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Predictable dividends

Empirical support for the predictability of quarterly dividend increases using accounting data, financial distress predictions and smoothing behaviour

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Abstract

We investigate whether, and show support for that, quarterly dividend increases can be predicted using accounting data combined with smoothing behaviour and financial distress predictions. The empirical findings are achieved through the development of a probabilistic model for dividend increase prediction with data for U.S. manufacturers from year 2000 to year 2016. However, there is reason to doubt the general applicability of the model, as differences are shown both over time and across sub-industries. Despite positive initial results, the financial distress prediction variables are not clearly beneficial to the model. When using the proposed dividend increase prediction model with a suggested cut-off probability for our sample, a Naïve model is outperformed and the results improve further for our separate validation sample. A strategy to purchase the shares of the companies for which dividend increases are predicted achieve abnormal returns which are significant at the 0.10 level.

Keywords: Dividends, Dividend Prediction, Financial Distress, Smoothing, Signalling

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1. Introduction

This thesis strengthens the case that accounting data, financial distress predictions and dividend smoothing can be used to accurately predict quarterly cash dividend increases. These dividend predictions could potentially be used to generate abnormal returns. By developing a probabilistic cash dividend increase prediction model, which is correct in 94.4 percent of its predictions, a Naïve model is outperformed. Using this model in a trading strategy yields abnormal returns of 151 percent, which are statistically significant at the 0.10 level.

Dividends are an integral part when investing in shares and are the focus of various valuation models. With the current environment in the financial markets with low, or even negative, interest rates, dividends could potentially act as an alternative for investors. While analysing short-term dividend increases might not revolutionize the valuation of companies, Miller and Modigliani (1961) presented a link between dividend increases and positive share price reactions. We consider this link to provide motivation for predicting cash dividend increases and for considering a trading strategy based on these predictions.

The dividend increase prediction model is estimated through a logit regression. In this regression, a variable for a modified version of the dividend prediction model by Lintner (1956) is used in combination with a variable for historic accounting profits, in line with Fama and Babiak (1968), as well as variables for lagged dividends and variables to incorporate financial distress predictions. The model is developed in order to achieve the purpose of the thesis, namely to answer the research question:

Can accounting data, financial distress predictions and smoothing behaviour be used to predict dividend changes, and in turn be used to earn abnormal returns?

When developing the model, we have two considerations in mind. First, we believe that predictions of financial distress could provide important additions to the current usage of dividend prediction models as, intuitively, a company would decrease its dividends when facing the threat of bankruptcy. This intuition is supported by the findings of DeAngelo and DeAngelo (1990) that companies swiftly lowered their dividends considerably when facing financial distress. We include modified versions of financial distress prediction models with both short (Ohlson 1980) and long (Skogsvik 1987) prediction horizons, in an attempt to capture the effects of companies facing imminent financial distress as well as those facing financial distress on the horizon. Second, we consider there to be a gap in the literature with regards to smoothing effects and their impact on the prediction of quarterly paid dividends. Supporting that dividend smoothing is relevant today, Brav, Graham, Harvey and Michaely (2005) found that companies, as in Lintner (1956), still "[…] smooth dividends from year to year" (Brav et al. 2005, p. 499). Whereas existing research has focused mainly on dividend smoothing on an annual basis, such as Lintner (1956) and Guttman, Kadan and Kandel (2010), we believe that dividend smoothing can be adapted for quarterly dividend prediction.

The resulting probabilistic dividend increase prediction model provides an Index Value, which can be converted into the probability of a relative increase of the quarterly cash dividend greater than a certain threshold. The higher the Index Value, the higher the probability of this dividend increase according to the model. The threshold, calculated as the annual inflation rate plus three percent, enables the model to predict a real increase instead of a nominal increase and also helps to avoid the predictions of negligible increases.

Our results support that the majority of companies perform dividend increases greater than the threshold only once per year, even though many companies in our sample pay cash dividends quarterly. These results are in line with the findings of Lintner (1956) that most companies change their dividends on an annual basis or less frequent. However, in almost 15 percent of the cases where at least one increase greater than the threshold occurred in the previous four quarters, at least one additional increase had occurred in the same period. We thus consider that existing dividend prediction models, such as Lintner (1956), could benefit by being extended to also consider quarterly dividends.

Although the financial distress variables show promising initial results, their general applicability can be questioned in the context of a dividend prediction model – mainly with regards to different sub-industries, but also across different time periods. Therefore, including financial distress variables could potentially harm the general applicability of the presented model. Despite these negative subsequent findings, we consider financial distress predictions as part of dividend predictions a promising area for future research. However, some adaptation to consider the prevailing economic climate is likely to be necessary.

The sample used in this thesis consists of U.S. registered manufacturing companies. This is in line with Lintner (1956) and Ohlson (1980), but provides some limitations as we have not tested the validity of our model for other sectors or jurisdictions.

Applying a trading strategy based on the dividend increase predictions we are able to generate abnormal returns of 151 percent which are significant at the 0.10 level. These positive abnormal returns could imply that information is communicated through dividends, in line with e.g. Miller and Modigliani (1961) and Nissim and Ziv (2001), although the latter focused on earnings and not share price. The results support that our model, with the use of accounting data, financial distress predictions and dividend smoothing, can predict increases conveying information. The significant abnormal returns are contradictory to the CAPM in that there should be no predictable deviations from the return predicted through it, as commented in the textbook by Bodie, Kane and Marcus (2011, p. 322). Furthermore, a strategy trading only on the correctly predicted dividend increases achieve 110 percent abnormal returns which are not significant. As these results are weaker than the results of the strategy using all dividend increase predictions, in regards both to significance and to abnormal returns, we are unable to justify any firm conclusions based on these findings. This is further strengthened by the low level of significance for the strategy using all dividend increase predictions. The results do, nevertheless, encourage future research within the combined area of dividend signalling and dividend prediction.

2. Previous Research and Theoretical Framework

In this section, we present the previous research considered most relevant to our field of study. First, research on the topic of why dividends are relevant to predict is presented, focusing on the effects dividends can have on the share price and earnings outlooks for companies. Second, we present previous research within the area of dividend prediction, underlying the key considerations used in our dividend increase prediction model. Third, the area of dividend prediction is linked to the area of financial distress prediction. This cross-section between financial distress prediction and dividend prediction is, to our knowledge, not a previously researched area. Our focus for this section is mainly on the relevant research within the financial distress prediction as well as the overall linkage between financial distress and dividends. Fourth and last, the theories used for implementing our trading strategy are presented.

2.1 Dividends – Why are they Relevant?

In 1961, Miller and Modigliani stated that "[…] given a firm's investment policy, the dividend payout policy it chooses to follow will affect neither the current price of its shares nor the total return to its shareholders." (Miller and Modigliani 1961, p. 414).

At first consideration, it could therefore seem unnecessary to predict dividends. However, Miller and Modigliani (1961) also commented on that there could actually be considerable price reactions as a response to dividend changes. The authors considered this to be due to information being conveyed in the dividend change and thus not to be contradictory to the above statement regarding share prices not being affected by payout policies. The concept of "informational content" (Miller and Modigliani 1961, p. 430) was described by the authors in the following way:

> "That is, where a firm has adopted a policy of dividend stabilization with a long-established and generally appreciated 'target payout ratio,' investors are likely to (and have good reason to) interpret a change in the dividend rate as a change in management's views of future profit prospects for the firm."
>
> (Miller and Modigliani 1961, p. 430).

Woolridge (1983) discussed how the variation in share prices followed dividend changes and how it was in line with the hypothesis of wealth transfer and thus not only signalling (or "informational content" as named by Miller and Modigliani (1961, p. 430)). The author found that signalling was of largest importance, although he could not reject the possibility of wealth transfer affecting share prices as well (Woolridge 1983).

Positively correlated movements in the share price in response to changes in dividends, as discussed by Miller and Modigliani (1961), was confirmed by the findings of Dhillon and Johnson (1994). However, even though information conveyed through dividends potentially could explain the results, the authors considered the results to rather strengthen the case of wealth redistribution between owners of debt and equity (Dhillon and Johnson 1994).

Furthermore, a study in line with the “informational content” (Miller and Modigliani 1961, p. 430) was Nissim and Ziv (2001), which showed that earnings in the forthcoming years could be explained, to some extent, by the signals embedded in the decision of dividend levels. Mainly, if the company increased its dividends, the increase implied a positive change in earnings for the coming years (Nissim and Ziv 2001).

A cut in dividends did however not provide explanatory value for earnings in the coming years (Nissim and Ziv 2001). This absence of explanatory value was argued to be an effect of conservative accounting, where expected losses are included in the reported earnings, but only realized profits (Ibid.). Therefore, with conservative accounting, the negative news leading to a cut in dividends would already have been incorporated into the reported earnings (Ibid.). Positive news would, however, be incorporated once realized and thus allowing positive dividend changes to communicate these news instead (Ibid.).

In contrast to the results in Nissim and Ziv (2001), companies cancelling dividend payments were shown to have larger changes in share prices than companies initiating dividends in Michaely, Thaler and Womack (1995). This was the case both when the dividend initiation (cancellation) was communicated and for a longer period of time after the communication, as the authors were able to show a drift effect resulting from dividend initiations (cancellations) (Michaely, Thaler and Womack 1995). The results in Michaely, Thaler and Womack (1995) were though questioned in Boehme and Sorescu (2002), which was only able to reconstruct them in special circumstances.

Finally, we consider that the prediction of dividend increases is relevant mainly in line with that information, in accordance to Miller and Modigliani (1961), is being conveyed in dividends. Even though future earnings changes are not the same as value changes, the suggestions from both Miller and Modigliani (1961) and Nissim and Ziv (2001) that increased dividends implied positive changes in coming years' earnings, we deem enough to justify the development of a model predicting dividend increases.

2.2 Dividend Prediction

Below follow the contributions within the area of dividend prediction used to arrive at our dividend increase prediction model. The area covers the model for dividend prediction as created by Lintner (1956), but also further extensions to his model and additional considerations regarding dividend smoothing behaviour. Not all of the articles explicitly mention cash dividends, which are the focus of this thesis, instead only dividends. Although we perceive that some of the authors, including Lintner (1956), refer to cash dividends when using the term, we have not been able to verify this. Nevertheless, at least it could be stated that the literature covering dividends in general likely also will be applicable to cash dividends, as a subset of dividends.

Sixty years ago, Lintner (1956) developed a dividend prediction model which is still frequently referenced in the area of dividend prediction (e.g. Brav, Graham, Harvey and Michaely (2005), Guttman, Kadan and Kandel (2010) and Lambrecht and Myers (2012)).

The dividend prediction model presented by Lintner (1956), was arrived at through interviews with representatives from 28 industrial companies which paid dividends either quarterly or less frequently. U.S. dividend-paying companies which pay less often than on a quarterly basis, however, seem uncommon in the 21st century according to the findings of Ferris, Noronha and Unlu (2010). By analysing U.S. dividend-paying companies, the authors found that 87 percent of them paid quarterly (Ibid.).

Although most companies in Lintner (1956) changed their dividends on an annual basis, four of them rather did so every second or third year. From the interviews, Lintner (1956) introduced the concept of speed of adjustment, representing at what speed a company will modify their dividends when facing earnings changes. A company with a higher speed of adjustment will more quickly conform its dividend level with any earnings changes, thereby reaching its targeted payout ratio faster (Ibid.). It follows from the speed of adjustment that dividends are anticipated to continue to increase as long as the target payout ratio has not been reached (Ibid.).

The Lintner (1956) model:

$$\Delta D_{it} = \alpha_i + c_i\left(D_{it}^* - D_{i(t-1)}\right) + u_{it} \tag{1}$$

(Lintner 1956, p. 107)

where:

$D_{it} = Dividend\ for\ Company\ i\ in\ year\ t$

$\Delta D_{it} = D_{it} - D_{i(t-1)}$
$= (Dividend\ for\ Company\ i\ in\ year\ t, less\ the\ Dividend\ for\ Company\ i\ in\ year\ t-1)$

$D_{it}^* = Company\ i's\ targeted\ payout\ ratio * Company\ i's\ Net\ Income\ year\ t$

$\alpha_i = Constant\ for\ Company\ i$

$c_i = Speed\ of\ adjustment\ coefficient\ for\ Company\ i$

$u_{it} = The\ error\ term$

Lintner (1956) found that the constant α_i in most cases was positive, as managers strived to not end up in scenarios where they would have to decrease dividends. This led to conservatism, as managers were unwilling to raise the dividend payout rate to levels they were not certain would be sustainable going forward (Ibid.). Lintner (1956) further argued that this conservatism by the managers reflected their notion that the shareholders preferred steady dividends, which was mainly achieved with the use of the speed of adjustment. It has later been termed that dividends were "[…] smoothed from year to year." (Brav et al. 2005, p. 484).

Fama and Babiak (1968) applied the model by Lintner (1956) to individual industrial companies' data and showed that it functioned in this setting. Furthermore, the authors managed to enhance Lintner's (1956) model through implementing a variable for historic earnings in addition to the current earnings already included.

The conservativeness of dividend policies, as found by Lintner (1956), was found to remain true in the more recent study of Brav et al. (2005). Using surveys and interviews, the study concluded that under normal conditions companies were disinclined to lower dividends even if that would include missing out on positive NPV opportunities (Brav et al. 2005). To a large extent, companies at the time still "[…] smooth dividends from year to year" (Brav et al. 2005, p. 499). The authors also showed that 40 percent of the CFOs targeted dividend levels, while only 28 percent targeted a specific payout ratio (Ibid.). Furthermore, Guttman, Kadan and Kandel (2010) showed that 66 percent of companies which did not adjust dividends in a certain year also left it unadjusted the following year, while 84 percent of companies which adjusted their dividends would do so in the following year as well. A connection between past and current dividend payments was also found in Skinner (2008), which showed that there was a positive relationship between the number of years a company had paid dividends and the probability of that company paying dividends in the future.

Furthermore, that share repurchases was a serious alternative to dividends was concluded in Brav et al. (2005). This finding was confirmed a few years later in Skinner (2008), in which the results implied that share repurchases, rather than dividends, was the leading way companies distributed their earnings.

Also in line with previous findings, the Lintner (1956) model should not predict only dividends – instead it should also include share repurchases according to Lambrecht and Myers (2012), in which a dynamic agency model was created based on theory to explain payout.

Lambrecht and Myers (2012) argued that the reported earnings should not be used in predicting the payout. Instead, an income measure based on the value of all future earnings for the company should be used (Lambrecht and Myers 2012).

Given the above, some doubt was cast over the focus on dividends as Brav et al. (2005), Skinner (2008) and Lambrecht and Myers (2012) all suggested that dividends were no longer as important as in Lintner (1956). Instead Lambrecht and Myers (2012) proposed that total payout should be predicted instead. The focus on dividends in this thesis will though remain, in line with the findings of Miller and Modigliani (1961) that information can be conveyed through dividends.

