Liquidity and the Business Cycle*

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Abstract

We document a strong relation between stock market liquidity and the business cycle. Stock market liquidity worsens when the economy is slowing down, and this effect is most pronounced for small firms. Using data for both the US and Norway, we show that stock market liquidity predicts the current and future state of the economy both in- and out-of-sample. We also show some evidence that can shed light on the link between stock markets and the real economy. Using stock ownership data from Norway, we find that the portfolio compositions of investors change with the business cycle, and that investor participation is correlated with market liquidity, especially for the smallest firms. This suggest a "flight to quality" during economic downturns where traders desire to move away from equity investments in general, and within their equity portfolios, move from smaller/less liquid stocks to large/liquid stocks. Overall, our results provide an new explanation for the observed commonality in liquidity.

Keywords: Market Microstructure, Liquidity, Business Cycles

JEL Codes: G10, G20

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Introduction

In the discussion the current financial crisis much is made of the apparent causal effects from a decline in the liquidity of financial assets to the crisis of the economy. In this paper we show that such effects are not new, changes in the liquidity of the US stock market has been coinciding with changes in the real economy at least since the second world war. Stock market liquidity is in fact a very good "leading indicator" of the real economy. Using data for the US in the period 1947 to 2008, we show that measures of stock market liquidity contains information about the real economy in addition to other financial variables such as stock returns and stock volatility.

We also look at potential causes of our results. We speculate that the observed effects can be explained as resulting from aggregate portfolio shifts from individual investors, where changes in the desired portfolios are driven by changes in individuals expectations of the real economy. We empirically show some evidence consistent with this hypothesis. First, looking at data for the US, we show that the informativeness of stock market liquidity for the real economy differs across stocks. In particular, the most informative stocks are those of small firms, which are the least liquid, are most informative.

Second, we use data from Norway, where we have extremely detailed information about the composition of ownership of the whole stock market. In the Norwegian data we first confirm the informativeness of liquidity for real economic variables, before we show that changes in liquidity coincide with changes in portfolio compositions of investors of the hypothesized type. Before economic recessions we observe a "flight to liquidity", where some investors leave the stock market altogether, and others shift their stock portfolios into more liquid stocks.

There is a large literature on forecasting economic growth using different asset prices including interest rates, term spreads, stock returns and exchange rates. The forward-looking nature of asset markets makes the use of these prices as predictors of the real economy intuitive. If a stock price equals the expected discounted value of future earnings, it seems natural that it should contain information about future earnings growth. Theoretically, a link between asset prices and the real economy can be established from a consumption smoothing argument. If investors are willing to pay more for an asset that pays off when the economy is thought to be in a bad state than an asset that pays off when the economy is thought to be in a good state, then current asset prices should contain information about investors' expectations about the future real economy. In their survey article, Stock and Watson [2003] conclude, however, that there is considerable instability in the predictive power of asset prices and that the predictive content of asset prices thus seem to have a strong situational dependence.

We shift focus to a different aspect of asset markets; namely the costs of trading stocks. It is a common observation that stock market liquidity tends to dry up during economic downturns, however, we show that the relationship between trading costs and the real economy is much more pervasive than previously thought.

A link from trading costs to the real economy is not as intuitive as the link from asset prices. The most likely explanation is that time varying aggregate liquidity in some way 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. The trades could also reflect time variation in investor's risk aversion. Intuitively, if investors hold stocks as hedges of consumption risk, and these hedging properties varies across stocks, the desired portfolio compositions of individual investors will change with people's expectations of the economy. A well known example of such portfolio changes is the idea of a "flight to liquidity," people moving out of less liquid investments in economic downturns, see for instance Longstaff [2004]. As long as expectations about the economy are not biased on average, changes in liquidity steaming from portfolio shifts in one direction should have predictive content.

If investors move away from equity in general, and small/illiquid stocks in particular, when they expect an economic downturn, we should observe a relationship between time variation in liquidity and market participation, i.e. liquidity should worsen when the number of participants in the market falls and vice versa. The correlations found between liquidity and market participation using a special data set on investor ownership from the Norwegian stock market do support this hypothesis.

Two recent papers on the relationship between equity order flow and macro fundamentals are closely related to our work. Beber et al. [2008] examine the information in order flow movements across equity sectors over the period 1993-2005 and find that an order flow portfolio based on cross-sector movements predicts the state of the economy up to three months ahead. They also find that the cross section of order flow across sectors contains information about future returns in the stock and bond markets. Kaul and Kayacetin [2009] study two measures of aggregate stock market order flow over the period 1988-2004 and find that they both predict future growth rates for industrial production and real GDP.

The common theme is that the trading process in stock markets contains leading information about the economy. Our results are by far the most robust ones as they are based on a sample period that spans over 60 years and cover 10 recessions. The two order flow papers also finds some evidence that order flow contains information about future asset price changes. Kaul and Kayacetin [2009] and Evans and Lyons [2008] argue that the extra information contained in order flow data can be explained by aggregate order flows bringing together dispersed information from heterogeneously informed investors. Another explanation for why liquidity seems to be a better predictor than stock price changes is that stock prices contain a more complex mix of information that makes the signals from stock returns more blurred (Harvey [1989]).

Fujimoto [2003] and Söderberg [2008] examine the relationship between liquidity and macro fundamentals. However, they both investigate whether time varying stock market liquidity has macroeconomic sources. They do not consider the possibility that the causality goes the other way around. Gibson and Mougeot [2004] find some evidence that a time varying liquidity risk premium in the US stock market is related to a recession index over the 1973-1997 period.

Our paper contributes the literature on liquidity as well as the literature on forecasting macro fundamentals. Commonality in liquidity is a well known empirical observation, however, we do not fully understand why this phenomenon is observed. Attempts to explain commonality have

been either linked to the standard microstructure concepts of private information and inventory costs (Huberman and Halka [2001], Fujimoto [2003]) or based on specific assumptions about liquidity providers (Brunnermeier and Pedersen [2009]) or investors (Vayanos [2004]). The problem with market microstructure models in this setting is that they typically treat liquidity as a fixed property of individual assets. It is therefore not obvious that these models can explain time variation in aggregate liquidity. In the Brunnermeier and Pedersen [2009] model, commonality in liquidity is explained by liquidity providers who face funding constraints. A problem with the model is that it cannot easily explain time varying liquidity in electronic limit order markets without designated dealers (as e.g. the Norwegian stock exchange). Even though one cannot rule out that limit order traders are also funding constrained in some ways during economic downturns, it is hard to believe that these constraints should affect all stocks in the way prescribed in the model. In the Vayanos [2004] model, investors are assumed to be fund managers, i.e. they receive fees depending on the wealth under management and face a risk of investor withdrawals. Again this is not a credible description of the trading process in real stock markets.

Our finding that time varying liquidity has a clear business cycle component is new and quite intriguing. It suggests that pricing of liquidity risk cannot be explained solely by uninformed investors who require a premium for ending up with the stock that the informed investors sell, as suggested in O'Hara [2003]. Hence, the traditional arguments for why market microstructure matter for asset returns might be too narrow.

By showing that microstructure liquidity measures are relevant for macroeconomic analysis our paper also enhances our understanding of the mechanism by which asset markets are linked to the macro economy. We show that the predictive power of liquidity holds up to the power of existing asset price predictors. Given the documented instability in the predictive power of asset prices, an incremental indicator that might react earlier or in some way differently to shocks in the economy might prove useful.

The rest of the paper is structured as follows. We first, in section 1, discuss possible empirical measures of asset liquidity. We define the measures we use, discuss the data sources, and give some summary statistics. Next, in section 2 we document that liquidity is related to the real economy using data for the US in the period 1947-2008. In the next section we look closer at the causes of this predictability by splitting stocks by size, and showing that the main source of the predictability is small, relatively illiquid stocks. In section 4 we use Norwegian data to do two things. First we confirm the US results, that stock market liquidity contains information about the macro economy. We go on to show some evidence of the causes of time variation in aggregate liquidity, by linking changes in liquidity to changes in the portfolio composition of all investors at the Oslo Stock Exchange. We construct several measures of changes in the portfolio composition of investors, and show that periods when liquidity worsen are the same as periods when there is a "flight to liquidity" in the stock portfolios of owners. Finally, section 5 offers some concluding remarks.

1 Liquidity measures and data

In this section we describe the chosen liquidity measures, discuss our data sources, and show some descriptive statistics.

1.1 Liquidity measures

Given that there are numerous theoretical definitions of liquidity, it should come as no surprise that there are many different empirical measures used to capture liquidity. Since our focus is on the link between liquidity and the real economy, we are agnostic about this. We use a number of common measures and show that the relevant links are relatively independent of which liquidity measures we employ. Our choices of liquidity measures are driven by our desire for reasonably long time series. Many liquidity measures require intra-day information on trades and orders to be calculated, which is not available for the long time period considered in this paper. We therefore employ measures that can be calculated using data available at the daily frequency. We consider the following four liquidity measures: Spread, the Lesmond et al. [1999] measure (LOT), the Amihud [2002] illiquidity ratio (ILR) and the Roll [1984] implicit spread estimator. These liquidity proxies are found in Goyenko and Ukhov [2009] and Goyenko, Holden, and Trzcinka [2009] to do well in capturing the spread cost (Spread, LOT and Roll measures) and price impact (ILR). Note that all the liquidity measures we employ in this study are measuring illiquidity. Thus, when the measures have a high value, market liquidity is low. So, when we state liquidity has improved, the liquidity measures have decreased in value.

Spread costs are observed in dealer markets as well as in limit order markets. The bid/ask spread is the difference between the lowest price sellers are willing to sell a certain volume of a stock (ask) and the highest price that buyers are willing to pay for it (bid). There are several empirical 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 measures the implicit cost of trading a small number of shares as a fraction of the price. In other words, it measures what fraction of the price needs to be paid to "cross" from the bid to the ask price, or vice versa.

Lesmond et al. [1999] suggest a measure of transaction costs (hereafter the LOT measure) that does not depend on information about quotes or the order book. Instead, the LOT measure is calculated from daily returns. It uses the frequency of zero returns to estimate an implicit trading cost. The LOT cost is an estimate of the implicit cost required for a stock's price *not* to move when the market as a whole moves. To get the intuition of this measure, consider a simple market model,

$$R_{it} = a_i + b_i R_{mt} + \varepsilon_{it} \tag{1}$$

where R_{it} is the return on security i at time t, R_{mt} is the market return at time t, b is a regression coefficients, a is a constant term, and ε is an error term. In this model, for *any*

change in the market return, the return of security i should move according to (1). If it does not, it could be that the price movement that *should* have happened is not large enough to cover the costs of trading. Lesmond et al. [1999] estimate how wide the transaction cost band around the current stock price has to be to explain the occurrence of no price movements (zero returns). The wider this band, the less liquid the security. Lesmond et al. shows that their LOT measure is closely related to the bid/ask spread.

We also employ as a liquidity measure the Roll [1984] estimate of the implicit spread. This spread estimator, also called the effective bid/ask spread, is measured from the serial covariance of successive price movements. Roll shows that assuming the existence of a constant effective spread s, this can be estimated as $\widehat{s} = \sqrt{-Scov}$ where $Scov$ is the first-order serial covariance of successive returns.[1] We calculate the Roll estimator based on daily returns.

Our final liquidity measure, Amihud [2002]'s ILR 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. Thus, cost measures and elasticity measures are strongly 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. The daily Amihud measure is calculated as,

$$ILR_{i,T} = 1/D_T \sum_{t=1}^{T} \frac{|R_{i,t}|}{VOL_{i,t}} \tag{2}$$

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 $VOL_{i,t}$ is the trading volume (in units of currency) on day t. 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, ILR captures how much the price moves for each volume unit of trades.

1.2 Liquidity data

To calculate the liquidity measures we use data on stock prices, returns, and trading volume. For the US, the data source is CRSP, and the sample we are looking at covers the period 1947 through 2008. To keep the sample as homogeneous as possible through the entire period, we restrict the analysis to stocks listed at the New York Stock Exchange (NYSE).[2] For Norway we have similar data to the CRSP data. These data are obtained from the Oslo Stock Exchange data service.[3] The Norwegian sample covers the period 1980-2008. For both the US and Norway

[1] This estimator is only defined when $Scov < 0$. Harris [1990] suggests defining

$$\widehat{s} = -2\sqrt{Scov} \text{ if } Scov > 0,$$

but this would lead to an assumed *negative* implicit spread. A negative transaction cost for equity trading is not meaningful. We therefore only use the Roll estimator for stocks with $Scov < 0$, and leave the others as undefined.

[2] We only look at ordinary common shares, and remove securities with exchange codes -2 (trade halt), -1 (suspended), 0 (not listed), 4 (NYSE Arca) and 31-34 (when issued trading at the NYSE, AMEX, NASDAQ and NYSE Arca respectively).

[3] 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. [2008], 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.

sample, we calculate the different liquidity measures each quarter for each security, and then take averages across securities. In table 1 below we give a number of descriptive statistics for the series of liquidity measures. Note that for the US, we do not have complete data for bid/ask spreads, and will therefore have to leave these out in our time series analysis of the US.[4]

Table 1 Describing liquidity measures

We describe the liquidity measures used. Panels A and B gives descriptive statistics for respectively the US and Norway. The liquidity measures are calculated for each available stock once each quarter. In the tables we first list the average and median of the liquidity measures. We then list the number of different securities that have been used, and the total number of observations (Each security is observed in several quarters). We then show estimates of average liquidity measures for different subperiods. The liquidity proxies examined are the relative bid-ask spread (RS), the Lesmond et al. [1999] measure (LOT), the Amihud [2002] illiquidity ratio (ILR) and the Roll [1984] implicit spread estimator (Roll). The US sample covers the period from 1947 through 2008. Note that the Relative Spread is not universally available, the CRSP data only include full data on spreads starting in 1980, but there are some observations earlier. The Norwegian sample covers the period from 1980 through 2008. In panels C and D we shows the correspoding correlations between liquidity measures for the US and Norway. Note that the correlations are correlations across all stocks and times, ie the liquidity measures are calculated for each available stock once each quarter, and the correlations are pairwise correlations between these liquidity measures. In each pairwise correlation we use quarters when we observe both of those two liquidity measures, we do not require that all three liquidity measures be present to use that observation.

