Essays on Market Microstructure for a Portfolio of Dividend Paying Firms around Ex-Dividend Days

by

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A thesis submitted for the degree of Doctor of Philosophy in Finance

Essex Business School
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Date of submission (October 2014)

To my family

Acknowledgments

This thesis could not have been accomplished without the help of the Almighty Allah who provided me with health, knowledge, strength, courage, and patience then the guidance of my supervisors, help from my family, and support from my friends.

First and foremost, my deep and sincere appreciation goes to my supervisor, Dr Norvald Instefjord. I am full of appreciation for his time, guidance, support, patience, creative suggestions and valuable ideas over these years. His valuable ideas and helpful suggestion have led me to the finishing line. It would be absolutely impossible to complete this thesis without his excellent supervision. I am also extremely grateful to my second supervisor, Dr Hardy Thomas. I really appreciate his patience, support and suggestions. I thank him for spending so generously his time discussing my work and giving detailed and insightful comments, which were essential for improving the thesis. I am deeply grateful to Professor Richard Payne, my examiner, for his invaluable feedback in the final stages of my degree. I also own thanks to my internal examiner Dr Nick Constantinou, who has sadly passed away a few months after my Viva.

I gratefully acknowledge the Centre for Computational Finance and Economic Agents at the University of Essex for supplying the data used in this thesis, and in particular, Dr Steve Phelps, and, Dr Neil Rayner, for helpful assistance in the early stages of the research.

For completing this thesis, I wish to give a significant credit to my uncle, Rdwan Alhalboni, who has always gives me super support and care at every single step. I am quite indebted to him in particular for believing in me and encouraging me. Sincerely, I would not reach this stage in my life without him. I must express my heartfelt gratitude to my ever-supportive and ever-loving family especially my parents, my lovely sister, Marwa, and my lovely two brothers, Kamal, and, Karm, for their support, patience, sacrifices, love and consistent pray.

Furthermore, I would like to express the deepest appreciation to my friends for their incredible support throughout my PhD. There are too many names, to all of them, my heartfelt thanks. I have also been quite fortunate to have had a fantastic group of colleagues, and I am thankful for having studied with each and every one of them. I am also indebted to all the staff in the Essex Business School for their assistance at various stages of this study.

Last but not least I offer my regards and blessings to all of those who supported me in any respect and who have directly or indirectly contributed to the completion of this work.

Abstract

This thesis contributes to the existing literature on market microstructure by presenting three essays on the market microstructure around ex-dividend days. The first essay studies the market microstructure "footprints" associated with trading and tax-arbitrage activity around ex-dividend day using a sample of FTSE 100 stocks. Specifically, the first essay asks whether bid-ask spreads, price volatility and order submission strategies change as stocks transition to the ex-dividend day. From the results there is evidence of the presence of both tax- arbitrageurs and liquidity suppliers around ex-dividend day. Furthermore, the findings support that increases in spread, volatility, return and execution probability around ex-dividend day attract liquidity suppliers and tax-arbitrageurs.

The second essay investigates whether the lack of liquidity prevents the presence of ex-dividend trade activities, and how the behaviour of tax-arbitrage traders, if there are any, could affect bid-ask spreads, price volatility and order submission strategies using a sample of FTSE SmallCap stocks. The results show that illiquidity seems not to prevent tax-arbitrage activities altogether. Although, the findings suggest effects associating order submission to spread, volatility and to return, they do not support any effect associating order submission to execution probability.

The third and final essay analyses intraday patterns related to bid-ask spread, trade volume and price volatility around the ex-dividend day for a sample of FTSE 100 companies. The results show that volume towards the end of the trading day is greater both on ex- and cum-dividend days , among firms that are the most attractive targets for tax-arbitrage. The findings show that the spread towards the end of the day is greater both on ex-dividend and cum-dividend days also though here the effect is confined to the last half hour of the trading day for the firms that are the most attractive targets for tax-arbitrage. The classification of whether a firm is an attractive target for tax-arbitrage is based on whether the price impact less than a specified threshold. Finally, the results and patterns noted above become masked in the large pool comprising all firms because the effects that are identified for firms that are the most attractive targets for tax-arbitrage are offset by the effects that are identified for the firms that are the least attractive targets for tax arbitrage.

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List of Abbreviations

A-T-Q	At-The-Quote
AT-F	Low price impact firms - Arbitrage Firms
B-T-Q	Behind-The-Quote
C-Cum	Corresponding to cum-dividend day in control week (Tuesday) (day2)
C-Ex	Corresponding to ex-dividend day in control week (Wednesday) (day3)
Class1	Classification 1
Class2	Classification 2
Cont.w	Control week
Cum.day	Cum-dividend day
DMA	Direct Market Access
Ex.day	Ex-dividend day
Ex.w	Ex-dividend week
I-T-Q	Inside-The-Quote
IA-F	High price impact firms - Information Asymmetry Firms
LSE	London Stock Exchange
M-A	Marketable

MAC	The Exchange's Member Authorised Connectivity
NC-F	No-Classification
Num	Number
Num.of Tran.	Number of Transaction Liquidity Measure
Rel.Turnover	Relative Turnover Liquidity Measure
SETS	The Stock Exchange Electronic Trading System
Vol.	Volume Liquidity Measure

Chapter 1

Introduction

> The world isn't run by weapons anymore, or energy or money. It's run by ones and zeroes, little bits of data. It's all just electrons. [...] There's a war out there, old friend, a world war. And it's not about who's got the most bullets. It's about who controls the information: what we see and hear, how we work, what we think. It's all about the information.
> Cosmo (Ben Kingsley) in Sneakers (1992)

This thesis provides an empirical study on London Stock Exchange market (LSE). It contributes to the existing literature by addressing three main issues which cover the fields of market microstructure and corporate finance. The first essay, presented in the second chapter, focuses on the market microstructure effects around ex-dividend day for a sample of FTSE 100 stocks. The second essay, presented in the third chapter investigates the impact of liquidity on market microstructure around the ex-dividend day using a sample of FTSE SmallCap stocks. The final essay, presented in the fourth chapter, examines the impact of the ex-dividend day on intraday trading patterns for a sample of FTSE 100 stocks.

For a clearer understanding of the London Stock Exchange market, this chapter presents a brief introduction to the London Stock Exchange market and the UK taxation system, explains the motivations behind the thesis and the briefly scouts the data employed in the thesis, outlines the main contributions and presents the structure of the thesis.

1.1 Motivation

Ex-dividend trading activities remain a prevalent feature of equity markets worldwide.[1] Traders, who aim to receive the dividend payments for a specific stock, should hold this stock on the cum-dividend day. Traders who buy this stock on the ex-dividend day or any day after the cum-dividend day will not receive that particular dividend payment. Trading activities around ex-dividend day can become intense–especially for stocks that are actively traded and have a great current dividend yield. Some investors may prefer dividends over capital gains for tax reasons. For example, individual investors who pay income tax are at a better tax position if the dividend payments are between £9200 and £34,600, everything else being equal. The tax rate for dividend payment that are between £9200-£34,600 is 10% however the tax rate for capital gain that are between £9200-£34,600 is 22%. Such individual investors may buy stocks on cum-dividend day, to get the upcoming dividend, and then sell them on ex-dividend day, assuming trading volume justifies transaction costs. While dividend-capturing investors buy stocks on cum-dividend day and sell them on ex-dividend day, some traders may do just the opposite. With a high dividend yield and above-average trading volume, stock prices on cum-dividend day may increase because of trading intensity. Considering that the stock price is to be adjusted lesser on the ex-dividend day and expecting a potential sell off by dividend-capturing investors on ex-dividend day, some traders might "short" the stock on cum-dividend day. This is completed by borrowing stocks and selling them at a greater price on cum-dividend day and then buying them back at a lesser price on ex-dividend day to capture capital gains.

[1] See, for example, Kalay (1982); Eades et al. (1984); Lakonishok and Vermaelen (1986); Michaely (1991); Michaely and Vila (1996); and Rantapuska (2008).

For investors who have standing holdings, cum-dividend day can be a profit making opportunity sometimes. Trading activities could become intensive on cum-dividend day as investors who prefer dividends over capital gains scramble to buy shares at the last minute, potentially moving the price higher. For existing stockholders considering selling during days before the ex-dividend day present the best opportunity.

On the other hand, days around the ex-dividend day might also be an opportunity for investors who wish to buy the stock for future holdings. Investors who do not like to get dividend realise stocks the day before the ex-dividend day. The selling might possibly prompt a price drop in case of absent of strong buying behaviour from dividend-capturing investors. Furthermore, days after the cum-dividend day could offer better opportunities for future investors to buy shares at even lower prices.

The focus of the existing ex-dividend day literature and the corresponding empirical results refer, almost exclusively, to abnormal returns and abnormal volume.[2] This thesis contributes to the literature and informs the debate by investigating empirically the effects of tax-arbitrage trading activities on bid-ask spreads, price volatility and order submission strategies, by examining the effects of liquidity on tax-arbitrage activities and by studying the intraday patterns of bid–ask spread, price volatility and trading volume around the ex-dividend day using high frequency data from the London Stock Exchange market (LSE).

It is of interest to investigate whether immediacy concerns have an impact on order submission around the ex-dividend day in addition to spread and volatility factors for the following reasons. First, traders around the ex-dividend day could have a different subjective valuation of the stock, which could reflect differences between tax rates on capital gains and tax rates on dividend payment and the

[2]Previous studies report a drop in stock price on ex-dividend day by amount less than the amount of dividend. This drop has explained by tax-effect (e.g. Elton and Gruber, 1970), short-term trading (e.g. Kalay, 1982), or price discreteness (e.g. Bali and Hite, 1998). In addition, previous studies also report an increase in trading volume around ex-dividend day Michaely and Vila (1995, 1996).

ability to utilize tax credits. For example, dividend-capture traders will buy stock on the cum-dividend day and/or sell it on the ex-dividend day. Tax-arbitrage trading activities occur mostly on the cum-dividend day and ex-dividend day and are more likely to be one-sided (either buying pressure or selling pressure).[3] Second, trading activities around ex-dividend day could be viewed as dividend related trading which does not include information since information asymmetry is more likely to be lower following dividend announcements that predate the ex-dividend day. Third, Foucault et al. (2005) and Roşu (2009) find theoretically that waiting costs should affect the order submission decision.[4] They argue that high competition among patient traders motivates them to submit aggressive orders increasing probability of execution.[5] If waiting costs are high, traders will seek to reduce execution time by submitting more aggressive orders. Most ex-dividend trading is submitted and executed prior to the ex-dividend day, which makes traders sensitive to execution risk (Ainsworth et al., 2011). As the ex-dividend day approaches and both the waiting costs and the risk of non-execution increase, the proportion of impatient traders are expected to increase with the approaching deadline and will be more likely to switch to using relatively more aggressive orders. Fourth, since tax-arbitrageurs keen to unwind their position on cum-dividend day, liquidity suppliers can take advantage of them and trade strategically around ex-dividend day Admati and Pfleiderer (1988). Finally, traders who are indifferent between capital gain and dividend can also take advantages from the tax-arbitrageurs who need to liquidate their positions around ex-dividend day Brunnermeier and Pedersen (2005). The ex-dividend day, therefore, provides a natural experiment to study the market microstructure when in at low information asymmetry environment and with a limited and dynamically closing time window for execution.

[3] By "pressure" we mean the temporary imbalance in the flow of orders. For example, traders who prefer dividend payments more than capital gains will buy stocks on the cum-dividend day and sell stocks on the ex-dividend day and vice versa for investors who prefer capital gain more than dividend payments.

[4] Waiting cost : is the total delay between order submission and order execution

[5] Impatient traders have a higher waiting cost per unit of time and are more likely to submit aggressive orders than patient traders.

Hypothesis 1: we expect to find evidences of the presence of both tax-arbitrageurs and liquidity suppliers around ex-dividend day for FTSE100 stocks

The expected execution probability for illiquid stocks is lower than the expected execution probability for liquid stocks. Further, the expected waiting cost for illiquid stock is higher than the expected waiting cost for liquid stocks. Traders in illiquid markets could face a risk of significant price change in response to there being available only few orders. Bayraktar and Ludkovski (2012) reports that dramatic price changes could occur if one order matches up with all orders on the opposite side of the market, but Seppi (1997) reports that in liquid markets submitted orders have only a small impact on stock prices. Aggressive orders and large orders could amplify the significant effect of illiquidity on stock prices. Aggressive orders could quickly consume all orders on the opposite side of the market (Lebedeva, 2012). Large orders could raise an imbalance between the two sides of the market. The only way to wash out this imbalance between two sides of the market is by changing the stock prices (Damodaran, 2005). In addition to bid-ask spreads and commission costs, Treynor (1981) argues that waiting for the "right time" to liquidate an investment is valuable. In illiquid markets, this value is higher than in liquid markets, so traders may wait longer to liquidate their investments than in liquid markets. Both the non-execution costs and the value of waiting before submitting orders are expected to be higher for the illiquid stocks than for the liquid stocks. It is of interest, therefore, to investigate whether tax-arbitrage traders seek to avoid trading in illiquid stocks and how the activities of tax-arbitrage traders, if there are any, could affect bid-ask spreads, price volatility and order submission strategies.

Hypothesis 2: we think that the lack of liquidity prevents the tax-arbitrageurs from applying their trading strategy around ex-dividend day on FTSE SmallCap stocks.

Several studies have found evidence of general intraday patterns in volatility, spread and trading volume in equity market and other markets. More specifically, they find U-shaped patterns in volatility, spread and volume.[6] Studies rationalise U-shaped patterns by information asymmetry effects at the beginning of the day and by market closure at the end of the day. Information asymmetry leads to greater spreads and greater volatility because of adverse selection costs and information revelation and also greater volumes because more informed trading takes place. At market closure, the traders who otherwise risking holding their position overnight when they have limited access to information and trading liquidity, will choose to close their positions. Therefore, the liquidity suppliers quote larger spreads to take advantage of those closing their position and the resulting trading activity leads to greater price volatility and volumes (Slezak, 1994). Tax arbitrageurs are averse to adverse selection costs and execution risk and should consequently prefer to trade in the companies were these are the lowest and at a time of day when these are the lowest. It is of interest, therefore, to investigate the impact the trading activity around the ex-dividend day on intraday patterns of spread, volume and volatility.

Hypothesis 3: we expect that the tax-arbitrage trading activities affect the intraday pattern of bid-ask spread, price volatility and trading volume for FTSE 100 stocks.

To date, there is little empirical evidence on this issue. For instance, while Graham et al. (2003), study spread effects on cum- and ex-dividend days for NYSE stocks but focus on the effects of the decimalisation of tick size. Ainsworth et al. (2008) study the spreads around ex-dividend day and find higher spreads on ex-dividend day compared to cum-dividend day on the Australian Stock Exchange. Effective spread has been found to decrease on cum-dividend days and increase on ex-dividend days by Ainsworth and Lee (2011) who also report that for executed orders, traders are more aggressive on cum-dividend days and less aggressive on ex-dividend days on the Australian Stock Exchange. Evidence of abnormal volumes around the ex-dividend day is reported by Jun et al. (2008)

[6] some studies indicate that there is an L-shape or inverted J-shape for the intraday pattern of spreads, volume and volatility (Chan et al., 1995 and McInish and Van Ness, 2002)

though they focus on explaining the ex-dividend price drop. Lakonishok and Vermaelen (1986) demonstrate that the ex-dividend day is associated with an increase in trading activity while Frank and Jagannathan (1998) and Jakob and Ma (2004) find evidence of order imbalance around ex-dividend day. Finally Ainsworth et al. (2008) and Jun et al. (2008) find evidence of abnormal volume and price volatility around ex-dividend day.

1.2 Contribution

This thesis focuses on investigating market microstructure and intraday trading patterns around the ex-dividend day. The effects of ex-dividend day trading on market microstructure are evaluated using a multinomial logit and an ordered probit analysis and the intraday patterns are examined using a GMM and difference in difference analysis. The main contributions of this thesis are in the following ways.

Most of the ex-dividend literature focuses on price effects and volume effects of the ex-dividend day but this thesis focuses on investigating market microstructure effects.[7] Chapter 2 contributes to the literature by investigate the presence of both tax-arbitrageurs and liquidity suppliers. The results reveal the presence of "footprints" of tax-arbitrage trading and of liquidity supply effects around the ex-dividend day. The aggressive inflow of tax-arbitrageurs around the ex-dividend day is quickly offset by less aggressive inflow of liquidity suppliers. Interestingly, the level of order aggressiveness, for both tax-arbitrageurs and liquidity suppliers, is affected by the spread, volatility, return and duration. One sided buying or selling pressure drives prices away from fundamentals and increase returns and spreads. The large spread and the price deviation from the fundamental value attract the liquidity suppliers to trade aggressively. Moreover, one sided buying or selling pressure raises price volatility. That is, the tax-arbitrageurs become

[7] That is, how ex-dividend trading mechanisms affect bid-ask spreads, price volatility, order submission strategies and the intraday trading pattern.

more aggressive and these effects are stronger on cum-dividend days. We see this in the light of an approaching cum-dividend deadline to trade and the potential after tax return that would be forgone.

Other main contributions of this thesis are a deeper investigation of whether tax-arbitrageurs focus only on high liquid stocks such as the FTSE 100. Specifically, Chapter 3 uses stocks from FTSE SmallCap to examine the effect of liquidity on the activities of tax-arbitrageurs around the ex-dividend day. Chapter 3 finds that illiquidity does not prevent tax-arbitrage activities altogether. Similar to Chapter 2, Chapter 3 finds, for illiquid stocks, effects that link order submission to spreads, volatility and returns but not to order arrival rate.

The final contribution of this thesis is that Chapter 4 explores the intraday pattern of bid-ask spread, price volatility and trade volume around the ex-dividend day. Furthremore, Chapter 4 investigates differences between firms with high price impact (less attractive target to tax-arbitrage traders) and those with low price impact (more attractive target to tax-arbitrage traders). Further, on the cum-dividend day, competition between traders, increases as a result of high waiting cost of not trading, resulting in higher volumes and lower spreads. Moreover, the findings show ex-dividend day effects in the intraday patterns can become "masked" in lower frequency investigations. We find that that tax-arbitrage traders are more likely to trade in firms with the lowest price impact since this minimises both adverse selection costs and execution risk. Across all the firms in the sample of Chapter 4, there is no measurable impact on spreads and volumes on the ex-dividend day and cum-dividend days but when the sample is split into low price impact firms and high impact firms, the results show greater spreads and volumes at the end of the ex-dividend day and cum-dividend day for low price impact firms and smaller spreads and volumes at the end of the day for the high price impact firms. The total sample masks, therefore, the two opposing effects.

1.3 Background

1.3.1 UK Taxation

Income earned in the UK is usually subject to UK taxation regulations regardless of either citizenship of an individual or the place of registration of a company. Capital gain is calculated on the basis of the difference between the current price and the original purchase price plus allowable related expenditure. From 6th April 2008, individuals and companies however, have had different capital gains tax rates from previously. Companies apply, moreover, an "indexation relief" to the original cost, increasing the purchase cost with the Retail Prices Index. Individuals are taxed at a flat rate of 18% (since 22nd June 2010 and at 28% for higher rate taxpayers) without indexation relief though realised capital losses can be brought forward.[8]

Table 1.1shows the tax rates and allowances in the UK for (2007-2008) and (2008-2009), which are the years relevant to this study.

[8]Sourced from various locations: see Scopulus Limited (2013); Taxcafe UK Limited (2013); Government Digital Service (2013).

Table 1.1 – Tax rates, allowances and bands for UK
*The Small companies rate raises from 19% to 20% in April 2007, but then to 21% in April 2008 and 22% in April 2009

Tax rate , Allowance and Bands for UK	2007-08 (£)	2008-09 (£)
INCOME TAX ALLOWANCES:		
Personal allowance	5,225	6,035
Personal allowance for people aged 65-74	7,550	9,030
Personal allowance for people aged 75 and over	7,690	9,180
Income limit for age-related allowances	20,900	21,800
Married couple's allowance - aged 75 or more	6,365	6,625
Minimum amount of married couple's allowance	2,440	9,180
Blind person's allowance	1,730	1,800
Dividend income taxable bands		
Rate 10%	below 34,600	below 34,800
Rate 32.5%	Over 34,600	Over 34,800
CAPITAL GAINS TAX ANNUAL EXEMPT AMOUNT		
Individuals	9,200	9,600
Other trustees	4,600	4,800
Inheritance tax threshold	300,000	312,000
Taxable bands		
Starting rate 10%	0 - 2,230	-
Basic rate 22% (for 2008-09 is 20%)	2,231 - 34,600	0 - 34,800
Higher rate 40%	Over 34,600	Over 34,800
Band Corporation tax profits		
0 - 300,000	* 20%	21%
300,001 - 1,500,000	Marginal relief	Marginal relief
1,500,001 or more	30%	28%

It is difficult to determine whether traders would prefer either capital gains or dividends since that depends on a trader's needs and obligations. For example, in the tax year between April 2007 and April 2008, the individual tax allowance income level is lower than the individual tax allowance for capital gains. Individuals are indifferent between dividends and capital gains if the return is lower than £5225. Capital gains or dividends equal to or less than £5225 are tax free. The capital gains are however, more tax efficient if the return is between £5225 and £9200, everything else being equal. Capital gains equal to or less than £9200 are tax free but dividends that are between £5225-£34,600 are taxed at 10% rate. Dividends are more tax efficient if the return is more than £9,200, everything else being equal since capital gains that are between £9200 and £34,600 are taxed at 22% rate. The UK system of taxation will, therefore, generate a variation in tax status across investors motivating tax arbitrage

1.3.2 London Stock Exchange (LSE)

The Stock Exchange Electronic Trading System (SETS) was introduced on the London Stock Exchange (LSE) on 20th October 1997 for FTSE 100 stocks but now also covers the FTSE 250, FTSE SmallCap Index.[9] SETS is also indirectly accessible from many platforms through Direct Market Access (DMA) and the Exchange's Member Authorised Connectivity (MAC) (London Stock Exchange, 2013).[10] London Stock Exchange (LSE), by the use of SETS, has moved from quote driven market structures to order driven market structures. In order driven market structures, the market makers are not obligated to quote the stocks and the public are allowed to compete directly.

1.3.3 Market participants

Issuers

An issuer of a security is a legal entity that develops, registers and sells securities to investors, who in turn exchange these stocks with other investors to balance their holdings and intermediaries facilitate. Issuers are legally responsible for the obligations of the issue and for providing all relevant information (i.e. financial conditions, material developments and any other operational activities) to all investors on a timely basis as required by the regulations of their jurisdictions. Publishing of news and of periodic financial reports is often required and is assumed to be of help investors to help evaluate the value of the company.

[9] It also acts as a platform for various other securities also such as ETFs, ETCs, ETNs, liquid AIM, liquid Irish stocks and liquid international equity stocks.

[10] SETS is considered one of the most liquid electronic order books in Europe and more than 230 companies trade directly on SETS through market makers, agency brokers and private client brokers (London Stock Exchange, 2013).

Investors

Investors are initially the source of market activities. An "investor" is an individual or an institution who allocates capital with the expectation of a financial return using a wide range of trading strategies. This definition makes no distinction between those in the primary markets and secondary markets. That is, someone who provides a business with capital and someone who buys stock are both investors. Fundamental analysis and technical analysis are thought to be used by investors to determine the "true" value of the stock prices. Recent studies suggest a link between market microstructure and technical analysis. Price trends may be the result of dynamic adjustment of prices to the incoming information (Schwartz and Francioni, 2004). The price level may reflect also excess liquidity available at a certain price.

Intermediaries

An intermediary is a third party that offers intermediation services between two trading parties. Financial intermediaries could be classified into market makers and brokers. A market maker is a person or a firm in the business of buying and selling securities for their own account, whether through a broker or otherwise. Market makers are the designated counterparties for the rest of the market participants - when a trader wants to transact, he/she can trade immediately with a market maker at price that latter quotes. The key concept to understand about the market maker's role is that by committing to trading at all times, the market maker participates in the market as a principal. A market maker is distinct from a trader in that buying and selling securities is part of its regular business, while a trader buys and sells securities for his or her own account but not on a business basis. Market makers are the central player in many organised markets though the LSE SETS are a notable exception. Here, there is no *designated* market makers and all trading occurs by directly matching each orders with other orders. This does not mean that the market makers' services are not needed.

The main feature that differentiates brokers from market makers is that a market maker acts as a principal while trading on its own account, as opposed to a broker who is paid gets by commission for arranging transactions on behalf of their clients. Brokers do not take on risk. In the most cases, brokers help find the best execution venue for those actors who do not have direct access to the market - individual investors often transact through brokers.

1.3.4 Market organisation

Order types

An order is an instruction to either a broker or directly to the market (if trader has access) to either buy or sell a specified number of securities. When submitting a limit order, a trader specifies a reservation price at which the trader is willing to transact. For example, when a trader submits a buy (sell) limit order, he/she is willing to buy (sell) a specified quantity of stock at a limit price or lower (higher). Incoming limit orders that cannot execute immediately at their specified prices join one queue of orders set at different price levels and organized according to their order time arrival and they transact against incoming market orders. New limit buy (sell) orders of size (x) increases the size of the bid (ask) queue by (x). Market orders directs the broker to transact immediately at the best price that can be found or executes immediately against the best price quoted in the market in the case of direct access. Market order with size (x) decreases the queue size by (x). Limit orders submitted at the best available price are executed against market orders (Cont and De Larrard, 2012). Limit orders are subject to different types of risk which can be summarized by the following: being in front-run; execution uncertainty; revealation of intentions to the market; being subject to picking off; and trade with informed traders (D'Hondt et al., 2003).[11,12] Market order is

[11] Front running is when a trader submits an order in front of another order in the same direction. For example, when a broker-dealer trades ahead of large investors' orders either on behalf of other customers or for themselves, this is 'front running'.

[12] A limit order may take time to fill and that order may be filled following a sudden change in the stock price. The notion of being 'picked off' refers to a situation where investors react to

subject to risk of execution price uncertainty.

Market mechanisms

Market mechanisms are generally classified into two categories: quote-driven and order-driven. A quote-driven market is an electronic stock exchange system in which prices are determined from bid and ask quotations made by market makers or specialists – investors cannot transact directly with one another, all trade flow goes through market makers. It is essential to understand that even though all traders go through the market maker the market maker does *not set* prices in the market. Quote–driven markets can feature multiple specialists in the same securities, competing for the order flow among themselves - public investors will only transact with the specialist who has the highest bid or the lowest ask in the market.

A pure order-driven (or auction) market is a market where all buyers and sellers display the prices at which they wish to buy or sell a particular security, as well as the amounts of the security desired to be bought or sold. Traders transact directly with one another by submitting limit and market orders since there are no *designated* market makers. Major exchanges (e.g. the NYSE, NASDAQ, the Tokyo Stock Exchange and the London Stock Exchange (LSE)) have switched to electronic order driven platforms either completely or partially through “hybrid” systems.[13,14] In order-driven markets, limit orders provide liquidity to the market (essentially performing the function of the market maker in the quote-driven market) and market orders consume liquidity.

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the arrival of relevant information before the limit order investors are able to amend their own now ‘mispositioned’ limit orders so that newly arriving market order will execute with them.

[13]The trading process in financial markets, can be summarized as a pure order-driven market such as Euronext, Helsinki, Hong Kong, Swiss, Tokyo, Toronto, and many electronic communication networks, hybrid markets such as NYSE, NASDAQ and London Stock Exchange (LSE) and quote driven markets such as London SEAQ. In hybrid markets, while market makers do exist, they are involved only in a small number of transactions and have to compete with other traders (Hasbrouck and Sofianos, 1993).

[14]Examples of Electronic Communications Networks include Archipelago, Instinet, Brut and Tradebook.

Rule, regulation and frictions

Important aspects of financial markets, useful for the understanding of models and applications, are the rules of precedence and tick size. These rules differ (slightly) for each market. The rules of precedence, while complex in reality, for the purpose of this thesis can be summarized as follows: buy (sell) orders with highest (lowest) price executes first. The rules of precedence are closely tied to tick size - the smallest increment (tick) by which the price can move.

The effects of tick size are not clear-cut. The backers of tick reduction state that smaller tick size raises the competitiveness (or aggressive) of limit orders, which leads to narrower spreads and decreases the cost of trading. The opponents of tick reduction claim smaller tick size makes it easier to jump into the front of a queue of limit orders. If jumping to the front of limit orders costs practically nothing, which makes the time priority rule basically useless and leaves limit orders move vulnerable, this will discourage the submission of limit orders. While the spreads are narrower, the pre-committed liquidity or depth at those quotes is much lesser than with larger tick sizes when spreads were wider, which makes trading more expensive. Whether the effect of tighter spreads dominates the effect of reduced liquidity has been studied by several researches, but no clear consensus has emerged thus far (see Goldstein and Kavajecz, 2000 and Chordia and Subrahmanyam, 1995).

1.4 Data

Rather unusually the dataset is described here merely to avoid repetition since it has been employed throughout all chapters for this thesis. The main part of the data set contains tick by tick data from the London MIDAS[15] order book, which contains three files: an ORDERS file, with information about order submissions, a HISTORY file, with information about executed trades and a TRADE REPORT

[15] MIDAS holds day by day historical trading information for the London Stock Exchange and is housed within a SQL server and on large terabyte databases.

file, with price data for the executed trades. The TRADE REPORT file is merged with the HISTORY file to link prices for each executed trade. ORDERS contains information about each submitted limit order but there is no information about market orders and no information about withdrawn orders (i.e. those that are never executed). A market order will appear in the HISTORY file. The trade executions are classified into four groups: a limit buy trade, a limit sell trade, a market buy trade, and a market sell trade. A limit buy (sell) trade is the transaction that takes place following the submission of a limit buy (sell) order. Such an order will appear in all three files, ORDERS, HISTORY, and TRADE REPORT. A market buy (sell) trade is the transaction that takes place following the submission of a market buy (sell) order. This order will appear only in the HISTORY and TRADE REPORT files. If an incoming limit order is partially executed, the whole order will appear in the ORDERS file, the executed part will appear as a separate limit order in the HISTORY and TRADE REPORT files and the non-executed part will eventually appear as a separate order in the two latter files if and when execution takes place. Typically the time interval between the two is very short and the initial order is labelled “p” and the final order is labelled “m”. Deleted orders appear in the HISTORY file and a modified order is shown as a deleted order in the HISTORY file followed by a new order submission in the ORDERS file. The data do not include orders routed via floor brokers and only those linked to the electronic submission of orders. The data include transactions carried out between 7:50 a.m. till 4:35 p.m.

The data sets for Chapter 2, Chapter 3 and Chapter 4 are constructed based on the following criteria:

1. The stock must be included in the FTSE 100 index for Chapter 2 and Chapter 4 (or in the FTSE SmallCap index for Chapter 3) during the sample period, from June 2007 to June 2008.

2. The stock paid a cash dividend during the sample period with the ex-dividend day on a Wednesday,to avoid trading activity related to weekend

effects documented in the literature, and where there is no bank holiday in the ex-dividend week or in the week before (which we classify as the control week).[16]

The stocks in the FTSE SmallCap index contains execution data in the HISTORY file but the data for a number of liquidity measures were poor compared to the FTSE 100 index stocks. The resulting sample contained 47 FTSE 100 stocks and 43 FTSE SmallCap stocks. For each stock, all trade data from the ORDERS, the HISTORY, and the TRADE REPORT files were collected from Monday to Friday in the week containing the ex-dividend day (the ex-dividend week), and the corresponding data for Monday to Friday in the week prior (the control week). [17]

Further, the data sets for robustness test in Chapter 2, Chapter 3 and Chapter 4 are constructed based on the following criteria:

1. The stock must be included in the FTSE 100 index for Chapter 2 and Chapter 4 (or in the FTSE SmallCap index for Chapter 3) during the sample period, from June 2007 to June 2008.

2. The stock paid a cash dividend during the sample period.

For firms that paid a cash dividend several times during the sample period, we include all events, each event is counted as a separated stock. The resulting sample contained 167 FTSE 100 stocks and 77 FTSE SmallCap stocks. For each stock, all trade data from the ORDERS, the HISTORY, and the TRADE REPORT files were collected for cum-dividend day, ex-dividend day and 10 days after ex-dividend day, as a controlling period. By considering 10 days after ex-dividend day

[16] Weekend effects have been documented by French (1980). Where these firms are not excluded, potential confounding issues are run, since it will be unable to distinguish the documented weekend effect from any tax-arbitrage evidence it may found. A small number of cases where there is a bank holiday in the two-week period are also excluded, to exclude potential contemporaneous effects that might be associated with bank holiday related trading activity but not associated with tax-arbitrage.

[17] The time distance between the announcement date and the ex-dividend date varies with different stocks. The minimum time difference between ex-dividend date and announcement date is one month which ensures that our control week is free from dividend related trading activity.

as a control period, we avoid the period that might be contaminated by dividend related activity.

Finally, daily data is used from DataStream covering the period from June 2007 to June 2008 as the basis for computing liquidity measures and estimating the preliminary regressions. For each firm the closing price, the ask price, the bid price, the daily volume, the number of daily transactions and dividend payments are collected. Information about the ex-dividend day for each stock was taken from the various companies' web-sites.

1.5 Overview and structure of the thesis

The reminder of the thesis is set up as follows. Chapter 2 studies market microstructure effects around the ex-dividend day and investigates what effects tax-arbitrage activities may have on spreads, price volatility and order submission strategies using data from the FTSE 100 index. The spread and the volatility are compared between the ex-dividend week and the control week and between the cum-dividend day and the ex-dividend day. The changes in the marginal aggressiveness level of buy orders and sell orders are also examined on cum-dividend day and ex-dividend days as compared to the control week and to the *rest* of the ex-dividend week. Whereas Chapter 2 looks at FTSE 100 stocks, Chapter 3 studies market microstructure effects around the ex-dividend day using data from FTSE SmallCap stocks. Stocks that are listed in the FTSE SmallCap index are classified as illiquid stocks. This difference in liquidity is confirmed empirically in Chapter 3, employing a range of liquidity measures. Chapter 4 studies the intraday patterns of bid–ask spreads, price volatility and trading volume around the ex-dividend day for a sample of FTSE 100 companies. We also investigate the differences between the intraday trading patterns change of those firms that are the most attractive targets for tax-arbitrage traders compared with the patterns for the least attractive targets for tax-arbitrage traders. Chapter 5 briefly summarises the key findings of the thesis and concludes.

Chapter 2

Market Microstructure Effects around Ex-Dividend Day

2.1 Introduction

Among the several longstanding questions in market microstructure are what the optimal trading strategies are around specific events and what can be inferred, from high frequency trading data, concerning the informational environment that firms face. This chapter studies market microstructure effects of trading associated with ex-dividend day price changes. The ex-dividend day is known to attract trading activity associated with tax-arbitrage (Elton and Gruber, 1970; Kalay, 1982). Specifically, this study investigates tax-arbitrage effects on spreads, price volatility and order submission strategies, using data from the London Stock Exchange (LSE). In particular, there is an expectation that such tax-arbitrage activity around the ex-dividend day can be one-sided due either to buying pressure or to selling pressure. Investors who prefer dividend are more likely to buy stocks on cum-dividend day and sell it on ex-dividend day, however investors who prefer capital gain are more likely to sell stocks on cum-dividend day and buy it back on ex-dividend day. Therefore, the spread and volatility may increase because limit orders are eroded faster on one side of the market than on the other. However, since this tax-arbitrage trading is a known exogenous event, it is likely to attract liquidity suppliers who seek to profit by catering to that need. More specifically, though trading activity can itself be seen as a source of price volatility, this study argues that since inflows of uninformed trade could make informed speculation less likely, the latter effect may reduce price volatility around the ex-dividend day. The net effect on spread and volatility is, therefore, unclear and in any case, there is little empirical evidence on this issue. For instance, while Graham et al. (2003), study spread effects on cum- and ex-dividend days for NYSE stocks, they focus on the effects of the decimalisation of tick size. Evidence of abnormal volumes around the ex-dividend day is reported by Jun et al. (2008) though they focus on explaining the ex-dividend price drop. Effective spread has been found to decrease on cum-dividend days and increase on ex-dividend days by Ainsworth and Lee (2011) who also report that for executed orders, traders are more aggressive on cum-dividend days and less aggressive on ex-dividend days.

While this study investigates also whether spread and volatility differ between cum- and ex-dividend days, the focus is on order submission strategies on cum- and ex-dividend days. Furthermore, since spread, volatility, return, and duration between submitted orders affect the order submission strategy, in this chapter we investigate also how their effects vary between cum- and ex-dividend days. The optimal submission trading strategy is a trade-off between the cost of delay in execution, which is the execution risk of submitting limit orders on the one hand and on the other, the cost of immediacy, which is the price concession of submitting market orders. Since tax-arbitrage driven trading activity around the ex-dividend day has a limited time-window for execution, because tax-arbitrage trades need to be executed prior to the close of trade on the cum-dividend day, tax-arbitrage is likely concentrated on one side of the market with aggressive orders, it can transpire that liquidity-supplying traders on the other side of the market will employ relatively passive orders. The aggregate net effect on order submission is, therefore, unclear and it could be that both passive and aggressive orders are used more frequently. More specifically, Foucault et al. (2005) and Roşu (2009) investigate, theoretically, how waiting costs affect the choice of order type and predict that an increase in the cost of waiting will lead to more aggressive order submission. It would be then reasonable to observe either a switch to market orders from limit orders or a switch to more aggressive pricing within limit orders and this study, therefore, investigates whether immediacy concerns have an impact on order submission around ex-dividend days, in addition to spread, volatility, return, and duration factors.

We empirically investigate these issues, employing data on order submissions and executions in the ex-dividend week, and in a control week, and for shares constituting the FTSE 100 going ex-dividend between June 2007 and June 2008. This study is restricted to only those firms that go ex-dividend on a Wednesday, to avoid trading activity related to weekend effects documented in the literature, and where there is no bank holiday in the two weeks concerned. What findings could be reasonably expected? This is conditional on whether tax-arbitrage traders place their orders and even if orders were placed, the answer can further be conditioned on how sensitive the equilibrium in the limit order book is to external changes. For instance, if an inflow of tax-arbitrageurs is quickly offset by a similar inflow of liquidity suppliers, it is not obvious that there are strong market microstructure effects. In this event, this chapter seeks "footprints" of tax-arbitrage trading and of liquidity supply effects. When traders face high waiting costs, they become more likely to submit aggressive orders to reduce the cost of delayed execution. The aggressiveness level is affected by the proportion of patient and impatient traders. On cum-dividend days, as the deadline for the close of trading approaches, both waiting costs and the risk of non-execution are likely to increase. We argue that when the cost of delayed execution increases beyond a latent threshold level, a subset of the patient traders will become impatient and submit more aggressive orders whereas, the remaining patient traders are not necessarily independent of other traders. Therefore, traders may turn out to be less patient and submit more aggressive orders. We argue that order aggressiveness can be detected from the limit order book by observing specific patterns of trading and these patterns we label as “footprints”.

Evidence of “footprints”, this study argues, is the best overall description of the findings, which are outlined next. First, we find that spread and volatility are higher in the ex-dividend week compared to the control week and on the cum-dividend day compared to the ex-dividend days, within the ex-dividend week. Seen in isolation, this effect appears hard to explain, without also studying order submission strategies.

Second, we report results for both sides of the market: arbitrageurs and liquidity providers. There is evidence that behind the quote buy orders and marketable sell orders are less likely on the cum-dividend day and behind the quote buy orders and at the quote and inside the quote sell orders are more likely on the ex-dividend day, consistent with tax arbitrage, which involves a round-trip of buying on the cum-dividend day and selling on the ex-dividend day. There is also evidence that behind the quote sell orders are more likely on the cum-dividend day and behind the quote buy orders are more likely on the ex-dividend day, consistent with liquidity suppliers taking advantage of tax-arbitrage activity.

Third, we find effects linking order submission to spread, volatility, return and duration. One pattern that may be expected is that one-sided trading of tax-arbitrageurs may drive prices away from fundamentals and in that process increase return and spread. They are likely to attract liquidity suppliers, who may trade aggressively either to take advantage of the difference between transaction prices and fundamental prices, or to profit from the larger spread. In addition, one-sided buying or selling pressure increases price volatility, which motivates the tax-arbitrager to submit aggressive orders.

The reminder of the paper is organised as follows: Section 2.2 presents the prior literature, whereas Section 2.3 specifically presents the extant theory. The data and methodology are in Sections 2.4 and Section 2.5 respectively, while section

2.6 reports and interprets the results, section 2.7 displays a robustness tests and a final section concludes.

2.2 Literature Review

There are several strands of literature related to this chapter. First, there is a literature on ex-dividend effects but not related to market microstructure. Second, there is a literature specifically on market microstructure effects. Third, there is a strand that looks at market microstructure effects linked specifically to the period around the ex-dividend day.

In an economy with perfect capital markets with no tax and transaction costs, Miller and Modigliani (1961) showed that shareholders are indifferent as to whether they receive income in the form of either dividends or capital gains. This implies that the stock price should decline on the ex-dividend day by an amount equal to the dividend payment. However, early empirical studies (e.g., Campbell and Beranek, 1955; Durand and May, 1960) have shown that prices on the ex-dividend day fall by an amount less than the amount of the dividend. Elton and Gruber (1970) introduce what can be called a long–term trading hypothesis or tax-effect hypothesis. They argue that differences in tax status motivate trading around the ex-dividend day. If the cum-dividend stock price is(P_c), the tax rate on capital gain is (t_g) , the purchase price of the stock is (P_0) , the dividend amount is(D), the ex-dividend stock price is (P_e) , and the tax rate on divided is(t_g).[1]

$$(P_c) - (P_c - P_0) \times t_g = (P_e) - (P_e - P_0) \times t_g + D \times (1 - t_d) \tag{2.1}$$

$$\frac{(P_c - P_e)}{D} = \frac{(1 - t_d)}{(1 - t_g)} \tag{2.2}$$

[1] (t_g):the tax rate on capital gain when the price, ex-dividend, exceeds the purchase price.

Tax-driven trading around the ex-dividend day has been evidenced and hypothesised also by a number of other studies.[2] Kalay (1982) introduces what can be called a short-term trading hypothesis. He argues that the ex-dividend day price drop attracts tax arbitrage. Investors who are indifferent between the tax rate on dividend and the tax rate on capital gain, can generate profits by trading around the ex-dividend day. Though the short-term trading hypothesis is supported by several studies, since several others find no support (Lakonishok and Vermaelen, 1983; Poterba and Summers, 1984; Kaplanis, 1986; Booth and Johnston, 1984 and Menyah, 1993), we argue that this tax-arbitrage rationale is contentious.[3] This chapter is, therefore, partly motivated by the notion that tax-driven trading is likely to take place around the ex-dividend day and that such evidence is more likely to be discernible in high frequency trading data than those based on daily data alone.

While the trade-off between the use of limit orders and market orders in a static model has been studied the extension into a dynamic framework has also been investigated while linking depth and spread to order type.[4,5] Although the empirical literature on this link is quite extensive, more recent studies have argued that the link is conditional on various features observable in the market, such as the degree of informed trading (Beber and Caglio, 2005), while others have studied the effects on the choice of order type conditional on the presence of impatient traders (Foucault et al., 2005; Roşu, 2009).[6] This chapter contributes to this literature, relying on it as the basis for hypotheses development.

[2]For example, see Lakonishok and Vermaelen (1983); Eades et al. (1984); Poterba and Summers (1984); Kaplanis (1986); Barclay (1987); Fedenia and Grammatikos (1993); Lasfer (1995); Michaely and Vila (1995, 1996); Bell and Jenkinson (2002); Callaghan and Barry (2003); Graham et al. (2003); Elton et al. (2005); Zhang et al. (2008).

[3]Examples of studies that support short-term trading hypothesis include Eades et al. (1984); Lakonishok and Vermaelen (1986) and Michaely (1991).

[4]Several studies such as Cohen et al. (1981); Copeland and Galai (1983); and Handa and Schwartz (1996) examine the static case.

[5]See Parlour (1998); Foucault (1999); Handa et al. (2003); Foucault et al. (2005); Goettler et al. (2005); and Rosu (2009) for the extension to the dynamic case.

[6]A typical array of the empirical literature would include Biais et al. (1995); Harris and Hasbrouck (1996); Parlour (1998); Foucault (1999); Al-Suhaibani and Kryzanowski (2000); Griffiths et al. (2000); Sandas (2001); Ranaldo (2004); Beber and Caglio (2005); Goettler et al. (2005, 2009); Foucault et al. (2005); Ellul et al. (2007); Rosu (2009) and Menkhoff et al. (2010).

Discreteness in prices as compared to the continuity of dividends is the reason, claim Bali and Hite (1998), for the ratio of dividend to the ex-dividend price drop not being equal to one. They argue that investors would never be willing to pay more than the value of the dividend, pushing the price to drop to the tick above the cum-dividend price minus the dividend. However, when quotes were decimalised in the U.S., evidence against Bali and Hite (1998) was found by Graham et al. (2003) and by Jakob and Ma (2004). Specific exchange trading rules have been suggested as a possible rationale by Dubofsky (1992) who suggests that NYSE Rule 118, AMEX Rule 132 and price discreteness are the reasons for ex-dividend abnormal returns. These rules state that buy limit orders on the ex-dividend day should be adjusted downwards by the cash amount of the dividend. In those cases where the cum-dividend price less the dividend is not equal to a tick multiple, the buy limit order price is further adjusted downwards to the nearest tick multiple. These results, relating to these rules, were supported by Jakob and Ma (2005). However, given that a smaller drop-off ratio is documented in Canada relative to the U.S., which it is argued is related to outstanding limit orders, on the Toronto Stock Exchange, not being adjusted as noted above, the results for Canada do not support the price discreteness explanation proposed by Bali and Hite (1998).[7] Frank and Jagannathan (1998) provide a market microstructure argument to explain that transactions on the cum-dividend day occur relatively more often at the bid price and on the ex-dividend day relatively more often at the ask price. Their claim is that, since for some individuals there is a collection cost burden if they were to be paid the dividend (i.e. to have to go through the procedure of collecting it), the majority of investors will prefer not to receive the dividend. They then further argue that since collection cost is not a burden for market makers, market makers will buy stocks on the cum-dividend day. As a result, most trades will occur on the bid side on the cum-dividend day while most trades should occur on the sell side on the ex-dividend day. There is empirical

[7] The drop-off ratio is a standard statistic used to compare drop-offs across companies. It defines as the ex-dividend price drop divided by the dividend.

evidence which shows that there is an increase in trade size around the ex-dividend day which could be explained by an increase in the cost of delay in execution in this period (see Michaely and Vila, 1995; McDonald, 2001 and Rantapuska, 2008). While these studies focus on price effects associated with executed orders, we focus on market microstructure effects associated with submitted orders (which may or may not be finally executed). We next turn to a more detailed discussion of bid-ask spreads, volatility and to the details associated with limit order submission.

2.3 Theory

Spread

It is unclear, what effects on spread should be observed on the ex-dividend day. While no difference in quoted and effective spreads between ex-dividend day and cum-dividend day was found by Graham et al. (2003), wider spreads around ex-dividend periods have been reported by Koski and Michaely (2000) in the US and, on the Australian Stock Exchange Ainsworth et al. (2008) find that the effective bid-ask spread increases on the ex-dividend day. Ainsworth et al., (2008) attribute this finding to a decrease in the cost of delaying execution on the ex-dividend day, and uncertainty about the ex-dividend price drop. These effects result in less aggressive limit orders and thus higher spreads on the ex-dividend day

Meanwhile, Foucault (1999) studies the costs associated with submitting limit orders, with the argument that while on the one hand, there may be price uncertainty and the trader risks execution at adverse prices, there is also, on the other hand, the risk of non-execution. On cum-dividend days, the cost of price uncertainty is low but the cost of non-execution is high while on ex-dividend days, the cost of price uncertainty is greater but the cost of non-execution is small. Foucault (1999) shows that in markets with traders who have varying tax status and given that these traders will, therefore, have varying valuations of the stock, trading using limit orders should increase execution risk. Hence, the bid-ask spread should also increase. The increase in spread has a different impact in a market with relatively more impatient traders than in a market with relatively more patient traders (see Foucault et al., 2005). Foucault et al. (2005) claim that for a given spread, patient traders are more likely to submit limit orders and impatient ones more likely to submit market orders, this suggests the spread on the cum-dividend day should narrow because of this switch to markets orders, but will widen on ex-dividend days because of the switch back to limit orders. There are, therefore, two effects: variation in valuation because of tax-status on the cum-dividend day, which will widen the spread on the cum-dividend day relative to the ex-dividend day together with an increase in the number of impatient traders on the the cum-dividend, which will narrow the spread on the cum-dividend day relative to the ex-dividend day.

Hypothesis 1 : we expect that the bid-ask spread will increase on cum-dividend day because of the presence of liquidity suppliers and the differences in stock valuation by tax-arbitrageurs.

Hypothesis 2 : Because of the increases in price uncertainty on ex-dividend day, we expect the bid-ask spread will increase as well.

Volatility

Copeland and Galai (1983) show that submitting limit orders is equivalent to offering an option for other traders to trade at the limit price. Since the value of this option increases if price uncertainty increases, uninformed traders submitting limit orders are more likely to incur adverse selection costs of trading with informed traders, unless they adjust their limit order prices. Accordingly, the spreads are likely to widen when prices are more volatile. Foucault (1999) and Foucault et al. (2005) show that large differences in investor valuation of a stock, (arising from different tax status, for instance), can give rise to such price uncertainty and that the net effect is an increase in spreads as well as a switch to relatively increased use of limit orders. We should, therefore, expect an increase in price volatility on cum-dividend days. Furthermore, order imbalances are also a source of price volatility and evidence of order imbalances around the ex-dividend day is reported by Frank and Jagannathan (1998) and Jakob and Ma (2004) while Ainsworth et al. (2008) and Jun et al. (2008) find evidence of abnormal volume and price volatility around the ex-dividend day. This study argues that tax arbitrage can lead to order imbalances on both the cum- and ex-dividend days, increasing the volatility on both days.