Considering the findings within the area of dividend prediction, we decide to include a version of the Lintner (1956) model in our dividend increase prediction model, as well as historic earnings in line with the contribution by Fama and Babiak (1968). We also decide to take into account dividend smoothing effects in line with e.g. Brav et al. (2005).

2.3 Financial Distress Predictions – Useful in Dividend Predictions?

Somewhat surprisingly, to date there seems to be no research incorporating predictions of financial distress to dividend predictions. Intuitively, companies in financial distress would, at least to some extent, adjust their dividend levels as a response to this threat of existence.

One article considering the cross-section between dividends and financial distress is DeAngelo and DeAngelo (1990), which analysed the impact that long-lasting financial distress had on dividends for companies listed in the United States. The authors found that companies generally raised their dividends in the years leading up to financial distress, but that a swift and considerable lowering of the dividends when facing financial distress was the common reaction by the companies in the study. The authors further showed that there is an apparent disinclination to completely cancel dividends, instead of just lowering them. This disinclination was partly explained by the amount of years the company had paid dividends previously: the more years a company had paid dividends, the more disinclined was it to cancel them completely (DeAngelo and DeAngelo 1990).

We consider the results of DeAngelo and DeAngelo (1990) to support the intuition that predictions of financial distress could be useful in dividend predictions. More specifically, we consider the results of DeAngelo and DeAngelo (1990) to suggest that the probability of a dividend increase would be lower for companies in financial distress, *ceteris paribus*. With this knowledge, examining predictions of financial distress, aiming to include variables based on these predictions, seem rational in the development of our dividend increase prediction model.

After confirming the existence of a link between dividends and financial distress, various models for predicting financial distress are considered, all with their respective benefits and shortfalls. The focus is on predictions of financial distress mainly based on accounting data, i.e. financial figures from the companies in question, as we in our research question want to investigate if accounting data can be useful in predicting dividend increases.

Through the use of ratio analysis, Altman (1968) presented a model for predicting if a company will be surviving, failing or placed into limbo between the two. The model accurately predicted bankruptcy both for the first year (95 percent correct) and second year (72 percent correct) (Altman 1968). However, for the third year the model only predicted 48 percent of the companies correctly, with even fewer correct predictions for the subsequent years (Altman 1968).

Further developing the area of financial distress prediction was Ohlson (1980). The author presented probabilistic models for predicting bankruptcy in industrial companies using data from the annual reports of 2,163 companies. The model predicting bankruptcy within two years was accurate in 92.84 percent of its predictions (Ohlson 1980). These numbers could be compared to the 91.15 percent accuracy achieved by a Naïve model predicting every company to survive (Ibid.). Furthermore, Ohlson (1980) stated that certain data used in other bankruptcy prediction models was available first after the company had already declared bankruptcy, leading to positively biased results.

The model for predicting bankruptcy within two years, according to Ohlson (1980), is:

$$Y = 1.13 - 0.478SIZE + 5.29TLTA - 0.99WCTA + 0.062CLCA - 1.91OENEG - 4.62NITA - 2.25FUTL - 0.521INTWO + 0.212CHIN$$

where:

The index value Y can be converted into the probability of bankruptcy within two years, where a higher value of Y indicates a higher probability of bankruptcy (Ohlson 1980),

and:

> "1. SIZE = log(total assets/GNP price-level index). The index assumes a base value of 100 for 1968. Total assets are as reported in dollars. The index year is as of the year prior to the year of the balance sheet date. […]
>
> 2. TLTA = Total liabilities divided by total assets.
>
> 3. WCTA = Working capital divided by total assets.
>
> 4. CLCA = Current liabilities divided by current assets.
>
> 5. OENEG = One if total liabilities exceeds total assets, zero otherwise.
>
> 6. NITA = Net income divided by total assets.
>
> 7. FUTL = Funds provided by operations divided by total liabilities.
>
> 8. INTWO = One if net income was negative for the last two years, zero otherwise.
>
> 9. CHIN = $(NI_t - NI_{t-1})/(|NI_t| + |NI_{t-1}|)$, where NI_t is net income for the most recent period. […]"
>
> (Ohlson 1980, pp. 118-119)

Probabilistic models for predicting financial distress were developed also by Skogsvik (1987), described more briefly in Skogsvik (1988). Skogsvik (1988) presented separate models predicting the probability of financial distress in 1-6 years into the future, respectively. The same models were first introduced in Skogsvik (1987). Each separate model provides the probability of financial distress in the specific year given survival up until that year (Skogsvik 1988). To achieve the findings, Skogsvik (1988) used data from annual reports of 379 industrial companies, whereof 51 failed. Furthermore, all the companies used in the model by Skogsvik (1988) were Swedish-registered. Using the model, 83.3 percent of the predictions were correct for the one-year model, decreasing to 73.3 percent six years in advance (Skogsvik 1988). Moreover, with the model for predictions six years in advance Skogsvik (1988) still predicted over 80 percent of the failing companies correctly.

In the short-term, the Skogsvik (1988) model did not achieve better result than the above-mentioned Altman (1968) and Ohlson (1980). However, when the prediction horizon was extended, the Skogsvik (1988) model outperformed these.

The original Skogsvik (1987, p. 351) model for predicting business failure in 6 years is:

$$V = -1.39 + 17.47R(1)_{Sk} + 1.00TVL(1) - 0.41LI(3)_I - 1.54SD(1)$$

where, in accordance to Skogsvik (1987, p. 347):

$$R(1)_{Sk} = (Interest\ expense)/(All\ liabilities\ and\ deferred\ taxes)$$

$$TVL(1) = (Inventory)/(Revenues)$$

$$LI(3)_I = (Cash)/(Current\ liabilities)$$

$$SD(1) = (Owners'\ equity)/(All\ assets)$$

According to Skogsvik (1987, p. 177), average values for the balance sheet items should be used in the cases where a variable use data from the balance sheet and the income statement.

The dependent variable V can subsequently be converted into the probability of failure for a company in the 6th year given survival years 1-5, where a higher value of V implies a higher probability of failure (Skogsvik 1988).

2.4 Trading Strategy

To test whether our proposed trading strategy earns abnormal returns, we need to calculate what a normal return would be during the same time period. Equation 11.22 in the textbook by Berk and DeMarzo (2011) gives us the following formula for the expected return through the Capital Asset Pricing Model (CAPM):

$$E[R_i] = r_i = r_f + \beta_i * (E[R_{Mkt}] - r_f)$$

(Berk and DeMarzo 2011, p. 359)

where:

$\beta_i * (E[R_{Mkt}] - r_f)$ is "Risk premium for security *i*" (Berk and DeMarzo 2011, p. 359).

The authors further define the market portfolio as "[…] the portfolio of all stocks and securities in the market." (Berk and DeMarzo 2011, p. 357).

Equation 11.23 in the same textbook provides a definition of the security's beta:

$$\beta_i = \frac{SD(R_i) * Corr(R_i, R_{Mkt})}{SD(R_{Mkt})} = \frac{Cov(R_i, R_{Mkt})}{Var(R_{Mkt})}$$

(Berk and DeMarzo 2011, p. 360)

Berk and DeMarzo (2011) also describes that the CAPM is based on three main assumptions:

1. "*Investors can buy and sell all securities at competitive market prices (without incurring taxes or transactions costs) and can borrow and lend at the risk-free interest rate."* (Berk and DeMarzo 2011, p. 357)
2. "*Investors hold only efficient portfolios of traded securities—portfolios that yield the maximum expected return for a given level of volatility."* (Berk and DeMarzo 2011, p. 357)
3. "*Investors have homogeneous expectations regarding the volatilities, correlations, and expected returns of securities.*" (Berk and DeMarzo 2011, p. 358)

Furthermore, as commented in the textbook by Bodie, Kane and Marcus (2011, p. 322) there should be no forecastable deviations from the return forecasted by the CAPM, for any security.

The actual outcome may differ from this, yielding either a positive or negative excess return, however, such deviations are not possible to know beforehand (Bodie, Kane and Marcus 2011, p. 322).

Moreover, the findings of Bajaj and Vijh (1995) also need to be considered when evaluating the results from our trading strategy. The authors found that the abnormal returns for announcements of cash dividends had a negative correlation to the size of the companies (Ibid.).

3. Method

In this thesis, a simplification necessary for the data gathering is to use the narrower cash dividend instead of dividend. Thus, the dividends referred to in relation to our variables and the developed dividend increase prediction model will all be cash dividends only. To facilitate the reading experience, we frequently refer to dividends in parts of the thesis related to our model. For other literature, the dividend commented on is not necessarily a cash dividend but uses the authors definition of dividends in the specific case.

3.1 Dividend Increase Prediction Model

3.1.1 Data Retrieved

The majority of the data used for the dividend increase prediction model is retrieved through Wharton Research Data Services Compustat (2016a). The data retrieved is for North American companies with quarterly information available during at least one quarter in the period of 1990-2016 on a consolidated level, although in the end only data for 2000-2016 is used for the estimation and validation of the model. We retrieve information for companies that are denominated in USD, companies that are included in the population source "Domestic" and companies that are not in the financial services industry. Both active and inactive companies are included to mitigate the survivorship bias.

The focus on quarterly dividends in our model is somewhat different to the model by Lintner (1956) as that model mainly focused on annual dividends, although Lintner's (1956) sample included both companies paying quarterly and annual dividends.

The variables retrieved, as named by the Fundamentals Quarterly database in the Wharton Research Data Services Compustat (2016a), are shown in Appendix A, Table 1.

In addition, a Gross National Product: Chain-type Price Index, henceforth referred to as GNP Index, is retrieved from Federal Reserve Bank of St. Louis (Federal Reserve Bank of St. Louis 2016).

3.1.2 Data Used in the Data Set

We split the observations into one Estimation sample, used to estimate the model, and one Validation sample, used to validate the model. The split is performed by dividing the data set into two time periods, the Estimation sample being based on the period 2004-2013 and the Validation sample on 2014, 2015 and the first half of 2016.

For the GNP Index data, we use the index levels from the last day of the previous quarter as the level of the current quarter.

We then prepare the dataset containing the quarterly fundamental variables retrieved from Wharton Research Data Services Compustat (2016a). Companies with SIC codes lower than 2000 and equal to or higher than 4000 are excluded, leaving only companies in the manufacturing industry. Using only data for manufacturing companies we consider to be reasonably in line with e.g. Lintner (1956), Fama and Babiak (1968), Ohlson (1980) and Skogsvik (1987). The samples in these articles mainly consisted of either manufacturing or industrial companies, which manufacturing companies arguably is a subset within. For the Estimation sample, we then drop all observations for the years 2014-2016, as these are used only to validate the model. Next, all non-US companies, all companies that do not report on a quarterly basis and all companies where the fiscal year is not matching the calendar year are removed from the sample, in order to increase the homogeneity and reduce data problems.

To further increase the homogeneity of our sample, all observations where the total assets are less than USD 10 million two quarters prior for the specific company are excluded. The reason we do not look at the same quarter is because our model uses data from two previous quarters as its most recent source for assets. This is further discussed in Section 3.1.4. Furthermore, all observations which lack data in any of the four variables of Cash Dividends, Net Income, Assets or Liabilities are omitted, since Cash Dividends is used in several variables in our dividend increase prediction model and since we do not expect being able to use observations without data as fundamental as the latter three.

To further avoid data quality issues, where duplicates exist we remove all but one of these duplicate observations. Also, we search the data set for occurrences where the same company has observations for more than four quarters within the same calendar year. All observations for this year are dropped.

At this point, we remove any data that contain gaps in quarters, keeping the latest available data. Using the variable Cash Dividends ($DVY_{i,t}$), a variable for Quarterly Cash Dividends ($DVQ_{i,t}$) is created. This is done by setting $DVQ_{i,t}$ to $DVY_{i,t}$ if the observation is in the first quarter and by setting $DVQ_{i,t}$ to $DVY_{i,t}$ subtracted by $DVY_{i,t-1}$ if the observations are in any of the second, third or fourth quarter. As Quarterly Cash Dividends cannot be negative, we drop those which are negative according to our data, since they imply data quality issues. After this, we again need to remove any data that contain gaps in quarters, once again keeping the latest available data.

Because of how we calculate the variable $DVQ_{i,t}$, we drop the first observations for every company until Q1 is the first observation. This is to minimize the risk of data quality issues in previous quarters incorrectly affecting the, for our model crucial, variable $DVQ_{i,t}$. We thereafter check for observations with negative numbers of Cash Dividends or of any of the balance sheet items used in the model, as this would be another sign of data quality issues. However, none of the checked items – ATQ, ACTQ, INVTQ, LTQ, LCTQ, DVY or DVQ – had any negative observations and therefore no observation had to be omitted due to this.

The quarterly fundamentals dataset is then transformed into panel data with Ticker Symbol (TIC) being used as group and the combination of year and quarter as the time variable.

Finally, if input to any of the variables used in our dividend increase prediction model is missing, the corresponding observation for the specific company is excluded. Therefore, since one of the variables used need at least sixteen historic observations, all companies for which we do not have continuous data for at least four years are excluded as well.

At this point, we would like to point out the possibility that the companies we exclude are different from the ones included. For example, it could be that the companies which do not report on a quarterly basis are different in some way and that our exclusion of them leads to a failure of incorporating this diverseness. This means a limitation to our dividend increase prediction model, as it is only applicable to companies with the characteristics of our final sample.

3.1.3 Statistical Model

For the dividend increase prediction model, we use a logit model for binary response as described in the textbook by Wooldridge (2009, pp. 575-578). The logit model for binary response is chosen over a linear probability model due to the results being confined to probabilities varying from 0 to 100 percent, as described by Wooldridge (2009, pp. 575-576).

The rationale behind using a probabilistic model in the first place is to enable the incorporation of the results from financial distress prediction models based on financial ratios. Both Lintner (1956) and Fama and Babiak (1968) presented models to predict the actual change in dividends in USD. However, due to the characteristics of financial ratios, as used in the financial distress prediction models of Altman (1968), Ohlson (1980) and Skogsvik (1987), we need to be able to adjust the dividends to a common size measure. Due to the inherent problem with using change in dividends as a percentage, as it in many cases has the value of 0, and the, to our knowledge, lack of market conventions of indexing the size of dividends, a probabilistic model is the preferred choice to us. A probabilistic model generating the actual probabilities for an increase greater than a certain threshold also has the benefit of being useful in a trading strategy.

Furthermore, the logit model used is a panel data logit model for binary response with random effects. The choice of using a model for panel data is mainly based on the expectations that companies to some extent are heterogeneous which, in line with the textbook by Baltagi (2008, p. 6), could lead to biased results if not accounted for. Moreover, using panel data can reduce collinearity, increase efficiency and allow to incorporate information regarding changes for separate companies between periods (Baltagi 2008, p. 7).

