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**Liquidity
Concepts, Ideas and the Financial Crisis**

by

**Kjell G. Nyborg
Per Östberg**

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CRISIS, RESTRUCTURING AND GROWTH

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Liquidity

Concepts, Ideas, and the Financial Crisis¹

Kjell G. Nyborg² Per Östberg³

1. Introduction

The financial, or subprime, crisis has brought attention to the importance of the market for liquidity for the broader financial markets. Many commentators identify the beginning of the crisis with the sharp increase in the Libor-OIS spread during the second week of August 2007, when this spread tripled⁴. Subsequently, the spread continued its rise and interbank volume fell, especially at the longer end (Cassola, Holthausen, and Lo Duca, 2008). In short, there was a breakdown in the interbank market for liquidity. To combat this, central banks around the world injected vast amounts of liquidity into the banking system to counteract banks' unwillingness to lend to each other.

The problems in the interbank market appear to have propagated to other markets. Lending of banks to non-bank businesses also fell (Ivashina and Scharfstein, 2008) and the prices of stocks and other securities decreased dramatically. With respect to the decline in stock prices, it is not hyperbole to say that the stock markets collapsed. From August 2007 to March 2009, major stock markets around the world were down 40 to 50 percent, and some emerging markets even more.

The way events unfolded during the crisis thus suggests that there is a link between the market for liquidity and the broader financial markets. For example, it appears that a higher degree of allocational inefficiency in the market for liquidity or an increase in the price of liquidity translate into lower asset prices. There is a logic to this view which is not crisis-dependent: a higher price of liquidity in the interbank market may in turn lead to higher funding costs for investors and speculators, as banks pass on the increased costs of liquidity to their customers. In turn, this depresses asset prices.

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² University of Zürich, Swiss Finance Institute, CEPR, NHH, nyborg@isb.uzh.ch

³ Norwegian School of Economics and Business Administration, Per.Ostberg@nhh.no

⁴ Libor: London interbank offered rate. OIS: overnight index swap, a fixed-floating interest rate swap, where the floating leg is the overnight rate.

In this regard, an important question is whether different assets are affected to a different degree by changes to the price of liquidity. For example, does the degree of liquidity of a security affect its sensitivity to the price of liquidity in the interbank market?

Financial economists have developed a variety of ways to measure the liquidity of financial assets. But it is not clear whether these measures are related to, or capture any element of, the concept of liquidity we have in mind when we speak of the interbank market for liquidity. What we are referring to here, of course, is high powered money. What financial economists refer to when they say that one asset is more liquid than another is that it is “cheaper” to trade it, in terms of price impact or, more broadly, transaction costs. One way to interpret the financial economics concept of liquidity is as follows: an asset is more liquid than another if it is “cheaper” to convert it into higher powered money.

Taking this perspective, the hypothesis that more liquid assets react differently to the ongoing in the interbank market than less liquid assets seems plausible. Examining this is potentially important for a variety of reasons. For example, it can help improve our understanding of the extent to which monetary policy is transmitted to financial markets, since monetary policy may affect the state of the interbank markets. Understanding the link between interbank markets and the broader financial market is also important because it may have asset pricing, and thus asset allocation, implications.

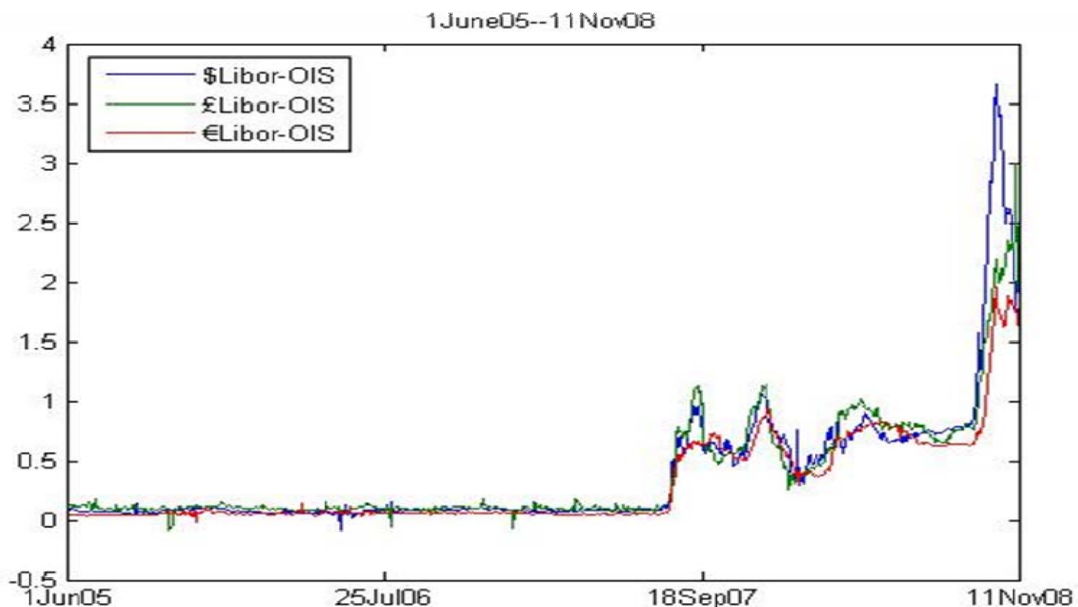
In this paper, we essentially do two things. First, we provide an overview of the crisis from the perspective of the market for liquidity. This also includes taking a look at what happened to the stock markets as the price of liquidity rose to dizzying heights and then fell back to less dramatic levels. Second, we review the financial economics literature on liquidity, with an eye towards understanding the various measures of liquidity that have been developed and their merit. Most of this literature focuses on the stock markets. The objective is thus to set the stage for further work down the line that looks more closely at the liquidity link between the interbank and stock markets.

2. An Overview of the Market for Liquidity and Stock Markets during the Crisis

2.1 Libor – OIS spread

Figure 1 shows the Libor-OIS spread for three major currencies, USD, GBP, and the euro. The figure reveals a dramatic spike in the spread for each currency during the second week of August 2007. As high as these spreads may have seen at the time, they were quite modest compared to the spike in spreads we saw in the aftermath of the bankruptcy of Lehman Brothers (the weekend prior to 15/9/08). Table 1 presents average spreads during different subperiods in the June 05 to November 08 period. For example, the average USD Libor-OIS spread increased from 7.9 basis points (bp) during the July 2005 to June 2007 to 67.9 bp during the first stage of the crisis (August 2007 to 12 Sep 2008). In the aftermath of the Lehman bust, here the period 15 September to 11 November, it increased to 223.9 bp. The numbers for the GBP and the euro are similar.

Figure 1. 3 month Libor-OIS spreads, June 05 to November 08



Note: The y-axis is in percentage points.

Table 1. 3month Average Libor-OIS spreads during different time periods

	3 month Libor – OIS (basis points)		
	USD	GBP	Euro
1 Jul 05 – 29 June 07	7.9	9.8	5.7
1 Aug 07 – 12 Sep 08	67.9	70.2	62.1
15 Sep 08 – 13 Oct 08	223.9	153.7	116.0
14 Oct 08 – 11 Nov 08	251.8	220.1	174.2

The importance of the Libor-OIS spread is that it is a measure of the price of liquidity. A "Libor transaction" gives the borrower a fixed quantity of liquidity for a fixed period of time. The alternative (in the unsecured end of the market) is borrowing overnight and hedging the interest rate risk using the OIS. But this entails quantity risk; a bank cannot be sure that it will get the desired quantity of liquidity every day over the next three months, say. There is also some interest rate risk, since a bank's overnight borrowing costs will not necessarily equal the rate that inputs into the OIS contract.