Hypothesis 3 : we expect an increase in price volatility on both cum- and ex-dividend days.

Order Submission

An important characteristic of order submission is order aggressiveness which indicates the degree to which the order offers a price concession – with the most aggressive orders offering a higher price concession (for instance, a market order) and the least aggressive orders offering little or no concession (such as for a limit order). How various factors influence order aggressiveness has been investigated by several studies.[8] More specifically, how volatility, spread, and depth influence aggressiveness has been studied.[9] Anand et al. (2005) find that informed traders are more likely to submit limit orders in the first half of the day whereas they are more likely to submit market orders in the second half of the day. Furthermore, informed traders appear to be more likely than liquidity traders, to submit limit orders and for informed traders to submit more market orders earlier in the day and to switch to limit orders over time whereas liquidity traders do the reverse (Bloomfield et al., 2005).While Chakravarty and Holden (1995) as well as Cao et al. (2004) report evidence that informed traders do submit limit orders, order submission is affected by changes in the waiting cost for execution (Foucault et al., 2005 and Roşu, 2009). More specifically, high competition among patient traders

[8] Among others see Griffiths et al. (2000); Ranaldo (2004); Ellul et al. (2007) and the study by Cao et al. (2009).

[9] Studies include Al-Suhaibani and Kryzanowski (2000); Ahn et al. (2001); Hall and Hautsch (2006, 2007) and Foucault et al. (2007).

motivates them to submit aggressive orders to reduce execution time (Foucault et al., 2005). If waiting costs are high, traders will seek to reduce execution time by submitting more aggressive orders.

Particularly, as the ex-dividend day approaches and both waiting costs and the risk of non-execution increase, it is expected that the proportion of impatient traders will increase with the approaching deadline and they will be increasingly more likely to switch to using relatively more aggressive orders. Harris and Hasbrouck (1996) find, however, that even in the presence of non-execution costs and market order price improvement, limit orders play a dominant role for trading. Guéant et al. (2012) find that approximately 60% of orders are non-aggressive.

Hypothesis 4a : we expect an increase in order aggressiveness around ex-dividend day.

Hypothesis 4b : we expect an increase in the submission of passive order around ex-dividend day.

Order Submission and Spread

Market frictions include two types of costs: explicit trading cost (commission and taxes) and implicit trading costs (bid-ask spread, thin markets, trade size, price impact). The bid-ask spread represents a significant cost of immediate trading, which should have implications for the choice of order type. Foucault (1999) and Foucault et al. (2005) argue, for instance, that spread is the cost of submitting a market order over a limit order. Empirical studies confirm that spread is a determinant of the choice of order type.[10] Foucault (1999) demonstrates, theoretically, that increases in spread around the end of a trading day, will decrease competition between limit order traders, leading to less aggressive limit orders. Furthermore, Foucault et al. (2005) claim, in one of the first dynamic models of the limit order book, that the trade decision is determined by the bid–ask spread.

For specific spread levels, patient traders are more likely to submit limit or-

[10] See for example, Biais et al. (1995); Harris and Hasbrouck (1996); Ranaldo (2004); Anand et al. (2005); Hall and Hautsch (2006) as well as Pascual and Veredas (2009).

ders, whereas impatient traders are more likely to submit market orders. As the spread increases, traders tend to submit more limit orders. Furthermore, liquidity providers are enthusiastic to supply larger spread improvements when the spread is large. Biais et al. (1995); Al-Suhaibani and Kryzanowski (2000); Beber and Caglio (2005); and Ellul et al. (2007), among others, argue that traders are more likely to submit aggressive orders as spread decreases, though, Ranaldo (2004) and Hall and Hautsch (2006) argue that order aggressiveness and trading intensity both decrease as the bid ask spread decreases.

Order Submission and Volatility

Handa and Schwartz (1996) argue that the switch to limit orders as the volatility increases applies when there is a transitory increase in volatility but not when there is a permanent increase in volatility. An opposite view was proposed by Cohen et al. (1981) who shows that when price uncertainty increases, risk-averse traders will be willing to pay a premium for the certainty that comes with immediate execution (such as a ,market order). As a result, an increase in price volatility should lead to relatively increased use of market orders (more aggressive orders).

Order Submission and Return

Chordia et al. (2001) report empirically effects of returns and volatilities on trading activities. They document a significant negative relation between expected returns and the variability of trading activity while Chordia and Subrahmanyam (2004) predict these effects theoretically. Chan (2005) reports that returns from previous orders influence upcoming order decisions, i.e. after positive returns, traders are more willing to submit aggressive buy orders, whereas they become less willing to submit sell orders and, conversely, a decline in prices motivates sellers to submit aggressively.

Lasfer and Zenonos (2003); Armitage et al. (2006), and Isaksson and Islam (2013) report a drop in stock price and an abnormal return around the ex-dividend day on the London Stock Exchange. Lasfer's research (1995) was on the UK market and presented the effect of the changes before and after the Income and Corporation Taxes Act 1988. His model concluded a significant positive return on stock prices before 1988 due to the differentiation in taxation (both on capital gain and dividend). Moreover, the model presented a negative insignificant return after 1988, when there is no significant difference in taxation laws regarding both dividend and capital gain. Finally, he claimed that dividend yield and the duration of the settlement period generate a positive return on the ex-dividend day, not the bid-ask-spread, transaction costs, short-term trading, or other means of dividend distribution strategies. In the opposite direction, Frank and Jagannathan (1998) theoretically and Jakob and Ma (2003) empirically argue that the price drop-off ratio is affected directly by the order imbalances which may exist around the ex-dividend day.

Order Submission and Duration

Diamond and Verrecchia (1987) and Easley and O'Hara (1992) stress the importance of the time distance between two consecutive orders. They argue that the importance of time distance between orders comes from its power to reveal important information about the future value of the asset. How important time distance between orders is, has been studied empirically.[11] The theoretical arguments in Rosu (2008) propose that a high arrival rate of trade should decrease the expected time for the submitted order to execute. Therefore, the traders are incentives to be submitting more aggressive orders. Tkatch and Kandel (2006) and Linnainmaa and Rosu (2008) confirm these results empirically. Foucault et al. (2005) illustrates that high competition between patient traders and high waiting costs motivate traders to submit more aggressive orders to decrease both the execution time and the execution cost of delays.

[11] Among others see Engle and Russell (1998) and Cho and Nelling (2000).

2.4 Data

The sample of data for this chapter is constructed based on criteria that are specified on data section in the first chapter. The resulting sample contained 47 FTSE 100 stocks. Table 2.1 reports summary statistics for order submission and order execution for these stocks. [12]

Table 2.1 – Summary statistics (numbers in million)
This table reports the aggregate number of buy (sell) submitted and executed order and the aggregate volume of buy (sell) submitted and executed order for 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or in control week. These aggregate numbers are calculated for control week, ex-dividend week, corresponding to cum-dividend day in control week (Tuesday) (day2), cum-dividend day, corresponding to ex-dividend day in control week (Wednesday) (day3) and ex-dividend day.

Variable	Num. of buy	Num. of sell	Volume of buy	Volume of sell	Num. of buy	Num. of sell	Volume of buy	Volume of sell
All week			Ex.w				Cont.w	
Submission	2.227	2.171	10,407.220	10,795.964	2.162	2.217	9,670.909	9,808.216
Execution	0.563	0.539	1,396.679	1,386.406	0.563	0.539	1,409.586	1,389.144
Tuesday			Cum.day				C-Cum	
Submission	0.460	0.414	1,910.945	1,858.809	0.432	0.438	1,928.550	1,864.651
Execution	0.114	0.108	285.146	274.450	0.115	0.108	284.386	286.434
Wednesday			Ex.day				C-Ex	
Submission	0.485	0.435	1,963.781	1,871.669	0.421	0.467	1,869.073	2,082.989
Execution	0.119	0.115	308.532	308.962	0.111	0.109	268.596	281.201

The main message is that the aggregate data do not indicate that there are large differences between the ex-dividend week and the control week and there are also no large differences between the cum- and ex-dividend days.

The likelihood of choosing a given submission decision (i.e. limit versus market order, buy versus sell order) is analysed by defining a "representative trader" within each group. The "representative trader" is the weighted average of the volume of each type of submission. Since traders can choose not to trade, the no activity

[12] Ex.w: is ex-dividend week. Cont.w: is control week. C-Cum: is corresponding to cum-dividend day in control week. C-Ex: corresponding to ex-dividend day in control week. Cum.day: is cum-dividend day. Ex.day: is ex-dividend day.

event is also defined by five minutes passing without activity.[13] Table 2.2 shows the "representative trader" for submitted and executed orders on each trading day in control week and ex-dividend week.

Table 2.2 – Representative trader

This table reports the "Representative trader" for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The "Representative trader" is calculated for submitted and executed orders for each trading day in both control week and ex-dividend week.

Week		Limit Buy	Market Buy	Limit Sell	Market Sell
	Day 1				
Ex.w	Execute	0.458	0.034	0.477	0.030
	Submit	0.493	0.000	0.507	0.000
Cont.w	Execute	0.464	0.033	0.458	0.045
	Submit	0.495	0.000	0.505	0.000
	Day 2				
Ex.w	Execute	0.475	0.027	0.472	0.027
	Submit	0.498	0.000	0.502	0.000
Cont.w	Execute	0.464	0.035	0.484	0.018
	Submit	0.519	0.000	0.481	0.000
	Day 3				
Ex.w	Execute	0.475	0.022	0.474	0.030
	Submit	0.482	0.000	0.518	0.000
Cont.w	Execute	0.475	0.024	0.478	0.023
	Submit	0.529	0.000	0.471	0.000
	Day 4				
Ex.w	Execute	0.480	0.025	0.468	0.026
	Submit	0.478	0.000	0.522	0.000
Cont.w	Execute	0.486	0.022	0.469	0.023
	Submit	0.464	0.000	0.536	0.000
	Day 5				
Ex.w	Execute	0.485	0.030	0.448	0.037
	Submit	0.514	0.000	0.486	0.000
Cont.w	Execute	0.479	0.036	0.449	0.036
	Submit	0.499	0.000	0.501	0.000

FTSE 100 traders trade intensively, so no activity event records zero for all trading days in both control week and ex-dividend week. Generally, there are no large differences between the ex-dividend week and the control week and there are also no large differences between the cum- and ex-dividend days.

[13] We do so following other studies in this vein such, Easley et al. (1997), and Ellul et al. (2007).

Preliminary regression

Tax-arbitrage traders either buy on the cum-dividend day and sell on ex-dividend day the “long-short” or sell on the cum-dividend day and buy on the ex-dividend day the “short-long”. The following logit model for each stock i and day t is estimated to examine whether one of these trading strategy dominates the other:

$$Tradeactivity_{i,t} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{i,t} \tag{2.3}$$

where:

$x_{i,t}$: is dividend yield of the stock i and day t.

$Tradeactivity_{i,t}$: is an indicator variable that takes value of 1 if the condition is met and 0 otherwise, for each stock i and day t.

For the first (second) case, of buying (selling) on the cum-dividend day and selling (buying) on the ex-dividend day, three different dependent variables are constructed.

1. BS(L) (SB(L)), is an indicator variable, equals one if the conditions below are both satisfied, and zero otherwise:

$$\begin{cases} \text{buy trade size on Cum.day (Ex.day)} - \text{sell trade size on Cum.day (Ex.day)} & > 0 \\ \text{And} & \\ \text{buy trade size on Ex.day (Cum.day)- sell trade size on Ex.day (Cum.day)} & < 0 \end{cases} \tag{2.4}$$

2. BS(M) (SB(M)), is an indicator variable, equals one if the conditions below are both satisfied , and zero otherwise:

$$\begin{cases} \dfrac{\text{buy trade size on Cum.day (Ex.day)-sell trade size on Cum.day (Ex.day)}}{\text{buy trade size on Cum.day (Ex.day)+sell trade size on Cum.day (Ex.day)}} & > 0.02 \\ \text{And} & \\ \dfrac{\text{buy trade size on Ex.day (Cum.day)- sell trade size on Ex.day (Cum.day)}}{\text{buy trade size on Ex.day (Cum.day)+ sell trade size on Ex.day (Cum.day)}} & < -0.02 \end{cases} \tag{2.5}$$

3. BS(H) (SB(H)), is an indicator variable, equals one if the conditions below are both satisfied, and zero otherwise:

$$\begin{cases} \dfrac{\text{buy trade size on Cum.day (Ex.day)-sell trade size on Cum.day (Ex.day)}}{\text{buy trade size on Cum.day (Ex.day)+sell trade size on Cum.day (Ex.day)}} & > 0.05 \\ \text{And} & \\ \dfrac{\text{buy trade size on Ex.day (Cum.day)- sell trade size on Ex.day (Cum.day)}}{\text{buy trade size on Ex.day (Cum.day)+ sell trade size on Ex.day (Cum.day)}} & < -0.05 \end{cases} \tag{2.6}$$

Assume $\hat{P}_i$ is the probability that an event can occur. Then, the logit model specification is:

$$log\frac{\hat{P}_i}{1-\hat{P}_i} = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} \tag{2.7}$$

The non-linearity of binary outcome logit models makes the straightforward interpretation of their coefficients quite difficult. It is, therefore, common to relate logit model equations back to the odds rather than to the log-odds by exponentiating both sides. The critical point of odds ratios is 1 rather than 0. If the odds ratio is equal to 1, the related variable leaves the odds unchanged. If the odds ratio is larger (smaller) than 1, the related variable increases (decreases) the odds or the related variable effects positively (negatively) the probability that the event will occur, holding other covariates constant (see Harrell, 2001).[14] Exponentiated coefficients or so called “odds ratios” are calculated for model (2.3) and Table 2.3 reports the odds ratios for all logit models.

[14]More explanations are detailed in Appendix A.

Table 2.3 – Estimation of logit regression

This table reports the odds ratio of estimate Eq. (2.3) for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variables are indicators variables. (BS) is an indicator variable refers to "long-short" trading strategy. (SB) is an indicator variable refers to "short-long" trading strategy. For each type of trading strategy, we generate three different indicator variables. The low degree indicators BS(L) and SB(L) are defined as following : if buy trade size on Cum.day – sell trade size on Cum.day $>$ 0 and buy trade size on Ex.day – sell trade size on Ex.day $<$ 0 then BS(L) equal one , otherwise zero; if buy trade size on Cum.day – sell trade size on Cum.day $<$ 0 and buy trade size on Ex.day – sell trade size on Ex.day $>$ 0 then SB(L) equal one , otherwise zero. The medium degree indicators BS(M) and SB(M) are defined as: if (buy trade size on Cum.day -sell trade size on Cum.day)/(buy trade size on Cum.day +sell trade size on Cum.day)>0.02 and (buy trade size on Ex.day -sell trade size on Ex.day)/(buy trade size on Ex.day +sell trade size on Ex.day)<-0.02 then BS(M) equal one, otherwise zero; (buy trade size on Cum.day -sell trade size on Cum.day)/(buy trade size on Cum.day +sell trade size on Cum.day)<-0.02 and (buy trade size on Ex.day -sell trade size on Ex.day)/(buy trade size on Ex.day +sell trade size on Ex.day)>0.02 then SB(M) equal one, otherwise zero. Finally, the high degree indicators BS(H) and SB(H) are defined as : if (buy trade size on Cum.day-sell trade size on Cum.day)/(buy trade size on Cum.day+sell trade size on Cum.day)>0.05 and (buy trade size on Ex.day -sell trade size on Ex.day)/(buy trade size on Ex.day +sell trade size on Ex.day)<-0.05 then BS(H) equal one, otherwise zero; (buy trade size on Cum.day -sell trade size on Cum.day)/(buy trade size on Cum.day +sell trade size on Cum.day)<-0.05and (buy trade size on Ex.day -sell trade size on Ex.day)/(buy trade size on Ex.day +sell trade size on Ex.day)>0.05 then SB(H) equal one, otherwise zero. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	BS(L)	BS(M)	BS(H)
Buy-Sell			
Dividend Yield	1.548*	1.453	0.916
	(1.92)	(1.62)	(-0.18)
	SB(L)	SB(M)	SB(H)
Sell-Buy			
Dividend Yield	0.924	1.865*	1.463
	(-0.27)	(1.75)	(0.71)

The results refer to patterns in the trading activity around the ex-dividend day. There is weak evidence of the presence of both types of trading strategies.

2.5 Methodology

Spread

In limit order book, trades take place at best prices posted by the traders. Potential traders pay the spread between the bid and the ask. The quoted spread, which is the difference between the bid and ask prices, measures the cost of completing a round trip (buy and sell), if trades are executed at the quoted prices. However, trades are sometimes executed either inside or outside the quoted bid-ask spread.

In this chapter, we, therefore, measure the spread in two different ways: we calculate, for each point of time, the difference between the best live submitted ask price and best live submitted bid price. A full detail will be present in Robustness test section (2.7).

The quoted spread may overstate trading costs since trades can occur at prices within this spread, and this motivates us to calculate the effective spread using Roll measure. Roll (1984) proposes an estimator of implied effective spread based on measuring the negative autocorrelation produced by bounces between the bid and ask. Roll measure assumes that orders are executed at the best bid price or at the best ask price, the probabilities of buying and selling are equal and probability of continuation is same as reversal. Roll's measure is define as following:

$$Roll = \sqrt{max(0, -\mathrm{cov}(\Delta p_{i,j} \Delta p_{i,j-1}))}$$

This measure is computed on a rolling 5-minute interval for each day and for each stock. For each day, transactions are ordered according to their time arrival and price changes, $\Delta p_{i,j}$ calculated.[15] The covariance between adjacent-interval price changes is computed to find the Roll spread for that interval. The spread for stock i, in a 5-minute time interval n, is $S_i^n(w)$, where $w = 1$ for the ex-dividend week and $w = 0$ for the control week. To investigate more about the spread in ex-dividend week, cum-dividend day and ex-dividend day, several regressions are run. The first regression examines the overall picture of spread in ex-dividend week in compere to control week. A regression model specified as follows is estimated:

$$S_i^n(1) = \alpha + \beta S_i^n(0) + \delta_1 DC_i + \delta_2 DE_i + \delta_3 C.DC_i + \delta_4 C.DE_i + \varepsilon_i^n \qquad (2.8)$$

[15]For some transactions which arrive at the same time, they are sorted according to their Message Sequence Number (a sequence number used to assist in sorting orders received in the same second)

where:

$S_i^n(w)$: is the spread for stock i, in the 5-minute time interval n, and w $= 1$ for the ex-dividend week and zero for the control week.

DC_i: is an indicator variable takes value of 1 on cum-dividend day and 0 otherwise.

DE_i: is an indicator variable takes value of 1 on ex-dividend day and 0 otherwise.

$C.DC_i$: is an indicator variable takes value of 1 on the corresponding to cum-dividend day the in control week (day2) and 0 otherwise.

$C.DE_i$: is an indicator variable takes value of 1 on the corresponding to ex-dividend day the in control week (day3) and 0 otherwise.

The previous regression is run over both control week and ex-dividend week. Then, the following model is estimated for cum-dividend day, ex-dividend day, second day of control week and third day of control week:

$$S_i^n(1) = \alpha + \beta S_i^n(0) + \delta_1 DC_i + \delta_2 C.DC_i + \varepsilon_i^n \tag{2.9}$$

Finally, the model is also estimated for the cum-dividend day and the ex-dividend day alone.

$$S_i^n(0)_{cum} = \alpha + \beta S_i^n(0)_{ex} + \varepsilon_i^n \tag{2.10}$$

where:

$S_i^n(0)_{cum}$: is the spread for stock i, in 5-minute time interval n, for the cum-dividend day.

$S_i^n(0)_{ex}$: is the spread for stock i, in 5-minute time interval n, for the ex-dividend day.

To avoid the problem of measurement error in the right hand side variables, the following model is estimated using the difference in spreads between a 5-minute interval in the ex-dividend week and the corresponding interval in the control week:

$$
\begin{aligned}
\Delta S_i^n = {} & \alpha + \beta_1 \Delta Vo_i^n + \beta_2 \Delta Vu_i^n + \beta_3 \Delta Re_i^n + \beta_4 \Delta Bs_i^n + \beta_5 \Delta Ss_i^n + \delta_1 DC_i + \delta_2 DE_i \\
& + \beta_6 \Delta Vo_i^n * DC_i + \beta_7 \Delta Vu_i^n * DC_i + \beta_8 \Delta Re_i^n * DC_i + \beta_9 \Delta Bs_i^n * DC_i + \beta_{10} \Delta Ss_i^n * DC_i \\
& + \beta_{11} \Delta Vo_i^n * DE_i + \beta_{12} \Delta Vu_i^n * DE_i + \beta_{13} \Delta Re_i^n * DE_i + \beta_{14} \Delta Bs_i^n * DE_i + \beta_{15} \Delta Ss_i^n * DE_i \\
& + \varepsilon_i^n
\end{aligned}
\tag{2.11}
$$

where:

ΔVo_i^n: is volatility difference between control week and ex-dividend week in every five minutes. The volatility is the tick-by-tick standard deviation of returns over a five minute interval.

ΔVu_i^n: is volume difference between control week and ex-dividend week in every five minutes. The volume is the natural logarithm of the average number of shares per transaction in a five minute interval divided by the average number of shares per transaction on the day.

ΔRe_i^n: is return difference between control week and ex-dividend week in every five minutes. The return defines as the average tick-by-tick return over a five minute interval.

ΔBs_i^n: is buy trade size difference between control week and ex-dividend week in every five minutes. Buy trade size is the accumulated volume of buy transactions over a five minutes interval before the event.

ΔSs_i^n: is sell trade size difference between control week and ex-dividend week in every five minutes. Sell trade size is the accumulated volume of sell transactions over a five minutes interval before the event.

DC_i: is an indicator variable takes value of 1 on cum-dividend day and 0 otherwise.

DE_i :is an indicator variable takes value of 1 on ex-dividend day and 0 otherwise.

The model is also estimated for the ex-dividend week alone.

To investigate more about the spread differences between ex-dividend week, cum-dividend day, ex-dividend day, second day of control week, third day of control week and control week, we run the following regression:

$$SP_i^n = \alpha + \delta_1 DC_i + \delta_2 DE_i + \delta_3 C.DC_i + \delta_4 C.DE_i + \delta_5 DCW_i + \varepsilon_i^n \qquad (2.12)$$

where:

SP_i^n: is the spread for stock i, in the 5-minute time interval n.

DC_i: is an indicator variable takes value of 1 on cum-dividend day and 0 otherwise.

DE_i: is an indicator variable takes value of 1 on ex-dividend day and 0 otherwise.

$C.DC_i$: is an indicator variable takes value of 1 on the corresponding to cum-dividend day the in control week (day2) and 0 otherwise.

$C.DE_i$: is an indicator variable takes value of 1 on the corresponding to ex-dividend day the in control week (day3) and 0 otherwise.

DCW_i: is an indicator variable takes value of 1 in control week and 0 otherwise.

Finally, we run the following spread determinants regression, to examine whether these determinants affect differently on spread on cum- and ex-dividend days:

$$\begin{aligned} SP_i^n = {} & \alpha + \beta_1 X_i^n + \beta_2 DC_i + \beta_3 DE_i + \beta_4 DCW_i + B_5 C.DC_i + B_6 C.DE_i \\ & + \beta_7 X_i^n * DC_i + \beta_8 X_i^n * DE_i + \beta_9 X_i^n * DW_i + \beta_{10} X_i^n * C.DC_i + \beta_{11} X_i^n * C.DE_i \\ & + \varepsilon_i^n \end{aligned} \qquad (2.13)$$

where:

SP_i^n: is the spread for stock i, in the 5-minute time interval n.

DC_i: is an indicator variable takes value of 1 on cum-dividend day and 0 otherwise.

DE_i: is an indicator variable takes value of 1 on ex-dividend day and 0 otherwise.

$C.DC_i$: is an indicator variable takes value of 1 on the corresponding to cum-dividend day the in control week (day2) and 0 otherwise.

$C.DE_i$: is an indicator variable takes value of 1 on the corresponding to ex-dividend day the in control week (day3) and 0 otherwise.

DCW_i: is an indicator variable takes value of 1 in control week and 0 otherwise.

X_i^n: are the spread determinants which are: volatility (the tick-by-tick standard deviation of returns over a five minute interval), volume (the natural logarithm of the average number of shares per transaction in a five minute interval divided by the average number of shares per transaction on the day), return (the return defines as the average tick-by-tick return over a five minute interval), buy trade size (the accumulated volume of buy transactions over a five minutes interval before the event), sell trade size (sell trade size is the accumulated volume of sell transactions over a five minutes interval before the event).

Volatility

To investigate volatility in the ex-dividend week as compared to that in the control week, the following regression model is estimated

$$Vol_i^n(1) = \alpha + \beta Vol_i^n(0) + \delta_1 DC_i + \delta_2 DE_i + \delta_3 C.DC_i + \delta_4 C.DE_i + \varepsilon_i^n \quad (2.14)$$

where:

$Vol_i^n(w)$: is the volatility of the tick-by-tick return of stock i in the 5-minute interval n for the ex-dividend week (w = 1) and for the control week (w = 0).

Similarly to spread, the following model is estimated for cum-dividend day, ex-dividend day, second day of control week and third day of control week:

$$Vol_i^n(1) = \alpha + \beta Vol_i^n(0) + +\delta_1 DC_i + \delta_2 C.DC_i + \varepsilon_i^n \tag{2.15}$$

The model is also estimated for the cum-dividend day and the ex-dividend day alone.

$$Vol_i^n(0)_{cum} = \alpha + \beta Vol_i^n(0)_{ex} + \varepsilon_i^n \tag{2.16}$$

where:

$Vol_i^n(0)_{cum}$: is the volatility for stock i, in 5-minute time interval n, on the cum-dividend day.

$Vol_i^n(0)_{ex}$: is the volatility for stock i, in 5-minute time interval n, on the ex-dividend day.

To investigate more about the volatility differences between ex-dividend week, cum-dividend day, ex-dividend day, second day of control week, third day of control week and control week, we run the following regression:

$$VO_i^n = \alpha + \delta_1 DC_i + \delta_2 DE_i + \delta_3 C.DC_i + \delta_4 C.DE_i + \delta_5 DCW_i + \varepsilon_i^n \tag{2.17}$$

where:

VO_i^n: is the volatility for stock i, in the 5-minute time interval n.

DC_i: is an indicator variable takes value of 1 on cum-dividend day and 0 otherwise.

DE_i: is an indicator variable takes value of 1 on ex-dividend day and 0 otherwise.

$C.DC_i$: is an indicator variable takes value of 1 on the corresponding to cum-dividend day the in control week (day2) and 0 otherwise.

$C.DE_i$: is an indicator variable takes value of 1 on the corresponding to ex-dividend day the in control week (day3) and 0 otherwise.

DCW_i: is an indicator variable takes value of 1 in control week and 0 otherwise.

Order Submission

While there is, in the market microstructure literature, an emphasis on the choice between market orders and limit orders.[16] Orders are, however, categorized according to their price aggressiveness.[17] Aggressiveness is essentially a measure of the price concession the trader makes when submitting the order. For example, if a buy limit order is submitted with a limit price higher than the prevailing bid price it will be considered as aggressive, and similarly for a sell order with a limit price lower than the prevailing ask price. Limit orders are categorized into four groups with varying aggressiveness: behind-the-quote, at-the-quote, inside-the-quote and marketable. Specifically, for each order, limit price of the order is compared with the price of the buy (sell) transaction in the previous five minute interval which was executed at the highest (lowest) price. Denoting the price of the buy transaction in the previous five minute interval with the highest price as Max-5min, and the price of the sell transaction in the previous five minute interval with the lowest price as Min-5min, then

1. Behind-the-quote (B-T-Q) buy (sell) orders is defined by the criterion that it has a limit price less (more) than Max-5min (Min-5min);

2. At-the-quote (A-T-Q) buy (sell) orders is defined by the criterion that it has a limit price equal to Max-5min (Min-5min);

3. Inside-the-quote (I-T-Q) order is defined by the criterion that it has a limit price between Max-5min and Min-5min;

[16] See Handa and Schwartz (1996); Parlour (1998); Bae et al. (2003); Bloomfield et al. (2005).

[17] Doing so following several other studies in this vein such as Biais et al. (1995); Griffiths et al. (2000); Goettler et al. (2005); Ellul et al. (2007); and Tkatch and Kandel (2006).

4. Marketable (M-A) limit buy (sell) order is defined by the criterion that it has a limit price greater (less) than or equal to Min-5min (Max-5min).

Behind-the-quote limit orders are deemed the least aggressive and marketable orders the most aggressive orders. Since there is no data about the actual bid-ask spread or the higher tiers of the limit order book in real time, this procedure has applied to approximate the level of aggressiveness of submitted orders.

A multinomial logit regression is estimated to investigate factors that may be determining the aggressiveness with which orders are submitted.[18]Factors reported in the literature are: *spread*, which is Roll's measure of spread over a five-minute interval, *volatility*, which is the tick-by-tick standard deviation of returns over a five-minute interval, *buy (sell) trade size*, which is the accumulated volume of buy (sell) transactions over a five-minute interval before the event, *relative volum*e, which is the natural logarithm of the average number of shares per transaction in a five-minute interval divided by the average number of shares per transaction on the day, *buy (sell) trade duration*, which is the time in seconds of a buy (sell) transaction since the last buy (sell) trade, *the expected return*, on the stock which is the average tick-by-tick return over a five-minute interval, *time from noon square*d, which is the log of one plus the time distance (measured in number of five-minute interval) from noon, *number of buy (sell) transactions*, which is the number of buy (sell) trades in a five-minute interval. The multinomial logit model specified

[18]Following previous studies such Griffiths et al. (2000); Ellul et al. (2007) as well as Hasbrouck and Saar (2009) in this regard.

below is estimated: [19,20,21,22,23,24,25,26,27,28,29]

$$
\begin{aligned}
Eventtype_{(i,t)} = {} & \alpha + \beta_{1,i} X_{i,t} + \delta_{1,i} Z_{i,t} \\
& + \beta_{2,i} DW_i + \beta_{3,i} DW_i * X_{i,t} + \delta_{2,i} DW_i * Z_{i,t} \\
& + \beta_{4,i} DC_i + \beta_{5,i} DC_i * X_{i,t} + \delta_{3,i} DC_i * Z_{i,t} \\
& + \beta_{6,i} DE_i + \beta_{7,i} DE_i * X_{i,t} + \delta_{4,i} DE_i * Z_{i,t} \\
& + \sum_{i=1}^{n} \beta_{8,i} D(i) + \varepsilon_{i,t} \qquad (2.18)
\end{aligned}
$$

where:

i and t : indices for firms and time respectively,

$X_{i,t}$: are the model variables,

$Z_{i,t}$: are the control variables,

DW_i :is the indicator variable and takes value of 1 on ex-dividend week and 0 otherwise,

[19] Examples of studies that report the spread include Cohen et al. (1981); Harris (1998); Foucault (1999); Wald and Horrigan (2005); Jones and Lipson (2004); Foucault et al. (2005); Bloomfield et al. (2005) and Hasbrouck and Saar (2009).

[20] Examples of studies that report the volatility include Foucault (1999); Handa and Schwartz (1996); Easley et al. (2002); Wald and Horrigan (2005) and Hasbrouck and Saar (2009).

[21] Examples of studies that report the buy (sell) trade size include Hasbrouck and Saar (2009) as well as Menkhoff et al. (2010).

[22] Examples of studies that report the relative volume include Ellul et al. (2007).

[23] Examples of studies that report the trade duration include Madhavan et al. (1997); Foucault et al. (2005); Tkatch and Kandel (2006) as well as Rosu (2009).

[24] Examples of studies that report the return include Wald and Horrigan (2005) as well as by Hasbrouck and Saar (2009).

[25] Examples of studies that report the time from noon include Ellul et al. (2007).

[26] Number of buy (sell) transactions is a measure of momentum is employed in Menkhoff et al. (2010).

[27] Unordered multinomial logit models are typically employed when there are multiple categories but the order among the categories is not of concern. A multinomial logit model compares each category of the unordered response variable to one category, designated a-priori, for this purpose, as the benchmark.

[28] Probit and logit models are essentially the same; the difference is in the distribution: Logit: cumulative standard logistic distribution (F), probit: cumulative standard normal distribution (Φ). Both probit and logit models present similar results (Institute for Digital Research and Education, 2015).

[29] Use multinomial logit model is similar to use ordered logit regression, except that it is assumed that there is no order to the categories of the dependent variable (i.e., the categories are nominal)(Institute for Digital Research and Education, 2015).

DE_i: is the indicator variable and takes value of 1 on ex-dividend day and 0 otherwise,

DC_i: is the indicator variable that takes value of 1 on cum-dividend day and 0 otherwise,

$D(i)$: is the indicator variable takes value of 1 on firm i and 0 otherwise.

The multinomial logit regression is a model that is used to predict the probabilities of the different possible outcomes of a categorically distributed dependent variable, given a set of independent variables (which may be continuous variable , binary variable, categorical variable, etc.). Therefore, we use multinomial logit estimation to predict the probabilities of choose a specific aggressive buy order in compare to sell order generally. More specifically, we predict the probabilities of each type of four aggressive buy order (behind the quote - at the quote - inside the quote and marketable) using all sell order (without any classification) as baseline and vice versa for sell order. A full explanation of multinomial logit regression is provided in Appendix A.

Several versions of equation (2.18) are estimated separately for buy and sell orders as well as a number of alternative specifications of the variables in the regressions. A list of the models is detailed in Table 2.4.

Table 2.4 – List of Model Variations

This table reports the specification for five different multinomial models where DW is the indicator variable takes value of 1 on ex-dividend week and 0 otherwise, DE is the indicator variable takes value of 1on ex-dividend day and 0 otherwise and DC is the indicator variable takes value of 1 on cum-dividend day and 0 otherwise.

Model	Model Variables (X)	Control Variables (Z)	Dummies
M1	Spread, Volatility, Return, Duration	Controls	-
M2	As M1	Controls	DW
M3	As M1 plus Spread*DW, Volatility*DW, Return*DW, Duration*DW	Controls Controls*DW	As M3
M4	As M3	Controls Controls*DW	As M3 plus DC, DE
M5	As M4 plus Spread*DC, Spread*DE, Volatility*DC, Volatility*DE Return*DC, Return*DE, Duration*DC, Duration*DE	Controls Controls*DW Controls*DC Controls*DE	As M4

2.6 Results

Spread and Volatility

The results from estimating models presented in the methodology section are as follows. Table 2.5 shows the results of model (2.8) and (2.14), using the data for both the ex-dividend week and the control weeks, whereas Table 2.6 shows the results of models (2.9) and (2.15) using the data for only days 2 and 3 of the two weeks (Days 2 and 3 in the ex-dividend week are the cum- and ex-dividend days, respectively). Table 2.7 shows the results of models (2.10) and (2.16) using the data only for the cum-dividend day and the ex-dividend day.

Table 2.5 – Estimation of OLS regression

This table shows the results of OLS estimates regression of Eq (2.8) and Eq (2.14) for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The regression is robust for heteroskedasticity and autocorrelation. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	Spread.Ex	Variables	Volatility.Ex
Spread	0.316***	Volatility	0.462***
	(7.06)		(9.68)
Cum.day	-0.000	Cum.day	0.000
	(-0.09)		(0.08)
Ex.day	-0.000	Ex.day	0.000
	(-0.17)		(1.57)
Spread#C-Cum	0.021	Volatility#C-Cum	0.010
	(0.27)		(0.16)
Spread#C-Ex	0.010	Volatility#C-Ex	-0.090
	(0.18)		(-1.31)
constant	0.000***	constant	0.000***
	(11.11)		(9.83)

Table 2.6 – Estimation of OLS regression

This table shows the results of OLS estimates regression of Eq (2.9) and Eq (2.15) for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week.The regression is robust for heteroskedasticity and autocorrelation. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	Spread. Ex	Variables	Volatility. Ex
Spread	0.326***	Volatility	0.371***
	(5.25)		(6.72)
Cum.day	0.000	Cum.day	-0.000
	(0.01)		(-1.22)
Spread#C-Cum	0.010	Volatility#C-Cum	0.100
	(0.12)		(1.25)
constant	0.000***	constant	0.000***
	(12.43)		(8.47)

Table 2.7 – Estimation of OLS regression
This table shows the results of OLS estimates regression of Eq (2.10) and Eq (2.16) for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week.The regression is robust for heteroskedasticity and autocorrelation. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Spread.Cum.day		Volatility.Cum.day
Spread.Ex.day	0.386***	Volatility.Ex.day	0.531***
	(6.23)		(6.84)
constant	0.000***	constant	0.000***
	(6.71)		(6.55)

The results show several significant effects. First, the constant term is significantly positive in all regressions. This indicates that, in general, the spread and the volatility are higher in the ex-dividend week than in the control week and are higher on the cum-dividend day than on the ex-dividend day within the ex-dividend week. Second, the coefficients on the corresponding spread observations and the volatility observations in the two weeks are positive in all tables, which indicate that there are intra-day patterns in both the spread and the volatility variables. The general picture is therefore, that there are spread and volatility effects in the ex-dividend week.

We estimate two versions of model (2.11). First, we regress the difference in the spread between the ex-dividend week and the spread in the control week for corresponding 5-minute intervals, on a set of determining variables, which are themselves also differences between corresponding 5-minute interval in the dividend and control weeks. Second, we regress the level of the spread in the ex-dividend week on the same right hand side variables which are volatility, volume, return, buy-size, sell-size, and dummies for the cum-dividend day and the ex-dividend day and the results are reported in Table 2.8

Table 2.8 – Estimation of OLS regression over spread determinants
This table shows the results of OLS estimates regression of Eq (2.11) for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The second columns estimate the determinants of the difference in spread between control week and ex-dividend week for corresponding 5-minute intervals. The third columns estimate the determinants of the spread over ex-dividend week. The regression is robust for heteroskedasticity and and autocorrelation. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Control week + Ex-dividend week	Ex-dividend week
Volatility		
All Week	0.558***	0.578***
	(20.32)	(16.73)
Cum-dividend day	-0.008	-0.023
	(-0.18)	(-0.55)
Ex-dividend day	0.011	-0.030
	(0.23)	(-1.07)
Volume		
All Week	-0.000***	-0.000***
	(-2.92)	(-3.08)
Cum-dividend day	-0.000**	0.000
	(-2.00)	(0.07)
Ex-dividend day	0.000	-0.000
	(0.10)	(-0.20)
Return		
All Week	0.002	0.032
	(0.03)	(0.38)
Cum-dividend day	-0.074	-0.019
	(-0.61)	(-0.22)
Ex-dividend day	0.027	0.123
	(0.26)	(1.26)
Buy Size		
All Week	-0.000	0.000
	(-0.74)	(1.30)
Cum-dividend day	0.000	0.000
	(0.96)	(0.22)
Ex-dividend day	0.000	0.000
	(0.94)	(0.19)
Sell Size		
All Week	0.000	0.000
	(0.13)	(0.42)
Cum-dividend day	0.000*	0.000
	(1.68)	(0.00)
Ex-dividend day	-0.000	-0.000
	(-0.08)	(-0.04)
Dummies		
Cum-dividend day	0.000	0.000
	(0.93)	(0.43)
Ex-dividend day	0.000	0.000
	(1.04)	(0.94)
constant	-0.000***	-0.000***
	(-2.93)	(-5.39)

Columns two in Table 2.8 show the determinants of the difference in spread. We find that the spread overall is greater in the ex-dividend week than in the control week. Furthermore, we find that the difference in spread is explained, in general, by the difference in volatility by a positive association but there are no specific cum-dividend day and ex-dividend day effects. There is also a negative association with the difference in volume and this effect is amplified on the cum-dividend day. An increase in the difference in the trading volume from the control week to the ex-dividend week, therefore, leads to a decrease in the difference in the spread over the same period, which is amplified on the cum-dividend day. We find similar results when using levels. In general, when the volatility is higher or when the trading volume is lower, the spread levels are higher.

Table 2.9shows the results of model (2.12) and (2.17) , using the data for both the ex-dividend week and the control weeks.

Table 2.9 – Estimation of OLS regression

This table shows the results of OLS estimates regression of Eq (2.12) and Eq (2.17) for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The regression is robust for heteroskedasticity and autocorrelation. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dummies	Spread	Volatility
Cum.day	-0.006	-0.004
Ex.day	0.002	-0.002
Cont.w	0.003	-0.003
C-Cum	-0.002	-0.013
C-Ex	-0.004	-0.026**
constant	0.169***	0.462***

The results of these regression confirm the previous results that volatility is higher on ex-dividend week in compere to control week. Further, the constants in two regressions are also positive confirming the potential intra-day patterns in both the spread and the volatility variables.

Table 2.10shows the results of models (2.13) using the data for both the ex-dividend week and the control weeks.

Table 2.10 – Estimation of OLS regression over spread determinants
This table shows the results of OLS estimates regression of Eq (2.13) for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The regression is robust for heteroskedasticity and and autocorrelation. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	Ex.w	Cum.day	Ex.day	Cont.w	C-Cum	C-Ex
Volatility	0.503***	-0.058*	-0.027	0.030	-0.000	0.000
Volume	-1.042*	-1.017	-0.069	0.001	-191.664	-22.151
Return	0.041	0.058	0.178	-0.061	0.000	-0.000
Buy Size	0.000	0.000	0.000	-0.000	0.000	0.005
Sell Size	-0.000	-0.000	-0.000	0.000	0.003	-0.004
Dummies	-0.065***	0.018	0.013	-0.009	-0.002	-0.015

The significant positive effect of volatility and negative effect of volume have been confirmed in this regression. However, the positive effect of the volatility on spread has been reduced on cum-dividend day.

Order Submission

The results of the order submission analysis are presented here. All models presented in the methodology section were estimated for both the buy side and the sell side. Only the results of M5, however, are discussed here and presented in Table 2.11 and Table 2.12 for buy side and sell side respectively. [30] Table 2.11 and Table 2.12 report the relative risk ration RRR for multinomial logit estimation of model (2.18). The coefficients that multinomial logit estimation usually report is not easy to interpret. Therefore, we calculate the relative risk ration which is much easier to interpret, a full explanation is provided in the Appendix A.

[30] The results of the remainder of models are reported in Appendix B

Table 2.11 – Relative risk ratios–M5–buy side
This table reports the relative risk ratios of estimates regression Eq. (2.18) for -M5-buy side on a stock-by-stock basis. The relative risk ratios are reported for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable for buy regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q buy order (2) A-T-Q buy order (3) I-T-Q buy order (4) M-A buy order (5) sell order. Sell order set as reference category for buy regression. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Dummy variables				
Baseline	0.614***	0.186***	0.096***	0.334***
DW	0.919***	0.917***	1.109**	1.092***
DC	1.069***	0.852***	0.825**	0.894***
DE	1.197***	1.301***	1.692***	1.005
Baseline * DW	0.564	0.171	0.106	0.365
Baseline * DW * DC	0.603	0.145	0.088	0.326
Baseline * DW * DE	0.675	0.222	0.180	0.367
Spread variables				
Spread	1.217***	1.143***	0.965**	0.853***
Spread # DW	0.828***	0.838***	0.958*	1.021
Spread # DC	1.136***	1.250***	1.116***	0.745***
Spread # DE	1.108***	0.969	0.814***	0.800***
Spread * Spread # DW	1.008	0.958	0.924	0.871
Spread * Spread # DW * Spread # DC	1.145	1.197	1.032	0.649
Spread * Spread # DW * Spread # DE	1.117	0.928	0.753	0.697
Volatility variables				
Volatility	0.793***	0.979	1.214***	1.066***
Volatility # DW	1.187***	1.099***	1.068***	0.99
Volatility # DC	0.949***	1.013	1.181***	1.254***
Volatility # DE	0.903***	0.867***	1.161***	0.950***
Volatility * Volatility # DW	0.941	1.076	1.297	1.055
Volatility * Volatility # DW * Volatility # DC	0.893	1.090	1.531	1.323
Volatility * Volatility # DW * Volatility # DE	0.850	0.933	1.505	1.003
Return variables				
Return	0.745***	1.015	1.238***	1.779***
Return # DW	1.066***	1.005	0.765***	0.917***
Return # DC	1.051*	1.001	1.376***	1.734***
Return # DE	0.794***	0.870**	1.231***	1.323***
Return * Return # DW	0.794	1.020	0.947	1.631
Return * Return # DW * Return # DC	0.835	1.021	1.303	2.829
Return * Return # DW * Return # DE	0.631	0.887	1.166	2.158
Duration variables				
Duration	1.001***	1.004***	1.002***	0.996***
Duration # DW	1.001***	1.001***	1.001*	0.997***
Duration # DC	1.001	1.003***	1.000	1.002***
Duration # DE	1.001***	1.003***	0.999	1.003***
Duration * Duration # DW	1.002	1.005	1.003	0.993
Duration * Duration # DW * Duration # DC	1.003	1.008	1.003	0.995
Duration * Duration # DW * Duration # DE	1.003	1.008	1.002	0.996

Table 2.12 – Relative risk ratios–M5–sell side

This table reports the relative risk ratios of estimates regression Eq. (2.18) for -M5-sell side on a stock-by-stock basis. The relative risk ratios are reported for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable for sell regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q sell order (2) A-T-Q sell order (3) I-T-Q sell order (4) M-A sell order (5) buy order. Buy order set as reference category for sell regression. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Dummy variables				
Baseline	0.578***	0.168***	0.076***	0.427***
DW	1.038***	1.207***	1.252***	0.966***
DC	1.060***	0.760***	0.797***	0.950***
DE	0.913***	1.249***	0.951	0.877***
Baseline * DW	0.600	0.203	0.095	0.412
Baseline * DW * DC	0.636	0.154	0.076	0.392
Baseline * DW * DE	0.548	0.253	0.090	0.362
Spread variables				
Spread	0.994	0.917***	0.908***	0.793***
Spread # DW	1.250***	0.980	1.085***	1.032**
Spread # DC	0.786***	1.141**	1.160***	1.067***
Spread # DE	0.787***	1.099*	0.545***	1.252***
Spread * Spread # DW	1.243	0.899	0.985	0.818
Spread * Spread # DW * Spread # DC	0.977	1.025	1.143	0.873
Spread * Spread # DW * Spread # DE	0.978	0.988	0.537	1.025
Volatility variables				
Volatility	0.981***	1.133***	1.424***	1.149***
Volatility # DW	0.840***	0.944**	0.930***	0.990
Volatility # DC	1.081***	1.067*	0.853***	0.828***
Volatility # DE	1.219***	1.023	1.801***	0.897***
Volatility * Volatility # DW	0.824	1.070	1.324	1.138
Volatility * Volatility # DW * Volatility # DC	0.891	1.141	1.130	0.942
Volatility * Volatility # DW * Volatility # DE	1.005	1.094	2.385	1.020
Return variables				
Return	1.309***	0.877***	0.824***	0.530***
Return # DW	1.003	1.149***	1.206***	1.347***
Return # DC	1.017	0.945	0.721***	0.560***
Return # DE	1.099***	1.046	1.196***	0.691***
Return * Return # DW	1.313	1.008	0.994	0.714
Return * Return # DW * Return # DC	1.335	0.952	0.716	0.400
Return * Return # DW * Return # DE	1.443	1.054	1.189	0.493
Duration variables				
Duration	1.002***	1.005***	1.000	0.994***
Duration # DW	0.999***	0.999	1.001	1.001***
Duration # DC	0.999***	1.003***	1.004***	0.998***
Duration # DE	0.999***	1.000	0.992***	0.998***
Duration * Duration # DW	1.001	1.004	1.001	0.995
Duration * Duration # DW * Duration # DC	1.000	1.007	1.005	0.993
Duration * Duration # DW * Duration # DE	1.000	1.004	0.993	0.993

Table 2.11 and Table 2.12 are divided into the following sections: dummy variable, spread variable, volatility variable, return variable and duration variables. In the dummy variables section, the baseline refers to the control week, DW refers to ex-dividend week, DC refers to cum-dividend day and DE refers to ex-dividend day. To calculate the overall effect of ex-dividend week, we need to multiply the RRR of the baseline by RRR of the ex-dividend week DW. Similarly, in order to observe the overall effect of cum-dividend day (ex-dividend day), we need to multiply the RRR of baseline by the RRR of ex-dividend week and RRR of cum-dividend day (ex-dividend day). For the other parts of the table, spread variable, volatility variable, return variable and duration variable refer to the RRR of these variables in control week, whereas (one variable) # DW refers to the RRR of that variable in ex-dividend week (e.g., Spread # DW refers to the RRR of spread variable in ex-dividend week). Further, (one variable) # DC (DE) refers to the RRR of that variable in cum-dividend day (ex-dividend day) (e.g., Spread # DC refers to RRR of spread variable on cum-dividend day). In same way as dummy variables part, in order to observe the overall effect of one variable in ex-dividend week, we should multiply the RRR of this variable in control week by RRR of that variable in ex-dividend week (e.g., the overall effect of spread variable in ex-dividend week can be calculated by multiply the RRR of spread variable in control week by RRR of spread variable in ex-dividend week). Finally, in order to see the overall effect of one variable on cum-dividend day (ex-dividend day), we should multiply the RRR of this variable in control week by RRR of same variable in ex-dividend week and RRR of samet variable on cum-dividend day (ex-dividend day) (e.g., the overall effect of spread variable on cum-dividend (ex-dividend) day can be calculated by multiply the RRR of spread variable in control week by RRR of spread variable in ex-dividend week and RRR of spread variable on cum-dividend (ex-dividend) day). The full explanation why we do that is presented in Appendix (A).

While these are a rather complex set of results, the general picture, is as follows. First, there are clear effects linked to the likelihood of the submission of orders on the cum dividend day, the ex-dividend day and the rest of the ex-dividend week, compared to the control week. On the cum-dividend day there is a reduction in the base-line likelihood of the submission of a buy order of any kind and on the ex-dividend day there is an increase in the base-line likelihood of the submission of a buy order of any kind, compared to the base-line likelihood for the control week. This can be inferred from Table 2.11, by comparing the "Baseline" relative risk ratio (RRR) with the interaction terms on the "Baseline" variables such as the relative risk ratios on "Baseline* DW * DC" and on "Baseline * DW * DE".[31] This comparison takes into account the effect on the baseline from inclusion in the dividend week (by the *Indicator* variable DW) and the inclusion in the cum-dividend day (by the *Indicator* variable DC) and the ex-dividend day (by the *Indicator* variable DE), respectively. Meanwhile the picture is different for sell orders.