The random effects model is chosen over a fixed effects model due to several reasons. To be able to calculate the actual probability of a dividend increase, we want to estimate the effects of variables that do not fluctuate as time passes, something the standard method for fixed effects cannot help us achieve according to a textbook by Paul D. Allison (2009, p. 3).

Furthermore, while the fixed effects model solely benefits from the information in the variation for a specific company, the random effects model allows for information in the variation both between companies and for the specific company to be utilized (Allison 2009, p. 3). Therefore, a fixed effects estimate yield inaccurate results if the independent variables mainly vary between companies, rather than the variable varying in each company as time passes (Allison 2009, p. 3). The problems with inaccurate results due to low variance for the independent variables would be an issue for us since a large part of our sample consists of companies with low variance, both in some of the explanatory variables and in the independent variable. However, with the random effects model we could also use the changes that occurred between companies and thus make use of the model also for companies that e.g. have never paid dividends previously. This reasoning is also confirmed in the textbook by Wooldridge (2009, p. 493) commenting that the effect of an explanatory variable, which does not change as time passes by, could not be estimated by fixed effects.

Given the above reasons we consider us unable to perform a Hausman test to confirm whether or not random effects could be used. The Hausman test states the differences between the fixed effects model and the random effects model for the coefficients of the independent variables that vary over time and test if these differences are significant (Wooldridge 2009, p. 493). However, a fixed effects method would remove a considerable portion of our sample, e.g. when the dependent variable is constant for all observations for a company. Furthermore, as commented above, the fixed effects method would give inaccurate estimates when there is low variance in our independent variables for a specific company across time. Considering these issues with sample reduction and low variance for some of the independent variables, the Hausman test would inevitably lead to a rejection of the random effects model. This, we consider, would be an incorrect test as it is mainly due to issues related to variables having low or no variability. These observations could arguably be excluded, allowing the fixed effects model to be used. However, we deem these observations to be important for the general applicability of our model as they include information from the variability between companies used in the random effects model. The general applicability could also be questioned as the fixed effects model would not be applicable for companies which have never paid dividends.

Despite the above reasoning with positive impacts of choosing the random effects model, some negative consequences with random effects models need to be considered. Mainly, the independent variables used in a random effects model should not be correlated with the unobserved effect, according to one of the underlying assumptions (Wooldridge 2009, p. 489). This assumption is probably not satisfied. The choice between random effects and fixed effects could thus partly be considered as a choice between efficiency and bias, in line with Allison (2009, p. 3). By using the random effects, we will be able to utilize the information in the variability between companies at the cost of introducing bias in the estimates (Allison 2009, p.3). Furthermore, the random effects estimate will also include an intercept (Wooldridge 2009, p. 489). The intercept we receive using the logit model for panel data with random effects, as found in the STATA Manual (StataCorp n.d.b), is common for all the companies. A common intercept will make the model easier to use for new companies, since a new intercept would not need to be estimated for that specific company.

When deciding which statistical method to use, the possibility of pooled OLS regressions is also considered. However, as noted by Wooldridge (2009, p. 493), a pooled OLS regression is typically less efficient than a random effects estimation.

With all the above in mind, we decide to use the logit model for binary response using random effects and test the validity of the model in multiple ways to be able to confirm the achieved results. These tests are discussed in detail in Section 3.1.5.

3.1.4 Course of Action: Estimating the Dividend Increase Prediction Model

For our dividend increase prediction model, we would prefer to use as recent data as possible. However, if the model would use data from the most recent quarter for predicting the dividend in the current quarter, we expose ourselves to the risk that the dividend announcement would already have occurred by the time this data is released. The risk of predicting what is already known in a substantial part of the sample makes us unable to justify the use of data this recent.

Instead, we use data for the quarter prior to the most recent one, as well as information from the dividend announcement for the dividend being paid in the most recent quarter. There are probably still occurrences where the dividend announcement is presented before the data is available, although we expect a large part of the issue to be mitigated by this approach. However, it is important to note that this will likely cause a bias in the prediction model. We perform some quantification of this issue of dividends being announced prior to all data being available and present it in Section 4.3.

Below follows the course of action for estimating our dividend increase prediction model. It should once again be stressed that the model predicts only cash dividends and not total payout, thus share repurchases, stock dividends and other forms of payout are not considered.

Below follows a description of the variables. Unless stated otherwise, the subscript t-1 indicates one quarter prior to the quarter which the model predicts the Index Value for.

3.1.4.1 Dependent Variable

Index Value: The dependent variable in our model is an Index Value, which can be converted into the probability that the company will increase its cash dividend more than a threshold. This relation can be expressed as:

$$\frac{DVQ_{i,t} - (Last\ cash\ dividend\ paid\ within\ the\ previous\ four\ quarters)_{i,t}}{(Last\ cash\ dividend\ paid\ within\ the\ previous\ four\ quarters)_{i,t}} > Threshold_t$$

If the company paid no cash dividend within the previous four quarters, any positive $DVQ_{i,t}$ will be seen as a dividend increase greater than the threshold.

For each quarter, the threshold is set to:

$$Annual\ inflation\ rate_t + 3\% \quad (2)$$

where:

$$Annual\ inflation\ rate_t = (GNP\ Index_{t-2}/GNP\ Index_{t-6}) - 1$$

As Ohlson (1980) considered the GNP Index to be a good inflation adjustment for his sample of industrial companies, we use the same measure as our general inflation measure for manufacturing companies. As previously mentioned, the GNP Index is retrieved from Federal Reserve Bank of St. Louis (2016).

Several factors need to be considered when choosing this threshold. First, we want it to cover the inflation so that the model implies a real increase and not only a nominal increase. Second, we further raise the threshold, in order to avoid predictions of negligible dividend increases. The additional, somewhat arbitrarily set, 3 percent avoids this risk. Throughout the thesis, when the threshold is mentioned, it refers to Equation 2.

We create $DivInc_{i,t}$, the variable we want to predict with our model, which captures if a cash dividend increase greater than the threshold occurs. $DivInc_{i,t}$ is binary, assuming the value of 1 if $DVQ_{i,t}$ is increased more than the threshold in comparison to the last prior dividend paid (in the four quarters prior to $DVQ_{i,t}$). If there has been no cash dividend payment in the four quarters prior to $DVQ_{i,t}$, $DivInc_{i,t}$ will assume the value of 1 if $DVQ_{i,t} > 0$. In all other scenarios, $DivInc_{i,t}$ assumes the value of 0.

3.1.4.2 Lintner

As we want to extend the Lintner (1956) model, a modified version of it is included as an independent variable in our model. As described in Section 2.2, Equation 1, the original Lintner (1956) model is:

$$\Delta D_{it} = \alpha_i + c_i\left(D_{it}^{*} - D_{i(t-1)}\right) + u_{it} \tag{1}$$

(Lintner 1956, p. 107)

Since we are considering quarterly data, all components used in the modified version of the Lintner (1956) model are adjusted to use quarterly figures instead. The term $D_{i(t-1)}$ is therefore replaced with our variable $DVQ_{i,t-1}$. D^{*}_{it}, however, is the product of the net income for the current period and the targeted payout ratio in Lintner (1956) and both of these factors pose problems. First, as we for all variables use data from two quarters previously, the profits of the current quarter must be estimated, by using previous quarters' Net Income (Loss), *NIQ*:

$$Predicted\ Net\ Income\ (Loss)_{i,t} = NIQ_{i,t-4} + (NIQ_{i,t-1} - NIQ_{i,t-5})$$

With regards to the net income prediction, we also consider the income measure in Lambrecht and Myers (2012). However, including such an income measure for all observations would be unreasonable considering our time constraint. Furthermore, in the context of Lambrecht and Myers' (2012) theoretical model, it is possible that the income measure presented is reasonable – however, no empiric evidence has, to our knowledge, shown that this would be more suitable to use in practice. Therefore, the above approach is chosen.

Second, the target payout ratio is different for every company. Lintner (1956) found these ratios by interviewing representatives from all of his sample companies. For our thesis and data set, however, this method is not feasible due to time constraints, why the target payout ratio is instead estimated. The first step in this estimation is to calculate an actual payout ratio:

$$Payout\ ratio_{i,t} = DVQ_{i,t}/NIQ_{i,t-1}$$

The previous quarter's net income, $NIQ_{i,t-1}$, is used since $DVQ_{i,t}$ is not likely to be a function of $NIQ_{i,t}$, but possibly of $NIQ_{i,t-1}$. The target payout ratio is then calculated as the average of all historic payout ratios for each company. Including negative historic payout ratios in this calculation, however, would be inadequate, as they would lower the target payout ratio. Since dividends paid out cannot be negative, a negative payout ratio means that the company has paid dividends even though the previous quarter's net income was negative, which rather is a positive indication of the company's target payout ratio. The impact of a negative payout ratio, in comparison with a positive one, is not easily interpreted though. Our chosen solution to this problem is to assign negative payout ratios a value similar to that of the mean payout ratio for a comparable sample. According to FactSet financial data and analytics (2016), the S&P 500 Dividend Payout Ratio – Trailing Twelve Months was approximately 0.4 for industrial companies in September 2016. The S&P 500 Industrial companies may not be entirely homogenous with the companies in our sample but it is deemed a reasonable proxy.

After this adjustment, we calculate the average of every (at this point non-negative) payout ratio for each company and assign them this value as the targeted payout ratio. If this targeted payout ratio is above 3, however, it is set to 3, to mitigate the effect of outliers.

In Lintner (1956), the companies' targeted payout ratios were rarely altered. A targeted payout ratio of 3 may therefore seem unreasonably high, but is recalculated each quarter in our model, making it a short-term estimation.

This targeted payout ratio times the expected earnings is then the expected cash dividend. All negative expected cash dividends are set to 0, since cash dividends cannot be negative. The expected cash dividend, we compare to the most recent cash dividend paid in the previous four quarters. This way, companies will have its most recent cash dividend included in the calculation, not dependent on whether they pay annually or more frequently. The comparison to a previous dividend is necessary for being able to include the variable in our dividend increase prediction model, although different from the Lintner (1956) model which predicts a dividend change in absolute values.

Finally, the *Lintner* variable used in our model is calculated as:

$$Lintner_{i,t} = \frac{Expected\ cash\ dividend_{i,t}}{(Last\ cash\ dividend\ paid\ within\ the\ previous\ four\ quarters)_{i,t}} - 1$$

For the cases where there has been no cash dividend payment in the previous four quarter's, we set *Lintner* to 1 if Expected cash dividend > 0 and to 0 if Expected cash dividend= 0. One final adjustment is made for this variable: in the cases where *Lintner* is greater than 5, it is replaced with the value of 5. Although somewhat arbitrarily, this is deemed a reasonable pragmatic approach to avoid extreme cases, where a minimal dividend in a previous period leads to an unreasonably high value of *Lintner*. With this adjustment, the *Lintner* variable can take on any value equal to or between -1 and 5.

3.1.4.3 PE – Positive Earnings Last Year

The contribution from Fama & Babiak (1968) to enhance the Lintner (1956) model through a lagged variable for earnings is also considered. However, due to earnings between quarters being volatile we do not compare the actual change in Net Income (Loss). Instead we calculate a variable assuming the value of the number of the previous four quarters in which positive earnings were reported. A variable as simple as this have shortfalls, such as being unable to account for differences between small and large earnings in every respective quarter as long as they have the same sign. We accept this shortfall, since we believe that the variable despite it could serve the model well.

The *PE* variable can take on any integer value equal to or between 0 and 4.

3.1.4.4 Lagged Dividend Variables

To thoroughly take into effect the smoothing behavior of dividends, we include several different lagged dividend variables, capturing both changes in dividends and whether or not dividends have been paid. In line with the speed of adjustment in Lintner (1956), dividends could be anticipated to continue to increase as long as the targeted payout ratio has not been reached, implying that an increase in dividends is expected for the current quarter given no decrease in earnings. This would indicate that a positive change in dividends for previous periods would also imply a higher probability for an increase in the upcoming period. The relation between changes from previous periods and the upcoming period was also confirmed by Guttman, Kadan and Kandel (2010), showing that 84 percent of companies which adjusted their dividends in a certain year also would do so in the following year. However, none of these explicitly considered dividend changes in quarterly periods, which is why *DivInc1-DivInc4* are included as separate variables, incorporating the possibility of dividends mainly being changed on a yearly basis.

For capturing less recent changes, we include *DivIncL1Y* and *DivIncL2Y*. These variables are included mainly for the possibility that there are companies in our sample which – as in Lintner (1956) – change dividends every second or third year.

PaidL1Q-PaidL4Q are included to further take into account the pattern of when cash dividends are paid. In 87 percent of dividend-paying U.S. companies, dividends were paid on a quarterly basis according to Ferris, Noronha and Unlu (2010). This makes it probable that the majority of our sample do as well, but the inclusion of *PaidL1Q-PaidL4Q* enable the model to better predict dividends for companies not paying them quarterly. Finally, the variable *HP* is included as we not only believe it to be relevant whether a company has increased its cash dividend more than the threshold in the previous years, but also if it has ever paid a cash dividend or not. Mainly the *HP* variable is included to cover for companies which choose to use other forms of payout, deemed necessary as Skinner (2008) found that share repurchases was the leading way companies distributed their earnings.

Again, the variable *DVQ* is the quarterly cash dividend.

DivIncX= Cash Dividend Increase Lagged 1, 2, 3 or 4 Quarter(s): The variable $DivInc1_{i,t}$ is binary assuming the value of 1 if $DVQ_{i,t-1}$ is increased more than the threshold compared to the last prior cash dividend paid (in the four quarters prior to $DVQ_{i,t-1}$). If no cash dividend has been paid in the four quarters prior to $DVQ_{i,t-1}$, the variable assumes the value of 1 if $DVQ_{i,t-1} > 0$.

