payers, and vice versa.

The term $CONTROLS_{i,t-1}$ represents our ten control variables: $LogMVE_{i,t-1}$, $BTM_{i,t-1}$, $LogAge_{i,t-1}$, $ROA_{i,t-1}$, $OP_{i,t-1}$, $RE_{i,t-1}$, $EarnVol_{i,t-1}$, $RetVol_{i,t-1}$, $Inst\%_{i,t-1}$ and $EA\ Delay_{i,q}$. Full definitions are provided in section 3.3.3. and Table A1 in Appendix A.1. Following Ham et al. (2023), we also include interactions between $UE_{i,q}$ and each control variable, as well as year indicators to allow the ERC to vary across time. Finally, we include year-by-industry fixed effects ($YEAR * IND_FE_{i,t-1}$), where industry is defined using the two-digit GICS code, to capture industry-specific effects. We use robust standard errors clustered at the firm level.

3.2.2. H2: Earnings Persistence Model

To test H2, we follow the same modelling approach as Ham et al. (2023) and estimate a multivariate regression similar to Equation (1), but with a different dependent variable. In this specification, we examine whether unexpected earnings are less persistent for dividend-paying firms. The regression model is defined as follows:

$$\begin{aligned} Earn_{i,t} = & \beta_0 + \beta_1 UE_{i,q} + \beta_2 DIV_{i,t-1} + \beta_3 UE_{i,q} * DIV_{i,t-1} + \gamma_k CONTROLS_{i,t-1} \\ & + \mu_k UE_{i,q} * CONTROLS_{i,t-1} + \phi_k YEAR * UE_{i,q} + \omega_k YEAR \\ & * IND_FE_{i,t-1} + \varepsilon \end{aligned} \quad (2)$$

Where i denotes the firm, q the current fiscal quarter and $t - 1$ the previous fiscal year. The dependent variable $Earn_{i,t}$ represents the cumulative EPS over the next four quarters ($q + 1$ to $q + 4$), scaled by share price. The main variables are defined as in Equation (1): $UE_{i,q}$ captures the earnings surprise for the quarter, and $DIV_{i,t-1}$ indicates whether the firm paid a dividend in the previous fiscal year. The coefficient of interest is β_3 . A negative sign would indicate that UEs today translate less strongly into future earnings for dividend payers, consistent with dividends substituting for earnings information.

The model includes the same set of control variables as in Equation (1): $LogMVE_{i,t-1}$, $BTM_{i,t-1}$, $LogAge_{i,t-1}$, $ROA_{i,t-1}$, $OP_{i,t-1}$, $RE_{i,t-1}$, $EarnVol_{i,t-1}$, $RetVol_{i,t-1}$, $Inst\%_{i,t-1}$, $EA_Delay_{i,q}$, along with interactions between $UE_{i,q}$ and the control variables as well as yearly indicators. We also include year-by-industry fixed effects. As a robustness step, we also run a secondary specification with additional terms to account for non-linearities in $UE_{i,q}$, following Fama and French (2000) and Ham et al. (2023). These are $UE_{i,q}$ decile fixed effects, $UE_{i,q}$ scaled by share price, the square of $UE_{i,q}$ scaled by price, an indicator set to 1 for negative earnings surprises, and the $UE_{i,q}$ scaled by share price multiplied by the negative earnings surprise indicator. For both specifications, robust standard errors are clustered at the firm level.

3.2.3. H3: Investor Attention Model

To test whether dividend-paying firms receive less investor attention at EAs, we estimate a multivariate regression following Ham et al. (2023):

$$\begin{aligned}
 EA_Measure_{i,q} &= \beta_0 + \beta_1 DIV_{i,t-1} + \gamma_k CONTROLS_{i,t-1} + \mu_k UE_Decile\ FE_{i,q} \\
 &+ \omega_k YEAR * IND_{FE}_{i,t-1} + \varepsilon
 \end{aligned} \tag{3}$$

Where i represents the firm, q the current fiscal quarter, and $t - 1$ the previous fiscal year. Investor attention is captured using two alternative dependent variables, $EA_Vol_{i,q}$ and $EA_Ret_{i,q}$, represented by' $EA_Measure_{i,q}$ in the equation above. $EA_Vol_{i,q}$ follows Roychowdhury and Sletten (2012) and measures trading volume over the three-day window centred on the EA scaled by total trading volume for the quarter, excluding the EA window. $EA_Ret_{i,q}$ is defined analogously but uses the absolute daily market-adjusted returns of the share price instead. The key variable is the dichotomous dividend indicator $DIV_{i,t-1}$, equal to 1 if the firm paid a dividend

in the previous fiscal year. Thus, a negative β_l coefficient would indicate that dividend-paying firms attract less investor attention at EAs.

The model includes the same set of control variables used in the previous specifications ($LogMVE_{i,t-1}$, $BTM_{i,t-1}$, $LogAge_{i,t-1}$, $ROA_{i,t-1}$, $OP_{i,t-1}$, $RE_{i,t-1}$, $EarnVol_{i,t-1}$, $RetVol_{i,t-1}$, $Inst\%_{i,t-1}$, $EA\ Delay_{i,q}$), as well as UE decile fixed effects to absorb the impact of earnings-surprise magnitude on investor and analyst reactions. We also include year-by-industry fixed effects to capture time-varying industry-level factors. Robust standard errors are clustered by firm, following our methodology for the other two models.

3.3. Variable Definitions

This section describes the variables used in our empirical models. Detailed statistical definitions of the variables are provided in Table A1 in Appendix A.1.

3.3.1. Dependent Variables

To measure the stock market's reaction to EAs in Equation (1), we use CARs around the EA, following Ham et al. (2023), where a higher CAR would indicate that the market perceives the announcement as more informative. We define $CAR_{i,q}$ as the three-day abnormal returns around the EA date. Abnormal returns are computed relative to the country market. We would expect $CAR_{i,q}$ to be greater with more positive earnings surprises.

To capture whether earnings surprises carry over into next year's earnings, we follow Ham et al. (2023) and use future earnings as the dependent variable in Equation (2). This captures earnings persistence, that is, the extent to which current earnings contain information about a firm's future profitability. $Earn_{i,t}$ is defined as the sum of the actual EPS over the four preceding fiscal quarters, from the current quarter, scaled by share price to make the earnings comparable across firms. If any of the required EPS values are missing, the observation is excluded. We would expect a positive relationship between current earnings surprises and future earnings because a higher-than-expected EA should reflect underlying operational strength that carries over into subsequent quarters.

To examine whether dividend payers attract less investor attention during EAs, we use two alternative proxies: $EA\ Vol_{i,q}$ (trading volume) and $EA\ Ret_{i,q}$ (return volatility). Trading volume increases sharply around EAs when new information is released (Beaver, 1968), and abnormal volume increases are positively related to the magnitude of the earnings surprise (Bamber,

1986). Return volatility similarly rises when the information environment becomes more informative, as investors have greater incentives to acquire and process information (Kim and Verrecchia, 1991). We define $EA Vol_{i,q}$ as the natural logarithm of the three-day EA-window trading volume standardised against the non-EA trading volume for the quarter, following Ham et al (2023) and Roychowdhury and Sletten (2012). $EA Ret_{i,q}$ is defined similarly and measures the spike in return volatility around the EA. It equals the natural logarithm of the three-day EA-window absolute abnormal returns standardised by the absolute abnormal returns for the quarters, adjusted for the EA-window. We expect both measures to exhibit a negative relationship with $DIV_{i,t-1}$, consistent with the substitution mechanism underpinning H3.

3.3.2. Variables of Interest

The variable $UE_{i,q}$ captures the difference between a firm's actual quarterly earnings and the corresponding analyst consensus forecast. It is defined as the actual reported EPS less the most recent analyst consensus forecast, standardised against the share price. The values are decile-ranked on a range from 0 to 1, following Ham et al. (2023). Thus, a higher value would indicate a more positive earnings surprise (adjusted for stock price), and vice versa. We expect $UE_{i,q}$ to have a positive coefficient in both Equation (1) and (2), as a more positive EA should yield greater positive abnormal returns and have positive implications for the firm's future earnings.

The dichotomous variable $DIV_{i,t-1}$ is central to our research design and is used to separate dividend-payers from non-dividend-payers. The variable equals 1 in firm-quarters for firms that paid a dividend in the previous fiscal year and 0 otherwise. It thus serves as a proxy for a firm's dividend policy. In Equation (3), $DIV_{i,t-1}$ is the variable of interest. We expect a negative coefficient, which represents less attention paid to the EAs of dividend-payers, consistent with H3 and the substitution mechanism. $DIV_{i,t-1}$ is also included in Equations (1) and (2), following Ham et al (2023), but not as the variable of interest. Nevertheless, we expect $DIV_{i,t-1}$ to have a coefficient close to zero in Equation (1) as abnormal returns for a dividend-payer should be zero if expected earnings match the actual earnings. In Equation (2), we expect a positive sign as firms typically pay dividends when they are confident in their long-run cash flows.

In both Equations (1) and (2), we also include the interaction term $UE_{i,q} * DIV_{i,t-1}$, that captures whether the sensitivity of returns (H1) or future earnings (H2) to UE differs between dividend-paying and non-paying firms. This follows Ham et al. (2023), who show that substitution or complementarity is identified through the interaction term rather than the main effect of dividend status. We expect negative coefficients in both Equations (1) and (2), consistent with

H1 and H2, and the notion that dividends serve as an informational substitute for information otherwise provided through EAs.

3.3.3. Control Variables

To ensure that our results are not driven by firm characteristics other than dividend policy, we follow Ham et al. (2023) and include the same set of control variables. Prior research shows that these characteristics are related to both a firm's decision to pay dividends and to the information content of its EAs.

Dividend-paying firms tend to be larger on average and have higher book-to-market ratios than non-payers (Ham et al., 2023). These patterns are consistent with capital structure theories suggesting that financing frictions and investment opportunities influence dividend decisions (Bolton et al., 2011; Myers and Majluf, 1984). We therefore control for size using $LogMVE_{i,t-1}$, defined as the natural logarithm of the market value of equity (MVE), defined as shares outstanding multiplied by share price. We also include $BTM_{i,t-1}$, to separate the substitution effect of dividends from the underlying growth characteristics that affect earnings persistence, defined as the book equity divided by MVE , as described above. Both variables are expected to be positive, since larger and high-BTM firms tend to have more established operations and more predictable earnings patterns, which should strengthen the informativeness of their EAs.

Life-cycle theory predicts that mature firms with accumulated internal capital tend to pay dividends to reduce free cash flow problems (DeAngelo et al., 2006). We include $LogAge_{i,t-1}$, which functions like a proxy for firm maturity. It is the natural logarithm of the number of years a firm has existed on Compustat Global as of year $t - 1$. Dividend-paying firms also exhibit higher levels of retained earnings relative to total equity (Denis and Osobov, 2008). We therefore include $RE_{i,t-1}$, defined as a firm's retained earnings divided by its total assets. Both variables are expected to be positive, as more mature and internally financed firms generally have more stable and predictable earnings, which should strengthen the informativeness of EAs.

Dividend-paying firms exhibit higher earnings persistence, fewer losses and more stable earnings (Skinner and Soltes, 2011). We therefore include $ROA_{i,t-1}$, measured by the firm's operating income divided by total assets, and $OP_{i,t-1}$, which is a firm's operating profitability divided by book equity. We control for earnings stability using $EarnVol_{i,t-1}$, calculated as the standard deviation of a firm's net income for years $t - 1$ to $t - 5$, scaled by total assets, following Ham et al. (2023). $ROA_{i,t-1}$ and $OP_{i,t-1}$ are expected to be positive, as stronger performance tends

to be associated with more persistent earnings. Earnings volatility is expected to be negative, as less stable earnings should reduce the EA's credibility and informativeness.

