# Liquidity and the Business Cycle*

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**Abstract**

We show evidence of a contemporaneous relation between stock market liquidity and the business cycle. Stock market liquidity worsen when the economy is slowing down, and this effect is most pronounced for small firms. Using data for both the US and Norway, we find strong evidence that stock market liquidity predict the current and future state of the economy. 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. Our results suggest that an important explanation for the equity premium in general, and the equity size premium in particular, may be related to time variation in stock market liquidity at business cycle frequencies.

**Keywords**: Market Microstructure, Liquidity, Business Cycles

**JEL Codes:** G10, G20

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## Introduction

The link between the stock market and the real economy has long been of interest, both for analysts of financial markets and investigators of the macro economy. Stock prices (returns) and volatility have a long history as leading - although imperfect - indicators of the state of the economy. In this paper we show that another aspect of stock markets, *liquidity*, has a stronger relation to the real economy than stock prices and returns. While it is common knowledge that liquidity tends to dry up during economic downturns, we show that the relationship between liquidity and the business cycles is much more pervasive than previously thought. We also show evidence that changes in investors' portfolio composition and participation during economic up- and downturns help explain the relationship between liquidity and the real economy.

The contribution of our paper is based on an empirical analysis of the relationship between stock market liquidity and the real economy in two different countries, the US and Norway, over the period 1980-2007. Our contribution is twofold. First, we show that stock market liquidity strongly predicts current and future real activity variables, such as GDP growth, the change in the unemployment rate, consumption growth and output gap. More specifically, we use a VAR analysis to show that the Granger causality between these variables go *from* liquidity *to* the macroeconomic variables. Figure 1 serves to illustrate this finding. In the plot on the left (a) we show the time series of the US unemployment rate together with the aggregate illiquidity for the US stock market, measured by Amihud [2002]'s illiquidity ratio (`ILR`). Overall, the figure shows that when unemployment is increasing (downturns), the stock market liquidity is decreasing.[1] The plot also indicate the NBER recessions over the sample period. For all four recessions, we see that the market illiquidity peaks, and was worsening already at the onset of the recessions. The plot on the right (b) shows the time series of output gap and aggregate stock market illiquidity for Norway, measured by the relative bid ask spread. The pattern found for Norway is similar to the US pattern. When the Norwegian economy is in a downturn, with a low or decreasing output gap, the stock market tend to become illiquid, as shown by the high spread.[2] Note that for both data sets, the macro series is not contemporaneously observable with the liquidity series, i.e. while liquidity is observed in real time, the official macro figures are published with a lag.

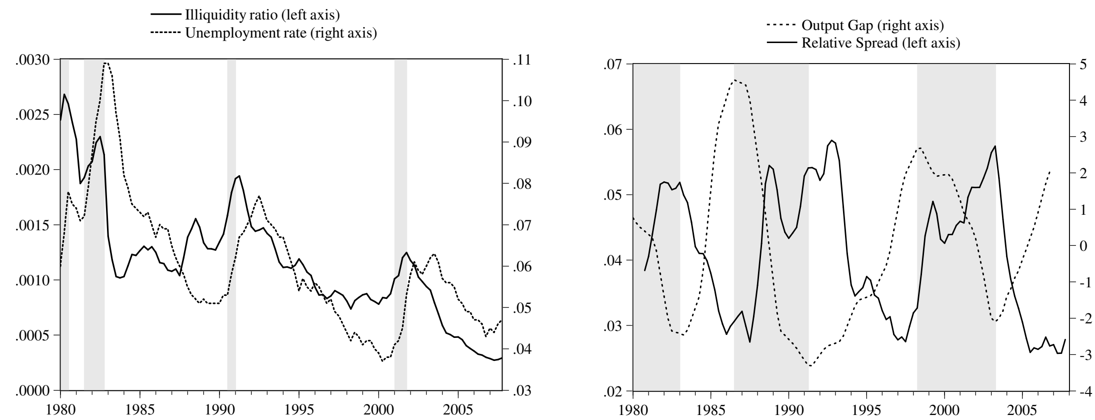
Our second finding follows from an analysis of the *mechanism* that makes liquidity a superior indicator of real activity. This analysis is the prime reason for using data for Norway. In this market we have access to complete monthly portfolio holdings over a 15 year period for all market participants at the Oslo Stock Exchange. By linking our measures of liquidity to the variations in portfolio holdings of individual investors, we show that time variation in stock market liquidity is related to changes in investors' portfolio composition and participation. Intuitively, if investors hold stocks as hedges of consumption risk, and these hedging properties

[1]Note that stock market liquidity is decreasing when the illiquidity ratio is high. One has to be careful about the terminology concerning liquidity, since there are many different measures of liquidity. The Amihud [2002] illiquidity measure used to proxy for liquidity here is low when the market is liquid, and high when the market is illiquid. Other liquidity measures, such as turnover, have the opposite interpretation.

[2]Similarly to the illiquidity ratio above, spreads are large when the market is relatively illiquid.

**Figure 1** Stock market liquidity and real economic activity

Figure (a) shows the time series evolution of quarterly stock market illiquidity, measured by the Amihud Illiquidity ratio (`ILR`), for stocks on NYSE, AMEX and NASDAQ over the period 1980 to 2007. The `ILR` is equally weighted and the grey bars indicate the NBER recession periods. Figure (b) shows the time series evolution of stock market liquidity, measured by the relative bid ask spread, and output gap for Norway for the period 1980-2007. The relative bid ask spread is measured as the difference between the ask and bid quote divided by the bid ask midpoint. We then average the relative spread across all listed securities for each quarter. The output gap figures are from Norges Bank (Central Bank of Norway).




(a) Unemployment and Illiquidity ratio for the US (b) Output gap and relative spread for Norway

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" where investors move out of less liquid investments in economic downturns.

The rest of the paper is structured as follows. We first, in section 1, give some theoretical and empirical background for the analysis of the paper, placing it in the context of the literature. We then, in section 2, introduce the empirical measures of stock liquidity. We define the measures we use, discuss the data sources for liquidity measures, and give some summary statistics both for the US and Norway. Next, in section 3, we use a VAR analysis to show that liquidity is related to the real economy both in the US and in Norway. We then, in section 4, use the ownership data of all investors at the Oslo Stock Exchange to construct several measures of changes in portfolio compositions, and show that periods when liquidity worsen are the same as periods when there is a "flight to liquidity" in the stock portfolios. Finally, section 5 offers some concluding remarks.

# 1 Literature

To place our empirical findings in the context of the vast literature on liquidity, we restrict our attention to theoretical and empirical work on two research questions: (i) Why is liquidity time varying? and (ii) what is the link between liquidity and the real economy?

## 1.1 Time varying liquidity

There is a large literature in finance on the liquidity of asset markets, typically with a starting point of market microstructure.[3] For our purposes, the most important empirical findings are that stock market liquidity, however defined, has a systematic time varying component, which is important for the pricing of the cross-section of stock returns.[4]

In the market microstructure literature, illiquidity is typically treated as a fixed property of individual stocks. Hence, it is not obvious that the sources of this illiquidity, order processing costs, inventory costs, and costs related to asymmetric information, can explain time variation in aggregate liquidity. Fujimoto [2003] argues that asymmetric information is unlikely to affect the dynamics of aggregate liquidity, and that the main drivers of time varying liquidity are factors that simultaneously affect the inventory risk of many firms.[5]

Our empirical findings are more aligned with recent theoretical models that disregard explanations based on asset characteristics altogether and instead explain commonality in liquidity by characteristics of the market participants.

Brunnermeier and Pedersen [2007], develop a model where commonality in liquidity is explained by liquidity providers (dealers, hedge funds, or investment banks) who are facing funding constraints. Shocks to the liquidity providers' funding constraints imply commonality in liquidity because the reduction in available funding affects all stocks. A problem with this explanation is that binding funding constraints for dealers cannot explain time varying liquidity in electronic limit order markets without designated dealers (as e.g. the Oslo 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. Funding constraints for arbitrageurs (liquidity providers) also generate time varying liquidity in Gromb and Vayanos [2002].

In Vayanos [2004], 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. The key state variable in the model is asset payoff volatility. The model generates time-varying liquidity premia that increase with volatility, i.e. times of high volatility are associated with flight to liquidity. In Saar [2006]'s model, uncertainty about investors' preferences and endowments creates uncertainty about the risk premium in the economy. Liquidity is not time varying because illiquidity is a cost or a risk that investors need compensation for. Rather, time varying liquidity is the result of the market's attempt to learn about the state of the risk premium. Watanabe and Watanabe [2008] develop a model where investors face uncertainty about their trading counterparties' preferences. Changes in the prevailing level of investor preference uncer-

[3] See O'Hara [2003] and Biais et al. [2005] for surveys.

[4] For empirical evidence on commonality and time variation in stock market liquidity measures, see Chordia et al. [2000], Huberman and Halka [2001] and Hasbrouck and Seppi [2001] for US evidence and Næs et al. [2008a] for Norwegian evidence. It is also well documented that this time variation is affecting asset returns, see for example Pastor and Stambaugh [2003] and Acharya and Pedersen [2005] for US evidence, and Næs et al. [2008b] for evidence from Norway.

[5] On the other hand, flight-to-liquidity from uninformed investors during bad times may result in higher adverse selection costs in the market (through a higher probability of trading against an informed investor).

tainty imply time variation in liquidity betas and the liquidity risk premium. Using a Markov regime-switching model and monthly data from the US stock market over the 1965-2004 period, the authors find some supporting evidence for the model.

Eisfeldt [2004]'s model explicitly links liquidity to business cycles (measured by productivity), and predicts that markets are more liquid in good times. Liquidity, defined as the cost of transferring the value of expected future payoffs from long-term assets into current income, is endogenously determined as a function of productivity. High productivity leads to higher investment in risky assets. Higher investments in risky assets induce more rebalancing trades mitigating adverse selection problems and improving liquidity.

### 1.2 Liquidity and the real economy

To understand the links between stock market liquidity and the real economy, it is fruitful to start with the role(s) of the stock market in the economy. The obvious role of the stock market is to supply capital to companies. At the same time, the stock market is a vehicle for the saving of individual investors. The amount of capital available for companies depends on the aggregate desire for equity investment in the economy.

The traditional asset pricing literature focus on investors and investment decisions. Within this perspective, liquidity can be linked to business cycles through a relationship with a time varying risk premium.[6] We argue that one should also expect to see time variation in the number of investors participating in the stock market as a function of the state of the economy. One explanation for this could be that consumers change the composition of their portfolios in anticipation of an economic downturn, i.e. that they move away from equity in general, and small/illiquid stocks in particular. Chetty and Szeidl [2007] show theoretically how "consumption commitments" can amplify risk aversion with respect to moderate shocks and induce investors to hold safer portfolios. A related explanation is that an economic downturn hit some investors before others, for example investors with cyclically sensitive jobs or households with high consumption commitments, and that trading costs increase as these investors have to liquidate stocks to finance consumption. In both cases, we should find a positive relationship between liquidity and stock participation, and a link between liquidity and economic conditions. For instance, an increase in market participants in economic upturns will increase competition and improve liquidity, particularly in limit order markets where there are no designated market makers providing liquidity.[7]

The other possible link between liquidity and the real economy is through the production side of the economy. Tirole [2008] notes that liquidity does not necessarily mean the same for investors and companies. From investors point of view, an asset is liquid if a large quantity of it can be traded quickly at low costs and a small price impact, whereas from companies'

[6] If for instance investors' optimal portfolios change over time because their hedging needs change with the state of the economy, this would lead to a time varying risk premium.

