The information content of market liquidity: An empirical analysis of liquidity at the Oslo Stock Exchange

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Abstract

We investigate the information content of aggregate stock market liquidity and ask whether it may be a useful realtime indicator, both for financial stress, and real economic activity in Norway. We describe the development in a set of liquidity proxies at the Oslo Stock Exchange (OSE) for the period 1980-2008, with particular focus on crisis period 2007 through 2008, showing how market liquidity and trading activity changed for the whole market as well as for individual industry sectors. We also evaluate the predictive power of market liquidity for economic growth both in-sample and out-of-sample.

Keywords: Liquidity, Business Cycles, Financial crisis, Economic Activity

JEL Codes: G10, G20

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Introduction

In finance, liquidity is a concept with many interpretations, and many uses. Following the recent financial crisis there has been a huge increase in research on liquidity related topics both with respect to macro liquidity, funding liquidity, the liquidity of different asset classes and markets as well as the flow of funds between different assets and markets.

In this paper we look at the link between equity market liquidity and the real economy. In the discussion of the current financial crisis, much attention has been on the apparent casual effect from a dry up in the liquidity of financial assets to the crisis of the economy. Næs et al. [2009b] show that such links between aggregate stock market liquidity and the macro economy are not new, rather, they have been a stable feature of the US stock market at least since the Second World War. They show, using data for the US from 1947 through 2008, that equity market liquidity is a very good leading indicator of the real economy. We look at similar issues using data from the Norwegian equity market (Oslo Stock Exchange – OSE). We examine the liquidity of the Norwegian equity market represented by the stocks listed on the OSE over the period 1980 through 2008.

The goal of this study is twofold. First, we give a general descriptive analysis of the liquidity and trading activity of the Oslo Stock Exchange (OSE) for the period 1980 through 2008,[1] with particular focus on the crisis period 2007-2008. With respect to the crisis we examine how liquidity and trading activity changed through the crisis for the market as a whole, across important firm risk characteristics (mainly firm size) and for individual industry sectors.

Secondly, we examine in more detail to what degree market liquidity is informative about future economic conditions in Norway.[2] We perform an in-sample analysis where market liquidity is used as a predictor of macroeconomic aggregates such as growth in real GDP, unemployment, credit, consumption and investments. We also do Granger causality tests between the variables, as well as out-of-sample evaluations of simple linear forecasting models where we examine whether liquidity might be of use for predicting macro conditions in real time. In both the in-sample and out-of-sample analysis we compare the performance of market liquidity to other financial predictors.

The structure of the paper is as follows. We start by a brief overview of the current research on equity market liquidity and its links with the macroeconomy before we in section 2 describe the data and the construction of our liquidity measures. In section 3 we provide some descriptive statistics for the variables and examine the time series development in liquidity across the whole sample period 1980-2008 with particular focus on the crisis period. In section 4 we examine the predictive ability of liquidity for several macroeconomic variables both in-sample and out-of-sample. We also examine the causality relation between liquidity and macroeconomic variables. Finally, in section 5 we summarize the results.

[1] This part of the project builds on the analysis in Næs et al. [2008a], extending the time series and looking in more detail at the crisis period 2005-2008.

[2] This is essentially an extension of Næs et al. [2009b] who focus mainly on the US market. In this paper, we take a closer look at the Norwegian market.

1 Research on equity market liquidity and the macro economy

There is a long history of research on the liquidity and microstructure of equity markets. The early research on equity market liquidity was however done within a market microstructure framework focusing on intra-day patterns and trader behavior in single securities. In recent years there has been an increased focus on the broader implications of the market microstructure for the cross section of asset prices. Most of the attention of this literature has been on asset pricing implications of liquidity.[3]

Research that links the liquidity of the stock market and the real economy is however much more scarce. There are only a few studies that examine this relationship, and the typical question asked in these studies is whether macroeconomic variables affect stock market liquidity. For example, using data from the US stock market over the 1962-2001 period, Fujimoto [2003] employs a VAR approach to investigate if time varying aggregate stock market liquidity has macroeconomic sources. The main conclusion of her study is that "market liquidity has become more resilient to both market-level and economy-wide shocks." Shocks in some nominal macroeconomic variables (inflation and monetary policy variables) are found to affect aggregate liquidity, but only in the years before the mid 1980's when the business cycle dynamics was more volatile. A similar analysis is done for Scandinavian countries in Söderberg [2008] where he finds similar results. Goyenko and Ukhov [2009] also examine how bond market liquidity and equity market liquidity is linked. More specifically, they examine whether changes in the liquidity in the two markets is driven by shocks to real and nominal macro variables. They find that monetary policy shocks and shocks to inflation impact both bond and stock market liquidity, while shocks in real variables (industrial production) they find have no effect on the liquidity of either the US bond- or equity markets.

None of these studies find any effect from shocks in real economic variables to market liquidity, which is not surprising, since they actually do not test for a causality relation from market liquidity to real variables. This causality direction was first investigated in Næs et al. [2009b], who examine the hypothesis that equity liquidity is informative about future real economic variables. They find that average market liquidity have predictive power for future growth in real GDP, unemployment, investments and consumption for the period 1947-2008 in the US. The conjecture in Næs et al. is that the time variation in market liquidity is related to portfolio rebalancing caused by changing risk preferences and expectations about future investment opportunities. Thus, market liquidity changes as investors move wealth out of equities into other asset classes (e.g. bonds or cash) and vice versa. They also show evidence that this effect also occur within equities, between e.g. large firms and small firms. Their argument is related to the literature on forecasting economic growth using asset prices, where the forward looking nature of asset markets suggest that, as long as expectations about the economy is not biased on average, shocks to expectations about relevant real variables should be reflected in

[3] For some well known examples of such studies on the US market we refer to Pastor and Stambaugh [2003] and Acharya and Pedersen [2005]. This literature has recently been summarized in Amihud et al. [2005]. For an investigation of the Norwegian market see Næs et al. [2009a].

prices and risk premia. However, since liquidity is not an asset price, the expected cash flow argument does not apply directly. Their suggested explanation is that the time variation in aggregate liquidity reflects transactions investors do today to hedge their perceived consumption risk tomorrow. In a standard Merton [1973] consumption-portfolio decision problem, these trades would constitute hedging demand related to state variables that forecast changes in the investment-opportunity set. Thus, when a large number of investors move out of equities, the cost of trading equities changes, as there are potentially fewer liquidity suppliers left. To support their conjecture Næs et al. show, using ownership data for Norway, that market liquidity is correlated with the number of investors moving in and out of the market.

In practice, there are several dynamic asset allocation strategies that shift wealth between stocks and bond markets. During times of economic distress such strategies causes rebalancing towards less risky and more liquid securities. Consistent with this, Beber et al. [2008] find that equity market order-flow across equity sectors at different stages of the business cycle is consistent with a sector-rotation strategy where investors re-balance their portfolios into sectors that is perceived as having better relative performance at different stages of the business cycle.[4] Similarly, Kaul and Kayacetin [2009] find that aggregate equity market order-flow is informative about future macro fundamentals. They show that there is a portfolio shift from small stocks to large stocks prior to economic downturns, and argue that this is a consequence of an increase in market-wide risk aversion. Albuquerque et al. [2007] show that there is a close relationship between liquidity and order-flow. Their results suggest that variation in market-wide order-flow is mainly due to liquidity co-movement and not related to measures of private information. Their results may indicate that the results in Beber et al. [2008] and Kaul and Kayacetin [2009] may be explained by market liquidity rather than private information.

Thus, if investors have rational (or at least unbiased) expectations, and rebalance their portfolios over the business cycle, one implication is that liquidity should have predictive power for real economic variables that are important for firms earnings and risks. As investors move out of an asset, liquidity in that asset should fall as participation falls. In support of this, Gibson and Mougeot [2004] find evidence that a time varying liquidity risk premium in the US stock market is related to a recession index over the 1973-1997 period.

Similarly, several studies within the empirical asset pricing literature suggest that also other risk factors that explain the cross-section of stock returns are linked to future economic growth, see Liew and Vassalou [2000] and Vassalou [2003]. Several papers find support for a "flight-to-quality" or "flight-to-liquidity" during economic downturns. Longstaff [2004] finds that there is a flight-to-liquidity premium in Treasury bond prices, and that the premium is related to changes in consumer confidence and flows into equity and money market mutual funds. Goyenko and Sarkissian [2008] develop and test an international asset pricing model using the relative spread on US Treasury bonds as a proxy for a joint flight-to-liquidity/flight-to-quality risk factor. Results from asset pricing tests show that there is a significant risk premium related to a bond illiquidity factor.