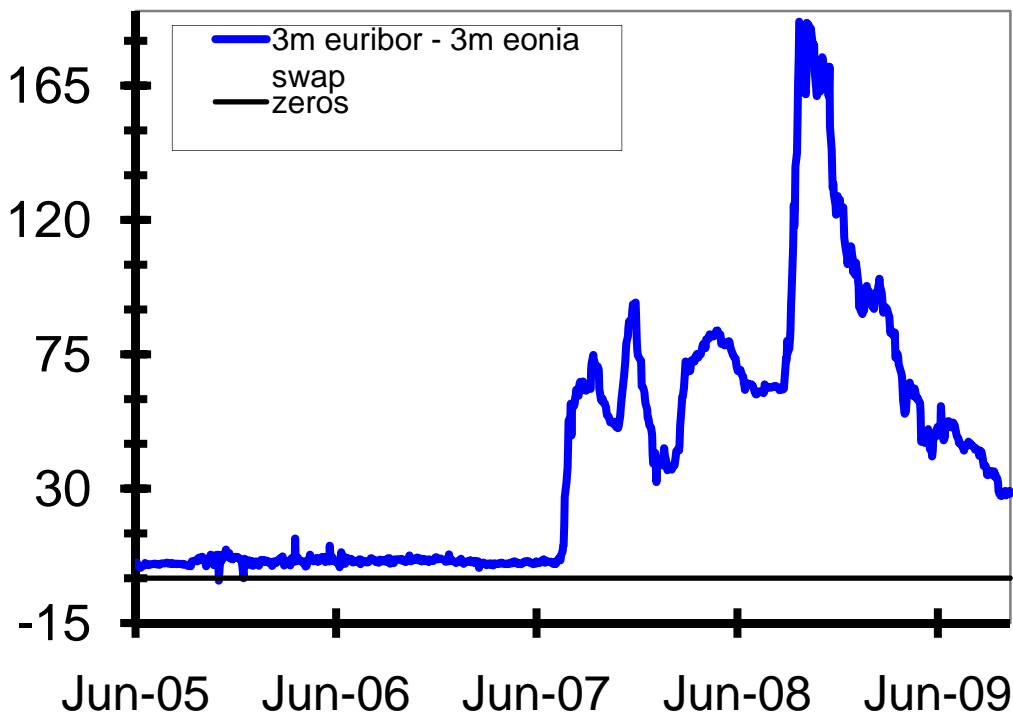
While the spread thus captures the extra cost of having the liquidity for sure, we believe it also reflects at least an element of allocational inefficiency, e.g., credit rationing. The drop in interbank activity during the crisis supports this view. In addition, Gorton and Metrick (2009) find that high Libor-OIS spreads coincide with increased haircuts in repos. From a theoretical perspective, standard Akerlof (1970) adverse selection reasoning would yield a positive relation between the price of liquidity and unsatiated demand. Recent work by Bindseil, Nyborg, and Strebulaev (2009) shows that there is a degree of allocational inefficiency, for example arising from credit rationing, in the interbank market even during

normal times. We can thus think of the Libor-OIS spread not just as the price of liquidity but as a measure of the “tightness” of the interbank market for liquidity.

2.2 Tightness in the Interbank Market and Stock Market Performance

Figure 2 shows the 3 month Euribor – Eonia Swap spread, which is available to us for a longer time period than the Libor-OIS spread. The Euribor – Eonia Swap spread is essentially the euro version of the Libor-OIS spread. This is to say, it is determined by panel banks in the euro area, rather than set in London, and it exists only for euro interbank transactions. Three month Euribor and euro Libor have a correlation of approximately 0.999. The Eonia Swap is the overnight index swap in the euro area. Thus, the Euribor- Eonia Swap spread captures the same thing as the Libor – OIS spread.

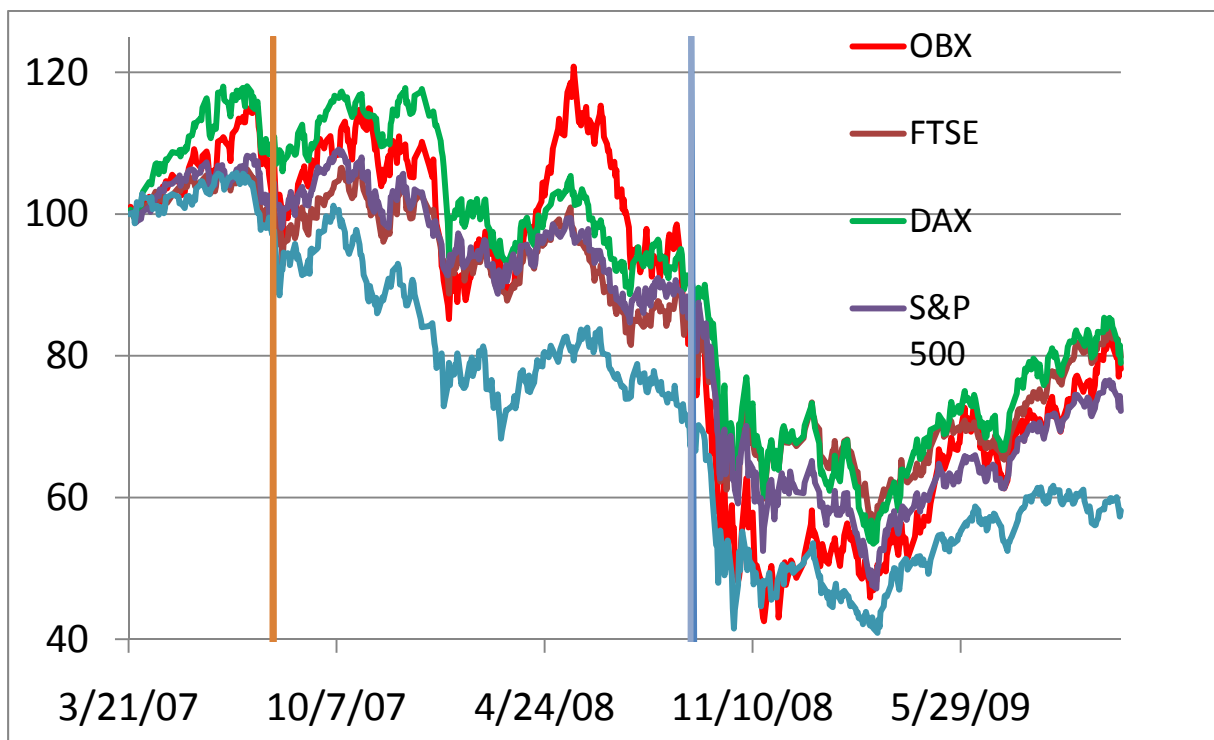
Figure 2. 3 month Euribor – Eonia Swap spread, 20 June 05 to 20 October 09



Note: The y-axis is in basis points.

Figure 3 depicts the performance of 5 stocks indices during the period August 2007 to October 2009, namely the OBS, FTSE 100, DAX, S&P 500, and the Nikkei.

Figure 3. Stock Market Collapse and Recovery, 22 March 07 to 30 October 09



Note: All indices are normalized to 100 as of 22 March 07. The y-axis thus measures returns in percent. Index returns are in local currency.

The orange vertical bar in Figure 3 is on 7 August 2007 (the middle of the second week of August 2007, when spreads started moving up). The blue vertical bar is 12 September 2008 (the Friday before the weekend of the Lehman bankruptcy).

The graph shows that stock markets around the world collapsed during the crisis, but started to recover around the beginning of the second quarter of 2009. Thus the collapse in the stock markets and the subsequent recovery mirrors the breakdown in the interbank market

of liquidity and its subsequent recovery, as seen in the Libor-OIS (or Euribor – Eonia Swap) spread.

Table 2 puts numbers to the stock returns illustrated in Figure 3. We see that all markets that are tabulated fell around 40 to 50 percent in local currency. In terms of Norwegian Kroner, the returns are in the range of 30 to 50 percent. The table thus implicitly shows the poor performance of the kroner during the crisis.

Table 2. Stock Market Collapse. Returns 1 August 2007 to 31 March 2009

	S&P 500 (US)	DAX (DE)	Nikkei (JAP)	FTSE 100 (UK)	OBX (NO)
Local currency	-45.7%	-46.4%	-52.2%	-40.8%	-52.5%
In NOK	-37%	-40%	-32%	-52%	-52.5%

Table 3 illustrates the subsequent recovery of the stock markets. From the end of March 2009 to the end of October 2009, the tabulated markets improved from approximately 20 to 46 percent, in local currency. In terms of NOK, the improvements were from 8 to 46 percent. These numbers show the improvement in the NOK during this recovery phase.

Table 3. Stock Market Recovery. 31 March 2009 to 30 October 2009

	S&P 500 (US)	DAX (DE)	Nikkei (JAP)	FTSE 100 (UK)	OBX (NO)
Local currency	27.8%	31.1%	20.1%	27.5%	46%
In NOK	8.2%	23.4%	10.5%	24.2%	46%

In conclusion, the crisis has to a large extent been a liquidity crisis; the market for liquidity has taken center stage and many of the central bank policies seen during the crisis were concerned with trying to get this market to function better. Eventually, the massive injections of liquidity injected by central banks and the buying out or funding of “toxic assets” helped banks improve their balance sheets and the interbank market recovered. As illustrated above, at the same time this also helped improve the stock markets.

While the overview presented here does not establish with certainty that there is a link between the interbank market and the stock markets, it is suggestive. Given the importance of these markets, this also suggests that it is worthwhile to investigate this further.