[7] The effects of changing participation in the stock markets are also studied in several papers, see Heaton and Lucas [2000] for a survey. However, the focus of these papers are on the effect of participation on returns (and the equity premium), not liquidity. Moreover, participation is typically related to the life cycle of investors (see [Constantinides et al., 1998]) and not the business cycles.

point of view, an asset is liquid if it can be used by the company "as a cushion to address pressing needs."[8] There is a large literature in macroeconomics on the role of capital market imperfections in creating cycles in investments, through the time variation in the availability of capital.[9] In addition, Lipson and Mortal [2007] find that firms with more liquid equity tend to have lower leverage and are more likely to choose equity over debt when raising capital. In such an analysis time variation in the stock market's ability to raise capital can have real effects, and therefore be linked to business cycles.[10] There is empirical evidence that liquidity is positively associated with raising of capital. When current and expected market conditions are bad and liquidity is low, IPO and SEO activity also tend to be minimal.[11]

Tirole [2008] and Holmstrom and Tirole [2001] argue that asset prices are driven jointly by consumers and firms with liquidity needs, i.e. that firms demand for (macroeconomic) liquidity also drives the pricing of assets.[12] If so, firms might also contribute to time varying trading costs by moving away from stocks into liquid bonds in anticipation of recessions.

We are not the first to examine empirically the relationship between time varying liquidity and the macro economy. Based on data from the US stock market over the 1962-2001 period, Fujimoto [2003] uses a VAR approach to investigate if time varying aggregate stock market liquidity has macroeconomic sources. The main conclusion of the study is that "market liquidity has become more resilient to both market-level and economy-wide shocks." Shocks in some macroeconomic variables are found to affect aggregate liquidity, but only in the years before the mid 1980's when the business cycle dynamics was more volatile.[13]

On the other hand, Gibson and Mougeot [2004] find evidence that a time varying liquidity risk premium in the US stock market *is* related to a recession index over the 1973-1997 period.[14] While Fujimoto [2003] focus on how unexpected *shocks* in macro variables affects liquidity, our results suggest that there is also a strong causality going the other way; market liquidity seem to capture changes in expectations about future developments in the macro economy.[15] Moreover, our access to stock ownership data enables us to make probable that this story is in fact plausible.

Several papers find support for a "flight-to-quality" or "flight-to-liquidity" during economic

[8]Hence, whereas a Treasury bond and a stock market index may be equally liquid according to a microstructure understanding, a Treasury bonds will by definition be more liquid than a stock market index according to the production side view, since the latter loose value in recessions.

[9]See Matsuyama [2007] for a survey of the macroeconomic implications of credit market imperfections for the business cycle.

[10]The decision to raise capital will depend on the perceived probability of success, together with the price concessions necessary to succeed. These price concessions will depend on liquidity. In illiquid markets it is necessary to give large price concessions to succeed in capital issues.

[11]See e.g. Pastor and Veronesi [2005] for a recent study of IPO waves.

[12]In the CAPM prices are determined entirely by the consumer sector.

[13]Similar analysis is done for Scandinavia in Söderberg [2008].

[14]Gibson and Mougeot [2004] examine whether systematic liquidity risk is priced using a bivariate GARCH(1,1)-in-mean specification for excess market returns on the S&P 500 Index. The standardized number of shares traded in the S&P 500 Index during a month is used as a proxy for liquidity. The Experimental Recession Index provided by NBER is used as an instrumental variable to characterize the evolution of the time-varying liquidity risk premium.

[15]Several studies within the empirical asset pricing literature suggest that risk factors found to explain the cross-section of stock returns are linked to future economic growth, see Liew and Vassalou [2000] and Vassalou [2003].

downturns. Longstaff [2004] finds that there is a flight-to-liquidity premium in Treasury bond prices, and that the premium is related to changes in consumer confidence and flows into equity and money market mutual funds. Goyenko and Sarkissian [2008] develop and test an international asset pricing model using the relative spread on US Treasury bonds as a proxy for a joint flight-to-liquidity/flight-to-quality risk factor. Results from asset pricing tests show that there is a significant negative risk premium related to bond illiquidity.[16] Interestingly, bond illiquidity is found to predict both illiquidity and returns in the stock markets, but not vice versa.

## 2 Liquidity measures and data

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.

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

### 2.1 Liquidity measures

Our choices of liquiditity measures are driven by our desire for reasonably long time series. Many common liquidity measures require high frequency trading information, which is not available for long periods. We therefore employ measures which can be calculated using data at the lower frequency of daily observations. In our analysis we will use three different measures: bid/ask spreads, the Lesmond et al. [1999] measure (`LOT`) and the Amihud [2002] illiquidity ratio (`ILR`).

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

Lesmond et al. [1999] suggested a measure of transaction costs (hereafter the `LOT` measure) that does not depend on information about quotes or the limit 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 firm's price

[16]Provided that this illiquidity factor change over time in response to investors' portfolio shifts to and from risky assets, an asset's sensitivity to this factor should be positively related to its expected return. The premium should be negative because the covariance between bond illiquidity and returns is negative on average.

*not* to move when the market as a whole moves. To get the intuition of this measure, consider a simple market model,

$$R_{it} = a_i + b_i R_{mt} + \varepsilon_{it} \quad (1)$$

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 $\varepsilon$ is an error term. In this model, for *any* change in the market return, the stock 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.

Our final liquidity measure, Amihud [2002]'s ILR measure, is a measure of the elasticity dimension of liquidity. Elasticity measures of liquidity try to take into account how much prices move as a response to trading volume. Thus, cost measures and elasticity measures are strongly related. Kyle [1985] defines price impact as the response of price to order flow. Amihud proposes a price impact measure that is closely related to Kyle's measure. The daily Amihud measure is calculated as,

$$\mathtt{ILR}_{i,T} = 1/D_T \sum_{t=1}^{T} \frac{|R_{i,t}|}{VOL_{i,t}} \quad (2)$$

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, such as dollars or NOK) 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, the illiquidity measure captures how much the price moves for each volume unit of trades.

## 2.2 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.[17] For Norway we have similar data to the CRSP data from the OSE data service.[18] We use data for 1980-2007. We calculate the different liquidity measures each quarter for each security, and then take averages across securities. The bid/ask spread is the average for the quarter. In table 1 below we give a number of descriptive statistics for the series of liquidity measures. We also provide time series plots of the various liquidity measures in figures 2 and 3.

[17]We use all stocks listed at either NYSE, AMEX or Nasdaq. We only use ordinary common shares. Securities are assigned to an exchange based on the EXCHD (exchange code) in the CRSP file which identify at which exchange the security is currently listed. We 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).

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

**Table 1** Describing liquidity measures

This table describes the liquidity measures used in this paper. Panels A and C gives descriptive statistics for respectively the US and Norway. Panels B and D give correlations between the liquidity measures. The liquidity measures are calculated for each available stock once each quarter. In the descriptive tables we first list the average and median of the liquidity measures. We then list of many different securities have been used, and the total number of observations (Each security is observed in several quarters). We then show estimates of average liquidity measures in three subperiods: 1980–1989, 1990–1999 and 2000-2007. In addition to the mean for each subperiod we list how many securities has been used in the subperiod. The correlations are pairwise correlations between the two liquidity measures. In each pairwise correlation we use quarters when we observe both of those two liquidity measures, we do not require that all three liquidity measures be present to use that observation.

Panel A: Describing liquidity measures, US

| | | | | | | Means subperiods | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Liquidity | | | | | | 1980-1989 | | 1990-1999 | | 2000-2007 | |
| measure | Exchange | mean | median | no secs | no obs | mean | no secs | mean | no secs | mean | no secs |
| RS | All | 0.042 | 0.027 | 13622 | 348787 | 0.051 | 3045 | 0.051 | 10338 | 0.024 | 7809 |
| | NYSE | 0.019 | 0.012 | 2387 | 69511 | | 0 | 0.025 | 1913 | 0.013 | 1805 |
| | AMEX | 0.046 | 0.028 | 914 | 16883 | | 0 | 0.061 | 560 | 0.039 | 640 |
| | NASDAQ | 0.047 | 0.033 | 10322 | 262393 | 0.051 | 3045 | 0.057 | 7865 | 0.026 | 5364 |
| LOT | All | 0.129 | 0.052 | 16947 | 485029 | 0.190 | 7847 | 0.128 | 11008 | 0.049 | 7959 |
| | NYSE | 0.028 | 0.018 | 2919 | 117939 | 0.033 | 1280 | 0.034 | 1967 | 0.017 | 1848 |
| | AMEX | 0.066 | 0.041 | 1316 | 33975 | 0.063 | 622 | 0.089 | 618 | 0.058 | 646 |
| | NASDAQ | 0.159 | 0.067 | 12712 | 333115 | 0.238 | 5945 | 0.154 | 8423 | 0.059 | 5465 |
| ILR | All | 9.275 | 0.342 | 17279 | 466357 | 12.988 | 7979 | 10.521 | 11208 | 3.495 | 7811 |
| | NYSE | 0.505 | 0.011 | 2920 | 114453 | 0.689 | 1279 | 0.468 | 1979 | 0.325 | 1806 |
| | AMEX | 10.972 | 1.659 | 1370 | 32934 | 19.169 | 640 | 10.290 | 657 | 4.917 | 642 |
| | NASDAQ | 11.127 | 0.632 | 12991 | 318970 | 15.051 | 6060 | 12.961 | 8572 | 4.410 | 5363 |

Panel B: Correlations between liquidity measures, US

| | RS | LOT |
|---|---|---|
| LOT | 0.77 | |
| ILR | 0.36 | 0.08 |

Panel C: Describing liquidity measures, Norway

| | | | | | Means subperiods | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Liquidity | | | | | 1980-1989 | | 1990-1999 | | 2000-2007 | |
| measure | mean | median | no secs | no obs | mean | no secs | mean | no secs | mean | no secs |
| RS | 0.040 | 0.028 | 1109 | 14109 | 0.042 | 207 | 0.047 | 340 | 0.036 | 332 |
| LOT | 0.058 | 0.039 | 1055 | 14166 | 0.061 | 208 | 0.070 | 344 | 0.049 | 334 |
| ILR | 0.754 | 0.196 | 1040 | 14199 | 1.199 | 209 | 0.877 | 341 | 0.394 | 332 |

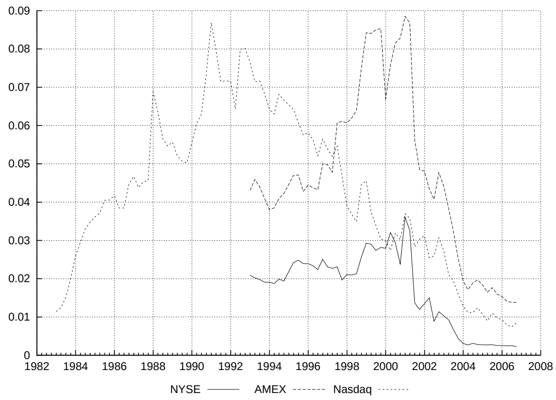
Panel D: Correlations between liquidity measures, Norway

| | RS | LOT |
|---|---|---|
| LOT | 0.70 | |
| ILR | 0.41 | 0.35 |

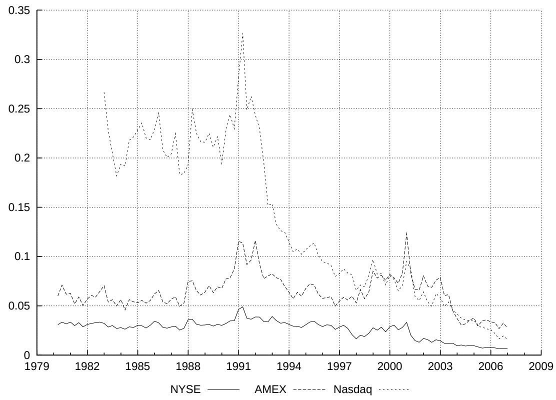
**Figure 2** Time series evolution of liquidity measures, US

The figures show time series plots of liquidity measures for the US. We first split the securities by exchange (NYSE, AMEX, NASDAQ), and then take average across all available securities in a quarter.

