Stockholm School of Economics

Department of Finance

Master Thesis

Fall 2012

Shorter Settlement Cycle, Return and Liquidity: A Test Using London Stock Exchange Data

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Abstract: *The move from T+5 to T+3 on London Stock Exchange is used to study how the length of settlement cycle would affect returns and market liquidity. We conduct an event study, and find significant increases both in returns and liquidity after T+3 was implemented. We also discover a significantly positive association between CARs and liquidity changes, a result that is contrary to most of the existing empirical findings. This paper is probably the first one addressing the issue of settlement cycle changes, and consequently contributes to the ongoing discussion concerning the move from T+3 to T+2 Europe wide.*

Key Words: Settlement Cycle, Liquidity, Asset Pricing, Liquidity Premium, London Stock Exchange

JEL Classification: G12 G14 G18

Tutor: Bige Kahraman

Date: December 10, 2012

Acknowledgment: We would like to thank our tutor, Bige Kahraman for aspiring and guidance during the process of writing this thesis. We are also thankful Chaiwat Pattanapongsa, Delphine Gauthier, Florian Deichmüller, Julia Niedermair, Martin Welz, Micka Lin and Tommy Chen for support and exceptional discussion.

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1. INTRODUCTION

A T+3 settlement period on stock market requires the seller/buyer to transfer ownership of the stock/cash within three days after the transaction date. During the three-day window, the buyer receives a number of benefits in acquiring the security without actually having to make the payment. For instance, he receives all gains in the security price between trade date and settlement date. On the contrary, the seller no longer claims ownership of the security yet does not get paid either. The seller consequently finances the buyer during the settlement cycle.

In 2004, the U.S. Securities and Exchange Commission (SEC) sought to improve the clearance and settlement system by adopting a new rule, requiring the confirmation and affirmation processes to be completed on the trade date. The SEC issued a concept release proclaiming that time equals risk and risk surrounding the process of clearance and settlement is directly related to the length of time it takes for the trade to settle. Settling sooner helps reduce institutional trade exposure, risks in the clearing house and risks associated with failure to settle[3]. However, the mentioned concept was unable to gain enough support from market participants at that time, mostly due to the overwhelming costs associated with settling within trading day. On one hand, it requires strong electronic system as the technology backup, putting pressure on stock exchanges. On the other hand, investors also need immediate finance upon a deal, which could be costly and even add to bankruptcy probability on their side. In 2011, the Depository Trust and Clearing Corporation (DTCC) issued a preliminary analysis of shortening the settlement cycle for U.S.equity1 trades from the current trade date plus three business days (T+3) to T+2 or T+1 in order to gather more input from the market to explore the case for making a change. In this analysis, it mentioned arguments in favour of shortening the settlement cycle such as a reduction of risks inherent in T+3 settlement, a freeing up of capital and seller financing of open trade obligations[4]. To implement a shorter settlement cycle requires both modification in the central infrastructure and strong support from regulators and the industry.

Furthermore, the European Commission has released a proposal in pursuance of harmonising the European central securities depositories' network. One of the key aspects of this proposal

[3] Concept Release: Securities Transactions Settlement; U.S. Securities and Exchange Commission, 17 CFR PART 240, Release No. 33-8398; 34-49405; IC-26384; File No. S7-13-04

[4] Proposal to launch a new cost-benefit analysis on shortening the settlement cycle; The Depository Trust & Clearing Corporation, Dec 2011

is to implement mandatory T+2 settlement for all 30 CSDs across Europe[5]. They believed that this would help improve the European securities market and reduce transaction costs since certain risks and costs are prolonged by the settlement period. Despite the argument that T+2 would force market makers to increase inventories, leading to higher costs, wider spreads, and fewer market makers, the European Union moves ahead towards this agreement which has apparently expanded globally, including to Japan and the US.

We found it insightful to look into the impact of a shorter settlement cycle may have on the stock market. In November 23, 1999, the Bank of England, the London Stock Exchange (LSE) and CREST jointly proposed a shorter settlement cycle – a change from T+5 to T+3 for UK's equity and corporate debt market. On February 2, 2001, LSE announced the 'Introduction of T+3 Standard Settlement Period' which was executed on February 5, 2001. We found this manoeuvre worthy of an in-depth study given the probability of gaining some insights into what we can expect after the introduction of T+2 throughout Europe. Another comparable event was the shortening of settlement from T+5 to T+3 in the U.S on June 7, 1995. However, considering the impact of information technology development on every aspect ranging from macro-economy to microstructures such as trading and delivery methods, we found it more insightful to look at the later event, i.e. the change of settlement cycle on LSE.

This paper used data from LSE. Before the change of settlement cycle, post-trading settlement of securities on LSE took place after five business days. In a usual week without any holiday, the payment was due on the same weekday of the following week (an additional business day for clearing check included). Consequently, in a non-holiday week, the purchase of stocks on business days other than Friday gave the buyer seven (or eight if including clearing check) calendar days before losing funds for stock purchases. Trading on a Friday effectively meant that the transaction was settled only after ten calendar days. The two-calendar-day difference in settlement lifted prices on Fridays and led to higher daily returns on Fridays and lower returns on Mondays. After February 5, 2001, settlement for domestic equities and fixed income securities took only three business days. We expected that it has substantially changed the market.

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5 Proposal for a regulation of the European Parliament and of the Council on improving securities settlement in the European Union and on central securities depositories (CSDs) and amending Directive 98/26/E; European Commission, Brussels, 7.3.2012

There are mainly two drivers derived from this change in regulation, which might affect returns. The first one is the reduction in risks. As stated by Chris Broad, Head of Broker Services at the London Stock Exchange, ‘the move to T+3 settlement will mark a significant step in enhancing the efficiency of trading on our markets. The shorter settlement cycle will assist in risk reduction…’[6]Consequently we could expect a lower risk premium. Yet on the other hand, a shorter settlement cycle also indicates a shorter time for investors to get financed, and thus a higher financing cost, which would then drive up required returns. The first part of the paper is dedicated to studying this problem and getting an insight into which trend is predominant.

Another topic of interest is liquidity. Apart from risk reduction, another target of LSE in executing a shorter settlement period is to promote paperless share-holding. "The increased efficiency and risk reduction of shorter settlement cycles means that investors who trade frequently should now think about the advantages of electronic holdings.[7]" Thus on one hand, short term traders might benefit from such a development due to decreasing holding costs and increasing transaction efficiency, and consequently they could boost trading volume and improve market liquidity. Additionally, under the assumption that risk is reduced and transaction cost is decreased due to paperless procession, we can reasonably expect a decrease in the bid-ask spread, since two components of the bid-ask spread are derived from information asymmetry and transaction costs. A lower spread, in turn, would most likely lead to a more liquid market. However, another side of the coin is that due to a possible increase in financing costs and a request for faster financing, traders might be more cautious when they put orders and some noise traders might even step out of the market. In this way the liquidity might even shrink. Consequently, it is again of interest to study which effect would prevail over the other.

The last part of our analysis investigates the association of liquidity and returns. As reported by many previous studies, liquidity is negatively related to returns. This is because in case of a distress, the investor may need to quickly liquidise the asset. And with a less active market, or in other words, if the asset is not liquid enough, a fire sale might be triggered. Under the assumption that other investors are rational, they would try to press the price down so as to benefit the most of the transaction. Thus a fire sale costs more than a normal sale on the asset

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[6] Introduction of T+3 Standard Settlement Period

[7] Toby Davies, Head of Domestic Settlement Policy at CRESTCo Ltd

holder’s side. In this case, when buying a less liquid asset the investor would require a higher premium. Therefore, liquidity is negatively associated with returns.

This paper is thus dedicated to discussing how returns, liquidity and the interaction between them are influenced by a change in settlement cycle. After careful and thorough research, it can be safely said that the present paper is most probably the first to address this issue, and thus contributes to the current discussion about moving to T+2 from T+3 Europe wide. The data sample is also further split into several subsamples by size and by whether or not the stocks are included in FTSE 100. Inherent additional risk and larger premiums on equity of small sized companies are constantly discussed topics (Fama, French, (1992, 1993); Banz, (1981); Chen, (1981, 1983)). Also, it is documented that such a premium is more due to common risk factors involved with risks than due to abnormal returns. Thus it is worthy of a study to research whether such a regulation change as shortening of settlement cycle would affect big and small firms in a different way. This paper also looks at the different reactions from stocks in FTSE 100 and that of stocks outside of this index. This is because stocks on FTSE 100 are traded in an order driven system whereas other stocks, which are comparatively thinly traded, go under a quote driven system. Although due to the market makers’ efforts, a quote driven market is supposed to be more liquid than an order driven one, stocks outside FTSE 100 by themselves are less liquid. One purpose of putting them under order driven system is to eliminate market illiquidity. Thus it is insightful to see whether there is still any significant difference between these two subsamples in the sense of liquidity, returns, how they are associated with each other, and how these are affected by a shorter settlement period.

As conclusions, we found a positive abnormal return after shortening of the settlement cycle on LSE, with small companies enjoying higher increases in returns. Liquidity was further increased by this change in regulation, also with bigger firms reacting more severely. Other than most of the previous research, we found a positive relation between changes in liquidity and abnormal returns, and this association is smaller for less liquid stocks.

The rest of the paper is organized as follows: Section Two offers a review of relevant previous literatures. Section Three presents the descriptive data and some of the important concepts involved. Section Four looks into the data and presents the results of the empirical research conducted. Section Five contains the robustness test. Section Six concludes the analysis. Seven talks about critics of this research and Eight suggests further area of research.

2. LITERATURE REVIEW

2.1. RETURN AND LIQUIDITY

There are many researchers studying the relationship between asset pricing and liquidity. Amihud (2002) illustrated that stock returns are negatively related over time to contemporaneous unexpected illiquidity. Over time, market expected illiquidity affects the ex ante stock excess return. Expected stock excess returns are not constant but rather vary over time as a function of changes in market illiquidity. Later on, Amihud and Mendelson (2003) conducted a survey on research on the effects of liquidity on asset prices and returns and showed that liquidity is an important factor in capital asset pricing. Pastor and Stambaugh (2003) studied how liquidity associates with temporary price fluctuations, which are induced by order flow. They documented that returns of liquidity-sensitive assets are usually higher than that of the liquidity-insensitive ones. Amihud, Mendelson and Pedersen (2005) found the effects of liquidity on asset prices to be statistically significant and economically important. In their study, by testing on prices of assets which share the same cash flow, yet differ in liquidity, and liquidity changes over time and how they are associated with prices, they controlled for traditional risk measures and asset characteristics. Bekaert, Harvey and Lundblad (2007) examined impact of liquidity on expected returns on emerging market. The idea is that most of the research was done in the U.S. which is the most liquid market in the world. By examining the emerging market where the liquidity effects may be particularly strong it could yield powerful and independent test. They used the proportion of daily zero firm returns averaged over the month (Lesmond (2005) and Lesmond et al. (1999)) to measure liquidity and transaction costs. They found that the zero measure significantly predicts returns and unexpected liquidity shocks are positively correlated with returns and negatively correlated with dividend yields. Lynch and Tan (2011) manifested the large spread in expected returns for portfolios formed on the basis of liquidity.

