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Analysis of the bid-ask spread and its implication for portfolio returns

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ABSTRACT

Liquidity in financial markets is often thought of as the ease to trade an asset. In most financial models it is assumed that it is always possible to trade, which implies that liquidity is high and constant. The financial crisis of 2007-2009 showed that this assumption does not hold. During the financial crisis, the global stock market saw a substantial decline in asset prices and a period of high volatility, and periods of extremely tough markets tot trade in. This illustrates the importance of liquidity on the effective functioning of the financial markets. On account of the theoretical underpinning on market liquidity and why it is an important source of priced risk for assets, in particular for stocks, we apply a cost-based measure of market liquidity, namely the bid-ask spread on all Norwegian stocks as well as the market (i.e., OSEBX). One of the most popular measures for the bid-ask spread, namely Corwin and Schultz (2012) and a newly derived estimator for the bid-ask spread, what we have denoted Alpha, and derived by Leirvik (2015), are applied in this thesis with both estimators using observations of daily high and low prices.

We find that: (1) liquidity is a time-varying risk factor, both for the individual stocks listed on the Norwegian stock exchange and of the market; (2) the portfolio which comprises of stocks with wide bid-ask spread, has on average higher returns than all other portfolios; (3) the least liquid portfolio outperforms the most liquid portfolio, an indication of the presence of liquidity premium for the Norwegian stocks; (4) the stocks of both large and small firms for the least liquid decile outperform the stocks of large and small firms for the most liquid decile respectively; (5) the stocks of large firms outperform the stocks of small firms for both the least and most liquid deciles; (6) the average return difference between the least liquid and the most liquid stocks are positive every year; (7) the market outperforms the stocks of small firms for both the least and most liquid deciles on an annual basis whiles the stocks of large firms for the least liquid decile outperform the market on a yearly basis; (8) the volatility of liquidity (i.e spread) for the average liquidity of Norwegian stocks is relatively high in comparison to the overall market by applying CS estimator as compared to applying Alpha estimator.; (9) the return volatility on the least liquid stocks is relatively high in comparison to the most liquid stocks by applying both Alpha and CS estimators; (10) the volatility of excess returns and returns in general are higher by applying CS estimator than applying Alpha estimator.

Keywords: financial crisis, bid-ask spread, liquidity premium, risk and returns, market liquidity

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CHAPTER ONE

INTRODUCTION

1.1 Overview

Over the past decades, there has been a growing interest regarding the factors that affect expected stock returns among both academic and practitioner audiences. The basis of some of the recent studies on these issues has originated from two of the most important independent intellectual traditions. The first is derived from the asset pricing literature which examine whether idiosyncratic risk plays a role in expected stock returns while the second originates within the financial market microstructure literature which shows how liquidity is related to expected returns. Our thesis is related to the second tradition as the literature on asset liquidity has received much attention in recent years.

Liquidity is often separated into two terms: funding liquidity and market liquidity. Funding liquidity refers to funds available for traders to carry out their trades. Market liquidity is the ease of trading assets in the financial market. Of course, funding liquidity and market liquidity is closely tied together, as is highlighted in a paper by Brunnermeier and Pedersen (2009). In this thesis, we focus on market liquidity, and in particular a specific cost-based measure of market liquidity, namely the bid-ask spread. Market makers are often called liquidity providers, as they take the opposite position to the traders who want to buy or sell an asset. For this role, the liquidity provider charges a fee, just as a restaurant sells its food for more than the cost of raw materials. This is the bid-ask spread that market makers set, and is an essential component of transaction costs faced by liquidity demanders (i.e., the investors) in a financial market. Market makers play a key role in price discovery and stabilization.

Price discovery refers to the process of determining the price of a security through supply and demand factors related to the market as well as other factors associated with transactions. Market makers facilitate the determination of accurate prices by their own quotes (i.e., bid and ask prices) which directly set market prices and indirectly influence public traders' reaction in order flow. On the other hand, price stabilization has been defined by the Securities and Exchange Commission (SEC) as the execution of transactions that aim at preventing or retarding a drop in the market price of a security to facilitate its distribution to the public (offering). The liquidity provided by market makers helps to stabilize price fluctuations in the short run. This lowers the risk of adverse price movements for investors who are generally averse to transaction price uncertainty.

Market makers actively buy and sell securities for their own account in response to expected fluctuations in security prices in the short-run. Thus, the central role of market makers is to initiate and drive the process of setting equilibrium prices within a bid and ask spread as well as to react to the response of these prices. In securities markets with quoted bid and ask prices, which represent the buying and selling prices respectively, the buy transaction is in normal times executed at a higher price relative to the sell transaction, giving rise to a bid-ask spread. Notably, the bid and ask prices apply only to limited trade quantities. Market makers therefore provide liquidity in the market by standing ready to buy and sell securities at a prevailing market price. If an investor wants to buy a security for example, the market makers sell. Similarly, if an investor wants to sell a security, the market makers buy. For this service provision, market makers buy at a low bid price, $P_{b,}$ and sell at a high ask price, $P_{a,}$ so that they are likely to profit in the transactions. The bid-ask spread (BAS) represents the margin, which is the difference of the bid price and the ask price, $BAS = P_a – P_{b,}$ and is a measure of market liquidity and of a trading cost. Thus, high trading cost is associated to illiquidity. The trading costs depend on the structure of the market where the securities are traded.

Forward-looking investors demand higher future yields on their investments when they anticipate a persistent increase in market illiquidity. This causes the required return to increase and consequently results in a fall in securities prices. The effect of market liquidity shocks on the market prices of securities introduces additional risk to market returns beyond the risk that is related to shocks about the expectations of future cash flows. In the presence of market liquidity and price shocks, risk-averse investors prefer securities with lower liquidity risk (i.e., securities with returns that are not affected by times of low liquidity). Therefore, the higher liquidity risk is, the higher the expected return that is demanded as compensation. The extra return demanded by investors as reward for holding assets that may not be easily converted into cash is referred to as liquidity premium.

1.2 Background of this thesis

The Global Financial Crisis began to erupt in 2007 when the subprime mortgage crisis unfolded in the US and spread rapidly to most financial markets around the globe. The financial crisis was associated with severe liquidity shocks in global stock and bond markets. The global stock markets experienced a substantial fall in asset prices and subsequently entered a period of high volatility. The financial institutions were in the centre of the crisis, and many major banks and financial institutions faced serious liquidity problems. Liquidity problems that for some turned into solvency problems, as it did for Lehman Brothers. At the same time governments and central banks around the world attempted to coordinate efforts to provide financial rescue. In spite of these coordinated efforts, the stock market crash accelerated. The week beginning October 2008, experienced the worst weekly decline in the history of the United States (U.S.). A number of the world's largest institutions and financial system were almost at the verge of collapse. The stock prices of major global banks declined by about 50% on average during the fourth quarter of 2008, resulting in a loss of market value of about 640 billion US dollars. As a consequence, the world trade and the world's Gross Domestic Product (GDP) witnessed a decline of about 25% and 6% respectively at an annualized rate.

Figure 1 shows the TED spread and its components: the three-month London Interbank Offered Rate (LIBOR); and U.S. Generic Government 3 Month (USGG3M) yield over the period July 2006-July 2009. The TED spread which is the margin between its components increased significantly during the financial crisis, indicating an increase in perceived credit risk.

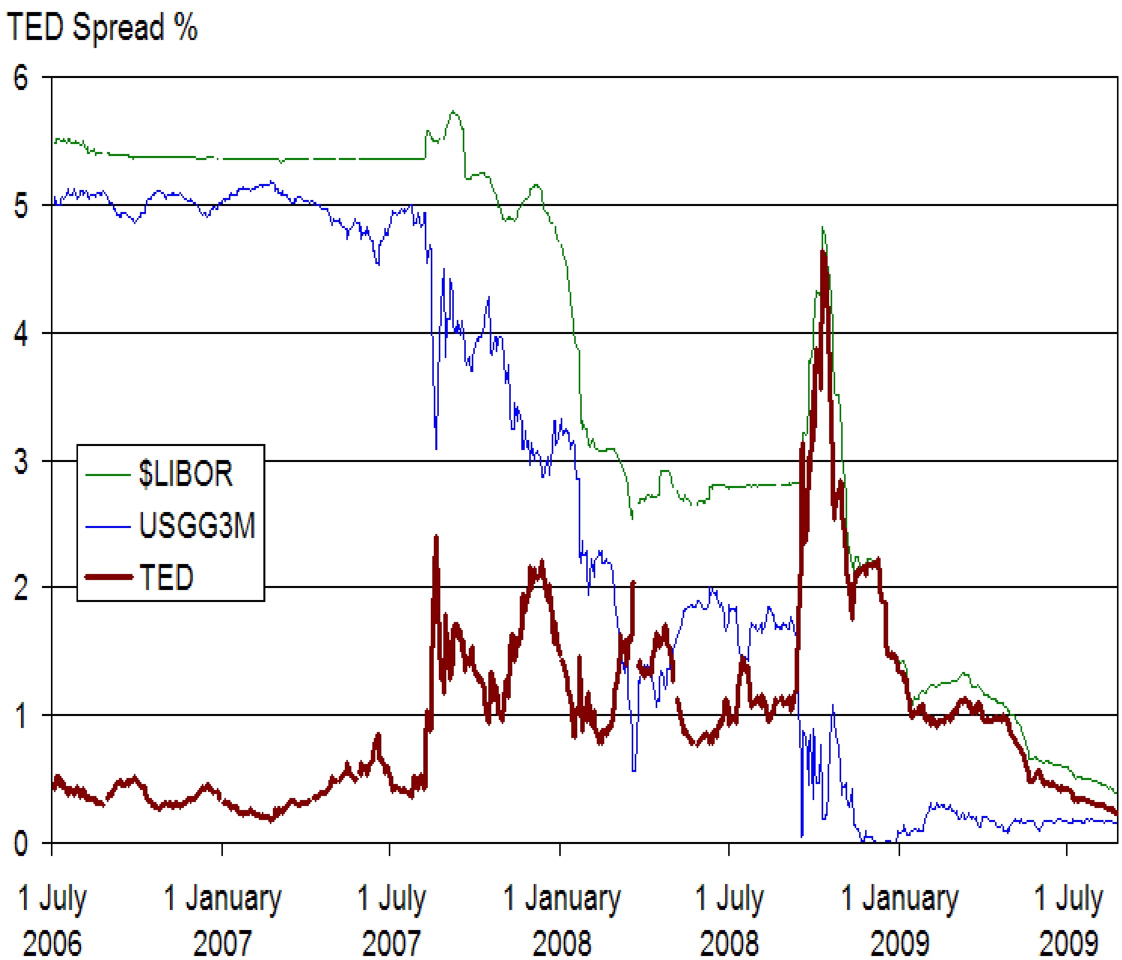

Figure 1: The figure illustrates the TED spread and its components during the recent financial crisis

Another example is the May 6th 2010 flash crash, which started at 2:32pm and lasted about 36 minutes. During that short time, stock indices, such as the SandP500 and the Dow Jones Industrial Average, collapsed and then rebounded very quickly. The Dow Jones Industrial Average had its biggest intraday point drop (from the opening) up to that point, plunging 998.5 points (about 9%), most of it within minutes, only to recover a large part of the loss. During this time, it was very difficult to trade, as investors, many of them so-called algo-traders, underbid each other at an exceptional pace. This made it virtually impossible to trade around the last traded price, and liquidity dried up to historically low levels (see for example, Easley et al., 2011a; 2011b) However, measuring liquidity is not without problems, as the paper by Andersen and Bondarenko, (2014) shows. Figure 2 illustrates the evolution of the E-mini SandP500 stock index futures contract and its probability of informed trading (PIN) as well as confidence. The order flow toxicity is measured as probability of informed traders such as hedge funds to adversely select uninformed traders. For example, market makers was at historically high levels an hour before the flash crash. This caused market makers to become liquidity demanders rather than liquidity providers.

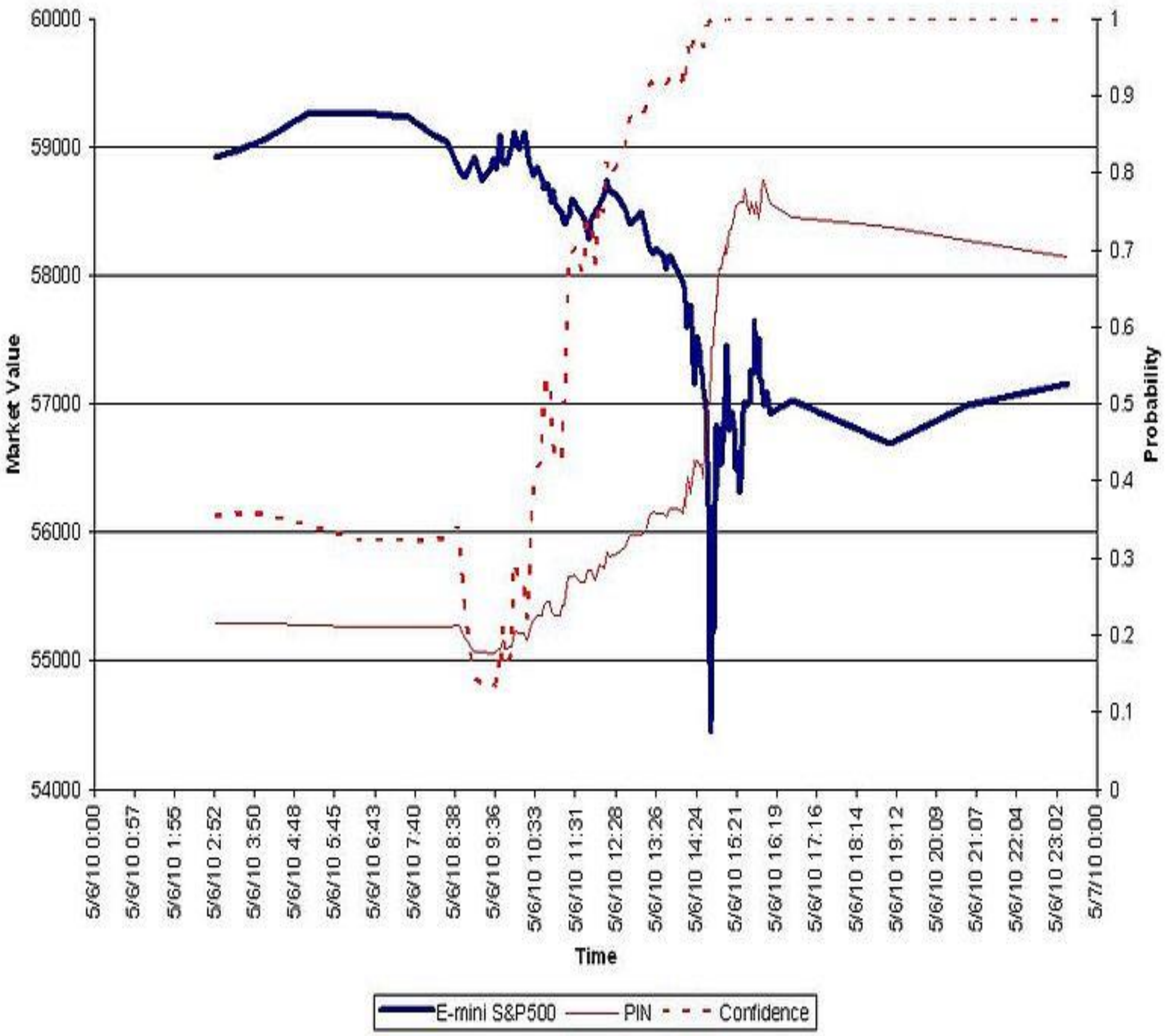

Figure 2: The figure illustrates market value in E-mini SandP500 futures and the order flow toxicity (expressed by PIN) an hour before the flash clash as well as confidence

As a last example, we include the Euro debt crisis that has been taking place since 2009. In these recent years, several Eurozone countries were not able to refinance their debt. Due to the problems of repaying debt, many European countries were downgraded by credit-rating agencies. Trade in the bonds issued by these countries reflected both the increased credit risk and liquidity risk, as the investors shied away from these bonds unless there was a significant reduction in price. See Figure 3 for an illustration of long-term interest rates in the Euro area over the period October 2009-August 2015.

