Pieces to the Puzzle: New Evidence on the Interpretation of Dividends

A Study on the Information Content of Dividends Hypothesis using the Novel Approach of High-Frequency Data and Systematic Risk

A Master's Thesis by

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Abstract

Using intra-day equity prices and recently developed variance estimators of high frequency data, the informational content of dividend announcements is examined. This is done by estimating changes in systematic risk (beta) on the day of the dividend announcement hereby enabling an examination of investors' reaction to an unexpected change in the dividend level. The main high frequency estimator applied is the realised (co)variance estimator used to construct *realised beta* values but due to potential biases in this model additional estimators of realised (multivariate) kernels, bi-power (co)variance, and the Hayashi-Yoshida estimator accompany it for additional testing. Using a sample of all S&P 500 firms in the period 2000-2012, the daily beta estimates are regressed on event day dummies to model the dynamics of beta. It is found that beta increases on the announcement day in the order of 0.21 when a firm decreases the dividend level by at least 20%. After a series of robustness tests, it is found that the estimated change in beta range from 0.13 to 0.37 following announcements of a dividend decrease. These results are both statistically and economically significant. For a dividend increase no change in beta is found on the announcement day and all robustness tests consistently confirm this. In light of these results, it is concluded that no relationship exist between dividend increases and beta while beta exhibits an inverse relationship w.r.t dividend decreases. This is partially in support of the Information Content of Dividends Hypothesis which postulates an inverse relationship between unexpected dividend changes and beta. The application of beta is due to its positive association with the expected return of a stock which is difficult to observe in practice. The inverse correlation is then hypothesised to be related to the variability of a firms future cash flows. As the variability of the cash flows increase, the firm decreases dividend payments to create more room to manoeuvre financially. Due to the positive relationship between beta and expected return, investors should be aware of dividend decreases as this can affect financial portfolios' risk/return composition. The missing link between dividend increases and beta can potentially be explained by three factors; (i) the model presented by Lintner (1956) in the sense that the market might see a dividend increase as a move towards the long term dividend target of the firm. Hence all the information related to a dividend increase is already incorporated in the market at the time when the firm first decides to pay out dividends. (ii) The use of actual dividend changes and not unexpected changes due to data availability issues and (iii) if the postulated inverse relationship exists for dividend increases then managers can lower the firm's cost of capital by increasing the dividend. Assuming a rational market, investors anticipate such sub-optimisation by managers and refrain from decreasing the beta value of the stock in the wake of a dividend increase. These conclusions can however only be discussed qualitatively as further research is required to allow for a better understanding of the asymmetric findings of this paper.

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Above all, dividend policy should always be clear, consistent and rational.

(Buffett, 2013, p.21), Letter to Shareholders 2012 - Berkshire Hathaway Inc.

Chapter 1

Introduction

Financial events occur constantly throughout the year - they include firm specific announcements, industry based key ratios or national employment figures to name a few. Some events are highly anticipated by the market, create international headlines and can make or break an economic upturn or a firm's ability to raise new funds. Other events have proven much more difficult to interpret with opinions about the economic relevance contradicting each other. One of the most discussed and perplexing of such events has for long been the payment of dividends where no consensus regarding the meaning has been agreed upon. The discussion of the relevance of dividends has been going on for the better half of a century and has fostered a large amount of interpretations and findings. Yet, no particular explanation or empirical evidence has granted a definitive conclusion for a complete and unifying understanding of the nature of dividend payments.

A highly examined interpretation of dividends is the *Information Content of Dividends Hypothesis* which suggest that information asymmetry exist between the *insider* (management) and the *outsider* (investors). In this context dividends are hypothesised to convey information from the insiders to the outsiders. Two main interpretations of how information in dividends can be estimated have been suggested. The most studied method investigates stock price changes with the expectation that a dividend increase (decrease) leads to an immediate stock price increase (decrease). The empirical research of this hypothesis has however resulted in numerous conflicting findings. The other approach uses systematic risk adjustments as an applicable estimator of the expected return of a stock and has been suggested in the wake of the inconclusive findings of the original approach. This relationship is inverse, or more precisely, an unexpected dividend increase (decrease) is hypothesised to lead to a decrease (increase) in systematic risk (and expected return as they are positively related). Still, neither method has been able to produce solid answers even though the research of the past decades has left a startling amount of literature.

Until recently it may have appeared as if this research area was exhausted due to the already extensive use of different theoretical methods and data in former studies. The latest availability of data recordings of intra-day, tick-by-tick stock prices have however reopened the options available for analysis by granting much more precise data. Simultaneously, econometric scholars have developed new methods for utilizing this *high-frequency* data optimally to estimate volatility given the noise concerns that also arise when such data is employed. Especially the approach estimating information through systematic risk can gain from this technical improvement as it is now possible to focus on a specific event day which is not possible with lower frequency data. No literature has thus far utilised the improved and more precise data and methods now available to examine the hypothesised dividend relationship. An analysis of this relationship, using the improved data, can therefore provide new insight to this research area. In the application of high-frequency data and recent econometrical developments this thesis will bring forth a new approach and analysis which can provide improved insight to the Information Content of Dividends discussion beyond what was formerly possible. This study will therefore not merely add another finding to the research field but one which improve the precision of the estimation technique and the following results. The research is not just a hunt for a theorised relationship but may have practical implications for investors since a systematic risk adjustment of stocks can alter the risk composition of financial portfolios. The findings may therefore have empirical financial significance besides academic relevance.

1.1 Research Question

The objective of this paper is to determine whether the Information Content of Dividends can be supported through empirical investigation by testing if outsiders interpret a dividend as containing information w.r.t systematic risk. To shed light on the matter above the following research question is stated:

> *Do unexpected dividend changes convey information as expected by the Information Content of Dividends Hypothesis when measured as adjustments in firms' systematic risk (beta) caused by investor reaction on the announcement day?*

Due to the focus on changes in systematic risk on the dividend announcement day, it is necessary to apply high frequency data in order to estimate the parameter of interest. This is not a straight forward exercise and require extensive consideration. Along with this, a few other questions must be addressed to answer the research question fully, due to the context which it will be answered within. A series of sub-questions will therefore be considered in this thesis:

i) *Does the prevalent model for measuring high frequency variance and covariance correctly estimate systematic risk given high frequency data constraints and how can potential issues be mitigated?*
ii) *What is the economic consequence of the empirical findings for investors?*
iii) *What are the implications of the findings of this thesis on the existing findings within the research area?*

1.2 Overview of Findings

The research question is answered by the use of a longitudinal regression analysis and it is found that announcements of dividend decreases cause an economically significant increase in the betas value of stocks of 0.21 relative to a non-announcement average as expected by the Information Content of Dividends Hypothesis. A dividend increase announcement causes no significant effect on the beta value and does not support the hypothesis. The stated research question is therefore partially supported by the findings of this thesis. The results have asymmetric relevance for investors as the beta adjustment may change the risk profile of a portfolio and investors must therefore be aware of dividend decreases but not dividend increases. The findings have implications for former studies showing a beta decrease following a dividend increase as there is clearly no effect on the specific event day according to these findings. A possible explanation for the asymmetric findings is that managers might have incentive to sub-optimise by increasing the dividend since this will reduce the required rate of return and thereby the cost of capital. If investors are aware of this misalignment of interest they will naturally not react to a dividend increase. Another explanation is that firms may choose a long run dividend target, in which case the information on dividend increases may already be known to the market. The results also reveal that beta values estimated from high-frequency data using the *realised method* are consistent and contain economic information when estimated using a 15 minute intra-day sampling frequency. This approach can therefore be developed further to approach the true underlying beta value even more precisely. A critical point concerning this study is the absence of data on analysts' expectations which has led to the application of actual dividend changes as a proxy for unexpected dividend changes. More research is required to shed light on the reason for the asymmetric findings of this paper; if the current theoretical framework can be develop to comprehend potential incentive concerns of insiders; how the high frequency measures can be developed to deliver even more robust beta estimations; and if a market reaction to a dividend change can be seen in the post-announcement financial figures of the firms.

1.3 Outline

The remainder of this chapter will provide insight into the delimitations of this thesis and formally introduce some key background areas of the thesis. The rest of the thesis is divided into the following parts: Chapter 2 discusses the methodological aspects including the theoretical and econometric approach and the event study method applied. Chapter 3 is concerned with the underling theory and previous literature on the topics handled. Chapter 4 discusses the data handling complications. Chapter 5 presents the main regression results and robustness tests. In Chapter 6 the results are analysed in relation to previous research and the economic relevance of the findings where after they are view in a critical perspective. Finally, chapter 7 concludes on the findings and provide recommendations for further research.

1.4 Delimitations

The list of potential methods for estimating variance and covariance using high-frequency data is long and all approaches may provide additional insight relevant to this study or aide as robustness tests of the results[1]. However due to page and time limitations only a representative set of such estimation methods will be applied covering the main problematic areas of high-frequency data.
High frequency data demands large data storage capacity as only a few days of time-line data can quickly take up several gigabytes when using an index of around 800 firms. This has limited the frequency at which data is extracted to a 1 minute maximum. A higher frequency of data is available but with the storage capacity at hand it is simply not possible to store the data at for example the highest available frequency of 1 second as it would demand several terabytes of capacity.

Due to the necessity of intra-day data for the completion of this thesis, only a data pool from 2000 is available as the data quality before this point is inadequate. This is mainly due to the data recordings not being complete enough prior to this point in time. Additionally, the access to certain data bases containing specific types of data, such as *analysts' dividend*

[1] McAleer and Medeiros (2008) summarise and discuss an extensive list of specifications for analysing high-frequency stock prices.

expectations which is available through the Institutional Brokers' Estimate System (I/B/E/S) database is not accessible to CBS students. To this end, alternative approaches have been necessary as a second best solution. This will be commented upon further below.

This paper attempts to shed light on whether dividends contain information which is in essence a two sided analysis that can be disclosed from either the insiders' point of view or from the outsiders' point of view. As a result hereof, this analysis can only be used to interpret how a dividend payment is perceived from the outsiders' perspective as it examines the reaction of this agent. An analysis of the insiders' beliefs concerning dividends and whether they contain information is beyond the scope of this paper.

An alternative method of distributing cash to stockholders is stock repurchase. Like dividends, the effect of stock repurchases has been examined thoroughly and they are often argued to be substitutes. Share repurchases will briefly be covered below but further discussion of stock repurchases is left out of this thesis as no direct inference or implications can be drawn based on the underlying theory or regression analysis.

1.5 The Principle of Dividends

1.5.1 Corporate Cash Distributions

Firms have different ways of distributing cash to shareholders which can either be through dividends or share repurchases. A share repurchase occurs when a company buys back shares from shareholders with the intention of retiring the shares or to keep them as treasury stock for other purposes. The company hereby limits the availability and liquidity of its shares in the open market (Horngren et al., 2011). A share repurchase does not force investors to sell their shares but provides the opportunity to do so. It is therefore not a necessity that all shareholders receive a direct cash payment due to a stock repurchase. Alternatively, the company can distribute cash dividends to the shareholders in which case all shareholders entitled to a dividend will receive a cash amount. Dividends are usually paid as a fraction of a firms profits with every share receiving an equal amount - a dividend per share. The amount received by a shareholders is hence a function of the amount paid out and the number of shares held. Companies often have multiple types of shares with different legal rights generally referred to as *common stock* and *preferred stock*. Preferred stocks grant the owner preferential treatment over common stockholders often in terms of liquidation rights or dividend payments (Horngren et al., 2011). Preferred stockholders generally receive dividends prior to common stockholders and common stock holders only receive a dividend if the rights of the preferred stock holders have already been met[2].

Far from all companies today have issued preferred stocks, and when referring to a stock or a stock dividend one usually refer to common stock. All dividends and shares discussed and used throughout this thesis are based on common stocks as this is the type of stock which all the publicly traded firms studied have issued and which the theories and hypotheses discussed in this paper are based on.

In many countries dividends and repurchases are taxed differently with dividends being taxed as personal income and repurchases as capital gains. Generally capital income is taxed at a lower rate than personal income giving repurchases a financial advantage. Dividends are however still widely used potentially due to the hypothesised reasons to be covered later. As the applied stock index is based on firms from the U.S.A. the tax environment here is of most relevance but due to the globalisation of the stock markets and bilateral tax agreements set in place to mitigate the issue of double taxation, investors are subject to different tax regimes. However in most academic literature it is assume that dividends are taxed at a higher level than capital gains. Share repurchases as a subject will not be considered in further depth as the corporate choice between the two falls outside the scope of this thesis.

1.5.2 The Dividend Payment Process

Several dates are important in relation to dividend payments and to avoid potential confusion a short explanation and description of the relevant dates is in order.

The *dividend announcement date*, or declaration date, refers to the date on which information about the forthcoming dividend payment is released by a firm to the shareholders. No actual transfer takes place at this stage as it is merely a news announcement which often happens in relation to other events such as a general assembly. At this point stocks are said to be *cum dividend*, or with dividend, implying that anyone who purchases the share at this point in time is entitled to the coming dividend payment. The next relevant date is the *ex-dividend date*, or without-dividend, on which shares purchased or sold no longer carry the right to the declared dividend payment. After the ex-dividend point anyone who purchase a share will not

[2] One could go into a lengthy discussion on the details regarding the rights of preferred stock holders such as whether they are cumulative/non-cumulative, participating/non-participating, etc. This is however not directly relevant for the themes discussed in this thesis.

receive the scheduled dividend payment which will be accrued to the seller of the stock.

Table 1.1: The Dividend Payment Process

Dividend Announcement Date
↓
Ex-dividend Date
↓
Record Date
↓
Dividend Payment Date

The dividend process from announcement to payment of dividends (Own contribution).

The *date of record* follows after the ex-dividend date. On this date the dividend distributing firm refers to its records to see which shareholders are entitled to receive the dividend payment and what amount the different shareholders are entitled to. The final step is the actual payout of the dividend. The *date of payment* is thus the day on which the dividend is physically distributed to the shareholders authorised to receive it. This concludes the dividend payment procedure and all current shareholders become cum dividend again, ready for the next payment. The chronology of the dividend process is depicted in table 1.1

For this thesis, only the dividend announcement date is considered since it is at this date information regarding the size and existence of the dividend payment becomes public knowledge and is assumed to become incorporated into the market. The dividend payment in itself is therefore not of further relevance and it is important to distinguish between the news of the dividend and the payment of the dividend.

1.6 Intra-day Data and its Quandaries

The following section will introduce high frequency data and the noise component which might be present in high frequency data.

1.6.1 High Frequency Data

All the methods and estimators described and used in this thesis are available thanks to the advent of high frequency equity price data. The increased availability and improved quality of high-frequency data, has given rise to new opportunities with regards to estimation of statistical measures which were previously beyond the reach of researches. With data on exchanges now recorded at the millisecond level it is in theory possible to approach the true underlying volatility of an asset's price process because information on prices now arrive almost continuously. This makes it possible to estimate volatility more precisely than what is possible with estimators using lower frequency data, such as end-of-day prices. When standard measures such as variance and covariance are estimated at a high-frequency level they are often referred to as *Realised Variance* (RV) and *Realised Covariance* (RCov). The titles refer to a specific way of estimating the high frequency measures and other titles exist which will become apparent in due time. As it is first in recent years that high frequency data has become available on a wide scale, the sampling possibilities are still limited. The authors have found that the data ranging back to around 2000 on the most traded U.S. firms is of a high enough quality for further use but before this point consistent data is rather scarce. By taking advantage of the new data sources, the estimation of systematic risk using high-frequency, intra-day data has become possible, opening up new roads for research into the dynamics of beta. When beta is calculated using high-frequency data, it is usually referred to as *Realised Beta* (RB) if the RV and RCov are the underlying components. Other titles exist depending on the underlying estimation method but for generalisation it will be referred to as Realised Beta, or merely beta if the context allows. At first glance, analytical options therefore seem endless as it is now possible to approach underlying concepts like beta at a level previously out of reach. High frequency data hence appears to provide researchers with the ultimate foundation for analysing equity market tendencies and for testing theories - and in many ways this might also be the case. Regrettably, high frequency data has also brought with it a new set of concerns which must be addressed when using it, which will be covered next.

1.6.2 Market Microstructure Noise & Discontinuities

The availability of high frequency stock price data is not without its issues as high-frequency data contains noise arising from bid-ask bounce, infrequent trading, non-synchronous trading, discreteness of prices, and more. These are all issues commonly referred to as *market microstructure noise* and have no predictive ability for the volatility of equities (Andersen et al., 2011). If market microstructure noise is not considered when manipulating and analysing high frequency data, the following results are likely to be biased and provide wrong results as the noise distorts the observability of the true price process. Figure 1.1 below illustrates how market microstructure noise affects the observability of the real underlying price both positively and negatively.

Figure 1.1: Illustration of Market Microstructure Noise

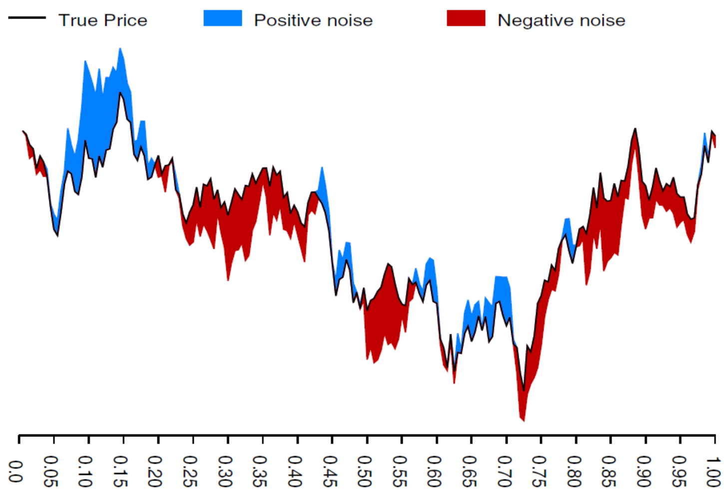


Illustration of the effect of market microstructure noise on the true asset price. Illustration from EURANDOM (2006)

Bid-ask bounce referrers to a pattern of trading where transactions happens close to either the bid or the ask price. This pattern creates price changes merely due to trading frictions and hence convey no useful information (Brownlees and Gallo, 2006). At increasingly higher frequencies the effect of bid-ask bounce will therefore become more prominent due to less time between observations. In general it is found that the mean return has a significant upwards bias when created using the bid-ask spread from high frequency transaction data and that lower priced stocks are more affected by the bounce since the bid-ask spread is relatively larger (percentage wise) causing more significant bounces (Campbell et al., 1997). To counter the effect of bid-ask bounces one can lower the sampling frequency or alternatively only considering price changes above a certain threshold, such as changes larger than the bid-ask spread, to ensure that only trades containing information are considered (Brownlees and Gallo, 2006). Handling the noise from the bid-ask bounce is therefore manageable if one use lower sampling frequencies.

Stocks are traded independently and irregularly at different points in time, or in other words, *non-synchronously*. This is important because when prices are recorded at different times this yields measurement implications in the situation where the time series of different stocks are to be compared directly to each other[3]. Biases can arise in the interpretation of for example covariances and autocorrelations as the information content of price changes is misrepresented

[3]For instance when calculating the covariance of two or more stocks.

(Campbell et al., 1997). The problem of non-synchronous trading is especially large for high frequency data since all stocks may not be traded at the same frequency. One could for example choose a frequency of one second but some stocks may only be traded every few seconds. This becomes apparent if considering two stocks of uneven liquidity such that stock X is traded more frequently than stock Y. If new information equally relevant to both stocks is released it is likely that the information will be incorporated into the price of X faster than Y since stock Y may not fully absorb the information right away due to a lower level of liquidity. The issue of non-synchronousness was presented by Epps (1979) who showed that at increasing sampling frequencies correlations between equities decrease. Hence, as the sampling frequency goes to infinity it results in a covariance biased towards zero. This has been dubbed the Epps Effect and has been attributed to non-synchronousness and infrequent trading. If measuring volatility using intra-day prices the non-synonymousness will not be apparent from the data and the relationship between the stocks will be misinterpreted (Campbell et al., 1997). To mitigate the effect one can use lower frequencies or recently developed (co)variance estimators robust to non-synchronousness. In general, non-synchronousness therefore limits the frequency at which one can gather equity data without loosing informational content.

Discreteness of prices pose a problem in high frequency sampling since, on a transaction base level, most trades will not alter the price of the equity as stock prices are limited to a certain number of decimals by the stock exchange. A significant number of trades will therefore not affect the trading price. The effect is larger when using very high frequency data as observation intervals are smaller and hence there is less chance that trades will affect the recorded stock prices (Russell and Engle, 2010). Lowering the sampling frequency will counter the effect by increasing the length of the individual observation intervals thereby allowing the stock prices to be affected by more trades and thus also fluctuate more. Again, this advocates using a lower sampling frequency but comes at the cost of fewer observations.

Besides noise being more prevalent at high frequencies, *discontinuities* (jumps) occur where the price of an asset, or the market, in a very short period of time (like a few ticks) either increase of decrease heavily. This disrupts the continuous price process of an asset (Mikosch et al., 2009). Unlike some of the market microstructure noise issues, jumps are not as easily mitigated by decreasing the sampling frequency and may therefore be present at frequencies which are generally regarded as being absent of market microstructure noise. Jump robust (co)variance estimators have however been developed which can aid in mitigating the problem.

The above issues are the main obstacles when working with high frequency data as they may significantly influence the estimators. Several steps will be taken to counter the effect of these issues which will be discussed in section 3.3 along with how market microstructure noise more precisely interfere with the price process.

Chapter 2

Methodology

The following section will establish and discuss the research approach, the statistical methods used, and introduce the main regression specification applied in this thesis.

2.1 Literature

The sources of literature for the paper at hand have solely been academic articles or text -and handbooks. The articles used have been published in accredited academic journals such as the *Journal of Finance*, *Journal of Econometrics*, *Journal of Financial Economics*, etc. These articles have in general been retrieved through data bases available through the CBS Library, especially EBSCOHost. In most cases these sources have been sufficient to retrieve the material desired but on occasion relevant material has been out of reach due to limitations of the available databases. It has been the aim to use original articles but as some original articles have not been available, second best options of textbooks or articles summarising the results of the original pieces have been used instead.

Within the main theoretical and empirical areas where academic literature is used, primarily being dividend theory, systematic risk, and high-frequency econometrics, it has been the goal to represent all matters from the full spectrum of opinions and findings. Some areas of literature are very extensive, especially concerning dividend theory at it has developed over half a century rendering a bibliography of studies beyond what can be handled within the limits of this paper. In some cases only representative findings and arguments are therefore considered to represent the literature within certain areas. Overall, the literature forming the foundation of this paper is of high quality as it has been peer reviewed and published.

2.2 Theoretical Approach

The Information Content of Dividends theory has been approached from different angles theoretically which has led to two main methods of estimating information. The original, which focuses on stock price change, and the later approach focusing on beta value change. The dividend/beta relationship was observed empirically before concrete/theoretical reasons for the relationship was developed. The theory has therefore been developed via inductive reasoning meaning that observations lay the ground for the derived theory. The issue with this approach is that it is not logically true, as opposed to deductive reasoning, since it is not certain that the next "observation" will not contradict the developed theory (Bell and Bryman, 2003). Hence, observing a change in a firm's beta value following a dividend change does not imply that this will also be the case for the next firm that changes its dividend if some unobserved conditions are involved, which were not accounted for in the observations laying ground for the theory. In using inductive reasoning there is therefore a chance that new observations will undermine the theory. It should however still be noted that inductive reasoning is reliable as it can be objectively proven through statistical/empirical tests (Bell and Bryman, 2003).

The null hypothesis (H_0) underlying the regressions run throughout this paper is that dividends do not contain information and the beta value of an asset should therefore not be significantly different from zero at dividend announcement dates. This viewpoint is consistent with the principle of the Irrelevance of Dividends Hypothesis which stands opposed to the Information Content of Dividends Hypothesis. The Irrelevance of Dividends Hypothesis will therefore also be discussed further at a later stage though the main discussion will surround the Information Content of Dividends Hypothesis.

The hypothesised relationship between dividends and systematic risk will be developed in-depth below but for now it is enough to note that the Information Content of Dividends, when focusing on beta values suggest an inverse relationship. Hence, an increase (decrease) in the dividend level should imply a decrease (increase) in the absolute beta value which entails that the null hypothesis and the alternative hypothesis tested in this paper are:

H_0: *An unexpected increase (decrease) in a firm's dividend level does not cause a decrease (increase) in the firm's systematic risk, beta, on the dividend announcement day*[1].

[1]To avoid any confusion, both increases and decreases are stated in absolute terms. Thus a firm with a negative beta which decreases will move towards zero.

H_1: An unexpected increase (decrease) in a firm's dividend level causes a decrease (increase) in the firm's systematic risk, beta, on the dividend announcement day.

This hypothesis is used to test the reactions of agents outside the firm, such as investors, and hereby determine if outsiders interpret an unexpected dividend changes as containing information, measured by beta. The approach has its strength in estimating the effect of a dividend change but also has its limits as it does not check if firms actually perform as hypothesised after the dividend change. A rejection of the null hypothesis is taken to entail support for the Information Content of Dividends Hypothesis given that the discovered relationship is that characterised by H_1.

Though only one null hypothesis is stated above, the inverse relationship makes it apparent that there are actually two hypotheses involved; the case of an increase in the dividend level and the case of a decrease. These must be tested individually in two separate regressions. The reason for stating these as one hypothesis above is that only in the case of a rejection of both underlying hypotheses can the results fully favour the Information Content of Dividend Hypothesis.

When drawing conclusions on the Information Content of Dividend Hypothesis in this paper it is important to note that it is the above relationship which is referred to unless otherwise noted[2]. This is an important point to make because any adjustment of systematic risk not in accordance with the stated hypothesis[3] could also be regarded as investors interpreting some information in the dividend. In such a case there would however not be a theorised relationship underlying the findings and this will therefore not be considered as directly supporting the Information Content of Dividends Hypothesis.

2.3 The Event Study Method

An event study approach will be applied to answer the stated research question which entails several methodological decisions. These aspects will be discussed in this section to provide background knowledge of the decisions and approach used throughout the thesis.

[2]An alternative interpretation using the stock price as the estimator of information will also be covered but the distinction will be clear in the context.

[3]This could for example be an observed positive relationship between dividends and beta instead of the hypothesised inverse one.

2.3.1 The Event Study Setup

For studying the Information Content of Dividends Hypothesis, the event study method is a natural choice since the focal point of the analysis is a single event day. It is a useful tool under the assumption that financial markets are rational such that news contained in an event is instantly integrated into the stock price after the event has occurred (Campbell et al., 1997). Campbell et al. (1997) outlines a set of steps for performing a quantitative event study based on financial data:

1. Event definition and event window definition
2. Selection criteria
3. Normal and abnormal returns
4. Estimation procedure
5. Testing procedure
6. Presentation of empirical results
7. Interpretation and conclusion

These steps will lay the framework for how this event study of dividends is handled and will be presented in natural order as the thesis progresses. The event has already been defined above and will be developed further in-depth later on. Regarding the second part of point 1, concerning the event window Campbell et al. (1997) recommends not including the event window periods in the estimation of the normal return to ensure that it does not influence the non-announcement estimations. Following this recommendation, the event window days are isolated from the remaining sample. The length of the event window is therefore a balancing act. On one hand enough event days are needed to make sure that the announcement day is different from the surrounding days in order to ensure that any significant change can be attributed to the studied event. On the other hand, increasing the amount of event days decreases the number of observations used to define the non-announcement beta (defined below). A length of 10 pre-event days and 10 post event days are included providing a total event window of 21 days. The subsequent steps will be covered in due time before the estimated results are interpreted in terms of their economic relevance and in relation to the theoretical ideas underpinning the entire procedure. Finally, an all-encompassing conclusion will round off the study.

2.3.2 Selection of Event Study Method

Different methodologies exist within the sphere of event studies and the choice can have a profound effect on the results of the event study and the conclusions which can be drawn. The traditional event study method has been presented in Fama et al. (1969) to examine if a systematic effect is significantly different from zero when observed in a cross-sectional analysis following a predefined event. The method identifies and selects specific strings of data based on the occurrence of a certain event within these strings which (potentially) cause a non-zero reaction in a hypothesised way when a regression is run using the selected data. This method therefore only uses data that exhibit a certain characteristic which makes for a clear selection criteria but it does not come without potential issues. The method has been criticised for treating expected and unexpected event equally even though it is in fact only the (to the market) unexpected event and non-events which are of relevance. Only the unexpected news should be included as the origin for causing a market reaction, as summarised in Prabhala (1997). In using *all* events instead of those based on the expectation of the event, it is argued that the method above causes unreliable inference between the event and the independent variables in the regression (Prabhala, 1997). Because expected events are included, one effect is that the results may become downward biased towards zero which pulls any non-zero estimation down. The inclusion of expected event will therefore dampen the immediate effect expected on an event day hereby lowering the observable effect across the sample.

A more sophisticated method, referred to as the *conditional event study*, relies on ex-ante expectations about the event such that one can distinguish between the informational content in an event and the mere happening of an event. This method is hereby correctly specified in a rational expectations setting, opposite of the traditional approach (Prabhala, 1997). The conditional method allows one to use non-event data for instance when a firm chooses not to perform an action which was otherwise anticipated. In the presence of data on expectations and non-events the conditional method is found to be superior to the traditional method, however, as pointed out in Prabhala (1997), such data is not necessarily available and in its absence the conditional method is not found to provide superior results.

For the analysis at hand the first best option for testing the Information Content of Dividends Hypothesis is the conditional method. Using this approach it is possible to draw optimal inference and differ between events and non-events by using the dividend expectations of financial analysts. Such data is as mentioned available through the I\B\E\S but unfortunately expectational data has not been available for this study. The principles of the conditional method have therefore not been applicable and a second-best option of using actual dividend changes is used instead. An unexpected dividend change will therefore be classified as one where the change in the dividend from period *t-1* to *t* is larger than 20% in absolute value. This is an arbitrary cut-off point but is selected as it excludes very small changes e.g. due to inflation adjustments while retaining enough dividend changes for the regressions. It is hereby assumed that the market has not expected the change in the dividend and hence the actual dividend change can be used as a proxy for the expectational data. Though this is not the optimal solution it is important to note that the results can still be relied upon as any inference from already expected dividend change will have a strictly downward bias effect on the regression estimation. Any significant results will therefore be economically significant *despite* the bias and not *because* of it.

2.4 Statistical Methods

The regressions in this paper are based on tested statistical and econometric methods but there are still several subjective factors which will influence the results and the analysis. For any result it will be necessary to determine if the results are significantly different from zero which is a subjective decision. For this study, a significance level of 95% will serve as the definitive level which is also the generally accepted level in financial and economic studies. It may at times be noted if a result is significant at the 99% level as well as the 90% level if it provides additional insight. The chosen level of significance allows for some potential discrepancies which can have an influence on the later analysis and conclusion, both for and against the hypothesis. A study similar to this one but with a different significance level will therefore potentially lead to alternative conclusions if results live up to one study's standards and not another's.

An additional and relevant arbitrary decision is the choice of intra-day data sampling frequencies. As will be discussed further in a following chapter, generally accepted high-frequency data sampling intervals for high frequency (co)variance differ greatly depending on the particular study. There is no generally accepted optimal frequency for all types of data and samples, and no econometric literature suggesting that one particular frequency is superior to another as this depends on both the data and the estimator used. Some estimation models are better suited for ultra-high frequencies while other work better at lower frequencies with less noise. To overcome this issue, different frequencies and models will be considered for robustness tests.

The choice of the scale and scope of the dataset is in itself a subjective decision in choosing the length of the time series and the number of firms to include. To standardise this process the Standard & Poor's 500 index (S&P 500) is chosen as it represents a large and diversified portfolio of traded stocks. As a proxy for the S&P 500 return (the market return) the exchange traded fund (ETF) SPDR, traded on ARCA under the ticker SPY, is used as it tracks the return on the index. The S&P 500 index is not perfect as it only consider the largest and most traded assets from the U.S.A. thereby inducing a geographical and firm specific bias.

As the results found in this paper are treated as objective and generalisable these biases are important to keep in mind since the results may differ if less traded stocks or stocks from other geographical regions (subject to different regulation) is used. The chosen sampling period when using high-frequency data is restricted since the availability of high-frequency intra-day stock data is rather sparse before the turn of the millennium. The sampling period from 2000 to 2012 is therefore the maximum available time series length with the necessary data quality required.

Another important subjective measure is what constitutes a *change in the dividend level*. No studies have so far analysed how much a dividend must change, either in percentage or in nominal value, before an effect is observable in the absence of expectations data - instead an arbitrary level has been selected. The primary level chosen for this study is 20% as previous studies have found significant effects at this level of change. However, to decrease the degree of subjectivity a robustness tests will be performed with a dividend change level of minimum 50%, which naturally comes at the cost of having fewer dividend observations.