Panel A: Relative spread




Panel B: `LOT`




Panel C: Amihud `ILR`

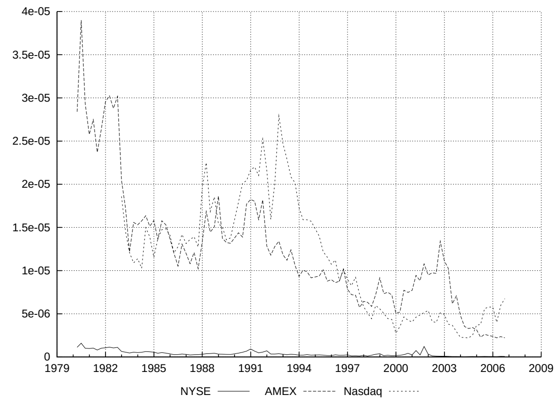
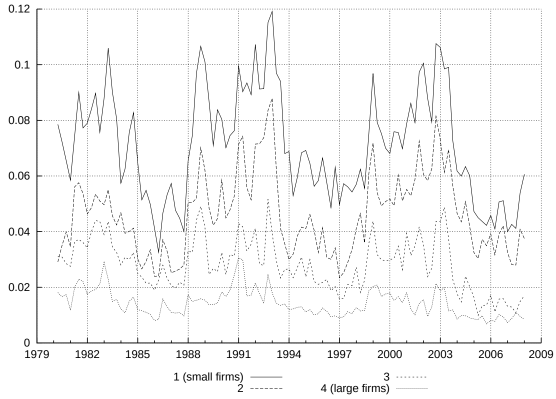


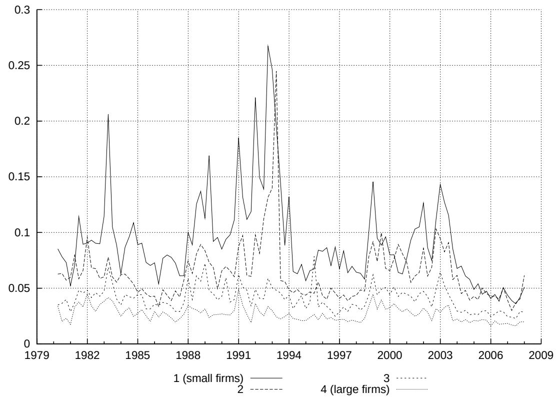
**Figure 3** Time series evolution of liquidity measures, Norway

The figures show time series plots of the three liquidity measures relative spread, `LOT` and `ILR` for Norway. In panels A and B we first sort the stocks at the OSE into four portfolios based on size, and then take crossectional averages each quarter. In panel C we only show one time series, the crossectional average of `ILR` for all stocks at the OSE.

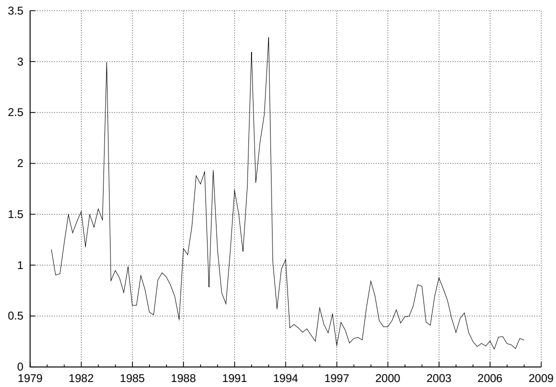
Panel A: Relative spread, size sorted portfolios




Panel B: `LOT`, size sorted portfolios




Panel C: Amihud `ILR`, all firms



A first observation to make is that for the US (CRSP) data, spreads are unfortunately not available for the whole period. We therefore mainly use the alternative liquidity measures for our US analysis. As shown in panel B of table 1, all the liquidity measures are positively correlated, although the correlation between `LOT` and `ILR` is low, the correlations of both with spread are higher. For the US we split the securities by exchange. There is a marked difference between NYSE securities and the others, with the NYSE clearly the most liquidy as measured by all our liquidity measures. As shown by the time series plots and the subperiod averages, liquidity varies over time. For the US, there has been a trend of liquidity improvement, a trend which is not as clear at the OSE. For the OSE we split the securities into four size-sorted portfolios and calculate the liquidity measures separately for each liquidity group. The group of smallest securities is clearly the least liquid, and liquidity improves with firm size.

# 3 The link between stock market liquidity and real economic variables

## 3.1 Predicting economic activity

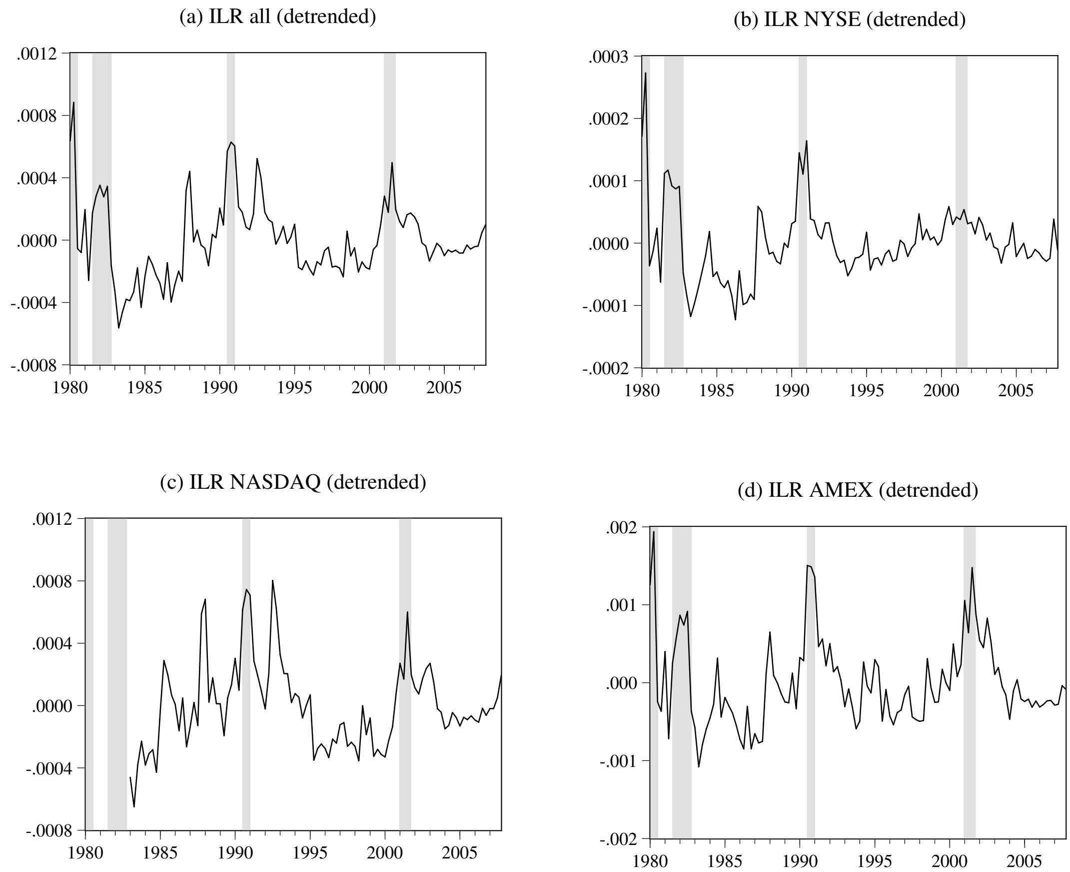
There are several studies that suggest that financial variables contain information about economic growth. Fama [1981], Fama [1990] and Schwert [1990] all find a strong positive relation between real stock returns and future production growth rates in the US. Fama argues that stock returns are determined by forecasts of real variables and that the relation between current stock returns and future production growth reflects market expectations about future cash flows that is impounded in stock prices. Liew and Vassalou [2000] and Vassalou [2003] find strong evidence that the Fama and French [1993] size (SMB) and value (HML) factors contain significant information about future GDP growth. Fama-French argue that the size and value factors act as state variables that predict future changes in the investment opportunity set in the context of the intertemporal asset pricing model of Merton [1973]. The results in Liew and Vassalou [2000] to a large extend strengthen this argument.

In this section we investigate to what degree *stock market liquidity* contain information about variables that measure real economic activity. Already from figure 1 we had strong indications that a liquidity measure *might* be of use in forecasting real economic variables such as unemployment or output gap. This question is also be related to the recent literature on "nowcasting" of real GDP growth using real time data observed at higher frequencies than the variable of interest. In the next subsection, 3.2, we examine the relationship between equity market liquidity and real economic variables in the US for the period 1980-2007. Then, in subsection 3.3 we examine the relationship for Norway. In addition to being a robustness check, there are two main reasons for also looking at the Norwegian market. First, as discussed in the descriptive part in section 2, we have access to more precise liquidity measures over the period we are looking at. In addition, as mentioned in the introduction, we have monthly stock ownership data for all Norwegian investors in all Norwegian companies for the period 1991 through 2007. This makes it possible to examine whether the systematic liquidity variations are linked to portfolio shifts by investors caused by a "flight to quality" during economic downturns where traders desire to move away from equity investments in general. This hypothesis will be examined in section 4.

## 3.2 The US evidence

**Figure 4** Market illiquidity and NBER recessions

Figure (a) shows the time series evolution of the detrended quarterly market illiquidity, measured by the Amihud Illiquidity ratio (`ILR`), for the US over the period 1980 to 2007. The `ILR` is equally weighted. Figure (a) shows the average `ILR` for all securities, (b) the average `ILR` for only NYSE listed securities, (c) the average `ILR` for only NASDAQ listed securities and (d) for AMEX listed securities. The grey bars indicate the NBER recession periods.




In figure 4 we show the time series pattern of the detrended Amihud Illiquidity ratio (`ILR`) for the period 1980 to 2007 measured at a quarterly frequency for (a) all US securities and for securities listed on the (b) NYSE, (c) NASDAQ and (d) AMEX. We only look at ordinary common shares and apply some additional filters to reduce noise.[19] For each quarter we calculate

[19]Stocks that have a two digit share code (*shrcd*) in the range 10-18 (Ordinary Common shares). We also require the stock to be traded on the last day of the month (to ensure that the close price in CRSP reflect a transaction). In addition, we require the the trade volume in a stock to be greater than 500 shares during a month, and stocks with a price lower than USD 1 and greater than USD 1000 are removed.

the ILR for each security and take the cross-sectional average. As seen in figure 1a, the ILR is falling over the sample period, indicating an overall improvement in market liquidity. To preserve stationarity, the ILR figures are detrended.[20] In figure 4, the NBER recessions are indicated by grey bars.[21] Clearly liquidity is time varying and is detoriating (increasing ILR) in economic downturns. Thus, the real-time observable market illiquidity measure picks up the major recessions in the US during the sample period.

To more formally test this observation we use a VAR formulation. In table 2 we show the estimation results for unrestricted bivariate VAR models of the quarterly GDP growth rate and the illiquidity ratio (ILR). Note that the GDP figure measuring quarter $t$ is not officially announced before the following quarter (at $t + 1$). In other words, in the estimations, we are using the actual GDP growth for the quarter it is measuring which is not contemporaneously observable with the liquidity variable at $t$. The ILR measures are plotted in figure 4. Panel (a) of the table shows the model estimated with the ILR measured for all securities, while panel (b) to (d) show the results with ILR calculated for only NYSE, NASDAQ and AMEX listed securities, respectively. The first thing to note across all panels is that the ILR at $t - 1$ has a significant negative coefficient across all models in the dGDP equations, while the lagged dGDP is not significant in any of the ILR equations. The right columns of the table shows the results from Granger causality tests between ILR and GDP growth. The two null hypotheses tested in each panel are that ILR *do not* Granger cause dGDP and that dGDP *do not* Granger cause ILR. In all cases we reject the null that ILR *do not* Granger cause GDP growth, while we cannot reject the reverse causality (of dGDP not causing ILR). This result strongly suggest that there is information in market liquidity about future GDP growth, especially when taking into account that the GDP figures are not observed before $t + 1$.