[4] Their results suggest that fund flows into the materials sector predict future economic growth, while flows into financials, telecom and consumer discretionaries predict lower economic growth one year ahead.

There are several studies that suggest that financial variables contain information about future economic growth. Fama [1981], Fama [1990] and Schwert [1990] all find a strong positive relation between real stock returns and future production growth rates in the US. Fama argues that stock returns are determined by forecasts of relevant real variables and that the relation between current stock returns and future production growth reflects market expectations about future cash flows that is impounded in stock prices. Also, Liew and Vassalou [2000] and Vassalou [2003] find strong evidence that the Fama [1993] size (SMB) and value (HML) risk factors contain significant information about future GDP growth. Fama-French argue that the size and value factors act as state variables that predict future changes in the investment opportunity set in the context of the intertemporal asset pricing model of Merton [1973]. The results in Liew and Vassalou [2000] to a large extend strengthen this argument. In addition, Harvey [1988], Estrella and Hardouvelis [1991] and Estrella and Trubin [2006] find that the slope of the yield curve predict real economic variables such as consumption and investment growth. Also, Bernanke [1990] and more recently Gilchrist et al. [2009] find that the credit spread has predictive power for economic growth.

Overall, there is a number of studies that suggest that financial market variables lead macro variables as shocks to expectations about future investment opportunities causes prices to change to new equilibrium levels. This is the same story proposed in Næs et al. [2009b] with respect to liquidity. If shocks to expectations generate order-flow and alters trading activity between assets with different risk characteristics, this could provide an explanation for why we observe commonality in liquidity. Furthermore, if this is the case, one would also expect liquidity to predict macroeconomic growth.

2 Liquidity measures and data

The empirical literature on market microstructure have developed a large number of empirical measures of liquidity. This plethora of empirical measures to some degree reflect that there are numerous theoretical definitions of liquidity. In this article we look at a few commonly used measures of liquidity, and refer to Næs et al. [2008a] for an examination of a broader range of liquidity measures for the Oslo Stock Exchange. In this section we briefly explain the construction of the liquidity measures used and list the data sources.

2.1 Liquidity proxies

Our choices of liquidity measures are driven by our need for for reasonably long time series so we cover as many business cycles as possible. Many common liquidity measures require high frequency trading information, which is not available for long periods. We therefore employ measures which can be calculated using data at the lower frequency of daily observations. In our analysis we will focus on two much used measures of liquidity; the relative bid/ask spread (`RS`) and the Amihud [2002] liquidity ratio (`ILR`). In addition we will examine turnover as a measure of trading activity. Thus, our three measures capture the implicit cost of trading a small volume (spread), the average price impact of observed transactions (ILR), and the trading activity (turnover).

Our first liquidity measure is the *relative spread*. A spread is the difference between a bid and ask price. Spread costs are observed in dealer markets as well as in limit order markets, and there are several empirical variations of spread measures available including quoted spread, relative quoted spread, effective spread, and amortized spread. The quoted bid/ask spread is simply the difference between the best ask quote and the best bid quote. The midpoint between the best bid and ask quotes is often used as an estimate of the true value of the security. The relative bid/ask spread, RS, is the quoted spread as a fraction of the midpoint price, and provides a relative measure of trading costs, what fraction of the price needs to be paid to "cross" from the bid to the ask price, or vice versa. A high spread indicate an *illiquid* market where the implicit costs of trading is large.

Our second liquidity measure is a measure of the elasticity dimension of liquidity. Elasticity measures of liquidity try to take into account how much prices move as a response to trading volume (i.e. price impact). Thus, cost measures and elasticity measures are related. Kyle [1985] defines price impact as the response of price to order flow. Amihud proposes a price impact measure that is closely related to Kyle's measure, which we employ in our analysis. The Amihud measure is calculated as,

$$\mathsf{ILR}_{i,T} = 1/D_T \sum_{t=1}^{T} \frac{|R_{i,t}|}{\mathsf{VOL}_{i,t}} \tag{1}$$

where D_T is the number of trading days within a time window T, $|R_{i,t}|$ is the absolute return on day t for security i, and $\mathsf{VOL}_{i,t}$ is the trading volume (in NOK) on day t. The Amihud measure is calculated over different time intervals, such as days, months or quarters. It is standard to multiply the estimate by 10^6 for practical purposes. The Amihud measure is called an illiquidity measure since a high estimate indicates low liquidity (high price impact of trades). Thus, the ILR measure captures how much the price moves for each NOK unit of trades. Moreover, a high price impact suggest that the market depth is low, such that a smaller volume is needed to move the price.

As mentioned earlier, there are many proposed proxies for liquidity in the literature. We focus on the Amihud illiquidity ratio (ILR) and relative spread (RS). The ILR measure is shown by Goyenko et al. [2009] to be among the best proxies for price impact for long time series when intra-day based liquidity measures are not available. There are also several alternative estimators for various spread measures, however since we observe the closing spread directly we do not examine alternative spread proxies.

Stock turnover is measure very much related to liquidity. Turnover is a common measure of activity, and is calculated as the total number of shares traded during a time interval, relative to the number of outstanding shares in the security. We usually express turnover in percentage terms. Thus, turnover measures the percentage of the issued shares that changes hands during a trading window (e.g. day, month, quarter). Turnover is a measure that reflect the trading activity in the market scaled by the number of issued shares. In general one thinks about an active market as a liquid market where it is easy to liquidate or rebalance a portfolio. On the other hand, an increase in turnover does not always mean that it a stock has low trading costs. It may also reflect that investors are willing to pay a high cost to liquidate or rebalance their portfolios. This point was first made by Aitken and Comerton-Forde [2003] who show that, especially during crisis periods, turnover has a tendency to high at the same time as transaction costs are high (liquidity low). Thus, so-called trade-based liquidity measures should be used with caution as they may give wrong signals about liquidity in certain periods.

A second measure of trading activity is the number of trading days. This measure is simply calculated by counting the number of days during a time period, such as a quarter or a year, that the stock in question traded (had trading volume larger than zero).

2.2 Equity data

The data we use in the analysis is obtained from the OSE data service (OBI).[5] The data covers the period from 1980 through 2008. We calculate daily, monthly, quarterly and yearly versions of the different liquidity measures for each security. To obtain the market-wide liquidity variables we take averages across all securities of the respective liquidity measure.

In the analysis we will also stratify the firms on the exchange, both by grouping by firm size and by industry. When we group by size, at the beginning of each year we rank all firms by their market capitalization (MCAP). We then quartile the sample by putting the 25 % of the firms with the lowest MCAP in group 1, the next 25 % in group 2 and so on. Group 4 contains the 25 % largest firms. The industry groups are based on the GICS standard.[6] Initially, there are 10 GICS industry sectors. However, we only look at the five largest sectors in terms of number of companies, since there are several GICS groups that contains very few companies. The sectors we look at in this paper are Energy, Industrials, Consumer goods (discretionary), Financials and IT.

Panel A of table 1 gives descriptive statistics for the sample. The liquidity of the OSE has improved over the sample period 1980-2008, but has also varied across subperiods. From Panel B we see that all the liquidity proxies are strongly positively correlated. Overall, the high correlation between these measures suggest they contain some of the same information.

2.3 Macroeconomic data

To proxy for the state of the real economy we use real GDP (GDPR), unemployment rate (UE), real consumption (CONSR) and real investment (INV). GDP is the real Gross Domestic Product for Mainland Norway (excluding oil production). UE is the Unemployment Rate (AKU),

[5]We use all equities listed at the OSE with the exception of very illiquid stocks. Our criteria for filtering the data are the same as those used in Næs et al. [2008a], i.e. that we remove years where a stock is priced below NOK 10, and remove stocks with less than 20 trading days in a year.

[6]Global Industry Classification Standard was developed by Morgan Stanley Capital International (MSCI) and Standard & Poors. For companies that were delisted before 1997 there is no official OSE classification. We have therefor manually reconstructed the classification of these companies for the period 1980-1997. A more detailed description of the industry structure at the OSE for the period 1980-2006 can be found in Næs et al. [2009a] and Næs et al. [2008b], and we refer to that paper for more details about the grouping procedure.

Table 1 Describing liquidity measures

Panels A and B show descriptive statistics for the liquidity measures. The Norwegian sample covers the period from 1980 through 2008. The liquidity measures examined are the relative bid-ask spread (RS) and the Amihud [2002] illiquidity ratio. The liquidity measures are calculated for each available stock once each quarter. Panel A shows the mean and median of the liquidity measures, the number of securities used, the total number of observations (each security is observed in several quarters), and estimates of average liquidity measures for different subperiods. Panel B shows correlation coefficients between the liquidity measures. The correlations are calculated across all stocks and time, i.e. the liquidity measures are calculated for each available stock once each quarter, and the correlations are pairwise correlations between these liquidity measures.