For the regressions performed throughout this paper the *Ordinary Least Square* estimation method (OLS) is used which allows for an estimation of the unknown parameters in a linear regression model. The OLS is based on the *Classical Linear Regression Model* (CLRM) assumptions providing the *Best Linear Unbiased Estimator* (BLUE) of the parameters of the variance and the explanatory variables coefficients (Gujarati and Porter, 2009). To draw inference about the true parameters in the regression the assumptions of the CLRM must hold in order to approximate the true value (Gujarati and Porter, 2009). Some of these assumptions are more likely not to be complied with than others and will be discussed here.
A core assumption is that of no autocorrelation between any two variables. In case this assumption is violated the OLS estimator does not have minimum variance. This creates an understatement of the variance which renders the significance tests (such as t-test) unusable (Gujarati and Porter, 2009). To control for autocorrelation the Augmented Dickey-Fuller test (ADF) is applied through Matlab by running tests with 1-10 lags. The ADF tests reject the null hypothesis of unit root and and stationarity can be assumed. Moreover, the number of estimated parameters must be lower than the number of observations. This assumption is fulfilled with ease as there are only 34 variables in the base regression while there are 400,000+ observations used to obtain the regression results. Another important aspect is that the error terms must be homoscedastic. A violation of the assumption of homoscadisticity implies that the error terms are heteroskedastic (unequal variance). This invalidates the assumption that the error terms are normally distributed as the variance of the error term varies across observations (Verbeek, 2005). This issue can be controlled for ex-ante through Matlab as it

allows for the use of heteroskedasticity robust errors. Further regarding the error term, the mean should be zero which is especially relevant for the following analysis due to the specification of the regression model without an intercept[4]. The ex-post mean of the error term is calculated showing a value of zero and the assumption is therefore not violated. Given that the regression model to be defined soon uses a ray of dummy variables there is a chance that the regression might fall victim to perfect multicollinearity between the independent variables which will violate the OLS assumptions (Gujarati and Porter, 2009). Matlab controls for this potential problem in all regression specifications used and no multicollinearity is found. OLS is build on more assumptions than these assumptions which cannot be controlled for in the same straight forward fashion as above since they relate to e.g. the specification of the regression. This is for example the case of the assumption that the variables are independent of the error term (Gujarati and Porter, 2009). Given the context of the analysis at hand, the steps taken to mitigate the issues which may conflict with the OLS assumptions are handled to an extent where it can be assumed that the OLS assumptions hold and the results and inference can be considered to have economic relevance.

2.5 The Regression Model

In the following, the background for why panel data is used for the regression analysis in this thesis will be discussed along with the factors one must be aware of when using panel data. As the literature on panel data regression models is vast, only a limited portion of the general theory and specifications directly relevant for the later analysis will be discussed. The exact panel data regression model used in this paper and its specifications will furthermore be introduced.

2.5.1 Panel Data in General

The regression models applied in this paper are based on panel data, or longitudinal data, which combine cross-sectional and time-series data in one regression model. The standard cross-sectional regression models examine different variables (such as different countries, firms, individuals, etc.) at the same point in time while time-series regression models examine the same variable over multiple time periods (such as a stock price). The panel data regression is therefore multi-dimensional in using the two dimensions together in one regression (Wooldridge, 2009). In other words, panel data requires that the *same* cross sectional relationship (at least

[4]The exact regression specification will be covered shortly.

two variables) are observed over multiple points in time (Baltagi, 2008).

The combination of using both time-series and cross-sectional data heightens the ability to model complex situations thereby allowing for the extraction of information which the two other regressions types does not permit individually (Wooldridge, 2002). Panel data hence has a higher informational content than the two other types of regressions as it opens the possibility to analyse the reason for why individual units portray different behaviour than others at a given point in time but also why it behaves differently across different time periods (e.g. due to a different historical past) (Verbeek, 2005). The panel data analysis therefore let the researcher analyse information at more depth provided that data is available in two dimensions. Due to the multi-dimensional structure of panel data regressions, they generally have a high degrees of freedom, allowing for higher sample variability and more exact inference of the model parameters, thereby overall improving the efficiency of the regression estimates (Hsiao, 2006). In the simplest case the panel data regression is known as a pooled panel data regression where all observations are pooled together disregarding the cross-sectional and time series aspects of the data. This formulation assumes that the regression coefficients for the independent variables are the same. This can cause problems as it may hide heterogeneity among the variables which will subsequently be captured by the error term and the variables may therefore be correlated causing biased or inconsistent estimations (Gujarati and Porter, 2009).
To allow for heterogeneity among the variables a model of *fixed effects* can add an additional layer to the panel data regression that controls for individual aspects that are otherwise not captured by the pooled regression model. The fixed effects model uses dummy variables such that only the variable intended is affected by the fixed effects. Similarly to how the variation in the variables can be accounted for across parameters, it can be accounted for over time using time period fixed effects. This tests if there is individuality over time such as yearly differences or changes caused by e.g. economic conditions which need to be considered. The fixed effects regression is also known as a *least squares dummy variable estimator* (LSDV) (Gujarati and Porter, 2009).
A constraint often generated by the use of the fixed effects specification is that the amount of variables used, due to the added dummy variables, reduce the degrees of freedom in the estimation (Verbeek, 2005). This will however not be a substantial issue for the regressions in this thesis due to the fact that the dataset used is so large that the small reduction in degrees of freedom caused by the use of dummy variables is irrelevant.

Having introduced the concept of the panel data method, the specific base case regression model applied in this thesis will be presented next.

2.5.2 Regression Specification

In order to estimate the behaviour of betas around dividend announcements the approach set forth in Patton and Verardo (2012) is followed by regressing the realised beta estimates on event day dummies and firm-yearly fixed effect dummies as specified below:

$$\begin{aligned} R\beta_{it} = \delta_{-10} I_{i,t+10} + ... + \delta_0 I_{i,t} + ... + \delta_{10} I_{i,t-10} \\ + \bar{\beta}_{i1} D_{1t} + \bar{\beta}_{i2} D_{2t} + ... + \bar{\beta}_{i13} D_{13t} + \epsilon_{it} \end{aligned} \tag{2.1}$$

where $R\beta_{it}$ is the realised beta estimate for stock i on day t and $I_{i,t}$ are dummy variables for every day in the 21 day event window defined so that $I_{i,t} = 1$ if day t is a dividend announcement day for stock i and otherwise $I_{i,t} = 0$. So $I_{i,t+10} = 1$ on the first day in the event window because the announcement day is $t + 10$ days away. All other dummies are by definition zero on this day. At the last day of the event window then $I_{i,t-10} = 1$ because the event day is ten days back in time $(t - 10)$. The firm-year fixed effects are estimated by the parameters $\bar{\beta}_{i,y}$, where y is every year from 2000-2012 and hence the dummy variables D_{1t} to D_{13t} represent the 13 years in the sample. When in year 2000 $D_{1t} = 1$, while in year 2005 $D_{6t} = 1$ and so forth. This is to control for yearly fixed effects related to a specific stock/company which could distort the findings. In this way a realised beta change in 2002 can be regressed with a realised beta change in 2007 without yearly disturbances biasing (or favouring) any particular result. The way the regression is specified allows for the detection of changes in beta due to a dividend announcement by looking at the event day dummy parameter estimates $\delta_j, j = -10, -9, ..., 10$. These show the change in beta on the given day in the event window compared to an average non-announcement beta. The average beta outside of the event window is captured by the firm-year fixed effects and the δ_j estimates represent the deviation of beta from this average on the given event day. (Patton and Verardo, 2012)

The specification of the regression model allows for observations to be clustered on any given day and it is robust to within-cluster correlation (Patton and Verardo, 2012) but this is given that the number of clusters is large compared to the number of observations within-cluster (Wooldridge, 2002). Hence, it is assumed that firms do not systematically announce dividends on the same day and that it is not the same firm that systematically announces dividend changes. As can be seen in section 4.6 and table A.1 in the appendix this is not the case. The sample used contains a large number of days and ticker symbols (clusters) and a small number of announcements per day/ticker (observations within-cluster) and the assumption is taken to be valid. Further this estimation procedure allows for clusters of different size which is the case with the unbalanced sample used here (Patton and Verardo, 2012).

It is also worth mentioning that the regression does not contain an intercept term. This is done in order to allow the dummies in the regression to represent every year instead of excluding one year which then becomes the base year against which all the other dummies are compared. The intercept is thus excluded to avoid the dummy variable trap, or multicollinearity. This specification can potentially cause problems as the inclusion of a intercept term validates the Gauss-Markov assumption that the expected value of the error-term is zero. In order to test whether this assumption is broken the mean of the error-term estimates (the residuals) are calculated and it is found that the mean is very small (a factor of E^{-14}) and thus the aforementioned assumption is concluded to hold.

Having controlled for the typical econometric issues relating to regression analysis is a good step towards ensure that the results will be economically relevant. Several other issues however also exist regarding the regression analysis of this paper which must be accounted for to ensure that the results have interpretable meaning. Several robustness tests will therefore be performed especially focusing on the issues with using high frequency data and to control for problems such as serial correlation in beta values.

Chapter 3

Theory & Literature

This chapter will cover the main theoretical models and principles used in this paper. Both the core models and their empirical applicability will be addressed taking into account former literary contributions and how the approach of this thesis relates to the theories.

3.1 Systematic Risk - Beta

The following section will introduce systematic risk in its classic form and discuss some of the critical areas which may have influence on the application of beta in this thesis. Later, beta will be discussed in the set-up of high frequency data.

3.1.1 The Origin of Beta

Systematic risk, or beta, measures the risk of a stock that cannot be diversified away. It is the relationship between the return on an asset and the return on the market portfolio measured as the covariance between the stock price and the market over the variance of the market portfolio[1]. As systematic risk cannot be diversified away it differs from the non-systematic (idiosyncratic) risk parameter which can be diversified away by increasing the number of different stocks in a portfolio[2].

The risk principle underlying beta originates from the portfolio optimisation theory presented in Markowitz (1952) but is formalised in the *Capital Asset Pricing Model* (CAPM) developed individually by Sharpe (1964), Lintner (1965), and Mossin (1966). Markowitz's theory is based

[1] This relationship will be developed further shortly.

[2] Assuming that the stocks included vary w.r.t e.g geograpichal location or industry etc.

on a portfolio approach where risky assets are bundled together in portfolios to create a specific risk and return profile. This systematic decision pattern can also be illustrated by plotting portfolios in relation to their expected return and risk giving the *efficient frontier* depicted in figure 3.1. The efficient frontier shows all the risky portfolios which maximise the return for a given risk level (standard deviation). The portfolios can further be combined with investing in a risk-free asset, such that investors can obtain portfolios along a *Capital Allocation Line* (CAL) with a slope of

$$r_p = r_f + \sigma_p \left(\frac{r_m - r_f}{\sigma_m} \right) \tag{3.1}$$

where r_p is the return on the portfolio, r_f is the risk free rate of return, σ_p is the standard deviation of the portfolio, r_m is the return on the market, and σ_m is the standard deviation of the market return. The highest attainable CAL which becomes tangent to the efficient frontier at point m in figure 3.1 is known as the *Capital Market Line* (CML) and the tangency point is referred to as the *market portfolio*.

The CAPM builds on the approach of Markowitz but instead of looking at entire portfolios it focuses on individual assets[3]. The CAPM relies on a series of assumptions including no transaction costs, investors being price-takers, all risky assets are publicly traded, and the investor can borrow and lend at the risk free rate (Bradford et al., 2011). Further, under the assumption that all investors are mean-variance utility maximisers, investors will construct a portfolio to maximise the expected return given the variance and minimise the variance given the expected return. All investors have the same information and evaluate stocks accordingly. Taking the assumptions of Markowitz (1952) a step further it is also assumed that all investors will prefer a combination of the market portfolio and the risk free asset. The CAPM assumes a linear relationship between risk and return defined by the systematic risk level, thus for more risk an equally higher return is required on an asset and it is assumed that all investors perform the same analysis enabling the right risk classification of assets (Allen et al., 2011). The underlying principle of the relationship between beta and expected return in the CAPM can be shown by starting with the marginal return of a single asset k:

$$k = E(r_i) - A\sigma_{im} \tag{3.2}$$

where $E(r_i)$ is the expected return on stock i, A represents the average risk aversion of the investor and σ_{im} is the covariance of a stock i with the market m. It is assumed that the

[3]It can however also be seen in a portfolio perspective.

marginal utility is the same for all assets because if the marginal utility of one asset is superior to another, one would invest more in the asset with the higher marginal utility and less in the other, which generates the equilibrium condition. Considering equation 3.2 above for risky assets the coefficients A and k are not observable but considering the fixed risk-free rate

$$k = E(r_f) - A\sigma_{r_f m} \tag{3.3}$$

where $\sigma_{r_f m} = 0$ as the risk-free rate has a variance of zero hence a covariance with the market of zero the equation can be rewritten as

$$k = E(r_f) \Rightarrow k = r_f \tag{3.4}$$

since the risk-free rate is known and fixed, it is not an expectation but the actual rate of return. Similarly, looking at the marginal return on the market

$$k = E(r_m) - A\sigma_m^2 \tag{3.5}$$

the covariance of the market with itself equals its variance and rearranging the above in terms of A and substituting r_f for k from equation 3.4

$$A = \frac{E(r_m) - r_f}{\sigma_m^2} \tag{3.6}$$

thereby explaining the formerly unknown coefficient A. Now, substituting equation 3.6 into equation 3.2 and r_f for k:

$$r_f = \ E(r_i) - \frac{E(r_m) - r_f}{\sigma_m^2}\sigma_{im} \tag{3.7}$$

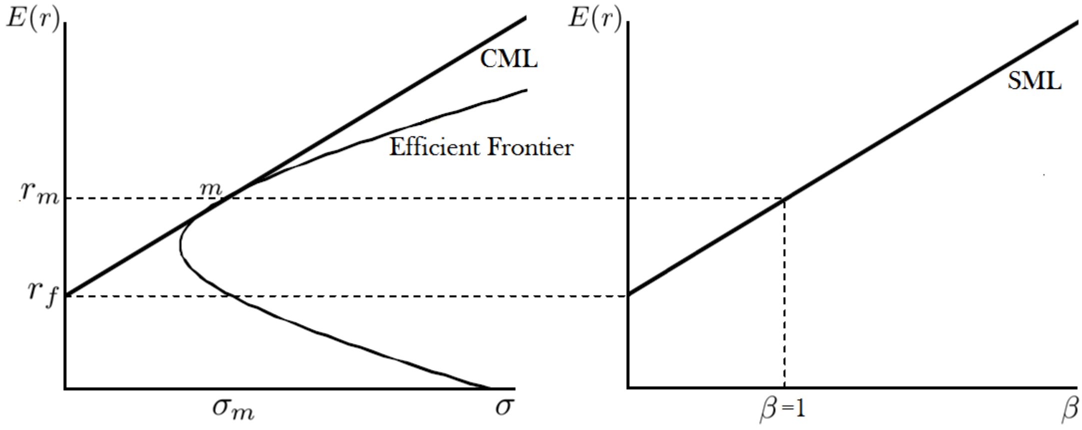
and rearranging for $E(r_i)$ such that

$$E(r_i) = r_f + \frac{\sigma_{im}}{\sigma_m^2}\left[E(r_m) - r_f\right] \tag{3.8}$$

Equation 3.8 implies that the expected return on an asset equals the risk-free rate plus the covariance between the market and asset i over the variance of the market timed with the risk premium (market return above the risk-free rate). Given the excess return on the market, the systematic risk component, beta, is the term dictating the return on the asset by its co-movement with the market portfolio. Beta is then defined as

$$\beta_i = \frac{\sigma_{im}}{\sigma_m^2} \tag{3.9}$$

Figure 3.1: The Efficient Frontier, Capital Market Line, and Security Market Line



(Own contribution)

and equation 3.8 can be restated as

$$E(r_i) = r_f + \beta \left[E(r_m) - r_f\right] \tag{3.10}$$

Equation 3.10 implies that the expected return on an asset equals the risk-free rate plus beta timed with the market risk premium. Given that assets are correctly priced assets will have a constant systematic risk level and the CAPM therefore states that the expected return on a stock is linear in beta and increasing at the rate of the risk premium (Blume, 1971). This linear relationship is referred to as the *Security Market Line* (SML) and is related to the efficient frontier and CML. This can be represented visually as the tangency point of the market portfolio also represent beta at the value of one, or the average market risk, in the SML in figure 3.1. The CML differs from the SML as it is defined for diversified portfolios only, while the SML is defined for any asset or portfolio. As also represented in figure 3.1 the CML uses standard deviation as a risk measure while the SML of course uses beta.

The beta of the market portfolio is 1 as it is the average of all the companies in the portfolio, and an asset with a beta of exactly one therefore moves exactly as the market. This makes intuitive sense as σ_{mm}, or the covariance of the market with itself, is just its variance. Effectively the beta calculation for the market against itself is its variance over its variance:

$$\frac{\sigma_{mm}}{\sigma_m^2} = 1 \tag{3.11}$$

A beta above one indicates that the return on the asset is more volatile than the market portfolio, thus if the return of the market portfolio increases, the return of the asset will increase even more. In the same manner an asset with a beta lower than one is relatively less volatile than the market. Beta can equally have a negative value implying that the assets return fluctuates in the opposite direction of the market portfolio. It goes from this that an asset with a beta of zero is not affected by market movements at all and is defined as being the risk-free asset.

The CAPM has received much critique over the years which questions its empirical applicability. The next section will address these issues and provide reasoning for why the CAPM and beta may still be useful for empirical analysis.

3.1.2 On the Validity and Interpretation of Beta

The CAPM, and the beta coefficient in itself, has received substantial criticism since its conception. For the purpose of this thesis the discussed critique will primarily be regarding the concept of beta since the intention of this thesis is not to test the CAPM in its entirety. This is not to say that the CAPM is completely disregarded but in the empirical estimations used here only beta is applied.

Roll (1977) criticises the CAPM and beta, by pointing out that construction of the true market portfolio is not empirically feasible as this would entail that *all* risky assets should be included. The validity of the model lies in the market portfolio being mean-variance efficient but if all investment opportunities are not observable it is not possible to test if the market portfolio is actually mean-variance efficient. It is therefore not possible to actually estimate the beta coefficient since it cannot be correctly specified in practise.

Furthermore, the process of estimating beta may generate a bias due to thin or non-synchronous trading of an asset if new information is not incorporated into the asset at the same time it is incorporated into the market portfolio. Mirza (2005) finds that this provides biased betas estimations. It can be countered by using stocks which are highly liquid so to avoid this bias only a certain type of assets should be considered. The problem with this is that it may impede the construction of a valid market portfolio if only stocks that are very heavily traded are taken into account. These arguments complicate the process of defining the market portfolio since one area of critique states that as many assets as possible should be used while another argues that one should only use very liquid stocks. As mentioned earlier, the S&P 500 is applied which balances these effects because it is a wide index representing many industries and sectors and at the same time consists of very liquid stocks.

The underlying assumption of beta being constant as well as the proposed linear relationship between beta and expected return (see the SML) have laid ear to extensive scrutiny over the years. In essence, the theoretical concept has in many respects not been reflected outside theory when tested empirically. Beta should in theory be applicable as a forecast tool of future return given that it has a fixed value for individual stocks. The assumption that beta is constant is necessary in order to obtain the linear risk/return relationship of the CAPM. A beta value calculated for one historical period should therefore equal one from another period all else equal. Studies have however questioned whether beta is fixed in finding that it is unlikely that systematic risk is actually constant over time (Mirza, 2005) and it has generally been found that betas tend to vary over time due to changes in e.g. economic conditions[4] (Bodie et al., 2011) or even without precise explanation. It is therefore generally found that two beta estimates of the same firm may be different going against the principle of the theoretical model. Another way of testing for the usefulness of beta is to determine if a time series of beta estimates are stationary over time. If beta values are stationary over time it would imply that they may still be useful for forecasting and hence in determining the expected return of a stock. If there is no consistency in the values over time, this undermines the foundation of using beta altogether both in the CAPM or as an isolated risk measure. Thus, if beta estimates fluctuate significantly from sampling period to sampling period without explanation it would suggest that the measure is not as informative as theorised. In response, empirical studies have suggested that calculating betas based on data spanning long time horizons can provide stationary results. Using weekly data Levy (1971) showed that individual firm betas based on a 52 week sampling period are more stable than shorter sampling periods of 26 and 13 weeks respectively, hereby suggesting that longer sampling periods provide beta estimates which are closer to the true beta value of the firm. Baesel (1974) likewise finds that longer periods increase the stability of beta values when comparing estimation periods between 12 and 108 months. The longer sampling periods were more stable and correlated than was the shorter periods. Altman et al. (1974) equally support this result in finding that the longer the time horizon of a sample, the higher the correlation between betas in different sampling periods. The results therefore suggest that to use beta values long sampling periods are necessary to provide beta results which can be applied as an estimator of a firm's systematic risk. Statistically this also makes sense as longer sampling periods contain more observations (everything else equal) giving lesser weight to potential outliers.

For the analysis at hand the above results raise some important questions regarding the validity of betas based on many observations but very short horizons as is the case for betas estimated

[4]This particular effect will be accounted for by the use of firm-year fixed effects in the panel data regression

using intra-day data. At the high intra-day frequencies there are a substantial amount of data points but if beta only converges to its true value when regressed over longer (calendar) time horizons regardless of the amount of observations within a day, calculations using high-frequency data may not provide results of economic consequence.

On the other hand one must also keep in mind that since empirical beta values are "just" estimations, they are bound to be measured with error (Hawthorne et al., 1979) and the lack of observed constant beta values can therefore possibly be due to estimation errors. The sparser the data sampling the large can such errors be expected to be. Using very sparse sampling it therefore seems clear why a longer horizon is needed to obtain enough data plots. By using high frequency data, it is possible to obtain a large amount of data points within one day. There are thus two conflicting issues at play in attempting to estimate beta as it is not clear if the long (calendar) time horizons used by former studies are necessary to obtain a relevant beta or if it is purely a matter of enough individual observations. When using high frequency data a natural question therefore becomes if the increased sampling frequency actually improves the analytical potential of beta. In this regard, Patton and Verardo (2012) show that regressing many daily beta values over time, provides estimations from which systematic effects can be observed. These findings suggest that even though the realised betas are estimated over short time series they still provide relevant results when regressed together over time. Also, as with lower frequency beta estimates, individual daily beta estimates (for the same firm) are not constant on a day-to-day basis (Andersen et al., 2006) providing concerns regarding the economic relevance of individual daily beta estimates. It begs the question if it is actually possible to deduct information from a change of individual beta values when it is clear that they are not constant to begin with. In other words, how can a theorised adjustment be expected empirically if the beta value varies in any case? With this is mind, it is relevant to question whether results of an event study focusing on specific event day beta values will provide useful information if beta varies excessively. To this end, Patton and Verardo (2012) have shown consistent empirical results for specific event day betas finding significant effects around earnings announcements [5]. Thus by regressing across many daily beta values on specific event days, they show that even though daily betas are not constant, they still contain systematic information which can be derived in regression analysis across many betas. The fact that beta values are not constant may be due to estimation errors and noise but regardless of the fact that there might be variation,

[5]The authors found that an unexpectedly positive or negative earnings announcement increased the beta-value thereby suggesting that individual firms' earnings surprises contained information about the entire state of the market portfolio.

the former study show that specific effects can still be measured. To ensure that event day betas are actually consistent and informative an event window surrounding the announcement day will be used.

With the above results in mind, there is reason to believe that intra-day betas do contain information about firms' true beta values from a long term regression perspective but also for individual event day beta estimates which become evident when regressed across a larger sample. It therefore indicate the increased sample correlations found in previous studies are due to the increased number of observations when applying longer sampling periods and not the use of longer historical time series.

Moreover for this study the market is expected to immediately adjust the beta value of a stock given that new information causes a change in the characteristics of the stock. This challenges the validity of the constant beta assumption if different events can cause sudden beta adjustments. However, it is not to say that beta is spurious but that the value is expected to change due to new information being incorporated into the stock in the wake of relevant news releases. Betas are expected to adjust and the strictly constant assumption of beta is therefore not fully fulfilled as beta may vary with relevant information. From the CAPM perspective this implies that beta should constantly be re-estimated and that one long-term calculation is perhaps not adequate if unpredicted periodic changes occur. This goes somewhat against the assumption of the standard model, but there is intuition to the argumentation as it is natural that the risk profile of a firm ought to be adjusted if the underlying financial characteristics of a firm change[6].

Using high frequency data to estimate beta is a relatively new field of study but as shown above the sparse evidence with daily betas indicate that betas found from high frequency data, is a relevant estimator of the underlying true beta. This also makes intuitive sense as high frequency estimations use more complete data and thereby provide statistically superior variance estimates compared to lower frequency data all else equal[7]. However, expecting that individual beta values are constant over time as posed by the underlying theory is not the case empirically. The constant, or predictive, element of beta is therefore first to be expected following additional aggregation across betas.

[6]Beta can also change because the market as a whole changes i.e because of legislation.

[7]Hence, over a fixed time interval having more relevant observations is preferable to less observations (Agresti and Franklin, 2008) everything else equal.

An additional concern with the CAPM is the assumption that all firms can be categorized similarly in the risk/return framework along the SML. This has on many occasions been shown to not be the case as many firms have either been over or undervalued when plotted on the SML. In this respect, several models have been presented claiming to provide more information on systematic risk than what the standard beta coefficient provide by considering additional factors. Fama and French (1993) propose a model of two additional systematic factors, known as *The Three-Factor Model*, taking into consideration firm size (small cap vs. large cap) and the book-to-market ratio (high vs. low) in addition to the classical beta. They find that these additional systematic factors significantly improve the standard model's calculation of expected returns. The three-factor model and similar models therefore suggest that there are more factors which are relevant to a firm than what is captured by the standard beta calculation. In essence it is however still very similar to the CAPM in theorising a positive relationship between beta and the expected return.

Although beta has received immense criticism it is still used substantially in academic research instead of alternative estimates such as the multi-factor models (Andersen et al., 2006). These models provide additional information but they themselves have received criticism as the economic interpretation of the involved factors is not clear (Andersen et al., 2006). Compared to such models beta therefore has its strength in its simplicity and the fact that, as shown above, it actually becomes more stable with the proper sampling size/period hereby providing further evidence that it has a meaningful interpretation. Firms are naturally different in many respects such as size, growth potential, industry, and other factors which one may consider but for the further analysis beta is viewed without these "extensions". This is important since all firms are then assumed to be similar with respect to beta as under the standard theory. On the one hand this assures the ease of economic interpretation but on the other hand may cause a loss of some interpretable parameters.

Overall, expecting that the beta/expected return relationship is completely linear is a strong empirical conjecture due to the assumptions of the CAPM. For example the assumption that investors make the same analysis concerning individual assets, that they are not taxed, and that there is no transaction costs are far fetched from reality. For this analysis, beta is however still applicable as long as a theoretical relationship between dividend changes and beta can be hypothesised through an informational link. Investors may have made different initial analyses regarding the beta of a stock but if it can be expected that beta will increase (decrease) when dividends decrease (increase) this will still be measurable across a large sample if investors interpret a dividend change similarly.

In total, the most important factors for this paper is not that investors are completely alike but that they understand a dividend in the same way and that daily betas are not completely spurious, which has been found not to be the case in previous studies. With this in mind, a further analysis can therefore creditably be performed using systematic risk.

3.2 On the Relevance of Dividends

The discussion of the interpretation and importance of dividends is not new. One of the most fundamental theories concerning dividends was developed in Gordon and Shapiro (1956) where the authors use dividends to determine the intrinsic value of a stock by discounting the future dividends and assuming a constant and perpetual dividend growth rate:

$$P_0 = \frac{D_1}{(k - g)} \tag{3.12}$$

where P_0 is the intrinsic stock price, D_1 is the expected dividend per share in the following period, k is the investor's required rate of return, and g is the perpetual growth rate of the dividend. The model discounts the future dividend payments such that the price of the stock is the present value of the future dividend payments. This model has been named the *Gordon Constant Growth Model* and everything else constant, a higher dividend therefore implies a higher stock price. The model has been the foundation for much of the later dividend theory which will be discussed next.

The research done on the subject of dividends in general has developed into a significant ray of different hypotheses, theoretical models, and empirical findings which has expanded through decades of research. To clarify the differences and similarities between the main suggestions an overview will follow. Also within the sphere of the information content of dividends itself issues arrive due to conflicting empirical findings and disagreements in the analytical approach which has left the research area divided and non-transparent. To this end, the literature review will reach broadly to fathom the current standpoint of the research area and to clarify the relevance of the approach of this thesis.

3.2.1 The Theory and Literature on Dividends

A noticeable amount of different hypotheses have been presented in the search for a full explanation as to why firms pay (or do not pay) dividends. Some of the most influential and researched hypotheses are the Bird-in-Hand, Information Content, Agency Cost, Tax Effect, Irrelevance of Dividends, and Clientele Effect Hypothesis. Many of these are partly derived in response to other hypotheses and they often contain elements of each other as well. The information content of dividends is for example derived from principles of the bird-in-hand hypothesis and in response to the irrelevance of dividends hypothesis. The research area is therefore rather opaque as it is not clear where one should necessarily start when studying the reason for the (non)payment of dividends. After over half a century of research within this field, any particular theory has yet to reveal definitive evidence in its favour (Baker et al., 2002). This conclusion becomes even more striking when realising that Fisher Black came to a similar point already in 1976 in stating that "*the harder we look at the dividend picture, the more it seems like a puzzle, with pieces that just don't fit together*" (Black, 1976, p.5).

A complete analysis and test of all hypotheses including empirical findings from the past decades is outside the scope of this paper and will not add substantial enough value to justify such a disposition. Thus, only theory, hypotheses, and previous findings which may contain directly relevant knowledge, information, and argumentation, will be further discussed. The focus is narrowed to the Information Content of Dividends Hypothesis and the theoretical development necessary in order to answer the stated research question. This includes a short discussion on the Irrelevance of Dividends Hypothesis which will be covered next before moving to the core of the Information Content of Dividends discussion.

3.2.1.1 The Irrelevance of Dividends Hypothesis

One of the most influential and debated contributions to the dividend discussion is presented in Miller and Modigliani (1961) where the authors showed that under perfect market conditions, dividend policy does not affect firm value. The straight forward argumentation in a perfect market setting with full information is that a firm cannot make an investor better off by distributing dividends as the investor can offset any distribution decision of the firm since the values of the firm "[...] *are determined solely by "real" considerations — in this case the earnings power of the firm's assets and its investment policy — and not by how the fruits of the earnings power are "packaged" for distribution.*" (Miller and Modigliani, 1961, p. 414). Thus, shareholder value does not come from dividend decisions but from the investment decisions at the firm, making the investor indifferent between receiving a capital gain and receiving a dividend. The value of the firm is therefore independent of the dividend payment.

The empirical evidence of the irrelevance of dividends hypothesis is mixed but holds key support from Black and Scholes (1974) who find no evidence against the hypothesis as their research show no significant difference in the expected return of low yielding and high yielding stocks. Black and Scholes (1974) preliminarily argue that there are different kinds of investors who will prefer different levels of dividends determined by e.g. taxes levels such that a tax-exempt investor will invest in a high yielding portfolio. Yet, when such portfolios are constructed with one consisting of high yielding stocks and the other low yielding stocks, no difference in returns can be observed indicating that investors cannot increase their overall return based on dividends (Black and Scholes, 1974). Similar results are found by Miller and Scholes (1982). Considering that dividends are taxed higher than capital gains they investigates if investors of high dividend stocks also receive a higher risk adjusted rate of return, such that they are compensated for the tax burden of dividend income and find that this is not the case. More recently, Bernstein (1996) dismisses the hypothesis that dividends can be used to forecast future stock prices, developing a hypothetical S&P 500 index where no dividends are paid from 1960s to 1990s and showing that in the long run returns are similar[8].

Critique of the Irrelevance of Dividends Hypothesis originates from different arguments confronting either the stringent underlying assumptions or by finding empirical results contradicting it. Contradicting findings generally arise as the perfect market assumptions of Miller and Modigliani (1961) are loosened such as in Casey and Dickens (2000) who in applying a model of optimal dividend payouts[9] show that the tax difference between capital gains and ordinary income influences the dividend level. Such diversions from the perfect market setting create more complexities and one should have in mind that the irrelevance hypothesis considers how markets *should* work if they were perfect (Al-Malkawi and Rafferty, 2010). All together it is a hypothesis which has been difficult to properly test due to the somewhat improbable assumptions about perfect information, tax, etc. Following hereof, research has continued by loosening certain assumptions to a large extent in order to understand the reason for dividend payments.

3.2.1.2 Information Content of Dividends Hypothesis

Research within the Information Content of Dividends Hypothesis branches into two main directions, one focusing on the direct price changes of a firm's stock following dividend announcements and one focusing on the changes in systematic risk following dividend announcements. The principle idea is the same as both methods predict that information concerning future prospects of the firm is conveyed from insiders to outsiders by dividend payments. For a full understanding of the current findings and theoretical developments, a discussion of both theoretical directions is relevant to add complete lucidity to the current interpretation and

[8] The main assumption being that the return on equity (ROE) is similar to that of dividend paying firms such that the spread between ROE and the cost of capital is not driven down by poor investment decisions.

[9] Originally developed by Rozeff (1982).

development of the research area.

One of the core assumptions of the irrelevance of dividends hypothesis is that insiders and outsiders hold identical information enabling the investors to correctly value the specific firm. The Information Content of Dividends Hypothesis on the other hand assumes that there exist *asymmetric information* between the two parties and that dividends signal expectations concerning the firm's future prospects providing outsiders new knowledge (Baker et al., 2002).

The foundation of the Information Content of Dividends Hypothesis leads back to Lintner (1956) who suggests a simple theoretical model driving the dividend decision by firms towards a target future level:

$$\Delta D_{it} = a_i + c_i(D^*_{it} - D_{i(t-1)}) + u_{it} \tag{3.13}$$

where ΔD_{it} is the change in dividend payments of firm i, $D_{i(t-1)}$ is the dividend paid in prior period, D^*_{it} is the target dividend, c_i is a partial adjustment coefficient constant where $c_i < 1$, a is a constant reflecting firm i's reluctance to reduce dividends compared to increasing it as a reduction will have a negative interpretation. Finally u_{it} reflects the error term from e.g. firms rounding off the optimal dividend rate to a certain number of decimals. (Lintner, 1956)

The main arguments of Lintner (1956) is that managers set long run dividend targets and only increase the dividend when increased earnings are expected to be sustainable to avoid having to decrease the dividend level later. Managers therefore do not increase dividends immediately to the target level but only partially adjust the dividend level towards the target dividend level as they want to avoid having to revert the dividend. A dividend change therefore signals the managements belief in future earnings growth and sustainability. The model is also referred to as a partial-adjustment model due to the partial adjustment of dividends over time towards the target level.

