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An Empirical Analysis of Cost-Based Market Liquidity Measures for U.S. & Norwegian Banks

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Abstract

The financial crisis of 2007-2009 highlights the role banks play in our economy, and how interconnected banks in reality are. This increases the risk that a liquidity squeeze develops into a solvency problem. Based on the theoretical foundation on market liquidity, and why it is a priced risk factor for assets, and in particular for stocks, I apply a particular measure of market liquidity, namely the bid-ask spread, on US banks' stocks and Norwegian banks' stocks, as well on their market, S&P500 Index and OSEBX, respectively. The two estimators for the bid-ask spread applied in this thesis, was derived by Roll (1984) and in a recent paper by Corwin and Schultz (2012).

I find that (a) liquidity has substantial time-variation, both for banks' stocks and for markets overall within both countries investigated; (b) a systemic liquidity breakdown appears in the recent financial crisis which led traders to suffer losses, as the costs, bid-ask spreads, for trading banks' stocks, S&P500 Index and OSEBX increases; (c) liquidity has commonality for the individual stocks and markets within the country; (d) the volatility of liquidity increases significantly after the Lehman Brother's insolvency, both for the market as a whole and for banks' stocks, thus the liquidity premium demanded by investors on trading banks' stocks, S&P500 Index and OSEBX increases; and, finally, (e) the tendency of Norwegian banks' stocks liquidity and OSEBX liquidity to respond to swings in the US banks' stocks liquidity and S&P500 Index liquidity, respectively, increases after the Lehman Brother's bankruptcy. The analysis has potential implications for central banks, traders, performance evaluation, risk managers, and academic research.

Keywords: financial crisis, banks' stocks, liquidity risk, time-varying bid-ask spread, commonality in liquidity

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CHAPTER 1

1.1 Introduction

Over the past years, there has been growing interest in issues related to financial market microstructure, a branch of finance concerned with the details of how exchange occurs in the market. In a financial market, an important component of transaction costs faced by investors is the bid-ask spread that market makers set. Market makers provide liquidity by taking the opposite side of a transaction. If an investor wants to sell a security, the market makers buy and vice versa. In exchange of this service, market makers buy at a low bid price, P^b, and sell it at a higher ask price, P^a. This ability insures that the market makers likely make some profits. The difference of, $P^a - P^b$, is the bid-ask spread – a trading cost and measure of market liquidity. High trading cost is linked to illiquidity.

A rise in market illiquidity forces forward-looking investors to require higher future yields on their investments as they expect the illiquidity to persist. This increase in the required return leads to a decline in securities prices. The impact of market liquidity shocks on securities prices introduces additional risk to market returns beyond the risk that is associated with shocks to expectations about future cash flows. Therefore, the higher expected return is required as compensation for the presence of higher liquidity risk.

The objective of this thesis is to estimate the bid-ask spread (liquidity) for banking stocks of U.S. and Norwegian banks before, during and after the financial crisis of 2007-2009, using daily observations of high, low, and closing prices. The motive to do so is that the literature has captured the recent banking crisis either from the liability side or from the asset side or from both sides of the banks' balance sheets, but there is a very limited literature available regarding the bid-ask spread of banks' securities during the financial crisis.

Due to the central role of banks in general, and investment banks in particular, I am hypothesizing that liquidity (bid-ask spread) of U.S. and Norwegian banks decreased (increased) in the financial crisis 2007-2009. This helps to analyze whether the increased stocks' trading cost was one of the problems for these banks, which led them to suffer losses during this financial crisis.

I will subsequently analyze the change in both the average level of liquidity, the volatility of liquidity for banks' stocks and the corresponding markets where they are listed, as well as the correlation between the two countries examined and the banking sector in these markets. To establish any link between the banking sector and the market as a whole, I construct a bank index, which is a capitalization weighted average of all the banks in the sample. This is done for both the US and Norway. This is important, as a common market is one reason for commonality in liquidity. Therefore, creating an index helps to disclose a systematic liquidity risk for banks' stocks within the broader markets if the liquidity deteriorates, as it did in the recent financial crisis.

Due to the wide drawbacks in the recent financial crisis, it is important to quantify the reaction of investors on these stocks of banks in particular, and markets in general after the Lehman Brother filed for bankruptcy. The insolvency of Lehman Brother, 150-year old investment bank, is widely considered to be the most devastating event of the ongoing financial crisis, and as a consequence, sent the global economy into a severe financial crisis.

After its bankruptcy, billions of dollars claimed by creditors and counterparties were sitting in various corners of the financial system as well as placed in complex derivatives, making it difficult to estimate the liquidation value of Lehman Brothers. This fueled the uncertainty among investors about the state of other banks, and the market started to decline rapidly, in particular stock prices of banks. For this reason, I will consider the bankruptcy of Lehman Brothers as an event for which I will study the effects on market liquidity before and after this event. To do this, I will analyze a time series of bid-ask spreads. Moreover, I investigate the correlation between the liquidity of the two countries banks in particular, as well between the liquidity of markets in general before, and after the Lehman Brother collapse.

These questions are important to analyze, as banks, in particular banks with a large capitalization, has a tremendous importance for how financial markets work. If the volatility of the market liquidity of such banks has increased, it means that investors consider them as more risky, and hence prone to rapid, steep, and large declines in prices. Moreover, if the correlation of liquidity between banks has increased, then this is an indication that investors are aware of the interconnection of banks, where the downfall of one bank might lead to a systemic liquidity shortage.

I find a systemic breakdown of liquidity for banks' stocks and the financial markets overall in the recent financial crisis. Hence, the trading costs, bid-ask spreads, increase. After the insolvency of the Lehman Brothers in September 2008, a systemic shortage of liquidity appears for banks' stocks, an effect that was still possible to detect more than five years after its insolvency. Moreover, liquidity uncertainty increases on financial markets as well, yet to a lesser degree than observed in the banking sector after the Lehman Brother's bankruptcy.

1.2 Background

The Global Financial Crisis of 2007-2009 illustrates the importance of liquidity on the functioning of financial markets. It is perceived as the worst financial crisis since the Great Depression of the 1930s. The crisis spread globally with substantial deterioration in banks' and other financial institutions' balance sheets – a run on the shadow banking system, and the failure of many high profile firms, such as Lehman Brothers, a large US investment bank.

The financial crisis did not lead to an economic depression because of the worldwide government intervention through bailout of financial institutions, and extraordinary actions by the Federal Reserve, and other countries' central banks, to overcome this crisis involving both liquidity provision to support orderly functioning of financial markets and monetary policy to stimulate the economy.

Although the problem was originated in the U.S., the wake-up call for the crisis came from Europe, a sign of how extensive the globalization of financial markets had become. After announcing ratings downgrades on mortgage-backed securities by Standard & Poor's and Fitch, on August 7, 2007, BNP Paribas, a French investment bank, suspended redemption of shares held in some of its money market funds, which sustained large losses.

During the financial crisis, European governments conducted massive bailouts of more than $10 trillion, in order to prop up their banking systems. Despite huge injections of liquidity into the financial system by the Federal Reserve and the European Central Bank, banks were avoiding to lend to each other. In September 2007, the deterioration of credit caused the first major bank failure, Northern Rock, in the United Kingdom in over 100 years, who relied on short-term borrowing in the repo market rather than deposits for its funding.

Other European financial institutions suffered as well. Particularly hard hit were economies like Ireland, which up until this crisis was seen as one of the most successful economies in Europe in recent time, with a very high economic growth rate. The impact of the financial crisis led to the major players in the financial markets to take drastic decisions.

In March 2008, the fifth-largest investment bank in the U.S., Bear Stearns, which invested heavily in subprime-related securities, had a run on its repo funding. As a result, it was forced to sell itself to J. P. Morgan for a price almost 95 percent below its value a year earlier. In July 2008, the two privately owned government-sponsored enterprises, Freddie Mac and Fannie Mae, were propped up by the Federal Reserve and the U.S. Treasury after the institutions suffered substantial losses from their holdings of subprime securities.

After suffering large losses on holding of subprime securities, on September 14, 2008, Merrill Lynch, the third-largest investment bank announced its sale to Bank of America for less than 60 percent of what it had worth just a year earlier. The day after, Lehman Brothers, the fourth-largest investment bank by asset size with over $600 billion in assets and 25,000 employees became insolvent, after also suffering losses in the subprime market, making it the largest bankruptcy filing in the history of the United States.

On September 16, 2008, American International Group (AIG), an insurance giant with assets of over $1 trillion, suffered a severe liquidity crisis after its credit rating was downgraded. It had written over $400 billion of insurance contracts that had to make payouts on possible losses from subprime mortgage securities. The U.S. government then conducted a massive bailout with over $150 billion of loans to AIG.

In September 2008, the financial crisis reached its peak after the House of Representatives, who were against to bailing out Wall Street, voted down a $700 billion dollar bailout package proposed by the Bush administration. However, the Emergency Economic Stabilization Act finally passed the bailout package in October 2008.

Despite these efforts, the stock market crash accelerated, with the week beginning October, 2008, making it the worst weekly decline in the history of the United States. Many of the world's largest institutions and the financial system were almost close to the point of collapse. The equity prices of major global banks declined by around 50% on average during the fourth quarter of 2008 which counted around $640 billion loss of market value. As a result, world trade and world GDP fell around 25% and 6% respectively at an annualized rate.

The recent crisis vividly demonstrates that liquidity can suddenly dry up and is not constant, as is often assumed in standard asset pricing studies. It changes over time for individual securities and for the market as whole. It varies for a number of reasons. First, it depends in part on the transparency of information about securities' value, which varies over time.

Second, the number of liquidity providers and their access to capital is a crucial determinant of market liquidity. When liquidity providers (i.e., trading firms, market makers, hedge funds, and banks) have constraints to securitized funding and lose capital – as happened in 2008 – then the liquidity supply decreases. Thus, market liquidity declines simultaneously for most assets. Third, increased uncertainty about liquidity makes the provision of liquidity riskier and increases the compensation that liquidity providers demand, that is, the trading cost increases.

The willingness to trade on one market side facilitates trading for investors on the other side of the trade, whereas unwillingness to trade by some investors decline liquidity for others and exacerbates the liquidity shortfall in the market, see for example Mendelson (1985). When more investors trade, they provide liquidity to each other and draw more traders into the market. It leads to rise in market liquidity. Conversely, when more investors withdraw from the market, another side of liquidity; funding liquidity, decreases and, leads to deterioration in market liquidity, consequently affecting asset prices, see, for example Brunnermeier and Pedersen (2009).

Liquidity shocks represent variations or changes in market liquidity relative to the expected value. When these variations are persistent, the new level of liquidity affects aggregate securities prices. For instance, when the aggregate liquidity deteriorates and trading costs increases, these costs likely to be higher for a while, thus stock prices decline. This is because; investors expect higher returns on holding positions to compensate for higher trading costs. That is, investors discount future corporate cash flows at higher rates. It leads to a decline in stock prices. Aggregate liquidity shocks generate shocks to asset prices and uncertain asset returns. Thus, market-wide liquidity shocks are a source of systematic risk that must be priced by risk-averse investors.

CHAPTER 2

2.1 Literature Framework

Liquidity is a time-varying risk factor (Huberman and Halka, 1999; Chordia et al., 2000; Hasbrouck and Seppi, 2001). The risk arises from situations in which a security cannot be traded quickly enough to prevent or minimize a loss. The reason may come from the lack of its marketability in the market in which it trades. In the last decades, the liquidity risk has gained an increased focus from both academic researchers as well as practitioners. One feature of liquidity is its high volatility, which implies it can vanish within minutes and become a problem for traders and even turn into systemic risk. It may disappear from the market; see for example Black Monday in 1987, Asian Slump in 1997, the financial crisis of 2007-2009, as well as the flash crash of May 6th 2010, and the sovereign debt crisis of the summer 2012.

Liquidity can be separated into funding liquidity and market liquidity, see Brunnermeier and Pedersen (2009). Funding liquidity refers to the ease with which borrowers can obtain funding, whereas the ease with which an asset can be sold refers to market liquidity. This paper focus on market liquidity and in particular one specific measure of market liquidity, namely the bid-ask spread. This is important since market liquidity affects traders' ability to trade, thus market liquidity risk has become particularly important among users of financial liquidity. Persaud (2003) argues that the principal challenge among users of financial liquidity – traders, investors, and central bankers, is the variability and uncertainty of market liquidity.

Market microstructure can be described as the purest form of financial intermediation where financial assets are traded. The costs of providing transaction services and the impact of these costs on securities prices are concerns of market microstructure research. The literature on asset pricing often assumes highly liquid markets – where securities can be traded at no cost (Duffie, 1996 and Cochrane, 2001) at all times. However, market frictions exist in actual markets. Market friction is anything that interferes with trade (see, for example Degennaro and Robotti 2007), change over time, and generate real costs for traders.