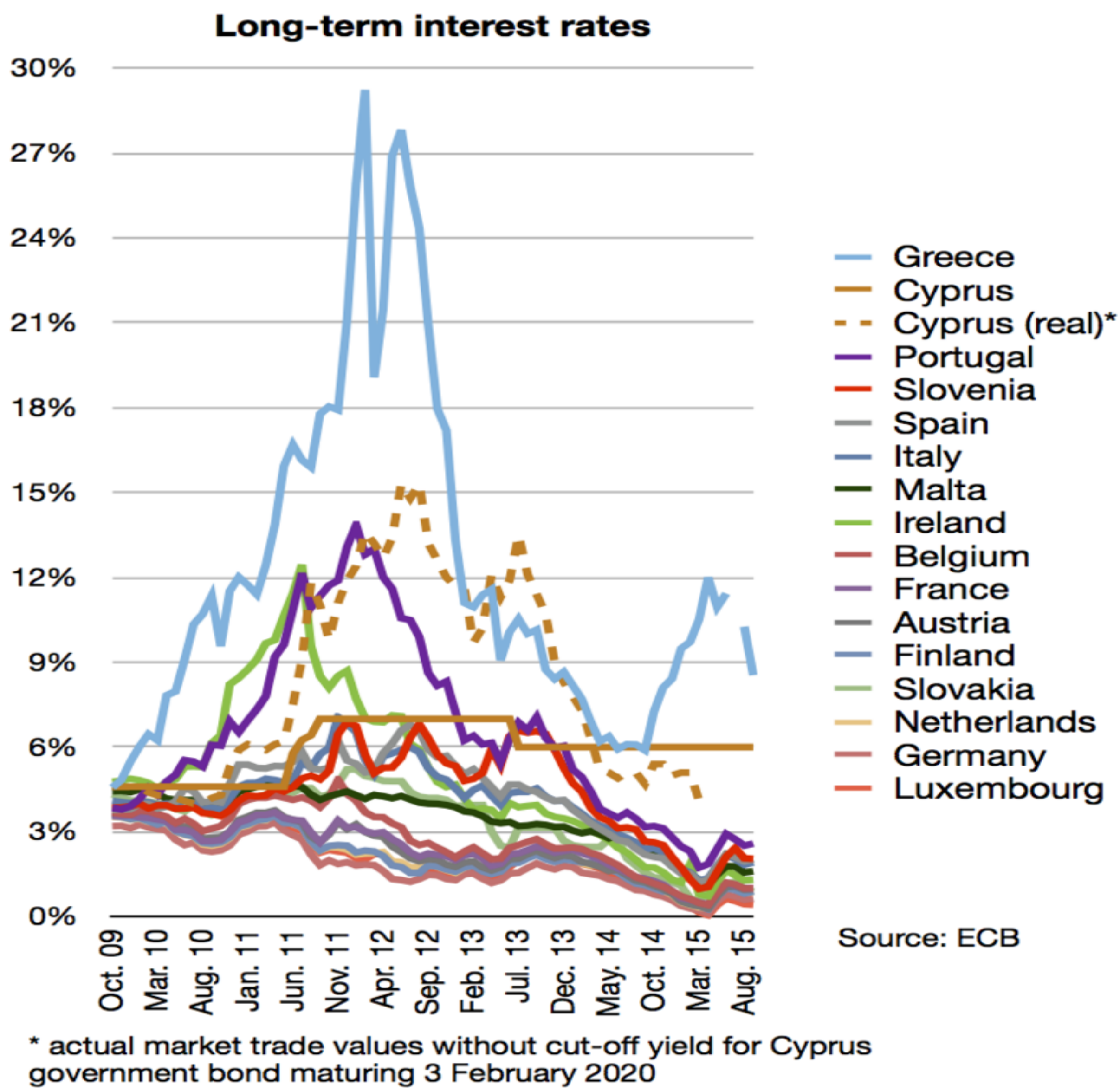

Figure 3: The figure illustrates the long-term interest rates on bonds issued by countries in the Euro area.

The recent financial events clearly demonstrate that liquidity can suddenly deteriorate dramatically and is not constant, as standard asset pricing studies usually assume. Thus, liquidity changes over time for individual securities and for the market at large. It varies for a number of reasons. First, it is dependent in part on the transparency of information about the value of a security, which changes over time. Second, the number of liquidity providers and their access to capital is a key determinant of market liquidity. Less liquidity is provided when liquidity providers (for e.g., market makers, trading firms, banks and hedge funds) lose capital and have constraints regarding access to securitized funding as evident in 2008. As a consequence, market liquidity drops contemporaneously for most securities. Finally, increased uncertainty regarding liquidity makes the provision of liquidity more risky and increases the compensation that liquidity providers demand (i.e., the trading cost increases).

When more investors have the willingness to engage in trading, they tend to provide liquidity to each other and attract more traders into the market, which consequently broadens the aggregate market liquidity. On the other hand, the unwillingness of a considerable number of investors to trade or the withdrawal of more investors from the market causes, at least temporarily, a decline in funding liquidity and a subsequent drop in market liquidity. This consequently affects asset prices on the entire market. Thus, liquidity can suddenly dry up, an unfavorable condition in a market that market makers, traders, and investors want to avoid or guard against. For instance, during the recent financial crisis, investors experienced severe decline in liquidity and were scared that liquidity would dry up even further.

Investors are concerned about liquidity because a dramatic decline in liquidity would lead to a fall in securities prices and a rise in the required return as evidenced in the recent liquidity crisis. This will subsequently contribute to a large drop in securities prices as the crisis worsens. This can be a plausible explanation to why prices rebounded so strongly when the liquidity crisis eased off, beginning from March 2009. Here, liquidity crisis is referred to as a situation where market-wide liquidity suddenly drops as market makers and dealers widen bid-ask spreads, refuse to use their phones, or bring their operational activities to a close as they run out of cash at their trading houses. It is also related to a state where they take their money off the table and securities prices drop dramatically as well as volatility increases.

Variations in the overall market liquidity relative to expected value are commonly referred to as liquidity shocks. The new level of liquidity affects aggregate securities prices, if these changes are persistent. Thus, when the overall market liquidity exacerbates and trading costs rise, these costs are more likely to remain higher for a while and, as a consequence, stock prices fall. The plausible explanation for this is that, forward-looking investors demand higher expected returns on trade securities as a reward for bearing higher trading costs. In other words, investors discount future corporate cash flows at higher rates, which cause stock prices to decline, ceteris paribus, see Acharya and Pedersen (2005).

Market-wide liquidity shocks generate shocks to asset prices and are associated with uncertainty about asset returns. These aggregate liquidity shocks are considered as a source of systematic risk that should be priced by risk-averse investors. Empirical evidence regarding the notion that exposure to liquidity shocks is priced has been presented in literature, see, for e.g., Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005. However, the connection between market-wide liquidity shocks and asset prices differ across securities.

Liquidity is considered the most critical factor in financial market growth and assessment, thus, maintaining market liquidity is necessary for the market to become more stable and help accelerate its growth. Moreover, it is multi-dimensional and is characterized by trading quantities, trading speed, trading cost and price impact, see Liu, 2004. Liquidity is considered to be essential for effective market functioning. In recent years, there has been a growing interest regarding the role of liquidity in empirical finance, see Datar et al. (1998); Lesmond et al. (1999); Lesmond (2005); and Goyenko et al. (2009).

Different scholars and researchers concerned with market liquidity have proposed different liquidity measures, for example, Roll, 1984; Lesmond et al., 1999; Amihud, 2002; Hasbrouck, 2004; Holden, 2009; Corwin and Schultz, 2011, to demonstrate the significant role of liquidity in asset pricing and to document how liquidity affects assets prices as well as the overall securities market performance. However, each existing measure typically focuses on one dimension of liquidity, mainly trading costs or price impact. This is due to the fact that the liquidity premium compensate for price impact, see Lou and Shu, 2014, and trading costs are among the fundamental characteristics of many investment plans and financial assets, Amihud and Mendelson (1986).

Further, a number of empirical studies have employed several liquidity measures to analyse the effect of liquidity on asset pricing and provide a prediction of how liquidity is related to expected returns of portfolios across different securities. Amihud and Mendelson developed a model in 1986 that gave rise a two major predictions. The first prediction is that in equilibrium, the return on an asset with higher trading costs is equal to the return that would be earned on a similar risk asset with perfect liquidity (involving zero trading costs) plus a return premium that compensate investors bearing the higher transaction costs (i.e., higher trading costs result in an asset price discount). The second prediction is that the marginal increase in these costs on the returns required by investors is lower due to the clientele effect. This happens because in equilibrium, investors with longer holding periods tend to hold low-liquidity assets.

After testing these predictions on the return-trading cost relation using data on stock traded on the AMEX and NYSE and the relative bid-ask spread measure of liquidity, their results supported the predictions of the theoretical model. However, they concluded that, “liquidity is priced: stocks with a high bid-ask spread have a higher cost of capital or lower price for any given cash flow that these stocks generate” (Amihud and Mendelson, 1986). Several later studies (for example, Brennan and Subrahmanyam, 1996; Datar et al., 1998; Loderer and Roth, 2005) confirm the predictions of the theoretical model of liquidity as measured by bid-ask spread (i.e., a measure of the trading cost dimension of liquidity) and average portfolio returns. As a result of this, market liquidity as measured by the bid-ask spread has gained a lot of attention among scholars, researchers and market participants.

The global financial crisis of 2007-2009 has been perceived as the worst financial crisis after the great depression of the 1930’s and illustrates the importance of understanding liquidity and liquidity risk and the impact on securities prices and on the functioning of financial markets. Because the oil and gas industry is a major part of the Norwegian economy, we will consider the current turmoil in the energy markets, in particular the oil market and the effect on market liquidity. In light of this, we aim to test the behavior of these two measures for the bid-ask spread before, during and after the financial crisis as well as the current turmoil in oil market and how they affect the liquidity of the Norwegian stock market.

Early studies have proposed liquidity measures based on daily return and volume data as proxies for investors' liquidity and transaction costs. However, most of these studies (for example, Lesmond et al., 1999; Lesmond, 2005; Hasbrouck, 2009) tested whether a relationship exists between security returns and these liquidity measures but hardly tested whether the measures actually measured transaction costs. Goyenko et al. (2009) argued that the proposed liquidity measures which are believed to capture the transaction costs of market participants are rarely tested. This is because in the US markets, readily available transaction data are limited and in many other markets there are no transaction data at all. In addition, only a few proposed liquidity measures have been previously tested and liquidity benchmarks used in the literature are very limited. There is therefore no doubt that there are conflicting views about which measure is better and there exists little evidence that the proposed measures are related to investor experience (Goyenko et al., 2009).

According to Corwin and Schultz (2011), there is still little research on the potential application and analysis of the prominent liquidity measures for the bid-ask spread regarding which measure(s) provides the much-needed assurance of liquidity measurement. Meanwhile, there are a few recent innovations for a measure of the bid-ask spread with little consensus on which measure is a better measure of liquidity. There is also little evidence that these proposed measures of the bid-ask spread actually measure liquidity. That is, whether these measures actually capture the transaction costs of market participants (Goyenko et al., 2009). Butler et al. (2005) also posed an important: should firms be interested in the market liquidity of their securities? It has been established in the literature that liquidity is priced in the cross section of stock returns, see Amihud and Mendelson (1986); Brennan and Subrahmanyam (1996); Easley et al. (2002). Some existing literature tries to answer this question by linking liquidity to a firm's cost of capital, however, they find no supporting empirical evidence on this issue in the case of stocks, (for example, Reingamum, 1990; Eleswarapu and Reingamum, 1993). This therefore creates a need for further studies to address this gap in the literature by relating these proposed measures for the bid-ask spread (i.e., liquidity) to portfolio returns and further control for firm size to come to a conclusion. Subsequently, it can be fruitful to investigate whether liquidity risk is priced, hence it is also important to analyse how the bid-ask spread affects portfolio returns as well as make a comparison with the market index (i.e. OSEBX).

1.3 Statement of the problem

As highlighted in section 1.2, liquidity is especially important for investors and plays a crucial role in facilitating the effective and efficient functioning of markets. The gap in literature has also been discussed in this section. Our main motive for this research is to provide an answer to the main research question: *How does the bid-ask spread measure of liquidity affect returns?* The lion's share of this thesis will be concerned about this question. However, there are many subquestions that can be addressed, such as; *Are returns on the least liquid stocks higher than that of the most liquid stocks? Does the size of the firm explain any patterns in returns due to liquidity?; How does the volatility of returns between the least and most liquid stocks differ?;* and *Is the volatility of liquidity for the average Norwegian stocks relatively high in comparison to the OSEBX spreads?* These questions are important because there is very limited literature available regarding the bid-ask spread of Norwegian stocks during the financial crisis of 2007-2009. Further, the literature regarding which of the few recent innovations for a measure of the bid-ask spread provide a better measure of liquidity is also limited. As the research conducted up to date has mostly focused on U.S. and large international markets, our main contribution will be to investigate whether how market liquidity affects portfolio returns using data from the Norwegian stock market. This has not been done explicitly for the Norwegian market up to this date.