Panel A: Describing liquidity measures, US

Liquidity					Means subperiods					
measure	mean	median	no secs	no obs	1947-59	1960-69	1970-79	1980-89	1990-99	2000-08
RS	0.021	0.014	4248	146262	0.021	0.019		0.020	0.027	0.016
LOT	0.035	0.022	5177	340076	0.027	0.031	0.051	0.037	0.040	0.027
ILR	0.657	0.056	5178	340668	1.900	0.818	0.829	0.294	0.366	0.176
Roll	0.017	0.013	5141	174326	0.012	0.013	0.015	0.015	0.017	0.018

Panel B: Describing liquidity measures, Norway

Liquidity					Means subperiods		
measure	mean	median	no secs	no obs	1980-1989	1990-1999	2000-2008
RS	0.042	0.029	788	14942	0.041	0.046	0.040
LOT	0.054	0.039	753	14852	0.055	0.064	0.049
ILR	0.772	0.205	770	15092	1.149	0.875	0.452
Roll	0.027	0.021	663	7209	0.027	0.026	0.026

Panel C: Correlations between liquidity measures, US

	RS	LOT	Roll
LOT	0.72		
Roll	0.40	0.62	
ILR	0.41	0.38	0.32

Panel D: Correlations between liquidity measures, Norway

	RS	LOT	Roll
LOT	0.64		
Roll	0.65	0.51	
ILR	0.40	0.34	0.49

Looking first at the descriptive statistics for the US in panel A of table 1 we see that the average relative spread for the full sample period was 2.1% of the price, while the relative spread of the median firm was 1.4%. Looking at the sub-period statistics we see that there has been

[4]This is due to these not being present in the CRSP data for the whole period. They have been backfilled for the early period, but in the fifties throught the seventies there is essentially no spread data in the CRSP series.

some changes over time across all liquidity measures. Panel C shows the correlations between the liquidity proxies for the US. We see that all the liquidity measures are positively correlated. The lowest correlation is between ILR and Roll, but this is still as high as 0.32.

Panel B of table 1 shows the descriptive statistics for the Norwegian sample covering the period 1980-2008. The liquidity of the Norwegian market has improved over the sample, but has also varied across sub periods. From Panel D we see that all the liquidity proxies are strongly positively correlated also for Norway. Overall, the high correlations between these measures are supportive that they contain some of the same information.

1.3 Macro data

To proxy for the state of the real economy we use real GDP (GDPR), unemployment rate (UE), real consumption (CONS) and real investment (INV).[5] We also use a number of financial variables which are shown in the literature to contain leading information about economic growth. Two variables directly from the equity market is *Excess market return (Rm)*, calculated as the value weighted return on the S&P500 index in excess of the 3 month T-bill rate, and a proxy for equity *Market volatility (Vola)*, measured as the cross sectional average volatility of the sample stocks. Additionally, as non-equity control variables we use the *term spread (Term)*, calculated as the difference between the yield on a 10-year Treasury bond benchmark and the yield on the 3 month t-bill, and the *credit spread (Cred)* measured as the yield difference between the Moody's Baa credit benchmark and the yield on a 30 year government bond benchmark. The Moody's long term corporate bond yield benchmark consists of seasoned corporate bonds with maturities as close as possible to 30 years.[6] For Norway we use similar macro series to the US.[7] In the analysis we will work with differenced versions of the macro variables.[8]

1.4 Norwegian ownership data

An important reason for including Norwegian data in the paper is that we can use data on in stock market ownership for all investors at the Oslo Stock Exchange, to investigate aggregate patterns in stock ownership. We can for example look at changes in participation in total, see how different types of owners shift their portfolios, look at ownership concentration, and so on.

Our data on stock ownership is from the centralized records on stock ownership in Norway. All ownership of stocks at the Oslo Stock Exchange is registered in a single, government-

[5]The GDP series is the Real Gross Domestic Product, UE is the Unemployment rate for fulltime workers, CONSR is real Personal Consumption Expenditures, and INV is real Private Fixed Envestments. All series are seasonally adjusted. GDP and INV are from the Federal Reserve Bank of St Luis, UE is from the US Bureau of Labor Statistics, and CONSR from the US Dept of Commerce.

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

[7]GDP is the real Gross Domestic Product for Mainland Norway (excluding oil production). UE is the Unemployment Rate (AKU), 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).

[8]dGDPR is the real GDP growth, calculated as $\mathsf{dGPDR} = \ln(\mathsf{GDP}_t/\mathsf{GDP}_{t-1})$. dUE is the change in unemployment rate , calculated as $\mathsf{dUE} = \mathsf{UE}_t - \mathsf{UE}_{t-1}$, dCONSR is the real consumption growth, calculated as $\mathsf{dCONS} = \ln(\mathsf{CONS}_t/\mathsf{CONS}_{t-1})$ and dINV is the real growth in investments , calculated as $\mathsf{dINV} = \ln(\mathsf{INV}_t/\mathsf{INV}_{t-1})$.

controlled entity, the Norwegian Central Securities Registry (VPS). From this source we have access to monthly observations of the equity holdings of the complete stock market. At each date we observe the number of stocks held by every owner. Each owner has a unique identifier which allows us to follow the owners' holdings over time. For each owner the data also includes a sector code that allows us to distinguish between such types as mutual fund owners, financial owners (which include mutual funds), industrial (nonfinancial corporate) owners, private (individual) owners, state owners and foreign owners. This data allows us to at each data construct the actual portfolios of all investors at the stock exchange, as well as for each stock, construct measures of ownership dispersion and the like.[9] Table 2 shows some descriptive statistics for stock ownership at the Oslo Stock Exchange, to help understand the nature of the data.

Table 2 Descriptive statistics for the ownership data

The table shows some summary statistics for the ownership data. For each stock we calculate the fraction of the stock held by its largest owner (Largest owner) and three largest owners (Three largest), the total number of owners, and the fraction of the firm held by the five different mutually exclusive owner types: State, foreign, financial, nonfiancial and individual owners.

	1989–2007			1989–1994			1995–1999			2000–2007		
	average		med	average		med	average		med	average		med
	vw	ew		vw	ew		vw	ew		vw	ew	
Largest owner	37.2	27.6	21.0	28.4	26.2	20.8	29.4	27.0	21.0	44.8	28.3	21.1
Three largest	50.9	44.1	41.9	45.1	43.4	38.5	44.8	43.4	41.8	56.6	44.7	43.1
Total no owners	13956	2327	860	7861	1853	654	7511	1847	814	19884	2775	965
Fraction State Owners	26.9	6.2	0.5	21.2	6.5	1.0	19.6	6.3	0.4	33.3	6.0	0.4
Fraction Foreign Owners	31.7	22.8	12.7	29.3	20.5	13.3	33.4	22.5	13.7	31.2	23.6	11.2
Fraction Financial Owners	16.8	18.7	16.6	18.5	20.6	18.1	20.5	21.0	19.4	13.9	16.7	14.3
Fraction Nonfinancial Owners	19.1	35.0	28.9	25.6	41.0	40.8	20.9	33.6	28.8	16.0	34.1	27.6
Fraction Individual Owners	7.5	19.7	13.3	10.9	18.3	12.4	8.8	20.0	13.0	5.7	19.9	13.7

1.5 Some preliminary evidence of links between liquidity and the real economy

We will in the next section investigate more closely the links between liquidity and the real economy, but let us first show some preliminary illustrations of such links. In figure 1 we show time series of the various stock market liquidity measures, and link them to macroeconomic measures. For the US the results are shown in the lefthand figures (panel A), where we plot liquidity together with indications of NBER recessions (grey vertical bars). It is very clear from these figures that liquidity is worsening before and during the first part of a recession. Similarly, for Norway we have in panel B linked liquidity and changes in (detrended) real GDP. The detrended GDP measures the output gap, which is a proxy for economic activity. A negative output gap indicates that the economy is *not* operating at full capacity, while a positive output gap indicates that production is higher than what is sustainable given the existing resources in the economy, which is commonly used as an early warning indicator of inflationary pressure.

[9] More details about this data can be found in e.g. Bøhren and Ødegaard [2001],Bøhren and Ødegaard [2006] and Ødegaard [2008].

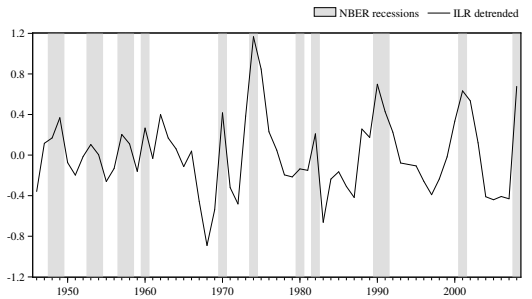
Also for Norway we see that when economic activity is falling, market liquidity worsens and vice versa. Overall, the figures suggest that both for the US and Norway, there is a strong relation between market liquidity and the business cycle.

To give some impressions between the contemporaneous relations between liquidity and the different market and real variables table 3 provides the contemporaneous correlations between the different variables used in the analysis for the US. Looking at the three liquidity measures, we see that all three are negatively correlated with the term structure and positively correlated with the credit spread. Thus, when market liquidity worsens, the term spread decreases and the credit spread increases. With respect to equity market variables, we see that there is a positive correlation between all liquidity measures and market volatility, and a negative correlation between liquidity and the excess return on the market (Rm). Thus, when market liquidity is low, market volatility is high and realized market returns are low. With respect to the correlation between the liquidity measures and the macroeconomic variables, we see that all liquidity variables are negatively correlated with growth in GDP, investments and consumption, and positively correlated with unemployment. Note that the macro variables are not known to the market participants before the following quarter, thus, these correlations is a first indication that there is real time information about current underlying economic growth in market liquidity variables. Furthermore, we also see that the term spread has a significant positive correlation with GDP growth and consumption growth, while the credit spread is negatively correlated with GDP growth, investment growth, consumption growth and positively correlated with unemployment. The signs of these correlations are what we would expect. With respect to equity market volatility and return, these variables are not significantly correlated with any of the macro variables, except with consumption growth. Finally, as one would expect, all the macro variables are significantly correlated with each other, and have the expected signs.

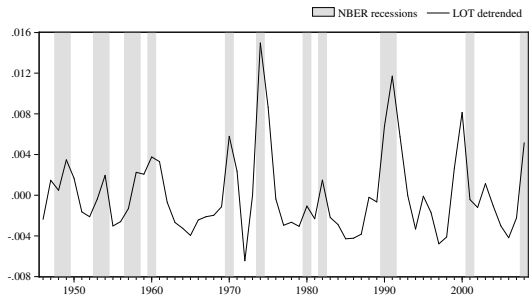
Figure 1 Time series evolution of liquidity measures

Panel A shows time series plots of annual version of the three liquidity measures ILR, LOT and Roll for the US for the period 1947-2008. The gray bars are the NBER recession periods. Note that both the ILR and LOT measures are de-trended using a Hodrick-Prescott filter. Panel B shows time series plots for Norway for ILR, LOT and the relative spread (RS) for the period 1980 through 2008. Also for Norway, the ILR and LOT measures are de-trended, while the RS measure is not. Since we do not have a recession index for Norway, the dotted lines show the de-trended real GDP (output gap) for Norway as a measure of the variation in economic growth of the Norwegian economy over the sample. For both the US and Norway, the market liquidity is calculated as the equally weighted cross-sectional average of the respective liquidity measure for each year.