Demsetz (1968) relates the role of a market microstructure to immediacy. A demander of immediacy, i.e., an investor who wants an immediate trade, would trade at the best available price – the bid price if buying, or the ask price if selling. Thus, the bid-ask spread is the difference between the bid price that a buyer wants to pay of an asset and the ask price for which a seller wants to sell it. Bid-ask prices are established by suppliers of immediacy – market makers that quote bid-ask prices and investors that place limit orders.

Investors include individual and institutional investors such as pension plans and mutual funds. The market makers, i.e., broker-dealer firms, enable continuous trading by accepting the risk of holding securities. The National Association of Securities Dealers Automated Quotation (Nasdaq) is one example of an operation of market makers.

The bid-ask spread has long been of interest to traders, regulators, and researchers due to the fact that it is a useful measure of trading costs and thus a proxy for market liquidity (Amihud and Mendelson, 1986; Huang and Stoll, 1997; Corwin and Schultz, 2012; Banti et al., 2012; Mancini et al., 2013). The size of the spread indicates a stock's liquidity – the ease and cost of trading a stock. A small spread reflects higher liquidity, whereas a wide spread is an indicator of an unwillingness by a dealer to buy a stock without compensation that imposes cost on a seller.

The available literature on the bid-ask spread is extensive, see for example Amihud and Mendelsohn (1989), other Corwin and Schultz (2012). In general, there are two categories of statistical models that empirically measure the spread. The first class of models is based on the serial covariance properties of the observed transaction prices (Roll, 1984; Choi et al., 1988; Stoll, 1989; George et al., 1991; Huang and Stoll, 1994; Lin et al., 1995).

The second class relies on a trade initiation indicator variable (Glosten and Harris, 1988; Madhavan and Smidt, 1991). Other related articles include Huang and Stoll (1994), who find that changes in the short-run price of stocks can predict on the basis of microstructure factors, Hasbrouck (1988, 1991, and 1993), and Hamao and Hasbrouck (1995), who apply a vector autoregression framework to make inferences about the sources of spread.

Statistical models have been applied in several different contexts, for example: to examine the source of short-run return reversals (Jegadeesh and Titman, 1995), to study the dealer and auction markets (Affleck-Graves et al., 1994; Lin et al., 1995a; Porter and Weaver, 1996), to examine adverse selection costs (Neal and Wheatley, 1994), and to assess the sources of spread fluctuations (Madhavan et al., 1997).

The literature has concentrated on three factors in determining the bid-ask spread: adverse selection costs (Akerlof, 1970; Bagehot, 1971; Copeland and Galai, 1983; Glosten and Milgrom, 1985; Easley and O´Hara, 1987), inventory holding costs (Demsetz, 1968; Stoll, 1978; Amihud and Mendelson, 1980; Ho and Stoll, 1981, 1983) and order processing costs (Brock and Kleidon 1992). However, Huang and Stoll (1997) developed a model of a three-way decomposition combining the three components of the spread. They empirically document the significant importance of order processing, adverse selection and inventory components to estimate the true spread.

When more securities become information-sensitive, financial markets are perceived as illiquid, see for example Gorton and Metrick, 2009. In case of informed counterparty, trading may end up with a loss. An informed stock's buyer would buy a security at ask if he has information justifying a higher price. An informed stock's seller would sell a security at the bid if his information justifying a lower price. This cause of an adverse selection problem: informed investors with good news are likely to buy and informed investors with bad news have an incentive to sell.

Traders with private information about the fundamental value of the security are likely to take into account the price effect of their trades, and market makers have incentives to protect themselves against informed traders. The market makers gain from uninformed traders and lose from trading with informed traders. It widens the bid-ask spread, which compensates the market maker for his losses to the informed traders.

Glosten and Milgrom (1985) model the bid-ask spread in the following simple manner: assume two possible values for an asset with equal probability for a high value (v^H), and a low value (v^L). Informed traders of good news are present with probability π. Assuming risk neutrality, uninformed traders of bad news value the security at:

$$\overline{v} = \frac{(v^H + v^L)}{2} \tag{1}$$

The ask price, A, is the expected value of the security conditional on a trade at:

$$A = v^H \pi + \overline{v}(1-\pi) \tag{2}$$

The bid price is

$$B = v^L \pi + \overline{v}(1-\pi) \tag{3}$$

The ask price exceeds the bid price, because an informed trader would trade at ask (bid) only if the security value is v^H (v^L). Clearly, the model implies that the bid-ask spread, A-B= $\pi(v^H - v^L)$, is greater in case of higher probability of trading with informed investors.

In addition to private information about the fundamental value of the security, the literature also illuminates the importance of private information about order flow; see, for example, Madrigal (1996), Vayanos (2001), Gallmeyer et al. (2004), and Brunnermeirer and Pedersen (2005b). If a trading desk anticipates that a hedge fund will liquidate a large position which would depress prices, then the trading desk has incentive to sell early at high prices and buy later at lower prices. There is a positive relationship between order size and spread. Informed buyers tend to have large trades which increase dealers' potential losses. Therefore, dealers likely widen the spread.

The spread compensates dealers who offer immediacy by accepting the risk of holding inventory. Dealers are viewed as risk aversion agents who provide liquidity and optimize their own securities portfolios. Dealers quote bid-ask prices in order to maximize their expected utility. Furthermore, not all investors are present in the market at all times, so a seller (i.e., a security holder) may arrive to the market at a time when a natural buyer may not be immediately available. This gap between the seller and buyer is bridged by market makers.

A security can be sold to a market maker who buys in anticipation of being able to resell it to the buyer. However, the market maker faces the risk of price fluctuations in the meantime and should be compensated for this risk – compensation in terms of imposing a cost on the seller. The bid-ask prices quoted by a monopolist market maker affect the intensity of arrival of both buyers and sellers, see for example, Garman (1976). German finds that constant bid-ask prices can cause the possible failure of market maker.

The quoted bid-ask prices depend on the market maker's inventory of the traded security (Amihud and Mendelson, 1980 and Ho and Stoll, 1981). Ho and Stoll (1981) assume a risk-averse market maker who tends to reduce his risk exposure. Amihud and Mendelson (1980) assume that a market maker constrains his inventory position due to reasons such as the risk of his position or capital constraint. The greater the price volatility of the security traded (Ho and Stoll, 1981), or the smaller the market maker's inventory position is due to capital constraint and risk (Amihud and Mendelson, 1980; Brunnermeier and Pedersen, 2005a), the greater is the bid-ask spread set by market makers.

The spread is compensation for dealers who offer immediacy while bearing some fixed costs of market making. Such costs include administrative expenses, and connection to the dealing system etc. In the short run, order processing costs are stable. Ding (2009) finds that in case of trading a large volume, the compensation for each unit of transaction is likely to be smaller, thus, the spread would be negatively affected by the order size.

Duffie et al. (2003, 2005) study the effects of search and bargaining problems on asset prices. They reveal that such problems also widen bid-ask spreads. Duffie et al. (2002) consider a model of over-the-counter (OTC) market for short-selling – a short seller must search the lendable securities, and negotiate for their lending fee. The study reveals that the lending fee increases the security's value. The spot markets and the securities lending markets are OTC search markets, see for example, Vayanos and Weill (2005). They show that a security with a large lending fee and a high price is liquid in equilibrium.

Illiquidity can rise in OTC markets, such as so-called dark pools, where investors trade bilaterally over computer networks and by phone. In such markets, search and bargaining problems tighten liquidity. For instance, when a trader wants to lay off his position, he needs to search for a counterparty that is willing to buy. Once the potential counterparty is found, the trader negotiates the price in a less than perfectly competitive environment as alternative counterparties are not immediately available. Intermediaries can have market power due to the bilateral trading in OTC markets, allowing them to get a price concession on trade. A searching trader bear illiquidity cost in terms of selling at a discount.

2.2 Variation and Commonality in Liquidity

Researchers have been able to use electronic computers in order to study the behavior of lengthy price series since the early 1950s. Kendall (1953) studies U.K. stocks and commodity price series, and argues that ‘‘*in series of prices which are observed at fairly close intervals the random changes from one term to the next are so large as to swamp any systematic effect which may be present.*’’

Liquidity has commonality across stocks and it varies over time, see, for example Kamara et al. (2008). It is important to understand the source of systematic liquidity variation, because it is perceived as a priced source of risk (Brennan and Subrahmanyam, 1996; Jones, 2002; and Pastor and Stambaugh, 2003). The debt market crisis of 1998 and the equity markets break of 1987 and 1989 can be perceived as systematic breakdowns in liquidity.

Chordia et al. (2000) examine the case of common liquidity movements across 1,169 stocks listed in NYSE over 200 trading days during 1992. They empirically document that individual liquidity co-moves with market liquidity. This result is consistent with the findings of Hasbrouck and Seppi (2001) on the Dow 30 stocks.

In addition, Chordia et al. (2000) also test whether liquidity co-variation is the cause of systematic variation in inventory or adverse selection costs, or both. They find that common influences remain significant even after controlling for individual liquidity determinants. However, Hasbrouck and Seppi (2001) conclude that common factors in liquidity are weak, such as one common factor explains roughly 12% of variation in the percentage quoted spread.

In general, liquidity risk is center in any financial crisis (Schnabel and Shin, 2004). They examine the financial crisis of 1763. In the cross-sectional analysis, they document that liquidity deterioration forced intermediaries to sell their stocks of commodities at prices below their fundamental values. In addition, they claimed a complete breakdown of the financial system, spreading internationally as far as Sweden and England, in the absence of official intervention.

From a liquidity supply perspective, Coughenour and Saad (2004) argue that common market makers are one reason for commonality in liquidity. For example, liquidity co-variation arises as each market maker provides liquidity for many stocks. They show in cross-sectional and time-series analysis that liquidity co-variation is positively related to market makers' capital constraints or to the risk of their holding positions. Brockman and Chung (2002) and Bauer (2004) provide the evidence of systematic liquidity in an order-driven market structure (i.e., markets without any designated liquidity suppliers) for the Hong Kong Stock Exchange, and the Swiss Stock Exchange, respectively.

Brunnermeier and Perdersen (2009) argue that market liquidity is correlated across stocks due to the fact that market makers' funding constraint affects all securities. Traders' ability to provide market liquidity depends on their capital and margin requirements (i.e., the percentage of a security's value that can be used as collateral). A trade can be financed through collateralized borrowing from financiers who set the margins. Speculators cannot borrow the entire price of an asset which is used as collateral. The difference between the security's price and collateral value refers to the margin which is financed by the own capital of the trader.

During periods of tight funding liquidity (i.e., capital constraints and high margins), market liquidity decreases because traders are uncertain to take positions. A decline in market liquidity leads to higher volatility (Benston and Hagerman, 1974 and Amihud and Mendelson, 1989). However, the market liquidity is insensitive to marginal changes in capital and margins during abundant availability of capital. This leads to higher market liquidity.

Conversely, funding liquidity depends on market liquidity. When market liquidity is low, margins increase because the higher risk is associated with financing a trade. Traders face the higher risk of margins because financiers can reset margins in each period to control their value-at-risk. During the liquidity crisis of 1987, 1990, 1998, and 2007, margins increased for S&P 500 futures, see for example Brunnermeier and Perdersen (2009).

A reinforcing mechanism between funding liquidity and market liquidity leads to liquidity spirals; margin and loss spirals. Margin spiral refers to margin rise causes by a funding shock, leading market illiquidity. As margin rises, traders are forced to reduce their position (i.e., de-lever), see for example Adrian and Shin (2010). A loss spiral arises due to a decline in asset value. A funding shock lowers market liquidity, leading to losses on speculators' existing position. Speculators are forced to sell more to maintain its leverage ratio, causing a further price drop, and so on.

The liquidity fluctuations make the future trading cost of selling an asset uncertain. The variation in liquidity can increase asset price volatility as liquidity affects assets' prices. Amihud et al. (1990) study if the liquidity fluctuations lead to variations in asset prices. They test this hypothesis on the stock market crash of October 19, 1987. They document that mean spread for stocks listed in the S&P 500 Index increased from 27 cents to 37 cents. They also reveal that stocks that suffered the greatest decline in liquidity on the day of stock market crash also had the greatest decline in prices. However, stocks whose liquidity recovered by October 30, 1987 had a great recovery in prices.

The connection between funding shocks, illiquidity and volatility causes of a risk for investors that is priced (Fontaine et al., 2013). They examine the role of funding liquidity in the cross-section of stocks traded in NYSE and AMEX from 1986 to 2012. Their findings are consistent with the model of Brunnermeier and Pedersen (2009). In the cross-section analysis, they find a positive relationship of the illiquidity and volatility of individual portfolios with the funding constraint. In addition, they document a negative relationship between funding constraint and the portfolio returns.