1.4 Objective of this thesis

The main objective of this thesis is to estimate the bid-ask spread (i.e., liquidity) for Norwegian stocks using daily observations of high and low prices. We further assess its implication for portfolio returns, sorting stock into deciles of lowest to highest liquidity. Due to the key role of capital markets in general, and stock markets in particular, we hypothesize that liquidity (i.e. bid-ask spread) of Norwegian stocks decreased (increased) in the financial crisis of 2007-2009 as well as in the current scenario of the oil market. This helps to analyse whether decreased liquidity (i.e., high stocks' trading cost) was associated to losses suffered during this crisis. In addition, this thesis is to address the gap in the literature by providing a comprehensive study of the bid-ask spread measure of liquidity in the Norwegian context. This thesis further seeks to compare the few recent innovations for a measure of the bid-ask spread to find out how the least liquid stocks perform in comparison to the most liquid stocks and the overall market as well as after controlling for firm size. To do this, we construct portfolios based on liquidity, control for firm size and assess the performance of the portfolios for each of the measures (i.e., models). This is important, as it helps in analysing the implication of the bid-ask spread (i.e., liquidity) for stock returns. The dataset applied for this thesis is available from TITLON, a database with financial data from Oslo Stock Exchange for all universities and university colleges in Norway. It contains detailed daily financial data with fully adjusted prices. The data sample consists of daily observations of high-low, opening and closing prices from January 3rd, 2000 through December 31st, 2015.

1.5 Significance of this thesis

The analysis of this thesis is expected to have important implications for traders, portfolio and risk managers, performance evaluation and academic research. For example, our findings may guide investors in balancing expected trading costs against expected returns, when it comes to their portfolio selection. Our thesis aim to highlight the significance of securities market microstructure in the determination of asset returns and hopefully provide a link between main stream research on capital markets and this area.

In addition, the outcome of this thesis is expected to enrich the researchers' and other readers' knowledge on how liquidity, as measured by bid-ask spread, affects portfolio returns. New discoveries are bound to be made since an in-depth research is to be carried out. Finally, this thesis is timely and its findings are expected to serve as a basis for further studies.

1.6 Research questions

The following research questions help this thesis achieve its desirable objectives:

1. How does the bid-ask spread measure of liquidity affect returns?
2. Are returrns on the least liquid stocks higher than that of the most liquid stocks?
3. Does the size of the firm explain any patterns in returns due to liquidity?
4. How does the volatility of returns between the least and most liquid stocks differ?

5. Is the volatility of liquidity for the average Norwegian stocks relatively high in comparison to the OSEBX spreads?

1.7 Chapter Organization

This thesis is organized in five chapters as follows:

Chapter one: This chapter focuses on the introduction of this thesis. It includes an overview, background of this thesis, statement of the problem, objectives of this thesis, significance of this thesis, research questions, and chapter organization.

Chapter two: This chapter deals with a theoretical framework on the topic. It reviews existing literature related to the topic.

Chapter three: This chapter deals with data and methods. It includes descriptive statistics about the Norwegian stock market.

Chapter four: This chapter emphasizes on the discussions and findings.

Chapter five: This chapter focuses on the conclusion of this thesis.

CHAPTER TWO

LITERATURE REVIEW

2.1 Theoretical framework

Liquidity, marketability or transaction costs are regarded as key attributes of assets which influence investors' portfolio decisions (Demsetz, 1968). Thus, liquidity and the risk associated with potential illiquidity are essential factors for many investors in their investment decisions. Liquidity has been described as a time-varying risk factor (for example, Chordia et al., 2000; Hasbrouck and Seppi, 2001) arising from the difficulty in trading securities quickly enough to avoid or minimize a loss. This situation arises due to the lack of relative ease at which securities in the market can be traded. Trading problem of a security can also arise due to the volatility (which is a feature of liquidity) of the security. This has made liquidity and liquidity risk popular topics among scholars and researchers (see, for example, Diamond, 1991; Diamond and Rajan, 1999; Acharya and Pedersen, 2005; Cornett et al., 2011) to find some new aspects about liquidity.

Liquidity is regarded as a key concept in financial markets. It is often described as an elusive concept (Amihud, 2002). Generally, the concept of liquidity usually denotes a desirable feature of a well-organized financial market. A market is considered liquid when the prevailing structure of transactions provides a prompt and secure link between the demand and supply of assets, hence, the ability to buy and sell assets quickly at low cost (Gabrielsen et al., 2011). Brunnermeier and Pedersen (2009) have classified liquidity into two forms: market liquidity and funding liquidity. To them, market liquidity is concerned with the ease with which a security can be traded. For example, a security is regarded as liquid if its trading cost is low, which is an indication of low bid-ask spread and a small market impact. On the other hand, funding liquidity relates to the ease with which borrowers (individual traders or institutions) can obtain funding. For instance, a security is deemed to have a good funding if it is easy to obtain funding using the security as collateral.

It has been established that market liquidity and funding liquidity interact to create what is commonly referred to as liquidity spirals (Brunnermeier and Pedersen, 2009). This means that, when traders such as market makers, dealers and other liquidity-providing traders have good funding (i.e. easy access to available funding), then market liquidity is high. As a consequence, customers experience lower trading costs. Similarly, market liquidity improves funding: favorable market liquidity and lower volatility provide traders with easy access to funding, thus, lowering their margin requirement. During a downturn, this two-way interaction works in reverse but with a more severe impact. Generally, liquidity is not constant, but changes over time for individual securities and for the market as a whole. Market liquidity can suddenly deteriorate dramatically in the wake of volatility increases, sharply security price drop, halt operations as trading houses run out of cash or widen bid-ask spread by market makers (as evident during the financial crisis of 2007-2009).

Market liquidity is also important because it affects traders' ability to trade a lot and better in terms of being able to accommodate customers' demands to sell or buy securities. This has made market liquidity risk a popular subject of debate among users of financial liquidity. However, this thesis focuses on market liquidity with specific reference to the bid-ask spread as a measure of liquidity. The variability and uncertainty of market liquidity is the main challenge facing users of financial liquidity such as market makers, dealers, central bankers and investors among others (Persaud, 2003). Thus, there is a high tendency for liquidity providers to demand high reward as uncertainty of market liquidity increases. This makes the provision of liquidity very risky and causes the cost of trading to rise. It has been shown in the work of Amihud and Mendelson (1980) that, when the short and long positions that market makers can assume become constrained, the bid-ask spread that they charge increases.

According to Spulber (1996), market microstructure is concerned with this thesis of the institutions of exchange and intermediation. Market microstructure literature is related to how the actual transaction process affects the determinants of transaction costs, prices, quotes, volume and trading behavior, thus plays an essential role in the pricing of securities. A key insight into the composition and significance of transaction costs has been provided by the studies of market microstructure and the transaction process (Naes and Skjeltorp, 2006). Market microstructure has a broader scope and interest, with implications for asset pricing. The main idea in the theory of market microstructure is that security prices need not possess equal full-information expectations of value due to market frictions. Theories of asset pricing normally assumes highly liquid markets, which provide the opportunity for securities to be exchanged at no transaction cost at any time the investor want.

Intermediaries like market makers smooth the pattern of exchange in securities markets. They achieve this by creating market liquidity through inventory holding. Demsetz (1968) has shown that the ask-bid spread is the markup that is paid for the provision of immediacy of exchange in organized markets. Thus, an investor who seeks an immediate purchase or sale of securities would buy or sell at the best available price, the bid price or ask price respectively. The difference between what a buyer wants to pay (the bid price) and what a seller wants to accept (the ask price) is the bid-ask spread. For effective market functioning, providers of liquidity and immediacy or market makers quote bid-ask prices and demanders of immediacy - investors (i.e., individual and institutional investors like endowment funds, mutual funds, insurance companies etc.) place limit orders. The U.S. Securities and Exchange Commission refers to a "market maker" as a firm that stands ready to buy and sell securities on a regular and continuous basis at a publicly quoted price, thus, creating liquidity in the market. For instance, the National Association of Securities Dealers Automated Quotations (NASDAQ) is one of the prime market makers.

In an efficient financial market, securities prices always fully reflect available information. Thus, the market price always equals the fundamental value and as soon as new information comes out, prices immediately react to fully reflect the new information. Investors would not be able to earn excess return over the market return (i.e., investors cannot outperform the market) if markets are fully efficient. However, the market price can differ from the fundamental value and the discrepancy between the two values has two possible interpretations: first, it shows a trading opportunity, where an investor buys (sells) a security if the market price is less (more) relative to the theoretical value; and second, it can reflect that the fundamental value is not correct. In case such trading opportunities arise repeatedly, then they give rise to a trading strategy. Trading strategies employed by sophisticated investors such as hedge funds do sometimes succeed in exploiting such opportunities in the market. Although prices are kept in check by intense competition among money managers, prices may also differ from their fundamental values due to demand pressures and institutional frictions. This causes the market to become inefficient to an efficient extent, that is, inefficient enough to make money managers demand compensation for their costs and risks through superior performance and efficient enough that the compensations after transaction costs discourage the entry of new money managers or additional capital. Securities' returns net of transaction costs, liquidity risk and funding costs are not far from their fully efficient levels, making it extremely difficult to outperform the market in a consistent manner. Prices can deviate substantially from the present value of future cash flows despite the fact that, returns are nearly efficient. Thus, in an efficient market, the fundamental value of securities fluctuates randomly.

Over the past few years, the bid-ask spread has received growing attention among traders, regulators, scholars and researchers. The bid-ask spread is regarded as a useful measure of trading costs and a better proxy for market liquidity (Amihud and Mendelson, 1986; Huang and Stoll, 1997; Corwin and Schultz, 2012; Mancini et al., 2013). The size of the bid-ask spread is an indication of the ease with which one can trade a security and the trading costs associated with that security. If spread is zero, then it is frictionless asset and a security with a small spread is associated with higher liquidity. Thus, securities with a tight bid-ask spread is more liquid relative to securities with wide bid-ask spread.

The bid-ask spread measure of liquidity has been widely explored in the available literature on liquidity (Corwin and Schultz, 2012). Many models of the spread have focused on three main factors in determining the cost components of the quoted spread: adverse selection costs (for example, Bagehot, 1971; Copeland and Galai, 1983; Glosten and Milgrom, 1985); inventory holding costs (for instance, Demsetz, 1968; Amihud and Mendelson, 1980; Ho and Stoll, 1983); and order-processing costs (Tinic, 1972; Brock and Kleidon, 1992). Investors expect financial assets to be liquid, thus, easily traded in large amount without losing their value. These assets are to be characterized by low trading cost, easy trading and timely settlement as well as large trades having a limited price impact.

Statistical models used in available literature to measure the bid-ask spread can be separated into two: models developed on the basis of the serial covariance properties of the observed transaction prices (see, e.g., Roll 1984; Huang and Stoll, 1994); and those which are based on a trade initiation predictor variable (for example, Glosten and Harris, 1988; Madhavan and Smidt, 1991). Several studies have applied these statistical models in different contexts such as to examine adverse selection costs (Neal and Wheatley, 1995), to explore the dealer and auction markets (Porter and Weaver, 1996) and to assess the sources of short-term return reversal (Jegadeesh and Titman, 1995) as well as of spread fluctuations (Madhavan et al., 1997).

Asymmetric information plays a significant role in financial markets during crisis period (for example, Gorton, 2008) and financial markets are believed to be illiquid when securities become information-sensitive (Gorton and Metrick, 2009). Bolton et al., (2008) provides a theory of liquidity provision with information asymmetry. They included three sets of agents: investors with a short horizon; investors with a long horizon; and financial intermediaries with a long horizon and argued that the main source of inefficiency is information asymmetry about asset values between intermediaries and long horizon investors. In this case, long horizon investors are unable to differentiate an asset sale to get rid of low quality securities from an asset sale that is due to a liquidity need. On the hand, informed investors would sell a security at the bid price only if available information justifies a lower price. Similarly, informed investors would buy a security at the ask price only if available information justifies a higher price. As a consequence, trading may result in loss in case of informed counterparty. This asymmetric information leads to an adverse selection problem (i.e. an informed investor is more likely to buy or sell when he has good news or bad news respectively) and consequently to a price discount.

The fundamental problem intermediaries face if they are hit by a liquidity shock is whether to sell their assets now at a discount or to hold them and ride out the crisis at the risk having to sell at a greater discount if crisis persist than expected. Bolton et al., (2008) assumed intermediaries learn more about the assets they hold over time. They revealed that, there exist two kinds of rational expectations equilibrium: the immediate trading equilibrium (i.e. where intermediaries sell securities immediately to ensure they have enough liquidity and the delayed trading equilibrium (i.e. where intermediaries hold their assets to ride out the crisis and only sell if they have an urgent need to). They further showed that the delayed trading equilibrium is Pareto superior when both are present. Their argument was based on the fact that long horizon investors undervalue cash while short horizon investors undervalue long-run assets. In this way, intermediaries have an incentive to induce long horizon investors to hold more cash and short horizon investors to hold more long-run assets in order to make some gains. This is what the delayed trading equilibrium can do and the worse the asymmetric information problem gets, the less the gain that can be made. This is because it impedes the operations of the market for the long-run assets.

According to Kyle (1985), the degree of liquidity of the market is based on three aspects: tightness; depth; and resilience. The tightness is measured with the bid-ask spread of assets, which is a direct measure of trading cost, excluding operational costs. The depth of the market is measured with the size of transaction required to alter the price of assets whiles the market resilience is the speed with which prices tend to return to their equilibrium after a market shock has been experienced. It has been established in literature that the depth and resilience aspects of market liquidity are difficult to measure due to the fact that, their measurement requires detailed information on every single transaction in the market which may not be readily available.

Similarly, Sarr and Lybek (2002) combined the market characteristics during periods of stress and liquidity risk from the market participant's perspective to come up two additional aspects along with those stated by Kyle (1985). They identified breadth and immediacy as the two additional characteristics of market liquidity. They used Kyle's definition of depth for the characteristic breadth and described it as the existence of abundant orders, with either actual or easily presence of prospective seller and buyers, both below and above the price at which an asset trades. They also described immediacy as the speed with which orders can be executed, reflecting efficiency of trading, clearing and settlement (Santoso et al., 2010).