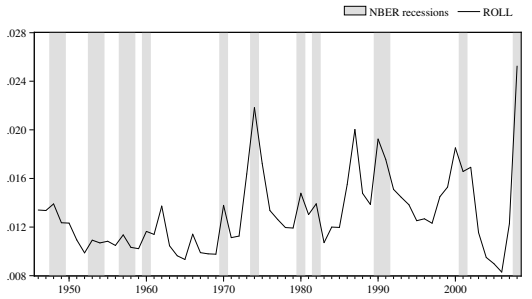
Panel A: Liquidity in the US (1947-2008)



(a) ILR

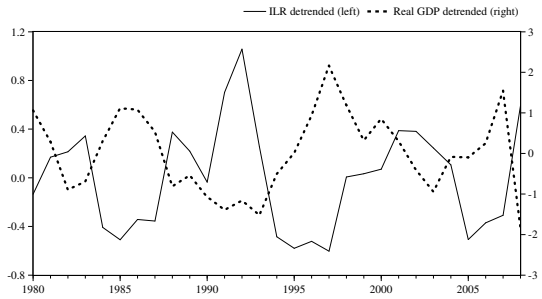


(b) LOT

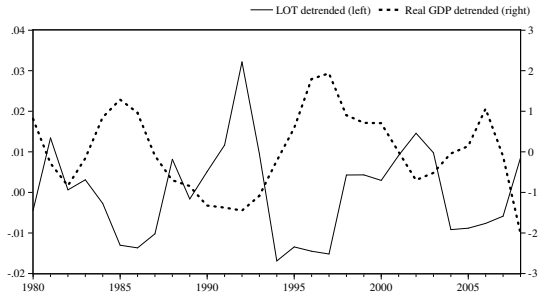


(c) Roll measure (Roll)

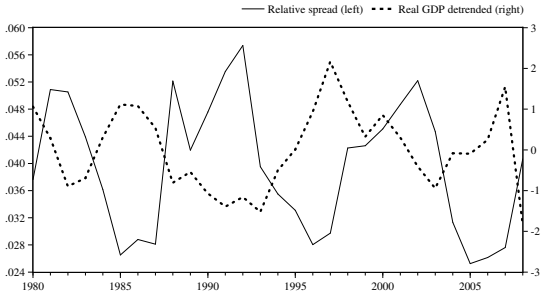
Panel B: Liquidity in Norway (1980-2008)



(d) ILR



(e) LOT



(f) Relative spread (RS)

Table 3 Correlations

The table shows the Pearson correlations between the variables used in the analysis for the US. The associated p-values are reported in parenthesis below each correlation coefficient. Correlations in bold are significant at the 5% level or lower. *dILR*, *dLOT* and Roll are the three liquidity measures, *Term* is our proxy for the term spread and *Cred* is the credit spread. With respect to additional equity market variables, we examine market volatility (*Vola*) which is calculated as the cross sectional average volatility of all stocks in the CRSP database, and excess market return (R_m) which is the return on the S&P500 index in excess of the risk free rate (proxied by the 3 month t-bill rate). With respect to macroeconomic variables, *dGDPR* is the real GDP growth, *dINV* is the growth in investments, *dUE* is the change in the unemployment rate and *dCONSR* is the real consumption growth.

	Market variables							**Macro variables**		
	ILR	LOT	Roll	Term	Cred	Vola	Rm	dGDPR	dINV	dCONSR
Term	**-0.17**	**-0.14**	-0.04							
	(0.00)	**(0.04)**	(0.55)							
Cred	**0.32**	**0.34**	**0.42**	**-0.21**						
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**						
Vola	**0.30**	**0.57**	**0.47**	**-0.15**	**0.42**					
	(0.00)	**(0.00)**	**(0.00)**	**(0.02)**	**(0.00)**					
Rm	**-0.53**	**-0.19**	**-0.35**	**0.33**	**-0.17**	**-0.33**				
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.01)**	**(0.00)**				
dGDPR	**-0.16**	-0.10	**-0.31**	**0.16**	**-0.27**	0.01	0.09			
	(0.02)	(0.15)	**(0.00)**	**(0.02)**	**(0.00)**	(0.87)	(0.19)			
dINV	**-0.16**	**-0.17**	**-0.40**	0.18	**-0.26**	-0.07	0.09	**0.73**		
	(0.02)	**(0.01)**	**(0.00)**	(0.00)	**(0.00)**	(0.27)	(0.21)	**(0.00)**		
dCONSR	**-0.27**	**-0.15**	**-0.38**	**0.21**	**-0.34**	-0.08	**0.16**	**0.68**	**0.57**	
	(0.00)	**(0.02)**	**(0.00)**	**(0.00)**	**(0.00)**	(0.24)	**(0.01)**	**(0.00)**	**(0.00)**	
dUE	**0.16**	**0.15**	**0.33**	-0.10	**0.28**	0.08	-0.04	**-0.65**	**-0.62**	**-0.56**
	(0.01)	**(0.03)**	**(0.00)**	(0.14)	**(0.00)**	(0.21)	(0.58)	**(0.00)**	**(0.00)**	**(0.00)**

2 Predicting US economic growth with market illiquidity

In this section we investigate to what degree US stock market illiquidity contains information about variables that measure real economic activity in the US. We will assess the predictive ability of market illiquidity both in and out of sample. We will also examine the causality relation between GDP growth and market liquidity both for the full sample and subsamples. We use data for the period 1947-2008.

2.1 In-sample evidence

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

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

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

For the US, we use three different proxies for equity market illiquidity; ILR, LOT and Roll. Since both the ILR and LOT measure have a downward trend during the sample period, we use the log difference of these variables in our analysis. The Roll measure is not differenced since it is stationary. With respect to dependent variables (y_{t+1}), our main variable of interest is real GDP growth. However, we also examine additional macro variables that are related to economic growth.

We start our analysis by estimating predictive regressions of the three different illiquidity proxies on the macro series without including any financial control variables in the models. However, we include one lag of the dependent variable.[10] Table 4 summarize the results from these regressions. We see that the coefficient on market illiquidity ($\hat{\beta}$) is highly significant for most models regardless of which illiquidity proxy we use. An increase in market illiquidity predicts a lower real GDP growth, an increase in unemployment and a slowdown in consumption and investments. [11] In summary, the results in table 4 indicate that market illiquidity contains significant information about future economic growth. The in-sample predictability is both significantly and relatively stable across sub-samples. When market liquidity worsens, this is followed by a slowdown in economic growth.

To illustrate the performance of liquidity as a predictive variable, in figure 2 we show time series plots of the realized growth in the different macro variables and the fitted (expected) growth in these variables from a model using four lags of the ILR measure. The prediction model does not include any lags of the dependent variable or other control variables. While

[10] We have also estimated the models with different lag specifications with up to four lags of the dependent variable and the liquidity variables. This does not affect the results.

[11] In results not reported in the paper, we also estimate these regressions for sub-periods where we split the sample in the middle and re-estimate the models for the periods 1947-1977 and 1978-2008. The results from the sub-sample analysis yields very consistent results for the ILR and Roll measures, both with respect to the significance, sign and size of the coefficients. On the other hand, for the LOT measure, the results are much weaker for the second sub-sample.

Table 4 Predicting macro with market illiquidity

The table shows the results from predictive regressions where we regress next quarters growth in different macro variables on three proxies for market illiquidity for the period 1947-2008. Market illiquidity (LIQ^j) is proxied by one of three illiquidity measures: the Amihud Illiquidity ratio (ILR), the LOT measure and the Roll measure (Roll). We use the log difference in ILR and LOT to preserve stationarity, while the Roll measure is not differenced. The model estimated is

$$y_{t+1} = \alpha + \beta LIQ_t^j + \gamma y_t + u_{t+1}$$

where y_{t+1} is next quarter real GDP growth (dGDPR), growth in the unemployment rate (dUE), real consumption growth (dCONSR) or growth in private investments (dINV). We also include one lag of the dependent variable (y_t). The Newey-West corrected t-statistics (with 4 lags) is reported in parentheses below the coefficient estimates, and $\bar{R}^2$ is the adjusted R^2. The sample period is from 1947-2008.

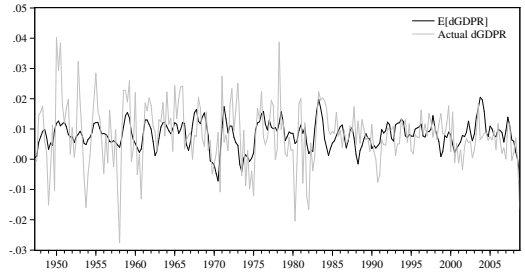
Dependent variable (y_{t+1})	ILR				LOT				Roll			
	$\hat{\alpha}$	$\hat{\beta}^{ILR}$	$\hat{\gamma}$	$\bar{R}^2$	$\hat{\alpha}$	$\hat{\beta}^{LOT}$	$\hat{\gamma}$	$\bar{R}^2$	$\hat{\alpha}$	$\hat{\beta}^{Roll}$	$\hat{\gamma}$	$\bar{R}^2$
dGDPR	0.006	-0.013	0.224	0.13	0.007	-0.017	0.168	0.06	0.019	-0.813	0.133	0.10
	(7.58)	(-5.37)	(3.68)		(7.52)	(-2.77)	(2.58)		(5.96)	(-4.12)	(2.10)	
dUE	0.003	0.074	0.300	0.13	0.003	0.129	0.261	0.10	-0.074	5.206	0.236	0.12
	(0.61)	(3.68)	(5.14)		(0.47)	(3.14)	(4.42)		(-3.07)	(3.28)	(4.23)	
dCONSR	0.006	-0.006	0.305	0.11	0.006	-0.009	0.282	0.09	0.013	-0.437	0.264	0.11
	(7.07)	(-3.33)	(4.46)		(7.03)	(-1.74)	(3.85)		(4.22)	(-2.28)	(3.37)	
dINV	0.006	-0.034	0.265	0.15	0.007	-0.039	0.218	0.07	0.040	-2.228	0.169	0.12
	(2.95)	(-6.18)	(3.97)		(3.03)	(-2.56)	(3.20)		(4.29)	(-3.61)	(2.65)	

there is a lot of variation in the realized macro variables that is not captured by the model, we still see that the pure liquidity model predicts the underlying movements in the macro series relatively well.

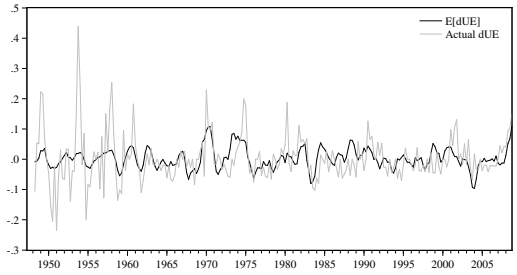
Before we move on to a multivariate setting where we control for additional predictor variables, we want to address the question of causation. We are primarily interested in predicting macroeconomic conditions with liquidity, but one may also think of causality going in the opposite direction, i.e. does changes in economic conditions affect market illiquidity? We know from earlier studies that monetary policy shocks have an effect on stock and bond market illiquidity (see e.g. Söderberg [2008] and Goyenko and Ukhov [2009]) while there is no effect of shocks to real economic variables on stock market illiquidity. On the other hand, neither of these studies consider the reverse causality from market liquidity to real economic variables. To directly look at causality directions we perform Granger causality tests between the different illiquidity proxies and real GDP growth. Table 5 report the results from these tests. The tests are done in a Vector Auto Regression (VAR) framework where we choose the optimal lag length based on the Schwartz criterion. We perform the tests for the whole sample and for different sub-samples where we split the sample period in the middle, and also for five 20 year sub-periods (overlapping by 10 years). The first row of table 5 shows the number of quarterly observations in each sample period, and the second row shows the number of NBER recessions that occurred within each sample period. In part (a) of the table we run Granger causality tests between ILR and dGDPR. Looking first at the column labeled "Whole sample", we see that the null hypothesis

Figure 2 Expected and realized macro fundamentals

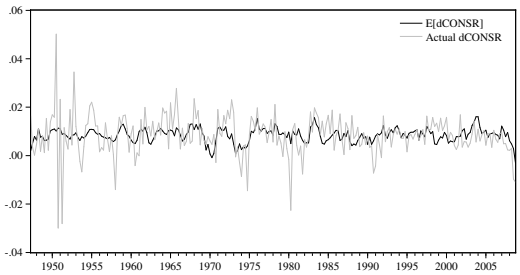
The figures plots the time series of realized quarterly growth in (a) real GDP, (b) unemployment rate, (c) consumption and (d) investments (light gray lines). The black lines show the predicted (expected) growth in these variables from a model with four lags of market liquidity measured by ILR and a constant term.



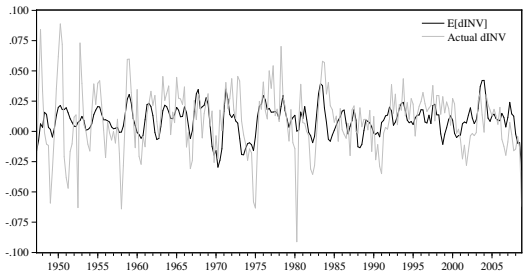
(a) GDP growth (dGDPR)



(b) Growth in unemployment rate (dUE)



(c) Consumption growth (dCONSR)



(d) Growth in investments (dINV)

that GDP growth *does not* Granger cause ILR (dGDPR $\nrightarrow$ dILR) can not be rejected, while the hypothesis that ILR *does not* Granger cause GDP growth (dILR $\nrightarrow$ dGDPR) is rejected at the 1% level. Looking at the tests for the different sub periods we see that the relation is remarkably stable. Thus, part (a) of the table suggest a strong and stable one way Granger causality from market illiquidity, proxied by ILR, to GDP growth, while there is no evidence of a reverse causality from GDP growth to ILR. In part (b) and (c) of the table, we perform the same tests for the LOT and Roll measures respectively. For the full sample period, we find a similar strong support for a one way Granger causality from LOT and Roll to GDP growth, while there is no evidence of a reverse causality. Also for the sub-periods, we find a one-way Granger causality from the Roll measure to dGDPR, except for the first 20 year period were we are only able to reject the null that the Roll measure do not Granger cause real GDP growth at a 10% significance level. Looking at the sub samples results for the LOT measure we cannot reject the null that LOT *does not* Granger cause dGDPR in the second half of the sample.[12] One potential reason for why the LOT measure has become less informative over the sample period may be due to the increased trading activity. Recall that the LOT measure uses zero return days to identify the implicit transaction cost for a stock. Thus, if the number of zero return days has decreased at the same time as the trading activity has increased, the LOT measure may have become a more noisy estimator of actual transaction costs in the last part of the sample.