Higher return volatility is associated with greater cash-flow uncertainty and a lower likelihood of paying dividends (Chay and Suh, 2009). We thus include $RetVol_{i,t-1}$, which measures the volatility of stock returns, calculated as the average of the absolute values of the stock's daily abnormal returns over the previous year, following Ham et al. (2023). We expect a negative sign as firms with more volatile returns operate in noisier information environments, which should weaken the market reaction to EAs.

Institutions tend to prefer dividend-paying firms (Grinstein and Michaely, 2005). Those particularly subject to prudent-man constraints tend to tilt toward stocks which reflect long and consistent earnings and dividend histories (Del Guercio, 1996). This may affect dividend policy and market reaction to EAs. We therefore include $Inst\%_{i,t-1}$, the percentage of institutional ownership at the end of the previous year. We expect a positive coefficient, as firms with higher institutional ownership typically face greater monitoring, improving the information environment, which in turn should amplify the market response to EAs.

Later-than-expected EAs are associated with worse subsequent earnings news, whereas earlier EAs precede stronger news (Johnson and So, 2018). This affects how much EA revises investors' expectations. We therefore include $EA\ Delay_{i,q}$, defined as the number of days between the fiscal quarter q end date and its EA date. We expect a negative sign as longer delays tend to signal weaker forthcoming news and reduce the informativeness of the EA.

3.4. Statistical Considerations

Financial return and accounting data frequently violate OLS assumptions. We therefore implement several statistical measures to ensure valid inference. To address heteroskedasticity and within-firm correlation, all regressions are estimated with heteroskedasticity-robust standard errors clustered at the firm level. This allows for arbitrary correlation of residuals within firms over time and cross-sectional heterogeneity in variance, thereby preventing downward-biased standard errors and overstated statistical significance.

To address endogeneity concerns, particularly omitted variable bias, we include industry-by-year fixed effects. These absorb common variations in EA responses arising from macroeconomic shocks, regulatory changes, and other industry- and year-specific factors. This restricts comparisons to firms within the same industry and year. For models that include UE

(H1 and H2), we interact the term with all control variables and year indicators. This allows the ERC and the persistence of earnings surprises to vary across firm characteristics such as size, profitability, and volatility, as well as over time.

Following Fama and French (2000) and Ham et al (2023), we include additional variables in H2 to account for potential non-linearities in *UE*. This reduces the risk that any weaker link between today's *UE* and next year's earnings that we attribute to dividends is instead driven by non-linear or asymmetric responses to *UE*. For H3, we also include *UE* decile fixed effects because investor attention could vary with the size of the earnings surprise. Thus, we ensure that differences in surprise magnitude do not drive potential differences in attention between dividend-payers and non-payers.

To mitigate the influence of outliers, we winsorise all continuous variables at the 1st and 99th percentiles, which reduces the impact of extreme observations on our regression results. We do not winsorise *EA Delay*, as it is a discrete count variable that captures the actual number of days between the fiscal period-end and the EA, reflecting genuine variation in reporting timeliness. While financial data often exhibit non-normal distributions, our sample size of just under 10,000 observations allows us to rely on the Central Limit Theorem to ensure asymptotic normality of the OLS estimators. To address potential non-linearities, we employ logarithmic transformations for certain variables such as firm size and age, following Ham et al. (2023).

Finally, we assess potential multicollinearity among the regressors by examining pairwise correlations and computing variance inflation factors (VIFs) for all control variables. Because multicollinearity primarily affects the precision of estimates rather than their unbiasedness, we focus the VIF analysis on whether any control exhibit unusually high collinearity. High VIF values among control variables are typically less concerning than among key interaction terms, as they are included to account for background variation rather than to test specific hypotheses.

3.5. Sample Selection and Treatment of Data

3.5.1. Sample Selection

To construct our sample, we first use the Refinitiv DataStream database to obtain a list of Swedish firms that were publicly listed at any point from 2024 and backwards. We predominantly use ISIN codes as firm identifiers to merge the data, except for I/B/E/S, where we use the 8-character code provided by the database, which follows the format: “SS” + a 6-character SEDOL code. Firm-level accounting data, industry classifications, fiscal period end

dates, daily share prices, and trading volumes are obtained from Compustat Global. Actual quarterly EPS, analyst consensus forecasts for quarterly EPS, and the quarterly earnings announcement dates are collected from the I/B/E/S database. Cumulative abnormal returns and daily market-adjusted returns are computed using the WRDS Event Study tool. Finally, institutional ownership data is sourced from Refinitiv Workspace. The collected data is compiled into a unified dataset.

When defining the dividend indicator value, we account for the fact that the dividend value sometimes includes other items, such as share swap agreements. We therefore introduce a relative threshold to improve classification robustness. When the dividend decreases by 85% or more relative to the firm's historical median, the dichotomous variable is assigned a value of zero, provided it remains below the absolute threshold of SEK 100 million.

If a particular variable is missing, we leave it blank, except for institutional ownership (*Inst%*), for which we impute a value of 0 if the value is missing due to poor coverage, otherwise resulting in an unjustifiable loss of observations. Another variable with similarly low coverage is *EA Delay*. We do not impute a value here because the missing observations stem from missing EA dates, rendering the observation invalid, as it is necessary to compute *CAR*. Random observations are continuously selected, computed manually, and compared with the firm's actual financial statements throughout the process to ensure accuracy.

We filter the observations according to several criteria. First, we exclude firm-quarters with total assets or market capitalisation below SEK 100 million, following a similar approach to Ham et al. (2023). Following prior literature, we exclude financial and utility firms (GICS 40 and 55) to avoid industry-specific regulation effects. This is motivated by evidence that dividend policy in these industries is heavily influenced by sector-specific regulations, which could bias our results, such as Basel capital requirements for banks and regulated pricing for utilities (Chen et al., 2023; Kanas, 2013). We also exclude firms with non-Swedish ISIN codes and firms not listed on the exchanges Nasdaq Stockholm, First North, Nordic Growth Market, and Spotlight Stock Market. Finally, we restrict the sample to firm-quarters with complete data for all required variables and exclude years with fewer than 100 observations to ensure stable estimation and avoid sparsely populated periods.

3.5.2. Alternative Sample Constructions

We further construct three alternative samples to strengthen our analysis. First, we create a

sample using propensity score matching (PSM) to better balance the distributions of firm characteristics across payers and non-payers. This approach works even when the effect of these characteristics on outcomes may be non-linear and ensures sufficient common support (overlap). When the two groups occupy different regions of the data, for instance, if most payers are large firms while most non-payers are small, standard regressions must extrapolate beyond the observed data. Such extrapolation can make estimates sensitive to modelling choices and potentially unreliable (Ho et al., 2007).

Following Ham et al. (2023), we estimate each firm's propensity to pay dividends using logistic regression on the control variables *LogMVE*, *BTM*, *LogAge*, *ROA*, *OP*, *RE*, *EarnVol*, *RetVol*, *Inst%*, as well as industry and year fixed effects. For completeness, we also choose to include *EA Delay* in the regression. We perform one-to-one nearest neighbour matching without replacement, using a calliper distance of 0.025, determined by comparing different distances against the statistical balance between the two groups.

However, PSM also has limitations, including the inability to achieve exact balance and the need to discard a substantial number of observations, which can reduce statistical power. Entropy balancing addresses these issues by reweighting the non-payers (control group) to achieve exact balance on the specified moments of the covariate distributions without discarding observations (Hainmueller, 2012). In our third sample, we therefore apply entropy balancing to reweight each non-payer observation such that the weighted non-payer group matches dividend payers on the means of all ten matching variables.

We initially attempted to balance on the first three moments (mean, variance, and skewness) but were unable to achieve convergence, likely because some covariate distributions had limited overlap between payers and non-payers. We therefore use mean-only balancing, which matches the average of each variable between payers and non-payers while keeping the weights as close to equal as possible to preserve information. We restrict this analysis to propensity scores between 0.1 and 0.9 to avoid assigning extreme weights to non-payers that look fundamentally different from all payers and thus accept a smaller sample size in favour of a balanced sample.

While entropy balancing achieves exact mean balance, we were only able to balance on the first moment due to convergence issues. We therefore also utilise overlap weighting in a fourth sample, which offers a complementary approach that naturally downweights observations in regions of poor overlap. Following Li and Thomas (2018), this method assigns each observation

a weight based on its propensity scores (PS): treated units (dividend payers) receive a weight of $(1-PS)$, while control units (non-payers) receive a weight of PS . This weighting scheme automatically emphasises observations in the region of strong overlap, i.e., where the PS is around 0.5, indicating the firm could reasonably be either a payer or a non-payer. Using the same propensity scores from our logistic regression, we restrict the sample to observations with PS between 0.2 and 0.8. We arrived at this range by testing different cutoffs and evaluating the trade-off between covariate balance and sample size.

3.5.3. Quarterly Analysis

As mentioned in section 2.4., reporting and payout conventions for dividends differ between Sweden and the U.S. Swedish firms typically distribute one annual dividend, whereas U.S. firms tend to pay quarterly. To allow the estimated coefficients to vary across the fiscal year, we complement our main analysis by partitioning the sample by fiscal quarter and estimating regressions separately for each quarter. This approach allows us to examine whether the informational content of dividends varies systematically across reporting periods, potentially reflecting differences in the timing of information releases and investor expectations.

4. Results

4.1. Summary Statistics

Table 1. Sample selection

Data Restrictions	Firm-Quarters	Firm-Years	Firms
Total number of firm-quarters for all firms in the sample	51,855	14,998	1,135
Less:			
Firm-quarters with MVE or assets below SEK 100m	-28,387	-8,530	-412
Financial and utility firm-quarters (GICS 40 or 55)	-690	-202	-22
Firm-quarters of non-Swedish firms	0	0	0
Firm-quarters of non-Swedish exchanges	0	0	0
Firm-quarters missing required variables	-7,248	-1,930	-143
Firm-quarters missing I/B/E/S data for earnings	-5,528	-1,403	-139
Firm-quarters in years with >100 observations	-91	-54	0
Maximum sample size for regressions	9,911	2,879	419
The sample includes all firms from the Refinitiv Datastream list that have corresponding and available records in Compustat Global. Note that Compustat Global provides full-year data starting in 1988. Some data from 1987 and 2025 are available, but coverage for that year is incomplete and is thus excluded from our sample			

Using the Refinitiv DataStream tool, we obtain a list of 1,999 Swedish firms that were (or are still) listed by 2024. When linking with the Compustat Global Database, this number decreases to 1,135 firms. After applying our exclusion criteria as defined in section 3.5., we obtain a

maximum sample of 419 firms with 9,911 firm-quarters, as shown in Table 1. The biggest reason for the loss of observations was a market capitalisation or total assets below SEK 100 million, followed by missing data. The final sample spans the period 2005 – 2024. Table 1 documents the stepwise reduction in the number of firms and observations. The filter for non-Swedish firms and non-Swedish exchanges both display a decrease of 0 observations, as earlier criteria had already filtered out firms with those characteristics.

Table 2 summarises the descriptive statistics. The unmatched sample (Panel A) exhibits poor covariate balance between payers and non-payers. The PSM (Panel B) and overlap-balanced sample (Panel D) achieve moderate to good balance, but with multiple statistically significant differences on both the mean and median values. The entropy-balanced sample (Panel C) shows no statistically significant differences at the mean level and a few at the median level.

Winsorisation at the 1st and 99th percentiles constrain extreme values across all continuous variables. Untabulated analysis confirms that several controls (e.g. *BTM*, *OP*, and *RE*) exhibit heavy-tailed distributions. The winsorisation procedure effectively reduces the influence of outliers, while mean and median values shift minimally for most variables.

Observing the correlation matrices in Table 3 reveals several patterns. We note a moderately positive correlation between *CAR* and *UE*, consistent with the notion that EAs drive market reactions and with our theoretical framework. We also observe that multiple variables exhibit statistically significant correlations, which may introduce issues with multicollinearity. However, many of these correlations are expected and theoretically justified. For example, a positive correlation between *LogAge* and *LogMVE* across all four panels is natural as firms typically expand their operations over time.