Following empirical testing Lintner (1956) concludes that the model explains the main determinants affecting the dividend payout level of firms, with an R^2 of 85% and that firms set their dividend such that they will not end in a position where the dividend will have to be reduced later on. Lintner (1956) does not provide theoretical reasoning for why dividends have a long term target as the model was not derived but constructed based on interviews with managers of industrial firms. Yet, the model has served as a foundation for later research on the subject of dividend distribution.

3.2.1.3 The Stock Price Approach to Dividends

Different theoretical models have been proposed which further sophisticate and formalise the ideas of Lintner (1956) using similar concepts but differ in their underlying assumptions. The most influential theoretical models are provided in Bhattacharya (1979); Miller and Rock (1985); John and Williams (1985) who also introduce the term *Dividend Signalling Theory* to clarify that dividends can signal the expectations of future prospects. The terms signalling and Information Content of Dividends Hypothesis will be used interchangeable throughout this thesis. The theories of the authors differ to some extent in their approach to the signalling hypothesis but the core elements such as asymmetric information between insiders and outsiders and conclusions that dividend payments contain economic information are similar. Bhattacharya (1979) shows that even when dividends are taxed heavier than capital gains, there is still incentive to pay dividends under information asymmetry, assuming that the planning horizon of the shareholders is shorter than the time span where firms create cash flows. Additionally, if a firm's cash flows are insufficient to finance the payout of dividends the firm will have to retrieve the cash from outside the firm. Bhattacharya (1979) argue that this manoeuvre is more costly as there is friction in outside financing. This removes the incentive to payout excessive dividends which ensures that managers do not increase dividends too much or refrain from decreasing them. Managers cannot communicate the future prospects of the firm without moral hazard if they do not commit by paying out cash to investors, and investors will therefore prefer a certain degree of dividend payment even if this has a tax cost attached. A firm with poor future investment opportunities will not be able to sustain a dividend level while a firm with more positive outlooks can pay a larger dividend. Dividends can therefore be used by managers to creditably signal the size of the expected future cash flows under the assumption of asymmetric information.

The main addition by John and Williams (1985) is that investors can observe the investment level of firms and other important factors, but they do not know the value of the future cash inflows from investments. To creditably signal the value of the future investments the insiders can use dividends and under the assumption that the insiders maximize investor wealth a firm with truly less valuable investments will, in signalling equilibrium, pay a lower dividend as the information of the dividend does not equal out the cost of taxes. The dividend level is therefore used by outsiders to distinguish between firms and the market will force the price of the share to the correct level (John and Williams, 1985).

In line with the models above, Miller and Rock (1985) develop a model where dividends provide information about a firm's current earnings above what the accounting numbers of an earnings announcement provide. Dividends are hence an indirect, or additional, source of information to the investors concerning the accurate level of the current earnings which then serves as the parameter for future prospects of the firm. Opposite of the model in John and Williams (1985) this model emphasises the possibility that insiders may attempt to temporarily boost the stock price by increasing the dividend payouts to a level larger than what was expected by the market. This increase will come at the cost of lower investments which will become apparent with time, at which point the stock price will fall again. Yet, for insiders with compensation packages related to short run stock level performance this may still be a profitable solution. To counter this effect firms that are actually efficient must set an adequately high dividend level to distinguish themselves from poor performers who cannot follow suit implying that the size of the dividend change must be sufficiently high before outsiders will react.(Miller and Rock, 1985)

All three models could be developed much further in-depth but as their purpose in this thesis is to provide a theoretical backbone to the below empirical findings, further detail is dispensable.

3.2.1.4 Empirical Findings of the Stock Price Approach

Empirically both evidence for and against the signalling hypothesis has been found using different methodologies. A main area in the empirical arguments concerning the hypothesis arise from looking at stock price movements subsequent to dividend announcements which have yielded varying results. In an early contribution to the mounting research, Pettit (1972) showed that dividends contain important information and that after a dividend increase (decrease) the firm's stock price increases (decreases) and further argued that dividends contain information above what is conveyed by earnings announcements. Aharony and Swary (1980) provide support for the hypothesis by showing that stock prices react in accordance with the hypothesis to dividend announcements, after removing potentially disturbing earnings announcements, and conclude that changes in dividends thus convey information. By checking for effects of earnings announcements they also establish that dividend announcements and earnings announcements are not perfect substitutes in conveying information to outsiders enhancing the importance of the tangible cash dividend. Empirical results by Woodridge (1983) shows that unexpected dividend increases (decreases) are followed by significant increases (decreases) in the return on a firm's stock price.

Taking a slightly different approach Asquith and Mullins Jr. (1983) test how the outsiders (or the market) react to dividend initiation or resumption after a period of at least ten years without dividend payments. In an interval of 21 days they find excess returns on firms' stocks following the dividend initiation and that the return is high enough to offset taxes on dividends. They further find that larger dividends cause a higher excess return on the announcement date hereby showing that the size of the dividend payment matters as a higher dividend is received more positively than a smaller dividend initiation. Following the principle in Asquith and Mullins Jr. (1983), Michaely et al. (1995) looks not only at dividend initiation but also at omissions in relation to stock prices. In a sample of 561 initiations and 887 omissions they find a significant result for both events on the excess return on stocks. They find that initiations had a positive effect on stock prices and omissions had a negative effect but the effect of omissions is stronger than for initiations [10]. Looking at a longer perspective the authors show that firms that choose to initiate dividends still have a positive excess return three years later while firms with dividend omissions have a negative abnormal return after three years [11].

The research above advocates that dividends do affect the stock market around the announcement date but it does however not provide much evidence of whether the alleged information provided by insiders materialise into measurable results later on. To test for this, a widely used approach has been to determine to what extent dividend changes are actually followed by changes in the financial results of firms over time and by looking at whether profitability significantly increases or decreases after a change in the dividend. Healy and Palepu (1988) find that earning announcements following dividend initiations (omissions) experience positive (negative) changes, and that "[...] *the magnitude of the stock price reactions to earnings announcements following the dividend initiation or omission is significantly less than normal, indicating that these earnings changes are anticipated by the market at the date of the dividend announcement.*" (Healy and Palepu, 1988, p.151). Using data from 1967 to 1990 Aharony and Dotan (1994) substantiate the hypothesis in showing that firms that increase (decrease) their dividends have larger (smaller) unexpected earnings in following periods. The authors' approach was to examine whether firms experienced unexpectedly large or small earnings following a change in their dividend level where unexpected change in earnings is simply defined as the difference between the actual and expected earnings.

Denis et al. (1994) find support for the Information Content of Dividends Hypothesis by showing that after a dividend increase, firms actually increase their capital expenditure while lowering it after having decreased dividends. The results indicate that managements change the dividends to signal the true future prospects of the firm as anticipated by the theoretical models and in-

[10] The effect of omissions is found to be larger than for initiations with a effect of -7% for the former and a +3.7% for the latter

[11] Initiations lead to a +24.8% excess return while omissions lead to a -15.3% return

vestors can hence use dividends as a signal of future prospects. Denis et al. (1994) further show that analysts equally re-evaluate their expectations after a change in the dividend level meaning that the outsiders also trust that dividends contain information. Nissim and Ziv (2001) finds that changes in dividends are positively associated with changes in future earnings in the two years following the change. No significant effects were found on decreased dividends which the authors associated with accounting conservatism. This therefore provides partial support for the theory on signalling by showing that dividends are an indication of future prospects of the firm when the prospects are positive.

The pattern mentioned above, where price changes of stocks follow the direction of a change in dividends has been shown to have empirical support numerous times, but an equally mounting amount of literature contradicts the notion that dividends provide information to outsiders. Riding (1984) does not find support for the Information Content of Dividends Hypothesis as he finds no significant evidence of stock price reactions to an unexpected dividend announcement in his sample of firms from 1974 to 1979. In a similar study, but focusing on the effect of accounting numbers, Gonedes (1978) looks at whether investor behaviour is consistent with the hypothesis that dividends effectively signal information to contribute to the accounting information otherwise received by investors. His findings suggest that dividends do not convey significant managerial information concerning predictability of income.

By examining whether the actual future earnings results of firms are adequate to justify the increased dividend Watts (1973) tests whether unexpected dividend changes contain more information than what is contained in earnings announcements by regressing year t+1 earnings on the dividends in year *t*. In his test, Watts does find that dividends contain information about the future earnings changes. Yet, even though the results are consistent with the Information Content of Dividends Hypothesis, the size of the change is too small to justify dividend payout as the associated transaction costs will outweigh the earnings information gained. He equally tests the effect on stock prices of unexpected dividend payments to see whether an investor can make an abnormal profit following an unexpected dividend payment if the investor was the first to receive the information. In line with the above results he does not find clear evidence that stock prices change following a dividend announcement. Dividend announcements therefore cannot be used to gain abnormal returns since the effects does not outweigh transaction costs. DeAngelo et al. (1996) similarly do not find significant results supporting the Information Content of Dividends Hypothesis in attempting to detect if dividend changes can be used to identify firms with superior earnings prospects. According to the findings, firms that increase their dividend are therefore not more likely to have superior future earnings results than firms that do not. The authors moreover test if dividend changes can be used by firms with good future prospects but average current results to differentiate themselves. Again, the empirical results do not provide adequate support to conclude that firms can use dividends to separate themselves from other firms. They go on to examine reasons why dividends may not be a good signals of information and find that any signals conveyed will not be reliable due to an over-optimism bias on behalf of the management about future results and the limited cash commitment necessary to increase dividends. They therefore suggest that the notion that managers need to have reliable information about future earnings and have to be highly committed to a dividend change is not observed empirically.

These results are in line with those of Benartzi et al. (1997) who argue that dividends do not signal the future earnings of firms but merely the past as firms that increase their dividend level in period *t* have had significant increases in earnings in period *t* and *t-1* but have no unexpected growth in earnings afterwards. At the same time, firms cutting their dividends in period *t* had reduced earnings in *t* and *t-1* but in fact experience earnings increases in t+1. They do however find some support for the model presented by Lintner (1956) as firms that increase their current dividend level show a decreased chance of experiencing reductions in future earnings.

The empirical evidence of the theoretical model is rather contradicting and no evidence exists to properly substantiate a point for or against the hypothesis. Based on the literature, findings supporting or refuting the idea that stock prices react in the same direction as a dividend change reduce the overall transparency of the studies. Whether the unexpected dividend change materialises into improved future performance is equally unclear. For every study finding solid support for the Information Content of Dividends Hypothesis another disputes it with an equally vindicated argumentation and methodological approach and so far it is not clear if dividends signal future prospects or merely previous financial results. To a large extend this reveals the current issues concerning the signalling theory, and the general issue of other dividend theories; this being that the empirical methodology available for constructing models, finding relevant data, and choosing relevant variables is so broadly defined that it can be unclear exactly which approach yield superior results.

Carter and Shawn-Schmidt (2008) add that the large number of ambiguous results found when examining stock price movements around dividend announcements directly are because the factors affecting stock price movement are too complex and too individual for firms to provide consistent information through dividends. As such, looking at stock price changes in isolation will contain noise making the results less reliable, explaining why results from the past decades are often inconsistent from one another. This same point is made in Dyl and Hoffmeister (1986) in arguing that the stock price is affected by many factors. Carter and Shawn-Schmidt (2008) point out that one must isolate different factors of the stock price instead of attempting to find results from the absolute price changes. Hence, trying to draw inference between the information content of dividends and the stock price is potentially not the optimal approach.

3.2.1.5 The Systematic Risk Approach to Dividends

The predominant part of the research within the Information Content of Dividends Hypothesis has focused on the direct effect on stock prices as presented above. A growing body of literature has however examined how a dividend change is interpreted by outsiders using the risk level of firms as the measuring unit instead of the value of the stock. This approach hence explains the information content provided in dividends through the systematic risk of a stock instead of the absolute price change. The systematic risk parameter is used due to its relation to expected return, which is difficult to observe empirically. Systematic risk however, is much more easily observable and under the generally accepted condition that there is a positive relationship between systematic risk and expected return[12], beta can be used as a proxy for expected return - a point which will now be developed.

In their article "*The Relationship Between Dividend Payouts and Systematic Risk: a Mathematical Approach*" Carter and Shawn-Schmidt (2008) show that since beta is linear in the return on a stock an increase (decrease) in the dividend will cause a decrease (increase) in the firm's beta. Carter and Shawn-Schmidt (2008)'s point of departure is the Gordon Constant Growth Model. Gordon (1959) shows that the value of a firm's stock price can be represented by the present value of the sum of the discounted future dividends:

$$P_0 = \sum_{t=1}^{n} \frac{D_t}{(1+k)^t} \tag{3.14}$$

Assuming that the dividend payments are perpetual and introducing a constant growth rate for the dividend, g, where $k>g$ the equation can be restated as

$$P_0 = \frac{D_1}{(k-g)} \tag{3.15}$$

[12]This is a common feature of the CAPM, the Fama French 3 Factor Model, and ATP models.

In order to show the relationship between a firms dividend and systematic risk Carter and Shawn-Schmidt (2008) takes the full differentiation[13] of the Gordon Growth Model in equation 3.15

$$dP = \left(\frac{1}{(k-g)}\right)\delta D + \left(\frac{-D}{(k-g)^2}\right)\delta k + \left(-\frac{-D}{(k-g)^2}\right)\delta g \tag{3.16}$$

Which can be written as

$$dP = \left(\frac{D}{k-g} \times \left[\frac{\delta D}{D} + \left(\frac{1}{k-g}\right) \times [\delta g - \delta k)\right]\right) \tag{3.17}$$

Given that the growth rate $g = \frac{\delta D}{D}$, dP can be written as

$$dP = P\left(g + \frac{D}{k-g} \times \frac{1}{D}(\delta g - \delta k)\right) \tag{3.18}$$

Now solving[14] equation 3.18 for $\frac{dP}{P}$

$$\frac{dP}{P} = g + \frac{\delta g - \delta k}{Y} \tag{3.19}$$

Where $\frac{dP}{P}$ is the capital gain and $Y = \frac{D}{P}$ is the dividend yield.

The expected return for the stock is a combination of the dividend yield and the capital gain (Carter and Shawn-Schmidt, 2008) and can hence be written as :

$$E(r) = Y + \frac{dP}{P} \tag{3.20}$$

Now entering equation 3.19 into equation 3.20 gives

$$E(r) = Y + g + \frac{\delta g - \delta k}{Y} \tag{3.21}$$

and rewriting equation 3.15 such that

$$k - g = \frac{D_1}{P_0} \tag{3.22}$$

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[13] Here the standard differentiation rules are applied. For the first term the constant factor rule $(k \cdot f(x))' = k \cdot f'(x)$ and for the latter two the quotient rule: $\left(\frac{f(x)}{g(x)}\right)' = \frac{f'(x)\cdot g(x) - f(x)\cdot g'(x)}{g(x)^2}$

[14] Since it is known from eq. 3.15 that $P_0 = \frac{D_1}{(k-g)}$ eq. 3.18 can be shortened to $dP = P\left(g + \frac{P}{D}(\delta g - \delta k)\right)$ Denoting the dividend yield Y as $\frac{D}{P}$, where the inverse is $\frac{1}{Y} = \frac{1}{D/P}$, eq. 3.18 can be further restated as $dP = P\left(g + \frac{(\delta g - \delta k)}{Y}\right)$ Dividing with P on both sides hence provides eq. 3.19.

allow the substitution of equation 3.22 into 3.21 since $Y = \frac{D}{P} = k - g$ yielding

$$E(r) = k + \frac{\delta g - \delta k}{Y} \tag{3.23}$$

Carter and Shawn-Schmidt (2008) conclude that "*Since the expected return on any asset is a linear function of its systematic risk, a low dividend yield will result in a higher risk, all other things being equal.*" (Carter and Shawn-Schmidt, 2008, p.98). Hence everything else equal, the higher the dividend level, the higher the dividend yield and the lower the expected rate of return. As the expected return is positively correlated with beta, the lower the return, the lower the beta. The authors argue that the mechanism for this relationship relies on stock duration[15]. Higher dividend paying stocks will, everything else equal, have a shorter duration and investors will therefore more quickly recover the cost of the stock (Carter and Shawn-Schmidt, 2008). Hereby they further imply that the investors are less affected by interest rate risk or the discount factor. This diminishes the systematic risk as investors' income is more dependent on short term gain than long term capital gain of the stock (Carter and Shawn-Schmidt, 2008). A further consequence of the relationship above is that the change in the expected return will change the cost of capital[16] for the dividend changing firm and managers can therefore decrease the cost of capital by increasing the dividend (Carter and Shawn-Schmidt, 2008). There is naturally a cost in increasing the dividend but Carter and Shawn-Schmidt (2008) do not develop a potential equilibrium condition between the two to show the maximum size a dividend payment can be before it outweighs the gain of a lower cost of capital.

Under the assumption of asymmetric information, Grullon et al. (2002) provide qualitative argumentation for this relationship by inferring that the future cash flows of a firm's existing tangible investments are more certain than the future cash flows of future investment opportunities. In other words, firms with a high level of growth opportunities generally have many positive NPV projects to undertake. Firms with more volatile future cash flows therefore have a higher expected return due to the high volatility and hence a higher beta while firms with more predictable future cash flows will have lower beta due to the lower volatility of cash flows (less potential upside and downside), all else equal. Such firms will therefore minimise dividends due to large capital expenditures and because the future cash flows of the non-realised investments are attached with a higher level of uncertainty than that of established projects.

[15]The duration of an asset is a calculation of the weighted average of the time necessary to recover the current cost of an asset (MacAuley, 1938)

[16]Cost of capital is here defined as: Cost of capital $= r_{Debt} \frac{Debt}{Firmvalue} + r_{Equity} \frac{Equity}{Firmvalue}$, where a change in the expected return hence alters cost of capital (Berk and DeMarzo, 2010).

As firms' investment opportunities materialise and capital expenditures decrease, there will be more certain future cash flows which are less affected by changes in the general market conditions. Management can signal that the firm has changed its characteristics, or risk profile, by changing the dividend level accordingly (Grullon et al., 2002). It follows that management increase (decrease) dividends when realising that the firm is less (more) affected by the market, or systematic risk factors. Rational investors will then react to this by re-evaluating their positions in the stock to reflect the new systematic risk level which help drive the change in beta. Thus, when the firm begins to rely more on the future cash flows of existing investments relative to that of future investments, the overall future cash flows of the company becomes more predictable and a relatively larger part of the firms total future cash flows become less affected by systematic risk. Dividends can therefore be used by management to convey information about the firm's development from one with high expenditures where the value is dependent on future investments to one with less expenditure where existing assets are more importation for the value (Grullon et al., 2002).

3.2.1.6 Empirical Findings of the Systematic Risk Approach

Empirically research of the dividend and beta relationship has primarily been done by testing for subsequent effects on systematic risk after a dividend announcement and is derived from the notion that firms with more certain or predictable future cash flows are better able to pay and sustain larger dividends to their shareholders. Stocks paying large dividends therefore have a lower absolute beta indicating that future cash flows are less affected by uncertainty from non-diversificable risk.

Dielman and Oppenheimer (1984) find partial empirical support for the relationship by determining pre -and post announcement betas with daily data. The authors find significant evidence of increases in beta for dividend decreases and omissions and decreases in beta following dividend resumptions. They also find that beta decrease when dividends are increased but this result is statistically insignificant. The findings are therefore mostly supportive of the Information Content of Dividends Hypothesis with three out of four tests confirming the relationship and the authors conclude that "[...]*the "announcement" effect, as we have defined it, is large*" (Dielman and Oppenheimer, 1984, p. 204). The authors moreover find that due to dividend announcements occurring after market closing it is relevant to include day t+1 which strengthen their findings further. Grullon et al. (2002) equally find significant results of the inverse relationship using monthly estimates by showing that firms increasing their dividends have decreasing systematic risk while a decrease in dividends increases the systematic risk. Carter and Shawn-Schmidt (2008) randomly select 100 firms of the S&P 500 and regress the firms' betas on the dividend yield in the period from 2002 to 2006 to test their model presented above and find a significant inverse relationship between beta and dividend yield and conclude that this is favour of the theorised relationship.

Charest (1978) provides slightly more contradicting findings when estimating monthly betas. Measuring nominal dividend changes, he finds no evidence of beta changing when dividends are increased but do find evidence of beta increasing gradually by 0.45[17] on average in the two years following the dividend change when dividends are decreased. The issue with these results is that since the betas are monthly, changes taking place right around the announcement date are not observable, which is generally an issue in former studies of beta. Dyl and Hoffmeister (1986) focus on the payout ratio of firms and finds that a high payout ratio is associated with lower betas compared to firms with lower payout ratios. Dyl and Hoffmeister (1986) conclude that these results are consistent with the hypothesis that managers can use dividends to affect the risk level of their stock. They additionally argue that the relationship between beta and dividends may be one of the underlying factors affecting stock price movements thereby contributing to the issues related to analysing the effect of dividends on stock price as mentioned earlier.

In contrast to the results above, which are mainly in favour of using beta as an estimation tool of dividend information, Eades et al. (1985) find no significant changes in beta in the dividend announcement period. Also, in a more ambiguous study, contradicting the findings of former studies[18] Carroll and Sears (1994) actually do find results in accordance with the hypothesised inverse relationship but argue that these results are caused by order biases in the magnitude of the pre-announcement beta values which are not taken into consideration. More precisely they show that particularly high (low) betas tend to fall (rise) around the announcement day irrespectively of the particular announcement type. Specifically, Carroll and Sears (1994) divide their sample into three groups according to whether they increase their dividend, decrease it, or perform no changes. They hereafter divide these groups according to the size of the pre-announcement beta level. They show that even firms which did not change their dividend experience a beta increase (decrease) if the pre-announcement beta was low (high)[19]. Results confirming the Information Content of Dividends Hypothesis may therefore merely be due to drift toward the mean in the high and low betas skewing the results. The results should therefore not be accredited to an unexpected dividend change according to the authors. Carroll

[17]The beta change is from 1.025 to 1.07.

[18]Specifically Charest (1978) and Dielman and Oppenheimer (1984).

[19]The point is also mentioned in Dyl and Hoffmeister (1986) as the authors note that betas tend to drift towards the mean.

and Sears (1994) does not deny the potential presence of the inverse dividend/beta relationship but argue that one must consider the potential bias caused by the magnitude of the betas.

The findings above reveal that there is to a large extent empirical support for the information content of dividends estimated by beta but also that there are findings against the hypothesis. The most fundamental concern is that supportive results may be caused by order bias issues. Moreover, even though the results are primarily supporting the hypothesis and the conclusions of the theoretical models the results are based on quite low data frequencies. It is not clear if outsiders react immediately to the dividend announcement or if beta slowly adjusts or even if potentially other systematic effects surrounding the dividend announcement interfere[20]. All findings both for and against the hypothesis lack the direct observability of how beta behaves on the dividend announcement day.

3.2.2 Discussion of Literature

The theoretical reasoning behind the dividend-beta and the dividend-stock price approach differs to some extent in their way of formalising the information content of dividend hypothesis. Yet the main assumption about asymmetric information between insiders and outsiders is similar. Hence both these approach provide theoretical reasoning for why insiders pay out dividends under asymmetric information.

The current findings and evidence are wide in range of estimation specifications and results, with the approach of measuring stock price changes subsequent to dividend changes showing mixed results. On the basis of this multiple authors[21] have suggested that the stock price in itself is too complex to effectively be used as an indicator of the Information Content of Dividends Hypothesis but that isolating specific components such as systematic risk may provide more information. An intuitive explanation of this, as shown by Carter and Shawn-Schmidt (2008), is that the expected future return is difficult to estimate whereas systematic risk is much more observable. The fundamental difference between the two approaches is that the dividend-stock price method predicts an instant gain/loss of a dividend change while the dividend-beta approach predicts an instant risk adjustment with implications for the expected return. Even though it has been argued that the dividend-beta method should be more precise than the alternative, empirical results are not unanimously supportive with multiple contradicting findings. An explanation for this could be the lack of precision due to data limitations. The

[20]For instance earnings announcements.

[21]Such as Carter and Shawn-Schmidt (2008) & Dyl and Hoffmeister (1986)

estimations performed in the systematic risk literature is based on very long calendar time-series, which is needed when estimating beta values from end-of-day or monthly prices. Unlike the research focusing on stock price changes, the beta-literature does therefore not hold any literature suggesting that the market derives information from a dividend change immediately as news becomes public. Key evidence suggesting that the dividend announcement causes a prompt re-evaluation of a firm's beta is therefore not completely clear. The empirical findings are therefore not as strongly founded as those focusing on stock price changes as these are observed at a much higher (daily) frequency.

Definitive conclusions based on the current literature are therefore not obvious as they are estimated based on very low frequency sampling periods where the change in beta is observed on a weekly or monthly basis.
It is clear that more research is required to further understand the reaction of outsiders as also concluded by recent literature[22]. The research in this paper will shed further light on the Information Content of Dividends Hypothesis by narrowing the sampling frequency through the application of intra-day data, hereby allowing the behaviour of beta to be modelled on a day-to-day basis. It will thus bring new information to the discussion by using a novel method in the estimation of beta dynamics by focusing on the specific dividend announcement day.

As mentioned earlier, beta is theoretically expected to be constant over time while the above models and findings are actually advocating a change. It may therefore appear as if this field of study is removing the principle of beta completely from its original setting, which would also imply that the theoretical interpretation cannot be transferred directly as well. The important point about the beta change is that it is not just a random change but an adjustment due to a fundamental change in the outsiders' risk perception (or knowledge) of the asset. As such it does not completely counter the assumption of the constant beta but merely assumes that beta change due to the firm changing characteristics. Even if beta is expected to change in this context it does not imply that the assumption of it being constant is disregarded. Instead beta must be viewed as still being constant given the current available information of the outsiders which (supposedly) change following unexpected dividend change.

Though the empirical literature respectively focusing on stock price and beta is not completely comparable, the research area of post-announcement financial changes can be generalised across the two. Hence, even though the literature on beta is not as developed the post-performance

[22] Al-Malkawi and Rafferty (2010) and Baker et al. (2002)

literature can add insight regarding whether the theorised dividend-beta relationship materialise in actual performance changes. As reported, the post-announcement studies find varying results which therefore does not bring enhanced clarity overall. However, two points suggested concerning the mixed results may help explain why there is in general found more support for the dividend-beta relationship following a dividend decrease than following an increase, these being; (i) that insiders have an over-optimism bias and that (ii) dividend cash commitment is limited providing incentive to increase dividends[23]. If this is the case, there may be a good reason for why actual financial changes are not found in the wake of a dividend adjustment and rational investors should naturally be more sceptical when dividends are increased if such announcements can be bias or caused by sub-optimisation. Hence, if investors expect that dividend increases can be biased they will not react (as strongly) which may be why there is not found as strong evidence of this in the dividend-beta literature.
This is only reflections since the current model for the dividend-beta relationship does not take sub-optimisation or moral hazard into account which limits it to a setting where insiders are assumed to have the best interest of the investors in mind. The theory is therefore not as developed as the older model of the dividend-stock price approach which has been developed to include sub-optimisation behaviour[24]. Hence, why investors do not seem to be adjusting the beta value after a dividend increase can only be discussed on a qualitative level.

From the sections above it is clear that the Information Content of Dividends Hypothesis has been studied intensely but has not come up with consistent evidence either for or against the concept of dividends conveying information. This may be due to the research focusing on the wrong estimation parameters or perhaps that there is in essence no all-encompassing information in dividends which can be systematically measured by stock market reactions. When further considering that the Information Content of Dividends Hypothesis is just one of numerous dividend hypothesis developed by academia the overall picture becomes even more unclear. Still, referring to the research covered above, one place where there is a potential for improvement to the current literature is within the dividend-beta research sphere. No studies have researched the behaviour of systematic risk on the dividend announcement day - probably due to inadequate data - which imply that this is an area where the research can be extended without merely redoing studies already done previously.

[23] A mentioned by DeAngelo et al. (1996) in the above section.
[24] As done in (Miller and Rock, 1985).

3.3 High Frequency Estimation

Not all estimators are created equal and in recent years the number of high frequency (co)variance estimators has grown substantially from the introduction of the concept of realised variance by Andersen et al. (2001b, 2003); Barndorff-Nielsen and Shephard (2002a) to the concept of realised kernels (Barndorff-Nielsen et al., 2008, 2009, 2011) and other multivariate estimators (Zhang, 2011). They vary w.r.t. their assumptions about data and noise. Some assume no noise is present, others that noise is independent (iid) and a few are robust to dependent and endogenous noise. In this chapter the different high frequency measures (realised measures) used for estimating systematic risk and their underlying assumptions will be covered. Firstly, the theoretically most stringent and well known high-frequency estimator, the realised (co)variance estimator, and its foundation will be presented. Afterwards, alternative models will be introduced that account for the shortcomings of the realised variance estimator.

3.3.1 Realised Beta: Systematic Risk in a High Frequency Setting

To calculate the systematic risk of a firm, the variance of the market and the covariance with the market are needed. Combining this with the use of high-frequency data create estimation obstacles which must be considered. In a perfect setting high frequency data can be used to determine the true variance and covariance needed hereby theoretically granting the ability to calculate the true beta value. This is however not empirically feasible due to hurdles at high frequencies. To approximate the "truth", the realised variance and covariance can be applied and to entirely understand why this is the case the concept of integrated variance will be introduced first to provide background knowledge on the RV and RCov covered in section 3.3.1.2.

3.3.1.1 Integrated Variance

In theory and under the assumption of a frictionless market with no price jumps, it is possible to obtain the true volatility of an asset's price when a perfect, continuous data stream is available, which high frequency data approaches given that tick-by-tick millisecond data is available. With this in mind, the price process underlying the classical RV measure can be introduced. An often used specification is defined by Mikosch et al. (2009). Here the true logarithmic price process, p^*, in a continuous-time diffusive and frictionless setting, is defined by the stochastic differential equation:

$$dp^*(t) = \mu(t)dt + \sigma(t)dW(t), \quad 0 \leq t \leq T \tag{3.24}$$

Where T is the time period over which volatility (often one trading day) is measured and t is an integer $1 \leq t \leq T$ for the unit period. $\mu(t)$ is a locally bound and predictable time-varying drift, $\sigma(t)$ is the diffusive càdlàg instantaneous volatility process, and W is a standard Brownian motion process. Further it is assumed that W and $\sigma(t)$ are orthogonal so that there is no leverage effect. In this setting $\mu(t)$ and $\sigma(t)$ hence represent the mean and volatility of the log price return in a setting with perfect market conditions. The continuously compounded returns, r, over an arbitrary time period between t-κ and t, where 0<κ<t, is then define as:

$$r^*(t,\kappa) = p^*(t) - p^*(t-\kappa) = \int_{t-\kappa}^{t} \mu(\tau)d\tau + \int_{t-\kappa}^{t} \sigma(\tau)dW(\tau) \tag{3.25}$$

The true return on the asset is therefore a factor of innovations in the mean and in the variance. Given the specification in eq. (3.25) the total variation or quadratic variation is then:

$$QV(t,\kappa) = \int_{t-\kappa}^{t} \sigma^2(\tau)d\tau \tag{3.26}$$

which is the ex-post variation (in contrast to the ex-ante expected variation) over the interval given and can thus be interpreted as the actual return variance of a stochastic process (Mikosch et al., 2009). From eq. (3.26) above it is evident that the innovations to the mean component $\mu(\tau)$ does not affect variation of the sample path. Mikosch et al. (2009) explains this with the fact that the mean term $\mu(\tau)d\tau$ is of a lower order than the diffusive innovations $\sigma(\tau)dW(\tau)$ and thus when accumulated across many high frequency returns over a short interval they can be neglected. Given this specification of QV when considering only the diffusive variation over the interval $t-\kappa$ to t this is referred to as the integrated variance (IV) which is the continuous component of the quadratic variation measuring the amount of variation at a time point t accumulated over a given interval [t-κ,t] (Duan et al., 2012). In this setting where it is assumed that no price jumps exist, is equal to the QV resulting in:

$$IV(t,\kappa) = \int_{t-\kappa}^{t} \sigma^2(\tau)d\tau \tag{3.27}$$

This is the object of interest and what can be estimated using realised measures. Following from semimartingale theory[25] Mikosch et al. (2009) show that:

$$RV(t,\kappa) \to QV(t,\kappa) \qquad \text{as } n \to \infty \tag{3.28}$$

where n is the sampling frequency. So the RV estimator over the interval [t-κ,t] approximates the IV over the same interval as the sampling frequency increases. This result is important because it, in theory, allows the estimation of the real ex-post variation of the returns. In the section to follow the exact details on how the RV estimate is calculated and the situation where noise or jumps are present will be covered as this alters the underlying price process assumptions.

3.3.1.2 The Realised Variance estimator

Having covered the underlying price process of the RV estimator it is now time to define the estimator more precisely.
In short, the RV estimator attempts to estimate the underlying variance of a semimartingale price process introduced in Barndorff-Nielsen and Shephard (2002a). It is defined as the sum of the squared intra-day returns. Barndorff-Nielsen and Shephard (2002a) showed that the RV estimator is an asymptotically unbiased and consistent estimator of the QV of a diffusive price process as it converges to the true variance as the number of observations, n goes to infinity $n \to \infty$ for a specified sampling interval.

Given the specification of the price and returns process set forth in eq. (3.24), and (3.25) respectively the RV estimator can be defined as follows:

$$RV_*^{(n)} = \sum_{i=1}^{n} (r_{i,n}^*)^2 \tag{3.29}$$

The realised variance is thus defined as the sum of the squared intra-day log returns, where the interval $[t-\kappa, t]$ has been partitioned into n subintervals so $n = t/\delta$ is a positive integer representing the number of intra-day returns and δ is the time interval between sampled observations (the length of each interval). Hence for $\delta = 15$ minutes $m = 5.5 * \frac{1}{15/60} = 22$ intra-day observations if $t = 5.5$ hours (the length of our trading day after controlling for opening/closing intra-day seasonality). As a result, the higher the sampling frequency, the shorter the interval between observations.