For the first four observations available for each company, the variable $DivInc1_{i,t}$ is considered a missing value as we do not have the full set of four historic cash dividends to compare to. In all other scenarios, $DivInc1_{i,t}$ assumes the value of 0. The variables $DivInc2_{i,t}$, $DivInc3_{i,t}$ and $DivInc4_{i,t}$ are defined as follows:

$$DivInc2_{i,t} = DivInc1_{i,t-1}$$

$$DivInc3_{i,t} = DivInc1_{i,t-2}$$

$$DivInc4_{i,t} = DivInc1_{i,t-3}$$

DivIncL1Y= Cash Dividend Increases Lagged 1 Year: This variable considers if the company has a history of making increases in cash dividends greater than the threshold in a recent, although not the most recent, time period. The variable can take on integer values between 0 and 4, increasing with 1 for each of the four variables $DivInc1_{i,t-4}$ to $DivInc1_{i,t-7}$ being positive, thus calculated as:

$$DivInc1_{i,t-4} + DivInc1_{i,t-5} + DivInc1_{i,t-6} + DivInc1_{i,t-7}$$

DivIncL2Y= Cash Dividend Increases Lagged 2 Years: This variable is similar to *DivIncL1Y*, but look four additional quarters back in time. Hence, the variable can take on integer values between 0 and 4, increasing with 1 for each of the four variables $DivInc1_{i,t-8}$ to $DivInc1_{i,t-11}$ being positive, thus calculated as:

$$DivInc1_{i,t-8} + DivInc1_{i,t-9} + DivInc1_{i,t-10} + DivInc1_{i,t-11}$$

DivIncL0Y= Cash Dividend Increases Lagged 0 Years: We also create the variable *DivIncL0Y*, which is not part of our dividend increase prediction model but enables us to draw conclusions from the sample. The variable is similar to *DivIncL1Y*, but looks at the most recent four quarters. Hence, the variable can take on integer values between 0 and 4, increasing with 1 for each of the four variables $DivInc1_{i,t}$ to $DivInc1_{i,t-3}$ being positive, thus calculated as:

$$DivInc1_{i,t} + DivInc1_{i,t-1} + DivInc1_{i,t-2} + DivInc1_{i,t-3}$$

PaidLXQ = Paid Lagged 1, 2, 3 or 4 Quarter(s): The variable $PaidL1Q_{i,t}$ is binary assuming the value of 1 if $DVQ_{t-1} > 0$ and 0 otherwise. The variables $PaidL2Q_{i,t}$, $PaidL3Q_{i,t}$ and $PaidL4Q_{i,t}$ are defined as follows:

$$PaidL2Q_{i,t} = PaidL1Q_{i,t-1}$$

$$PaidL3Q_{i,t} = PaidL1Q_{i,t-2}$$

$$PaidL4Q_{i,t} = PaidL1Q_{i,t-3}$$

HP= Has Paid: This variable is binary, assuming the value of 1 if the company, according to our data, at least once has paid cash dividends previously, or 0 if it has not.

3.1.4.5 Financial Distress

Predictors for financial distress are included in two separate variables: in a version of the model by Ohlson (1980) for near-term financial distress and in a version of the model by Skogsvik (1987) for financial distress on the horizon.

When choosing which of the financial distress prediction models to apply, other models were considered as well. The main option was the model by Altman (1968) which, although superior prediction results compared to Ohlson (1980), was deemed to be of less use in our probabilistic model. The index value in Altman (1968) is not fit to be used as a continuous variable, as there is no clear conclusion that a high value means less risk of bankruptcy than a value just above the cut-off. The Ohlson (1980) model and other probabilistic models will thus likely provide better input, as we believe that in general, the higher the risk of bankruptcy, the higher the probability that the company faces financial distress. Therefore, in line with the findings of DeAngelo and DeAngelo (1990), which showed that companies lowered their dividends when facing financial distress, we believe that a higher risk of bankruptcy will reduce the probability of a dividend increase. As we for a company going bankrupt within two years expect evident signs of financial distress, we choose Ohlson's (1980) model for this prediction horizon.

A version of Skogsvik (1987) is included as well, to complement the imminent financial distress predicted in Ohlson (1980) with a model for predicting financial distress in six years, given survival in the previous five years. The six-year prediction horizon in Skogsvik (1987) is chosen as this is the longest horizon included and we aim to catch the earliest perceptible signs of financial distress. The long-term financial distress prediction could be beneficial both in the same way as described for Ohlson (1980) above but also if, as in DeAngelo and DeAngelo (1990), companies raise their dividends in the years leading up to financial distress. The Skogsvik (1987) models predicting financial distress in years 3, 4 and 5 could have been included as well, but would increase the number of variables potentially without benefitting the dividend increase prediction accuracy. Therefore, the choice is made to use only the model for financial distress in the 6th year by Skogsvik (1987).

Both financial distress variables can take on any value equal to or between 0 and 1.

Ohlson: Our data set consists of quarterly data, compared to data from annual reports in Ohlson (1980). It follows that in our data set, some variables are calculated by summing its respective numbers from the previous four quarters, thus all quarters do not necessarily belong to the same calendar year. We believe this makes a good proxy to the original model, but most often does not equal the annual figures. Furthermore, not all of the variables used in the original Ohlson (1980) model exist in our data set and therefore the model requires additional modification.

The *Ohlson* variable, used in our model to predict the Index Value, is calculated as:

$Ohlson_{i,t} = e$^(*O-score*$_{i,t}$)/(1+e^(*O-score*$_{i,t}$))

where:

O-score$_{i,t}$= $1.13 - 0.478O_{SIZE,i,t} + 5.29O_{TLTA,i,t} - 0.99O_{WCTA,i,t} + 0.062O_{CLCA,i,t} - 1.91O_{OENEG,i,t} - 4.62O_{NITA,i,t} - 2.25O_{FUTL,i,t} - 0.521O_{INTWO,i,t} + 0.212O_{CHIN,i,t}$

and:

$O_{SIZE,i,t} = \ln((ATQ_{i,t-2} * 1{,}000{,}000)/GNP\ Index_{i,t-2})$

This GNP Index is calculated as described by Ohlson (1980) and as presented in Section 2.3, although we use quarterly data and thus our index quarter will be the quarter Q_{t-6}.

$O_{TLTA,i,t} = LTQ_{i,t-2}/ATQ_{i,t-2}$

$O_{WCTA,i,t} = WCAPQ_{i,t-2}/ATQ_{i,t-2}$

$O_{CLCA,i,t} = LCTQ_{i,t-2}/ACTQ_{i,t-2}$

$O_{OENEG,i,t} = 1\ if\ LTQ_{i,t-2} > ATQ_{i,t-2}. Otherwise, O_{OENEG,i,t} = 0$

$O_{NITA,i,t} = (NIQ_{i,t-2} + NIQ_{i,t-3} + NIQ_{i,t-4} + NIQ_{i,t-5})/ATQ_{i,t-2}$

$O_{FUTL,i,t} = (\text{OANCFQ}_{i,t-2} + \text{OANCFQ}_{i,t-3} + \text{OANCFQ}_{i,t-4} + \text{OANCFQ}_{i,t-5})/LTQ_{i,t-2}$

$O_{INTWO,i,t} = 1\ if\ NIQ_{i,t-2} < 0\ \&\ NIQ_{i,t-6} < 0. Otherwise, O_{INTWO,i,t} = 0$

$$O_{CHIN,i,t} = \frac{(NIQ_{i,t-2} + NIQ_{i,t-3} + NIQ_{i,t-4} + NIQ_{i,t-5}) - (NIQ_{i,t-6} + NIQ_{i,t-7} + NIQ_{i,t-8} + NIQ_{i,t-9})}{|NIQ_{i,t-2} + NIQ_{i,t-3} + NIQ_{i,t-4} + NIQ_{i,t-5}| + |NIQ_{i,t-6} + NIQ_{i,t-7} + NIQ_{i,t-8} + NIQ_{i,t-9}|}$$

As shown in Appendix A, Table 1, ATQ= Total Assets, LTQ= Total Liabilities, WCAPQ= Working Capital, LCTQ= Current Liabilities, ACTQ= Current Assets, NIQ= Net Income (Loss) and OANCFQ= Net Cash Flow from Operating Activities. All variables refer to quarterly numbers.

The resulting probability of bankruptcy is the independent variable *Ohlson* used in our model.

Skogsvik: A slightly modified version of the Skogsvik (1987) model is used, where the variable included in our model is the resulting probability of the company failing in the sixth year, given survival in the five prior years. The modifications are performed to enable the use of the model for quarterly data, considering the data available, and described below.

In our data set, we have quarterly data, compared to annual data in Skogsvik (1987). Some variables are therefore calculated by summing its respective numbers from the previous four quarters, which, similar to the discussion above, makes a good proxy but most often does not equal the annual figures. Furthermore, not all of the variables above were to be found in our data set, why the model requires additional modification. Therefore, our version of the Skogsvik (1987) model, the *Skogsvik* variable, is calculated as follows:

$$Skogsvik_{i,t} = Normal(-1.39 + 17.47Skogsvik_{RS,i,t} + 1.00Skogsvik_{TVL,i,t} - 0.41Skogsvik_{LI,i,t} - 1.54Skogsvik_{SD,i,t})$$

where:

$$Skogsvik_{RS,i,t} = \frac{\mathrm{XINTQ}_{i,t-2} + XINTQ_{i,t-3} + XINTQ_{i,t-4} + XINTQ_{i,t-5}}{(LTQ_{i,t-2} + LTQ_{i,t-3} + LTQ_{i,t-4} + LTQ_{i,t-5} + LTQ_{i,t-6})/5}$$

$$Skogsvik_{TVL,i,t} = \frac{(INVTQ_{i,t-2} + INVTQ_{i,t-3} + INVTQ_{i,t-4} + INVTQ_{i,t-5} + INVTQ_{i,t-6})/5}{SALEQ_{i,t-2} + SALEQ_{i,t-3} + SALEQ_{i,t-4} + SALEQ_{i,t-5}}$$

$$Skogsvik_{LI,i,t} = CHEQ_{i,t-2}/LCTQ_{i,t-2}$$

$$Skogsvik_{SD,i,t} = \mathrm{SEQQ}_{i,t-2}/ATQ_{i,t-2}$$

As shown in Appendix A, Table 1, XINTQ= Interest and Related Expense, LTQ= Total Liabilities, INVTQ= Total Inventories, SALEQ= Sales/Turnover (Net), CHEQ= Cash and Short-Term Investments, LCTQ= Current Liabilities and SEQQ= Stockholders Equity. All variables refer to quarterly numbers.

We would prefer to make an unbiased estimate when calculating the probability of financial distress. To do this, we would however need to know the fraction of companies facing financial distress within our sample. This fraction is unfortunately unknown to us, why we cannot perform this adjustment. In the regression, the coefficients of the financial distress variables will be automatically adjusted which will mitigate this effect.

3.1.4.6 Expected Coefficients of the Independent Variables

For each of the variables specified above, the expected sign of the coefficients and the rationale underlying these expectations are presented below.

Lintner: We expect the *Lintner* variable to have a positive coefficient, as the higher the variable, the higher expected cash dividend increase is predicted by our modified version of the Lintner (1956) model.

PE: We expect *PE* to have a positive coefficient. This would be in line with the findings of Fama and Babiak (1968), although our variable is structured differently, focusing on whether the earnings have been positive or not, instead of the actual earnings in USD.

DivInc1-DivInc4: These variables are more complicated to predict the coefficients of, as the literature, to our knowledge, has not touched upon the effect of dividend smoothing for individual quarters. The rationale underlying the expectancy of positive signs is mainly connected to the speed of adjustment as presented in Lintner (1956). In relation to the speed of adjustment, Lintner (1956) argued that dividends are expected to continue to increase as long as the targeted payout ratio has not been reached. Therefore, an increase greater than the threshold in the previous period could arguably be expected to be followed up with further increases of the same kind. Furthermore, the results in Guttman, Kadan and Kandel (2010) showed that 84 percent of the companies which adjusted their dividends in a certain year would do so in the following year as well. These results could, according to us, also imply that changes should be expected given increases in previous quarters.

The possible expectancy of negative signs we argue would be in line with the findings of Brav et al. (2005). The authors showed that 40 percent of the CFOs targeted dividend levels, while only 28 percent targeted a specific payout ratio (Brav et al. 2005).

Weighing the different findings, our main expectation is that the coefficients will be positive, as supported by Lintner (1956) and Guttman, Kadan and Kandel (2010). However, as both Lintner (1956) and Guttman, Kadan and Kandel (2010) mainly focused on annual data it would not be surprising to see other signs for *DivInc1-DivInc3*. *DivInc4* is more likely to be positive, as we believe it is probable that a company increasing its dividend once a year will do it in the same quarter every year.

DivIncL1Y and DivIncL2Y: We expect both of these variables to have positive coefficients. This is likely the case if many companies in our sample increase their dividends every second or third year, as part of Lintner's (1956) sample did. Companies which continuously increase their dividends more frequently than this are also likely to positively affect the coefficient.

PaidL1Q-PaidL4Q: The signs of these variables' coefficients will depend much on the fraction of companies that pay quarterly dividends. As 87 percent of the dividend-paying U.S. companies paid quarterly dividends in Ferris, Noronha and Unlu (2010), it is reasonable to believe a majority in our sample do so as well. Skinner (2008) showed a positive relationship between the number of years a company had paid dividends and the likelihood of that company paying dividends in the future. In line with this finding, a payment in either of the four prior quarters should increase the probability of a payment in the predicted quarter. As being expected to pay dividends is a prerequisite for being expected to pay cash dividends greater than the previously paid cash dividend, we believe that these four variables all will have positive coefficients.

If many companies in our sample would pay annual dividends, however, it is possible that only *PaidL4Q* will have a positive coefficient. For a company paying only once a year, a payment in either of the three previous quarters would imply that there will be no payment in the predicted quarter.

HP: We expect the *HP* variable to have a positive coefficient. Similar to the argument above, a positive coefficient for *HP* would be in line with Skinner (2008), as being expected to pay dividends is a prerequisite for being expected to pay cash dividends greater than the previously paid cash dividend.

Ohlson: We expect the *Ohlson* variable to have a negative coefficient, as we expect the probability of bankruptcy to increase with higher values for the variable incorporating the Ohlson (1980) model. A negative coefficient would according to us then be in line with DeAngelo and DeAngelo (1990), which showed that companies lowered their dividends swiftly and considerably when facing financial distress.

Skogsvik: We expect the *Skogsvik* variable to have a negative coefficient, although DeAngelo and DeAngelo (1990) showed that companies generally increased their dividends in the years leading up to financial distress. The expectancy of a negative coefficient is due to the modified Skogsvik

(1987) model used aims to provide a measure of the likelihood of financial distress in the sixth year given survival in the first five years and does not consider the likelihood of financial distress in the first five years. The *Skogsvik* variable is therefore rather expected to predict if the company is facing long-lasting financial distress. A negative coefficient would consequently, as for the *Ohlson* variable, be in line with that DeAngelo and DeAngelo (1990) found that companies lowered their dividends swiftly and considerably when facing financial distress.

3.1.4.7 The Dividend Increase Prediction Model

Our proposed cash dividend increase prediction model, given the above defined variables, is:

$$
\begin{aligned}
Index\ Value_{i,t} \\
&= \beta_0 + \beta_1 Lintner_{i,t} + \beta_2 PE_{i,t} + \beta_3 DivInc1_{i,t} + \beta_4 DivInc2_{i,t} + \beta_5 DivInc3_{i,t} \\
&+ \beta_6 DivInc4_{i,t} + \beta_7 DivIncL1Y_{i,t} + \beta_8 DivIncL2Y_{i,t} + \beta_9 PaidL1Q_{i,t} \\
&+ \beta_{10} PaidL2Q_{i,t} + \beta_{11} PaidL3Q_{i,t} + \beta_{12} PaidL4Q_{i,t} + \beta_{13} HP_{i,t} + \beta_{14} Ohlson_{i,t} \\
&+ \beta_{15} Skogsvik_{i,t} + \varepsilon_{i,t}
\end{aligned}
$$

where the probability of a cash dividend increase greater than the threshold in the current quarter, as compared to the last cash dividend paid in the previous four quarters, can be calculated according to this formula:

$$\frac{e^{Index\ Value}}{1 + e^{Index\ Value}}$$

It follows that the higher the Index Value, the higher the probability, according to the model.