Time-series variations in market liquidity are found to be a determinant of conditional expected stock returns, see Jones (2002). The author studies the time series effects of aggregate liquidity on Dow Jones stocks from 1900 to 2000, measured by bid-ask spread and brokerage fees. The findings show that spreads are cyclical, and wide spreads predict high stock returns. The time-series relationship between market liquidity and expected returns is further examined by Amihud (2002) and Bekaert et al. (2007). The results of both theses papers are consistent with the findings of Jones (2002) that returns increase in illiquidity.

Furthermore, Severo (2012) examines whether the equity returns of 53 global banks are exposed to a systemic liquidity risk index (SLRI) between 2004 and 2010. The findings show that Lehman Brother's bankruptcy caused a widespread systemic illiquidity problem. The results of Severo (2012) also reflect a strong positive correlation between liquidity risk and the volatility of banks stocks. However, the level of banks' stocks returns is not directly affected by the SLRI. He indicates that U.K. and U.S. banks' stocks were much more volatile due to liquidity deterioration. For this reason, Severo (2012) suggests that academics and policymakers should monitor systemic liquidity risk due to the severe consequences of an evaporation of liquidity in securities and funding markets during a potential financial crisis.

Beneish and Whaley (1996), and Erwin and Miller (1998) argue that changes of liquidity due to additions to and deletions from the Standard and Poor's (S&P) 500 Index. Hedge and McDermott (2003) examined the effects of additions to and deletions from the S&P 500 Index on stocks' liquidity. They measured liquidity through bid-ask spread, trading frequency, volume, and the Kyle's estimated parameters. The analysis shows that stocks that are added to the S&P 500 index enjoyed an increase in liquidity, whereas deleted stocks suffer a decline in their liquidity.

Macey et al. (2008) study stocks that are involuntarily delisted from NYSE in 2002. They find huge costs to involuntarily delisting with volatility doubling and percentage spreads tripling. Angel et al. (2005) find similar results on stocks that are involuntarily delisted from the Nasdaq and subsequently traded on the OTC Bulletin Board. They reveal that stocks prices fall by 18% which are significantly associated with deterioration in liquidity. However, Bollen and Whaley (2004) find that voluntarily transferring of stocks do not cause decreasing liquidity and prices which reflect self-selection due to favorable information. They show that stocks that are transferred from Nasdaq to the NYSE experienced an increase in their prices and liquidity.

2.3 Bid-Ask Spread Estimators

To measure the stocks' liquidity, I rely on two bid-ask spread estimators: Roll (1984) and Corwin and Schultz (2012). The Roll estimator requires only price and not transactions data. It is the most widely used estimator which has also been extended in later research (Choi et al., 1988; Stoll, 1989; George et al., 1991; Hasbrouck 2004, 2009). The Corwin and Schultz (CS) estimator has low data frequency requirements and it is simple to compute, as it requires only daily high-low prices.

2.3.1 Roll (1984) Estimator

Under the assumption that a market maker bear only order-processing costs, the Roll (1984) estimator is based on the serial covariance of the change in price as follows.

$$V_t = V_{t-1} + e_t. \tag{4}$$

Where V_t is the unobservable fundamental value of the stock on day t, and e_t is the mean-zero, serially uncorrelated public information shock on day t. The last observed trade price the security at day t, is then given by

$$P_t = V_t + \frac{1}{2} S \cdot Q_t. \tag{5}$$

S is the effective spread and Q_t is a buy/sell indicator for the last trade that is equally probable to be +1 for a buy order or -1 for a sell order, given by

$$Q_t = \begin{cases} +1 & \text{Buy order} \\ -1 & \text{Sell order} \end{cases} \tag{6}$$

Q_t is serially uncorrelated and is independent of e_t. By taking the first difference of equation (5) and combining it with equation (4) we get a following expression for the price return

$$\Delta P_t = \frac{1}{2} S \Delta Q_t + e_t. \tag{7}$$

Where Δ is the first order difference operator. Under ideal conditions, the serial covariance of price changes is

$$Cov(\Delta P_t, \Delta P_{t-1}) = \frac{1}{4} S^2. \tag{8}$$

Effective bid-ask spread can then be estimated by

$$S = 2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})}. \tag{9}$$

More specifically, the model proposed by Roll (1984) assumes that the true value of a stock follows a random walk, so buy and sell orders are equally likely and serially independent, and the value of stock is independent of the order flow. The Roll estimator is biased when its assumptions are not valid. Thus, it is of interest to study a number of refinements which have been tested and proposed to the Roll estimator; therefore, I give a brief introduction.

Roll's measure provides accurate spread estimates with intraday data when researchers have trade prices but not quotes, see for example Schultz (2000a). Corwin and Schultz (2012) find that the covariance of price changes is frequently positive with a long time-series of daily data, forcing researchers to arbitrarily convert an imaginary number into a spread estimate.

Harris (1990) studies the small-sample properties of the Roll estimator and claims that bias is a decreasing function of the sample size, whereas the Roll estimator is unbiased with the infinite sample size. Harris (1990) observed the following problems in the Roll estimator as, a) the serial covariance estimator yields poor results for small data size, b) the square root in the estimator is not properly defined, and c) daily estimates are smaller than weekly estimates. In addition, Harris (1990) reveals that the Roll estimator underestimates the spread when the volatility of transaction prices is high.

George et al., (1991) study daily and weekly data of NYSE/AMEX and NASAQ stocks and reveal that between 77 and 97 percent of the downward bias in the Roll estimator is due to the time variation in expected returns. They introduced a modified Roll model which is unbiased when the mid-price is autocorrelated.

Glosten (1987) claim that the presence of adverse selection and inventory costs arising from the risk borne by a market maker can cause the downward bias in spreads estimated by the Roll estimator. Stoll (1989) obtains similar results by analyzing the spread components using Roll's framework. He argues that the model would underestimate the true spread, for it only considers the order processing part.

Hasbrouck (2006) uses Roll's measure to estimate the spreads for NYSE trades. Hasbrouck finds that estimated spreads are too low. A problem observed is that price changes are estimated to be positively serially correlated rather than negatively. There may be some other factors, for example, information, which can cause of the serial correlation. Hasbrouck (2006) demonstrates that Gibbs estimates of spreads are more accurate than Roll's estimated spreads, but the procedure of estimating the spreads is computationally intensive.

Holden (2009) studies the Roll estimator and finds that the Center for Research in Security Prices (CRSP) records the midpoint of its bid-ask range as its closing price when a stock does not trade for a day. He modified the Roll's measure in which the covariance of price changes is divided by the percentage of days with trading.

Goyenko et al., (2009) argue that because the formula of computing Roll estimator is undefined if the sample serial covariance is positive, they substitute a default numerical value of zero and modified Roll estimator as:

$$Roll = \begin{cases} 2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})} & when\ Cov(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0 & when\ Cov(\Delta P_t, \Delta P_{t-1}) \geq 0 \end{cases} \tag{10}$$

2.3.2 Corwin and Schultz (2012) Estimator

Corwin and Schultz (2012) develop a bid-ask spread estimator from daily high and low prices. They reason that because daily high prices are almost always buyer-initiated trades, and daily low prices are always seller-initiated trades, the ratio of high-to-low prices for a day reflects both the fundamental volatility of the stock (stock's variance) and the stock's bid-ask spread. The variance component of the high-low price ratio is proportional to the return interval, while the spread component stays relatively constant over a short period.

This implies that the sum of the daily price ranges over 2 consecutive single days reflects 2 days' volatility and twice the bid-ask spread, while the price range over a 2-day period reflects 2 days' volatility and one bid-ask spread. Based on these simple insights, Corwin and Schultz (2012) derive a spread estimator as follow.

Let β be the expectation of the sum of the price ranges over 2 consecutive single days.

$$\beta_t = E\left[\sum_{j=0}^{1} [\ln(\frac{H_{t+j}^0}{L_{t+j}^0})]^2\right] \tag{11}$$

Where H_t^0 is the observed high price at day t, while L_t^0 is the observed low price for day t. Next, let γ be the maximum range of the high-to-low price ratio for a two-day period, given in Equation (12):

$$\gamma_t = [\ln(\frac{H_{t-1,t}^0}{L_{t-1,t}^0})]^2 \tag{12}$$

The reason for (t, t-1) in the High and Low prices, is that the measure is not forward looking, but rather looks at past prices. Where $H_{t-1,t}$ ($L_{t-1,t}$) is the maximum (minimum) price for the two-day period consisting of days t-1 and t. After we estimate β and γ from stock return data, a proportional difference between β_t and γ_t given in Equations (11) and (12) can be derived. The difference is:

$$\alpha_t = \frac{\sqrt{2\beta_t}-\sqrt{\beta_t}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma_t}{3-2\sqrt{2}}} = (1+\sqrt{2})(\sqrt{\beta_t}-\sqrt{\gamma_t}) \tag{13}$$

The first term in Equation (13) with β_t and γ_t is equivalent to that of CS, but it can be simplified to the last term. The α_t will have substantial time variation as it is computed from observed values, and in particular observed high and low prices. A drawback of this model as a foundation for the bid-ask spread is that γ_t might be larger in value than β_t, and as a consequence α_t will be negative. It is possible to reduce the chance of negative values for α_t by taking into account overnight trading. The negative values of the bid-ask spread will be further discussed later.

From Equation (13), the bid-ask spread is then given by the relationship:

$$S = \frac{2(e^{\alpha_t} - 1)}{1 + e^{\alpha_t}} \tag{14}$$

For small spreads, α_t and the estimate of the spread, S, will be approximately equal. The high-low spread estimator is easy to compute, making it ideal for large samples compared to those estimators that are computationally intensive, such as, Gibbs estimator, maximum likelihood estimation (LOT), and Holden (2009) measure.

Moreover, through comparisons to TAQ data from 1993-2006, it outperforms the Roll (1984) estimator, the LOT measure of Lesmond et al. (1999) and the effective tick estimator of Holden (2009), in capturing the cross-sections of both spread levels and month-to-month changes in spreads, see for example, Corwin and Schultz (2012).

A negative bid-ask spread is the drawback of this high-low estimator. It is clearly a violation of reality. Spread should always be a positive number, since it is defined as ask-price minus a bid price. Corwin and Schultz (2012) assume that the expectation of observed two-day variance is twice as large as the expectation of a single day variance. If the observed two-day variance is large enough, in cases for the overnight return, the estimator may produce a negative bid-ask speak. When such a situation occur, they set spread equal zero.

Yan (2012) examine the impact of short-term momentum on spread estimated by Corwin and Schultz (2012). He argues that a big shortcoming of Corwin and Schultz (2012) measure is the estimation of its negative spread. Like Corwin and Schultz (2012), he uses the same time period from 1993-2006, and finds that the percentage of negative spread is too high with a grand mean of 58 percent. Thus, more than 50 percent of stock monthly spread is not valid.

Lin (2013) studies the estimation accuracy of Corwin and Schultz (2012) high-low spread estimator. He claims that the performance of this estimator depends on the level of transaction frequency, the size of the spread, and price volatility. Analyzing the probability of measurement error, it is demonstrated that the accuracy of the high-low spread estimator increases with the size of the spread and transaction frequency, but decreases with higher price volatility.

Chapter 3

3.1 Data

This part presents the dataset used in the analysis, and provides summary descriptive statistics of the liquidity measures for the data sample. Despite their shortcomings, I will apply the bid-ask spread estimators derived by Roll (1984) and Corwin and Schultz (2012) as proxies for stocks of banks and markets, as S&P500 Index and OSEBX.

To compute bid-ask spreads, I select a random sample of 17 US and 3 Norwegian banks listed in S&P500 Index and OSEBS, respectively, see Appendix 1 and 2. The data used in this research is obtained from the Center for Research in Securities Prices, and some additional information from Yahoo Finance and EUROINVESTOR for S&P500 Index, US and Norwegian banks, and OSEBX, respectively. The data sample consists of daily observations of high, low, and closing prices from January 2003 to December 2013.

I take the average of the liquidity (spreads) of US and Norwegian banks' stocks separately, and investigate potential structural changes in their average liquidity, as well in markets' liquidity over time within the countries. As some banks are bigger than others, I then create the Index for US and Norwegian banks separately, and study the liquidity variations over time as well. This is an important question to address, as banks sits in the heart of any economy, distributing funds to investors, and other agents, needing money for investors.

I then apply linear regression analyses between the average liquidity of banks' stocks and markets within the countries for the three datasets, as the entire daily data 2003 to 2013, the daily data 2003 to 2006, and 2007 to 2013. For the regression analyses of the US bank Index, and the Norwegian bank Index with their own markets, I follow the same datasets. It helps to understand that how exposed stocks of banks are to their own market liquidity risk for the entire period, as well as before and after the financial crisis.

