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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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.

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Introduction

In the discussion of 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 over the period 1947 to 2008, we document that measures of stock market liquidity contains leading information about the real economy, also after controlling for other asset price predictors. Figure 1 serves to illustrate the relationship found between stock market liquidity and the business cycles. Liquidity is measured by the Amihud (2002) illiquidity ratio (ILR) and NBER recession periods are marked with grey bars. Observe how liquidity is worsening (illiquidity increasing) well ahead of the onset of a recession.

We speculate that the observed effects are the results of aggregate portfolio shifts from individual investors, where changes in desired portfolios are driven by changes in individuals' expectations of the real economy. We find some empirical evidence consistent with this hypothesis. First, using 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. Second, using data for Norway, where we have unusually detailed information about the composition of ownership of the whole stock market, 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.

Our results are related to several strands of the literature. One important strand is the 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, that the predictive content of asset prices has a strong situational dependence.

We shift focus to a different aspect of asset markets, the liquidity of the stock market, i.e. the costs of trading equities. 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. There is no direct link, however, from asset pricing models to the behavior of liquidity. 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 stemming 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 links found between liquidity and market participation using a special data set on investor ownership from the Norwegian stock market supports such a hypothesis.

Two recent papers on the relationship between equity order flow and macro fundamentals are closely related to our work. Beber, Brandt, and Kavajecz (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 of these two papers and our research 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, 1988).

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. 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 also contributes to the market microstructure literature on liquidity. Commonality in liquidity is well documented in this literature, however, it is not fully understood 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 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 adding 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 section 3 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 macroeconomy. 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

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 a daily frequency. We consider the following four liquidity measures: Relative spread, the Lesmond, Ogden, and Trzcinka (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.

Spread costs are observed in dealer markets as well as in limit order markets. The relative 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.

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 estimate 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

[1] This estimator is only defined when $Scov < 0$. Harris (1990) suggests defining $\widehat{s} = -2\sqrt{Scov}$ 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 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).

obtained from the Oslo Stock Exchange data service.[3] The Norwegian sample covers the period 1980-2008. For both the US and Norwegian 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 these 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]

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 subperiod statistics we see that there has been some changes over time across all liquidity measures. Panel B 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 the correlation is still as high as 0.32.

Panel C of table 1 gives 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 suggest 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 (CONSR) 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. From the equity market we use *Excess market return* ($\mathsf{R_m}$), calculated as the value weighted return on the S&P500 index in excess of the 3 month T-bill rate, and *Market volatility* (*Vola*), measured as the cross sectional average volatility of the sample stocks. We also use the *term spread* (*Term*), calculated as the difference between the yield on a 10-year Treasury bond benchmark and the yield on the 3 month t-bill, and the *credit spread* (*Cred*) measured as the yield difference between the Moody's Baa

[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, Skjeltorp, and Ødegaard (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.

[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 through the seventies there is essentially no spread data in the CRSP series.

[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 Investments. 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.

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] We use similar macro series for Norway.[7] In the analysis we differentiate the macro variables.[8]

Table 2 shows the contemporaneous correlations between the different variables used in the analysis for the US. All three liquidity measures 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. 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 ($\mathsf{R_m}$). Thus, when market liquidity is low, market volatility is high and realized market returns are low. 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. Stock market volatility and return are not significantly correlated with any of the macro variables, except for consumption growth. Finally, as one would expect, all the macro variables are significantly correlated with each other, and have the expected signs.

1.4 Norwegian ownership data

An important reason for including Norwegian data in the paper is the availability of data on stock market ownership for all investors at the Oslo Stock Exchange, which we use to investigate aggregate patterns in stock ownership.

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-controlled entity, the Norwegian Central Securities Registry (VPS). From

[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 $\mathsf{dCONSR} = \ln(\mathsf{CONSR_t}/\mathsf{CONSR_{t-1}})$ and dINV is the real growth in investments , calculated as $\mathsf{dINV} = \ln(\mathsf{INV_t}/\mathsf{INV_{t-1}})$.

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 allow 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 3 shows some descriptive statistics for stock ownership at the Oslo Stock Exchange.

2 Predicting US economic growth with market illiquidity

2.1 In-sample evidence

We start by assessing the in-sample predictive ability of market illiquidity. 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.