3.1.5 Course of Action: Validating the Dividend Increase Prediction Model

To validate the result of the dividend increase prediction model, we use multiple ways including statistical tests of the estimated model and separate validation samples, as described below.

3.1.5.1 Statistical Test for the Estimated Dividend Increase Prediction Model

Multiple statistical tests are performed to test the validity of our dividend increase prediction model. First, to see if the model has explanatory value, we calculate a pseudo R-squared measure based on McKelvey & Zavoina's R-squared, as in Enzmann (n.d.).

Moreover, a quadrature check is performed to test the model. The estimations from the model are deemed dependable if the coefficients do not have relative differences above 0.01 percent when altering the number of quadrature points, in accordance with the STATA Manual (StataCorp. n.d.a).

Wald tests are also performed, to test that the coefficients for the variables in the estimated model are not all equal to zero at the same time, in accordance with the STATA Manual (StataCorp. n.d.c).

Furthermore, we perform a likelihood-ratio test for rho= 0 testing if the variance at the panel-level relative to the total variance can significantly be shown to not be equal to zero, in accordance with the STATA Manual (StataCorp. n.d.b).

3.1.5.2 Test of Prediction Accuracy on Estimation Sample

When the model is estimated, we perform a test of the prediction accuracy on our Estimation sample. This methodology is similar to what in the textbook by Wooldridge is called "percent correctly predicted" (Wooldridge 2009, p. 581). First, we calculate the total prediction accuracy by dividing the number of correctly predicted observations with the total number of predictions. Second, we group every prediction into four categories: Correctly predicted increases greater than the threshold (Correct positives), Incorrectly predicted increases greater than the threshold (False positives), Correctly predicted non-increases greater than the threshold (Correct negatives) and Incorrectly predicted non-increases greater than the threshold (False negatives). These categories are used to calculate a measure of correctly predicted increases greater than the threshold, defined as Correct positives divided by (the sum of Correct positives and False positives). Using this sample, we are able to adjust a cut-off value for the prediction, i.e. for which probability of a cash dividend increase greater than the threshold we will maximize the performance of our model. The desirable outcome is considered to be the cut-off value maximizing the ratio of Correct positives to False positives. This implies that the optimal cut-off value is likely going to be different from the most intuitive cut-off of 0.5.

As discussed in Section 2.1, in Nissim and Ziv (2001) a cut in dividends did not provide explanatory value for earnings in the coming years, although an increase did. With that in mind, a possible trading strategy could be to only maximize the number of Correct positives, as trading on False positives presumably would not result in negative returns. One problem with this strategy is that if we trade on many False positives, we increase the risk of including cancellations of dividends, which were linked to adverse changes in share prices in Michaely, Thaler and Womack (1995).

It also follows that with the mindset that we are OK with trading on False positives as well, we could trade in every single company. In order to test the usefulness of the model, by examining whether it is possible to reach abnormal returns through trading on dividend increasing shares, we deem it reasonable to maximize the ratio of Correct positives to False positives.

However, one additional constraint for the cut-off is set regarding the least required number of observations to trade on. In order to remove a considerable part of the idiosyncratic risk (Berk and DeMarzo 2011, pp. 311-312), we strive to achieve at least 100 observations for our trading strategy. As the cut-off is set when maximizing the above-mentioned ratio in the Estimation sample, we need to approximate which number of observations that is probable to result in at least 100 observations in the Validation sample. As the Estimation sample consists of 10 years of data and the Validation sample of 2.5 years of data, a reasonable estimate is that there are four times as many observations in the Estimation sample. Because of the uncertainty in the estimation, we also include a 10 percent margin, thus setting the constraint of least required number of observations in the Estimation sample to 440.

The optimized cut-off is achieved by looping through all the possible probabilities between 0 and 1 with 0.0002 increments, finding the maximum ratio subject to the constraint of least required number of observations.

The prediction accuracy test on our Estimation sample is compared to the prediction accuracy test of the Naïve model, to give us an estimate on how good our model is. The Naïve model is defined as the variable *DivInc1*, assuming the value of 1 and thus predicting a cash dividend increase greater than the threshold if the company performed an increase greater than the threshold in the previous quarter. If the company did not perform this increase in the previous quarter, the Naïve model assumes the value of 0 and thus no increase greater than the threshold is predicted. As the Naïve model is included as an independent variable in our dividend increase prediction model in the form of *DivInc1*, it is crucial that our model outperforms the Naïve model considerably. Otherwise, it would imply that the other independent variables do not add much, or possibly even destroy, information value. For further evaluation of the model, we also compare its results to those received by a model predicting that no increase greater than the threshold will occur.

3.1.5.3 Validation Sample – Prediction Accuracy and Re-estimated Model

The final and most important test is to test the model on our Validation sample, which is constructed in the same way as the Estimation sample, described in Section 3.1.2. However, the prediction results in the Validation sample are modelled for the years 2014-2016. This means that the two samples will mainly consist of the same companies, although there will be some differences, for example because of newly listed companies. As for the Estimation sample, a comparison with the Naïve model is included. The Naïve model is here designed in the same way as for the Estimation sample. Also similar to the Estimation sample, we include a comparison with a model predicting that no increase greater than the threshold will occur. Furthermore, the cut-off value used for the Validation sample is the optimal cut-off as calculated for the Estimation sample.

In addition to the prediction accuracy test, we also re-estimate the full model for our Validation sample. If the model is generally applicable, the result for different time-periods should be in line with the estimated model from our Estimation sample.

3.1.5.4 Separate Estimation for Sub-samples

The model is also tested on different sub-samples to determine whether or not it is generally applicable. More specifically, we re-estimate the model for three sub-samples of industries as well as two sub-samples which differ in time and state of the economy.

The three sub-samples of industries, based on SIC code groups, allow us to put the general applicability of the model to the test. In our sample of manufacturing companies, we have twenty different SIC code groups with regards to the first two digits (20-39). Out of these twenty, the three SIC code groups with most observations are chosen for comparison.

Furthermore, there is the possibility of different economic situations affecting the model. In an attempt to test the applicability of the model regarding different time periods, we test the model both for the period 2004-2007, representing positive economic climate, and for the period 2008-2012, representing negative economic climate. These results are described in Section 4.1.5.

3.2 Trading Strategy

3.2.1 Data Retrieved

For the trading strategy, the individual share price data and dividend declaration data is retrieved through Wharton Research Data Services Compustat (2016b). Data is only downloaded for companies which the dividend increase prediction model suggests us to trade in. The variables retrieved, as named by the Security Daily database in the Wharton Research Data Services Compustat (2016b), are found in Appendix A, Table 2.

The Ticker Symbol is used to match this data with our data set for the dividend increase prediction model, which is necessary to know which companies to trade in and when. The dates in the downloaded data range from January 1, 2010 to September 30, 2016.

Furthermore, we retrieve the mid-rate for United States Treasury Constant Maturity 10 Years (Daily) (Thompson Reuters Datastream 2016b) and the FTSE All World United States Dollar index (AWWRLD$) (Thompson Reuters Datastream 2016a), both for the period January 1, 2010 to September 30, 2016.

3.2.2 Data Used in the Data Set

The threshold used in the dividend increase prediction model is beneficial also for our trading strategy, as it helps us avoid to invest on predictions of negligible dividend increases. These types of increases would presumably convey less information affecting the market price.

The mid-rate of the United States Treasury Constant Maturity 10 Years (Daily) (FRTCM10) (Thompson Reuters Datastream 2016b) functions as a proxy for the risk-free rate. For the risk-free rate for each of the periods, the accrued interest $r_{f,t}$ is used, calculated as follows:

$$r_{f,t} = \text{FRTCM10}_{t-1} * \left(\frac{Date_t - Date_{t-1}}{Number\ of\ days\ in\ current\ year}\right) \tag{3}$$

In Equations 3 and 4, the subscript *t-1* refers to the previous day.

The FTSE All World United States Dollar index (AWWRLD$) (Thompson Reuters Datastream 2016a) is used in the following way as a proxy for the market return for each period t, $r_{m,t}$:

$$r_{m,t} = \frac{\text{AWWRLD\$}_t}{\text{AWWRLD\$}_{t-1}} - 1 \tag{4}$$

The FTSE All-World index only captures a limited amount of shares and not any other types of marketable securities and is therefore not ideal, however, it is deemed to be the best proxy for the market return available to us.

For each of the companies where an increase greater than the threshold is predicted and data is available, we estimate a weekly beta, β_i. The weekly beta is estimated by regressing the weekly stock return against the weekly market return, using a period of 52 weeks prior to the day of the purchase of the share of the company. The regression used for this procedure is a standard linear OLS regression. The close of the last trading day of the week is used both for the respective company's return and the market return, with the market return calculated as above. The choice of using weekly data for estimating the beta and an estimation period of 52 weeks is in line with the methodology in Penman, Richardson and Tuna (2007).

For each of the companies, the daily returns are calculated using the following formula:

$$r_{i,t} = (\mathrm{PRCCD}_{i,t} * TRFD_{i,t})/(\mathrm{PRCCD}_{i,t-1} * TRFD_{i,t-1}) - 1 \qquad (5)$$

In Equation 5, the subscript *t-1* refers to the previous day. The same methodology applies for the weekly returns used for the beta estimation, although the subscript *t-1* in this case refers to the previous week.

Next, the daily abnormal return $AR_{i,t}$ for share i and day t are estimated through the use of the expected normal return, as achieved through the CAPM:

$$AR_{i,t} = r_{i,t} - (r_{f,t} + \beta_i(r_{m,t} - r_{f,t}))$$

Finally, the cumulative abnormal return (CAR) for each of the companies is calculated as the sum of the daily abnormal return for the full trading period. This way of calculating the cumulative abnormal return is in line with the textbook by Bodie, Kane and Marcus (2011, p. 382).

3.2.3 Course of Action: Trading Strategy

For the trading strategy, we focus on Miller and Modigliani's (1961) finding that information is conveyed in dividend changes, rather than the possible effects of wealth transfer. This focus is in line with Woolridge (1983), finding that the signalling effect was of larger importance than any impact from wealth transfer.

In the cases where we predict a cash dividend increase greater than the threshold, our strategy will be to purchase the share at the close of the day after we receive the data necessary. This is to reduce the amount of noise coming from price reactions linked to the release of the data. To do this we want to have at least a full day of trading after the data has been announced before we purchase the share. Preferably, we would wait until the day before the dividend announcement, however, the problem with this methodology is that announcements could occur any day, without the market knowing it in advance. By waiting additional days before purchasing the share we would risk losing investment opportunities. This is the rationale behind us investing the day after the accounting data is released, despite the associated shortfalls, including noise and drift effects. Although Michaely, Thaler and Womack (1995) was able to show a drift effect as a result of dividend initiations and cancellations, these results were questioned by Boehme and Sorescu (2002), which was only able to reconstruct them in special circumstances. With this in mind, we decide to not take any further consideration for drift effects for the trading strategy.

One day after the dividend announcement, at the close, we sell the investment, thus not exposing us to more noise than deemed necessary. It is however possible that we predict a dividend increase greater than the threshold in quarters when there will be no dividend payment. Unfortunately, our data set do not include the announcement date for these and thus we do not know when it is communicated that there will be no dividend payment. For these cases, we wait until the last day of the quarter before selling the shares – the investment in a company for which we predicted a dividend increase greater than the threshold in a certain quarter is, therefore, at latest sold in the last day of the quarter in which the dividend would be paid. It follows that a position cannot be held longer than two quarters – not even in the extreme case, when data for quarter Q_t is available to us in the first day of quarter Q_{t+1} and no dividend is announced for quarter Q_{t+2}. The relatively short holding period reduces the risk of us incorrectly proclaiming abnormal returns, as Kothari and Warner (1997) found to be a common mistake in studies with holding periods over several years.

There could also be companies which we want to trade in, which already will have announced their dividends before we receive the data necessary to predict it. We are not able to trade in these companies and they will not be included in the trading strategy.

We further realize that there are occasions when companies announce dividends more than once for a specific quarter. One possible way to handle this could be to sell our investment at the end of the quarter, instead of the day after the (first) dividend announcement. However, we consider the extra noise which would follow from this method to overweigh the benefits of it.

To be able to draw further conclusions about the nature of this trading strategy, we also check the returns for the Correct positives separately.

3.2.4 Statistical Test for the Trading Strategy

To validate the result of the trading strategy, the statistical test of a one-sample t test is used and tests the null hypothesis that the mean of the cumulative abnormal returns is equal to zero, in accordance with the STATA Manual (StataCorp, n.d.d).

4. Results & Analysis

The results and analysis are divided into three sections. First, we present and analyse the results for the developed dividend increase prediction model and the related robustness tests in Section 4.1. Second, in Section 4.2 we comment on the results related to the trading strategy which is performed using the predictions from our dividend increase prediction model. Third, further limitations for the study are presented in Section 4.3.

4.1 Dividend Increase Prediction

4.1.1 Estimated Model

The estimated model for dividend increase predictions is summarized in Table 3 below. All of the variables have significant coefficients and most have signs in line with our expectations.

Table 3: Estimated Cash Dividend Increase Prediction Model – Estimation Sample

Variable	Coefficient	Sign: Act/(Exp)	Description
Index Value			*The dependent variable. The Index Value can be converted into the probability of a cash dividend increase greater than a threshold*
Lintner	0.114***	+ / (+)	*Modified version of the Lintner (1956) model*
PE	0.197***	+ / (+)	*Increases with 1 for each positive Net Income in the previous four quarters*
DivInc1	−1.041***	− / (+)	*Binary variables capturing whether the company increased its cash dividend more than a threshold in the previous 1-4 quarters, each compared to the last cash dividend paid in the previous four quarters*
DivInc2	−0.310***	− / (+)	
DivInc3	−0.206**	− / (+)	
DivInc4	2.146***	+ / (+)	
DivIncL1Y	0.531***	+ / (+)	*Constructed as lagged versions of DivInc1-DivInc4, being the sum of DivInc1-DivInc4 as seen one and two years previously, respectively*
DivIncL2Y	0.122***	+ / (+)	
PaidL1Q	0.837***	+ / (+)	*Binary variables capturing whether the company paid cash dividends in the previous 1-4 quarters*
PaidL2Q	0.591***	+ / (+)	
PaidL3Q	−0.283**	− / (+)	
PaidL4Q	−0.306**	− / (+)	
HP	1.213***	+ / (+)	*Binary variable capturing if the company at least once has paid cash dividends in the data period*
Ohlson	−1.890***	− / (−)	*Modified version of the Ohlson (1980) model, predicting financial distress within two years*
Skogsvik	0.793**	+ / (−)	*Modified version of the Skogsvik (1987) model, predicting financial distress in six years*
Constant	−5.326***	− / (N/A)	*The intercept*

Observations 33,312 || Number of companies 1,479 || *** p<0.01, ** p<0.05, * p<0.10

The variables which do not have coefficients significant at the 0.01 level are *DivInc3*, *PaidL3Q*, *PaidL4Q* and *Skogsvik* which all have coefficients that are significant at the 0.05 level, as shown in Table 3. The pseudo R-squared using McKelvey & Zavoina's R-squared model, calculated as per Enzmann (n.d.), is 46.44 percent.