The crisis of Lehman Brother highlights that how a breakdown of one bank can in many cases pull other banks with them down the drain, thus might lead to a systemic liquidity shortage. Therefore, I separate the entire daily dataset into two groups, as group A and B.

Group A represents the time period between January 01, 2003 and September 14, 2008, whereas group B refers to the period between September 15, 2008 and December 31, 2013.

I try with these simple models to see if there are any signs that liquidity uncertainty has increased for stocks of banks in particular and markets in general within the countries after the Lehman Brother's bankruptcy. If this liquidity risk among banks within the countries has increased, then this is an indication that investors perceive them less safer investment.

Although this crisis was originated in the US, but it caused a widespread systemic illiquidity problem around the world. Thereby, the last section discloses the commonality of liquidity between the two countries examined for the entire daily data 2003 to 2013, as well as before and after the Lehman Brother's collapse. If the correlation in commonality of liquidity between the two countries has increased, it then reveals that how exposed the liquidity of Norwegian banks' stocks and OSEBX are to US banks' stocks and S&P500 Index liquidity risks, respectively.

Table 1 shows descriptive statistics of variables computed on the liquidity measures. It reveals a clear difference in statistics for the data sample. Therefore, the difference in statistics results due to these proxies is likely to have influence later on the measurement of liquidity, as well the regression analyses between variables.

As noted in Table 1, the skewness is negative for spreads computed by the CS estimator. This implies that left skewed distributions of variables with extreme values to the left of their means; see for example values of mean and min in each panel of Table 1 computed by CS estimator. In contrast, the skewness is relatively high for variables computed by the Roll estimator. The variables thereby have right skewed distributions with extreme values to the right of their means; see for example values of mean and max in each panel of Table 1. Moreover, the kurtosis is relatively higher for variables by applying both estimators. It indicates a higher probability for extreme values (See Figure 1).

In general, the Roll estimator computes higher max, and min values of variables, as well values for some other statistics compare to CS estimator. This is because the CS estimator gives sometime negative spreads for my data sample. This is discussed in detail in the following chapter. This shortcoming of CS estimator gives negative values for some statistics.

Table 1: Descriptive Statistics

Variables	Max	Min	Mean	Median	Standard deviation	Skewness	Kurtosis
Panel A: Descriptive Statistics for S&P500 Index and US Banks by applying CS estimator							
S&P500 Index spreads	0,0468	-0,1097	-0,0011	0,0007	0,011	-1,99	13,87
Average Liquidity of US banks	0,0788	-0,2059	-0,002	0,001	0,019	-3,53	26,06
US Bank Index spreads	0,1781	-0,3498	-0,0003	0,0048	0,025	-3,38	31,41
Panel B: Descriptive Statistics for S&P500 Index and US Banks by applying Roll estimator							
S&P500 Index spreads	0,1187	0,0003	0,0128	0,009	0,013	3,41	18,18
Average Liquidity of US banks	0,2901	0,0012	0,022	0,014	0,025	4,11	24,59
US Bank Index spreads	0,3158	0,0001	0,022	0,013	0,029	4,12	24,79
Panel C: Descriptive Statistics for OSEBX and Norwegian Banks by applying CS estimator							
OSEBX spreads	0,0701	-0,1344	-0,003	-0,0007	0,014	-1,63	9,85
Average Liquidity of Norwegian banks	0,1119	-0,1668	-0,0032	-0,0003	0,02	-2,11	11,51
Norwegian Bank Index spreads	0,10764	-0,2321	-0,0012	0,004	0,025	-2,48	13,79
Panel D: Descriptive Statistics for OSEBX and Norwegian Banks by applying Roll estimator							
OSEBX spreads	0,1446	6,4E-10	0,0158	0,0118	0,015	2,93	13,75
Average Liquidity of Norwegian banks	0,1848	8,6E-10	0,0256	0,0201	0,02	2,36	8,46
Norwegian Bank Index spreads	0,1869	0,0004	0,0215	0,0152	0,021	2,47	8,57

Chapter 4

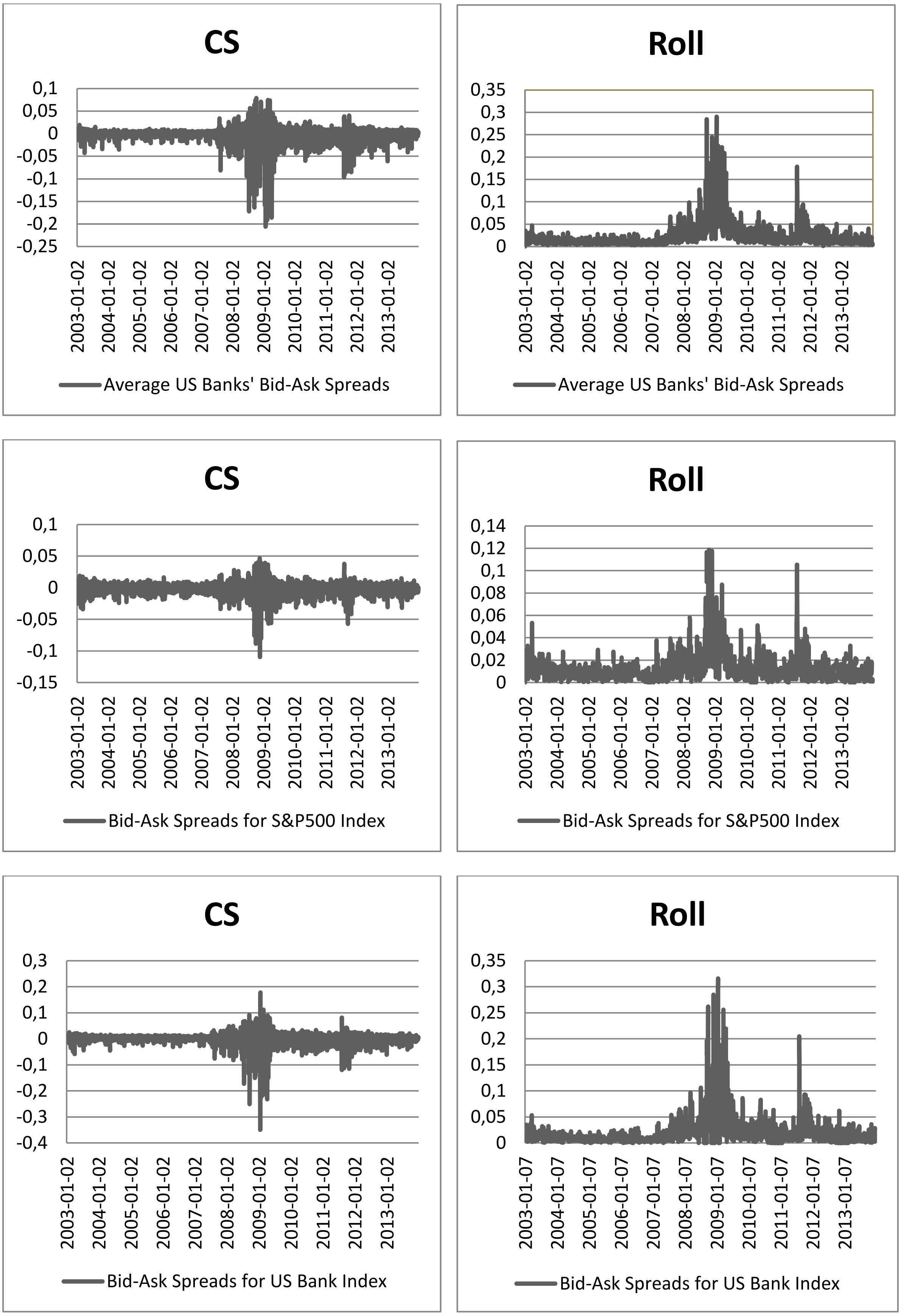
4.1 Analyses and discussion

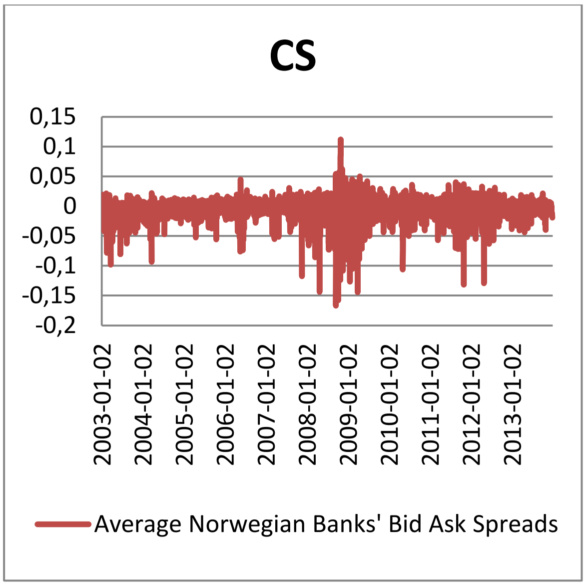
This section presents and discusses findings from analyses. The first section applies liquidity measures separately to show time variations in liquidity over stocks of banks and their markets (i.e., S&P500 Index and OSEBX). Further, it reveals the commonality of liquidity between stocks of banks and markets within countries. The second section finds the liquidity risk for stocks of banks in particular and markets in general within countries before, and after the Lehman Brothers Insolvency. The last part discloses the commonality of liquidity between the two countries before, and after the Lehman Brother filed for insolvency.

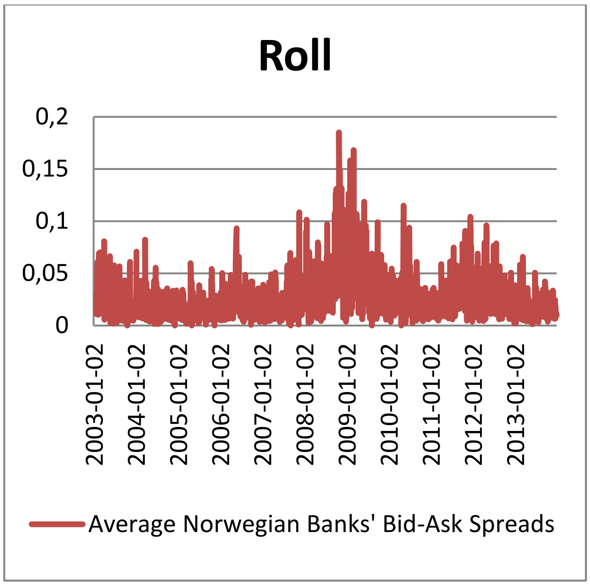
4.1.1 Variations and Commonality in Liquidity

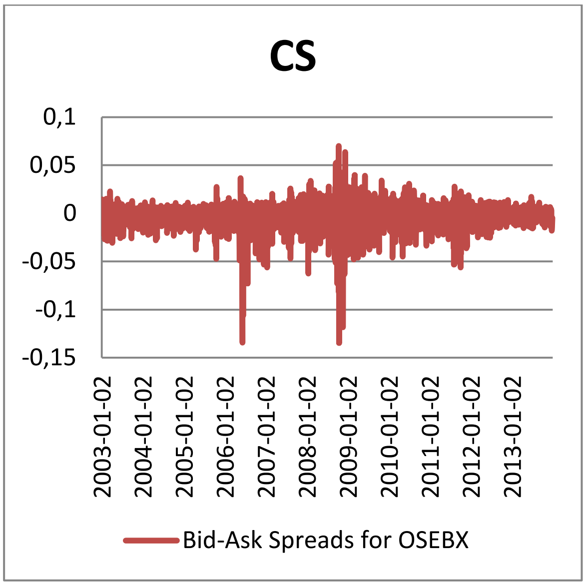
The time variations in liquidity are presented in Figure 1. It helps to understand the source of systematic liquidity variations, and how it is a priced source of risk. During the recent financial crisis, if the market illiquidity arises over the stocks of banks, and the markets where they are listed, then this is an indication that the risk is appeared to be a systematic breakdown in liquidity. Moreover, it reveals that investors perceive them as more risky, and hence prone to rapid, steep, and large declines in prices. For example, the greater the risk of liquidity is, the higher the trader compensates in terms of selling at a discount. It shows that the stocks are not traded quickly enough to prevent or minimize a loss. Therefore, liquidity risk seems to be priced.