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 passes stationarity tests. Our main dependent variables (y_{t+1}) is real GDP growth. However, we also examine additional macro variables related to economic growth.

Table 4 summarizes the results from the various regression specifications. The first specification only include the liquidity variable and one lag of the dependent variable.[10] 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

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

[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 materially affect the results.

and investments.[11] In sum the results indicate that market illiquidity contains significant information about future economic growth. When market liquidity worsens, this is followed by a slowdown in economic growth.

Several other financial variables have been found to contain information about future macroeconomic conditions. We therefore also consider regression specifications where we control for these variables. Table 2 showed that 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. We start by including two non-equity control variables (in addition to the lag of the dependent variable). The control variables we include are the term spread (*Term*) and credit spread (*Cred*). These regression specifications are also listed in table 4. Looking first at the estimation results for GDP growth, we see that while *Cred* enters significantly in all three models, the coefficients on liquidity retains its level, sign and significance. Interestingly, the coefficient on the term spread ($\hat{\gamma}^{\mathsf{Term}}$) is not significant in the models that includes ILR or LOT. In unreported specifications we find that excluding ILR and LOT in these models restores the significance of *Term*. The results for the other macro variables 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 the model just containing liquidity and lagged dependent variables.

As a final exercise, we include the equity market variables excess market return ($\mathsf{R_m}$) and volatility (*Vola*) into the models in addition to the term spread and credit spread. In the models for GDP growth 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 the results are 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 we see that market

[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.

liquidity (regardless of liquidity measure) is rendered insignificant when the excess return on the market is included in the model. Finally, in the models for investment growth the liquidity coefficients are unaffected by the inclusion of the market return.

Overall, the results show that while other financial variables clearly are useful for predicting future economic growth, we find that there is additional information in market illiquidity, even after controlling for well known alternative 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.

Causality

We are primarily interested in predicting macroeconomic conditions with liquidity, but one may also think of causality going in the opposite direction, i.e. that 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. We therefore look directly at this issue by performing Granger causality tests. We return to the specification with only liquidity and real variables, and 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 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. For the different sub-periods we see that the relation is remarkably stable. Thus, part (a) of the table show 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 parts (b) and (c) of the table we perform the same tests for the LOT and the Roll measures. For the full sample period, we find 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 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. Based on the sub-sample 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 is 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.

Timing of information

The in-sample results on the predictive content of liquidity for macro variables can be summarized by a form of "event study." We use the onset of a recession as the "event date," and show the evolution of the various series of interest around this date in a plot. In panel A of figure 2 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 averaged across all the 10 NBER recessions (shaded area) in our sample from 1947-2008.[13] This style of analysis also lets us give informative comparisons of informational content of the different predictive variables. Panel B of figure 2 shows similar plots, where we also add the financial control variables term spread, credit spread, excess market return and 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

[12]This is consistent with the sub-sample results for the specification with only liquidity and lagged explanatory variables, discussed in footnote 11, 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.

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 therefore 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 about the timing of the data so it reflects what would have been available to the forecaster when a forecast is made. 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

[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.

to the forecaster (investor) when making his forecast. However, since the question we are asking is whether financial variables contain information about expected economic growth, we want to forecast the last vintage. The argument for this is that since the revisions are mainly 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. 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 compare the performance of a model with market liquidity as the predictor against models with other financial variables. We also compare the illiquidity model against a benchmark model where we forecast GDP growth using an autoregressive 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 performance 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, Leybourne, and Newbold (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 $E[\bar{d}] = 0 \ \forall \ t$, 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 calculated as:

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

and the modified DM statistic is 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.

Panel A in Table 6 shows the results when we compare different forecasting models for quarterly GDP growth using different proxies for market liquidity. 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. The second number shows the modified Diebold/Mariano statistic (MDM) which provides a statistic to test for whether the MSE of model 1 is significantly different from that of 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. The MDM statistic cannot however reject the null that the MSE of the LOT model is not significantly different from the MSE of the Roll model.

Overall, the results in panel A of table 6 show 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. In the rest of the out-of-sample analysis we therefore use the ILR as our liquidity predictor variable.

Out-of-sample performance of illiquidity versus other variables

We next 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*, R_m) 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. We also compare the models with the other financial variables to the restricted autoregressive model for GDP growth.