On the cum-dividend day there is an increase in the likelihood of the submission of the least aggressive sell orders and a decrease (or constant) in the likelihood of the submission of any other kind of sell order, compared to the control week. On the ex-dividend day there is a reduction in the likelihood of the submission of the least aggressive sell order and the most aggressive sell order and an increase in the likelihood of the submission of any other kind of sell order, compared to the control week. At one level there is a symmetry that can be seen between buy and sell orders, however: the change in likelihood is going in opposite directions on the cum-dividend day and the ex-dividend day, compared to the control week, for both buy and sell orders of any kind. The likelihood of the least aggressive buy orders and the three most aggressive sell orders is reduced on the cum-dividend day, while the likelihood of the least aggressive buy order and the second and third most aggressive sell orders is increased on the ex-dividend day, consistent with more aggressive buying behaviour on the cum-dividend day and more aggressive selling

[31]A full explanation of relative risk ratios and why it is used is detailed and provided in Appendix A.

behaviour on the ex-dividend day. Traders submit a premium for their buy orders on the cum-dividend day. On the ex-dividend day, though there is no guillotine type deadline pressure, traders still act aggressively, but not as aggressively as they do on cum-dividend days, so they avoid most aggressive sell orders. This is evidence of the presence of tax-arbitrage traders.

There is, however, an increase in the likelihood of the least aggressive sell orders on the cum-dividend day and an increase in the likelihood of the least aggressive buy orders on the ex-dividend day, consistent with liquidity suppliers seeking to benefit from the activity of the relatively more aggressive behaviours of the tax-arbitrageurs.

Second, there are patterns in the way that order submission is associated with changes in spread occurring in the ex-dividend week relative to the control week. While, most sell orders, respond more positively to spread increases on the cum-dividend day than the control week, only the second and third least aggressive buy orders respond more positively to increases in spread on the cum-dividend day than the control week. The second least aggressive sell orders and the most aggressive sell orders respond more positively to spread increases on the ex-dividend day than the control week. All buy order types respond more negatively to an increase in spread on the ex-dividend day than the control week - a conclusion that can be inferred from Table 2.11 and Table 2.12, from the relative risk ratios on the "Spread" variables.[32]

It is more likely that we see more aggressive sell orders submitted following an increase in the spread on the cum-dividend day but less likely that we will see more aggressive buy orders submitted following an increase in spread on the ex-dividend day. This can be consistent with liquidity provision by sellers on the cum-dividend day. If there is buying pressure on the cum-dividend day and selling pressure on the ex-dividend day from arbitrageurs, there should be temporary increases in spread that is subsequently filled by more aggressive orders from the

[32]For example, compare the "Spread" relative risk ratio (RRR) with the "Spread * Spread #DW * Spread #DC" and "Spread * Spread #DW * Spread #DE" relative risk ratios.

opposite side of the market, on both the cum- and ex-dividend days. This effect is observed on the cum-dividend day but not on the ex-dividend day, which could be explained by there being a cum-dividend day deadline for placing tax-arbitrage transactions and the absence of such a deadline on the ex-dividend day. The fact the liquidity supplying orders are aggressive does not mean the liquidity provision is not profitable, since the trading pressure may push the bid and ask prices away from the fundamentals. For example, if a liquidity provider is submitting an aggressive order relative to the current spread, the order may not be aggressive relative to the fundamental price.

Third, there is evidence of patterns in the differences seen in the way that order submission is associated with return changes in the ex-dividend week as compared to the control week. All types of buy orders respond more positively to return increases on the cum-dividend day than the control week. The three least aggressive sell orders respond more positively to return increases on the ex-dividend day than the control week. Consistent with the literature, in the control week, there is a positive association between return and the likelihood of the submission the three most aggressive buy order types, and of the submission of the least aggressive sell order. It is expected that this effect is particularly strong on the cum-dividend day for buy orders and the opposite effect is expected for sell orders on ex-dividend day, since it is aggressive buying (selling) pressure that is more likely to be driven on the cum-dividend (ex-dividend) day by arbitrageurs who need to place their orders before the end of the cum-dividend day. This assertion is supported by the data, since the positive association between the submission of buy orders and returns is amplified on the cum-dividend day and the positive association between the submission of least aggressive sell orders and returns is excited on the ex-dividend day. This can be inferred from comparing the relative risk ratios (RRR) for "Return" variable in Table 2.11 and Table 2.12 with those for the interaction terms with "Return". This is evidence of the presence of tax-arbitrage traders.[33]

It is more likely to see two least aggressive sell orders submitted following an increase in the return on cum-dividend day and more likely to see aggressive buy orders submitted following an increase in the return on ex-dividend day. This can be consistent with liquidity provision by sellers on the cum-dividend day and buyer on the ex-dividend day. If there is buying pressure on the cum-dividend day and selling pressure on the ex-dividend day from arbitrageurs temporary increases in the return may be seen that is subsequently taken by more orders on the other side on both the cum-dividend day and the ex-dividend day.

Fourth, there are patterns also in the way order submission is associated with volatility changes occurring in the ex-dividend week relative to the control week. All buy order types respond more positively to volatility increases on the cum-dividend day than in the control week. In the control week, there is a positive association between and volatility and the likelihoods of the submission of the three most aggressive sell order types and of the submission of the two most aggressive buy orders types. This is evidence that trading activity is associated with and perhaps even drives price volatility. It is expected that this effect is particularly strong on the cum-dividend day for buy orders, since more aggressive buying pressure (which is more likely to move prices) is more likely on cum-dividend days from the activity of arbitrageurs who need to place their orders before the end of the cum-dividend day (i.e. an approaching guillotine type deadline). There is evidence for this assertion in the data , since the positive association between the submission of the two most aggressive buy orders and price volatility is amplified on the cum-dividend day. This conclusion can be inferred from the relative risk ratios in Table 2.11 and Table 2.12, by comparing the relative risk ratio (RRR) for "Volatility" with the interactions terms on "Volatility".[34] This is evidence of the

[33]More specifically, this can be seen by comparing the "Return" relative risk ratio (RRR) with the "Return * Return # DW * Return # DC" and "Return * Return # DW * Return # DE" relative risk ratios.

[34]For example, see Volatility * Volatility # DW * Volatility # DC" and "Volatility * Volatility # DW * Volatility # DE" relative risk ratios.

presence of tax-arbitrage traders.

Fifth, there are some links between duration changes taking place in ex-dividend week relative to control week and order submission. The likelihood of the most aggressive buy order increases when duration decreases in control week. This effect amplifies on cum-dividend day for buy side. The most three aggressive sell orders respond more positively to duration decreases on ex-dividend day comparing to control week. This can be inferred from Table 2.11 and Table 2.12, by comparing the relative risk ratios.[35] When the duration increases on cum-dividend (ex-dividend) day, the traders submit less aggressive buy (sell) order. Duration variable was intended to capture the influence of expected time to execution, an increase in which should discourage limit orders according to existing theory (Foucault et al., 2005; Rosu 2008, 2009). Evidence for this hypothesis is provided in Tkatch and Kandel (2008). We offer the following potential explanation of this otherwise puzzling result. In some markets, like the LSE, trading tends to occur most frequently at the market open, when information asymmetries are strongest because trading has been suspended during an extended overnight period (Madhavan et al., 1997). If so, the trade duration variable might capture these shifts in the information environment. Higher trade duration would reflect a dearth of new information arrivals and would therefore be associated with the relatively heavy use of less aggressive orders consistent with our results.

Overall, the results point to traces of foot-prints associated with tax arbitrage and liquidity supply around the ex-dividend event. One picture that emerges is that increases in the price volatility on the cum-dividend (ex-dividend) day motivate tax-arbitrageurs to buy (sell) aggressively. Furthermore, aggressive tax arbitrage buying on the cum-dividend day leads to high returns (as prices are pushed away from fundamentals) and higher spreads are associated with buying and selling pressure on the cum- and ex-dividend days . The increases in return

[35]For example, by comparing the "Duration" relative risk ratio (RRR) with the "Duration * Duration # DW * Duration # DC" and "Duration * Duration # DW * Duration # DE" relative risk ratios.

and spread attract liquidity suppliers, particularly on the cum-dividend day, where it is more likely they can exploit the immediacy needs of tax-arbitrageurs. Consequently, there is also, therefore, an increase in the likelihood of order submission strategies and that is as expected from liquidity suppliers.

2.7 Robustness Test

This section provides additional tests to examine the robustness of the results presented above. The results point to traces of foot-prints associated with tax arbitrage and liquidity supply around the ex-dividend day. They also show patterns in the way that order submission is associated with changes in spread, volatility and return occurring on the cum- and ex- dividend days. To perform the robustness test - firstly, instead of restricting our sample to firms that are listed on the FTSE100 which have paid a cash dividend on Wednesday, we are including all firms that have paid a cash dividend, regardless of the trading day. Furthermore, if a firm pays a cash dividend several times during the sample period, we will include them all as ex-dividend events with each taken as a separate stock. Our final sample has 167 ex-dividend events. Secondly, in the previous section the sample period included the week with the ex-dividend day as well as the week prior, as a control week. However, for robustness test, we collected data for cum- and ex-dividend days as well as ten days after the ex-dividend day as the control period as to avoid any dividend related trade activities that otherwise might contaminate the control week. Thirdly, we calculated the actual bid-ask spread as follows:

1. For each day, all submitted orders from the start of the day were collected.

2. For a given order submitted at a given time on that day, we took all orders from step 1 still live up to that point (i.e. not executed or deleted).

3. The most competitive buy and sell orders still live are the bid-ask spread at the submission of the order in point 2.

4. Some live orders were deleted. These were orders where (i) data on volume is missing or (ii) the best bid price exceeds the best ask price.

5. The steps 2 – 4 were repeated for all orders submitted during each trading day.

The error correction procedure in step 4 leads to the elimination of 2% of the orders.

Fourth, to investigate further the spread (volatility) effects on cum and ex-dividend days, we have run two OLS regressions. The first regression examines the overall picture of the spread during the study period by estimating the following model:

$$Spread_i^n = \alpha + \delta_1 DC_i + \delta_2 DE_i + \varepsilon_i^n \tag{2.19}$$

where:

$Spread_i^n$: is the average spread for stock i during the five minutes n.

DC_i: is an indicator variable takes value of 1 on cum-dividend day and 0 otherwise.

DE_i :is an indicator variable takes value of 1 on ex-dividend day and 0 otherwise.

We then add the following spread determinants: volatility, volume, return, buy size, sell size and their interaction with cum-dividend day and ex-dividend day dummies. The second regression examines whether these determinants affect spread on cum- and ex-dividend days differently in comparison to the control period by estimating the following model: [36]

[36]The control period is the ten days after ex-dividend day.

$$\begin{aligned} Spread_i^n = {} & \alpha + \beta_1 Vo_i^n + \beta_2 Vu_i^n + \beta_3 Re_i^n + \beta_4 Bs_i^n + \beta_5 Ss_i^n + \delta_1 DC_i + \delta_2 DE_i \\ & + \beta_6 Vo_i^n * DC_i + \beta_7 Vu_i^n * DC_i + \beta_8 Re_i^n * DC_i + \beta_9 Bs_i^n * DC_i + \beta_{10} Ss_i^n * DC_i \\ & + \beta_{11} Vo_i^n * DE_i + \beta_{12} Vu_i^n * DE_i + \beta_{13} Re_i^n * DE_i + \beta_{14} Bs_i^n * DE_i + \beta_{15} Ss_i^n * DE_i \\ & + \varepsilon_i^n \end{aligned} \tag{2.20}$$

where:

$Spread_i^n$: is the average spread for stock i during the five minutes n.

Vo_i^n: is volatility for stock i during the five minutes n. The volatility is the tick-by-tick standard deviation of returns over a five minute interval.

Vu_i^n: is volume for stock i during the five minutes n. Volume is the natural logarithm of the average number of shares per transaction in a five minute interval divided by the average number of shares per transaction on the day.

Re_i^n: is return for stock i during the five minutes n. The return defines as the average tick-by-tick return over a five minute interval.

Bs_i^n: is buy trade size for stock i during the five minutes n. Buy trade size is the accumulated volume of buy transactions over a five minutes interval before the event.

Ss_i^n: is sell trade size for stock i during the five minutes n. Sell trade size is the accumulated volume of sell transactions over a five minutes interval before the event.

Also, to investigate more regarding the volatility on cum- and ex- dividend days, we estimated the following model:

$$Vo_i^n = \alpha + \delta_1 DC_i + \delta_2 DE_i + \varepsilon_i^n \tag{2.21}$$

Finally, we performed an ordered probit test of model 2.18 as follows: The results presented so far consider four types of different aggressive buy orders

(Behind-the-quote, At-the-quote, Inside-the-quote and Marketable) in comparison with all sell orders as one block and four types of different aggressive sell orders (Behind-the-quote, At-the-quote, Inside-the-quote and Marketable) in comparison with all buy orders as one block. In this section, we classify the submitted orders according to their price aggressiveness, in a similar way described in section 2.5 (2.5 order submission), and categorise orders from the least aggressive orders (i.e. behind the quote) to the most aggressive orders (i.e. marketable). More specifically, behind the quote orders are denoted as the lowest rank while marketable orders are denoted as the highest rank. We then run an ordered probit regression for the buy and sell sides separately.

Table 2.13 shows the results of models (2.19), (2.20) and (2.21). The first row shows the results of model (2.19), the second row shows the results of model (2.21) and the rest of the table shows the results of model (2.20).

Table 2.13 – Estimation of OLS regression over spread and volatility
This table shows the results of OLS estimates regression of Eq (2.19,2.20,2.21) for sample of 167 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008 and they paid a cash dividend during the sample period. The regression is robust for heteroskedasticity and autocorrelation. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	Cum.day	Ex.day	After.Ex.day
Spread	-0.069*	-0.109**	1.762***
Volatility	-0.001	-0.020**	0.467***
Spread Determinants			
Volatility	-0.242	0.006	0.980***
Volume	0.103	-0.068	0.170***
Return	0.009	-0.011	0.003
Buy Size	-0.005	-0.004	0.005*
Sell Size	0.004	0.005	0.004
Dummies	0.087	-0.082	1.247***

The results show several significant effects confirming the previous results. Firstly, the constant term is significantly positive in spread and volatility dummies regressions. This indicates that, in general, the spread and the volatility are significantly positive in the control period which is the ten days after ex-dividend day. Secondly, the coefficients on the corresponding spread observations and the volatility observations are positive in the control period and significantly decrease on ex-dividend day, which indicate that there are intra-day patterns in both the spread and the volatility variables.

Furthermore, we find that the spread is explained, in general, by volume, volatility and buy size by a positive association but there are no specific cum-dividend day and ex-dividend day effects.

Table 2.14 presents the predicted probabilities of submitting orders with varying levels of aggressiveness, on the cum-dividend day, ex-dividend day and 10 days after ex-dividend day, for both the buy side as well as the sell side. Table 2.15 reports the coefficient of ordered probit regression for the buy and sell sides separately.

Table 2.14 – The predicted probabilities to submit different level of aggressive buy order and sell order This table reports the predicted probabilities of each level of aggressiveness over buy and sell side separately. The predicted probabilities are reported for sample of 167 ex-dividend events from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008 and they paid a cash dividend during the sample period.

	Buy Side			Sell Side		
Aggressiveness	After.Ex	Cum.day	Ex.day	After.Ex	Cum.day	Ex.day
B-T-Q	0.5107	0.5105	0.5148	0.5025	0.5055	0.5015
A-T-Q	0.0111	0.0111	0.0111	0.0129	0.0129	0.0129
I-T-Q	0.0021	0.0021	0.0021	0.0020	0.0020	0.0020
M-A	0.4761	0.4763	0.4720	0.4826	0.4795	0.4836

Table 2.15 – Ordered probit regression

This table reports the ordered probit regression coefficients over buy and sell side separately. The coefficients are reported for sample of 167 ex-dividend events from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008 and they paid a cash dividend during the sample period. The significant levels are defined as follows: * p < 0.10, ** p < 0.05, *** p < 0.01

Variables	Buy Side	Variables	Sell Side
Spread-After-Ex.Day	0.091***	Spread-After-Ex.Day	0.062***
Spread-Cum.Day	-0.002	Spread-Cum.Day	-0.021***
Spread-Ex.Day	0.018*	Spread-Ex.Day	-0.031***
Return-After-Ex.Day	0.001***	Return-After-Ex.Day	-0.002***
Return-Cum.Day	0.006***	Return-Cum.Day	0.001***
Return-Ex.Day	0.002***	Return-Ex.Day	-0.002***
Volatility-After-Ex.Day	-2.872***	Volatility-After-Ex.Day	-0.896***
Volatility-Cum.Day	5.483***	Volatility-Cum.Day	-0.604*
Volatility-Ex.Day	0.988**	Volatility-Ex.Day	0.130
Duration-After-Ex.Day	-0.006***	Duration-After-Ex.Day	-0.006***
Duration-Cum.Day	0.001***	Duration-Cum.Day	0.000
Duration-Ex.Day	0.000	Duration-Ex.Day	0.000*
Cum-dividend day	0.000	Cum-dividend day	-0.008**
Ex-dividend day	-0.010**	Ex-dividend day	-0.003***

Figures 2.1 and 2.3 present the variation in the predicted probabilities for each level of aggressiveness against the spread variable, holding other variables constant over the ex-dividend day, for sell and buy orders respectively. Similarly, Figures 2.2 and 2.4 apply for cum-dividend day. Figures 2.5 and 2.7 present the variation in the predicted probabilities for each level of aggressiveness against the return variable, holding other variables constant over the ex-dividend day, for buy and sell orders respectively. Similarly, Figure 2.6 and 2.8apply for cum-dividend day. Figures 2.9 and 2.11 present the variation in the predicted probabilities for each level of aggressiveness against the volatility variable, holding other variables constant over the ex-dividend day, for sell and buy orders respectively. Similarly, Figure 2.10 and 2.12 apply for cum-dividend day. Figures 2.13 and 2.15 present the variation in the predicted probabilities for each level of aggressiveness against the duration variable, holding other variables constant over the ex-dividend day, for sell and buy orders respectively. Similarly, Figures 2.14 and 2.16applies for cum-dividend day.

Figure 2.1 – Predicted Probabilities - Spread - Sell order - Ex.Day

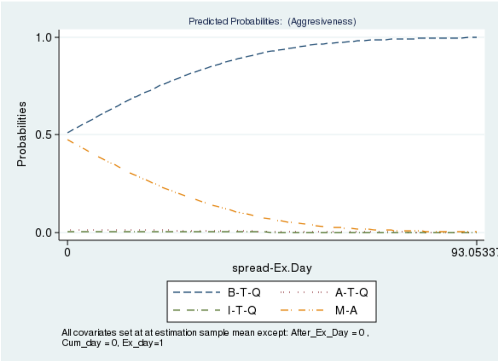


Figure 2.2 – Predicted Probabilities - Spread - Sell order - Cum.Day

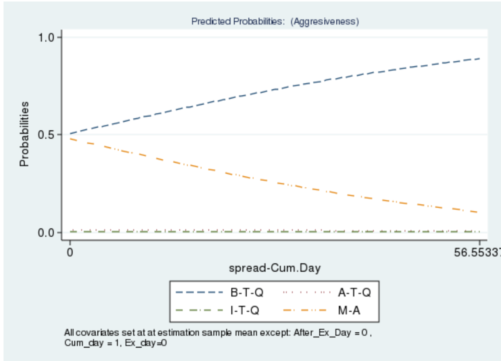


Figure 2.3 – Predicted Probabilities - Spread - Buy order - Ex.Day

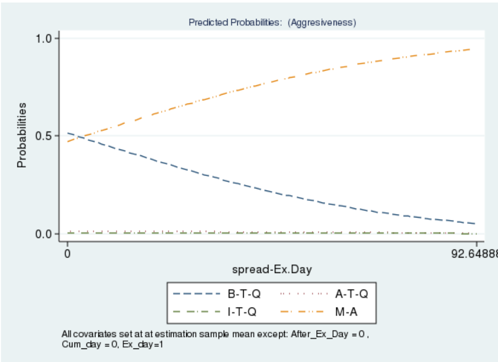


Figure 2.4 – Predicted Probabilities - Spread -Buy order - Cum.Day

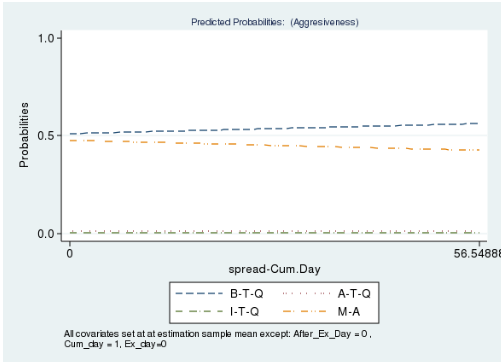


Figure 2.5 – Predicted Probabilities - Return - Buy order - Ex.Day.

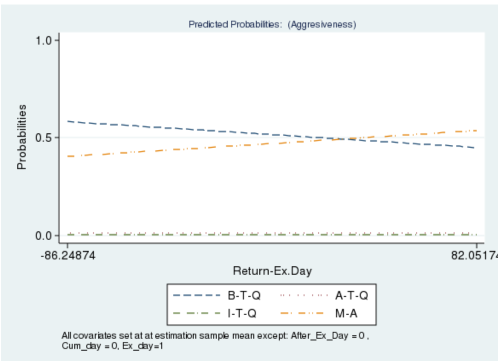


Figure 2.6 – Predicted Probabilities - Return - Buy order - Cum.Day.

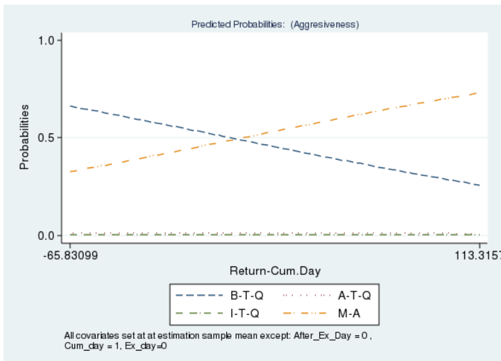


Figure 2.7 – Predicted Probabilities - Return - Sell order - Ex.Day.

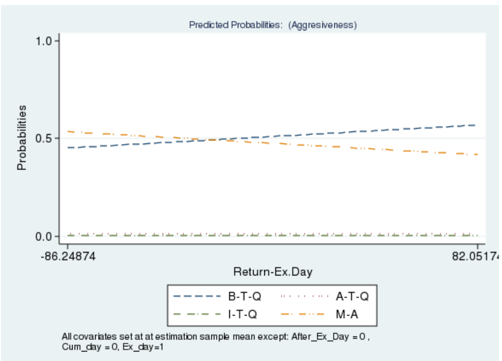


Figure 2.8 – Predicted Probabilities - Return - Sell order - Cum.Day.

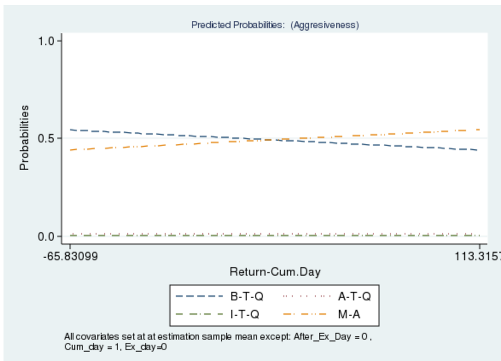


Figure 2.9 – Predicted Probabilities - Volatility - Sell order - Ex.Day

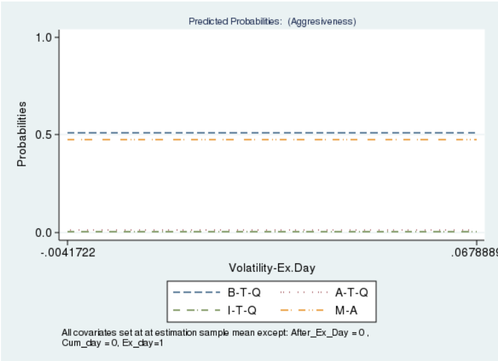


Figure 2.10 – Predicted Probabilities - Volatility - Sell order - Cum.Day

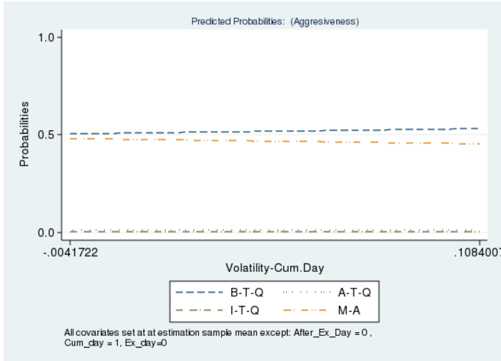


Figure 2.11 – Predicted Probabilities - Volatility - Buy order - Ex.Day

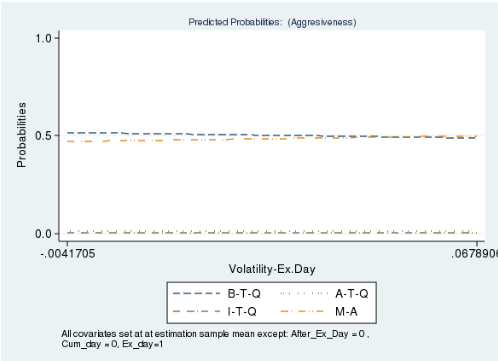


Figure 2.12 – Predicted Probabilities - Volatility - Buy order - Cum.Day

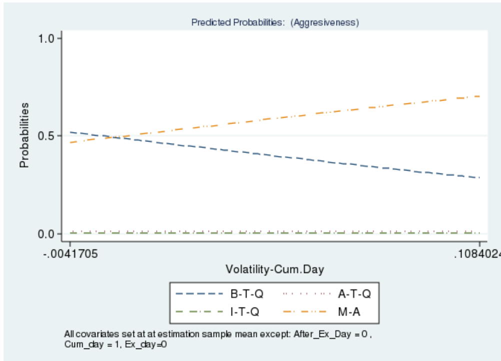


Figure 2.13 – Predicted Probabilities - Duration - Sell order - Ex.Day.

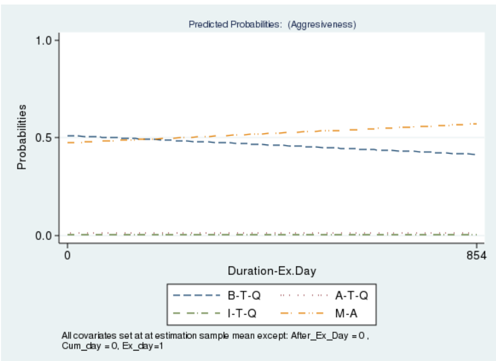


Figure 2.14 – Predicted Probabilities - Duration - Sell order - Cum.Day.

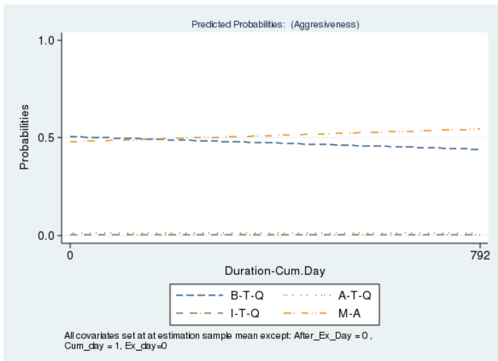


Figure 2.15 – Predicted Probabilities - Duration - Buy order - Ex.Day.

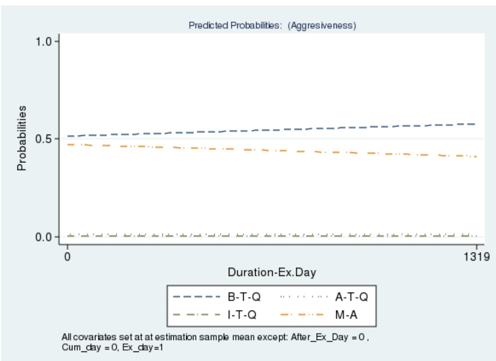
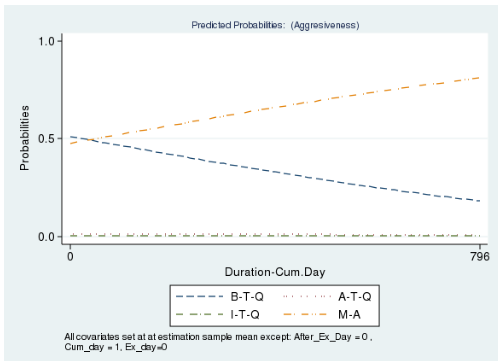


Figure 2.16 – Predicted Probabilities - Duration - Buy order - Cum.Day.



We observe that by considering the new sample of data, calculating the actual live spread and analysing buy orders and sell orders separately, the ordered probit specification does not overrule the previous results. Interestingly, we find that the highest predicted probability for marketable buy orders is on the cum-dividend day (0.4763) and the highest predicted probability for marketable sell order is on ex-dividend day (0.4836), confirming aggressive buy behaviour on the cum-dividend day and aggressive sell behaviour on the ex-dividend day. Second, there are patterns in the way that order submission is associated with changes in spread occurring on the cum- and ex-dividend days relative to the control period.[37] Table 2.15 shows that the aggressiveness level of buy orders responds positively to spread increases on ex-dividend day. Meanwhile, the negative signs associated with spread variables in Table 2.15 show that the aggressiveness level of sell orders respond negatively to spread increases on both cum- and ex- dividend days, on the cum-dividend day the aggressiveness level of sell orders responds less negatively than the aggressiveness level of sell orders on ex-dividend day. This conclusion is inferred from Figures 2.2 and 2.3.

It is more likely that we see more aggressive sell orders submitted following an increase in the spread on the cum-dividend day and more aggressive buy orders submitted following an increase in the spread on the ex-dividend day. This can be consistent with liquidity provision by sellers on the cum-dividend day and by buyers on the ex-dividend day. If there is buying pressure on the cum-dividend day and selling pressure on the ex-dividend day from arbitrageurs, there should be temporary increases in spread that is subsequently filled by more aggressive orders from the opposite side of the market, on both the cum- and ex-dividend days. This effect is observed on cum- and ex- dividend days. The fact that liquidity supplying orders are aggressive does not mean liquidity provision is not profitable, since trading pressure may push bid and ask prices away from fundamentals. For example, if a liquidity provider is submitting an aggressive order relative to current

[37] The control period is the ten days after ex-dividend day.

spread, that order may not be aggressive relative to fundamental price.

Third, there is evidence of patterns in the changes seen in the way that order submission is associated with return changes on cum- and ex- dividend days compared to the control period. The positive return coefficients over buy side in Table 2.15 can be interpreted, consistently with the previous results and with the prior literature, as a positive association between return increases and the likelihood of the submission of more aggressive buy order types. It is expected that this effect is particularly strong on the cum-dividend day, since it is aggressive buying pressure that is more likely to be driven on the cum-dividend day by arbitrageurs who need to place their orders before the end of the cum-dividend day. This assertion is supported by the results, since the positive association between the submission of buy orders and returns is amplified on the cum-dividend day and is inferred from Figures 2.6 .

Fourth, there are also patterns in the way order submission is associated with volatility changes occurring on cum- and ex- dividend days compared to the control period. Table 2.15 shows that the aggressiveness level of buy (sell) orders responds more positively to volatility increases on the cum-dividend (ex-dividend) day than on ex-dividend (cum-dividend) day. This is evidence that trading activity is associated with and perhaps even drives price volatility on the cum- and ex-dividend days. This conclusion can be inferred from Figure 2.12

Finally, there are some links between duration changes on cum- and ex- dividend days relative to the control period. The duration variable was intended to capture the influence of expected time to execution and as noted by existing theory (see Foucault et al., 2005; Rosu 2008, 2009), an increase in duration should discourage limit orders. The positive signs of the most duration coefficients in Table 2.15, confirm this. This effect is stronger on cum-dividend day.

Overall, the robustness results confirm the traces of foot-prints associated with tax arbitrage and liquidity supply around the ex-dividend event. On one hand, increases in the price volatility and order return motivate tax-arbitrageurs to buy on cum-dividend day and sell on ex-dividend day aggressively. On the other hand, aggressive tax arbitrage buying on the cum-dividend day and selling on ex-dividend day leads to higher spreads which attract liquidity suppliers to trade aggressively.

2.8 Conclusion

This chapter studies market microstructure effects associated with ex-dividend price drops and investigates tax-arbitrage driven trading around ex-dividend days and searching for their tell-tale "footprints". First, there are no strong effects in the aggregate trading data but spread and volatility are higher in the ex-dividend week compared to the control week and spreads in the ex-dividend week is affected by price volatility as well as trading volume. These effects are not directly interpretable without simultaneously studying the order submission book.

Second, the order submission analysis report an increased in the likelihood of relatively more aggressive buying on the cum-dividend day and relatively more aggressive selling on the ex-dividend day, supporting the presence of tax-arbitrage trading "footprints". Also, the results present an increase in the likelihood of relatively less aggressive selling on the cum-dividend day and of relatively less aggressive buying on the ex-dividend day. These findings are consistent with tax-arbitrage and liquidity supply occurring simultaneously.

Third, there are clearly effects associating order submission to spread, volatility, return and duration. On the cum-dividend (ex-dividend) day, increases in the price volatility motivate tax-arbitrageurs to buy (sell) aggressively. More, the aggressive behaviour of tax arbitrager on the cum- and ex- dividend days leads to high returns and higher spreads. The increases in return and spread attract liquidity suppliers, particularly on the cum-dividend day, to trade aggressively. The interpretation of the overall effect is that, one-sided trading pressure either buying or selling drive prices away from fundamentals and increase returns as well as spreads. These departures attract liquidity suppliers who trade aggressively either when prices are driven away from fundamentals or when spreads become large enough to profit from. In addition, one-sided pressure either buying or selling increases price volatility which motivates tax-arbitrageurs to submit their orders aggressively. The conclusion is that these conjectured behaviours are stronger on cum-dividend days because of an approaching cum-dividend day guillotine-type horizon for placing tax-arbitrage transactions.

Finally, after we expand our sample period, calculate the actual spread and analyse buy order and sell order separately, the regression specification confirms most of the results.

2.9 Appendix A

2.9.1 Multinomial Logit Regression

Definitions

Odds: odds are ratio

$$Odds = \frac{p}{1-p} \tag{2.22}$$

Log odds: natural log of odds, also known as logit.

$$Logodds = logit = log(\frac{p}{1-p}) \tag{2.23}$$

Odds ratio: odds ratio is ratio of odds.

$$Odd - ratio = \frac{Odd1}{Odd2} = \frac{\frac{p_1}{1-p_1}}{\frac{p_2}{1-p_2}} \tag{2.24}$$

Computing odds ratio from logistic regression coefficient:

$$Odd - ratio = exp(b) \tag{2.25}$$

Computing probability from logistic regression coefficient:

$$probability = \frac{exp(Xb)}{1 + exp(Xb)} \tag{2.26}$$

whereXb is the linear predictor.

Introduction

Multinomial logit models are used to model the relationship between categorical response variable and set of regressor variables. Multinomial logit models are applied in case of discrete dependent variable

$$y_n \in 1, 2, \cdots J \tag{2.27}$$

where the values of y_n have no natural order.

Econometric model

The Choice of one of J alternatives is driven by a polytomous variable often interpreted as indirect utility:

$$U_{nj} = \alpha_j + X_n' \beta_j + \varepsilon_{nj} \tag{2.28}$$

whereα_j is a constant and β_j is a vector of regression coefficients, for $j = 1, 2, \cdots J-1$. Only $J-1$ equations are needed to explain a dependent variable with J response categories. The exogenous variables X_n explain only the individual and are identical across alternative. However, the parameter β_j differs among alternative. An individual n chooses alternative j if it offers the highest value of indirect utility. The observed choice y_n of an individual n is:

$$y_n = \begin{cases} 1 \text{ if } U_{n1} \geq U_{nt} \text{ for all } i \\ 2 \text{ if } U_{n2} \geq U_{nt} \text{ for all } i \\ \vdots \\ j \text{ if } U_{nj} \geq U_{nt} \text{ for all } i \end{cases} \tag{2.29}$$

For further details, see Verbeek (2008).

Identification

The parameter vectors β_j, $j = 1, 2, \cdots, J-1$, are not uniquely defined: any vector c added to all vectors $\beta_j^* = \beta_j + c$ cancels in the choice probabilitiesP_{nj}.

$$P_{nj} = \frac{exp(x'_n(\beta_j + c))}{\sum_{i=1}^{j} exp(x'_n(\beta_i + c))} = \frac{exp(c)exp(x'_n\beta_j)}{exp(c)\sum_{i=1}^{j} exp(x'_n\beta_i)} = \frac{exp(x'_n\beta_j)}{\sum_{i=1}^{j} exp(x'_n\beta_i)} \quad (2.30)$$

One equation sets β to zero, so that the problem is identifiable. The associated outcome is the base reference group (see Hardin et al., 2007).

Model probabilities

$$U_{nj} = ln\frac{P_{nj}}{P_{nJ}} = \alpha_j + X'_n\beta_j \quad (2.31)$$

Adopting the convention that $U_{nJ} = 0$

$$P_{nj} = \frac{exp(U_{nj})}{\sum_{i=1}^{j} exp(U_{ni})} \quad (2.32)$$

For $j = 1, 2, \cdots J - 1$. By exponentiate the first equation,

$$P_{nj} = P_{nJ}exp(U_{nj}) \quad (2.33)$$

The convention $U_{nJ} = 0$ makes this formula valid for all j. Sum over j and use the fact that $\sum_j P_{ij} = 1$ lead to

$$P_{nJ} = \frac{1}{\sum_j exp(U_{nj})} \quad (2.34)$$

As in Verbeek (2008).

Maximum likelihood

Estimation of the parameters of this model by maximum likelihood (ML) proceeds by maximization of the multinomial likelihood with the probabilities P_{nj} viewed as function of α_j and β_j parameters. The log likelihood function:

$$LogL = \sum_{n=1}^{N}\sum_{j=1}^{J} d_{nj}log(p_{nj}) \quad (2.35)$$

$$d_{nj} \begin{cases} 1 & \text{if the observation i has outcome j (if } y_i = j) \\ 0 & \text{Otherwise} \end{cases}$$

The maximum likelihood estimator$\hat{\beta}$ is consistent, asymptotically efficient and normally distributed (see Hardin et al., 2007).

Interpretation

The parameters of the multinomial logit model are hard to explain. Neither the sign nor the magnitude of the parameter has direct intuitive meaning because of the nonlinearity of the link function and the incorporate of the base reference group.

Relative risk aversion

For easier interpretation, an alternative metric that admits a transformation of the coefficients could be motivated. Since the model is fitted using one of the outcome as a base reference group, the probabilities that are calculated relative to that reference group. Relative risk ratio (RRR) for an observation i can be defined as the risk of outcome falling in the comparison group compared to the risk of the outcome falling in the base group. RRR define by exponentiating the multinomial logit coefficient.

$$\text{Relative risk for out come j} = exp(U_{nj}) \tag{2.36}$$

This ratio can be calculates for each outcome and each covariate.

For example, let's assume a model with two covariates x_1 and x_2 along with a constant. The RRR for x_1 and outcome j is calculated as:

$$RRR = \frac{Odds(\text{if the correspoding variable is incremented by 1})}{Odds(\text{if the varaible not incrmented})}$$

$$RRR\ for\ x_1 = \frac{exp(\alpha_0 + (x_{1jn} + 1)\beta_1 + x_{2jn}\beta_2)}{exp(\alpha_0 + x_{1jn}\beta_1 + x_{2jn}\beta_2)} \tag{2.37}$$

$$= exp(\beta_1) \tag{2.38}$$

An important property of RRR is that there is no dependent on a particular observation. The RRR is constant, it is independent of the particular value of covariate. A RRR>1 means as the variable increases, there is an increase in the risk of the outcome to fall in the comparison group relative to the risk of outcome falling on the base group. A RRR<1 means as the variable increases, there is a decrease in the risk of the outcome to fall in the comparison group relative to the risk of outcome falling on the base group (as in Hardin et al., 2007).

Interaction in non- linear model

The exponentiated coefficients introduce for one unite change in the explanatory variable, the ratio by which the dependent variable changes, that is, the effect is presented in a multiplicative scale Long and Freese (2006). To illustrate this, let's assume a model with two variables and their interaction like the following:

$$y_{jn} = \alpha_0 + x_{1jn}\beta_1 + x_{2jn}\beta_2 + x_{12jn}\beta_3 \tag{2.39}$$

where:

x_1: is a dummy variable

x_2: is a dummy (continuous) variable.

Generally, adding an interaction term to a model drastically changes the interpretation of the entire coefficient if there is no interaction effect term. If there is no interaction effect β_2 would be interpreted as the unique effect of x_2 but after include the interaction term the effect of x_2 depend on both β_2 and β_3. So, β_1 presents the effect of x_1 when $x_2 = 0$, if x_2 is dummy variable otherwise β_1 presents the effect of x_1 when x_2 is at its mean, if x_2 is continues variable. β_2 presents the effect of x_2 when $x_1 = 0$. if x_2 is dummy variable,β_3 presents the effect of x_1 when $x_2 = 1$ dividend by the effect of x_1 when $x_2 = 0$, otherwise if x_2 is continuous variable β_3 presents the effect of x_1 dividend by the effect of x_1 when x_2 is at its mean and vice versa. The overall effect of x_2 is represented by $\beta_2 * \beta_3$ (for further details, see Buis, 2010).

2.9.2 Probit Regression

The Ordered Probit model is an extension of the binary probit model that can be used in cases where there are multiple and ranked discrete dependent variables. The central idea is that there is a latent continuous metric underlying the ordinal responses observed by the analyst. Thresholds partition the real line into a series of regions corresponding to the various ordinal categories. The latent continuous variable, y * is a linear combination of some predictors, x, plus a disturbance term that has a standard Normal distribution.

Lets consider the simple case, where the dependent variable Y takes the values 0, 1, or 2. An unobserved index function Y* is defined as:

$$Y_i^* = \sum_{k=1}^{K} \beta_k X_{ki} + \varepsilon_i \quad \varepsilon_i \sim N(0,1), \forall\, i = 1, \cdots, N \tag{2.40}$$

and assume:

$$Y = \begin{cases} 0 & if\ Y_i^* < k1, \\ 1 & if\ k1 \leq Y_i^* < k2, \\ 2 & if\ k2 \leq\ Y_i^* \end{cases} \tag{2.41}$$

where k1 and k2 are "cut points" and k1 $<$ k2.

The concerned is on how changes in the predictors translate into the probability of observing a particular ordinal outcome. Consider the probabilities of each ordinal outcome:

$$\begin{aligned}
Pr(Y=0|X) =& Pr(\sum_{k=1}^{K}\beta_k X_{ki} + \varepsilon_i < k1) \\
=& Pr(\varepsilon_i < -\sum_{k=1}^{K}\beta_k X_{ki} + k1) = \Phi(-\sum_{k=1}^{K}\beta_k X_{ki} + k1), \\
Pr(Y=2|X) =& Pr(\sum_{k=1}^{K}\beta_k X_{ki} + \varepsilon_i > k2) \\
=& Pr(\varepsilon_i > -\sum_{k=1}^{K}\beta_k X_{ki} + k2) = 1 - \Phi(-\sum_{k=1}^{K}\beta_k X_{ki} + k2) \\
Pr(Y=1|X) =& 1 - Pr(Y=0) - Pr(Y=2) \\
=& \Phi(-\sum_{k=1}^{K}\beta_k X_{ki} + k2) - \Phi(-\sum_{k=1}^{K}\beta_k X_{ki} + k1)
\end{aligned} \tag{2.42}$$

where Φ is the cumulative distribution function of residual ε_i .