The dividend increase prediction model using the coefficients as stated in Table 3 will hereinafter be referred to as the Main Model. The estimation results using the Estimation sample are in line with our expectations for the *Lintner* and the *PE* variables, both having a positive effect on the probability for a dividend increase greater than the threshold.

With regards to the dividend increase variables, we note that *DivInc1-DivInc3* all have negative coefficients, which differs from our expectations. However, these are the variables which we were the least certain of what to expect of, since the previous literature did not provide any strong indications, as discussed in Section 3.1.4.6. That *DivInc4* is significant and positive is in line both with our expectations and with the finding, that an adjustment in a certain year would often be followed with an adjustment in the following year as well, by Guttman, Kadan and Kandel (2010). We consider the combination of the coefficients for *DivInc1-DivInc4* to support our reasoning from Section 3.1.4.6, that if a company increases its dividend levels on an annual basis it is likely to do so in the same quarter as it did in the previous year. The remaining lagged dividend increase variables, *DivIncL1Y* and *DivIncL2Y*, both have significant positive coefficients, with the coefficient of *DivIncL1Y* being more than four times larger than the coefficient of *DivIncL2Y*. The positive coefficients are in line with our expectations and with the findings of Lintner (1956) that some companies change their dividends less frequently than on an annual basis. These coefficients imply that the more often a company increased its dividends in quarters Q_{t-8}-Q_{t-12} and, even more important, in quarters Q_{t-4}-Q_{t-7}, the more likely is it to do so in the future.

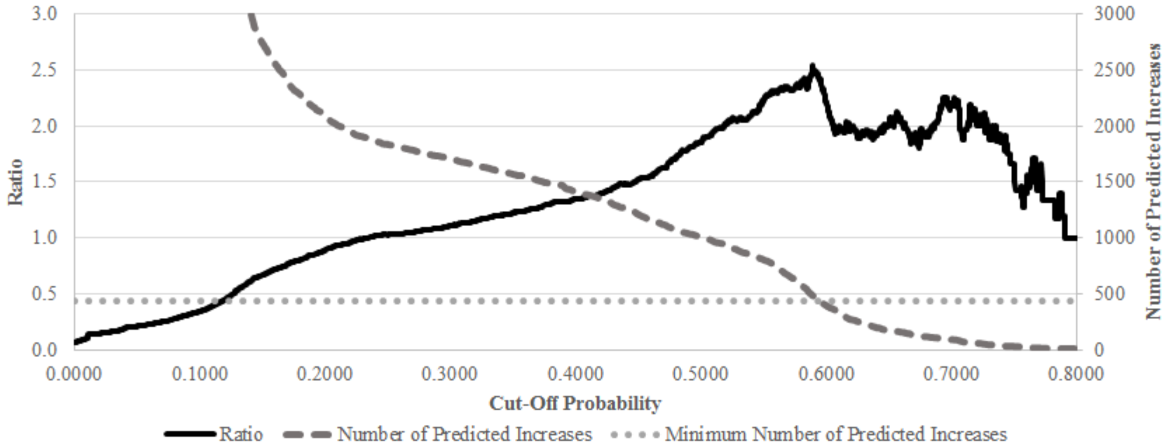
The effects from the variables capturing whether a company has paid cash dividends previously are not all in line with expectations, with *PaidL1Q* and *PaidL2Q* having positive coefficients, whereas *PaidL3Q* and *PaidL4Q* have negative coefficients. We cannot find any support in the literature confirming why having paid dividends three or four quarters previously would actually reduce the probability of a dividend increase greater than the threshold going forward. Neither can we attribute it to companies in our sample paying annual dividends, as this would rather have positive implications on *PaidL4Q* in comparison with the other three variables. It is possible that a dividend payment in quarter Q_{t-3} or quarter Q_{t-4} increases the probability of a dividend payment in quarter Q_t, but that this dividend is rarely an increase greater than the threshold. However, this is something we can only speculate about. Finally, the *HP* variable has a positive coefficient, in line with our expectations.

Regarding the financial distress variables, *Ohlson* has a negative coefficient as expected, implying that the more likely a company is to go bankrupt within the coming two years, the less probable is it to increase its dividend more than the threshold. The second financial distress variable, *Skogsvik*, surprisingly has a positive coefficient, implying that the larger the probability of financial distress six years from now, given survival up to that point, the larger the probability of a dividend increase greater than the threshold. Although unexpected, this is in line with DeAngelo and DeAngelo (1990), finding that companies generally raised their dividends in the years leading up to financial distress. Furthermore, it could be an indication of managements draining money from their companies and benefitting the equity owners. This draining could thus provide a link to the area of wealth transfers related to dividends, which is discussed in Woolridge (1983) and in Dhillon and Johnson (1994). However, we do not have data to draw such a conclusion, which is why we merely conclude that researching this further could be interesting.

4.1.2 Prediction Accuracy Test on Estimation Sample

For the prediction accuracy test on the estimation sample, the optimal cut-off probability is shown in Graph 1 below. Given the constraint of at least 440 predicted increases, the graph shows the probability maximizing the ratio of correctly predicted dividend increases greater than the threshold (Correct positives) to incorrectly predicted dividend increases greater than the threshold (False positives), by the Main Model for the Estimation sample. The optimal cut-off probability is 58.92 percent, which results in a ratio of 2.54 and a total number of predicted dividend increases greater than the threshold (the sum of Correct positives and False positives) of 485.

Graph 1: The Ratio of Correct Positives to False Positives and Number of Predicted Increases for Different Cut-Off Probabilities



With the 58.92 percent probability cut-off, the Naïve model is outperformed by the Main Model in the prediction accuracy results for the Estimation sample, as shown in Table 4. Both the number of Correct positives and the total number of correct predictions (the sum of Correct positives and Correct negatives) are higher for the Main Model than for the Naïve model. Out of the 485 observations where increases greater than the threshold are predicted, the Main Model is correct 348 times, an accuracy of 71.8 percent. Considering the total amount of predictions, the Main Model is correct in 94.4 percent of its predictions, compared to a total of 93.8 percent which would be achieved by simply assuming that no company would increase its cash dividends more than the threshold, or 88.6 percent achieved by the Naïve model.

Table 4: Prediction Accuracy for the Estimation Sample

	Correct positives	Correct negatives	False positives	False negatives	Obs
Main Model:	348	31,106	137	1,721	33,312
Naïve Model:	161	29,353	1,890	1,908	33,312

That the Main Model performs well in a prediction accuracy test in the Estimation sample is not unexpected due both to the high R-squared received in the model estimation and to the model being optimized for this sample. The Naïve Model, defined as the independent variable *DivInc1*, being outperformed indicates that the independent variables besides *DivInc1* do add information value to the Main Model.

4.1.3 Prediction Accuracy Test on Validation Sample

The prediction accuracy results for the Main Model applied on the Validation sample, using the same cut-off of 58.92 percent, is in Table 5 shown to outperform the Naïve model. Furthermore, the achieved results are better than those for the Estimation sample. Out of the 161 observations in the Validation sample where increases greater than the threshold are predicted, the Main Model is correct 123 times – an accuracy of 76.4 percent, or a ratio of 3.24. Considering the total amount of predictions, the Main Model is correct in 92.7 percent of its predictions, compared to a total of 91.5 percent which would be achieved by simply assuming that no company would increase its cash dividends more than the threshold, or 84.5 percent achieved by the Naïve model.

Table 5: Prediction Accuracy for the Validation Sample

	Correct positives	Correct negatives	False positives	False negatives	Obs
Main Model:	123	6,425	38	475	7,061
Naïve Model:	43	5,926	537	555	7,061

That the Main Model has better results for the Validation sample than for the Estimation sample is interesting, considering it is optimized for the Estimation sample. Since the Naïve model is outperformed the results are promising, however, the improvement for the Validation sample is not only positive as this also indicates that the model is not generally applicable. A model which is generally applicable should instead deliver the same results across different samples. The improved results could potentially depend on the changed time period or on the, to some extent, different sample of companies.

4.1.4 Descriptive Statistics

To describe the sample used in the estimation of the Main Model we first show in Table 6 how the 99,530 observations of U.S. manufacturers are scaled down to the 33,312 observations used. The respective steps are described in more detail in Section 3.1.2.

More than 53,000 observations are removed as we clean the sample from data quality issues and make it more homogenous. Furthermore, as historical data is used when estimating the Main Model, almost 13,000 observations required as background information cannot be used in the model estimation. More than 33,000 observations remain, which is considered a sufficiently large sample. However, due to potential characteristics in the omitted observations, the model might not be generally applicable to all U.S. manufacturers.

Table 6: Narrowing Down All U.S. Manufacturers to Final Sample

Description	**Obs**
All observations of U.S. manufacturers 2004-2013	**99,530**
Not reporting on quarterly basis	-15
Split fiscal year	-29,443
Assets below USD 10 million	-10,184
Cash Dividends, Net Income, Assets and/or Liabilities missing	-6,329
Duplicate observations	0
More than four quarters within the same calendar year	-26
Gaps in data	-4,514
Negative values of Cash Dividends	-84
Gaps in data	-769
First company-observation not first quarter	-1,925
Observations after cleaning of the data	**46,241**
Observations required as background data	-12,929
Observations used for estimating the Main Model	**33,312**

Further descriptive statistics for these 33,312 observations are shown in Table 7. First, *DivInc* shows that in 6.2 percent of the observations, cash dividend increases greater than the threshold occur. Since many of the observations are the same in *DivInc* and *DivInc1-DivInc4*, it is no surprise that these variables have mean values similar to *DivInc*. By the same reasoning, *DivIncL1Y* and *DivIncL2Y* should have approximately four times higher mean values, which they have. That both these variables have mean values under 0.23, with a maximum possible value of 4, is interesting. In Section 4.1.2, we discussed how the positive coefficient of the variables implied that frequent historical increases make future increases more probable. The mean value being this low could, however, rather strengthen the case that dividends are usually increased once per year.

Table 7: Descriptive Statistics for the Estimation Sample

Variable	Obs	Mean	Median	Std. Dev.	Min	Max
DivInc	33,312	0.062	0.000	0.241	0.000	1.000
Lintner	33,312	0.364	0.000	1.086	-1.000	5.000
PE	33,312	2.653	3.000	1.557	0.000	4.000
DivInc1	33,312	0.062	0.000	0.240	0.000	1.000
DivInc2	33,312	0.061	0.000	0.240	0.000	1.000
DivInc3	33,312	0.060	0.000	0.238	0.000	1.000
DivInc4	33,312	0.060	0.000	0.237	0.000	1.000
DivIncL1Y	33,312	0.223	0.000	0.487	0.000	4.000
DivIncL2Y	33,312	0.212	0.000	0.477	0.000	4.000
PaidL1Q	33,312	0.331	0.000	0.471	0.000	1.000
PaidL2Q	33,312	0.329	0.000	0.470	0.000	1.000
PaidL3Q	33,312	0.327	0.000	0.469	0.000	1.000
PaidL4Q	33,312	0.326	0.000	0.469	0.000	1.000
HP	33,312	0.504	1.000	0.500	0.000	1.000
Ohlson	33,312	0.132	0.022	0.255	0.000	1.000
Skogsvik	33,312	0.080	0.025	0.153	0.000	1.000

The definition of *DivIncL0Y* is found in Section 3.1.4.4. Descriptive statistics of this variable, of *DivIncL1Y* and of *DivIncL2Y* are shown in Table 8. Analysing these statistics, we find that in 15.0 percent of the cases when *DivIncL0Y* is larger than 0, *DivIncL0Y* is also larger than 1. The corresponding numbers for *DivIncL1Y* and *DivIncL2Y* are 13.7 and 13.8 percent, respectively. There is thus a considerable part of the sample for which multiple cash dividend increases greater than the threshold occur during a period of four quarters, indicating that the prediction of quarterly dividends is relevant.

Table 8: Descriptive Statistics for the Variables DivIncL0Y, DivIncL1Y and DivIncL2Y

DivIncL0Y	Freq.	Percent	DivIncL1Y	Freq.	Percent	DivIncL2Y	Freq.	Percent
0	26,379	79.19	0	26,855	80.62	0	27,169	81.56
1	5,898	17.71	1	5,571	16.72	1	5,294	15.89
2	918	2.76	2	808	2.43	2	782	2.35
3	105	0.32	3	71	0.21	3	61	0.18
4	12	0.04	4	7	0.02	4	6	0.02
Total	**33,312**	**100.00**	**Total**	**33,312**	**100.00**	**Total**	**33,312**	**100.00**

In Table 7, we also notice that the mean value of *Lintner* seems high in comparison to *DivInc* and that a cash dividend increase of on average 36.4 percent are expected for the observations, according to our modified version of the Lintner (1956) model. Furthermore, the binary *HP* variable has a mean value of just above 50 percent, meaning that almost 50 percent of the companies used to estimate our Main Model have never paid cash dividends during the period covered by our data set. Compared to companies which have paid dividends in the past these companies are, in line with Skinner (2008), less probable to use dividends as the means of distribution going forward.

Comparing the descriptive statistics for the Validation sample to the descriptive statistics for the Estimation sample, some notable differences are shown in Table 9. The mean of the variable *DivInc*, the actual outcome of cash dividend increases greater than the threshold, is 36 percent higher in the Validation sample and could potentially be part in explaining the increased performance of the model. Given the increased mean value of *DivInc*, we are not surprised that the *HP* variable has also increased, with a mean value of 56 percent in the Validation sample.

Whereas *Skogsvik* shows an unchanged mean value, *Ohlson* has a higher mean value than in the Estimation sample. We will return to the financial distress variables when comparing the Main Model with the re-estimated model for the Validation sample, as well as estimated models for sub-samples over time and across industries.