We evaluate 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

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

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, $\varepsilon_{u,t+1}$ 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 nonstandard and we use the bootstrapped critical values provided by Clark and McCracken (2001).[15]

Panel B of table 6 provides the results for nested model comparisons of 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 are included in the unrestricted model, and the second column shows which variable 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. Based on the ENC-NEW test we reject the null that the unrestricted models are encompassed by the restricted model at the 1% significance level for 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 based on the MSE-F test we cannot reject the null and claim that the MSE of a model with ILR and R_m is better than a model with only R_m. The ENC-NEW test, however, supports the claim that ILR contains additional information to R_m.

One more observation from Panel B is worth noting. The model that adds the term spread does not improve the MSE relative to the restricted autoregressive model in the one-quarter-ahead forecast comparison. However, when we compare the one-quarter-ahead and two-quarter-ahead performance of the unrestricted models, the term spread specification 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 better for longer horizons.

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

In Panel C of table 6 we change the baseline model to an autoregressive model for GDP growth, and 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, R_m and *Cred* significantly improves the MSE relative to the baseline model. Adding the term spread or volatility to the model does not significantly reduce the MSE. The more powerful ENC-NEW test rejects the null that the baseline model encompass the unrestricted model at 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 all variables except market volatility improve 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.

3 Firm size and the information content of liquidity

Small firms are relatively more sensitive to economic downturns than large firms. Therefore firm size might be of particular interest 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 be higher than the liquidity variation of large firms, and also the liquidity of small firms to be more informative about future macro fundamentals. To examine this more closely we run in-sample predictive regressions with liquidity variables based on different firm size quartiles. 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. We use two liquidity variables, one based on the liquidity of the 25% smallest firms and one based on the liquidity of the 25% largest firms.

Table 7 reports the results from regression models where we include the different control variables used earlier. In the models where we try to predict next quarters GDP growth, the liquidity of small firms has a significant coefficient ($\hat{\beta}_S^{LIQ}$) for all three liquidity proxies. The liquidity of large firms has an insignificant coefficient ($\hat{\beta}_L^{LIQ}$) for all liquidity proxies in all models, a result which is also confirmed in table 8, which shows the results from Granger causality tests between the liquidity proxies for small and large firms and GDP growth. 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 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 7 and 8 suggest that the illiquidity of smaller 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. We have actually in unreported analysis investigated measures of trading volume and found it to be less informative than other liquidity measures about real variables, but looking at volume may still help in our understanding of the mechanisms. In figure 3 we therefore 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 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. Since this pattern is 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.

4 Systematic liquidity variations and portfolio shifts - Evidence from Norway

We conjecture that the systematic liquidity variations found are linked to portfolio shifts and changes in market participation during economic downturns, i.e. that traders desire to move away from equity investments in general ("flight to quality") and from small illiquid stocks in particular ("flight to liquidity"). Using special data on stock ownership from the Oslo Stock Exchange (OSE), we can actually examine this conjecture. Moreover, the Norwegian data set provides a valuable robustness check of our results from the US market.

4.1 The Norwegian evidence of predictability

We have to first check that we get similar results on predictability as in the US case, and start by assessing the in-sample predictive ability of market liquidity for the macro variables real GDP growth (dGDPR), growth in the unemployment rate (dUE), real consumption growth (*dCONSR*) and growth in investments (dINV). We use the Amihud illiquidity ratio (ILR) and relative spread (RS) as our liquidity proxies. Both the ILR and RS pass stationarity tests, so we do not difference the liquidity series.

In table 9 we show the results from the in-sample predictive regressions. We look at two model specifications. In the first specification 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 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.[16]

In the second model specification we control for other variables. In the US analysis, we used four financial control variables; the term spread, credit spread, market returns and market volatility. In Norway, no credit spread series are 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 other three variables. The results from regressions based on this specification is reported in columns 5-7 in table 9. The coefficient on market liquidity (β) is highly significant for all models except for consumption growth. None of the other financial variables have significant coefficients, however it should be noted that if we exclude the relative spread, the term spread enters significantly into the models for dGDPR and dUE (but 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 performed an out-of-sample analysis for Norway. For the sake of brevity we do not show the results, only summarize the main findings. In nested model comparisons between RS and the other financial control variables (*Term*, R_m, *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, where we are not able to reject the null that RS is encompassed by a model with only *Term* or R_m. However, the ENC-NEW test suggests that *Vola* does not encompass RS. We also compare the out-of-sample forecast performance of liquidity to

[16]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.

an autoregressive model for GDP growth. Adding either RS or ILR to the autoregressive GDP model significantly improves the MSE. In addition, the null that the restricted GDP model encompass an unrestricted model that either adds RS or ILR is strongly rejected. We also checked the Granger causality between our two proxies for market liquidity and the different macro variables. 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.