[25] Being a continuous time diffusion process with brownian motion (Barndorff-Nielsen and Shephard, 2002b).

It is however found that as the time interval between observations goes to zero the RV (and RCov) estimator is not robust due to an increase in market microstructure noise (Zhang et al., 2005) which is a breach of the fundamental assumption of no noise. In the presence of noise the RV estimator becomes inconsistent and instead of only estimating the QV, it becomes an estimate of the variance of the noise (Zhang et al., 2005; Bandi and Russell, 2006). This property of the original RV estimator is useful to know as the estimator can then be used to correct for noise in other models (Aït-Sahalia et al., 2010). Because of this, Andersen and Bollerslev (1998) argues that one should not use data at a higher frequency than 5 minutes to avoid the effects of market microstructure noise in the realised measures and in general it is argued that anything higher is certain to be highly influenced by noise. This therefore limits the amount of observations in an intra-day sample from which the RB can be determined. The effect of noise will be discussed more in-depth below.

3.3.1.3 Realised Covariance

The realised covariance measure will now be presented as it is defined in Patton and Verardo (2012). Here RCov is estimated as the sum of the products of the intra-day returns and takes the form shown below:

$$RCov_{i,m,t} = \sum_{j=1}^{n} r_{i,t,j} r_{m,t,j} \tag{3.30}$$

This measures the covariance between the geometric return of the single asset i and the market m at the specified interval frequency (McAleer and Medeiros, 2008). Here the intraday period is denoted by j and m refers to the market portfolio while i refers to the asset so that $r_{i,t,j}$ refers to the j^{th} intra-day return for asset i at time t and $r_{m,t,j}$ refers to the j^{th} intra-day return on the market portfolio at time t.

Just as with the RV estimator, the RCov estimator relies on a no-noise assumption and thus falls victim to the same challenges but furthermore has its unique issues which must be considered. The RCov estimator assumes that data is synchronous (regularly spaced) (Hayashi and Yoshida, 2005). If observations in the two time series used to calculate RCov are non-synchronous, that is prices arrives at different points in time, the estimator has a downward bias resulting in the Epps effect. This is especially prevalent when the sampling frequency is high so that the length of the intra-day periods is small relative to the frequency of actual trades (Hayashi and Yoshida, 2005). Thus sampling at lower frequencies might cause beta estimates to be biased downwards and the nominator in eq. (3.31) displayed below becomes smaller. To counter this effect Hayashi and Yoshida (2005) introduce a RCov estimator which account for the bias caused by non-synchronousness which will be used as a test of robustness later on. It is discussed in detail in section 3.3.6 below.

3.3.1.4 The Measure Realised Beta

The realised beta is, like its low frequency counterpart, defined as the ratio of the covariance over the variance of the market, except now the variance and covariance estimates are calculated using realised measures (Andersen et al., 2001a). This approach therefore simply uses the standard definition of beta but configures it to a high-frequency setting yielding:

$$R\beta_{i,t} = \frac{RCov_t^{(n)}}{RV_t^{(n)}} \tag{3.31}$$

where $R\beta_{i,t}$ refers to the realised beta of asset i at time t. $RCov_t^{(n)}$ is the covariance between asset i and the market at time t and $RV_t^{(n)}$ is the variance of the market at time t, both sampled with frequency n. The realised beta is therefore not that different from the classic beta.

3.3.2 The Noise Bias of High Frequency Data

Because of market microstructure effects there is a mismatch between asset pricing theory based on semimartingales and the data obtained. As a result it is appropriate to introduce noise into the price process and look at the effects of this on the RV estimator. In the presence of market microstructure noise the price can be defined as the true (log) price (p^*) plus a noise error term u which is due to market microstructure noise (or measurement error).

$$p = p^* + u \tag{3.32}$$

the true price is latent so only p is observed. This gives an observable intra-day return of

$$r = r^* + \varepsilon \tag{3.33}$$

where $r^* = p_t^* - p_{t-1}^*$ is the efficient return and $\varepsilon = u_t - u_{t-1}$ is the noise increment. The result is that the observed RV is now defined as (Hansen and Lunde, 2006):

$$RV^{(n)} = \sum_{i=1}^{n} (r_{i,n}^*)^2 + 2\sum_{i=1}^{n} r_{i,n}^* \varepsilon_{i,n} + \sum_{i=1}^{n} \varepsilon_{i,n}^2 \tag{3.34}$$

where $\sum_{i=1}^{n}(r_{i,n}^{*})^2 = RV_{*}^{(n)}$ is the RV estimated under no noise. The last term on the right hand side, $\sum_{i=1}^{n}\varepsilon_{i,n}^2$, is the unobservable RV of the noise and the second last term, $\sum_{i=1}^{n} r_{i,n}^{*}\varepsilon_{i,n}$, is the potential dependence between the noise and the efficient price (Hansen and Lunde, 2006). From this Bandi and Russell (2008) show that RV is a biased estimator of IV and that the bias diverges to infinity as the sampling frequency increases ($\delta \rightarrow 0$):

This bias can be reduced by sparse sampling but this leads to an increase in the variance (Barndorff-Nielsen and Shephard, 2002b) and thus creates a bias-variance trade-off. The effect of the bias depends on the assumptions one makes about the noise term. The most common assumptions are (McAleer and Medeiros, 2008):

1. No Noise
2. General Noise
    - Noise has zero mean and is covariance stationary
3. IID Noise
    - Noise is iid with zero mean
    - Noise is independent of the efficient price
4. Dependent Noise
    - Noise is time dependent
    - Noise is independent of the efficient price

with the exception of the no-noise assumption all the different noise assumptions above renders the regular RV estimator biased and inconsistent. Zhang et al. (2005) show this for the case where iid noise is assumed and Aït-Sahalia et al. (2010) for the case where dependent noise is assumed. In their article Hansen and Lunde (2006) also states that the iid assumption of noise might not hold as they find some evidence of serial correlation in the noise process and further also find that the noise might be correlated with the efficient price introducing endogeneity. Hansen and Lunde (2006) uncover three "ugly" facts about the noise relevant here; (i) the noise is negatively correlated with the efficient price, (ii) the noise is autocorrelated and (iii) the noise is smaller than one might think. Estimators that rely on the assumption that noise is iid might therefore not be appropriate. Hansen and Lunde (2006) find that when the sampling frequency is high noise is likely time-dependent and endogenous where as at lower frequencies[26] the iid

[26] Hansen and Lunde (2006) suggests 20 min sampling frequency to avoid time-dependence and engogeniety.

noise assumption might be acceptable. Duan et al. (2012) finds that noise is most prevalent at frequencies higher than 1-5 minutes and that the iid noise assumption is only broken at ultra high frequencies such as 0.5 minute.

The fact that the noise is smaller than one might expect is especially prevalent after 2001. The noise becomes smaller after 2001 due to decimalization (that is the minimum tick size is no longer 1/16 but now minimum tick size is 1 cent on NYSE) (Hansen and Lunde, 2006). This fact influences some of the alternative estimators given below and will be discussed when appropriate.

The noise assumptions mentioned above also plays an important role w.r.t. how one corrects for the biased introduced by noise. Among other things the noise assumption plays a role when having to estimate the variance of the noise in the application of alternative estimations methods. Again this will be mentioned below when appropriate. For an overview of the the different estimators used in this thesis and the assumptions about the noise they rely on see table 3.1 on page 65.

Having covered the situation where the price process is affected by microstructure noise the next step is to go over the situation where the price process exhibit discontinuities.

3.3.3 Jumps in the Price Process

As jumps violate the continuous price process from equation 3.24 (Mikosch et al., 2009) they can cause the estimation to become biased making the realised beta estimates unreliable. One such jump comes from over-night trades which lead to a jump on the following trading day. This can easily be mitigated by the exclusion of trades affected by overnight prices as they are easily identifiable. This is accomplished by sampling from 10:00 am instead of 9:30 am. Another situation in which jumps might occur is when new information arrives in the market (for instance macro economic news or firm specific news) which cannot be as swiftly excluded from a sample. A third reason for talking about jump-diffusive asset price processes has to do with how data is observed. Prices are only observed a finite number of times a day and since they can only change by a tick the price process cannot be purely diffusive but must exhibit some discontinuity. Hence, some of the sample paths of the price process must exhibit jumps induced by the way the price is observed in practice. In this setting of a less than friction free market a jump parameter can be introduced to equation (3.24) which account for jumps in the asset price affecting the variance of the returns. The practical effect and mitigation of this will be discussed below.

To model the above described situation, changes to the stochastic differential equation presented in eq. (3.24) is needed. The log price process is modified to include a jump term and the result is presented in eq. (3.35) (Duan et al., 2012):

$$p_t^* = \int_{t-\kappa}^{t} \mu(s)ds + \int_{t-\kappa}^{t} \sigma(s)dW(s) + \sum_{j=1}^{N(t)} k(s_j) \tag{3.35}$$

where the $N(t)$ process counts the finite number of jumps occurring with time-varying intensity $\lambda(t)$ and jump size $k(s_j)$. Given a price process with jumps the RV estimator still converges in probability to the quadratic variation but now the QV is given by (Duan et al., 2012):

$$QV(t,\kappa) = \int_{t-\kappa}^{t} \sigma^2(\tau)d\tau + \sum_{j=N(t-1)+1}^{N(t)} k^2(s_j) \tag{3.36}$$

Now the QV is not equal to the IV as the IV is only the continuous part $\int_{t-k}^{t} \sigma^2(\tau)d\tau$. Under these conditions the RV estimator still consistently measures the QV and the result of eq. (3.28) still holds but in order to estimate the IV it is necessary to correct for the discontinuous jump part. This is because the true total variation (QV) aggregates both the continuous and discontinuous risk and thus the IV is no longer estimated through the QV. To disentangle the effect of jumps Barndorff-Nielsen and Shephard (2004) proposed the bi-power estimator displayed in eq. (3.48) and described in section 3.3.5.1 (page 60) which becomes unaffected by jumps and consistently estimates the IV as $n \to \infty$. To test the robustness of the RV/RCov based estimations to jumps in the price series this estimator will be applied.

3.3.4 Realised Kernel Beta

The following section will introduce the components of a market mircostructure noise robust beta estimator which can help correct some of the fundamental flaws of the realised beta.

3.3.4.1 Realised Kernels

The market microstructure noise discussed above is a major hurdle for further progress towards the determination of the true variance of asset prices and therefore also the true beta coefficient. Barndorff-Nielsen et al. (2008) suggest an alternative measure of variance known as *Realised Kernels* which is a robust estimation of asset price variance even in the presence of market frictions at high frequencies, as opposed to the RV. The authors test the realised kernel against the realised variance estimators showing that the realised kernel is a superior estimator at the ultra high-frequencies such as 1 minute where the presence of market microstructure noise is imminent.

The realised kernel estimator was first proposed in Barndorff-Nielsen et al. (2008) and derives its name from the fact that it uses a kernel weighing function to adjust the RV estimator. The idea is to capture serial correlation (Hautsch, 2012) and use it to correct for market frictions.The kernel estimator presented below (eq. (3.37)) is the flat-top kernel but later the non-flat-top kernel of Barndorff-Nielsen et al. (2009) is introduced as this is the kernel used here in practice. The reason for starting with the flat-top kernel is because it is the first realised kernel to be introduced and thus makes for a good starting point. It is given by:

$$RK_{FT}^{(n)} = RV^{(n)} + \sum_{h=1}^{H} K\left(\frac{h-1}{H}\right)(\gamma_h + \gamma_{-h}) \tag{3.37}$$

where $RV^{(n)}$ is the realised variance calculated as show in equation 3.29 and $K(\cdot)$ is a deterministic kernel function weighing the autocovariance γ_h and γ_{-h} which is given by:

$$\gamma_h = \sum_{j=1}^{n}(r_j r_{(j+h)}) \tag{3.38}$$

where r_j is the j^{th} intraday high frequency return.

In other words the realised kernel function is the realised variance plus an adjustment for noise made up of a weighing of the autocovariances. Hence, the correction made to realised variance due to market noise can be estimated as RK-RV. The kernel function depends on the bandwidth H. In order for the RK estimator to eliminate noise H has to increase with n and hence H is defined as being proportional to n in the following way (Hautsch, 2012):

$$H = c\xi\sqrt{n} \tag{3.39}$$

The c in eq. (3.39) is a function of the kernel used and the integrated quarticity. Barndorff-Nielsen et al. (2008) find that the optimal value is $c^*= 4.77$ for the Parzen kernel[27] when c is chosen so that the asymptotic variance of the estimator is minimized. The ξ can be thought of

[27] Other kernel function include the Bartlett kernel $[K(x) = 1-x]$ and the cubic kernel $[K(x) = 1-3x^2+2x^3]$. The one used here is the Parzen as recommended by Barndorff-Nielsen et al. (2009)

as a noise to signal ratio and is defined by:

$$\xi^2 = \omega^2 / \sqrt{\int_0^1 \sigma_u^4 du} \tag{3.40}$$

where $\int_0^1 \sigma_u^4 du$ is the integrated quarticity (IQ) and ω^2 is the variance of the noise which can be estimated as shown in the two equations below:

$$\hat{\omega}^2 = \frac{1}{q}\sum_{i=1}^{q} \hat{\omega}^2_{(i)} \tag{3.41}$$

with

$$\hat{\omega}^2_{(i)} = \frac{RV^{dense}_{(i)}}{2\tilde{n}_{(i)}} \qquad \text{i = 1,...,q} \tag{3.42}$$

where $\tilde{n}_{(i)}$ is the number of non-zero returns used to compute $RV^{dense}_{(i)}$ which is an estimate of the RV calculated using all observations.

As it is evident from eq. (3.40) the signal-to-noise term ξ (and thus also the bandwidth H) is dependent on two unknown parameters, namely the variance of the noise and the IQ, Barndorff-Nielsen et al. (2009) introduce a method to estimate these two parameters. The integrated quarticity $\int_0^1 \sigma_u^4 du$ is estimated by calculating a low frequency estimate of the realised variance where sampling is uniform with 39 observation[28]. This provides an estimate of the lower bound of the IQ.

The variance of the noise ω^2 is also an unknown parameter. To estimate it the method set forth in Barndorff-Nielsen et al. (2009) which is displayed in eq. (3.41) and (3.42) is used. First the method displayed eq. (3.42) is used to compute the RV of every q^{th} trade. These q results are then averaged as shown in eq. (3.41) to find the final estimate of ω^2. When q=1 this is the estimator proposed by Bandi and Russell (2008) and Zhang et al. (2005). It is this estimator that will be used to estimate ω^2. RV^{dense} is calculated using the standard RV method which use all prices. As also discussed in section 3.3.1.2 and as shown in Bandi and Russell (2008); Zhang et al. (2005); McAleer and Medeiros (2008) this becomes a consistent estimator of the variance of the noise instead of an estimator of the IV in the presence of microstructure frictions. A problem with the noise estimator is that the assumption about independent noise might not hold at high frequencies whereby this estimator does not estimate the variance of the noise

[28] This frequency is optimised for liquid NYSE TAQ data and follows the recommendations for IQ estimation in Sheppard et al. (2013); Sheppard (2013).

correctly since the bias is no longer given by $2n\omega^2$. (Hansen and Lunde, 2006). Another issue is that the variance of the noise (ω^2) needs to be large compared to $QV/2\tilde{n}_i$ which might not be then case when the noise is small as mentioned in Hansen and Lunde (2006). As a result the estimator of the variance of the noise can exhibits a small upward bias. Although unbiased estimates are naturally preferred a small bias in the estimate of ω^2 might not pose a problem. A small bias will yield more conservative estimates of the bandwidth H and as mentioned in Barndorff-Nielsen et al. (2009) this might be an advantage as too small values of H do more harm than too large values. Further large values of H makes the kernel more robust to serial dependence.

For practical application the non-flat-top kernel estimator (RK^{NFT}) is used given by:

$$RK_{NFT}^{(n)} = RV^{(n)} + \sum_{h=1}^{H} K\left(\frac{h}{H}\right)(\gamma_h + \gamma_{-h}) \tag{3.43}$$

This kernel is used as it is guaranteed to be non-negative and robust to noise in the sense that it does not assume noise to be iid or noise and price to be independent. The cost of these advantages is that the estimator no longer converges as fast ($n^{1/5}$) and has a small asymptotic bias (Duan et al., 2012). As argued by Barndorff-Nielsen et al. (2011) the benefits of being robust to endogeneity and serial dependence outweighs the cost of the small bias and thus the non-flat-top kernel is the one used in practice because it is based on more realistic assumptions about the noise and is positively semi-defined.
The Parzen kernel is used to compute the realised kernels as recommended by Barndorff-Nielsen et al. (2009). The Parzen kernel is given by:

$$K(x) = \begin{cases} 1 - 6x^2 + 6x^3 & \text{for } 0 \leq x \leq \frac{1}{2} \\ 2 - (1-x)^3 & \text{for } \frac{1}{2} < x < 1 \\ 0 & \text{for } x \geq 1 \end{cases} \tag{3.44}$$

This kernel is used because it satisfies the smoothing criteria $k'(0) = k'(1) = 0$ and guarantees non-negative estimates (Barndorff-Nielsen et al., 2009).
The optimal bandwidth H for is selected as

$$H^* = c^* \xi^{4/5} n^{3/5} \tag{3.45}$$

In order to eliminate the variance of the noise $H \propto n^{\frac{1}{3}}$ is needed and to eliminate the bias

$H \propto n^{\frac{1}{2}}$ is needed (Barndorff-Nielsen et al., 2009). Hence, eq. (3.45) gives the optimal choice of bandwidth given that this is a bias-variance trade-off situation. The optimal value for c in Barndorff-Nielsen et al. (2009) is found to be $c^* = (12^2/0.269)^{1/5} = 3.5134$ and this is the value used for the regression. The estimation of ξ and ω follows the methods set forth in eq. (3.40) and (3.41) respectively.

Lastly it is worth noting that in the absence of noise in the data using RK does not yield an advantage over RV (Barndorff-Nielsen et al., 2008). In the absence of noise RV is better because it is computationally easier and relies on fewer parameters since it is not not necessary to estimate the bandwidth etc. It is as such far more stringent and results are not influenced by partially subjective weights and similar decisions.

The above approach is used to estimate a different measure for market variance. This is of course only half the story about beta and to find a measure for covariance the multivariate realised kernel estimator is used.

3.3.4.2 Multivariate Realised Kernels

The Multivariate realised Kernel (RMK) estimator is useful because it deals with the problems that (i) price is affected by market noise, (ii) data is not equidistant and (iii) the market microstructure effects are not independent of the true price process (Barndorff-Nielsen et al., 2011). To estimate the ex-post covariation of log-prices in a consistent and unbiased fashion Barndorff-Nielsen et al. (2011) propose the following estimator:

$$RMK^{(n)} = \sum_{h=-n}^{n} K\left(\frac{h}{H}\right)\Gamma_h \tag{3.46}$$

where

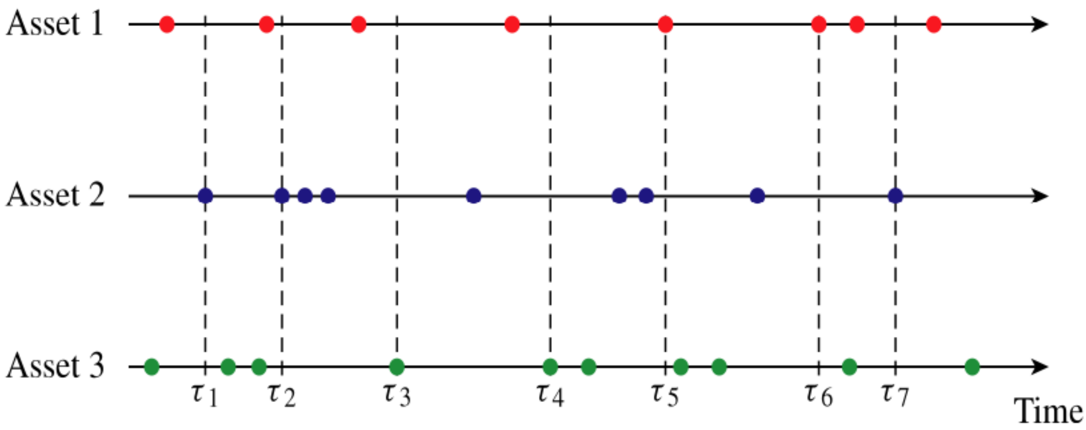
$$\Gamma_h = \sum_{j=h+1}^{n} r_j r'_{j-h} \qquad \text{for h } \geq 0 \tag{3.47}$$

and $\Gamma_h = \Gamma'_{-h}$ for $h < 0$.

Just as with the RCov estimator the RMK estimator is plagued by non-synchronous trading. In order to be able to estimate RMK one must filter the price series such that it is in refresh time. This is done to synchronize data in order to overcome the problem with transaction prices arriving at irregularly spaced intervals. Refresh time is defines as the first time where all the assets have traded i.e τ_1 is the time it takes before all assets have traded for the first time and τ_2 is the first time at which all assets have traded again after τ_1. For an graphical illustration of this see figure 3.2.

Further to obtain a consistent estimator it is necessary to jitter the prices at the beginning and the end of the day. This means that it is necessary to average x prices at both ends of the trading day. If x is small compared to the total number of observations jittering helps because

Figure 3.2: Illustration of Refresh Times



The dashed vertical lines represent refresh times. The dots represent the actual arrival time of transaction prices.
Source: Barndorff-Nielsen et al. (2011)

taking the mean averages out part of the error where by a more efficient price is obtained. Although jittering theoretically is very important in practice it can be ignored. (Barndorff-Nielsen et al., 2009, 2011)

The kernel defined in eq. (3.47) has the same pros and cons as the univariate version presented in eq. (3.43) and converges at a rate of $n^{1/5}$ too. One of the further advantages of using both the RMK and RK estimator is that this class of estimators deliver similar results on both transaction and quote data thereby making the results robust to some of the issues mentioned in section 4.1. With the RK and RMK it is possible to calculate a market microstructure and non-synchronous robust beta estimator which will be referred to as the Realised Kernel Beta (RKB)

3.3.5 Bi-power Beta

The standard RB and RKB estimators above are not robust to discontinuities and to correct for this the bi-power beta (BPB) can be applied. Its variance and covariance components are presented below.

3.3.5.1 Bi-power Variation

The bi-power variation estimator (BPV) proposed by Barndorff-Nielsen and Shephard (2004) is applied in the form shown in Duan et al. (2012):

$$BPV^{(n)} = \frac{\pi}{2}\sum_{j=2}^{n}|r_j||r_{j-1}| \tag{3.48}$$

When the sampling frequency $n \to \infty$ ($\delta \to 0$) then this estimator becomes robust to jumps and estimates the integrated variance consistently and thus one can estimate the discontinuous jump part as

$$BPV - RV = \sum_{j=N(t-1)+1}^{N(t)} k^2(s_j)$$

The estimator has a small upward bias and to correct for this it is scaled by $\frac{n}{n-1}$ (Sheppard, 2013) obtaining the estimator from Huang and Tauchen (2005):

$$BPV^{(n)} = \frac{n}{n-1}\frac{\pi}{2}\sum_{j=2}^{n}|r_j||r_{j-1}| \tag{3.49}$$

The principle is that if assuming that jumps are rare and two jumps do not follow each other immediately, the jump will stand out among consecutive returns. Taking the product of the large return (the jump) and the smaller return preceding (or following) the jump, will yield an overall smaller return hereby neutralising the jump effect. By multiplying the subsequent absolute returns, the effect of the jump is mitigated and the BPV estimator can be compared to the RV measure which sums over squared returns. This is used to calculate a jump robust variance estimate which can be used as a robustness test for jumps in the calculation of the RB.

3.3.5.2 Bi-power Covariation

This estimator remedies the problem the RCov estimator has concerning jumps. To obtain a jump robust estimator of the realised covariance, an equally weighted portfolio consisting of an asset and the market portfolio is constructed. The return of the portfolio is (Bodie et al., 2011):

$$r_p = \frac{1}{2}r_i + \frac{1}{2}r_m$$

where r_i is the return on the asset and r_m is the return on the market portfolio. With this the familiar variance of the portfolio is given by (Bodie et al., 2011):

$$
\begin{aligned}
Var(r_p) &= \left(\frac{1}{2}\right)^2 Var(r_i) + \left(\frac{1}{2}\right)^2 Var(r_m) + 2\left(\frac{1}{2}\right)\left(\frac{1}{2}\right) Cov(r_i, r_m) \\
&= \frac{1}{4} Var(r_i) + \frac{1}{4} Var(r_m) + \frac{1}{2} Cov(r_i, r_m)
\end{aligned}
$$

Rearranging yields

$$
Cov(r_i, r_m) = 2\left[Var(r_p) - \frac{1}{4} Var(r_i) - \frac{1}{4} Var(r_m)\right] \tag{3.50}
$$

The covariance has hereby been decomposed into a measure of three different variance estimates. Using BPV to estimate the variances in eq. (3.50) grants a jump robust estimate of the RCov resulting in the bi-power covariation (BPCV):

$$
BPCV = 2\left[BPV_p - \frac{1}{4} BPV_i - \frac{1}{4} BPV_m\right] \tag{3.51}
$$

where BPV_p is the bi-power variation calculated using the returns of the equally weighted portfolio , BPV_i is the bi-power variation of asset i and BPV_m is the bi-power variation of the market portfolio.
Having now obtained both a jump robust variance and covariance measure it is possible to estimate a jump robust RB estimate.

3.3.6 Hayashi and Yoshida Estimator

This estimator was proposed by Hayashi and Yoshida (2005) as a solution to the problem of non-synchronisity in RCov. The observant reader may have noted that this problem was technically already surpassed using the RMK and thus question why the topic is brought back to life. The reason for this disposition is that the RMK framework is optimal at frequencies higher than 5 minutes when market microstructure noise is most likely present. At lower frequencies where market microstructure noise is far more unlikely to be influential, this estimator by Hayashi and Yoshida (2005) will be used together with the RV estimator to test more specifically for the effect of asynchronicity. The estimator is given as (Lacus, 2011):

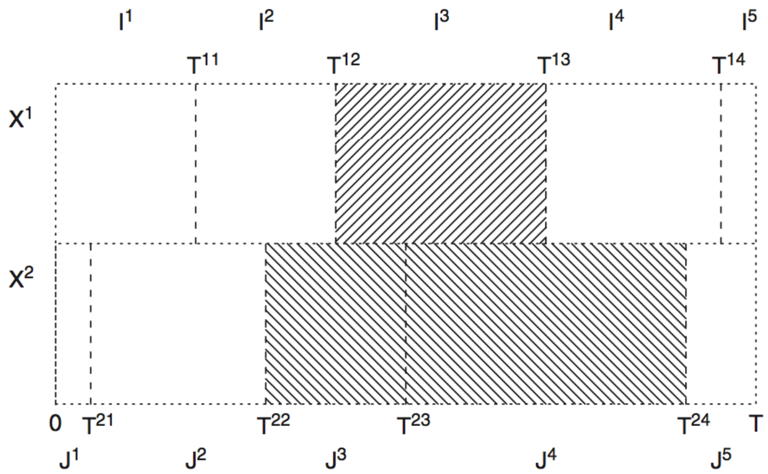
$$
HY = \sum_{i,j:T^{1i} \leq T, T^{2j} \leq T} X^1_{T^{1i}} - X^1_{T^{1\{i-1\}}} X^2_{T^{2j}} - X^2_{T^{2\{j-1\}}} \mathbb{1}_{\{I^i \cap J^j \neq \emptyset\}} \tag{3.52}
$$

where $T \in (0, \infty)$ is the terminal time for the possible observations and the increasing sequence of times $T^{ik}(k = 0, 1, ..., T)$ is the interval over which the process X^i is observed and thus the quantities of interest are $(T^{ik}, X^{i,k})$. When having two assets, one has two sequences of time namely T^{1k} and T^{2j} which in general are asynchronous and spaced irregularly as displayed in fig. 3.3.

From eq. (3.52) it can be seen that the product of every pair of increments will make a contribution to the summation only if the intervals I^i and J^j are overlapping. It is noted that each increment may contribute to the sum multiple times if the corresponding intervals overlap (Hayashi and Yoshida, 2005). This is displayed in figure 3.3 where I^i and J^j are determined by the subsequent elements of the random time sequences T^{1k} and T^{2j} respectively. This estimator is consistent for $n \to \infty$ if the max length between two consecutive observations tend to 0. Hence the HY estimator does not suffer from the Epps effect. (Lacus, 2011). Hayashi and Yoshida (2005) explain this with the fact that the bias of the RCov estimator comes from the fact that each increment contributes to the sum only when both X^1 and X^2 move together in the interval of length δ. Thus, all the other situations where only one of the two prices move are ignored. Such occasions of zero increment begin to dominate as δ becomes smaller. On the other hand, coarser δ may not be able to capture rapid movements of the processes (when multiple jumps occurred during δ) resulting in the realised covariance estimator failing to reflect these microscopic movements (which are crucial for variance-covariance estimation). In other words, large δ leads to inefficient use of data. The proposed estimator (3.52) circumvents this dilemma by not operating with the concept of δ.

Lastly it seems appropriate to note that the application of the HY and RK estimators in Matlab is challenging why their implementation is inspired by Sheppard (2013) but modified to the setting of this thesis.

Figure 3.3: Overlapping



Source: Lacus (2011)

3.3.7 Overview of Estimators

The availability of high-frequency equity prices has given way for new opportunities within (co)variance estimation but at the same time has led to new technical issues. The above variance and covariance estimators all have individual pros and cons and are based on slightly different assumptions making them adequate to control for different issues. The realised (co)variance estimator is by far the most *pure* choice as it weighs all observations equally and can theoretically approach the true price variation in a very stringent fashion. Like many beautiful things it is however also exceedingly fragile and does not handle disturbance well. The alternative methods can make up for these issues but at the cost of alterations of the data handling and in the absence of the specific types of noise they become less than optimal. They are therefore considered as second best options for robustness tests of the areas where the realised (co)variance may experience issues.

In table 3.1 below an overview of the different estimators used and the characteristics of these is presented.

Table 3.1: Overview of Estimators

Estimator	Equation	Unbiased	Consistent	Jump robust	Noise assumption	Price model	Noise and price
Univariate Estimators							
RV	(3.29)	Yes	Yes	No	No Noise	Diffusion	Independent
		No	No	No	Dependent / IID	Diffusion	Dependent / Independent
RK^{FT}	(3.37)	Yes	Yes	No	IID	Diffusion	Independent
		No	No	No	Dependent	Diffusion	Dependent
RK^{NFT}	(3.43)	No	Yes	No	Dependent	Diffusion	Dependent
BPV	(3.48)	Yes	Yes	Yes	No Noise	Jump	Independent
Multivariate Estimators							
RCov	(3.30)	Yes	Yes	No	No Noise	Diffusion	Independent
		No	No	No	Dependent / IID	Diffusion	Dependent / Independent
RMK	(3.47)	No	Yes	No	Dependent	Diffusion	Dependent
BPCV	(3.51)	Yes	Yes	Yes	No Noise	Jump	Independent
HY	(3.51)	Yes	Yes	Yes	No Noise	Jump	Independent

Considering large sample (asymptotic) attributes. Source: McAleer and Medeiros (2008); Duan et al. (2012)

Chapter 4

Data

The data used is obtained through the TAQ, CRSP and COMPUSTAT databases accessible via the Wharton Research Data Services (WRDS) website. From CRSP data on all the constituents of S&P500 from 2000 to 2012 is obtained. COMPUSTAT is used to retrieve information on dividend announcements and from TAQ high frequency information on transaction prices is found. The software used for data retrieval and data manipulation is SAS whereas calculation of the RB and regressions are carried out in Matlab. This setup is chosen because WRDS allows one to work with SAS directly on their servers (through WRDS cloud). Taking into account the amount of data to be processed, access to the computing cluster at WRDS presents a significant increase in the computing power available and is a necessity for the feasibility of this thesis. To give the reader an idea of the amount of data to be considered one may note that the size of one month of TAQ data according to WRDS takes up about 1 terabyte of space (October 2008) and the size is increasing. With a horizon of 13 years this means that sampling of the data require large amount of capacity.

In short, high-frequency data on all the members of the S&P500 index in the given period is retrieved and used to calculate a daily realised beta for these companies. This is done by linking data found in the three different databases mentioned above with each other.
In the following sections the data cleaning and manipulation necessary to construct a time series of the realised beta estimates used to obtain the regression results about the dynamics of beta around dividend announcements will be covered.

4.1 Choice of Price: Transaction Data vs. Quote Data

There are different issues tied to using different types of price series data. When it comes to microstructure noise the causes of noise are different for quote and transaction data and thus the problem with noise and how to tackle it depends on what type of data is used. Below some of the problems and advantages of the two different types of price series data will be discussed and reasons for the choice of transactions data and not quote data will be provided.

Transactions data specifically suffer from the market microstructure effect called bid-ask bounce where the price moves even if no new news reached the market as discussed previously. Assuming that buy and sell orders arrive randomly this will make the transaction price fluctuate between the bid and ask price. This is most rampant in tick-by-tick data and induces negative autocorrelation in returns which violates the semimartingale assumption of the log price process.(Duan et al., 2012)

When using *quote data* there are two issues related to market microstructure one should be aware of: The first issue is strategic quoting where quotes does not represent the underlying value of the asset but is rather a position taken for strategic reasons. This moves the price even though the true value of the asset has not changed[1]. When one instead uses mid-quotes there might be an issue with price staleness. Because the price used here is the average of the bid and ask quote it moves rarely and are affected by non-synchronous moves of the bid or ask prices. Thus the mid quote might change because the bid and ask quotes does not move at the same time and not because the true value of the asset changed. According to Vuorenmaa (2010) data errors tend to be larger and occur more frequently and systematically in quote data. For this reason, data cleaning and filtering is especially important with quote data. Also (Sheppard et al., 2013, table 4) find that for data sampled at 15 minutes, using the RV estimator transaction data is significantly superior to mid-quote data[2].