In this paper we are also concerned with speculative activities. We believed that these speculative activities would create noise in the market; however, there are conflicts in research paper discussing whether noises would make market more liquid or not. Glosten and Milgrom (1985) perused that a bid-ask spread can be an informational phenomenon. Traders with superior information lead to a positive bid-ask spread even when specialists are risk-neutral and make zero expected profits. Black (1986) interpreted that noise makes trading in financial markets possible, and thus allows us to observe prices for financial assets. Noise makes markets somewhat inefficient, but on the other hand also often prevents us from taking advantage of inefficiencies. The more noise trading there is the more liquid the markets will be, in the sense of having frequent trades that allow us to observe prices. The price of a stock reflects both the information that information traders trade on and the noise that noise traders trade on. Greene and Smart (1999) found that substantial increases in trading volume and significant but temporary abnormal returns occur when analysts recommend stocks. Price rises in response to the increased trading, but subsequently falls, spreads may increase in response to trading volume shocks and increases in noise trading reduces the adverse selection problem for the dealer and causes increased liquidity. They also found the positive relationship between trading volume and market liquidity. Chordia, Roll, and Subrahmanyam (2001) studied a sample of stocks over an 11 year-period and found that spreads and depths in the stock and bond markets are predictable using lagged spreads and lagged order imbalances. Unexpected liquidity shocks are positively and significantly correlated across stock and bond markets. There is a downtrend in spreads and uptrend in depth and volume, which are consistent findings and all together indicate an increase in liquidity. Equity market returns and recent market volatility influence liquidity and trading activity. Short term interest rate and term spread significantly affect liquidity as well as trading activity. There are strong day-of-the week regularities in liquidity and in trading activity. Liquidity declines and trading activity slows on Fridays. Lakonishok and Levi (1982) demonstrated that returns depend on the day of the week and adjusted interest gains on Friday and holidays to reduce the daily effect. Brusa, Liu and Schulman (2000) re-examined on the weekend effect, the well recognized calendar anomaly, where there is robust evidence showing that Monday returns tend to be negative and smaller than the returns on other days of the week with more recent data and found the ‘reverse’ effect where Monday returns are positive and greater than return on other day of week. However, they found the effect significant for large firms instead of small ones, which is opposite to most of the previous studies. Later, Brusa, Liu and Schulman (2003) further examined the traditional and reverse weekend effect by sorting companies by industries, and found that the weekend effect and the reverse weekend effect appearing in broad indices also exist in industry indices as well. Though Monday return patterns are different between the pre- and post 1988 sub-periods, the patterns are similar between broad indices and industry indices.

2.2. Theories on Short Term Trading

According to conventional theories, trading horizons should not affect returns given that in an efficient market, all information should be perfectly incorporated in prices. Or, in other words, the price reflects the fundamental value of the assets, regardless of when investors buy and sell their assets. However, it has been documented that trading in the short-term can be profitable due to predictability of short-term returns. Lehmann (1990) tested 'winners' and 'losers' within one week, and found significant return reversal in the next week. Based on empirical research and data, Jegadeesh (1990) reported a significant negative first-order serial correlation of monthly returns on individual stocks. Lo and MacKinlay (1990) documented that weekly portfolio returns are significantly and positively auto-correlated and cross-serially correlated, i.e. returns of small firm portfolio are correlated with lagged returns of big firm portfolio. Chang, McLeavey and Rhee (1995) also found positive short-term returns for contrarian strategies in Tokyo Stock exchange. Harvey (1994) went one step further and studied return predictability of emerging markets, and found the phenomenon was more significant there. However, there also were studies evidencing opposite facts: Al-Khazali, Ding and Pyun (2007) reported that in all 8 countries in MENA, stock returns computed from published indices, after adjusting for statistical biases, follow a random walk; or in other words, returns are unpredictable.

Scholars also developed different explanations for negative autocorrelation in returns. Two possible reasons are changes in fundamental values or overreaction of investors. Lehmann (1990) attributed return predictability to market inefficiency and overreaction. Similar results were also documented by Jegadeesh (1990). According to his study, abnormal returns of predictive portfolios remain positive even after adjusting for size-based risks, time varying market risk premium, bid-ask spread and infrequent trading, factors that could cause changes in expected returns. Later, Lo and MacKinlay (1990) reported different sources of return predictability, and argued that more than half of expected profits from contrarian strategies are due to cross-serial correlation, and not due to market overreaction. This conclusion is not necessarily unarguable. Jegadeesh and Titman (1993) examined a relative strength strategy over a 3-12 month horizon. They denied that profits following such a strategy come either from systematic risk or lead-lag effects in stock prices, as was suggested by Lo and MacKinlay (1990). Instead, Jegadeesh and Titman (1993) believed that the profit is caused by under-reaction of market towards firm-specific information. Furthermore, though most previous researches rejected systematic risk or changes in fundamental value as reasons for predictability of short-horizon returns, this may not apply to all markets. An analysis on emerging markets from Harvey (1994) argued that the time-varying risk exposure of stocks in emerging markets accounts for the extra predictability of stock returns there. A recent study by Shamsuddin and Kim (2009) looked into 50 international equity markets to study how equity market development and completeness would affect price predictability. They adopted measures of predictability and market development rankings from Financial Time Stock Exchange, S&P and the World Bank, and suggested that a lower turnover, less investor protection as well as short selling restrictions would lead to more prevalent price predictability.

Reading through previous literature, we can clearly see that there are different explanations for predictability. Such inconsistency could partly be attributed to different choices of horizons (from weekly to 12 months) and time period, etc. Market microstructure may be another reason. Boudoukh, Richardson and Whitelaw (1994) compared three schools of theories on short-term return-profitability, and concluded that market frictions are most likely to be the source of such predictability of short-horizon returns. Microstructure effects such as bid-ask bounce (Conrad, Gultekin, and Kaul (1992)), transaction costs (Mech (1993)), and trades as an informative tool (Hasbrouck (1991)) can all be possible reasons. Those studies are stimulating to us, especially if we consider the possible effects of a shorter settlement cycle on other microstructure mechanisms such as bid-ask spreads, liquidity, volume and trading strategies.

Short-term trading also has an effect on liquidity. Berkman and Eleswarapu (1997) conducted one event study on Bombay Stock Exchange around abolition and reinstatement of Badla, a facility that allows investors to purchase securities with borrowed money with BSE as the intermediary, and consequently affects short-term trading. They documented a significant decrease in liquidity after the ban, indicating the significant positive effects done by short-term traders on market liquidity. On the other hand, short-term traders may also cause a liquidity black hole problem. According to Morris and Shin (2003), as prices fall to marginal levels, for short-horizon investors to hold the equities, they would sell simply because others do so. This type of herding behavior leads to a dry-up of liquidity.

Short term trading also has effects on information efficiency. According to Froot, Scharfstein and Stein (1992), short-horizon traders would be better off only if the information that they are trading on is incorporated in prices, thus they would prefer to herd on the same information even if it does not reflect the real value of the security. In this way, short-horizon traders might actually increase information inefficiency by ‘over’-studying one specific information or even irrelevant information, as long as this information is also studied by other investors. From this theory, we can expect that any regulatory changes that might limit short-term trading will also lead to a decrease in information noise and thus a lower return and volatility.

2.3. Size, Book to Market Ratio, and Stock Returns

It has been long studied that CAPM by far cannot explain stock returns. More systematic risks than the one related to market are priced and integrated into required returns. Some of the factors considered include size (i.e. market capital), book-to-market value, earnings price ratio, cash flow-price ratio and past sales growth (Fama, French, 1996). We can obviously expect that some of these anomalies are related and thus mutual explanatory, which is indeed the case. Using both cross sectional and time series analysis approaches, Fama and French (1992, 1993) narrowed explanatory factors to only three: market portfolio return, size (Market value of equity) and book to market ratio. The positive relation between return and both size and book to market ratio indicates that 1) size is associated with one common risk factor and 2) the relative profitability of high value companies is another source of a systematic risk. Their research conclusion is of great importance to us since they offer us a proper model to construct normal stock returns.

One important literature regarding size effect comes from Banz (1981). He studied the relationship between return and total market value of NYSE common stocks, and reported that returns for smaller sized stocks are too high to be explained by CAPM. Also the size effect is not linear to market capital, i.e. such effect is significant for firms with very small ME, but not for those with average or large sizes. Chen (1981, 1983) further analyzed returns on size with APT, and documented that the effects failed to sustain after adjusted for risk factors. This indicated that return on size is not abnormal but a compensation for certain undefined risks. Fama and French (1992) further confirmed such effect. They documented positive abnormal return for small size firms, both with cross sectional data and time series data. One possible explanation for size effect is default risk. Chan, Chen and Hsieh (1985) adopted multi-factor approach to explain returns, and suggested that difference in returns between the low-grade bond and high-grade ones, i.e. the risk premium, is a significant factor after considering both market premium and seasonality.

3. DATA SELECTION AND METHODOLOGY

This paper aims to study the effect of a shorter settlement period on stock returns and liquidity. This section discusses data selection and methodology. First, we demonstrate how data was selected. The second section gives a general introduction to event study methodology, the computation of abnormal return and the measurement of liquidity.

3.1. DATA SELECTION

Sample Data

On Friday February 2nd, 2001, London Stock Exchange and CRESTCo confirmed the introduction of T+3 standard settlement periods, with execution on Monday February 5th, 2001. The adoption of T+3 would apply to domestic equities and fixed interest securities traded on London Stock Exchange[8]. Thus, we obtained data from Datastream and included equities incorporated in UK and traded on LSE during 1999.1.28 – 2001.9.7. Financial firms were excluded due to their significantly higher leverage. Stocks with either missing data or negative book value were also eliminated. After screening, 110 stocks were kept. The dataset contained price, turnover by volume, ask price, bid price, price to book value and market value.