Table 3 shows similar VAR estimations to those in table 2, but for the change in the unemployment rate (dUE) instead of GDP growth. The unemployment rate shows a downward trend during our sample period, and we use the first difference to make it stationary. The results in table 3 are very similar to the results we obtained for quarterly GDP growth. We see that the lagged ILR is significant and positive in the unemployment equation across all models, while the lagged unemployment is not significant in the ILR equation for any of the models. Thus, a high illiquidity ratio predict an increase in the unemployment rate. With respect to the Granger causality tests, we reject the null that ILR *do not* cause unemployment (UE) for all models. For the reverse causality tests (UE $\nrightarrow$ ILR) we are able to reject the null for NASDAQ securities, that the change in unemployment do not cause liquidity, at the 10% level. However, for NYSE and AMEX there is no causality from the unemployment rate to ILR. Overall, the results are very similar to the results for the GDP growth, and suggest that the market illiquidity contain leading information about the future unemployment rate.

Acharya and Pedersen [2005] show that their liquidity-adjusted CAPM gives a reasonable good fit for portfolios sorted on size. This suggest that the Fama-French size factor (SMB) is closely related to a liquidity risk premium. In section 2 we saw that small firms are generally

[20]The detrending is done by using a Hodrick-Prescott filter.

[21]The NBER recession periods are 1980Q1-1980Q3, 1981Q3-1982Q4, 1990Q3-1991Q1 and 2001Q1-2001Q4.

**Table 2** Illiquidity ratio and US GDP growth

Results from an unrestricted VAR model for the quarterly growth rate in GDP ($\mathsf{dGDP_t}$) and market illiquidity ($\mathsf{ILR_t}$). The period is from first quarter 1980 to fourth quarter 2007. Note that the unemployment rate figure is the actual unemployment for the respective quarter and is published at $t+1$. Numbers in brackets are t-values for the estimates. The three last columns shows the results from Granger causality tests. In each panel the two null hypothesis tested are that `ILR` *do not* cause GDP growth and that GDP growth *do not* cause `ILR`.

| **(a) All securities** | Const. | $dGDP_{t-1}$ | $ILR_{t-1}$ | $R^2$ | **Causality tests** | $\chi^2$ | p-val |
|---|---|---|---|---|---|---|---|
| $dGDP_t$ | **0.01** | **0.30** | **-7.94** | 0.22 | ILR↛dGDP | **7.92** | **0.00** |
| | **[6.96]** | **[3.29]** | **[-2.81]** | | | | |
| $ILR_t^{ALL}$ | 0.00 | 0.00 | **0.62** | 0.46 | dGDP↛ILR | 0.34 | 0.56 |
| | [0.28] | [-0.59] | **[8.64]** | | | | |
| **(b) NYSE securities** | | | | | | | |
| $dGDP_t$ | **0.01** | **0.30** | **-38.37** | 0.24 | ILR↛dGDP | **11.12** | **0.00** |
| | **[7.16]** | **[3.44]** | **[-3.34]** | | | | |
| $ILR_t^{NYSE}$ | 0.00 | 0.00 | **0.51** | 0.35 | dGDP↛ILR | 0.30 | 0.59 |
| | [0.14] | [-0.55] | **[6.96]** | | | | |
| **(c) NASDAQ securities** | | | | | | | |
| $dGDP_t$ | **0.01** | **0.40** | **-4.44** | 0.27 | ILR↛dGDP | **5.07** | **0.02** |
| | **[5.87]** | **[4.20]** | **[-2.25]** | | | | |
| $ILR_t^{NASDAQ}$ | 0.00 | 0.00 | 0.71 | 0.54 | dGDP↛ILR | 0.15 | 0.70 |
| | [0.48] | [-0.39] | [9.55] | | | | |
| **(d) AMEX securities** | | | | | | | |
| $dGDP_t$ | **0.01** | **0.28** | **-4.05** | 0.24 | ILR↛dGDP | **10.54** | **0.00** |
| | **[7.19]** | **[3.12]** | **[-3.25]** | | | | |
| $ILR_t^{AMEX}$ | 0.00 | 0.00 | **0.57** | 0.40 | dGDP↛ILR | 0.49 | 0.48 |
| | [0.39] | [-0.70] | **[7.47]** | | | | |

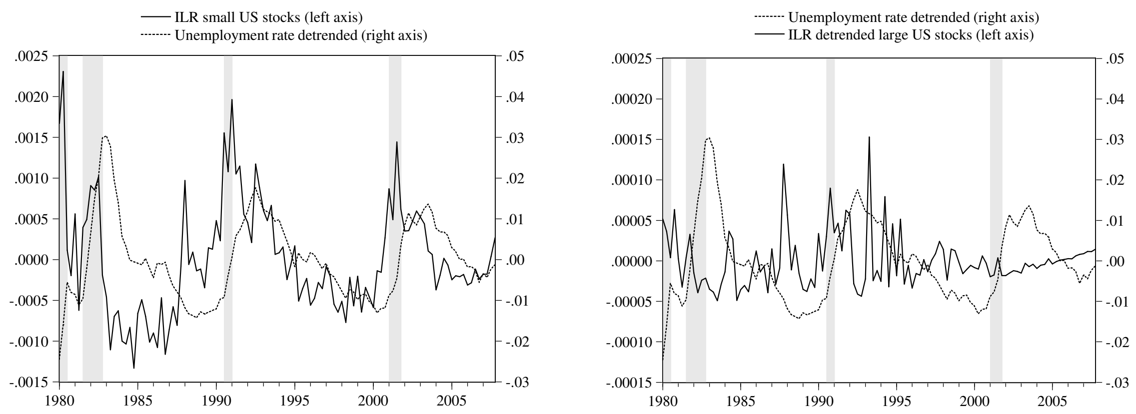
**Table 3** Illiquidity ratio and the US unemployment rate

Results from an unrestricted VAR model for the change in the unemployment rate ($dUE_t$) and market illiquidity measured by the Amihud illiquidity ratio ($ILR_t$). The unemployment figure is the number of unemployed persons as a percent of the civilian labor force from the U.S. Bureau of Labor Statistics. The period is from first quarter 1980 to fourth quarter 2007. Note that the unemployment rate is the actual unemployment for the respective quarter, and is not officially announced before $t+1$. Numbers in brackets are t-values for the estimates.

| **(a) All securities** | Const. | $dUE_{t-1}$ | $ILR_{t-1}$ | $R^2$ | **Causality tests** | $\chi^2$ | p-val |
|---|---|---|---|---|---|---|---|
| $dUE_t$ | 0.000 | **0.327** | **5.964** | 0.47 | ILR↛dUE | **31.07** | **0.00** |
| | [-0.49] | **[ 4.14]** | **[ 5.57]** | | | | |
| $ILR_t^{ALL}$ | 0.000 | 0.003 | **0.620** | 0.46 | dUE↛ILR | 0.21 | 0.64 |
| | [-0.58] | [ 0.46] | **[ 8.03]** | | | | |
| **(b) NYSE securities** | | | | | | | |
| $dUE_t$ | 0.000 | **0.285** | **30.606** | 0.55 | ILR↛dUE | **54.27** | **0.00** |
| | [-0.53] | **[ 3.92]** | **[ 7.36]** | | | | |
| $ILR_t^{NYSE}$ | 0.000 | 0.001 | **0.506** | 0.35 | dUE↛ILR | 0.22 | 0.64 |
| | [-0.80] | [ 0.46] | **[ 6.33]** | | | | |
| **(c) NASDAQ securities** | | | | | | | |
| $dUE_t$ | 0.000 | **0.406** | **2.768** | 0.34 | ILR↛dUE | **10.49** | **0.00** |
| | [-1.59] | **[ 4.52]** | **[ 3.24]** | | | | |
| $ILR_t^{NASDAQ}$ | 0.000 | 0.013 | **0.676** | 0.55 | dUE↛ILR | 2.88 | 0.09 |
| | [ 0.74] | [ 1.70] | **[ 9.22]** | | | | |
| **(d) AMEX securities** | | | | | | | |
| $dUE_t$ | 0.000 | **0.277** | **3.077** | 0.52 | ILR↛dUE | **43.89** | **0.00** |
| | [-0.57] | **[ 3.58]** | **[ 6.63]** | | | | |
| $ILR_t^{AMEX}$ | 0.000 | 0.005 | **0.578** | 0.40 | dUE↛ILR | 0.12 | 0.73 |
| | [-0.57] | [ 0.34] | **[ 6.92]** | | | | |

less liquid (have a higher ILR) than larger firms. In addition, small firms are potentially more affected by market-wide liquidity shocks. Motivated by this, we examine the illiquidity ratio for the 25% smallest firms and 25% largest firms in the US as a whole as well as within the separate exchanges. Figure 5 shows the average (detrended) illiquidity ratio for small firms (a) and large firms (b) plotted against the detrended unemployment rate and the NBER recession periods (grey bars). The first thing to note from the figures is that the illiquidity of the small firms show a much more distinct increase around the NBER recessions. In addition, the illiquidity of the smallest firms shows a very systematic pattern relative to the US unemployment rate, while the ILR for the 25% largest firms do not. We also see that the illiquidity of the smallest firms are leading the unemployment rate, especially when taking into account that the unemployment rate is published with a lag relative to the series plotted in the figure that measure the actual unemployment rate of the respective quarters. It should also be noted that these patterns are similar if we look at the ILR for small and large stocks within each exchange.

**Figure 5** Illiquidity ratio for large and small US firms, unemployment rate and NBER recessions




(a) ILR small firms and unemployment

(b) ILR large firms and unemployment

Figure (a) shows the time series evolution of the detrended Amihud illiquidity ratio (ILR) for the 25% *smallest* US firms (solid line), the detrended unemployment rate (dotted line) and the NBER recession periods (gray bars). Figure (b) shows the time series of the detrended Illiquidity ratio (ILR) for the 25% *largest* US firms (solid line) plotted against the detrended unemployment rate (dotted line) and NBER recession periods (grey bars).

If small firms are more sensitive to economic downturns or increased uncertainty about future economic conditions, we argue that this difference in pattern between small and large stocks may reflect a "flight to quality" effect. If investors' changing expectations (or changing uncertainty in their expectations) about future economic conditions affect the desired riskiness of their portfolios, the increase in market illiquidity may reflect a portfolio shift out of the most risky stocks (small firms) into safer assets (large stocks or bonds). If this is the case we would also expect the illiquidity of the smallest (most risky) firms be most informative about future economic conditions. To examine this more closely, we run a similar VAR regression as in table 2, but now look at the illiquidity ratio for small and large firms.

Panel (a) of table 4 shows the results from Granger causality tests (the $\chi^2$ test statistic and p-values in parenthesis) for GDP growth (dGDP) and `ILR` for small and large firms for all US firms as well as for small and large firms within each exchange. Panel (b) of the table shows similar tests for the change in the unemployment rate (dUE) and the illiquidity of small and large firms. These causality tests are based on unrestricted VAR(1) models.[22] The null hypothesis tested is that the variables in the first row (in each panel) *do not* Granger cause the dependent variables. The table shows the $\chi^2$ statistic with the associated p-values in parenthesis.