Overall, transaction data is chosen for further analysis because quote data entails substantial noise issues compared to transaction data and because of computational constrains: The computational resources required to handle the amount of data is not available to the authors if having to use both quotes and trades price series keeping in mind that quotes take up more space than transactions since there are two prices for every observation. Further many of the filters applied to quote data require working across columns (vertically) in SAS which as discussed below is infeasible to do in SAS given the amount of data[3]. Hence it seems most appropriate to choose transactions data as this improves the RV estimator without affecting

[1]This is especially prevalent in FX markets (Osler et al., 2011).

[2]This also holds for the RK estimator when using data sampled every 1 minute or above.

[3]SAS is very fast when looking across rows but is not as strong in working across columns, making this kind of programming very tedious and inefficient.

the RK estimator too much[4].

In Barndorff-Nielsen et al. (2009); Brownlees and Gallo (2006) it is suggested that one constrains the transaction data somehow either by using quote data[5] or by applying an algorithm that takes the average of the neighbouring observations into account. The reason this paper does not try to constrain the transactions data used is because this is not feasible to do in SAS. As mentioned before SAS handles data by reading it in row by row which makes it very good (fast) at handling large amounts of data. In order to make use of quote data or algorithms to constrain the transaction data it is necessary to be able to look across all rows simultaneously which SAS (and many other software packages as well) cannot do in an efficient manner. Doing so would require that one either loops over every row or loads all the data into memory which is either not possible or extremely time consuming given the amount of data used. Moreover, in order to use quote and transaction data together the two datasets need to be combined. This is typically done using the Lee and Ready (1991) algorithm but this approach is not without problems as discussed by Vergote (2005)[6]. In light of the issues presented here the authors have chosen not to attempt to constrain transactions data using quote data as it seems the resources involved in doing so are better applied to other parts of this thesis.

4.2 Sampling Data

When it comes to high-frequency data how (and how often) one samples data is very important and influences how well the realised estimators work. In the following some of the issues related to the sampling of data and how this has been approach will be discussed. The importance of sampling frequency will be covered along with which sampling scheme to use.

4.2.1 Sampling Frequency

The data available is aggregated to the nearest second but some databases provide data sampled at the millisecond level. This constitutes a lot of data which is generally good from a statistical point of view. Things, unfortunately, become more problematic in the context of realised

[4]The RK estimator is not very sensitive to the choice of data type as mentioned in section 4.2.2. When sampling below 1 minute the RK estimator is indifferent between quote and transactions data (Sheppard et al., 2013).

[5]For instance by deleting observations where the transaction price is above the ask price plus the bid-ask spread.

[6]Vergote (2005) finds that the time difference between quote and trade reporting varies across stock and time and thus the 5 second rule suggested by Lee and Ready (1991) might not be appropriate in every setting.

variance. As it follows from the theory of the RV estimator it is desired that one can sample as often as possible (have m as large as possible) but this is true only under the no noise assumption. In practice it is necessary to sample at lower frequencies to minimize the impact of noise. Exactly what frequency to choose varies from situation to situation but many papers (see among others Barndorff-Nielsen et al. (2008, 2009); Hansen and Lunde (2006); Patton and Verardo (2012)) have found a sampling frequency somewhere in the interval 5-30 minutes to yield the best results. For instance Duan et al. (2012) finds that the noise for transactions data is largest for frequencies higher than 5 minutes, Hansen and Lunde (2006) recommends a frequency of 20 min and Patton and Verardo (2012) use 25 minute intervals. In light of these results a sampling frequency of 15 minutes is chosen to strike a balance between having a sufficient amount of intra-day observations and obtaining results without market excessive microstructure noise.

4.2.2 Sampling Scheme

Prices are in practice not observed at regularly spaced points in time but instead arrive at irregular and random intervals. This poses a challenge since a lot of the methods related to estimating realised measures rely on data being equidistant. When it comes to deciding on how to sample this needs to be considered with some depth as it has an effect on the noise present in the data. Within the framework of sampling high-frequency data four different sampling schemes exist (Oomen, 2006; Duan et al., 2012):

1. Calendar Time Sampling
2. Business Time Sampling
3. Transaction Time Sampling
4. Tick Time Sampling

When sampling in *Calendar Time* (CTS) an equidistant grid of intra-day times is build and then the observation that is closest to the grid is chosen. For instance choosing to sample every 5 minutes by building a grid that goes from 09:30:00, 09:35:00 ... 15:25:00, 15:30:00 and selecting the transaction that is closest to the grid. This can be done by using both the previous-tick-approach or the next-tick-approach. In this paper the previous-tick-approach is used as Hansen and Lunde (2006) show this is a sensible way to sample in CTS. One could also use interpolation to sample but an issue with interpolating that is worth mentioning is that in case the stock is illiquid interpolating might use information that is not really available since for a thinly traded stock the distance between observations can be large. Using the previous-tick-approach having the following observations: 09:34:46, 09:34:58 the latter is chosen and it is mapped at 09:35:00. One issue with using this method is if the distance between observations is larger than the selected grid intervals because this will provide an intra-day return of zero. (Brownlees and Gallo, 2006)

Transaction Time (TrTS) is when sampling prices every x^{th} transaction - for instance every 2^{nd} or every 5^{th} tick. The first and last observation of the day is automatically included. So if having a trading day of 5.5 hours and one wishes to sample every 15 minutes: $\frac{5.5*60}{15} = \frac{330}{15} + 1 = 22$ evenly spaced prices are needed. As the first and last price is always included one needs to choose 21 evenly spaced prices meaning having to skip every k = (total no. of transactions/21) *th* trade (rounded down if necessary). If having a total of 2142 observations this means that one needs to skip every 102^{nd} observation. This evenly spaced grid in transaction time is variably spaced in calendar time when in a setting where trade activity vary during the day. Therefore this approach samples periods with high activity more frequently resulting in fewer samples from periods with low activity which might contain more noise related to irregular trading. (Oomen, 2006)

Tick Time (TkTS) is a scheme where one samples prices every time a price change is recorded. Oomen (2006) shows that this is equivalent to TrTS for high levels of noise and once a first-order bias correction is applied to the RV estimator TrTS is preferable (Duan et al., 2012). Thus this method might not be appropriate for very high sampling frequencies.

In *Business Time* (BTS) sampling times are chosen such that $IV_{i,t} = \frac{IV_t}{n_t}$ so that the IV of the intra-day intervals are all equal. When sampling in BTS the observation times are latent and not observable as they depend on the IV. This makes the BTS scheme infeasible (Duan et al., 2012) although it can be approximated by prior estimates of the IV or by using non-parametric smoothing measures on the transaction times (Oomen, 2006). Empirical results by Andersen and Bollerslev (1997) suggest that BTS can be approximated by TrTS (Duan et al., 2012). The BTS is hence applicable but entails a significant amount of constraints and complications in practical use.

All schemes sample at equidistant points and are thus all valid ways of sampling the data for use with the RV estimator (as well as the other estimators mentioned).
According to Oomen (2006) and Hansen and Lunde (2006) the best sampling scheme is Transaction time. The sampling scheme does not affect the bias of the RV estimator but it does

affect the efficiency[7]. This is however only true under the no-noise assumption. If having noise the bias of the RV estimator is larger under TTS than under CTS (Oomen, 2006, proposition 2) and no scheme is superior w.r.t efficiency. In light of the above results calendar time is chosen as sampling scheme in line with Patton and Verardo (2012); Barndorff-Nielsen et al. (2009, 2011) and many others.

4.3 Data Cleaning

Because market microstructure noise plays an important role when it comes to estimating realised measures proper cleaning and filtering of the data is required before applying it. This is done using the filters in Barndorff-Nielsen et al. (2009) as well as filters proposed by WRDS (Yuxing Yan, 2007). The filters applied are listed below:

F1: Delete observations outside the interval 10:00 - 15:30.
F2: Delete observations where the transaction price or volume is equal to zero.
F3: Retain only observations from NYSE, NASDAQ, AMEX and ARCA.
F4: Delete observations with corrected trades (CORR $\neq$ 0,1,2).
F5: Delete observations with abnormal sales conditions (COND is O, Z, B, T, L, G, W, J, K).
F6: If multiple observations have the same timestamp then use mean price.

Intuitively one would think that having as much data as possible would be preferable and in statistics this is usually desirable. The justification for cleaning the data and thus "throwing away" information is that the discarded data contains more noise than useful information. For high-frequency data Hansen and Lunde (2006) show that removing a large part of their data through some of the data cleaning procedures presented above, is actually beneficial when it comes to improving the estimates of their volatility estimator.

The filtering rule F1 is chosen to make sure the selected assets are sufficiently traded before commencing the sampling (it is not uncommon that actual trading starts later than 09:30 (Brownlees and Gallo, 2006)). Hence sampling starts half an hour after the exchanges open and stops half an hour before they close. This also helps reduce noise as the trading that occurs around opening and closing of the exchange including over-night trades which are often more noisy than the trading that takes place throughout the day (Lockwood and Linn, 1990).
Only observations from NYSE, NASDAQ, AMEX and ARCA (F3) are included in the sampling because prices from other exchanges often carry more noise. For instance Barndorff-Nielsen

[7] Measured as the one that minimizes the MSE.

et al. (2009) find that the RV estimator is sensitive to data that comes from many exchanges[8]. As the ticker symbols used are traded on more than one exchange the data cannot be constrained to only come from one exchange as in Barndorff-Nielsen et al. (2009). The solution is to include only NYSE plus the three other major exchanges listed above as these are the primary exchanges for the ticker symbols when NYSE is not their primary exchange[9]. Also Brownlees and Gallo (2006) only constrain quote data using F3 not transaction data in that they find that NYSE and non-NYSE transaction data exhibits the same dynamics[10] whereas this is not the case for quote data.

Filtering rule F4 and F5 helps sort out data that might be contaminated or in other ways recorded incorrectly[11].

Filter F6 is necessary because millisecond data is not accessible to the authors and it is thus not possible to separate observations arriving within the same second from each other. The approach applied is the same one taken by several papers[12] and it seems to be the de facto standard. Lastly filter F2 helps ensures that obvious data errors are filtered out.

4.4 Data Management

In this section the construction of the different SAS datasets will be discussed. The data in the TAQ database does not have a unique key but is instead indexed using ticker symbol. This poses a challenge as ticker symbols are not unique over time and some companies have changed ticker symbol over the life of the company. An example of this is Sun Microsystems that traded under the symbol SUNW from 1986 to 2007 and under the symbol JAVA from 2007 to 2010. As a result another key is needed to identify and associate the ticker symbol with constituency of S&P500 as well as dividend announcement dates. In outline the CRSP database is used, as this assigns a unique key (PERMNO) to every company, to build a list of ticker symbols for every company in the sample and the dates for which the given ticker symbol was assigned to the company in question. Having a dataset consisting of all the constituents of S&P500, their respective ticker symbols and the dates for which these are valid a new dataset can be constructed where the dividend announcement dates are added for announcements where the change in dividend was either positive or negative compared to last periods dividend

[8] Regarding this it should be noted that the RK estimator is not very sensitive to data aggregated across several exchanges Barndorff-Nielsen et al. (2009).

[9] An example of this is MSFT which is listed on NASDAQ, SPY listed on ARCA and DVN listed on AMEX.

[10] Although non-NYSE data contains more outliers.

[11] For details of what the different status codes mean the authors refer to NYSE TAQ documentation.

[12] Among others Hansen and Lunde (2006); Barndorff-Nielsen et al. (2009, 2011); Sheppard et al. (2013); Brownlees and Gallo (2006)

announcement. This dataset is split in two such that one dataset contains ticker symbols and dates for dividend announcements where the change in dividend is negative and one where the change is positive. This is done because of the hypothesised inverse relationship between dividends and beta. With this new dataset in place, data can be retrieved from TAQ for the selected ticker symbols and it is possible to mark the position of the individual dates relative to the announcement date. This is needed later for use in Matlab in order to run the panel data regression. This is just a rough outline of the composition and more details follow below on how exactly the different datasets are constructed.

4.4.1 Constituents Data

To carry out the analysis information about the constituents of S&P500 ranging from 2000 to 2012 is required. This is found using the CRSP database. Information is obtained on the constituents of S&P500 from the table *MSP500LIST*. This data is merged with data form the table *MSEnames*. The table contains information on the trading symbol (ticker) of a given company and the date-interval for when this symbol was in use. This leaves a dataset with information on when a given company was using which ticker symbols and allow for the compiling of a list of valid ticker symbols to be used in retrieving data from TAQ. In the process of merging the two tables data cleaning steps are also applied. The data is cleaned so that only the ticker symbols which has either NYSE, NASDAQ, AMEX or ARCA as its primary exchange is obtained and ticker symbols with a trading status different from active (TRDSTAT not A) are deleted. This is done to exclude ticker symbols for pink sheet stocks from the sample. The final dataset of constituents contains 829 different companies and 999 different ticker symbols.

4.4.2 Dividend Data

With the dataset of constituents and their appropriate ticker symbols obtained in the previous section the next step is to obtain information on the dividend announcements of these companies. This information is retrieved from the COMPUSTAT database. As this database uses a different unique key (GVKEY) than CRSP the link-table (*ccmxpf_linktable*) provided by WRDS is used to link the unique keys in the two databases. Afterwards the dividend announcement date is compared with the date-interval for the tick symbol thereby linking the dividend announcement with the ticker symbol used at the time of the announcement. The final step is to build an event day window around the announcement date. Around every announcement day a window of +/- 10 days is build. In doing so it is ensured that non-trading days such as weekends, public holidays and other days where the exchanges were closed are avoided. This is done using the CRSP database table *DSI* which holds information on trading days. With a dataset now consisting of various event windows and their ticker symbols the dataset is split into two depending on whether the change in dividend was negative or positive.

Next, the two datasets are filtered by three criteria; (i) a dataset only containing observations where the dividend announcement date is more than +/- 10 days away from the earnings announcement date and other dates in the dividend process (referred to as earnings adjusted), (ii) a dataset where the absolute change in dividend is greater than 20% and (iii) a dataset where the absolute change in dividend is greater than 50%. This results in eight different datasets. One with positive dividend changes and one with negative changes for every filtering method. So for every positive or negative announcement there exists (i) a raw dataset which is not used because dividend announcements and earnings announcements cannot be separated, (ii) a dataset referred to as earnings adjusted because all the observations where the earnings announcement date is within a range of +/- 10 days of the dividend announcement is removed (iii) a dataset filtered for earnings announcements but only changes in dividend above 20% is included and lastly (iv) where only change above 50% is include (again filtered for earnings announcements). The datasets will differ slightly w.r.t the number of event windows included as the number of announcement dates depend on filtration method as well as whether it is related to positive or negative dividend changes. This will affect the estimation of the non-announcement beta as it is represented by the number of observations outside the event window. An overview of the datasets including how many dividend announcement dates they have for the different types of filtering used is presented in table 4.1 below.

Table 4.1: Number of Dividend Announcement Dates

	Positive Change	Negative Change
Raw - No Adj.	3798	748
Earnings Adj.	903	150
Div Change > 20%	252	135
Div Change > 50%	91	54

The table shows the number of dividend announcement dates in the different datasets categorized by the way the dataset is filtered.

In general there are more announcement dates that report a positive change in dividend than a negative change. Also a lot of the dividend announcements happen at the same time as earnings announcements and filtering these out leaves a sample with roughly one fifth of the original dates.

The number of unique ticker symbols in the eight different datasets are displayed in table 4.2 below.

Table 4.2: Number of Unique Ticker Symbols

	Positive Change	Negative Change
Raw - No Adj.	541	380
Earnings Adj.	228	119
Div Change > 20%	150	111
Div Change > 50%	81	52

The table shows the number of unique ticker symbols in the different datasets categorized by the way the dataset is filtered.

From table 4.2 it is clear that for the dataset with no filters every ticker in the sample, on average, have several dividend announcement dates, but as a more restrictive adjustment filters are applied only a few ticker symbols, on average, have more than one dividend announcement date. As the regression model averages over all the announcement dates this should not pose a problem unless one company is responsible for a large percentage of the announcements which, judging from table 4.5 below, is not the case.

The approach above is not based on expectations as the authors do not have access to the Institutional Brokers' Estimate System (I/B/E/S) database and thus do not have access to the dividend expectations of analysts. Instead a model where it is assumed that the expected dividend is equal to the dividend paid out in the previous period is used. An unexpected dividend change is therefore classified as one where the change in dividend from period t-1 to t is larger than 20% in absolute value. In doing so it is assumed that the market has not expected the change in dividend and hence the change in dividend is used as a proxy for changes in market expectations w.r.t dividend.

4.4.3 TAQ Data

Having compiled eight datasets in total with information on the ticker symbols and event-days the next step is to retrieve data on transaction prices from the TAQ database. In doing so one must make sure that the data obtained from the TAQ database is cleaned using the above mentioned filters. For all the days from Jan. 1st 2000 to Dec. 31st 2012 data is obtaining on the

transaction price, time, and date of all the ticker symbols in the dataset. For every observation (transaction) it is checked if it complies with the filters F1-F5. Afterwords if having more than one observation per time-stamp F6 is applied and the average price of the transactions is calculated. After this is done the data is sampled at intervals of either 1 or 15 minutes using the previous tick method. The base method is to sample every 15 minutes adjusting for earnings announcements and dividend changes below 20%.
An excerpt of what the data looks like in the SAS dataset before being exported to Matlab is presented in table 4.3 below.

Table 4.3: Excerpt of Data Sampled Every 15 Minutes

Symbol	Date	Time	rTime	Price	Day
...	...	...	...	...	...
MSFT	20040702	15.15.00	15.14.56	28.541	.
MSFT	20040702	15.30.00	15.29.58	28.54	.
MSFT	20040706	10.00.00	09.59.59	28.1805	-10
MSFT	20040706	10.15.00	10.14.58	28.2	-10
...	...	...	...	...	...
MSFT	20040707	10.00.00	09.59.58	28.005	-9
MSFT	20040707	10.15.00	10.14.59	28.06	-9
MSFT	20040707	10.30.00	10.29.59	28.016125	-9

The table shows an excerpt of one of the SAS datasets sampled every 15 minute.

One challenge related to the use of the TAQ database is the problems that arise due to the sheer size of the data which needed to be extracted and processed. An example of this is the time it took retrieving the data from WRDS. This ranged from 4 hours to 2 days depending on sampling frequency and in total extracting data took a combined 2 weeks. Further considerable time had to be devoted to optimising the SAS code in order to keep computation time down. An important step in this was to optimise the SAS datasteps as much as possible by using where-statements and do-loops instead of if/else-statements as well as designing if/else-statements to be more efficient when their use could not be avoided[13]. As a side-effect of sampling the data in 1 and 15 minute intervals some of the problems associated with data size are mitigated since sampling reduces the amount of data employed. After retrieval of the data from TAQ, to

[13]This is among other things achieved by constructing the logic of the control flow so it takes into account the result of previous if/else statements.

make the preceding calculations as easy and fast as possible every, every ticker symbol and its corresponding data was exported to its own file and processed individually in Matlab. Next, the process of calculating daily realised beta estimates in Matlab will be described.

4.5 Computation in Matlab

After having retrieved the data from WRDS using SAS it is exported to .csv format as Matlab cannot read SAS datasets. Further because the amount of data is too large it cannot just be exported to a single flat .csv file and then import it into Matlab as this would take up too much memory. One important difference between Matlab and SAS is that Matlab reads all data into memory and thus cannot handle large datasets the size of the one used here. Having every ticker symbol in its own .csv file allows for iterations over every file importing only one file/ticker at a time. The advantage of this is that it is computationally easier to handle. The disadvantage is that more resources have to be spend on importing the data.

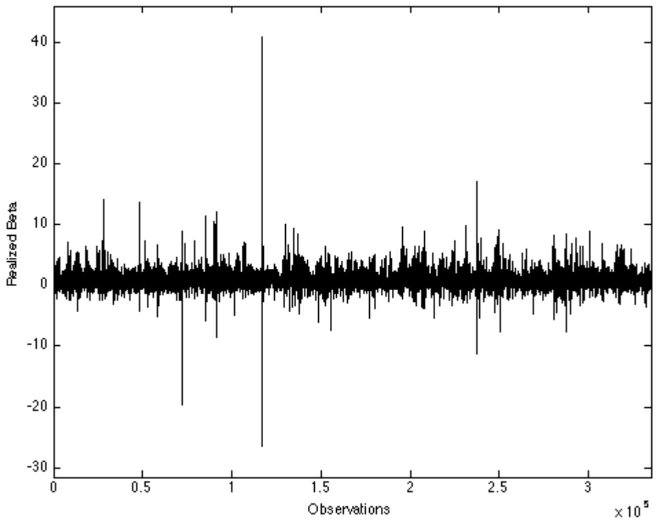
Having imported the relevant ticker into Matlab the program iterates over all the dates in the dataset (all trading days between 2000-2012). For every date (trading day) a intra-day return is calculated for every timestamp which of course varies with sampling frequency. These are used to obtain a realised variance and covariance estimate for the given day which is then used to find the realised beta of that day. After having calculated realised betas for all ticker symbols the regression specified in eq. (2.1) is run.
The procedure mentioned above is repeated for data with different sampling frequency. That is, the procedure above is followed first for data sampled at 15 minutes, then for 1 minute. Furthermore this is also repeated for the different estimators mentioned in chapter 3.3 only changing the way RV and RCov are estimated.

The time it takes to compute the different measures increase with the number of observations. When sampling at higher frequencies more observations are used and thus when moving from a sampling frequency of 15 minutes to 1 minute computation time increases. The same is true when moving from filtering for dividend announcements above 50% to no filter.
One of the functions that take up a lot of time in Matlab is the conversion of time and date to a format Matlab can handle. Also the RK estimator is the most time consuming measure to estimate of all the different measures due to the many estimations involved of not only the final IV estimate but also the IQ, the bandwidth (H), and the noise (ω).

4.6 Descriptive Statistics

In the following descriptive statistics is presented on the beta estimates. First beta estimates are plotted in order to inspect them visually to capture potential outliers which could be due to data errors.

Figure 4.1: Plot of Realised Betas



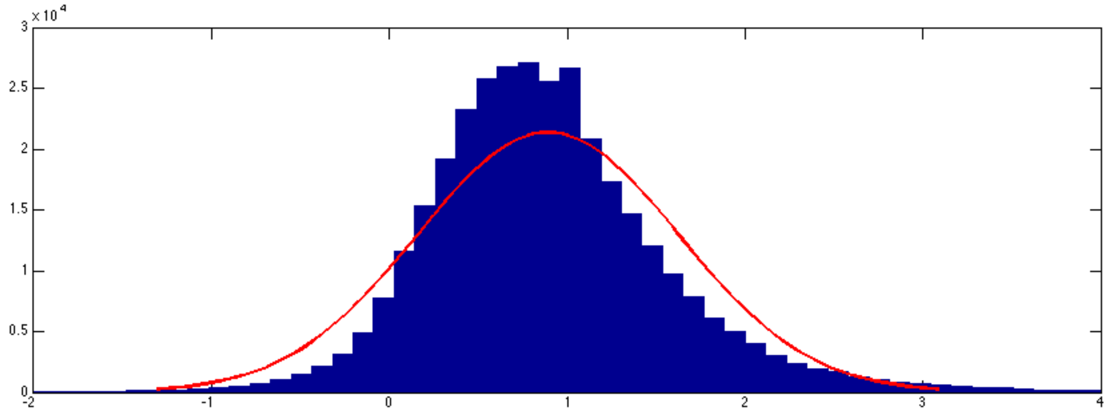
The figure shows a plot of the Realised Beta estimates for all ticker symbols sampled at a 15 minute intra-day interval.

From figure 4.1 above it can be seen that the RB estimates of firms are centered around zero and mainly lay in the interval [-5,5] but also that there are some larger estimates that in magnitude exceed 10 (in absolute value). The maximum beta is 40.9 and occurs on 29-12-2000 and is related to ticker FTR. The large magnitude of the beta estimate is because the covariance estimate for this day is relatively large. The minimum beta estimate is -26.53 and occurs on 08-12-2000 for the same ticker and again it is the covariance estimate that is large relative to the variance estimate. Upon checking the data it is found that this is again due to low trading activity.

As it is evident from figure 4.1 above there are a few excessively large beta estimates. Regressions have been run without them and this did not change the result. Also it has been checked if the largest betas are recorded on or close to an announcement date and this was not the case so they are assumed not to have abnormal influence the results. Overall, the RB values

have expected values given that daily beta estimates have previously been found to vary on a daily basis and with the knowledge that the outlier betas due not have significant individual influence the estimates appear structured enough for further analysis.
Next a histogram is plotted of the realised beta estimates to graphically investigate their distribution.

Figure 4.2: Histogram of Realised Betas Estimates



The figure shows a histogram of the Realised Beta estimates.

As can be seen from figure 4.2 above the distribution of the realised beta estimates are not exactly normal but exhibit leptokurtic features such as larger kurtosis and fatter tails. Figure 4.2 further helps confirm what has just been described above. Namely that the beta estimates fall within a reasonable interval - as seen in the figure almost all observations are in the interval [-1,3]. Having a visual view of the RB estimates provides good insight into the behaviour of the betas but for more precision table 4.4 displays some descriptive statistics about the distribution.

Table 4.4: Distribution of Beta Estimates

Median	Mean	Std.	5^{th} Quantile	95^{th} Quantile
0.8268	0.8923	0.7329	-0.0636	2.1048

The table displays descriptive statistics for the distribution of the realised beta estimates.

From table 4.4 it can be seen that the median of the realised beta estimate is roughly around 0.8 with a standard deviation around 0.7. Moreover, 95% of the beta estimates are below 2.1 and only 5% are below -0.06. Thus, 90% of the observed betas lie in the interval [-0.6,2.1] which is a reasonable interval for a beta estimate across a wide index where it would be expected that most firms have a beta value within an interval which does not react too sharply to market changes (such as with a value of e.g. 5). The standard deviation of the realised beta values is quite high relative to the mean value indicating that there might be a large amount of noise in the betas affecting the results.

Table 4.5: Top 3 Tickers with the Most Dividend Announcement

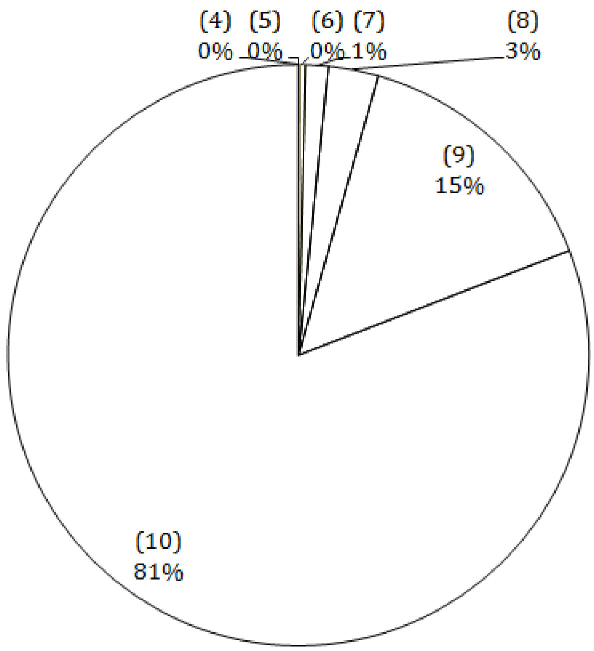
	Positive		Negative	
	Ticker	# of Announcements	Ticker	# of Announcements
Raw - No Adj.	AMB	45	AMB	43
	MEE	40	MEE	40
	MCHP	35	MCO	22
Earnings Adj.	FAST	16	FAST	4
	MO	13	PBCT	3
	PG	13	EXC	3
Div Change > 20%	HRS	7	FAST	4
	FAST	6	PBCT	3
	LLTC	5	AA	2
Div Change > 50%	FAST	3	CMS	2
	DCN	2	SNV	2
	LMT	2	WY	2

The table displays the three ticker symbols with the most dividend announcements dates in the different filtering categories along with the number of announcement dates for each ticker symbol.

Due to the way the panel data regression in eq. 2.1 is constructed it is important to make sure that every firm does not have too many announcements compared to the number of firms in the sample[14] as this can cause problems with the OLS standard errors (Wooldridge, 2003). From table 4.5 it is evident that specific firms only have a large amount of announcements in the raw dataset before any filtering has taken place. Table 4.5 also shows that no single firm dominates and that no ticker has a large number of announcement dates compared to the number of ticker symbols.

[14] Further it is important that not too many firms announce dividend on the same day. This is not the case as displayed by table A.1 in the Appendix.

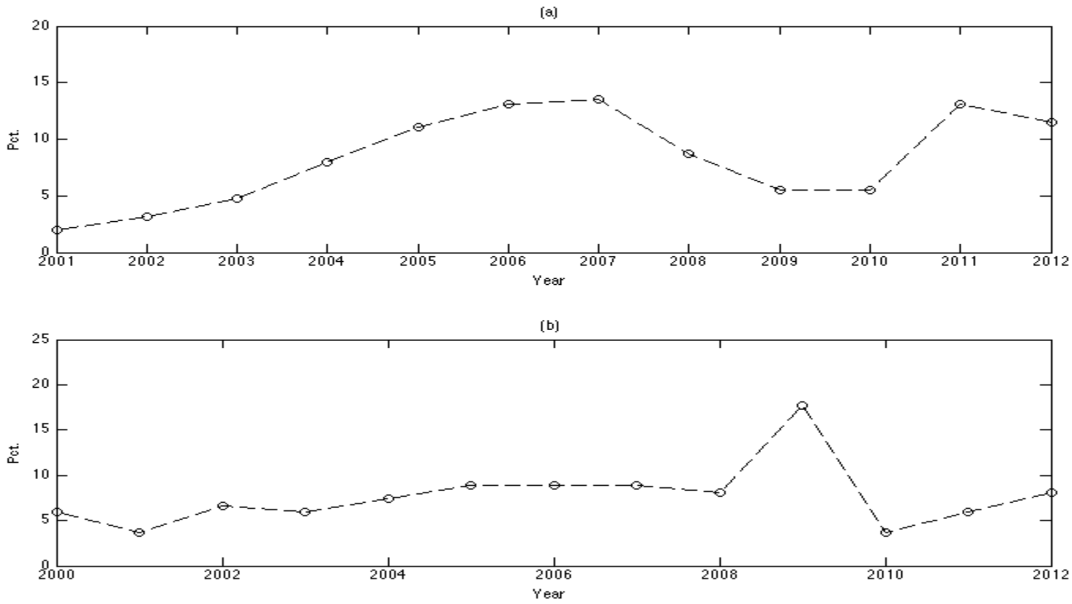
Figure 4.3: Overview of Market Cap. of Firms



The figure shows a pie chart of the distribution of the firms in the sample w.r.t market capitalisation. The index is obtained from CRSP and it runs from 1 to 10 with 10 indicating the largest market cap.

Figure 4.3 gives an overview of how the firms in the dataset are distributed in terms of market capitalisation when divided into 10 categories with 1 being the firms with the lowest market cap and 10 being the highest. This is a categorisation constructed by CRSP and aide in telling the sampled firms apart. From the figure it is evident that most of the firms in the sample are part of the category constituting the largest firms in terms of market cap. This is to be expected since S&P500 constituents are used and these firms have a considerable size bias. Actually there are no firms in the lowest categories of 1 to 4. The ability to generalise is naturally affected by this large cap bias and one must be aware of this when generalising since the results may not be representative of smaller firms. Newly listed firms with a very low market capitalisation will for example not be included even though such firms may portray a different general characteristic in terms of dividend payments and beta values. Due to the bias, generalisation of the results necessitates an assumption that investors will treat dividend payments of all firms equally such that any systematic effects found in this thesis also goes for firms with a smaller cap size.

Figure 4.4: Yearly Distribution of Dividend Announcement Dates



The figure shows the distribution of dividend announcement dates into yearly buckets measured as pct. of total announcement dates. Panel (a) is for positive dividend announcements and panel (b) for negative dividend announcements.

From figure 4.4 it can be seen that right after the height of the global financial crisis (2009) there is a spike in negative dividend announcements while the number of positive dividend announcements fall during the crisis and until 2011. It can also be deduced that some years have more observations then others. For instance the year 2007 contains around 14% of all positive dividend announcements whereas only about 6% of the positive dividend announcements happened in 2000. To correct for this the yearly fixed effect dummies are included in the regression specification so this distribution of announcement dates should not have an effect on the results.

Chapter 5

Results & Robustness Tests

In the following chapter results from the previously defined regression model using realised (co)variance for estimating the realised beta will be presented and discussed. A further analysis of the results in plenum also considering the underlying theory and robustness tests will follow. The empirical estimation is based on a 15 minute sampling interval, to balance receiving results absent market microstructure noise while at the same time obtaining a sufficient amount of intra-day observations. Regressions will be run on data using a definition of a dividend change as one where the change is >20%. The effect of this filtering schemes will be challenged further in the robustness section.

There is both a regression focusing on announcements containing dividend increases and one focusing on dividend decreases, thus each regression and robustness test will entail two separate results which will be handled individually and analysed together at a later stage. It is general for the following regressions results that they are checked for intraday seasonality caused by overnight prices and overlapping earnings announcements.

5.1 Results

First it is investigated how a dividend announcement conveying an unexpected reduction in the dividend affects the daily realised beta estimates whereafter the same situation with dividend increases will be handled.

5.1.1 Dividend Decrease

Table 5.1 presents estimated realised beta changes for every day within the event window, where event day 0 is the dividend announcement day. The $\triangle\beta$ column shows the estimated deviation in the value of beta from the average non-announcement beta on the specific day. Standard errors are reported in parentheses below the parameter estimates. Along with these figures the t-statistic and p-value are provided. An asterisk indicates that the result is significantly different from zero at the 5% p-value level while two asterisks indicate significance at the 1% level. The yearly fixed effects are portrayed below the event window estimates in the second part of table 5.1. This set-up will be constant throughout the results section, but for the robustness section some columns will be specified in the appendix as they become trivial when repeated across different estimations.