Event and Estimation Window

Event date, i.e. time zero, included both announcement day (February 2nd, 2001) and execution day (February 5, 2001). Event window should capture all effects concerning the adoption of T+3. Therefore, after some preliminary research, we included in our window 50 days before announcement and six months after execution. One reason to cut the window by then is that the stocks market seemed to have integrated the new information in returns. Another reason is the terrorist attack upon United States on September 11, 2001, which caused another huge and worldwide shock in the market. Estimation window extended from August 2, 1999 (day -394) to November 24th (day -51). Taking away non trading days, we have 334 days included in estimation window.

3.2. METHODOLOGY

This paper used event study approach to investigate change in return and liquidity upon shortening of settlement period. An event study assesses the impact of an event on stock prices, assuming that market is efficient enough to integrate all information into prices. In this

[8] Introduction of T+3 Standard Settlement Period; London Stock Exchange Press Release, 2-Feb -2001

case, implementation of a shorter settlement period on LSE was defined as the event. The basic idea is to find the cumulative abnormal returns attributable to the event by taking the cumulative difference between real returns and modelled normal returns.

Abnormal return and Cumulative Abnormal return

In event study, we would examine whether information of implementation of T+3 would be incorporated into the stock prices and thus results in an increase in the expected return, under the condition that market is efficient and price will reflect information. The abnormal return is the difference between the actual return of a security and the modelled normal return;

$$AR_{i,\tau} = R_{i,\tau} - E(R_{i,\tau} | X_{i,\tau})$$

By fitting a model for returns with pre-event data, we construct our model following that of Fama and French (1993), with two extra dummies added:

$$R_{i,\tau} = \beta_{0,i} + \beta_{mkt,i} * (R_{mkt,\tau} - R_{riskfree,\tau}) + \beta_{size,i} * SIZE_{i,\tau} + \beta_{B/M} * B/M_{i,\tau} + \ +\gamma_{dec,i} * D_{dec} + \gamma_{jan,i} * D_{jan} + \epsilon_{i,\tau}$$

We then calculated the cumulative abnormal return across different time periods to see how the effects developed over time.

$$CAR_i(\tau_1,\tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau}$$

Average cumulative abnormal return is then calculated as

$$\overline{CAR}(\tau_1,\tau_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i(\tau_1,\tau_2)$$

with variance as

$$V\left(\overline{CAR}(\tau_1,\tau_2)\right) = \frac{\tau_2 - \tau_1 + 1}{N^2}\sum_{i=1}^{N} \hat{\sigma}^2_{\epsilon,i}$$

where $\hat{\sigma}^2_{\epsilon,i} = \frac{1}{\tau_2-\tau_1-k}\sum_{t=\tau_1}^{\tau_2} \epsilon^2_{i,\tau}$, k is the number of coefficients to be estimated in the normal return model and thus $\tau_2 - \tau_1 - k$ the degree of freedom. T statistic for average CAR is thus

$$\frac{\overline{CAR}\,(\tau_1, \tau_2)}{\sqrt{\mathrm{V}\left(\overline{CAR}\,(\tau_1, \tau_2)\right)}}$$

Liquidity Measurement

Apart from returns, liquidity is another indicator for market efficiency. The process of price discovery is after all realized by investors' constant trading and hence price adjustment. However, unlike returns, liquidity cannot be observed or measured directly, but is approximated by different methods. This paper mainly used two measurements for liquidity.

1. *LOGVO: Logarithm of Trading Volume* is the natural logarithm of aggregated number of shares traded on a particular day. In general, the trading volume is a well know measurement for liquidity; the higher the volume, the more liquidity is present and the more competitive the market will be. However since volume cannot be negative, we took logarithm of it to mitigate the bias.
2. *ILLIQMA:* This measurement for illiquidity is given by Amihud (2002). In his paper, he for the first time started a measurement for illiquidity as

$$\mathrm{ILLIQ_{iy}} = 1/\, \mathrm{D_{iy}} \sum_{\mathrm{t=1}}^{\mathrm{D_{iy}}} \left|\mathrm{R_{iyd}}\right| /\ \mathrm{VOLD_{ivyd}}\ ,$$

where $\mathrm{ILLIQ_{iy}}$ is the liquidity measurement for company i at year y. $\mathrm{D_{iy}}$ is the number of days in year y. $\mathrm{R_{iyd}}$ is daily return of firm i at day d of year y. $\mathrm{VOLD_{ivyd}}$ is the daily trading volume by value for stock i, i.e. price multiplied by turnover by volume.

Then in order to stabilize the variable, he calculated average ILLIQ over firms as

$$\mathrm{AILLIQ_y} = 1/\mathrm{N_y} \sum_{\mathrm{t=1}}^{\mathrm{N_y}} \mathrm{ILLIQ_{iy}}\ ,$$

Where $\mathrm{N_y}$ is the number of firms in year y. Then Amihud took the ratio of individual firm's liquidity against the average:

$$\mathrm{ILLIQMA_{iy}} = \mathrm{ILLIQ_{iy}}/\mathrm{AILLIQ_y}$$

Amihud's measurement tells us how sensitive return is towards liquidity changes, approximated by turnover by value, and thus offers an insight into illiquidity. When this measurement is high, tiny changes in trading volume could lead to a big shift in returns, indicating an illiquid market for the asset.

4. EMPIRICAL RESULTS AND ANALYSIS

In this section we first started analyzing reaction of stock price towards the change of settlement cycle on LSE. Next, we examined how liquidity changed due to the event. In the third part we discussed about the association of liquidity with returns.

4.1. CHANGE IN RETURNS

4.1.1. CUMULATIVE ABNORMAL RETURNS ANALYSIS

To study how stock returns on LSE reacted to the change in settlement period, we used Cumulative Abnormal Returns (CARs) as the measurement. We followed the method from Fama and French (1992) to model normal returns. Their model is as below:

$$R_{i,\tau} = \beta_{0,i} + \beta_{mkt,i} * \left(R_{mkt,\tau} - R_{riskfree,\tau}\right) + \beta_{size,i} * SIZE_{i,\tau} + \beta_{B/M} * B/M_{i,\tau} + \epsilon_{i,\tau}$$

Since it has been widely documented that returns are comparatively higher on January and December each year, we also added dummies for these two months in our model to account for month effect. Thus our final model is as below:

$$R_{i,\tau} = \beta_{0,i} + \beta_{mkt,i} * \left(R_{mkt,\tau} - R_{riskfree,\tau}\right) + \beta_{size,i} * SIZE_{i,\tau} + \beta_{B/M} * B/M_{i,\tau} + +\gamma_{dec,i} * D_{dec} + \gamma_{jan,i} * D_{jan} + \epsilon_{i,\tau} \quad (1)$$

In our model, $R_{i,\tau}$ is the weekly returns of stock i at day τ, where we took five trading days as one week. $R_{mkt,\tau}$ and $R_{riskfree,\tau}$ are weekly market returns and risk free returns at day τ. Here we used FTSE All Share index as market portfolio, and LIBOR as risk free rate. $SIZE_{i,\tau}$ is the natural logarithm of market equity of firm i at time τ. $B/M_{i,\tau}$ is the natural logarithm of the ratio of Book value over market value of equity for firm i. To make sure that the accounting data is known at the time of τ, we used book to market value of six months ago, as was done by Fama and French (1992). D_{dec} is a dummy for December, which equals 1 if the month is December. D_{jan} is a dummy for January which equals 1 if the month is January.

As the shortening of settlement period was proposed since November, 1999 already, and has been discussed ever since until final execution, we thus expected there would have been some anticipation before the event day. After some preliminary analysis, we believed that the shock had been thoroughly absorbed after six months. Consequently, we took event window as day -50 to +132 and built our model for normal returns basing on data from August 2, 1999 (day -394) to November 24th (day -51), with 343 days included.

We were most interested in weekly returns. As stated in many previous researches, in a T+5 settlement market Monday effect tends to exist. Thus a change in settlement cycle might have an effect on weekly returns. Under T+3, deals engaged on Monday and Tuesday would be exempted from weekend risks, which might lead to some extra decrease in return.

Basically we assumed that the change of settlement cycle might have triggered two drivers which could have had an impact on returns. The first driver was a decrease in risks. As settlement period shortened, less counterparty risk was involved in transactions, thus investors required less risk premium. Also market makers would put less bid-ask spread, further boosting liquidity and causing a decrease in required return. Yet another driver was the increase in cost of financing, especially for those investing on short horizon speculations. A shorter settlement cycle surely indicated less time to get finance, oppressing short-term traders' willingness to trade, and thus leading to decrease in liquidity and increase in returns. In this section, we would study which driver was the bigger one.

Figure 4.1.1 shows the average CARs of weekly returns from day -50 to day 154, which is September 7, 2001. Though our event window was cut at day 132 already, we would like to extend our plotting to day 154 for better reference. Had we included more post event days in the graph, what we would have seen would be a sharp decrease in CARs. As shown in Figure 4.1.1, average CARs were relatively stable by day 132, fluctuating around 1.1%. This was a sign that market had successfully digested the shock by then. Thus we found it reasonable to drop observations afterwards. The graph also supports our assumption that after half a year (132 days) the effect from a change in settlement cycle should have been integrated into returns extensively.