Panel A: Descriptive statistics, Liquidity measures

					Means subperiods		
Liquidity					1980-1989	1990-1999	2000-2008
measure	mean	median	no secs	no obs			
RS	0.042	0.029	788	14942	0.041	0.046	0.040
ILR	0.772	0.205	770	15092	1.149	0.875	0.452

Panel B: Correlation coefficients, liquidity measures

	RS
ILR	0.40

CONSR is the real Households Consumption Expenditure and INV is real Gross Investments. All numbers are seasonally adjusted. The data source is Statistics Norway (SSB). In the analysis we differentiate the macro variables.[7]

We also use a number of financial variables which are shown in the literature to contain leading information about economic growth. From the equity market we use *Excess market return* (R_m), calculated as the value weighted return on a broad stock market index in excess of a short term interest rate, and *Market volatility* (*Vola*), measured as the cross sectional average volatility of the sample stocks. We also use the *term spread* (*Term*), calculated as the difference between the yield on a 10-year Treasury bond benchmark and the 3 month NIBOR interest rate.[8][9]

2.4 Correlations

The correlations between the variables can be seen in table 2. The period we consider is from the first quarter of 1980 through the fourth quarter of 2008. Correlations that are significantly different from zero is in bold. Most notably is the very high correlation between *Term* and the two liquidity measures (RS and ILR). This correlation is to a large degree driven by a large decline in the term spread in 1992. At this time the short interest rate almost doubled to 20% while the long rate was largely unaffected. Also the spreads and price impacts in the

[7] dGDPR is the real GDP growth, calculated as $dGPDR = \ln(GDP_t/GDP_{t-1})$. dUE is the change in unemployment rate, calculated as $dUE = UE_t - UE_{t-1}$. dCONS is the real consumption growth, calculated as $dCONS = \ln(CONS_t/CONS_{t-1})$. dINV is the real growth in investments, calculated as $dINV = \ln(INV_t/INV_{t-1})$.

[8] The source of these variables is Ecowin/Reuters.

[9] We would also have liked to include a credit spread measure, since it was shown to be an important predictor of real GDP growth for the US in Næs et al. [2009b]. However, a long enough time series of credit spreads is not obtainable for the Norwegian market.

Table 2 Correlations

The table shows the correlations between the variables we examine in this study. The period is from 1980-2008, and the data frequency is quarterly. Numbers in bold denote correlations that are significantly different from zero at the 5% level or better. Numbers in parentheses are p-values.

	Market variables					**Macro variables**			
	RS	ILR	Term	Rm	Vola	dGDPR	dUE	dCONS	dCRED
ILR	**0.69**								
	(0.00)								
Term	**-0.55**	**-0.70**							
	(0.00)	**(0.00)**							
Rm	**-0.34**	-0.15	**0.21**						
	(0.00)	(0.14)	**(0.04)**						
Vola	**0.47**	**0.43**	**-0.47**	**-0.63**					
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**					
dGDPR	**-0.27**	**-0.23**	0.16	0.06	-0.02				
	(0.00)	**(0.02)**	(0.12)	(0.58)	(0.87)				
dUE	**0.42**	**0.35**	-0.12	-0.07	0.09	**-0.35**			
	(0.00)	**(0.00)**	(0.26)	(0.52)	(0.4)	**(0.00)**			
dCONS	**-0.25**	-0.18	0.14	0.15	-0.09	**0.38**	**-0.23**		
	(0.01)	(0.08)	(0.19)	(0.14)	(0.37)	**(0.00)**	**(0.02)**		
dCRED	**-0.55**	**-0.51**	0.16	0.04	-0.16	**0.20**	-0.12	0.07	
	(0.00)	**(0.00)**	(0.11)	(0.72)	(0.13)	**(0.05)**	(0.26)	(0.50)	
dINV	-0.15	-0.13	0.14	-0.05	0.01	**0.27**	-0.06	0.02	0.06
	(0.14)	(0.20)	(0.18)	(0.61)	(0.93)	**(0.00)**	(0.57)	(0.87)	(0.56)

equity market increased markedly indicating a dry-up in market liquidity during this event. Another noticeable correlation is between the credit growth and the two liquidity measures, which suggests that when credit growth is high, market liquidity is good (i.e. low RS and ILR). This is what one would expect if credit growth reflects an increased risk tolerance and is accompanied by increased investments in equities. Another interesting result is that all the financial variables (*Term*, $\mathsf{R_m}$, *Vola*) have a strong and significant correlation with the two liquidity measures. However, none of the non-liquidity financial variables are correlated with any of the macro variables. This result indicates that market liquidity contains information about macro variables that is not reflected in the other financial variables.

3 The liquidity of the Norwegian stock market

3.1 Development in liquidity for the period 1980-2008

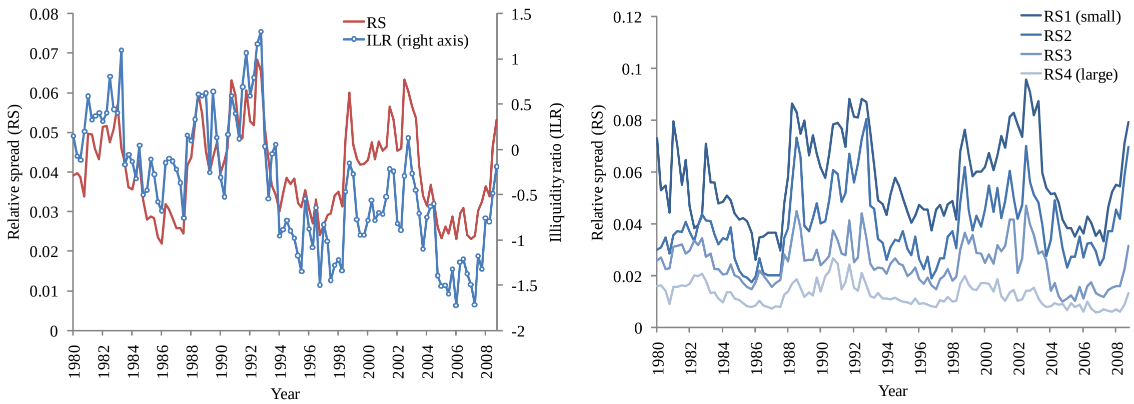
Let us first examine the development in liquidity and activity proxies for the full sample period for the market as a whole, for firm size groups and for individual industry sectors.

Market liquidity

We start with the liquidity of the whole market. In figure 1 look at the time series evolution of the relative spread (RS) and the Amihud Illiquidity ratio (ILR). The left plot in the figure shows the quarterly time series of the (equally weighted) averages. There are several things to note. First, both variables are highly correlated. This is the case for many different types of liquidity

Figure 1 Development in market illiquidity at the OSE (1980-2008)

The left plot shows the quarterly market liquidity at the Oslo Stock Exchange over the period 1980 through 2008. Market liquidity is proxied by the relative spread (`RS`) and the Amihud Illiquidity ratio (`ILR`). Note that the figure plots the log of `ILR` for scaling reasons. The right figure shows the relative spread for four size groups of stocks. Each group contains 25% of the listed securities. Group 1 (small firms) contains the 25% of the firms with the smallest market capitalization, while Group 4 (large firms) contains the 25% of the firms with the highest market capitalization.