In summary, both the in-sample and out of sample results for Norway 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 of market, market structure and trading system.

4.2 The importance of firm size

To examine whether the informativeness of the liquidity about future GDP growth differs between small and large firms, we 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. For brevity we only report results of Granger causality tests, shown in table 10. The results are similar to what we found for the US in table 8. 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.

4.3 Portfolio shifts and liquidity

A possible channel through which the documented relationship between stock market liquidity and business cycles may work is changes in portfolio compositions. In this section we therefore investigate whether investors do in fact tilt their portfolios towards more liquid assets in economic downturns. Our Norwegian data set includes monthly ownership of all investors in all Norwegian companies listed at the OSE over the period 1991-2007. The challenge lies in constructing aggregate measures of changes in portfolio composition. We do this in two different ways. First we focus on market participation and look at the full portfolio of each investor. Then we look at concentration and movements between owner types for individual stocks, without controlling for the portfolios *across* stocks.

Market participation on an investor-by-investor basis

Our ownership data lets us construct the actual portfolios of all investors, and how they change over time. We want a variable 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. The measure should mainly be influenced by actual changes in stock ownership. This 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 the number of shares across stocks, since this is again sensitive to price differences across shares. Instead, we simply ask: When do an owner realize the portfolio? Obviously when he sell all his stocks. Our measure of aggregate changes uses these cases to identify aggregate movements in and out of the market, or a group of stocks, such as a size portfolio.

Our time series is constructed by comparing the set of participants at two following dates. The set of investors which were present at the first date, but not on the second date is the set 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 used as a measure of the change in portfolio composition. The net change in investors is calculated for all owners as well as for each of the owner types (personal, foreign, financial, nonfinancial(corporate) and state owners).[17] Panel A of Table 11 shows some descriptive statistics for the net change in portfolio compositions at the annual level. 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 over the period. Panel A also shows the average number of investors leaving and entering the market within each owner type. Note that in the calculations for different owner types we only consider owners *of the given type*, i.e. 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]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

As we saw for both the US and Norway, the time series of small firms' liquidity have more predictive content than the time series of large firms' liquidity. We therefore construct measures of changes in participation for different size quartiles, 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 investor 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.

Panel B of Table 11 shows 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.

Movements between owner types for individual stocks

A problem with the measure of participation above may be that it *only* considers cases of complete withdrawal from the market. We therefore also calculate a measure for individual stocks. If participation falls (i.e. the net change is negative), 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 11 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. There is also some interesting patterns with respect to owner type. When the spread is increasing financials tend to decrease their stake in small stocks but increase the stake in large

on the 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.

stocks.

To sum up, using two different measures of changes in portfolio compositions, we find evidence consistent with our hypothesis that liquidity changes are related to portfolio shifts.

5 Conclusion

In the current financial crisis there has been a great deal of attention 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 useful information 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. The relationship is also very similar for two different markets, the US and Norway. Second, we find evidence 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 the finding that the liquidity of the smallest firms contain the most information about future economic conditions. In addition to suggesting a new financial market based predictor, our results provide a new explanation for the observed commonality in liquidity.

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 and "nowcasts" (Giannone, Reichlin, and Small, 2008) 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.

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Figure 1 Liquidity and the business cycle

The figure shows time series plots of annual ILR for the US over the period 1947-2008. The gray bars are the NBER recession periods. ILR is detrended using a Hodrick-Prescott filter.