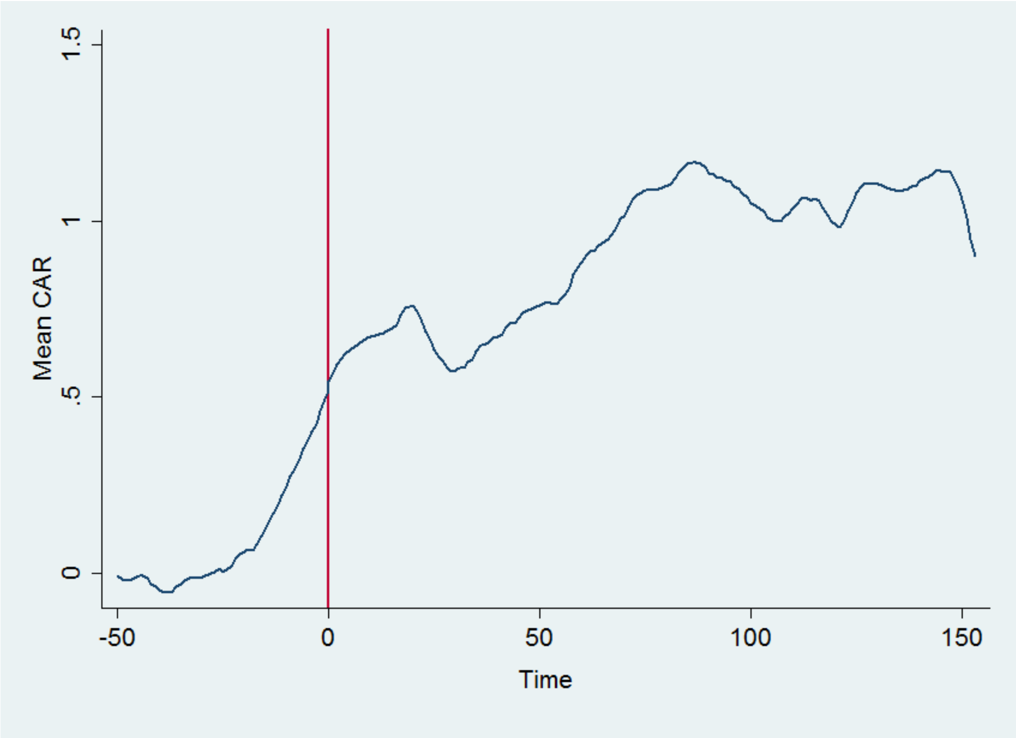

Figure 4.1.1-1: Average CARs over time

This figure shows the average CARs of weekly returns from day -50 to day 154. Estimation window extended from August 2, 1999 (day -394) to November 24th (day -51). Taking away non trading days, we have 334 days included in estimation window. Normal returns are estimated following model (1). By the end of event window, i.e. at day 132, average CARs were stable and fluctuating around 1.1%. Thus after approximately 6 months (132 days) the effect from a change in settlement cycle should have been integrated into returns thoroughly.

According to the graph we can see that CARs started from around zero and began to have almost continuous increase roughly from day -25 until around day 150. Then return fell due to the huge shock from 9.11. At the end of the event window, day 132, the CARs reach 1.09%.

Additionally, taking a closer look at the 25 days before the event, we could clearly observe an upward trend of CARs as time approached event date. After the event, CARs continued growing, reversed a bit around day 20 to day 30, and then headed up again. Such uptrend lasted until roughly day 80. Then the return reversed a bit and stayed quite stable afterwards until roughly day 150, when it began to drop dramatically. The jump is understandable because on day 155, the famous 9.11 happened. We computed weekly returns by taking the difference between price of today and that of one week later. Thus expected returns dropped one week before September 11. Such findings are supportive of our theory that the increase in abnormal returns were mostly likely caused by the shortening of settlement cycle.

4.1.2. Cross sectional analysis of CARs

Still we would like to exclude from our CARs analysis effects caused by any other event than change of settlement cycle. To accomplish this we conducted a cross sectional analysis. We took Frankfurt Stock Exchange (FWB) as the benchmark to compare with. We found these two markets comparable for several reasons. First, FWB is the second biggest stock exchange in Europe in terms of market capitalization, ranking right after LSE. Thereby we expected that they share similar amount of risks such as counterparty and operational risks. Also the similarity in size can be interpreted as an indicator for their importance in stock market. A second point is that both FWB and LSE are in developed markets. As documented by numerous studies (Harvey (1994); Bekaert, Harvey and Lundblad (2007)), emerging markets share different characteristics from developed ones in terms of returns and liquidity, as well as how they affect each other. Thus any stock exchange in emerging markets would be unqualified for a cross sectional analysis by nature. Further considering the fact that they are located in similar geographic area, we can expect them to share similar market wide shocks, and we could exclude the time zone problems from our analysis. Additionally, FWB is an order driven market, whereas on LSE, stocks in FTSE 100 index are traded under the order driven SETS systems. This means that on LSE, the major trading venue is order driven system, with only thinly traded stocks traded under a quote driven system. This similarity in microstructure matters in the sense that markets under the two systems vary a lot in terms of liquidity. In an order driven market, buyers and sellers display prices at which they are willing to buy or sell, and the electronic system would match orders together and get transactions done. However, in a quote driven market, prices are determined by bid and ask prices offered by market makers, dealers and specialists, who tend to be the liquidity provider when liquidity dries up. Consequently quote driven markets are in general more liquid than order driven ones. Summing up, considering the similarities in size and liquidity by LSE and FWB, and considering the fact that they probably share similar market-wide shocks, we find FWB suitable for a cross-sectional analysis. By comparing the difference between CARs on LSE and that on FWB, we would be able to exclude abnormal returns derived from any other market wide shock, and make our CARs ‘clean’.

For cross sectional analysis, we included stocks from DAX30 and MDAX indices in our sample as to avoid biases caused by size and industries. DAX 30 includes 30 largest German companies traded on FWB in terms of order book volume and market capitalization. MDAX comprises of another top 50 non-technology firms ranking right below those in DAX 30.

Likewise how we selected samples for LSE, financial firms, firms with incomplete data or negative book values were excluded from samples in FWB. DAX30 index is quoted as market returns and 10-year Germany government bond rate as risk free rate. We followed our model for LSE stock analysis in this part as well. We computed model for normal return with data from day -394 to day -51, and then predicted abnormal returns for day -50 to day 132 in order to compare with CARs on LSE around the event. Figure 4.1.2-1 shows the CARs on FWB.

As shown in the graph, indeed there was a positive shock on FWB around our event window, causing a CARs increase of around 0.4%. Yet the effect on returns was not sustainable. Instead, CARs decreased to around 0 and fluctuated around it until the end of event window, day 132.

We presented the gap between CARs of FWB and that of LSE as the clean effect derived from change of settlement cycle. In Figure 4.1.2-1 and Figure 4.1.2-2 we can see that the gap between CARs of LSE stocks and that of FWB stocks became bigger along time: at the beginning, both CARs were on the same level around zero. Then around day -30 both markets were experiencing positive abnormal returns due to certain market-wide shock. Yet LSE was having an even larger increase for most of the time, with the gap increasing over time. We contributed such phenomenon to an anticipation of a shorter settlement cycle. Also the decrease in returns around day 20 to 30 now is explainable: most likely it was because of another market wide shock, which also resulted in a jump in returns on FWB. After the event day the two markets began to develop in different ways; while LSE maintained its positive abnormal returns, FWB lost the benefits they gained from the previous shock.

Consequently, we find it reasonable to use CARs on day 132 for analysis, since by then the positive marketwide shock, which also led to a positive CAR on FWB around the event day, was no longer having an influence, and thus CARs of six months later should include only effects from the change of the settlement cycle.

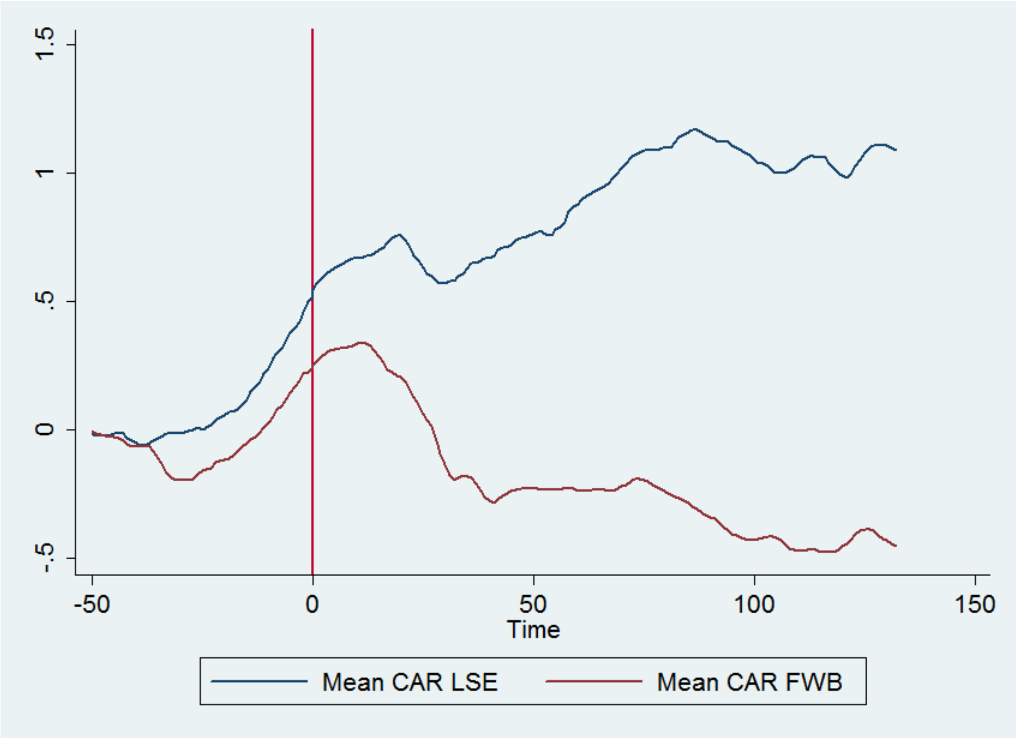

Figure 4.1.2-1: Mean CARs on LSE and FWB

This figure illustrates the CARs on FWB in comparison to CARS on LSE. Event window is from day -50 to day 132. Estimation window extended from August 2, 1999 (day -394) to November 24th (day -51). Normal returns for both stock exchanges are estimated following model (1). From the figure, we can see that there was a positive shock on FWB around our event window, causing a CARs increase of around 0.4%. However, this effect on returns was not sustainable. CARs decreased to around 0 and fluctuated around it until the end of event window.

Additionally, looking at one month before and after events, as shown in Figure 4.1.2-2 we can observe that the gap between CARs on LSE and that on FWB kept increasing as the event date approached, and that after the event, it continued to increase, even after the market-wide shock faded away or was offset by another shock after day 20. This indicates that more shocks affected returns in LSE than the one that occurred to FWB.