To illustrate the predictive content of liquidity for real variables in terms that are more familiar to financial economists, in figure 3 we show the relationship between market liquidity and GDP growth in an "event" type of analysis, where we plot changes in liquidity relative to the onset of a recession, as defined by the NBER. For each NBER recession, we first calculate the quarterly GDP growth starting 5 quarters before ($\mathsf{t} = -5\mathsf{Q}$) the first NBER recession quarter (NBER1) and ending 5 quarters after the end of each NBER recession ($\mathsf{t} = 5\mathsf{Q}$). Next, we average the GDP growth for each quarter across all recessions, and then accumulate the average GDP growth over the event window. Then we do the same for the ILR measure. Thus, the figure shows the average pattern in ILR before, during and after US recessions. Figure 3 (a) plots the cumulative growth in ILR (solid line) and the accumulated average growth in real GDP, averaged across all the 10 NBER recessions (shaded area) in our sample from 1947-2008.[13] Sub-figure (b) and (c) shows the plots when we look at the 5 first recessions and last 5 recessions. Looking at figure (a) first, we see that the ILR starts to increase markedly (a worsening of market liquidity) already three quarters before the start of the NBER recessions. Note that at the same time, the average GDP growth (bars) is still increasing. When we get to the first NBER recession quarter (denoted as NBER1 on the x-axis), the ILR has increased by 50% relative to 5 quarters before. Also note that the ILR peaks in the middle of the recession, and starts falling before the GDP growth starts increasing again. Looking at sub-figures (b)

[12] This is consistent with the sub sample results discussed in footnote 11 in conjunction with the results in table 4, where LOT was rendered insignificant in the second part of the sample.

[13] Note that some NBER recessions only lasts for 3 quarters (e.g. 1980Q1-1980Q3), while there are some recessions that lasts up to 6 quarters (e.g. 1973Q4-1975Q1 and 1981Q3-1982Q4). However, the most important point of the figure is that all NBER recessions are aligned to start at the same point (NBER1) in event time.

Table 5 Granger causality tests

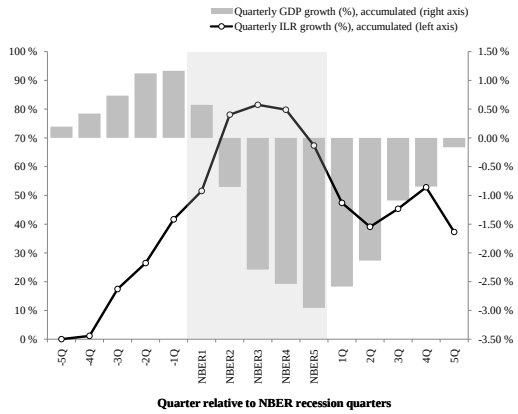
The table shows Granger causality tests between the quarterly real GDP growth (dGDPR) and the (a) Amihud Illiquidity ratio (ILR), (b) the LOT measure and (c) the Roll measure. The test is performed for the whole sample, and different sub-periods. For each measure we first test the null hypothesis that real GDP growth *do not* Granger cause market illiquidity and the whether market illiquidity *do not* Granger cause real GDP growth. We report the χ^2 and p-value (in parenthesis) for each test. We choose the optimal lag length for each test based on the Schwartz criterion. For each illiquidity variable the test is performed on the whole sample period (1947q1-2008q4), the first (1947q1-1977q4) and second half (1978q1-2008q4) of the sample, and for rolling 20 year subperiods overlapping by 10 years. The first two rows report the number of quarterly observations covered by each sample period and the number of NBER recession periods within each sample.

	Whole sample	First half	Second half	20 year sub-periods				
	1947 2008	1947-1977	1978-2008	1950-1970	1960-1980	1970-1990	1980-2000	1990-2008
N (observations)	243	119	124	84	84	84	84	76
NBER recessions	11	6	5	5	4	4	2	3
(a) ILR measure								
H0: dGDPR↛ dILR								
χ^2	4.08	1.66	3.13	3.84	3.56	3.35	2.83	2.66
p-value	(0.13)	(0.44)	(0.21)	(0.15)	(0.17)	(0.19)	(0.24)	(0.26)
H0: dILR↛ dGDPR								
χ^2	31.97**	19.01**	14.50**	16.42**	8.89**	11.70**	11.64**	11.85**
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
(b) LOT measure								
H0: dGDPR↛ dLOT								
χ^2	2.21	1.77	1.13	2.20	1.48	1.21	0.06	1.05
p-value	(0.14)	(0.18)	(0.29)	(0.14)	(0.22)	(0.27)	(0.80)	(0.31)
H0: dLOT↛ dGDPR								
χ^2	9.55**	13.37**	1.45	8.24**	7.70**	6.81**	1.22	0.99
p-value	(0.00)	(0.00)	(0.23)	(0.00)	(0.01)	(0.01)	(0.27)	(0.32)
(c) ROLL measure								
H0: dGDPR↛ Roll								
χ^2	0.09	0.31	0.75	0.27	0.01	2.30	1.33	0.01
p-value	(0.77)	(0.58)	(0.39)	(0.60)	(0.91)	(0.13)	(0.25)	(0.91)
H0: Roll↛ dGDPR								
χ^2	15.96**	5.56*	10.80**	2.95	10.74**	9.31**	4.43*	10.18**
p-value	(0.00)	(0.02)	(0.00)	(0.09)	(0.00)	(0.00)	(0.04)	(0.00)

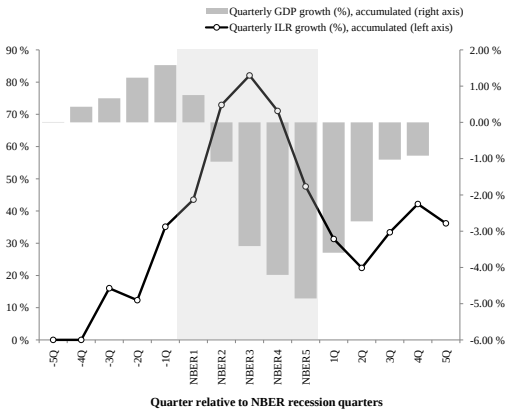
and (c), we see that this pattern is independent of sample period. Using the other liquidity measures produces very similar patterns.

Figure 3 Market illiquidity around NBER recessions

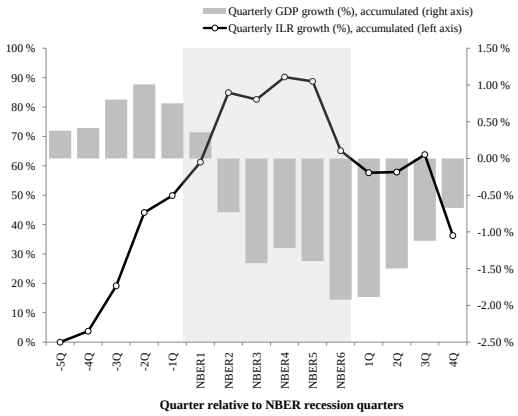
The figures shows the accumulated growth in ILR (solid line) and accumulated GDP growth (bars) averaged in event time across different NBER recession periods. All NBER recession periods are aligned to start at NBER1. Figure (a) shows the results when look at all 10 NBER recessions during the full sample period 1947-2008. Figure (b) and (c) shows the figure when we look at the first 5 recessions and last 5 recessions, respectively.



(a) Full sample period: 1947-2008



(b) First half: 1947-1977



(c) Second half:1978-2008

Controlling for other financial variables

In table 4 we found that market illiquidity had predictive power for several macroeconomic variables. However, there are several financial variables that contain leading information about future macroeconomic conditions that we did not control for. As we saw in the correlation table our liquidity proxies are correlated with the term spread, the credit spread as well as the market return and volatility. This is what we would expect, since our hypothesis is that variations in market liquidity capture the same expectations about future growth as the other financial variables. The main purpose of adding other financial control variables to the models

is to determine whether changes in liquidity provides an additional (or less noisy) signal about future macro fundamentals.

In table 6 we start by including two, non equity, control variables (in addition to the lag of the dependent variable) and re-estimate the models in table 4. The control variables we include are the term spread (*Term*) and credit spread (*Cred*). In each panel in the table we estimate three models using different liquidity proxies (denoted in the first column).

Looking first at the estimation results in panel A for GDP growth, we see that while *Cred* enters significantly in all three models, the coefficients on liquidity retains its level, sign and significance compared to table 4. Interestingly, the coefficient on the term spread ($\hat{\gamma}^{\text{Term}}$) is not significant in the models that includes ILR or LOT. However, excluding ILR and LOT in these models restores the significance of *Term*. The results for the other macro variables, in panels B to D, yields the same results. The coefficients on liquidity is robust to the inclusion of the term spread and credit spread in the models. However, the results suggest that both the term spread and credit spread are important predictor variables, and a model containing all three variables improves the adjusted R-squared compared to table 4.

As a final exercise, we include two equity market control variables into the models in addition to the term spread and credit spread. The equity market variables included are the excess market return (*Rm*) and volatility (*Vola*). Table 7 shows the results from these regressions. In the models for GDP growth in panel A we find that while market volatility is insignificant in all models, market return enters significantly with a positive coefficient. However, this does not affect the significance of any of the liquidity coefficients. Thus, market liquidity retains its predictive power for real GDP growth. In the models for the unemployment rate, in panel B, the result is more mixed. In the model with ILR, we see that adding market return renders the ILR coefficient insignificant. However, in the models with Roll and LOT, the coefficients are unaffected. In the models for real consumption growth in panel C, we see that market liquidity (regardless of which measure we use) is rendered insignificant when the excess return on the market is included in the model. Finally, in the models for investment growth, in panel D, the liquidity coefficients are unaffected by the inclusion of the market return.

Overall, the results suggest that while other financial variables clearly are useful for predicting future economic growth, we find support for there being additional information in market illiquidity after controlling for several both equity and non-equity variables. Market liquidity seems to be a particularly strong and robust predictor of real GDP growth, unemployment and investment growth. For future real consumption growth, however, there does not seem to be additional information in liquidity that is not already reflected in the term spread and market return.

Let us finally use the event style analysis to make some simple comparisons of informational content of the different predictive variables. Figure 4 shows similar plots as we constructed in figure 3, but now we also add the financial control variables. In figure 4 (a) and (b) we plot the cumulative average change in the term spread and credit spread, respectively, from five quarters before the NBER recessions until 5 quarters after the end of the NBER recessions. Similarly,

Table 6 Predicting macro with market liquidity controlling for non-equity variables

The tables shows the multivariate OLS estimates from regressing next quarters growth in different macro variables on current market liquidity and two control variables in addition to the lag of the dependent variable. The estimated model is $y_{t+1} = \alpha + \beta LIQ_t + \gamma' \mathbf{X}_t + u_{t+1}$ where y_{t+1} is the growth in the respective macro variable, $\mathbf{X_t}$ contains the in addition to the lagged dependent variable (y_t) and the non-equity control variables ($Term_t$, $Cred_t$). γ' is the vector with the respective coefficient estimates (γ^y, γ^{Term}, γ^{Cred}) for the control variables. The title of each panel denote the dependent variable (y_{t+1}). E.g. in Panel A, the dependent variable is real GDP growth (dGDPR). The Newey-West corrected t-statistics (with 4 lags) is reported in parentheses below the coefficient estimates, and $\bar{R}^2$ is the adjusted R^2.

Panel A: Real GDP growth (dGDPR)

Liquidity proxy (LIQ)	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^y$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\bar{R}^2$
ILR	0.005	-0.011	0.214	0.001	-0.005	0.159
	(5.02)	(-4.60)	(3.67)	(1.17)	(-2.29)	
Roll	0.017	-0.744	0.167	0.001	-0.005	0.143
	(5.29)	(-3.95)	(2.66)	(2.20)	(-2.20)	
LOT	0.006	-0.012	0.135	0.001	-0.006	0.099
	(5.06)	(-2.13)	(2.18)	(1.35)	(-2.86)	

Panel B: Unemployment rate (dUE)

Liquidity proxy (LIQ)	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^y$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\bar{R}^2$
ILR	0.015	0.057	0.303	-0.009	0.042	0.175
	(1.95)	(3.02)	(5.23)	(-2.83)	(3.19)	
Roll	-0.051	4.732	0.273	-0.012	0.037	0.182
	(-2.28)	(3.32)	(4.67)	(-3.90)	(2.97)	
LOT	0.015	0.089	0.252	-0.010	0.045	0.156
	(1.86)	(2.46)	(4.67)	(-3.02)	(3.56)	

Panel C: Consumption growth (dCONSR)

Liquidity proxy (LIQ)	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^y$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\bar{R}^2$
ILR	0.004	-0.005	0.305	0.001	-0.001	0.133
	(3.86)	(-2.88)	(4.48)	(2.32)	(-0.66)	
Roll	0.011	-0.482	0.286	0.002	0.000	0.146
	(3.97)	(-2.61)	(3.99)	(3.18)	(-0.24)	
LOT	0.004	-0.006	0.263	0.001	-0.001	0.118
	(3.98)	(-1.35)	(3.38)	(2.44)	(-0.89)	

Panel D: Investment growth (dINV)

Liquidity proxy (LIQ)	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^y$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\bar{R}^2$
ILR	0.001	-0.027	0.247	0.004	-0.018	0.228
	(0.45)	(-5.23)	(3.98)	(2.58)	(-3.84)	
Roll	0.031	-2.047	0.209	0.005	-0.016	0.226
	(3.86)	(-3.85)	(3.35)	(3.69)	(-3.95)	
LOT	0.002	-0.021	0.165	0.004	-0.021	0.169
	(0.57)	(-1.58)	(2.89)	(2.85)	(-4.65)	

Table 7 Predicting macro with market liquidity - all control variables

The tables shows the multivariate OLS estimates from regressing next quarters growth in macro variables on current change in market illiquidity and four financial control variables. In addition to the lagged dependent variable, we include the term spread (*Term*), the credit spread (*Cred*), market volatility (*Vola*) and the excess market return (*Rm*). As before, we we examine three different proxies for market illiquidity (ILR, Roll and LOT). The estimated model is $y_{t+1} = \alpha + \beta dLIQ_t + \gamma' \mathbf{X}_t + u_{t+1}$ where y_{t+1} is the growth in the respective macro variable, $\mathbf{X_t}$ contains the control variables, and γ' is the vector with the coefficient estimates (γ^y, γ^{Term}, γ^{Cred}, γ^{Vola}, γ^{Rm}) for the control variables. The Newey-West corrected t-statistics (with 4 lags) is reported in parentheses below the coefficient estimates, and $\bar{R}^2$ is the adjusted R^2.