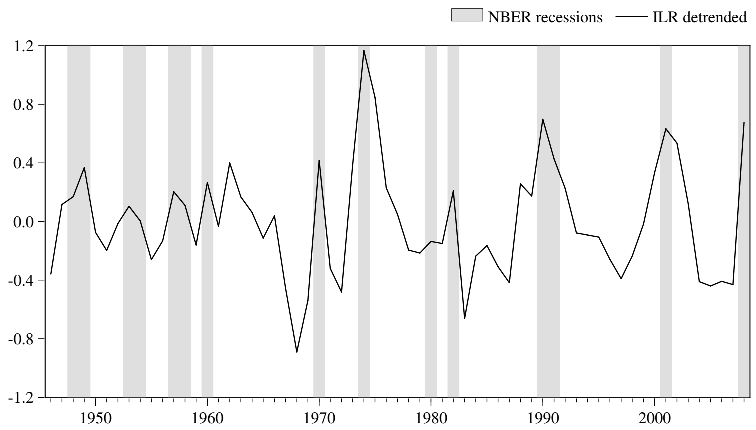
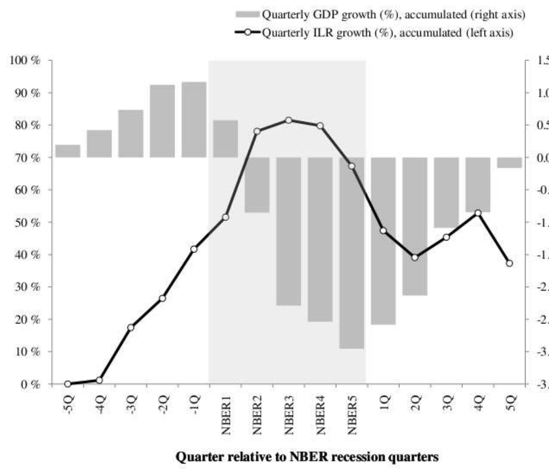


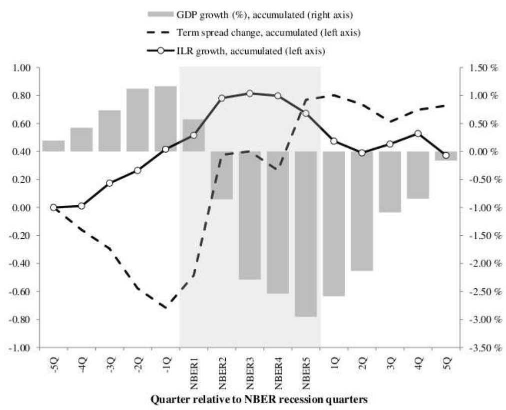
Figure 2 Market illiquidity around NBER recessions

In panel A the figure 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. The figure shows the results when looking at all 10 NBER recessions during the full sample period 1947-2008. In Panel B we show similar figures, adding similar evolutions of the cumulative average changes in (a) term spread, (b) credit spread, (c) excess market return and (d) volatility.

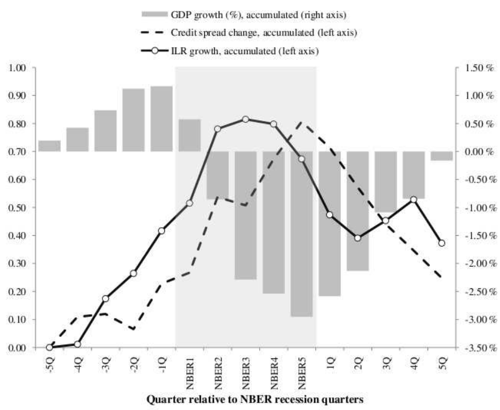
Panel A: Liquidity evolution approaching recessions.



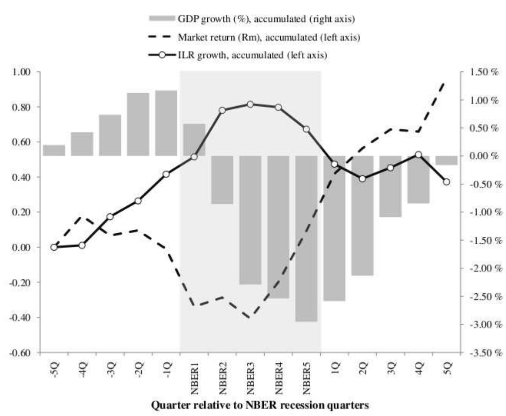
Panel B: Comparing to other financial variables.