The results reported in table 5.1 show that event days -6 and +1 are significantly different from zero at the 5% level while event day 0, or the announcement day, is significantly different from zero at the 1% level with a deviation from the non-announcement beta of 0.2094. This result is interesting because it behaves according to the expectation of the Information Content of Dividends Hypothesis. Why beta increases on day +1 by a magnitude of 0.15824 is not as clear since an efficient market is expected to integrate new information into the stock price immediately. The results therefore indicate that some information is first integrated the next day. A similar effect is found by Dielman and Oppenheimer (1984). The interpretation of the significant increase in the beta value on day -6 is not directly explainable by the expectation of the Information Content of Dividends Hypothesis and may have numerous interpretations. Robustness tests will be used to analyse if this unexpected increase occurs persistently across different filtering schemes and regression specifications. The adjusted R^2 ($\bar{R}^2$) for the regression is 0.10 and the independent variables therefore explains a tenth of the variation in the dependent variable. This may be considered relatively low and implies that other factors not included in the regression model might explain the variation in beta. Noise may also play a part due to the variability of realised beta estimates as found in (Andersen et al., 2006). What is important to note is that it is not the purpose of the regression to explain as much of the realised beta as possible and a high R^2 is therefore not a prerequisite of drawing conclusions from the regression. It is reasonable to believe that other factors may influence the RB than what is included in the regression and that this regression should explain the entire variation in RB is unlikely given the set-up. Nonetheless the regression however still has explanatory power in its current form by explaining part of the variation in the RB.
It should further be noted that the values of the standard errors[1] are all very similar across the event window which is due to the large sample leading to very stable standard deviations.

[1]The standard error is defined as $\frac{\sigma}{\sqrt{n}}$ where σ is the sample standard deviation and n is the amount of observations

Table 5.1: Estimated Beta change following a dividend decrease using fifteen minute sampling

Estimated beta change							
Day	$\triangle\beta$	t-stat	p-value	Day	$\triangle\beta$	t-stat	p-value
-10	0.0774740 (0.0598595)	1.294	0.196	1	0.1303380* (0.0598596)	2.177	0.029
-9	0.0198422 (0.0598594)	0.331	0.740	2	0.0214917 (0.0598596)	0.359	0.720
-8	0.0380054 (0.0598594)	0.635	0.525	3	-0.024357 (0.0598596)	-0.407	0.684
-7	0.0145629 (0.0598594)	0.243	0.808	4	-0.021787 (0.0598593)	-0.364	0.716
-6	0.1378966* (0.0598595)	2.304	0.021	5	-0.014155 (0.0598592)	-0.236	0.813
-5	0.0151402 (0.0598595)	0.253	0.800	6	0.0970294 (0.0598592)	1.621	0.105
-4	0.0948967 (0.0598595)	1.585	0.113	7	-0.021930 (0.0598592)	-0.366	0.714
-3	0.0598427 (0.0598595)	1.000	0.317	8	0.0222185 (0.0598595)	0.371	0.711
-2	0.0001121 (0.0598595)	0.002	0.999	9	-0.073851 (0.0598595)	-1.234	0.217
-1	0.0568198 (0.0598595)	0.949	0.343	10	-0.031251 (0.0598595)	-0.522	0.602
0	0.2093883** (0.0594208)	3.524	0.000				
Yearly Fixed Effects							
Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.3699492** (0.0042822)	86.391	0	2007	0.9967591** (0.0042913)	232.270	0
2001	0.5454968** (0.0042849)	127.304	0	2008	1.0400690** (0.0043058)	241.546	0
2002	0.7082280** (0.0042436)	166.893	0	2009	1.2019884** (0.0043599)	275.691	0
2003	0.7879419** (0.0042265)	186.426	0	2010	1.1231989** (0.0043896)	255.873	0
2004	0.8300294** (0.0042236)	196.521	0	2011	1.0796012** (0.0044186)	244.331	0
2005	0.9264399** (0.0042352)	218.747	0	2012	1.0656330** (0.0045593)	233.727	0
2006	0.9810170** (0.0042700)	229.744	0				

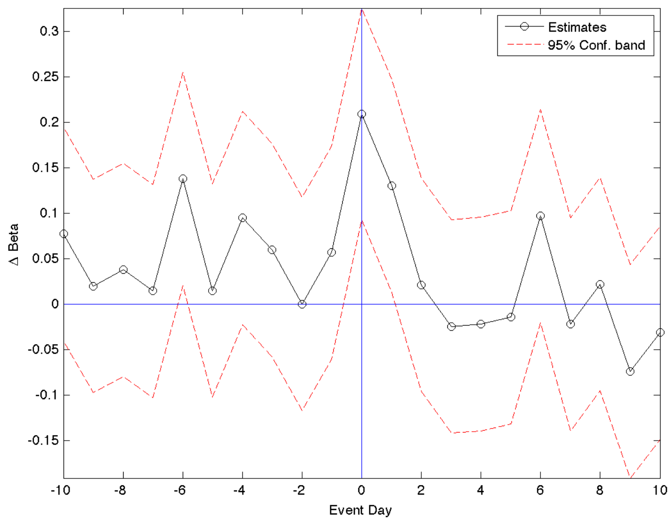
This table presents the estimated change in β values within the event window around quarterly dividend announcements and yearly fixed effects betas. An * represent values which are significant at the 5% p-value level and ** represent significance at the 1% level. Numbers in parentheses are the standard errors of the estimations. $\bar{R}^2$ is 0.10.

When divided by the square root of the 300.000+ observations, the differences are often first observed around the ninth decimal, which has been rounded off in the representation in the table.

The yearly fixed effects reported in the lower part of table 5.1 are all highly significant at a level where Matlab returns a p-value of 0% and are thus significant far beyond the 1% level due to the very large t-statistics and high level of degrees of freedom. A quick view across the development of the years demonstrate that the fixed effects are increasing in value up towards the "crisis years" of 2008 to 2010 whereafter it starts to fall in 2011. Intuitively this seems reasonable due to the increased market fluctuations in this period. Beta changes in these years will therefore be adjusted more due to yearly effects than other years with lower yearly fixed effects.

Figure 5.1 depicts the estimated changes in beta within the event window including 95% confidence interval bounds. The confidence interval is relatively large making it clear that there is

Figure 5.1: Estimated Changes in Beta around Dividend Decrease



Presents the changes in beta reported in table 5.1 where the event day is 0. The point estimates are marked by a solid line and the lower and upper bound of the 95% confidence interval is depicted by a dashed line.

still some level of uncertainty regarding the size of the changes in betas but for the significant values both the upper and lower bounds are positive at the 95% level as shown in the table above. The visual representation in figure 5.1 shows that the remaining event window days vary around zero, being either slightly positive or negative. No pattern can be observed in the insignificant value which is also to be expected as all days except the announcement date should not represent a systematic effect across the sample. If other days within the event window are systematically significant it raises questions on whether the significant result on the announcement day is actually caused by the dividend announcement. The significant values on days around the announcement date therefore calls for further analysis[2].

5.1.2 Dividend increases

The regression concerned with dividend increases is based on a sample that holds a total 252 dividend announcement days belonging to 150 different tickers. The sample is therefore slightly large than the one for dividend decreases. The results of the regression are presented in table 5.2. Increases in beta are found to be significant on event day -3 (0.0971), +6 (0.1243), and +10 (0.1494), where the former is significant at the 5% level and the latter two at the 1% level. The dividend announcement day itself is not significantly different from zero. There is thus no indication that the hypothesised relationship of a beta decrease after a dividend increase is present on the dividend announcement day.

The significant increases observed on day -3, +6, and +10 in the event window are unexpected as no systematic effects should be present on any other day than the announcement day. The fact that two of the event days are highly significant at the 1% give further concerns regarding the Interpretability of the regression results.

As it was also the case for dividend decreases the yearly fixed effects are again all highly significant and closely resemble those of the regression above which is natural as the difference between the two samples in estimating the fixed effects is quite small. The fixed effects therefore also imply that there is an adjustment to beta values for being in a specific period .The $\bar{R}^2$ is rather low at 0.05 and the regression model therefore only explain a limited amount of the variation of the realised beta. As with the regression above this makes intuitive sense as the regression model applied only contains a stringent set of factors. There are therefore adequate room for other factors to explain the dependent variable and the results should not be disregarded due to this as they still have explanatory power of the RB.

[2]For details on this see section 5.2

Table 5.2: Estimated Beta change following a dividend increase using fifteen minute sampling

Estimated beta change							
Event Day	$\triangle\beta$	t-stat	p-value	Event Day	$\triangle\beta$	t-stat	p-value
-10	0.0329323	0.711	0.477	1	0.0170906	0.369	0.712
	(0.0463250)				(0.0463250)		
-9	0.0378840	0.818	0.413	2	0.0576842	1.245	0.213
	(0.0463250)				(0.0463250)		
-8	-0.006900	-0.149	0.882	3	0.0566040	1.219	0.223
	(0.0464172)				(0.0464172)		
-7	0.0410649	0.885	0.376	4	0.0007613	0.016	0.987
	(0.0464172)				(0.0464172)		
-6	0.0657535	1.419	0.156	5	0.0341688	0.736	0.462
	(0.0463251)				(0.0464172)		
-5	0.0220977	0.477	0.633	6	0.1242486**	2.682	0.007
	(0.0463251)				(0.0463250)		
-4	0.0340386	0.735	0.462	7	0.0103923	0.224	0.822
	(0.0463251)				(0.0463250)		
-3	0.0971774*	2.094	0.036	8	0.0400899	0.864	0.388
	(0.0464172)				(0.0464172)		
-2	0.0374288	0.806	0.420	9	0.0840754	1.811	0.070
	(0.0464172)				(0.0464172)		
-1	0.0781639	1.684	0.092	10	0.1494279**	3.219	0.001
	(0.0464172)				(0.0464172)		
0	0.0700118	1.579	0.114				
	(0.0443441)						

Yearly Fixed Effects							
Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.4718751**	120.16	0	2007	0.9610756**	245.85	0
	(0.0039271)				(0.0039092)		
2001	0.6495330**	166.99	0	2008	1.0049088**	253.48	0
	(0.0038897)				(0.0039643)		
2002	0.7751663**	201.78	0	2009	1.1111102**	277.08	0
	(0.0038415)				(0.0040100)		
2003	0.8319089**	217.20	0	2010	1.0533154**	263.60	0
	(0.0038301)				(0.0039959)		
2004	0.8770291**	228.63	0	2011	1.0095515**	251.55	0
	(0.0038359)				(0.0040133)		
2005	0.9364410**	243.87	0	2012	0.9827704**	241.04	0
	(0.0038399)				(0.0040771)		
2006	1.0007035**	259.40	0				
	(0.0038577)						

This table presents the estimated change in β values within the event window around quarterly dividend announcements and yearly fixed effects betas. Estimates of dividend increases of at least 20% are included. An * represent values which are significant at the 5% p-value level and ** represent significance at the 1% level. Numbers in brackets are the standard errors of the estimations. $\bar{R}^2$ is 0.05.

5.1.3 Summary of Results

The empirical results presented above provide both answers and questions as no completely clear picture emerges. Referring to the regression results of a dividend decrease support is found for the Information Content of Dividends Hypothesis as beta on the announcement day increases significantly. Additional days within the event window are also significant which is not directly explainable by the hypothesis. The fact that day +1 is significant may be explainable if it is assumed that information is not traded into the asset immediately, such as if the asset is very thinly traded. The additional significance of event day -6 is peculiar because it suggests that an event, which has not been controlled for, happens systematically 6 days prior to a dividend announcement. Overall, the dividend announcement day results provide some evidence in favour of the tested hypothesis that outsiders will re-evaluate the systematic risk profile of a stock immediately when a dividend decrease occurs. More tests are however required before further analysis can be performed.

The regression results for a dividend increase portray a very different nature than those related to a negative change. Referring to the announcement day, this is found to be insignificantly different from zero and the hypothesised relationship is therefore not supported as a fall in the beta value is expects but the opposite occurs. The results therefore do not indicate any market reaction in the wake of a dividend change.
Both regressions present relatively low values of the adjusted $\bar{R}^2$ which is as such not a problem since the purpose is not to explain as much variation as possible in the realised beta but just a component of the variation around the dividend announcement day.

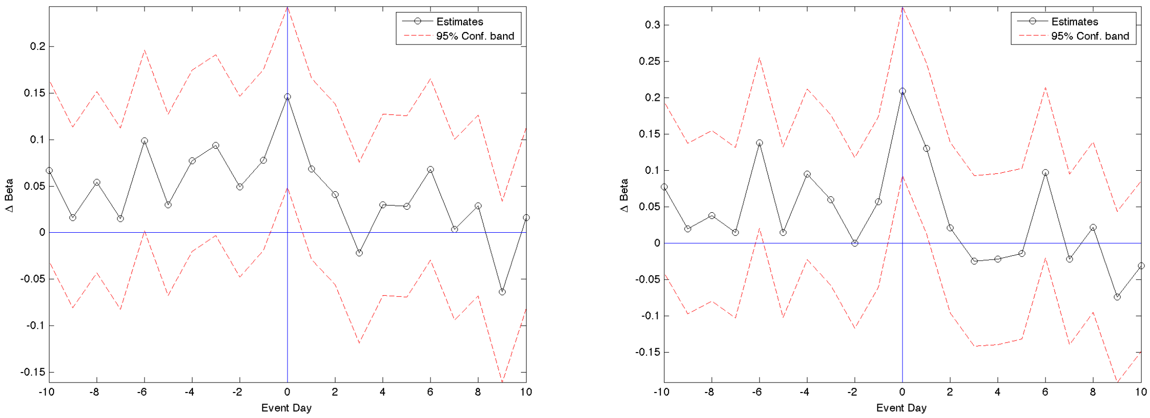
All together there is some support for the Information Content of Dividends Hypothesis but also findings which contradict it. Additional tests are necessary to investigate whether the results are caused by noise, a wrong specification of the regression model or the choice of (co)variance estimator.

5.2 Robustness Tests

In the following results for several different robustness tests are presented. Three different estimators are tested, namely the Realised Kernel Beta, the Hayashi-Yoshida estimator and the Bi-power Beta estimator. Further it is tested for serial correlation among the realised beta estimates, order bias in betas, and the arbitrary dividend size is challenged.

Figure 5.2: Plot of Estimated Changes in Beta RK vs. RV

(a) RK (b) RV



The figure shows a plot of the estimated change in beta for a dividend decrease. Result in panel (a) is using the RK estimator and panel (b) is using the regular RV estimator.

5.2.1 Realised Kernel Beta

Using RK and RMK as substitutes for the RV and RCov, a market microstructure noise robust beta is estimated. As with the base scenario dividend announcements are only included if the change in dividend is >20%. What differs is that a sampling frequency of 1 minute is applied to assure that the results will be plagued with market microstructure noise since the estimator is robust to this and works less optimally when no noise is present. Since the RK estimator is used with a different frequency than the base case[3] there will be some discrepancy between the results. As the purpose is only to control if the announcement day portray the same characteristic and not if one estimator is superior to the other it will still serve the purpose well. It can hereby be confirmed if the nature of the results at the 15 sampling interval are significantly affected by noise.

5.2.1.1 Dividend Decrease

Using data sampled at the 1 minute frequency it is found that the dividend announcement day experience a significant increase in the beta value of 0.1459 with a p-value far below the 1% level as presented in table 5.3 in column RK β and visualised in figure 5.2 panel(a). Event day -6 is as before significant at the 5% level with an estimated increase in beta of 0.0989 while day +1 no longer exhibit a change statistically different from zero. The results found

[3]But with the same overall dataset.

using the RKB resemble those found using the regular RV estimator but the insignificance of day +1 indicates that the result seen on this day in the base regression might be due to noise or asynchronicity. Hence the RV estimator might be plagued by some microstructure issues despite the low sampling frequency. With estimated changes in beta being significant on the announcement day this supports the results found using the lower frequency as the effect on day 0 has not been caused by noise. The RV estimator at the 15 minute frequency thus seems to be mostly unaffected by market microstructure noise since the RK estimator is robust against this and show comparable results.

5.2.1.2 Dividend Increase

With respect to regression results for dividend increase, beta changes, when estimated using the RK estimator, vary around zero for all days across the entire event window and non come close to being significant even at the 10% level as represented in table 5.4. The insignificant value found on the event day is therefore not due to a downward bias caused by market microstructure noise.
The RK estimator raise questions regarding the economic importance of the significant beta changes found by the RV estimator on the surrounding event days -6, -3, and +10 since they do not show up using the RK estimator. As mentioned above, this conclusion should be drawn with caution as it is based on a different frequency and more robustness tests will help establish if any of these changes are economically relevant.

Overall, the results found using the RK estimator are mostly equivalent to the results of the base case regression as the announcement day is insignificant. Moreover, the results for the positive dividend change casts doubt on the unexpected significant increases on multiple event window days around the announcement in the base regression. Some noise may have influenced the results but not in a way which have had influence on the economic interpretation on the announcement day. The announcement day results for the RV estimator at the 15 minute frequency are therefore not extensively damaged by market microstructure noise and the results can be used for further analysis. Additional robustness tests are however still in order to examine other aspects of the results before a complete conclusion can be drawn.

5.2.2 Effect of Dividend Cut-off Point

The dividend cut-off point of 20% is an arbitrarily chosen level and is a trade-off between the number of dividend announcement days in the sample and the size of a dividend change. To challenge the cut-off point a decreased tolerance has been introduced to the data such that only dividend changes over or equal to 50% are considered.

5.2.2.1 Dividend Decrease

Column "Div. Size" in table 5.3 show the results from the regression based on dividend decreases. Based on a sample size of 152,992 observations and 54 dividend announcements, the announcement day show a significant increase at the 5% level of 0.2102 while event day +9 show a significant decrease of -0.2221 at the 5% level. The event day is therefore still positively different from zero as expected by the Information Content of Dividends Hypothesis when conditions are tightened. At the same time the unexplainable significant event day -6 from the previous regression is now no longer significant indicating that it is not an economically relevant beta adjustment. The fact that event day +1 is no longer significant places doubt in whether the systematic risk of the stocks is still being integrated into the price the day after the announcement as discussed for the base regression results. The significant decrease appearing in the robustness regression at day +9 is unexpected and could be caused by the decrease in the number of event windows to "just" 54 allowing outliers or price jumps to become visible in the regression results. Further tests will determine if this result is more than just a fluke.

5.2.2.2 Dividend Increase

For dividend increases of at least 50% the regression is based on 248,095 observations and 91 announcement dates. Results are reported in column "Div. Size" in table 5.4. No days in the event window are significant at the 5% level and in general all dates hover closely around zero including the announcement day. The results are therefore much more static than the original regression where multiple event days were significantly positive. These unexpected increases therefore do not appear to be relevant for a further analysis. The insignificant results previously found for the positive dividend change are confirmed as there is no ground for concluding that the size of the dividend increase matters or that outsiders retrieve information from a dividend increase.

5.2.3 Bi-Power Beta

Rare jumps in stock prices can affect the volatility even at lower frequencies. They can hence also interfere with estimations at the 15 minute interval and hereby have subsequent effects on the beta results obtained with the RV and RCov estimators since there are not jump robust like the BPV and BPCV estimators.

5.2.3.1 Dividend Decrease

The result of a dividend decrease is shown in column "BP β" in table 5.3. The effect on the dividend announcement day is positive and significant at the 1% level with a beta increase of 0.3698 while no other days are significant at the 5% level. The formerly significant event day -6 is now only significant at the 10% level. The results indicate that a downward bias from jumps affects the results on the event day in the base case model since the estimated beta increase is now larger than before. Intuitively this seems reasonable as jumps on the announcement day may cause the stock price to fluctuate more relative to the market. The covariance between the stock and the market is hereby decreased (assuming that the jump is idiosyncratic to the stock) which effectively decrease the stock's beta estimate all else equal. As the previously unexpected results on event day -6 is no longer significant it appears that it has been biased upward due to jumps. It is therefore possible to explain all unanticipated changes around the announcement day following a dividend decrease while the Information Content of Dividends Hypothesis is still supported by the bi-power regression results.

5.2.3.2 Dividend Increase

The results of a dividend increase while controlling for jumps, are displayed in column "BP β" in table 5.4. The change in beta on the announcement day remain insignificantly different from zero. Event days +6 (0.1672) and +10 (0.1341) exhibit significant increases at the 1% and 5% level respectively which were also the situation for the base case regression. The formerly significant event day -3 is no longer significant and can therefore be explained by a bias due to jumps. Controlling for jumps therefore due not grant further support for the Information Content of Dividends Hypothesis - jumps have not caused the announcement day results to change significantly. Some of the noise from other event days has however been explained as jumps and provide more clarity to the surrounding event days which are expected to be insignificant.

Table 5.3: Robustness Tests: Dividend Decrease

	RK β		BP β		HY β		Serial Corr.		Div. Size		Order Bias	
Day	$\triangle\beta$	p-value	$\triangle\beta$	p-value	$\triangle\beta$	p-value	$\triangle\beta$	p-value	$\triangle\beta$	p-value	$\triangle\beta$	p-value
-10	0.0667	0.179	0.0995	0.241	0.1343*	0.020	0.0057	0.909	0.0333	0.747	0.1326**	0.002
-9	0.0164	0.741	0.0355	0.675	0.0449	0.438	-0.0567	0.262	0.0134	0.897	0.0168	0.702
-8	0.0541	0.276	0.0522	0.539	0.0538	0.353	-0.0310	0.539	0.0754	0.466	0.0218	0.618
-7	0.0151	0.760	-0.0190	0.823	0.0259	0.655	-0.0474	0.348	-0.0108	0.917	0.0292	0.505
-6	0.0989*	0.046	0.1559	0.066	0.1557**	0.007	0.0815	0.107	0.1264	0.222	0.0947*	0.031
-5	0.0300	0.546	0.0816	0.336	-0.0086	0.882	-0.0514	0.309	-0.1125	0.277	0.0480	0.273
-4	0.0774	0.119	0.0959	0.259	0.0592	0.307	0.0264	0.602	0.0620	0.550	0.0338	0.440
-3	0.0940	0.058	0.0527	0.535	0.0893	0.123	-0.0082	0.871	0.0291	0.779	0.0438	0.317
-2	0.0494	0.319	0.0510	0.548	0.0134	0.817	-0.0644	0.203	-0.1116	0.281	0.0113	0.797
-1	0.0780	0.116	0.1467	0.084	0.0798	0.168	0.0056	0.912	-0.0259	0.803	0.0368	0.400
0	0.1459**	0.003	0.3698**	0.000	0.1525**	0.007	0.1460**	0.004	0.2102*	0.041	0.1304**	0.003
1	0.0685	0.168	0.0504	0.553	0.0917	0.114	0.0525	0.299	0.1167	0.260	0.0656	0.134
2	0.0411	0.408	0.0821	0.333	-0.0149	0.797	-0.0595	0.239	0.0786	0.448	-0.0114	0.794
3	-0.0216	0.663	0.0580	0.494	-0.0287	0.620	-0.0948	0.061	-0.0402	0.698	-0.0173	0.693
4	0.0299	0.546	0.0306	0.718	-0.0147	0.800	-0.0788	0.119	-0.1111	0.283	-0.0376	0.390
5	0.0283	0.569	-0.0498	0.557	-0.0796	0.169	-0.0609	0.228	-0.1366	0.187	0.0070	0.872
6	0.0678	0.172	0.1378	0.104	0.0476	0.411	0.0496	0.326	0.1228	0.236	0.0195	0.656
7	0.0033	0.947	-0.0332	0.696	-0.0576	0.320	-0.0800	0.113	-0.0085	0.934	0.0170	0.698
8	0.0289	0.560	0.0439	0.605	0.0222	0.702	-0.0299	0.554	0.0336	0.746	0.0179	0.682
9	-0.0636	0.200	0.0104	0.903	-0.0270	0.641	-0.1231*	0.015	-0.2221*	0.032	-0.0155	0.722
10	0.0160	0.747	-0.0257	0.762	-0.0299	0.605	-0.0640	0.206	-0.0591	0.568	-0.0267	0.541

The table shows the estimated change in beta in the 21 day event window following a dividend decrease. RK β is estimated using the RK and RMK estimators and a sampling frequency of 1 minute. This is the only estimator using a sampling frequency of 1 minute. All other estimators use data sampled every 15 min. BP β is found using the BPV and BPCV estimators and HY β refers to betas found using the Hayashi-Yoshida estimator. Lag is when 125 beta lags are included in the regression and Order Bias is a regression which includes quantile dummies. All estimators use data where a dividend change has to be $\geq 20\%$ except for the results in column 5 where a restriction of a dividend change is set to be $\geq 50\%$. The adjusted R^2 is 0.14, 0.04, 0.09, 0.36, 0.13, 0.52 for RK, BP, HY, Serial. Corr, Div. Size and Order Bias respectively. Detailed results and figures can be found in appendix B and C.

Table 5.4: Robustness Tests: Dividend Increase

	RK β		BP β		HY β		Serial Corr.		Div. Size		Order Bias	
Day	$\triangle\beta$	p-value	$\triangle\beta$	p-value	$\triangle\beta$	p-value	$\triangle\beta$	p-value	$\triangle\beta$	p-value	$\triangle\beta$	p-value
-10	-0.0050	0.936	0.0980	0.106	0.0652	0.579	-0.0126	0.748	-0.0282	0.729	-0.0043	0.902
-9	-0.0582	0.356	0.0245	0.686	-0.0669	0.569	-0.0111	0.778	-0.0807	0.322	0.0323	0.352
-8	-0.1081	0.086	-0.0284	0.640	0.0195	0.869	-0.0496	0.208	-0.1244	0.127	-0.0228	0.512
-7	-0.0717	0.255	-0.0316	0.603	-0.0726	0.537	-0.0035	0.929	-0.0919	0.259	0.0059	0.865
-6	0.0130	0.836	0.0452	0.455	0.2108	0.073	0.0255	0.516	0.0345	0.672	-0.0151	0.662
-5	-0.0516	0.413	0.0287	0.636	0.1305	0.266	-0.0235	0.549	-0.0456	0.576	0.0011	0.974
-4	-0.0741	0.239	0.0708	0.242	0.1194	0.309	-0.0073	0.853	-0.0476	0.559	0.0467	0.179
-3	0.0336	0.594	0.0629	0.300	0.0035	0.977	0.0556	0.158	0.0485	0.552	0.0271	0.436
-2	-0.0646	0.305	-0.0044	0.942	-0.0749	0.524	-0.0083	0.833	-0.0888	0.276	-0.0061	0.861
-1	-0.0529	0.401	0.0419	0.490	0.0288	0.807	0.0386	0.327	0.0159	0.845	0.0152	0.661
0	0.0034	0.957	0.0650	0.225	0.1478	0.155	0.0533	0.157	0.0018	0.980	-0.0210	0.546
1	-0.0091	0.885	0.1153	0.057	0.0823	0.483	-0.0283	0.471	-0.0232	0.776	-0.0264	0.447
2	-0.0125	0.842	0.0262	0.666	-0.0827	0.481	0.0122	0.756	0.0480	0.556	0.0193	0.578
3	-0.0302	0.631	0.0449	0.460	0.1337	0.256	0.0085	0.829	-0.0150	0.854	0.0201	0.563
4	-0.0606	0.336	-0.0010	0.987	0.1641	0.163	-0.0434	0.271	-0.1027	0.207	0.0154	0.658
5	-0.0690	0.273	0.0517	0.394	-0.0329	0.779	-0.0058	0.883	-0.0717	0.379	0.0294	0.398
6	0.0048	0.939	0.16723**	0.006	0.0352	0.764	0.08355*	0.034	0.0326	0.689	0.0442	0.202
7	-0.0798	0.205	0.0134	0.825	0.0398	0.735	-0.0380	0.333	-0.1078	0.186	-0.0114	0.743
8	-0.0199	0.753	0.0421	0.488	0.24427*	0.038	-0.0027	0.944	-0.0459	0.573	0.0131	0.707
9	0.0313	0.620	0.0762	0.209	0.0099	0.933	0.0388	0.324	0.0246	0.762	0.0590	0.090
10	-0.0514	0.415	0.13412*	0.027	0.2046	0.082	0.10080*	0.010	0.0208	0.799	0.08860*	0.011

The table shows the estimated change in beta in the 21 day event window following a dividend increase. RK β is estimated using the RK and RMK estimators and a sampling frequency of 1 minute. This is the only estimator using a sampling frequency of 1 minute. All other estimators use data sampled every 15 min. BP β is found using the BPV and BPCV estimators and HY β refers to betas found using the Hayashi-Yoshida estimator. Serial Corr. is when 125 beta lags are included in the regression and Order Bias is a regression which includes quantile dummies. All estimators use data where a dividend change has to be $\geq 20\%$ except for the results in column 5 where a restriction of a dividend change is set to be $\geq 50\%$. The adjusted R^2 is 0.074, 0.02, 0.005, 0.32, 0.04, 0.47 for RK, BP, HY, Serial Corr., Div. Size and Order Bias respectively. Detailed results and figures can be found in appendix B and C.

5.2.4 Hayashi & Yoshida Estimator

To account for the potential bias in the covariance (the Epps effect) caused by non-synchronousness the estimator in Hayashi and Yoshida (2005) described above is applied.

5.2.4.1 Dividend Decrease

Column "HY β" in table 5.3 show that the change in beta on the announcement day is positive and significant at the 1% level with a value of 0.1525. Additionally day -10 (0.1343) and -6 (0.1557) are significant at the 5% and 1% level respectively. Non-synchronous price processes has therefore not biased the results in a way substantially altering findings of the announcement day. The results are therefore still in favour of the Information Content of Dividends Hypothesis, though the two additional significant event days are not explainable. To account for these, an overall assessment taking all robustness regressions into account is necessary regarding the economic relevance of the unexplainable and significant event days.

5.2.4.2 Dividend Increase

Referring to table 5.4 of positive dividend changes looking at the column $HY\beta$ it is seen that the announcement day exhibit no significant change in beta while day $+8$ is positive and significant at the 5% level. The insignificant announcement day result found in the base regression is therefore not due to a downward bias from non-synchronousness. The information content hypothesis thus still finds no support regarding positive changes in the dividend.

5.2.5 Serial Correlation Control

To ensure that the results are not due to serial correlation in the RB estimates themselves, a regression specification using lagged realised beta estimates will be applied to the base regression. Using the Schwarz Information Criteria it is found that the optimal number of lags is 125. This may seem like a lot but intuitively it makes sense that the beta values exhibit a large degree of serial correlation due to the expected relation to the market and this number of lags is therefore used.

5.2.5.1 Dividend Decrease

The results of a dividend decrease when lags are included are presented in column "Serial Corr." in table 5.3. The estimated beta change on the announcement day is positive with a value of 0.1588 and significant at the 1% level while day $+9$ is negative and significant at the 5% level with a value of -0.1231. Some change have therefore occurred regarding the surrounding days as day -6 is no longer significant when controlling for serial correlation yet day +9 now exhibit a decrease. The results reveal that the significant increase in beta on the announcement day is not due to serial correlation as the positive change on day 0 remains significant.

5.2.5.2 Dividend Increase

When including lags in the regression estimating the results of a dividend increase the change in beta on the announcement day remains insignificant with a p-value of 15.7% similar to the findings from the base regression. Day +6 and +10 are positive and significant at the 5% and 1% levels. The formerly significant day -3 from the base regression is no longer significant and it therefore seems like it can be explained by serial correlation. The fact that the announcement day is not significant in the base regression can therefore not be attributed to serial correlation biasing the findings and no evidence suggest that the market interprets the dividend increase as containing relevant information.

5.2.6 Order Bias Control

Carroll and Sears (1994) finds convincing evidence that significant beta changes around dividend announcements may be caused by order bias in the magnitude of beta values. Remarkably low and high betas are therefore controlled for. As shown in the Data Section, 90% of the beta values calculated are within a range from -0.06 to 2.1. These betas can be regarded as being in an anticipated range while the surrounding betas can, arbitrarily, be argued to be high or low.

5.2.6.1 Dividend Decrease

The dividend decrease regression, when controlling for order bias, shows a significant change in beta on the announcement at day the 1% level with a beta change of 0.1304. Day -10 and +6 also show changes in beta which are significant at the 1% and 5% level respectively. The size of the significant effect is lower than for the base regression which could imply that there has been an effect of the highest and lowest beta results. Any order bias present is however not the reason for the economic relevance of the results.

5.2.6.2 Dividend Increase

The regression looking at the effect of a dividend increase shows that day +10 exhibits a significant (at the 5% level) change in beta while no other days show significant changes in beta. The announcement day portray a negative change of -0.021 which is in accordance with the expectation but the result is highly insignificant. This result is however slightly interesting as it is the first regression where the announcement day result is in the expected direction according to the Information Content of Dividends Hypothesis. An order bias may therefore have had an effect on the regression but this is not enough to draw any further conclusions due to the high level of insignificance.

5.2.7 Summary of Robustness Results

Following a dividend decrease, the robustness tests provide significant estimates of beta changes ranging from 0.1304 to 0.3698 and as the only day in the event window the announcement day is consistently significant throughout all tests. These can all be regarded as being economically relevant due to the reasonable size and comparable to the base case regression which showed an increase of 0.2094. Along with this result, the other significant days in the event window have been explained by the different robustness tests and none are consistently significant across tests as is the case with the announcement day. The regressions for dividend decreases therefore support the Information Content of Dividends Hypothesis.