Untabulated results show that some control variables exhibit high VIF values. Across the four sample constructions, *LogMVE* has a VIF of 26.10 – 29.84, and *LogAge* has a VIF of 20.31 – 29.55. This indicates strong collinearity concerning firm size and age. *RetVol* and *Inst%* also show elevated VIF values in the intervals 6.74 – 11.02 and 5.16 – 5.93, respectively. The remaining controls exhibit VIF values below three across all panels. However, as these variables are included as controls rather than key variables of interest and as high VIF values primarily affect standard errors, we deem it unlikely that the multicollinearity will materially compromise our regression results.

Table 2. Descriptive statistics

	Dividend-Paying Firms						Non-Dividend-Paying Firms							
Variable	N	Mean	StdDev	Q1	Median	Q3	N	Mean		StdDev	Q1	Median		Q3
Panel A: Unmatched Sample														
CAR	7,516	0.0045	0.0725	-0.0384	0.0040	0.0471	2,395	-0.0039	***	0.0956	-0.0584	-0.0068	***	0.0501
UE	7,516	0.5202	0.2846	0.3333	0.5556	0.7778	2,395	0.4711	***	0.3752	0.1111	0.4444	***	0.8889
Earn	5,863	0.0483	0.0936	0.0179	0.0426	0.0710	1,425	0.0165	***	0.3813	-0.0354	0.0090	***	0.0575
EA Ret	7,324	2.3255	0.7091	1.8692	2.3671	2.8229	2,299	2.1930	***	0.7584	1.6960	2.2339	***	2.7218
EA Vol	7,319	3.1938	1.3829	2.2269	3.0462	4.0868	2,300	2.9953	***	1.3376	2.0619	2.8603	***	3.7549
LogMVE	7,516	8.8088	1.7778	7.4965	8.7562	10.0844	2,395	7.3581	***	1.4109	6.2800	7.2177	***	8.2962
BTM	7,516	0.5431	0.4938	0.2538	0.4112	0.6725	2,395	0.7147	***	0.8795	0.2129	0.4460	***	0.8418
LogAge	7,516	2.7382	0.4661	2.3979	2.8332	3.0910	2,395	2.4458	***	0.4768	2.0794	2.3979	***	2.7726
ROA	7,516	0.1081	0.0733	0.0631	0.0925	0.1365	2,395	-0.0402	***	0.1896	-0.0784	0.0123	***	0.0621
OP	7,516	0.4079	0.3169	0.2392	0.3420	0.4843	2,395	0.2970	***	0.5378	0.0444	0.1986	***	0.4280
RE	7,516	0.2564	0.1925	0.1552	0.2617	0.3675	2,395	-0.3703	***	0.8957	-0.5838	-0.0193	***	0.1321
EarnVol	7,516	0.0327	0.0354	0.0134	0.0215	0.0391	2,395	0.0822	***	0.0948	0.0212	0.0506	***	0.1027
RetVol	7,516	0.0138	0.0045	0.0106	0.0133	0.0163	2,395	0.0213	***	0.0060	0.0170	0.0204	***	0.0248
Inst%	7,516	0.4585	0.2046	0.3120	0.4621	0.6102	2,395	0.3670	***	0.2421	0.1576	0.3476	***	0.5659
EA Delay	7,516	31.1046	11.2721	22.0000	28.0000	40.0000	2,395	36.3791	***	13.2112	25.0000	37.0000	***	47.0000
Panel B: Propensity Score Matched Sample														
LogMVE	1,184	7.5381	1.5350	6.3169	7.3861	8.6296	1,184	7.7587	***	1.4833	6.6537	7.6684	***	8.7043
BTM	1,184	0.7696	0.7449	0.3284	0.5498	0.9228	1,184	0.7407		0.8602	0.2462	0.4633	***	0.8982
LogAge	1,184	2.4738	0.4748	2.0794	2.4849	2.8332	1,184	2.5147	**	0.4868	2.1972	2.4849	*	2.9444
ROA	1,184	0.0586	0.0534	0.0376	0.0582	0.0843	1,184	0.0523	**	0.0746	0.0133	0.0488	***	0.0833
OP	1,184	0.3462	0.3810	0.1545	0.2640	0.4136	1,184	0.3534		0.4865	0.1251	0.2366	***	0.4278
RE	1,184	0.0914	0.2511	0.0149	0.1150	0.2345	1,184	0.1016		0.2298	-0.0041	0.0918		0.2384
EarnVol	1,184	0.0408	0.0486	0.0122	0.0229	0.0485	1,184	0.0479	***	0.0483	0.0157	0.0320	***	0.0627
RetVol	1,184	0.0167	0.0047	0.0133	0.0157	0.0194	1,184	0.0191	***	0.0052	0.0154	0.0182	***	0.0224
Inst%	1,184	0.4025	0.2301	0.2285	0.3952	0.5788	1,184	0.4131		0.2433	0.2186	0.3996		0.6193
EA Delay	1,184	35.2441	12.2817	25.0000	36.0000	45.0000	1,184	34.2044	**	12.9415	24.0000	33.0000	**	45.0000

Variable	Dividend-Paying Firms						Non-Dividend-Paying Firms					
	N	Mean	StdDev	Q1	Median	Q3	N	Mean	StdDev	Q1	Median	Q3
Panel C: Entropy Balanced Sample												
<i>LogMVE</i>	2,438	7.7630	1.5377	6.6333	7.5969	8.8172	1,444	7.7591	1.4530	6.6959	7.6735	*** 8.5765
<i>BTM</i>	2,438	0.7074	0.6567	0.3064	0.5271	0.8709	1,444	0.7093	0.7383	0.2327	0.4601	0.8998
<i>LogAge</i>	2,438	2.5486	0.4823	2.1972	2.5649	2.8904	1,444	2.5477	0.5088	2.1972	2.5649	2.9957
<i>ROA</i>	2,438	0.0709	0.0515	0.0452	0.0669	0.0974	1,444	0.0703	0.0653	0.0329	0.0606	*** 0.0943
<i>OP</i>	2,438	0.3765	0.3748	0.1720	0.2900	0.4482	1,444	0.3758	0.3951	0.1591	0.2880	0.4795
<i>RE</i>	2,438	0.1445	0.2036	0.0582	0.1549	0.2527	1,444	0.1428	0.1822	0.0357	0.1595	*** 0.2590
<i>EarnVol</i>	2,438	0.0369	0.0456	0.0122	0.0220	0.0461	1,444	0.0371	0.0401	0.0134	0.0217	0.0491
<i>RetVol</i>	2,438	0.0159	0.0045	0.0128	0.0148	0.0185	1,444	0.0160	0.0034	0.0134	0.0155	** 0.0178
<i>Inst%</i>	2,438	0.4198	0.2249	0.2441	0.4075	0.5963	1,444	0.4193	0.2156	0.2724	0.4007	0.5926
<i>EA Delay</i>	2,438	33.5681	12.0269	24.0000	33.0000	43.0000	1,444	33.6055	13.1090	23.0000	30.0000	44.0000
Panel D: Overlap Weighted Sample												
<i>LogMVE</i>	1,261	7.5079	1.4981	6.3555	7.3353	8.6569	1,047	7.4779	1.4408	6.2942	7.3280	8.5765
<i>BTM</i>	1,261	0.7716	0.7221	0.3422	0.5724	0.9325	1,047	0.8114	0.8170	0.2727	0.5385	*** 1.0469
<i>LogAge</i>	1,261	2.4620	0.4775	2.0794	2.4849	2.8332	1,047	2.4590	0.4746	2.0794	2.3979	2.7726
<i>ROA</i>	1,261	0.0593	0.0485	0.0373	0.0579	0.0851	1,047	0.0327	*** 0.0533	0.0028	0.0342	*** 0.0615
<i>OP</i>	1,261	0.3657	0.4151	0.1509	0.2675	0.4287	1,047	0.3402	0.5331	0.1045	0.2040	*** 0.3787
<i>RE</i>	1,261	0.1034	0.2186	0.0204	0.1153	0.2270	1,047	0.0439	*** 0.1853	-0.0538	0.0389	*** 0.1563
<i>EarnVol</i>	1,261	0.0358	0.0396	0.0113	0.0215	0.0434	1,047	0.0478	*** 0.0469	0.0154	0.0321	*** 0.0647
<i>RetVol</i>	1,261	0.0168	0.0044	0.0134	0.0159	0.0195	1,047	0.0200	*** 0.0053	0.0162	0.0188	*** 0.0230
<i>Inst%</i>	1,261	0.4011	0.2267	0.2223	0.3955	0.5758	1,047	0.4031	0.2465	0.1956	0.3895	0.6147
<i>EA Delay</i>	1,261	34.8588	12.2040	25.0000	36.0000	45.0000	1,047	35.3701	13.0911	24.0000	36.0000	46.0000

This table reports descriptive statistics for dividend-paying and non-dividend-paying firms across four samples, with continuous variables winsorised by year at the 1st and 99th percentiles. For Panels A and B (unweighted samples), we use t-tests for mean differences and Wilcoxon tests for median differences to assess statistical significance. For Panels C and D (weighted samples), we use weighted t-tests for mean differences and the Hodges-Lehmann estimator for median differences, which accounts for the sample weights in the estimation. ***, **, * denote significant differences between the means or median values for dividend-paying and non-dividend-paying firms at the 1%, 5%, and 10% levels, respectively