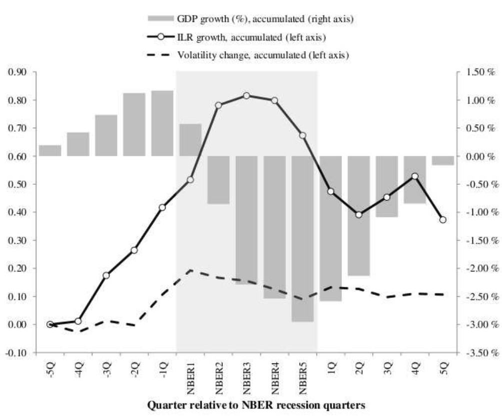
(a) Term spread



(b) Credit spread



(c) Market return



(d) Volatility

Figure 3 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. Turnover is measured as the shares traded divided by the number of outstanding shares. All the NBER recession periods are aligned to start at NBER1.

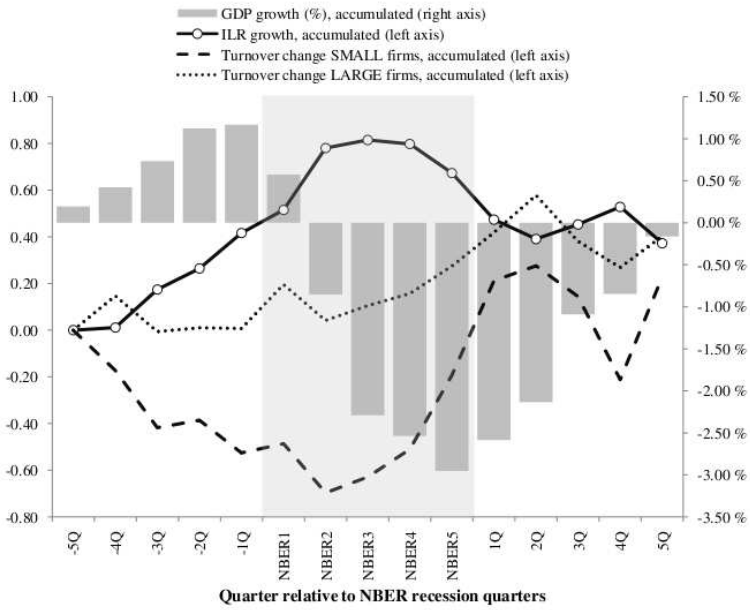


Table 1 Describing liquidity measures

Panels A and B show descriptive statistics for the US liquidity measures. The US sample covers the period from 1947 through 2008. The liquidity measures 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*). 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 liquidity measures are calculated for each available stock once each quarter. Panel A shows the mean and median of the liquidity measures, the number of securities used, the total number of observations (each security is observed in several quarters), and estimates of average liquidity measures for different subperiods. Panel B shows correlation coefficients between the liquidity measures. The correlations are calculated across all stocks and time, i.e. the liquidity measures are calculated for each available stock once each quarter, and the correlations are pairwise correlations between these liquidity measures. Panels C and D show corresponding statistics for the Norwegian liquidity measures. The Norwegian sample covers the period from 1980 through 2008.

Panel A: Descriptive statistics, US liquidity measures

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: Correlation coefficients, US liquidity measures

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

Panel C: Descriptive statistics, Norwegian liquidity measures

					Means subperiods		
Liquidity					1980-1989	1990-1999	2000-2008
measure	mean	median	no secs	no obs			
RS	0.042	0.029	788	14942	0.041	0.046	0.040
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 D: Correlation coefficients, Norwegian liquidity measures

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

Table 2 Correlations

The table shows the Pearson correlation coefficients 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)**

Table 3 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, nonfinancial 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