Next, we turn to a review of the liquidity literature in financial economics. Our focus is on the various measures that financial economists have come up with in order to capture the notion of the liquidity of an asset. These measures may play an important role in taking further the analysis and ideas we have outlined above.

3. Stock Market Liquidity: Background

One of the key aspects of the recent financial crisis is frequent reports of the 'drying' up of liquidity across markets. This fall in liquidity has been observed across money markets, stock markets, credit instruments and even the real economy. Arguably, the changes in liquidity are an indicator of the gravity of the crisis. To understand the factors underlying the financial crisis we also have to understand liquidity. Fortunately, there is a wealth of academic research on stock market liquidity that we can draw on. Academic research has primarily focused on stock market liquidity for two reasons. Firstly, the stock market is a large and central part of the economy. Secondly, stock market data is of relatively high quality. Therefore in this report we will attempt to summarize some of the academic knowledge concerning stock market liquidity. Due to this literature being extensive we will focus on issues that we believe are key to the financial crisis. To get an understanding of what liquidity is we first consider what characterizes a liquid stock and then we review how the literature proposes to measure liquidity. Following this we examine issues studied in the liquidity literature of pertinence to the crisis, like the relation between liquidity and returns and whether there is commonality in liquidity. Finally, we point towards issues that we think that the crisis highlights that academic research should focus upon.

Over the last 30 years financial economists have considered what characterizes a liquid asset. A liquid asset has some or more of the following features. It can be sold rapidly, with minimal loss of value, any time within market hours. An essential characteristic of a liquid market is that there are ready and willing buyers and sellers at all times. Another definition of liquidity is the probability that the next trade is executed at a price equal to the last one. A market may be considered deeply liquid if there are ready and willing buyers and sellers in large quantities. Put differently, in a deeply liquid market even a large trade will not affect the price significantly.

Most liquidity measures can be divided into two categories, *spread* and *depth* measures. Spread measures attempt to capture the transaction cost associated with investing in the asset (i.e. the purchase and sale of the asset). These measures estimate / use the bid-ask

spread quoted for the asset. The bid-ask spread is the difference between the prices at which a market maker is willing to sell and buy the asset. To an investor this represents an expectation of the transaction costs associated with buying and selling the asset.

The second category of liquidity measures are the *depth* measures. Depth measures attempt to capture whether an asset's price is altered a lot or little for a given sized trade. An asset whose price is altered a lot as a result of a trade is said to have low depth. Markets where even large trades do not lead to a large price change are said to be have high depth. Clearly, unless you are considering a very small trade it is much more costly to trade in a market with low depth than in a high depth market.

These liquidity measures have then been used to study various hypotheses. One of the central issues that has been studied is whether low liquidity stocks offer investors higher *returns*. The intuition for this is that stocks that have low liquidity have to compensate investors for the expected large transaction costs with higher returns. For example, if you purchase an asset that has a large bid-ask spread, then once you have sold the asset you would have paid the bid-ask spread to the market maker. Therefore, all other things equal, investors will require a return premium to invest in assets with large bid-ask spreads.

Early work in market microstructure focused on explaining what are the determinants of liquidity. Why are some assets more liquid than others? In particular, a large literature focused on the role of the market maker and how *inventory management* and *asymmetric information* may lead to particular return patterns that are observed in intra-day data.

An important issue that has been considered in the liquidity literature is that of *commonality* in liquidity across assets. Is it the case that assets experience changes in liquidity simultaneously? For example, Roll (1988) comments that the October 1987 crash was not associated with a single noteworthy event, but resulted in a dramatic fall in liquidity across stocks. Research in this area has tried to uncover the factors that influence market wide changes in liquidity and volume.

4. Measures of Liquidity

Liquidity measures are often classified along two dimensions, the frequency of data that is used in their estimation and whether the measure attempts to capture the *spread* or *depth* component of liquidity. High-frequency measures are measures that use data of higher than daily frequency whereas low frequency measures use data of daily frequency. This section starts by describing high and low frequency *spread* measures followed by the *depth* measures.

4.1 Spread Measures

High Frequency Measures

Effective Spread

Often the Trade and Quote (TAQ) database is used to calculate the effective spread. The TAQ database is a collection of intraday trades and quotes for all securities listed on the New York Stock Exchange, American Stock Exchange, Nasdaq National Market System and SmallCap issues. TAQ provides historical tick by tick data of all stocks listed on NYSE from 1993 to 2005.

The TAQ effective spread of a particular stock on the k^{th} trade is defined as,

$$\text{Effective Spread}(TAQ)_k = 2 \cdot |\ln(P_k) - \ln(M_k)|$$

Where P_k is the price of the k^{th} trade and M_k is the midpoint of the consolidated best bid and offer (BBO) at the time of the k^{th} trade. The BBO is the highest bid price and lowest ask available for a given stock at a moment in time. The bid price is the price at which the market maker is willing to buy the asset and the offer is the price at which the market maker is selling the asset. It is common to report $\text{Effective Spread}(TAQ)_i$ as dollar-volume-weighted average of $\text{Effective Spread}(TAQ)_k$ computed over all trades in the time interval i (either a month or a year).

Realized Spread

Huang and Stoll (1996) consider the realized spread which is the temporary component of the effective spread. The realized spread for a stock on the k^{th} trade is calculated as follows,

$$\text{Realized Spread}(TAQ)_k = \begin{cases} 2 \cdot (\ln(P_k) - \ln(P_{k+5})) & \text{when the } k^{\text{th}} \text{ trade is a buy} \\ 2 \cdot (\ln(P_{k+5}) - \ln(P_k)) & \text{when the } k^{\text{th}} \text{ trade is a sell} \end{cases}$$

Where P_{k+5} is the price of trade five minutes after the k^{th} trade. Like for the effective spread, it is normal to calculate the $\text{Realized Spread}(TAQ)_i$ over the time interval i as the dollar-volume-weighted average of $\text{Realized Spread}(TAQ)_k$ computed over all trades in time interval i .

Since the above procedure requires knowing whether the k^{th} trade is a buy or a sell we need some procedure for determining the sign of the trade. The Lee and Ready (1991) algorithm is frequently used in this literature. The algorithm classifies a trade as buyer (seller) initiated if it is closer to the ask(bid) of the prevailing quote. The quote must be at least five seconds old. If the trade is exactly at the midpoint of the quote, a "tick test" classifies the trade as buyer (seller) initiated if the last price change prior to the trade is positive (negative). Of course, there is some assignment error, but consensus in the literature seems to be that the Lee-Ready algorithm does a fairly good job

Effective Spread – Rule 605 data

Securities and Exchange Commission ("SEC") rule 605 requires market makers to publicly disclose statistics in a number of standardized categories based on certain assumptions about order execution and order routing practices. This implies that researchers have access

to a database with actual orders. Therefore the effective spread can be calculated from this data as,

$$Realized\ Spread(TAQ)_k = \begin{cases} 2 \cdot (\ln(P_k) - \ln(m_k)) & \text{for marketable buys} \\ 2 \cdot (\ln(m_k) - \ln(P_k)) & \text{for marketable sells} \end{cases}$$

where m_k is the midpoint of the consolidated BBO at the time of receipt of the k^{th} order at the exchange. Like the previous measures this measure is often calculated over a time interval like a month or a year and trades are dollar-weighted.

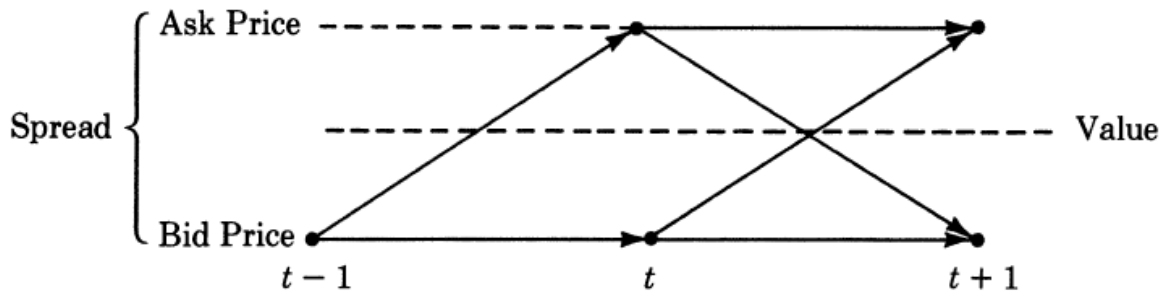
In principle, the Rule 605 data implies an improvement over the TAQ data since the midpoint using the Rule 605 data is based on the time of receipt as opposed to the time of execution as in the TAQ data. This means that the trade is more closely related to the information that the investors has. Additionally, since the Rule 605 data contains information about whether the order was a buy or a sell there is no need to sign the trade using the Lee and Ready (1991) algorithm. Lee and Radhakrishna (2000) use the Rule 605 data to document that the Lee and Ready (1991) algorithm that is often applied to TAQ data incorrectly classifies 24% of inside-the-spread trades that have a clear trade initiator. Unfortunately, this data is only available from 2001 and any order that is re-routed through market centers may be double counted. Another drawback with the Rule 605 data is that it does not include block trades.