A number studies have investigated the relation of liquidity risk to expected returns (for example, Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Datar et al., 1998). These empirical studies have used a variety of liquidity measures to find that less liquid stocks are associated with higher average returns. Amihud has documented evidence of a time-series relation of market liquidity and expected returns. The findings of an empirical study conducted by Chordia et al., (2000) show a significant cross-sectional relation between the variability of liquidity and stock returns, where liquidity was measured using trading activity such as turnover and volume as proxies. However, an unexpected result was discovered in their study, which measured liquidity risk as firm-specific variability in liquidity. They reported that the more volatile a stock's liquidity is, the lower its expected returns.

Several empirical studies (e.g. Amihud, 2002; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Liu, 2006) support a liquidity premium and show that liquidity premium is a rational compensation for increased opportunity cost (Grossman and Miller, 1987), risk of flight-to-liquidity (Acharya and Pedersen, 2005) and higher risks of bankruptcy in recessions – due to funding liquidity risk (Liu, 2006). Amihud (2002) documented an interesting experiment performed by Amihud and Lauterbach regarding changes in stock returns resulting from movement from an illiquid market to a liquid market. They found that the change in liquidity was associated with a premium of 5.5%. Acharya and Pedersen (2005) introduced a liquidity augmented CAPM, adjusted for both market-wide liquidity and asset liquidity. The authors found evidence pointing towards an annual liquidity risk premium of 3.5%, which they explain as a response to a strong positive correlation between market return and illiquidity costs.

The paper by Liu (2006) based on the new liquidity measure over a sample period from 1963 to 2003 shows that liquidity affects the risk of holding illiquid assets because they underperform in recessions (liquidity risk). The empirical evidence in the Liu (2006) paper shows that a significant liquidity exists based on non-traded and traded liquidity factors, which is an indication that liquidity risk is priced and important for asset pricing. Liu (2006) found that the relative bid-ask spread increases monotonically from most liquid portfolio to least liquid portfolio and consistent with the high correlation between the new liquidity measure and bid-ask spread. The high negative correlation (i.e. -0.649) between the liquidity factor and the market factor illustrates the state nature of liquidity: when the market is in downturn states then it is less liquid and investors demand higher returns to compensate them for the higher risk they bear in less liquid states.

Amihud and Mendelson (1986) show theoretically that the level of liquidity of financial assets affects their returns, a prediction that has been supported by evidence present in a number of empirical studies (for example, Amihud and Mendelson, 1989; Brennan and Subrahmanyam, 1996; Amihud, 2002). Other studies also document that liquidity covaries cross-sectionally with stocks (see, e.g., Chordia et al., 2000; Hasbrouck and Seppi, 2001). Both the demand-side and supply-side can be the source of this commonality in liquidity. While some studies (for example, Coughenor and Saad, 2004; Comerton-Forde et al., 2008) show evidence of support for supply-side sources, other studies (for example, Brockman and Chung, 2002; Bauer, 2004) argued that, all the commonality in liquidity cannot be explained by the supply-side sources suggested in Coughenor and Saad (2004) for instance.

Many studies (like Chordia et al., 2000; Karolyi et al., 2008) have documented the existence of commonality in liquidity in the U.S. market and in other major international markets. Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) have highlighted the essence of commonality in liquidity for asset pricing in their theoretical work that found evidence of commonality as a priced risk factor. Other studies have found support for the empirical evidence on commonality as a priced risk factor (see, for e.g., Sadka, 2006; Korajczyk and Sadka, 2008). Existing literature that attempt to explain the commonality in liquidity has mainly focused on the supply-side sources suggested in Coughenor and Saad (2004). Their proposition was that the commonality could arise from the NYSE specialist providing liquidity for various stocks. The findings of their study revealed that stocks with the same specialist have commonality in liquidity, which is consistent with the evidence present in a similar empirical study conducted by Comerton-Forde et al., (2008). Though several papers conclude that liquidity is a priced risk factor, Zhang and Yang (2014) finds that the bid-ask spread estimator derived by Corwin and Schultz does not provide a liquidity premium. This problem may be due to a technical issue with the Corwin-Schultz estimator, as it is sensitive to overnight price changes in prices. We aim to conduct a similar analysis on the Norwegian market, with well-known fixes for the Corwin-Schultz estimator.

2.2 The bid-ask spread

Glosten (1987) model the bid-ask spread by decomposing it into two parts: the first part is due to asymmetric information and the other part is due to other factors such as monopoly power. The author assumes that at any point in time all investors with only common-knowledge information (i.e., an investor without inside information) agree on the true price (p).

The bid price, P_b is given by:

$$P_b = p - Z_b - C_b \tag{1}$$

The ask price, P_a is as follows:

$$P_a = p + Z_a + C_a \quad (2)$$

The two parts of the adverse-selection of the spread, Z_a and Z_b represent the magnitude of the adjustments in the true price, p in response to an investor purchase at the ask price and a sale at the bid price respectively. Thus, p represents the (common-knowledge) true price prior to a transaction. The gross profit components, C_a and C_b are the exogenously given levels of gross profit for a purchase and a sale respectively. The spread can be separated into two parts: the first part is the adverse-selection component which is due to the believe presence of informed traders and the other part is the gross profit component which represents an addition to cover the transaction costs and inventory costs of market maker as well as a normal rate of return to being a market maker.

The adverse-selection component: $Z_a + Z_b$

The gross profit component: $C_a + C_b$

The bid-ask spread, $A – B = (Z_a + Z_b) + (C_a + C_a)$

Glosten (1987) shows that the part of spread due to asymmetric information (adverse-selection) could be the source of the downward bias in spread estimate.

2.2.1 Roll (1984) estimator

Roll (1984) develops an estimator based on the serial covariance of the change in price. The author takes into account the unobservable fundamental value of the stock on day t and the mean-zero, serially uncorrelated public information shock on day t as well as the last observed trade price on day t in deriving the estimator. An important shortcoming of this estimator is that when the sample serial covariance is positive, then the effective spread is undefined.

2.2.2 Gibbs

Hasbrouck (2004) introduces a Gibbs sampler estimation of the Roll model using prices from all days. The author assumes that the public information shock e_t in the Roll estimator is normally distributed with mean of zero and variance of σ_e^2. The author denotes the half spread in the Roll estimator as $C = \frac{1}{2}S$.

The author uses the Gibbs sampler to numerically estimate the model parameters {C, σ_e^2}, the latent buy, sell or no trade indicates $Q = \{Q_1, Q_2, Q_3,\ldots\ldots\ldots., Q_T\}$, and the latent efficient prices, $V = \{ V_1, V_2, V_3,\ldots\ldots\ldots., V_T\}$, where T is the number of days in the time interval.

2.2.3 LOT

Lesmond, Ogden, and Trzcinka (1999) develop an estimator of the effective spread based on the assumption of informed trading on non-zero-return days and absence of the informed trading on zero-return days. The LOT model is simply the difference between the percent buying and selling costs. A standard "market model" relationship holds on non-zero-return days, but a flat horizontal segment applies on zero-return days. The authors assume that the unobserved true return of a stock (R_j) on day t is related to the sensitivity of the stock to the market return on day t as well as a public information shock on day t, which is normally distributed with mean of zero and variance of σ_j^2.

2.2.4 Corwin And Schultz (2012) Estimator

Corwin and Schultz (2012) estimator (i.e., referred to in this thesis as the CS estimator) is based on daily high and low prices. The reason behind is that the high prices are always buyer-initiated trades and low are seller-initiated and the ratio of high-to-low prices for a day reflects the volatility of the stock(stock's variance) and the bid-ask spread of the stock. Variance component of the high-to-low ratio is proportional to the return interval while the spread internal stays relatively constant for the shorter time span. The sum of the daily price ranges for the two consecutive single days reflects the volatility of two days and twice the bid-ask spread, while the price range for two consecutive days reflects the volatility of two days but one bid-ask spread.

On the basis of the insight above, Corwin and Schultz (2012), developed the estimator as follows:

Let β be the expectation of the sum of the price ranges for two consecutive single days.

$$\beta_t = E\left[\sum_{j=0}^{1}\left[ln\left(\frac{H_{t+j}^0}{L_{t+j}^0}\right)\right]^2\right] \quad (3)$$

Where,

H_t^0 = Observed high price at day t

L_t^0 = Observed low price at day t

Now, let γ be the maximum range of the high-to-low ratio for the two day period. This can be expressed as follow:

$$\gamma_t = \left[ln\left(\frac{H_{t-1,t}^0}{L_{t-1,t}^0}\right)\right]^2 \qquad (4)$$

The measure is not forward looking as it can be seen from (*t*, *t-1*) in prices as $H_{t,t-1}$ $(L_{t,t-1})$ is maximum (minimum) for the two-day period consisting of days t and t-1. Subsequent to the estimated β and γ from stock return data, a proportional difference between β_t and γ_t given in equations (3) and (4) to derive the difference as follows:

$$\alpha_t = \frac{\sqrt{2\beta_t}-\sqrt{\beta_t}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma_t}{3-2\sqrt{2}}} = (1+\sqrt{2})(\sqrt{\beta_t} - \sqrt{\gamma_t}) \qquad (5)$$

The first term in equation (5) with β_t and γ_t is equivalent to that given as Corwin and Schultz (2012), referred to as CS estimator in this thesis and can be further simplified to the last term. The alpha at t will have substantial time variation because it is computed from observed values and specifically, observed high and low prices. There is a possibility for apha at t to be negative as y at t might be larger in value relative to beta at t. This is a limitation of the model for measure of the bid-ask spread. Taking into account overnight trading may reduce the possibility of negative values for alpha at t. The negative values of the bid-ask spread is another limitation of this model.

From equation (5), the bid-ask spread is given as follows:

$$S = \frac{2(e^{\alpha_t}-1)}{1+e^{\alpha_t}} \qquad (6)$$

The estimate of the spread, S and alpha will approximately be equal for small spreads. As the high-low estimators are easy to compute, making it preferable for large samples as compared to other estimators which are difficult to compute such as Gibbs estimator and LOT estimator.

2.2.5 Leirvik (2015) Estimator:

A newly derived estimator for the bid-ask spread, what we have denoted Alpha, and derived by Leirvik (2015) is also used in this thesis. The estimator is based on daily high and low prices. To start with, daily high prices are almost always initiated by buyers and daily low prices are initiated by sellers. This implies that ratio of high to low prices for a day reflects the bid-ask spread of the stock as well as the volatility associated with that particular stock. Secondly, as volatility is proportional to the trading interval, the high-to-low price ratio increase shows the increase in volatility. Thus, the sum of the price ranges over two consecutive single days reflects two days volatility and double the spread, while the one two-day period price range reflects two days volatility and one spread.

The author assumes that there is a spread between the actual price and observed price which is equal to $L/2\%$. The actual price is denoted by a capital "*A*" superscript. Notice the following: Highest actual price of the security during time "*t*" $= H_t^A$

Lowest actual price of the security during time "*t*" $= L_t^A$

Highest observed price during day "*t*" $= H_t^O$

Lowest observed price during day "*t*" $= L_t^O$

The author again assumed that the daily high price is a buyer-initiated trade and is thus, grossed up by half the spread, whereas the daily low price is a seller-initiated trade and is therefore discounted by one and a half of the spread.

The log-range between high and low prices (following Corwin and Schultz) are given by;

$$ln\left(\frac{H_t^O}{L_t^O}\right) = ln\left(\frac{H_t^A\ 2+L}{L_t^A\ 2-L}\right) \tag{7}$$

The bid-ask spread can be computed from equation (7) which shows the relationship between daily high and low prices.

The logarithm of the observed high and low prices is as follows:

$$ln\left(\frac{H_t^O}{L_t^O}\right) = ln\left(\frac{H_t^A}{L_t^A}\right) + ln\left(\frac{2+L}{2-L}\right) \tag{8}$$

Alpha (α_t) is also defined as:

$$\alpha_t = ln\left(\frac{2+L}{2-L}\right) \tag{9}$$

By taking the expectation of equation (7) and solve for alpha, resultant expression is given as:

$$\alpha_t = -\mathbb{E}_{t-1}[Y] \pm \sqrt{\mathbb{E}_{t-1}[Y]^2 - \mathbb{E}_{t-1}[Y^2] + \frac{\beta_t}{2}} \tag{10}$$

As *Y* contains the actual prices so it is necessary to derive expressions with expectation to present alpha in terms of observed prices which contains the observed prices. Let γ_t be the log-range of the maximum high and minimum low prices of two consecutive days then the expression will be:

$$\gamma_t = ln\frac{\max\{H_{t-1}^O, H_t^O\}}{\min\{L_{t-1}^O, L_t^O\}} = ln\frac{H_{t-1,t}^O}{L_{t-1,t}^O} \tag{11}$$

Equation (11) can be rewritten in terms of Y, α_t and the log-range between maximum and minimum prices as:

$$\gamma_t = ln\frac{H_{t-1,t}^O}{L_{t-1,t}^O}$$

$$\gamma_t = ln\frac{H_t^O}{L_t^O} + ln\frac{H_{t-1,t}^O . L_t^O}{L_{t-1,t}^O H_t^O}$$

$$\gamma_t = Y + \alpha_t + ln\frac{H_{t-1,t}^O . L_t^O}{L_{t-1,t}^O H_t^O}$$

$$\gamma_t = Y + \alpha_t + \lambda_t \tag{12}$$

By taking the conditional expectation:

$$\mathbb{E}_{t-1}[\gamma_t] = \mathbb{E}_{t-1}[Y] + \alpha_t + \lambda_t \tag{13}$$

And by solving this expression;

$$\gamma_t = \lambda_t + \sqrt{\mathbb{E}_{t-1}[Y]^2 - \mathbb{E}_{t-1}[Y^2] + \frac{\beta_t}{2}} \quad (14)$$

So by solving and through all these expressions, alpha can be written as:

$$\alpha_t = -\mathbb{E}_{t-1}[Y_t] \pm \sqrt{\frac{\beta_t}{2} - \mathbb{E}_{t-1}[Y_t^2] + (\gamma_t - \lambda_t)^2 - \frac{\beta_t}{2} + \mathbb{E}_{t-1}[Y_t^2]} \quad (15)$$

$$\alpha_t = \sqrt{(\gamma_t - \lambda_t)^2} - \mathbb{E}_{t-1}[Y_t] \quad (16)$$

$$\alpha_t = \sqrt{(\gamma_t - \lambda_t)^2} - \sqrt{(\gamma_t - \lambda_t)^2 - \frac{\beta_t}{2} + \mathbb{E}_{t-1}[Y_t^2]} \quad (17)$$

As log-range of observed high and low price is approximately normally distributed (see *Alizadeh et al., 2002*) so the variance represents the variance over two consecutive days of the log-range which implies that *Y* is also normally distributed.