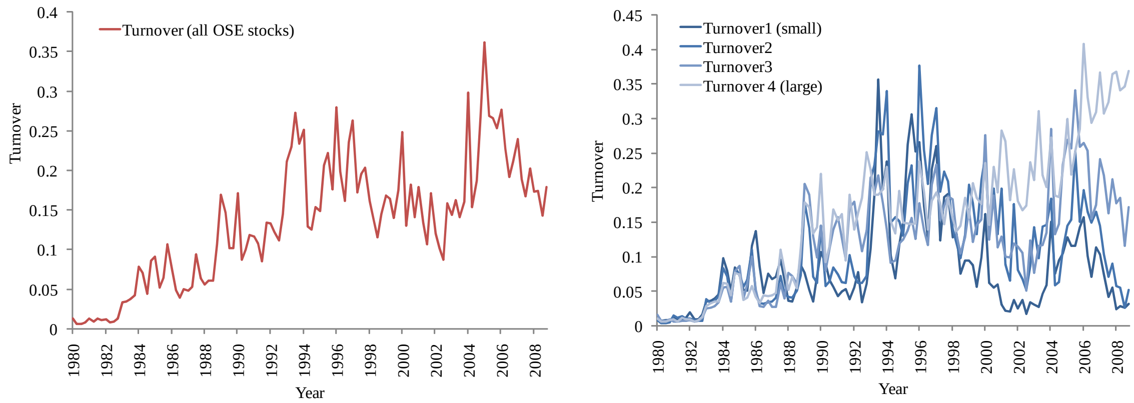


measures. However, since various liquidity measures capture different sides of liquidity (e.g. `RS` measures spread costs, `ILR` measures price impact/depth), they may also diverge in certain periods. The second thing to note is that both series have a slight downward trend, suggesting that both price impact and the spread cost has fallen over the sample period. This is also a common feature of other liquidity measures as well as other markets, suggesting that implicit trading costs have fallen over time. The third thing to note is that both series show a cyclical pattern. This is similar to what is found for the US over a longer sample. We investigate this feature of the data closer in the second part of the paper. Finally, we see that market liquidity has worsened (an increase in `RS` and `ILR`) during the current crisis.

In the righthand picture in figure 1 we split the listed firms into four groups based on their market capitalization, and calculate the average relative spread for each group. From the figure for the size groups there are several things to note. First, we see that the level of the spread is falling with firm size, which reflects that large firms are generally more liquid and less costly to trade than smaller firms. Second, the figure illustrates the strong commonality in liquidity across sub samples of firms, as the liquidity of all groups are highly correlated. Thirdly, we also see that a cyclical pattern is evident for sub-samples of firms. Finally, we see that the time variation in liquidity is much greater, in absolute terms, for small firms than large firms. Also, looking at the last few years, we see that the liquidity of the smallest firms (RS1 and RS2) seems to worsen earlier than for the largest firms in groups 3 and 4.

Figure 2 Development in turnover at the OSE (1980-2008)

The left figure shows the average quarterly turnover of the at stocks listed at the Oslo Stock Exchange over the period 1980 through 2008. Turnover is measured as the volume of shares traded divided by the number of outstanding shares in each stock. Thus, it measures the fraction of shares that changes hands over the quarter. The right figure shows the turnover for four size groups of stocks. Each group contains 25% of the listed securities. Group 1 (small firms) contains the 25% of the firms with the smallest market capitalization, while Group 4 (large firms) contains the 25% of the firms with the highest market capitalization.



In figure 2 we investigate market activity, by showing the development of the average turnover. In the picture we see that the average turnover for all stocks at the Oslo Stock Exchange has increased over the sample period. While the quarterly turnover was varying around 15% during the 1990s and first half of the 2000s, it shows a marked decrease after 2005. More specifically, after a peak in 2005, turnover for 2008 was back to the level in the beginning of 2000. Looking at the second plot in figure 2, where we plot the average turnover for the four firm-size groups, we see that only the turnover for the largest firms have increased steadily through the sample period. For the two smallest groups of firms the average turnover have had large variation, and the turnover during the last few years has fallen to the level in the early part of the sample (middle 1980s).

3.2 A closer look at the liquidity and trading activity before and during the crisis period (2005-2008)

In this section we examine more closely the period 2005-2008. In addition to looking in more detail at the firm size groups, we also examine how liquidity and trading activity of the different industry sectors were affected by the crisis.

How does liquidity vary with firm size?

In figure 3, we show the development in liquidity (part a) and activity (part b) for the individual years 2005 through 2008 for the firm size portfolios. The left diagram in part (a) shows the average relative spread for each year for the four firm size groups, and similarly for the `ILR` in the second diagram. For all size groups we see that both the relative spread and `ILR` increased markedly in 2008 compared to the other years, although the increase is much less pronounced for the largest firms in absolute terms. In part (b) of the figure, we look at two activity measures (average quarterly turnover and average number of trading days per year). For turnover, we see that there was a drop in turnover for all groups, except for the largest firms in group 4. We can only speculate why we observe an increased turnover for large firms. One potential reason for this pattern is that investors liquidated the most liquid stocks (large companies) to free up cash during the crisis. We have some anecdotal evidence of this happening during the periods when the equity market fell the most in 2008. The result that turnover for large stocks increased at the same time as transaction costs increased illustrates the point made in Aitken and Comerton-Forde [2003] that increased trading activity does not necessarily imply improved liquidity.

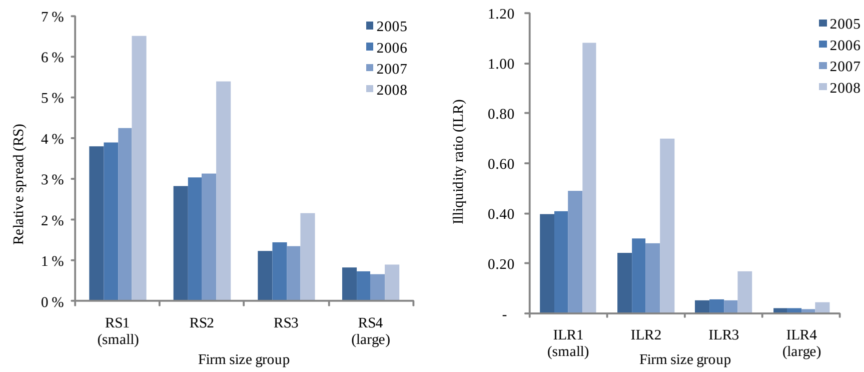
When we look at the number of days that the firms in the different groups was actually trading, we see a similar pattern as for turnover. There was a significant drop for the smallest firms (group 1 and 2), and an increase for the largest firms (group 4) in 2008. Thus, the trading activity in small firms were clearly negatively affected by the crisis, while the large firms experienced an increase in trading activity.

Table 3 shows the numbers associated with figure 3. In the last two rows in each panel we have calculated the absolute and percentage change between the 2008 number and the average for the period 2005-2007 which was a period with a large increase in equity values compared to 2008. Looking first at the relative spread and `ILR`, we see that the absolute change (diff.) was the largest for the smallest firms. E.g. for the firms in group 1 the costs of trading was 2.5 percentage points (0.025) higher in 2008 compared to the average over the previous three years. This was an increase of 64 % in implicit transaction costs. Note also that the spread captures the cost of trading a small volume at the best quotes. Thus, for larger trades the implicit cost would be higher. We see a similar pattern for `ILR`. `ILR` reflects the average price movement caused by one NOK unit of trade. Since `ILR` is multiplied by 10^6 for scaling purposes, the numbers in the table would reflect the average percentage price movement (price impact) from a trade of 10000 NOK. Thus, for the smallest firms a trade of size 10000 NOK in 2008, would cause an average price impact of about 1 %. In comparison, the number was 0.04 %

Figure 3 Liquidity and activity of firm size groups during the crisis

The figures in part (a) shows the average relative spread (`RS`) and illiquidity ratio (`ILR`) for each size group for the years 2005 through 2008. Similarly, part (b) shows the average quarterly turnover and the number of trading days for each of the size groups for the the years 2005 through 2008.

(a) Liquidity



(b) Activity

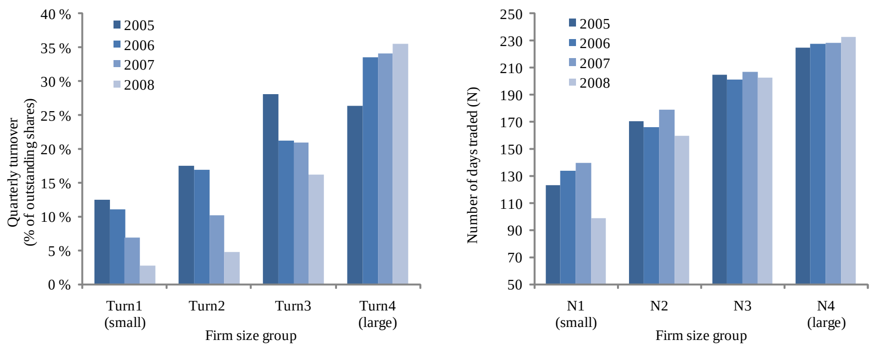


Table 3 Liquidity and activity for firm size groups (2005-2008)

Panel (a) and (b) of the table shows the average liquidity (measured by the relative spread and ILR) and the average activity (measured by average quarterly turnover and average number of trading days) for four firm size groups for the years 2007-2008. In the last two rows of each table we calculate the first difference and percentage change between 2008 and the average of the period 2005-2007.