2.10 Appendix B

Table 2.16 – Relative risk ratios–M1

This table reports the relative risk ratios of estimates regression Eq.(2.18) for -M1-buy side and sell side on a stock-by-stock basis. The relative risk ratios are reported for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable for buy regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q buy order (2) A-T-Q buy order (3) I-T-Q buy order (4) M-A buy order (5) sell order. Sell order set as reference category for buy regression. The dependent variable for sell regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q sell order (2) A-T-Q sell order (3) I-T-Q sell order (4) M-A sell order (5) buy order. Buy order set as reference category for sell regression.The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Buy side				
Baseline	0.601***	0.179***	0.103***	0.347***
Spread	1.131***	1.068***	0.946***	0.825***
Volatility	0.850***	1.010	1.294***	1.080***
Return	0.760***	1.008	1.111***	1.813***
Duration	1.001***	1.005***	1.002***	0.995***
Sell side				
Baseline	0.586***	0.182***	0.083***	0.412***
Spread	1.068***	0.946***	0.927***	0.832***
Volatility	0.919***	1.096***	1.389***	1.106***
Return	1.325***	0.949***	0.894***	0.589***
Duration	1.001***	1.004***	1.0000	0.994***

Table 2.17 – Relative risk ratios–M2

This table reports the relative risk ratios of estimates regression Eq.(2.18) for -M2-buy side and sell side on a stock-by-stock basis. The relative risk ratios are reported for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable for buy regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q buy order (2) A-T-Q buy order (3) I-T-Q buy order (4) M-A buy order (5) sell order. Sell order set as reference category for buy regression. The dependent variable for sell regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q sell order (2) A-T-Q sell order (3) I-T-Q sell order (4) M-A sell order (5) buy order. Buy order set as reference category for sell regression. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Buy side				
Dummy variables				
Baseline	0.620***	0.172***	0.102***	0.353***
DW	0.944***	1.075***	1.021	0.967***
Baseline * DW	0.585	0.185	0.104	0.341
Spread	1.132***	1.065***	0.946***	0.825***
Volatility	0.850***	1.012	1.294***	1.080***
Return	0.759***	1.01	1.113***	1.812***
Duration	1.001***	1.005***	1.002***	0.995***
Sell side				
Dummy variables				
Baseline	0.565***	0.165***	0.072***	0.408***
DW	1.070***	1.205***	1.278***	1.018***
Baseline * DW	0.605	0.199	0.092	0.415
Spread	1.067***	0.941***	0.925***	0.832***
Volatility	0.919***	1.099***	1.387***	1.106***
Return	1.326***	0.953***	0.900***	0.589***
Duration	1.001***	1.004***	1.000	0.994***

Table 2.18 – Relative risk ratios–M3-buy side

This table reports the relative risk ratios of estimates regression Eq.(2.18) for -M3-buy side on a stock-by-stock basis. The relative risk ratios are reported for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable for buy regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q buy order (2) A-T-Q buy order (3) I-T-Q buy order (4) M-A buy order (5) sell order. Sell order set as reference category for buy regression. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Buy side				
Dummy variables				
Baseline	0.615***	0.187***	0.096***	0.333***
DW	0.961***	0.919***	1.164***	1.076***
Baseline * DW	0.591	0.172	0.112	0.358
Spread variables				
Spread	1.218***	1.145***	0.965**	0.853***
Spread # DW	0.864***	0.863***	0.949**	0.934***
Spread * Spread # DW	1.052	0.988	0.916	0.797
Volatility variables				
Volatility	0.791***	0.973	1.214***	1.065***
Volatility # DW	1.155***	1.087***	1.130***	1.028***
Volatility * Volatility # DW	0.914	1.058	1.372	1.095
Return variables				
Return	0.744***	1.015	1.241***	1.776***
Return # DW	1.042***	0.981	0.829***	1.048**
Return * Return # DW	0.775	0.996	1.029	1.861
Duration variables				
Duration	1.001***	1.004***	1.002***	0.996***
Duration # DW	1.002***	1.002***	1.001	0.998***
Duration * Duration # DW	1.003	1.006	1.003	0.994

Table 2.19 – Relative risk ratios–M3-sell side

This table reports the relative risk ratios of estimates regression Eq.(2.18) for -M3-sell side on a stock-by-stock basis. The relative risk ratios are reported for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable for sell regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q sell order (2) A-T-Q sell order (3) I-T-Q sell order (4) M-A sell order (5) buy order. Buy order set as reference category for sell regression.The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Dummy variables				
Baseline	0.579***	0.170***	0.077***	0.426***
DW	1.030***	1.171***	1.153***	0.934***
Baseline * DW	0.596	0.199	0.089	0.398
Spread variables				
Spread	0.994	0.917***	0.910***	0.793***
Spread # DW	1.148***	1.042	1.038*	1.092***
Spread * Spread # DW	1.141	0.956	0.945	0.866
Volatility variables				
Volatility	0.983***	1.125***	1.418***	1.149***
Volatility # DW	0.881***	0.962*	0.965**	0.934***
Volatility * Volatility # DW	0.866	1.082	1.368	1.073
Return variables				
Return	1.308***	0.877***	0.823***	0.530***
Return # DW	1.021	1.168***	1.165***	1.211***
Return * Return # DW	1.335	1.024	0.959	0.642
Duration variables				
Duration	1.002***	1.005***	0.999	0.994***
Duration # DW	0.998***	1.000	1.001	1.001*
Duration * Duration # DW	1.000	1.005	1.000	0.995

Table 2.20 – Relative risk ratios–M4-buy side

This table reports the relative risk ratios of estimates regression Eq.(2.18) for -M4-buy side on a stock-by-stock basis. The relative risk ratios are reported for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable for buy regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q buy order (2) A-T-Q buy order (3) I-T-Q buy order (4) M-A buy order (5) sell order. Sell order set as reference category for buy regression. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Dummy variables				
Baseline	0.616***	0.185***	0.096***	0.334***
DW	0.982***	0.948**	1.028	1.094***
DC	0.994**	0.838***	1.294***	0.970***
DE	0.889***	1.064***	1.403***	0.946***
Baseline * DW	0.605	0.175	0.099	0.365
Baseline * DW * DC	0.601	0.147	0.128	0.354
Baseline * DW * DE	0.538	0.187	0.138	0.346
Spread variables				
Spread	1.218***	1.144***	0.964**	0.853***
Spread # DW	0.865***	0.861***	0.946***	0.935***
Spread * Spread # DW	1.054	0.985	0.912	0.798
Volatility variables				
Volatility	0.791***	0.977	1.216***	1.065***
Volatility # DW	1.153***	1.080***	1.134***	1.026***
Volatility * Volatility # DW	0.912	1.055	1.379	1.093
Return variables				
Return	0.745***	1.015	1.241***	1.776***
Return # DW	1.044***	0.983	0.824***	1.048**
Return * Return # DW	0.778	0.998	1.023	1.861
Duration variables				
Duration	1.001***	1.004***	1.002***	0.996***
Duration # DW	1.002***	1.002***	1.001	0.998***
Duration * Duration # DW	1.003	1.006	1.003	0.994

Table 2.21 – Relative risk ratios–M4-sell side

This table reports the relative risk ratios of estimates regression Eq.(2.18) for -M4-sell side on a stock-by-stock basis. The relative risk ratios are reported for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable for sell regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q sell order (2) A-T-Q sell order (3) I-T-Q sell order (4) M-A sell order (5) buy order. Buy order set as reference category for sell regression. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Dummy variables				
Baseline	0.578***	0.168***	0.077***	0.425***
DW	1.001	1.195***	1.104**	0.923***
DC	1.037***	0.837***	0.980	1.003
DE	1.123***	1.139***	1.258***	1.068***
Baseline * DW	0.579	0.201	0.085	0.392
Baseline * DW * DC	0.600	0.168	0.083	0.393
Baseline * DW * DE	0.650	0.229	0.107	0.419
Spread variables				
Spread	0.994	0.917***	0.910***	0.793***
Spread # DW	1.146***	1.039	1.035	1.090***
Spread * Spread # DW	1.139	0.953	0.942	0.864
Volatility variables				
Volatility	0.983***	1.128***	1.419***	1.148***
Volatility # DW	0.883***	0.956**	0.968**	0.935***
Volatility * Volatility # DW	0.868	1.078	1.374	1.073
Return variables				
Return	1.308***	0.877***	0.823***	0.530***
Return # DW	1.021	1.170***	1.163***	1.211***
Return * Return # DW	1.335	1.026	0.957	0.642
Duration variables				
Duration	1.002***	1.005***	0.999	0.994***
Duration # DW	0.998***	1.000	1.001	1.001*
Duration * Duration # DW	1.000	1.005	1.000	0.995

Table 2.22 – Relative risk ratios–M5–buy side

This table reports the relative risk ratios of estimates regression Eq. (2.18) for -M5-buy side on a stock-by-stock basis. The relative risk ratios are reported for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable for buy regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q buy order (2) A-T-Q buy order (3) I-T-Q buy order (4) M-A buy order (5) sell order. Sell order set as reference category for buy regression. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Dummy variables				
Baseline	0.614***	0.186***	0.096***	0.334***
DW	0.919***	0.917***	1.109**	1.092***
DC	1.069***	0.852***	0.825**	0.894***
DE	1.197***	1.301***	1.692***	1.005
Baseline * DW	0.564	0.171	0.106	0.365
Baseline * DW * DC	0.603	0.145	0.088	0.326
Baseline * DW * DE	0.675	0.222	0.180	0.367
Spread variables				
Spread	1.217***	1.143***	0.965**	0.853***
Spread # DW	0.828***	0.838***	0.958*	1.021
Spread # DC	1.136***	1.250***	1.116***	0.745***
Spread # DE	1.108***	0.969	0.814***	0.800***
Spread * Spread # DW	1.008	0.958	0.924	0.871
Spread * Spread # DW * Spread # DC	1.145	1.197	1.032	0.649
Spread * Spread # DW * Spread # DE	1.117	0.928	0.753	0.697
Volatility variables				
Volatility	0.793***	0.979	1.214***	1.066***
Volatility # DW	1.187***	1.099***	1.068***	0.99
Volatility # DC	0.949***	1.013	1.181***	1.254***
Volatility # DE	0.903***	0.867***	1.161***	0.950***
Volatility * Volatility # DW	0.941	1.076	1.297	1.055
Volatility * Volatility # DW * Volatility # DC	0.893	1.090	1.531	1.323
Volatility * Volatility # DW * Volatility # DE	0.850	0.933	1.505	1.003
Return variables				
Return	0.745***	1.015	1.238***	1.779***
Return # DW	1.066***	1.005	0.765***	0.917***
Return # DC	1.051*	1.001	1.376***	1.734***
Return # DE	0.794***	0.870**	1.231***	1.323***
Return * Return # DW	0.794	1.020	0.947	1.631
Return * Return # DW * Return # DC	0.835	1.021	1.303	2.829
Return * Return # DW * Return # DE	0.631	0.887	1.166	2.158
Duration variables				
Duration	1.001***	1.004***	1.002***	0.996***
Duration # DW	1.001***	1.001***	1.001*	0.997***
Duration # DC	1.001	1.003***	1.000	1.002***
Duration # DE	1.001***	1.003***	0.999	1.003***
Duration * Duration # DW	1.002	1.005	1.003	0.993
Duration * Duration # DW * Duration # DC	1.003	1.008	1.003	0.995
Duration * Duration # DW * Duration # DE	1.003	1.008	1.002	0.996

Table 2.23 – Relative risk ratios–M5–sell side

This table reports the relative risk ratios of estimates regression Eq. (2.18) for -M5-sell side on a stock-by-stock basis. The relative risk ratios are reported for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable for sell regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q sell order (2) A-T-Q sell order (3) I-T-Q sell order (4) M-A sell order (5) buy order. Buy order set as reference category for sell regression. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Dummy variables				
Baseline	0.578***	0.168***	0.076***	0.427***
DW	1.038***	1.207***	1.252***	0.966***
DC	1.060***	0.760***	0.797***	0.950***
DE	0.913***	1.249***	0.951	0.877***
Baseline * DW	0.600	0.203	0.095	0.412
Baseline * DW * DC	0.636	0.154	0.076	0.392
Baseline * DW * DE	0.548	0.253	0.090	0.362
Spread variables				
Spread	0.994	0.917***	0.908***	0.793***
Spread # DW	1.250***	0.980	1.085***	1.032**
Spread # DC	0.786***	1.141**	1.160***	1.067***
Spread # DE	0.787***	1.099*	0.545***	1.252***
Spread * Spread # DW	1.243	0.899	0.985	0.818
Spread * Spread # DW * Spread # DC	0.977	1.025	1.143	0.873
Spread * Spread # DW * Spread # DE	0.978	0.988	0.537	1.025
Volatility variables				
Volatility	0.981***	1.133***	1.424***	1.149***
Volatility # DW	0.840***	0.944**	0.930***	0.990
Volatility # DC	1.081***	1.067*	0.853***	0.828***
Volatility # DE	1.219***	1.023	1.801***	0.897***
Volatility * Volatility # DW	0.824	1.070	1.324	1.138
Volatility * Volatility # DW * Volatility # DC	0.891	1.141	1.130	0.942
Volatility * Volatility # DW * Volatility # DE	1.005	1.094	2.385	1.020
Return variables				
Return	1.309***	0.877***	0.824***	0.530***
Return # DW	1.003	1.149***	1.206***	1.347***
Return # DC	1.017	0.945	0.721***	0.560***
Return # DE	1.099***	1.046	1.196***	0.691***
Return * Return # DW	1.313	1.008	0.994	0.714
Return * Return # DW * Return # DC	1.335	0.952	0.716	0.400
Return * Return # DW * Return # DE	1.443	1.054	1.189	0.493
Duration variables				
Duration	1.002***	1.005***	1.000	0.994***
Duration # DW	0.999***	0.999	1.001	1.001***
Duration # DC	0.999***	1.003***	1.004***	0.998***
Duration # DE	0.999***	1.000	0.992***	0.998***
Duration * Duration # DW	1.001	1.004	1.001	0.995
Duration * Duration # DW * Duration # DC	1.000	1.007	1.005	0.993
Duration * Duration # DW * Duration # DE	1.000	1.004	0.993	0.993

Chapter 3

Impact of Liquidity on Market Microstructure around Ex-Dividend Day

3.1 Introduction

Whereas the previous chapter investigated FTSE 100 firms, this chapter studies market microstructure effects around the ex-dividend day for FTSE SmallCap firms. Stocks that are listed on FTSE SmallCap Index are classified as illiquid stocks and this notion is empirically documented using a range of liquidity measures.

The expected execution probability for illiquid stocks is lower than the expected execution probability for liquid stocks. The expected waiting cost for illiquid stock is higher than the expected waiting cost for liquid stocks. On the other hand, the ex-dividend day is known to attract trading activity (Elton and Gruber, 1970 and Kalay, 1982). This trading activity is a unique window of opportunity to profit from tax arbitrage trading for some investors the non-execution cost of trading, especially on the cum-dividend day may, therefore, be higher than on other normal trading days. If traders fail to execute their submitted order on the cum-dividend day, they could face the risk of potential losses or negative returns. Further, the existence of the profitability of short term trading around the ex-dividend day is determined by the liquidity and transaction cost (see for example, Kalay, 1982; Boyd and Jagannathan, 1994; Michaely and Vila, 1996; and McDonald, 2001). Therefore, it is an interesting to examine the critical role the liquidity could have in tax-arbitrager decision. This chapter investigates whether the lack of liquidity prevents the presence of tax-arbitrage trading around the ex-dividend day and how the activities of tax-arbitrage traders, if there are any, could affect bid-ask spreads, price volatility and order submission strategies. The previous chapter found evidence that tax-arbitrage trading was present among FTSE 100 stocks and in this chapter we investigate whether similar evidence of tax arbitrage can also be found among the illiquid FTSE SmallCap stocks.

Market liquidity has been defined in various ways. Keynes (1930) and Hicks (1962) define liquidity by phrases like "future volatility of market prices" or the "possibility of immediate execution of a transaction." To decide whether the market is liquid or not Bagehot (1971) focused on factors like adverse selection, price impact and spreads. In the context of market microstructure theory, a liquid market is described by phrases like tightness (cost of rebalancing portfolios), depth (trading volume required to move prices) and resiliency (time required to reach a new equilibrium after price changes). Black (1971) defines a liquid market as one where the "bid-ask price is always quoted, its spread is small enough, and small trades can be immediately executed with minimal effect on price." Grossman and Miller (1988) argue that liquidity can be measured as the ability to execute trades quickly under the current quoted prices. Muranaga et al. (1999) similarly define a liquid market as one where a large volume of orders can be executed immediately at minimum impact on price.

While market makers provide liquidity in a quote driven market by setting bid and ask quotes, in a limit order market, public orders, provide the liquidity. In limit order markets, there is no specified market maker and counterparties are matched impersonally and usually electronically. The liquidity in limit order book depends on the decision of liquidity supplier (traders who submit sell orders at a price above the pre-trend prices of stocks or submit buy orders at prices below the pre-trend prices of stocks) and liquidity demanders (traders who submit orders at a premium or a discount to ensure a faster execution). The limit order book may, therefore, face the problem of lack of liquidity if there is an imbalance between liquidity suppliers and liquidity demanders.

Traders in illiquid markets could also face the risk of a potential shortage in counterparties and the risk of a significant price change in response to only few orders being carried on the limit order book. Bayraktar and Ludkovski (2012) reports that dramatic price changes could occur if one order matches up with many or all orders on the opposite side of the market but Seppi (1997) reports that in liquid markets, submitted orders have only a small impact on stock prices. Aggressive orders and large orders could amplify the effect of illiquidity on stock prices since aggressive orders will fast consume all orders on the opposite side of the market (Lebedeva, 2012). Large orders could also increase the imbalance between two sides of the market. The only way to reduce this imbalance between two sides of the market is by changes in price (Damodaran, 2005). In addition to bid-ask spreads and commission costs, Treynor (1981) argues that being able to wait for the "right time" to liquidate an investment is also valuable. In illiquid markets, this option to wait value is higher than in liquid markets, so traders may wait longer to liquidate their investments than in liquid markets. Both non-execution costs and the value of waiting before submitting orders are expected to be higher for illiquid than for liquid stocks. This chapter investigates, whether tax-arbitrage traders may, therefore, seek to avoid trading in illiquid stocks. Moreover, since increases in non-execution costs lead to increases in the aggressiveness of submitted orders, as predicted by the theoretical models in Foucault et al., (2005) and Roşu (2009), the expectation is that these costs are likely to be higher on cum-dividend days. Hence, if tax-arbitrageurs exist around the ex-dividend day on illiquid markets, the aggressiveness of submitted orders is expected to increase on cum-dividend days.

On the matter of bid-ask spreads, Foucault (1999) and Foucault et al. (2005) argue that bid-ask spreads should affect the order submission decisions of traders. Several empirical studies confirm this effect (for example, Biais et al., 1995; Harris and Hasbrouck, 1996; Ranaldo, 2004; Anand et al., 2005; Hall and Hautsch, 2006 and Pascual and Veredas, o2009). Many factors could affect the bid-ask spread around the ex-dividend day. Foucault et al., (2005) claim that while patient traders are more likely to submit limit orders, for a given level of spread, impatient traders are more likely to submit market orders. They also argue as the spread increases, in addition to liquidity suppliers, traders are more likely to submit limit orders, widening the spread even more. On cum-dividend days, the bid-ask spread could be narrow, since the high non-execution cost on cum-dividend day motivates traders to submit more aggressive orders. On the ex-dividend day, when there is not such a high non-execution cost, traders are less likely to submit aggressive orders and the spread may be wider. Furthermore, tax-arbitrage trades around the ex-dividend day are expected to be more on one side of the market, creating either buying pressure or selling pressure, leading to wider spreads. Moreover, Foucault (1999) argues that bid-ask spreads include a reservation element related to adverse selection and an execution risk element related to non-competitive behaviour. Around the ex-dividend day, price uncertainties are more likely to be high, increasing the risk of being picked off and hence, spread could also increase. Foucault (1999) shows that in markets with traders who have varying tax status and given that these traders will, therefore, have varying valuations of the same stock, trading using limit orders should increase execution risk. The bid-ask spread will therefore be expected to increase too. Wyss (2004) states that there is a negative relation between market liquidity and bid-ask spreads. To sum up, the aggregate net effect of ex-dividend day tax driven trading on bid-ask spread is theoretically unclear and remains an empirical issue.

Several previous studies report a negative relation between market liquidity and price volatility (e.g., Ahn et al., 2001; Bae et al., 2003; Ranaldo, 2004; Foucault, 1999 and Foucault et al., 2007). While Foucault et al. (2007) argue that liquidity suppliers will submit less aggressive orders as volatility increases, thereby also decreasing liquidity, Cohen et al. (1981) claim traders place a premium on certainty in the execution of their trades by submitting aggressive order as the price uncertainty increases. Frank and Jagannathan (1998) and Jakob and Ma (2003) report evidence of order imbalances around the ex-dividend day. Ainsworth et al. (2008) and Jun et al. (2008) find evidence of abnormal volume and price volatility around the ex-dividend day. We therefore expect that tax-arbitrage trades will lead to order imbalances on both the cum- and ex- dividend days, increasing price volatility. Furthermore, in the presence of high non-execution costs on the cum-dividend day, consistent with Cohen et al. (1981) we expect that traders will be willing to offer a premium to increase the execution probability of their orders by submitting aggressive orders as the volatility increases.

The theoretical arguments of Foucault et al. (2005) and Rosu (2008) suggest a high arrival rate of trade should increase waiting costs, motivating traders to submit aggressive orders and Tkatch and Kandel (2006) and Linnainmaa and Rosu (2008) confirm these results empirically. Less liquid markets are characterised by low order arrival rates. We expect that the arrival time between two orders will not affect order submission decisions around the ex-dividend day for FTSE SmallCap stocks.

We employ data on orders submissions and executions in the ex-dividend week (Monday to Friday in the week containing the ex-dividend day), and the control week (the corresponding data for Monday to Friday in the week prior) for FTSE SmallCap firms, which went ex-dividend between June 2007 and June 2008. We restrict our study to the firms that had stocks going ex-dividend on a Wednesday and where there is no bank holiday in the two weeks concerned.

The results of this chapter can be summarized as follows. First, similarly to the

FTSE 100, we find that the spread and volatility are higher in the ex-dividend week compared to the control week and on the cum-dividend day compare to and ex-dividend days within the ex-dividend week. To gain further insight, we investigate these results together with their associated order submission strategies.

Second, there is evidence of the existence of both tax-arbitrage traders and liquidity suppliers "footprints" around the ex-dividend day for FTSE SmallCap firms. Illiquidity seems not, therefore, to prevent tax-arbitrage activity altogether. There is evidence that tax-arbitrage traders buy on cum-dividend day and sell on ex-dividend day. The results show that behind the quote buy orders and the at the quote and inside the quote sell orders are less likely on the cum-dividend day and behind the quote buy orders and the inside the quote and marketable sell orders are more likely on ex-dividend day. There is also evidence that liquidity suppliers take advantage of tax-arbitrage activity around ex-dividend day. The results show that behind the quote sell orders are more likely on the cum-dividend day and behind the quote buy orders are more likely on the ex-dividend day.

Third, this research finds influences connecting order submission to spreads, volatility and returns. One pattern that can be expected is that one-sided trading of tax-arbitrageurs may drive prices away from fundamentals and in that process increases spread as well as return. They are likely to attract liquidity suppliers, who may trade aggressively either to take advantage of differences between transaction prices and fundamental prices or to profit from the larger spread. In addition, one-sided buying or selling pressure increases price volatility and return which motivates tax-arbitrageurs to submit their orders aggressively. This study finds no evidence of a relation between order arrival rates and order submission decisions around the ex-dividend day for FTSE SmallCap firms.

The reminder of the paper is organised as follows. Section 3.2 introduces different liquidity measures. Section 3.3 describes the data and Section 3.4 presents the results of different liquidity measures. Section 3.5 outlines the main methodology employed in the chapter. Section 3.6 presents results. Section 3.7 displays a robustness tests and a final section concludes.

3.2 Liquidity Measures

Several uni-dimensional and multidimensional liquidity measures are used to capture different aspects of liquidity (Wyss, 2004; Goyenko et al., 2009; and Lo and Wang, 2000).

3.2.1 One-Dimensional Liquidity Measures

One-dimensional liquidity measures can be divided into four groups: liquidity measures related to the size of the firm, liquidity measures related to the volume of trades, liquidity measures related to the time between adjacent trades and liquidity measures related to the bid-ask spread.[1] One-dimensional liquidity measures that we employ are:

Volume-related Liquidity Measures

- Trading volume (number of shares traded in a given time interval)[2];
- Turnover (money value of the trades in a given time interval) (e.g. Amihud and Mendelson, 1986);
- Relative turnover (turnover divided by the free float, where free float is calculated as the difference between the total number of shares outstanding and the total number of shares owned by the firm) (e.g. Brunner, 1996)

Time-related Liquidity Measures

- Number of transactions in a given time interval (e.g. Walsh, 1998)

[1] The liquidity measures that are related to the size of the firm are not applied anymore. These kinds of liquidity measures present no enough variation in term of the intraday context Wyss (2004).

[2] E.g. (Chordia et al., 2001; Elyasiani et al., 2000; George and Hwang, 1998; Gervais et al., 2001; Hasbrouck and Saar, 2001; Hasbrouck and Seppi, 2001; Kamara and Koski, 2001; Karagozoglu, 2000; Lee et al., 1993; Lee et al., 2001; Lin et al., 1995; Van Ness et al., 2000 and Yang and Liu, 2002)

Spread-related Liquidity Measures

- Roll's (1984) spread measure, which is defined as:

$$\sqrt{max(0, -cov(\Delta P_t \Delta P_{(t-1)}))} \tag{3.1}$$

where:

ΔP_t: is the price change over a 5-minute time-interval and ,

$\Delta P_{(t-1)}$: is the price change over the prior 5-minute interval.

3.2.2 Multi-Dimensional Liquidity Measures

Amivest's liquidity measure

Amivest's liquidity measure is defined as the ratio of turnover to absolute price change in a given time interval using non-zero returns.[3] The greater the volume, the more that price movements can be absorbed. A high value on Amivest's liquidity measure is interpreted as a highly liquid market (e.g. Baker, 1996; Elyasiani et al., 2000; Kluger and Stephan, 1997; and Ranaldo, 2000).

$$\text{Amivest measure} = \frac{V_t}{|r_t|} \tag{3.2}$$

where:

r_t :is the return over a given time interval.

V_t :is the turnover over a given time interval.

Elyasiani et al. (2000) suggest that the Amivest liquidity measure is a useful measure for daily data.

Amihud's (2002) liquidity measureo

Amihud liquidity measure is defined as the ratio of absolute price changes to trading volume during a given time interval. Amihud's liquidity measure is a price impact measure (a high price impact indicates an illiquid market). Though

[3]For zero returns, Amivest liquidity measure is set to zero.

Amihud's liquidity measure is a common measure it could be affected by extreme values.

$$\text{Amihud measure} = \frac{|r_t|}{Q_t} \tag{3.3}$$

Where:

r_t: is the return over a given time interval.

Q_t: is the volume over a given time interval.

Lo and Wang's (2000) liquidity measure

Lo and Wang (2000) estimate liquidity in the spirit of the Amihud liquidity measure but Hwang and Lu (2007) report two shortcomings of the Amihud measure. First, the Amihud measure uses the monetary trading volume, so it will have a higher value when the stock prices increase, even if liquidity remains constant. Moreover, the Amihud measure can be correlated with market capitalization (Nagel, 2005; Lo and Wang, 2000) which, in turn, is also known to affect liquidity (e.g. Chordia et al., 2000). Hwang and Lu (2007) following the proposal of Lo and Wang (2000) use the natural logarithm of the ratio between absolute return to monetary turnover to minimize the effect of outliers commonly observed during periods of low trading activity and the monetary turnover measure is an attempt to be free of market capitalization. A high value on the Lo and Wang measure indicates an illiquid market.

$$\text{Lo and Wang measure } = ln\left(\frac{|r_t|}{V_t}\right) \tag{3.4}$$

where:

r_t :is the return over a given time interval.

V_t :is the turnover over a given time interval.

Ranaldo's (2000) liquidity measure

Ranaldo's liquidity measure is defined as the ratio of the Amivest liquidity measure to the free float. A high value on the Ranaldo measure indicates a liquid market.

$$\text{Ranaldo measure} = \frac{\text{Amivest liquidity ratio}}{\text{free float}} \tag{3.5}$$

Brunner's (1996) liquidity measure

Brunner's (1996) measure is defined as the average price change per transaction over a given time interval and a high value of the Brunner measure indicates an illiquid market.[4]

$$\text{Brunner measure} = \frac{\sum_{i=1}^{N_t} r_i}{N_t} \tag{3.6}$$

where:

r_i: is the return for transaction i

N_t: is the number of trades over a given time interval

Zeroes liquidity measure

The Lesmond et al. (1999) measure of liquidity looks at the proportion of days with zero returns since illiquid stocks are more likely to have zero volume days and zero return days.

$$\text{Zeroes measure} = \frac{\text{Number of days with zero returns}}{M} \tag{3.7}$$

where:

M: is the number trading days in a given month.

Bekaert et al. (2007) use an alternative version of the zero measure and their version also looks at those days with zero return but only those days that also have positive trading volume:

[4]For zero returns, Brunner liquidity measure is set to zero.

$$\text{Zero.positive measure} = \frac{\text{positive volume days with zero returns}}{M} \qquad (3.8)$$

3.3 Data

The sample of data for this chapter is constructed based on criteria that are specified on data section in the first chapter. The resulting sample contained 43 FTSE SmallCap stocks. Table 3.1 shows the aggregate number and volume of submitted transactions and the aggregate number and volume of executed transactions over the all control and ex-dividend weeks, cum-and ex- dividend days, and day 2 and day 3 (corresponding to cum- and ex-dividend days in ex-dividend week) in control week.

Table 3.1 – Summary statistics (numbers in million)
This table reports the aggregate number of buy (sell) submitted and executed order and the aggregate volume of buy (sell) submitted and executed order for 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or in control week. These aggregate numbers are calculated for control week, ex-dividend week, corresponding to cum-dividend day in control week (Tuesday) (day2), cum-dividend day, the corresponding to ex-dividend day in control week (Wednesday) (day3) and ex-dividend day

Variable	Num. of buy	Num. of sell	Volume of buy	Volume of sell	Num. of buy	Num. of sell	Volume of buy	Volume of sell
All week			Ex.w				Cont.w	
Submission	0.201	0.206	640.908	689.478	0.210	0.210	644.967	643.137
Execution	0.033	0.031	50.415	48.711	0.034	0.032	58.564	59.896
Tuesday			Cum.day				C-Cum	
Submission	0.041	0.041	127.890	139.375	0.037	0.042	113.810	130.302
Execution	0.007	0.007	12.204	11.330	0.008	0.007	12.336	11.863
Wednesday			Ex.day				C-Ex	
Submission	0.038	0.040	132.551	144.128	0.042	0.044	127.293	131.451
Execution	0.007	0.007	8.923	10.168	0.006	0.007	11.314	12.512

The volume of submitted buy and sell orders on cum- and ex- dividend days is higher than the volume of submitted buy and sell orders on day 2 and day 3 in the control week. Further, the volume of submitted buy and sell orders on the ex-dividend day is higher than the volume of submitted buy and sell orders on the cum-dividend day. There is a general effect of the ex-dividend day on the trading activity on both the cum-dividend day and the ex-dividend day.

Similarly to Chapter 2, the "representative trader" is defined for FTSE Small-Cap stocks and Table 3.2 reports the "representative trader" for all submitted orders, executed orders and the "no activity event" for each trading day in the control and ex-dividend weeks.

Table 3.2 – Representative trader

This table reports the "Representative trader" for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The "Representative trader" is calculated for submitted and executed orders for each trading day in both control week and ex-dividend week.

Order Type	Ex- dividend week		Control week	
	Execute	Submit	Execute	Submit
Day 1				
All order	0.836	0.962	0.783	0.951
Limit buy	0.445	0.495	0.391	0.455
Limit sell	0.437	0.467	0.380	0.496
Market buy	0.006	-	0.006	-
Market sell	0.007	-	0.006	-
No activity	0.164	0.038	0.217	0.049
Day 2				
All order	0.821	0.947	0.795	0.956
Limit buy	0.418	0.450	0.413	0.479
Limit sell	0.391	0.497	0.373	0.477
Market buy	0.005	-	0.005	-
Market sell	0.007	-	0.004	-
No activity	0.179	0.053	0.205	0.044
Day 3				
All order	0.824	0.965	0.743	0.956
Limit buy	0.403	0.470	0.349	0.480
Limit sell	0.412	0.495	0.385	0.476
Market buy	0.006	-	0.006	-
Market sell	0.004	-	0.004	-
No activity	0.176	0.035	0.257	0.044
Day 4				
All order	0.869	0.969	0.811	0.966
Limit buy	0.446	0.484	0.423	0.465
Limit sell	0.414	0.485	0.375	0.501
Market buy	0.005	-	0.007	-
Market sell	0.005	-	0.006	-
No activity	0.131	0.031	0.190	0.035
Day 5				
All order	0.873	0.962	0.794	0.953
Limit buy	0.452	0.480	0.398	0.465
Limit sell	0.409	0.483	0.378	0.487
Market buy	0.006	-	0.009	-
Market sell	0.005	-	0.009	-
No activity	0.127	0.038	0.206	0.048

In general, all trading days in the control week have a higher percentage of "no-activity" events than the ex-dividend week for both order submissions and order executions.[5] For example, ex-dividend day records 18% for the no-activity event, whereas the no-activity event records 26% on day 3 in the control week. It is suggested that the ex-dividend day affects trading activity around the ex-dividend day. In addition, the cum-dividend day has a higher execution of buy orders than executions of sell orders. The ex-dividend day has a higher execution of sell orders than executions of buy orders. However, similar results are also observed for day 2 and day 3 in the control week. These results cannot be properly interpreted without investigating the limit order books and associated order submission strategies.

3.4 Liquidity Measures Results

Although stocks that are listed on the FTSE SmallCap Index are considered as illiquid stocks, a number of liquidity measures are used, to confirm that illiquidity prevails on among FTSE SmallCap firms. The results of these measures are compared between FTSE SmallCap sample and FTSE 100 sample from Chapter 2 and Table 3.3 reports summary statistics for the liquidity measures.[6]

[5] Except order submission on cum-dividend day

[6] *Vol.* is a volume liquidity measure. *Rel. Turnover* is a relative turnover liquidity measure. *Num. of .Tran.* is a number of transaction liquidity measure.

Table 3.3 – Descriptive statistics for liquidity measures

This table reports descriptive statistics for 12 liquidity measures for 43 stocks from FTSE SmallCap and 47 stocks from FTSE 100 index. These stocks achieve the following criteria: they paid a cash dividend on Wednesday during sample period (June 2007 – June 2008) and there is no bank holiday in the ex-dividend week or in control week. The samples of 11 liquidity measures calculate using daily data over one year from 1-June 2007 to 1-June -2008. The Roll measure calculate using tick data over ex-dividend week and control week.

Variable	Mean	Std	Min	Max
Vol.				
FTSE 100	14587.099	32835.056	322.309	243376.297
FTSE SmallCap	726.033	1434.841	29.418	7568.800
Turnover				
FTSE 100	4016709.642	6690664.012	1942.593	37389269.600
FTSE SmallCap	180362.554	346057.300	4256.228	1891757.625
Rel. Turnover				
FTSE 100	48819.782	84060.047	41.510	457356.563
FTSE SmallCap	2480.332	5289.312	0.000	26895.268
Num. of Tran.				
FTSE 100	3664.946	2386.765	181.861	12257.044
FTSE SmallCap	235.194	491.024	6.600	2759.281
Roll				
FTSE 100	0.000	0.000	0.000	0.014
FTSE SmallCap	0.001	0.001	0.000	0.029
Amivest				
FTSE 100	16216.623	21782.681	440.067	127622.188
FTSE SmallCap	921.510	1435.131	64.928	7344.690
Amihud				
FTSE 100	0.001	0.001	0.000	0.008
FTSE SmallCap	0.051	0.081	0.000	0.354
Lo and Wang				
FTSE 100	-13.286	2.488	-16.919	-6.786
FTSE SmallCap	-10.313	1.505	-13.784	-6.704
Ranaldo				
FTSE 100	75613.560	121043.833	108.072	610933.250
FTSE SmallCap	3327.080	6866.670	0.000	33413.242
Brunner				
FTSE 100	0.603	4.740	0.000	37.325
FTSE SmallCap	0.062	0.067	0.001	0.311
Zeroes				
FTSE 100	0.045	0.024	0.011	0.138
FTSE SmallCap	0.084	0.041	0.028	0.243
Zeroes positive				
FTSE 100	0.046	0.024	0.011	0.135
FTSE SmallCap	0.081	0.038	0.028	0.222

The mean values of the Roll measure, Amihud measure, Lo and Wang measure, Zeroes measure and Zero.Positive measure are all lower for FTSE 100 than FTSE

SmallCap. The volume measure, turnover measure, relative turnover measure, number of transaction measure, Amivest measure, Ranaldo measure and Brunner measure are all higher for FTSE 100 than FTSE SmallCap. For all measures, the average FTSE 100 stock is more liquid than the average FTSE SmallCap stock, although, the most liquid FTSE SmallCap stock tends to be more liquid than the least liquid FTSE 100 stock.

3.5 Methodology

Rather than repeat here the methodology for this chapter, we note that the same methodology is applied here for illiquid stock as employed for the liquid stocks on the FTSE 100 firms. Table 3.4 reports the odds ratios for all logit models that are listed in the preliminary regression section in Chapter 2.

Table 3.4 – Estimation of logit regression

This table reports the odds ratio of estimate Eq. (2.3) for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variables are indicators variables. (BS) is an indicator variable refers to "long-short" trading strategy. (SB) is an indicator variable refers to "short-long" trading strategy. For each type of trading strategy, we generate three different indicator variables. The low degree indicators BS(L) and SB(L) are defined as following : if buy trade size on Cum.day – sell trade size on Cum.day > 0 and buy trade size on Ex.day – sell trade size on Ex.day < 0 then BS(L) equal one , otherwise zero; if buy trade size on Cum.day – sell trade size on Cum.day < 0 and buy trade size on Ex.day – sell trade size on Ex.day > 0 then SB(L) equal one , otherwise zero. The medium degree indicators BS(M) and SB(M) are defined as: if (buy trade size on Cum.day -sell trade size on Cum.day)/(buy trade size on Cum.day +sell trade size on Cum.day)>0.02 and (buy trade size on Ex.day -sell trade size on Ex.day)/(buy trade size on Ex.day +sell trade size on Ex.day)<-0.02 then BS(M) equal one, otherwise zero; (buy trade size on Cum.day -sell trade size on Cum.day)/(buy trade size on Cum.day +sell trade size on Cum.day)<-0.02 and (buy trade size on Ex.day -sell trade size on Ex.day)/(buy trade size on Ex.day +sell trade size on Ex.day)>0.02 then SB(M) equal one, otherwise zero. Finally, the high degree indicators BS(H) and SB(H) are defined as : if (buy trade size on Cum.day-sell trade size on Cum.day)/(buy trade size on Cum.day+sell trade size on Cum.day)>0.05 and (buy trade size on Ex.day -sell trade size on Ex.day)/(buy trade size on Ex.day +sell trade size on Ex.day)<-0.05 then BS(H) equal one, otherwise zero; (buy trade size on Cum.day -sell trade size on Cum.day)/(buy trade size on Cum.day +sell trade size on Cum.day)<-0.05and (buy trade size on Ex.day -sell trade size on Ex.day)/(buy trade size on Ex.day +sell trade size on Ex.day)>0.05 then SB(H) equal one, otherwise zero. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	BS(L)	BS(M)	BS(H)
Buy-Sell			
Dividend Yield	0.863	0.863	0.897
	(-1.01)	(-1.01)	(-0.70)
	SB(L)	SB(M)	SB(H)
Sell-Buy			
Dividend Yield	0.941	0.912	0.926
	(-0.38)	(-0.52)	(-0.41)

All results in Table 3.4 are insignificant. The results of the estimations do not supply enough evidence to suggest that a specific tax-arbitrage trading strategy is being executed among FTSE SmallCap stocks.

3.6 Results

Spread and Volatility

The results for the spread and volatility models (presented in the methodology sections in Chapter 2) are as follows. Table 3.5 reports results for models (2.8) and

(2.14) using the data from FTSE SmallCap for both the ex-dividend week and the control weeks, whereas Table 3.6 reports models (2.9) and (2.15) employing data also from the FTSE SmallCap but only for days 2 and 3 in the control week and ex-dividend week . Table 3.7 reports results of models (2.10) and (2.16) using again the data from FTSE SmallCap but only for the cum-dividend and the ex-dividend days.

Table 3.5 – Estimation of OLS regression
This table shows the results of OLS estimates regression of Eq (2.8) and Eq (2.14) for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The regression is robust for heteroskedasticity and autocorrelation. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	Spread.Ex	Variables	Volatility.Ex
Spread	0.262***	Volatility	0.356***
	(3.45)		(4.38)
Cum.day	0.000	Cum.day	0.000
	(0.72)		(0.67)
Ex.day	-0.000	Ex.day	-0.000
	(-1.45)		(-0.19)
Spread#C-Cum	-0.096	Volatility#C-Cum	-0.132**
	(-1.17)		(-1.97)
Spread#C-Ex	-0.011	Volatility#C-Ex	-0.085
	(-0.11)		(-1.28)
constant	0.001***	constant	0.001***
	(5.30)		(5.81)

Table 3.6 – Estimation of OLS regression
This table shows the results of OLS estimates regression of Eq (2.9) and Eq (2.15) for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week.The regression is robust for heteroskedasticity and autocorrelation. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	Spread. Ex	Variables	Volatility. Ex
Spread	0.251***	Volatility	0.271***
	(3.49)		(4.28)
Cum.day	0.000	Cum.day	0.000
	(1.57)		(0.85)
Spread#C-Cum	-0.085	Volatility#C-Cum	-0.047
	(-0.90)		(-0.64)
constant	0.001***	constant	0.001***
	(5.08)		(11.45)

Table 3.7 – Estimation of OLS regression
This table shows the results of OLS estimates regression of Eq (2.10) and Eq (2.16) for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The regression is robust for heteroskedasticity and autocorrelation. The significant levels are defined as follows: * p < 0.10, ** p < 0.05, *** p < 0.01.

	Spread. Cum. Day		Volatility. Cum. Day
Spread.Ex.day	0.312***	Volatility.Ex.day	0.366***
	(4.51)		(5.64)
constant	0.001***	constant	0.001***
	(9.60)		(10.67)

First, the constant term is significantly positive for all models. This indicates that, in general, the spread and the volatility are higher in the ex-dividend week than in the control week and are higher on the cum-dividend day than on the ex-dividend day within the ex-dividend week. Second, the coefficients on the corresponding spread observations and the volatility observations in the two weeks are positive in all tables, which indicate that there are intra-day patterns in both the spread and the volatility variables. The general picture is therefore, that there are spread and volatility effects in the ex-dividend week.

Two versions of model (2.11) are estimated. First, a model in differences and second a model in levels is estimated. The difference in spread between the ex-dividend week and the corresponding 5-minute time interval in the control week is regressed, on a set of determining variables which are also differences between the two weeks. For the levels estimation, the level of the spread in the ex-dividend week is regressed on the levels of a set of determining variables. The determining variables are volatility, volume, return, buy-size, sell-size as well as indicators for the cum-dividend day and the ex-dividend day and the results are reported in Table 3.8.

Table 3.8 – Estimation of OLS regression over spread determinants
This table shows the results of OLS estimates regression of Eq (2.11) for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The second columns estimate the determinants of the difference in spread between control week and ex-dividend week for corresponding 5-minute intervals. The third columns estimate the determinants of the spread over ex-dividend week. The regression is robust for heteroskedasticity and and autocorrelation. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Control week + Ex-dividend week	Ex-dividend week
Volatility		
All Week	0.729***	0.725***
	(16.49)	(16.50)
Cum-dividend day	0.010	0.015
	(0.13)	(0.21)
Ex-dividend day	-0.004	-0.036
	(-0.05)	(-0.81)
Volume		
All Week	-0.000**	-0.000
	(-2.25)	(-1.34)
Cum-dividend day	0.000	-0.000
	(0.69)	(-0.00)
Ex-dividend day	0.000	-0.000
	(1.21)	(-0.39)
Return		
All Week	0.048	0.042
	(0.76)	(0.86)
Cum-dividend day	0.039	0.066
	(0.38)	(0.76)
Ex-dividend day	-0.204	0.100
	(-1.42)	(1.10)
Buy Size		
All Week	0.000	-0.000**
	(0.42)	(-2.23)
Cum-dividend day	-0.000	-0.000
	(-0.77)	(-0.19)
Ex-dividend day	-0.000*	-0.000
	(-1.72)	(-0.48)
Sell Size		
All Week	-0.000	-0.000*
	(-2.42)	(-1.80)
Cum-dividend day	0.000	-0.000
	(1.05)	(-0.48)
Ex-dividend day	-0.000	-0.000
	(-0.94)	(-0.18)
Dummies		
Cum-dividend day	0.000	0.000
	(0.21)	(0.12)
Ex-dividend day	0.000*	0.000
	(1.80)	(0.48)
constant	-0.000	-0.000**
	(-1.11)	(-2.50)

In Table 3.8, column two shows the determinants of the difference in spread and column three shows the determinants of spread. We find that the spread overall is greater in the ex-dividend week than in the control week but low on ex-dividend day. Furthermore, we find that the difference in spread is explained, in general, by the difference in volatility by a positive association but there are no specific cum-dividend day and ex-dividend day effects. There is also a negative association with the difference in volume. For level regression, when either volatility is higher or when trade sizes (buy or sell size) are lower, spread levels are higher. This effect is, however, not linked to cum- or ex-dividend days, specifically. The general picture is, therefore, that there is little effect on spread in the ex-dividend week.

Table 3.9shows the results of model (2.12) and (2.17) , using the data for both the ex-dividend week and the control weeks.

Table 3.9 – Estimation of OLS regression

This table shows the results of OLS estimates regression of Eq (2.12) and Eq (2.17) for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The regression is robust for heteroskedasticity and autocorrelation. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dummies	Spread	Volatility
Cum.day	0.040	0.161
Ex.day	-0.041	0.002
Cont.w	0.029	-0.083
C-Cum	-0.056	-0.044
C-Ex	-0.070	-0.173
constant	0.874***	1.971***

The results of these regression confirm the previous results that volatility is higher on ex-dividend week in compere to control week. Further, the constants in two regressions are also positive confirming the potential intra-day patterns in both the spread and the volatility variables.

Table 3.10shows the results of models (2.13) using the data for both the ex-dividend week and the control weeks.

Table 3.10 – Estimation of OLS regression over spread determinants
This table shows the results of OLS estimates regression of Eq (2.13) for sample of 47 stocks from FTSE 100 index. These stocks achieve the following criteria: They are listed on FTSE100 index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The regression is robust for heteroskedasticity and and autocorrelation. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	Ex.w	Cum.day	Ex.day	Cont.w	C-Cum	C-Ex
Volatility	0.640***	0.074	0.135	-0.117	-0.000	0.000
Volume	-4.124	18.755**	2.401	-5.799	-96.894	-462.513
Return	0.052	0.117	-0.115	-0.118	0.000	-0.000***
Buy Size	0.000	-0.000	-0.000	-0.000	-0.376	-1.454***
Sell Size	-0.000	-0.000	0.000	-0.000	-0.073	1.157**
Dummies	-0.195**	0.030	-0.187	0.152*	0.072	0.055

The significant positive effect of volatility has been confirmed in this regression. However, volume show a larg significant positive effect on spread on cum-dividend day which may suggest that the volume derive the spread on cum-dividend day.

Order Submission

The results of the order submission models are however more revealing of trading strategies and patterns. All five models described in the methodology section of Chapter 2 are estimated for both the buy side and the sell side, separately. Only the results of model M5 are discussed and presented here as the other models are special cases of this model. Table 3.11 and Table 3.12 report the results of regression M5 for the buy side and sell side respectively. [7]

[7] The results of the remainder of models are reported in Appendix C

Table 3.11 – Relative risk ratios–M5–buy side

This table reports the relative risk ratios of estimates regression Eq.(2.18) for-M5-buy side on a stock-by-stock basis. The relative risk ratios are reported for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable is aggressiveness which is classified in to 5 levels: (1) B-T-Q buy order (2) A-T-Q buy order (3) I-T-Q buy order (4) M-A buy order (5) sell order. Sell order set as reference category. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Dummy variables				
Baseline	0.774***	0.048***	0.085***	0.125***
DW	1.052***	1.050	1.007	1.069***
DC	0.825***	1.284***	0.805***	1.092**
DE	0.968	1.010	1.301***	0.604***
Baseline * DW	0.814	0.050	0.086	0.134
Baseline * DW * DC	0.672	0.065	0.069	0.146
Baseline * DW * DE	0.788	0.051	0.111	0.081
Spread variables				
Spread	1.021***	0.994	0.954***	0.913***
Spread # DW	0.989**	0.973	1.048***	1.042***
Spread # DC	1.001	1.062*	0.978	0.917***
Spread # DE	1.013	1.121***	1.038**	0.888***
Spread * Spread # DW	1.010	0.967	1.000	0.951
Spread * Spread # DW * Spread # DC	1.011	1.027	0.978	0.872
Spread * Spread # DW * Spread # DE	1.023	1.084	1.038	0.845
Volatility variables				
Volatility	0.972***	0.979**	1.092***	0.966***
Volatility # DW	1.012***	1.014	0.976***	1.035***
Volatility # DC	0.994	1.020	1.055***	1.044***
Volatility # DE	0.986**	0.993	1.014	1.041***
Volatility * Volatility # DW	0.984	0.993	1.066	1.000
Volatility * Volatility # DW * Volatility # DC	0.978	1.013	1.124	1.044
Volatility * Volatility # DW * Volatility # DE	0.970	0.986	1.081	1.041
Return variables				
Return	0.990***	1.012**	1.056***	1.033***
Return # DW	0.999	0.996	1.016**	0.990**
Return # DC	1.020***	0.980	0.904***	1.042***
Return # DE	1.006	1.000	0.989	0.988
Return * Return # DW	0.989	1.008	1.073	1.023
Return * Return # DW * Return # DC	1.009	0.988	0.970	1.066
Return * Return # DW * Return # DE	0.995	1.008	1.061	1.010
Duration variables				
Duration	1.000***	1.000***	1.000***	1.000***
Duration # DW	1.000	1.000	1.000	1.000**
Duration # DC	1.000***	1.000	1.000	1.000
Duration # DE	1.000**	1.000	1.000	1.000
Duration * Duration # DW	1.000	1.000	1.000	1.000
Duration * Duration # DW * Duration # DC	1.000	1.000	1.000	1.000
Duration * Duration # DW * Duration # DE	1.000	1.000	1.000	1.000

Table 3.12 – Relative risk ratios–M5–sell side

This table reports the relative risk ratios of estimates regression Eq.(2.18) for-M5-sell side on a stock-by-stock basis. The relative risk ratios are reported for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable is aggressiveness which is classified in to 5 levels: (1) B-T-Q sell order (2) A-T-Q sell order (3) I-T-Q sell order (4) M-A sell order (5) buy order. Buy order set as reference category. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Dummy variables				
Baseline	0.842***	0.073***	0.142***	0.145***
DW	0.979*	0.768***	0.676***	0.911***
DC	1.066***	1.285***	1.154*	1.428***
DE	1.007	1.083	1.626***	1.319***
Baseline * DW	0.824	0.056	0.096	0.132
Baseline * DW * DC	0.879	0.072	0.111	0.189
Baseline * DW * DE	0.830	0.061	0.156	0.174
Spread variables				
Spread	0.987***	1.008	1.066***	0.991
Spread # DW	1.029***	0.967	0.916***	0.974**
Spread # DC	0.993	1.055	1.046***	1.039**
Spread # DE	0.973***	1.071*	1.031*	1.037**
Spread * Spread # DW	1.016	0.975	0.976	0.965
Spread * Spread # DW * Spread # DC	1.009	1.028	1.021	1.003
Spread * Spread # DW * Spread # DE	0.988	1.044	1.007	1.001
Volatility variables				
Volatility	1.013***	0.979***	1.054***	0.976***
Volatility # DW	0.981***	1.021	1.027***	1.003
Volatility # DC	1.002	0.919***	0.993	0.927***
Volatility # DE	0.992	0.940**	1.029**	0.996
Volatility * Volatility # DW	0.994	1.000	1.082	0.979
Volatility * Volatility # DW * Volatility # DC	0.996	0.919	1.075	0.907
Volatility * Volatility # DW * Volatility # DE	0.986	0.940	1.114	0.975
Return variables				
Return	1.001	1.004	1.020***	0.929***
Return # DW	1.008***	1.008	0.970***	1.033***
Return # DC	0.995	0.947***	0.955***	1.031***
Return # DE	1.011**	0.978	1.004	0.938***
Return * Return # DW	1.009	1.012	0.989	0.960
Return * Return # DW * Return # DC	1.004	0.958	0.945	0.989
Return * Return # DW * Return # DE	1.020	0.990	0.993	0.900
Duration variables				
Duration	1.000***	1.000***	1.000	1.000*
Duration # DW	1.000	1.000	1.000**	1.000
Duration # DC	1.000*	1.000	1.000*	1.000**
Duration # DE	1.000	1.000	1.000*	1.000
Duration * Duration # DW	1.000	1.000	1.000	1.000
Duration * Duration # DW * Duration # DC	1.000	1.000	1.000	1.000
Duration * Duration # DW * Duration # DE	1.000	1.000	1.000	1.000

A number of results and patterns seem to emerge. First, the likelihood that orders will be submitted is significantly different for the cum dividend day, ex dividend day and for the rest of the ex-dividend week when compared to the same likelihoods for the control week. On the cum-dividend day there is an increase in the likelihood of the submission of the least aggressive sell order and most aggressive sell order and a decrease in the likelihood of the submission of any other kind of sell order, compared to the control week. On the ex-dividend day there is a reduction in the likelihood of the submission of the first two least aggressive sell orders and an increase in the likelihood of the submission of the last two most aggressive sell orders, compared to the control week. On the cum-dividend day there is an increase in the likelihood of the submission of the second least aggressive buy order and most aggressive buy order, and a decrease likelihood of the submission of any other kind of buy order, compared to the control week. On the ex-dividend day there is a reduction in the likelihood of the submission of the most aggressive buy order and an increase in the likelihood of the submission of any other kind of buy order, compared to the control week.

At one level we observe what appears to be symmetry between the buy and sell orders. For instance, the change in the likelihood runs in opposite directions on the cum-dividend day and the ex-dividend day, compared to the control week, but this applies equally to the buy and sell orders and to order of any level of aggressiveness. The likelihood of the least aggressive buy orders and the second and third most aggressive sell orders is reduced on the cum-dividend day compared to the control week and the likelihood of the least aggressive buy order and the two most aggressive sell orders is increased on the ex-dividend day, consistent with more aggressive buying behaviour on the cum-dividend day and more aggressive selling behaviour on the ex-dividend day.

This can be inferred from Table 3.11 and Table 3.12, by comparing the results for the baseline relative risk ratio (RRR) with the interaction terms with the baseline relative risk ratio. See the values reported for "Baseline" relative risk ratio (RRR) with the "Baseline * DW * DC" and "Baseline * DW * DE" relative risk ratios. This comparison takes into account the effect on the baseline from inclusion in the ex-dividend week (by the *indicator* variable DW) and the inclusion on the cum-dividend day (by the *indicator* variable DC) and the ex-dividend day (by the *indicator* variable DE), respectively. This can interpreted as evidence of the presence of tax-arbitrage trading around the ex-dividend day for this sample of FTSE SmallCap stocks.