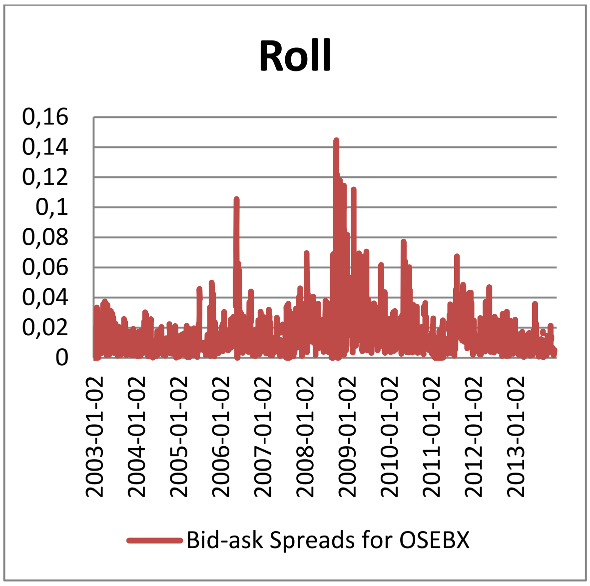
Figure 1: Time-Variations in Liquidity




CS
0,15
0,1
0,05
0
-0,05
-0,1
-0,15
-0,2
2003-01-02
2004-01-02
2005-01-02
2006-01-02
2007-01-02
2008-01-02
2009-01-02
2010-01-02
2011-01-02
2012-01-02
2013-01-02
Average Norwegian Banks' Bid Ask Spreads


Roll
0,2
0,15
0,1
0,05
0
2003-01-02
2004-01-02
2005-01-02
2006-01-02
2007-01-02
2008-01-02
2009-01-02
2010-01-02
2011-01-02
2012-01-02
2013-01-02
Average Norwegian Banks' Bid-Ask Spreads


CS
0,1
0,05
0
-0,05
-0,1
-0,15
2003-01-02
2004-01-02
2005-01-02
2006-01-02
2007-01-02
2008-01-02
2009-01-02
2010-01-02
2011-01-02
2012-01-02
2013-01-02
Bid-Ask Spreads for OSEBX


Roll
0,16
0,14
0,12
0,1
0,08
0,06
0,04
0,02
0
2003-01-02
2004-01-02
2005-01-02
2006-01-02
2007-01-02
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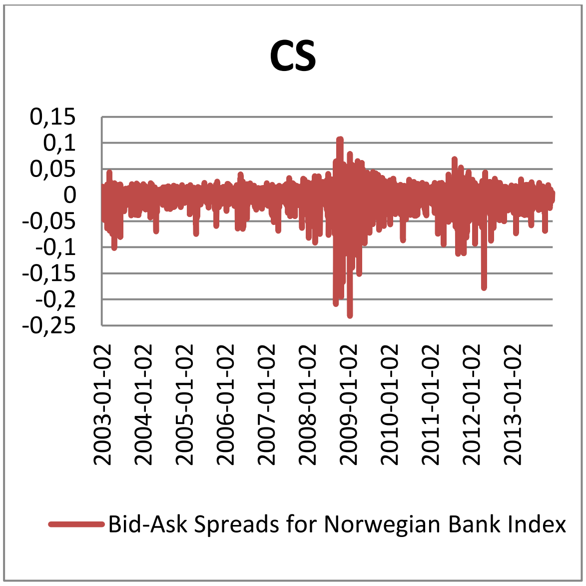
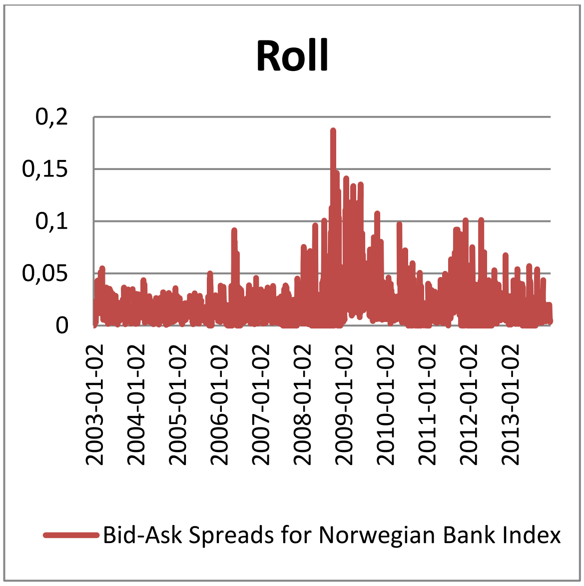
2009-01-02
2010-01-02
2011-01-02
2012-01-02
2013-01-02
Bid-ask Spreads for OSEBX


CS
0,15
0,1
0,05
0
-0,05
-0,1
-0,15
-0,2
-0,25
2003-01-02
2004-01-02
2005-01-02
2006-01-02
2007-01-02
2008-01-02
2009-01-02
2010-01-02
2011-01-02
2012-01-02
2013-01-02
Bid-Ask Spreads for Norwegian Bank Index


Roll
0,2
0,15
0,1
0,05
0
2003-01-02
2004-01-02
2005-01-02
2006-01-02
2007-01-02
2008-01-02
2009-01-02
2010-01-02
2011-01-02
2012-01-02
2013-01-02
Bid-Ask Spreads for Norwegian Bank Index

The time series plots show a very clear difference between results of estimators. The reason is that both estimators are accurate only under their ideal conditions. To compute Roll spreads, the serial covariance of price changes, $\mathrm{Cov}(\Delta P_t, \Delta P_{t-1})$, must be negative. When the serial covariance of price changes is positive, then the Roll estimator fails to produce spreads.

A problem observed in Roll estimator is that price changes are estimated to be positively serially correlated around 33 percent for S&P500 Index, 31 percent for US Bank Index, and between 30 and 33 percent for US banks. Moreover, Roll estimator failed to produce bid-ask spreads for OSEBX, Norwegian Bank Index, and Norwegian banks around 32 percent, 34 percent, and between 27 and 32 percent, respectively. The results are consistent with the findings of Hasbrouck (2006) that price changes are estimated to be positively correlated rather than negatively.

A drawback observed in CS estimator is the estimation of its negative spreads. When prices are observed sporadically in cases for the overnight returns, the CS estimator underestimates spreads. In addition, its accuracy decreases with higher price volatility. This implies that CS estimator may produce negative spreads for the data sample when the aggregate liquidity deteriorates. This is because; the variation in liquidity can increase asset price volatility as the new level of liquidity affects securities prices. Thus, liquidity shocks generate shocks to asset prices and increase the trading costs (i.e., bid-ask spreads) which can be observed from 2007 to 2009 in plots of Figure 1.

For this dataset, the percentages of negatives spreads are around 46 for S&P500 Index, 36 for US Bank Index, between 36 and 44 for US banks, 52 for OSEBX, 40 for Norwegian Bank Index, and between 37 and 44 for Norwegian banks. The findings are consistent with the results of Yan (2012) and Lin (2013) that CS estimator gives negative spreads.

However despite these shortcomings of both estimators, it can still be vividly observed that liquidity is not constant and it suddenly dries up for individual stocks and markets as whole (See Figure 1). These results are consistent with the findings of Huberman and Halka (1999), Chordia et al., (2000), and Hasbrouck and Seppi (2001) that liquidity is a time-varying risk factor.

Moreover, the empirical findings do not support the assumptions of Duffie (1996) and Cochrane (2001) on highly liquid markets where securities can be traded at no cost at all times. The analysis discloses that market friction, bid-ask spread, changes over time and generate higher trading costs on stocks of banks, and markets particularly in the recent financial crisis.

The empirical investigation on the US banks shows that their average liquidity and the liquidity of US Bank Index decrease in the recent financial crisis. This is an indication of illiquid market where investors are unwilling to buy stocks of banks without compensation that imposes cost on a seller. Thus, the risk is appeared to systemic liquidity shortage.

The plots reveal the difference in average liquidity for stocks of US banks, as well in the liquidity of US Bank Index before, during and after the financial crisis. The liquidity increases after 2009 which can be clearly observed in Figure 1. However, the variations in liquidity are still observed after the financial crisis. For the period 2011-2012, the average illiquidity for the US banks' stocks and illiquidity for the US Bank Index increases, this reflects the affects of sovereign-debt crisis on US banks. Nonetheless, its consequences seems not severe in comparison to liquidity risk appeared on US banks in the financial crisis.

Moreover, the empirical findings disclose that the global financial crisis has had some affects on Norwegian banks. Figure 1 shows a vivid difference in the average liquidity of stocks of Norwegian banks and the liquidity of Norwegian Bank Index, before, during, and after the financial crisis. Although some noise in the average liquidity for Norwegian banks' stocks, as well in the liquidity of Norwegian Bank Index can be observed before the financial crisis, but it is not persistent.

The average liquidity is observed to be decreased for the Norwegian banks in the financial crisis. This result is consistent with the findings of Norwegian Bank Index liquidity that decreases in the financial crisis. It reveals that Norwegian banks are exposed to a systemic liquidity risk where investors perceive them risky as well, thus their trading costs increase. After the global financial crisis, the variations in the average liquidity of Norwegian banks and the liquidity of Norwegian Bank Index can still be observed. It seems clearly in Figure 1 that the sovereign-debt crisis has had some affects on Norwegian banks as well.

Besides the average liquidity variations over stocks of banks, it seems that their average liquidity co-moves over time with the own markets' liquidity (See Figure 1). Moreover, it seems in Figure 1 that the liquidity of the US Bank Index, as well of the Norwegian Bank Index co-moves with the own markets as well. However, it matters to know the relationship between banks and markets within the country. Therefore, the linear regression analyses are structured into three datasets, as the entire daily data 2003 to 2013, the daily data 2003 to 2006, and 2007 to 2013. Findings of variables' relationship are summarized in Table 2.

The regression analyses reveal that the coefficients (β) tend to be positive in each dataset. This implies that there is a positive relationship of the average liquidity banks' stocks and the liquidity of banks' indexes with the liquidity of own markets. It refers to a systematic liquidity risk for banks and markets as whole within the country. Thereby, liquidity seems to be priced. The findings of analyses are generally consistent with the results of Chordia et al. (2000), and Hasbrouck and Seppi (2001) that individual liquidity co-moves with the market liquidity.

However, it is important to understand that how exposed stocks of banks are to their own markets' liquidity risk. As displayed in Panel A of Table 2 for the entire period 2003 to 2013, the estimated betas are 1.02 and 1.6 for CS and Roll estimators, respectively. This implies that the average liquidity of stocks of US banks is more volatile and risky than the market. In addition, it reflects to higher return for stocks of US banks than the market.

Moreover, the Panel A of Table 2 shows that the movement of the average liquidity of US banks is generally in the same direction as, but is less than the movement of the market for the period 2003 to 2006. Whereas, the Panel A of Table 2 reveals that the average liquidity of US banks becomes more volatile and riskier than the market between 2007 and 2013.

These findings are consistent with the regression analysis between the US bank Index liquidity and S&P500 Index liquidity. The Panel B of Table 2 discloses that the liquidity of US bank Index moves generally with the market, but is more volatile between 2003 and 2013, as well as after the financial crisis. Whereas, the liquidity of US bank Index is being less volatile than the market before the financial crisis.

The Panel C of Table 2 discloses for the entire period 2003 to 2013, that the movement of the average liquidity of Norwegian banks' stocks is generally in the same direction with the market's movement, but is less than the movement of the market in that direction. The Panel C of Table 2 reports, that the estimated beats are 0.31 and 0.63 for CS and Roll estimators, respectively using the data 2003 to 2006, and 0.54 and 0.88 for CS and Roll estimators, respectively using the data 2007 to 2013. This implies that the tendency of the average liquidity of Norwegian banks' stocks to respond to swings in the market increases after the financial crisis.

These results are consistent with the regression analysis between the Norwegian Bank Index liquidity and OSEBX liquidity. The Panel D of Table 2 reveals that the liquidity of Norwegian Bank Index moves generally in the same direction with the market, but is less than the movement of the market in that direction for each dataset. However, its tendency to respond to swings in the market increases as well after the financial crisis.

The empirical fit (R-Squared) of the average liquidity of banks' stocks and the liquidity of banks' indexes to the regression models are illustrated in Table 2 for the entire datasets, as well before and after the financial crisis. The panels in Table 2 show, the higher the R-Squared, the higher the proportion of variation in average liquidity of stocks of banks, and the liquidity of banks' indexes are explained by the own markets' liquidity within the regression models for each dataset.