Panel (a): Liquidity

	Relative spread				Illiquidity ratio (ILR)			
Year	RS1	RS2	RS3	RS4	ILR1	ILR2	ILR3	ILR4
2005	0.038	0.028	0.012	0.008	0.394	0.240	0.049	0.020
2006	0.039	0.030	0.015	0.007	0.405	0.300	0.054	0.018
2007	0.043	0.031	0.014	0.007	0.488	0.277	0.050	0.014
2008	0.065	0.054	0.022	0.009	1.080	0.697	0.166	0.044
diff.	0.025	0.024	0.008	0.002	0.65	0.42	0.12	0.03
%change	64 %	80 %	60 %	20 %	152 %	156 %	226 %	149 %

Panel (b): Activity

	Quarterly turnover				Trading days			
Year	Turn1	Turn2	Turn3	Turn4	N1	N2	N3	N4
2005	13 %	18 %	28 %	26 %	123	171	205	225
2006	11 %	17 %	21 %	34 %	134	166	202	228
2007	7 %	10 %	21 %	34 %	140	179	207	229
2008	3 %	5 %	16 %	36 %	99	160	203	232
diff.	-7 %	-10 %	-7 %	4 %	-33	-12	-2	5
%change	-73 %	-68 %	-31 %	14 %	-25 %	-7 %	-1 %	2 %

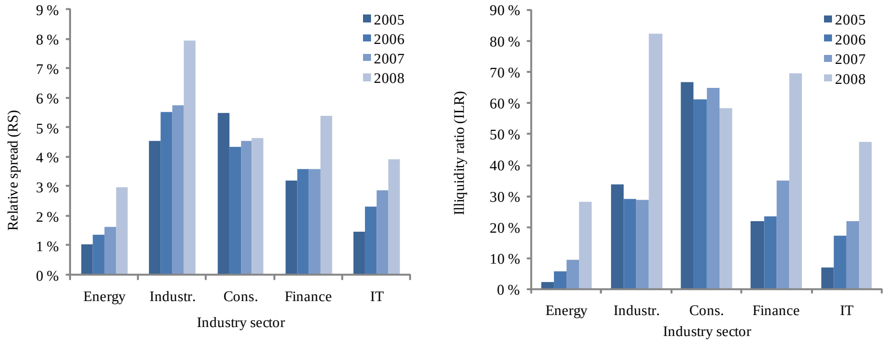
for the largest firms. The relative increase in ILR in 2008 relative to the three previous years was similar across size groups (around 150 %), except for group 3 there there was more than a doubling of ILR relative to previous years. This may be due to group 3 containing certain firms that were particularly affected by the crisis.

In Panel (b) of the table we see that the turnover declined for groups 1 to 3, while there was an increase of 14 % in turnover for the group containing the largest firms. This development is similar when looking at the number of trading days, where there was a decline in trading days of 25 % (33 days) for the smallest firms.

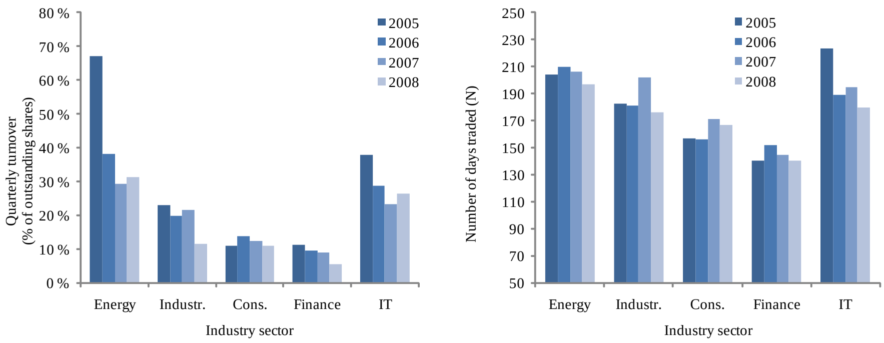
Figure 4 Liquidity and activity of industry groups during the crisis

The figures in part (a) shows the average relative spread (RS) and illiquidity ratio (ILR) for 6 different industry groups (GICS) for the years 2005 through 2008. Similarly, part (b) shows the average quarterly turnover and the number of trading days for each of the industry groups for the the years 2005 through 2008.

(a) Liquidity



(b) Activity



Are there differences in liquidity across industries?

In figure 4 and table 4 we do the same exercise for the industry portfolios as we did for the firm size groups. Looking first at the relative spread and ILR in part (a), we see that both liquidity measures increased for all groups except for Consumer goods. The sector with the largest change was the Energy sector. This is probably related to the large swings in oil prices during the crisis years. While we would expect the financial sector to see the largest changes in 2008, it does not stand out as being more affected than other sectors. In part (b) of figure 4 and table 4 we see that turnover and the number of trading days fell from 2007 to 2008 for the Industry, Consumer and Financial sector, while there was an increase in turnover for Energy and IT. Compared to the average turnover over the previous three years, we see in the last row in part (b) of table 4 that the turnover was lower in 2008 across all industries.

Table 4 Liquidity and activity for industry groups (2005-2008)

Panel (a) and (b) of the table shows the average liquidity (measured by the relative spread and `ILR`) and the average activity (measured by average quarterly turnover and average number of trading days) for the five major industry groups at the OSE for the years 2007-2008. In the last two rows of each table we calculate the difference and percentage change between 2008 and the average of the period 2005-2007.

Panel (a): Liquidity

	Relative spread					Illiquidity ratio (ILR)				
Year	Energy	Industr.	Cons.	Finance	IT	Energy	Industr.	Cons.	Finance	IT
2005	0.010	0.045	0.055	0.032	0.015	0.023	0.338	0.665	0.219	0.067
2006	0.014	0.055	0.044	0.036	0.023	0.057	0.291	0.611	0.234	0.170
2007	0.016	0.058	0.045	0.036	0.029	0.092	0.287	0.649	0.348	0.218
2008	0.030	0.080	0.047	0.054	0.039	0.281	0.821	0.584	0.693	0.473
diff.	0.016	0.027	-0.002	0.019	0.017	0.22	0.52	-0.06	0.43	0.32
%change	120 %	51 %	-3 %	56 %	77 %	388 %	169 %	-9 %	160 %	211 %

Panel (b): Activity

	Quarterly turnover					Trading days				
Year	Energy	Industr.	Cons.	Finance	IT	Energy	Industr.	Cons.	Finance	IT
2005	67 %	23 %	11 %	11 %	38 %	204	183	157	140	223
2006	38 %	20 %	14 %	9 %	29 %	210	182	156	152	189
2007	29 %	22 %	12 %	9 %	23 %	206	202	171	145	195
2008	31 %	11 %	11 %	6 %	26 %	197	176	167	140	180
diff.	-14 %	-10 %	-2 %	-4 %	-3 %	-9	-13	5	-5	-23
%change	-30 %	-47 %	-13 %	-44 %	-12 %	-5 %	-7 %	3 %	-3 %	-11 %

4 Predicting real economic variables with market liquidity

While the previous section looked at the development in liquidity during the current crisis, the results in Næs et al. [2009b] suggest that market liquidity is informative about future economic growth. Næs et al. mainly focus on the US market. It is interesting to see whether this result is unique to the US. In this section we will therefore explore the predictive ability of stock market liquidity for Norway.

4.1 In-sample evidence

We start by assessing the in-sample predictive ability of market liquidity for various macro variables for Norway. The models we examine are predictive regressions on the form,

$$y_{t+1} = \alpha + \beta \mathrm{LIQ}_t + \gamma' \mathbf{X}_t + u_{t+1} \tag{2}$$

where y_{t+1} is the growth in the macro variable over quarter t+1, LIQ_t is the market liquidity measured for quarter t, and $\mathbf{X}_t$ is a set of control variables observed at t.

We start by a very simple specification, with only market liquidity and the lagged dependent variable as predictors for next quarter macro variables. In table 5 we show the results from these predictive regressions. We see that regardless of choice of liquidity proxy, the coefficient on market liquidity (β) is highly significant across all models and have the expected signs. A worsening of market liquidity (increase in RS or ILR) predict a decrease in next quarter GDP, consumption, credit, investment and an increase in the unemployment rate. We have also examined models with different lags of the explanatory variables in addition to not including the lag of the dependent variable. The size and significance of the coefficient on RS and ILR is largely unaffected by these variations in model specification.