Panel A: Real GDP growth (dGDPR)

Liquidity proxy (LIQ)	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^y$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
ILR	0.006	-0.008	0.203	0.000	-0.005	0.000	0.016	0.16
	(5.72)	(-3.90)	(3.57)	(0.92)	(-2.38)	(-0.02)	(2.01)	
Roll	0.016	-0.614	0.138	0.001	-0.005	0.005	0.022	0.16
	(4.68)	(-3.03)	(2.38)	(1.58)	(-2.46)	(0.88)	(2.83)	
LOT	0.007	-0.012	0.162	0.000	-0.006	0.005	0.029	0.14
	(6.16)	(-2.07)	(2.80)	(0.81)	(-2.92)	(0.90)	(3.74)	

Panel B: Unemployment rate (dUE)

Liquidity proxy (LIQ)	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^y$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
ILR	0.006	0.021	0.307	-0.008	0.048	-0.033	-0.235	0.213
	(0.79)	(1.14)	(6.25)	(-2.64)	(3.56)	(-0.93)	(-4.58)	
Roll	-0.043	3.492	0.275	-0.010	0.044	-0.063	-0.226	0.227
	(-1.75)	(2.26)	(5.98)	(-3.31)	(3.41)	(-1.61)	(-4.77)	
LOT	0.005	0.107	0.290	-0.007	0.048	-0.084	-0.269	0.227
	(0.67)	(2.63)	(6.02)	(-2.54)	(3.65)	(-2.02)	(-5.48)	

Panel C: Consumption growth (dCONSR)

Liquidity proxy (LIQ)	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^y$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
ILR	0.005	-0.001	0.302	0.001	-0.001	0.002	0.026	0.171
	(4.76)	(-0.39)	(4.43)	(2.29)	(-1.04)	(0.34)	(3.38)	
Roll	0.010	-0.331	0.278	0.001	-0.001	0.005	0.023	0.184
	(3.64)	(-1.82)	(3.92)	(2.89)	(-0.70)	(0.96)	(3.66)	
LOT	0.005	-0.006	0.291	0.001	-0.001	0.005	0.027	0.176
	(5.02)	(-1.17)	(4.30)	(2.26)	(-1.02)	(0.84)	(4.41)	

Panel D: Investment growth (dINV)

Liquidity proxy (LIQ)	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^y$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
ILR	0.003	-0.020	0.243	0.004	-0.019	0.007	0.048	0.238
	(1.16)	(-3.74)	(3.91)	(2.54)	(-3.95)	(0.55)	(2.14)	
Roll	0.030	-1.833	0.171	0.005	-0.019	0.024	0.058	0.252
	(3.72)	(-3.35)	(2.94)	(3.26)	(-4.20)	(1.83)	(2.94)	
LOT	0.005	-0.023	0.216	0.003	-0.021	0.017	0.079	0.218
	(1.61)	(-1.70)	(3.42)	(2.53)	(-4.57)	(1.15)	(4.00)	

sub-figures (c) and (d) look at the cumulative average excess market return (multiplied by 5 for scaling purposes) and the cumulative average change in volatility. Looking first at the term spread (dotted line) in picture (a) we see that there is a systematic decline in the term spread in all the quarters prior to the first NBER recession quarter (NBER1). This is consistent with the notion that the yield curve has a tendency to flatten and invert before recessions. We also see that the term spread increases again already during the first quarters of the recession, predicting the end of the recession and increased growth. Thus, before the recession, the signal from both the term spread and market liquidity (solid line) seems to capture similar information about GDP growth. For the credit spread in picture (b), both market liquidity and the credit spread seems to share a very similar path, although the liquidity series is changing earlier than the credit spread. As we will see later in the out-of-sample analysis, the credit spread and market liquidity have very similar out-of-sample performance when predicting GDP growth. In picture (c) we see that the accumulated excess market return is relatively stable until the quarter just before the NBER recession starts. Thus, it seems to be responding later than the other variables. Finally, in picture (d), we see that volatility increases in the quarter just before the NBER recessions starts. However, consistent with the regression results, the information in market volatility seems small compared to the other variables.

2.2 Out-of-sample evidence for the US

In the previous section we found that market illiquidity 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 is able to forecast quarterly real GDP growth out of sample.

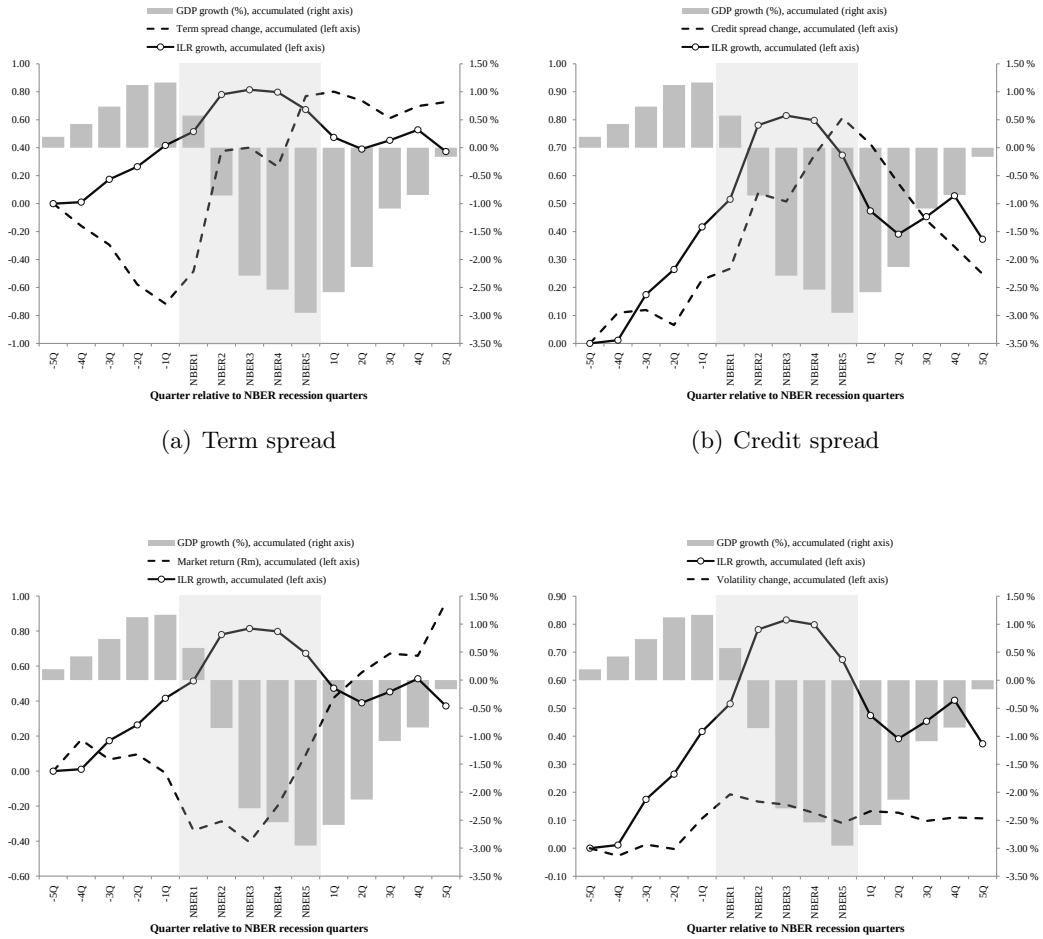
Methodology and timing of information

When setting up our out-of-sample procedure, we need to be careful with the timing of the data so it reflects what would have been available to a forecaster at every point in time. While 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.[14] 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.

[14]The Bureau of Economic Analysis releases the *final* GDP figure for quarter t-1 in the last month of the following quarter (t). However, they also release an "advance" estimate in the first month of the following quarter as well as a "preliminary" release in the second month of the following quarter. Thus, at the end of t, a forecaster have the "final" number available for t-1 GDP growth.

Figure 4 Market illiquidity and other financial variables around NBER recessions

The figures shows the accumulated average growth in ILR (solid line) and accumulated average GDP growth (bars) averaged in event time before, during and after NBER recession periods. In addition, the dotted lines show the cumulative average change in (a) term spread, (b) credit spread, and the (c) cumulative average excess market return and cumulative average change in volatility (d). All NBER recession periods are aligned to start at NBER1.



(a) Term spread

(b) Credit spread

(c) Market return

(d) Volatility

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 last vintage series.

In our out-of-sample analysis we consider a *rolling* estimation scheme with a fixed width of 20 quarters (5 years). For all models, our first out-of-sample forecast is made in the end of the first quarter of 1952 for GDP growth for the second quarter of 1952. More specifically, at the end of the first quarter of 1952, we estimate each model using data from the first quarter of 1947 through the fourth quarter of 1951 (which is the most recent GDP observation available to us in the first quarter of 1952). We then produce a forecast of real GDP growth for the second quarter of 1952 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 next quarter. Next, we move the window forward by one quarter, re-estimate the models, and produce a new forecast for the next quarter, and so on. The last forecast is made at the fourth quarter of 2008 for GDP growth for the first quarter of 2009.

We evaluate the performance of a model with market liquidity as the predictor against models with other financial variables. In addition, we compare the illiquidity model against a benchmark model where we forecast GDP growth using an AR(1) model. In that case, the most recent observation of GDP available to us at the end of the first quarter of 1952 is GDP for the fourth quarter of 1951. Thus, we estimate the autoregressive model for GDP growth with data including the fourth quarter of 1951, and construct a forecast for the second quarter of 1952 based on the estimated coefficients and the most recent GDP observation available, which is the final figure for GDP growth for the fourth quarter of 1951.

Out-of-sample comparison of different liquidity measures

We begin by evaluating univariate forecast models for real GDP growth using the three different liquidity proxies. The models are evaluated by comparing the mean squared forecast error (MSE) from the series of on-quarter ahead forecasts. Since we compare models for the same dependent variable, but with different predictor variables, the models are non-nested. We use two statistics to compare the out-of-sample performance of the different liquidity measures; the mean-squared forecasting error (MSE) ratio and the modified Diebold-Mariano (MDM) encompassing test proposed by Harvey et al. [1998] which has greater power than the original Diebold and Mariano [1995] test, especially in small samples. In addition, Harvey et al. [1998] advocate the comparison of the MDM statistic with critical values from the Student's t distribution, instead of the standard normal distribution.

The Diebold and Mariano [1995] statistic (hereafter DM) is calculated in the following way. Suppose we have a candidate predictor i and a competing predictor k. We want to test the null

hypothesis of equal predictive accuracy that $E[\bar{d}]=0$ for all t, where $\bar{d} = P^{-1} \cdot \sum_t (\varepsilon^2_{k,t+1} - \varepsilon^2_{i,t+1})$, P is the number of rolling out-of-sample forecasts, and $\varepsilon^2_{k,t+1}$ and $\varepsilon^2_{i,t+1}$ are the squared forecast errors from the two models. The DM statistic is then calculated as,

$$DM = \frac{\bar{d}}{(\sigma^2_{\bar{d}}/P)^{1/2}} . n \tag{4}$$

The modified DM statistic is then calculated as,

$$MDM = \left[\frac{P + 1 - 2h + P^{-1}h(h-1)}{P} \right]^{1/2} DM \tag{5}$$

where DM is the original statistic, P is the number of out-of-sample forecasts and h is the forecast horizon (overlap). The MDM statistic is compared with critical values from the Student's t distribution with (P-1) degrees of freedom.

We first want to find which liquidity measure performs best out of sample. We therefore show results from comparisons of different forecasting models for quarterly GDP growth using different proxies for market liquidity in in table 8, which we use to to choose the best performing illiquidity variable. We then use the chosen illiquidity variable as our predictor in the rest of the out-of-sample analysis.

The liquidity variables labeled in the first row (under Model 1) constitute the respective candidate variable (i), and the liquidity variables labeled in the first column (under Model 2) are the competing variables (k). For example, the first pair of numbers compares the MSE from a model (Model 1) that uses the ILR as predictor variable against a model (Model 2) that uses LOT as the predictor variable. The first number shows the relative MSE between the two models which is 0.89. This means that the model with ILR as a predictor variable has a lower MSE than the model that uses LOT instead. The second number shows the modified Diebold/Mariano statistic (MDM) which provides a statistic to test for whether the MSE between model 1 is significantly different from Model 2. The last row in the table shows the MSE for each model specification labeled under Model 1. Looking first at the last row, we see that the model with ILR has the lowest MSE across the models. Also, when comparing the forecast performance of the different models against each other we see that model with ILR in all cases has a significantly lower MSE compared to models with LOT and Roll as predictor variables. The model with LOT as the predictor variable has a lower MSE than the Roll model, however, the MDM statistic cannot reject the null that the MSE of the LOT model is lower than that of the Roll model. While not reported in the table, it should also be noted that while the in-sample analysis suggested that the illiquidity for small firms was most informative about future GDP growth, the out of sample tests do not indicate any significant difference in the forecast performance of liquidity sampled for all firms relative to the liquidity sampled for only small firms.