Table 4 In-sample prediction of macro variables

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

Panel A: ILR liquidity measure

Dependent variable (y_{t+1})	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
dGDPR	0.006	-0.013	0.224					0.13
	(7.58)	(-5.37)	(3.68)					
dUE	0.003	0.074	0.300					0.13
	(0.61)	(3.68)	(5.14)					
dCONSR	0.006	-0.006	0.305					0.11
	(7.07)	(-3.33)	(4.46)					
dINV	0.006	-0.034	0.265					0.15
	(2.95)	(-6.18)	(3.97)					
dGDPR	0.005	-0.011	0.214	0.001	-0.005			0.16
	(5.02)	(-4.60)	(3.67)	(1.17)	(-2.29)			
dUE	0.015	0.057	0.303	-0.009	0.042			0.18
	(1.95)	(3.02)	(5.23)	(-2.83)	(3.19)			
dCONSR	0.004	-0.005	0.305	0.001	-0.001			0.13
	(3.86)	(-2.88)	(4.48)	(2.32)	(-0.66)			
dINV	0.001	-0.027	0.247	0.004	-0.018			0.23
	(0.45)	(-5.23)	(3.98)	(2.58)	(-3.84)			
dGDPR	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)	
dUE	0.006	0.021	0.307	-0.008	0.048	-0.033	-0.235	0.21
	(0.79)	(1.14)	(6.25)	(-2.64)	(3.56)	(-0.93)	(-4.58)	
dCONSR	0.005	-0.001	0.302	0.001	-0.001	0.002	0.026	0.17
	(4.76)	(-0.39)	(4.43)	(2.29)	(-1.04)	(0.34)	(3.38)	
dINV	0.003	-0.020	0.243	0.004	-0.019	0.007	0.048	0.24
	(1.16)	(-3.74)	(3.91)	(2.54)	(-3.95)	(0.55)	(2.14)	

Panel B: LOT liquidity measure

Dependent variable (y_{t+1})	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
dGDPR	0.007	-0.017	0.168					0.06
	(7.52)	(-2.77)	(2.58)					
dUE	0.003	0.129	0.261					0.10
	(0.47)	(3.14)	(4.42)					
dCONSR	0.006	-0.009	0.282					0.09
	(7.03)	(-1.74)	(3.85)					
dINV	0.007	-0.039	0.218					0.07
	(3.03)	(-2.56)	(3.20)					
dGDPR	0.006	-0.012	0.135	0.001	-0.006			0.10
	(5.06)	(-2.13)	(2.18)	(1.35)	(-2.86)			
dUE	0.015	0.089	0.252	-0.010	0.045			0.16
	(1.86)	(2.46)	(4.67)	(-3.02)	(3.56)			
dCONSR	0.004	-0.006	0.263	0.001	-0.001			0.12
	(3.98)	(-1.35)	(3.38)	(2.44)	(-0.89)			
dINV	0.002	-0.021	0.165	0.004	-0.021			0.17
	(0.57)	(-1.58)	(2.89)	(2.85)	(-4.65)			
dGDPR	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)	
dUE	0.005	0.107	0.290	-0.007	0.048	-0.084	-0.269	0.23
	(0.67)	(2.63)	(6.02)	(-2.54)	(3.65)	(-2.02)	(-5.48)	
dCONS	0.005	-0.006	0.291	0.001	-0.001	0.005	0.027	0.18
	(5.02)	(-1.17)	(4.30)	(2.26)	(-1.02)	(0.84)	(4.41)	
dINV	0.005	-0.023	0.216	0.003	-0.021	0.017	0.079	0.22
	(1.61)	(-1.70)	(3.42)	(2.53)	(-4.57)	(1.15)	(4.00)	

Table 4 (Continued)

Panel C: *Roll* liquidity measure

Dependent variable (y_{t+1})	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
dGDPR	0.019	-0.813	0.133					0.10
	(5.96)	(-4.12)	(2.10)					
dUE	-0.074	5.206	0.236					0.12
	(-3.07)	(3.28)	(4.23)					
dCONSR	0.013	-0.437	0.264					0.11
	(4.22)	(-2.28)	(3.37)					
dINV	0.040	-2.228	0.169					0.12
	(4.29)	(-3.61)	(2.65)					
dGDPR	0.017	-0.744	0.167	0.001	-0.005			0.14
	(5.29)	(-3.95)	(2.66)	(2.20)	(-2.20)			
dUE	-0.051	4.732	0.273	-0.012	0.037			0.18
	(-2.28)	(3.32)	(4.67)	(-3.90)	(2.97)			
dCONSR	0.011	-0.482	0.286	0.002	0.000			0.15
	(3.97)	(-2.61)	(3.99)	(3.18)	(-0.24)			
dINV	0.031	-2.047	0.209	0.005	-0.016			0.23
	(3.86)	(-3.85)	(3.35)	(3.69)	(-3.95)			
dGDPR	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)	
dUE	-0.043	3.492	0.275	-0.010	0.044	-0.063	-0.226	0.23
	(-1.75)	(2.26)	(5.98)	(-3.31)	(3.41)	(-1.61)	(-4.77)	
dCONSR	0.010	-0.331	0.278	0.001	-0.001	0.005	0.023	0.18
	(3.64)	(-1.82)	(3.92)	(2.89)	(-0.70)	(0.96)	(3.66)	
dINV	0.030	-1.833	0.171	0.005	-0.019	0.024	0.058	0.25
	(3.72)	(-3.35)	(2.94)	(3.26)	(-4.20)	(1.83)	(2.94)	