Table 3. Correlation matrices

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: Unmatched Sample															
	<i>CAR</i>	<i>UE</i>	<i>Earn</i>	<i>EA Ret</i>	<i>EA Vol</i>	<i>LogMVE</i>	<i>BTM</i>	<i>LogAge</i>	<i>ROA</i>	<i>OP</i>	<i>RE</i>	<i>EarnVol</i>	<i>RetVol</i>	<i>Inst%</i>	<i>EA Delay</i>
(1) <i>CAR</i>	1.00														
(2) <i>UE</i>	0.32***	1.00													
(3) <i>Earn</i>	0.04***	0.05***	1.00												
(4) <i>EA Ret</i>	0.05***	0.03**	0.04***	1.00											
(5) <i>EA Vol</i>	-0.02*	0.05***	0.07***	0.41***	1.00										
(6) <i>LogMVE</i>	0.02	0.11***	0.05***	0.17***	0.54***	1.00									
(7) <i>BTM</i>	0.02	-0.03***	-0.06***	0.00	0.11***	-0.20***	1.00								
(8) <i>LogAge</i>	-0.00	0.08***	0.02**	0.10***	0.27***	0.43***	0.08***	1.00							
(9) <i>ROA</i>	0.04***	0.03**	0.10***	0.07***	0.03**	0.19***	-0.19***	0.07***	1.00						
(10) <i>OP</i>	-0.02	-0.00	0.06***	0.03**	0.09***	0.07***	-0.13***	-0.03**	0.30***	1.00					
(11) <i>RE</i>	0.05***	0.04***	0.10***	0.09***	0.07***	0.27***	0.01	0.17***	0.66***	0.08***	1.00				
(12) <i>EarnVol</i>	-0.04***	-0.03***	-0.04***	-0.09***	-0.04***	-0.24***	-0.07***	-0.17***	-0.30***	0.05***	-0.42***	1.00			
(13) <i>RetVol</i>	-0.02**	-0.07***	-0.08***	-0.12***	-0.25***	-0.56***	0.09***	-0.40***	-0.26***	-0.07***	-0.33***	0.32***	1.00		
(14) <i>Inst%</i>	0.03***	0.02	0.03**	0.08***	0.02	0.28***	-0.07***	0.08***	0.06***	-0.02**	0.09***	-0.16***	-0.22***	1.00	
(15) <i>EA Delay</i>	0.01	-0.04***	-0.04***	-0.17***	-0.12***	-0.24***	-0.01	-0.21***	-0.11***	-0.07***	-0.13***	0.09***	0.25***	-0.20***	1.00
Panel B: Propensity Score Matched Sample															
	<i>CAR</i>	<i>UE</i>	<i>Earn</i>	<i>EA Ret</i>	<i>EA Vol</i>	<i>LogMVE</i>	<i>BTM</i>	<i>LogAge</i>	<i>ROA</i>	<i>OP</i>	<i>RE</i>	<i>EarnVol</i>	<i>RetVol</i>	<i>Inst%</i>	<i>EA Delay</i>
(1) <i>CAR</i>	1.00														
(2) <i>UE</i>	0.34***	1.00													
(3) <i>Earn</i>	0.05**	0.05*	1.00												
(4) <i>EA Ret</i>	0.05*	0.04*	0.01	1.00											
(5) <i>EA Vol</i>	0.01	0.05*	0.02	0.39***	1.00										
(6) <i>LogMVE</i>	0.03	0.11***	0.01	0.13***	0.38***	1.00									
(7) <i>BTM</i>	-0.00	-0.07***	-0.10***	0.02	0.16***	-0.22***	1.00								
(8) <i>LogAge</i>	-0.03	0.04*	-0.01	0.03	0.13***	0.12***	0.21***	1.00							
(9) <i>ROA</i>	0.01	0.02	0.00	-0.02	-0.08***	0.04	-0.27***	-0.05**	1.00						
(10) <i>OP</i>	-0.05*	-0.01	0.02	-0.04	0.05**	0.02	-0.08***	-0.01	0.24***	1.00					
(11) <i>RE</i>	-0.01	-0.02	-0.06**	-0.03	-0.02	0.02	0.03	0.22***	0.17***	-0.02	1.00				
(12) <i>EarnVol</i>	-0.04	-0.05**	0.16***	-0.10***	-0.09***	-0.20***	-0.05**	-0.06**	0.09***	0.13***	-0.07***	1.00			
(13) <i>RetVol</i>	0.01	-0.02	-0.03	-0.05*	-0.05*	-0.24***	0.06**	-0.12***	-0.12***	-0.07***	-0.08***	0.24***	1.00		
(14) <i>Inst%</i>	0.01	0.04	0.02	0.08***	0.07***	0.41***	-0.11***	-0.01	0.10***	-0.05*	-0.01	-0.14***	-0.25***	1.00	
(15) <i>EA Delay</i>	0.04*	-0.02	0.00	-0.18***	-0.04	-0.12***	-0.09***	-0.15***	0.06**	-0.05**	0.02	-0.02	0.15***	-0.23***	1.00

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel C: Entropy Balanced Sample															
	<i>CAR</i>	<i>UE</i>	<i>Earn</i>	<i>EA Ret</i>	<i>EA Vol</i>	<i>LogMVE</i>	<i>BTM</i>	<i>LogAge</i>	<i>ROA</i>	<i>OP</i>	<i>RE</i>	<i>EarnVol</i>	<i>RetVol</i>	<i>Inst%</i>	<i>EA Delay</i>
(1) <i>CAR</i>	1.00														
(2) <i>UE</i>	0.33***	1.00													
(3) <i>Earn</i>	0.02	0.02	1.00												
(4) <i>EA Ret</i>	0.03*	0.02	0.01	1.00											
(5) <i>EA Vol</i>	-0.02	0.06***	0.03	0.39***	1.00										
(6) <i>LogMVE</i>	0.03	0.10***	0.01	0.12***	0.42***	1.00									
(7) <i>BTM</i>	0.01	-0.03	-0.11***	0.03	0.18***	-0.18***	1.00								
(8) <i>LogAge</i>	-0.01	0.06***	-0.02	0.01	0.17***	0.19***	0.17***	1.00							
(9) <i>ROA</i>	0.04**	0.03	0.01	-0.01	-0.09***	0.04*	-0.28***	-0.07***	1.00						
(10) <i>OP</i>	-0.01	-0.01	0.05**	-0.05**	0.03	0.01	-0.11***	-0.02	0.29***	1.00					
(11) <i>RE</i>	0.02	0.02	-0.07***	0.01	-0.00	0.03	0.08***	0.16***	0.05***	-0.03	1.00				
(12) <i>EarnVol</i>	-0.03*	-0.05**	0.14***	-0.09***	-0.05**	-0.13***	-0.08***	-0.01	0.01	0.12***	-0.05***	1.00			
(13) <i>RetVol</i>	-0.01	-0.02	-0.06***	-0.03	-0.05**	-0.26***	0.05***	-0.14***	-0.17***	-0.11***	-0.11***	0.21***	1.00		
(14) <i>Inst%</i>	0.03	0.02	0.01	0.07***	0.08***	0.44***	-0.08***	-0.03	0.07***	-0.05***	0.01	-0.12***	-0.23***	1.00	
(15) <i>EA Delay</i>	0.02	-0.02	-0.02	-0.14***	-0.03	-0.12***	-0.06***	-0.16***	0.04**	-0.02	0.06***	-0.01	0.19***	-0.20***	1.00
Panel D: Overlap Weighted Sample															
	<i>CAR</i>	<i>UE</i>	<i>Earn</i>	<i>EA Ret</i>	<i>EA Vol</i>	<i>LogMVE</i>	<i>BTM</i>	<i>LogAge</i>	<i>ROA</i>	<i>OP</i>	<i>RE</i>	<i>EarnVol</i>	<i>RetVol</i>	<i>Inst%</i>	<i>EA Delay</i>
(1) <i>CAR</i>	1.00														
(2) <i>UE</i>	0.31***	1.00													
(3) <i>Earn</i>	0.00	0.03	1.00												
(4) <i>EA Ret</i>	0.02	0.02	0.01	1.00											
(5) <i>EA Vol</i>	-0.03	0.07***	0.04	0.39***	1.00										
(6) <i>LogMVE</i>	0.00	0.09***	0.00	0.11***	0.39***	1.00									
(7) <i>BTM</i>	0.03	-0.04*	-0.09***	0.07***	0.15***	-0.19***	1.00								
(8) <i>LogAge</i>	-0.02	0.05**	-0.02	0.02	0.09***	0.04	0.22***	1.00							
(9) <i>ROA</i>	0.05**	0.05*	-0.03	-0.02	-0.10***	0.01	-0.30***	-0.13***	1.00						
(10) <i>OP</i>	-0.01	-0.02	0.07**	-0.06**	0.02	-0.02	-0.13***	-0.04	0.28***	1.00					
(11) <i>RE</i>	0.01	-0.00	-0.06**	-0.02	-0.03	-0.04*	0.11***	0.15***	-0.07***	-0.09***	1.00				
(12) <i>EarnVol</i>	-0.07***	-0.05*	0.14***	-0.13***	-0.07***	-0.17***	-0.09***	-0.00	0.01	0.18***	-0.06**	1.00			
(13) <i>RetVol</i>	-0.03	-0.02	-0.04*	-0.01	-0.01	-0.16***	0.00	-0.07***	-0.09***	-0.13***	-0.03	0.22***	1.00		
(14) <i>Inst%</i>	0.02	0.01	0.00	0.07***	0.08***	0.46***	-0.05**	-0.10***	0.04	-0.06**	-0.06**	-0.14***	-0.18***	1.00	
(15) <i>EA Delay</i>	-0.00	-0.01	0.00	-0.16***	0.02	-0.08***	-0.10***	-0.12***	0.05*	-0.04	0.05**	-0.03	0.13***	-0.22***	1.00
This table presents Pearson correlation coefficients among key variables across four sample specifications. Panel A reports correlations for the full unmatched sample, while Panels B, C, and D present correlations for the PSM, entropy-balanced, and overlap-weighted samples, respectively. For Panels C and D, correlations are weighted using the respective sample weights. The Pearson correlation test evaluates the null hypothesis that the correlation between two variables equals zero. ***, **, and * indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively															

4.2. Dividends and Their Effect on Earnings Response Coefficients (H1)

This section presents the empirical results for H1, which tests whether dividend-paying firms exhibit smaller ERCs at quarterly EAs compared to non-payers, as specified in Equation (1). Table 3 reports the regression estimates across our four sample constructions. In the unmatched sample, the interaction term $UE * DIV$ is positive and statistically significant at the 5% level ($t = 2.07$). In the PSM, entropy-balanced, and overlap-weighted samples, the interaction coefficient remains positive but not statistically significant. The positive sign of the interaction term indicates that the CAR associated with unexpected earnings is larger for dividend-paying firms than for non-payers.

Table 4. Dividends and earnings response coefficients

	Expected Sign	(1) CAR	(2) CAR	(3) CAR	(4) CAR
<i>DIV</i>	N/A	-0.0064 (-1.20)	0.0033 (0.46)	0.0010 (0.15)	-0.0071 (-0.87)
<i>UE</i>	+	0.0982** (2.40)	0.1025 (1.32)	-0.0659 (-0.96)	0.1444** (2.01)
<i>UE * DIV</i>	–	0.0183** (2.07)	0.0073 (0.61)	0.0098 (0.88)	0.0130 (0.93)
Industry * Year FE		Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes
Controls * UE		Yes	Yes	Yes	Yes
Year * UE		Yes	Yes	Yes	Yes
Sample		Unmatched	PSM	Entropy	Overlap
Observations		9,911	2,368	3,882	2,308
Adjusted R ²		0.132	0.137	0.160	0.124

The table reports the OLS regression results. The dependent variable is the cumulative abnormal returns (*CAR*) surrounding the EA. Our variables of interest are the dividend indicator (*DIV*), unexpected earnings (*UE*), and the interaction variable $UE * DIV$, which is bolded. We include ten control variables: *LogMVE*, *BTM*, *LogAge*, *ROA*, *OP*, *RE*, *EarnVol*, *RetVol*, *Inst%*, and *EA Delay*, as well as industry-year fixed effects, and interaction terms for $UE * CONTROLS$ and $UE * YEAR$. We utilise robust standard errors clustered on the firm level. ***, **, * indicate statistical significance for two-tailed test at the 1%, 5%, and 10% level, respectively. T-statistics are reported in parentheses below the coefficient

As a robustness check, we estimate a parsimonious specification of Equation (1) that excludes $UE * CONTROLS$ and $UE * YEAR$ interactions. Table A2 in Appendix A.1. shows that $UE * DIV$ remains positive across all four samples, reaching statistical significance at the 1% level ($t = 4.46$) in the unmatched sample. The adjusted R² values for the parsimonious model are roughly in line with the full model, which fall between 0.132 to 0.160. The coefficient on *DIV* varies in sign and is statistically insignificant, and the *UE* coefficient is mostly positive and statistically significant, as hypothesised.