Low Frequency Spread Measures

All of these measures are estimated using daily data rather than trade by trade data as in the high-frequency section. For all of the measures below t refers to the day of observation.

Roll (1984)

In his seminal paper Roll (1984) develops an estimator of the effective spread in efficient markets based on covariation of prices over time. Roll makes two important assumptions. First, that the asset is traded in an informationally efficient environment and second that the probability distribution of observed price changes is stationary. These assumptions put restrictions on price paths that we can observe. If the price at $t-1$ is a bid price then Roll illustrates future price paths in the following diagram



Since the market is informationally efficient, a price change will only occur if the price changes to a bid price from an ask price or vice versa. Put differently, since no new information is contained in an investor's decision to purchase or sell an asset repeated transaction on either the bid or the ask side will not result in a price change. The above figure illustrates the possible price paths (the arrows) that can be observed if the t-1 price is a bid price. Notice that all price changes are equal to the spread s . The difference between the bid and ask price is the spread and the true value of the stock is denoted by the dashed line titled Value.

This means that the probability distribution of price changes consists of two parts,

	$p_{(t+1)}$ is at the bid		$p_{(t+1)}$ is at the ask		
	$\Delta p_t =$		$\Delta p_t =$		
	0	+s	-s	0	
$\Delta p_{(t+1)} =$	-s	0	$\frac{1}{4}$	0	$\frac{1}{4}$
	0	$\frac{1}{4}$	$\frac{1}{4}$	$\frac{1}{4}$	$\frac{1}{4}$
	+s	$\frac{1}{4}$	0	$\frac{1}{4}$	0
					$= \Delta p_{(t+1)}$

In each cell the probability of observing any given price change (either +s or -s) is denoted. So if $p_{(t+1)}$ is at the bid then since the market is informationally efficient and the price distribution is stationary the price will never decrease (it is already at its minimum) and

therefore the probability of observing a price change of $-s$ is 0. Similarly, if $p_{(t+1)}$ is at the bid then either the price remains the same or increases with $+s$ with equal probability (since the $p_{(t+1)}$ is equally likely to be at the ask price this probability is $1/4$).

Similar arguments can be made if the price is at the ask to fill in the left table. Combining the two above tables and we get the following joint distribution of price changes,

		$\Delta p_t =$		
		$-s$	0	$+s$
$\Delta p_{(t+1)} =$	$-s$	0	$1/8$	$1/8$
	0	$1/8$	$1/4$	$1/8$
	$+s$	$1/8$	$1/8$	0

To calculate the covariance notice that the mean of Δp_t and $\Delta p_{(t+1)}$ are zero. This implies that the middle row and column can both be ignored. This implies that the covariance of successive price changes can be calculated as,

$$\text{Cov}(\Delta p_t, \Delta p_{(t+1)}) = 1/8(-s^2 - s^2) = -s^2/4$$

This is of course a powerful result since we can easily calculate the covariance of price changes and this provides us with an estimate of the spread. Rearranging implies,

$$s = 2[-\text{Cov}(\Delta p_{t+1}, \Delta p_t)]^{1/2}$$

So the covariation of stock prices over days can be used to calculate a measure of the effective spread. Put differently, in an efficient market any observed serial correlation must be due to the effective spread and therefore we can use time-series price covariation to estimate the size of the effective spread.

Notice that in the above equation s is not defined if the covariance of prices turns out to be positive. So when estimating the effective spread it is common to set the covariance to zero when it is positive.

The above equations are normally estimated using traditional method of moments. However, Hasbrouck (2004) argues that in markets where bids and offers are not necessarily recorded it may be advantageous to use Bayesian estimation. He develops a Bayesian estimation method and applies this to futures trading on the Chicago Mercantile Exchange (CME) where bids and offers expire rapidly and he finds that Bayesian estimation techniques results in smaller liquidity coefficients than method of moments estimators.

Effective Tick

A stylized fact of closing prices, intra-day prices and bid-ask quotes are that they are clustered. For example, Harris (1991) states that

“Stock price clustering is pervasive. On December 31st in 1987, 2431 of the 2510 closing prices reported in the CRSP Daily Stock Master Database are divisible by $1/8$. Whole numbers (17.3 percent) are more common than halves (15.1), which are more common than odd quarters (12.8 and 14.1 percent) and odd eighths (10.1, 10.5, 9.5, and 10.5 percent). This frequency distribution is significantly different from the uniform distribution that would be expected if prices were randomly selected from the discrete set of eighths.”

Harris argues that this clustering might be an optimal way of reducing negotiation costs between traders. Holden (2007) and Goyenko, Holden and Trzcinka (2009) assume that the above clustering is completely determined by the spread size. For example, if the spread is $1/4$ then the model assumes that the bid and ask only employ even quarters. The quote can be $10 \frac{1}{4}$ bid, and $10 \frac{1}{2}$ offered, but never $10 \frac{3}{8}$ and $10 \frac{5}{8}$. So, if a price with an odd eighth (e.g., $10 \frac{3}{8}$) is observed then the spread is assumed to be $1/8$. This line of argumentation implies that it is possible to calculate probabilities of different spreads given a price series and eventually an estimate of the spread for the asset.

Notice that the same line of argumentation can be applied for a decimal price system. The frequency of off pennies, off nickels, off dimes and off half dollars can be used to estimate probabilities of different spreads.

Below we sketch how the observed prices can be used to infer spreads given that there is clustering. Assume that the closing trade of the day is drawn from a set of possible spreads s_j with probabilities γ_j . So, for a price system that allows increments of $1/8$, S_t is modeled as having a probability of γ_1 of $s_1 = 1/8$ spread, γ_2 of $s_2 = 1/4$ spread, γ_3 of $s_3 = 1/2$ spread and γ_4 of $s_4 = 1$ spread. Let N_j be the empirical number of special trade prices corresponding to the j^{th} spread. In the $1/8$ increment price system, N_1 through N_4 are the empirical number of odd $1/8$ prices, the number of odd $1/4$ prices, the number of odd $1/2$ prices, and the number of whole dollar prices.

Let F_j be the empirical probabilities of corresponding to the j^{th} spread. These empirical probabilities are calculated as follows

$$F_j = \frac{N_j}{\sum_{j=1}^J N_j}$$

Let U_j be the unconstrained probability of the j^{th} spread. So the unconstrained probabilities are given by

$$U_j = \begin{cases} 2F_j & j = 1 \\ 2F_j - F_{j-1} & j = 2, \dots, J-1 \\ F_j - F_{j-1} & j = J \end{cases}$$

The effective tick model assumes clustering on rounder increments, but in small samples it is possible to observe reverse clustering on rounder increments (implying that it is less likely to observe round increments). This may cause the unconstrained probabilities of some spread sizes to go above 1 or below 0. To solve this, the constrained probability $\hat{\gamma}_j$ is calculated as follows

$$\hat{\gamma}_j = \begin{cases} \text{Min}[\text{Max}[U_j, 0], 1] & j = 1 \\ \text{Min}\left[\text{Max}[U_j, 0], 1 - \sum_{k=1}^{j-1} \hat{\gamma}_k\right] & j = 2, \dots, J \end{cases}$$