Table 2: Regression Analyses

Spread Proxies	β	R-Squared
Panel A: Regression Analysis between S&P500 Index Spreads and Average Liquidity of US Banks		
	Using the entire daily data, 2003-2013	
CS	1,02	29%
Roll	1,61	59%
	Using the daily data, 2003-2006	
CS	0,53	33%
Roll	0,69	58%
	Using the daily data, 2007-2013	
CS	1,04	30%
Roll	1,62	59%
Panel B: Regression Analysis between S&P500 Index Spreads and US Bank Index Spreads		
	Using the entire daily data, 2003-2013	
CS	1,3	31%
Roll	1,75	61%
	Using the daily data, 2003-2006	
CS	0,74	33%
Roll	0,87	60%
	Using the daily data, 2007-2013	
CS	1,42	31%
Roll	1,74	61%
Panel C: Regression Analysis between OSEBX Spreads and Average Liquidity of Norwegian Banks		
	Using the entire daily data, 2003-2013	
CS	0,48	13%
Roll	0,87	38%
	Using the daily data, 2003-2006	
CS	0,31	7%
Roll	0,63	23%
	Using the daily data, 2007-2013	
CS	0,54	14%
Roll	0,88	39%
Panel D: Regression Analysis between OSEBX spreads and Norwegian Bank Index spreads		
	Using the entire daily data, 2003-2013	
CS	0,66	15%
Roll	0,92	42%
	Using the daily data, 2003-2006	
CS	0,41	10%
Roll	0,69	36%
	Using the daily data, 2007-2013	
CS	0,75	16%
Roll	0,93	42%

4.1.2 Liquidity Uncertainty before and after the Lehman Brother's Insolvency

This section discloses the perceptions of investors regarding their investments decisions toward stocks of banks in particular and markets in general within the country, before and after the collapse of Lehman Brother. I compute 100 days moving standard deviation and 100 days moving average of banks' average spreads, spreads of banks' indexes and markets on both liquidity proxies before, and after the Lehman collapse.

Group A contains the time series for the time period between January 01, 2003 and September 14, 2008. Group B contains the time series from September 15, 2008, through December 31st, 2013. F-tests at the 95 percent confidence interval show that the true variance of 100 days moving standard deviation in Panel A of Table 3 and 100 days moving average in Panel B of Table 3 for markets' spreads, banks' average spreads, and spreads of banks' indexes is significantly different between group A and B on both estimators.

Table 3: F-tests at the 95 Percent Confidence Interval

	CS	**Roll**
Panel A: F-tests of the difference in varinace of the two groups on 100 days moving Standard Deviation		
S&P500 Index spreads	0,17	0,18
Average Liquidity of US banks	0,22	0,13
US Bank Index spreads	0,15	0,10
OSEBX spreads	0,56	0,54
Average Liquidity of Norwegian banks	0,29	0,27
Norwegian Bank Index spreads	0,12	0,42
Panel B: F-tests of the difference in varinace of the two groups on 100 days moving Average		
S&P500 Index spreads	0,46	0,22
Average Liquidity of US banks	0,06	0,14
US Bank Index spreads	0,08	0,13
OSEBX spreads	0,77	0,30
Average Liquidity of Norwegian banks	0,11	0,19
Norwegian Bank Index spreads	0,28	0,14

If the 100 days moving standard deviation for group B is higher than that of group A, it implies that the volatility of liquidity increases, and hence it is more likely that it will be difficult to trade those assets in the future. This means that investors are more averse to invest in these stocks. Moreover, if the 100 days moving average for group B has increased, it indicates then that the bid-ask spread is higher, and hence investors demand a higher liquidity premium after the Lehman Brother's bankruptcy.

4.1.2.1 Liquidity Uncertainty for US Banks and S&P500 Index

The 100 days moving standard deviation and 100 days moving average before, and after the Lehman Brother go bankrupt are presented in Figure 2. It seems that there are similarities between the estimators on computations of 100 days moving standard deviation, whereas a very clear difference can be seen between estimators on computations of 100 days moving average. Therefore, I apply the correlation between estimators (See Table 4).

Panels A and B of Table 4 show a very strong positive relationship between estimators on findings of 100 days moving standard deviation before, and after the collapse of Lehman Brothers. This implies that both estimators are positively correlated to reveal the risk of liquidity after the Lehman Brother filed for insolvency. Panels *a*, *b*, *c*, and *d* in Figure 2 clearly show that 100 days moving standard deviation of banks' average spreads, S&P500 Index spreads, and US Bank Index spreads in group B has increased.

This implies that, after the Lehman bankruptcy, investors are generally more cautious about investing in these stocks and S&P500 Index. This is due to the uncertainty and sudden variability of the liquidity of banks' stocks and market after the Lehman Brother's collapse, an effect that was still possible to detect more than five years after the bankruptcy.

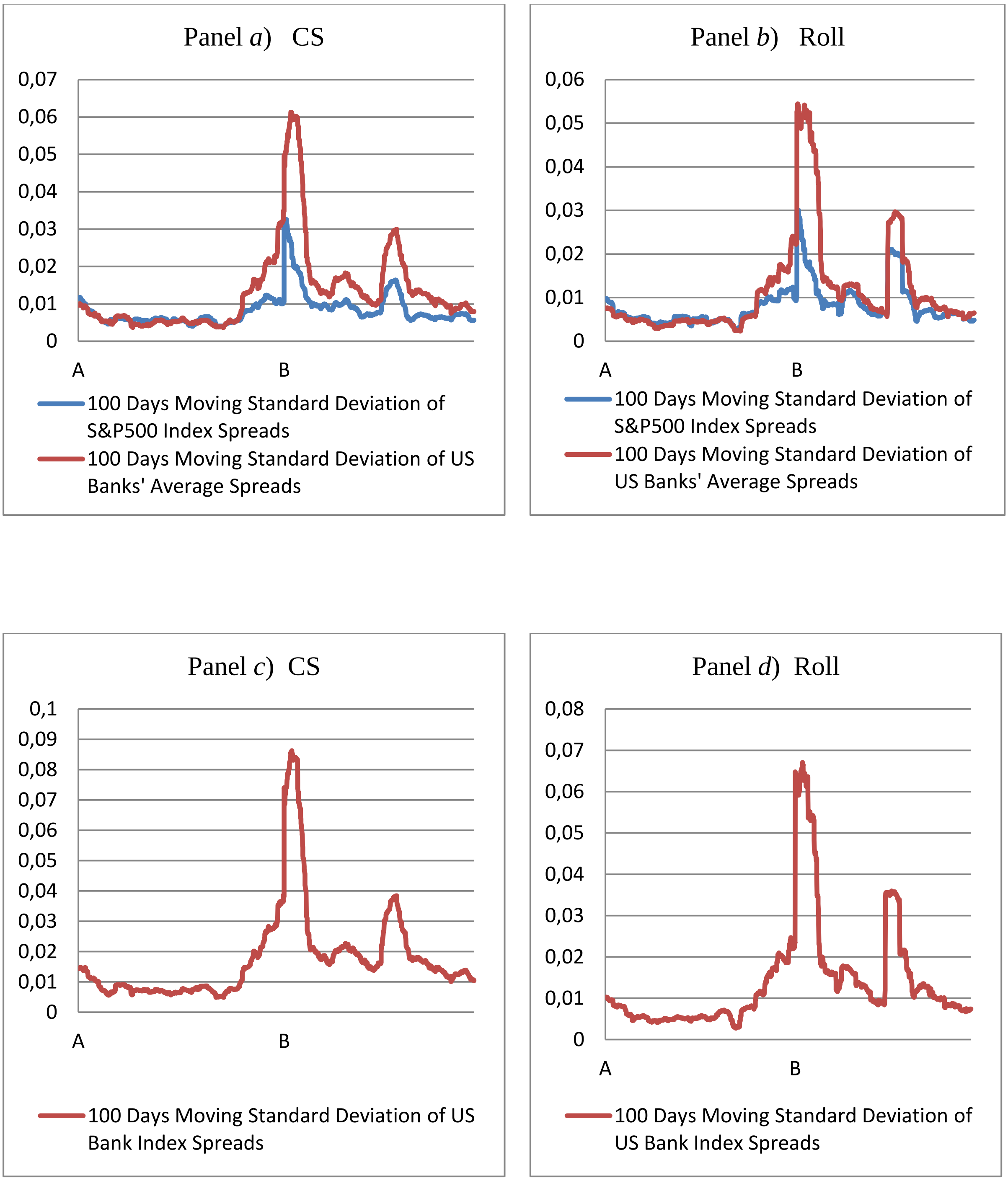
However, it is also of interest to quantify the level of liquidity uncertainty for banks' stocks compared to the market as whole. Figure 2 discloses that the level of uncertainty for the average liquidity of banks' stocks and the liquidity of US bank Index is higher than the market's liquidity uncertainty as whole. This is an indication that these US banks are seen at higher risk after the Lehman bankruptcy.

Moreover, Panels C and D of Table 4 reveal a very strong negative relationship between estimators on results of 100 days moving average in group A, as well in group B. As earlier discussed, that the accuracy of CS estimator decreases during the higher liquidity deterioration which causes to higher price volatility, and hence it then may produce negative spreads. It seems that the 100 days moving average on CS estimator for the data sample is negative when the liquidity deteriorates and price volatility increases. Thereby, estimators are negatively correlated in group A and B of 100 days moving average.

However based on only Roll estimator, it can vividly be observed that 100 days moving average of US banks' spreads, US Bank Index spreads, and S&P500 Index spreads has increased after the crisis of Lehman Brother, see Panels *f* and *h* in Figure 2. It shows that the liquidity premium on trading of these banks' stocks and S&P500 Index has increased, and hence the bid-ask spread is higher.

Moreover, it discloses that investors are demanding higher liquidity premium for trading these US banks' stocks in comparison to S&P500 Index. After the collapse of Lehman Brothers, increased liquidity uncertainty around these stocks banks thereby makes the provision of liquidity riskier. Thus, the compensation that liquidity providers' demand increases, that is, the trading cost of these banks' stocks rises in comparison to the market as whole.

Figure 2: 100 Days Moving Standard Deviation and 100 Days Moving Average of US Bank' Average Spreads, US Bank Index Spreads and S&P500 Index Spreads



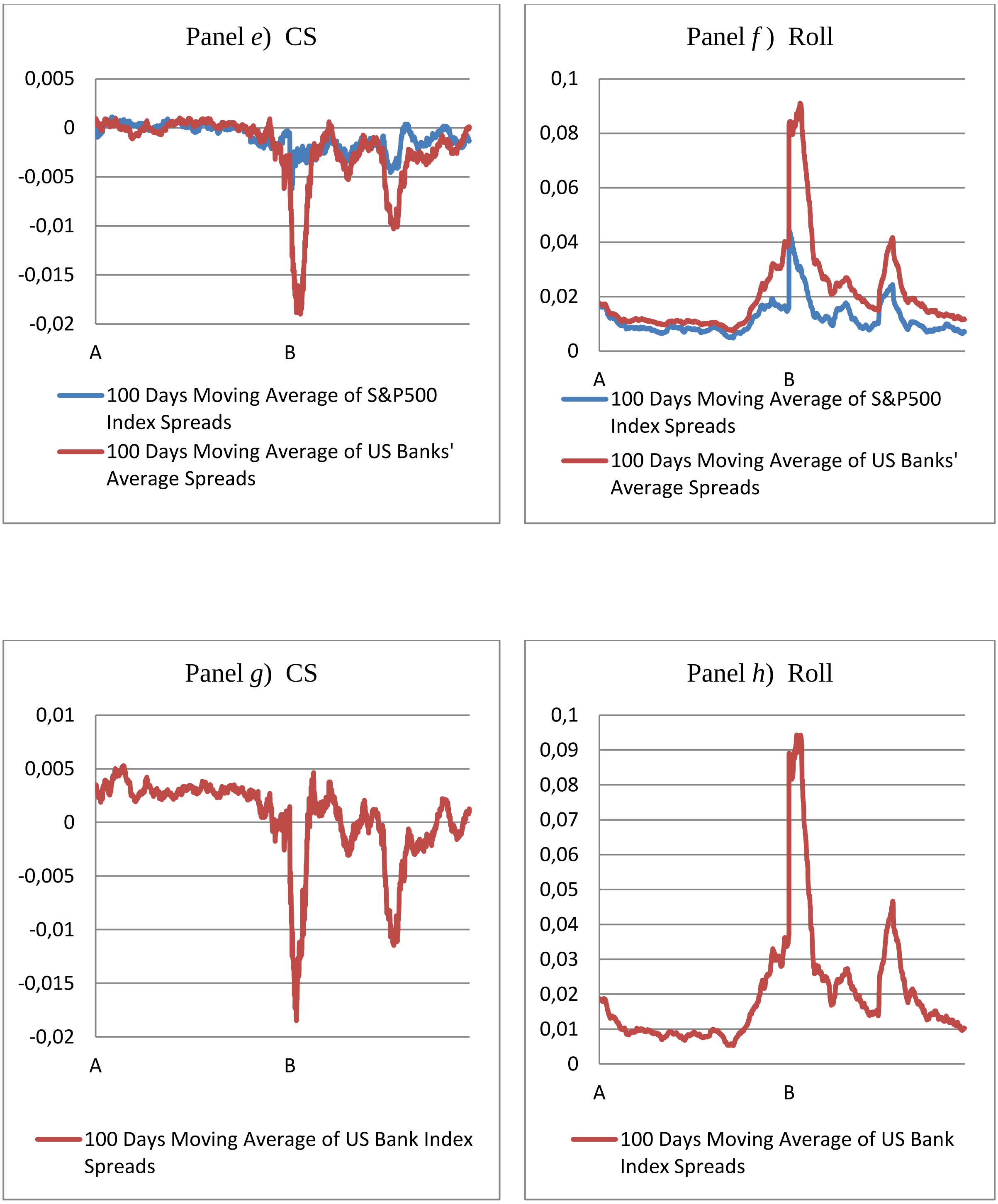

Panel e) CS
0,005
0
-0,005
-0,01
-0,015
-0,02
A
B
100 Days Moving Average of S&P500 Index Spreads
100 Days Moving Average of US Banks' Average Spreads
Panel f) Roll
0,1
0,08
0,06
0,04
0,02
0
A
B
100 Days Moving Average of S&P500 Index Spreads
100 Days Moving Average of US Banks' Average Spreads
Panel g) CS
0,01
0,005
0
-0,005
-0,01
-0,015
-0,02
A
B
100 Days Moving Average of US Bank Index Spreads
Panel h) Roll
0,1
0,09
0,08
0,07
0,06
0,05
0,04
0,03
0,02
0,01
0
A
B
100 Days Moving Average of US Bank Index Spreads

Table 4: Correlation between estimators on findings of 100 days moving standard deviation and 100 days moving average of S&P500 Index spreads, US banks' average spreads, and US Bank Index spreads. The column to the left represents the Corwin-Schultz bid-ask spreads, whereas the upper row represents the Roll estimator.