We argue that this evidence of the increase in the likelihood of the least aggressive sell orders on the cum-dividend day and the increase in the likelihood of the least aggressive buy orders on the ex-dividend day is consistent with liquidity suppliers seeking to benefit from the activity of the relatively more aggressive behaviour of the tax-arbitrageurs.

Second, turning to spread related results, we find patterns in the way order submission is associated with spread changes in the ex-dividend week relative to the control week. For example, all types of sell orders, except the third least aggressive sell order, respond more positively to spread increases on the cum-dividend day than the control week. All types of sell orders, except the second least aggressive sell order, respond more positively to spread increases on the cum-dividend day than on the ex-dividend day. All types of buy orders, except the most aggressive buy order respond more positively to spread increases on the ex-dividend day than on the cum-dividend day and in the control week.

This can be inferred from Table 3.11 and Table 3.12, by comparing the "Spread" RRRs with the interaction terms for spread. See the results for "Spread * Spread #DW * Spread #DC" and "Spread * Spread #DW * Spread #DE" relative risk ratios. Aggressive sell orders submitted following an increase in the spread are more likely on the cum-dividend day and we are more likely to see more aggressive buy orders, but not for the most aggressive buy order, submitted following an increase in the spread on the ex-dividend day. This appears consistent with liquidity provision by sellers on the cum-dividend day and buyers on the ex-dividend day. If there is buying pressure on the cum-dividend day and selling pressure on the ex-dividend day from arbitrageurs, temporary increases in the spread that is subsequently filled by more aggressive orders may be observed on the other side on both the cum-dividend day and the ex-dividend day. This effect is observed on the cum-dividend day and the ex-dividend day.

Third, turning to volatility issues, there are patterns in the way that order submission is associated with volatility changes in the ex-dividend week as compared to the control week. All types of buy orders respond more positively to volatility increases on the cum-dividend day than on the ex-dividend day and in the control week. All types of sell orders, except the inside-the-quote (ITQ) sell orders, respond more negatively to volatility increases on cum- and ex- dividend days than in the control week. All types of sell orders, except the least aggressive sell orders, respond more positively to volatility increases on the ex-dividend day than on cum-dividend day. On the cum-dividend (ex-dividend) day, arbitrageurs are expected to place more aggressive buy (sell) orders (which are more likely to move prices). It is, therefore, expected that there will be a positive association between the likelihood of the submission of buy orders and volatility on the cum-dividend day. A positive association between the likelihood of the submission of sell orders and volatility is expected on ex-dividend day. This assertion is found to be supported by the data and can be inferred from Table 3.11 and Table 3.12, by comparing the "Volatility" RRRs with the RRRs for "Volatility * Volatility # DW * Volatility # DC" and "Volatility * Volatility # DW * Volatility # DE".

Fourth, we report results associated with returns and find there are patterns in the way that order submission is associated with return changes in the ex-dividend week relative to the control week. The least and the most aggressive buy orders respond more positively to return increases on the cum-dividend day than on the ex-dividend day and compared to the control week. The least aggressive sell orders respond more positively to return increases on the ex-dividend day than the control week. All sell orders, except the most aggressive sell orders respond more positively to return increases on the ex-dividend day than the cum-dividend day. Consistent with the literature, in the control week, there is a positive association between on the one hand the likelihood of the submission the most aggressive buy order and of the likelihood of the submission of the least aggressive sell order and on the other hand return. This effect is expected to be amplified on the cum-dividend day and the opposite effect is expected on the ex-dividend day. This is because arbitrageurs are expected to place more aggressive buy orders on the cum-dividend day and more aggressive sell orders on the ex-dividend day. We find that this assertion is supported in the data, since the positive association between the submission of the most aggressive buy orders and of return is amplified on the cum-dividend day and there is a positive association between the submission of the three least aggressive sell orders and of return on the ex-dividend day. Again these results can be inferred from Table 3.11 and Table 3.12, by comparing the RRRs with the RRRs for "Return * Return # DW * Return # DC" and "Return * Return # DW * Return # DE". This is an evidence of the presence of tax-arbitrage trading.

We are more likely to see least aggressive sell orders submitted following an increase in returns on the cum-dividend day and more likely to see the three aggressive buy orders being submitted following an increase in return on the ex-dividend day. This is consistent with liquidity provision by sellers on the cum-dividend day and by buyers on the ex-dividend day. If arbitrageurs submit more buy orders on the cum-dividend day and more sell orders on the ex-dividend day, they may temporarily increase the return that is subsequently filled by more aggressive orders on the other side on both the cum- and the ex- dividend days.

Finally, we found no evidence of any relations between order arrival rates and order submission decisions around the ex-dividend day for FTSE SmallCap traders.

Overall, the results here point to traces of the foot-prints left by tax arbitrage and liquidity supply trading around the ex-dividend event and there is evidence of effects that link order submission to spread, volatility and return. One explanation is that one-sided trading by tax-arbitrageurs may drive prices away from fundamentals and that process increase spread and returns, which attracts liquidity suppliers, who may then trade aggressively either to take advantage of the difference between transaction prices and fundamental prices or to profit from the larger spread. In addition, one-sided buying or selling pressure increases price volatility and return which motivates tax-arbitrageurs to submit more aggressive orders. We find no evidence of a relation between order arrival rates and order submission decisions around the ex-dividend day for FTSE SmallCap traders.

3.7 Robustness Test

This section provides additional tests to examine the robustness of the results presented above. A full description of how we performed these robustness tests is described in section 2.7. Table 3.13 shows the results of models (2.19), (2.20) and (2.21). The first row show the results of model (2.19), the second row show the results of model (2.21) and the rest of the table show the results of model (2.20).

Table 3.13 – Estimation of OLS regression over spread and volatility
This table shows the results of OLS estimates regression of Eq (2.19), (2.20) and (2.21) for sample of 77 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend during the sample period. The regression is robust for heteroskedasticity and autocorrelation. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Spread	Cum.day	Ex.day	After.Ex.day
Spread	-0.279	-0.377	3.082***
Volatility	-0.289	0.699	2.625***
Spread Determinants			
Volatility	-0.086	-0.034	0.041
Volume	-0.062	-0.029	0.202
Return	-0.015	0.016	0.013
Buy Size	-0.438	0.726*	-0.170
Sell Size	0.234	-0.583	-0.024
Dummies	-0.019	-0.533	3.457***

The results show few significant effects. Firstly, the constant term is significant positive in spread and volatility dummies regressions. This indicates that, in general, the spread and the volatility are significant positive in the control period which is the ten days after ex-dividend day. Furthermore, there is a positive significant, at the 10% significance level, association between spread and buy size on cum-dividend day.

Table 3.14 presents the predicted probabilities of submitting orders with varying levels of aggressiveness, on the cum-dividend day, ex-dividend day and 10 days after ex-dividend day, for both the buy-side as well as the sell side. Table 3.15 reports the coefficient of ordered probit regression for the buy and sell sides separately.

Table 3.14 – The predicted probabilities of different level of aggressiveness of buy orders and sell orders This table reports the predicted probabilities of each level of aggressiveness over buy and sell side separately. The predicted probabilities are reported for sample of 77 ex-dividend events from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend during the sample period.

		Buy Side			Sell Side	
Aggressiveness	After.Ex	Cum.day	Ex.day	After.Ex	Cum.day	Ex.day
B-T-Q	0.6480	0.9453	0.9685	0.7290	0.6796	0.7563
A-T-Q	0.0023	0.0007	0.0004	0.0017	0.0018	0.0016
I-T-Q	0.0023	0.0007	0.0004	0.0026	0.0028	0.0024
M-A	0.3474	0.0533	0.0306	0.2667	0.3158	0.2397

Table 3.15 – Ordered probit regression

This table reports the ordered probit regression coefficients over buy and sell side separately. The coefficients are reported for sample of 77 ex-dividend events from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend during the sample period. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Variables	Buy Side	Variables	Sell Side
Spread-After-Ex.Day	-0.058***	Spread-After-Ex.Day	-0.186***
Spread-Cum.Day	0.314***	Spread-Cum.Day	-0.116***
Spread-Ex.Day	-0.197***	Spread-Ex.Day	0.118***
Return-After-Ex.Day	0.000	Return-After-Ex.Day	0.005***
Return-Cum.Day	-0.022***	Return-Cum.Day	-0.006***
Return-Ex.Day	0.012***	Return-Ex.Day	0.050***
Volatility-After-Ex.Day	0.622***	Volatility-After-Ex.Day	3.138***
Volatility-Cum.Day	14.959***	Volatility-Cum.Day	3.08***
Volatility-Ex.Day	-14.185***	Volatility-Ex.Day	19.386***
Duration-After-Ex.Day	0.000*	Duration-After-Ex.Day	0.000***
Duration-Cum.Day	0.001***	Duration-Cum.Day	0.000
Duration-Ex.Day	0.001***	Duration-Ex.Day	0.000
Cum-dividend day	-1.221***	Cum-dividend day	0.143***
Ex-dividend day	-1.479***	Ex-dividend day	-0.085

Figures 3.1 and 3.3 present the variation in the predicted probabilities for each level of aggressiveness against the spread variable, holding other variables constant over the ex-dividend day, for sell and buy orders respectively. Similarly, Figures 3.2 and 3.4 apply for cum-dividend day. Figures 3.5 and 3.7 present the variation in the predicted probabilities for each level of aggressiveness against the return variable, holding other variables constant over the ex-dividend day, for sell and buy orders respectively. Similarly, Figures 3.6 and 3.8 apply for cum-dividend day. Figures 3.9 and 3.11 present the variation in the predicted probabilities for each level of aggressiveness against the volatility variable, holding other variables constant over the ex-dividend day, for sell and buy orders respectively. Similarly, Figures 3.10 and 3.12 apply for cum-dividend day. Figures 3.13 and 3.15 present the variation in the predicted probabilities for each level of aggressiveness against the duration variable, holding other variables constant over the ex-dividend day, for sell and buy orders. Similarly, Figures 3.14 and 3.16 apply for cum-dividend day.

Figure 3.1 – Predicted Probabilities - Spread - Sell order - Ex.Day

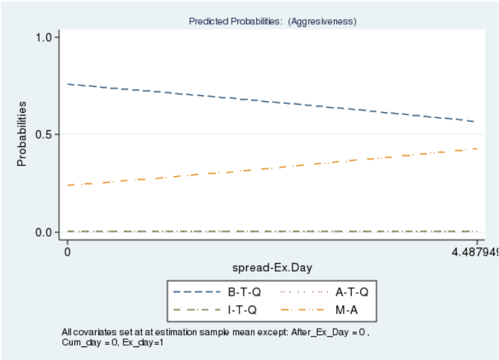


Figure 3.2 – Predicted Probabilities - Spread - Sell order - Cum.Day

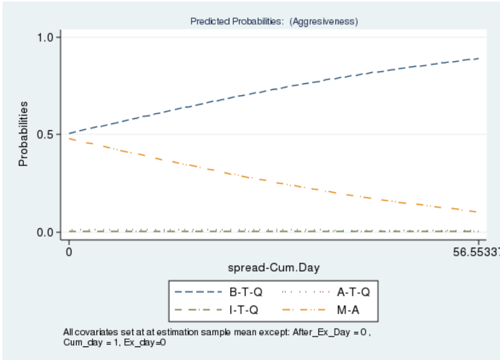


Figure 3.3 – Predicted Probabilities - Spread - Buy order - Ex.Day

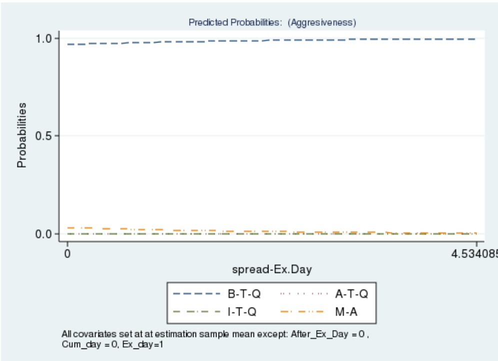


Figure 3.4 – Predicted Probabilities - Spread - Buy order - Cum.Day

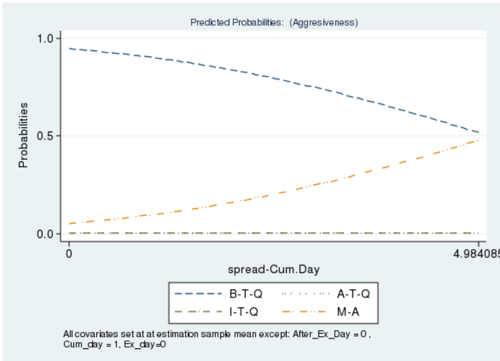


Figure 3.5 – Predicted Probabilities - Return - Sell order - Ex.Day

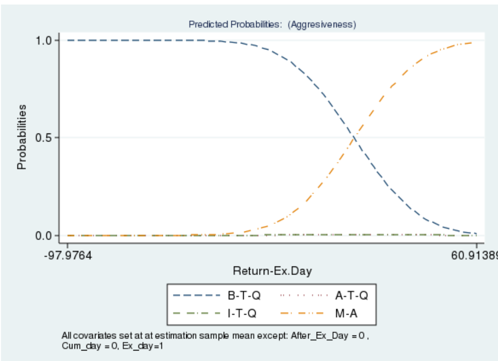


Figure 3.6 – Predicted Probabilities - Return - Sell order - Cum.Day

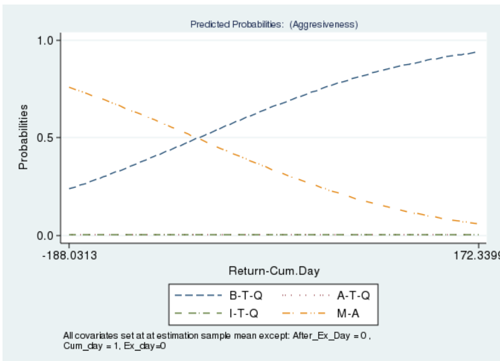


Figure 3.7 – Predicted Probabilities - Return - Buy order - Ex.Day

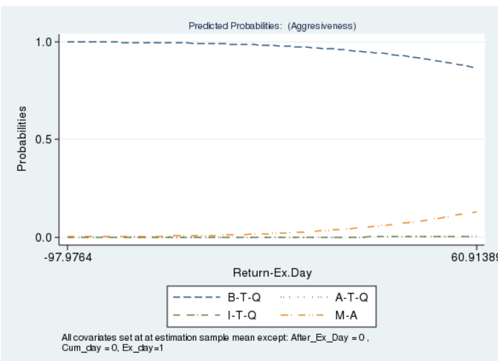


Figure 3.8 – Predicted Probabilities - Return - Buy order - Cum.Day

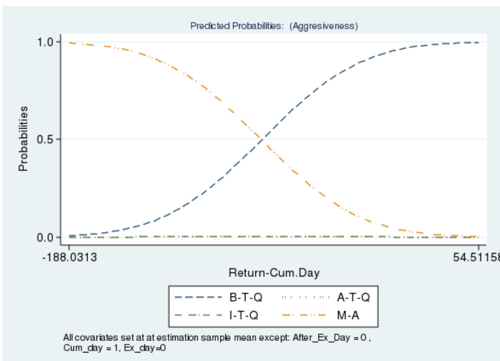


Figure 3.9 – Predicted Probabilities - Volatility - Sell order - Ex.Day

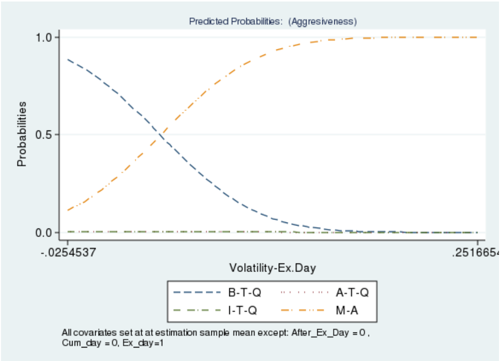


Figure 3.10 – Predicted Probabilities - Volatility - Sell order - Cum.Day

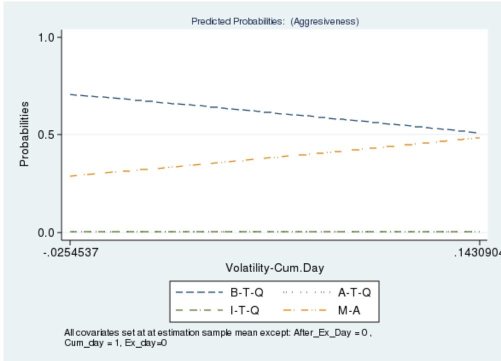


Figure 3.11 – Predicted Probabilities - Volatility - Buy order - Ex.Day

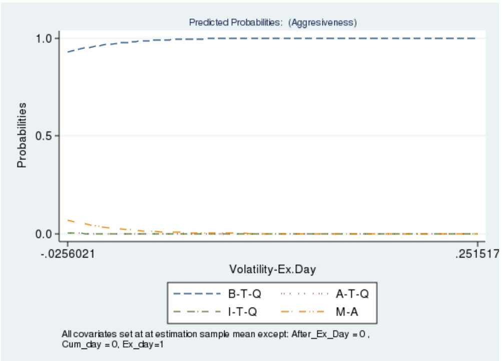


Figure 3.12 – Predicted Probabilities - Volatility - Buy order - Cum.Day

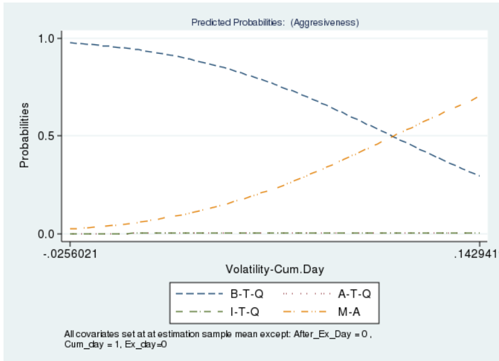


Figure 3.13 – Predicted Probabilities - Duration - Sell order - Ex.Day

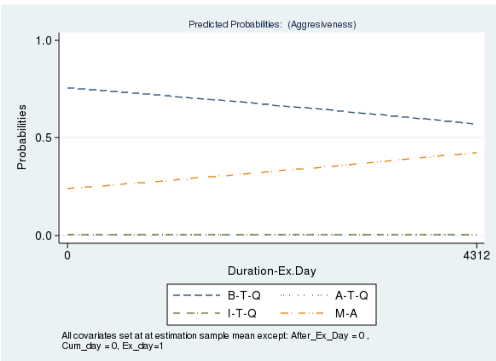


Figure 3.14 – Predicted Probabilities - Duration - Sell order - Cum.Day

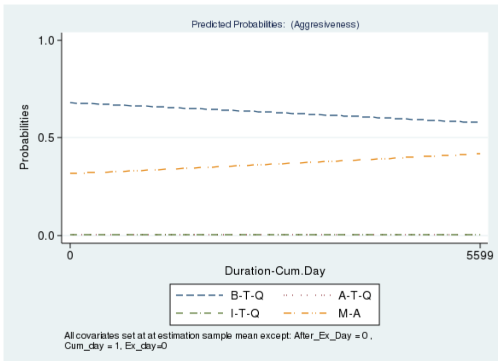


Figure 3.15 – Predicted Probabilities - Duration - Buy order - Ex.Day

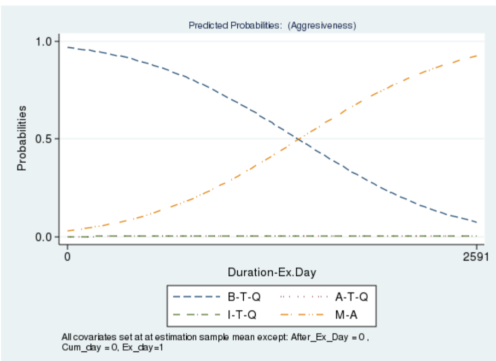
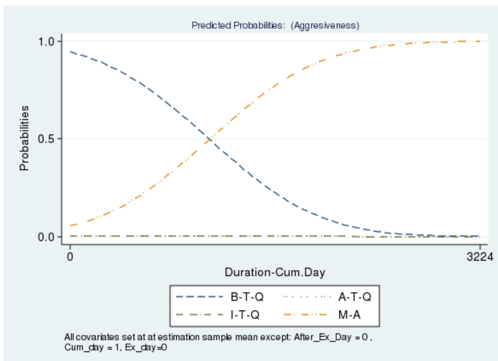


Figure 3.16 – Predicted Probabilities - Duration - Buy order - Cum.Day



After we examine the new sample of data, analyse buy side and sell side separately and calculate the actual spread, the results do not change in most cases. Starting with predicted probabilities of different aggressive types of sell and buy orders, the negative signs in Table 3.15 over buy side on both cum- and ex- dividend days suggest that the aggressiveness level of buy order decreases on both cum- and ex-dividend days. The predicted probabilities on cum-dividend day for both buy and sell sides in Table 3.15 show that the aggressiveness level of buy and sell orders is higher on cum-dividend day that on ex-dividend day. The predicted probabilities of the least aggressive buy order (behind the quote) show a high value on cum-dividend day (0.9453). The predicted probabilities of the least aggressive sell order (behind the quote) show a high value on ex-dividend day (0.7563). In general, most of buy (sell) order are submitted passively on cum-dividend (ex-dividend) day. Second, the positive spread coefficient over buy side on cum-dividend day in Table 3.15 suggests that the aggressiveness level of buy order respond positively to spread increases on cum-dividend day and the positive spread coefficient over sell side on ex-dividend day suggests that the aggressiveness level of sell order respond positively to spread increases on ex-dividend day. These results can be inferred from Table 3.15 and Figures 3.1 and 3.4.

In the general case, for FTSE SmallCap stocks, most of buy order and sell order are submitted passively on cum-dividend day and ex-dividend day respectively. It is, however, more likely that we see more aggressive buy orders submitted following an increase in the spread on the cum-dividend day and more aggressive sell orders submitted following an increase in the spread on the ex-dividend day. This can be consistent with that, for illiquid stocks, tax-arbitrageurs place a premium on certainty in the execution of their trades by submitting aggressive order as the spread increases.

Third, turning to volatility issues, there are patterns in the way that order submission is associated with volatility changes on cum- and ex- dividend days relative to the control period. The positive volatility coefficients for sell side on ex-dividend day and for buy side on cum-dividend day in Table 3.15 suggest that the aggressiveness level of sell (buy) orders respond positively to volatility increases on ex-dividend (cum-dividend) day. Figures 3.9 and 3.10 show that the positive response of the aggressiveness level of sell orders to the volatility increases is higher on ex-dividend day than on cum-dividend day. This is evidence that trading activity is associated with and perhaps even drives price volatility on the cum- and ex-dividend days.

Fourth, we report results associated with returns and find that there are patterns in the way that order submission is associated with return changes on cum- and ex- dividend days relative to the control period. Consistent with the prior literature, in the control period and ex-dividend day, there is a positive association between the aggressiveness level of buy order and return. The increase in returns on the ex-dividend day positively affects the aggressiveness level of sell orders. These results can be inferred from Table 3.15 and Figure 3.5.

Finally, consistent with the previous theories (Foucault et al., 2005; Rosu 2008, 2009), the positive coefficient of the duration as reported in Table 3.15 suggests an increase in order aggressiveness as duration increases.

Overall, the robustness results confirm traces of foot-prints associated with tax arbitrage and liquidity supply around the ex-dividend event. There is high passive buy behaviour on cum-dividend day and high passive sell behaviour on ex-dividend day. Furthermore, increases in bid-ask spread and price volatility motivate tax-arbitragers to buy on cum-dividend day and sell on the ex-dividend aggressively to ensure the execution of their orders.

3.8 Conclusion

This chapter studies market microstructure effects associated with the ex-dividend day price drop FTSE SmallCap firms. FTSE SmallCap stocks are considered illiquid stocks. Employing different liquidity measures we empirically confirm the illiquidity of the FTSE SmallCap stocks. This study investigates tax-arbitrage driven trading around the ex-dividend day and searches for tell-tale “footprints”. There are no strong effects in the aggregate trading data though we do find that that spread and volatility are higher in the ex-dividend week compared to the control week. Furthermore, spread in the ex-dividend week affects by price volatility, size of the buy order and the size of the sell order. These effects are not directly interpretable without also studying the limit order submission details.

We find that the order submission results support the presence of tax-arbitrage “footprints”, since there is an increased likelihood of relatively more aggressive buying on the cum-dividend day and of relatively more aggressive selling on the ex-dividend day. We also find that there is an increase in the likelihood of relatively less aggressive selling on the cum-dividend day and relatively less aggressive buying on the ex-dividend day. These findings are consistent with tax-arbitrage and liquidity supply occurring simultaneously.

There are clear links between order submission and spread, volatility as well as return. One pattern we find is that one-sided trading of tax-arbitrageurs may drive prices away from fundamentals and thereby increase spread and return, which attracts liquidity suppliers, who trade aggressively either to take advantage of the difference between transaction prices and fundamental prices or to profit from the resulting larger spread. In addition, one-sided buying or selling pressure increases price volatility and return which motivates tax-arbitrageurs to submit aggressive orders. There is no of an association between order arrival rate and the order submission decision around the ex-dividend day for FTSE SmallCap stocks.

Finally, after we expand our sample period, analyse buy order and sell order separately and calculate the actual tradable spread, the regression specification confirms most of the results.

3.9 Appendix C

Table 3.16 – Relative risk ratios–M1

This table reports the relative risk ratios of estimates regression Eq.(2.18) for-M1-buy side and sell side on a stock-by-stock basis. The relative risk ratios are reported for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable for buy regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q buy order (2) A-T-Q buy order (3) I-T-Q buy order (4) M-A buy order (5) sell order. Sell order set as reference category for buy regression. The dependent variable for sell regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q sell order (2) A-T-Q sell order (3) I-T-Q sell order (4) M-A sell order (5) buy order. Buy order set as reference category for sell regression. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Buy side				
Baseline	0.781***	0.050***	0.086***	0.126***
Spread	1.016***	1.002	0.975***	0.921***
Volatility	0.976***	0.984**	1.088***	0.991***
Return	0.992***	1.008*	1.051***	1.030***
Duration	1.000***	1.000***	1.000***	1.000***
Sell side				
Baseline	0.833***	0.065***	0.121***	0.148***
Spread	0.999	1.000	1.037***	0.988***
Volatility	1.004**	0.974***	1.067***	0.968***
Return	1.006***	0.998	1.001	0.943***
Duration	1.000***	1.000***	1.000***	1.000**

Table 3.17 – Relative risk ratios–M2

This table reports the relative risk ratios of estimates regression Eq.(2.18) for-M2-buy side and sell side on a stock-by-stock basis. The relative risk ratios are reported for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable for buy regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q buy order (2) A-T-Q buy order (3) I-T-Q buy order (4) M-A buy order (5) sell order. Sell order set as reference category for buy regression. The dependent variable for sell regression is aggressiveness which is classified in to 5 levels: (1) B-T-Q sell order (2) A-T-Q sell order (3) I-T-Q sell order (4) M-A sell order (5) buy order. Buy order set as reference category for sell regression The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Buy side				
Dummy variables				
Baseline	0.778***	0.052***	0.088***	0.121***
DW	1.008*	0.948***	0.944***	1.091***
Baseline * DW	0.784	0.049	0.083	0.132
Spread	1.016***	1.001	0.975***	0.921***
Volatility	0.976***	0.984**	1.088***	0.991***
Return	0.992***	1.008*	1.051***	1.030***
Duration	1.000***	1.000***	1.000***	1.000***
Sell side				
Dummy variables				
Baseline	0.843***	0.070***	0.128***	0.145***
DW	0.978***	0.872***	0.892***	1.045***
Baseline * DW	0.824	0.061	0.114	0.152
Spread	0.999	1.000	1.036***	0.988**
Volatility	1.004**	0.974***	1.068***	0.969***
Return	1.005***	0.998	1.000	0.943***
Duration	1.000***	1.000***	1.000***	1.000**

Table 3.18 – Relative risk ratios–M3–buy side

This table reports the relative risk ratios of estimates regression Eq.(2.18) for-M3-buy side on a stock-by-stock basis. The relative risk ratios are reported for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable is aggressiveness which is classified in to 5 levels: (1) B-T-Q buy order (2) A-T-Q buy order (3) I-T-Q buy order (4) M-A buy order (5) sell order. Sell order set as reference category. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Dummy variables				
Baseline	0.774***	0.048***	0.085***	0.125***
DW	1.018	1.092*	1.001	1.017
Baseline * DW	0.788	0.052	0.085	0.127
Spread variables				
Spread	1.021***	0.994	0.954***	0.913***
Spread # DW	0.989**	1.017	1.048***	1.014
Spread * Spread # DW	1.010	1.011	1.000	0.926
Volatility variables				
Volatility	0.972***	0.979**	1.092***	0.966***
Volatility # DW	1.010***	1.015	0.993	1.049***
Volatility * Volatility # DW	0.982	0.994	1.084	1.013
Return variables				
Return	0.990***	1.012**	1.056***	1.033***
Return # DW	1.003	0.990	0.987**	0.994
Return * Return # DW	0.993	1.002	1.042	1.027
Duration variables				
Duration	1.000***	1.000***	1.000***	1.000***
Duration # DW	1.000*	1.000	1.000	1.000***
Duration * Duration # DW	1.000	1.000	1.000	1.000

Table 3.19 – Relative risk ratios–M3–sell side

This table reports the relative risk ratios of estimates regression Eq.(2.18) for-M3-sell side on a stock-by-stock basis. The relative risk ratios are reported for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable is aggressiveness which is classified in to 5 levels: (1) B-T-Q sell order (2) A-T-Q sell order (3) I-T-Q sell order (4) M-A sell order (5) buy order. Buy order set as reference category. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Dummy variables				
Baseline	0.842***	0.073***	0.142***	0.145***
DW	0.981*	0.791***	0.732***	1.045**
Baseline * DW	0.826	0.058	0.104	0.152
Spread variables				
Spread	0.987***	1.008	1.066***	0.991
Spread # DW	1.024***	0.988	0.937***	0.993
Spread * Spread # DW	1.011	0.996	0.999	0.984
Volatility variables				
Volatility	1.013***	0.979***	1.054***	0.976***
Volatility # DW	0.981***	0.992	1.029***	0.983***
Volatility * Volatility # DW	0.994	0.971	1.085	0.959
Return variables				
Return	1.001	1.004	1.020***	0.929***
Return # DW	1.009***	0.985*	0.963***	1.026***
Return * Return # DW	1.010	0.989	0.982	0.953
Duration variables				
Duration	1.000***	1.000***	1.000	1.000*
Duration # DW	1.000	1.000	1.000*	1.000
Duration * Duration # DW	1.000	1.000	1.000	1.000

Table 3.20 – Relative risk ratios–M4–buy side

This table reports the relative risk ratios of estimates regression Eq.(2.18) for-M4-buy side on a stock-by-stock basis. The relative risk ratios are reported for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable is aggressiveness which is classified in to 5 levels: (1) B-T-Q buy order (2) A-T-Q buy order (3) I-T-Q buy order (4) M-A buy order (5) sell order. Sell order set as reference category. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Dummy variables				
Baseline	0.774***	0.048***	0.085***	0.125***
DW	1.070***	1.032	0.933	1.077***
DC	0.809***	1.360***	1.158***	0.857***
DE	0.907***	0.990	1.253***	0.816***
Baseline * DW	0.828	0.050	0.079	0.135
Baseline * DW * DC	0.670	0.067	0.092	0.115
Baseline * DW * DE	0.751	0.049	0.099	0.110
Spread variables				
Spread	1.021***	0.994	0.954***	0.913***
Spread # DW	0.991**	1.013	1.047***	1.014
Spread * Spread # DW	1.012	1.007	0.999	0.926
Volatility variables				
Volatility	0.972***	0.979**	1.092***	0.966***
Volatility # DW	1.008**	1.016	0.995	1.047***
Volatility * Volatility # DW	0.980	0.995	1.087	1.011
Return variables				
Return	0.990***	1.012**	1.056***	1.033***
Return # DW	1.003	0.991	0.988**	0.994
Return * Return # DW	0.993	1.003	1.043	1.027
Duration variables				
Duration	1.000***	1.000***	1.000***	1.000***
Duration # DW	1.000*	1.000	1.000	1.000**
Duration * Duration # DW	1.000	1.000	1.000	1.000

Table 3.21 – Relative risk ratios–M4–sell side

This table reports the relative risk ratios of estimates regression Eq.(2.18) for-M4-sell side on a stock-by-stock basis. The relative risk ratios are reported for sample of 43 stocks from FTSE SmallCap index. These stocks achieve the following criteria: They are listed on FTSE SmallCap index in a period between June 2007 and June 2008, they paid a cash dividend on Wednesday during the sample period and there is no bank holiday in their ex-dividend week or control week. The dependent variable is aggressiveness which is classified in to 5 levels: (1) B-T-Q sell order (2) A-T-Q sell order (3) I-T-Q sell order (4) M-A sell order (5) buy order. Buy order set as reference category. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	B–T-Q	A-T-Q	I–T-Q	M-A
Dummy variables				
Baseline	0.842***	0.073***	0.142***	0.145***
DW	0.952***	0.661***	0.642***	0.985
DC	1.131***	2.054***	1.532***	1.239***
DE	1.067***	1.258***	1.356***	1.162***
Baseline * DW	0.802	0.048	0.091	0.143
Baseline * DW * DC	0.907	0.099	0.140	0.177
Baseline * DW * DE	0.855	0.061	0.124	0.166
Spread variables				
Spread	0.987***	1.008	1.066***	0.991
Spread # DW	1.023***	0.982	0.935***	0.992
Spread * Spread # DW	1.010	0.990	0.997	0.983
Volatility variables				
Volatility	1.013***	0.979***	1.054***	0.976***
Volatility # DW	0.982***	0.996	1.033***	0.985**
Volatility * Volatility # DW	0.995	0.975	1.089	0.961
Return variables				
Return	1.001	1.004	1.020***	0.929***
Return # DW	1.009***	0.988	0.964***	1.026***
Return * Return # DW	1.010	0.992	0.983	0.953
Duration variables				
Duration	1.000***	1.000***	1.000	1.000*
Duration # DW	1.000	1.000	1.000*	1.000
Duration * Duration # DW	1.000	1.000	1.000	1.000

Chapter 4

Ex-dividend Day and Intraday Trading Patterns

4.1 Introduction

In this chapter the focus is on microstructure effects at the high frequency tick-by-tick intraday level of trading. We investigate patterns in the bid–ask spread, price volatility and trading volume around the ex-dividend day for a sample of FTSE100 companies. It is well known that some of the trading activity around the ex-dividend day is linked to tax-arbitrage, which has a predictable impact on these intraday patterns. A standard view is that tax arbitrageurs are averse to adverse selection costs and execution risk and should consequently prefer to trade in the stocks of companies with the lowest costs and at a time of the trading day when these costs are the lowest. Therefore, it is expected that tax-arbitrageurs focus on low price volatility firms more than on high price volatility firms. This chapter examines whether the effect of ex-dividend day on the intraday pattern of spread, volatility and volume differs between low price volatility firms and high price volatility firms.

Many studies find evidence of general intraday patterns in volatility, spread and trading volume in the equity and in other markets, specifically U-shaped patterns in volatility, U-shaped patters in trading volume, and U-shaped patterns in spreads, while some studies indicate that there is an L-shape or inverted J-shape for the intraday pattern for spreads, volumes and volatility (Chan et al., 1995 and McInish and Van Ness, 2002).[1,2,3,4]Studies typically rationalise the U-shaped patterns via information asymmetry effects at the beginning of the day and by the effects of market closure, at the end of the day. Information asymmetry leads to greater spreads and greater volatility because of adverse selection costs and information revelation, as well as to greater volumes because more informed trading takes place. At market closure, the argument is that traders, otherwise risking holding their position overnight when they have limited access to information and to limited trading liquidity, choose instead to close out their positions. Therefore, liquidity suppliers quote larger spreads to take advantage of those needing to close their position and the resulting trading activity leads to greater price volatility and volumes (Slezak, 1994). This chapter studies what impact trading around the ex-dividend day has on these established patterns.

Many studies have investigated the behaviour of equity prices around the ex-dividend day. For example, while Lakonishok and Vermaelen (1986) demonstrate that the ex-dividend day is associated with an increase in trading volume, Ainsworth et al. (2008) study spreads around the ex-dividend day and find higher spreads on ex-dividend days compared to cum-dividend days on the Australian Stock Exchange, whereas Graham et al. (2003) find no such effects on the NYSE. Evidence of order imbalance around ex-dividend days is reported by Frank and Jagannathan (1998) as well as Jakob and Ma (2004) while evidence of abnormal

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[1]Chan et al. (1995) suggest that intraday trading patterns exhibit differences between pure order driven markets as compared with hybrid markets because of structural differences between such markets.

[2]Studies reporting results for volatility include Wood et al. (1985); Harris (1986); McInish and Wood (1990); Foster and Viswanathan (1993); Lee et al. (1993); Chan et al. (1995) as well as Ke et al. (2004).

[3]Studies reporting results for volume include Jain and Joh (1988); McInish and Wood (1990); Foster and Viswanathan (1993); Lee et al. (1993); Chan et al. (1995) as well as Ke et al. (2004).

[4]Studies reporting results for spread include Brock and Kleidon (1992); Lau and McInish (1995); Brockman and Chung (1999); Ahn and Cheung (1999); Chung at al. (1999); Chung and Van Ness (2001); Ke et al. (2004) as well as Vo (2007).

volume and price volatility around ex-dividend days is reported by Ainsworth et al. (2008) and Jun et al. (2008).

Several studies report an increase in the trade size around ex-dividend days.[5] Both cum- and ex- dividend days are expected to generate higher volumes. Cum-dividend days and ex-dividend days need not necessarily display the same intraday patterns. Immediacy concerns, for instance, are likely to be more pronounced on cum-dividend days than on ex-dividend days. From a theoretical point of view, waiting costs are shown to influence order submission strategies since Foucault et al. (2005) and Roşu (2009) both argue, that higher waiting costs can lead to the submission of more aggressive orders. More submission of more aggressive orders can lead to narrower spreads and this effect should also be more pronounced on cum-dividend days than ex-dividend days. The effects on ex-dividend days are more likely to be associated with an unwinding of tax-arbitrage positions and will therefore, be more aligned closer to the "close of trading" perspective posited above. There are, however, other effects that could increase spreads around the ex-dividend day. First, if immediacy concerns arise from traders who seek to trade in the same direction, they are likely to lead to wider spreads because liquidity suppliers may not necessarily be able to keep up with the one-sided demand. Second, if there is increased demand for liquidity, suppliers of that liquidity may increase the price for that liquidity, which also can lead to higher spreads.

This chapter empirically investigate these issues, employing data on order submissions and executions in the ex-dividend week, and in a control week, and for shares constituting the FTSE 100 going ex-dividend between June 2007 and June 2008. This study is restricted to only those firms that go ex-dividend on a Wednesday and where there is no bank holiday in the two weeks concerned.

The results of this chapter can be summarized as follows. First, while intraday patterns of spread display an L-shape, consistent with some previous literature, volume exhibits an U-shape and, in general, is consistent with most prior litera-

[5] Evidence of this increase in trade size is reported by Michaely and Vila (1995); McDonald (2001); Rantapuska (2008) as well as Ainsworth and Lee (2011).

ture. Second, consistent with tax-arbitrage effects, spreads and volumes on both ex-dividend days and cum-dividend days, for firms that are most attractive targets for tax-arbitrage[6], are higher than normal for the last part of the trading day. The fact that tax-arbitrage is more likely in the final part of the trading day can be explained by the relatively higher adverse selection costs of trading in the first part of the day. Since, both spreads and volatility are higher in the first part of the day, in general, it is rational to avoid that period. Third, there is evidence that some of the effects on intraday patters around ex-dividend days can become "masked". When the sample is split, into classifications, based on price volatility, the results show that tax-arbitrageurs are likely to prefer trading in companies with the lowest price volatility, because this minimises both adverse selection costs and execution risks. Across all firms in the sample, there is no measurable impact on spreads and volumes on the ex- and cum-dividend days but when the sample is split into low-high volatility firms, the results show greater spreads and volumes at the end of the ex- and cum-dividend days for low volatility firms and smaller spreads and volumes at the end of the day for high volatility firms. The total sample masks, therefore, the two opposing effects.

The remainder of the chapter is organized as follows. Section 4.2 reviews the extant literature and develops the relevant hypotheses while the data and sample are outlined in Section 4.3 and section 4.4 describes the methodology and specifies the variables employed. The results are presented and discussed in section 4.5. while a final section concludes.

[6]The sample of data in this chapter is classified, depending on the price volatility, into two groups: 1- firms that are most attractive target for tax-arbitrageurs, which are the firms with low price volatility and 2- firms that are least attractive target for tax-arbitrager, which are the firms with high price volatility.

4.2 Literature Review

Spread Patterns

The prior literature has found that the intraday variation of bid-ask spread tends to be U-shaped, L-shaped or an inverted J-shaped (Chan et al., 1995 and McInish and Van Ness, 2002).[7] There are three microstructure models that seek to explain this intraday variation in spreads: inventory models, specialist market power models and information asymmetry models.

The inventory based models (Stoll, 1978; Amihud and Mendelson, 1980 and Ho and Stoll, 1981) argue that the spread effect is explained by the premium that market makers require for internalising the cost of carrying undesired inventory. When market makers are forced away from their optimum inventory positions, they adjust bid-ask spreads so as to attract orders to regain their preferred inventory positions. Amihud and Mendelson (1982) and Madhavan and Smidt (1993) argue that the quote revisions are positively linked to order imbalances. For example, Madhavan and Smidt (1993) argue that since trading volume tends to be higher at the start and at the end of the trading day, order imbalances and wider spreads will more likely occur at these times. Associated with trading activity, Lee et al. (1993) find that for a sample of NYSE stocks, spread widens with higher trading volume while Hasbrouck and Sofianos (1993) report that trades involving NYSE specialists have a larger and faster impact on spreads than trades not involving specialists. Chan et al. (1995) show that spreads of NYSE stocks exhibit an intra-day pattern that is U-shaped, though the spread of NASDAQ stocks decreases throughout the day while increasing slightly in the last 30 minutes of trading. They attribute the difference in intraday variation of spreads between NYSE and NASDAQ stocks to the structural differences between the market specialists and the market dealers. More specifically, market specialists might need

[7] Among others, studies reporting U-shaped include, Brock and Kleidon (1992); McInish and Wood (1992); Lee et al. (1993); Chan et al. (1995); Abhyankar et al. (1997); Ahn and Cheung (1999); Chung et al. (1999); Freihube et al. (2001) as well as Ahn et al. (2002).

to hold larger inventory positions during periods of intense trading activity, hence, bid-ask spreads might widen at the start and end of trading, reflecting the elevation in trading activity. Spreads may narrow however, since the market dealers, with no special knowledge of order flow and little market power, will engage in inventory management and desire to 'go home flat'. This prediction is consistent with the theoretical work of Ho and Macris (1985).

Specialist market power based models link the intraday patterns in spreads to the potential monopoly power of the specialist. Brock and Kleidon (1992) claim that specialists on the NYSE are monopolistic market makers and they illustrate that the demand for transaction is both less elastic and greater, at the open and close of trading than at other times, for two reasons. First, the accumulation of overnight information is likely to alter investors' optimal portfolio (for the open period). Second, due to the imminent non-trading hours, optimal portfolio could be different from the ones during continuous trading hours (for the close period). The market makers, therefore, can discriminate during these periods by charging higher prices. Consistent with this model, McInish and Wood (1992) and Chan et al. (1995) report a U-shaped pattern in intraday spreads on the NYSE, arguing that the inelastic periods at the opening and closing of the trading day, lets specialists use their market power to extract economic rents from traders.

Information based models, relate the intraday pattern of the spread to the adverse selection risk experienced by market makers, who are at an informationally disadvantaged position relative to informed traders.[8] Market makers will, therefore, keep their spreads sufficiently wide to ensure the gains made from trading with liquidity traders adequately compensates for losses made from trading with informed traders. Since information asymmetry is more likely during the opening and closing periods of the trading day, spreads are highest during these periods. However, Foster and Viswanathan (1994) argue that it is the competition between

[8] Information models are developed and investigated by several prior studies including Copeland and Galai (1983); Glosten and Milgrom (1985); Kyle (1985); Easley and O'Hara (1987, 1992); Hasbrouck (1988); Foster and Viswanathan (1990, 1994); Madhavan (1992) as well as Admati and Pfleiderer (1988).

informed traders that leads to higher volume, higher return variances and higher spreads, at the beginning of trading day. Madhavan (1992) claims that since trade resolves information asymmetry during early trading hours, spreads should decrease throughout the trading day.

Many different effects associated with the intraday variation in spreads are expected on both the cum- and ex- dividend days. Foucault (1999) develops a theoretical model and argues that bid-ask spread increases at the close of trading are negatively related to the level of competition among limit order traders. On one hand, if higher waiting costs, because of an approaching trading deadline, result in more aggressive pricing on the cum-dividend day, spread is anticipated to be narrower on the cum-dividend day. On other hand, Frank and Jagannathan (1998) and Jakob and Ma (2004) find evidence of order imbalance around the ex-dividend day. If immediacy concerns arise on cum- and ex- dividend days from traders who seek to trade in the same direction, they are likely to widen spreads because liquidity suppliers may not necessarily be able to keep up with such one-sided demand. Finally, if there is increased demand for liquidity on cum- and ex-dividend days, suppliers of that liquidity may increase the price for that liquidity, which also can lead to higher spreads. While the net effect of cum-dividend day tax-arbitrage driven trading on spreads is not clear, the effect of ex-dividend day tax-arbitrage driven trading is expected to increase the spreads.

Volume Patterns

The intraday variation of trading volume tends to be U-shaped for many markets.[9] Gerety and Mulberin (1992) report a U-shaped pattern in trading volumes for the NYSE. They illustrate that the optimal closing portfolios may be different, due to the imminent non-trading period, from the portfolios that are considered optimal

[9] such as, the Sweden market (Niemeyer and Sandas, 1994); the Finland market (Hedvall, 1994); the Paris market (Biais et al., 1995); the Toronto market (McInish and Wood, 1990); the London market (Werner and Kleidon, 1996); the Hong Kong market (Ho and Cheung, 1991); NASDAQ (Chan et al., 1995); NYSE (Gerety and Mulberin, 1992) and the Taiwan market (Lee et al., 2001)

during continuous trading hours. Some traders cannot bear overnight risk but trade with those who can, which leads to high trade volumes at close of trade. Brock and Kleidon (1992) argue that at the start of a trading day, traders again modify their portfolios. This periodic fluctuation in the demand for trading results in higher volumes at the start and close of trading. Furthermore, institutional fund managers tend to trade near the close of trading to match the market index, which increases volume further.[10]

Lakonishok and Vermaelen (1986) find that trading volume around the ex-dividend day is higher than trading volume during normal trading days.[11] They suggest that no abnormal trading volume should be observed under the Elton and Gruber (1970) framework, whereas positive and negative abnormal volumes should be observed under the Kalay (1984) framework. They argue that investors with high marginal tax rates would desire to sell before the ex-dividend day and investors with low marginal tax rates would desire to buy before the ex-dividend day. If all categories of traders exactly 'match' each other, (i.e., if the amount of accelerated purchases (and sales) is exactly equal to the amount of delayed purchases (and sales)), then no abnormal volume will be observed.

We therefore expect that, trading volume should be higher on both the cum- and ex-dividend days. Moreover, since tax-arbitrageurs may avoid trading during the first part of the trading day since this period faces relatively higher adverse selection costs, trading volume should be higher in the final part of both the cum- and ex-dividend trading days.

Volatility Patterns

Previous studies suggest a U-shaped pattern for the intraday variation in volatility while Harju and Hussain (2011) report a reversed J shaped for four European

[10]Similar results have been reported by Jain and Joh (1988) as well as Lockwood and Linn (1990).

[11]Evidence of this increase in trade size is reported by Michaely and Vila (1995); McDonald (2001); Milonas and Travlos (2001); Rantapuska (2008) as well as Ainsworth and Lee (2011).

stock market indices (namely, FTSE 100, DAX30, SMI and CAC40).[12] Harju and Hussain (2011) argue that at the start of the trading day volatility is high before declining fast until 14:30 CET and after 14:30 CET, volatility displays a clear level shift and then three major jumps points at 14:35 CET, 15:35 CET, and 16:05 CET. Harju and Hussain (2011) associated this series of level shifts and rise in volatility to the programmed macro news announcements in the US ato 14:30 CET and 16:00 CET, and to the opening of the NYSE at 15:30 CET. Harju and Hussain (2011) verify empirically that after 09:15, the intraday volatility pattern presents a U-shaped *after* controlling for the NYSE.

Foucault (1999) and Foucault et al. (2005) show that price uncertainty can increase because of large differences in investor valuation of a stock, for instance, different tax status. In this study we, therefore, expect an increase in price volatility on the cum-dividend days. Order imbalances are also a source of price volatility and Frank and Jagannathan (1998) as well as Jakob and Ma (2004) find evidence of order imbalance around the ex-dividend day while Ainsworth et al. (2008) and Jun et al. (2008) find evidence of abnormal volume and abnormal price volatility around the ex-dividend day. This study argue that volatility increase on both cum- and ex-dividend days as a result of order imbalance generate by tax-arbitrage activity.

Furthermore, the bid-ask spreads, trading volumes and price volatility are related to each other. Volume and volatility are jointly endogenous and co-vary in response to the rate of information flow into the market as shown in theoretical models, [13]while the notion that volatility and volume move simultaneously was suggested by Copeland (1976) as well as Jennings et al. (1981). More recently, Foucault (1999) suggests a direct positive relationship between bid-ask spreads and price volatility.

[12]Studies suggest a U-shaped pattern include Abhyankar et al. (1997); Andersen and Bollerslev (1997); Gerety and Mulherin (1994); Harris (1986, 1989); McInish and Wood (1990); Werner and Kleidon (1996); Lockwood and Linn (1990); Rogalski (1984); Smirlock and Starks (1986) as well as Wood et al. (1985).

[13]See, Clark (1973); Epps and Epps (1976) as well Tauchen and Pitts (1983).