The effective tick is then calculated as the probability-weighted average of each effective spread size divided by \bar{P}_i , the average price in time interval i

$$\text{Effective Tick} = \frac{\sum_{j=1} \hat{\gamma}_j s_j}{\bar{P}_j}$$

Holden

Huang and Stoll (1997) introduce a model that separates the spread into components, order-processing, inventory and asymmetric information costs. They define Q_t as a buy sell indicator for the transaction price P_t . It equals +1 if the transaction is buyer initiated and takes place above the midpoint, -1 if the transaction is seller initiated and takes place below the midpoint. They model the unobservable V_t as follows

$$V_t = V_{t-1} + \alpha \frac{S}{2} Q_{t-1} + \epsilon_t$$

where α is the percentage of the half-spread attributable to adverse selection and S is the constant spread. While V_t is not observable, the mid-point of the bid-ask spread M_t is. Additionally, inventory models postulate that market makers set spreads such as to reduce order imbalances. So, if a market maker has received ten buy orders in a row his inventory might be low and as a result he might increase the asking price. This implies that the quoted

spread depends on past trades. If all trades are of equal size these models imply that the midpoint of the bid-ask spread is

$$M_t = V_t + \beta \frac{S}{2} \sum_{i=1}^{t-1} Q_i$$

where β is the proportion of the half spread attributable to inventory holding costs and $\sum_{i=1}^{t-1} Q_i$ is the net position of the market makers inventory. If we take the first difference of

the above equation and combine it with the first equation we arrive at

$$\Delta M_t = (\alpha + \beta) \frac{S}{2} Q_{t-1} + \epsilon_t$$

So, if we assume that there is a constant spread then

$$P_t = M_t + \frac{S}{2} Q_t + \eta_t$$

Finally combining the two above equations yields the regression model

$$\Delta P_t = \frac{S}{2} (Q_t - Q_{t-1}) + \lambda \frac{S}{2} Q_{t-1} + e_t \quad (1)$$

where $\lambda = \alpha + \beta$. This implies that by estimating λ Huang and Stoll (1997) are able to determine the size of *asymmetric information* and *inventory* costs. Additionally, it is also possible to estimate the portion of the half-spread not due to inventory or asymmetric information by calculating $1 - \lambda$. This is the portion of the half-spread associated with order processing. If there is price clustering which the *Effective Tick* measure is based on then the effect of price clustering will be attributed to the portion of the spread associated with price clustering (i.e., $1 - \lambda$). Huang and Stoll (1997) take their model to high frequency intra-day data and estimate the above regression. They conclude that there is a large order processing component ($1 - \lambda$) and a smaller component that is due to asymmetric information and inventory costs (λ).

The Huang and Stoll (1997) model like the Roll (1984) model is based on serial correlation in prices. On the other hand the *Effective Tick* is based on price clustering. Holden (2007) allows

for both serial correlation and price clustering. In fact his model incorporates the Roll (1984) and the *Effective Tick* as special cases. Holden (2007) relaxes the Huang and Stoll (1997) assumption that the spread is constant and allows it to be time-varying. The above equation becomes

$$\Delta P_t = \frac{S_t}{2} Q_t + (1 - \lambda) \frac{S}{2} Q_{t-1} + e_t$$

where the spread varies over t. Holden estimates the spread by observing three consecutive prices and using an iterative procedure that both takes into account serial correlation (of the three consecutive prices) and price clustering when determining what is the most likely spread.

Lesmond Ogden Trzcinka - LOT

The basic assumption behind the Lesmond, Ogden and Trzcinka (1999) measure is that there is informed trading on non-zero return days and no informed trading on zero return days. The LOT measure takes into account that the observed return on positive (negative) return days is lower (higher) than the actual return due to transaction costs. In their paper they assume that returns are determined by a standard market model on non-zero return days.

The unobserved “true return” R_{jt}^* on stock j on day t is given by

$$R_{jt}^* = \beta_j R_{mt} + \varepsilon_{jt},$$

Where β_j is the sensitivity of the stock j to the market return R_{mt} and ε_{jt} is a noise term. Let $\alpha_{1j} < 0$ is return cost of selling the asset and $\alpha_{2j} > 0$ is the return cost of buying the asset. This implies the following relationship between unobserved true return R_{jt}^* and observed return R_{jt}

$$\begin{aligned} R_{jt} &= R_{jt}^* - \alpha_{1j} && \text{when } R_{jt}^* < \alpha_{1j} \\ R_{jt} &= R_{jt}^* && \text{when } \alpha_{1j} < R_{jt}^* < \alpha_{2j} \\ R_{jt} &= R_{jt}^* - \alpha_{2j} && \text{when } \alpha_{2j} < R_{jt}^* \end{aligned}$$

The LOT measure is simply the difference between the percent buying cost and the percent selling cost

$$LOT = \alpha_{2j} - \alpha_{1j}$$

So to get an estimate of the trading costs we need to estimate the model's parameters which include α_{2j} , α_{1j} and β_j . Lesmond et al. (1999) estimate the model using maximum likelihood.

A simple yet informative liquidity measure that is also suggested by Lesmond et al. (1999) is called *zeroes*. Basically, it is measured as the proportion of days with zero return. Stocks with low liquidity are more likely to have zero volume days and are therefore more likely to have zero return days. Lesmond et al. (1999) suggest that zeroes can be estimated as either the proportion of days with zero return or as the proportion of positive volume days that have zero return.

4.2 Depth Measures

A stock that is liquid should be able to accommodate significant trading without the price changing significantly. A stock whose price is altered more than another stock for a given dollar volume of trade is said to be less liquid. In general, this concept is referred to as market depth and is measured in various ways in the literature. Below we have listed a number of measures of depth that utilize both high-frequency and low frequency data.

High-Frequency Measures

Static Price Impact 605

These measures attempt to capture what would the increased trading cost be of trading a larger amount. So, it can be thought of the first derivative with respect to the order size. The

high frequency data is ideal to measure this due to the small time difference between trades that implies that the slope coefficient is measured accurately. Goyenko, Holden and Trzcinka (2009) use three high-frequency spread measures. The first is based on the Rule 605 data and calculates the differential spread for large and small trades.

$$\text{Static Price Impact (605)}_i = \frac{(\text{Effective Spread(605)}_{\text{Big Orders},i} / \bar{P}_i) - (\text{Effective Spread(605)}_{\text{Small Orders},i} / \bar{P}_i)}{(\text{Ave Trade Size(605)}_{\text{Big Orders},i}) - (\text{Ave Trade Size(605)}_{\text{Small Orders},i})}$$

Where Big Orders, i is all orders in the range 2,000 – 9,999 shares that are executed in the time interval i and Small Orders, i refers to all orders in the range 100 – 499. This measure has as numerator the price difference between placing a large and a small order and as denominator the size difference between large and small orders, effectively capturing the effect on the spread of increasing the trade size.

Hasbrouck TAQ depth

Hasbrouck (2006) develops a price impact measure that uses TAQ data. It is estimated as follows,

$$r_n = \lambda (\text{TAQ}) (\text{Signed} \sqrt{\text{Dollar Volume}}) + \varepsilon_n.$$

where r_n is the return of the stock over the five minute period n , $\text{Signed} \sqrt{\text{Dollar Volume}}$ is the square root of the signed dollar volume and ε_n is a noise term. The object of the exercise is to estimate the slope coefficient $\lambda (\text{TAQ})$, which is a proxy for price impact.

Midpoint Quote Changes (TAQ)

A natural definition of depth is how much the midpoint increases (decreases) following a buy (sell). The idea is to determine whether a transaction is a buy or a sell using Lee and Ready

(1991) and then once the transaction is signed determine what happens to the midpoint five minutes later. More specifically the change in midpoint is measured as follows,

$$5 - \text{minute Price Impact(TAQ)}_k = \begin{cases} 2 \cdot \ln(M_{k+5}) - \ln(M_k) & \text{when the } k\text{th trade is a buy} \\ 2 \cdot \ln(M_k) - \ln(M_{k+5}) & \text{when the } k\text{th trade is a sell} \end{cases}$$

where M_k refers to the midpoint at the k^{th} trade and M_{k+5} refers to the midpoint 5 minutes after the k th trade. To determine the sign of the trade it is common to use the Lee and Ready (1991) algorithm. It is common to dollar weight the 5-minute Price Impact over a time interval such as a month or a year.

Low Frequency Price Impact Measures

Amivest Liquidity Ratio

The Amivest Liquidity ratio that has been used by Cooper, Groth and Avera (1985), Khan and Baker (1993) and Amihud, Mendelson and Lauterbach (1997) is the trading volume divided by the absolute change in price. Formally stated

$$Liquidity = Average \left(\frac{Volume_t}{|r_t|} \right)$$

where t refers to the day of observation, and r is the stock return on day t . The average is calculated over non-zero return days. A large value of *Liquidity* implies that large volumes do not result in a large price impact. Given that this ratio only requires daily frequencies of volume and prices this measure can be calculated using solely the CRSP or equivalent database.

Amihud Illiquidity

A similar measure to the Amivest is the *Illiquidity* measure that was developed by Amihud (2002). It measures the absolute change in price divided by the trading volume. The Illiquidity measure is given by

$$Illiquidity = Average\left(\frac{|r_t|}{Volume_t}\right)$$

where all the components are defined as in the Amivest measure. Additionally, as with the Amivest measure it can be calculated using daily data of volumes and prices. This measure can be intuitively interpreted as the absolute return per unit of 1 million dollar volume.