Overall, the results in table 8 suggest that ILR has the lowest forecast error for GDP growth among the three liquidity proxies we examine. This is consistent with the in sample results where ILR was the strongest and most robust predictor of GDP growth. Thus, in the

Table 8 Out of sample tests - predicting GDP growth with different liquidity proxies

The table reports the results of one-quarter ahead, non-nested, forecast comparisons between models with different liquidity proxies. The variable being forecast is the quarterly GDP growth. Each pair of numbers compare two alternative univariate forecast models (which includes a constant term). The table compares the out-of-sample MSE of a model that uses one of the liquidity variables labeled under Model 1 as a predictor, with a model that uses one of the variables labeled in the first column under Model 2. For each model pair, the table shows the relative MSE between model 1 and model 2, and the modified Diebold/Mariano test statistic (labeled MDM). The null hypothesis for the MDM test is that the MSE of Model 2 and Model 1 are equal against the alternative that the MSE for model 1 is less than that of model 2. A MDM test statistic with * reject the null of equal forecast ability at the 5% level. The last row in the table shows the MSE (multiplied by 10^3) for each model.

		Model 1		
Model 2	Statistic	ILR	LOT	Roll
LOT	MSE_1/MSE_2	0.89	-	
	MDM	1.74*	-	
Roll	MSE_1/MSE_2	0.82	0.91	-
	MDM	1.89*	0.47	-
	MSE (x10^3)	0.088	0.099	0.108

rest of the out-of-sample analysis we focus on ILR as our candidate liquidity predictor variable.

Out-of-sample performance of illiquidity versus other variables

Next, we want to evaluate the out-of-sample predictive ability of ILR against different baseline models. We assess the out-of-sample performance of ILR against two types of baseline models. The first set of baseline models are models where GDP growth is regressed on *one* of the financial control variables (Term, Cred, Vola, Rm) that we used in the in-sample analysis. Each of these models is then a restricted (nested) version of a larger model where GDP growth is regressed on the control variable *in addition* to ILR. The second type baseline model that we compare ILR to is an autoregressive model for GDP growth. In that case, the autoregressive GDP model is the restricted version of a model where we include both lagged GDP growth and ILR as predictor variables for next quarter GDP growth. For comparison reasons, we also evaluate the models with the other financial variables to the restricted autoregressive model for GDP growth.

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 ILR), encompasses the unrestricted model that includes ILR. If the restricted model *does not* encompass the unrestricted model, that means that the additional predictor (ILR) in the larger, unrestricted, model improves forecast accuracy relative to the baseline. 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 given as,

$$\text{ENC-NEW} = (P - h + 1) \cdot \frac{P^{-1} \sum_t \left[\varepsilon^2_{r,t+1} - \varepsilon_{r,t+1} \cdot \varepsilon_{u,t+1}\right]}{MSE_u} \tag{6}$$

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

$$\text{MSE-F} = (P - h + 1) \cdot \frac{MSE_r - MSE_u}{MSE_u} \tag{7}$$

where MSE_r is the mean squared forecast error from the restricted model that excludes ILR, and MSR_u is the mean squared forecast error of the unrestricted model that includes ILR. Both the ENC-NEW and MSE-F statistics are non standard and we use the bootstrapped critical values provided by Clark and McCracken [2001].[15]

Panel A of table 9 provides the results for nested model comparisons for one-quarter ahead and two-quarter-ahead out-of-sample forecasts of GDP growth for the full sample period 1947-2008. The first column shows which variables that are included in the unrestricted model, and the second column shows the variable that constitute the restricted (baseline) model. In column three to five we report the relative mean squared error between the unrestricted (MSE_u) and restricted model (MSE_r), the MSE-F test statistic and the ENC-NEW statistic for the one-quarter-ahead forecasts, and in the last three columns we report the same test statistics for the two-quarters-ahead forecasts.

Looking first at the one-quarter-ahead forecasts we see that the relative MSE is less than one for all model comparisons except in the case when the baseline model is the credit spread (CRED). The MSE-F test for equal MSE between the unrestricted and restricted model reject the null of equal MSE, in favor of the MSE_u being lower than MSE_r for all models except in the case when credit spread (*Cred*) constitutes the baseline model. Looking at the ENC-NEW test we reject the null at the 1% significance level that the unrestricted models are encompassed by the restricted model in all cases. These results provide strong support that ILR improves forecast accuracy relative to all of the baseline models.

For the two-quarters-ahead forecasts, we get similar results, although we cannot reject the null that the MSE of a model with ILR and Rm is different from a model with only Rm. However, the ENC-NEW test still give strong support for ILR containing additional information to Rm.

In Panel B of table 9, we change the baseline model to a an autoregressive model for GDP growth. Thus, now we test test whether adding ILR (or any of the other financial variables) improves forecast accuracy of GDP growth relative to an autoregressive model for GDP growth. Looking first at the one-quarter-ahead forecasts, we find that ILR, Rm and Cred, significantly improves the MSE relative to the baseline model, while adding the term spread or volatility to the model, does not significantly reduce the MSE. On the other hand, the more powerful ENC-NEW test reject the null that the baseline model encompass the unrestricted model at

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

the 1% level for all variables except for market volatility where the null is rejected at the 5% level.

For the two-quarters-ahead forecasts, we see that all variables except market volatility improves the forecast accuracy of the autoregressive baseline model. Note also that the unrestricted model that includes ILR shows the greatest improvement in MSE over the baseline model when giving two-quarters-ahead forecasts. Another interesting thing to note from the results in Panel B, is that the model that add the term spread did not improve the MSE relative to the restricted autoregressive model in the one-quarter-ahead forecast comparison. However, when comparing the one-quarter-ahead and two-quarter-ahead performance of the unrestricted models, the term spread model has the greatest improvement in MSE. This is consistent with results in the literature that suggest that the forecast ability of the term spread is greater for longer horizons.

Table 9 Nested model comparisons

Panel A report the results from nested model comparisons for predicting quarterly real GDP growth out of sample one-quarter and two-quarter ahead. The first column shows the variables in the unrestricted model, and the second column shows the variable included in the restricted (baseline) model. Columns 3 to 5 shows the relative MSE, the MSE-F test for equality of MSE and the ENC-NEW test for the one-quarter-ahead forecast. Columns 6 to 8 shows the test statistics for the two-quarter-ahead forecasts. Panel B shows the results from when the baseline model is an autoregressive model (of order 1) for GDP growth. In that case the unrestricted models adds ILR and each of the other financial variables to the restricted model.

Panel A: Forecasting real GDP growth: Illiquidity (ILR) versus other financial variables

		1 quarter-ahead forecasts			2 quarters-ahead forecasts		
Unrestricted model	Restricted model	$\frac{MSE_u}{MSE_r}$	MSE-F	ENC-NEW	$\frac{MSE_u}{MSE_r}$	MSE-F	ENC-NEW
ILR, TERM	TERM	0.917	20.95**	41.96**	0.927	18.09**	31.49**
ILR, Rm	Rm	0.976	5.69**	14.39**	1.003	-0.59	12.33**
ILR, CRED	CRED	1.000	0.02	18.73**	0.964	8.53**	22.86**
ILR, Vola	Vola	0.889	28.76**	50.91**	0.895	26.88**	35.98**

Panel B: Forecasting real GDP growth: Financial variables versus an autoregressive model for GDP growth

		1 quarter-ahead forecasts			2 quarters-ahead forecasts		
Unrestricted model	Restricted model	$\frac{MSE_u}{MSE_r}$	MSE-F	ENC-NEW	$\frac{MSE_u}{MSE_r}$	MSE-F	ENC-NEW
ILR, dGDP	dGDP	0.849	41.16**	60.17**	0.803	56.36**	40.60**
TERM, dGDP	dGDP	0.988	2.91	34.75**	0.866	35.44**	28.99**
Rm, dGDP	dGDP	0.905	24.20**	45.54**	0.850	40.66**	30.91**
CRED, dGDP	dGDP	0.838	44.63**	51.37**	0.850	40.54**	28.77**
Vola, dGDP	dGDP	1.109	-22.77	9.92*	1.049	-10.81	1.26

In table 10 we examine whether the out-of-sample performance of ILR for forecasting GDP growth is robust across the sub-samples. In panel A and B of the table we run the similar model comparisons as in Panel A and panel B of table 9 respectively. Parts (a) and (f) report the results that an econometrician standing in 1970 with only data up to 1970 would have obtained, and similarly for 1980 (part b and g), 1990 (part c and h), 2000 (part d and i) and finally in the end of 2007 (part e and j). Looking first at panel A, where the baseline (restricted) models only include each of the control variables and the unrestricted model adds ILR to the baseline model. We see that ILR significantly improves the forecast accuracy (ENC-NEW) of all baseline models

for all sub samples except when the baseline model contains the credit spread. Compared to the baseline model with *Cred*, the unrestricted model that includes ILR has similar out-of-sample performance as the restricted model when looking at the MSE-F statistic. However, the ENC-NEW test suggest that a model with both ILR and CRED is better than a model with only CRED.

In panel B we compare ILR and the different control variables against an autoregressive model for dGDP as the baseline. We see that adding ILR always improves the baseline model. However, this is also the case for all other financial variables, except for market volatility that always increase the MSE relative to the restricted model, and is always encompassed by the baseline model.

Table 10 Nested model comparisons - sub period results

The table shows sub-period out-of-sample test results for forecasting real GDP growth one quarter ahead. In Panel A (part a through e), we perform the same analysis as in Panel A of table 9 where an unrestricted models with market illiquidity (ILR) in addition to one of the four financial variables (Term, Rm, Cred, Vola) is compared to restricted models where ILR is excluded from the model. The first column of the table shows the variables in the unrestricted model. The second variable is the variable used in the restricted model. In Panel B we report the sub-sample results similar to the full sample analysis in Panel B of table 9 where the restricted (baseline) model is an AR(1) model for GDP growth, and the unrestricted model adds either ILR, Term, Rm, Cred, or Vola to the baseline model. All sub-samples start in 1947, but we increase the end date, simulating what an econometrician standing in the last year of each sample period would have concluded.

Panel A: ILR vs. different baseline models

Unrestricted model	$\frac{MSE_u}{MSE_r}$	MSE-F	ENC-NEW
(a) Forecasting from 1947 to 1970			
ILR, TERM	0.862	12.34**	26.41**
ILR, Rm	0.887	9.79**	11.31**
ILR, CRED	1.017	-1.25	10.84**
ILR, Vola	0.804	18.81**	30.47**
(b) Forecasting from 1947 to 1980			
ILR, TERM	0.893	14.02**	29.14**
ILR, Rm	0.954	5.63**	9.62**
ILR, CRED	0.992	0.89*	12.86**
ILR, Vola	0.849	20.87**	35.07**
(c) Forecasting from 1947 to 1990			
ILR, TERM	0.904	16.59**	32.35**
ILR, Rm	0.968	5.23**	11.36**
ILR, CRED	1.008	-1.21	13.43**
ILR, Vola	0.867	24.03**	39.52**
(d) Forecasting from 1947 to 2000			
ILR, TERM	0.912	18.92**	38.08**
ILR, Rm	0.974	5.20**	13.00**
ILR, CRED	1.013	-2.53	15.39**
ILR, Vola	0.884	25.77**	45.12**
(e) Forecasting from 1947 to 2007			
ILR, TERM	0.918	20.45**	42.24**
ILR, Rm	0.979	4.91**	14.13**
ILR, CRED	1.004	-0.96	18.56**
ILR, Vola	0.886	29.52**	51.59**

Panel B: All variables vs. AR(1) model for dGDP

Unrestricted model	$\frac{MSE_u}{MSE_r}$	MSE-F	ENC-NEW
(f) Forecasting from 1947 to 1970			
ILR, dGDP	0.6830	35.73**	47.87**
TERM, dGDP	0.9879	0.94*	8.29**
Rm, dGDP	0.8829	10.22**	21.90**
CRED, dGDP	0.6562	40.35**	40.36**
Vola, dGDP	1.1920	-12.40	-0.54
(g) Forecasting from 1947 to 1980			
ILR, dGDP	0.7984	29.54**	41.18**
TERM, dGDP	0.8882	14.73**	29.22**
Rm, dGDP	0.9152	10.84**	25.77**
CRED, dGDP	0.7413	40.83**	39.91**
Vola, dGDP	1.0562	-6.22	7.10*
(h) Forecasting from 1947 to 1990			
ILR, dGDP	0.8315	31.82**	46.71**
TERM, dGDP	0.9657	5.58**	28.36**
Rm, dGDP	0.8943	18.56**	35.25**
CRED, dGDP	0.8034	38.43**	41.60**
Vola, dGDP	1.1160	-16.32	6.02
(i) Forecasting from 1947 to 2000			
ILR, dGDP	0.8393	37.72**	55.30**
TERM, dGDP	0.9696	6.17**	33.76**
Rm, dGDP	0.8958	22.90**	42.45**
CRED, dGDP	0.8114	45.78**	49.83**
Vola, dGDP	1.1281	-22.37	6.80
(j) Forecasting from 1947 to 2007			
ILR, dGDP	0.8497	40.52**	60.31**
TERM, dGDP	0.9845	3.60**	35.64**
Rm, dGDP	0.9048	24.10*	45.96**
CRED, dGDP	0.8313	46.46**	52.90**
Vola, dGDP	1.1199	-24.52	9.03

3 The differential information content of liquidity of small and large firms

The previous section established the predictive content of stock market liquidity for macroeconomic conditions. In this section we look more closely at this, and ask whether we can find out more of which aspects of liquidity is important. We find that the predictive content is mainly driven by the liquidity of small, relatively illiquid stocks. Small firms are relatively more sensitive to economic downturns than large firms. This makes looking at the liquidity of small firms particularly interesting for the purpose of this paper. If the business cycle component in liquidity is caused by investors moving out of assets that has a tendency to perform particularly bad in recessions, we would expect that the liquidity of small firms should reflect this effect most strongly. Thus, we would expect the liquidity variation of small firms to vary more than for large firms, and also to be more informative about future macro fundamentals. To examine this more closely, we run a similar analysis as in table 7, but now split firms into size quartiles and calculate each liquidity measure for the firms in each group. Firms are assigned into size quartiles at the beginning of the year based on their market capitalization the last trading day of the previous year. In the analysis we use the liquidity variable that measures the liquidity for the 25% smallest firms and the 25% largest firms.