Before we move on to a multivariate setting where we control for additional financial predictor variables, we want to address the question of causation; i.e. does changes in economic conditions affect market liquidity? We know from earlier studies done for the US that monetary policy shocks have an effect on stock and bond market liquidity (see e.g. Söderberg [2008] and Goyenko and Ukhov [2009]) while there is no effect of shocks to real economic variables on stock market liquidity. On the other hand, neither of these studies examine the reverse causality of whether there is a causality running from liquidity to real economic variables. We therefore perform Granger causality tests between our two proxies for market liquidity and the different macro variables. In each case we choose the optimal number of lags based on the Schwartz Criterion. The results from these causality tests are shown in table 6.

In the first part of the table, labeled "RS", we run causality tests between macro variables and market liquidity measured by the relative spread (RS), and in the second part of the table labeled "ILR " we perform causality tests when using ILR as our liquidity proxy. Looking first at the causality tests for RS and the different macro variables labeled in the first column. The column labeled "H0" states the null hypothesis. The next two columns shows the χ^2 test statistic and the p-value respectively. Thus, in the first test we test the null that dGDP *does not*

Table 5 In-sample predictive regressions

The table shows the results from predictive regressions for different macro variables. The regressions estimated are $y_{t+1} = \alpha + \beta \mathtt{LIQ}_t + \gamma' \mathbf{X}_t + u_{t+1}$, where LIQ is either RS or ILR, and the only element in $\mathbf{X}$ is the lagged dependent variable. The first column shows the respective dependent variables in the different models. The Newey-West corrected t-statistics (with 4 lags) is reported in parentheses below the coefficient estimates.

Dependent variable (y_{t+1})	RS				ILR			
	$\hat{\alpha}$	$\hat{\beta}_{RS}$	$\hat{\gamma}_1$	$\bar{R}^2$	$\hat{\alpha}$	$\hat{\beta}_{ILR}$	$\hat{\gamma}_1$	$\bar{R}^2$
dGDPR	0.023	-0.397	-0.243	0.12	0.012	-0.006	-0.225	0.11
	(5.28)	(-4.03)	(-4.03)		(5.99)	(-3.04)	(-3.69)	
dUE	-0.443	11.387	-0.150	0.12	-0.108	0.141	-0.080	0.06
	(-3.94)	(3.95)	(-1.56)		(-2.16)	(2.49)	(-0.82)	
dCONS	0.016	-0.216	-0.153	0.03	0.011	-0.004	-0.142	0.04
	(3.75)	(-2.43)	(-1.62)		(5.85)	(-2.72)	(-1.49)	
dCRED	0.013	-0.215	0.755	0.78	0.006	-0.003	0.784	0.77
	(4.25)	(-3.50)	(15.90)		(4.13)	(-3.11)	(16.97)	
dINV	0.073	-1.686	-0.415	0.19	0.021	-0.018	-0.404	0.16
	(3.79)	(-4.01)	(0.19)		(2.23)	(-2.44)	(-4.94)	

Granger cause RS, which cannot be rejected. The reverse hypothesis that RS *do not* Granger cause dGDP is however rejected at the 1% significance level. We see that this is the case for all the macro variables. I.e. we cannot reject the null that any of the macro variable *do not* Granger cause RS, while the null hypothesis that RS causes the macro variable is rejected at the 1% level in most cases. For ILR, in the second part of the table, we find similar support for a one-way Granger causality from ILR to the different macro variables, except in the case for unemployment, where there is support for a two-way causality, and for growth in investments, where there no causality either way.

In summary, the result that we cannot find support for macrovariables causing market liquidity is in line with the results for the US discussed earlier. However, we find evidence of a strong one-way Granger causality from market liquidity to macroeconomic variables. These results are similar to the results found for the US in Næs et al. [2009b].

We conclude our in-sample analysis by adding a number of financial variables to the set of potential predictors. In the international literature, the most successful such predictors are the term premium, credit spread, and market returns. To examine whether such variables also predict economic growth in Norway, and whether liquidity contains additional information to these variables, we extend the models estimated in table 5 to also include three additional financial variables, the term spread, a measure of stock market excess return (Rm) and stock market market volatility ($Vola$).

In table 7 we present the results from predictive regressions when we add the financial

Table 6 Granger causality tests

The table shows a series of Granger causality tests between the two measures of market liquidity and different macro variables. The Newey-West corrected t-statistics (with 4 lags) is reported in parentheses below the coefficient estimates. *, ** and *** denote rejection of H0 at the ten, five and one percent significance level, respectively.

	RS			ILR		
	H0:	χ^2	p-value	H0:	χ^2	p-value
(a) dGDP	dGDP$\nrightarrow$ RS	2.58	0.11	dGDP$\nrightarrow$ ILR	2.52	0.11
	RS$\nrightarrow$ dGDP	14.64	0.00***	ILR$\nrightarrow$ dGDP	13.83	0.00***
(b) dUE	dUE$\nrightarrow$ RS	0.38	0.54	dUE$\nrightarrow$ ILR	4.23	0.04**
	RS$\nrightarrow$ dUE	17.14	0.00***	ILR$\nrightarrow$ dUE	9.58	0.00***
(c) dCRED	dCRED$\nrightarrow$ RS	0.40	0.53	dCRED$\nrightarrow$ ILR	2.70	0.10
	RS$\nrightarrow$ dCRED	10.51	0.00***	ILR$\nrightarrow$ dCRED	6.22	0.01***
(d) dCONS	dCONS$\nrightarrow$ RS	1.47	0.22	dCONS$\nrightarrow$ ILR	1.03	0.31
	RS$\nrightarrow$ dCONS	3.84	0.05**	ILR$\nrightarrow$ dCONS	5.05	0.02**
(e) dINV	dINV$\nrightarrow$ RS	0.47	0.49	dINV$\nrightarrow$ ILR	0.00	0.99
	RS$\nrightarrow$ dINV	8.46	0.00***	ILR$\nrightarrow$ dINV	3.17	0.07*

variables as predictors (in addition to the lagged dependent variable). Looking first at the results in Panel (a), we see that the coefficient on market liquidity (β) is highly significant for all models except for consumption growth where the coefficient becomes insignificant when adding the other financial variables. While none of the other financial variables have significant coefficients, it should also be noted that when we run the regressions without the relative spread included the term spread enters significantly into the models for dGDPR and dUE. However, the adjusted R-squared of the models are more than halved. Thus, although *Term* is highly correlated with our liquidity proxies, there seem to be a significant amount of additional information in liquidity.

4.2 Out-of-sample evidence

In the previous section we found that market (il)liquidity had predictive power for economic growth, for the whole sample period, for subperiods and when controlling for other financial variables that are found in the literature to be informative about future economic growth. However, in-sample predictability does not necessarily mean that the predictor is a useful predictor out-of-sample. In this section we examine whether market illiquidity would have been useful to forecast quarterly real GDP growth out of sample.

Methodology and timing of information

When setting up our out-of-sample procedure, we need to be careful about the timing of the data so it reflects what would have been available to a forecaster at every point in time. While

Table 7 In-sample predictive regressions - additional control variables

The table shows the results from predictive regressions for different macro variables. The regressions estimated are,

$$y_{t+1} = \alpha + \beta \mathrm{LIQ}_t + \gamma' \mathbf{X}_t + u_{t+1}. \quad (3)$$

where LIQ is either RS or ILR, and the variables in $\mathbf{X}$ is the lagged dependent variable in addition to the *Term*, *Vola* and R_m, with coefficient estimates γ_1 for the lagged dependent variable, γ_2 for the term spread, γ_3 for market volatility and γ_4 for the market return.