Extended Amihud Proxies

Goyenko, Holden and Trzcinka (2009) suggest the Amihud model can be augmented to incorporate the decomposition of Huang and Stoll (1997). To do this they divide Eq. (1) by P_{t-1} to get

$$\frac{P_t - P_{t-1}}{P_{t-1}} = \frac{\frac{S}{2}(Q_t - Q_{t-1}) + \lambda \frac{S}{2} Q_{t-1}}{P_{t-1}} + \frac{e_t}{P_{t-1}}$$

where $\frac{P_t - P_{t-1}}{P_{t-1}}$ can be rewritten as r_t , the numerator of the Amihud measure. The first

term on the right hand side of the above equation is the liquidity component and the second term is the non-liquidity component. Like in Huang and Stoll (1997) the liquidity effect of inventory and asymmetric information is captured by λ . Replacing the above equation into the *Illiquidity* ratio yields

$$Ext\ Amihud = Average \left(\frac{\frac{S}{2}(Q_t - Q_{t-1}) + \lambda \frac{S}{2} Q_{t-1}}{P_{t-1}}}{Volume_t} \right)$$

Notice that the term e_t / P_{t-1} is by assumption independent from the liquidity component and therefore it is dropped. In low-frequency datasets we do not observe the numerator in the above equation and therefore one possibility is to replace it with a low frequency spread proxy. For example, if we consider the Roll measure we could calculate a *Roll Impact* based on the Extended Amihud as follows

$$Roll\ Impact_i = Average \left(\frac{Roll_i}{Average\ Daily\ Volume_i} \right)$$

where i refers to the observation period (normally a day).

Pastor and Stambaugh

In a recent contribution, Pastor and Stambaugh (2003) test whether liquidity is a priced factor in cross-sectional stock returns. They devise a new measure of price impact which is defined as follows

$$r_{i,d+1,t}^e = \theta_{i,t} + \phi_{i,t} r_{i,d,t} + \gamma_{i,t} sign(r_{i,d,t}^e) \cdot v_{i,d,t} + \varepsilon_{i,d+1}$$

where $r_{i,d,t}$ is the return on stock i on day d in month t ; $r_{i,d+1,t}^e = r_{i,d,t} - r_{m,d,t}$ where $r_{m,d,t}$ is the return on the CRSP value-weighted market return on day d in month t ; and $v_{i,d,t}$ is the dollar volume for stock i on day d in month t . The parameter $sign(r_{i,d,t}^e)$ takes either the value 1 or -1 depending on whether the previous day's excess return over the CRSP value

weighted market return was positive or negative. The parameter of interest is $\gamma_{i,t}$ which measures the reverse of the previous days order shock. If there is reversal then we would expect a negative sign and the larger $\gamma_{i,t}$ is the larger is the price impact.

4.3 What measure should be used?

Even though our survey of liquidity measures is far from exhaustive it is clear that there is significant choice of liquidity measures. There are spread and depth measures that may either be based on daily or high frequency data. So what recommendations does the existing literature provide as to the choice of measure?

An important aspect concerning the choice of measure is what kind of trade is the liquidity measure trying to measure transaction costs for? For small trades, that most likely will not change the price a spread measure might be more appropriate. However, if you are considering large trades that will have a significant impact a depth measure might be more appropriate.

Additionally, if you are studying phenomena like the financial crisis depth measures might be more appropriate since they are probably closer approximations to trading costs when markets are in free fall.

Should you use high frequency data or is it sufficient with daily data? There are several advantages and disadvantages with both choices. First, the intra-day data has incredible detail, which provides for accurate estimation, but with the cost of considerable computational complexity and time. These datasets are so large that researchers often consider only a sample of all stocks available in the data. This implies that using high frequency data might imply less cross-sectional variation due to a reduced sample of stocks. Secondly, the high-frequency data are only available for limited time periods. For example, the TAQ database starts in 1993 which implies that when using TAQ data one cannot be sure

that the results would hold for an extended time period. Thirdly, for many countries there is no equivalent to the TAQ database so the researcher has to use low-frequency measures.

So given that there are justifications for and occasionally a necessity to use low-frequency data a natural question to ask is whether the low frequency measures are significantly different from high-frequency measures. Several studies have considered how good approximations low-frequency measures are of the high-frequency equivalents. Hasbrouck (2006) uses Bayesian methods to estimate the Roll (1984) measure using daily data. He find that this estimate has a correlation of 0.965 with the estimate calculated using the TAQ data.

Goyenko et al. (2009) estimate a substantial amount of low and high frequency liquidity measures and estimate these at a monthly and annual frequency. They conclude that “The evidence is overwhelming that both monthly and annual low-frequency measures usefully capture high-frequency measures of transaction costs. ... In many applications the correlations are high enough and the mean-squared error low enough, so that the effort of using high frequency measures is simply not worth the cost.” Goyenko et al. (2009) also have recommendations concerning what low frequency measures to use as proxies for the spread and depth. They single out among others the “Effective Tick” as a good spread measure. They also mention that the Amihud and the Pastor Stambaugh measures are not appropriate as measures for the spread. Concerning proxies for depth, Goyenko et al. (2009) conclude that the Amihud measure performs well. Hasbrouck (2006) reports that: “among the daily proxies, the Amihud illiquidity measure is most strongly correlated with the TAQ-based price impact coefficient.”

4.4 The Determinants of Liquidity

So far we have discussed how to measure whether a particular stock is liquid or not. However, we have omitted a discussion concerning what factors make a particular stock liquid or illiquid. In this section we examine the determinants of liquidity. In a seminal paper Demsetz (1968) notes that the bid-ask spread is a major part of trading costs and that the bid-ask spread is often set by a market maker (a financial institution that is obliged to both

buy and sell the asset). Therefore to understand the determinants of liquidity we have to understand how the market maker sets the bid-ask spread. He argues that the market maker provides a service to investors of “predictive immediacy” for which the bid-ask spread is the appropriate return. Competition among several market makers will ensure that the bid-ask spread is a fair return for the risk borne by the market maker. As Stoll (1985) points out this is particularly true for market makers on the NYSE (specialists) which do not only face competition from other market makers, but also from floor traders, limit orders and other exchanges.⁵

Empirical research has tested the predictions of Demsetz (1968) and examined what are the determinants of the bid-ask spread. The main determinants of the bid-ask spread are volume, stock volatility, price and firm size. The spread is increasing in stock volatility, the stock price and decreasing in volume and firm size. Intuitively, very volatile stocks are risky for the market maker and therefore the competitive return (bid-ask spread) is higher in these kinds of stocks. Stocks that have high volumes are safer for the market maker since he can easily unload any surplus inventory rapidly. For the same reason firm size is negatively related to the bid-ask spread. Stocks that have high prices have lower volumes because their high prices may discourage certain investors from purchasing them and therefore the lower volume results in a higher bid-ask spread.

Smidt (1971) argues that market makers also consider their *inventory* when setting spreads. Having a large inventory when the price falls is risky and likewise having virtually no inventory when the price is rising is also risky. Therefore market makers also take into account their inventory levels when setting spreads and the stock price may depart from expected values when inventory levels deviate from target levels. Essentially, the market maker increases (decreases) the bid (ask) when inventory levels are higher (lower) than desired. Garman (1976) formally models the relation between inventory levels and spreads.

A large part of the market microstructure literature incorporates inventory aspects and influential work like Stoll (1978), Amihud and Mendelson (1980), Zabel (1981) and O’Hara and Oldfield (1986) all incorporate the market makers inventory into their analysis.

⁵ A buy (sell) limit order is an order to buy an asset at any price below (above) the limit.

Another key determinant of spreads is pointed out by Walter Bagehot (1971). He argues that traders may differ in their information about the stock, some traders are motivated by intertemporal consumption smoothing (they might be consuming saved wealth in retirement), these traders are known as uninformed traders. Informed traders may have information about the stock that is not known by the market as a whole and trade to capitalize on this information. To the market maker, whether a trader is informed or uninformed makes a big difference. If you are making market in a stock where a lot of investors may have information that you do not, you can protect yourself by widening the spread. Bagehot argues that the market maker loses money on informed traders and recoups these losses on uninformed traders.⁶ The idea that there is *asymmetric information* among investors and the market maker is central to the market microstructure literature.

The asymmetric information paradigm has been taken further by Glosten and Milgrom (1985) and Easley and O'Hara (1987) among others. A large part of the empirical literature has focused on separating *asymmetric information* and *inventory* portions of trading costs. Perhaps the most influential paper in the *asymmetric information* vein is Kyle (1985) that considers the trading pattern of an investor that has superior information. The market maker cannot identify whether an investor has superior information or not, but she / he can observe the trading decisions of individual traders (volume and whether it is a buy or a sell). On observing the order flow the market maker makes inferences about whether the trader is informed and sets prices accordingly. If the market maker assigns a high probability to the sell (buy) order being informed the market maker increases (decreases) the price. The informed trader knows that this is how the market maker sets prices and optimizes how to trade so as to get the most out of her /his superior information. It turns out that an important consideration for the informed trader is the depth of the market (Kyle's λ). The quantity $1/\lambda$ measures the "depth" of the market, i.e. the order flow necessary to induce prices to rise or fall by one dollar.