Looking first at the results in panel A in table 4, we see that we cannot reject the null hypothesis that the GDP growth *do not* Granger cause the illiquidity of either small firms or large firms when we use the `ILR` calculated for all US stocks, or for the separate exchanges. However, both in the case for NYSE stocks and AMEX stocks, we reject the null hypothesis that the illiquidity of the smallest firms *do not* Granger cause GDP growth at the 1% level. In panel (b), where we look at the causality between `ILR` and dUE, we reject the null hypothesis in all models, that the illiquidity ratio for the small firms *do not* cause the unemployment rate. However, in the case of NYSE firms we reject the null that the change in unemployment do not cause the illiquidity of large firms. Also in the case for NASDAQ firms we reject the null hypothesis that the change in unemployment do not cause the illiquidity of small firms. Thus, for NASDAQ firms, there is evidence of a two-way causality between unemployment and the illiquidity of the smallest firms, while this is not the case for the other exchanges. Overall, the results in table 4 support a hypothesis that the illiquidity of small firms contain the most information about future economic conditions.

As a final exercise we examine whether the market illiquidity variable is still significant when we include additional financial variables that typically are argued to contain information about future economic conditions. The variables we include are the *term spread* (calculated as the difference in yield between a 10 year government bond and the 3 month T-bill), the *forward P/E ratio* (which is based on the 12 month forward looking expected earnings for the SP500 stocks) and the return on the MSCI total return index. The first part of table 5 shows the results from the VAR regressions for the quarterly GDP growth. The second part of the table shows the Granger causality tests between the variables. When we look at the dGDP equation we see that the market illiquidity (`ILR`) is significantly predicting the next quarter GDP growth, while none of the other variables have significant coefficients. In the equations for the term spread and P/E-ratio, only their own lagged values are significant. In the market return equation ($r_t^{MSCI}$) we see that the lagged P/E value is significantly predicting the next quarter market return. Finally, in the `ILR` equation, we see that the lagged market return is significantly predicting the next quarter `ILR`. Thus, a large positive market return causes market illiquidity to fall the next quarter, and vice versa. This is in line with earlier studies that find that large market moves affect market liquidity. The causality tests in the second part of the table confirm the regression results where we reject the null that the `ILR` *do not* cause dGDP, and that the causality runs from the P/E-ratio to market returns as well from market returns to the `ILR`.

[22]We do not show the causality tests of the illiquidity between the size groups to make the table clearer. In addition, we do not show the results from the VAR estimations to preserve space. These results can be obtained on request.

**Table 4** Illiquidity ratio for small and large firms, GDP growth and unemployment

Panel (a) shows the results from causality tests between the GDP growth rate (dGDP) and the illiquidity for small and large firms for all US firms ($ILR^{small}_{ALL}$ and $ILR^{large}_{ALL}$) as well as for small and large firms within the different exchanges. Panel (b) of the table shows similar tests for the change in the unemployment rate (dUE) and the illiquidity of small and large firms. The causality tests are based on unrestricted VAR(1) models. The null hypothesis tested is that the variables in the first row (in each panel) *do not* Granger cause the dependent variables. The table shows the $\chi^2$ statistic with the associated p-values in parenthesis.

**Panel A:** GDP growth and ILR small/large firms

| | Dependent variable | | |
|---|---|---|---|
| | dGDP | $ILR^{small}$ | $ILR^{large}$ |
| *All US stocks:* | | | |
| dGDP | | 1.71<br>(0.19) | 0.15<br>(0.70) |
| $ILR^{small}_{ALL}$ | 2.44<br>(0.12) | | |
| $ILR^{large}_{ALL}$ | 0.81<br>(0.37) | | |
| *NYSE stocks:* | | | |
| dGDP | | 1.21<br>(0.27) | 3.17<br>(0.08) |
| $ILR^{small}_{NYSE}$ | **11.76**<br>**(0.00)** | | |
| $ILR^{large}_{NYSE}$ | 2.25<br>(0.13) | | |
| *AMEX stocks:* | | | |
| dGDP | | 1.40<br>(0.24) | 0.01<br>(0.91) |
| $ILR^{small}_{AMEX}$ | **7.66**<br>**(0.01)** | | |
| $ILR^{large}_{AMEX}$ | 0.51<br>(0.48) | | |
| *NASDAQ stocks:* | | | |
| dGDP | | 1.75<br>(0.19) | 0.06<br>(0.81) |
| $ILR^{small}_{NASDAQ}$ | 2.19<br>(0.14) | | |
| $ILR^{large}_{NASDAQ}$ | 0.10<br>(0.75) | | |

**Panel B:** Unemploment and ILR small/large firms

| | Dependent variable | | |
|---|---|---|---|
| | dUE | $ILR^{small}$ | $ILR^{large}$ |
| *All US stocks:* | | | |
| dUE | | 2.54<br>(0.11) | 1.84<br>(0.18) |
| $ILR^{small}_{ALL}$ | **26.35**<br>**(0.00)** | | |
| $ILR^{large}_{ALL}$ | 0.23<br>(0.63) | | |
| *NYSE stocks:* | | | |
| dUE | | 1.67<br>(0.20) | **7.63**<br>**(0.01)** |
| $ILR^{small}_{NYSE}$ | **33.19**<br>**(0.00)** | | |
| $ILR^{large}_{NYSE}$ | 0.44<br>(0.51) | | |
| *AMEX stocks:* | | | |
| dUE | | 1.45<br>(0.23) | 2.91<br>(0.09) |
| $ILR^{small}_{AMEX}$ | **35.57**<br>**(0.00)** | | |
| $ILR^{large}_{AMEX}$ | 0.00<br>(0.95) | | |
| *NASDAQ stocks:* | | | |
| dUE | | **6.70**<br>**(0.01)** | 0.46<br>(0.50) |
| $ILR^{small}_{NASDAQ}$ | **15.83**<br>**(0.00)** | | |
| $ILR^{large}_{NASDAQ}$ | 0.88<br>(0.35) | | |

We find these results interesting for several reasons. First, ILR retains its significance in the GDP growth equation in the face of other financial variables. In addition, since there is a causality link from the P/E-ratio to market returns, and again from market returns to the ILR variable, this may suggest that market illiquidity is a product of changes in expectations reflected in lagged prices, expected earnings and returns. One hypothesis is that there are portfolio shifts caused by changes in expectations that first is impounded into prices, and in the next stage affect market illiquidity.

**Table 5** Illiquidity ratio, US GDP growth and additional financial variables

The table shows the results from an unrestricted VAR model for the quarterly GDP growth ($dGDP_t$) and market liquidity ($ILR_t$). In addition, we include the variables *term spread* (calculated as the difference between the yield on a 10 year government benchmark and the 3 month T-bill), the P/E ratio (which is based on the 12 month forward looking expected earnings for the SP500 stocks) and the return on the MSCI total return index. The period is from first quarter 1980 to fourth quarter 2007. Numbers in brackets are t-values for the estimates. The second part of the table shows the Granger causality tests between the variables. The null hypothesis is that the variables in the first row *do not* Granger cause the dependent variable in column 2 to 6. The table shows the $\chi^2$ statistic with the associated p-values.

| | const. | $dGDP_{t-1}$ | Term $spread_{t-1}$ | $P/E^{SP500}_{t-1}$ | $r^{MSCI}_{t-1}$ | $ILR_{t-1}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| $dGDP_t$ | **0.010** | **0.312** | 0.000 | 0.000 | 0.012 | **-7.097** | 0.235 |
| | **[5.31]** | **[3.37]** | [0.05] | [-0.21] | [1.39] | **[-2.39]** | |
| Term $spread_t$ | -0.415 | -2.880 | **0.749** | -0.001 | 1.092 | -93.205 | 0.575 |
| | [-1.85] | [-0.26] | **[11.46]** | [-0.02] | [1.06] | [-0.26] | |
| $P/E^{SP500}_t$ | **0.315** | -4.027 | 0.143 | **0.867** | -0.602 | 458.445 | 0.758 |
| | **[0.97]** | [-0.25] | [1.52] | **[17.15]** | [-0.41] | [0.90] | |
| $r^{MSCI}_t$ | **0.026** | 0.441 | 0.001 | **-0.009** | 0.088 | 20.924 | 0.078 |
| | **[1.21]** | [0.42] | [0.14] | **[-2.74]** | [0.90] | [0.62] | |
| $ILR_t$ | 0.000 | -0.002 | 0.000 | 0.000 | **-0.001** | **0.583** | 0.522 |
| | [1.78] | [-0.97] | [1.52] | [0.19] | **[-3.23]** | **[8.10]** | |

| *Granger causality tests:* | Dependent variable | | | | |
|---|---|---|---|---|---|
| | dGDP | Term spread | $P/E^{SP500}$ | $r^{MSCI}$ | ILR |
| dGDP | | 0.07 | 0.06 | 0.18 | 0.94 |
| p-value | | 0.80 | 0.80 | 0.68 | 0.33 |
| Term spread | 0.00 | | 2.30 | 0.02 | 2.31 |
| p-value | 0.96 | | 0.13 | 0.89 | 0.13 |
| $P/E^{SP500}$ | 0.04 | 0.00 | | **7.53** | 0.04 |
| p-value | 0.83 | 0.98 | | **0.01** | 0.85 |
| $r^{MSCI}$ | 1.95 | 1.13 | 0.17 | | **10.40** |
| p-value | 0.16 | 0.29 | 0.68 | | **0.00** |
| ILR | **5.73** | 0.07 | 0.80 | 0.38 | |
| p-value | **0.02** | 0.79 | 0.37 | 0.54 | |

## 3.3 The Norwegian evidence

In this section we complement the above US evidence by examining in more detail the relationship between market-wide liquidity and the business cycle using data from the Oslo Stock Exchange. Næs et al. [2008b] show evidence of a large and significant liquidity risk premium in the Norwegian market. In the stochastic discount rate framework, this means that liquidity is an important factor in the pricing kernel. In general, if one think about the pricing kernel as measuring changes in marginal utility of consumption, liquidity may act as a state variable that contain information about the investment opportunity set and should be related to economic activity. Therefore it is interesting to examine how the fluctuations we observe in market-wide liquidity variables is related to macroeconomic variables.

In table 6 we show the average of four liquidity measures for the whole sample period (1980-2007) and for two economic growth regimes; decreasing output gap (dOG<0) and increasing output gap (dOG>0). The low economic growth periods are shown as grey areas in figure 1. We see that the liquidity is significantly lower in periods when economic growth is slower than the historical trend compared to periods when economic activity is picking up. The last column show the p-value from a test for the difference in the respective liquidity measures between the two regimes are significantly different from zero. In all cases we reject that the difference is equal to zero at the 1% level.