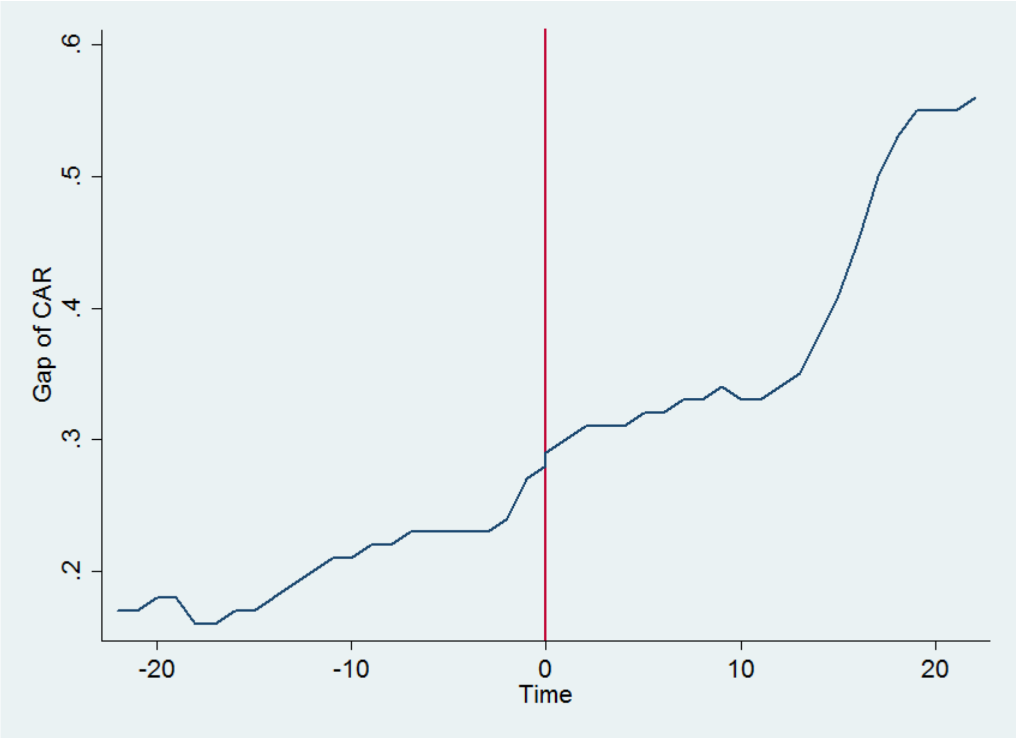

Figure 4.1.2-2: Gap between CARs of LSE and that of FWB

This figure shows the gap between CARs of LSE stocks and that of FWB stocks, CAR(LSE) - CAR(FWB). It can be observed that this gap kept increasing as the event date approached and that after the event, it continued to increase, even after the market-wide shock faded away or was offset by another shock after day 20 or so. This indicated that more shocks affected returns in LSE than the one occurred to FWB.

4.1.3. Statistical Significance CARs

Table 4.1.3 shows some statistics regarding CARs of our interest. At day 132, the average CAR reached 1.09%, with a highly significant t-statistic of 13.15. Thus, we can say that the shortening of the settlement cycle leads to an increase in returns market wide.

Table 4.1.3-1: Statistics of CARs

This table demonstrates that at day 132, average CAR reached 1.09%, with a highly significant T statistic of 13.15. Please refer to Methodology part to see how T statistic is calculated.

CAR Mean	CAR Variance	T Statistics
1.0930	0.0069	13.1526

4.1.4. Size, market microstructure and CARs

In this section we further discuss CARs for firms of different sizes and stocks in and outside of the FTSE100 index. The major driver behind this analysis is the effect of liquidity on returns. On one hand, as widely documented, bigger companies' stocks have better liquidity and lower returns on average. Although reasons for size premiums are mostly unknown so far, some scholars attribute them to the bigger financial distress probability of small firms. On the other hand, a study of subsamples of FTSE 100 stocks is interesting because after October 1997, these stocks began to be traded under an order driven system. Yet the other stocks on LSE remained under a quote driven systems. Hence, this difference in trading systems offers an obvious opportunity to compare how trading systems might affect returns and liquidities.

Documented by Berkman and Eleswarapu (1997), a change in liquidity would have bigger effect on less liquid stocks. Market perceives liquidity provided by short term traders as valuable and thus rewards it. Therefore, when short-horizon trading is limited somehow, the originally less liquid stocks would suffer more, partly because short-term investors would first abstain from holding and trading traded of those stocks. In our case, we also expect a decrease in short-horizon trading activities due to an increase in financing costs following the adoption of T+3. Consequently, we could expect that stocks in FTSE 100, and those issued by small companies, might have bigger positive CARs after we control for other factors such as size, B/M and calendar effects.

Meanwhile a shorter settlement cycle also indicates less risk, which leads to a decrease in returns. Considering the fact that smaller firms tend to be thinly traded partly due to the bigger counterparty risk their trading bears, we have reason to believe that they might also have benefited more from an elimination of the risks, thanks to a shorter settlement period.

Following the argument above, we would like to see which one of the drivers is more dominant for smaller firms, and also to investigate if our hypothesis regarding FTSE 100 firms is correct.

Size

We define firms with top 30% market capitalization as big firms, those 30% with the smallest market capitalization as small firms, and the rest as middle sized firms. Consequently, we have 33 big firms, 33 small firms and 44 middle sized firms. For market capitalization, we use data of six month before the event date, i.e. data at day -132. The choice of date would not have a big impact on the results as we double checked our results using the respective market capitalizations as of February 1 and 2, 2001.

From Figure 4.1.4-1, we can observe that CARs for small firms are positive and the biggest among three categories. CARs of small firms started from zero, went down slightly and then headed all the way up. By the end of event window, small firms' CARs were still increasing, and reached 2.6459%. As shown in Table 4.1.4-1, CARs of small firms are significant, with a T statistic of 15.2786. Biggest 30% firms also had positive CARs, yet less than that of small firms. CARs of big firms stay quite stable as time approaches the end of the event window, with an average of 1.2840% and a t-statistic of 9.9522, i.e. significantly positive CARs. Middle sized firms are least affected by the change of the settlement cycle, presenting negative but insignificant CARs.

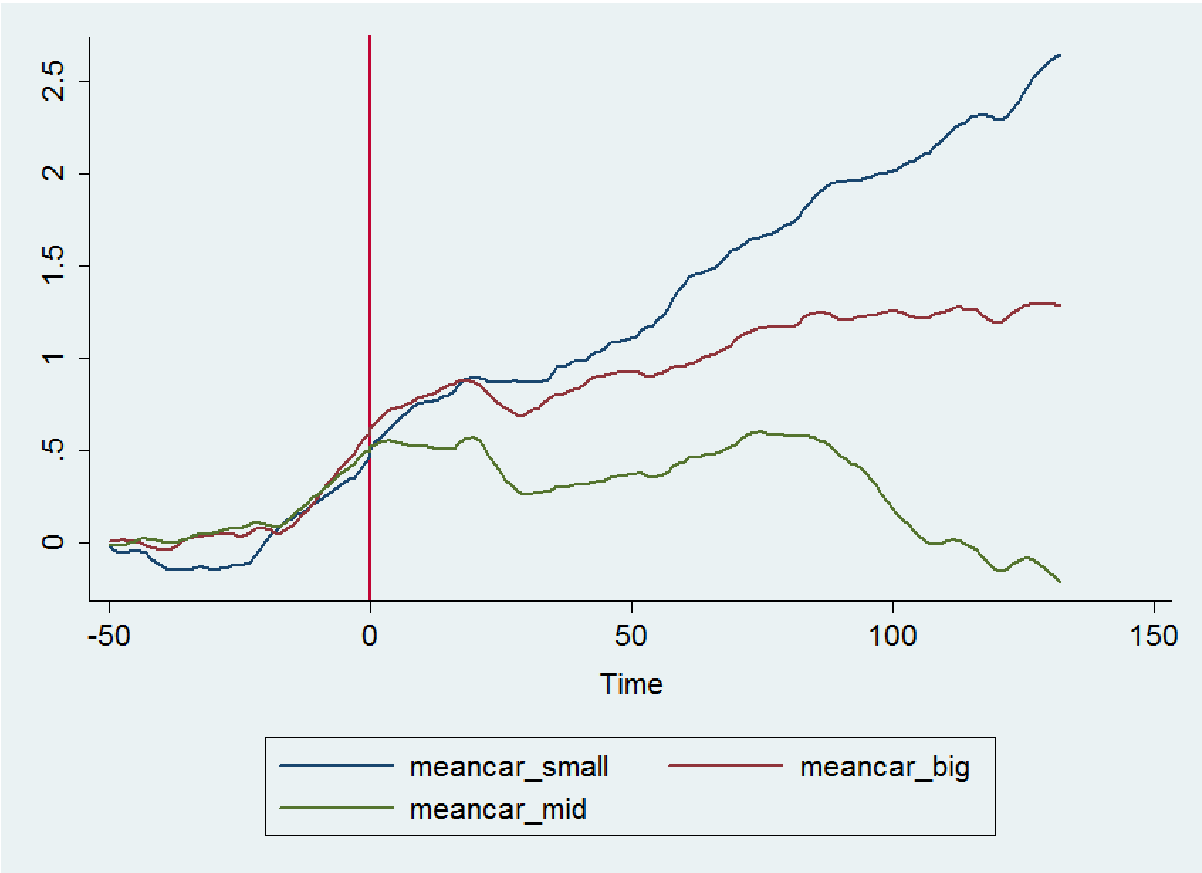

Figure 4.1.4-1: CARs of Big, Medium and Small Firms

This figure shows CARs of firms with different capitalization. Event window is from day -50 to day 132. Estimation window extended from August 2, 1999 (day -394) to November 24th (day -51). Normal returns for both stock exchanges are estimated following model (1). Firms with top 30% biggest market capitalizations were considered as big one, those with

30% smallest market capitalizations as small firms, and the rest as middle sized firms. We used as reference market capitalization of day -132, i.e. six months before announcement. CARs for small firms are positive and the biggest, reaching a 2.6459% average by then end of event window. Big firms also had positive CARs, yet with smaller scale and stayed quite stable as time approached end of the event window. Middle sized firms are least affected by change of settlement cycle, presenting negative but insignificant CARs.

Table 4.1.4-1: Big, Medium and Small Firm CARs Statistics

This table shows statistics of CARs for big, medium and small firms. CARs of small firms are significant, with a T statistic of 15.2786. Biggest 30% firms also had positive CARs, yet less than that of small firms. CARs of big firms stayed quite stable as time approached end of the event window, with an average of 1.2840% and T statistic of 9.9522, meaning significantly positive CARs. Middle sized firms are least affected by change of settlement cycle, presenting negative but insignificant CARs. Please refer to Methodology part to see how T statistics are computed.