The empirical evidence is perhaps not as clear. For instance, while Chordia et al. (2001) report a negative relationship between volatility and spreads for NYSE stocks and Rahman et al. (2002) find a positive and statistically significant though numerically very small effect for volume and for bid-ask spreads on conditional volatility for NASDAQ stocks. Nevertheless, similar positive relationships between trading volume and volatility are reported by others.[14] However, Worthington and Higgs (2003) conclude that the influence of bid-ask spreads on volatility is relatively large, though the effect of volume on volatility is relatively small on the S&P/ASX 50 index on the Australian stock market. Meanwhile, though Wang and Yau (2000) suggest a positive relationship between bid-ask spread and volatility and a negative relationship between lagged trading volume and volatility, Harris (1987) demonstrates that trading frequency should not affect volatility. On the other hand, based on the intuition that informed traders engage in stealth trading by dividing large trades into many smaller trades, Kyle (1985) documented a positive relationship between trading frequency and volatility results which are confirmed by Jones et al. (1994) and Huang and Masulis (2003).

4.3 Data

The dataset and the sample that are used in this chapter are the same as for chapter 2.[15] We describe here the additional data preparations steps performed for the tick-by-tick high frequency data employed in this chapter. The trading hours between 08:00 a.m. -16:30 p.m. are partitioned into 17 successive 30-minute intervals. The spread, volume, and volatility for each stock i during each 5-minute interval n are computed first, and in this manner, the time-series of values individually for all stocks, and from which time series, the mean of each variable for each 30-minute interval are computed as in Chung and Van Ness (2001). Table 4.1 shows the mean values of spread, volatility and volume for each

[14] Positive relationships between volume and volatility are reported by Darrat et al. (2003); Karpoff (1987); Schwert (1989); Gallant et al. (1992) and Easley et al. (1997).

[15] A full description of this dataset and sample can be found in Chapter 1 Section 1.4

30-minutes time interval during the ex-dividend and control weeks, and Table 4.2 shows the mean values of spread, volatility and volume for each 30-minutes time interval during cum- and ex-dividend days, as well as for days 2 and 3 in the control week, corresponding to the cum- and ex-dividend days respectively.

Table 4.1 – Summary statistics on spread, volatility and volume.
This table reports the mean value of the spread, volatility and volume variables for 47 stocks from FTSE 100 index. These stocks satisfy the following selection criteria: They are listed on FTSE 100 index in the period between June 2007 and June 2008, they paid a cash dividend on the Wednesday during the sample period and there is no bank holiday in their ex-dividend week or in control week. These mean values are calculated for the control week and ex-dividend week.

Time	Spread	Volatility	Volume	Spread	Volatility	Volume
	Cont.w			Ex.w		
08:00-08:30	0.373	0.001	1,762,964.896	0.395	0.001	1,571,077.774
08:30-09:00	0.216	0.000	1,355,917.860	0.205	0.000	1,332,688.499
09:00-09:30	0.194	0.000	1,318,159.859	0.224	0.000	1,369,165.627
09:30-10:00	0.194	0.000	1,314,403.085	0.187	0.000	1,306,116.554
10:00-10:30	0.187	0.000	1,432,010.042	0.171	0.000	1,319,881.206
10:30-11:00	0.177	0.000	1,253,107.647	0.214	0.000	1,266,510.751
11:00-11:30	0.190	0.000	1,290,096.710	0.180	0.000	1,242,043.719
11:30-12:00	0.185	0.000	1,220,107.816	0.182	0.000	1,164,141.797
12:00-12:30	0.178	0.000	1,204,907.447	0.182	0.000	1,232,454.230
12:30-13:00	0.170	0.000	1,202,735.792	0.165	0.000	1,126,972.692
13:00-13:30	0.169	0.000	1,200,999.209	0.169	0.000	1,160,169.877
13:30-14:00	0.187	0.000	1,258,638.363	0.181	0.000	1,170,680.296
14:00-14:30	0.167	0.000	1,263,940.561	0.181	0.000	1,182,768.383
14:30-15:00	0.161	0.000	1,251,445.599	0.170	0.000	1,249,750.034
15:00-15:30	0.151	0.000	1,247,769.673	0.171	0.000	1,251,504.322
15:30-16:00	0.163	0.000	1,281,705.677	0.172	0.000	1,257,643.976
16:00-16:30	0.173	0.000	1,416,581.371	0.187	0.000	1,409,108.936

Table 4.2 – Summary statistics on spread, volatility and volume

This table reports the mean value of the spread, volatility and volume variables for 47 stocks from FTSE 100 index. These stocks satisfy the following selection criteria: They are listed on FTSE 100 index in the period between June 2007 and June 2008, they paid a cash dividend on the Wednesday during the sample period and there is no bank holiday in their ex-dividend week or in control week. These mean values are calculated for the day corresponding to the cum-dividend day but in the control week (the Tuesday day 2), the cum-dividend day, the day corresponding to the ex-dividend day but in the control week (the Wednesday day3) and the ex-dividend day.

Time	Spread	Volatility	Volume	Spread	Volatility	Volume
		C-Cum			Cum.day	
08:00-08:30	0.418	0.001	1,781,789.355	0.335	0.001	1,533,062.782
08:30-09:00	0.244	0.000	1,308,838.444	0.200	0.001	1,362,421.332
09:00-09:30	0.184	0.000	1,251,694.286	0.218	0.000	1,498,644.695
09:30-10:00	0.152	0.000	1,146,573.553	0.151	0.000	1,267,291.734
10:00-10:30	0.178	0.000	1,185,143.402	0.142	0.000	1,299,825.413
10:30-11:00	0.158	0.000	1,256,316.913	0.169	0.000	1,241,392.825
11:00-11:30	0.194	0.000	1,225,850.554	0.165	0.000	1,225,092.681
11:30-12:00	0.166	0.000	1,301,674.489	0.166	0.000	1,115,944.898
12:00-12:30	0.175	0.000	1,243,151.625	0.176	0.000	1,156,310.603
12:30-13:00	0.161	0.000	1,189,972.787	0.177	0.000	1,201,228.656
13:00-13:30	0.204	0.000	1,387,760.209	0.155	0.000	1,108,575.713
13:30-14:00	0.173	0.000	1,345,925.915	0.144	0.000	1,161,805.569
14:00-14:30	0.140	0.000	1,254,634.649	0.160	0.000	1,143,542.972
14:30-15:00	0.165	0.000	1,310,371.289	0.177	0.000	1,325,535.097
15:00-15:30	0.141	0.000	1,247,225.365	0.144	0.000	1,232,310.579
15:30-16:00	0.153	0.000	1,268,876.845	0.149	0.000	1,257,954.696
16:00-16:30	0.165	0.000	1,490,702.520	0.201	0.000	1,422,204.157
		C-Ex			Ex.day	
08:00-08:30	0.322	0.001	1,806,534.652	0.443	0.001	1,710,872.663
08:30-09:00	0.163	0.000	1,301,419.858	0.233	0.000	1,384,228.131
09:00-09:30	0.190	0.000	1,366,939.689	0.205	0.000	1,305,846.693
09:30-10:00	0.196	0.000	1,469,548.359	0.162	0.000	1,316,142.634
10:00-10:30	0.196	0.000	1,309,369.209	0.141	0.000	1,176,889.024
10:30-11:00	0.175	0.000	1,257,462.229	0.166	0.000	1,293,056.664
11:00-11:30	0.140	0.000	1,281,192.329	0.227	0.000	1,162,090.246
11:30-12:00	0.185	0.000	1,239,119.021	0.235	0.000	1,186,429.188
12:00-12:30	0.155	0.000	1,209,911.667	0.215	0.000	1,320,166.676
12:30-13:00	0.143	0.000	1,097,655.401	0.144	0.000	1,111,244.714
13:00-13:30	0.131	0.000	1,109,153.091	0.177	0.000	1,253,364.476
13:30-14:00	0.209	0.000	1,274,202.192	0.179	0.000	1,122,015.058
14:00-14:30	0.205	0.000	1,264,017.052	0.163	0.000	1,158,581.247
14:30-15:00	0.150	0.000	1,326,082.909	0.169	0.000	1,260,725.768
15:00-15:30	0.147	0.000	1,237,037.938	0.158	0.000	1,303,333.168
15:30-16:00	0.167	0.000	1,338,618.416	0.175	0.000	1,315,365.218
16:00-16:30	0.169	0.000	1,368,607.455	0.172	0.000	1,407,461.334

The intraday variation in the spread, volatility and volume are easier to digest from Figures, the previous variables are plotted, during each 30-minutes interval, in Figures 4.1 to 4.12 showing the intraday variation across intervals.

Figure 4.1 – Intraday variation across 17 thirty- minute time intervals- mean spread - Cont.w.

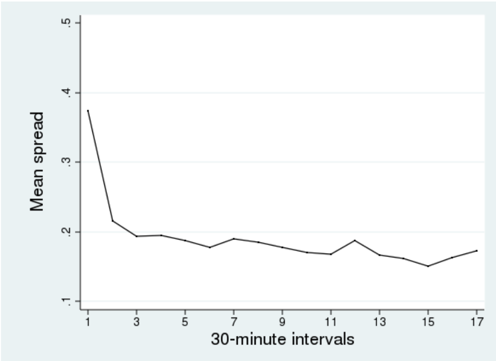


Figure 4.2 – Intraday variation across 17 thirty- minute time intervals -mean spread- Ex.w.

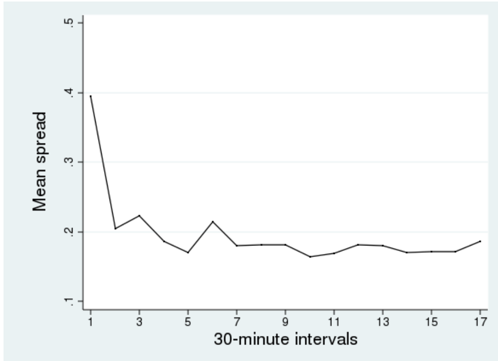


Figure 4.3 – Intraday variation across 17 thirty- minute time intervals -mean volatility - Cont.w.

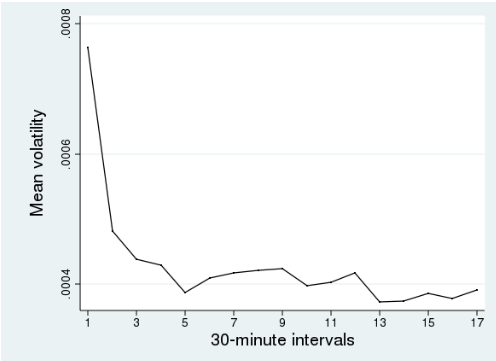


Figure 4.4 – Intraday variation across 17 thirty- minute time intervals - mean volatility - Ex.w

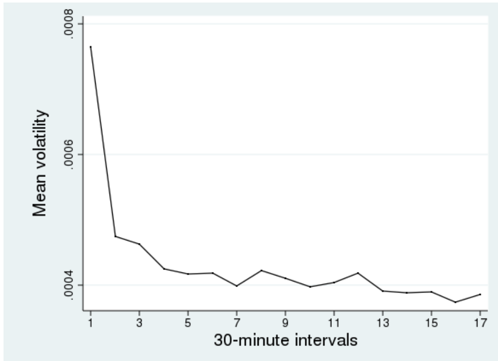


Figure 4.5 – Intraday variation across 17 thirty- minute time intervals - mean volume -Cont.w.

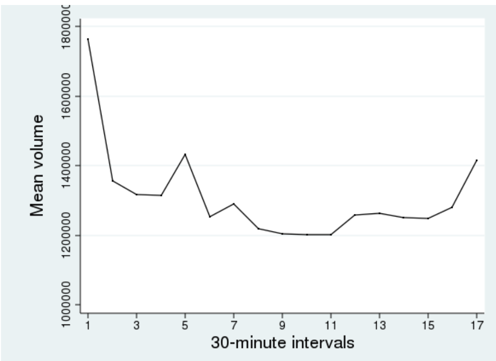


Figure 4.6 – Intraday variation across 17 thirty- minute time intervals -mean volume - Ex.w.

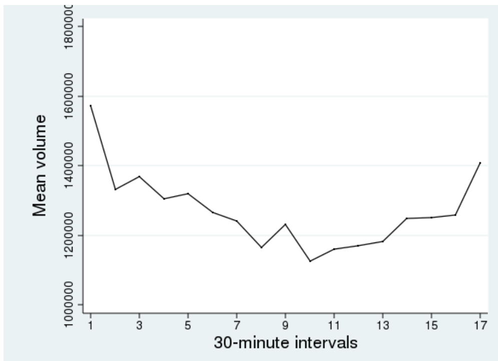


Figure 4.7 – Intraday variation across 17 thirty- minute time intervals -mean spread - C-Cum and C-Ex.

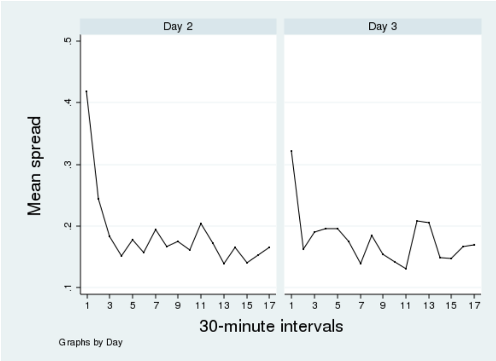


Figure 4.8 – Intraday variation across 17 thirty- minute time intervals- mean spread - Cum.day and Ex.day.

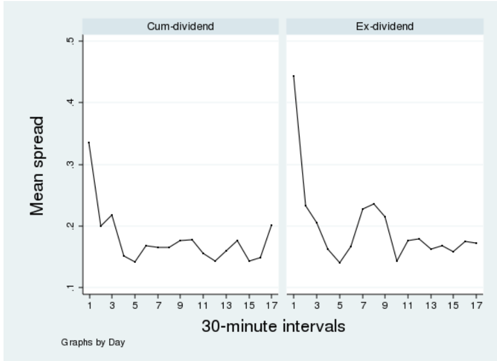


Figure 4.9 – Intraday variation across 17 thirty- minute time intervals- mean volatility- C-Cum and C-Ex.

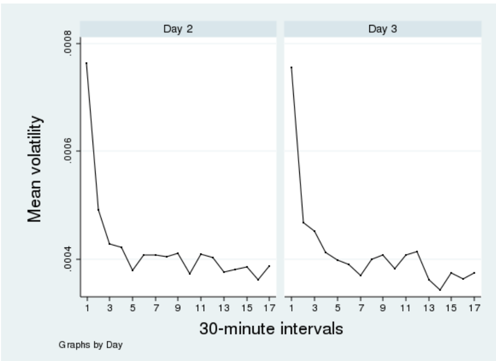


Figure 4.10 – Intraday variation across 17 thirty- minute time intervals- mean volatility- Cum.day and Ex.day.

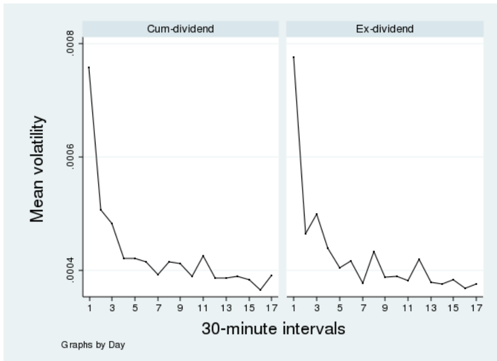


Figure 4.11 – Intraday variation across 17 thirty- minute time intervals- mean volume - C-Cum and C-Ex.

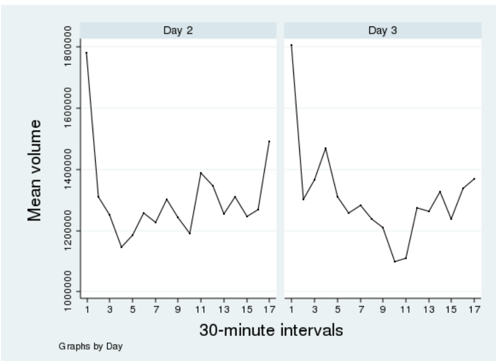
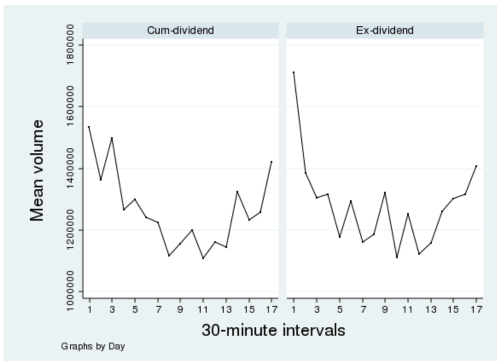


Figure 4.12 – Intraday variation across 17 thirty- minute time intervals- mean volume -Cum.day and Ex.day.



In general, the intra-day pattern for spread and volatility show an L-shaped pattern whereas volume presents a U-shaped pattern. Spread and volume in the first half an hour of cum-dividend day is lower than the spread and the volume in the first half an hour on ex-dividend day as well as, days 2 and 3 in the control week. The first half hour of day 3 in the control week has also lower spread. There is a need for a detailed analysis to test whether the ex-dividend day significantly affects the intraday patterns of spread, volatility and volume.

4.4 Methodology

4.4.1 Variables

For each stock i at trade j and during a five-minute time interval n, bid-ask spread, price volatility and trade volume are specified as:[16][17]

$$\text{Spread}_{(i,n)} = \begin{cases} \sqrt{-\text{cov}(\Delta p_{(i,j)} \Delta p_{(i,j-1)})} & \text{when } \text{cov}(\Delta p_{i,j} \Delta p_{i,j-1}) < 0 \\ 0 & \text{when } \text{cov}(\Delta p_{i,j} \Delta p_{i,j-1}) \geq 0 \end{cases} \tag{4.1}$$

$$\text{Volatility}_{(i,n)} = \sqrt{\sum_{j=1}^{N} \frac{(R_{(i,j)} - \overline{R}_{(i,n)})^2}{N-1}} \tag{4.2}$$

$$\text{Volume}_{(i,n)} = \frac{\sum_{j=1}^{N} Q_{(i,j)} * P_{(i,j)}}{N} \tag{4.3}$$

where:

$p_{(i,j)}$: is the price for stock i at trade j.

$Q_{(i,j)}$: is the number of share for stock i at trade j.

$R_{(i,j)}$: is the return for stock i at trade j.

$\overline{R}_{(i,n)}$: is the mean return for stock i during the n^{th} interval.

N: is the number of trades during the n^{th} interval.

[16] We scale the volatility variable by multiply it by 1000

[17] We scale the volume variable by divide it by 1000

4.4.2 Models

To reliably test whether the intraday variations in bid-ask spread, price volatility and trade volume around the ex-dividend day differs from those for other days, the Hansen (1982) Generalized Methods of Moments (GMM) procedure, together with the Parzen kernel correction for autocorrelation and heteroskedasticity have been employed. The GMM procedure is used since no particular structure can be imposed on the error term.[18]The GMM procedure yields consistent parameter estimates without a specific distribution assumption on the error term and allows for arbitrary cross-correlation, serial correlation and heteroskedastic errors (Andrews, 1991). For each stock i and five-minute time interval n, the following specification is estimated, using GMM:

$$V_{i,n} = \alpha_{i,0} + \sum_{k=1}^{12} \alpha_{i,k} D_{i,k} + \varepsilon_{i,n} \tag{4.4}$$

where:

$V_{i,n}$: is the relevant variable for stock i during five-minute time interval n. The variables are spread, volatility and volume.

$D_1 \sim D_{12}$: are time indicator variables. Each indicator represents one thirty-minute time interval.

Indicator variables $D_1 \sim D_6$ represent, in order, the first six thirty-minute time intervals of the trading day while variables $D_6 \sim D_{12}$ represent, in order, the last six thirty-minute time intervals of the trading day. The coefficients for the indicator variables, $a_1 \sim a_{12}$ measure the differences between the average value during each respective thirty-minute interval and the average value for the middle of the trading day, between 11:00 a.m. - 13:30 p.m.

The GMM estimation involves determining a set of moment restrictions to estimate the unknown coefficients. The normal equation, of the regression corresponding to equation (4.4), is used as the orthogonality conditions:

[18]The GMM technique has been applied in prior studies that have examined intraday patterns. See Foster and Viswanathan (1993); Chan et al. (1995); Chan et al. (1995); Abhyankar et al. (1997); Cai et al. (2004); and Frino et al. (2008).

$$E[\varepsilon_i] = 0 \tag{4.5}$$

$$E[D_k \varepsilon_i] = 0 \qquad k = 1, 2, ..., 12 \tag{4.6}$$

For each company, there are 13 orthogonality conditions (one for the fixed effect and 12 for each thirty-minute time interval indicator) and 13 parameters to be estimated. For 47 firms, there are 611 parameters to be estimated with 611 equations, so the system is just identified.[19]

Following Hansen (1982), if it is assumed that the error term is stationary and ergodic, for a large sample size, the sample moments can be assumed to, therefore, be close to the population moments. If $g_T(\hat{\alpha})$ is a 611-vector parameter of sample moments (where T is the number of observations) then for each company, $g_T(\hat{\alpha})$ includes:

[19] In doing so we are follow Bessembinder (1994) and take the explanatory variables as instruments for the GMM estimation.

O

$$g_T(\hat{\alpha}) = \frac{1}{T}\sum_{i=1}^{T}\begin{bmatrix} \varepsilon_i \\ D_1\varepsilon_i \\ D_2\varepsilon_i \\ D_3\varepsilon_i \\ D_4\varepsilon_i \\ D_5\varepsilon_i \\ D_6\varepsilon_i \\ D_7\varepsilon_i \\ D_8\varepsilon_i \\ D_9\varepsilon_i \\ D_{10}\varepsilon_i \\ D_{11}\varepsilon_i \\ D_{12}\varepsilon_i \end{bmatrix} \tag{4.7}$$

where $g_T(\hat{\alpha}) \to 0$ as $T \to \infty$.

To estimate α, the coefficients on the indicator variables, for each company, values that set the sample moment conditions as close to zero as possible are chosen. The quadratic form $g'Wg$ (that incorporates the Parzen kernel correction for autocorrelation and heteroskedasticity) is minimized, where, W, a symmetric weighting matrix, is a consistent estimator of the inverse of the asymptotic covariance matrix of $\sqrt{T}g_T(\hat{\alpha})$ after adjusting for serial correlation.[20] In this study, the system is just–identified, so there is a need only to solve $g_T(\hat{\alpha})$=0 and GMM produces the same coefficient as in OLS, but with the standard errors now robust to heteroskedasticity and to autocorrelation.

If D_T denotes a consistent estimator of $\partial g_T(\hat{\alpha})/\partial\hat{\alpha}$ and if we define $\hat{\alpha}$ to be an

[20] Although several microstructure studies while employing the GMM procedure, apply the Newey and West (1987) adjustment for autocorrelation and heteroskedasticity, we control for autocorrelation and heteroskedasticity using the Parzen kernel technique reported in Gallant (1987) since Andrews (1991), reports that the Bartlett kernel applied by Newey and West (1987) displays a higher bias and is 100% less efficient, asymptotically, than the Parzen kernel. Following Andrews (1991), $k^{1/5}$ is applied to calculate the lag truncation period.

estimate of α , then

$$\sqrt{T}(\hat{\alpha} - \alpha) \sim N(0, [D_T' W D_T]^{-1}) \tag{4.8}$$

The significance of the coefficient estimates is tested using the covariance matrix in the square brackets. For example, a significant positive (negative) spread coefficient α_1 would mean that the spreads are higher (lower) for the interval (08:00 a.m. - 08:30 a.m.) than the middle of the day (11:00 a.m. -13:30 p.m.).

Estimations in this chapter are produced in three different stages, for the ex-dividend and control weeks, cum- and ex-dividend days, as well as for days 2 and 3 in the control week. Variables that are discussed in this chapter may correlate across firms, therefore, in the first stage, for each variable, equation (4.4) is estimated simultaneously using GMM for all firms as one pool, as this should give more efficient estimates by exploiting the cross-correlations in the error term.[21]

In the second stage, having determined that there are significant variations in the sample, for each variable, equation (4.4) is estimated for each firm separately to pinpoint the source of the variation. The use of a test of an initial multivariate hypothesis, followed by a test of a univariate hypothesis is an accepted procedure to avoid finding spurious significance (see, for example, Savin, 1980, 1984 and Scheffe, 1977).[22] Then, for each variable, the GMM coefficients are stacked across all firms and the mean values are calculated for each thirty-minute time interval in the ex-dividend and control weeks, cum- and ex-dividend days, as well as for days 2 and 3 in the control week. Lastly, a t-test is conducted to determine whether the regression coefficients are significantly different from zero.

[21]For example, when a firm has a large trading volume on one day, other firms could have large trading volumes on that day as well.

[22]If the univariate test is used directly, the rejection region of the tests should partition to account for a number of hypotheses that are examined.

Many previous literatures attempt to measure and decompose trading costs into different components such as an adverse selection, order processing cost, and inventory cost (e.g., Glosten, 1987; Glosten and Harris, 1988; Stoll, 1989; Hasbrouck, 1991a; Amihud, 2002). The theoretical models of Glosten (1989), Kyle (1985), and Easley and O'Hara (1987) and the empirical analysis of Glosten and Harris (1988) suggest that the liquidity effects of asymmetric information are most likely to be captured in the price impact of a trade. Following previous literature, (e.g., Easley and O'Hara, 1987; Glosten and Harris, 1988; Stoll, 1989; Hasbrouck, 1991a; Lin et al., 1995), we construct a price impact measure based on Amihud (2002). Amihud (2002) proposes the ratio of absolute return to dollar trading volume as a measure of illiquidity. Our price impact measure is a modified version of the Amihud (2002) measure, where our impact measure is a weighted average absolute return instead of straight averge return. Previous studies document a strong positive relation between the Amihud (2002) measure and the high-frequency price impact benchmark e.g. Hasbrouck (2009), Goyenko, Holden, and Trzcinka (2009).

In the last stage, we classify the firms in to two approaches according to their price impact. Firstly, firms are divided into three types: firms that are most attractive targets for tax-arbitrage (low price impact) (Arbitrage) (AT-F), firms that are least attractive targets for tax-arbitrage (high price impact) (Information asymmetry) (IA-F), and firms that are neither (No classification) (NC-F). Secondly, firms are divided into two types: firms that are most attractive targets for tax-arbitrage (low price impact) (Arbitrage) (AT-F) and firms that are least attractive targets for tax-arbitrage (high price impact) (Information asymmetry) (IA-F).

Firms are classified by applying the following procedure. Firstly, the price impact of each trade is calculated for each stock (i) during a five-minute time interval (n):[23]

[23]This benchmark is defined separately for order submission data and for order execution data.

$$Price\,Impact = \frac{\sum_{j=1}^{J} \frac{|P_{i,j}-P_{i,j-1}|*Q_{i,j}}{\sum_{j=1}^{J} Q_{i,j}}}{\frac{\sum_{j=1}^{J} P_{i,j}}{J}} \tag{4.9}$$

where:

$Q_{i,j}$: is number of share for stock i at trade j.

$P_{i,j}$: is price of stock i at trade j.

J: is the number of observations during the n^{th} interval.

We calculated the mean value of price impact in the control week for each firm separately. We, then, divided the cross section of mean price impact into three groups to classify our sample of firms into low, medium and high price impact. Each category is denoted as follows, low price impact firms "Classification 1-Arbitrage", medium price impact firms "Classification 1- No classification" and high price impact firms "Classification 1- Information asymmetry". For the second approach of classification, we divided the cross section of mean price impact into two groups to classify our sample of firms into low and high price impact. Each category is denoted as follows, low price impact firms "Classification 2- Arbitrage (AT-F)" and high price impact firms as "Classification 2- Information asymmetry (IA-F)".

Furthermore, we seek to measure the effect that tax arbitrageurs might have on trading activity on the cum- and ex- dividend days. Effects are evaluated in two ways. Firstly, we evaluated the ratio of total monetary amount of all buy orders to the total monetary amount of sell orders. Secondly, we evaluated the ratio of total number of shares in the buy orders to the total number of share in the sell orders. In both cases, we computed the natural logarithm of the ratios. We further argue that such arbitrageurs will avoid implementing their trading strategies on those firms that are likely to have high price impact and focus instead on the low impact firms. Furthermore, we anticipate a timing preference among the arbitrageurs in that they are more likely to avoid the extremes of the trading day (i.e. opening and closing trading periods), focusing instead around the middle of the trading day. Hence, our approach is designed to isolate those firms and those periods in which such tax-arbitrageurs are most likely to be found. We proceed as follows: for each stock (i) and five-minute time interval (n), the GMM estimation is run for the following equation using two different dependent variables:

$$\begin{aligned} V_{i,n} = {} & \alpha_{i,0} + \sum_{k=1}^{12} \alpha_{i,k} D_{i,k} \\ & + b_{i,0} Firm_i + \sum_{k=1}^{12} b_{i,k} D_{i,k} * Firm_i \\ & + c_{i,0} DC_i + \sum_{k=1}^{12} c_{i,k} D_{i,k} * DC_i + \sum_{k=1}^{12} e_{i,k} D_{i,k} * DC_i * Firm_i \\ & + d_{i,0} DE_i + \sum_{k=1}^{12} d_{i,k} D_{i,k} * DE_i + \sum_{k=1}^{12} h_{i,k} D_{i,k} * DE_i * Firm_i \\ & + \varepsilon_{i,n} \end{aligned} \tag{4.10}$$

where:

$D_1 \sim D_{12}$: are time indicator variables. Each indicator represents one thirty-minute time interval.

$Firm_i$: is an indicator variable takes value of 1 if firm classify as high price impact firms and 0 if firm classify as low price impact firms.

DC_i: is an indicator variable takes value of 1 on cum-dividend day and 0 otherwise.

DE_i: is an indicator variable takes value of 1 on ex-dividend day and 0 otherwise.

The two dependent variables are defined for each stock (i) during a five-minute time interval (n) as follows:

$$Monetary\, Ratio = ln\left(\frac{\sum_{n=1}^{N} P_{i,j,B} * Q_{i,j,B}}{\sum_{n=1}^{N} P_{i,jS} * Q_{i,j,S}}\right) \tag{4.11}$$

$$Number\, Ratio = ln\left(\frac{\sum_{n=1}^{N} Q_{i,j,B}}{\sum_{n=1}^{N} Q_{i,j,S}}\right) \tag{4.12}$$

where:

$Q_{i,j,B}$: is number of share for stock (i) at trade (j) if the trade is buy order.

$Q_{i,j,S}$: is number of share for stock (i) at trade (j) if the trade is sell order.

$P_{i,j,B}$: is price of stock (i) at trade (j) if the trade is buy order.

$P_{i,j,S}$: is price of stock (i) at trade (j) if the trade is sell order.

Indicator variables $D_1 \sim D_6$ represent, in order, the first six thirty-minute time intervals of the trading day while variables $D_6 \sim D_{12}$ represent, in order, the last six thirty-minute time intervals of the trading day. The coefficients for the indicator variables,

$a_1 \sim a_{12}$ measure the differences between the average value during each respective thirty-minute interval and the average value for the middle of the trading day, between 11:00 a.m. - 13:30 p.m., for low price impact firms.

$b_1 \sim b_{12}$ measure the differences between the average value during each respective thirty-minute interval and the average value for the middle of the trading day, between 11:00 a.m. - 13:30 p.m., for high price impact firms.

$c_1 \sim c_{12}$ measure the differences between the average value during each respective thirty-minute interval and the average value for the middle of the trading day, between 11:00 a.m. - 13:30 p.m., for low price impact firms, on cum-dividend day.

$d_1 \sim d_{12}$ measure the differences between the average value during each respective thirty-minute interval and the average value for the middle of the trading day, between 11:00 a.m. - 13:30 p.m., for low price impact firms, on ex-dividend day.

$e_1 \sim e_{12}$ measure the differences between the average value during each respective thirty-minute interval and the average value for the middle of the trading day, between 11:00 a.m. - 13:30 p.m., for high price impact firms, on cum-dividend day.

$h_1 \sim h_{12}$ measure the differences between the average value during each respective thirty-minute interval and the average value for the middle of the trading day, between 11:00 a.m. - 13:30 p.m., for high price impact firms, on ex-dividend day.

Table 4.3 reports results of GMM estimation of model (4.10).[24,25,26]

Table 4.3 – GMM estimation of intraday variation in the ratio of total monetary amount of all buy orders to the total monetary amount of sell orders
The table presents the coefficient from estimating model (4.10) for all firms as one pool for the ratio of total monetary amount of all buy orders to the total monetary amount of sell orders. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * p < 0.10, ** p < 0.05, *** p < 0.01.

Time	AT-F	IA-F	AT-F/ Cum.day	AT-F/ Ex.day	IA-F/ Cum.day	IA-F/ Ex.day
08:00-08:30	-0.023	-0.018	0.004	0.115**	-0.033	0.004
08:30-09:00	-0.026	-0.011	0.059	0.059	-0.105*	0.112*
09:00-09:30	-0.01	-0.019	0.011	0.118**	0.015	-0.07
09:30-10:00	-0.013	-0.007	-0.055	0.247***	0.014	0.06
10:00-10:30	-0.007	0.005	0.109	0.039	0.046	-0.018
10:30-11:00	0.033	-0.057*	-0.155*	0.121**	-0.055	0.012
13:30-14:00	0.004	0.042	-0.056	0.137***	-0.145**	-0.032
14:00-14:30	0.014	0.023	-0.013	0.077	-0.024	-0.015
14:30-15:00	-0.031**	0.009	0.013	0.073*	0.000	0.136***
15:00-15:30	-0.007	-0.009	0.070*	-0.006	-0.003	0.073
15:30-16:00	0.035**	-0.079***	0.116**	0.024	0.003	0.027
16:00-16:30	0.016	-0.024	0.039*	-0.019	-0.024	0.058
Indicators	0.025***	-0.022*	-0.023	-0.070***	0.011	0.052

For low price impact firms on cum-dividend days, the log ratio of buy volume to sell volume (monetary ratio) has significantly positive coefficients in the final one and a half hours. For low price impact firms on ex-dividend day, the monetary ratio has significantly positive coefficients in most of the thirty minute time interval during the first half of the trading day. The implication here is a significant impact of tax-arbitrageurs trading activities towards the end of cum-dividend days and beginning of ex-dividend days. As the cum-dividend trading deadline approaches, the trading activities of the tax-arbitrageurs increase. The results also indicate that the liquidity suppliers try to unwind their position they had on cum-dividend days during the first half of those trading days.[27]

[24]Since the GMM estimation does not show much variation between Monetary and Number ratios, only the results for Monetary ration are further reported.
[25]AT-F: low price impact firms
[26]IA-F: high price impact firms
[27]We arrive at similar conclusions when we employ difference-in-difference estimation instead of GMM.

4.5 Results

The results of the models presented in the methodology section are as follows. Table 4.4 and Table 4.5 reports results of model (4.4) using the data for all firms as one pool whereas Table 4.6 and Table 4.7 reports results for the mean value of the firm-by-firm GMM estimation of model (4.4).

Table 4.4 – GMM estimation of intraday variation in spread, volatility and volume
The table presents the coefficient from estimating model (4.4) for all firms as one pool for spread, volatility and volume separately over the ex-dividend week and the control week. The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Ex-dividend week			Control week		
Time	Spread	volatility	volume	Spread	volatility	volume
08:00-08:30	0.230***	4.940***	13.725***	0.203***	5.218***	20.032***
08:30-09:00	0.039***	1.466***	7.919***	0.034***	1.508***	8.570***
09:00-09:30	0.029***	0.903***	6.928***	0.028***	0.691***	6.775***
09:30-10:00	0.027**	0.426*	5.612***	0.013	0.326***	4.407***
10:00-10:30	0.005	-0.053	5.637***	-0.004	-0.156	8.309***
10:30-11:00	0.013	0.184	3.072**	0.007	0.329**	4.083***
13:30-14:00	-0.002	-0.087	2.720**	-0.016**	-0.099	2.166*
14:00-14:30	-0.012*	-0.094	0.921	-0.029***	-0.344***	2.248*
14:30-15:00	-0.019**	-0.651***	6.682***	-0.025***	-0.417***	3.352***
15:00-15:30	-0.015**	-0.362*	8.410***	-0.022***	-0.175*	7.456***
15:30-16:00	-0.022***	-0.462**	7.189***	-0.020***	-0.180	7.562***
16:00-16:30	-0.013**	-0.224	17.445***	-0.011*	-0.068	16.117***
Constant	0.118***	4.901***	52.247***	0.121***	3.531***	59.407***

Table 4.5 – GMM estimation of intraday variation in spread, volatility and volume
The table presents the coefficient from estimating model (4.4) for all firms as one pool for spread, volatility and volume separately over the cum-dividend day, ex-dividend day, day 2 and day 3 in the control week. The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Time	Spread	volatility	volume	Spread	volatility	volume
		Cum-dividend day			Day2	
08:00-08:30	0.217***	5.564***	8.440***	0.170***	4.988***	12.202***
08:30-09:00	0.003	1.226***	6.837***	0.050***	2.024***	0.233
09:00-09:30	0.048	1.050***	9.681***	0.035*	0.745**	1.832
09:30-10:00	0.007	-0.005	6.813***	-0.002	0.560**	-2.188
10:00-10:30	0.021	0.342	6.476**	-0.017	0.063	-2.714
10:30-11:00	-0.005	-0.005	4.582*	0.021	0.933***	5.914**
13:30-14:00	-0.023	-0.139	2.539	-0.035***	0.088	0.841
14:00-14:30	-0.026*	-0.333	0.184	-0.038***	-0.201	3.528
14:30-15:00	-0.034***	-0.150	11.151***	-0.031***	-0.289	4.380**
15:00-15:30	-0.034**	0.069	8.285***	-0.012	-0.234	6.149***
15:30-16:00	-0.027**	-0.134	8.564***	-0.031***	-0.502**	6.208***
16:00-16:30	-0.022	-0.253	18.029***	-0.011	-0.043	19.750***
Constant	0.096***	3.323***	57.970***	0.154***	4.030***	53.498***
		Ex-dividend day			Day3	
08:00-08:30	0.241***	4.976***	19.568***	0.228***	5.429***	24.769***
08:30-09:00	0.044***	1.094***	5.392	0.010	1.347***	9.969***
09:00-09:30	0.022	0.540***	5.565	0.027*	1.161***	7.988***
09:30-10:00	0.028	0.227**	2.146	-0.010	0.096	8.250***
10:00-10:30	-0.023*	0.051	-1.305	-0.016	-0.180	8.370***
10:30-11:00	0.008	0.053	4.250	-0.013	0.261	7.140***
13:30-14:00	0.003	0.072	-1.769	0.014	0.274	3.145
14:00-14:30	-0.001	-0.254**	-0.997	-0.022*	-0.347*	2.246
14:30-15:00	-0.025**	-0.292***	6.476	-0.026**	-0.549***	6.169**
15:00-15:30	-0.025*	-0.218**	8.216*	-0.021*	-0.189	6.954***
15:30-16:00	-0.011	-0.378***	6.848	-0.005	-0.461**	10.823***
16:00-16:30	-0.003	-0.195*	15.378***	-0.002	0.144	16.633***
Constant	0.161***	3.864***	92.779***	0.087***	3.059***	62.670***

Table 4.6 – GMM estimation of intraday variation in spread, volatility and volume

The table presents the mean coefficient from estimating model (4.4) for firm by firm for spread, volatility and volume separately over the ex-dividend week and the control week. The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Ex-dividend week			Control week		
Time	Spread	volatility	volume	Spread	volatility	volume
08:00-08:30	0.234***	4.886***	13.160***	0.206***	5.063***	18.815***
08:30-09:00	0.037***	0.899**	7.655***	0.033***	1.710***	8.111***
09:00-09:30	0.029**	0.454**	6.596***	0.029**	0.610***	6.600***
09:30-10:00	0.028	0.147	5.204**	0.015	0.200	4.483*
10:00-10:30	0.003	-0.107	5.526***	-0.003	-0.256	8.332***
10:30-11:00	0.013	-0.024	3.103**	0.006	0.603	3.877***
13:30-14:00	-0.002	0.035	2.489	-0.016*	-0.128	1.933
14:00-14:30	-0.013	-0.358	0.625	-0.029***	-0.422**	2.191*
14:30-15:00	-0.020**	-0.425	6.319***	-0.025***	-0.473***	3.065*
15:00-15:30	-0.014*	-0.275*	8.185***	-0.022***	-0.165	7.334***
15:30-16:00	-0.022**	-0.456**	6.929***	-0.021***	-0.116	7.432***
16:00-16:30	-0.014	-0.278	17.137***	-0.012*	-0.021	15.961***
Constant	0.179***	5.094***	89.309***	0.169***	4.977***	90.114***

Table 4.7 – GMM estimation of intraday variation in spread, volatility and volume.
The table presents the mean coefficient from estimating model (4.4) for firm by firm for spread, volatility and volume separately over the cum-dividend day, ex-dividend day, day 2 and day 3 in the control week. The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Time	Spread	volatility	volume	Spread	volatility	volume
	Cum-dividend day			Day2		
08:00-08:30	0.233***	5.747***	7.862*	0.172***	5.216***	12.137**
08:30-09:00	0.004	1.237***	6.874*	0.050**	2.172***	0.026
09:00-09:30	0.060	0.890**	9.401**	0.045**	1.101***	2.105
09:30-10:00	0.012	0.093	6.574*	0.001	0.773***	-2.465
10:00-10:30	0.023	0.409**	6.552**	-0.014	0.214	-2.603
10:30-11:00	-0.007	-0.033	5.387	0.025	0.859**	5.721
13:30-14:00	-0.024	-0.075	2.341	-0.034*	0.051	0.695
14:00-14:30	-0.026	-0.288	-0.135	-0.035***	-0.073	3.460
14:30-15:00	-0.034**	0.003	10.758***	-0.027**	-0.075	4.292
15:00-15:30	-0.041**	-0.225	8.133**	-0.007	0.057	6.078*
15:30-16:00	-0.031*	-0.314	8.298***	-0.025***	-0.255	6.039*
16:00-16:30	-0.021	-0.243	17.763***	-0.007	0.095	19.767***
Constant	0.186***	4.842***	88.544***	0.167***	4.594***	92.068***
	Ex-dividend day			Day3		
08:00-08:30	0.253***	5.251***	20.037***	0.227***	5.273***	24.981***
08:30-09:00	0.049**	1.670***	4.956	0.011	1.325***	10.138**
09:00-09:30	0.025	1.036***	5.209	0.025**	0.993***	7.623*
09:30-10:00	0.034	0.664*	1.652	-0.011	0.118	7.864
10:00-10:30	-0.020	0.214	-1.276	-0.018	-0.339	8.161**
10:30-11:00	0.012	0.454	5.251	-0.017	-0.222	7.277**
13:30-14:00	0.002	0.051	-1.563	0.011	0.237	2.967
14:00-14:30	-0.001	0.112	-0.998	-0.023	-0.467*	2.058
14:30-15:00	-0.022	-0.344	7.295*	-0.028*	-0.650***	5.992
15:00-15:30	-0.024	-0.198	8.427**	-0.025***	-0.376**	6.883*
15:30-16:00	-0.009	-0.215	7.972**	-0.004	-0.377**	10.515***
16:00-16:30	-0.002	-0.033	16.206***	-0.010	-0.343	16.389***
Constant	0.177***	4.681***	91.655***	0.162***	4.670***	91.880***

The results are also presented graphically. Figures4.13 and 4.14 present results for the spread model when the sample is all firms and when estimated firm-by-firm respectively.

Figure 4.13 – GMM estimation of intraday variation in spreads- across the first six and the last six thirty- minute time intervals -All firms as one pool

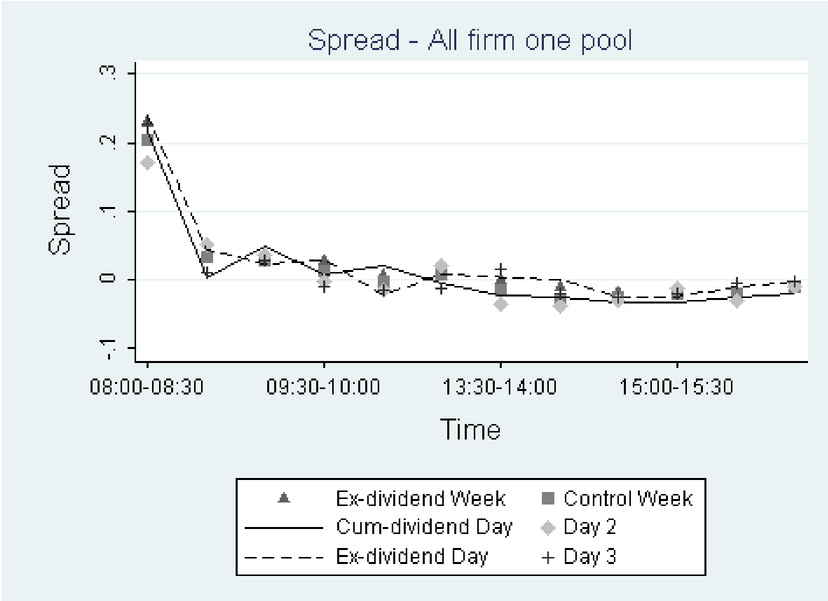
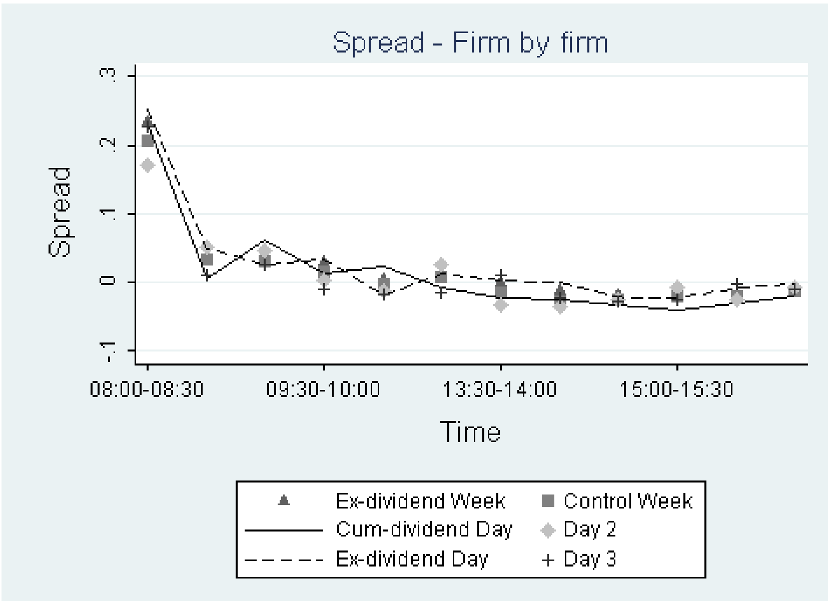


Figure 4.14 – The mean of GMM estimation of intraday variation in spreads - across the first six and the last six thirty- minute time intervals -firm by firm



For the spread model reported in Table 4.4, Table 4.5, Table 4.6, and Table 4.7, the first six thirty-minute time intervals are generally positive and the last six thirty-minute time intervals are negative. Consistent with Chan et al. (1995); McInish and Van Ness (2002) and Madhavan (1992) who find that spread is the highest during the opening hours, and then declines until the market closes, we find that, the results suggest spread, for a sample of FTSE 100 firms, shows an L-shaped pattern.

On the cum-dividend day the spread from 13:30 p.m. till the end of the trading day records the lowest value compared with the ex-dividend and control weeks, ex-dividend day, as well as for days 2 and 3 in the control week. This low spread on the second half of the cum-dividend day could be explained by the cum-dividend day trading deadline. As this deadline approaches, competition between traders increases, leading to lower spread. Furthermore, out of twelve thirty-minute time intervals, six reports the highest spread value on the ex-dividend day compared with the ex-dividend and control weeks, cum- dividend day, as well as for days 2 and 3 in the control week. In the absence of a trading deadline on the ex-dividend day, traders can submit less aggressive orders leading to wider spreads.

Figures 4.15 and 4.16 illustrate the results for the volume models for the sample of all firms and for firm-by-firm cases, respectively.

Figure 4.15 – GMM estimation of intraday variation in volume – across the first six and the last six thirty- minute time intervals -All firms as one pool

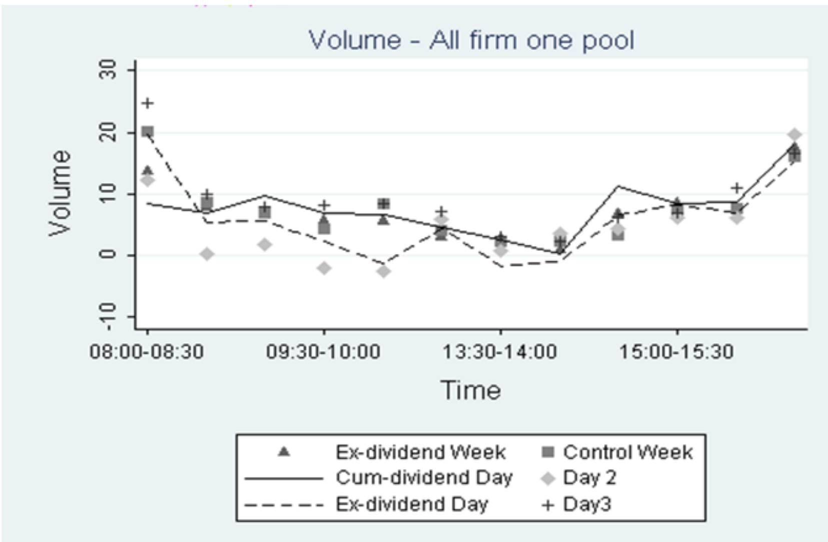
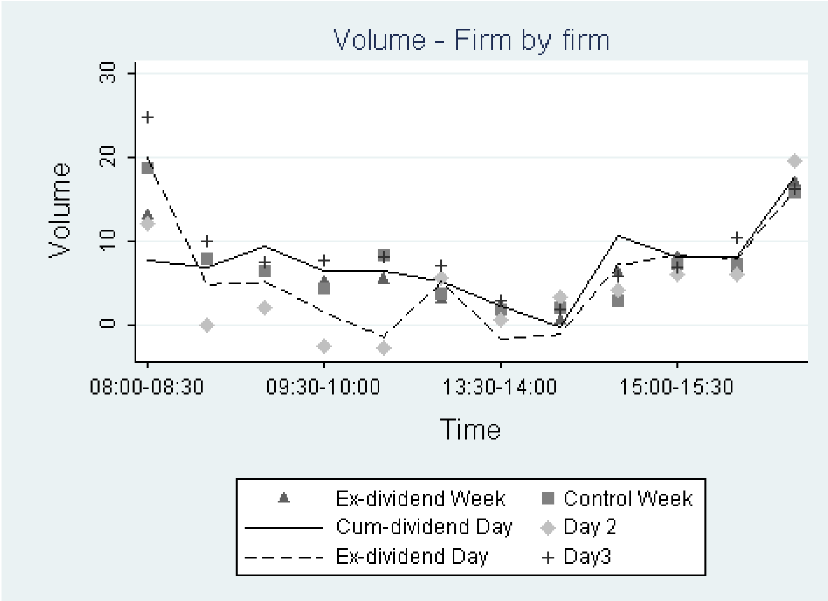


Figure 4.16 – The mean of GMM estimation of intraday variation in volume- across the first six and the last six thirty- minute time intervals -firm by firm



For the volume model reported in Table 4.4, Table 4.5, Table 4.6, and Table 4.7, most of the thirty-minute time intervals are positive. Consistent with studies in other markets,[28] we find that the intraday volume for a sample of FTSE 100 stocks shows a U-shaped pattern.