The second moment will therefore be:

$$\mathbb{E}[Y_t^2] = \sigma_t^2 \quad (18)$$

The expression derived for sample variance is

$$\sigma_t^2 = (Y_{t-1} - Y_t)^2 \quad (19)$$

So the final expression for alpha is given by:

$$\alpha_t = \sqrt{(\gamma_t - \lambda_t)^2} - \sqrt{(\gamma_t - \lambda_t)^2 - \frac{\beta_t}{2} + \sigma_t^2} \quad (20)$$

From equation (20), it is clear that the estimator will produce a real number as long as the variance is greater than $\frac{\beta_t}{2}$ and in case $\sqrt{(\gamma_t - \lambda_t)^2} < \sqrt{(\gamma_t - \lambda_t)^2 - \frac{\beta_t}{2} + \sigma_t^2}$ occurs, the resultant number will be negative.

2.2.6 Bid-Ask Estimators Used in this thesis:

For the purpose of this study, we rely on one of the most popular measures for the bid-ask spread, namely Corwin and Schultz (2012) estimator and a newly derived bid-ask spread estimator, namely Leirvik (2015). The Corwin and Schultz (2012) estimator is one of the most widely used measures for the bid-ask spread. Both Corwin and Schultz (2012) and Leirvik (2015) estimators are simple to compute as they require only daily high and low prices. At the same time, they have low data frequency requirements.

CHAPTER THREE

DATA AND METHODS

3.1 Data and methods

This section presents the data source and dataset used in the analysis. The dataset is obtained from the TITLON database. The sample we applied from the dataset consisted of daily observations of all stocks listed on the Norwegian stock Exchange from January 3rd 2000 through December 31st 2015. Our analysis used a survivor-bias free panel dataset from the Norwegian Stock Exchange. Additionally, we applied the bid-ask spread estimators derived by Corwin and Schultz (2012) and Leirvik (2015) as proxies for the Norwegian stocks. The portfolio construction follows a standard approach where at the beginning of each day *t*, all common stocks are first sorted into deciles for market capitalization. We formulated portfolios ranging from companies with small market capitalization in group 1 to companies with large market capitalization in group 5. Each market capitalization portfolio is further sorted into deciles for liquidity on the basis of the size of the bid-ask spread. Stock returns are then computed for each group of liquidity and controlled for firm size. We also provided descriptive statistics about the Norwegian stock market in Table 1 and summary statistics for the liquidity sorted portfolios used in this thesis in Table 2.

Tables 1-2 present mean, standard deviation (i.e., std. dev.), minimum and maximum in percent and maximum two decmals. As Table 1 shows, there exists a clear difference in statistics for the dataset. The difference in descriptive statistics resulting from these proxies is likely to affect the measurement of liquidity and variation of portfolio returns analyses between variables. As shown in Table 1, the skewness is negative for spreads computed by the CS estimator. This means that the CS estimator yielded left skewed distributions of variables with extreme values to the left of their means; see the values of mean and minimum in Panel B of Table 1. In contrast, the Alpha estimator yielded right skewed distributions with extreme values to the right of their means; see the values of mean and maximum in Panel A of Table 1. The skewness is relatively high for the average liquidity of Norwegian stocks in comparison to the OSEBX spreads by applying both estimators (i.e., relatively high positive and negative values for Alpa and CS estimators respectively). In addition, the kurtosis is relatively high for the average liquidity of Norwegian stocks in comparison to the OSEBX spreads by applying both estimators. This implies a higher probability for extreme values. Moreover, the mean return is higher for lowest liquid stocks as compared to that of highest liquid stocks by applying both estimators (see Table 2). As expected, higher risk comes with higher returns.

Table 1: Descriptive statistics for the Norwegian stocks and the market (i.e., OSEBX)

Variables	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Panel A: Descriptive statistics for Norwegian stocks and OSEBX by applying Alpha estimator						
Average Liquidity of Norwegian stocks	0.77	2.14	-71.82	201.49	9.23	382.74
OSEBX spreads	0.44	0.38	-1.10	5.92	3.80	31.64
Panel B: Descriptive statistics for Norwegian stocks and OSEBX by applying CS estimator						
Average Liquidity of Norwegian stocks	-1.00	5.82	-1088.45	69.31	-24.51	2828.21
OSEBX spreads	-0.24	1.30	-13.47	7.01	-1.28	10.81

Table 2: Summary statistics for liquidity sorted portfolios

Liquidity group	Mean return	Std Dev.	Minimum	Maximum	Obs.
Sample period January 2000 – January 2011					
Panel A: Summary statistics for liquidity groups by applying Alpha estimator					
Lowest	0.05	5.69	-354.54	153.02	171,303
2	-0.03	4.58	-180.40	301.48	164,831
3	-0.07 0	4.83	-186.60	436.31	160,223
4	-0.03	5.43	-252.82	229.45	158,153

Table 2 (continued)

Liquidity group	Mean return	Std Dev.	Minimum	Maximum	Obs.
Highest	-0.09	4.50	-223.14	414.62	268,175
Lowest – Highest	0.03	0.08	-0.23	0.25	934,730
Panel B: Summary statistics for liquidity groups by applying CS estimator					
Lowest	0.24	6.91	-249.67	436.31	171,295
2	-0.06	3.78	-252.82	91.63	164,839
3	-0.13	4.37	-354.54	94.61	160,223
4	-0.14	4.88	-180.40	190.95	158,153
Highest	-0.08	4.51	-227.53	414.62	268,175
Lowest – Highest	0.07	0.14	-0.10	0.53	934,730

CHAPTER FOUR

DISCUSSIONS AND ANALYSES

4.1 Overview

This section presents and discusses findings from data analyses in chapter in more depth. To facilitate understanding, this section is divided into two parts. The first part discusses the presence of liquidity premium for all Norwegian stocks based on liquidity sorted portfolios and also after controlling for firm size over the sample period from January 2000 to January 2011. The second part of this section compares the performance of the extreme portfolios and of the market in terms of risk and returns. Tables 3-7 present all results in percent and maximum two decimals.

4.1.1 The presence of liquidity premium

The presence of liquidity premium was checked by sorting all stocks into portfolios based on the two estimators applied in this thesis. Thus, if the least liquid portfolio consistently outperforms the most liquid portfolio, then, it is evidence of the presence of a liquidity premium. As Table 3 (Panels A and B) shows, the mean return on an annual basis of the least liquid portfolio outperforms the most liquid portfolio, even though there are three years where stocks with a low bid-ask spread outperform stocks with a high bid-ask spread. Table 3 clearly indicates that, the mean return of the least liquid portfolio is relatively higher than the mean return of the most liquid portfolio. The results from Table 3 show that the two liquidity measures predicts stock returns over the 12 month period. The least liquid decile earns the highest return in comparison with what the most liquid decile earns. This is consistent with the intuition that higher risk comes with higher return and further shows that liquidity is an important source of priced risk.

The results from Table 3 further show that the least liquid portfolio outperforms the market (i.e., OSEBX) in terms of annual average returns over the sample period, except for four years. Meanwhile, the market earns higher returns than the most liquid portfolio on average every year except for one. This one exception is seen when comparing the mean return of the market and that of the most liquid portfolio (see Table 3, Panel A). Similarly, Panel B of Table 3 indicates that the annual average returns of the market outperforms the annual average returns of the most liquid portfolio over the sample period, except for one year. The lowest–highest returns has been found to be relatively high in comparison to the market over the sample period, except for five and four years by applying the Alpha and CS estimators respectively (see Panels A and B of Table 3). We find that the return volatility of the lowest–highest portfolios is relatively low in comparison to the market for both estimators.

Table 3: Results of annual returns for each group of liquidity as well as OSEBX

Year	Least liquid	2	3	4	Most liquid	Lowest - Highest	OSEBX
Sample period January 2000 – January 2011							
Panel A: Mean returns and standard deviation (in parenthesis) of liquidity sorted portfolios as well as OSEBX by applying Alpha estimator							
2000	-0.01	-0.13	-0.06	-0.02	-0.02	0.03	0.01
	(5.90)	(4.73)	(4.84)	(4.97)	(4.62)	(0.08)	(1.26)
2001	-0.29	-0.39	-0.17	-0.10	-0.17	0.03	-0.13
	(7.16)	(6.37)	(6.44)	(6.29)	(5.73)	(0.80)	(1.39)
2002	0.07	0.03	0.14	0.10	0.16	0.03	0.13
	(6.89)	(5.92)	(6.13)	(7.20)	(6.69)	(0.08)	(1.10)
2003	0.21	0.15	0.09	0.15	0.08	0.02	0.13
	(3.36)	(2.60)	(2.87)	(3.87)	(3.60)	(0.08)	(0.84)
2004	0.21	0.09	0.06	0.07	0.05	0.03	0.11
	(3.46)	(2.90)	(2.80)	(3.13)	(3.09)	(0.08)	(1.46)
2005	0.02	-0.08	-0.23	-0.09	-0.12	0.04	-0.04
	(3.95)	(3.28)	(3.63)	(3.47)	(4.49)	(0.08)	(1.53)

Table 3 (continued)

Year	Least liquid	2	3	4	Most liquid	Lowest - Highest	OSEBX
2006	-0.20	-0.15	-0.22	-0.10	-0.11	0.04	-0.04
	(8.17)	(6.72)	(7.57)	(7.10)	(5.71)	(0.08)	(3.00)
2007	0.17	0.02	-0.10	-0.07	-0.10	0.03	0.06
	(5.11)	(4.64)	(4.23)	(5.45)	(3.31)	(0.08)	(1.35)
2008	0.06	0.01	-0.07	-0.08	-0.25	0.03	0.01
	(6.10)	(4.27)	(5.09)	(6.19)	(3.96)	(0.08)	(1.54)
2009	0.24	0.11	-0.01	0.02	-0.06	0.03	0.09
	(5.25)	(3.42)	(3.51)	(5.28)	(3.00)	(0.08)	(6.97)
2010	0.03	0.01	-0.14	-0.15	-0.19	0.03	0.00
	(5.09)	(3.45)	(3.61)	(5.09)	(4.43)	(0.08)	(1.10)
2011	0.07	-0.09	-0.24	-0.11	-0.33	0.01	-0.10
	(5.28)	(3.17)	(3.62)	(6.34)	(4.63)	(0.16)	(1.17)
Panel B: Mean returns and standard deviation (in parenthesis) of liquidity sorted portfolios as well as OSEBX by applying CS estimator							
2000	0.27	-0.09	-0.18	-0.11	-0.10	0.07	0.01
	(7.01)	(4.01)	(4.29)	(4.72)	(4.51)	(0.14)	(1.26)

Table 3 (continued)

Year	Least liquid	2	3	4	Most liquid	Lowest - Highest	OSEBX
2001	-0.23	-0.24	-0.23	-0.27	-0.15	0.07	-0.13
	(7.90)	(5.23)	(6.13)	(6.47)	(5.94)	(0.14)	(1.39)
2002	0.52	0.04	-0.03	-0.12	0.06	0.07	0.13
	(7.54)	(4.67)	(5.90)	(6.79)	(7.54)	(0.14)	(1.10)
2003	0.67	0.06	-0.02	-0.05	-0.02	0.07	0.13
	(4.33)	(2.22)	(2.52)	(3.15)	(3.67)	(0.14)	(0.84)
2004	0.51	0.02	0.01	-0.01	-0.03	0.07	0.11
	(4.45)	(2.35)	(2.46)	(2.77)	(2.94)	(0.13)	(1.46)
2005	0.04	-0.12	-0.18	-0.13	-0.11	0.08	-0.04
	(5.16)	(2.85)	(2.94)	(3.17)	(4.37)	(0.13)	(1.53)
2006	0.11	-0.30	-0.24	-0.18	-0.15	0.08	-0.04
	(10.19)	(5.71)	(6.26)	(6.75)	(5.54)	(0.13)	(3.00)
2007	0.26	0.02	-0.17	-0.12	-0.08	0.08	0.06
	(6.72)	(3.48)	(4.11)	(4.33)	(3.41)	(0.13)	(1.35)
2008	0.11	-0.06	-0.17	-0.26	-0.08	0.08	0.01
	(7.17)	(3.67)	(4.73)	(5.28)	(4.20)	(0.14)	(1.54)

Table 3 (continued)

Year	Least liquid	2	3	4	Most liquid	Lowest - Highest	OSEBX
2009	0.42	0.07	-0.06	-0.11	-0.05	0.08	0.09
	(6.72)	(2.67)	(3.19)	(3.82)	(3.05)	(0.14)	(0.70)
2010	0.08	-0.11	-0.16	-0.22	0.09	0.07	0.00
	(6.67)	(3.05)	(3.33)	(4.34)	(3.74)	(0.14)	(1.10)
2011	-0.27	0.00	-0.06	-0.28	-0.14	0.04	-0.10
	(7.12)	(3.59)	(3.75)	(4.34)	(4.06)	(0.13)	(1.17)

4.1.2 The performance of decile portfolios, after controlling for firm size on an nnual basis

Table 4 presents the performance of decile portfolios after controlling for firm size in comparison to the market. The previous section documented a significant liquidity premium by applying the two liquidity measures: the Alpha and CS estimators. We constructed two extreme portfolios for the two liquidity measures and controlled for the firm sizes. These extreme portfolios were further sorted into least liquid portfolio given large and small firm sizes as well as most liquid portfolio given large and small firm sizes. This was done so we can compare large and small firms for the same liquidity decile. We find that the least liquid portfolio given large firm size earns relatively higher returns every year (except for two years by the applying Alpha estimator) than that earned by small firms of the same liquidity decile for both estimators. Similarly, the large firms outperform the small firms for the most liquid portfolio every year by applying both estimators (see Panels A and B of Table 4). The liquidity measures applied in this thesis demonstrate the same pattern of performance of the extreme decile portfolios controlling for firm size. The results, however, may imply that the large firms have a bigger exposure than the small firms as the large firms form a greater part of the market and the economy. The results, here is not consistent with the so-called small-firm effect which argues that the stocks of smaller firms tend to outperform the stocks of large firms.