CS	**Roll**		
Panel A: Correlation of group A between estimators on results of 100 days moving Standard deviation			
	S&P500 Index spreads	US banks' average spreads	US Bank Index spreads
S&P500 Index spreads	0,89	-	-
US banks' average spreads	-	0,98	-
US Bank Index spreads	-	-	0,97
Panel B: Correlation of group B between estimators on results of 100 days moving Standard deviation			
	S&P500 Index spreads	US banks' average spreads	US Bank Index spreads
S&P500 Index spreads	0,91	-	-
US banks' average spreads	-	0,96	-
US Bank Index spreads	-	-	0,96
Panel C: Correlation of group A between estimators on results of 100 days moving Average			
	S&P500 Index spreads	US banks' average spreads	US Bank Index spreads
S&P500 Index spreads	-0,7	-	-
US banks' average spreads	-	-0,81	-
US Bank Index spreads	-	-	-0,79
Panel D: Correlation of group B between estimators on results of 100 days moving Average			
	S&P500 Index spreads	US banks' average spreads	US Bank Index spreads
S&P500 Index spreads	-0,73	-	-
US banks' average spreads	-	-0,88	-
US Bank Index spreads	-	-	-0,76

4.1.2.2 Liquidity Uncertainty for Norwegian Banks and OSEBX

Figure 3 presents the 100 days moving standard deviation and 100 days moving average before, and after the Lehman Brother's bankruptcy. Like in the previous case, the estimators seem to be positively correlated in group A and B on computations of 100 days moving standard deviation of OSEBX spreads, Norwegian banks' average spreads, and Norwegian Bank Index spreads. On other hand, a clear difference is seen between the estimators on computations of 100 days moving average. The results of the correlation between the estimators are summarized in Table 5.

A very strong positive relationship is seen between estimators on findings of 100 days moving standard deviation before and after the Lehman Brother crisis, see Panels A and B of Table 5). This means that the volatility of both estimators increases after the Lehman collapse, as the liquidity becomes more variable for individual stocks and the market as whole. It can be observed in Figure 3, that 100 days moving standard deviation of Norwegian banks' average spreads, Norwegian Bank Index spreads, and OSEBX spreads has increased after the insolvency of Lehman Brothers. It reveals the reaction of investors that seem averse to invest in the banking sector, as well as to invest in the OSEBX.

However, the level of uncertainty and variability for the average liquidity of Norwegian bank's stocks and the liquidity of Norwegian Bank Index is higher than the market's liquidity uncertainty as whole after the Lehman bankrupt, see Panels *a*, *b*, *c* and *d* in Figure 3. It implies that the increased market's liquidity uncertainty is not as higher to increased liquidity uncertainty of these banks' stocks. Hence, stocks of these Norwegian banks are seen as more risky after the Lehman collapse.

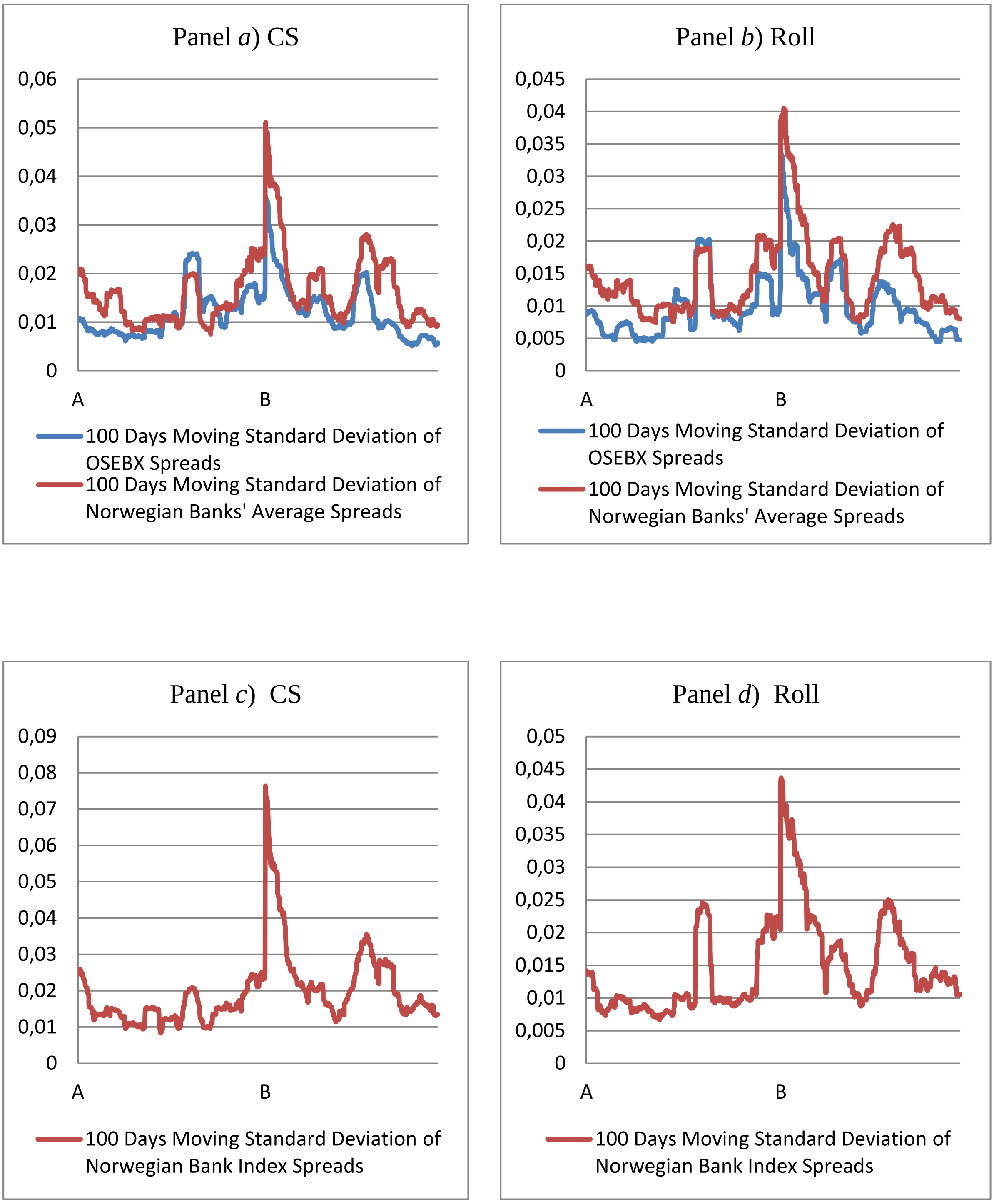
Panel C of Table 5 shows a weak negative relationship, and a modest negative relationship between estimators on findings of 100 days moving average of Norwegian banks' average spreads, Norwegian Bank Index spreads, and OSEBX spreads, respectively before the collapse of Lehman. In addition, a very strong negative relationship can be seen between estimators to reveal the intensity of liquidity premium, demands by investors after the insolvency of Lehman Brothers, see Panel D of Table 5.

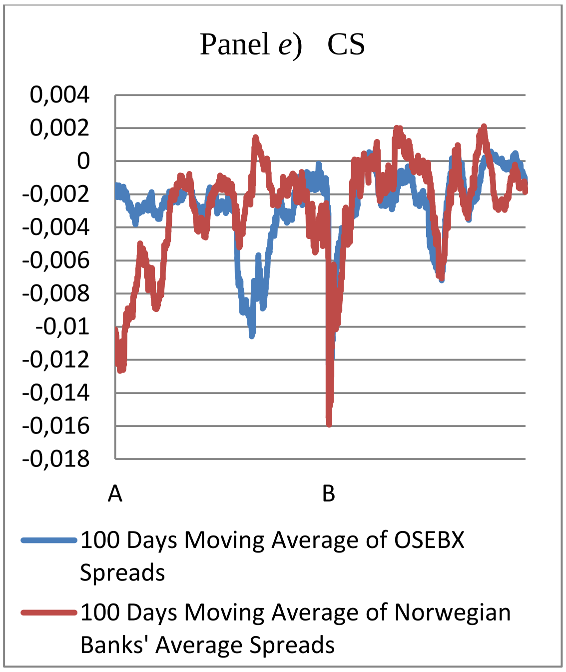
This is due to the negative spreads, a shortcoming of the CS estimator, which implies that the average is negative when the deterioration in liquidity creates shocks to the prices of individual stocks and OSEBX. Estimators are thereby negatively correlated.

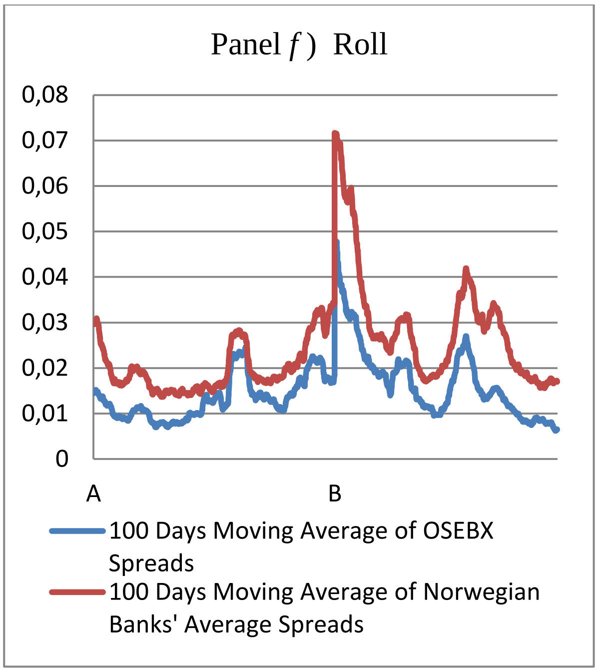
However, it can vividly be seen based on only Roll estimator that 100 days moving average of Norwegian banks' spreads, S&P500 Index spreads, and Norwegian Bank Index spreads has increased after the Lehman Brothers go insolvent, see Panels *f* and *h* in Figure 3. This is an indication of higher liquidity premium in general, demanded by investors for trading of these individual stocks and OSEBX, and thus the bid-ask spread is higher.

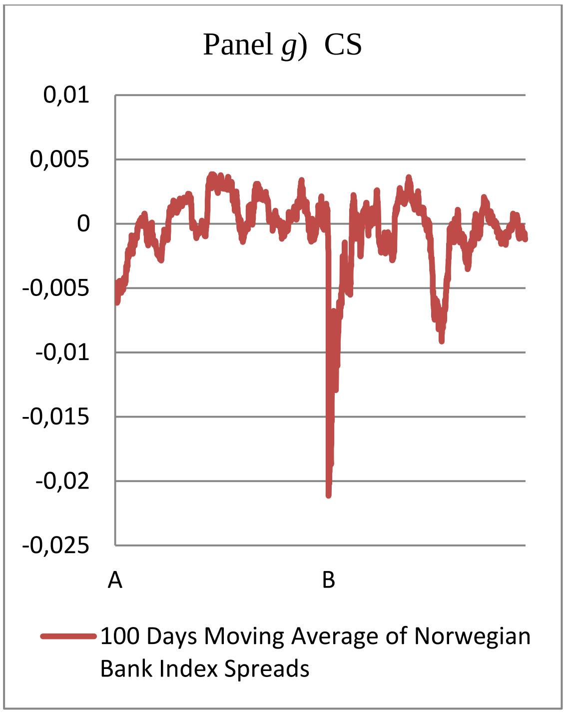
Moreover, it discloses that the intensity of the liquidity premium tends to increase more on trading of these Norwegian banks' stocks than liquidity premium demands by investors on OSEBX trading. The increased liquidity uncertainty of these banks stocks makes the provision of liquidity riskier than the risk of market liquidity as whole. Thus, investors demand a higher compensation, that is, the spread of these banks' stocks rises.