	Mean CARs	Variance CAR	T statistics
Big firms	1.2840	0.0166	9.9522
Mid firms	-0.215	0.0169	-1.6526
Small firms	2.6459	0.0300	15.2786

FTSE 100 Index

Figure 4.1.4-2 demonstrates how stock in and out of FTSE 100 reacted to the event. Consistent with our expectation, an increase in CARs was bigger for stocks listed in FTSE 100, i.e. those traded under the less liquid systems.

As shown in Figure 4.1.4-2, FTSE 100 stocks and non-FTSE 100 ones followed almost the same direction. However, at the beginning of the event window, stocks listed in FTSE 100 drop slightly in return and then bounce back, whereas such volatility does not appear for non-FTSE 100 stocks. As time approaches the event day, stocks in FTSE 100 achieve sharper growth in CARs, and outperform the non-listed in FTSE 100 ones after the event day. At the end of our event window, the two subsamples achieve roughly the same CARs, with CARs of FTSE 100 stocks being slightly higher. In general, we observe a bigger change in returns before and after the event for FTSE 100-stocks.

As shown in Table 4.1.4-2, CARs of both FTSE 100 and non FTSE 100 stocks are significant. FTSE 100 stocks reached an average CAR of 1.12%, with t statistic as 7.5217. Non FTSE 100 stocks had 1.08% CAR on average and significant with t statistic of 10.9274.

Figure 4.1.4-2: CARs of FTSE 100 and non-FTSE 100 subsamples

This figure demonstrates how stocks in and outside of FTSE 100 index reacted to the event. Event window is from day -50 to day 132. Estimation window extended from August 2, 1999 (day -394) to November 24th (day -51). Normal returns for both stock exchanges are estimated following model (1). FTSE 100 stocks and non-FTSE 100 ones followed almost the same direction. However, at the beginning of the event window, stocks listed in FTSE 100 dropped slightly in return and then bounced back, whereas such volatility did not appear for non-FTSE 100 stocks. As time approached event day, stocks in FTSE 100 achieved sharper growth in CARs, and outperformed the non-listed in FTSE 100 ones after the event day. At the end of our event window, the two subsamples achieved roughly the same CARs, with CARs of FTSE 100 stocks slightly higher. In general, we observed a bigger change in returns before and after event for FTSE 100 stocks.

Table 4.1.4-2: FTSE 100 and Non FTSE 100 stocks CARs Statistics

As shown in Table 4.1.4-2, CARs of both FTSE 100 and non FTSE 100 stocks are significant. FTSE 100 stocks reached an average CAR of 1.12%, with t statistic as 7.5217. Non FTSE 100 stocks had 1.08% CAR on average and significant with t statistic of 10.9274. Please refer to Methodology part to see how T statistics are computed.

	Mean CARs	Variance CAR	T statistics
FTSE 100	1.1165	0.0220	7.5217
Non FTSE 100	1.0849	0.0099	10.9274

4.2. *Change In Liquidity*

4.2.1. Liquidity Analysis For All Sample

We adopt two measurements of liquidity, as was stated in Section Three. One is LOGVO, which is simply the logarithm of trading volume. We compute and compare the average LOGVO of the pre-event period and that of the post-event period, both including 154 days. The 154 days are the maximum period we can take because after that 9.11 occurred, and liquidity quickly dried up in markets worldwide. A second measure is ILLIQMA. Following Amihud (2002)'s approach, we made some slight adjustments to his measurement. Instead of taking the yearly average, we took the average of the pre-event and post-event period, both including 154 days.

Table 4.2.1-1: Pre- and post-event liquidity

This table demonstrates how liquidity changed after the shortening of settlement cycle. We took average log volume or illiquidity measurement of 154 days before and after the event, and then took the difference as (Pre – Post). There was actually an increase in LOGVO after shortening of settlement period, with a mean of 0.0745 and a t statistic of 2.1816. No significant change was found for ILLIQMA.

	Mean(Pre-Post)
LOGVO	-.0744524 *
	(-2.1816)
ILLIQMA	-1.46e-08
	(0.00)
N	220

t statistics in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

Table 4.2.1 demonstrates that there was actually an increase in LOGVO after the shortening of the settlement period, with a mean of 0.0745 and a t-statistic of 2.1816. No significant change was found in ILLIQMA.

To further confirm our findings, we adopted another liquidity measurement, amortized bid ask spread, which is bid-ask spread multiplied by turnover by volume. As what we did with other measurements, we took average of pre and post event periods and compared them. As supportive evidence, we found a significant decrease, with a mean of -2620.236 and t statistic of 4.0788. Thus we found a sound pattern that liquidity was increasing due to the shorter settlement. Though T+3, compared with T+5, required faster financing, which would have led to more costs, still the reduction in risk overcame such costs and resulted in a more liquid market.

4.2.2. FTSE100, SIZE, AND LIQUIDITY

Going further, we separately looked at FTSE 100- and non-FTSE 100-stocks. First, we investigated whether there was any difference between liquidity of the two categories. In table 4.2.2-1 we can see that stocks in FTSE 100 were more liquid, as indicated by the logarithm of trading volume. On average, FTSE 100 stocks’ LOGVO exceed that of non-FTSE 100 stocks by 2234.8 with a t-statistic of 1.71, significant at the 10% level. This makes sense as FTSE 100-stocks are of much bigger size. ILLIQMA does not yield any significant results.

Table 4.2.2-1: Liquidity for FTSE 100 and Non-FTSE stocks

This table compares the liquidity of FTSE 100 stocks with that of non FTSE 100 stocks in general. We took 210 days average: 154 days before and after event, together with 2 event days. Stocks in FTSE100 were more liquid, as indicated by logarithm of trading volume. On average FTSE 100 stocks’ LOGVO exceed that of non-FTSE 100 stocks by 2234.8 with a t statistic of 1.71, significant on 10% level.

	Mean(NonFTSE) – Mean(FTSE)
LOGVO	-2234.8
	(-1.71)
ILLIQMA	0.109
	(0.33)
N	220

t statistics in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

We can also see from Table 4.2.2-2 that the change in liquidity was bigger for non-FTSE 100 stocks. The logarithm of trading volume increased by 0.1028 on average, and the t-statistic was 2.55, indicating a highly significant result. For stocks in FTSE 100, we observed a slightly negative change, yet insignificant. When considering the fact that we have only 28

FTSE 100 stocks included in sample, it is difficult to discuss liquidity changes pre- and post-event.

Table 4.2.2-2: Liquidity change for FTSE 100 and non-FTSE 100 stocks

The table demonstrates how liquidity changed before and after the event for FTSE 100 and non FTSE 100 stocks. We took average log volume or illiquidity measurement of 154 days before and after the event, and then took the difference as (Pre – Post). Change in liquidity was bigger for non-FTSE 100 stocks. The logarithm of trading volume increased by 0.1028 on average, and the t statistic was 2.55, indicating a highly significant result. For stocks in FTSE 100, we observed a slightly negative change, yet insignificant.

Mean (Pre-Post)	FTSE 100	Non FTSE 100
LOGVO	.0086	-.10281*
	(0.1374)	(-2.5547)
ILLIQMA	-0.2414	0.0824
	(-0.5989)	(-0.3944)
N	56	164

t statistics in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

Then we studied changes in liquidity regarding firms of different sizes. As we can see in Table 4.2.2-3 the impact of a shorter settlement cycle was actually biggest for the top 30% big firms. The logarithm of trading volume increased by 0.14 with a t-statistic of 3.31; and the illiquidity measurement decreased with a t-statistic of 2.77 and an average of 0.0022.

Table 4.2.2-3: Liquidity change for big, medium and small firms

The table demonstrates how liquidity changed before and after the event for firms with different market capitalization. We took average log volume or illiquidity measurement of 154 days before and after the event, and then took the difference as (Pre – Post). The impact of a shorter settlement cycle was actually biggest for the top 30% big firms. Logarithm of trading volume increased by 0.14 with a t statistic of 3.31; and illiquidity measurement decreased with a t stat of 2.77 and an average of 0.0022.

Mean (Pre-Post)	Big Firms	Mid Firms	Small Firms
LOGVO	-0.1367**	-0.0586	-0.0333
	(-3.3110)	(-1.1376)	(-0.4104)
ILLIQMA	0.0022**	-0.0897	0.1175
	(2.7666)	(-0.6214)	(0.1971)
N	66	88	66

t statistics in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

4.3. *LIQUIDITY AND CARS*

To study the association between changes in liquidity and returns, we used the model as used by Berkman and Eleswarapu (1997), which was also the one adopted by Amihud (1996):

$$\mathrm{CARs_i} = \alpha + \gamma_1 * \mathrm{X_i} + \gamma_2 * \mathrm{X_{i\_pre}} * \mathrm{X_i} + \epsilon_i \,,$$

where $\mathrm{X_i}$ stands for different approximations of liquidity change:

$$\mathrm{X_i} = \mathrm{LOGVO_{post,i}} - \mathrm{LOGVO_{pre,i}} \;\text{ or }\; \mathrm{X_i} = \mathrm{ILLIQMA_{post,i}} - \mathrm{ILLIQMA_{pre,i}}$$

Pre and post stand for the 154-day average of LOGVO or ILLIQMA pre and post event. $\mathrm{X_{i\_pre}}$ stands for the pre-event 154-day averages of liquidity measurements (LOGVO or ILLIQMA).

Table 4.3-1 demonstrates regression results. We adjusted for heterogeneity when computing standard errors. LOGVO did not provide much information for our analysis. However, ILLIQMA had an impact on CARs in the way contrary to both our hypothesis and most of the previous research results. As illiquidity increased, i.e. as liquidity decreased, CARs decreased as well; and the effect was highly significant with a t statistic of 2.61. The interaction item was also significantly positive with a t statistic of 3.28, meaning that the effect on returns of liquidity changes stemming from the shortening of the settlement cycle was smaller for the previously less liquid stocks. In other words, a less liquid security will not have as much increase in return as a liquid one does when an increase in liquidity occurred due to a shorter settlement cycle. This finding is opposite to that of Berkman and Eleswarapu (1997). The pattern was quite persistent if we also check regression results of small firms and non FTSE 100 stocks subsamples.

Additionally, the association was more significant for small and Non-FTSE 100 firms. The model regarding LOGVO did not provide many new findings. However, ILLIQMA model indeed offers some new input. For small firms, we report a -1.693 $\gamma_{1,\mathrm{illiqma}}$ with a t-statistic of 2.48; the interaction item is also positive at 0.138 and significant with a t-statistic of 3.54. For stocks outside of the FTSE 100 index, the coefficient for ILLIQMA is -2.848 with a t-statistic of 3.62, and the coefficient for the interaction item is 0.198 and significant at the 0.1% level, t statistic as 4.30.