Panel A of Table 4 shows that the least liquid portfolio given small firm size outperforms most liquid portfolio given small firm size on average annually over the entire sample period, except for four and three years by applying the alpha and CS estimators respectively. The results further show that, the least liquid portfolio given large firm size earns higher returns on average every year with the exception of five and two years by applying the alpha and CS estimators respectively. This is relative to that earned by the most liquid portfolio given large firm size (see Panel B of Table 4). Additionally, the market earns relatively high average returns every year, except for three years than the stocks of small firms for the lowest liquidity decile by applying both estimators. We also find that the market outperforms the stocks of small firms for the highest liquidity decile on an annual basis (see Panel A of Table 4). The results further show that the stocks of large firms for the least liquid decile outperform the market on a yearly basis by applying the CS estimator (but with the exception of one year by applying the Alpha estimator). The market outperforms the stocks of large firms for the most liquid decile on average every year, except for two years by applying the CS estimator. Meanwhile, the stocks of large firms for the most liquid decile underperforms the market on average in six years as well as outperforms the market on average in six years by applying the Alpha estimator (see Panel B of Table 4).

Table 4: Results of average returns every year for the least liquid and most liquid porfolios given firm size in comparison with the market

Year	Least liquid portfolio given small firms		Most liquid portfolio given small firms		Market index
	Alpha	CS	Alpha	CS	(OSEBX)
Sample period January 2000 – January 2011					
Panel A: Average returns for liquidity groups given small firm size by applying both estimators					
2000	-0.39	-0.21	-0.19	-0.35	0.01
2001	-0.66	-0.65	-0.21	-0.59	-0.13

Table 4 (continued)

Year	Least liquid portfolio given small firms		Most liquid portfolio given small firms		Market index
	Alpha	CS	Alpha	CS	(OSEBX)
2002	-0.78	0.04	-0.41	-0.57	0.13
2003	0.12	0.41	-0.10	-0.30	0.13
2004	0.20	0.29	-0.08	-0.19	0.11
2005	-0.22	-0.41	-0.25	-0.07	-0.04
2006	-0.66	-0.45	-0.39	-0.65	-0.04
2007	0.08	-0.18	-0.25	-0.38	0.06
2008	-0.16	-0.30	-0.82	-0.58	0.01
2009	0.31	0.10	-0.38	-0.26	0.09
2010	-0.04	-0.32	-0.634	-0.523	0.00
2011	-0.66	-2.02	-1.08	-0.56	-0.10

Table 4 (continued)

Year	Least liquid portfolio given large firms		Most liquid portfolio given large firms		Market index
	Alpha	CS	Alpha	CS	(OSEBX)
Panel B: Average returns for liquidity groups given large firm size by applying both estimators					
2000	0.05	0.46	0.01	-0.04	0.01
2001	-0.13	-0.10	-0.10	-0.05	-0.13
2002	0.17	0.42	0.20	0.06	0.13
2003	0.18	0.61	0.24	-0.02	0.13
2004	0.23	0.72	0.12	-0.02	0.11
2005	0.09	0.45	-0.06	-0.07	-0.04
2006	0.09	0.83	-0.04	-0.11	-0.04
2007	0.07	0.63	0.04	-0.03	0.06
2008	0.10	0.40	-0.01	-0.05	0.01
2009	0.09	0.57	0.12	0.00	0.09
2010	-0.01	0.23	-0.00	-0.04	0.00
2011	0.10	-0.02	-0.18	0.01	-0.10

4.1.3 The performance of decile portfolios, after controlling for firm size on a monthly basis

As stated earlier, we sorted the stocks into least and most liquid given firm size. Table 5 shows the average returns on a monthly basis over the defined period for the extreme portfolios: the least and most liquid stocks given small and large firm sizes.

Panel A of table 5 shows that the least liquid stocks given small firm size mostly outperform the most liquid stocks given large firm size except for two and three months when Alpha and CS are applied respectively. The results further indicate that the market earns relatively higher returns than both least and most liquid stocks given small firm size on average every month over the defined sample period. There is an exception for the least liquid stocks given small firm size where the market underperforms against such stocks for two and three months when Alpha and CS are applied respectively. Similarly, the least liquid stocks given large firm size outperform the most liquid stocks of the same firm size for both estimators (see Pane B of Table 5). However, the least liquid stocks given large firm size outperform the market on average every month for both estimators, except for two months when the Alpha estimator is applied. On the contrary, the most liquid stocks of the same firm size mostly underperform against the market on average every month for both estimators. The results clearly show that the least liquid stocks of both firm sizes outperforms the most liquid stocks given same firm size (see Panels A and B of Table 5). This implies that the least liquid stocks have relatively higher risk than the most liquid stocks given the same firm size and thus, require high returns as compensation. This is consistent with the intuition that higher risk comes with higher returns. Small firms are usually considered to be more risky and less liquid as compared to large firms.

Table 5: Results of average returns every month for the least liquid and most liquid porfolios given firm size in comparison with the market

Month	Least liquid portfolio given small firms		Most liquid portfolio given small firms		Market index
	Alpha	CS	Alpha	CS	(OSEBX)
Sample period January 2000 – January 2011					
Panel A: Average returns for liquidity groups given small firm size by applying both estimators					
January	-0.68	-0.64	-0.28	-0.46	-0.16
February	-0.13	-0.27	-0.48	-0.49	-0.06
March	-0.49	-0.36	-0.62	-0.46	-0.06
April	0.11	0.05	-0.31	-0.10	0.15
May	-0.14	0.18	-0.27	-0.67	0.13
June	0.05	-0.19	-0.29	-0.05	0.21
July	-0.23	0.02	-0.65	-0.46	-0.04
August	-0.16	-0.18	-0.39	-0.40	0.01
September	-0.25	-0.05	-0.25	-0.18	0.11
October	-0.06	0.16	-0.26	-0.40	0.06
November	-0.23	-0.23	-0.39	-0.48	0.00
December	-0.12	-0.40	-0.35	-0.28	0.00

Table 5 (continued)

Month	Least liquid portfolio given large firms		Most liquid portfolio given large firms		Market index
	Alpha	CS	Alpha	CS	(OSEBX)
Panel B: Average returns for liquidity groups given large firm size by applying both estimators					
January	-0.11	0.15	-0.25	-0.22	-0.16
February	-0.02	0.43	-0.05	-0.14	-0.06
March	-0.06	0.06	-0.04	-0.05	-0.06
April	0.34	0.86	0.05	0.04	0.15
May	0.25	0.72	0.11	0.03	0.13
June	0.26	0.91	0.20	0.06	0.21
July	0.07	0.35	-0.52	-0.08	-0.04
August	-0.06	0.19	-0.02	-0.06	0.01
September	0.15	0.64	0.14	0.01	0.11
October	0.10	0.63	0.03	-0.03	0.06
November	0.02	0.31	-0.03	-0.08	0.00
December	0.08	0.43	-0.02	-0.05	0.00

4.1.4 Descriptive statistics of the least and most liquid portfolios

Table 6 represents the descriptive statistics of the least and most liquid portfolios as well as the difference between the two extreme portfolios. Table 6 shows the comparison of both estimators, Alpha and CS over the sample period from January 2000 through January 2011. For the least liquid portfolio, the mean return is relatively lower using the Alpha estimator as compared to using to using the CS estimator. The return volatility is smaller for the Alpha estimator as compared to the CS estimator. On the contrary, the mean return of the most liquid portfolio is relatively higher using the Alpha estimator as compared to using the CS estimator. Meanwhile, the return volatility is relatively lower for the Alpha estimator relative to the CS estimator. The difference in average returns and return volatility are relatively smaller for the Alpha estimator in comparison to the CS estimator.

As shown in Table 6, the mean return of the least liquid portfolio is higher than the mean return of the most liquid portfolio with an excess return on average of 0.03% by applying the Alpha estimator. Similarly, the least liquid portfolio earns returns on average than the most liquid portfolio with an excess return on average of 0.07% by applying the CS estimator. The risk as measured by the deviation is higher for the least liquid portfolio relative to the most liquid portfolio by applying both estimators.

Table 6 further indicates that the maximum and minimum average returns are relatively higher for the least liquid portfolio than the most liquid portfolio. For the least liquid portfolio, the minimum and maximum average returns are both smaller when the Alpha estimator is applied; as compared to applying the CS estimator. Meanwhile, for the most liquid portfolio, the minimum average return is smaller. However, the maximum average return is larger for the Alpha estimator as compared to the CS estimator. The return volatility for both the least liquid and most liquid portfolios are smaller by applying Alpha estimator as compared to CS estimator. This implies that the risk as measured by the standard deviation is relatively higher for the CS estimator over the Alpha estimator.

Table 6: Results of average returns of least liquid and most liquid portfolios as well their difference

	Least liquid portfolio		Most liquid portfolio		Difference	
	Alpha	CS	Alpha	CS	Alpha	CS
Sample period January 2000 – January 2011						
Mean return	0.01	0.05	-0.02	-0.03	0.03	0.07
Std. Dev.	0.06	0.13	0.06	0.06	0.08	0.14
Min	-0.23	-0.10	-0.23	-0.25	-0.23	-0.10
Max	0.24	0.52	0.04	0.03	0.24	0.52

4.15 The performance of the least and most liquid stocks on a yearly basis

Table 7 represents the annual average returns and standard deviations of the least liquid and most liquid portfolios as well as the difference between them for both Alpha and CS estimators over the sample period. Panel A of Table 7 shows that the least liquid stocks earn higher average returns than the most liquid stocks every year over the sample period. Similarly, the least liquid stocks outperform the most liquid stocks in terms of average returns every year over the sample period (see Panel B of Table 7). The results show that the returns of the least liquid stocks are, on average 0.03% and 0.07% higher per year than the most liquid portfolio for Alpha and CS estimators respectively. Thus, both portfolios have similar annual average returns. The results further indicate that the average return difference between the least liquid and the most liquid portfolios are positive for every year over the sample period from January 2000 through January 2011. However, the return volatility is higher for the least liquid portfolio relative to the most liquid portfolio every year except for three years when the Alpha estimator is applied. The same pattern is seen, but the exception is for one year when the CS estimator is applied. The results show that the return volatility is relatively higher when the CS estimator is applied than when the Alpha estimator is applied.

Table 7: Results of average returns of low-liquid and high-liquid portfolios as well their difference for each year

Year	Least liquid portfolio		Most liquid portfolio		Difference	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Sample period January 2000 – January 2011						
Panel A: Average returns of low-liquid and high-liquid portfolios as well their difference for each year by applying Alpha estimator						
2000	0.01	0.06	-0.02	0.05	0.03	0.08
2001	0.01	0.06	-0.02	0.06	0.03	0.08
2002	0.01	0.07	-0.02	0.05	0.03	0.08
2003	0.01	0.06	-0.01	0.04	0.02	0.08
2004	0.01	0.06	-0.02	0.05	0.03	0.08
2005	0.01	0.06	-0.03	0.06	0.04	0.08
2006	0.01	0.06	-0.03	0.06	0.04	0.08
2007	0.01	0.06	-0.03	0.06	0.03	0.08
2008	0.01	0.06	-0.02	0.06	0.03	0.08
2009	0.01	0.06	-0.02	0.06	0.03	0.08
2010	0.01	0.06	-0.02	0.05	0.03	0.08
2011	-0.05	0.09	-0.06	0.10	0.01	0.16

Table 7 (continued)

Year	Least liquid portfolio		Most liquid portfolio		Difference	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Panel B: Average returns of low-liquid and high-liquid portfolios as well their difference for each year by applying CS estimator						
2000	0.05	0.13	-0.03	0.06	0.07	0.14
2001	0.05	0.13	-0.02	0.06	0.07	0.14
2002	0.06	0.14	-0.02	0.05	0.07	0.14
2003	0.05	0.14	-0.02	0.05	0.07	0.14
2004	0.05	0.13	-0.03	0.06	0.07	0.13
2005	0.04	0.13	-0.03	0.06	0.08	0.13
2006	0.04	0.13	-0.03	0.07	0.08	0.13
2007	0.05	0.13	-0.03	0.06	0.08	0.13
2008	0.05	0.13	-0.03	0.06	0.08	0.14
2009	0.05	0.14	-0.03	0.06	0.08	0.14
2010	0.05	0.14	-0.02	0.06	0.07	0.14
2011	-0.02	0.04	-0.06	0.11	0.04	0.13

The Figures 4-10 illustrate the time-series of daily returns for the different portfolios constructed as well as for OSEBX over the defined sample period. We noticed a straight line in Figure 10 and found that the returns are not up to the threshold that is why there is such straight line in the plot in 2003. The Figures 11-12 illustrates the histogram of the Alpha and CS spreads.

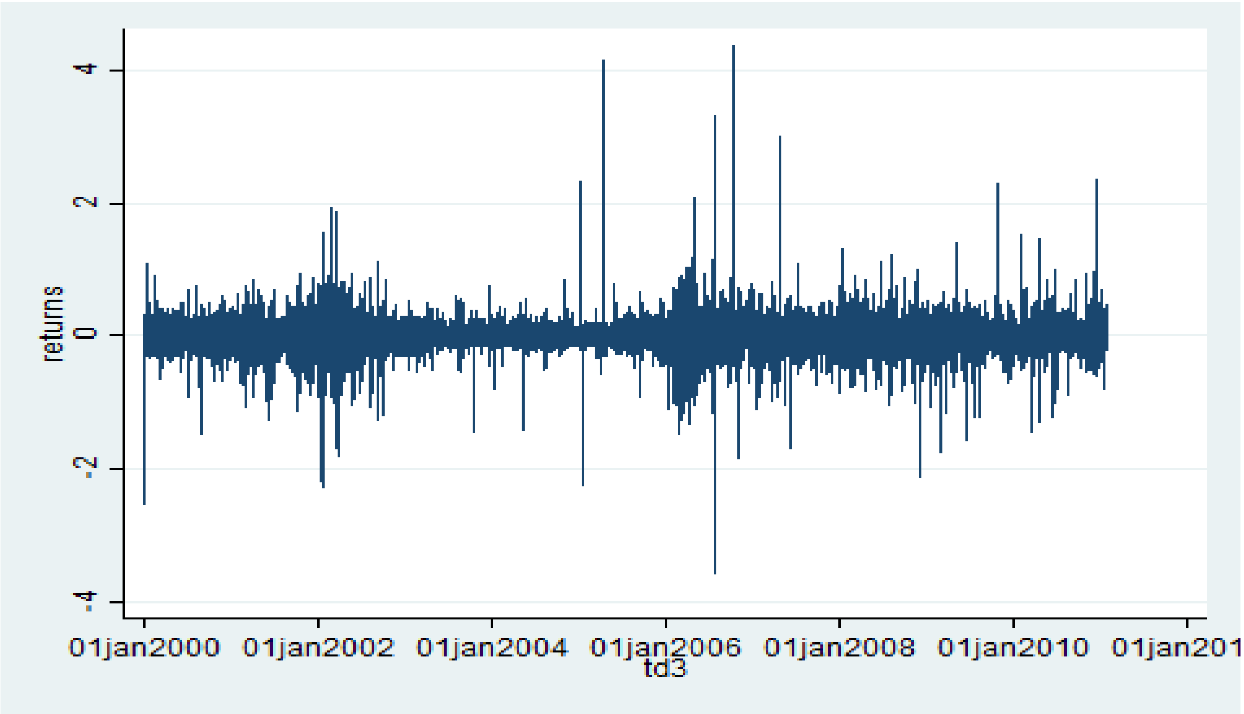

Figure 4: The figure illustrates a time-series of daily returns for OSEBX spreads over the sample period from January 2000 through January 2011. OSEBX has an average return of 0.029%, with a volatility of 23.78% over the sample period.