The volume in the first half hour of trading on the cum-dividend day is lower than the volume in the first half an hour for the ex-dividend and control weeks, the ex-dividend day, as well as for days 2 and 3 in the control week. However, the volume during the rest of the cum-dividend day has relatively higher value in comparison with the ex-dividend and control weeks, with the ex-dividend day, as well as for days 2 and 3 in the control week. The traders on the cum-dividend day may skip the first half an hour and trade during the rest of the cum-dividend day to avoid trading with the informed traders. Moreover, we find that as the cum-dividend trading deadline approaches, trading volume becomes much higher. Furthermore, the volume on the ex-dividend day is low between 08:30 a.m. - 11:00 a.m. and between 13:30 p.m. - 14:30 p.m. The constant term for the ex-dividend

[28]See Sweden (Niemeyer and Sandas, 1993); Finland (Hedvall, 1994); Paris (Biais et al., 1995); Toronto (McInish and Wood, 1990); London (Werner and Kleidon, 1996); Hong Kong (Ho and Cheung, 1991); NASDAQ (Chan et al., 1995); NYSE (Gerety and Mulberin, 1992) and Taiwan (Lee et al., 2001).

day volume model has significantly the highest value (92.779) in comparison with the ex-dividend and control weeks, cum-dividend day, as well as for days 2 and 3 in the control week. Similarly to the cum-dividend day, traders on the ex-dividend day might also avoid trading during the early hours of the trading day.

Figures 4.17 and 4.18 illustrate the results for the volatility models for the sample of all firms and for firm-by-firm cases, respectively.

Figure 4.17 – GMM estimation of intraday variation in volatility – across the first six and the last six thirty- minute time intervals -All firms as one pool

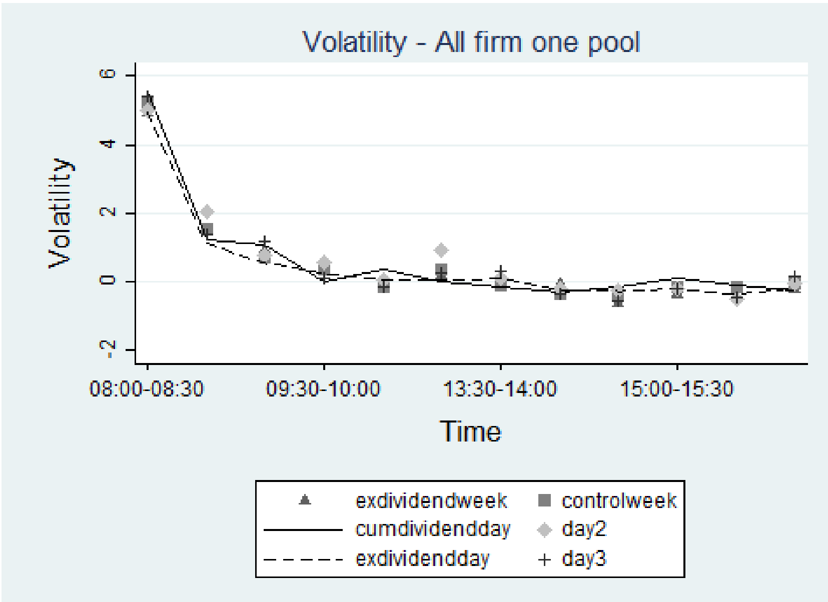
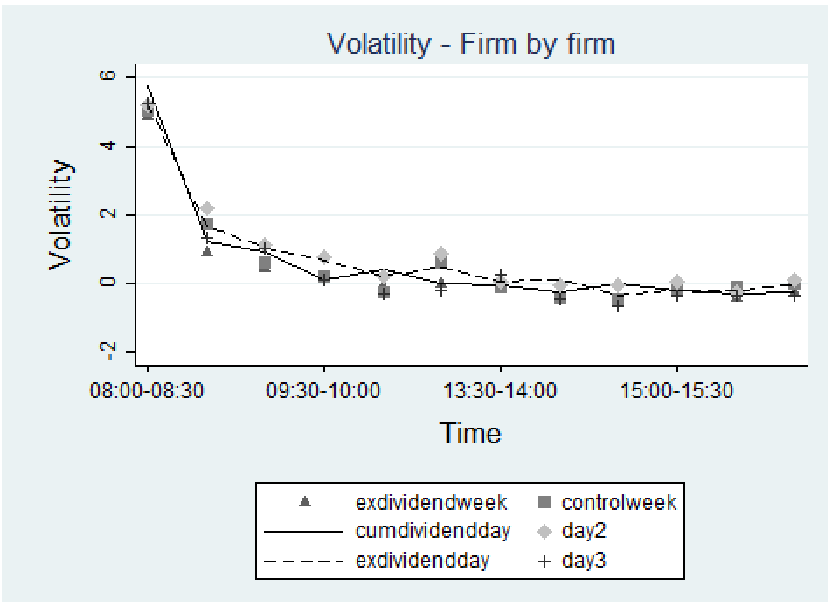


Figure 4.18 – The mean of GMM estimation of intraday variation in volatility- across the first six and the last six thirty- minute time intervals -firm by firm



For the volatility model reported in Table 4.4, Table 4.5, Table 4.6, and Table 4.7, most of the first six thirty-minute time intervals are generally positive and most of the last six thirty-minute time intervals are negative. We find that, the results suggest volatility, for a sample of FTSE 100 firms, shows an L-shaped pattern.

There is an effect of the ex-dividend day on the intraday patterns of spread and volume. The high waiting cost of no-trade on the cum-dividend day increases the competition between traders, resulting in higher volumes and lower spreads. The absence of trading deadlines on the ex-dividend day helps traders execute their orders with better prices leading to a wider spread. Furthermore, traders on the cum- and ex- dividend days may avoid the information effects associated with market opening trading. They may instead trade during the middle of the trading day.

Table 4.8, Table 4.9, Table 4.10, Table 4.11, Table 4.12 and Table 4.13 report, from employing the first classification, the mean values of the results from a GMM estimation for the firm-by-firm case of model (4.4) by Arbitrage, Information asymmetry and the "No classification" types.

Table 4.8 – GMM estimation of intraday variation in spread, volatility and volume
The table presents the mean coefficient from estimating model (4.4) firm by firm for all firms in the first type (Arbitrage) from classification 1 for spread, volatility and volume separately over the ex-dividend week and the control week. The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Ex-dividend week			Control week		
Time	Spread	volatility	volume	Spread	volatility	volume
08:00-08:30	0.152***	3.110***	19.618***	0.134***	3.480***	27.698***
08:30-09:00	0.024*	0.739***	11.638***	0.011**	0.665***	11.453***
09:00-09:30	0.024**	0.591***	6.491**	0.000	0.392***	7.347*
09:30-10:00	0.011	0.190*	8.913**	-0.002	0.227***	5.499
10:00-10:30	0.001	0.083	8.003***	-0.009	-0.084	12.137**
10:30-11:00	0.004	0.030	4.874***	0.000	-0.026	5.100**
13:30-14:00	0.003	0.168*	1.985	-0.003	0.005	1.168
14:00-14:30	0.006	-0.003	2.867	-0.019**	-0.246***	1.698
14:30-15:00	0.002	0.078	10.768***	-0.015*	-0.166***	3.223
15:00-15:30	0.001	0.063	11.212***	-0.021***	-0.157*	7.027**
15:30-16:00	0.001	-0.039	9.523***	-0.005	-0.198**	7.599*
16:00-16:30	0.013**	-0.037	23.657***	0.000	-0.128	20.183***
Constant	0.133***	3.135***	113.377***	0.145***	3.311***	117.269***

Table 4.9 – GMM estimation of intraday variation in spread, volatility and volume.
The table presents the mean coefficient from estimating model (4.4) firm by firm for all firms in the first type (Arbitrage) from classification 1 for spread, volatility and volume separately over the cum-dividend day, ex-dividend day, day 2 and day 3 in the control week . The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * p < 0.10, ** p < 0.05, *** p < 0.01.

Time	Spread	volatility	volume	Spread	volatility	volume
	Cum-dividend day			Day2		
08:00-08:30	0.082***	2.701***	16.649**	0.124***	3.225***	20.985**
08:30-09:00	0.009	0.811***	11.367	-0.002	1.018***	2.443
09:00-09:30	0.013	0.568***	2.919	-0.001	0.329	-0.677
09:30-10:00	-0.008	-0.051	11.083*	-0.005	0.392*	-3.294
10:00-10:30	-0.013	0.102	6.265	-0.026*	-0.130	-3.408
10:30-11:00	-0.012	-0.072	6.986	-0.012	-0.105	13.508*
13:30-14:00	-0.016	0.059	4.667	-0.002	0.066	-1.608
14:00-14:30	0.010	0.236**	4.832	-0.031**	-0.224	2.072
14:30-15:00	0.000	0.143	18.989***	-0.015	-0.117	5.615
15:00-15:30	-0.004	0.054	11.698**	-0.028**	-0.095	6.960
15:30-16:00	-0.005	-0.041	11.489*	-0.009	-0.276*	6.165
16:00-16:30	0.028	0.070	24.804***	-0.004	-0.056	22.175***
Constant	0.126***	3.024***	111.323***	0.147***	3.26***	118.29***
	Ex-dividend day			Day3		
08:00-08:30	0.160***	3.439***	26.584**	0.096***	2.874***	29.747***
08:30-09:00	0.020	0.572*	7.878	-0.001	0.483**	4.815
09:00-09:30	0.047	0.854**	8.209	0.003	0.291	10.704
09:30-10:00	-0.004	0.146	7.532	-0.009	0.054	5.277
10:00-10:30	-0.031	-0.122	-1.813	0.001	-0.338***	6.230
10:30-11:00	-0.017	0.011	7.208	0.022	-0.066	0.732
13:30-14:00	0.003	-0.011	-4.166	0.010	-0.143	-1.081
14:00-14:30	-0.008	-0.201	5.957	-0.001	-0.48***	1.000
14:30-15:00	0.014	0.004	16.116**	-0.014	-0.324***	-0.830
15:00-15:30	0.001	0.085	12.388**	-0.023**	-0.422***	0.008
15:30-16:00	0.019	-0.059	12.202*	0.008	-0.321*	6.559
16:00-16:30	0.007	-0.078	23.467***	0.012	-0.258	17.832*
Constant	0.140***	3.202***	115.733***	0.138***	3.407***	119.084***

Table 4.10 – GMM estimation of intraday variation in spread, volatility and volume.
The table presents the mean coefficient from estimating model (4.4) firm by firm for all firms in the second type (Information Asymmetry) from classification 1 for spread, volatility and volume separately over the ex-dividend week and the control week. The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Ex-dividend week			Control week		
Time	Spread	volatility	volume	Spread	volatility	volume
08:00-08:30	0.607*	10.460***	5.224	0.386***	8.476***	8.430
08:30-09:00	0.103**	2.074***	4.775	0.089**	2.470**	4.176
09:00-09:30	0.106	1.165*	8.382*	0.094	0.826	8.768**
09:30-10:00	0.127	1.101	3.881	0.061	1.032*	4.169
10:00-10:30	0.043	0.136	1.535	0.006	0.086	5.075
10:30-11:00	0.068	0.588	1.054	0.034	1.003	2.939
13:30-14:00	-0.046	0.125	3.101	-0.059	-0.180	0.744
14:00-14:30	-0.078	-0.213	-1.209	-0.060	-0.469	3.020
14:30-15:00	-0.038	-0.404	5.292*	-0.043**	-0.589	4.561
15:00-15:30	-0.068*	-0.809	6.416	-0.012	-0.010	8.942***
15:30-16:00	-0.083*	-0.908	4.388	-0.048*	-0.561	7.481**
16:00-16:30	-0.086*	-0.452	9.294**	-0.028	0.002	8.882***
Constant	0.319**	8.749***	51.302***	0.260**	7.684***	52.550***

Table 4.11 – GMM estimation of intraday variation in spread, volatility and volume.
The table presents the mean coefficient from estimating model (4.4) firm by firm for all firms in the second type (Information Asymmetry) from classification 1 for spread, volatility and volume separately over the cum-dividend day, ex-dividend day, day 2 and day 3 in the control week . The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Time	Spread	volatility	volume	Spread	volatility	volume
	Cum-dividend day			Day2		
08:00-08:30	0.491**	13.287***	9.881	0.046	4.246***	6.201
08:30-09:00	-0.001	2.163	10.395	0.114	1.701	-4.525
09:00-09:30	0.249	1.298	12.861*	0.144*	1.547	8.857
09:30-10:00	0.129	0.645	11.888*	0.053	1.908**	-5.114
10:00-10:30	0.113	0.774	7.749*	-0.042	0.236	-3.300
10:30-11:00	-0.052	0.129	7.632	0.122	2.543*	-0.232
13:30-14:00	-0.095	-0.827	-0.777	-0.133	-0.252	-8.049
14:00-14:30	-0.146*	-2.120*	-8.612**	-0.085	-0.820	-0.460
14:30-15:00	-0.103**	-1.184**	4.768	-0.074	-0.570	2.663
15:00-15:30	-0.162*	-1.274	1.444	0.058	-0.541	3.462
15:30-16:00	-0.107	-1.737**	2.690	-0.075**	-1.112**	-2.029
16:00-16:30	-0.201*	-2.621**	2.816	-0.013	-0.041	5.741
Constant	0.365**	10.111***	51.177***	0.284**	8.373***	57.000***
	Ex-dividend day			Day3		
08:00-08:30	0.712	8.294**	3.829	0.582**	12.164***	2.945
08:30-09:00	0.160*	3.400*	-2.274	0.036	2.878**	15.810
09:00-09:30	0.031	1.920*	7.394	0.108**	2.288***	11.379
09:30-10:00	0.145**	2.870*	1.324	-0.057	-0.152	19.494
10:00-10:30	0.026	0.951	2.853	-0.070	-0.910	11.649
10:30-11:00	0.103	1.568	-3.683	-0.109	0.151	14.924**
13:30-14:00	-0.062	1.108	7.099	-0.027	0.907	4.992
14:00-14:30	0.020	2.364	-5.338	-0.078	-0.305	6.078*
14:30-15:00	-0.086	0.072	-1.004	-0.077	-1.238	11.007**
15:00-15:30	-0.108	-0.814**	3.636	-0.034**	-0.705	8.137***
15:30-16:00	-0.062**	0.165	3.103	-0.030	-0.218	6.907*
16:00-16:30	-0.051	0.509	6.614	-0.077	-0.401	9.705*
Constant	0.288**	7.778***	51.652***	0.253***	7.399***	50.263***

Table 4.12 – GMM estimation of intraday variation in spread, volatility and volume.
The table presents the mean coefficient from estimating model (4.4) firm by firm for all firms in the third type (No-classification) from classification 1 for spread, volatility and volume separately over the ex-dividend week and the control week. The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Ex-dividend week			Control week		
Time	Spread	volatility	volume	Spread	volatility	volume
08:00-08:30	0.166***	4.562***	8.539**	0.215***	5.505***	12.206*
08:30-09:00	0.022	0.552	3.856**	0.036**	2.706***	5.639*
09:00-09:30	0.000	-0.058	5.890	0.036***	0.791	4.613
09:30-10:00	0.003	-0.358	1.026	0.014	-0.227	3.317*
10:00-10:30	-0.014	-0.467	4.200	0.000	-0.638	4.941*
10:30-11:00	-0.001	-0.382	1.774	0.001	1.229	2.734
13:30-14:00	0.013	-0.180	2.852	-0.013*	-0.276	3.484
14:00-14:30	-0.006	-0.885	-1.413	-0.027**	-0.628	2.440
14:30-15:00	-0.040**	-1.087	1.044	-0.028**	-0.816**	2.156
15:00-15:30	-0.009	-0.462	5.099**	-0.027**	-0.250	6.976***
15:30-16:00	-0.024**	-0.783*	4.769**	-0.028**	0.199	7.193***
16:00-16:30	-0.015	-0.508	12.389***	-0.019*	0.106	13.830***
Constant	0.172***	5.910***	76.048***	0.157***	5.859***	72.649***

Table 4.13 – GMM estimation of intraday variation in spread, volatility and volume.
The table presents the mean coefficient from estimating model (4.4) firm by firm for all firms in the third type (No-classification) from classification 1 for spread, volatility and volume separately over the cum-dividend day, ex-dividend day, day 2 and day 3 in the control week . The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Time	Spread	volatility	volume	Spread	volatility	volume
	Cum-dividend day			Day2		
08:00-08:30	0.319*	6.165***	-4.460	0.300**	8.44***	2.938
08:30-09:00	-0.001	1.359**	-1.065	0.089*	3.995***	-1.021
09:00-09:30	0.027	1.128**	16.161*	0.058**	1.939***	2.554
09:30-10:00	-0.021	0.014	-1.762	-0.017	0.730**	-0.001
10:00-10:30	0.026*	0.649**	6.361	0.015	0.677	-1.147
10:30-11:00	0.023	-0.062	2.262	0.027	1.344	-2.010
13:30-14:00	0.002	0.118	0.798	-0.028	0.182	8.234
14:00-14:30	-0.014	-0.093	-2.573	-0.016	0.510	7.329
14:30-15:00	-0.046	0.404	2.926	-0.020	0.230	3.287
15:00-15:30	-0.030*	-0.083	6.669	-0.011	0.564	6.172
15:30-16:00	-0.029	0.023	6.808*	-0.023	0.202	9.899**
16:00-16:30	0.004	0.515	15.686**	-0.008	0.371	23.470***
Constant	0.177***	4.706***	76.651***	0.136***	4.538***	73.547***
	Ex-dividend day			Day3		
08:00-08:30	0.144**	6.220***	19.192***	0.230**	5.126***	29.446**
08:30-09:00	0.034	2.316**	4.577	0.014	1.705***	14.622**
09:00-09:30	-0.011	0.844	0.300	0.014	1.312**	1.509
09:30-10:00	0.030	0.272	-5.804	0.008	0.340	5.607
10:00-10:30	-0.029	0.307	-2.524	-0.018	-0.055	9.073
10:30-11:00	0.008	0.505	6.924	-0.026	-0.623*	12.452
13:30-14:00	0.036	-0.393	-2.272	0.031	0.424	7.522
14:00-14:30	-0.001	-0.584	-7.955*	-0.027	-0.529	1.504
14:30-15:00	-0.041	-1.032**	-0.214	-0.021*	-0.803**	12.865
15:00-15:30	-0.016	-0.279	5.555	-0.022	-0.150	15.709***
15:30-16:00	-0.022	-0.619	4.789	-0.008	-0.533	17.758***
16:00-16:30	0.009	-0.243	11.323	-0.006	-0.431	17.747***
Constant	0.172***	5.166***	79.321***	0.150***	5.042***	75.285***

Figures 4.19, 4.20 and 4.21 present the results for the spread model for the Arbitrage type, Information asymmetry type and No classification type respectively.

Figure 4.19 – The mean of GMM estimation of intraday variation in spreads- across the first six and the last six thirty- minute time intervals -Classification 1- Arbitrage

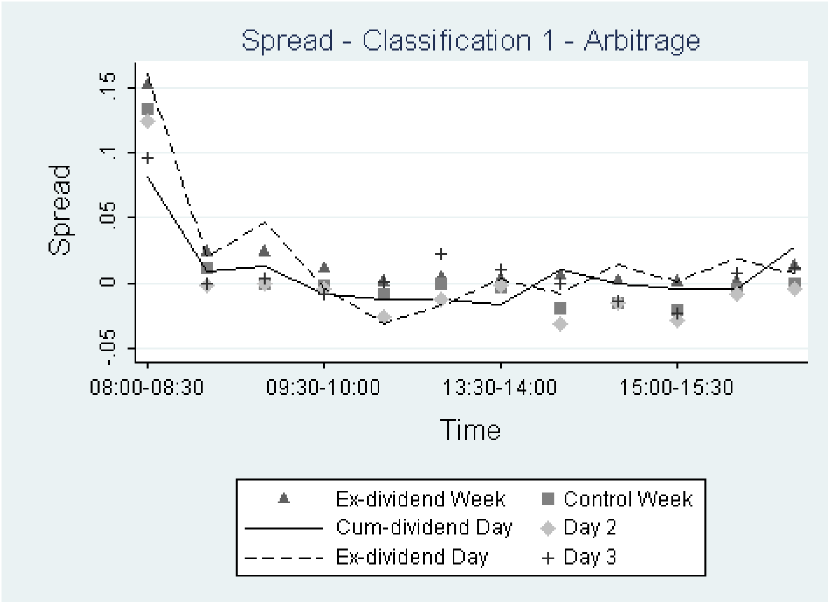


Figure 4.20 – The mean of GMM estimation of intraday variation in spreads- across the first six and the last six thirty- minute time intervals -Classification 1- Information asymmetry

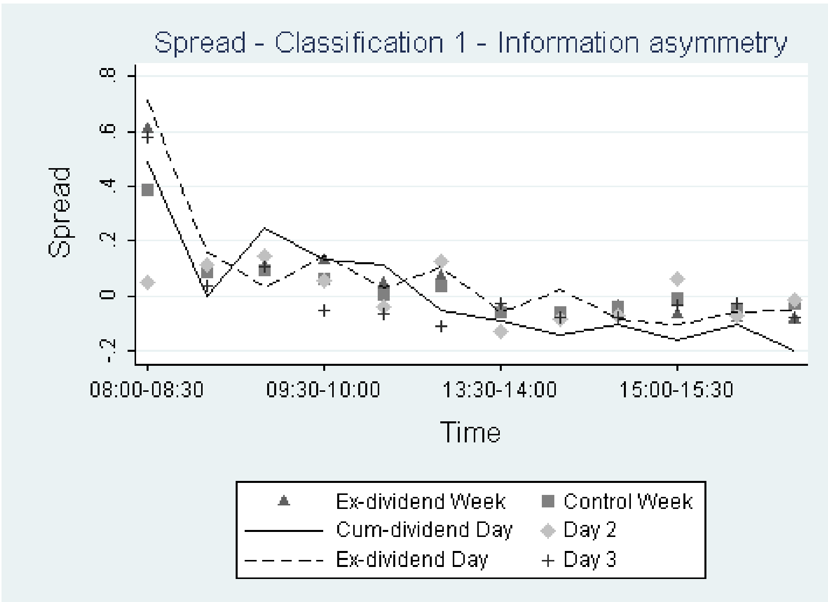


Figure 4.21 – The mean of GMM estimation of intraday variation in spreads- across the first six and the last six thirty- minute time intervals -Classification 1- No classification

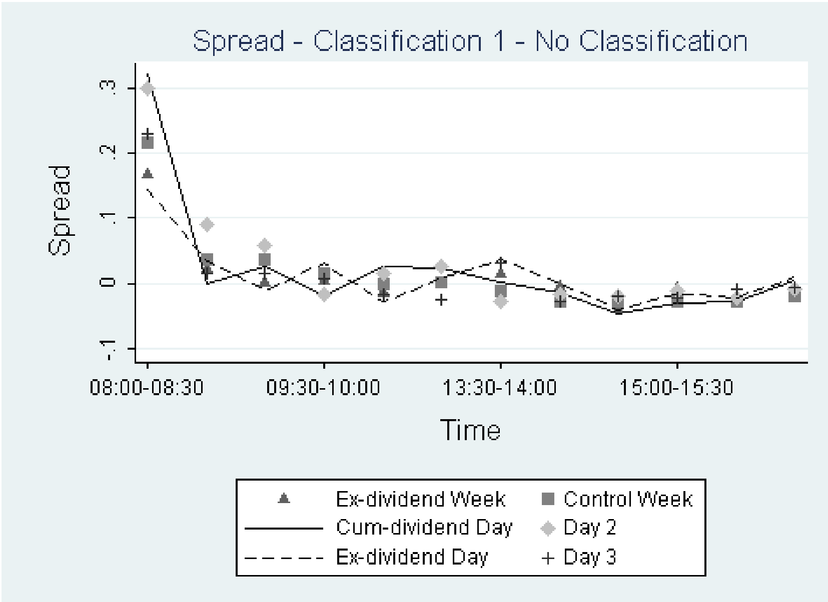


Table 4.14, Table 4.15, Table 4.16 and Table 4.17 report the mean values of firm-by-firm GMM estimation of model (4.4) for Arbitrage and Information asymmetry types respectively from the second classification.

Table 4.14 – GMM estimation of intraday variation in spread, volatility and volume.
The table presents the mean coefficient from estimating model (4.4) firm by firm for all firms in the first type (Arbitrage) from classification 2 for spread, volatility and volume separately over the ex-dividend week and the control week. The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Ex-dividend week			Control week		
Time	Spread	volatility	volume	Spread	volatility	volume
08:00-08:30	0.159***	3.110***	17.230***	0.145***	3.480***	26.561***
08:30-09:00	0.023**	0.739***	9.151***	0.012**	0.665***	10.789***
09:00-09:30	0.019**	0.591***	7.337**	0.012*	0.392***	7.337**
09:30-10:00	0.008	0.190*	7.485***	0.002	0.227***	4.825
10:00-10:30	0.003	0.083	7.561***	-0.006	-0.084	10.678***
10:30-11:00	0.000	0.030	3.999***	0.004	-0.026	5.650***
13:30-14:00	0.005	0.168*	3.081	-0.006	0.005	2.840
14:00-14:30	0.011*	-0.003	1.860	-0.021***	-0.246***	2.548
14:30-15:00	-0.004	0.078	7.811***	-0.017***	-0.166***	2.856
15:00-15:30	-0.004	0.063	9.233***	-0.020***	-0.157*	7.070***
15:30-16:00	-0.004	-0.039	8.358***	-0.011**	-0.198**	8.213***
16:00-16:30	0.010	-0.037	21.457***	-0.005	-0.128	19.594***
Constant	0.140***	3.135***	105.929***	0.145***	3.311***	106.938***

Table 4.15 – GMM estimation of intraday variation in spread, volatility and volume.
The table presents the mean coefficient from estimating model (4.4) firm by firm for all firms in the first type (Arbitrage) from classification 2 for spread, volatility and volume separately over the cum-dividend day, ex-dividend day, day 2 and day 3 in the control week . The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Time	Spread	volatility	volume	Spread	volatility	volume
		Cum-dividend day			Day2	
08:00-08:30	0.101***	2.701***	12.658**	0.153***	3.225***	17.723***
08:30-09:00	0.013	0.811***	10.395**	0.002	1.018***	2.910
09:00-09:30	0.016	0.568***	10.265*	0.010	0.329	1.654
09:30-10:00	-0.007	-0.051	9.533**	-0.007	0.392*	-2.084
10:00-10:30	-0.002	0.102	6.703*	-0.019	-0.130	-1.771
10:30-11:00	-0.004	-0.072	5.360	0.001	-0.105	8.818
13:30-14:00	-0.011	0.059	3.303	-0.011	0.066	3.708
14:00-14:30	0.015	0.236**	1.466	-0.028**	-0.224	5.043
14:30-15:00	-0.002	0.143	14.325***	-0.021	-0.117	3.248
15:00-15:30	-0.007	0.054	10.105**	-0.025***	-0.095	6.862
15:30-16:00	-0.005	-0.041	11.412***	-0.016	-0.276*	8.719*
16:00-16:30	0.029**	0.070	24.785***	-0.011	-0.056	25.654***
Constant	0.128***	3.024***	104.289***	0.147***	3.260***	106.419***
		Ex-dividend day			Day3	
08:00-08:30	0.147***	3.439***	24.750***	0.109***	2.874***	33.524***
08:30-09:00	0.012	0.572*	5.968	0.002	0.483**	9.495
09:00-09:30	0.032	0.854**	5.813	0.009	0.291	8.966*
09:30-10:00	-0.012	0.146	4.247	-0.004	0.054	6.808
10:00-10:30	-0.026	-0.122	-1.840	0.005	-0.338***	7.015*
10:30-11:00	-0.025**	0.011	7.553*	0.018	-0.066	6.635
13:30-14:00	0.007	-0.011	-2.955	0.011	-0.143	2.128
14:00-14:30	-0.004	-0.201	3.453	-0.008	-0.48***	3.246
14:30-15:00	-0.004	0.004	12.110**	-0.020*	-0.324***	6.946
15:00-15:30	-0.009	0.085	10.591**	-0.018*	-0.422***	6.994
15:30-16:00	0.007	-0.059	11.772**	-0.001	-0.321*	12.541***
16:00-16:30	0.002	-0.078	22.203***	0.005	-0.258	19.102***
Constant	0.147***	3.202***	108.214***	0.140***	3.407***	107.453***

Table 4.16 – GMM estimation of intraday variation in spread, volatility and volume

The table presents the mean coefficient from estimating model (4.4) firm by firm for all firms in the second type (Information Asymmetry) from classification 2 for spread, volatility and volume separately over the ex-dividend week and the control week. The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Ex-dividend week			Control week		
Time	Spread	volatility	volume	Spread	volatility	volume
08:00-08:30	0.418**	10.460***	4.779	0.363***	8.476***	2.639
08:30-09:00	0.072*	2.074***	5.205*	0.083***	2.470**	3.001
09:00-09:30	0.053	1.165*	6.166*	0.072*	0.826	5.405**
09:30-10:00	0.076	1.101	0.322	0.044	1.032*	4.606**
10:00-10:30	0.003	0.136	1.632	0.003	0.086	3.750
10:30-11:00	0.047	0.588	2.012	0.012	1.003	0.499
13:30-14:00	-0.017	0.125	1.010	-0.042	-0.180	-0.304
14:00-14:30	-0.067**	-0.213	-1.225	-0.050*	-0.469	1.093
14:30-15:00	-0.058**	-0.404	3.065	-0.045**	-0.589	4.281
15:00-15:30	-0.039	-0.809	6.304**	-0.028	-0.010	8.785***
15:30-16:00	-0.064**	-0.908	3.677	-0.048**	-0.561	6.642***
16:00-16:30	-0.069**	-0.452	8.512***	-0.030*	0.002	7.611***
Constant	0.276***	8.749***	53.137***	0.238***	7.684***	53.483***

Table 4.17 – GMM estimation of intraday variation in spread, volatility and volume.
The table presents the mean coefficient from estimating model (4.4) firm by firm for all firms in the second type (Information Asymmetry) from classification 2 for spread, volatility and volume separately over the cum-dividend day, ex-dividend day, day 2 and day 3 in the control week. The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the Generalized Methods of Moments (GMM) procedure together with the Parzen kernel correction for autocorrelation and heteroskedasticity with $k^{1/5}$ lags. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Time	Spread	volatility	volume	Spread	volatility	volume
	Cum-dividend day			Day2		
08:00-08:30	0.587**	13.287***	0.731	0.222*	4.246***	-2.008
08:30-09:00	-0.022	2.163	1.573	0.165**	1.701	-6.475
09:00-09:30	0.180	1.298	9.893*	0.133**	1.547	5.074
09:30-10:00	0.063	0.645	-0.027	0.022	1.908**	-2.534
10:00-10:30	0.090	0.774	7.396	-0.009	0.236	-3.770
10:30-11:00	-0.016	0.129	8.521	0.081*	2.543*	-0.426
13:30-14:00	-0.064	-0.827	-0.681	-0.092	-0.252	-6.608
14:00-14:30	-0.137**	-2.120*	-2.489	-0.054	-0.820	-0.296
14:30-15:00	-0.124***	-1.184**	4.195	-0.045	-0.570	7.719*
15:00-15:30	-0.135**	-1.274	4.702	0.038	-0.541	5.843
15:30-16:00	-0.104*	-1.737**	2.055	-0.051**	-1.112**	0.248
16:00-16:30	-0.158**	-2.621**	2.573	0.002	-0.041	7.327
Constant	0.351***	10.111***	52.623***	0.224***	8.373***	58.441***
	Ex-dividend day			Day3		
08:00-08:30	0.527	8.294**	9.420*	0.530***	12.164***	6.806
08:30-09:00	0.141**	3.400*	1.978	0.028	2.878**	11.743*
09:00-09:30	0.013	1.920*	4.503	0.065*	2.288***	4.898
09:30-10:00	0.148**	2.870*	-3.642	-0.032	-0.152	11.517
10:00-10:30	-0.001	0.951	0.378	-0.077*	-0.910	11.452
10:30-11:00	0.105**	1.568	0.027	-0.106**	0.151	8.564
13:30-14:00	-0.004	1.108	0.999	0.015	0.907	4.115
14:00-14:30	0.011	2.364	-10.059*	-0.061*	-0.305	-3.738
14:30-15:00	-0.063*	0.072	-2.854	-0.048	-1.238	4.058
15:00-15:30	-0.056	-0.814**	3.615	-0.044***	-0.705	6.144*
15:30-16:00	-0.044**	0.165	-0.786	-0.013	-0.218	5.470
16:00-16:30	-0.012	0.509	4.172	-0.046	-0.401	6.737*
Constant	0.255***	7.778***	55.773***	0.227***	7.399***	56.846***

Figures 4.22 and 4.23 present results for the spread model for the Arbitrage and Information asymmetry types respectively from the second classification.

Figure 4.22 – The mean of GMM estimation of intraday variation in spreads- across the first six and the last six thirty- minute time intervals -Classification 2- Arbitrage

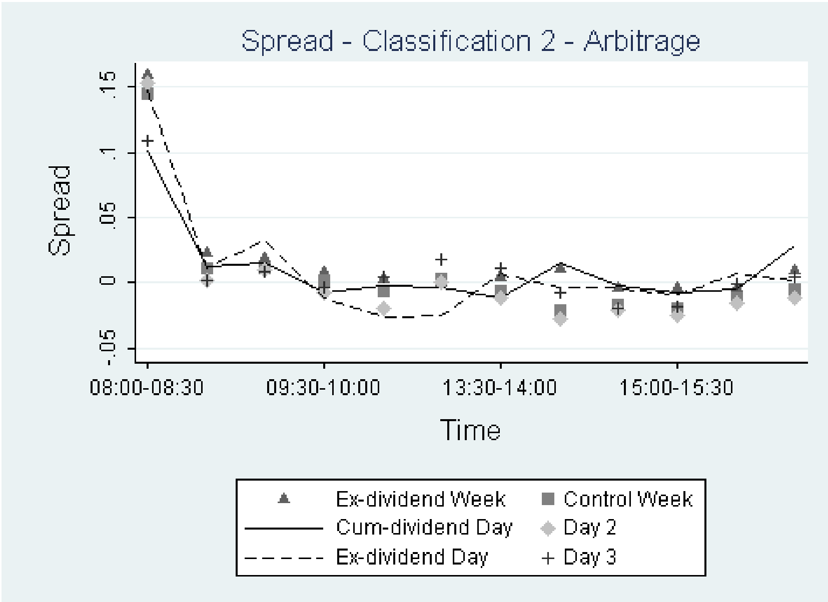
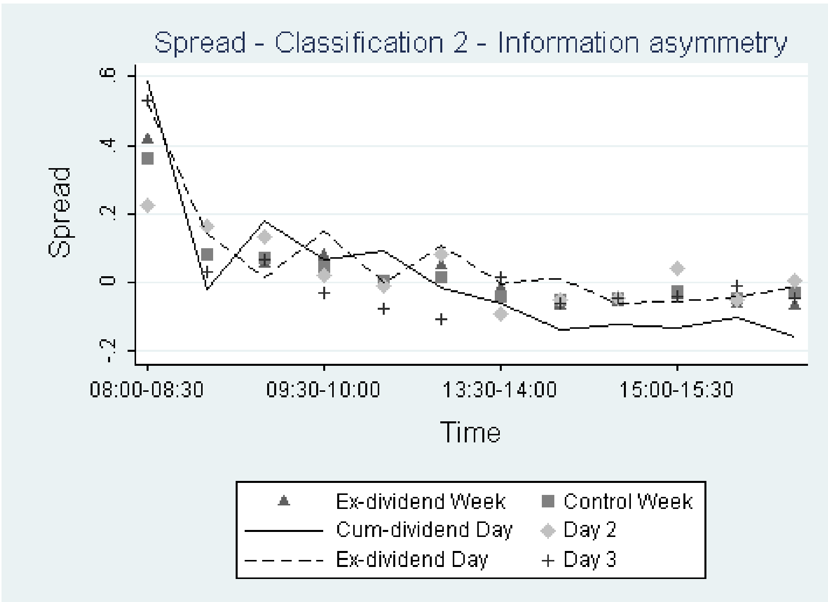


Figure 4.23 – The mean of GMM estimation of intraday variation in spreads- across the first six and the last six thirty- minute time intervals -Classification 2- Information asymmetry



For the Arbitrage type, in Figure 4.19, spread on the cum-dividend day has the lowest value during the first half an hour and the highest value during the last half an hour of trading. The second classification confirms this result. Similar patterns cannot be seen in the Information asymmetry or in the No classification types in the first classification and in the information asymmetry type in the second classification. The implication is that the arbitrager may seek to avoid the relatively higher adverse selection costs of trading in the first part of the day. Figures 4.20 and 4.23 show that the low value of spread during the second half of the day is related more to Information asymmetry. Figure 4.19 illustrates that on the ex-dividend day, spread, from 08:00 a.m. till 9:30 a.m. and from 14:30 p.m. till 16:00 p.m., records the highest value in comparison with ex-dividend and control weeks, cum- dividend day, as well as for days 2 and 3 in the control week, confirming that the absence of the cum-dividend deadline motivates the arbitrageur to trade less aggressively; consequently, the spread is wider.

Figures 4.24, 4.25 and 4.26 present the results for the volume model for Arbitrage type, Information asymmetry and No classification types respectively from the first classification.

Figure 4.24 – The mean of GMM estimation of intraday variation in volume- across the first six and the last six thirty- minute time intervals -classification 1 – Arbitrage

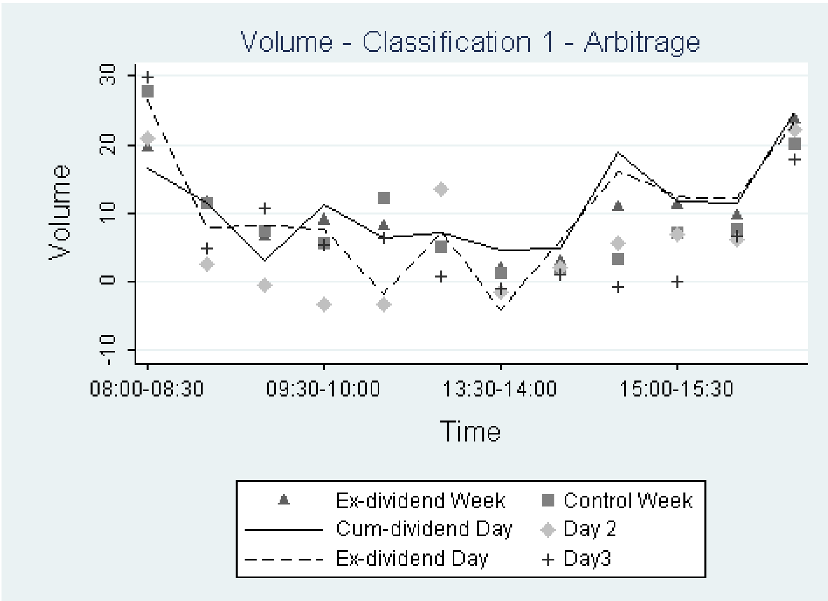


Figure 4.25 – The mean of GMM estimation of intraday variation in volume- across the first six and the last six thirty- minute time intervals -classification 1 – Information asymmetry

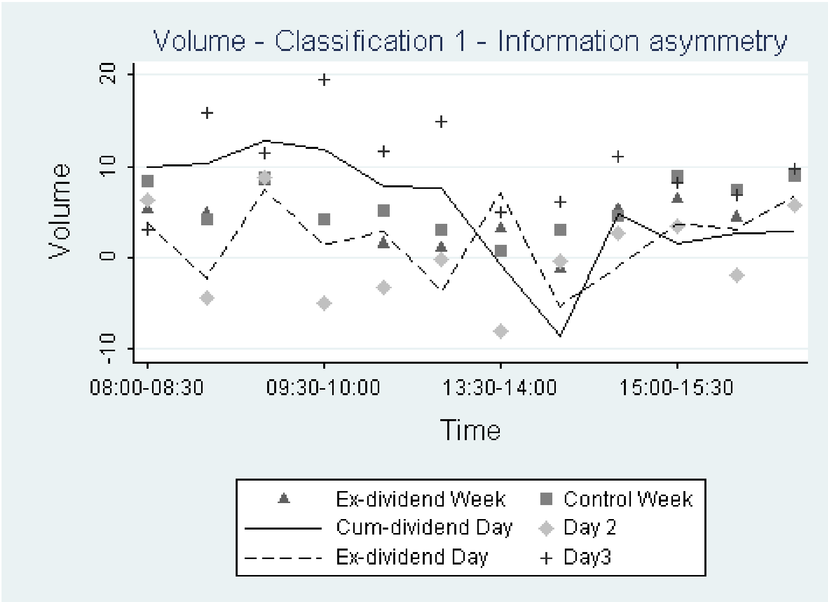
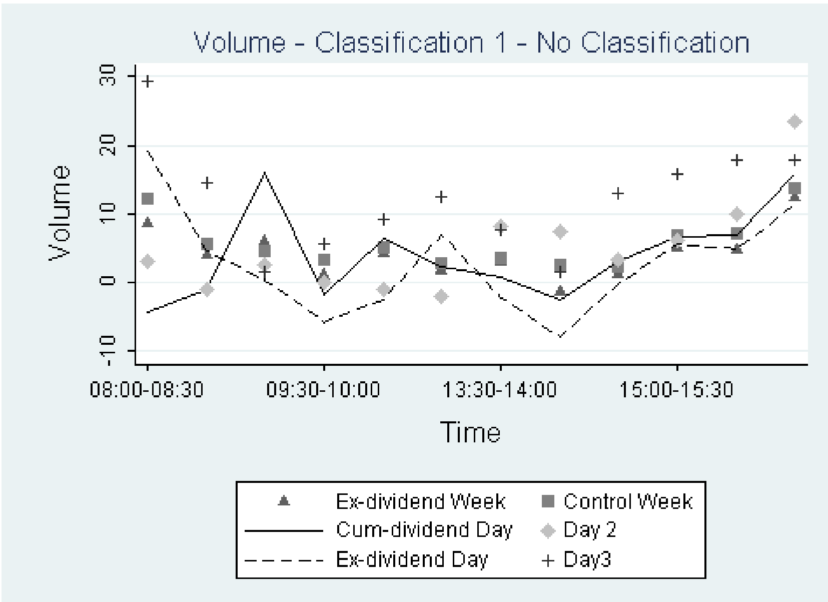


Figure 4.26 – The mean of GMM estimation of intraday variation in volume- across the first six and the last six thirty- minute time intervals -classification 1 – No classification



Figures 4.27 and 4.28 present the result for the volume model for the Arbitrage and Information asymmetry types respectively from the second classification.

Figure 4.27 – The mean of GMM estimation of intraday variation in volume- across the first six and the last six thirty- minute time intervals -classification 2 – Arbitrage

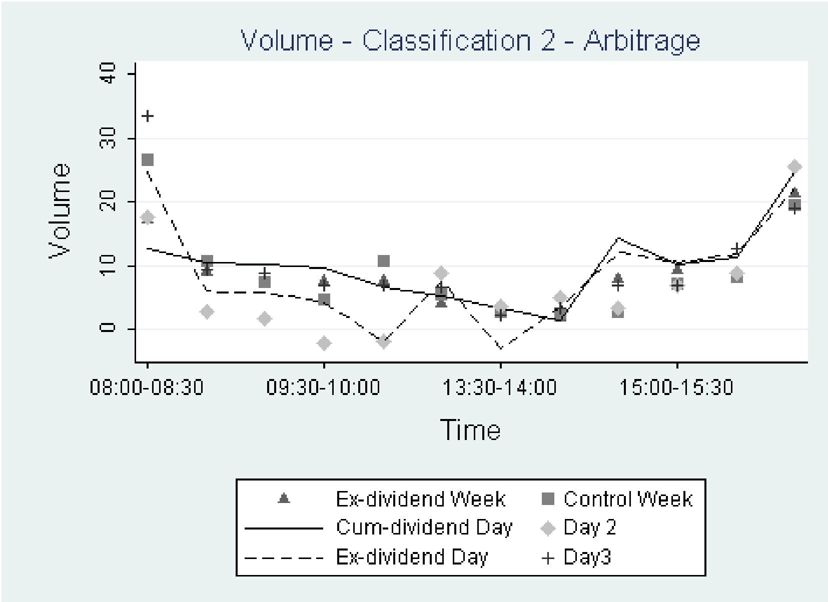
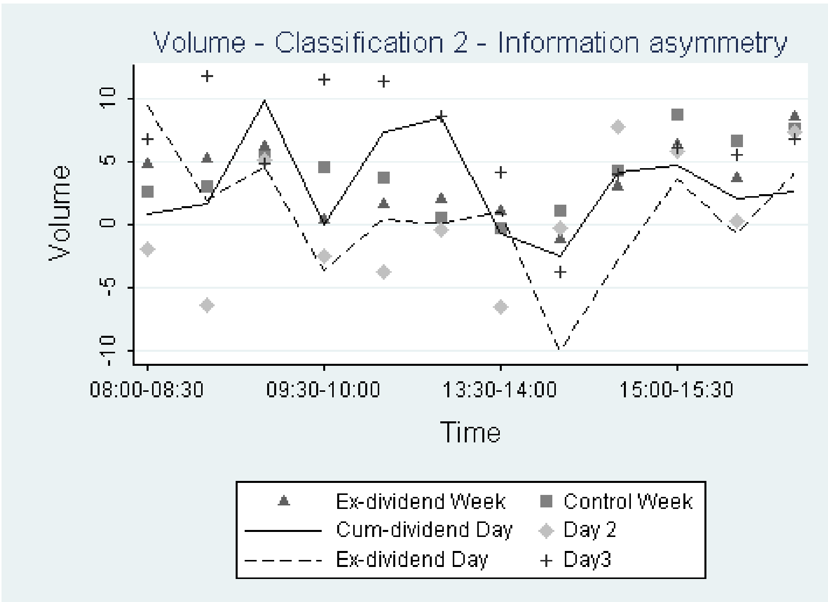


Figure 4.28 – The mean of GMM estimation of intraday variation in volume- across the first six and the last six thirty- minute time intervals -classification 2 – Information asymmetry



Figures 4.24 and 4.27 show a high value for volume on the cum-dividend day from 09:30 a.m. till the end of trading suggesting that high trading volumes around the cum-dividend day is more related to firms that are the most attractive to arbitrageurs. Moreover, in Figure 4.22 the ex-dividend day shows high trading volumes. The suggestion here is that a high volume of firms that are the most

attractive to arbitrageurs on cum-dividend day and ex-dividend day could be related to tax-arbitrage trading strategy. A similar pattern is not seen for the Information asymmetry and No classification types.

Figures 4.29, 4.30 and 4.31 present the results for the volatility model for Arbitrage type, Information asymmetry and No classification types respectively from the first classification.