The regression concerned with changes in beta after a dividend increase differs substantially from the one concerned with a dividend decrease and from the expectations of the Information Content of Dividends Hypothesis. The announcement day is consistently insignificant and shows no sign of beta decreasing following a dividend increase which is also the case across the various robustness tests. The base regression show significant increases on some surrounding event days but depending on the exact model specification the robustness tests shows that none of these are constantly present across tests indicating that no beta changes happen within the event window. The adjustment of the beta seen after a dividend increase is therefore not in accordance with the expectation of the Information Content of Dividends Hypothesis.

Chapter 6

Analysis

Having tested the robustness of the results in terms of the subjective decisions involved, data quality, statistical issues, and estimation methods it is clear that the main results are robust. As the results of a dividend increase contra a decrease suggest conflicting conclusions regarding the Information Content of Dividends Hypothesis further discussion is in order. The following section will comment and perspectivise on the economic relevance of the findings, analyse the implications on existing literature, and discuss the results in a critical light.

6.1 Discussion

The findings of this thesis show that investors react sharply and immediately when information about an unexpected dividend decrease is released by re-evaluating the risk profile of the stock towards a higher level of systematic risk. The null hypothesis of no change is therefore rejected and support is found for H_1 and hence the Information Content of Dividends Hypothesis. The stocks having decreased their dividend will therefore be more affected by changes in the market ex-post than before the dividend decrease. At the same time there is no indication that the dividend level reverts back to its pre-announcement level within the following ten days and it hence seems that the event has lasting effect on the beta level. This conclusion is only partial as a longer time horizon is needed to estimate if this is the case long term.

The lack of a change in the beta level on days with unexpected dividend increases suggest that the market does not interpret a dividend increase as a signal of a change in the systematic risk profile of the company in question. The null hypothesis is thus not rejected and the Information Content of Dividends Hypothesis is not supported by these results due to the absence of evidence concerning the inverse relationship. The result is in line with the expectations of the Irrelevance of Dividends Hypothesis which does not predict any change. Too much cannot be drawn from this however, as the stringent assumptions of the irrelevance hypothesis are not fulfilled[1] such as perfect information.

Full support for the Information Content of Dividends Hypothesis requires consistently supportive results from both the regressions of dividend increases and decreases. As there is only found supporting evidence for one part of H_1 the hypothesis is not strictly supported nor refuted by the findings. At the offset, it may seem puzzling that two so similar regressions, using similar data, exhibit so different results but some qualitative explanations may provide reasoning for these findings. First off all, the missing data on analysts' dividend expectations hinder a perfect definition of when a dividend change is expected or unexpected. As discussed previously, since the dividend changes of relevance are only the unexpected changes, a downwards bias of the results caused by potential inclusion of expected dividend changes may have dampened the effects observed on the announcement day. Such potential downward bias can conceal a beta decrease on the announcement day.
Assuming that insiders do not always optimise the return of the outsiders, a possible explanation may be that the insiders sub-optimise for short term gains. This can be done by increasing the dividend level if the insider anticipates a favourable or desired market reaction. Hence, the investors may not react to dividend increases if it is believed that the management is merely trying to alter the risk perception of the stock short term to accommodate own desires.
The model and findings of Lintner (1956) may provide reasoning as well, if firms tend to have a long run dividend target and the market has information on this target, then positive dividend adjustments can be seen as the company working its way towards this target. Hence knowledge of the increase in dividend may already be incorporated into -and expected by the market. If outsiders believe that even increases strictly equal to or above 50% are still below the long run dividend target, no observed changes would be expected from the data applied[2]. The above mentioned arguments are mere possible explanations but it may also just be the non-existence of valuable information in the dividend change. For this further research is required which potentially could involve more research of the ex-post financial figures of the dividend changing firms as well as data on analysts expectations (or a better proxy for expectations than the one used here).

Referring to the previous literature within the sphere of dividend changes and beta reaction,

[1]In its purest form the irrelevance hypothesis is furthermore not directed at the inverse relationship of the dividend-beta relation which also limits the ability to draw stringent conclusions.

[2]One could have increased the required percentage dividend change even further but this would come at the cost of fewer announcement days and potentially damage the statistical inference of the results.

the findings of this thesis are to a large extent similar. There has in general been much support for beta increases following dividend decreases but more spacial support for beta decrease following a dividend increase. The findings in this thesis therefore exhibit similar characteristics as previous studies but adds the crucial ingredient of estimating the change *on* the announcement day. In this regard, the findings provide new knowledge because it controls for earnings announcements and other miscellaneous effects which may affect the beta value long term and pinpoints the effect on the announcement day by the use of high frequency data. Naturally, this has been more difficult in former studies where lower frequency betas over longer time horizons have been applied. The partial support for the hypothesis is therefore more informative than previous findings due to increased precision and following from this, it also casts doubt on the validity of those findings which exhibit a negative beta change following the dividend increase.

In the framework of the hypothesised dividend-beta relationship under asymmetric information a dividend decrease will have economic consequence for investors. As shown by Carter and Shawn-Schmidt (2008), systematic risk can be used as a link between dividend and expected return of a stock given that beta and expected return are positively related[3]. A dividend decrease is hence linked to an increase in expected return due to the increase in beta. Following this, the findings of this paper propose uneven implications for stockholders due to the partial support for the Information Content of Dividends Hypothesis. On one hand, investors must be aware of beta increases which can now be expected immediately following a dividend decrease while on the other hand a dividend increase does not require much consideration in terms of effect on expected return. The finding can have implications for investors' portfolio diversification as an adjustment of the systematic risk of an asset in the wake of a dividend decrease can affect the balance of a portfolio's composition. One, or multiple, beta increases can therefore make a portfolio more risky than desired by the investor as an average beta adjustment of 0.21 can be argued to be relatively high. The effect of course depends on the weight of the specific dividend decreasing stock in the portfolio and the absolute effect on the expected return which add some discrepancies to the exact effect. Nonetheless, investors must be aware of the effect that dividend decreases can have on the riskiness of a stock and reconsider if their portfolio is properly optimised in terms of the desired risk profile.
Opposite of a dividend decrease investors do not need to immediately reconsider the risk profile of their portfolios due to an unexpected dividend increase as there is no observable effect on the beta value.

[3] As is the case for models like the CAPM, the Fama French 3 factor model or APT models.

One thing is the effect that the unexpected dividend cause in the stock market, another is what underpins the dividend change in the first place. Following the prevalent understanding of the discussed relationship, the results found infer that firms decreasing their dividends will in the foreseeable future experience more volatility in their expected future cash flows. This will cause them to decrease the dividend to avoid financial complications, all else equal. The uncertainty in cash flows may e.g. be due to future projects where the cash inflow is less predictable than that of established projects or due to a more unpredictable market situation. Referring to the data used in this paper, the number of dividend decreases grew during the global financial crisis loosely indicating that general market uncertainty has trickered a wave of dividend decreases. The yearly fixed effects betas in the regressions also increase in this period which correspond to firms generally having more uncertainty during the financial crisis.
In accordance with the above, investors interpret a dividend decrease as the firms' financial situation becoming more affected by the general market fluctuations and the systematic risk factors hence come to play an increasingly important part of the volatility of the asset.
This will potentially lead to lower or higher cash flows depending on market circumstances and thereby require an increased expected return for investors to take on the increased risk. Whether the future cash flows actually exhibit increased variance after an unexpected dividend decrease is beyond the scope of this thesis due to its primary focus on the reaction of outsiders to dividend announcements. Controlling for actual financial performance changes underlying the change in risk/return perception requires an alternative long term post-dividend regression analysis with a focus on financial and accounting figures. The available literature related to post-dividend changes in financial performance is rather contradicting and it is therefore currently difficult to conclude anything further based on previous research.

When dividends are increased unexpectedly investors do not expect cash flows to become more stable and the systematic risk level of the firm to become lower. This finding could be due to the ability of insiders to affect the cost of capital by changing the dividend as argued by Carter and Shawn-Schmidt (2008). If insiders generally prefer a lower cost of capital they may be inclined to increase the dividend without proper economic cause. If outsiders are aware of this sub-optimisation behaviour they will naturally not react to such a dividend increase due to the uncertainty of interpretation. This is of course assuming that insiders do not always have the best interest of investors at heart but may place personal gains higher. The assumption of no sub-optimisation is often argued to be inconsistent in a practical setting, and a discussion of this point is therefore in order.
Currently the principle of sub-optimisation in the dividend-beta setting is not quantitatively developed. The line of thought is therefore to some extent only hypothetical as there is no

proven equilibrium condition between the cost of a dividend change and the effect on the cost of capital. The theoretical framework provided by e.g. Carter and Shawn-Schmidt (2008) is therefore not as complete as the stock price approach where Miller and Rock (1985) have shown that when managers may sub-optimise there is still incentive to pay dividends which can affect the stock price.

Qualitatively the argumentation of Carter and Shawn-Schmidt (2008) is relevant assuming that the cost of increasing a dividend can be outweighed by the gain of a reduction in the cost of capital, which hence provide incentive for sub-optimisation. At the same time, the swift effect on beta after a dividend decrease is obvious if there is a universal belief that managers will always prefer a lower cost of capital and hence never decrease the dividend level unless utmost necessary.

In the context of the specific findings of this paper and taking the line of thought from above a step further, there is only downside for insiders in paying dividends, since the firm can be "punished" for decreasing the dividend but not "rewarded" for increasing it. One may therefore raise the question of why a firm would ever commence paying dividends. One explanation could be that investors may demand dividend payments to minimise agency conflicts and sub-optimisation on behalf of the management through wrongful use of firm resources (Baker et al., 2002). This can explain why dividend payments are actually commenced in the first place even though the market does not react by re-evaluating the systematic risk level. It is however only a qualitative argument deducted from the lack of reasoning currently provided by the theory behind the dividend-beta approach. It is a critical point for further development of the theory as it places some interpretable constraints on the underlying incentive schemes related to dividend increases or decreases.

Using realised measures is a relatively new approach to calculating beta values but one which has shown consistent results in empirical analysis though it, like low frequency betas, show a large degree of variation individually. Statistically there is little doubt that by the use of more complete data sets, the true variance and covariance can be more precisely estimated. There are nevertheless vital constraints empirically due to the shortcomings of financial data causing the RV and RCov to become inconsistent when market microstructure noise or jumps are present. Manipulating the sampling frequency and using other estimators can cope with these problems to a large extent but so far there is no single estimator which can handle all aspects at once. The RK estimator was e.g. used to test for market microstructure noise, but this estimator functions best at the ultra high frequencies where the RV estimator is bound to fail. The comparison of results must therefore be seen through the filter of different frequencies. At the same time the RK estimator is not robust to price discontinuities where as

the BP estimator is - but then again the BP estimator is not robust to market microstructure noise or non-synchronousness which the HY estimator is. On top of this assumptions about the structure of the noise matters as well.
Clearly, working with high-frequency (co)variance quickly becomes an involved task with many parts. The lack of a "perfect" estimator limits the overall strengths of the conclusions since it is currently not possible to test for everything with the use of a single estimator. All robustness tests therefore contain weaknesses which can influence the results of the individual regression in a way which cannot be controlled for. The final conclusions will therefore not be as strong as if it was possible to control for all high-frequency symptoms at the same time. Still, the effect on the announcement day has been consistently significant throughout all regressions and though it would have been preferable to have one superior estimator, all results are still found to partially reject the null hypothesis stated in the methodology chapter.

As a concept, the realised beta has been shown to be empirically applicable in the limited research done though it cannot be expected to be completely fixed on an individual basis as also found for lower frequency betas. What matters is not the historical span of the time series alone but the amount of data sampled, which is of course far denser w.r.t the realised beta. From this perspective, together with the statistical improvements, the realised beta estimates are on equal footing with the low frequency beta and in certain areas outperform previous results and methods. The results presented here can therefore be considered to bring relevant new information to the academic field shedding further light on the empirical methods used.

Bringing the above points of discussion together, provide as sense of both clarity and ambiguity . On the one hand, the realised measures have proven effective in providing new insight into the perceived relevance of dividends from the outsiders perspective. On the other, the results have a mixed nature which opens new questions and strains the underlying theory of the dividend-beta relationship as it does not have clear answers to the asymmetric findings and consequences of these. Bridging theory and empirics is therefore met by challenges that must be considered before it can become clear if the Information Content of Dividends is best research by systematic risk or if another parameter should be employed, such as the stock price as promoted in much literature.

6.2 Critique

Some areas of the thesis introduce critical aspects which must be considered when interpreting results. The application of the S&P 500 index has presented a significant size and origin bias into the results since the predominant part of the firms used a large cap firms and all stem form the United States. To generalise results it is assumed that all firms in the sample are similar to the extent that a dividend conveys the same degree of information to outsiders regardless of size, industry, pre-announcement financial situation etc. As some authors have previously shown, other factors may be relevant to consider in relation to systematic risk and a further sub-division of firms may provide more knowledge on whether some types of firms are more affected by dividend news than others. The data used furthermore only considers dividend changes and not omissions or resumptions which have in previous literature shown relevant results as well. The evidence both for and against the hypothesis found here therefore lack the additional options which firms have with regards to dividends. This makes the results less informative than if this these options had been added as well.

A key problematic area for this analysis is the absence of analysts' dividend expectations data which has led to the use of actual dividend changes as a second best option. Implicitly, this lead to the application of the strong assumption that all dividend changes above the arbitrary cut-off point are unexpected or convey information, which is not necessarily the case. There is therefore a chance that the results are downward biased due to data unavailability which must be kept in mind when analysing and generalising the findings.

The fact that the current theory behind the dividend-beta approach does not provide argumentation for why a dividend may be paid out in a setting of misaligned interest between insiders and outsiders place interpretable constraints on the findings. As long as a theory balancing the cost of increasing the dividend with a gain in the reduction of the cost of capital does not exist, the research area will be missing an important corner stone by not having introduced moral hazard to the incentive structure.

Chapter 7

Conclusion

The goal of this thesis has been to shed light on the Information Content of Dividends Hypothesis by using systematic risk as the estimator of expected return. A recently developed set of variance estimation methods for high frequency data are applied in order to precisely model the dynamics of beta around dividend announcements which has not been examined that closely before. The realised beta estimator serves as the main estimator due to its theoretically stringent character. Compared to previous papers this is a novel approach which gives rise to a much more detailed picture concerning how beta behaves on a daily basis within the chosen estimation window of 21 days. By using high frequency data this study has pushed the knowledge of the Information Content of Dividends Hypothesis. The approach has added new findings to the research by using beta as the estimator and it has shown that it is possible to observe a specific announcement day effect not possible with lower data frequencies.

The theoretically developed inverse relationship between dividend changes and beta is tested and it is found that beta changes by a magnitude of 0.21 relative to a non-announcement average on days when firms announce a dividend decreases of 20% or more. Meanwhile, no change is found in beta on days where the dividend is announced to increase with 20% or more. As high frequency data contain several deficiencies potentially biasing realised beta estimations, such concerns are tested for along with standard econometrical issues, via a series of robustness tests and controls. The findings were confirmed as being robust to issues such as market microstructure noise, discontinuities/jumps, non-synchronousness, order bias in beta, and serial correlation. Also issues relating to autocorrelation, heteroscedasticity, and multicollinearity were controlled for. The results of these test show a significant beta increase ranging from 0.13 to 0.37 depending on the specification. Though the results differ in absolute size they are economically relevant for stockholders as the immediate beta increase can alter the risk/return profile of a stockholder's portfolio. Similarly all tests confirm that a dividend increase does not affect the beta value of a firm, implying no direct economic consequence for investors. The results above might seem to contradict the theoretical notion that beta is constant, however as noted earlier the expected change is due to a fundamental adjustment of the market's interpretation of the firms character and the beta change is hence expected to reflect an adjustment to the new characteristics of the firm. Further, the realised beta is generally found to not be fixed on a daily basis, but when regressing across many daily beta values over time estimations are obtained, from which systematic effects can be derived. Lastly it is worth mentioning that when interpreting the results above it is important to keep in mind that the data used here (S&P500) is skewed towards large companies and the U.S.A. Thus the results obtained should be generalised with this bias in mind.

Formally, the obtained results relate to existing theory in an asymmetric way as the null hypothesis of no beta increase following a dividend decrease is rejected while the null hypothesis of no beta decrease following a dividend increase cannot be rejected. The inverse relationship examined between dividends and beta is hence in partial support of the Information Content of Dividends Hypothesis due to the inability of rejecting the null hypothesis w.r.t dividend increases. Following the Information Content of Dividends Hypothesis both dividend decreases and increases should cause an inverse change in beta and hence in the expected return on a stock. The rational here being that dividend payments signal information about the variability of the firm's cash flows and hereby its risk and financial shape which affect the expected return on a stock.

An explanation as to why this might not be the case for dividend increases can be attributed to three potential factors; (i) That firms set a dividend target and slowly work their way towards it. Thus dividend increases might be seen as the firm working its way towards its dividend target and increases are thus expected. This relates to the (ii) issue which is that this thesis uses actual dividend changes and not unexpected changes due to data availability constraints. Lastly the missing link might be because (iii) if the postulated inverse relationship exists for dividend increases then managers can lower the firm's cost of capital by increasing the dividend provided that managers have incentive to sub-optimise. Assuming that investors are rational, the market will anticipate this and thereby not react to the information of a dividend increase given the increased uncertainty. The last three points are merely possible explanations which need further research.

Further research may hence find fruitful results in using analysts' dividend expectations data to determine unexpected dividend changes and by researching potential incentive concerns which the current theory has not developed in detail. Econometrically, further development is recommended in the field of high frequency variance and covariance estimators to better approach the integrated variance in the presence of notorious financial data constraints, such that more robust estimates of beta can be obtained. Finally, more research on the ex-post financial effect may bring insight into the asymmetric relationship discovered in this thesis.

Though more research is needed and some areas deserve improvement, the approach of the study at hand has given new life and findings to a discussion which had otherwise reached a deadlock. By the use of new estimation techniques, improved data, and an alternative approach to estimating informational content (beta instead of the stock price), the final pieces to what Black (1976) titled the dividend puzzle may be discovered.

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Appendix A

Extra Descriptive Statistics

Table A.1: Top 5: Most Busy Announcement Dates

Date	# of Announcements
Positive	
20070118	11
20100204	11
20060119	10
20070201	10
20041021	9
Negative	
20081120	4
20000719	3
20001206	3
20010424	3
20020716	3

The table shows the five days with the largest number of dividend announcements along with the number of announcements for the dataset when we do not adjust it at all. No overlap was found when the 20% filtering rule is applied.

Appendix B

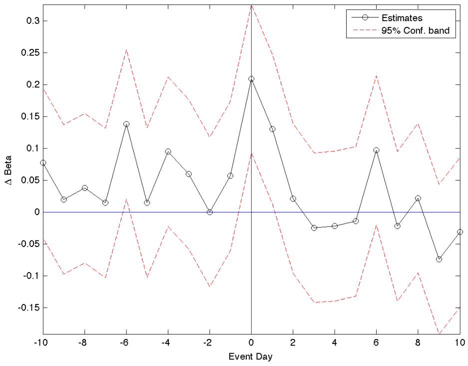
Figures

Here figures and plots of the robustness test are presented.

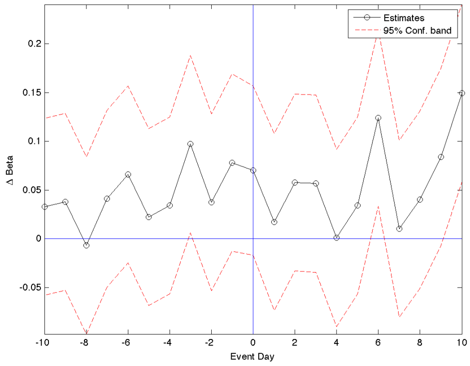
B.1 Fifteen Minutes

Figure B.1: Plot of Regression Results for Fifteen Minute Sampling

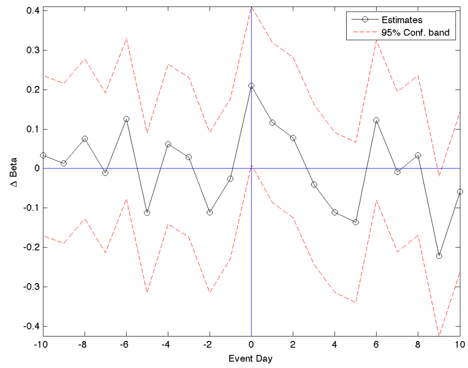
(a) 20%



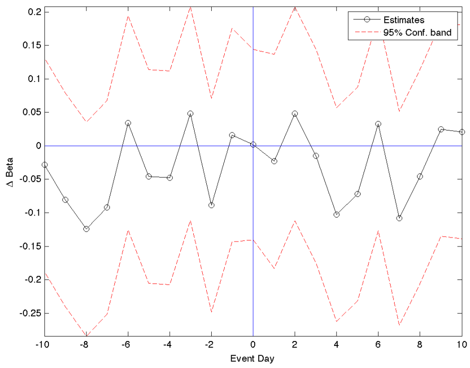
(b) 20%



(c) 50%



(d) 50%



Right column represents results for negative dividend announcements and the left column is for positive dividend announcements.

B.2 Robustness

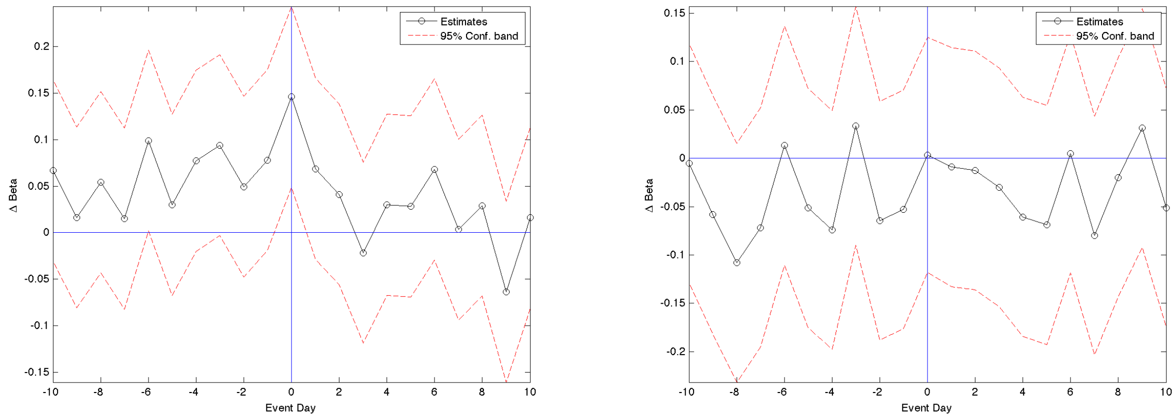
Here we present plots for the robustness tests we have run. All tests are run in data sampled at

B.2.1 Realised Kernel

Figure B.2: Plot of Regression Results for Realised Kernel

(a) 1 minute

(b) 1 minute

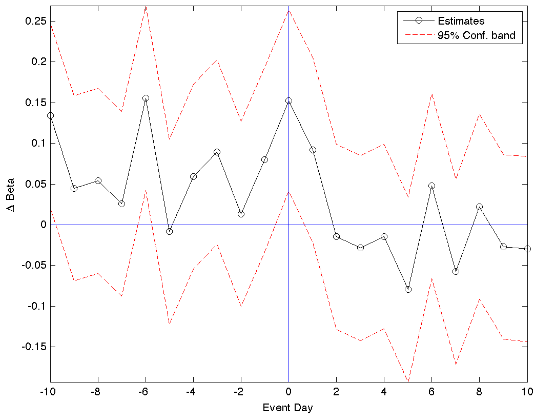


Right column represents results for negative dividend announcements and the left column is for positive dividend announcements. The estimator is the RK estimator of eq. (3.43) and (3.47).

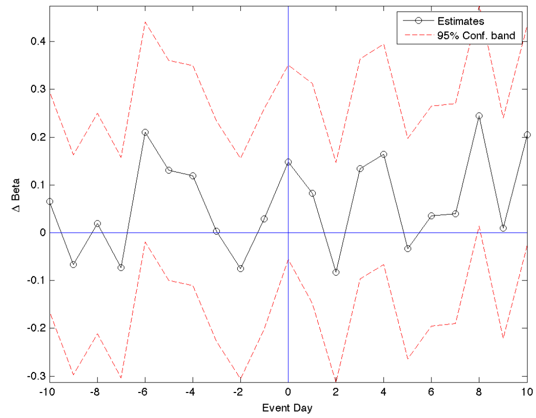
B.2.2 HY & Jumps

Figure B.3: Plot of Regression Results for HY and BPV

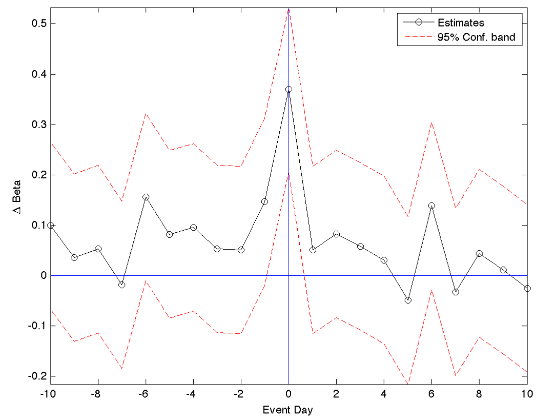
(a) HY



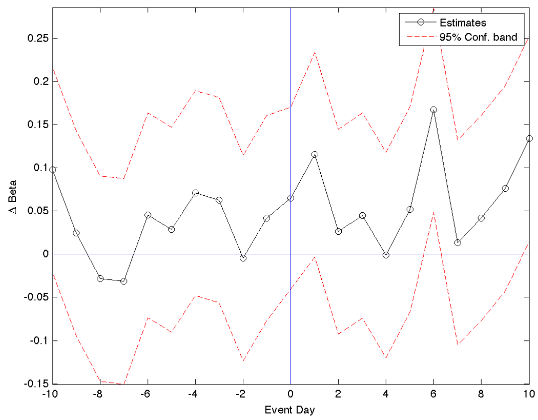
(b) HY



(c) BPV



(d) BPV

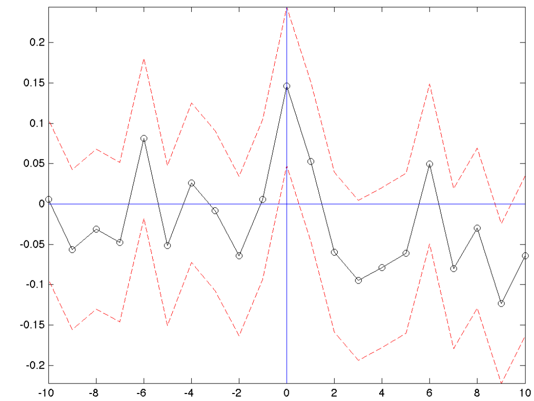


Right column represents results for negative dividend announcements and the left column is for positive dividend announcements. Sampling frequency is 15 minutes and we have applied the 20% dividend change filter.

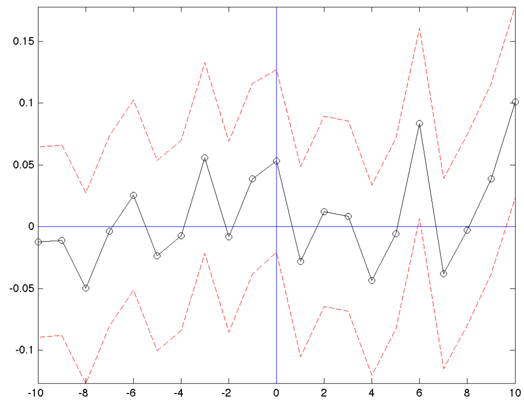
B.2.3 Lags & Quantiles

Figure B.4: Plot of Regression Results for Lag and Quantile Model

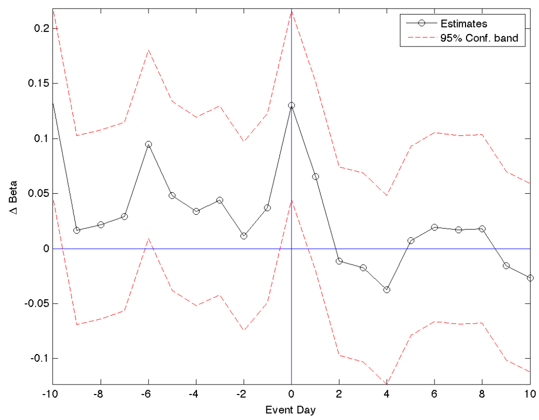
(a) Lag



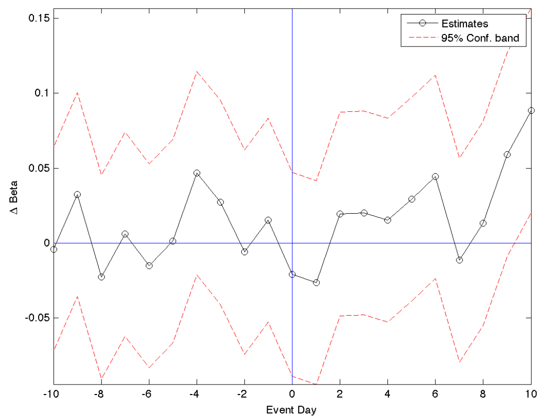
(b) Lag



(c) Quantile



(d) Quantile



Right column represents results for negative dividend announcements and the left column is for positive dividend announcements. Sampling frequency is 15 minutes and we have applied the 20% dividend change filter.