Panel (a) Relative spread (RS)

Dependent variable (y_{t+1})	α	β	γ_1	γ_2	γ_3	γ_4	$\bar{R}^2$
dGDPR	0.019	**-0.361**	-0.259	0.001	0.240	0.001	0.11
	(3.11)	**(-3.43)**	(-4.25)	(1.64)	(0.62)	(0.08)	
dUE	-0.358	**12.365**	-0.166	-0.007	-14.022	-0.183	0.11
	(-3.20)	**(3.05)**	(-1.39)	(-0.57)	(-1.00)	(-0.77)	
dCONS	0.018	-0.115	-0.127	0.000	-0.738	-0.010	0.03
	(2.83)	(-0.97)	(-1.33)	(0.22)	(-1.88)	(-1.20)	
dCRED	0.013	**-0.186**	0.765	0.000	-0.117	0.003	0.77
	(2.50)	**(-2.22)**	(15.55)	(-0.12)	(-0.54)	(0.41)	
dINV	0.052	**-1.325**	-0.418	0.003	0.547	0.044	0.18
	(1.56)	**(-2.66)**	(-5.03)	(0.93)	(0.24)	(0.73)	

Panel (b): Illiquidity ratio (ILR)

Dependent variable (y_{t+1})	α	β	γ_1	γ_2	γ_3	γ_4	$\bar{R}^2$
dGDPR	0.010	**-0.006**	-0.231	0.001	0.165	0.007	0.10
	(2.36)	**(-2.26)**	(-3.42)	(0.85)	(0.45)	(0.67)	
dUE	-0.012	**0.145**	-0.085	-0.007	-10.323	-0.335	0.05
	(-0.14)	**(2.22)**	(-0.78)	(-0.45)	(-1.01)	(-1.39)	
dCONS	0.016	-0.003	-0.128	0.000	-0.732	-0.007	0.04
	(3.71)	(-1.68)	(-1.32)	(-0.02)	(-1.85)	(-0.92)	
dCRED	0.006	**-0.003**	0.789	0.000	-0.096	0.006	0.77
	(2.47)	**(-1.98)**	(16.39)	(-0.27)	(-0.40)	(0.98)	
dINV	0.011	-0.009	-0.404	0.004	-0.071	0.057	0.16
	(0.50)	(-0.80)	(-4.96)	(1.06)	(-0.03)	(0.88)	

the illiquidity variables and the other financial variables are observable in real-time without revisions, real GDP growth is not. First, there is a publication lag of one quarter for GDP.[10] Secondly, there is an issue of later revisions in most macro variables. While the publication lag is easily accounted for, the revisions are more tricky. Basically, the question is whether we want to forecast the first or final vintage of GDP growth. This depends on the question we are asking. If we were using macro variables to predict financial variables (e.g. returns), we would want to use the first vintage (real time version) of the macro variable since the later vintages (revised figures) would not be known to the forecaster (investor) when making his forecast. However, since the question we are asking is whether financial variables contain information about expected economic growth, we want to forecast the last vintage. The argument for this is that since the revisions mainly are due to measurement errors in the first/early vintage series, market participants expectations about the underlying economic growth should be unrelated to ("see through") the measurement errors in the first vintages. Thus, we want to forecast the most precisely measured version of the macro variable, i.e. the most recent vintage series.[11]

In our out-of-sample analysis we consider both a *rolling* and *recursive* estimation scheme. In both cases we start out with a window of 56 quarters (14 years). The width of the window is chosen simply by splitting the sample period in the middle. Thus, our first out-of-sample forecast is made in the end of the first quarter of 1994 for GDP growth for the second quarter of 1994. At the end of the first quarter of 1994, we estimate each model using data from the first quarter of 1980 through the fourth quarter of 1993 (which is the most recent GDP observation available to us at the end of the first quarter of 1994). We then produce a forecast of real GDP growth for the second quarter of 1994 based on the estimated model coefficients and the most recent observation of the predictor variable. In the case when the predictor variable is market liquidity or any of the other financial variables, these are observed for the same quarter as we construct our forecast for the next quarter. Then, in the *rolling* scheme, we move the window forward by one quarter, re-estimate the models, and produce a new forecast for the next quarter, and so on. In the *recursive* scheme we add one quarter to the window, re-estimate and produce a forecast. The last forecast is made at the fourth quarter of 2008 for GDP growth for the first quarter of 2009.

Evaluating out-of-sample forecast performance of market liquidity

We want to evaluate the out-of-sample predictive ability of market liquidity against several baseline models. We assess the out-of-sample performance of liquidity against two types of baseline models. The first type of baseline model is an autoregressive model for GDP growth. The autoregressive GDP model is the restricted (nested) version of a larger model where we include both lagged GDP growth and liquidity as predictor variables. The second type of baseline models include the different financial control variables as predictors. In that case, each of these models are then restricted (nested) versions of a larger model where GDP growth is

[10]Statistics Norway (SSB) releases the *final* GDP figure for quarter t-1 in the last month of the following quarter (t). Thus, at the end of t, a forecaster have the "final" number available for t-1 GDP growth.

[11]Another issue is that first vintage data for Norway is not available before the beginning/mid 1990s.

regressed on the control variables in addition to the liquidity variable (`RS` or `ILR`).

We evaluate the forecast performance using two test statistics. The first test is an encompassing test (ENC-NEW) proposed by Clark and McCracken [2001]. The ENC-NEW test asks whether the restricted model (the model that do not include liquidity), encompasses the unrestricted model (which includes liquidity). If the restricted model *does not* encompass the unrestricted model, that means that the additional predictor (`RS` or `ILR`) in the larger, unrestricted, model improves forecast accuracy relative to the baseline model. Clark and McCracken [2001] shows that the ENC-NEW test has greater power than tests for equality of MSE. The ENC-NEW test statistic is specified as

$$\text{ENC-NEW} = (P - h + 1) \cdot \frac{P^{-1} \sum_t \left[\varepsilon_{r,t+1}^2 - \varepsilon_{r,t+1} \cdot \varepsilon_{u,t+1}\right]}{MSE_u}, \tag{4}$$

where P is the number of out-of-sample forecasts, $\varepsilon_{r,t+1}$ denotes the out-of-sample forecast errors from the restricted (baseline) model that excludes the liquidity variable, and $\varepsilon_{u,t+1}$ is the out-of-sample forecast errors from the unrestricted model that includes liquidity, and MSE_u denotes the mean squared error of the unrestricted model that includes liquidity.

The second test statistic we examine is an F-type test for equal MSE between two nested models proposed by McCracken [2007] termed MSE-F. This test is specified by

$$\text{MSE-F} = (P - h + 1) \cdot \frac{MSE_r - MSE_u}{MSE_u}, \tag{5}$$

where MSE_r is the mean squared forecast error from the restricted model that excludes liquidity, and MSR_u is the mean squared forecast error of the unrestricted model that includes liquidity. Both the ENC-NEW and MSE-F statistics are non standard, so we use the bootstrapped critical values provided by Clark and McCracken [2001].[12]

Market liquidity compared to an autoregressive model for GDP growth

First, we examine whether market liquidity can improve the forecast accuracy of an autoregressive model for GDP growth. We consider an AR(1) model for quarterly GDP growth based on tests for optimal lag length.[13]

When we compare the liquidity model to a benchmark model where we forecast GDP growth with it's own lag, it is important to be careful about what information would have been available to a forecaster at every point in time due to the publication lag of one quarter. Thus, the most recent observation of GDP available to a forecaster at the end of the first quarter of 1994 is GDP for the fourth quarter of 1993. Thus, for the first forecast, we estimate the autoregressive model for GDP growth with data from first quarter of 1980 up to and including the fourth quarter of 1993, and then construct a forecast for the second quarter of 1994 based on the

[12] The bootstrapped critical values are available at
`http:\\www.kansascityfed.org\Econres\addfiles\criticalvalues_tec.xls`

[13] As additional justification for sticking to just one lag we find that regardless of the number of AR terms, only the first lag is significant during our sample.

estimated coefficients and the most recent GDP observation available, which is the final figure for GDP growth for the fourth quarter of 1993. The difference to the case when we forecast using financial variables, is that we would observe the financial variables up to the time when we construct our forecast, which in this case would be at the end of the first quarter of 1994. However, we would still be limited to estimating the model up to the fourth quarter of 1993, since that is the last GDP observation we have.

In table 8 we compare a restricted autoregressive model for GDP growth to several unrestricted models where the model also includes a proxy for market liquidity in addition to the autoregressive term for GDP growth. In part (a) of the table we estimate the models in a recursive (expanding window) scheme, and in part (b) we use a rolling (fixed window) scheme. In both cases we estimate the models using the first half of the sample (56 quarters), and then forecast GDP growth one quarter ahead re-estimating the models for each quarter. Looking first at part (a) we see that a model with either relative spread (RS), the relative spread for the 25% smallest firms ($\texttt{RS}^{S}$), the Amihud Illiquidity ratio (ILR) and the small firm version of ILR ($\texttt{ILR}^{S}$), has lower MSE than a model with only lagged GDP growth as the predictor. Furthermore, we see that the relative MSE is the smallest for a model including RS. For all four liquidity variables, the MSE-F test rejects the null of equal MSE's. The ENC-NEW encompassing test also strongly suggests that market liquidity contains additional information about next quarter GDP growth compared to only its own lag. In part (b) of the table, where we use a rolling estimation window, we see that all the models that include liquidity improve the forecast accuracy over their restricted counterparts. Interestingly, the RS of the smallest firms provide the greatest improvement in forecast accuracy.