Table 5. Earnings response coefficients by quarter

Quarter	Expected Sign	Q1	Q2	Q3	Q4
Panel A: Unmatched Sample					
		(1) CAR	(2) CAR	(3) CAR	(4) CAR
<i>UE * DIV</i>	–	-0.0031 (-0.18)	0.0322** (2.00)	0.0227 (1.39)	0.0279* (1.66)
Observations		2,184	2,572	2,594	2,561
Adjusted R ²		0.137	0.187	0.140	0.089
Panel B: Propensity Score Matched Sample					
		(1) CAR	(2) CAR	(3) CAR	(4) CAR
<i>UE * DIV</i>	–	0.0101 (0.33)	0.0600** (2.01)	-0.0259 (-1.02)	-0.0131 (-0.51)
Observations		491	620	613	644
Adjusted R ²		0.027	0.245	0.132	0.105
Panel C: Entropy Balanced Sample					
		(1) CAR	(2) CAR	(3) CAR	(4) CAR
<i>UE * DIV</i>	–	0.0302 (1.30)	0.0304 (1.24)	0.0001 (0.01)	0.0040 (0.20)
Observations		821	980	1,022	1,059
Adjusted R ²		0.099	0.205	0.127	0.066
Panel D: Overlap Weighted Sample					
		(1) CAR	(2) CAR	(3) CAR	(4) CAR
<i>UE * DIV</i>	–	0.0162 (0.50)	0.0668* (1.90)	-0.0165 (-0.49)	0.0339 (1.15)
Observations		481	590	597	640
Adjusted R ²		0.094	0.176	0.125	0.029

The table reports the OLS regression results by quarter. The dependent variable is the cumulative abnormal returns (*CAR*) surrounding the earnings announcement. Our variables of interest are the dividend indicator (*DIV*), unexpected earnings (*UE*), and the interaction variable *UE * DIV*, which is bolded. We include ten control variables: *LogMVE*, *BTM*, *LogAge*, *ROA*, *OP*, *RE*, *EarnVol*, *RetVol*, *Inst%*, and *EA Delay*, as well as industry-year fixed effects, and interaction terms for *UE * CONTROLS* and *UE * YEAR*. We utilise robust standard errors clustered on the firm level. ***, **, * indicate statistical significance for two-tailed test at the 1%, 5%, and 10% level, respectively. T-statistics are reported in parentheses below the coefficient

Using the parsimonious specification, we quantify the difference in earnings reactions between dividend-paying and non-paying firms. It yields a single, stable coefficient that is most interpretable as the general market reaction to earnings. In the unmatched sample, *UE* is 0.0651, and *UE * DIV* is 0.0311, implying that dividend payers exhibit a 47.8% larger *CAR* response to unexpected earnings ($0.0311 / 0.0651 = 0.4777$). The corresponding differences remain

directionally positive in the matched and weighted samples: 13.2% (PSM), 8.8% (entropy-balanced), and 30.7% (overlap-weighted).

Table 5 presents the quarterly regressions. In Q1, the $UE * DIV$ interaction is statistically insignificant in all samples, and its sign varies across specifications. In Q2, the interaction term is positive in all four samples, with significance at the 5% level in the unmatched ($t = 2.00$) and PSM ($t = 2.01$) samples and at the 10% level ($t = 1.90$) in the overlap-weighted sample. The coefficient remains positive but insignificant in the entropy-balanced sample. In Q3, the interaction term is insignificant across all samples and shows no consistent sign pattern. In Q4, the estimates are positive for all samples except the PSM specification, although only the unmatched sample reaches 10% significance. Across quarters, Q2 produces the largest and most consistently positive estimates, whereas the remaining quarters show no systematic pattern.

Across all aggregate specifications, $UE * DIV$ is consistently positive, with statistical significance only in the unmatched sample. Across quarterly specifications, Q2 displays the largest and most frequently significant interaction estimates, whereas the other quarters show no systematic pattern. The results show directional stability but limited precision, and we do not find statistical evidence consistent with H1's prediction of smaller ERCs for payers.

4.3. Dividend Payers and the Persistence of Earnings Surprises (H2)

This section presents the results for H2, which tests whether UE for dividend-paying firms are associated with lower earnings persistence than for non-payers, following the specification in Equation (2). Table 6, Panel A, reports the estimates for the baseline model. Across all four sample constructions, the interaction term $UE * DIV$ is positive, attaining statistical significance at the 5% level ($t = 2.08$) only in the entropy-balanced sample. The unmatched, PSM, and overlap-weighted samples also yield positive coefficients, though not statistically significant.

Table 6 Panel B presents the results from the extended specification that incorporates non-linear UE controls. The pattern is unchanged: $UE * DIV$ remains positive in all four samples, with significance at 5% ($t = 2.40$) again limited to the entropy-balanced specification. Allowing for non-linearities therefore does not alter the direction or relative magnitude of the estimates, it remains stable across all eight regressions. We also note a higher explanatory power in the weighted samples, where adjusted R^2 significantly improves 0.308 – 0.369, compared to 0.128 – 0.138 in the unmatched sample.

Table 6. Dividends and earnings persistence

	Expected Sign	(1) Earn	(2) Earn	(3) Earn	(4) Earn
Panel A: Standard Model					
<i>DIV</i>	+	-0.0067 (-0.16)	-0.0364 (-0.98)	-0.0167 (-1.07)	-0.0145 (-0.60)
<i>UE</i>	+	0.1965 (1.50)	0.2558 (1.47)	-0.0253 (-0.26)	0.1217 (0.59)
<i>UE * DIV</i>	–	0.0054 (0.11)	0.0528 (0.99)	0.0458** (2.08)	0.0279 (0.65)
Industry * Year FE		Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes
Controls * UE		Yes	Yes	Yes	Yes
Year * UE		Yes	Yes	Yes	Yes
UE additional controls		No	No	No	No
Sample		Unmatched	Propensity	Entropy	Overlap
Observations		7,288	1,575	2,546	1,493
Adjusted R ²		0.128	0.313	0.308	0.343
	Expected Sign	(1) Earn	(2) Earn	(3) Earn	(4) Earn
Panel B: Additional UE Controls					
<i>DIV</i>	+	-0.0096 (-0.37)	-0.0372 (-1.26)	-0.0170 (-1.17)	-0.0194 (-0.70)
<i>UE</i>	+	0.1601* (1.76)	0.2102 (1.34)	-0.0435 (-0.38)	0.1386 (0.68)
<i>UE * DIV</i>	–	0.0180 (0.64)	0.0571 (1.39)	0.0496** (2.40)	0.0480 (1.14)
Industry * Year FE		Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes
Controls * UE		Yes	Yes	Yes	Yes
Year * UE		Yes	Yes	Yes	Yes
UE additional controls		Yes	Yes	Yes	Yes
Sample		Unmatched	Propensity	Entropy	Overlap
Observations		7,288	1,575	2,546	1,493
Adjusted R ²		0.138	0.317	0.322	0.369

The table reports the OLS regression results. The dependent variable is the forward four-quarter EPS (*Earn*). Our variables of interest are the dividend indicator (*DIV*), unexpected earnings (*UE*), and the interaction variable *UE * DIV*, which is bolded. We include ten control variables: *LogMVE*, *BTM*, *LogAge*, *ROA*, *OP*, *RE*, *EarnVol*, *RetVol*, *Inst%*, and *EA Delay*, as well as industry-year fixed effects, and interaction terms for *UE * CONTROLS* and *UE * YEAR*. We utilise robust standard errors clustered on the firm level. ***, **, * indicate statistical significance for two-tailed test at the 1%, 5%, and 10% level, respectively. T-statistics are reported in parentheses below the coefficient

As a robustness check, we re-estimate Equation (2) using a parsimonious specification that excludes *UE * CONTROLS* and *UE * YEAR* interactions. As presented in Table A3 in Appendix A.1., the *UE * DIV* coefficient stays positive across all four samples with 10% significance ($t = 1.88$) in the overlap-weighted sample when *non-linear UE controls* are included. Although statistical significance declines relative to the baseline specification, the directional pattern

remains consistent and is not sensitive to the inclusion of the interaction structure. We note that both *DIV* and *UE* overall yield statistically insignificant coefficients across all specifications. *DIV* is consistently negative, whereas the sign of *UE* varies, in contrast to our expectations.

We also estimate both baseline and extended models on a quarterly basis for all four samples, yielding 32 regressions. In the quarterly results, *UE * DIV* show no consistent pattern of statistical significance. Only two estimates reach 10% significance: a negative coefficient in the unmatched Q4 regression of the baseline model ($t = -1.89$), and a positive coefficient in the entropy-balanced Q1 regression of the extended model ($t = 1.67$). All remaining estimates are statistically insignificant, and signs vary across quarters and samples. Taken together, the results fail to find evidence of H2's prediction that earnings surprises contain less information about future earnings for dividend-paying firms.

4.4. Dividends and the Attention to Earnings (H3)

This section presents the results for H3, which examines whether announcement-window trading activity and return magnitudes are lower for dividend-payers compared to non-payers, following the specification in Equation (3). Table 7, Panel A, reports the regressions using trading volume (*EA Vol*) as the attention measure. Across all four sample constructions, the coefficient on *DIV* is statistically insignificant. The sign varies: it is negative in the unmatched sample and positive in the PSM, entropy-balanced, and overlap-weighted samples. The estimates imply no consistent association between dividend status and trading activity.

Table 7, Panel B, reports the regressions using absolute returns (*EA Ret*). As with trading volume, all *DIV* coefficients are statistically insignificant. However, they are all consistently positive. Thus, the magnitude of announcement-window stock price movements does not differ systematically between payers and non-payers. The explanatory power of this specification is notably lower ($R^2 = 0.115 - 0.166$) than in the trading-volume regressions ($R^2 = 0.302 - 0.406$).

As a robustness check, we estimate a parsimonious version of Equation (3) that excludes the *UE* decile fixed effects. As shown in Table A4 in Appendix A.1., the results closely mirror the baseline specification: the *DIV* coefficient remains statistically insignificant across all samples for both attention measures, and its sign continues to vary across constructions.

In unablated analyses, we estimate Equation (3) separately by fiscal quarter across all samples for trading volume and absolute returns, respectively. Only one estimate reaches marginal significance: in the unmatched sample for Q2 with *EA Vol*, the *DIV* coefficient is negative and

significant at the 10% level ($t = -1.86$). All other quarterly estimates for are statistically insignificant, and the signs vary across samples and quarters, indicating no recurring pattern.

Across all model specifications, *DIV* is statistically insignificant in all but one case. The sign also fluctuates across specifications and indicates no directional consistency. Overall, our results fail to find evidence that investors pay less attention to the EAs of dividend-payers.

Table 7. Dividends and investor earnings attention

	Expected Sign	(1) EA Vol	(2) EA Vol	(3) EA Vol	(4) EA Vol
Panel A: Trading Volume					
<i>DIV</i>	–	-0.0725 (-0.90)	0.0409 (0.49)	0.1273 (1.54)	0.0421 (0.45)
Industry * Year FE		Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes
UE decile FE		Yes	Yes	Yes	Yes
Sample		Unmatched	Propensity	Entropy	Overlap
Observations		9,619	2,278	3,730	2,218
Adjusted R ²		0.406	0.302	0.308	0.327
	Expected Sign	(1) EA Ret	(2) EA Ret	(3) EA Ret	(4) EA Ret
Panel B: Absolute Returns					
<i>DIV</i>	–	0.0063 (0.20)	0.0004 (0.01)	0.0193 (0.48)	0.0163 (0.35)
Industry * Year FE		Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes
UE decile FE		Yes	Yes	Yes	Yes
Sample		Unmatched	Propensity	Entropy	Overlap
Observations		9,619	2,278	3,730	2,218
Adjusted R ²		0.116	0.160	0.115	0.166

The table reports the OLS regression results. In Panel A, the dependent variable is trading volume (*EA Vol*), and in Panel B, return volatility (*EA Ret*). Our variable of interest is the dividend indicator (*DIV*), which is bolded. We include ten control variables: *LogMVE*, *BTM*, *LogAge*, *ROA*, *OP*, *RE*, *EarnVol*, *RetVol*, *Inst%*, and *EA Delay*, as well as industry-year fixed effects and *UE* decile fixed effects. We utilise robust standard errors clustered on the firm level. ***, **, * indicate statistical significance for two-tailed test at the 1%, 5%, and 10% level, respectively. T-statistics are reported in parentheses below the coefficient

5. Discussion

5.1. Dividends and Their Effect on Earnings Response Coefficients (H1)

H1 predicted that dividend-paying firms would exhibit weaker stock-price reactions to EAs, consistent with dividends substituting for earnings information. Across all model specifications, we fail to find support for this substitution effect. Instead, dividend payers appear to display stronger ERCs than non-payers. Thus, investors appear to adjust their expectations more strongly when a dividend-paying firm reports an earnings surprise, resulting in a larger stock-

price reaction around the EA. Rather than crowding out attention to earnings, the dividend seems to enhance the informational value of the EA.