We also report a 0.13 correlation between CARs and changes in LOGVO, and a -0.23 correlation between CARs and changes in ILLIQMA. Those findings are consistent with our regression results.

Table 4.3-1: CARs and liquidity analysis

The table demonstrates regression results of $\mathbf{CARs_i} = \square + \square_1 * \mathbf{X_i} + \square_2 * \mathbf{X_{i\_pre}} * \mathbf{X_i} + \square_i$, where $\mathbf{X_i}$ stands for different approximations of liquidity change: $\mathbf{X_i} = \mathbf{LOGVO_{post,i}} - \mathbf{LOGVO_{pre,i}}$ or $\mathbf{X_i} = \mathbf{ILLIQMA_{post,i}} - \mathbf{ILLIQMA_{pre,i}}$. Pre and post stand for the 154-day average of LOGVO or ILLIQMA pre and post event. $\mathbf{X_{i\_pre}}$ stands for the pre-event 154-day averages of liquidity measurements (LOGVO or ILLIQMA). $\mathbf{CARs_i}$ is the cumulative abnormal return of firm i at day 132. Regressions are run for total sample as well as subsamples of different market capitalization or whether the stock is in or out of FTSE 100 index. LOGVO did not provide much information. However, ILLIQMA had an impact on CARs in the way contrary to both our hypothesis and most of the previous research results. As illiquidity increased, i.e. as liquidity decreased, CARs decreased as well; and the effect was highly significant with a t statistic of 2.61. The interaction item was also significantly positive with a t stat of 3.28, meaning that the effect on returns of liquidity changes stemming from shortening of settlement cycle was smaller for the previously less liquid stocks. In other words, return of a less liquid security is less sensitive than a liquid one to liquidity change due to shortening of settlement cycle. And such pattern was quite persistent, proved by small firms and non FTSE 100 subsamples.

	All	All	Big Firms	Mid Firms	Small Firms	FTSE100	Non FTSE100	Big Firms	Mid Firms	Small Firms	FTSE100	Non FTSE100
$\gamma_{1,logvo}$	1.374		46.83	-29.46*	-13.22	28.62	-3.082					
	(0.10)		(1.59)	(-2.30)	(-0.74)	(1.78)	(-0.20)					
$\gamma_{2,logvo}$	0.217		-5.459	4.943*	2.897	-3.442	0.808					
	(0.11)		(-1.41)	(2.10)	(1.12)	(-1.41)	(0.34)					
$\gamma_{1,illiqma}$		-2.069*						-1689.5	-3.192*	-1.693*	1.767	-2.848***
		(-2.61)						(-1.72)	(-2.50)	(-2.48)	(0.77)	(-3.62)
$\gamma_{2,illiqma}$		0.150**						58108.0	-0.705	0.138**	-1.156	0.198***
		(3.28)						(1.35)	(-0.52)	(3.54)	(-1.08)	(4.30)
_cons	0.868	1.383	1.408	-0.335	2.522	1.707	0.815	0.465	0.0674	3.337*	1.076	1.387
	(1.08)	(1.97)	(1.63)	(-0.25)	(1.51)	(1.06)	(0.82)	(0.44)	(0.06)	(2.14)	(0.72)	(1.70)
N	110	110	33	44	33	28	82	33	44	33	28	82
R-sq	0.016	0.125	0.068	0.038	0.083	0.070	0.013	0.145	0.260	0.171	0.173	0.176
adj. R-sq	-0.002	0.108	0.005	-0.009	0.021	-0.004	-0.012	0.088	0.224	0.116	0.107	0.155

t statistics in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

5. CONCLUSION

This paper examined the abnormal return of stocks that had been affected by the adoption of a T+3 settlement cycle on LSE. A positive abnormal return was found due to the shortening of the settlement cycle. By further examining subsamples of firms of different sizes, we found that the smallest 30% firms had the biggest CARs, followed by the biggest 30%, and the middle sized firms were least affected in terms of returns.

We then looked into liquidity. By using the logarithm of trading volume and Amihud's (2002) measurement for illiquidity as two approximations for liquidity, we found an increase in liquidity after the implementation of T+3, with bigger firms experiencing a more significant and larger increase.

A third finding concerns the relationship between liquidity and abnormal returns. We found a positive relation between them, with most significant results find among small firms. We also prove that such positive association is smaller for illiquid stocks.

6. ROBUSTNESS TEST

In this section we further test the stability and robustness of our findings. We use monthly returns instead of weekly ones, and conduct tests for CARs, liquidity and how they are associated with each other. We reapply the same method as in the previous parts.

Looking at Figure 6-1, we observe a similar pattern for CARs as we find for weekly returns in the previous parts. From Table 6-1, we can observe that at day 132, mean CARs reached 3.6495%, with a t statistic of 23.9383, indicating a significantly positive abnormal return after the event.

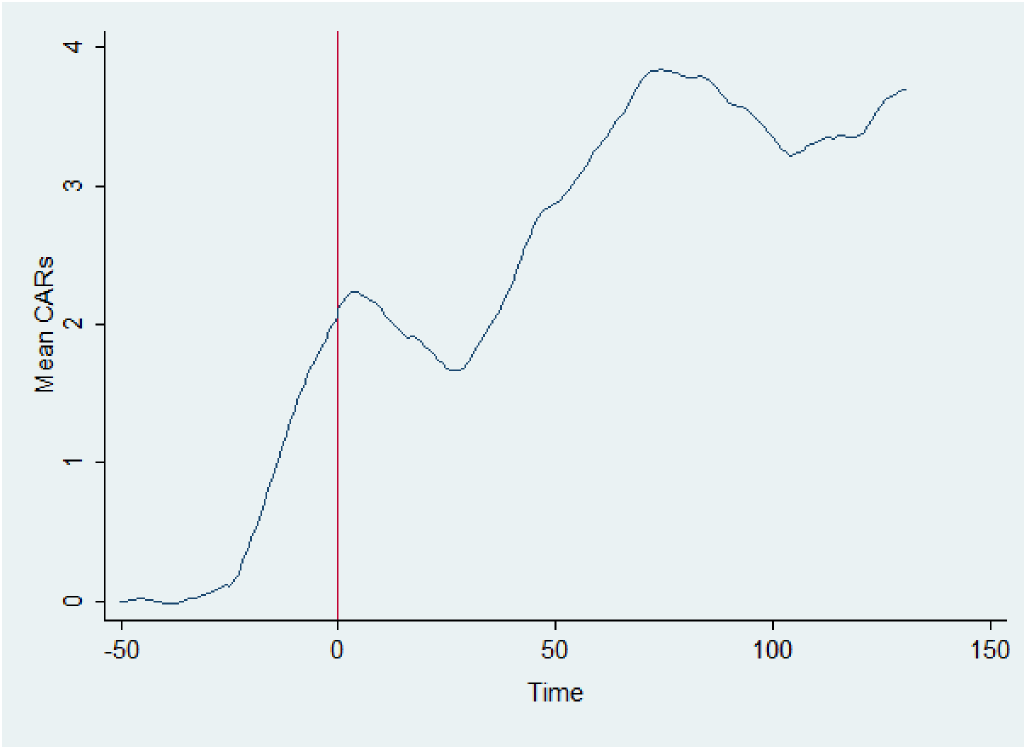

Figure 6-1: Monthly CARs

This figure demonstrates that we found the same pattern of CARs with monthly data as with weekly.

Table 6-1: Statistics of CARs

This table shows some statistics concerning CARs calculated with monthly data. At day 132, mean CARs reached 3.6495%, with a t statistic of 23.9383, indicating a significantly positive abnormal return after the event.

Mean CARs	Variance of CARs	T Statistic
3.6495	.0232	23.9383

Our findings regarding liquidity are also quite robust. Table 6-2 demonstrates the liquidity changes before and after the event. We did not change our way of computing LOGVO and consequently there is no change in results of this part. But for ILLIQMA, we used monthly returns this time. As is shown in Table 6-2, ILLIQMA is still not offering much new information. But in general, this illiquidity measurement is decreasing.

Table 6-3 presents regression results with monthly returns. Again, similar to our findings in previous parts, ILLIQMA is negatively related to CARs, with positive and significant coefficients for interaction items. Also, coefficients for small and non-FTSE 100 firms are more significant.

One thing worth mentioning is the extremely big $\gamma_{1,\text{illiqma}}$and $\gamma_{2,\text{illiqma}}$ among big firms. This is mostly because ILLIQMA measurement for big firms is much lower than that of others as a result of their big trading volumes and higher prices. Changes in ILLIQMA before and after event for big firms are even smaller. Thus the scale of ILLIQMA is extremely small, and that of the interaction item is even smaller. With CARs on roughly the same scale as with other firms, big firms have to have extremely big coefficients.

Table 6-2: Liquidity changes

This table demonstrates the liquidity changes before and after the event. The computation of LOGVO remained the same, and consequently there is no change for results of this part. However, for ILLIQMA, we used monthly returns instead of weekly return. Still, ILLIQMA does not offer any new information. In general, the illiquidity measurement is decreasing.

Mean (Pre-Post)	All	FTSE 100	Non FTSE 100	Big Firms	Mid Firms	Small Firms
LOGVO	-0.0745*	0.0086	-0.1028**	-0.1367**	-0.0586	-0.0333
	-2.1816	0.1374	-2.5547	-3.311	-1.1376	-0.4104
ILLIQMA	-6.20E-09	-0.032	0.0109	-0.0004	-0.0795	0.1064
	-0.0000	-0.1316	0.0373	-0.6776	-0.5228	0.1449
Obs	110	28	82	33	44	33

t statistics in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

Table 6-3: Liquidity change and CARs analysis, monthly data

The table demonstrates regression results of $\mathrm{CARs_i} = \alpha + \gamma_1 * \mathrm{X_i} + \gamma_2 * \mathrm{X_{i\_pre}} * \mathrm{X_i} + \epsilon_i$, where $\mathrm{X_i}$ stands for different approximations of liquidity change: $\mathrm{X_i} = \mathrm{LOGVO_{post,i}} - \mathrm{LOGVO_{pre,i}}$ or $\mathrm{X_i} = \mathrm{ILLIQMA_{post,i}} - \mathrm{ILLIQMA_{pre,i}}$. Pre and post stand for the 154-day average of LOGVO or ILLIQMA pre and post event. $\mathrm{X_{i\_pre}}$ stands for the pre-event 154-day averages of liquidity measurements (LOGVO or ILLIQMA). $\mathrm{CARs_i}$ is the cumulative abnormal return of firm i at day 132. Regressions are run for total sample as well as subsamples of different market capitalization or whether the stock is in or out of FTSE 100 index. Yet here we used monthly returns instead of weekly returns. Similar to our findings in previous parts, ILLIQMA is negatively related to CARs, with significantly positive coefficients for interaction items. The pattern is still quite persistent.