⁶ Walter Bagehot was a pseudonym used by Jack Treynor.

5. Liquidity and Stock Returns

5.1 The Level of Liquidity and Returns

A substantial amount of academic research has focused on documenting the relation between liquidity and expected returns. This section surveys this literature, but will focus on the empirical literature.

Amihud and Mendelson (1986) develop a model that predicts that there should be a relation between the *level* of liquidity and stock returns. The intuition for this relation is as follows; investing in a stock that has a large bid-ask spread implies a larger round-trip transaction cost than investing in a stock that has a small bid-ask spread and therefore investors require a return premium to compensate for the larger transaction costs. The model allows for investors having different holding periods. In this setting clienteles will arise to minimize transaction costs, investors that have short holding periods will incur significantly larger transaction costs when investing in stocks with large bid-ask spreads than investors that have long holding periods. This implies that stocks that have large bid-ask spreads should be held by investors with long holding periods and stocks with small spreads should be held by investors with shorter holding periods. This clientele effect helps to mitigate the relation between liquidity and returns, since securities will be held such as to minimize transaction costs.

Amihud and Menelson (1986) use Fitch quote sheets to examine the relation between bid-ask spreads and returns of NYSE stocks over the period 1961 to 1980. They test both whether there is a positive relation between the spread and whether this relation is less pronounced as the spread increases (due to clienteles). To achieve this they estimate a piece-wise linear regression that includes dummy variables for each of 7 spread levels. This methodology allows them to examine effects of the bid-ask spread on both the level and slope of returns.

Their results support both predictions of the model, returns increase with bid-ask spread, but the increase is lower at higher levels of the bid-ask spread. For example, going from spread portfolio 1 (the portfolio with the lowest spread) to spread portfolio 4 increases the spread by 0.659% and the monthly return increases by 0.242%. However, going from spread portfolio 4 to portfolio 7 increases the spread by 2.063% and return by 0.439%. From these results it is apparent that the prediction of the model that returns increase in the level of the spread is verified. Additionally, notice that the slope ($\Delta return / \Delta spread$) is $0.242 / 0.656 = 0.367$ when going from spread portfolio 1 to spread portfolio 4 while going from portfolio 4 to portfolio 7 implies a slope of $0.439 / 2.063 = 0.213$. This indicates that the slope is decreasing in the level of the spread as predicted by the model due to the presence of investor clienteles with differing investment horizons.

Following the seminal work of Amihud and Mendelson several authors have spent a lot of effort qualifying their results. Chen and Kan (1989) argue that the pooled cross-section and time-series methodology used by Amihud and Mendelson constrains the market risk premium to be constant over a 30 year period and instead advocate using the methodology of Fama-MacBeth (1973). Eleswarapu and Reinganum (1993) argue that requiring a stock to be present in the data for 11 years introduces a selection bias. When relaxing this restriction and utilizing the Fama-MacBeth methodology they find that the liquidity effect is only present during the month of January. All of the studies mentioned so far have considered stocks on the NYSE. Eleswarapu (1997) considers the liquidity-return relation for NASDAQ stocks. He argues that there are institutional reasons to expect the NASDAQ data to be more suitable. He finds stronger support for the Amihud and Mendelson (1986) model than any previous work that has used the Fama-MacBeth methodology.

Brennan and Subrahmanyam (1996) use intra-day data to revisit the liquidity return relation. They note that bid-ask spread (that was used in the previous literature) is a noisy measure of transaction costs since many large trades occur outside the spread and many small trades inside. Instead they consider the depth (Kyle's λ). They find a positive relation between the depth and return even after controlling for the Fama-French factors. Additionally, they find no evidence of seasonality in the depth-return relation. In their regression analysis they include the square of the depth as an explanatory variable squared term to capture a slope

effect. The estimated coefficient of the squared term is negative, which implies that as the spread increases the liquidity-return relation (as predicted by the clientele effects in Amihud and Mendelson (1986)).

Brennan, Chordia and Subrahmanyam (1998) use dollar trading volume as a measure of liquidity. The intuition being that a stock that has a large volume has low transaction costs. After controlling for known risk factors the authors find that there is a negative relation between volume and returns.

Amihud (2002) develops a measure of illiquidity based on the price impact coefficient (λ) of Kyle (1985). The estimation of the ILLIQ measure is described in the section on measures. The result of his empirical analysis is that ILLIQ is positively and significantly related to returns in the cross-section.

In a recent contribution, Ben-Rephael, Kadan and Wohl (2008) examine the liquidity return relation over time. They use as liquidity measures the Amihud (2002) ILLIQ measure, annual volume /annual turnover and the bid-ask spread as proxied by the Roll (1984) measure estimated as suggested by Hasbrouck (2006) by the Gibbs sampler. They relate liquidity to returns using Fama-MacBeth regressions while splitting up their sample into sub periods. They find that the sensitivity of returns to liquidity has declined from being economically and statistically significant in the 1960s and early 1970s to becoming economically small and statistically insignificant from the mid 1970s and onwards. The average annual liquidity premium was 1.8% in the 1960s to early 1970s, while in the subsequent period it has not been statistically different from 0. Additionally, trading strategies that buy stocks that are the least liquid according to the Amihud's ILLIQ measure and sell stocks that are the most liquid have decreased dramatically in profitability over time. The average annual four factor alpha of this trading strategy is 9.4% in the period 1964 to 1973. From the mid 1970s the returns to this strategy is not statistically different from zero.

All of the research mentioned so far has been performed on U.S. stock markets. A natural question to ask is whether liquidity is important in other markets such as Norway. Ødegaard and Naes (2007) consider the relation between the relative spread / turnover and returns on the Oslo Stock Exchange (OSE). They find that the relative spread is positively related to

returns in the period 1993 – 2003. Bekaert, Harvey and Lundblad (2007) consider the liquidity return relation in the context of 19 emerging markets. Due to data availability they consider the proportion of zero firm returns (based on the measure ZEROES) as a measure of overall market liquidity. They find that zeroes significantly predicts future returns while turnover does not. Additionally, they find that unexpected liquidity shocks are positively related to contemporaneous returns which is consistent with liquidity being a priced factor.

Overall, this literature presents a strong body of evidence that low liquidity firms have to compensate investors with higher returns than high liquidity firms. However, the work of Ben-Rephael et al. (2008) highlight that more research has to be done on liquidity return relation and the recent crisis presents an excellent opportunity to examine what happens to this relation under circumstances of extreme turbulence.

5.2 Changes in Liquidity and Returns

The previous section has primarily examined the existing evidence of a relation between the *level* of liquidity and returns. But additionally, there is mounting evidence that there is commonality in liquidity (Chordia et al. (2000), Chordia et al. (2001), Hasbrouck and Seppi (2001) and others). Given that there is commonality in liquidity, this implies that *changes* in liquidity represent a risk to investors. The intuition behind this is that if there is commonality then stocks will on average experience increases in trading costs simultaneously. This in turn implies that it is difficult to hedge against these increases in trading costs and therefore those assets whose liquidity does not co-move with market liquidity should be more expensive. So, a stock that is more sensitive to aggregate changes in liquidity should earn higher returns. In essence, this implies that *changes* in liquidity should be a priced risk factor.

A number of recent papers consider whether sensitivities to changes in market liquidity are related to returns. Pastor and Stambaugh (2003) first estimate each individual stock's liquidity as described in the measures section. They then construct a measure of market liquidity by taking the average of the stock level measures of liquidity. They measure time-

series changes in market liquidity as the difference in market liquidity over the month (while controlling for changes in market capitalization). A stock's sensitivity (liquidity beta) to aggregate changes in liquidity is estimated as the regression coefficient on changes in aggregate market liquidity with stock returns as the dependent variable. Pastor and Stambaugh (2003) then relate liquidity betas to stock returns. When ranking stocks into ten liquidity beta portfolios and examining alphas after adjusting for the market model, the Fama-French factors or a four factor model, they find stock return are increasing in liquidity beta. This implies that liquidity *risk* is priced.