The parsimonious model provides the clearest view of the economic magnitude. Across all four samples, the interaction between unexpected earnings and dividend status ($UE * DIV$) is positive, albeit the strength of the impact varies. In the unmatched sample, the results imply that dividend payers have an ERC roughly 48% stronger than non-payers. While this is the only estimate that can be determined with high confidence, the consistent pattern of positive signs across all sample constructions suggests a stable underlying relationship.

The full model is consistent with the same positive pattern. The inclusion of year-by-industry fixed effects helps capture variation tied to specific industries and years. The UE interactions with controls allow market responses around EAs to vary with firm-specific characteristics. Finally, the UE interaction with yearly indicators allows the market responses to vary over time. This helps isolate the specific role of dividend policy. While these additions allow us to control for multiple other effects, they also absorb a substantial amount of the variation that would otherwise contribute to estimating the $UE * DIV$ coefficient. Despite the inclusion of these effects, we still find evidence that market responses, captured by the earnings response coefficients, are larger for dividend-payers than non-payers. This reinforces the conclusion that dividend payers enhance the informational value of EAs rather than reduce it.

A second insight comes from our quarter-specific analysis. Only Q2 consistently exhibit the positive association between the dividend status and market reactions to EA. Most of the observations for this quarter are statistically significant, which means we can infer the pattern with high confidence. For Swedish firms, Q2 has an economically meaningful role, as it is the fiscal quarter that directly precedes the AGM season, during which the dividend is ratified and paid out. Because of this, the dividend decision might be particularly salient for investors, which in turn might influence its informational role relative to the Q2 earnings.

Our findings contrast with Ham et al. (2023), who instead document a clear substitution effect between dividends and earnings for U.S. dividend-paying firms. One potential explanation for the difference lies in institutional features and payout structure. U.S. firms declare dividends quarterly, often close to EAs, increasing the likelihood that the dividend announcement might become conjoined to investors and partly absorb the information in the earnings release.

In contrast, Swedish firms report quarterly but typically only declare dividends once per year. This creates a greater separation between dividend decisions and the quarterly reporting, which might reduce the possibility of a substitution effect. Thus, instead of replacing the role of earnings in assessing long-term profitability, dividends might serve as a broader credibility-enhancing signal. In line with signalling and agency theory (e.g. Easterbrook, 1984), where dividends function as a costly way for a firm to signal its performance and reduce agency conflicts, we therefore theorise that the dividend status strengthens the information in quarterly earnings, leading to a stronger stock-price reaction around EAs.

Another dimension of this phenomenon is the quarterly effect, which was not explored by Ham et al. (2023). Building on the signalling perspective, given the high salience of the dividend decision at the Q2 EA, the signalling mechanism might be particularly pronounced for investors at this time. Thus, the combination of a recently confirmed payout and the EA might amplify the credibility of the accompanying earnings, possibly explaining the stronger stock-price reaction relative to other quarters.

While the results seem to point toward a complementary relationship between earnings and dividends, other explanations must be considered. While our design attempts to mitigate unwanted biases and errors, the explanatory power of the full model remains relatively low. This implies that unobserved characteristics between payers and non-payers, such as governance quality, aggressiveness in revenue recognition, and management guidance policies, may still influence investor reactions.

Moreover, the strength of our results is constrained by the matching and weighting procedures, which reduce the sample size and prevent us from making conclusions with high confidence in the alternative samples. Compared to Ham et al. (2023), who have a maximum sample size of over 200,000 observations, our sample of roughly 10,000 firm-quarters limits our ability to detect small effects. Even so, the consistent positive association between dividend status and stock-price reactions around EAs gives us some confidence in our reasoning for the observed complementarity.

5.2. Dividend Payers and the Persistence of Earnings Surprises (H2)

H2 predicted that earnings surprises for payers would be less informative about future earnings than for non-payers, consistent with dividends substituting for information about their permanent earnings. This would imply a negative coefficient on the interaction between

unexpected earnings and dividend status ($UE * DIV$). Across our specifications, including a simplified version, we find no evidence of the substitution effect. Instead, our results suggest a positive association between the dividend status and future earnings. This implies that earnings surprises for dividend-payers carry greater information about the firm's earnings persistence than those of non-payers.

Although our results do not allow us to infer the effect with high confidence, the consistency of positive associations across samples indicates an underlying pattern pointing toward complementarity. As with H1, we also attempt to isolate the specific role of the dividend status in shaping the persistence of earnings surprises by controlling for various fixed effects. These attempt to capture any shocks tied to a particular industry or year and allow the relationship between current and future earnings to vary with firm characteristics. We also extend the model to allow for non-linearities in unexpected earnings, addressing the possibility that linear models might obscure any uneven market responses to large or small earnings surprises. While these interactions absorb meaningful variation, the association remains consistently positive across all samples. As the pattern remains intact despite greater model complexity, this strengthens the evidence that dividends do not reduce the predictive content of earnings surprises, reinforcing complementarity rather than substitution.

Unlike the pronounced Q2 effect found in H1, we find no such pattern in our quarterly analysis of H2. There is a lack of a recurring pattern and thus an inability to conclude whether dividend status conveys information about future earnings confidently. This suggests that dividends do not systematically affect how current earnings surprises translate into future earnings at different points throughout the fiscal year.

Our results again stand in contrast with the substitution effect documented by Ham et al. (2023). Instead of earnings surprises being more transitory for payers, we observe the opposite: their surprises appear to, if anything, be more persistent. Again, using a perspective from signalling and agency theory, the dividend might function as a credible commitment that implicitly communicates management's confidence in the firm's long-run prospects. This could make the accompanying earnings information more reliable and persistent, in line with the reasoning of Booth and Zhou (2017) and the findings of Skinner and Soltes (2011).

Particularly, in the Swedish setting, we theorise that the differing results again could be explained by the infrequent dividend updates. The greater disconnect between dividend declarations and quarterly reporting might make the dividend itself an independent source of

information about future firm performance. This could potentially make it less likely to substitute for the information contained in quarterly earnings surprises. This phenomenon might not prevail in the U.S. market, where the two signals are intertwined.

As with H1, the confidence of our findings is limited due to an even smaller sample size, negatively affecting our explanatory power. This could be a potential explanation as to why we are not able to infer any clear indications of an effect in the quarterly analysis. Given our low explanatory power, we leave room for unobserved firm characteristics or other effects that might influence the results. Despite this, the consistent positive pattern across all specifications reinforces the notion that dividends do not substitute for earnings but rather serve as informational complements.

5.3. Dividends and the Attention to Earnings (H3)

H3 predicted that dividend-paying firms receive less investor attention at EAs, consistent with dividends functioning as a salient alternative signal of firm performance that reduces reliance on the EA. Under this interpretation, dividend-paying firms would be expected to exhibit lower trading activity or smaller price movements around the announcement, reflected in a negative coefficient on dividend status (*DIV*). For both attention measures, we find no evidence supporting this mechanism. The association between dividend status and investor attention at EAs is both positive and negative, depending on the model version and the sample tested. Thus, dividends do not appear to reduce trading activity or mute price reactions when they release quarterly earnings in relation to non-payers.

As with the earlier hypotheses, we test for effects that might influence our results by including various fixed effects. These control for yearly and industry-specific variation. We also include a decile-ranked fixed effect for earnings surprises. This absorbs differences in investor reactions by ensuring that firms are compared only with others facing earnings surprises of similar magnitude. Including the full set of controls, as well as controlling for these additional sources of variation, helps isolate the association between dividend status and investor attention while holding the informational environment constant. Even under an implied model that excludes the fixed effect on earnings surprises, there is still no clear pattern between dividend status and investor attention. The absence of a negative association remains meaningful, as it suggests that dividends do not appear to affect the attention paid by investors at the quarterly EAs.

The quarterly analysis further supports the notion that there is no apparent relationship between dividend status and investor attention. Unlike the clear Q2 pattern in H1, no fiscal quarter consistently differentiates the attention that dividend payers receive at EAs. Overall, our results suggest that dividends do not appear to materially alter the attention investors pay to EAs.

Our results differ from Ham et al. (2023), who report lower investor attention to EAs among U.S. dividend payers. In Sweden, dividends do not appear to substitute for the information communicated through the EAs, nor do we find support for the opposite claim. Instead, dividend seem to play a limited role in shaping how much attention investors devote to EAs.

Although the H3 results are somewhat inconsistent with H1 and H2, the tension could potentially be explained by making a distinction between how strongly investors react and how many investors pay attention. In Sweden's annual dividend setting, dividends seem to enhance the credibility and informativeness of earnings, as reasoned in H1 and H2. Still, they might not be salient enough at the EA to change the level of attention investors allocate to it. Thus, dividends might affect the interpretation of earnings without necessarily affecting the attention allocated to the EA.

Another explanation is the low explanatory power of the model. If any true effect of dividends on investor attention is small, the low sample size, especially once partitioned by quarter, may limit our ability to even detect it. The lack of a pattern may therefore reflect constraints of the sample rather than the absence of an underlying economic effect. Nevertheless, the instability of signs and the uniformly insignificant results suggest that dividends do not materially influence investor attention at EAs in Sweden.

5.4. Integrated Interpretation of Results

Overall, our results are surprising. None of our findings align with Ham et al. (2023), which represents the closest proxy to our study, albeit in a U.S. setting. Contrary to our hypothesis, our results indicate that, in both H1 and H2, dividends and earnings exhibit a complementary relationship rather than a substitutional one. Dividend-paying firms appear to exhibit stronger market reactions to earnings news, and their EAs seem to contain more information about future earnings. For H3, the results are ambiguous, with no clear directional pattern found, implying that dividends neither enhance nor diminish investor attention at EAs. Although we only have limited confidence in many of our findings, the directionality of the results is remarkably stable across both H1 and H2, allowing us to infer a meaningful economic relationship.

On a quarterly basis, dividend-paying firms appear to experience stronger market reactions to earnings news in Q2, whereas no such pattern could be found for the other two hypotheses. However, this might be due to the restrictions discussed that are associated with a small sample size. With fewer observations, it becomes harder to distinguish real patterns from normal variation, increasing the uncertainty around the estimates. This issue is even more pronounced in the quarterly analyses, where each quarter contains only a fraction of the original sample. However, the fact that the pattern in Q2 is present despite these shortcomings makes it a particularly credible finding.

6. Conclusion

6.1. Summary and Contribution

The informational value of dividends has long been discussed in financial accounting, with multiple prevailing theoretical frameworks. Most research has focused on the U.S., where a stream of research has documented that dividends reduce the market's reliance on EAs to evaluate a firm's future performance. However, this leaves a research gap regarding the information value of dividends in a Swedish setting. Thus, this study aims to examine whether dividends substitute for the information provided in earnings.

Using a sample of listed Swedish firms comprising 419 firms and 9,911 firm-quarters from 2005 to 2024, we test three hypotheses related to share-price reactions, earnings persistence, and investor attention. Our empirical approach relies on multivariate regressions on samples with alternative weighting methods to address differences between dividend-paying and non-paying firms. We estimate ERCs, the relation between earnings surprises and actual future next twelve months earnings, and two measures of investor attention, all around the earnings announcement window.

We fail to find evidence that dividends substitute for, and reduce the informational value of earnings. For H1, stock-price reactions to earnings news are, if anything, stronger for dividend-paying firms. For H2, earnings surprises seem to be more informative about future performance for payers than for non-payers. For H3, dividend status does not influence trading activity or return movements at the time of the announcement. While statistical significance is limited, the overall consistency of coefficient signs provides evidence that dividend payers' earnings carry more information.

Thus, we find weak evidence of informational complementarity between dividends and earnings, consistent with signalling and agency theories. We also find weak evidence that this effect is most pronounced during the second fiscal quarter, following the AGM season and the ratification and payout of the dividend.