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$\nrightarrow$ 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$\nrightarrow$ 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$\nrightarrow$ 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$\nrightarrow$ 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$\nrightarrow$ 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$\nrightarrow$ 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)

Table 6 Results of out of sample tests

The table in panel A 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. Panel B 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 C 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: Choosing liquidity variable: Predicting GDP growth with different liquidity proxies

		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

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

Unrestricted model	Restricted model	1 quarter-ahead forecasts $\frac{MSE_u}{MSE_r}$	MSE-F	ENC-NEW	2 quarters-ahead forecasts $\frac{MSE_u}{MSE_r}$	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 C: Forecasting real GDP growth: Financial variables versus an autoregressive model

Unrestricted model	Restricted model	1 quarter-ahead forecasts $\frac{MSE_u}{MSE_r}$	MSE-F	ENC-NEW	2 quarters-ahead forecasts $\frac{MSE_u}{MSE_r}$	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

Table 7 Predicting macro with market liquidity - size portfolios

The table shows the multivariate OLS estimates from regressing next quarters 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*, *Cred*, *Vola* and R_m) 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: ILR liquidity measure

	$\hat{\alpha}$	$\hat{\beta}_S^{LIQ}$	$\hat{\beta}_L^{LIQ}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
dGDPR	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)	
dUE	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)	
dCONSR	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)	
dINV	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)	

Panel B: LOT liquidity measure

	$\hat{\alpha}$	$\hat{\beta}_S^{LIQ}$	$\hat{\beta}_L^{LIQ}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
dGDPR	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)	
dUE	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)	
dCONSR	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)	
dINV	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)	

Panel C: *Roll* liquidity measure

proxy (LIQ)	$\hat{\alpha}$	$\hat{\beta}_S^{LIQ}$	$\hat{\beta}_L^{LIQ}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{Rm}$	$\bar{R}^2$
dGDPR	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)	
dUE	-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)	
dCONSR	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)	
dINV	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)	

Table 8 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

Table 9 In-sample predictive regressions - Norway

The table shows the results from predictive regressions for different macro variables. The regressions estimated are $y_{t+1} = \alpha + \beta \text{LIQ}_t + \gamma' \mathbf{X}_t + u_{t+1}$, where LIQ is either RS or ILR, and the variables in $\mathbf{X}$ is the lagged dependent variable in addition to *Term*, *Vola* and R_m.

Panel A: RS liquidity measure

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	0.023	-0.397	-0.243				0.12
	(5.28)	(-4.03)	(-4.03)				
dUE	-0.443	11.387	-0.150				0.12
	(-3.94)	(3.95)	(-1.56)				
dCONS	0.016	-0.216	-0.153				0.03
	(3.75)	(-2.43)	(-1.62)				
dINV	0.073	-1.686	-0.415				0.19
	(3.79)	(-4.01)	(0.19)				
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: ILR liquidity measure

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	0.012	-0.006	-0.225				0.11
	(5.99)	(-3.04)	(-3.69)				
dUE	-0.108	0.141	-0.080				0.06
	(-2.16)	(2.49)	(-0.82)				
dCONS	0.011	-0.004	-0.142				0.04
	(5.85)	(-2.72)	(-1.49)				
dINV	0.021	-0.018	-0.404				0.16
	(2.23)	(-2.44)	(-4.94)				
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)	

Table 10 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

Table 11 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 data we use data between 1993:1 to 2006:12, giving 56 quarterly 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

	All firms		Firm size quartiles 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

Concentration measure	All firms	Firm Size Quartile 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 (ex 3 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

Owner type	All firms	Firm Size Quartile 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)