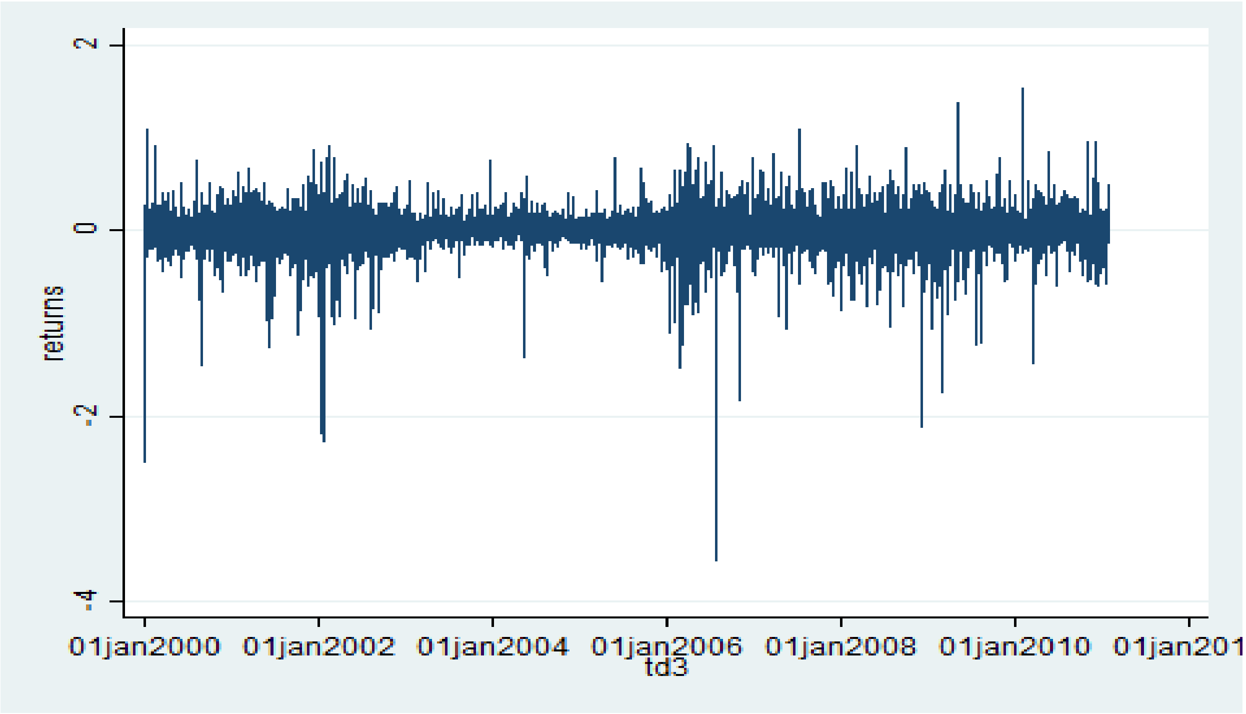

Figure 5: The figure illustrates a time-series of daily returns for the least liquid portfolio over the sample period from January 2000 through January 2011. The lowest liquid stocks have a return of 0.048% on average, with a volatility of 2.06% over the sample period.

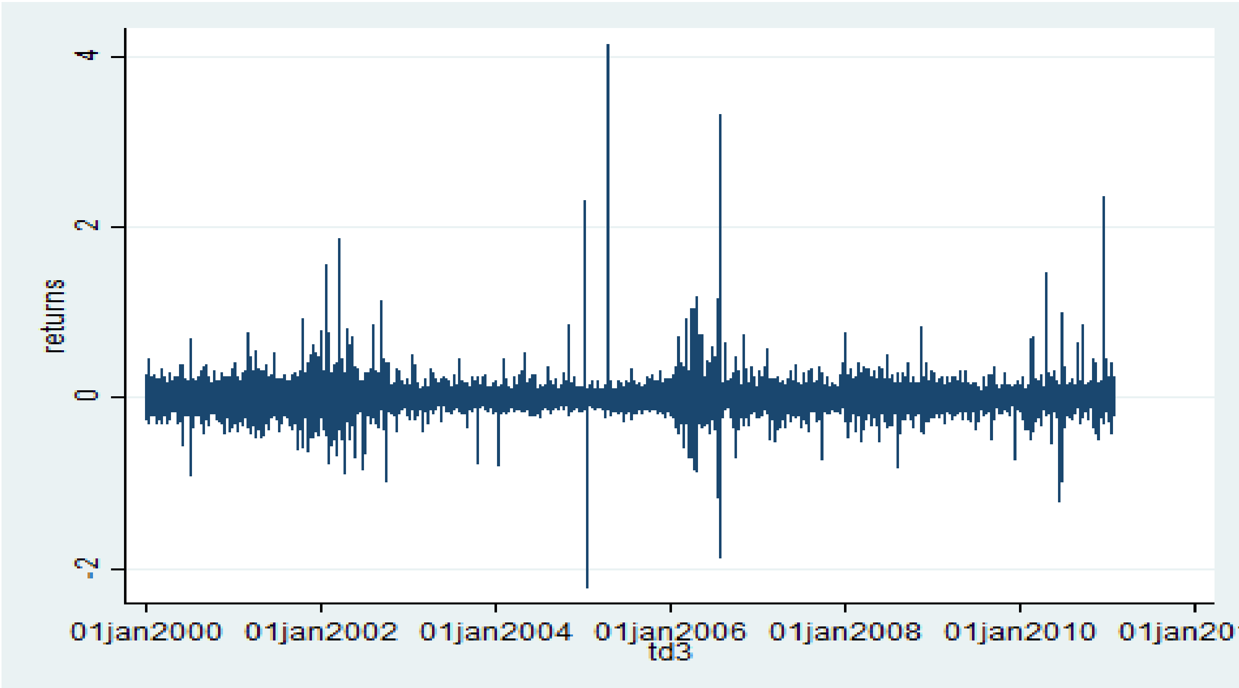

Figure 6: The figure illustrates a time-series of daily returns for the most liquid stocks over the sample period from January 2000 through January 2011. The most liquid portfolio has an average return of -0.027%, with a volatility of 0.92% over the sample period.

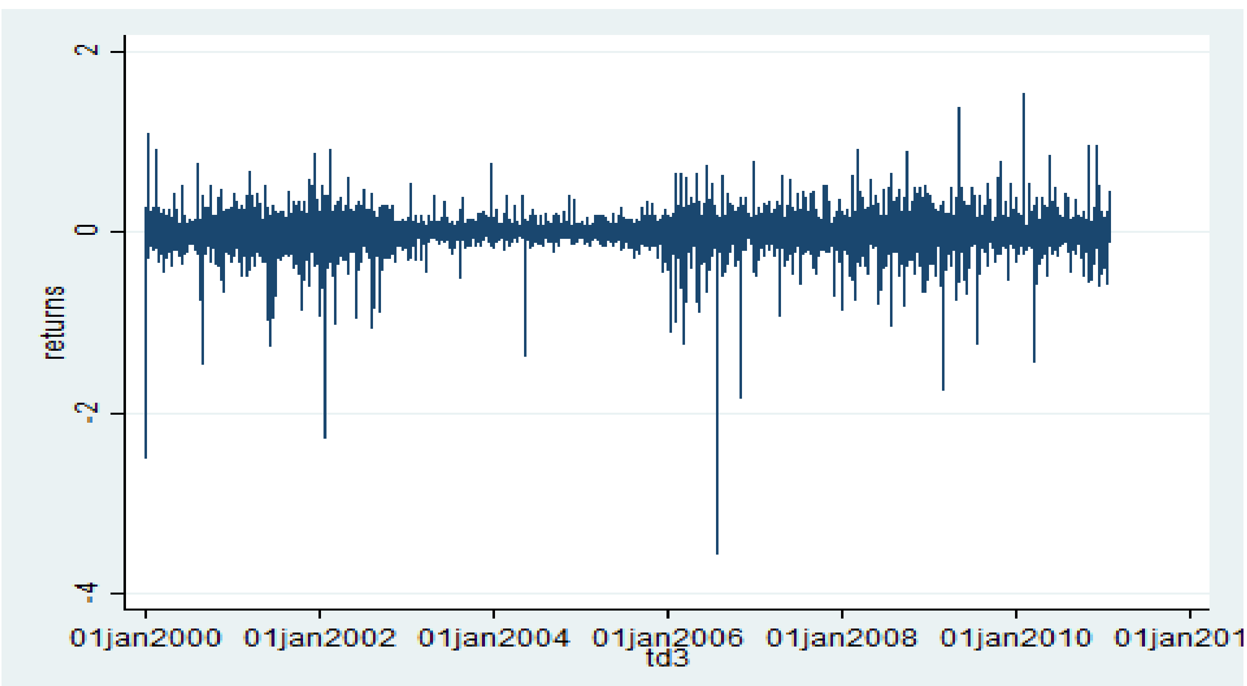

Figure 7: The figure illustrates a time-series of daily returns for the least liquid portfolio given small firm size over the sample period from January 2000 through January 2011. The lowest liquid stocks given small firm size has an average return of -0.163%, with a volatility of 159.7% over the sample period.

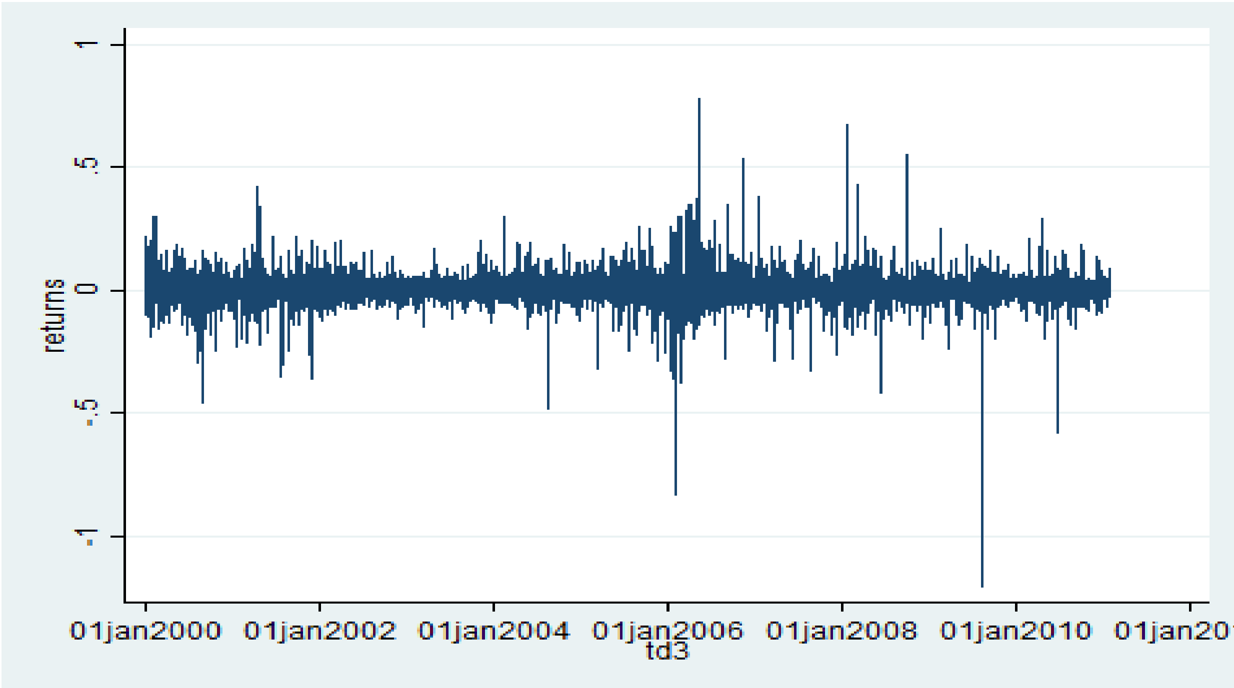

Figure 8: The figure illustrates a time-series of daily returns for the least liquid portfolio given large firm size over the sample period from January 2000 through January 2011. The lowest liquid stocks given large firm size has an average return of 0.472%, with a volatility of 94% over the sample period.

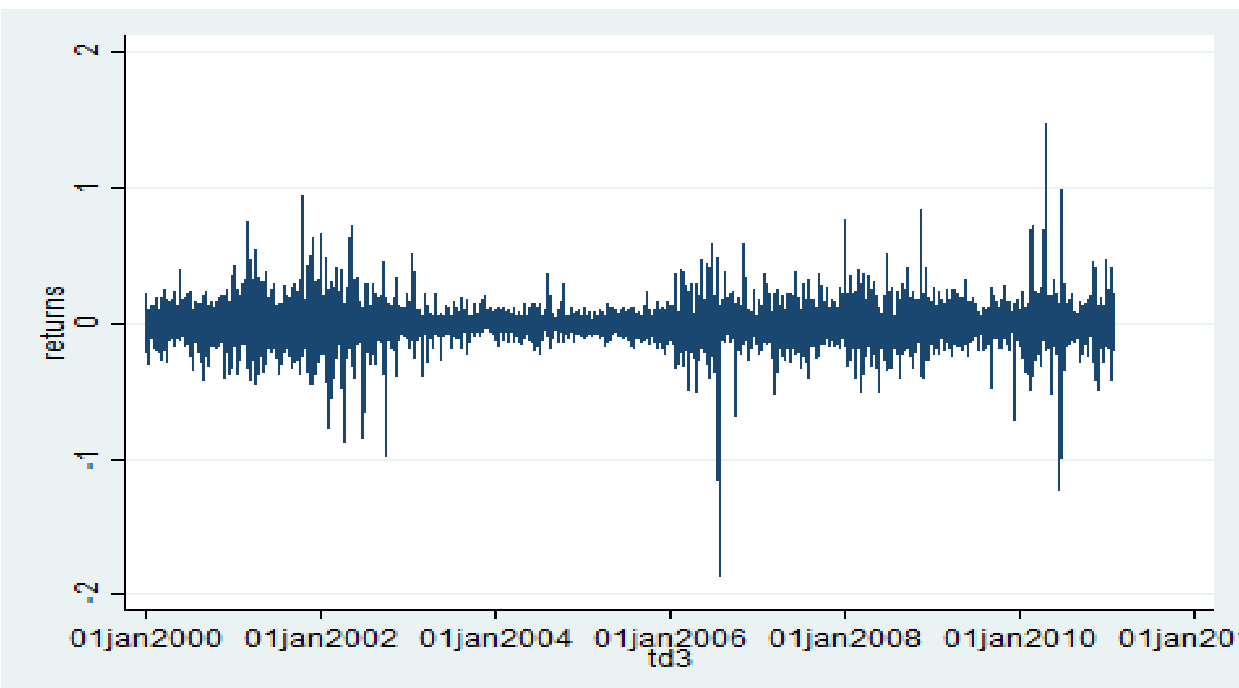

Figure 9: The figure illustrates a time-series of annual returns for the most liquid portfolio given small firm size over the sample period from January 2000 through January 2011. The most liquid stocks given small firm size has an average return of -0.407%, with a volatility of 120.4% over the sample period.