Appendix C

Full regression results

C.1 Beta Estimates: Realised (Co)Variance

Table C.1: Dividend Decrease: 15 minute sample with >50% cut-off

Day	$\triangle\beta$	t-stat	p-value	Day	$\triangle\beta$	t-stat	p-value
-10	0.0333420 (0.1035487)	0.32199	0.74746	1	0.1166555 (0.1035487)	1.12658	0.25992
-9	0.0133688 (0.1035487)	0.12911	0.89727	2	0.0785847 (0.1035487)	0.75892	0.4479
-8	0.0754430 (0.1035487)	0.72858	0.46626	3	-0.040224 (0.1035487)	-0.38846	0.69767
-7	-0.010816 (0.1035487)	-0.10446	0.91681	4	-0.111108 (0.1035464)	-1.07303	0.28326
-6	0.1264134 (0.1035487)	1.22081	0.22216	5	-0.136639 (0.1035464)	-1.3196	0.18697
-5	-0.112488 (0.1035487)	-1.08633	0.27733	6	0.1227996 (0.1035464)	1.18594	0.23565
-4	0.0619546 (0.1035487)	0.59831	0.54963	7	-0.008527 (0.1035464)	-0.08236	0.93436
-3	0.0290573 (0.1035487)	0.28062	0.77901	8	0.0335878 (0.1035482)	0.32437	0.74566
-2	-0.111594 (0.1035487)	-1.0777	0.28117	9	-0.222065* (0.1035484)	-2.14456	0.03199
-1	-0.025869 (0.1035487)	-0.24983	0.80272	10	-0.059054 (0.1035484)	-0.57031	0.56847
0	0.2101869* (0.1026024)	2.04856	0.04051				

Yearly Fixed Effects

Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.3920256** (0.0070214)	55.8325	0	2007	1.0727302** (0.0069505)	154.338	0
2001	0.5749336** (0.0069667)	82.5258	0	2008	1.2316616** (0.0069577)	177.02	0
2002	0.7470401** (0.0068991)	108.281	0	2009	1.4520022** (0.0070343)	206.417	0
2003	0.8251002** (0.0068855)	119.831	0	2010	1.3152998** (0.0070657)	186.151	0
2004	0.8820716** (0.0068725)	128.347	0	2011	1.2107042** (0.0071999)	168.154	0
2005	0.9535391** (0.0069132)	137.928	0	2012	1.2380530** (0.0075467)	164.051	0
2006	1.0056196** (0.0069676)	144.327	0				

Table C.2: Dividend Increase: 15 minute sample with >50% cut off

Event Day	$\triangle\beta$	t-stat	p-value	Event Day	$\triangle\beta$	t-stat	p-value
-10	-0.028248	-0.34669	0.72883	1	-0.023164	-0.28429	0.77619
	(0.0814826)				(0.0814825)		
-9	-0.080722	-0.99068	0.32184	2	0.0479933	0.589	0.55586
	(0.0814826)				(0.0814825)		
-8	-0.124355	-1.52616	0.12697	3	-0.015027	-0.18443	0.85368
	(0.0814826)				(0.0814825)		
-7	-0.091927	-1.12819	0.25924	4	-0.102709	-1.26051	0.20749
	(0.0814825)				(0.0814825)		
-6	0.0344761	0.42311	0.67222	5	-0.071748	-0.88054	0.37857
	(0.0814825)				(0.0814825)		
-5	-0.045611	-0.55977	0.57564	6	0.0326182	0.40031	0.68893
	(0.0814825)				(0.0814826)		
-4	-0.047565	-0.58375	0.55939	7	-0.107818	-1.32321	0.18577
	(0.0814825)				(0.0814826)		
-3	0.0484743	0.5949	0.55191	8	-0.045922	-0.56358	0.57304
	(0.0814825)				(0.0814826)		
-2	-0.088802	-1.08984	0.27579	9	0.0246366	0.30235	0.76238
	(0.0814825)				(0.0814826)		
-1	0.0158941	0.19506	0.84534	10	0.0207677	0.25487	0.79882
	(0.0814825)				(0.0814826)		
0	0.0017784	0.02454	0.98042				
	(0.0724793)						

Yearly Fixed Effects

Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.4981735**	89.4967	0	2007	0.9494929**	168.773	0
	(0.0055663)				(0.0056258)		
2001	0.6915173**	124.488	0	2008	0.9852248**	172.301	0
	(0.0055548)				(0.0057180)		
2002	0.8055882**	146.317	0	2009	1.0905165**	190.097	0
	(0.0055057)				(0.0057366)		
2003	0.8613743**	156.557	0	2010	1.0444010**	181.003	0
	(0.005502)				(0.0057700)		
2004	0.9054360**	164.245	0	2011	1.0002538**	173.584	0
	(0.0055127)				(0.0057623)		
2005	0.9339010**	169.152	0	2012	0.9724866**	165.098	0
	(0.0055210)				(0.0058903)		
2006	0.9857221**	177.748	0				
	(0.0055456)						

Table C.3: Dividend Decrease: 15 minute sample >20% cut off

Day	$\triangle\beta$	t-stat	p-value	Day	$\triangle\beta$	t-stat	p-value
-10	0.0774740 (0.0598595)	1.2942642	0.1955751	1	0.1303380* (0.0598596)	2.1773942	0.0294519
-9	0.0198422 (0.0598594)	0.3314812	0.7402812	2	0.0214917 (0.0598596)	0.3590357	0.7195686
-8	0.0380054 (0.0598594)	0.6349116	0.5254865	3	-0.024357 (0.0598596)	-0.406918	0.6840688
-7	0.0145629 (0.0598594)	0.24329	0.8077843	4	-0.021787 (0.0598593)	-0.363971	0.7158798
-6	0.1378966* (0.0598595)	2.3036704	0.0212418	5	-0.014155 (0.0598592)	-0.236482	0.8130586
-5	0.0151402 (0.0598595)	0.2529287	0.8003234	6	0.0970294 (0.0598592)	1.6209586	0.1050275
-4	0.0948967 (0.0598595)	1.5853237	0.1128937	7	-0.021930 (0.0598592)	-0.366372	0.7140879
-3	0.0598427 (0.0598595)	0.9997187	0.3174474	8	0.0222185 (0.0598595)	0.3711775	0.7105056
-2	0.0001121 (0.0598595)	0.0018741	0.9985047	9	-0.073851 (0.0598595)	-1.233749	0.2172974
-1	0.0568198 (0.0598595)	0.9492188	0.34251	10	-0.031251 (0.0598595)	-0.522087	0.6016098
0	0.2093883** (0.0594208)	3.5238159	0.0004254				
			Yearly Fixed Effects				
Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.3699492** (0.0042822)	86.390832	0	2007	0.9967591** (0.0042913)	232.27045	0
2001	0.5454968** (0.0042849)	127.30399	0	2008	1.0400690** (0.0043058)	241.54629	0
2002	0.7082280** (0.0042436)	166.8928	0	2009	1.2019884** (0.0043599)	275.69097	0
2003	0.7879419** (0.0042265)	186.42571	0	2010	1.1231989** (0.0043896)	255.87273	0
2004	0.8300294** (0.0042236)	196.52085	0	2011	1.0796012** (0.0044186)	244.33099	0
2005	0.9264399** (0.0042352)	218.7472	0	2012	1.0656330** (0.0045593)	233.72673	0
2006	0.9810170** (0.0042700)	229.74421	0				

Table C.4: Dividend Increase: 15 minute sample with >20% cut off

Event Day	$\triangle\beta$	t-stat	p-value	Event Day	$\triangle\beta$	t-stat	p-value
-10	0.0329323 (0.0463250)	0.7109	0.47715	1	0.0170906 (0.0463250)	0.36893	0.71218
-9	0.0378840 (0.0463250)	0.81779	0.41348	2	0.0576842 (0.0463250)	1.2452	0.21306
-8	-0.006900 (0.0464172)	-0.14866	0.88182	3	0.0566040 (0.0464172)	1.21946	0.22267
-7	0.0410649 (0.0464172)	0.88469	0.37632	4	0.0007613 (0.0464172)	0.0164	0.98691
-6	0.0657535 (0.0463251)	1.41939	0.15579	5	0.0341688 (0.0464172)	0.73612	0.46166
-5	0.0220977 (0.0463251)	0.47701	0.63335	6	0.1242486** (0.0463250)	2.68211	0.00732
-4	0.0340386 (0.0463251)	0.73478	0.46248	7	0.0103923 (0.0463250)	0.22434	0.8225
-3	0.0971774* (0.0464172)	2.09356	0.0363	8	0.0400899 (0.0464172)	0.86369	0.38776
-2	0.0374288 (0.0464172)	0.80636	0.42004	9	0.0840754 (0.0464172)	1.8113	0.0701
-1	0.0781639 (0.0464172)	1.68394	0.09219	10	0.1494279** (0.0464172)	3.21923	0.00129
0	0.0700118 (0.0443441)	1.57883	0.11438				

Yearly Fixed Effects

Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.4718751** (0.0039271)	120.159	0	2007	0.9610756** (0.0039092)	245.848	0
2001	0.6495330** (0.0038897)	166.987	0	2008	1.0049088** (0.0039643)	253.484	0
2002	0.7751663** (0.0038415)	201.784	0	2009	1.1111102** (0.0040100)	277.081	0
2003	0.8319089** (0.0038301)	217.2	0	2010	1.0533154** (0.0039959)	263.596	0
2004	0.8770291** (0.0038359)	228.635	0	2011	1.0095515** (0.0040133)	251.551	0
2005	0.9364410** (0.0038399)	243.867	0	2012	0.9827704** (0.0040771)	241.044	0
2006	1.0007035** (0.0038577)	259.404	0				

Table C.5: Dividend Increase: 15 minute sample with >0% cut off

Event Day	$\triangle\beta$	t-stat	p-value	Event Day	$\triangle\beta$	t-stat	p-value
-10	-0.055766** (0.0119756)	-4.6566	3.2E-06	1	-0.051909** (0.0119725)	-4.33569	1.5E-05
-9	-0.056271** (0.0119757)	-4.69878	2.6E-06	2	-0.078754** (0.0119709)	-6.57877	4.7E-11
-8	-0.061364** (0.0119725)	-5.12545	3E-07	3	-0.065782** (0.0119709)	-5.49512	3.9E-08
-7	-0.050840** (0.0119725)	-4.24642	2.2E-05	4	-0.068878** (0.0119694)	-5.75458	8.7E-09
-6	-0.057855** (0.0119709)	-4.83298	1.3E-06	5	-0.049256** (0.0119709)	-4.11462	3.9E-05
-5	-0.056308** (0.0119709)	-4.70373	2.6E-06	6	-0.058315** (0.0119694)	-4.87207	1.1E-06
-4	-0.064379** (0.0119694)	-5.37864	7.5E-08	7	-0.087208** (0.0119709)	-7.28502	3.2E-13
-3	-0.057763** (0.0119709)	-4.82532	1.4E-06	8	-0.055392** (0.0119710)	-4.62726	3.7E-06
-2	-0.052156** (0.0119709)	-4.35687	1.3E-05	9	-0.058074** (0.0119694)	-4.85186	1.2E-06
-1	-0.051170** (0.0119709)	-4.27457	1.9E-05	10	-0.069229** (0.0119694)	-5.78385	7.3E-09
0	-0.049195** (0.0113964)	-4.31676	1.6E-05				
			Yearly Fixed Effects				
Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.3959245** (0.0021204)	186.718	0	2007	0.9815204** (0.0021280)	461.238	0
2001	0.5754554** (0.0021274)	270.487	0	2008	1.0714462** (0.0021445)	499.624	0
2002	0.7194601** (0.0020928)	343.776	0	2009	1.1536526** (0.0021677)	532.184	0
2003	0.7936025** (0.0020914)	379.449	0	2010	1.0690972** (0.0021825)	489.842	0
2004	0.8357111** (0.0020900)	399.848	0	2011	1.0427174** (0.0021974)	474.521	0
2005	0.9085237** (0.0020912)	434.434	0	2012	1.0271988** (0.0022163)	463.457	0
2006	0.9728210** (0.0021064)	461.828	0				

Table C.6: Dividend Decrease: 15 minute sample with >0% cut off

Event Day	$\triangle\beta$	t-stat	p-value	Event Day	$\triangle\beta$	t-stat	p-value
-10	0.1256651** (0.0275950)	4.55391	5.3E-06	1	0.1584600** (0.0275396)	5.75389	8.7E-09
-9	0.1108578** (0.0275765)	4.02001	5.8E-05	2	0.1380408** (0.0275396)	5.01245	5.4E-07
-8	0.1496794** (0.0275765)	5.42778	5.7E-08	3	0.1217442** (0.0275396)	4.42069	9.8E-06
-7	0.1101807** (0.0275765)	3.99545	6.5E-05	4	0.1387975** (0.0275396)	5.03992	4.7E-07
-6	0.1567042** (0.0275765)	5.68252	1.3E-08	5	0.0979371** (0.0275396)	3.55623	0.00038
-5	0.1065339** (0.0275765)	3.86321	0.00011	6	0.1226369** (0.0275396)	4.45311	8.5E-06
-4	0.1401456** (0.0275580)	5.08547	3.7E-07	7	0.1411601** (0.0275396)	5.12571	3E-07
-3	0.1520941** (0.0275580)	5.51905	3.4E-08	8	0.1649466** (0.0275396)	5.98943	2.1E-09
-2	0.1620340** (0.0275580)	5.87973	4.1E-09	9	0.1463825** (0.0275395)	5.31535	1.1E-07
-1	0.1745384** (0.0275580)	6.33348	2.4E-10	10	0.1978788** (0.0275396)	7.18524	6.7E-13
0	0.0937367** (0.0250603)	3.74044	0.00018				

Yearly Fixed Effects

Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.3682966** (0.0025426)	144.847	0	2007	1.0252580** (0.0025546)	401.33	0
2001	0.5416770** (0.0025528)	212.186	0	2008	1.1493587** (0.0025814)	445.236	0
2002	0.7015087** (0.0025182)	278.573	0	2009	1.2610309** (0.0026306)	479.362	0
2003	0.7793598** (0.0025079)	310.755	0	2010	1.1465051** (0.0026473)	433.071	0
2004	0.8264179** (0.0025035)	330.092	0	2011	1.1178978** (0.0026792)	417.246	0
2005	0.9103826** (0.0025029)	363.729	0	2012	1.1049231** (0.0027306)	404.643	0
2006	0.9844402** (0.0025297)	389.139	0				

C.2 Beta Estimates: Realised (Multivariate) Kernels

Table C.7: Dividend Decrease: Realised kernels: 1 minute sample with >20% decrease

Event Day	$\triangle\beta$	t-stat	p-value	Event Day	$\triangle\beta$	t-stat	p-value
-10	0.0667275	1.34463	0.17874	1	0.0684878	1.3801	0.16756
	(0.0496250)				(0.0496251)		
-9	0.0163757	0.32999	0.74141	2	0.0410711	0.82763	0.40788
	(0.0496250)				(0.0496251)		
-8	0.0540538	1.08925	0.27605	3	-0.021634	-0.43595	0.66287
	(0.0496250)				(0.0496251)		
-7	0.0151488	0.30527	0.76016	4	0.0299299	0.60312	0.54643
	(0.0496250)				(0.0496248)		
-6	0.0989476*	1.99391	0.04616	5	0.0282708	0.56969	0.56889
	(0.0496250)				(0.0496248)		
-5	0.0299924	0.60438	0.54559	6	0.0678055	1.36636	0.17183
	(0.0496250)				(0.0496248)		
-4	0.0773643	1.55898	0.119	7	0.0032954	0.06641	0.94705
	(0.0496250)				(0.0496248)		
-3	0.0939853	1.89391	0.05824	8	0.0289388	0.58315	0.55979
	(0.0496250)				(0.0496250)		
-2	0.0494225	0.99592	0.31929	9	-0.063556	-1.28074	0.20029
	(0.0496250)				(0.0496250)		
-1	0.0780406	1.5726	0.11581	10	0.0159892	0.3222	0.7473
	(0.0496250)				(0.0496250)		
0	0.1459660**	2.94137	0.00327				
	(0.0496251)						

Yearly Fixed Effects

Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.3882586**	109.365	0	2007	0.9951473**	279.72	0
	(0.0035501)				(0.0035576)		
2001	0.5491236**	154.58	0	2008	1.0435796**	292.345	0
	(0.0035523)				(0.0035696)		
2002	0.7172875**	203.887	0	2009	1.2105186**	334.915	0
	(0.0035180)				(0.0036144)		
2003	0.7950683**	226.907	0	2010	1.1230429**	308.6	0
	(0.0035039)				(0.0036391)		
2004	0.8338527**	238.147	0	2011	1.0838929**	295.892	0
	(0.0035014)				(0.0036631)		
2005	0.9281841**	264.358	0	2012	1.0672305**	282.352	0
	(0.0035110)				(0.0037797)		
2006	0.9861410**	278.573	0				
	(0.0035399)						

Table C.8: Dividend Increase: Realised Kernels: 1 minute sample with >20% cut off

Event Day	$\triangle\beta$	t-stat	p-value	Event Day	$\triangle\beta$	t-stat	p-value
-10	-0.005041	-0.08003	0.93621	1	-0.009132	-0.14497	0.88473
	(0.0629960)				(0.0629959)		
-9	-0.058163	-0.92328	0.35586	2	-0.012546	-0.19916	0.84214
	(0.0629960)				(0.0629959)		
-8	-0.108145	-1.7167	0.08603	3	-0.030245	-0.48011	0.63115
	(0.0629960)				(0.0629959)		
-7	-0.071719	-1.13848	0.25492	4	-0.060620	-0.9623	0.3359
	(0.0629959)				(0.0629959)		
-6	0.0130312	0.20686	0.83612	5	-0.069036	-1.09588	0.27313
	(0.0629959)				(0.0629959)		
-5	-0.051585	-0.81887	0.41286	6	0.0048108	0.07637	0.93913
	(0.0629959)				(0.0629960)		
-4	-0.074140	-1.17691	0.23923	7	-0.079772	-1.26632	0.2054
	(0.0629959)				(0.0629960)		
-3	0.0335633	0.53279	0.59418	8	-0.019865	-0.31534	0.7525
	(0.0629959)				(0.0629960)		
-2	-0.064611	-1.02565	0.30506	9	0.0312594	0.49621	0.61974
	(0.0629959)				(0.0629960)		
-1	-0.052904	-0.83981	0.40102	10	-0.051359	-0.81528	0.41491
	(0.0629959)				(0.0629960)		
0	0.0033660	0.05431	0.95669				
	(0.0619821)						

Yearly Fixed Effects

Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.5265061**	122.353	0	2007	0.9487022**	218.118	0
	(0.0043031)				(0.0043494)		
2001	0.7044402**	164.046	0	2008	0.9880170**	223.494	0
	(0.0042941)				(0.0044207)		
2002	0.8137583**	191.197	0	2009	1.0949640**	246.884	0
	(0.0042561)				(0.0044351)		
2003	0.8695008**	204.414	0	2010	1.0449026**	234.231	0
	(0.0042536)				(0.0044609)		
2004	0.9066961**	212.75	0	2011	1.0044374**	225.46	0
	(0.0042618)				(0.0044550)		
2005	0.9351609**	219.102	0	2012	0.9763362**	214.391	0
	(0.0042681)				(0.0045539)		
2006	0.9885706**	230.59	0				
	(0.0042871)						

Table C.9: Dividend Decrease: HY Beta

Estimated beta change							
Day	$\triangle\beta$	t-stat	p-value	Day	$\triangle\beta$	t-stat	p-value
-10	0.1343483* (0.0579312)	2.3191	0.02039	1	0.0916685 (0.0579314)	1.58236	0.11357
-9	0.0449258 (0.0579312)	0.7755	0.43804	2	-0.014866 (0.0579314)	-0.25663	0.79747
-8	0.0538231 (0.0579312)	0.92909	0.35285	3	-0.028741 (0.0579314)	-0.49613	0.61981
-7	0.0258532 (0.0579312)	0.44627	0.6554	4	-0.014707 (0.0579311)	-0.25388	0.79959
-6	0.1556985** (0.0579313)	2.68764	0.0072	5	-0.079629 (0.0579310)	-1.37456	0.16927
-5	-0.008583 (0.0579313)	-0.14816	0.88222	6	0.0476134 (0.0579310)	0.8219	0.41114
-4	0.0591832 (0.0579313)	1.02161	0.30697	7	-0.057612 (0.0579310)	-0.99449	0.31998
-3	0.0893352 (0.0579313)	1.54209	0.12305	8	0.0221971 (0.0579313)	0.38316	0.7016
-2	0.0133746 (0.0579313)	0.23087	0.81742	9	-0.027006 (0.0579313)	-0.46617	0.64109
-1	0.0797880 (0.0579313)	1.37728	0.16843	10	-0.029949 (0.0579313)	-0.51699	0.60517
0	0.1525266** (0.0566848)	2.69078	0.00713				
Yearly Fixed Effects							
Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.3235761** (0.0041642)	77.703	0	2007	0.8848131** (0.0041731)	212.027	0
2001	0.4690830** (0.0041666)	112.581	0	2008	0.9497470** (0.0041876)	226.799	0
2002	0.6286224** (0.0041263)	152.345	0	2009	1.0602319** (0.0042405)	250.02	0
2003	0.6909598** (0.0041095)	168.133	0	2010	0.9804302** (0.0042697)	229.622	0
2004	0.7352070** (0.0041068)	179.02	0	2011	0.9689580** (0.0042981)	225.434	0
2005	0.8371398** (0.0041180)	203.285	0	2012	0.9250231** (0.0044363)	208.51	0
2006	0.8748355** (0.0041521)	210.693	0				

Table C.10: Dividend Increase: HY Beta

Estimated beta change							
Day	$\triangle\beta$	t-stat	p-value	Day	$\triangle\beta$	t-stat	p-value
-10	0.0651884 (0.1173990)	0.55527	0.57871	1	0.0822687 (0.1173992)	0.70076	0.48345
-9	-0.066877 (0.1173990)	-0.56966	0.56891	2	-0.082724 (0.1173992)	-0.70464	0.48103
-8	0.0194561 (0.1176327)	0.1654	0.86863	3	0.1337233 (0.1176328)	1.13679	0.25563
-7	-0.072649 (0.1176327)	-0.61760	0.53684	4	0.1640622 (0.1176328)	1.3947	0.16311
-6	0.2107940 (0.1173993)	1.79553	0.07257	5	-0.032943 (0.1176328)	-0.28006	0.77943
-5	0.1305281 (0.1173993)	1.11183	0.26621	6	0.0352441 (0.1173990)	0.30021	0.76402
-4	0.1193765 (0.1173993)	1.01684	0.30923	7	0.0397894 (0.1173991)	0.33892	0.73467
-3	0.0034509 (0.1176328)	0.02934	0.9766	8	0.2442766* (0.1176328)	2.0766	0.03784
-2	-0.074904 (0.1176328)	-0.63676	0.52428	9	0.0099037 (0.1176328)	0.08419	0.9329
-1	0.0287506 (0.1176328)	0.24441	0.80691	10	0.2045709 (0.1176328)	1.73906	0.08202
0	0.1477733 (0.1038488)	1.42297	0.15475				
Yearly Fixed Effects							
Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.5134708** (0.0099890)	51.4033	0	2007	0.7348449** (0.0099421)	73.9119	0
2001	0.6422686** (0.0098938)	64.9161	0	2008	0.9426476** (0.0100838)	93.4809	0
2002	0.7814085** (0.0097703)	79.9776	0	2009	0.9714456** (0.0102007)	95.2329	0
2003	0.7250755** (0.0097401)	74.4419	0	2010	0.8872464** (0.0101646)	87.2879	0
2004	0.8184354** (0.0097552)	83.8971	0	2011	0.9732737** (0.0102090)	95.3347	0
2005	0.8757281** (0.0097653)	89.677	0	2012	0.9205436** (0.0103723)	88.7499	0
2006	0.9134374** (0.0098114)	93.0989	0				

Table C.11: Dividend Decrease: Order Bias Control

Estimated beta change							
Day	$\triangle\beta$	t-stat	p-value	Day	$\triangle\beta$	t-stat	p-value
-10	0.1325976** (0.0437648)	3.02978	0.00245	1	0.0655948 (0.0437653)	1.49878	0.13393
-9	0.0167616 (0.0437646)	0.383	0.70172	2	-0.011427 (0.0437648)	-0.26111	0.79401
-8	0.0218052 (0.0437646)	0.49824	0.61832	3	-0.017257 (0.0437648)	-0.39432	0.69334
-7	0.0291954 (0.0437647)	0.66710	0.50471	4	-0.037582 (0.0437645)	-0.85875	0.39048
-6	0.0946734* (0.0437648)	2.16323	0.03052	5	0.0070362 (0.0437645)	0.16077	0.87227
-5	0.0480237 (0.0437647)	1.09732	0.2725	6	0.0194775 (0.0437648)	0.44505	0.65628
-4	0.0337919 (0.0437651)	0.77212	0.44004	7	0.0169742 (0.0437645)	0.38785	0.69813
-3	0.0437880 (0.0437650)	1.00052	0.31706	8	0.0179283 (0.0437647)	0.40965	0.68206
-2	0.0112831 (0.0437647)	0.25781	0.79655	9	-0.015545 (0.0437651)	-0.3552	0.72244
-1	0.0368276 (0.0437647)	0.84149	0.40007	10	-0.026745 (0.0437653)	-0.61112	0.54112
0	0.1303645** (0.0437650)	2.97874	0.00289				

Yearly Fixed Effects							
Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.7165413* (0.3621444)	1.97861	0.04786	2007	1.0696120** (0.3621428)	2.95356	0.00314
2001	0.7705308* (0.3621443)	2.12769	0.03336	2008	1.0873629** (0.3621431)	3.00258	0.00268
2002	0.8626545* (0.3621431)	2.38208	0.01722	2009	1.1348035** (0.3621411)	3.13359	0.00173
2003	0.9252910* (0.3621432)	2.55504	0.01062	2010	1.1356005** (0.3621449)	3.13576	0.00171
2004	0.9576900** (0.3621428)	2.64451	0.00818	2011	1.1154436** (0.3621444)	3.08011	0.00207
2005	1.0357740** (0.3621425)	2.86013	0.00423	2012	1.0796179** (0.3621446)	2.98118	0.00287
2006	1.0313634** (0.3621428)	2.84795	0.0044				

Table C.12: Dividend Increase: Order Bias Control

Estimated beta change							
Day	$\triangle\beta$	t-stat	p-value	Day	$\triangle\beta$	t-stat	p-value
-10	-0.004265 (0.0346861)	-0.12298	0.90212	1	-0.026360 (0.0346862)	-0.75998	0.44727
-9	0.0322994 (0.0346861)	0.93119	0.35175	2	0.0193168 (0.0346861)	0.5569	0.57759
-8	-0.022802 (0.0347551)	-0.65609	0.51176	3	0.0201078 (0.0347552)	0.57855	0.56289
-7	0.0059008 (0.0347551)	0.16978	0.86518	4	0.0153667 (0.0347551)	0.44214	0.65839
-6	-0.015147 (0.0346864)	-0.4367	0.66233	5	0.0293544 (0.0347551)	0.84461	0.39833
-5	0.0011168 (0.0346861)	0.0322	0.97431	6	0.0442211 (0.0346863)	1.27489	0.20235
-4	0.0466589 (0.0346861)	1.34518	0.17857	7	-0.011390 (0.0346861)	-0.32839	0.74261
-3	0.0270998 (0.0347553)	0.77973	0.43555	8	0.0130864 (0.0347552)	0.37653	0.70652
-2	-0.006071 (0.0347552)	-0.17469	0.86133	9	0.0589809 (0.0347552)	1.69704	0.08969
-1	0.0152440 (0.0347553)	0.43861	0.66094	10	0.0886026* (0.0347553)	2.54933	0.01079
0	-0.021004 (0.0347556)	-0.60434	0.54562				

Yearly Fixed Effects							
Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.6321238** (0.1176464)	5.37308	7.7E-08	2007	0.8933360** (0.1176337)	7.59421	3.1E-14
2001	0.6785488** (0.1176426)	5.76788	8E-09	2008	0.9209647** (0.1176381)	7.82879	4.9E-15
2002	0.7520868** (0.1176402)	6.39311	1.6E-10	2009	0.9597097** (0.1176418)	8.1579	3.4E-16
2003	0.8035611** (0.1176390)	6.83073	8.5E-12	2010	0.9590992** (0.1176411)	8.15275	3.6E-16
2004	0.8353930** (0.1176367)	7.10146	1.2E-12	2011	0.9382547** (0.1176354)	7.97595	1.5E-15
2005	0.8846059** (0.1176345)	7.51995	5.5E-14	2012	0.8998916** (0.1176378)	7.64968	2E-14
2006	0.8943689** (0.1176338)	7.60299	2.9E-14				

Table C.13: Dividend Decrease: Serial Correlation Control

Estimated beta change							
Day	$\triangle\beta$	t-stat	p-value	Day	$\triangle\beta$	t-stat	p-value
-10	0.0057449 (0.0505362)	0.11368	0.90949	1	0.0524952 (0.0505368)	1.03875	0.29892
-9	-0.056670 (0.0505361)	-1.12138	0.26213	2	-0.059518 (0.0505369)	-1.17773	0.23891
-8	-0.031049 (0.0505362)	-0.61441	0.53895	3	-0.094799 (0.0505370)	-1.87584	0.06068
-7	-0.047414 (0.0505362)	-0.93823	0.34813	4	-0.078813 (0.0505370)	-1.55952	0.11887
-6	0.0814645 (0.0505363)	1.612	0.10696	5	-0.060879 (0.0505371)	-1.20465	0.22834
-5	-0.051379 (0.0505363)	-1.01669	0.3093	6	0.0495981 (0.0505369)	0.98142	0.32639
-4	0.0263835 (0.0505363)	0.52207	0.60162	7	-0.079986 (0.0505370)	-1.58273	0.11348
-3	-0.008189 (0.0505363)	-0.16206	0.87126	8	-0.029895 (0.0505371)	-0.59156	0.55415
-2	-0.064398 (0.0505363)	-1.27431	0.20256	9	-0.123060* (0.0505371)	-2.43504	0.01489
-1	0.0055620 (0.0505365)	0.11006	0.91236	10	-0.063958 (0.0505375)	-1.26555	0.20567
0	0.1460947** (0.0501665)	2.91219	0.00359				
Yearly Fixed Effects							
Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	-0.023782** (0.0039681)	-5.99336	2.1E-09	2007	0.0588075** (0.0045126)	13.0319	8.2E-39
2001	0.0557851** (0.0038584)	14.458	2.3E-47	2008	0.0675101** (0.0045781)	14.7461	3.4E-49
2002	0.0486003** (0.0040318)	12.0541	1.9E-33	2009	0.0718264** (0.0048888)	14.6919	7.5E-49
2003	0.0460026** (0.0041570)	11.0661	1.9E-28	2010	0.0536027** (0.0048400)	11.0749	1.7E-28
2004	0.0493890** (0.0042104)	11.7301	9.1E-32	2011	0.0653567** (0.0047361)	13.7994	2.6E-43
2005	0.0603059** (0.0043314)	13.923	4.7E-44	2012	0.0405640** (0.0048957)	8.2855	1.2E-16
2006	0.0523680** (0.0044854)	11.6751	1.7E-31				

Table C.14: Dividend Increase: Serial Correlation Control

Estimated beta change							
Day	$\triangle\beta$	t-stat	p-value	Day	$\triangle\beta$	t-stat	p-value
-10	-0.012604 (0.0393063)	-0.32066	0.74847	1	-0.028333 (0.0393061)	-0.72083	0.47102
-9	-0.011060 (0.0393063)	-0.28139	0.77841	2	0.0122018 (0.0393061)	0.31043	0.75623
-8	-0.049627 (0.0393846)	-1.26008	0.20764	3	0.0085145 (0.0393844)	0.21619	0.82884
-7	-0.003509 (0.0393846)	-0.08911	0.929	4	-0.043363 (0.0393844)	-1.10103	0.27089
-6	0.0255497 (0.0393064)	0.65001	0.51568	5	-0.005815 (0.0393844)	-0.14765	0.88262
-5	-0.023544 (0.0393063)	-0.59899	0.54918	6	0.0835551* (0.0393061)	2.12576	0.03352
-4	-0.007303 (0.0393062)	-0.18581	0.8526	7	-0.038020 (0.0393063)	-0.96729	0.3334
-3	0.0555544 (0.0393844)	1.41057	0.15837	8	-0.002745 (0.0393846)	-0.06971	0.94443
-2	-0.008312 (0.0393845)	-0.21107	0.83284	9	0.0388318 (0.0393846)	0.98596	0.32415
-1	0.0385659 (0.0393844)	0.97922	0.32747	10	0.1008003* (0.0393846)	2.55938	0.01049
0	0.0532954 (0.0376762)	1.41457	0.1572				
Yearly Fixed Effects							
Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	-0.015203** (0.0036629)	-4.15066	3.3E-05	2007	0.0440399** (0.0040427)	10.8936	1.2E-27
2001	0.0571261** (0.0035932)	15.8983	6.7E-57	2008	0.0596453** (0.0041001)	14.5471	6.2E-48
2002	0.0509698** (0.0037094)	13.7407	5.9E-43	2009	0.0603075** (0.0042801)	14.0901	4.5E-45
2003	0.0451946** (0.0037927)	11.916	9.9E-33	2010	0.0464506** (0.0042268)	10.9895	4.3E-28
2004	0.0456472** (0.0038554)	11.8396	2.5E-32	2011	0.0562088** (0.0041518)	13.5382	9.5E-42
2005	0.0551153** (0.0039124)	14.0873	4.6E-45	2012	0.0342288** (0.0042174)	8.1161	4.8E-16
2006	0.0517388** (0.0040280)	12.8448	9.3E-38				

Table C.15: Dividend Decrease: Bi-power Beta

Estimated beta change							
Day	$\triangle\beta$	t-stat	p-value	Day	$\triangle\beta$	t-stat	p-value
-10	0.0995178 (0.0848995)	1.17218	0.24112	1	0.0504309 (0.0848997)	0.59401	0.55251
-9	0.0355419 (0.0848995)	0.41864	0.67548	2	0.0821416 (0.0848997)	0.96751	0.33329
-8	0.0521584 (0.0848995)	0.61436	0.53898	3	0.0580242 (0.0848997)	0.68344	0.49433
-7	-0.018988 (0.0848995)	-0.22366	0.82302	4	0.0306244 (0.0848993)	0.36071	0.71831
-6	0.1558741 (0.0848996)	1.83598	0.06636	5	-0.049802 (0.0848992)	-0.5866	0.55747
-5	0.0816453 (0.0848996)	0.96167	0.33622	6	0.1378455 (0.0848992)	1.62364	0.10445
-4	0.0958529 (0.0848996)	1.12901	0.25889	7	-0.033193 (0.0848992)	-0.39097	0.69582
-3	0.0527150 (0.0848996)	0.62091	0.53466	8	0.0438826 (0.0848995)	0.51688	0.60524
-2	0.0509791 (0.0848996)	0.60046	0.5482	9	0.0103620 (0.0848996)	0.12205	0.90286
-1	0.1467307 (0.0848996)	1.72828	0.08394	10	-0.025726 (0.0848996)	-0.30302	0.76188
0	0.3698240** (0.0830728)	4.4518	8.5E-06				

Yearly Fixed Effects							
Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.6610802** (0.0060736)	108.845	0	2007	1.0567202** (0.0060865)	173.617	0
2001	0.6386913** (0.0060774)	105.092	0	2008	1.0914977** (0.0061072)	178.723	0
2002	0.7731350** (0.0060187)	128.454	0	2009	1.2751533** (0.0061838)	206.208	0
2003	0.8432924** (0.0059946)	140.675	0	2010	1.2238021** (0.0062259)	196.565	0
2004	0.9049336** (0.0059906)	151.058	0	2011	1.1362997** (0.0062669)	181.316	0
2005	1.0100766** (0.0060068)	168.154	0	2012	1.1560988** (0.0064665)	178.782	0
2006	1.0951267** (0.0060562)	180.826	0				

Table C.16: Dividend Increase: Bi-power Beta

Estimated beta change							
Day	$\triangle\beta$	t-stat	p-value	Day	$\triangle\beta$	t-stat	p-value
-10	0.0979735 (0.0605685)	1.61756	0.10576	1	0.1153492 (0.0605686)	1.90444	0.05685
-9	0.0244822 (0.0605685)	0.40421	0.68606	2	0.0261798 (0.0605686)	0.43223	0.66557
-8	-0.028361 (0.0606890)	-0.46732	0.64027	3	0.0448802 (0.0606891)	0.73951	0.4596
-7	-0.031556 (0.0606891)	-0.51997	0.60308	4	-0.000961 (0.0606891)	-0.01584	0.98737
-6	0.0452163 (0.0605686)	0.74653	0.45535	5	0.0517497 (0.0606891)	0.8527	0.39382
-5	0.0286743 (0.0605686)	0.47342	0.63591	6	0.1672314** (0.0605685)	2.76103	0.00576
-4	0.0708264 (0.0605686)	1.16936	0.24226	7	0.0134112 (0.0605685)	0.22142	0.82476
-3	0.0628978 (0.0606891)	1.03639	0.30002	8	0.0420604 (0.0606891)	0.69305	0.48828
-2	-0.004403 (0.0606891)	-0.07255	0.94216	9	0.0762007 (0.0606891)	1.25559	0.20926
-1	0.0419284 (0.0606891)	0.69087	0.48965	10	0.1341260* (0.0606891)	2.21005	0.0271
0	0.0650410 (0.0535777)	1.21396	0.22477				
Yearly Fixed Effects							
Year	$\triangle\beta$	t-stat	p-value	Year	$\triangle\beta$	t-stat	p-value
2000	0.7467964** (0.0051350)	145.432	0	2007	1.0434823** (0.0051111)	204.158	0
2001	0.7523133** (0.0050866)	147.899	0	2008	1.0536409** (0.0051833)	203.276	0
2002	0.8581030** (0.0050233)	170.823	0	2009	1.1716444** (0.0052430)	223.468	0
2003	0.9065636** (0.0050079)	181.026	0	2010	1.1491645** (0.0052245)	219.954	0
2004	0.9553580** (0.0050156)	190.476	0	2011	1.0560682** (0.0052472)	201.262	0
2005	1.0363996** (0.0050208)	206.421	0	2012	1.0614615** (0.0053306)	199.123	0
2006	1.1243491** (0.0050444)	222.89	0				