Our study contributes to existing literature by extending our understanding of dividend informativeness to a new institutional environment characterised by different dividend payout and declaration conventions. Our results are contrary to previous findings on the topic and imply that the substitution effect described in the U.S. by Ham et al. (2023) is not directly generalisable to another institutional setting. Instead, under the Swedish institutional setting, dividends appear to function as a credibility-enhancing signal. Our findings are thus more consistent with Skinner and Soltes (2011) and Booth and Zhou (2017), who emphasise the role of dividends in conveying and predicting future profitability.

Our findings also provide a novel insight into the variation in the strength of the complementary effect between dividends and earnings based on which fiscal quarter the EA pertains to. This suggests that the informational value of dividends is not uniform throughout the fiscal year but might instead be tied to the time from the ratification of the dividend, for example.

From a practical standpoint, understanding how Swedish investors respond to earnings and dividends is relevant for firms' disclosure practices, investor relations strategies, and the interpretation of earnings announcements during the Swedish reporting season. Swedish firms cannot rely on dividends alone to convey information about their long-run earnings capacity. Still, this paper might help managers understand what signals their dividend policy conveys about future earnings.

6.2. Limitations

While our findings are informative, several limitations should be considered when interpreting the results. First, the smaller size of the Swedish market, combined with lower analyst coverage might reduce statistical power and lead to noisier measures of unexpected earnings, given less comprehensive consensus forecasts. This limits our ability to detect subtle differences between payers and non-payers.

Second, our dividend indicator may occasionally classify special dividends as regular payouts. Because special dividends carry different informational implications, this classification may introduce noise into the classification of dividend-paying versus non-paying firms. Although

the overall effect is likely modest, it reduces the precision with which we can separate firms based on their long-term dividend policy.

While matching, weighting, and fixed effects improve comparability, unobserved differences, such as governance practices or disclosure behaviour, may still influence dividend policy and market reactions. Given the limited statistical significance and low explanatory power across several specifications, it could imply that we fail to capture important factors in our regressions.

Finally, although we attempted to implement the timing mechanism between the dividend declaration date and EA, proposed by Ham et al. (2023), the Swedish institutional setting makes this infeasible. Almost all Swedish firms declare their dividend together with the Q4 EA. As a result, we cannot distinguish the market reaction to the dividend declaration from the response to the EA. This limitation reflects the structure of the Swedish reporting cycle rather than a methodological constraint.

6.3. Suggestions for Further Research

Given that our findings are not consistent with previous research, it would be interesting to conduct studies in similar markets such as Norway, Denmark, and Finland to examine whether our results generalise to countries with similar institutional features as Sweden. Furthermore, conducting a cross-Nordic study would also expand the sample size and mitigate statistical power limitations present in our paper.

Another extension concerns stock repurchases, an alternative payout channel not examined here. Repurchases may convey different information than dividends, and studying whether they substitute for, complement, or reshape the role of earnings would broaden our understanding of payout policy.

Finally, further research could explore whether the informational value of dividends depends on how closely payouts are tied to permanent earnings. Prior work by Ham et al. (2023), for example, examines how the informational value of dividends is affected when they are funded by large cash balances. Investigating such mechanisms in Sweden or similar markets would deepen our understanding of when dividends convey information about long-run earnings.

7. References

- Ali, Ashiq, and Paul Zarowin. 'Permanent versus Transitory Components of Annual Earnings and Estimation Error in Earnings Response Coefficients'. *Journal of Accounting and Economics* 15, no. 2 (1992): 249–64.
- Asquith, Paul, and David W. Mullins. 'The Impact of Initiating Dividend Payments on Shareholders' Wealth'. *The Journal of Business* 56, no. 1 (1983): 77–96.
- Bamber, Linda Smith. 'The Information Content of Annual Earnings Releases: A Trading Volume Approach.' *Journal of Accounting Research (Wiley-Blackwell)* 24, no. 1 (1986): 40–56. 6439970.
- Beaver, William H. 'The Information Content of Annual Earnings Announcements.' *Journal of Accounting Research (Wiley-Blackwell)* 6, no. 3 (1968): 67–92. 6405656.
- Bilinski, Pawel, and Mark T. Bradshaw. 'Analyst Dividend Forecasts and Their Usefulness to Investors.' *Accounting Review* 97, no. 4 (2022): 75–104. 158265394.
- Bolton, Patrick, Hui Chen, and Neng Wang. 'A Unified Theory of Tobin's q, Corporate Investment, Financing, and Risk Management'. *The Journal of Finance* 66, no. 5 (2011): 1545–78.
- Booth, Laurence, and Jun Zhou. 'Dividend Policy: A Selective Review of Results from around the World'. *Global Finance Journal* 34 (November 2017): 1–15.
- Brav, Alon, John R. Graham, Campbell R. Harvey, and Roni Michaeli. 'Payout Policy in the 21st Century'. *Journal of Financial Economics* 77, no. 3 (2005): 483–527.
- Carlsson, Filip, and Karl Steiner. 'Dividend Season and Updated Krona Forecasts.' *Skandinaviska Enskilda Banken AB*, 19 March 2025. Available at: <https://research.sebgroup.com/macro-ficc/reports/59307> (Accessed: 6 December 2025).
- Chay, J. B., and Jungwon Suh. 'Payout Policy and Cash-Flow Uncertainty'. *Journal of Financial Economics* 93, no. 1 (2009): 88–107.
- Chen, Ciao-Wei, Maria Correia, and Oktay Urcan. 'Accounting for Leases and Corporate Investment.' *Accounting Review* 98, no. 3 (2023): 109–33. 163763554.

- DeAngelo, Harry, Linda DeAngelo, and René M. Stulz. 'Dividend Policy and the Earned/Contributed Capital Mix: A Test of the Life-Cycle Theory'. *Journal of Financial Economics* 81, no. 2 (2006): 227–54.
- Del Guercio, Diane. 'The Distorting Effect of the Prudent-Man Laws on Institutional Equity Investments'. *Journal of Financial Economics* 40, no. 1 (1996): 31–62.
- Dempsey, Stephen J., and Hainan Sheng. 'Dividend Change Announcements, ROE, and the Cost of Equity Capital'. *International Review of Financial Analysis* 86 (March 2023): 102506.
- Denis, David J., and Igor Osobov. 'Why Do Firms Pay Dividends? International Evidence on the Determinants of Dividend Policy'. *Journal of Financial Economics* 89, no. 1 (2008): 62–82.
- Easterbrook, Frank H. 'Two Agency-Cost Explanations of Dividends'. *The American Economic Review* 74, no. 4 (1984): 650–59.
- Easton, Peter D., and Mark E. Zmijewski. 'Cross-Sectional Variation in the Stock Market Response to Accounting Earnings Announcements'. *Journal of Accounting and Economics* 11, nos 2–3 (1989): 117–41.
- Ed-Dafali, Slimane, Ritesh Patel, and Najaf Iqbal. 'A Bibliometric Review of Dividend Policy Literature'. *Research in International Business and Finance* 65 (April 2023): 101987.
- Fama, Eugene F., and Kenneth R. French. 'Taxes, Financing Decisions, and Firm Value'. *The Journal of Finance* 53, no. 3 (1998): 819–43.
- Fama, Eugene F., and Kenneth R. French. 'Forecasting Profitability and Earnings.' *Journal of Business* 73, no. 2 (2000): 161. 3168775.
- Feltham, Gerald A., and James A. Ohlson. 'Valuation and Clean Surplus Accounting for Operating and Financial Activities.' *Contemporary Accounting Research* 11, no. 2 (1995): 689–731. 10930908.
- Grinstein, Yaniv, and Roni Michaely. 'Institutional Holdings and Payout Policy'. *The Journal of Finance* 60, no. 3 (2005): 1389–426.
- Grullon, Gustavo, Roni Michaely, and Bhaskaran Swaminathan. 'Are Dividend Changes a Sign of Firm Maturity?' *The Journal of Business* 75, no. 3 (2002): 387–424.

- Guay, Wayne, and Jarrad Harford. 'The Cash-Flow Permanence and Information Content of Dividend Increases versus Repurchases'. *Journal of Financial Economics* 57, no. 3 (2000): 385–415.
- Hainmueller, Jens. 'Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies'. *Political Analysis* 20, no. 1 (2012): 25–46.
- Ham, Charles G., Zachary R. Kaplan, and Mark T. Leary. 'Do Dividends Convey Information about Future Earnings?' *Journal of Financial Economics* 136, no. 2 (2020): 547–70.
- Ham, Charles G., Zachary R. Kaplan, and Steven Utke. 'Attention to Dividends, Inattention to Earnings?' *Review of Accounting Studies* 28, no. 1 (2023): 265–306.
- Healy, Paul M., and Krishna G. Palepu. 'Earnings Information Conveyed by Dividend Initiations and Omissions'. *Journal of Financial Economics* 21, no. 2 (1988): 149–75.
- Hirshleifer, David, and Siew Hong Teoh. 'Limited Attention, Information Disclosure, and Financial Reporting'. *Journal of Accounting and Economics*, Conference Issue on, vol. 36, no. 1 (2003): 337–86.
- Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth A. Stuart. 'Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference'. *Political Analysis* 15, no. 3 (2007): 199–236.
- Jensen, Michael C. 'Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers'. *The American Economic Review* 76, no. 2 (1986): 323–29.
- Johnson, Travis L., and Eric C. So. 'Time Will Tell: Information in the Timing of Scheduled Earnings News.' *Journal of Financial & Quantitative Analysis* 53, no. 6 (2018): 2431–64. 133601590.
- Kanas, Angelos. 'Bank Dividends, Risk, and Regulatory Regimes'. *Journal of Banking & Finance* 37, no. 1 (2013): 1–10.
- Kim, Oliver, and Robert E. Verrecchia. 'Trading Volume and Price Reactions to Public Announcements.' *Journal of Accounting Research (Wiley-Blackwell)* 29, no. 2 (1991): 302–21. 6415340.

- KPMG. (2024). *IFRS compared to US GAAP: Handbook*. November 2024 edition. KPMG International. Available at: <https://kpmg.com/kpmg-us/content/dam/kpmg/frv/pdf/2025/isg-handbook-2025-ifs-compared-to-us-gaap.pdf> (Accessed: 22 October 2025).
- Leuz, Christian, Dhananjay Nanda, and Peter D Wysocki. 'Earnings Management and Investor Protection: An International Comparison'. *Journal of Financial Economics* 69, no. 3 (2003): 505–27.
- Li, Fan, and Laine E Thomas. 'Addressing Extreme Propensity Scores via the Overlap Weights'. *American Journal of Epidemiology*, ahead of print, 5 September 2018.
- Lintner, John. 'Distribution of Incomes of Corporations Among Dividends, Retained Earnings, and Taxes'. *The American Economic Review* 46, no. 2 (1956): 97–113.
- Miller, Merton H., and Franco Modigliani. 'Dividend Policy, Growth, and the Valuation of Shares'. *The Journal of Business* 34, no. 4 (1961): 411–33.
- Myers, Stewart C., and Nicholas S. Majluf. 'Corporate Financing and Investment Decisions When Firms Have Information That Investors Do Not Have'. *Journal of Financial Economics* 13, no. 2 (1984): 187–221.
- Roychowdhury, Sugata, and Ewa Sletten. 'Voluntary Disclosure Incentives and Earnings Informativeness.' *Accounting Review* 87, no. 5 (2012): 1679–708. 85164145.
- Rozeff, Michael S. 'Growth, Beta and Agency Costs as Determinants of Dividend Payout Ratios'. *Journal of Financial Research* 5, no. 3 (1982): 249–59.
- Skinner, Douglas, and Eugene Soltes. 'What Do Dividends Tell Us about Earnings Quality?' *Review of Accounting Studies* 16, no. 1 (2011): 1–28. 58527576.
- Swedish Companies Act (2005:551). Svensk författningssamling. Available at: https://www.riksdagen.se/sv/dokument-och-lagar/dokument/svensk-forfattningssamling/aktiebolagslag-2005551_sfs-2005-551/ (Accessed: 6 December 2025)