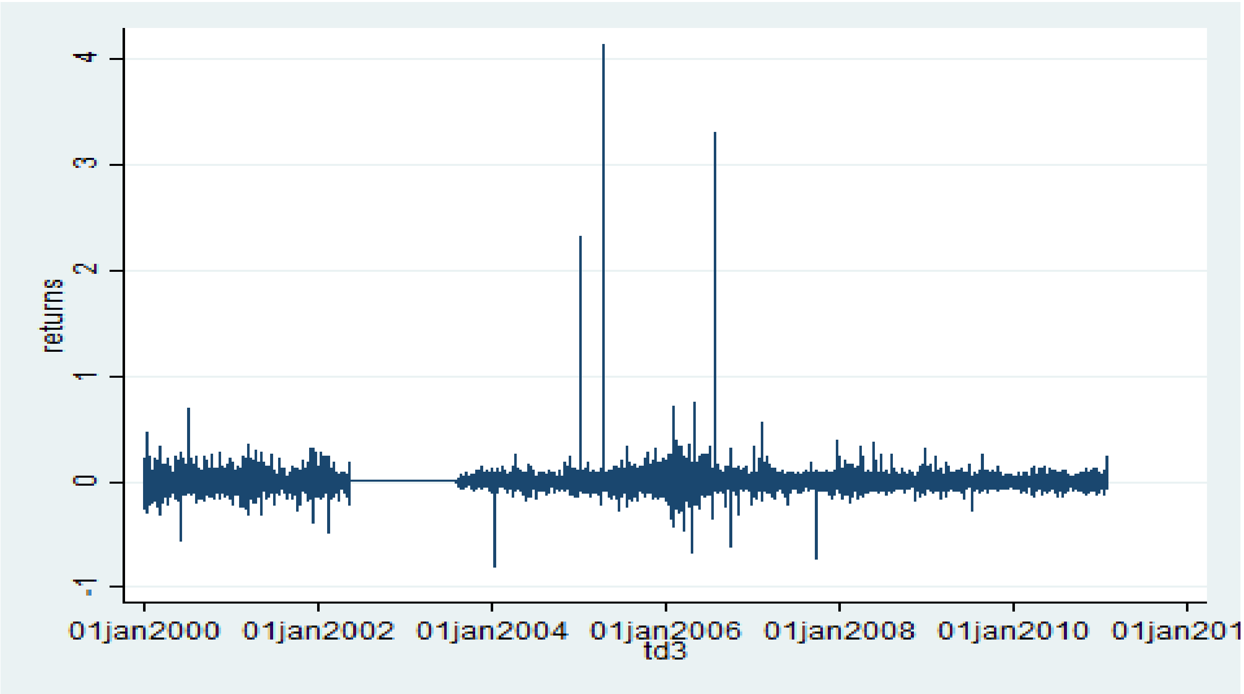

Figure 10: The figure illustrates a time-series of daily returns for the most liquid portfolio given large firm size over the sample period from January 2000 through January 2011. The most liquid stocks given large firm size has an average return of -0.049%, with a volatility of 52.56% over the sample period.

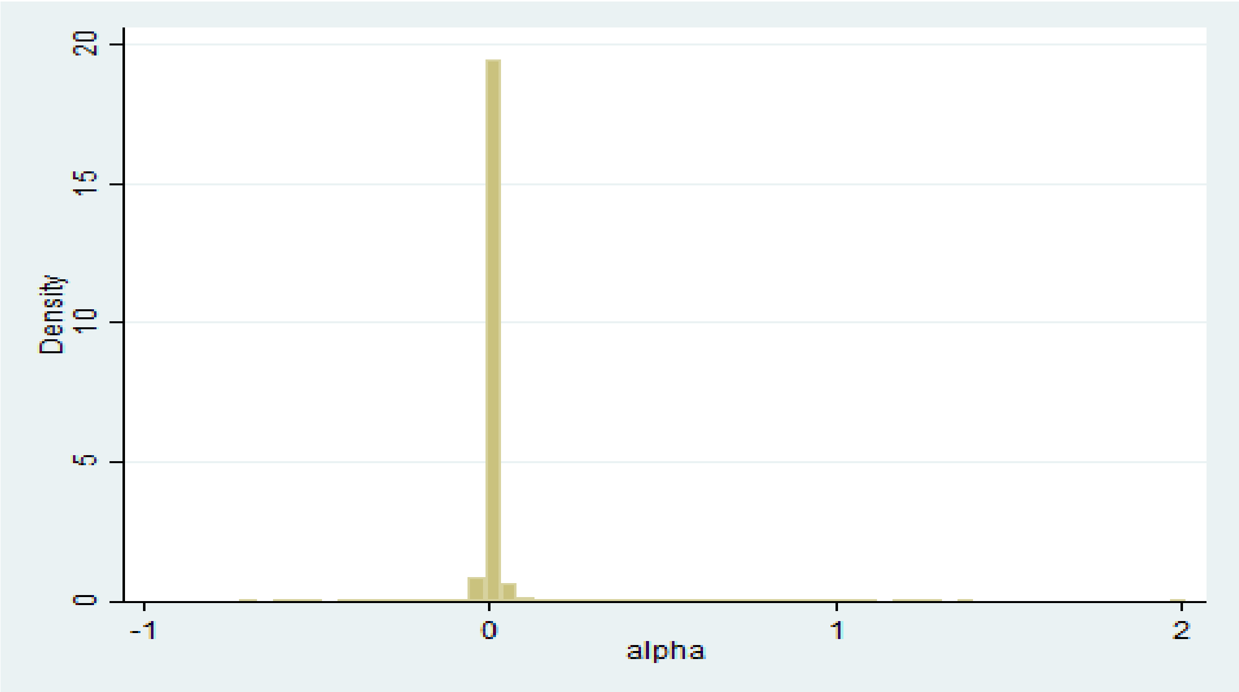

Figure 11: The figure illustrates the histogram of the Alpha spreads. The mean spread is 0.0077351 or 0.77% with a Standard deviation of 0.021437 with a maximum spread of 2.014903 and minimum of -0.718155.

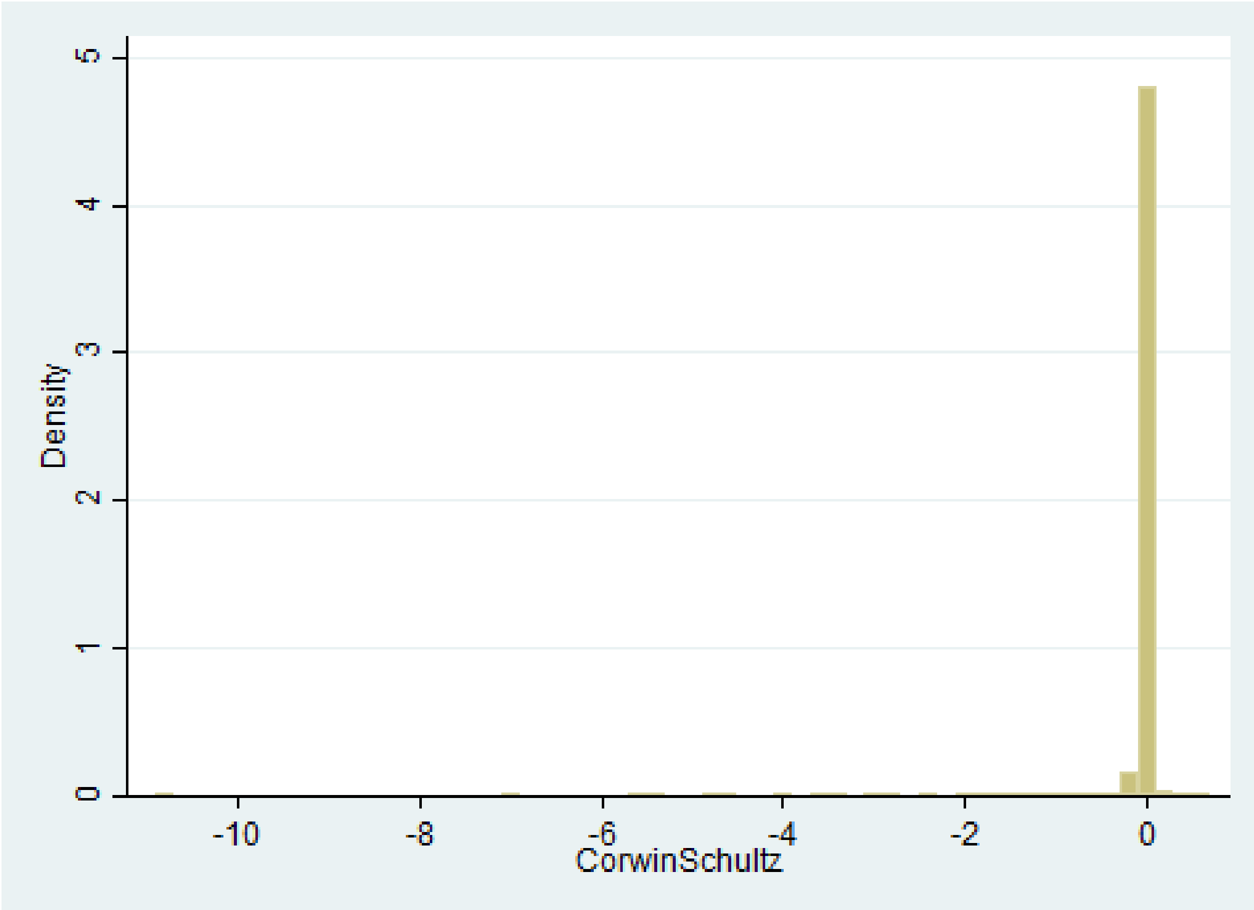

Figure 12: The figure illustrates the histogram of the CS spreads. The mean spread is -0.010014 or -1.0014% with a Standard deviation of 0.0582307 with a maximum spread of 0.6931472 and minimum of -10.88447.

CHAPTER FIVE

CONCLUSION

5.1 Conclusion

Using the two innovative measures of liquidity for individual Norwegian stocks, namely, the Alpha and CS estimators, we show that least liquid stocks tend to be small, low-priced and less traded with wide bid-ask spreads and higher returns which is consistent with the intuition properties of illiquid stocks. Based on the two liquidity measures, this thesis documents a significant liquidity premium over the sample period from January 2000 through January 2011. We find that the average returns of least liquid stocks are higher than the average returns of most liquid stocks using both estimators, consistent with the intuition that higher return comes with higher risk.

The empirical results of individual stocks listed on the Norwegian stock exchange and of the market clearly indicate that liquidity is a time-varying risk factor. The two measures of aggregate liquidity capture market liquidity conditions and fluctuations in aggregate liquidity generally correspond to market movements as expected. The results obtained show that returns on the lowest liquid stocks are, on average higher per year and per month than the most liquid stocks. We find that the portfolio, which comprises of stocks with wide bid-ask spread, has on average higher returns than all other portfolios. We noticed that the least liquid portfolio outperforms the most liquid portfolio, an indication of the presence of liquidity premium for t Norwegian stock over the defined sample period. This implies that, liquidity is an important source of priced risk.

We further find that the stocks of large firms earn relatively higher returns on average every year than the stocks of small firms for both the least and most liquid deciles. The results obtained show that the stocks of both large and small firms for the least liquid decile outperform the stocks of large and small firms for the most liquid decile respectively. The results indicate that the market outperforms the stocks of small firms for both the least and most liquid deciles on an annual basis. Meanwhile, the stocks of large firms for the least liquid decile outperform the market on a yearly basis. We also find that the market outperforms the stocks of large firms for the most liquid decile on average by applying the CS estimator but none performs better than the other by applying the Alpha estimator.

The empirical results reveal that the returns of the least liquid stocks are, on average 0.03% and 0.07% higher per year than the most liquid stocks for Alpha and CS estimators, respectively. We find that the average return difference between the least liquid and the most liquid stocks are positive every year over the sample period from January 2000 through January 2011. The lowest liquid stocks therefore outperform the most liquid stocks as well as the overall market on a yearly and a monthly basis while the market earns higher than the most liquid stocks.

The findings of this thesis indicate that the volatility of liquidity (i.e., spread) is higher for the average liquidity of Norwegian stocks as well as the overall market by applying CS estimator as compared to applying Alpha estimator. Moreover, the volatility of excess returns is higher by applying CS estimator than applying Alpha estimator. We find that return volatility is higher for the least liquid stocks relative to the most liquid stocks by applying both Alpha and CS estimators. The results also show that the volatility of returns in general is higher for the CS estimator relative to the Alpha estimator.

The empirical findings of this thesis are consistent with the underpinning asset pricing argument that stock prices reflect a premium that investors demand for holding illiquid stocks. Amimud and Mendelson (1986) show empirical evidence of such a premium for the bid-ask spread measure of liquidity. Existing literature on liquidity and asset pricing demonstrates the following: average liquidity cost and risk are priced; liquidity improves market efficiency; and liquidity strengthens the arbitrage connection between related markets. We expect that the findings of this thesis would serve as a basis for further research on liquidity and asset pricing. We therefore suggest for continued research on liquidity and asset pricing, in particular asset allocation which includes portfolio construction to check risk and returns based on some economic insight and factor models which include size, value, momentum, liquidity and the likes. It would also be important to include more innovative liquidity measures. Other research areas may include the time variation in liquidity premium to find out what the premium depend on as well as their movement during high and low price volatility periods.

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Appendix I

List of figures

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