Table 11 report the results from these regressions. We also include the different control variables used in the earlier part of the analysis. Looking first at panel A, we see that it is only the liquidity measured for the small firms that has a significant coefficient ($\hat{\beta}_S^{LIQ}$), while the coefficient on the liquidity of large firms ($\hat{\beta}_L^{LIQ}$) is insignificant in all models. In the models for the other macro variables, we get the similar results.

In table 12 we perform Granger causality tests between the different liquidity proxies for the small and large firms and GDP growth. As before, we use the Schwartz criterion to determine the optimal lag length in each model. The first column denotes which liquidity variable we are looking at. In the second and third column we report the χ^2 statistic and associated p-value from the test of the null that GDP growth does not Granger cause the respective liquidity variable. We see that we cannot reject the null for any of the models. In the two last columns we test the null that the liquidity variable does not Granger cause GDP growth. For all liquidity measures sampled for the small firms we reject the null at the 5% level or better.

Overall the results in tables 11 and 12 suggest that illiquidity of the smallest firms is most informative about future economic conditions. We view this result as consistent with our conjecture that variation in market liquidity is caused by portfolio shifts due to changing expectations about economic fundamentals.

Finally, if investors have a tendency to move out of small firms and this causes activity to drop and liquidity to worsen, we would expect this to show up in the trading activity of these firms. In figure 5 we examine whether the change in turnover (measured as the shares traded divided by the number of outstanding shares) is different for small and large firms. As before, the bars show the cumulative average quarterly growth in real GDP and the solid line

Table 11 Predicting macro with market liquidity - size portfolios

The table shows the multivariate OLS estimates from regressing next quarters real GDP growth in macro variables on current market illiquidity of small and large firms and four control variables. We examine three different proxies for market illiquidity, sampled for small and large firms. The estimated model is,

$$y_{t+1} = \alpha + \beta^S \, LIQ_t^{small} + \beta^L \, LIQ_t^{large} + \gamma \mathbf{X}_t + u_{t+1}$$

where y_{t+1} is real GDP growth, LIQ^{small} is the respective illiquidity proxy sampled for the 25% smallest firms and LIQ^{large} is the illiquidity of the 25% largest firms, $\mathbf{X_t}$ contains the additional control variables ($Term_t$, $Cred_t$, $Vola_t$ and Rm_t) and γ' is the vector with the respective coefficient estimates for the control variables. The Newey-West corrected t-statistics (with 4 lags) is reported in parentheses below the coefficient estimates, and $\bar{R}^2$ is the adjusted R^2.

Panel A: Real GDP growth (dGDPR)

Liquidity proxy (LIQ)	$\hat{\alpha}$	$\hat{\beta}_S^{LIQ}$	$\hat{\beta}_L^{LIQ}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
ILR	0.008	**-0.008**	0.003	0.000	-0.006	0.001	0.022	0.13
	(7.40)	**(-3.66)**	(1.01)	(0.74)	(-2.48)	(0.09)	(2.35)	
ROLL	0.017	**-0.303**	-0.272	0.001	-0.005	0.006	0.023	0.14
	(5.11)	**(-2.37)**	(-0.98)	(1.59)	(-2.47)	(1.12)	(2.83)	
LOT	0.008	**-0.014**	0.000	0.000	-0.007	0.008	0.030	0.13
	(7.34)	**(-2.15)**	(0.08)	(0.62)	(-3.04)	(1.45)	(3.67)	

Panel B: Unemployment rate (dUE)

Liquidity proxy (LIQ)	$\hat{\alpha}$	$\hat{\beta}_S^{LIQ}$	$\hat{\beta}_L^{LIQ}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
ILR	0.002	0.030	-0.042	-0.006	0.053	-0.029	-0.259	0.12
	(0.26)	(1.66)	(0.09)	(-1.78)	(3.61)	(-0.81)	(-4.00)	
ROLL	-0.050	**2.402**	0.859	-0.010	0.045	-0.073	-0.204	0.14
	(-1.73)	**(2.70)**	(0.35)	(-2.82)	(3.22)	(-1.75)	(-3.92)	
LOT	0.004	**0.110**	0.008	-0.006	0.052	-0.098	-0.246	0.14
	(0.43)	**(3.52)**	(0.22)	(-1.58)	(3.69)	(-2.46)	(-4.72)	

Panel C: Consumption growth (dCONSR)

Liquidity proxy (LIQ)	$\hat{\alpha}$	$\hat{\beta}_S^{LIQ}$	$\hat{\beta}_L^{LIQ}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
ILR	0.008	-0.001	0.002	0.001	-0.002	0.000	0.028	0.08
	(8.32)	(-0.37)	(0.54)	(2.00)	(-1.19)	(0.10)	(3.17)	
ROLL	0.014	**-0.300**	-0.010	0.001	-0.001	0.005	0.023	0.11
	(4.71)	**(-2.51)**	(-0.03)	(3.02)	(-0.53)	(0.94)	(3.42)	
LOT	0.008	-0.005	-0.005	0.001	-0.002	0.005	0.026	0.09
	(8.19)	(-1.42)	(-0.96)	(1.93)	(-1.04)	(0.91)	(3.95)	

Panel D: Investment growth (dINV)

Liquidity proxy (LIQ)	$\hat{\alpha}$	$\hat{\beta}_S^{LIQ}$	$\hat{\beta}_L^{LIQ}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
ILR	0.006	**-0.019**	0.010	0.004	-0.022	0.015	0.065	0.18
	(2.10)	**(-3.45)**	(1.09)	(2.25)	(-4.03)	(1.13)	(2.51)	
ROLL	0.033	**-1.063**	-0.625	0.005	-0.020	0.034	0.059	0.22
	(3.93)	**(-2.86)**	(-0.68)	(3.26)	(-4.10)	(2.68)	(2.84)	
LOT	0.007	-0.017	-0.009	0.003	-0.024	0.027	0.078	0.17
	(2.20)	(-1.22)	(-0.76)	(2.15)	(-4.50)	(1.85)	(3.79)	

Table 12 Granger causality - size portfolios

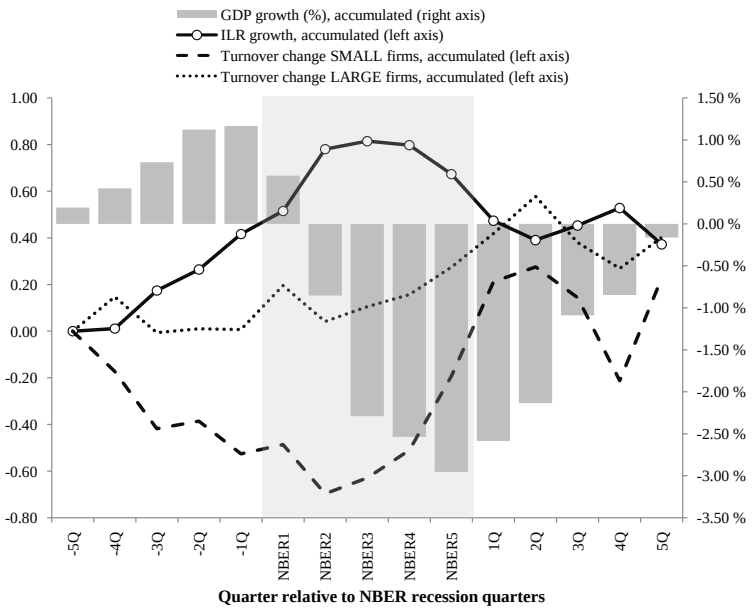
The table shows the results of Granger causality tests between real GDP growth and the illiquidity of small and large firms for the three different illiquidity proxies. The first column denote the liquidity variable, column two and three shows the χ^2 and associated p-value from Granger causality tests where the null hypothesis is that GDP growth *does not* Granger cause the liquidity variables. Similarly, columns four and five, show the results when the null hypothesis is that the liquidity variable *does not* Granger cause GDP growth.

Liquidity	$dGDPR \nrightarrow LIQ$		$LIQ \nrightarrow dGDPR$	
variable (LIQ)	χ^2	p-value	χ^2	p-value
ILR^S	4.34	0.23	10.33	0.02
ILR^L	6.86	0.08	1.32	0.72
$Roll^S$	0.67	0.72	6.44	0.04
$Roll^L$	0.19	0.91	5.60	0.06
LOT^S	3.19	0.07	9.84	0.00
LOT^L	0.20	0.65	0.03	0.87

the cumulative average change in ILR. The dashed line shows the cumulative average change in turnover for small firms, and the dotted line shows the same series for large firms. The result in the figure indicate a striking systematic difference between the trading activity in small and large firms before recessions. While the turnover for large firms are essentially unchanged before the first recession quarter, the turnover for small firms is falling steadily already from four quarters before the first recession quarter. Furthermore, both the turnover for small and large firms starts increasing already in the middle of the NBER recessions. While this pattern is also the strongest for small firms, it suggests that investors increase their demand for equities in general, and for smaller firms in particular, when they start expecting the future economic conditions to improve.

Figure 5 Market illiquidity and trading activity (turnover) around NBER recessions

The figure shows the accumulated average growth in ILR (solid line) and accumulated average GDP growth (bars) averaged in event time before, during and after NBER recession periods. In addition, the dashed line shows the accumulated average change in turnover for the 25% smallest firms and the dotted line shows the accumulated average change in turnover for the 25% largest firms. All the NBER recession periods are aligned to start at NBER1.



4 A confirmation and investigation of causes of the results–the case of Norway

In this section we first examine whether a similar relationship exists for Norway for the period 1980 through 2008. In addition to being a robustness check, the main reason for looking at the Norwegian data, is that we have complete monthly stock ownership data for all Norwegian investors in all Norwegian companies for the period 1991 through 2007. This makes it possible to examine our conjecture that the systematic liquidity variations are linked to portfolio shifts and changes in market participation during economic downturns where traders desire to move away from equity investments in general ("flight to quality") and from small illiquid stocks in particular ("flight to liquidity"). This will be examined in more detail in subsection 4.3.

4.1 The Norwegian evidence of predictability

Similar to the US investigation, we start by assessing the in-sample predictive ability of market liquidity for the same macro variables for Norway, i.e. real GDP growth (dGDPR), growth in the unemployment rate (dUE), real consumption growth (dCONSR) and growth in investments (dINV). For the Norwegian analysis, we focus on the Amihud illiquidity ratio (ILR) and relative spread (RS) as our liquidity proxies Both the ILR and RS are stationary through the entire sample, so we do not difference any of the liquidity series in the Norwegian analysis.

In table 13 we show the results from predictive regressions where we use only market liquidity and the lagged dependent variable as predictors for next quarter growth in the respective macro variables. 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) predicts a decrease in next quarter GDP, consumption, investment and an increase in the unemployment rate. We have also examined models with different lags of the explanatory variables as well as different lags of the dependent variable. The size and significance of the coefficient on RS and ILR is largely unaffected by these variations in model specification.

In unreported investigations we checked the Granger causality between our two proxies for market liquidity and the different macro variables.[16] We find that we cannot reject the null that GDP growth does not Granger cause RS, while we reject the reverse hypothesis at the 1% level. This result is similar when we use the ILR as our liquidity proxy. The results are similar for most of the other macro variables and illiquidity measures. One exception is in the test between ILR and dUE, where we reject the null that unemployment do not Granger cause ILR. In summary, the univariate in-sample results are very similar to the results for the US, suggesting that the result that market liquidity is related to future macro is robust to change in market, market structure and trading system.

Let us now go on to look at the sensitivity of the results on liquidity to additional explanatory variables. In the US analysis, we used four financial control variables; the term spread, credit

[16] These results are available upon request.

Table 13 In-sample predictive regressions - Norway

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

$$y_{t+1} = \alpha + \beta LIQ_t^j + \gamma y_t + u_{t+1}.$$

where LIQ^j is either RS or ILR, and the only control variable is the lagged dependent variable (y_t). 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			
	$\hat{\alpha}$	$\hat{\beta}^{RS}$	$\hat{\gamma}^y$	$\bar{R}^2$	$\hat{\alpha}$	$\hat{\beta}^{ILR}$	$\hat{\gamma}^y$	$\bar{R}^2$
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)	
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)	

spread, market returns and market volatility. For the Norwegian analysis, there is however no credit spread series available for the length of our sample period. This is mainly due to a historically very thin credit market in Norway. Thus, we are only able to control for the Term spread, market return and market volatility. The term spread (*Term*) is calculated as the interest rate differential between a 10 year government bond index and the short term rate; the excess market return (*Rm*) and market volatility (*Vola*).

In table 14 we present the results from multivariate (in sample) predictive regressions when we add the three financial control variables (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 market liquidity.