A. Appendix

A.1. Additional Tables

Table A1. Variable definitions

Variable	Definition
Panel A: Dependent Variables	
$CAR_{i,q}$	The sum of the abnormal returns for firm i around quarter q earnings announcement in a three-day interval centred on the earnings announcement date ($day = 0$). $\sum_{day=-1}^1 (daily\ return - country\ market\ return)$, where beta is assumed to equal one
$Earn_{i,t}$	The sum of EPS for firm i from quarter $q + 1$ to $q + 4$, divided by the share price at the beginning of quarter q . If any required quarterly EPS is missing, we leave the value empty
$EA\ Vol_{i,q}$	The natural logarithm of $100 * NEWS_RATIO_VOL$. $NEWS_RATIO_VOL$ is defined as the sum of the trading volume in a three-day interval centred around the quarter q earnings announcement (EAV) for firm i , divided by non-earnings announcement trading volume NEAV. NEAV is defined as the sum of the trading volume from two days after the quarter $q - 1$ earnings announcement to one day after quarter q earnings announcement, adjusted by the EAV according to the following formula: $NEAV = (1 + QVOL) / (1 + EAV) - 1$. The definition follows Ham et al. (2023) and Roychowdhury and Sletten (2012)
$EA\ Ret_{i,q}$	The natural logarithm of $100 * NEWS_RATIO$. $NEWS_RATIO$ is defined as the sum of the absolute values of daily abnormal returns ($\sum daily\ return - country\ market\ return $) over a three-day interval centred around quarter q earnings announcement (EAR) for firm i , divided by non-earnings announcement absolute returns (NEAR). NEAR is defined as the sum of the absolute value of daily abnormal returns over the quarter (QRET) from two days after the quarter $q - 1$ earnings announcement to one day after quarter q earnings announcement, adjusted by EAR according to the following formula: $NEAR = (1 + QRET) / (1 + EAR) - 1$. The definition follows Ham et al. (2023) and Roychowdhury and Sletten (2012)
Panel B: Variables of Interest	
$DIV_{i,q}$	A dichotomous variable that equals one if firm i paid a dividend in year t and zero otherwise. We account for the fact that the Compustat dividend values (dv ; dvc) sometimes include items other than dividends, such as

share swap agreements. Thus, we include a relative threshold: if the dividend decreases by 85% or more relative to a firm's historical median, the observation is assigned a value of zero, provided it remains below the absolute threshold of SEK 100 million. Otherwise, a value of one is assigned

$UE_{i,q}$

The actual reported EPS less the most recent analyst consensus forecast for firm i in quarter q , divided by the share price at the start of quarter q . The value is then decile-ranked in the range from 0 to 1, where 1 equals the highest decile, following Ham et al. (2023)

Panel C: Control Variables

$LogMVE_{i,t-1}$

The natural logarithm of $1 + MVE$ for firm i at the end of year $t - 1$. MVE represents the market value of equity and equals the Compustat common shares (cshoi) multiplied by the share price (prccd), at the end of year $t - 1$

$BTM_{i,t-1}$

Represents the book-to-market ratio for firm i at the end of year $t - 1$ and is calculated by dividing the book value by MVE, as defined above. Book value equals Compustat common/ordinary equity (ceq) + deferred taxes and investment tax credit (txditc). If ceq is unavailable, book value is computed as total assets (at) - total liabilities (lt) + txditc

$LogAge_{i,t-1}$

The natural logarithm of $1 + Age$ for firm i at the end of year $t - 1$. Age is defined as the number of years the firm i has existed on Compustat, as of the end of year $t - 1$

$ROA_{i,t-1}$

Represents the return on assets for firm i at the end of year $t - 1$. Defined as Compustat operating income after depreciation (oiadp) divided by total assets (at)

$OP_{i,t-1}$

Represents the operating profitability for firm i at the end of year $t - 1$. Defined as Compustat total revenue (revt) - cost of goods sold (cogs) - selling, general and administrative expenses (xsga) - research and development expenses (xrd) - interest and related expenses (xint), divided by book value as defined above. If cogs, sxga, xrd, or xint is missing we impute a 0

$RE_{i,t-1}$

Compustat retained earnings (re) divided by total assets (at) for firm i at the end of year $t - 1$

$EarnVol_{i,t-1}$

Represents the earnings volatility for firm i in year $t - 1$. Equals the standard deviation of Compustat net income (ib) for year $t - 1$, to $t - 5$, divided by total assets (at) at the end of year $t - 1$, following Ham et al. (2023)

$RetVol_{i,t-1}$	Represents the return volatility for firm i in year $t - 1$. Equals the average of the absolute value of Compustat daily abnormal returns (abret) in year $t - 1$, following Ham et al. (2023)
$Inst\%_{i,t-1}$	Equals LSEG Refinitiv percentage of shares held by institutional shareholders at the end of year $t - 1$
$EA\ Delay_{i,q}$	Equals the number of days between firm i 's quarter q fiscal year end date and the earnings announcement date for quarter q 's earnings

This table provides the definitions of the dependent variables, variables of interest, and control variables used in our regressions

Table A2. Parsimonious regression of model 1

	Expected Sign	(1) CAR	(2) CAR	(3) CAR	(4) CAR
<i>DIV</i>	N/A	-0.0125*** (-2.88)	0.0007 (0.10)	0.0022 (0.33)	-0.0089 (-1.16)
<i>UE</i>	+	0.0651*** (11.47)	0.0836*** (11.49)	0.0884*** (9.72)	0.0781*** (9.54)
<i>UE * DIV</i>	–	0.0311*** (4.46)	0.0110 (1.01)	0.0078 (0.71)	0.0181 (1.41)
Industry * Year FE		Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes
Controls * UE		No	No	No	No
Year * UE		No	No	No	No
Sample		Unmatched	PSM	Entropy	Overlap
Observations		9,911	2,368	3,882	2,308
Adjusted R ²		0.121	0.134	0.149	0.111

The table reports the OLS regression results. The dependent variable is the cumulative abnormal returns (*CAR*) surrounding the EA. Our variables of interest are the dividend indicator (*DIV*), unexpected earnings (*UE*), and the interaction variable *UE * DIV*, which is bolded. We include ten control variables: *LogMVE*, *BTM*, *LogAge*, *ROA*, *OP*, *RE*, *EarnVol*, *RetVol*, *Inst%*, and *EA Delay*, as well as industry-year fixed effects. We utilise robust standard errors clustered on the firm level. ***, **, * indicate statistical significance for two-tailed test at the 1%, 5%, and 10% level, respectively. T-statistics are reported in parentheses below the coefficient

Table A3. Parsimonious regression of model 2

	Expected Sign	(1) Earn	(2) Earn	(3) Earn	(4) Earn
Panel A: Standard Model					
<i>DIV</i>	+	-0.0069 (-0.17)	-0.0292 (-0.65)	-0.0131 (-0.66)	-0.0130 (-0.48)
<i>UE</i>	+	0.0232 (0.56)	0.0218 (0.40)	0.0043 (0.17)	0.0020 (0.04)
<i>UE * DIV</i>	–	0.0046 (0.11)	0.0420 (0.61)	0.0365 (1.32)	0.0226 (0.37)
Industry * Year FE		Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes
Controls * UE		No	No	No	No
Year * UE		No	No	No	No

UE additional controls		No	No	No	No
Sample		Unmatched	Propensity	Entropy	Overlap
Observations		7,288	1,575	2,546	1,493
Adjusted R ²		0.115	0.288	0.294	0.295
	Expected Sign	(1) Earn	(2) Earn	(3) Earn	(4) Earn
Panel B: Additional UE Controls					
<i>DIV</i>	+	-0.0120 (-0.60)	-0.0336 (-1.27)	-0.0121 (-0.70)	-0.0231 (-1.06)
<i>UE</i>	+	-0.0135 (-0.14)	0.0113 (0.10)	-0.0507 (-0.68)	-0.0284 (-0.25)
<i>UE * DIV</i>	-	0.0211 (1.08)	0.0540 (1.53)	0.0384 (1.63)	0.0559* (1.88)
Industry * Year FE		Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes
Controls * UE		No	No	No	No
Year * UE		No	No	No	No
UE additional controls		Yes	Yes	Yes	Yes
Sample		Unmatched	Propensity	Entropy	Overlap
Observations		7,288	1,575	2,546	1,493
Adjusted R ²		0.124	0.294	0.307	0.321

The table reports the OLS regression results. The dependent variable is the forward four-quarter EPS (*Earn*). Our variables of interest are the dividend indicator (*DIV*), unexpected earnings (*UE*), and the interaction variable *UE * DIV*, which is bolded. We include ten control variables: *LogMVE*, *BTM*, *LogAge*, *ROA*, *OP*, *RE*, *EarnVol*, *RetVol*, *Inst%*, and *EA Delay*, as well as industry-year fixed effects. We utilise robust standard errors clustered on the firm level. ***, **, * indicate statistical significance for two-tailed test at the 1%, 5%, and 10% level, respectively. T-statistics are reported in parentheses below the coefficient

Table A4. Parsimonious regression of model 3

	Expected Sign	(1) EA Vol	(2) EA Vol	(3) EA Vol	(4) EA Vol
Panel A: Trading Volume					
<i>DIV</i>	-	-0.1362 (-1.60)	0.0183 (0.21)	0.1071 (1.24)	0.0314 (0.33)
Industry * Year FE		Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes
UE decile FE		No	No	No	No
Sample		Unmatched	Propensity	Entropy	Overlap
Observations		9 619	2 278	3 730	2 218
Adjusted R ²		0.383	0.291	0.293	0.316
	Expected Sign	(1) EA Ret	(2) EA Ret	(3) EA Ret	(4) EA Ret
Panel B: Absolute Returns					
<i>DIV</i>	-	-0.0183 (-0.58)	-0.0071 (-0.18)	0.0123 (0.30)	0.0135 (0.28)
Industry * Year FE		Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes
UE decile FE		No	No	No	No
Sample		Unmatched	Propensity	Entropy	Overlap
Observations		9 619	2 278	3 730	2 218
Adjusted R ²		0.104	0.155	0.108	0.162

The table reports the OLS regression results. In Panel A, the dependent variable is trading volume (*EA Vol*), and in Panel B, return volatility (*EA Ret*). Our variable of interest is the dividend indicator (*DIV*), which is bolded. We include ten control variables: *LogMVE*, *BTM*, *LogAge*, *ROA*, *OP*, *RE*, *EarnVol*, *RetVol*, *Inst%*, and *EA Delay*, as well as industry-year fixed effects. We utilise robust standard errors clustered on the firm level. ***, **, * indicate statistical significance for two-tailed test at the 1%, 5%, and 10% level, respectively. T-statistics are reported in parentheses below the coefficient

A.2. AI-disclosure

In writing this paper, we have used generative AI as allowed by SSE guidelines. The tools used were ChatGPT 5.1 and 4o developed by OpenAI, Gemini 2.5 Flash and 3 Pro, developed by Google, as well as GitHub Copilot, which is an AI coding assistant integrated into VS Code that uses multiple models such as ChatGPT (4o), and Claude Sonnet 4.5 developed by Atrophic.

Versions of ChatGPT and Gemeni have been used throughout the process, mainly to correct grammar and find contractions when writing our thesis. GitHub Copilot has been utilised to support writing code for handling and analysing our data during our work process. Overall, we have found the contribution by the AI tools to be additive to our work and its quality. We have found it particularly useful to check for errors and solve issues regarding the code.

We recognise, however, that AI is prone to hallucinating and making mistakes, and we thus never rely on it to reason for us or draw conclusions based on our results. We have also manually checked the AI tools' work for factual and methodological correctness and to ensure that all work is our own.

Links:

Claude: <https://claude.ai/login?returnTo=%2F%3F#>

ChatGPT: <https://chatgpt.com>

Gemini: <https://gemini.google.com/app?hl=sv>

GitHub Copilot: <https://github.com/copilot>