**Table 6** Output gap and different liquidity measures

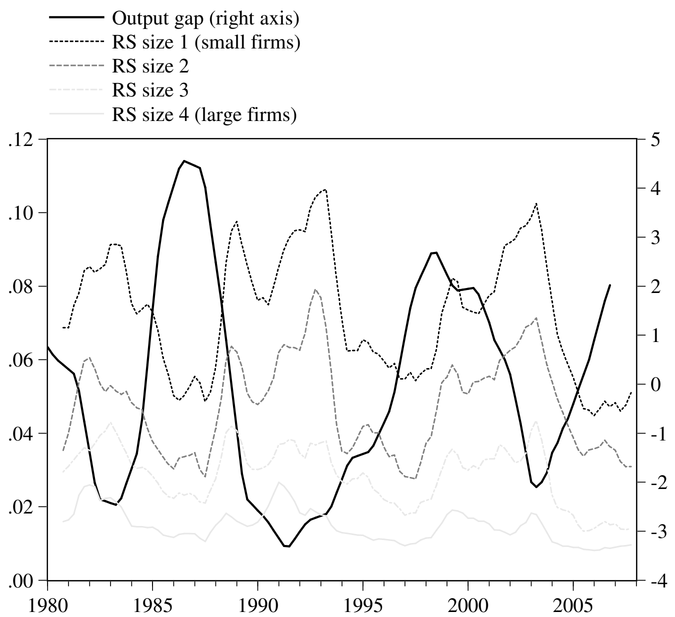
The table shows the average liquidity proxied by quoted spread, relative spread, the `LOT` measure and the Amihud `ILR` measures. The table shows the averages for the whole sample and for periods when output gap is decreasing (dOG<0) and increasing (dOG>0). The two last columns shows the difference in spreads between the two output gap "regimes" and p-values from a test for whether this difference is equal to zero.

| | Average liquidity (all firms) | | | | |
|---|---|---|---|---|---|
| | Whole sample | dOG<0 | dOG>0 | Diff. | p-value (diff=0) |
| Quoted spread (NOK) | 2.95 | 3.72 | 2.19 | 1.53 | <0.01 |
| Relative spread (%) | 4.1 % | 4.6 % | 3.6 % | 1.0 % | <0.01 |
| LOT (%) | 5.5 % | 6.1 % | 4.9 % | 1.2 % | <0.01 |
| ILR | 0.84 | 1.03 | 0.65 | 0.38 | <0.01 |

As shown in section 2 the level of liquidity is closely related to the size of the firm. In addition, the Fama-French size (SMB) factor are often associated with a higher default risk of small firms during recessionary periods. To examine whether there is a systematic difference in liquidity variation across firm sizes, we group all listed firms into four quartile portfolios at the beginning of each year based on the firms' market capitalization (MCAP). The portfolios are kept fixed through the year and rebalanced at the beginning of every year. In figure 6 we plot the average relative spread for firms in each of the four size portfolios. As expected, we see that average spread is falling with the increase in firm size. More interestingly, we see that the counter cyclical pattern we observed for the market average is evident for each of the portfolios, but the pattern gets more pronounced the smaller the firms in the portfolios are. This is similar to the pattern we observed for the US market in figure 5 relative to the unemployment rate. The correlation between relative spread and the output gap is decreasing monotonically from $-0.70$ for the smallest firms to $-0.52$ for the largest firms. As suggested earlier, one explanation for this systematic size effect is that liquidity is subject to "flight to quality." When future economic outlooks are bad, small and risky securities become more illiquid as investors shift their portfolios towards larger and "safer" securities, or out of equities altogether. If investors also shift their portfolios from equities to less risky asset classes during economic downturns, this intuition can also explain the counter cyclical pattern for the spread of the largest firms relative to the business cycle. If small firms are more sensitive to the business cycle than larger firms, the liquidity correlations we observe here may provide an explanation for the liquidity premium found in asset pricing tests of the Norwegian stock market in Næs et al. [2008b].

**Figure 6** Output gap and relative spread for different firm sizes

The figure shows the time series evolution of stock market liquidity for firm size groups, measured by the relative bid ask spread, and output gap for Norway. At the beginning of each year all firms are included in one of four size groups based on their market capitalization. The groups are kept constant until the beginning of the next year. The relative bid ask spread is measured as the difference between the ask and bid quote divided by the bid ask midpoint. We then average the relative spread across all listed securities within each size group for each quarter. The output gap are revised figures of output gap from Norges Bank.




In table 7 we show descriptive statistics for the average relative spread for the different size groups as well as industry portfolios across the two economic regimes where output gap is falling (dOG< 0) and increasing (dOG>0). We see that for the size groups the spread difference between the regimes is larger for small firms and monotonically decreasing with firm size. The difference is highly significant for all size groups. Also for the industry portfolios we see the same pattern for all industries except for Materials where the difference is insignificant.[23]

The causality relationship between the output gap and market liquidity is not clear since the output gap is measured as a filtered series which incorporates lagged information about production. Thus, we want to look at additional macro variables to determine whether our market liquidity measures reflect changes in expectations about future economic conditions.

[23]For the period 1980-2006 the average market capitalization in billion NOK for the industry groups were Energy: 20.75, Materials: 6.99, Industry: 31.46, Cons.Disc.:6.15, Financials: 17.52 and IT:5.36. More information about the sector composition at the Oslo Stock Exchange during the period can be found in Næs et al. [2008b].

**Table 7** Output gap and relative spread

The table shows the average relative spread for all firms, size quartiles and GICS industries for the whole sample and for periods when output gap is decreasing and increasing. The first column shows the average relative spread (in %) for for the whole sample from 1980 through 2007. The second and third columns show the average relative spread when the output gap is decreasing (dOG<0) and increasing (dOG>0) respectively. The two last columns shows the difference in spreads between the two output gap "regimes" and a t-test for whether this difference is equal to zero.

| | Average relative spread (%) | | | | |
|---|---|---|---|---|---|
| | Whole sample | dOG<0 | dOG>0 | Diff. | t-test (diff=0) |
| All firms | 4.1 % | 4.6 % | 3.6 % | 1.0 % | 10.47 |
| *Grouped by firm size (MCAP)* | | | | | |
| Size1 | 7.2 % | 7.9 % | 6.5 % | 1.4 % | 14.90 |
| Size2 | 4.7 % | 5.2 % | 4.2 % | 1.0 % | 10.79 |
| Size3 | 2.9 % | 3.3 % | 2.4 % | 0.9 % | 9.89 |
| Size4 | 1.5 % | 1.8 % | 1.2 % | 0.6 % | 5.86 |
| *Grouped by industry (GICS)* | | | | | |
| 10 Energy | 2.8 % | 3.3 % | 2.4 % | 0.9 % | 7.29 |
| 15 Materials | 3.6 % | 3.5 % | 3.6 % | -0.2 % | -1.02 |
| 20 Industry | 5.1 % | 5.6 % | 4.5 % | 1.2 % | 8.32 |
| 25 ConsDisc. | 6.1 % | 6.7 % | 5.4 % | 1.3 % | 6.59 |
| 40 Financials | 3.9 % | 4.2 % | 3.5 % | 0.7 % | 5.73 |
| 45 IT | 3.8 % | 4.4 % | 3.3 % | 1.0 % | 6.00 |

Similar to the US, we look at GDP growth and changes in the unemployment rate. We also show results for consumption growth. The quarterly unemployment figure is released with a lag of 5-6 weeks after the end of the previous quarter.[24] Similar to the US analysis, we estimate unrestricted VAR models with the lag length ($p$) determined by testing for the optimal number of endogenous lags and choosing the lowest number of lags suggested by the Akaike Information Criterion (AIC) and the Schwartz information criterion (SC). For all models the lowest optimal lag length is one quarter.

In table 8 we examine four models containing the average relative spread over each quarter and the (a) change in the unemployment rate[25], (b) GDP growth rate, (c) consumption growth rate as well as the (d) output gap published by Norges Bank (Central Bank of Norway). Similarly to the US data, the macro variables are *not* observed contemporaneously in the sense that while the market liquidity is observed in real time and is know at the end of each $t$, the macro figures are not published before $t + 1$. Table 14 in the appendix shows the estimation results when we use the Amihud illiquidity ratio ($\mathtt{ILR}$) instead of the relative spread.

The first row in Panel (a) in table 8 shows the unemployment rate equation with a constant and one lag of the change in unemployment and the market-wide relative spread respectively, and similarly the second row shows the relative spread equation with one lag of each variable. The first thing to note from the table is that the lagged relative spread is significantly explaining the next quarters change in unemployment, while there is no explanatory power from lagged change in unemployment on the relative spread. The last columns of panel (a) report the test

[24]The official unemployment figure (for quarter $t$) is not observed by market participants (announced by Statistics Norway) before the beginning/middle of the following quarter (at quarter $t + 1$).

[25]While the Norwegian unemployment rate is stationary at the 5% level when testing for a unit root, we take the first difference to make the results more readily comparable to the US analysis.

statistic and associated p-value from Granger causality tests. The null hypothesis in the first case, that the relative spread *do not* Granger cause the change in unemployment, is clearly rejected. In the second case we cannot reject the null that the change in unemployment does not Granger cause the unemployment figures.

In panel (b) of table 8 we estimate a similar unrestricted VAR model using the quarterly growth in GDP instead of the change in the unemployment rate. We see that the we get similar results, with a significant lagged relative spread in the GDP growth equation, and no effect from lagged GDP growth on the relative spread. The Granger causality tests show a strong Granger causality from market liquidity to GDP growth. However, we cannot reject that the causality also runs from GDP growth to market liquidity at the 10% level. In panel (c) we find strong support for market liquidity Granger causing consumption growth. Finally, in panel (d) we estimate the model for the output gap figure, suggesting that the causality runs from market liquidity to the output gap, and not from output gap to market liquidity. For robustness we also estimate similar regressions with the illiquidity ratio instead of the relative spread as our proxy for market liquidity. The results are the same as for the relative spread. The results from these estimations are shown in table 14 in the appendix. Overall, the results for Norway shows the same causality relations between market liquidity as found for the US market in section 3.2, suggesting that the relationship is robust across markets and market structures. In addition, the results are robust to the choice of liquidity measure.

Motivated by the results for the US, and that the liquidity of the smallest firms had a much stronger business cycle variation than larger firms in figure 6, we estimate an unrestricted VAR where we split the liquidity variable into the average relative spread for the smallest firms ($\mathsf{RS}^{\mathsf{Small}}$) and largest firms ($\mathsf{RS}^{\mathsf{Large}}$). This is similar to the estimation in table 4 for the US using the illiquidity ratio. Table 9 shows the results from this regression. We see that the lagged liquidity for the small firms predict the next quarters change in the unemployment rate, while the coefficient for the lagged liquidity of the largest firms is insignificant. Also the causality tests suggest that it is the liquidity of the smallest firms that contain information about the future change in unemployment. However, the causality tests also suggest that there is a causality running from the liquidity of the largest firms to the smallest firms. Overall, these results confirm the results found for the US.

As a final exercise we estimate a similar model as for the US market (US results shown in table 5) and include additional variables that are commonly argued in the literature to contain information about future investment opportunities. The variables we look at are the average dividend yield (D/P ratio) for the stocks listed on the Oslo Stock Exchange[26], the term spread proxying for the slope on the yield curve which is calculated as the difference in yield on a 10 year government bond benchmark and a 3 month note. Finally we also include the equally weighted average return for all stocks listed on the Oslo Stock Exchange ($r^{\mathsf{OSE}}$). Table 10 shows the estimation results and Granger causality tests from an unrestricted VAR between the GDP growth (dGDP), relative spread (RS), term spread, the D/P ratio and the equally weighted

[26]For the US we used the forward P/E ratio. However, valuation ratios containing expected earnings for the Norwegian market do not exist as far back as 1980. Thus, we use the realized D/P-ratio.

**Table 8** Relative spread and macro fundamentals

Results from four unrestricted bivariate VAR(1) models for the market liquidity ($RS_t$) and (a) change in the unemployment rate ($dUE_t$), (b) GDP growth ($dGDP$), (c) consumption growth ($dCONS$) and (d) output gap. Market liquidity ($RS_t$) is proxied by the relative spread. The number of endogenous lags is determined by the lowest number of lags suggested by the Schwartz and Akaike Info Criterion. The period is from first quarter 1980 to fourth quarter 2007. Note that the macro variables are measured as the quarterly growth in for the respective quarter. Numbers in brackets are t-values. The last two columns show the chi-squared statistics and p-value from Granger causality tests between the respective macro variable and the market liquidity. The null hypothesis is that the independent variable (in each equation) *do not* Granger cause the dependent variable.