Table 9: Descriptive Statistics for the Validation Sample

Variable	Obs	Mean	Median	Std. Dev.	Min	Max
DivInc	7,061	0.085	0.000	0.278	0.000	1.000
Lintner	7,061	0.311	0.000	1.066	-1.000	5.000
PE	7,061	2.613	3.000	1.593	0.000	4.000
DivInc1	7,061	0.082	0.000	0.275	0.000	1.000
DivInc2	7,061	0.082	0.000	0.274	0.000	1.000
DivInc3	7,061	0.086	0.000	0.280	0.000	1.000
DivInc4	7,061	0.084	0.000	0.278	0.000	1.000
DivIncL1Y	7,061	0.356	0.000	0.609	0.000	4.000
DivIncL2Y	7,061	0.330	0.000	0.597	0.000	4.000
PaidL1Q	7,061	0.391	0.000	0.488	0.000	1.000
PaidL2Q	7,061	0.387	0.000	0.487	0.000	1.000
PaidL3Q	7,061	0.385	0.000	0.487	0.000	1.000
PaidL4Q	7,061	0.378	0.000	0.485	0.000	1.000
HP	7,061	0.564	1.000	0.496	0.000	1.000
Ohlson	7,061	0.141	0.021	0.274	0.000	1.000
Skogsvik	7,061	0.080	0.024	0.161	0.000	1.000

4.1.5 Robustness Test

Despite the positive results in the prediction accuracy tests and the significance levels in the panel estimation, we find that the general applicability of the model can be questioned.

We first present the comparison of the results reached using a panel estimation and those reached using a pooled estimation. Regarding the use of panel estimation, the likelihood-ratio test for rho=0 for the estimation of the Main Model shows that we cannot reject the null hypothesis that the variance at the panel-level, as a part of the total variance, is equal to zero even at the 0.10 level, in accordance with the STATA Manual (StataCorp. n.d.b). Therefore, the outcome would not have differed considerably if performing a pooled estimation rather than a panel estimation (Ibid.). The output using a pooled estimation confirms that the differences are small, as they are visible only in the fifth decimal places and onwards. The pooled estimation results are shown in Appendix B, Table 10.

The Wald test performed on the Main Model estimation results, shown in Appendix B, Table 11, confirms that the null hypothesis of all coefficients being equal to zero at the same time can be rejected at less than the 0.01 level. Further Wald tests performed for the financial distress variables together (Appendix B, Table 12) and the dividend smoothing variables (Appendix B, Table 13) both confirm that the null hypothesis can be rejected at less than the 0.01 level. To a certain extent, this confirms the validity both for the full model and for the two separate areas of financial distress and dividend smoothing. The results from the quadrature check (Appendix B, Table 14) show that the relative differences for some of the coefficients are above 0.01 percent and thus do not satisfy the general guidelines on quadrature checks as per the STATA Manual (StataCorp. n.d.a). However, given the small magnitude of the relative differences exceeding 0.01 percent, in combination with the promising result from the comparison between the panel estimation and the pooled estimation, we consider the results using the fitted model to be reliable.

The estimation results for the re-estimated model using the Validation sample achieves a McKelvey & Zavoina's pseudo R-squared (Enzmann n.d.) of 46.39 percent. This re-estimated model is, together with comparisons to the Main Model, shown in Table 15.

Table 15: Comparison between Estimation and Validation Sample Regressions

	Estimation	Validation	Actual Difference	Relative Difference	Same Sign
Lintner	0.114***	0.094***	0.020	-0.173	Yes
PE	0.197***	0.277***	-0.080	0.406	Yes
DivInc1	−1.041***	-1.474***	0.433	0.416	Yes
DivInc2	−0.310***	-0.828***	0.518	1.671	Yes
DivInc3	−0.206**	-0.348**	0.142	0.689	Yes
DivInc4	2.146***	2.402***	-0.256	0.119	Yes
DivIncL1Y	0.531***	0.566***	-0.035	0.066	Yes
DivIncL2Y	0.122***	0.246***	-0.124	1.016	Yes
PaidL1Q	0.837***	0.917***	-0.080	0.096	Yes
PaidL2Q	0.591***	1.001***	-0.410	0.694	Yes
PaidL3Q	−0.283**	-0.885**	0.602	2.127	Yes
PaidL4Q	−0.306**	-0.058	-0.248	-0.810	Yes
HP	1.213***	0.682***	0.531	-0.438	Yes
Ohlson	−1.890***	-0.949	-0.941	-0.498	Yes
Skogsvik	0.793**	1.245*	-0.452	0.570	Yes
Constant	−5.326***	-5.267***	-0.059	-0.011	Yes

Observations in Estimation sample: 33,312. Number of companies in Estimation sample: 1,479
Observations in Validation sample: 7,061. Number of companies in Validation sample: 892

*** p<0.01, ** p<0.05, * p<0.10

The relative differences shown in Table 15 are considerable for some of the coefficients, the largest being 213 percent for *PaidL3Q*. All of the coefficients do, however, have the same sign and thus impact the probability of an increase in the same direction, although with a different magnitude. That the Estimation sample and the Validation sample are consistent with regards to the sign of the variables provides some indication of general applicability, however, the magnitude of the changes does not speak for this general applicability.

Furthermore, not all of the variables are significant in the estimation results for the re-estimated model on the Validation sample, with *Ohlson* and *PaidL4Q* not being significant at the 0.10 level. We therefore test the importance of the financial distress variables also for this re-estimated model. As is shown in Appendix B, Table 16, we cannot reject the null hypothesis that the coefficients for both *Skogsvik* and *Ohlson* are equal to zero, even at the 0.10 level. That this null hypothesis cannot be rejected, in combination with the *Ohlson* variable not being significant, could indicate that financial distress predictions after all do not contribute to the field of dividend predictions, as was indicated by the Main Model. If any of the coefficients for *Skogsvik* and *Ohlson* would have been considerably smaller in the Validation sample, arguments could potentially be made that the non-significance is due to a positive economic climate in the validation period 2014-2016, leading to the coefficient(s) being small and non-significant.

The *Ohlson* coefficient in the re-estimated model on the Validation sample is about half compared to in the Main Model, while *Skogsvik's* coefficient is increased by 57 percent. It is not necessarily conflicting that the variables diverge, as they have different prediction horizons. It does, however, open up for the possibility that the changes in the *Ohlson* variable could be due to the economic climate. However, as noted in Section 4.1.4, the mean value of the *Ohlson* variable actually increases in the Validation sample. Therefore, even if the economic climate can explain the decreased significance level of the coefficient, including the *Ohlson* variable might harm the general applicability of the model across time, as the values of the variable did not decrease simultaneously. An additional important consideration will be the other re-estimations of the model, performed for separate sub-samples of industries.

The results when re-estimating the model for different sub-samples further support that the model is not generally applicable, mainly with relation to sub-industries. The number of observations for each sub-industry in our sample is shown in Appendix B, Table 17. Chosen for comparison are the three largest subindustries, with SIC code 28, SIC code 36 and SIC code 38.

In the comparison to the three sub-industries in Table 18, it is shown that several of our independent variables are not significant even at the 0.10 level. The coefficients do not only vary in magnitude but also with regards to the sign, the most extreme example being the *Skogsvik* variable which's coefficient varies between 1.13 to -5.62, with the latter being significant at the 0.05 level. These variations in sign and magnitude provide clear reasons to believe that the model, and the financial distress variables in particular, is not consistent over the different sub-industries. Such inconsistencies in turn imply that there could be good reason to consider a narrower definition of industries when estimating a dividend increase prediction model.

Table 18: Comparison between the Estimation of the Main Model and the Re-Estimations for the Sub-Samples of Industries

Variable	Main	SIC 28	SIC 36	SIC 38
Lintner	0.114***	0.085**	0.041	0.047
PE	0.197***	0.183***	0.156*	0.039
DivInc1	-1.041***	-1.139***	-0.778***	-1.343***
DivInc2	-0.310***	-0.332*	0.004	-0.653**
DivInc3	-0.206**	-0.495**	-0.895***	-0.501*
DivInc4	2.146***	2.072***	1.982***	2.511***
DivIncL1Y	0.531***	0.696***	0.301**	0.362**
DivIncL2Y	0.122***	0.250**	0.227*	0.280*
PaidL1Q	0.837***	0.264	2.122***	1.710***
PaidL2Q	0.591***	1.197***	-0.116	-0.360
PaidL3Q	-0.283**	-0.142	0.700	0.116
PaidL4Q	-0.306**	-0.707**	-1.071**	-0.272
HP	1.213***	1.887***	0.746**	2.017***
Ohlson	-1.890***	-1.756**	-0.818	-5.784*
Skogsvik	0.793**	0.677	1.134	-5.618**
Constant	-5.326***	-5.752***	-5.280***	-5.520***
Observations	33,312	7,537	5,369	4,573
Number of companies	1,479	378	238	197

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

A comparison with different time periods is shown in Table 19. This comparison shows that the estimated model also changes over time, with the *Ohlson* coefficient being smaller and both *Ohlson* and *Skogsvik* being less significant in the positive economic period of 2004-2007. This is in line with the previous finding for the re-estimated model for the Validation sample and could imply that the financial distress variables only are applicable in times of economic downturn. For the majority of our variables though, the differences between sub-industries are of larger magnitude than the differences between time periods. The differences between time periods are also smaller than those seen when comparing the Main Model and the re-estimated model for the Validation sample.

Table 19: Comparison between the Estimation of the Main Model and the Re-Estimations for the Sub-Samples of Different Time Periods

Variable	Main	2004-2007	2008-2013
Lintner	0.114***	0.126***	0.110***
PE	0.197***	0.207***	0.198***
DivInc1	-1.041***	-1.180***	-0.971***
DivInc2	-0.310***	-0.389***	-0.279***
DivInc3	-0.206**	-0.260*	-0.187*
DivInc4	2.146***	2.329***	2.032***
DivIncL1Y	0.531***	0.563***	0.515***
DivIncL2Y	0.122***	0.094	0.139**
PaidL1Q	0.837***	0.509**	1.029***
PaidL2Q	0.591***	1.085***	0.346*
PaidL3Q	-0.283**	-0.485**	-0.200
PaidL4Q	-0.306**	-0.215	-0.348**
HP	1.213***	1.257***	1.163***
Ohlson	-1.890***	-1.313*	-2.207***
Skogsvik	0.793**	0.799	0.818*
Constant	-5.326***	-5.595***	-5.192***
Observations	33,312	13,420	19,892
Number of companies	1,479	1,116	1,195

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Last, as shown in Table 18 and Table 19, *PaidL3Q* and *PaidL4Q* are non-significant in four and two of the five sub-samples, respectively. This could indicate that the significant results in the estimation of the Main Model are coincidental, but considering the size of the sample such a conclusion seems far-fetched. Another possibility is that multicollinearity makes the interpretations of separate coefficients difficult. We are, however, forced to conclude that we cannot satisfactorily explain the coefficients of *PaidL3Q* and *PaidL4Q*, neither regarding their non-significance nor their sign.

4.2 Trading Strategy

4.2.1 Achieved Cumulative Abnormal Returns

The trading strategy is performed for a total of 142 observations. As shown in Table 20, together these observations generate a cumulative abnormal return of 150.9 percent over the full period of two and a half year in the Validation sample. Furthermore, the performed one-sample t-test in Table 21 shows that we can successfully reject the hypothesis that the mean of the cumulative abnormal returns for the 142 observations does not differ from 0, on the 0.10 level.

Table 20: Summary Statistics of the Cumulative Abnormal Returns

	Obs	Mean	Max	Min	p5	p50	p95	Total
CAR	142	0.01062	0.23342	-0.39036	-0.15162	0.01359	0.16432	1.50858

Table 21: One-Sample T-test of the Cumulative Abnormal Returns

	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
CAR	142	0.01062	0.00821	0.09783	-0.00561	0.02685
mean = mean(CAR)				t = 1.2941		
Ho: mean = 0				degrees of freedom = 141		
Ha: mean < 0		Ha: mean != 0		Ha: mean > 0		
Pr(T < t) = 0.9011		Pr(T > t) = 0.1977		Pr(T > t) = 0.0989		

Out of the 161 observations where a cash dividend increase greater than the threshold is predicted, 7 observations are removed due to data quality issues such as missing announcement dates data or missing price data. An additional 12 observations are removed due to the dividends already having been announced when the data used to trade on is available to us. This leaves us 142 observations to trade on.

The positive abnormal returns are in line with that information, in accordance to Miller and Modigliani (1961), is being conveyed in dividends. However, from a CAPM standpoint, as commented in the textbook by Bodie, Kane and Marcus (2011, p. 322), there should be no predicable deviations from the return predicted by the CAPM, for any security. The abnormal returns of 150.9 percent achieved could indicate that deviations can be forecasted, but as it is only statistically significant at the 0.10 level, we cannot make such a claim. Although no strong claim can be made, the results do encourage future research within this area.

Considering only the Correct positives, 106 tradeable observations remain. These observations generate a cumulative abnormal return of 110.4 percent, shown in Table 22. It is surprising that the abnormal returns are lower for the Correct positives on a standalone basis than when we are trading on the Correct positives as well as the False positives. Furthermore, for the sample of only Correct positives, the hypothesis that the mean of the cumulative abnormal returns does not differ from 0 cannot be rejected even at the 0.10 level as shown in Table 23.

Table 22: Summary Statistics of the Cumulative Abnormal Returns – Only Correct Positives

	Obs	Mean	Max	Min	p5	p50	p95	Total
CAR	106	0.01041	0.23342	-0.39036	-0.14929	0.01462	0.15497	1.10356

Table 23: One-Sample T-test of the Cumulative Abnormal Returns – Only Correct Positives

	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
CAR	106	0.01041	0.00909	0.09357	-0.00761	0.02843

mean = mean(CAR)		t = 1.1455
Ho: mean = 0		degrees of freedom = 105
Ha: mean < 0	Ha: mean != 0	Ha: mean > 0
Pr(T < t) = 0.8727	Pr(T > t) = 0.2546	Pr(T > t) = 0.1273

That the 36 observations of False positives yield positive cumulative abnormal returns could justify future research within the area. These observations are either cash dividend omissions, decreases, increases smaller than the threshold or unchanged cash dividends. The sample is unfortunately too small to draw any real conclusions from. However, since the abnormal returns actually decrease when excluding the False positives, an alternative strategy relating to dividend announcements could be to choose a lower probability cut-off.

4.2.2 Discussion of the Abnormal Returns

The abnormal returns reached could be dependent on an increased risk, which we have not been able to take into consideration. For example, as discussed in Section 2.4, Bajaj and Vijh (1995) found that abnormal returns for announcements of cash dividends had a negative correlation to the size of the companies. It is possible that we have taken on the higher risk associated with smaller companies and as a result achieve these abnormal returns.

Parts of the abnormal returns achieved could possibly also be explained by the assumption of no transaction costs, used in line with the CAPM, as in Berk and DeMarzo (2011, p. 357).