Acharya and Pedersen (2005) relate stock returns to three liquidity betas that are all based on the Amihud (2002) ILLIQ measure. First, they estimate the return premium due to commonality in liquidity ($cov(c^i, c^M)$). Where c^i is the liquidity of the individual stock and c^M is the liquidity of the market. They find that the return premium due to this covariance is 0.08% per year. As expected, a stock whose level of liquidity covaries significantly with the market has to offer investors higher returns. Secondly, they estimate the return premium to $cov(r^i, c^M)$. Where r^i is the return on stock i . The intuition for this is that if market liquidity is important to investors then investors will prefer stocks that yield high returns when market liquidity is low and therefore returns on these stocks will be bid down. Put differently, stocks that perform well when market liquidity falls are particularly valuable and therefore these stocks will be priced higher. The return premium associated with this covariance is 0.16% per annum. Thirdly, they estimate the return premium due to $cov(c^i, r^M)$. Where r^M is the return on the market. The intuition for this return premium is that investors prefer stocks which are liquid when the market falls. In their empirical estimations it turns out that this aspect (the covariance of stock liquidity with market returns) of liquidity is the most important of the three. The return premium is 0.82% per annum. The total effect of illiquidity risk on returns is then approximately 1.1% per annum. Additionally, the absolute values of the liquidity betas - the sensitivities to liquidity risk are larger the more illiquid the stock is. The higher liquidity risk of illiquid stocks are is consistent with the notion of "flight to quality" or "flight to liquidity": in times of liquidity crisis, the illiquid securities suffer the most. Combining the return premium due to risks in liquidity to

the premium associated with the level of liquidity (3.5% per annum) implies that the total compensation to investors for liquidity is 4.6% per annum.

Liu (2006) considers as a liquidity measure the turnover adjusted number of days with zero trading volume. This measure is then shown to be related to returns. Liu sorts stocks into groups on the basis of their liquidity. Return alpha's from the Fama-French model increase almost monotonically in the rank of illiquidity. The return difference between liquid and illiquid stocks is statistically significant. Liu (2006) additionally uses this measure to construct a liquidity factor which is defined as the profit of investing 1\$ in the low-liquidity portfolio and sells \$1 of the high liquidity portfolio. This factor is negatively related to the market - when the market drops investors require a high liquidity premium as compensation for liquidity risk. Liu proposes a model that includes the market and the liquidity factor and finds that the alpha's of this model are not related to firm size or book-to-market.

A lot of recent work has shown that liquidity risk is a priced factor in stock market returns. So a recent development in the liquidity literature is to document that there is not only a relation between the level of liquidity and returns, but also that changes in liquidity are also highly relevant.

6. Commonality in Liquidity

When examining stock market liquidity from a perspective of financial crises, an important issue is whether liquidity drops across all assets. If it is the case that there is commonality in liquidity then when there is a financial crisis, an investor cannot sell any asset without paying a large transaction cost. Put, differently when the crisis propagates liquidity premia across all assets increase.

Why do researchers believe that there might be commonality in liquidity? First, dealers use spreads as a way of protecting themselves from large price fluctuations. Most of the risk that a dealer faces is that there is significant price volatility. It is likely that there is a significant market component to volatility. So, when the price of one stock changes a lot so will prices for other stocks. If we observe one dealer protecting himself / herself by widening spreads due to an increase in volatility it is likely that other dealers also experience an increase in volatility and also widen the spread. Large-scale program trading may contribute to co-

movements in trader demands and therefore co-movement in volatility. Additionally, many financial institutions, like hedge funds, have similar investment strategies, which imply that they might cause co-movement in trading demands.

Second, the inventory of a dealer is important for liquidity and the major determinant of inventory is trading volume. From the above paragraph we expect there to be co-movement in trading volume and therefore inventory levels and ultimately spreads and other liquidity measures. Additionally, the cost of maintaining an inventory depends on interest rates, which means that a change in the interest rate results in a simultaneous change in inventory levels for all dealers. The change in inventory level represents a change in risk to the dealer and should therefore be associated with an appropriate change in spreads.

Thirdly, there might be changes in the degree of asymmetric information that is either economy or industry wide. For example a new technology might affect all firms in an industry and insiders might have information concerning the technology that the rest of the market does not have. This would result in spreads for all stocks in that industry to increase and we would observe commonality in our measures of liquidity.

What are the implications for commonality for the financial crisis? Firstly, and perhaps most centrally, commonality implies that it is difficult to insure against liquidity drops since all assets experience drops at the same time. Put differently, commonality implies that there will be a portion of liquidity costs that represent a non-diversifiable risk. Secondly, it is possible that if there is commonality in liquidity this may act as a feedback mechanism. If there is a price fall in an asset which results in a widening of spreads this might result in program trading and a further fall in the price in the asset. If this pattern is present in one asset and there is commonality this will also affect other assets.

A number of papers have considered whether there is commonality in liquidity. Chordia, Roll and Subrahmanyam (2000) examine whether there is commonality among NYSE stocks using high frequency data. They consider to what extent can market average levels of liquidity explain individual stock spread and depth measures. Essentially, they are asking whether the average change in spread and depth on the NYSE affects the spread and depth of individual stocks. They find that that there is a strong relation between the market liquidity and stock

liquidity even after accounting for well-known individual trading determinants of liquidity such as trading volume, volatility and price. However, they also find that there is a lot of stock variation in liquidity that is not explained by market liquidity.

Hasbrouck and Seppi (2001) also consider commonality in order flows. They use principal component analysis to document that there exists common factors in the returns and order flows of the stocks in the Dow Jones Industrial Average (DJIA). They find that the common factor in returns is highly correlated with the common factor in order flows. They also find some evidence of a common factor in quote-based proxies for liquidity.

In a similar vein, Huberman and Halka (2001) consider time-series innovations in both spread and depth proxies. They find like Chordia et al. (2000) that there is strong support for the hypothesis that there is commonality in liquidity.

In a subsequent paper Chordia, Roll and Subrahmanyam (2001) consider the patterns of market liquidity. They address questions such as how much does liquidity and trading activity change per day? Additionally, they consider whether there are time-series regularities in liquidity and trading activity. What is the effect of recent market performance on the costs of trading any given day? And finally, what drives changes in liquidity and trading activity? For example, are they determined by interest rates or changes in volatility? In addressing this question they process 3.5 billion transactions on the NYSE. They have a plethora of interesting results. First, market liquidity responds to short-term interest rates, the term spread, equity market returns and recent market volatility. Second, spreads respond asymmetrically to market movements, increasing much more in down markets than they decrease in up markets. Third, Tuesdays seem to be associated with increased trading activity and liquidity while the opposite is true for Fridays.

So, there is substantial evidence that there is commonality in liquidity. Given that there is co-movement in liquidity in stocks; changes in liquidity represent a risk to investors. It is difficult for investors to insure against changes in liquidity since changes in liquidity co-move for most stocks. Therefore stocks whose liquidity does not co-move with the rest of the market are particularly valuable and should therefore be priced higher and therefore yield lower returns. Essentially, if there is co-movement in liquidity then changes in liquidity should be a

priced factor in stock returns. Pastor and Stambaugh (2003) develop a liquidity measure (described above) and examine whether expected stock returns are related cross-sectionally to the sensitivities of returns to fluctuations in aggregate liquidity. They find that the average return on stocks with high sensitivities to liquidity exceeds that for stocks with low sensitivities by 7.5 percent annually, adjusted for exposures to the market return as well as size, value, and momentum factors. Additionally, they find that liquidity can explain a substantial proportion of the returns to momentum strategies.

7. Concluding Remarks

The crisis was too a large extent a liquidity crisis; one of its central features was the breakdown of the market for liquidity, as evidenced for example by extreme values in the Libor – OIS spread. The rise of the Libor – OIS spread, or the price of liquidity, was accompanied by falling stock prices around the world. As the spread started to come down, stock prices started to recover. This suggests that there may be a connection between the state of the interbank market for liquidity, for example as measured by the Libor – OIS spread, and the performance of the stock markets.

A substantial amount of work has been done on the liquidity of stock markets covering aspects such as liquidity premia (both for the level of liquidity and liquidity risk), commonality and how the organization of the trading environment affects liquidity. This literature has been reviewed in this article. However, we have seen that there is little by way of work that sheds light on how the *market for liquidity* affects the *liquidity of stocks*, or affects stocks differently depending on their degree of liquidity.

Examining this more closely is an important avenue for future research. It is important to understand the nature of the connection between the interbank market for liquidity and the broader financial markets and how it manifests itself, during normal times as well as during a liquidity crisis.

Other topics for further research include: What happened to stock liquidity levels during the crisis? How did the measures used in the literature respond to the crisis? Which of the

measures used in the literature are able to capture a drying up of liquidity? Did stocks that are identified by liquidity measures as being liquid outperform? Could the crisis have been predicted by liquidity measures?

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