**(a) Unemployment rate change (dUE)**

| | Const. | $dUE_{t-1}$ | $RS_{t-1}$ | $R^2$ | *Causality tests:* | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|---|
| $dUE_t$ | **-0.577** | -0.170 | **14.380** | 0.16 | H0: RS $\nrightarrow$ dUE | **20.79** | **0.00** |
| | **[-4.33]** | [-1.80] | **[4.55]** | | | | |
| $RS_t$ | **0.006** | -0.001 | **0.846** | 0.70 | H0: dUE $\nrightarrow$ RS | 0.310 | 0.58 |
| | **[2.59]** | [-0.55] | **[14.93]** | | | | |

**(b) GDP growth (dGDP)**

| | Const. | $dGDP_{t-1}$ | $RS_{t-1}$ | $R^2$ | *Causality tests:* | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|---|
| $dGDP_t$ | **0.026** | **-0.423** | **-0.438** | 0.26 | H0: RS $\nrightarrow$ dGDP | **23.84** | **0.00** |
| | **[6.60]** | **[-4.87]** | **[-4.88]** | | | | |
| $RS_t$ | **0.008** | -0.096 | **0.808** | 0.71 | H0: dGDP $\nrightarrow$ RS | 3.28 | 0.07 |
| | **[3.44]** | [-1.81] | **[14.73]** | | | | |

**(c) Consumption growth (dCONS)**

| | Const. | $dCONS_{t-1}$ | $RS_{t-1}$ | $R^2$ | *Causality tests:* | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|---|
| $dCONS_t$ | **0.020** | **-0.202** | **-0.278** | 0.07 | H0: RS $\nrightarrow$ dCONS | **6.10** | **0.01** |
| | **[3.97]** | **[-2.03]** | **[-2.47]** | | | | |
| $RS_t$ | **0.008** | -0.061 | **0.082** | 0.70 | H0: dCONS $\nrightarrow$ RS | 1.63 | 0.20 |
| | **[3.20]** | [-1.28] | **[14.70]** | | | | |

**(d) Output gap (OG)**

| | Const. | $OG_{t-1}$ | $RS_{t-1}$ | $R^2$ | *Causality tests:* | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|---|
| $OG_t$ | **1.085** | **0.934** | -25.968 | 0.98 | H0: RS $\nrightarrow$ OG | **65.42** | **0.00** |
| | **[7.95]** | **[59.14]** | **[-8.09]** | | | | |
| $RS_t$ | **0.006** | **0.000** | **0.849** | 0.68 | H0: OG $\nrightarrow$ RS | 0.35 | 0.55 |
| | **[2.35]** | [0.59] | **[ 13.81]** | | | | |

**Table 9** Relative spread of firm size groups, unemployment rate and GDP growth

Results from an unrestricted VAR(1) model for the change in the unemployment rate ($dUE_t$) and liquidity for small ($RS_t^{small}$) and large ($RS_t^{large}$) firms proxied by the relative spread. The number of endogenous lags is determined by the lowest number of lags suggested by the Schwartz and Akaike Info Criterion. The period is from first quarter 1980 to fourth quarter 2007. Note that the unemployment rate is the actual unemployment for the respective month. Numbers in brackets are t-values for the estimates and * and ** denote significance at the 5% and 1% level respectively. At the bottom of the table we show the results from the Granger causality tests.

**(a) Unemployment change**

| | Const. | $dUE_{t-1}$ | $RS_{t-1}^{small}$ | $RS_{t-1}^{large}$ | $R^2$ | *Causality tests (H0)* | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|---|---|
| $dUE_t$ | **-0.585** | -0.170 | **7.054** | 5.847 | 0.16 | $RS^{small} \nrightarrow dUE$ | **9.28** | **0.00** |
| | **[-4.28]** | [-1.79] | **[3.05]** | [0.73] | | $RS^{large} \nrightarrow dUE$ | 0.53 | 0.47 |
| $RS_t^{small}$ | **0.011** | 0.000 | **0.708** | **0.656** | 0.70 | $dUE \nrightarrow RS^{small}$ | 0.00 | 0.95 |
| | **[2.68]** | [0.06] | **[9.90]** | **[2.63]** | | $RS^{large} \nrightarrow RS^{small}$ | **6.94** | **0.01** |
| $RS_t^{large}$ | **0.003** | 0.000 | 0.019 | **0.684** | 0.52 | H0: $dUE \nrightarrow RS^{large}$ | 0.20 | 0.65 |
| | **[ 2.10]** | [-0.45] | [0.76] | **[7.59]** | | H0: $RS^{small} \nrightarrow RS^{large}$ | 0.57 | 0.45 |

**(b) GDP growth**

| | Const. | $dGDP_{t-1}$ | $RS_{t-1}^{small}$ | $RS_{t-1}^{large}$ | $R^2$ | *Causality tests:* | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|---|---|
| $dGDP_t$ | **0.025** | **-0.413** | **-0.153** | -0.385 | 0.24 | $RS^{small} \nrightarrow dGDP$ | **5.27** | **0.02** |
| | **[6.13]** | **[-4.71]** | **[-2.30]** | [-1.63] | | $RS^{large} \nrightarrow dGDP$ | 2.65 | 0.10 |
| $RS_t^{small}$ | **0.014** | -0.175 | **0.692** | **0.604** | 0.71 | $dGDP \nrightarrow RS^{small}$ | 3.71 | 0.06 |
| | **[3.37]** | [-1.93] | **[9.98]** | **[2.46]** | | $RS^{large} \nrightarrow RS^{small}$ | **6.06** | **0.01** |
| $RS_t^{large}$ | **0.004** | -0.058 | 0.012 | **0.662** | 0.53 | $dGDP \nrightarrow RS^{large}$ | 3.13 | 0.08 |
| | **[2.88]** | [-1.77] | [0.46] | **[7.44]** | | $RS^{small} \nrightarrow RS^{large}$ | 0.21 | 0.64 |

market return.

The first thing to note, is that the estimation results are essentially the same as the US results in table 5. In the dGDP equation, we see that only the lagged dGDP and lagged relative spread (RS) has significant coefficients. In the term-spread and D/P-ratio equations, only their own lags are significant, and in the equation for market returns ($r_t^{OSE}$) the lagged D/P ratio is significant. Similarly to the US results, we find that the lagged market return enters significantly in the RS equation, suggesting that market moves affect market liquidity. While this is consistent with other studies that find that large market moves affect market liquidity, the negative coefficient may just reflect that a large market move directly affect the denominator (price) in the relative spread calculation. The second part of the table also show that we reject the null hypothesis that the relative spread do not Granger cause the change in unemployment. Thus, including additional financial variables do not alter the previous results for Norway.

Table 18 in the appendix show the results from estimating similar models as in table 10, using the Amihud Illiquidity ratio as our proxy for market liquidity instead of relative spread. We see that including additional financial variables do not alter the result that `ILR` predict the change in unemployment. Comparing the results in table 10 where we found that the market return was leading the relative spread, we see that this is not the case for the `ILR` in Norway. This suggest that the effect of the market return on next quarter relative spread may come through the effect of the market on the denominator of the relative spread calculation. On the other hand, for the US, we found in table 5 that the market return was leading the illiquidity ratio.

The appendix also shows estimation results and causality tests when we estimate models for changes in unemployment and the relative spread (table 16) as well as the change in unemployment and the illiquidity ratio (table 17). The results in these regressions substantiate further the results in this section. Overall, the results are robust to different macro variables and liquidity measures. In addition the results are very similar across the US and Norway.

# 4 Stock market participation and liquidity

As argued before, we want to investigate the link between stock market participation and our liquidity results. To do so, we need to construct a measure of stock market participation that expresses peoples desire to go from less liquid assets (stocks) to more liquid assets, such as bonds or cash. Since our data contains the equity part of the portfolios only, we are limited to look at measures based on equities. We want a measure that is the result of active decisions by participants in the market, not one that is driven by price changes, which argues against using measures where market values enter, because these may change even if people hold their portfolio constant. In a limit order market where each trader supplies liquidity, an obvious thing to look at is the number of participants in the market, and how this changes.

**Table 10** Relative spread, GDP growth and other financial variables

The first part of the table shows the estimation results from an unrestricted VAR(1) model for the quarterly GDP growth ($\mathsf{dGDP_t}$), the relative spread (RS), the average dividend price ratio (D/P) for the firms listed at the Oslo Stock exchange, the term spread (difference in yield on a 10 year government bond index and a 3 month note). Finally we also include the equally weighted market return for firms listed on the Oslo Stock Exchange ($r^{OSE}$). The number of endogenous lags is determined by the lowest number of lags suggested by the Schwartz and Akaike Info Criterion. The period is from the first quarter 1980 to fourth quarter 2007. Note that the unemployment rate is the actual unemployment for the respective quarter, made public in the beginning of the next quarter $t+1$. Numbers in brackets are t-values. The second part of the table shows the Granger causality tests between the variables. The null hypothesis is that the variables in the first row *do not* Granger cause the dependent variable in column 2 to 6. The table shows the $\chi^2$ statistic with the associated p-values.

| | const. | $dGDP_{t-1}$ | Term $spread_{t-1}$ | $D/P^{OSE}_{t-1}$ | $r^{OSE}_{t-1}$ | $RS_{t-1}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| $dGDP_t$ | **0.021** | **-0.444** | 0.000 | 0.001 | 0.000 | **-0.397** | 0.26 |
| | **[3.91]** | **[-4.99]** | [0.12] | [0.93] | [-0.04] | **[-3.66]** | |
| Term $spread_t$ | 0.460 | -8.784 | **0.490** | 0.301 | 2.114 | -28.919 | 0.40 |
| | [0.48] | [-0.56] | **[5.36]** | [1.48] | [1.45] | [-1.51] | |
| $D/P^{OSE}_t$ | 0.507 | -4.460 | 0.010 | **0.840** | 0.101 | -2.252 | 0.71 |
| | [1.94] | [-1.06] | [0.42] | **[15.37]** | [0.26] | [-0.44] | |
| $r^{OSE}_t$ | -0.092 | 2.047 | -0.005 | **0.032** | 0.153 | 1.236 | 0.10 |
| | [-1.38] | [1.89] | [-0.82] | **[2.28]** | [1.53] | [0.94] | |
| $RS_t$ | **0.013** | -0.103 | 0.000 | -0.001 | **-0.012** | **0.775** | 0.71 |
| | **[4.07]** | [-1.94] | [0.12] | [-1.69] | **[-2.46]** | **[11.96]** | |

| *Granger causality tests:* | Dependent variable | | | | |
|---|---|---|---|---|---|
| | dGDP | Term spread | $D/P^{OSE}$ | $r^{OSE}$ | RS |
| dGDP | | 0.32 | 1.12 | 3.61 | 3.78 |
| p-value | | 0.57 | 0.29 | 0.06 | 0.05 |
| Term spread | 0.01 | | 0.18 | 0.67 | 0.01 |
| p-value | 0.90 | | 0.67 | 0.41 | 0.91 |
| $D/P^{OSE}$ | 0.87 | 2.20 | | **5.18** | 2.88 |
| p-value | 0.35 | 0.14 | | **0.02** | 0.09 |
| $r^{OSE}$ | 0.00 | 2.10 | 0.07 | | **6.04** |
| p-value | 0.97 | 0.15 | 0.80 | | **0.01** |
| RS | **13.42** | 2.29 | 0.19 | 0.88 | |
| p-value | **0.00** | 0.13 | 0.66 | 0.35 | |

## 4.1 Ownership data

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 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 owned by every owner. Each owner has a unique identifier which allows us to follow the owners' holdings over time. For each owner the data also includes a sector code that allows us to distinguish between such types as mutual fund owners, financial owners (which include mutual funds), industrial (nonfinancial corporate) owners, private (individual) owners, state owners and foreign owners.