Figure 3: 100 Days Moving Standard Deviation and 100 Days Moving Average of Norwegian Banks' Average Spreads, Norwegian Bank Index Spreads and S&P500 Index Spreads




Panel e) CS
0,004
0,002
0
-0,002
-0,004
-0,006
-0,008
-0,01
-0,012
-0,014
-0,016
-0,018
A
B
100 Days Moving Average of OSEBX Spreads
100 Days Moving Average of Norwegian Banks' Average Spreads


Panel f) Roll
0,08
0,07
0,06
0,05
0,04
0,03
0,02
0,01
0
A
B
100 Days Moving Average of OSEBX Spreads
100 Days Moving Average of Norwegian Banks' Average Spreads


Panel g) CS
0,01
0,005
0
-0,005
-0,01
-0,015
-0,02
-0,025
A
B
100 Days Moving Average of Norwegian Bank Index Spreads

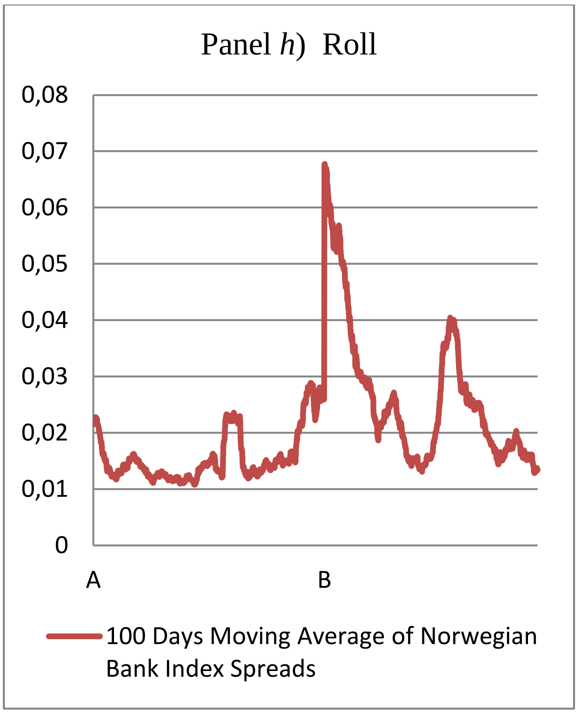

Panel h) Roll
0,08
0,07
0,06
0,05
0,04
0,03
0,02
0,01
0
A
B
100 Days Moving Average of Norwegian Bank Index Spreads

Table 5: Correlation between the estimators on findings of 100 days moving standard deviation and 100 days moving average of OSEBX spreads, Norwegian banks' average spreads, and Norwegian Bank Index spreads. The column to the left represents the Corwin-Schultz bid-ask spreads, whereas the upper row represents the Roll estimator.

CS	**Roll**		
Panel A: Correlation of group A between estimators on results of 100 days moving Standard deviation			
	OSEBX spreads	Norwegian banks average spreads	Norwegian Bank Index spreads
OSEBX spreads	0,88	-	-
Norwegian banks average spreads	-	0,92	-
Norwegian Bank Index spreads	-	-	0,76
Panel B: Correlation of group B between estimators on results of 100 days moving Standard deviation			
	OSEBX spreads	Norwegian banks average spreads	Norwegian Bank Index spreads
OSEBX spreads	0,95	-	-
Norwegian banks average spreads	-	0,94	-
Norwegian Bank Index spreads	-	-	0,94
Panel C: Correlation of group A between estimators on results of 100 days moving Average			
	OSEBX spreads	Norwegian banks average spreads	Norwegian Bank Index spreads
OSEBX spreads	-0,36	-	-
Norwegian banks average spreads	-	-0,27	-
Norwegian Bank Index spreads	-	-	-0,23
Panel D: Correlation of group B between estimators on results of 100 days moving Average			
	OSEBX spreads	Norwegian banks average spreads	Norwegian Bank Index spreads
OSEBX spreads	-0,8	-	-
Norwegian banks average spreads	-	-0,79	-
Norwegian Bank Index spreads	-	-	-0,78

4.1.3 Commonality in Liquidity between Countries

Based on the above analysis, it clearly seems that the collapse of Lehman Brothers affected the liquidity of US banks and the S&P500 Index. The bankruptcy also affected the Norwegian banks analyzed and the OSEBX as well. The analysis supports the findings of Severo (2012) that Lehman Brother's insolvency led to a widespread systemic liquidity breakdown.

However, to be able to prevent a crisis in one country due to a crisis in another, it matters to know how exposed Norwegian banks and the OSEBX in general are to the US banks and the S&P500 Index risk. In this section, I try to find the commonality in liquidity between countries. The findings of regression analysis on variables relationships are summarized in Table 6.

Panel A of Table 6 shows a negligible and weak positive relationship between markets' liquidity on CS and Roll estimators, respectively, for the entire period. Moreover, it reveals that markets are positively correlated before the Lehman collapse, but that relationship can be negligible, as it is not higher. However, it is seen that the tendency of the OSEBX liquidity to respond to swings in the S&P500 Index liquidity increases after the Lehman Brother filed for insolvency, but this relationship is only weakly positive.

Panel B of Table 6 discloses for the entire daily data, that there is a weak and moderate positive relationship between the average liquidity of US banks and Norwegian banks' average liquidity on CS estimator and Roll estimator, respectively. Before the collapse of Lehman Brothers, the average liquidity of these Norwegian banks is positively correlated with the average liquidity of US banks, however, no significant. In addition, Panel B of Table 6 discloses that the average liquidity of Norwegian banks are exposed to the risk of US banks' average liquidity after the Lehman Brother crisis, as the relationship between them is increased to 0,26 and 0,33 on CS estimator and Roll estimator, respectively.

This result is consistent with the findings of regression analysis between US Bank Index liquidity and Norwegian Bank Index liquidity. Panel C of Table 6 reports, that there is a positive correlation of Norwegian Bank Index liquidity with the liquidity of US Bank Index before the Lehman Brothers go insolvent. However, this relationship can neglect, as it is 0,09 and 0,19 on CS and Roll estimators, respectively. After the Lehman Brother's bankruptcy, the relationship between them increases. This implies that the Norwegian Bank Index liquidity is exposed to the US Bank Index liquidity risk as well.

The empirical fit of the OSEBX liquidity, the average liquidity of Norwegian banks' stocks and the liquidity of Norwegian Bank Index to the regression models are exhibited in Table 6 for the entire dataset, as well before and after the Lehman Brother's bankruptcy. Table 6 shows, that the higher the R-Squared, the higher the proportion of variation in OSEBX liquidity, the average liquidity of Norwegian banks' stocks and the liquidity of Norwegian Bank Index are explained by the S&P500 Index liquidity, the average liquidity of US banks' stocks, and the liquidity of US Bank Index, respectively within the regression models for each dataset.

The empirical investigation on commonality of liquidity between US and Norwegian banks do not reflect to a strong positive relationship revealed by Severo (2012) between liquidity risks of global banks' stocks after the insolvency of Lehman Brothers. The investigation discloses a negligible positive relationship between banks of US and Norwegian before the Lehman insolvent, which is consistent on both estimators.

Moreover, it can be clearly observed that the tendency of Norwegian banks' liquidity to respond to swings in the US banks' liquidity increases after the crisis of Lehman Brothers. It helps to understand, that these Norwegian banks' stocks are exposed to the risk that originated in the US. However, the relationship between banks of the two countries is weak and moderate positive on CS and Roll estimators, respectively.

Table 6: Regression Analyses

Spread Proxies	β	R-Squared
Panel A: Regression Analysis between S&P500 Index spreads and OSEBX spreads		
	Using the entire daily data, 01/01/2003 – 31/12/2013	
CS	0,16	0,014
Roll	0,27	0,056
	Using the daily data, 01/01/2003 – 14/09/2008	
CS	0,15	0,016
Roll	0,17	0,016
	Using the daily data, 15/09/2008 – 31/12/2013	
CS	0,2	0,012
Roll	0,22	0,04
Panel B: Regression Analysis between US banks' average spreads and Norwegian banks' average spreads		
	Using the entire daily data, 01/01/2003 – 31/12/2013	
CS	0,22	0,046
Roll	0,39	0,22
	Using the daily data, 01/01/2003 – 14/09/2008	
CS	0,13	0,009
Roll	0,19	0,014
	Using the daily data, 15/09/2008 – 31/12/2013	
CS	0,26	0,073
Roll	0,33	0,085
Panel C: Regression Analysis between US Bank Index spreads and Norwegian Bank Index spreads		
	Using the entire daily data, 01/01/2003 – 31/12/2013	
CS	0,23	0,056
Roll	0,34	0,233
	Using the daily data, 01/01/2003 – 14/09/2008	
CS	0,09	0,006
Roll	0,19	0,044
	Using the daily data, 15/09/2008 – 31/12/2013	
CS	0,27	0,076
Roll	0,32	0,235

Chapter 5

5.1 Conclusion

The empirical investigation of banks' stocks listed on S&P500 Index and OSEBX, as well of these markets clearly shows that the liquidity is a time-varying risk factor. It can lead to a systemic breakdown of liquidity for individual stocks and the financial markets overall, as was experienced in the recent financial crisis. The analysis reveals a systemic shortage of liquidity for banks' stocks and markets examined after the bankruptcy of the investment bank Lehman Brothers in September 2008.

The financial crisis had a great impact on US banks' stocks, while it had routes to Norwegian banks as well. The findings confirm the hypothesis that spreads increased for banks' stocks in the recent financial crisis. Moreover, the increased trading cost is seen for S&P500 Index and OSEBX in the financial crisis as well, yet to a lesser degree than observed in the banking sector.

Further, the investigation discloses the effects of the sovereign-debt crisis of 2011-12 on Norwegian banks, and OSEBX, while it also affected US banks and S&P500 Index as well. However, the increased trading costs for banks' stocks and markets are not higher in comparison to trading costs in the financial crisis, but it still reflects systemic liquidity risk. The sovereign-debt crisis is not the main focus of this thesis, therefore it has not been discussed in detail.

The results in commonality of liquidity for banks' stocks with markets where they are listed exhibit a very strong positive relationship. This relationship increases after the financial crisis. However, US banks' stocks are more variable than the US market liquidity risk after this crisis. This implies that the liquidity risk increased after the financial crisis, and affects returns on these banks' stock prices.

The commonality in liquidity between these individual stocks and markets within the country is due to common liquidity providers. Therefore, shocks in liquidity to the market are positively correlated across individual stocks. It reflects to systemic liquidity risk, as was vividly observed for banks' stocks and markets within the country in the financial crisis.

I further find that the volatility of liquidity increases after the Lehman Brother's insolvency, and show that liquidity uncertainty increases in general for banks' stocks and markets as well. However, this liquidity uncertainty is more exposed on banks' stocks examined. This implies that investors are more afraid to invest in banks' stocks, and thereby demands high liquidity premiums, quantified by the bid-ask spread in this thesis, on trading these stocks.

Moreover, the findings reveal that the tendency of OSEBX liquidity and Norwegian banks' stocks liquidity to respond to swings in the S&P500 Index liquidity and US banks' stocks liquidity, respectively increases after the bankruptcy of Lehman Brother. Nonetheless, this relationship is weak, yet positive, between markets. On other hand, the relationship is weak and moderate positive between banks' stocks liquidity of the two countries between the Corwin-Shultz bid-ask spread estimator (CS), and Roll bid-ask spread estimator (Roll), respectively.

By concluding this paper, I would briefly highlight the importance of continuing research on this topic in the future. As earlier discussed, that both estimators are accurate under their ideal conditions. The drawback of CS estimator is that it produces negative spreads during periods of high price volatility, which is probably exactly the periods when the liquidity is varying a lot too. The Roll estimator fails to produce spreads when the serial covariance of price changes is positive. These shortcomings of both estimators likely have influenced the findings of this research. Therefore, there is a need of future research in this area to establish an estimator that produces consistently positive bid-ask spreads.

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Appendix 1: List of US banks examined

Name of Banks
Bank of America Corp
The Bank of New York Mellon Corp.
BB&T Corporation
Citigroup Inc.
Comerica Inc.
Fifth Third Bancorp
Hudson City Bancorp
Huntington Bancshares
JPMorgan Chase & Co.
KeyCorp
M&T Bank Corp.
People's United Bank
PNC Financial Services
SunTrust Banks
U.S. Bancorp
Wells Fargo
Zions Bancorp

Appendix 2: List of Norwegian banks examined

Name of Banks
Storebrand
ABG Sunda Collier Holding
DNB