	All	All	Big Firms	Mid Firms	Small Firms	FTSE100	Non FTSE100	Big Firms	Mid Firms	Small Firms	FTSE100	Non FTSE100
$\gamma_{1,\mathrm{logvo}}$	35.18		180.8	-96.44	11.19	132.8	24.02					
	(0.67)		(1.55)	(-1.80)	(0.12)	(1.85)	(0.41)					
$\gamma_{2,\mathrm{logvo}}$	-3.472		-22.01	15.99	2.444	-15.38	-2.300					
	(-0.46)		(-1.53)	(1.58)	(0.18)	(-1.48)	(-0.28)					
$\gamma_{1,\mathrm{illiqma}}$		-7.252***						-5053.8*	-21.97**	-7.248***	-13.09*	-7.317**
		(-3.60)						(-2.67)	(-2.89)	(-4.03)	(-2.06)	(-3.35)
$\gamma_{2,\mathrm{illiqma}}$		0.318**						252594.8	8.493*	0.334***	2.772	0.316**
		(3.29)						(1.44)	(2.48)	(3.69)	(0.90)	(3.04)
_cons	2.997	4.871	5.107	-1.989	10.02	8.489	2.112	5.889*	4.485	14.15*	8.400	4.379
	(0.92)	(1.71)	(1.95)	(-0.37)	(1.44)	(1.46)	(0.52)	(2.62)	(1.25)	(2.10)	(1.75)	(1.32)
N	110	110	33	44	33	28	82	33	44	33	28	82
R-sq	0.021	0.122	0.152	0.024	0.099	0.133	0.011	0.337	0.323	0.209	0.113	0.136
adj. R-sq	0.003	0.105	0.096	-0.023	0.039	0.063	-0.014	0.292	0.290	0.157	0.042	0.114

t statistics in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

7. CRITICAL EVALUATION AND LIMITATIONS

Limitation of Methodology

One limitation of our study is the applied methodology. The basic approaches used in this paper are an event study and CAR as an approximation for impacts caused by the event. Three important prerequisites are that there are no events other than our objective happening around the event day, that there is no anticipation beforehand, and those markets are indeed efficient enough to integrate information into prices. However, neither prerequisite was satisfied in our study. Although we used certain approaches to fix the problems, these facts limit the credibility of our study and could have caused biases.

Limitation of Model

Another limit can be found in the model for normal returns, which is based on the one developed by Fama and French (1993). The model in this paper accounts for size, B/M, market returns and calendar effects. Yet, some other factors might be missed out such as industry effects and the dot-com bubble. Time series models could be another choice. Berkman and Eleswarapu (1997), when studying the effect of abandoning Badla, modeled returns of Badla stocks at time T with those of non-Badla stocks at time T and T-1.

Limitation of Data

Data availability also put limits on this study. On one hand, although we tried to include data of all UK equities traded on LSE, a big portion had to be excluded due to missing values. On the other hand, it would be better to include global depository receipts (GDR) traded on LSE for cross sectional analysis. But this paper had to turn to FWB due to unavailability of data for GDR.

Moreover, it was impossible to expand our study to more than 154 days due to 9.11, which would have distorted the results. However, one way to get around this problem would be to focus on another similar event: the adoption of T+2 in Germany. Yet, this paper could not study this event due to a lack of proper data.

8. SUGGESTIONS FOR FURTHER RESEARCH

First, a time series study would be valuable. This paper includes a cross sectional analysis to study how liquidity and CARs are correlated. However, it could be interesting to investigate whether this interaction changes over time. When conducting such a research, one should also account for the autocorrelation of CARs and liquidity, which can be expected to have decisive influence.

Secondly, whereas we studied subsamples of firms of different sizes as well as FTSE 100 versus other stocks, future research could start with a study on the question of how size and liquidity interact, and then carry on with the analysis done in this paper. A quantile analysis for securities with different liquidity could also be insightful.

Additionally, while this paper reports how returns and liquidity react to a change of the settlement cycle, it does not provide the underlying reasons. Given that we actually found a positive link between liquidity and return, which is to the contrary of most of previous findings, it would be insightful to look into the reasons.

Another interesting topic is drivers for liquidity. With intraday trading strategies such as algorithmic trading more and more widely adopted, daily trading volume is actually much higher than the liquidity position at the close of market. Thus, one might want to see how these liquidity drivers might have biased our study.

Similar studies looking at other countries could also be of interest. This would allow us to see whether any specific market or markets with certain characteristics would benefit more, in terms of efficiency, from getting a shorter settlement cycle.

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APPENDIX

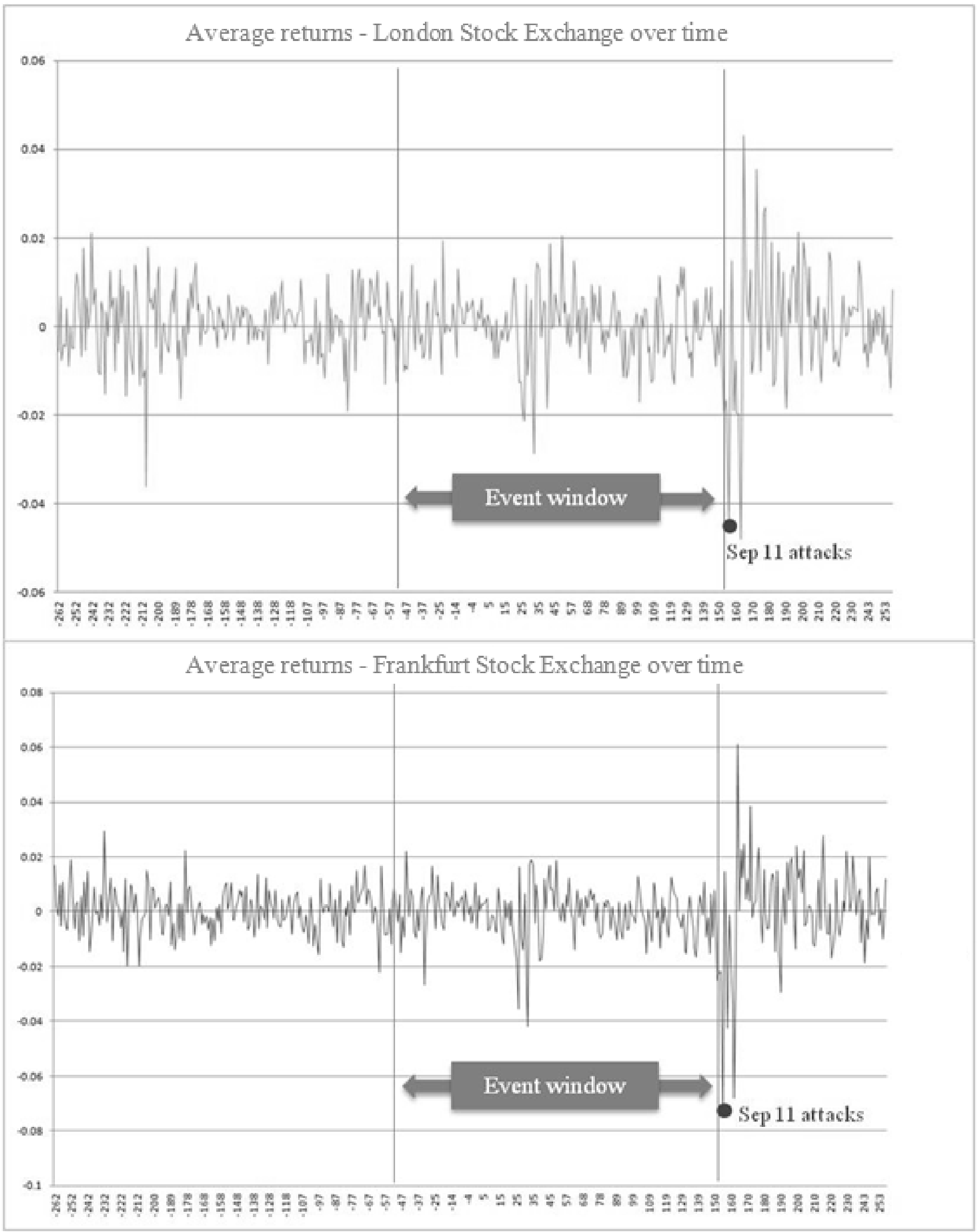

Figure I: Average Returns of London Stock Exchange and Frankfurt Stock Exchange over study window

This figure shows market returns over time period that we are interested in. By looking at the average returns in London Stock Exchange in comparison to the average returns in Frankfurt Stock Exchange. In this figure, it can be clearly seen the market shock resulting from the September 11 attack.

Table I: Descriptive Statistics of dataset used in this paper

Total	Price	Volume	Spread	Price to book	MKT Cap
Mean	508.312	5468.976	6.521	3.586	7416.339
SD	700.876	11548.498	23.062	4.757	17824.001
Coeff of variation	1.379	2.112	3.537	1.326	2.403
Median	317.380	1378.200	3.000	2.360	1158.330
Min	5.780	0.000	-95.000	0.100	13.420
Max	12495.050	381689.800	1532.280	109.570	151780.600

Before	Price	Volume	Spread	Price to book	MKT Cap
Mean	527.168	4497.800	7.089	4.111	7127.833
SD	753.510	9685.752	20.209	6.059	16783.471
Coeff of variation	1.429	2.153	2.851	1.474	2.355
Median	318.500	1194.700	3.050	2.460	1144.305
Min	10.630	0.000	-12.960	0.100	27.380
Max	12495.050	315681.600	816.450	109.570	151780.600

After	Price	Volume	Spread	Price to book	MKT Cap
Mean	492.020	6306.121	6.031	3.134	7665.618
SD	651.555	12882.223	25.254	3.171	18673.002
Coeff of variation	1.324	2.043	4.187	1.012	2.436
Median	316.190	1569.450	3.000	2.290	1167.425
Min	5.780	0.000	-95.000	0.220	13.420
Max	5750.010	381689.800	1532.280	28.560	145629.500