4.3 Further Limitations

In addition to the above-mentioned limitations in the Section 4.1.5 and Section 4.2.2, more general limitations to this paper are presented below.

A considerable limitation of this study is that it only considers cash dividend increases greater than a threshold. It thus ignores all other kinds of payout, including smaller increases of cash dividends.

Although a large sample is used in the thesis, one limitation is that we due to data quality issues, requirement of sixteen consecutive quarters of data and other considerations are not able to include all observations for the target industry of U.S. manufacturers. This could inevitably cause biased results, if the observations removed have certain characteristics. A further limitation is the selection of U.S. manufacturers as the model is only tested for this industry and jurisdiction.

In relation to the trading strategy, no information of the expected dividends has been included, which could have affected the results. Also, the dividends predicted are the total cash dividends paid by the company, which is a limitation since the relative increase for total cash dividends is not necessarily the same as the relative increase for the cash dividend per share.

In the dividend increase prediction model we use the most recent dividend announcement and data reported for the quarter prior to the most recent quarter to mitigate the risk of predicting cash dividends which have already been announced. However, as can be seen from the results in Section 4.2.1, a considerable part of all observations in the trading sample had to be omitted because dividends had already been announced. After excluding seven observations due to data quality issues, 154 observations we wanted to trade on remained. In 12 of these 154 observations, almost 8 percent, the dividend had already been announced when the data needed was available to us. If this fraction is applicable for the full sample it can imply that our results seem better than they actually are. If we would instead have used the data reported in the most recent quarter, the dividend would have been announced before the data was available in 99 of the observations, or 64 percent. We therefore seem to have mitigated a large part of the issue, although not to the degree we had initially hoped for.

We are also unable to ensure the quality of all the observations in the data set given its size, therefore it is possible that data quality issues affect the results of this paper. This is partly mitigated as the data used is from a well-known and trusted vendor.

5. Conclusions

This thesis shows that quarterly dividend increases can be predicted accurately with the use of accounting data, financial distress predictions and smoothing considerations. It also indicates that abnormal returns can be achieved using dividend predictions. These conclusions are reached through the development of a dividend increase prediction model. However, the general applicability of such a model could be questioned, mainly with regards to different sub-industries. The thesis contributes to the dividend prediction area in general and to dividend prediction based on accounting data, financial distress predictions and smoothing in particular.

We conclude that existing dividend prediction models, such as Lintner (1956), could benefit from including differentiated smoothing variables for quarterly and yearly smoothing effects if used to predict quarterly dividends. The importance of including smoothing behaviour overall is shown, which is in line with Brav, Graham, Harvey and Michaely (2005), but we also show the importance of accounting for both smoothing between years and separately between quarters. The smoothing between quarters tends to be focused on maintaining a stable dividend, however, 15 percent of the companies in our sample which increase cash dividends more than the threshold at least once in a period of four quarters does so at least one additional time in the same period.

Although initially promising, the results for the financial distress variables in the context of our dividend increase prediction model are inconsistent over time and, to an even larger extent, across sub-samples of industries. Including financial distress variables could therefore harm the general applicability of the model. In light of the positive initial results, we consider the area of financial distress predictions as part of dividend prediction a topic for further research, although some adaption to consider the prevailing economic climate is likely to be necessary.

The significant abnormal returns achieved using a trading strategy for the dividend increase predictions could imply that, in line with Miller and Modigliani (1961), information is conveyed in dividend changes. These results are contradictory to that there should be no predictable deviations from the return predicted by the CAPM, as commented by Bodie, Kane and Marcus (2011, p. 322). The low level of significance together with the positive abnormal returns for the False positives on a stand-alone basis would, however, make any conclusions based on these findings far-fetched. The results do, nevertheless, justify future research within the combined area of dividend signalling and dividend prediction.

5.1 Future Research

In line with the limitations found in this study, future research focusing on dividend prediction for smaller sections of industries would be beneficial, as our results indicate that the model is not generally applicable across sub-industries. For future considerations of financial distress predictions as a part of dividend predictions, some adaption of the approach presented in this thesis is necessary, mainly to include considerations for the state of the economy.

As noted for our trading strategy, seemingly our approach for maximizing the ratio of Correct positives to False positives is not optimal, given that False positives generated positive abnormal returns. With this in mind, an interesting area to conduct further studies into would be to adjust the cut-off, allowing for a larger number of both Correct positives and False positives.

The positive coefficient of the variable *Skogsvik*, based on the model for financial distress prediction in Skogsvik (1987), could have implications for managements of companies trying to drain money from their companies, however the data for such a conclusion is not available in this thesis. This potential draining could be connected to the area of wealth transfer as discussed by Woolridge (1983) as well as Dhillon and Johnson (1994) and be an interesting topic for future research.

Furthermore, this study has been conducted on U.S. manufacturing companies, which is only a small subset of all the dividend paying companies available. Considering other jurisdictions as well as other industry groups could be beneficial for future research.

The trading model included in this thesis is relatively simple. Future research could benefit by extending it to also incorporate the area of drift effects e.g. in line with the findings of Michaely, Thaler and Womack (1995) which showed a drift effect resulting from dividend initiations (cancellations).

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Appendix A

Table 1: Data Retrieved from Wharton Research Data Services Compustat Fundamentals Quarterly

The table shows the retrieved variables from Wharton Research Data Services Compustat (2016a), retrieved October 31, 2016, available at: Compustat - Capital IQ/ Compustat Monthly Updates/ North America/ Fundamentals Quarterly.

The code and the name are both as termed by the Fundamentals Quarterly database. The variables ACTQ and below in the table all refer to quarterly numbers.

Code	Name
TIC	Ticker Symbol
SIC	Standard Industry Classification Code
DATACQTR	Calendar Data Year and Quarter
DATAFQTR	Fiscal Data Year and Quarter
FQTR	Fiscal Quarter
FYEARQ	Fiscal Year
RP	Reporting Periodicity
ACTQ	Current Assets – Total
ATQ	Assets – Total
CHEQ	Cash and Short-Term Investments
DVY	Cash Dividends
INVTQ	Inventories – Total
LCTQ	Current Liabilities – Total
LTQ	Liabilities – Total
NIQ	Net Income (Loss)
OANCFY	Operating Activities – Net Cash Flow
SALEQ	Sales/Turnover (Net)
SEQQ	Stockholders Equity > Parent > Index Fundamental > Quarterly
WCAPQ	Working Capital (Balance Sheet)
XINTQ	Interest and Related Expense – Total

Table 2: Data Retrieved from Wharton Research Data Services Compustat Security Daily

The table shows the retrieved variables from Wharton Research Data Services Compustat (2016b), retrieved November 14, 2016, available at: Compustat - Capital IQ/ Compustat Monthly Updates/ North America/ Security Daily.

The code and the name are both as termed by the Security Daily database.

Code	Name
TIC	Ticker Symbol
ANNCDATE	Dividend Declaration Date
CSHOC	Shares Outstanding
DIVD	Cash Dividends – Daily
DIVDPAYDATE	Cash Dividends – Daily Payment Date
PAYDATE	Dividend Payment Date
PRCCD	Price – Close – Daily
RECORDDATE	Dividend Record Date
TRFD	Daily Total Return Factor

Appendix B

Table 10: Regression Output using Pooled Estimator

The table shows the regression output for the Estimation sample using pooled estimator rather than panel estimator. The coefficients are to a large extent similar, although variations in the fifth decimal point and onwards do exist, compared to the regression output using panel estimator. As the table includes three decimal points the only difference visible is for *PaidL3Q*, due to rounding. *PaidL3Q* to the fifth decimal point using the panel estimation was -2.83495 compared to -2.83502 in the pooled estimation.

VARIABLE	DivInc
Lintner	0.114***
PE	0.197***
DivInc1	-1.041***
DivInc2	-0.310***
DivInc3	-0.206**
DivInc4	2.146***
DivIncL1Y	0.531***
DivIncL2Y	0.122***
PaidL1Q	0.837***
PaidL2Q	0.591***
PaidL3Q	-0.284**
PaidL4Q	-0.306**
HP	1.213***
Ohlson	-1.890***
Skogsvik	0.793**
Constant	-5.326***
Observations	33,312

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table 11: Wald Test – Estimation Sample

The table shows the result from the Wald test performed on the estimation of our dividend increase prediction model for the Estimation sample, testing the null hypothesis that all the coefficients at the same time are equal to zero, in accordance with the STATA Manual (StataCorp. n.d.c). The null hypotheses can be rejected at less than the 0.01 level.

Wald Test:	
(1)	[DivInc]Lintner = 0
(2)	[DivInc]PE = 0
(3)	[DivInc]DivInc1 = 0
(4)	[DivInc]DivInc2 = 0
(5)	[DivInc]DivInc3 = 0
(6)	[DivInc]DivInc4 = 0
(7)	[DivInc]DivIncL1Y = 0
(8)	[DivInc]DivIncL2Y = 0
(9)	[DivInc]PaidL1Q = 0
(10)	[DivInc]PaidL2Q = 0
(11)	[DivInc]PaidL3Q = 0
(12)	[DivInc]PaidL4Q = 0
(13)	[DivInc]HP = 0
(14)	[DivInc]Ohlson = 0
(15)	[DivInc]Skogsvik = 0
chi2(15) = 3287.81	
Prob > chi2 = 0.0000	

Table 12: Wald Test – Estimation Sample, Financial Distress

The table shows the result from the Wald test performed on the estimation of our dividend increase prediction model for the Estimation sample for the two financial distress variables, testing the null hypothesis that both the coefficients at the same time are equal to zero, in accordance with the STATA Manual (StataCorp. n.d.c). The null hypotheses can be rejected at less than the 0.01 level.

Wald Test:	
(1)	[DivInc]Ohlson = 0
(2)	[DivInc]Skogsvik = 0
chi2(2) = 18.27	
Prob > chi2 = 0.0001	

Table 13: Wald Test – Estimation Sample, Dividend Smoothing Variables

The table shows the result from the Wald test performed on the estimation of our dividend increase prediction model for the Estimation sample for the dividend smoothing variables, testing the null hypothesis that all of the coefficients at the same time are equal to zero, in accordance with the STATA Manual (StataCorp. n.d.c). The null hypotheses can be rejected at less than the 0.01 level.

Wald Test:	
(1)	[DivInc]DivInc1 = 0
(2)	[DivInc]DivInc2 = 0
(3)	[DivInc]DivInc3 = 0
(4)	[DivInc]DivInc4 = 0
(5)	[DivInc]DivIncL1Y = 0
(6)	[DivInc]DivIncL2Y = 0
(7)	[DivInc]PaidL1Q = 0
(8)	[DivInc]PaidL2Q = 0
(9)	[DivInc]PaidL3Q = 0
(10)	[DivInc]PaidL4Q = 0
chi2(10) = 1975.57	
Prob > chi2 = 0.0000	

Table 14: Quadrature Check of the Estimation of the Main Model

The table shows the outcome of the log likelihood, the coefficients of the independent variables and the constant from our main regression model given different number of quadrature points. The estimations are deemed dependable if the coefficients do not have relative differences above 0.01 percent when altering the number of quadrature points, in accordance with the STATA Manual (StataCorp. n.d.a). Although marginally, the coefficients of the variables *DivInc2*, *DivInc3*, *DivIncL2Y* and *PaidL3Q* have relative differences larger than this.

	Fitted 12 points	**Comparison 8 points**	**Comparison 16 points**	
Log likelihood	-5367.727	-5367.7264	-5367.7264	
		1.14E-07	*-1.14E-07*	*Relative difference*
Lintner	0.11418094	0.11416985	0.11417352	
		9.71E-05	*-6.50E-05*	*Relative difference*
PE	0.19686021	0.19685332	0.1968556	
		3.50E-05	*-2.34E-05*	*Relative difference*
DivInc1	-1.0407437	-1.0406609	-1.0406883	
		7.96E-05	*-5.32E-05*	*Relative difference*
DivInc2	-0.3102496	-0.31016389	-0.31019224	
		2.76E-04	*-1.85E-04*	*Relative difference*
DivInc3	-0.2062034	-0.20612177	-0.20614878	
		3.96E-04	*-2.65E-04*	*Relative difference*
DivInc4	2.1455306	2.1455814	2.1455646	
		2.37E-05	*1.58E-05*	*Relative difference*
DivIncL1Y	0.530641	0.53068566	0.53067088	
		8.42E-05	*5.63E-05*	*Relative difference*
DivIncL2Y	0.12196778	0.12200186	0.12199058	
		2.79E-04	*1.87E-04*	*Relative difference*
PaidL1Q	0.83717874	0.83716914	0.83717232	
		1.15E-05	*-7.67E-06*	*Relative difference*
PaidL2Q	0.59068473	0.59068013	0.59068165	
		7.79E-06	*-5.21E-06*	*Relative difference*
PaidL3Q	-0.2834953	-0.28352433	-0.28351473	
		1.02E-04	*6.85E-05*	*Relative difference*
PaidL4Q	-0.3057002	-0.30571486	-0.30571002	
		4.79E-05	*3.20E-05*	*Relative difference*
HP	1.2125238	1.2125039	1.2125104	
		1.64E-05	*-1.10E-05*	*Relative difference*
Ohlson	-1.8898441	-1.8898604	-1.889855	
		8.59E-06	*5.75E-06*	*Relative difference*
Skogsvik	0.79330776	0.79330424	0.79330541	
		4.43E-06	*-2.96E-06*	*Relative difference*
Constant	-5.3258404	-5.3257842	-5.3258028	
		1.05E-05	*-7.05E-06*	*Relative difference*

Table 16: Wald Test – Validation Sample, Financial Distress

The table shows the result from the Wald test performed on the estimation of our dividend increase prediction model for the Validation sample for the financial distress variables, testing the null hypothesis that all of the coefficients at the same time are equal to zero, in accordance with the STATA Manual (StataCorp. n.d.c). The null hypotheses cannot be rejected at the 0.10 level.

Wald Test:	
(1)	[DivInc]Ohlson = 0
(2)	[DivInc]Skogsvik = 0
chi2(2) = 3.74	
Prob > chi2 = 0.1540	

Table 17: The Number of Observations within Each Sub-industry in Our Estimation Sample

In our sample of manufacturing companies, we have twenty different SIC code groups with regards to the first two digits (20-39). Out of these twenty, the three SIC code groups with most observations are chosen for comparison. As shown in Table 17, these are the groups with SIC code 28, SIC code 36 and SIC code 38.

SIC	Obs
SIC 20	1,218
SIC 21	170
SIC 22	293
SIC 23	734
SIC 24	387
SIC 25	480
SIC 26	954
SIC 27	544
SIC 28	7,537
SIC 29	572
SIC 30	904
SIC 31	436
SIC 32	434
SIC 33	1,023
SIC 34	1,210
SIC 35	4,082
SIC 36	5,369
SIC 37	1,695
SIC 38	4,573
SIC 39	697
	33,312