Figure 4.29 – The mean of GMM estimation of intraday variation in volume- across the first six and the last six thirty- minute time intervals -classification 1 – Arbitrage

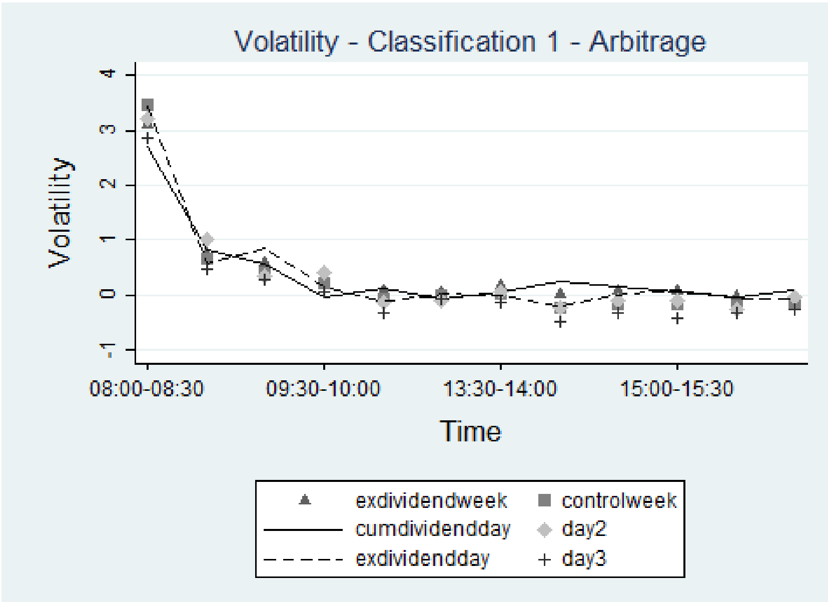


Figure 4.30 – The mean of GMM estimation of intraday variation in volume- across the first six and the last six thirty- minute time intervals -classification 1 – Information asymmetry

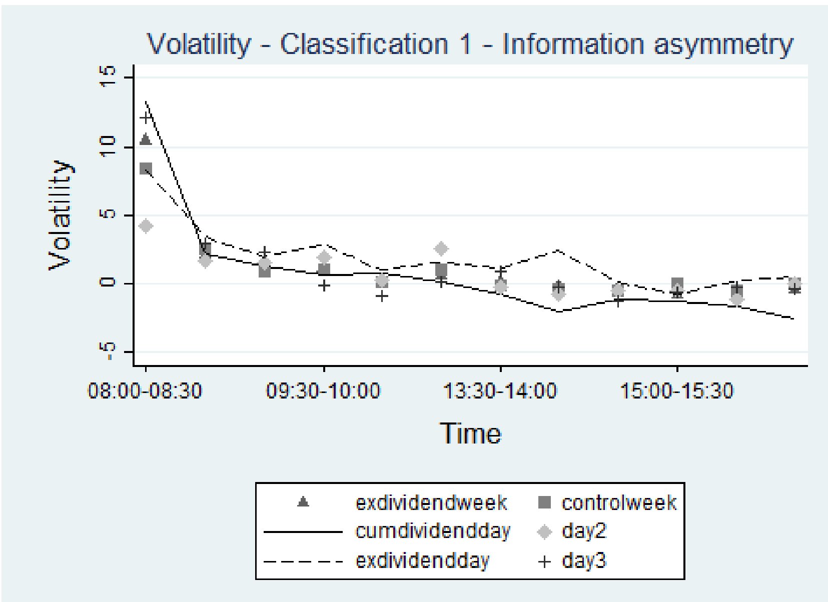
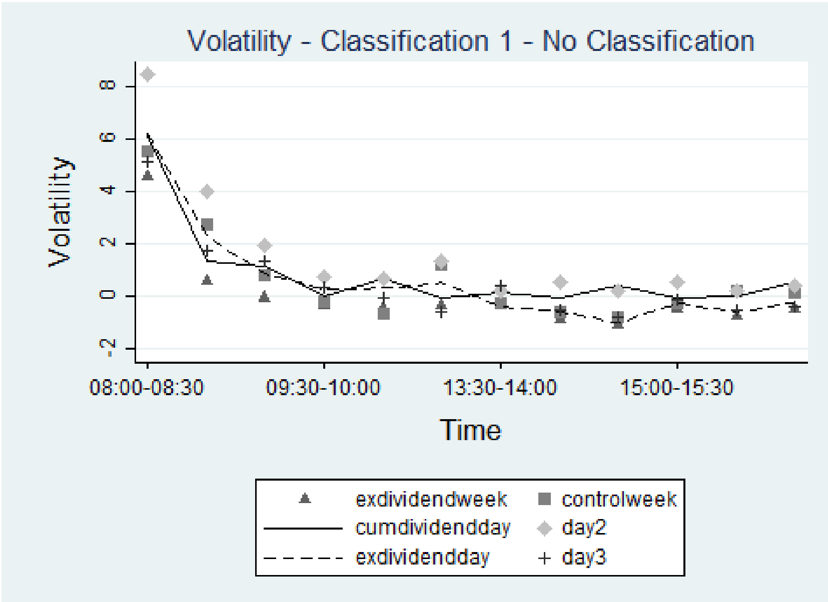


Figure 4.31 – The mean of GMM estimation of intraday variation in volume- across the first six and the last six thirty- minute time intervals -classification 1 – No classification



Figures 4.32 and 4.33 present the result for the volatility model for the Arbitrage and Information asymmetry types respectively from the second classification.

Figure 4.32 – The mean of GMM estimation of intraday variation in volume- across the first six and the last six thirty- minute time intervals -classification 2 – Arbitrage

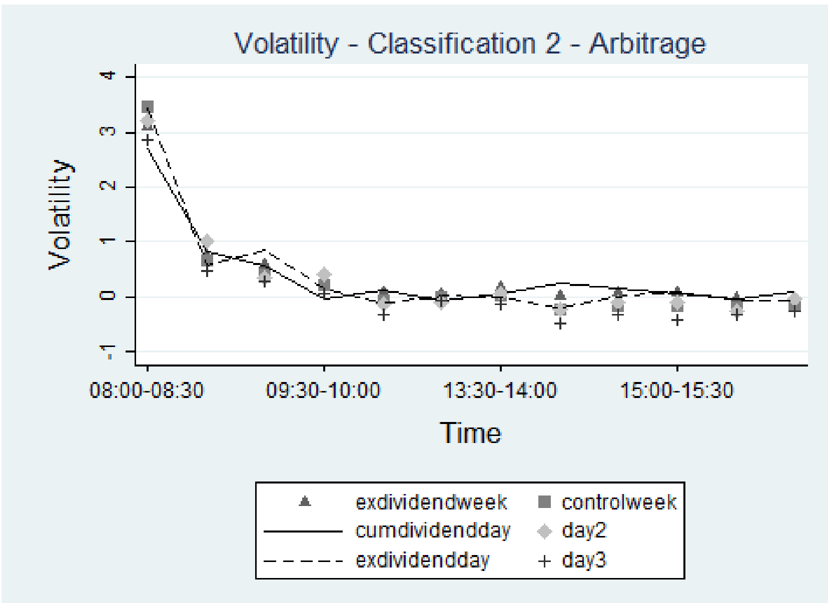
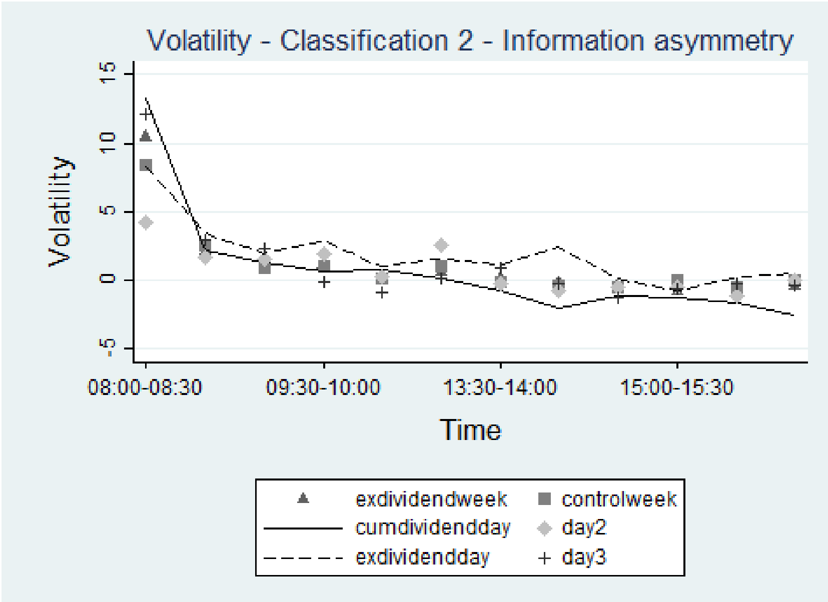


Figure 4.33 – The mean of GMM estimation of intraday variation in volume- across the first six and the last six thirty- minute time intervals -classification 2 – Information asymmetry



We can not see a significant effect of the ex-dividend event on intraday pattern of price volatility.

Finally, after distinguishing between firms that are the most attractive targets for tax-arbitrage (Arbitrage) and those that are the least attractive targets for tax-arbitrage (Information asymmetry), the conclusion is: There is high volume and spreads on both the cum-dividend day and the ex-dividend days confirming the effects of tax–arbitrage strategies on the spreads and trade volumes around the ex-dividend day. We report the differences in the spreads on cum- and ex-dividend days, but we cannot tell whether these differences are statistically significant just from looking at them. We do not, at the present time, know whether we can test for statistical significance in this context .

4.6 Robustness Test

This section provides additional tests to examine the robustness of the evidence presented above which documents, for firms that are most attractive target for tax-arbitrageurs (Arbitrage firms), a narrow (wider) spread at first (last) half an hour of cum-dividend day, a wide spread at the beginning and the end of ex-dividend day and high trading volume from 9:30 am till the end of cum-dividend day. For the robustness test, we first expand our sample to all firms that are listed on FTSE100 and have paid a cash dividend on any trading day between June 2007-June 2008. We also recalculate the spread variables using equation (**??**). Then, we apply differences in differences estimation using 167 ex-dividend events. The robustness test divides the sample periods, which consists of cum-dividend day, ex-dividend day and 10 days after ex-dividend days, into subsamples in order to determine if the change in bid-ask spreads and volume presented in above tables permanent through time and larger sample. The sample periods are divided into two subsamples according to their price volatility: high price volatility firms (IA-F) which is least attractive target for tax-arbitrageurs (84 firms) and low price volatility firms (AT-F) which is most attractive target firms for tax-arbitrageurs (83 firms). A full description how this classification has been done can be found in section 4.4.2.

Table (4.18) reports the difference in difference estimation of model (4.4), where the dependent variable is bid-ask spread in five-minutes interval, for both Arbitrage (AT-F) and Information asymmetry (IA-F) types over cum- and ex-dividend days and 10- days after ex-dividend day.

Table 4.18 – The differences in differences estimation of intraday variation in spread
The table presents the coefficient from estimating model (4.4) for all firms with low price volatility (Arbitrage (AT-F) and high price volatility (Information asymmetry (IA-F) for spread variable over cum-dividend day , ex-dividend day and 10 days after the ex-dividend day. The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the differences in difference procedure. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Spread	Middle interval (Mid) AT-F	Treated interval (Tre) AT-F	Middle interval (Mid) IA-F	Treated interval (Tre) IA-F	Diff-Mid&Tre (AT-F)	Diff-Mid&Tre (IA-F)	Diff-AT-F& IA-F (Tre)	Diff-AT-F& IA-F (Mid)	Diff-in-Diff
Cum-dividend day									
08:00-08:30	0.128	0.244	0.156	0.469	0.116***	0.314***	0.225***	0.028***	0.197***
08:30-09:00	0.128	0.155	0.156	0.226	0.027***	0.071***	0.071***	0.028***	0.043***
09:00-09:30	0.128	0.143	0.156	0.192	0.015	0.036***	0.049***	0.028***	0.021
09:30-10:00	0.128	0.137	0.156	0.175	0.009	0.019**	0.038***	0.028***	0.010
10:00-10:30	0.128	0.137	0.156	0.177	0.009	0.022**	0.041***	0.028***	0.013
10:30-11:00	0.128	0.133	0.156	0.173	0.005	0.017*	0.04***	0.028***	0.013
13:30-14:00	0.124	0.144	0.157	0.152	0.021**	-0.004	0.008	0.033***	-0.025*
14:00-14:30	0.129	0.125	0.157	0.152	-0.004	-0.004	0.027***	0.028***	-0.001
14:30-15:00	0.129	0.123	0.155	0.160	-0.006	0.005	0.037***	0.026***	0.011
15:00-15:30	0.130	0.122	0.154	0.162	-0.007	0.007	0.04***	0.025***	0.015
15:30-16:00	0.129	0.125	0.157	0.153	-0.003	-0.003	0.028***	0.028***	0.000
16:00-16:30	0.128	0.135	0.156	0.184	0.007	0.028***	0.049***	0.028***	0.021
Ex-dividend day									
08:00-08:30	0.134	0.240	0.163	0.320	0.106***	0.158***	0.081***	0.029***	0.052**
08:30-09:00	0.134	0.151	0.163	0.227	0.017*	0.064***	0.076***	0.029***	0.047***
09:00-09:30	0.134	0.149	0.163	0.179	0.015	0.017*	0.03**	0.029***	0.001
09:30-10:00	0.134	0.151	0.163	0.188	0.017	0.025**	0.036*	0.029***	0.008
10:00-10:30	0.134	0.134	0.163	0.164	-0.001	0.001	0.031**	0.029***	0.002
10:30-11:00	0.134	0.151	0.163	0.169	0.017*	0.006	0.018	0.029***	-0.011
13:30-14:00	0.133	0.138	0.161	0.171	0.005	0.010	0.032**	0.028***	0.005
14:00-14:30	0.134	0.135	0.162	0.168	0.001	0.006	0.033**	0.028***	0.006
14:30-15:00	0.135	0.130	0.164	0.156	-0.005	-0.008	0.026**	0.029***	-0.003
15:00-15:30	0.135	0.131	0.163	0.164	-0.004	0.001	0.032***	0.028***	0.005
15:30-16:00	0.134	0.136	0.164	0.156	0.003	-0.009	0.02*	0.031***	-0.011
16:00-16:30	0.134	0.155	0.163	0.167	0.021**	0.004	0.012	0.029***	-0.017
After Ex-dividend day									
08:00-08:30	0.141	0.269	0.169	0.441	0.128***	0.272***	0.172***	0.028***	0.144***
08:30-09:00	0.141	0.166	0.169	0.239	0.025***	0.071***	0.073***	0.028***	0.045***
09:00-09:30	0.141	0.154	0.169	0.214	0.013***	0.046***	0.061***	0.028***	0.033***
09:30-10:00	0.141	0.162	0.169	0.204	0.021***	0.035***	0.042***	0.028***	0.014***
10:00-10:30	0.141	0.149	0.169	0.189	0.008**	0.021***	0.041***	0.028***	0.013***
10:30-11:00	0.141	0.146	0.169	0.176	0.005	0.007**	0.03***	0.028***	0.002
13:30-14:00	0.140	0.145	0.165	0.181	0.005	0.016***	0.036***	0.026***	0.011**
14:00-14:30	0.140	0.143	0.166	0.177	0.002	0.011***	0.035***	0.026***	0.009*
14:30-15:00	0.141	0.140	0.169	0.168	-0.001	-0.001	0.028***	0.028***	0.000
15:00-15:30	0.142	0.136	0.171	0.159	-0.006*	-0.012***	0.023***	0.029***	-0.006
15:30-16:00	0.141	0.140	0.171	0.158	-0.001	-0.014***	0.018***	0.03***	-0.013***
16:00-16:30	0.141	0.157	0.169	0.175	0.016***	0.006*	0.018***	0.028***	-0.01**

Figures 4.34, 4.35 and 4.36 present the results graphically for the spread model over Arbitrage firm, Information asymmetry firms and difference in difference between both types respectively.

Figure 4.34 – The differences in differences estimation of intraday variation in spread across the first six and the last six thirty- minute time intervals -Arbitrage

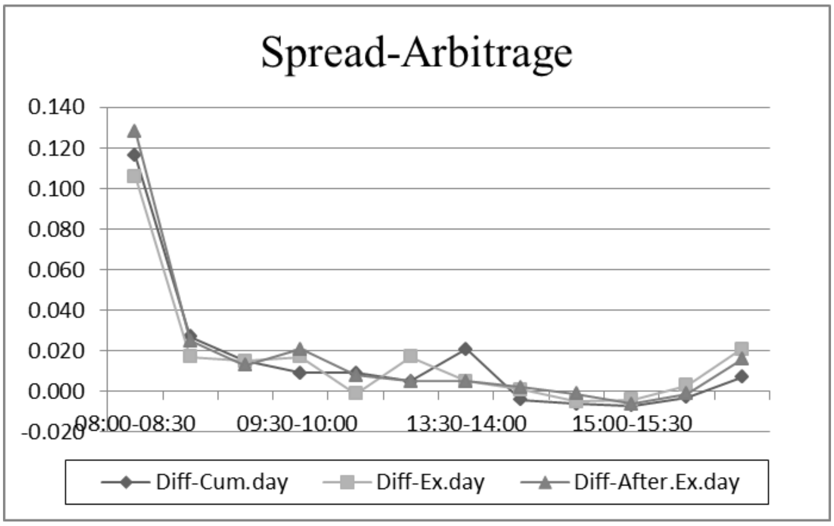


Figure 4.35 – The differences in differences estimation of intraday variation in spread across the first six and the last six thirty- minute time intervals -Information asymmetry

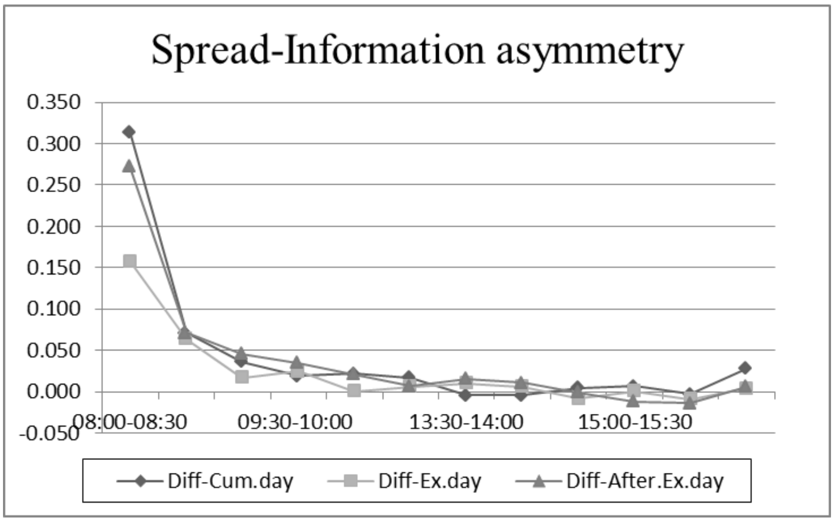
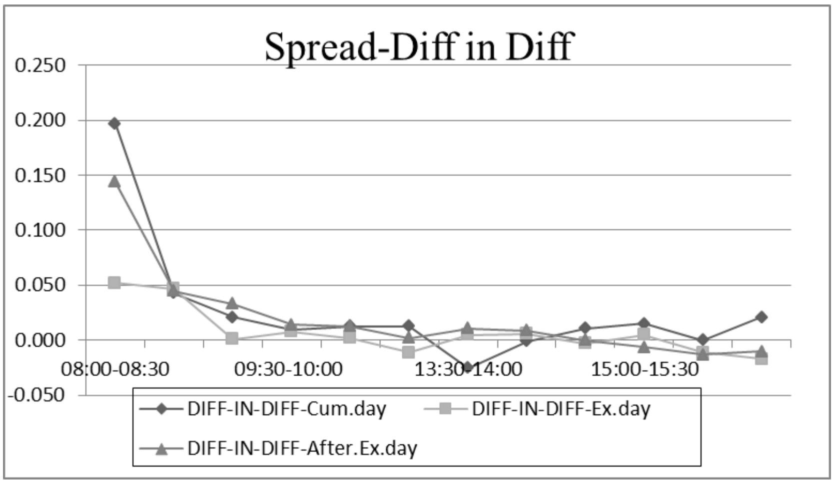


Figure 4.36 – The differences in differences estimation of intraday variation in spread across the first six and the last six thirty- minute time intervals



In Figure 4.36, the general picture is that the spread is wide at the start of the day then it decreases throughout the trading day. However, the spread on the cum-dividend day show an increase behaviour at the last half an hour. The implication is that the liquidity suppliers take advantage of tax-arbitrager by widening the spread on cum-dividend day, especially at the end of cum-dividend day, confirming the GMM estimation results. Interestingly, Figures 4.36 presents that the spread is low in the first half an our on ex-dividend day. The suggestion is that the liquidity suppliers are heavy currying their position from cum-dividend day, so they try to unwind their position early in the morning accepting cheaper prices. [29]

Table 4.19 reports the difference in difference estimation of model (4.4), where the dependent variable is trade volume in five-minutes interval, for both Arbitrage and Information asymmetry types over cum- and ex-dividend days and 10- days after ex-dividend day.

[29]We arrive at similar conclusions when we examine the live actual spread.

Table 4.19 – The differences in differences estimation of intraday variation in volume
The table presents the coefficient from estimating model (4.4) for all firms with low price volatility (Arbitrage (AT-F) and high price volatility (Information asymmetry (IA-F) for volume variable over cum-dividend day , ex-dividend day and 10 days after the ex-dividend day. The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the differences in difference procedure. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Volume	Middle interval (Mid) AT-F	Treated interval (Tre) AT-F	Middle interval (Mid) IA-F	Treated interval (Tre) IA-F	Diff-Mid&Tre (AT-F)	Diff-Mid&Tre (IA-F)	Diff-AT-F& IA-F (Tre)	Diff-AT-F& IA-F (Mid)	Diff-in-Diff
Cum-dividend day									
08:00-08:30	178.825	193.477	87.823	93.541	14.651***	5.718	-99.935***	-91.002***	-8.933
08:30-09:00	178.825	193.926	87.823	85.136	15.1***	-2.687	-108.79***	-91.002***	-17.788***
09:00-09:30	178.825	186.783	87.823	83.697	7.958*	-4.126	-103.086***	-91.002***	-12.083*
09:30-10:00	178.825	181.202	87.823	80.335	2.376	-7.488*	-100.867***	-91.002***	-9.865
10:00-10:30	178.825	175.643	87.823	80.720	-3.183	-7.103	-94.923***	-91.002***	-3.921
10:30-11:00	178.825	168.935	87.823	81.662	-9.89**	-6.161	-87.273***	-91.002***	3.729
13:30-14:00	182.599	163.733	88.759	84.056	-18.866***	-4.703	-79.676***	-93.839***	14.163**
14:00-14:30	179.461	176.262	89.234	82.059	-3.199	-7.175	-94.203***	-90.227***	-3.976
14:30-15:00	176.192	189.331	87.234	90.164	13.139***	2.931	-99.167***	-88.959***	-10.208
15:00-15:30	177.896	182.533	87.160	90.457	4.637	3.297	-92.076***	-90.736***	-1.340
15:30-16:00	177.976	182.216	86.717	92.195	4.241	5.478	-90.022***	-91.259***	1.237
16:00-16:30	178.825	215.110	87.823	99.945	36.284***	12.122**	-115.164***	-91.002***	-24.162***
Ex-dividend day									
08:00-08:30	181.506	209.733	87.816	93.760	28.227***	5.945	-115.973***	-93.69***	-22.283***
08:30-09:00	181.506	187.290	87.816	87.044	5.784	-0.771	-100.246***	-93.69***	-6.556
09:00-09:30	181.506	180.752	87.816	91.864	-0.754	4.048	-88.888***	-93.69***	4.802
09:30-10:00	181.506	183.366	87.816	84.066	1.860	-3.750	-99.3***	-93.69***	-5.610
10:00-10:30	181.506	170.658	87.816	82.837	-10.847**	-4.979	-87.822***	-93.69***	5.868
10:30-11:00	181.506	180.948	87.816	78.787	-0.557	-9.029**	-102.162***	-93.69***	-8.472
13:30-14:00	183.683	172.732	88.735	84.069	-10.951**	-4.666	-88.663***	-94.949***	6.285
14:00-14:30	184.026	171.427	88.976	83.144	-12.599***	-5.832	-88.283***	-95.05***	6.767
14:30-15:00	181.272	182.438	87.617	88.593	1.166	0.976	-93.845***	-93.654***	-0.190
15:00-15:30	179.080	191.203	86.944	91.307	12.123***	4.364	-99.896***	-92.136***	-7.760
15:30-16:00	179.462	189.655	86.799	91.854	10.193**	5.055	-97.801***	-92.663***	-5.138
16:00-16:30	181.506	207.886	87.816	99.308	26.38***	11.492**	-108.578***	-93.69***	-14.888***
After Ex-dividend day									
08:00-08:30	174.868	185.632	85.999	87.781	10.764***	1.781	-97.851***	-88.869***	-8.982***
08:30-09:00	174.868	177.103	85.999	87.364	2.235*	1.365	-89.739***	-88.869***	-0.870
09:00-09:30	174.868	173.594	85.999	85.032	-1.274	-0.968	-88.563***	-88.869***	0.306
09:30-10:00	174.868	168.177	85.999	81.997	-6.691***	-4.002***	-86.179***	-88.869***	2.689
10:00-10:30	174.868	179.879	85.999	85.300	5.011***	-0.700	-94.58***	-88.869***	-5.711**
10:30-11:00	174.868	168.281	85.999	83.279	-6.587***	-2.721**	-85.003***	-88.869***	3.866**
13:30-14:00	176.132	169.781	86.624	83.468	-6.351***	-3.156**	-86.313***	-89.509***	3.196*
14:00-14:30	176.039	170.174	86.343	84.603	-5.866***	-1.740	-85.571***	-89.697***	4.126**
14:30-15:00	173.901	178.724	85.955	86.176	4.822***	0.222	-92.547***	-87.947***	-4.6**
15:00-15:30	174.244	177.358	85.753	86.973	3.114**	1.220	-90.385***	-88.491***	-1.894
15:30-16:00	174.020	178.252	85.317	88.700	4.231***	3.383***	-89.552***	-88.703***	-0.849
16:00-16:30	174.868	201.013	85.999	97.203	26.144***	11.204***	-103.81***	-88.869***	-14.941***

Figures 4.37, 4.38 and 4.39 present the results graphically for the volume model over the Arbitrage firm, Information asymmetry firms and difference in difference between both types respectively. Figure 4.40 is exactly same as Figure 4.39 but we multiply all coefficients by (-1) to have a better view.

Figure 4.37 – The differences in differences estimation of intraday variation in volume across the first six and the last six thirty- minute time intervals -Arbitrage

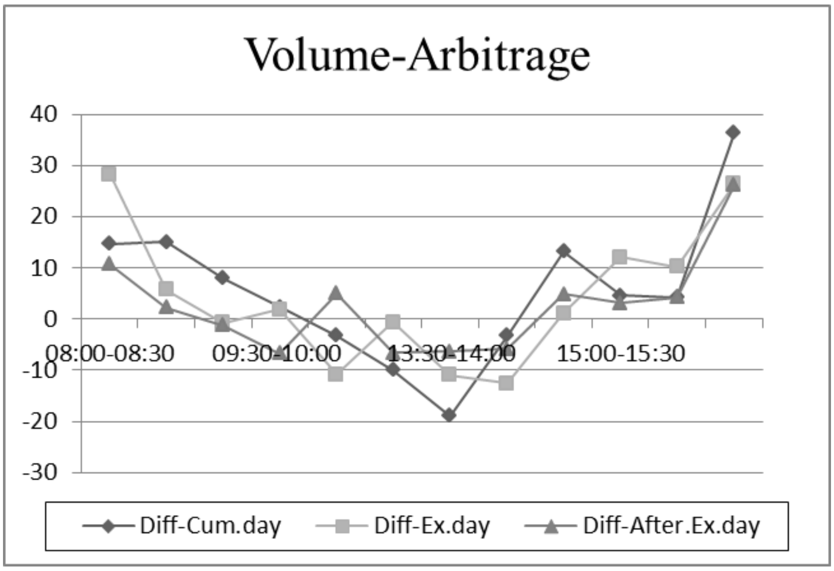


Figure 4.38 – The differences in differences estimation of intraday variation in volume across the first six and the last six thirty- minute time intervals -Information asymmetry

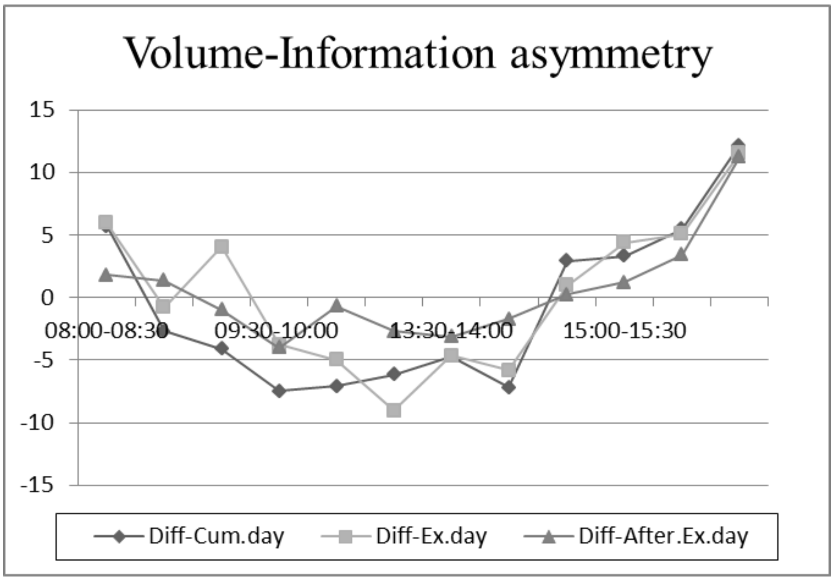


Figure 4.39 – The differences in differences estimation of intraday variation in volume across the first six and the last six thirty- minute time intervals -Information asymmetry

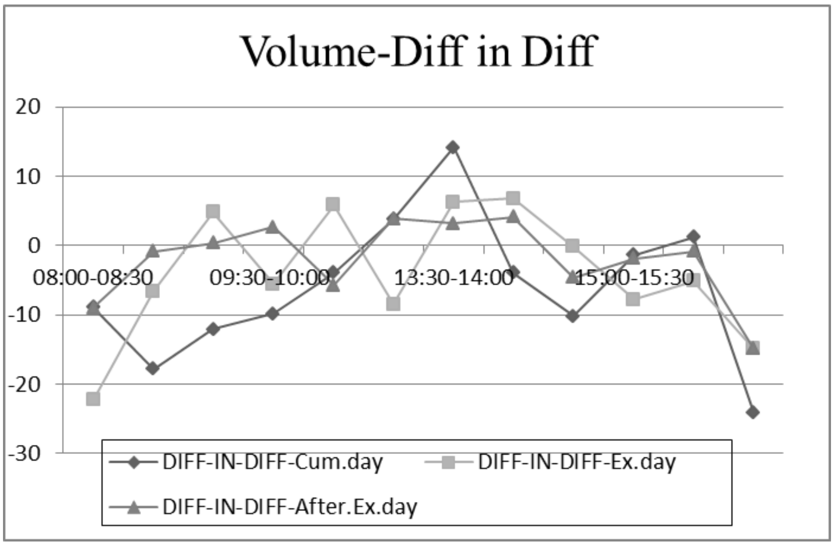
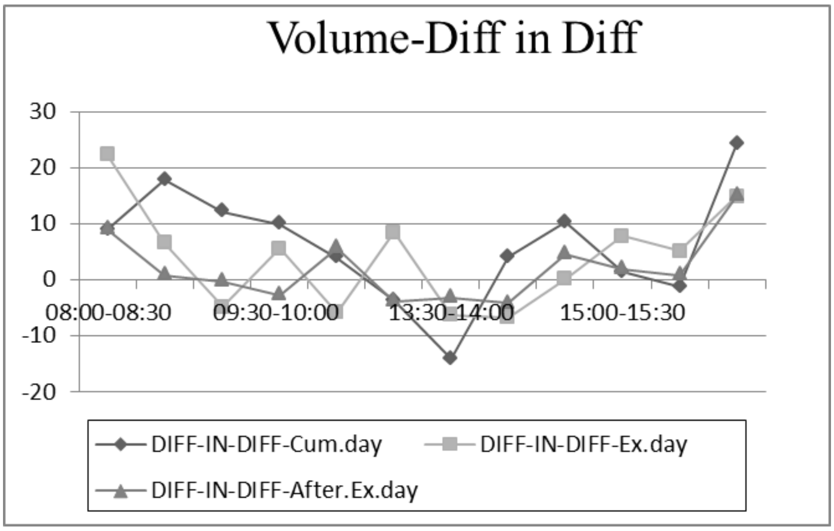


Figure 4.40 – The differences in differences estimation of intraday variation in volume across the first six and the last six thirty- minute time intervals



Figures 4.40 shows a high value for volume on most of the interval on cum-dividend day. Further, the last half an hour on cum-dividend day and first half an hour on ex-dividend day present a high value. The suggestion here is that a high value of volume in firms that are the most attractive target for arbitrageurs on cum-dividend day and ex-dividend day could be related to tax-arbitrage trading strategy.

Table 4.20 reports the difference in difference estimation of model (4.4), where the dependent variable is trade price volatility in five-minutes interval, for both

Arbitrage and Information asymmetry types over cum- and ex-dividend days and 10- days after ex-dividend day.

Table 4.20 – The differences in differences estimation of intraday variation in volatility
The table presents the coefficient from estimating model (4.4) for all firms with low price volatility (Arbitrage (AT-F) and high price volatility (Information asymmetry (IA-F) for volatility over cum-dividend day , ex-dividend day and 10 days after the ex-dividend day. The independent variables are indicator variables for the first and last six thirty-minute time intervals of the trading day. The model is estimated using the differences in difference procedure. The significant levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

volatility	Middle interval (Mid) AT-F	Treated interval (Tre) AT-F	Middle interval (Mid) IA-F	Treated interval (Tre) IA-F	Diff-Mid&Tre (AT-F)	Diff-Mid&Tre (IA-F)	Diff-AT-F& IA-F (Tre)	Diff-AT-F& IA-F (Mid)	Diff-in-Diff
Cum-dividend day									
08:00-08:30	2.962	5.094	4.770	11.797	2.133***	7.028***	6.703	1.808	4.895***
08:30-09:00	2.962	3.689	4.770	6.885	0.728***	2.115***	3.196	1.808	1.388***
09:00-09:30	2.962	3.318	4.770	6.108	0.356***	1.339***	2.790	1.808	0.982***
09:30-10:00	2.962	3.296	4.770	5.456	0.335***	0.686***	2.160	1.808	0.351**
10:00-10:30	2.962	3.064	4.770	5.270	0.102	0.5***	2.206	1.808	0.398**
10:30-11:00	2.962	3.037	4.770	5.311	0.075	0.542***	2.275	1.808	0.467***
13:30-14:00	2.920	3.128	4.777	4.739	0.208*	-0.038	1.611	1.857	-0.246
14:00-14:30	2.950	3.007	4.791	4.681	0.057	-0.110	1.674	1.841	-0.167
14:30-15:00	2.962	2.958	4.717	4.978	-0.004	0.261**	2.020	1.755	0.265*
15:00-15:30	2.972	2.921	4.763	4.798	-0.050	0.035	1.876	1.791	0.085
15:30-16:00	3.004	2.795	4.800	4.650	-0.209*	-0.151	1.855	1.797	0.058
16:00-16:30	2.962	2.948	4.770	5.297	-0.013	0.527***	2.348	1.808	0.54***
Ex-dividend day									
08:00-08:30	2.966	4.859	4.828	9.844	1.893***	5.016***	4.985***	1.862***	3.123***
08:30-09:00	2.966	3.582	4.828	6.858	0.616***	2.03***	3.276***	1.862***	1.414***
09:00-09:30	2.966	3.289	4.828	5.693	0.323***	0.865***	2.404***	1.862***	0.542***
09:30-10:00	2.966	3.255	4.828	5.731	0.289**	0.903***	2.476***	1.862***	0.614***
10:00-10:30	2.966	3.051	4.828	5.385	0.086	0.557***	2.334***	1.862***	0.472***
10:30-11:00	2.966	3.156	4.828	5.048	0.19*	0.22*	1.892***	1.862***	0.030
13:30-14:00	2.958	2.995	4.764	5.091	0.037	0.328***	2.096***	1.805***	0.291*
14:00-14:30	2.974	2.931	4.858	4.706	-0.043	-0.152	1.775***	1.884***	-0.109
14:30-15:00	2.960	2.988	4.836	4.797	0.027	-0.038	1.81***	1.875***	-0.066
15:00-15:30	2.963	2.977	4.832	4.809	0.015	-0.024	1.832***	1.87***	-0.038
15:30-16:00	2.973	2.937	4.850	4.741	-0.036	-0.108	1.804***	1.877***	-0.073
16:00-16:30	2.966	3.057	4.828	5.040	0.091	0.212*	1.983***	1.862***	0.121
After Ex-dividend day									
08:00-08:30	3.085	5.616	4.977	11.514	2.531***	6.537***	5.898***	1.892***	4.006***
08:30-09:00	3.085	3.807	4.977	6.897	0.722***	1.92***	3.09***	1.892***	1.199***
09:00-09:30	3.085	3.508	4.977	6.166	0.423***	1.189***	2.658***	1.892***	0.766***
09:30-10:00	3.085	3.359	4.977	5.799	0.274***	0.822***	2.44***	1.892***	0.548***
10:00-10:30	3.085	3.217	4.977	5.489	0.132***	0.512***	2.272***	1.892***	0.381***
10:30-11:00	3.085	3.134	4.977	5.139	0.048	0.162***	2.006***	1.892***	0.114**
13:30-14:00	3.057	3.199	4.904	5.277	0.142***	0.374***	2.078***	1.847***	0.231***
14:00-14:30	3.081	3.102	4.973	4.994	0.021	0.021	1.892***	1.892***	0.000
14:30-15:00	3.073	3.134	4.951	5.079	0.061	0.128***	1.945***	1.878***	0.067
15:00-15:30	3.098	3.033	5.014	4.830	-0.065*	-0.184***	1.797***	1.916***	-0.119**
15:30-16:00	3.117	2.958	5.044	4.715	-0.159***	-0.329***	1.757***	1.927***	-0.17***
16:00-16:30	3.085	3.198	4.977	5.182	0.113***	0.205***	1.984***	1.892***	0.092

Figures 4.41, 4.42 and 4.43 present the results graphically for the volatility model over the Arbitrage firm, Information asymmetry firms and difference in difference between both types respectively.

Figure 4.41 – The differences in differences estimation of intraday variation in volatility across the first six and the last six thirty- minute time intervals -Arbitrage

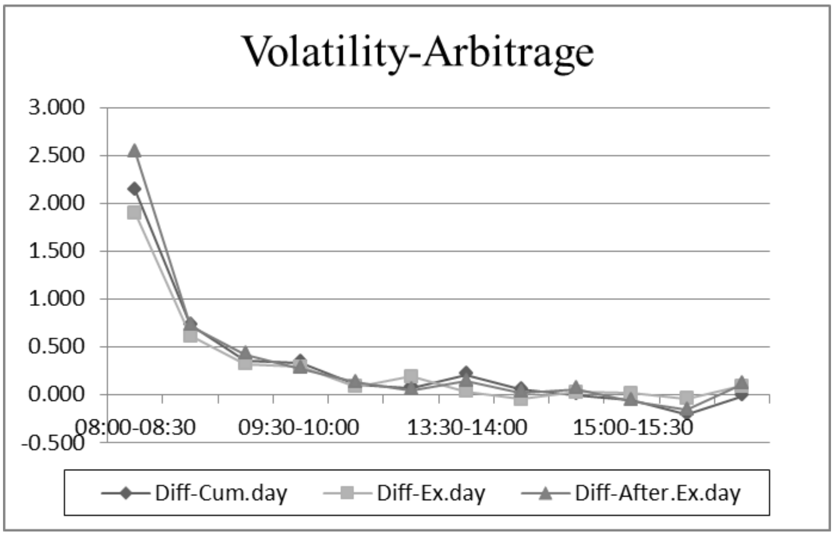


Figure 4.42 – The differences in differences estimation of intraday variation in volatility across the first six and the last six thirty- minute time intervals -Information asymmetry

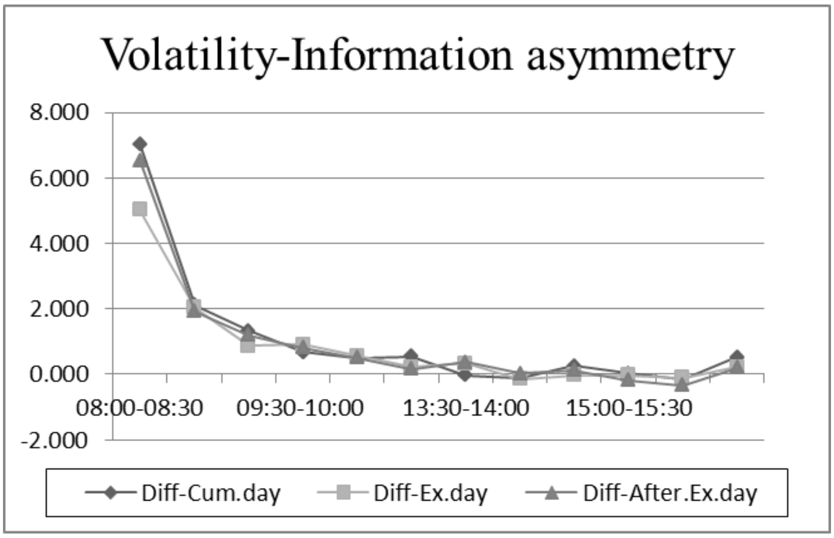
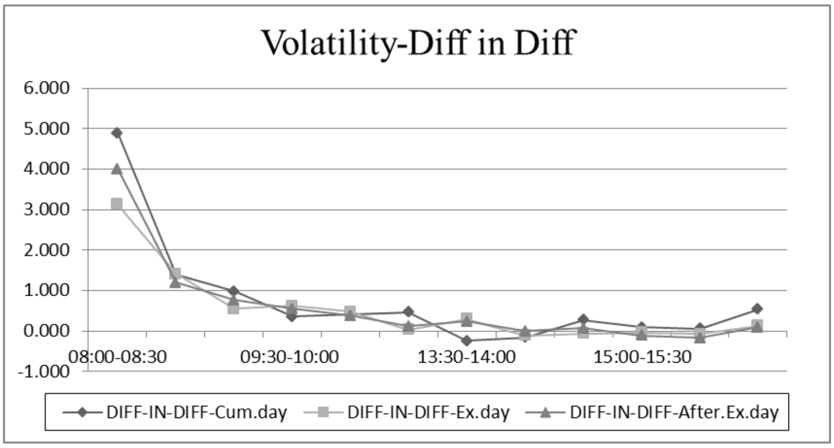


Figure 4.43 – The differences in differences estimation of intraday variation in volatility across the first six and the last six thirty- minute time intervals



We can not see a significant effect of the ex-dividend event on intraday pattern of price volatility confirming the GMM estimation results.

4.7 Conclusion

This chapter studies the changes in the intraday pattern of bid-ask spread, price volatility and trading volume around the ex-dividend day. The results, across ex-dividend week, control week, cum-dividend day, ex-dividend day, days 2 and 3 in the control week, confirm several findings of previous studies. Consistent with Chan et al. (1995); McInish and Van Ness (2002) and Madhavan (1992) the intraday distribution of the spread for a sample of FTSE 100 firms shows an L-shaped pattern. The intraday volume pattern for a sample of FTSE 100 stocks shows a U-shaped. This result is consistent with studies in other markets such as, the Swedish market (Niemeyer and Sandas, 1994); the Finnish market (Hedvall, 1994); the Paris market (Biais et al., 1995); the Toronto market (McInish and Wood, 1990); the London market (Werner and Kleidon, 1996); the Hong Kong market (Ho and Cheung, 1991); NASDAQ (Chan et al., 1995); NYSE (Gerety and Mulberin, 1992) and the Taiwan market (Lee et al., 2001).

There is no effect of the ex-dividend day on price volatility but there are effects on spread and volume. In both the aggregate sample and for firm by firm results, the findings are interesting. The high waiting cost of not being able to trade on the cum-dividend day increases competition between traders and results in higher volumes and lower spreads on the cum-dividend day. The absence of a trading deadline on the ex-dividend day helps traders to execute their orders at their desired price and leads to wider spreads. Further, traders on the cum and ex -dividend days may avoid the early period around the opening of the market and trade during the middle of the day to minimise information asymmetry effects known to be associated with opening periods.

Consistent with tax-arbitrage effects, spreads and volumes on both the cum- and ex- dividend days for firms that are the most attractive targets for tax-arbitrage (arbitrage) are higher than normal for the last part of the trading day. That tax-arbitrage based trading is more likely in the final part of the day can be explained by the relatively higher adverse selection costs of trading in the early part of the day. Since both spreads and volatility are higher in the first part of the day, anyway in general, it makes sense that tax-arbitrageurs avoid executing trades during that period. Moreover, there is evidence that the effects on intraday patters around ex-dividend day that we observe could be "masked".

We split our sample of firms into several classifications based on price volatility. The tax-arbitrageurs are likely to prefer trading in companies with the lowest price volatility since this minimises both adverse selection costs and execution risks. Across all firms in our sample there is no measurable impact on spreads and volumes of the ex and cum-dividend days but when the sample is split into low and high volatility firms, the results show greater spreads and volumes at the end of the day for low volatility firms and smaller spreads and volumes at the end of the day for high volatility firms. The total sample masks, therefore, these two opposing effects.

Chapter 5

Conclusion

5.1 Summary

Since the early 1990s electronic trading systems have become popular among financial markets worldwide and an understanding of their structure and operations is now thought almost a pre-requisite to being associated with such markets either as regulators or as investors trading in them. It is necessary since the optimal trade executions reduce the related transaction costs and increase the expected returns. Portfolio trading strategies implemented in markets today cannot but factor in the precise microstructure associated with the markets they trade in, whether they are arbitrage based trades, style based portfolios or standard buy-and-hold portfolios. This issue matters especially in situations where high frequency trading strategies are concerned.

For example, when considering the trading activity associated with the cum-dividend day and the day following it, the ex-dividend day, several tax-based and transaction costs based theories as well as associated empirical evidence have been known for several decades. In this light we find for example, that waiting costs may be greater on the cum-dividend day relative to other trading days, in light of the approaching cum-dividend guillotine type deadline to place (submit) order to trade and the after-tax return that is potentially forgone if they trade is not executed. That is, the opportunity cost of not executing is likely to be relatively high on the cum-dividend day compared to other trading days. Moreover, there is a little published evidence concerning the market microstructure around the ex-dividend day. Thus, this thesis reports on an empirical study of this event and associated trading patterns for the London Stock Exchange, and further investigates issues related to ex-dividend day effects on market microstructure in liquid and illiquid stocks and on intraday patterns. The thesis investigates two separate questions. First, whether there are effects on market microstructure from the trading activity observed, in the order submission, around ex-dividend days. Since, liquidity is an important concern in these situations this issue is investigated both for stocks with high liquidity (Chapter 2) and those with lower liquidity (Chapter 3). A second question is whether there are dividend-related effects observable at the tick-by-tick high frequency level in the trading patterns observable in the intra-day periods around ex-dividend days and this is also investigated in the order submissions and for both buy and sell orders on the limit order book (Chapter 4).

Chapter 2 contributes to the literature from the perspective of the effects of ex-dividend days on the market microstructure associated with liquid stocks. More specifically, it discusses the effect of ex-dividend days on spread, volatility and the order submission decisions for a sample of FTSE 100 stocks in a period between 2007-2008. Chapter 2 employs the ex-dividend week and as a control week, the week prior. This chapter adopts a pooled panel, logit, multinomial logit and ordered probit models. The results suggest that spread and volatility are higher in ex-dividend weeks compared to control weeks. Spread in the ex-dividend week is affected by price volatility and trading volume. The findings of the Chapter 2 are consistent with tax-arbitrage and liquidity supply occurring simultaneously around the ex-dividend day. Moreover, order submission decisions in highly liquid stocks is affected by spread, volatility, return and duration. The one-sided pressure expected on ex-dividend days appears to move prices may be increasing returns and spreads, motivating liquidity suppliers to trade aggressively. Furthermore, these trading pressures also increase price volatility, motivating tax-arbitrageurs to trade aggressively. These effects are stronger on cum-dividend days because of a cum-dividend day deadline for placing tax-arbitrage transactions.

Chapter 3 extends recent studies on the effect of liquidity on order submission decisions by studying the effects of a lack of liquidity on tax-arbitrage activities around the ex-dividend day. Chapter 3 used the ex-dividend week and a prior control week for a sample of FTSE SmallCap stocks in the period 2007-2008. Several liquidity measures commonly employed in the literature are computed to confirm empirically that there is illiquidity on FTSE SmallCap Index. Chapter 3 also adopted pooled panel, logit, multinomial logit and ordered probit models. The results show that there are tax-arbitrage activities around the ex-dividend day in illiquid stock as well as in the liquid stocks. The link, as in Chapter 2, between order submission decisions on the one hand and on the other spread, volatility and return is confirmed for FTSE SmallCap stocks, but the link between order submission and execution probability is not found.

High frequency effects are investigated in Chapter 4, which examines intra-day patterns of bid-ask spread, price volatility and trading volume around the ex-dividend day. Again several models are described and estimated using the Generalised Method of Moments (GMM) and difference in difference procedures. Previous literature suggests an L-shape[1] for the intra-day bid–ask spread and a U-shaped for intraday trading volume.[2] Chapter 4, finds that the intraday pattern of spread (volume) is L-shaped (a U-shaped) for FTSE 100 stocks. Moreover, the high waiting cost on the cum-dividend day increases competition between traders, leading to higher volumes and lower spreads. Traders on the cum-dividend day and the ex-dividend day are quite likely to avoid high information asymmetry periods in the intra-day period, which are often at the start of trading day and instead may trade more during the middle of the day. Consistent with tax-arbitrage

[1]See Chan et al. 1995; McInish and Van Ness 2002 and Madhavan 1992.

[2]See Niemeyer and Sandas 1993; Hedvall 1994; Biais et al. 1995; McInish and Wood 1990; Werner and Kleidon 1996; Ho and Cheung 1991; Chan et al. 1995; Gerety and Mulberin 1992; Lee et al. 2001.

effects, for the firms that are most attractive target for tax-arbitrage traders, the spreads and the volume on both cum-dividend day and ex-dividend day are greater than normal for the latter part of the trading day. As there are relatively higher adverse selection costs during the first part of the trading day, tax-arbitrageurs, therefore, are more likely to be present in the final part of a trading day. Since both spreads and volatility are higher in the first part of the day, in general, it makes sense to avoid that trading period.

5.2 Future Research

This thesis focuses on the effects of ex-dividend day on market microstructure. It would be interesting to analyse the effect on market microstructure of those corporate events that have high information asymmetry, such as, for example, time horizons prior to earning announcements. In this manner, I intent to investigate the effects on market microstructure of different events that have varying levels of information asymmetry.

Ex-dividend day effects on market microstructure are likely to present not only on the London Stock Exchange but also on other markets. It would be interesting to study ex-dividend day effects on other markets such as derivative and bond markets and on the markets of other types of countries, such as emerging markets.

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