We also perform an out-of-sample analysis for Norway. For the sake of brevity we do not show the results, only summarize the main findings. When performing nested model comparisons between RS and the other financial control variables (Term, Rm, Vola), the MSE-F test suggest that the MSE of an unrestricted model (including liquidity as a predictor), has a significantly lower MSE across all models. The results are a bit weaker with respect to the ENC-NEW test,

Table 14 In-sample predictive regressions (Norway) - additional control variables

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

$$y_{t+1} = \alpha + \beta LIQ_t + \gamma' \mathbf{X}_t + u_{t+1}.$$

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 *Rm*, 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)	
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})	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
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)	
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)	

where we are not able to reject the null that RS is not encompassed by a model with only Term or Rm. However, for Vola, the ENC-NEW test suggst that Vola does not encompass RS. As for the US, we also compare the out-of-sample forecast performance of liquidity compared to an autoregressive model for GDP growth. Adding either RS or ILR to the autoregressive GDP model significantly improves the MSE. In addition, we strongly reject the null that the restricted GDP model encompass an unrestricted model that either adds RS or ILR.

4.2 Differences across firm size

As we did for the US, we want to examine whether the informativeness of the liquidity about future GDP growth differs between small firms large firms. We therefore sort firms on the OSE into four groups based on their market capitalization at the end of the previous year, and calculate the average liquidity for each size group. We use the liquidity series for the smallest and largest group as explanatory variables. In table 15 we perform a Granger causality test between GDP growth and the liquidity series. The results are similar to what we found for the US in table 12, as we reject the null hypothesis that both RS^S and ILR^S sampled for the small firms *does not* Granger cause dGDPR, while we are unable to reject the null when using the liquidity measured for the largest firms.

Table 15 Granger causality Norway - size portfolios

The table shows the results of Granger causality tests between real GDP growth and the illiquidity of small and large firms for the two different liquidity proxies for the Norwegian sample. The first column denote the liquidity variable, column two and three shows the χ^2 and associated p-value from Granger causality tests where the null hypothesis is that GDP growth *does not* Granger cause the liquidity variables. Similarly, columns four and five, show the results when the null hypothesis is that the liquidity variable *does not* Granger cause GDP growth.

	dGDPR $\nrightarrow$ *LIQ*		*LIQ* $\nrightarrow$ *dGDPR*	
Liquidity variable (LIQ)	χ^2	p-value	χ^2	p-value
RS^S	0.69	0.71	**5.90**	**0.05**
RS^L	1.93	0.37	0.61	0.73
ILR^S	0.15	0.67	**4.92**	**0.03**
ILR^L	1.63	0.20	0.66	0.42

4.3 Portfolio changes, liquidity, and real variables

As we argued earlier, a possible channel through which the observed effects may work is changes in investors' desired portfolio compositions. For example, in downturns investor may want to tilt their portfolios towards more liquid assets. In this section we look at the equity portfolios of investors at the Oslo Stock Exchange, and investigate whether, in the aggregate, we see such changes in portfolio compositions. The challenge lies in constructing aggregate measures of changes in portfolio composition. We will do this two ways. One will be to look at measures that gets more at participation, by looking at the full portfolio of each investor. The other is

too look at concentration and movements between owner types for individual stocks, without controlling for the portfolios *across* stocks.

Let us begin with measuring participation on an investor-by-investor basis. What we can measure with our data is the actual portfolios of investors, and how they change over time. We need to construct a proxy that can be informative about both the degree to which investors move in and out of the stock market, and the degree to which the structure of their stock portfolios change. We would like a measure that mainly is influenced by actual changes in stock ownership, which rules out measures based on wealth changes, since such measures have the undesirable characteristic that wealth can change due to stock price changes, even if investors do not make any active portfolio changes. We therefore use the *number of shares* owned by an investor as the basic piece of data. We can not sum these across stocks, since this is again sensitive to price differences across shares. Instead, we simply ask: When do an owner realize the portfolio? Well, when he sell all his stocks. Our measure of aggregate changes uses such cases to identify aggregate movements in and out of the market, or a group of stocks, such as a size portfolio. In constructing our time series we look at the set of participants at two following dates, and find the set of investors which were there at the first date, but not on the second date. This is the number of investors *leaving* the market. Similarly, we count the number of investors present at the second date, but not at the first. This is the number of investors *entering* the market. The net change in investors is the number of investors entering the market less the number of investors leaving the market. This number is what we use as a measure of the change in portfolio composition.[17] To gain some intuition about these numbers, in table 16 we describe these numbers at the annual level. We show the number of owners and what fraction of owners this is. For example we see that on average about 15 thousand investors leave the market between one year and the next, which is about a quarter of the investors present at the beginning of the year. The net change is positive, which says that on average the number of investors on the exchange has been increasing in the period.

The descriptive numbers in panel A of table 16 concerns the cases where investors leave and enter the stock market completely. We will also calculate similar measures for portfolios. That is, we look at investors which invest in a group of securities, such as a size quartile portfolio. We then calculate the number of investors entering or leaving this group of securities. In addition to looking at all owners we also split the owners by their type, and show data split by personal, foreign, financial, nonfinancial(corporate) and state owners. In table 16 we also show average number of investors leaving and entering the market of these owner types. Note that in these calculations for different owner types we only consider owners *of the given type*, so the fraction of investors is conditioned on the type. For example, the average of 51 financial owners leaving corresponds to about 14% of financial investors, only. As is clear from the table the most common investor type is personal investors.[18]

[17] In implementing the calculation we attempt to reduce noise by removing trivial holdings of less than a hundred shares, since this is the minimum lot size at the Oslo Stock Exchange.

[18] Regarding foreign owners there is an institutional reason for the decrease in foreign investors. It is a reflection of the increased ownership through nominee accounts, where foreign owners register through a nominee account. The Norwegian Central Securities Registry do not have details on nominee ownership, they only have data on the

We now want to relate aggregate changes in portfolio compositions to changes in liquidity. As we saw for both the US and Norway, there are interesting cross-sectional patterns in liquidity across (firm) size groups, where in particular the time series of the group of small firms had the most predictive content. We therefore construct measures of changes in participation for the different spread groups, by each year finding the stocks in the different size components, i.e. we sort the stocks at the OSE based on size, and each year construct four size based stock portfolios. We then calculate the same participation measure, the net number of new owners, but now *only* for the stocks in each portfolio. So, if an investors had holdings in small stocks, only, but moved them to large stocks, we would count this as leaving the small stock portfolio and entering the large stock portfolio.

In panel B of table 16 we calculate the correlations between liquidity, measured by the relative bid ask spread, and portfolio changes for various owner types. If liquidity worsen (spreads increase) when the number of participants in the market falls, we should expect a negative correlation between spreads and changes in the number of investors. This relationship should be strongest for the least liquid stocks. That is exactly what we find. For the portfolio of the smallest stocks on the OSE there is a significantly negative correlation between relative spreads and changes in participation. The correlation becomes smaller in magnitude when we move to portfolios of larger firms, the correlation being smallest in magnitude for the portfolio of largest firms.

A problem with the measure of participation above may be that it *only* considers cases of complete withdrawal from the market. We therefore also look a measure we calculate for individual stocks. If participation falls, either completely or partially, this will result in increased ownership concentration among the remaining investors in a stock. There may also be portfolio shifts between owner types. These measures are much simpler to calculate, as they can be found on a stock-by-stock basis. In panels C and D in table 16 we show the results of looking at correlations between changes in liquidity and respectively ownership concentration and owner type. The interesting numbers are the differences between the portfolio of small firms (quartile 1) and large firms. We see that when for example the spread is increasing, the concentration is increasing for the portfolio of small stocks (positive correlation), but is decreasing for the portfolio of large stocks. Similarly, when the spread increases the number of owners is decreasing for the portfolio of small stocks, but increasing for the large stocks. Looking at owner type we see some interesting patterns there too. When the spread is increasing financials tend to decrease their stake in small stocks but increase the stake in large stocks.

In conclusion, for both ways of looking at ownership we find results consistent with our story of portfolio shifts between small stocks and large stocks.

total held in nominee accounts. The number of foreign investors we are using is the number of directly registered foreign owners, which has decreased, although the fraction of OSE held by foreigners has increased throughout the period.

Table 16 Changes in portfolio composition and liquidity

The table in panel A describes changes in ownership participation measured at an annual frequency. Each year in the sample we calculate the number of investors leaving the market totally, entering the market, and the net change. We also normalize the numbers by calculating what fraction of owners at the beginning of the period the numbers are. Panel B present correlations between stock market liquidity measured by the average relative bid ask spread in a period and the changes in stock market participation in the period. Change in stock market participation is the change in the number of investors in the stock market, or the given portfolio, of the specified types. For annual data we use each year from 1990 to 2006, giving 16 observations. For the calculations with quarterly and monthly data we use data between 1993:1 to 2006:12, giving 56 quarterly observations and 168 monthly observations.

Panel A: Describing annual changes in portfolio composition

Investor	Number of investors			Fraction of investors		
type	entering	leaving	net	entering	leaving	net
All	15220	11934	3286	24.1	18.5	5.6
Personal owners	13445	10087	3358	24.3	17.5	6.8
Foreign owners	862	1119	-256	33.7	35.3	-1.6
Financial owners	51	44	6	14.8	12.4	2.4
Nonfinancial owners	1013	838	175	24.4	19.6	4.8
State owners	14	11	3	20.8	15.1	5.7

Panel B: Correlation liquidity and change in stock market participation

	Firm size quartiles									
	All firms		Q1 (smallest firms)		Q2		Q3		Q4 (largest firms)	
All owners	-0.07	(0.32)	-0.35	(0.00)	-0.10	(0.22)	-0.20	(0.07)	-0.11	(0.22)
Personal owners	-0.02	(0.45)	-0.33	(0.01)	-0.09	(0.25)	-0.18	(0.09)	-0.08	(0.28)
Foreign owners	-0.18	(0.09)	-0.30	(0.01)	-0.16	(0.12)	-0.25	(0.03)	-0.23	(0.04)
Financial owners	-0.06	(0.33)	-0.11	(0.21)	0.01	(0.46)	-0.09	(0.25)	-0.08	(0.27)
Nonfinancial owners	-0.16	(0.12)	-0.35	(0.00)	-0.11	(0.21)	-0.21	(0.06)	-0.20	(0.06)
State owners	-0.06	(0.34)	-0.20	(0.07)	0.19	(0.08)	-0.10	(0.23)	-0.06	(0.34)

Panel C: Correlation change in liquidity and change in ownership concentration

		Firm Size Quartile			
Concentration measure	All firms	Q1 (smallest firms)	Q2	Q3	Q4 (largest firms)
largest owner	0.07 (0.30)	0.13 (0.15)	0.13 (0.16)	0.09 (0.25)	-0.06 (0.31)
Herfindahl	0.09 (0.24)	0.20 (0.06)	0.10 (0.22)	0.18 (0.08)	-0.12 (0.18)
No owners	0.37 (0.00)	-0.09 (0.23)	-0.22 (0.04)	-0.27 (0.02)	0.37 (0.00)
Herfindahl (excluding three largest)	0.18 (0.08)	0.29 (0.01)	0.23 (0.04)	-0.07 (0.29)	-0.05 (0.36)

Panel D: Correlation change in liquidity and movement across owner types

		Firm Size Quartile			
Owner type	All firms	Q1 (smallest firms)	Q2	Q3	Q4 (largest firms)
Financial fraction	-0.08 (0.26)	-0.15 (0.12)	-0.06 (0.34)	-0.04 (0.38)	0.22 (0.04)
Individual fraction	-0.12 (0.18)	-0.14 (0.14)	-0.10 (0.21)	-0.06 (0.32)	0.24 (0.03)
Nonfinancial fraction	-0.06 (0.31)	-0.13 (0.16)	-0.01 (0.48)	0.04 (0.37)	-0.18 (0.08)
Foreign fraction	-0.05 (0.34)	0.10 (0.22)	0.06 (0.33)	-0.16 (0.11)	-0.17 (0.09)
State fraction	0.05 (0.34)	-0.03 (0.42)	-0.14 (0.13)	0.01 (0.48)	0.06 (0.32)

5 Conclusion

In the current financial crisis a great deal of attention has been on the fact that a collapse in liquidity was a precursor to the recession in the real economy. We show that this is just the extreme case of a general relationship – that stock market liquidity contains information about current and future macroeconomic conditions.

The prime contribution of this paper is to provide two empirical observations. First, we show that the liquidity in the stock market contains information useful for estimating the current (and future) state of the economy. These results are shown to be remarkably robust to our choice of liquidity proxy and sample period. In addition, the relationship is also very similar for the US and Norway. Second, we show that time variation in equity market liquidity is related to changes in the participation in the stock market, especially for the smallest firms. Participation in small firms decreases when the economy (and market liquidity) worsen. This is consistent with a "flight to quality" effect and with our earlier finding that the liquidity of the smallest stocks contain the most information about future economic conditions.

There are a number of interesting ways to follow up our results. First, our results showing that (Granger) causality goes from the stock market to the real economy has interesting implications for prediction, particularly in a policy context. The ability to improve forecasts of such central macroeconomic variables as unemployment, GDP, consumption and the like will be particularly interesting for central banks and other economic planners. Second, while we have found evidence of the link from observed liquidity to the economy using data for the US and Norway, it would be interesting to also look at other stock markets. Finally, our finding that stock market participation is related to liquidity time variation should be important input to asset pricing theorists attempting to understand why liquidity seems to be priced in the cross-Section of stock returns. We are in the process of following up some of these thoughts, but at the moment they are left as promising avenues for future research.

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