Table 8 Out-of-sample comparison - liquidity versus an autoregressive GDP model

The table compares the out-of-sample forecast performance for quarterly GDP growth of a restricted model with lagged GDP growth as the only predictor variable against an unrestricted model where market liquidity is included in the model. Part (a) uses a recursive estimation scheme, and part (b) uses a rolling estimation scheme. The first and second columns denotes the variables included in the unrestricted and restricted model, respectively. The third column report the relative MSE between the unrestricted and restricted models. The fourth column report the MSE-F test statistic and the last column report the ENC-NEW statistic. For the MSE-F test, *, ** and *** denote a rejection of equality of mean squared errors (MSE) between the unrestricted (MSE_u) and restricted (MSE_r) model, at the ten, five and one percent significance level, respectively, in favor of the one-sided alternative that the unrestricted model has lower MSE. For the ENC-NEW test the stars denote the significance level of rejection that the restricted model encompass the unrestricted model. Rejection of the null is in favor of the alternative that market liquidity improves the accuracy of the restricted model.

(a) Recursive estimation scheme

Unrestricted model	Restricted model	$\frac{MSE_u}{MSE_r}$	MSE-F	ENC-NEW
RS, dGDP	dGDP	0.8881	7.43***	4.75***
RS^S, dGDP	dGDP	0.9042	6.25***	3.99***
ILR, dGDP	dGDP	0.9382	3.89***	2.38**
ILR^S, dGDP	dGDP	0.9273	4.62***	2.90**

(b) Rolling estimation scheme

Unrestricted model	Restricted model	$\frac{MSE_u}{MSE_r}$	MSE-F	ENC-NEW
RS, dGDP	dGDP	0.9102	5.82***	4.51***
RS^S, dGDP	dGDP	0.8955	6.88***	5.30***
ILR^S, dGDP	dGDP	0.9578	2.60**	1.53*
ILR, dGDP	dGDP	0.9663	2.06**	1.24*

Market liquidity compared to models with other financial variables

Next, we compare restricted models with the different control variables used in the in-sample analysis (*Term*, *Vola* and $\mathsf{R_m}$), to unrestricted models that also includes market liquidity. Table 9 summarize the results from these model comparisons. Looking first at the recursive setup in part (a), we see that when comparing a restricted model with only `ILR` to a model that adds `RS`, inclusion of `RS` significantly improves the forecast accuracy. This is consistent with the results in table 8 where we found that `RS` had lower MSE than a model with `ILR`. The next three model comparisons examine prediction models with the term structure (*Term*), market return ($\mathsf{R_m}$) and market volatility (*Vola*), and compare them to unrestricted models where `RS` is added to the model. In all cases we find strong evidence that `RS` improves forecast accuracy. When using `ILR` as our liquidity proxy, we see that it does not improve a forecast model that only includes *Term*. One important reason for this is probably the high correlation (-0.7) between `ILR` and *Term*, indicating that both variables to a large degree contains similar information. However, `ILR` still improve forecast accuracy relative to $\mathsf{R_m}$ and *Vola*. When we use a rolling scheme in part (b), we find much weaker evidence that market liquidity improves forecast accuracy relative to other financial variables. However, the ENC-NEW tests still suggest that the models including `RS` improves the restricted models at the 1% level.

Table 9 Out-of-sample comparison - liquidity versus other financial variables

The table compares the out-of-sample forecast performance for quarterly GDP growth between a restricted model with a financial variable as the only predictor variable against an unrestricted model where market liquidity is included in the model. Part (a) uses a recursive estimation scheme, and part (b) uses a rolling estimation scheme. The first and second columns denotes the variables included in the unrestricted and restricted model, respectively. The third column report the relative MSE between the unrestricted and restricted models. The fourth column report the MSE-F test statistic and the last column report the ENC-NEW statistic. For the MSE-F test, *, ** and *** denote a rejection of equality of mean squared errors (MSE) between the unrestricted ($\mathrm{MSE_u}$) and restricted ($\mathrm{MSE_r}$) model, at the ten, five and one percent significance level, respectively, in favor of the one-sided alternative that the unrestricted model has lower MSE than the restricted model. For the ENC-NEW test the stars denote the significance level of rejection that the restricted model encompass the unrestricted model. Rejection of the null is in favor of the alternative that market liquidity improves the accuracy of the restricted model.

(a) Recursive estimation scheme

Unrestricted model	Restricted model	$\frac{\mathrm{MSE_u}}{\mathrm{MSE_r}}$	MSE-F	ENC-NEW
RS, ILR	ILR	0.969	1.861**	1.200**
RS, Term	Term	0.974	1.590**	1.003*
RS, Rm	Rm	0.963	2.243**	1.427*
RS, Vola	Vola	0.946	3.351**	2.087**
ILR, Term	Term	1.004	-0.246	-0.062
ILR, Rm	Rm	0.967	2.015**	1.249**
ILR, Vola	Vola	0.979	1.245*	0.825

(b) Rolling estimation scheme

Unrestricted model	Restricted model	$\frac{\mathrm{MSE_u}}{\mathrm{MSE_r}}$	MSE-F	ENC-NEW
RS, ILR	ILR	0.969	1.914**	2.880**
RS, Term	Term	0.991	0.541	1.536*
RS, Rm	Rm	0.997	0.206	0.459*
RS, Vola	Vola	0.952	3.001**	3.575**
ILR, Term	Term	1.041	-2.334	-1.011
ILR, Rm	Rm	1.005	-0.281	-0.061
ILR, Vola	Vola	1.009	-0.517	-0.143

5 Summary

In this study we have examined the information content of equity market liquidity. We first looked at the development of market liquidity during the recent financial crisis. The results show that both the implicit transaction costs (relative spread) and price impact (Amihud illiquidity ratio) increased markedly at the Oslo Stock Exchange (OSE), especially during 2008. Similarly does turnover show a reduction in trading activity. When splitting OSE firms into size groups, we find more cross-sectional variation in liquidity and activity. First, we find that the liquidity worsened more for smaller firms at the exchange, although firms in all firm sizes experienced a decrease in liquidity. When looking at the activity measures turnover and number of trading days, we find that all firm size groups, except the 25% largest firms, experienced a decline in trading activity. Furthermore, the decline in liquidity and activity for the smallest firms is evident already in 2007. This suggest a "flight to quality/liquidity" during 2007/2008, where investors move out of small, less liquid and potentially more risky firms. The increased activity in large firms is consistent with anecdotical evidence that investors were liquidating positions in the largest and most liquid stocks. This because these stocks were the cheapest and easiest to liquidate, while positions in the smaller firms would have been very expensive to liquidate.

We also split the OSE firms into industry portfolios. All industry sectors, except the consumer goods sector, experienced a large increase in spreads and price impact in 2008. We do not find any evidence for financial stocks being more affected by the crisis than the other sectors. With respect to the activity of the different sectors, we find that the turnover of firms within the Energy and IT sector increased, while the turnover of firms in the Industy, Consumer goods and Financial sector declined. For all sectors we find that the average number of trading days fell in 2008.

In the second part of the study we examined whether market liquidity contain information about macro variables. This analysis is motivated by findings in Næs et al. [2009b], where they find that market liquidity predict US GDP growth for the period 1947 to 2008, both in-sample and out-of-sample. They conjecture that the common time variation in market liquidity across stocks is related to portfolio rebalancing caused by changing risk preferences and/or expectations about future investment opportunities. While there may be other explanations for the result, a "flight to liquidity/quality" explanation is most consistent with the literature that show that investors actions, represented by market-wide order-flow or risk premia, predict real variables as investors alter their portfolios.

We perform both in-sample and out-of-sample evaluations of market liquidity as a predictor of different macro aggregates. Overall, our results and conclusions are similar as those for the US, although the out-of-sample results are weaker. Market liquidity is found to be a strong predictor of quarterly economic growth. Furthermore, we find support for a strong one-way causality from liquidity to the macro variables. To evaluate whether liquidity would have been of practical use for forecasting, we evaluate different forecasting models for quarterly GDP growth. Compared to an autoregressive model for GDP growth, we find that market liquidity significantly improves forecast accuracy when added to the model. We also test whether market liquidity is encompassed by models that use other financial variables as predictors. The overall result is that the relative spread contains additional information about GDP growth relative to what is already reflected in the term spread and market returns (market volatility). However, when proxying market liquidity by price impact (ILR) we find that the term spread encompass ILR. The main reason for this is the strong correlation between the term spread and ILR.

To summarize, the results in this study indicate that market liquidity is informative about the current and the future economic growth. For the purpose of financial stability monitoring, it may prove as a useful additional leading indicator to capture financial stress or changing views on the economy in real time.

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