## 4.2 Portfolio changes

Our data allows us to construct time series of the portfolios of each stock market participant. We look at the set of participants at two following dates, and find the set of investors which were there at the first date, but not on the second date. This is the number of investors *leaving* the market. Similarly, we can count the number of investors there at the second date, but not at the first. This is the number of investors *entering* the market. The net change in investors is the number of investors entering the market less the number of investors leaving the market. This number is what we use as a measure of the change in participation. In implementing the calculation we attempt to reduce noise by removing trivial holdings of less than a hundred shares[27] To gain some intuition about these numbers, in table 11 we describe these numbers at the annual level. We show the number of owners and what fraction of owners this is. For example we see that on average about 15 thousand investors leave the market between one year and the next, which is about a quarter of the investors present at the beginning of the year. The net change is positive, which says that on average the number of investors on the exchange has been increasing in the period.

**Table 11** Describing annual changes in participation

The table describes our participation measure at an annual frequency. Each year in our 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.

| 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 |

In addition to looking at all owners we also split the owners by their type. While the data is anonymous, for each owner we have access to a sector code that lets us split the owners in

[27] At the Oslo Stock Exchange the minimum lot is one hundred shares.

one out of five types: Personal, Foreign, Financial, Nonfinancial(corporate) and State owners.[28] In table 11 we also do a similar calculation of changes in stock market participation for each of these owner types. Note that in these calculations for different owner types we only consider owners *of the given type*, so the fraction of investors is conditioned on the type. So 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.[29]

We now want to relate changes in ownership participation to changes in spread. As we saw from the time series of spreads in figure 3, there were interesting crossectional patterns in spreads across size groups, where for example the time series behaviour of the group of small firms was much more pronounced from the portfolio of largest firms, where we saw much less pronounced changes over time. We therefore construct measures of changes in participation for the different spread groups, by each year finding the stocks in the different size components, i.e. we sort the stocks at the OSE based on size, and each year construct four size based stock portfolios. We then calculate the same participation measure, the net number of new owners, but now *only* for the stocks in each portfolio. So, if an investors had holdings in small stocks, only, but moved them to large stocks, we would count this as leaving the small stock portfolio and entering the large stock portfolio.

In table 12 we calculate the correlations between liquidity, measured by the relative bid ask spread, and changes in participation for various owner types. If liquidity falls (spreads increase) when the number of participants in the market falls, we should expect a negative correlation between the spread and changes in participation. 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. This relationship is robust to the frequency we measure it over, we find it using annual, quarterly and monthly measurement.

# 5 Conclusion

The prime contribution of this paper is to provide two empirical observations. First, we show that the liquidity in the stock market contains information useful for estimating the current (and future) state of the economy. These results are remarkably robust to choice of liquidity proxy and measure of economic activity. In addition, the relationship is also very similar for the US and Norway, as well as for subsets of US securities listed on the different exchanges. This

[28] See Bøhren and Ødegaard [2001], Bøhren and Ødegaard [2006] and Ødegaard [2008] for more information about owner types at the OSE.

[29] Regarding foreign owners there is an institutional reason for the decrease in foreign investors. It is a reflection of the increased ownership through nominee accounts, where foreign owners register through a nominee account. The Norwegian Central Securities Registry do not have details on nominee ownership, they only have data on the total held in nominee accounts. The number of foreign investors we are using is the number of directly registered foreign owners, which has decreased, although the fraction of OSE held by foreigners has increased throughout the period.

**Table 12** Correlation liquidity and change in stock market participation – size quartiles

The tables present correlations between stock market liquidity measured by the average relative bid ask spread in a period and the changes in stock market participation in the period. Change in stock market participation is the change in the number of investors in the stock market, or the given portfolio, of the specified types. For annual data we use each year from 1990 to 2006, giving 16 observations. For the calculations with quarterly and monthly data we use data between 1993:1 to 2006:12, giving 56 quarterly observations and 168 monthly observations.

Panel A: Annual data

| | All firms | | Firm size quartiles: Q1 (smallest firms) | | Q2 | | Q3 | | Q4 (largest firms) | |
|---|---|---|---|---|---|---|---|---|---|---|
| All owners | -0.03 | (0.46) | -0.71 | (0.00) | -0.19 | (0.27) | -0.51 | (0.03) | -0.07 | (0.40) |
| Personal owners | 0.03 | (0.47) | -0.68 | (0.00) | -0.16 | (0.30) | -0.50 | (0.04) | -0.03 | (0.46) |
| Foreign owners | -0.01 | (0.48) | -0.64 | (0.01) | -0.06 | (0.42) | -0.45 | (0.05) | -0.21 | (0.24) |
| Financial owners | -0.08 | (0.40) | -0.51 | (0.03) | 0.12 | (0.34) | -0.21 | (0.24) | -0.15 | (0.31) |
| Nonfinancial owners | -0.61 | (0.01) | -0.81 | (0.00) | -0.39 | (0.09) | -0.65 | (0.01) | -0.50 | (0.03) |
| State owners | -0.32 | (0.14) | -0.51 | (0.03) | 0.37 | (0.10) | -0.04 | (0.44) | -0.14 | (0.32) |

Panel B: Quarterly data

| | 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: Monthly data

| | All firms | | Firm size quartiles: Q1 (smallest firms) | | Q2 | | Q3 | | Q4 (largest firms) | |
|---|---|---|---|---|---|---|---|---|---|---|
| All owners | 0.00 | (0.49) | -0.23 | (0.00) | -0.07 | (0.19) | -0.12 | (0.06) | -0.02 | (0.40) |
| Personal owners | 0.02 | (0.39) | -0.21 | (0.00) | -0.06 | (0.22) | -0.11 | (0.07) | -0.00 | (0.48) |
| Foreign owners | -0.09 | (0.12) | -0.18 | (0.01) | -0.10 | (0.09) | -0.14 | (0.03) | -0.12 | (0.06) |
| Financial owners | -0.05 | (0.26) | -0.10 | (0.09) | -0.01 | (0.44) | -0.07 | (0.17) | -0.07 | (0.19) |
| Nonfinancial owners | -0.08 | (0.15) | -0.22 | (0.00) | -0.07 | (0.20) | -0.14 | (0.04) | -0.10 | (0.09) |
| State owners | -0.02 | (0.38) | -0.07 | (0.18) | 0.12 | (0.06) | -0.07 | (0.18) | -0.02 | (0.41) |

result suggests that the relationship is similar across different market structures (order-/quote driven market). Second, we show that time variation in equity market liquidity is related to changes in the participation in the stock market, especially for the smallest firms. Participation in small firms decreases when the economy (and market liquidity) worsen. This is consistent with a "flight to quality" effect and with our earlier finding that the liquidity of the smallest stocks contain the most information about future economic conditions.

There are a number of interesting ways to follow up our results. First, our results showing that (Granger) causality goes from the stock market to the real economy has interesting implications for prediction, particularly in a policy context. The ability to improve forecasts of such central macroeconomic variables as unemployment, GDP, consumption and the like will be particularly interesting for central banks and other economic planners. For such uses an obvious extension of our work is to identify the "best" liquidity variables for forecasting purposes. We have shown that the liquidity variables considered in this paper have similar properties in VAR analyzes, but we have not identified which, or what combination of, liquidity variables are superior for forecasting purposes. 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 crossection of stock returns. We are in the process of following up some of these thoughts, but at the moment they are left as promising avenues for future research.

# A Additional results for the US

**Table 13** Illiquidity ratio, unemployment rate and additional financial variables

The table shows the results from an unrestricted VAR model for the change in the unemployment rate ($UE_t$) and market liquidity ($ILR_t$). In addition, we include the variables *term spread* (calculated as the difference between a 10 year government benchmark and the 3 month T-bill rate), the P/E ratio (which is based on the 12 month forward looking expected earnings for the SP500 stocks) and the return on the MSCI total return index. The unemployment rate figure is the unemployment as a percent of the civilian labor force from the U.S. Bureau of Labor Statistics. The period is from first quarter 1980 to fourth quarter 2007. Note that the unemployment rate is the actual unemployment for the respective quarter. Numbers in brackets are t-values for the estimates. The second part of the table shows the Granger causality tests between the variables. The null hypothesis is that the variables in the first row *do not* Granger cause the dependent variable in column 2 to 6. The table shows the $\chi^2$ statistic with the associated p-values.

| | const. | $dUE_{t-1}$ | Term $spread_{t-1}$ | $P/E^{SP500}_{t-1}$ | $r^{MSCI}_{t-1}$ | $ILR_{t-1}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| $dUE_t$ | 0.000 | **0.322** | 0.000 | 0.000 | 0.001 | **6.381** | 0.490 |
| | [0.91] | **[4.01]** | [1.61] | [0.44] | [0.42] | **[5.68]** | |
| Term $spread_t$ | **-0.440** | 47.438 | **0.753** | -0.006 | 0.908 | -404.572 | 0.587 |
| | **[-3.16]** | [1.76] | **[11.69]** | [-0.19] | [0.89] | [-1.07] | |
| $P/E^{SP500}_t$ | 0.268 | 39.727 | 0.146 | **0.862** | -0.743 | 217.841 | 0.760 |
| | [1.32] | [1.01] | [1.55] | **[17.08]** | [-0.50] | [0.40] | |
| $r^{MSCI}_t$ | **0.034** | 2.343 | 0.001 | **-0.010** | 0.074 | -1.737 | 0.084 |
| | **[2.52]** | [0.90] | [0.20] | **[-2.86]** | [0.76] | [-0.05] | |
| $ILR_t$ | 0.000 | 0.005 | 0.000 | 0.000 | **-0.001** | **0.573** | 0.522 |
| | [1.71] | [0.92] | [1.51] | [0.15] | **[-3.24]** | **[7.37]** | |

| *Granger causality tests:* | Dependent variable | | | | |
|---|---|---|---|---|---|
| | dUE | Term spread | $P/E^{SP500}$ | $r^{MSCI}$ | ILR |
| dUE | | 3.10 | 1.03 | 0.82 | 0.85 |
| p-value | | 0.08 | 0.31 | 0.37 | 0.36 |
| Term spread | 2.58 | | 2.42 | 0.04 | 2.27 |
| p-value | 0.11 | | 0.12 | 0.84 | 0.13 |
| $P/E^{SP500}$ | 0.19 | 0.03 | | **8.17** | 0.02 |
| p-value | 0.66 | 0.85 | | **0.00** | 0.88 |
| $r^{MSCI}$ | 0.17 | 0.80 | 0.25 | | **10.49** |
| p-value | 0.68 | 0.37 | 0.61 | | **0.00** |
| ILR | 32.20 | 1.15 | 0.16 | 0.00 | |
| p-value | **0.00** | 0.28 | 0.69 | 0.96 | |

# B Additional results for Norway

**Table 14** Causality between the illiquidity ratio and macroeconomic variables

Results from four unrestricted bivariate VAR(1) models for the market illiquidity ($ILR_t$) and (a) change in the unemployment rate ($dUE_t$), (b) GDP growth rate ($dGDP$), (c) consumption growth ($dCONS$) and (d) output gap ($OG$). Market illiquidity ($ILR_t$) is proxied by the Amihud illiquidity ratio. The number of endogenous lags is determined by the lowest number of lags suggested by the Schwartz and Akaike Info Criterion. The period is from first quarter 1980 to fourth quarter 2007. Note that the macro variables are measured as the quarterly growth in for the respective quarter. Numbers in brackets are t-values. The last two columns show the chi-squared statistics and p-value from Granger causality tests between the respective macro variable and the market liquidity. The null hypothesis is that the independent variable (in each equation) *do not* Granger cause the dependent variable.

**(a) Unemployment rate change (dUE)**

| | Const. | $dUE_{t-1}$ | $ILR_{t-1}$ | $R^2$ | *Causality tests:* | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|---|
| $dUE_t$ | **-0.167** | -0.130 | **0.252** | 0.11 | H0: ILR $\nrightarrow$ dUE | **13.05** | **0.000** |
| | **[-2.81]** | [-1.35] | **[3.61]** | | | | |
| $ILR_t$ | **0.153** | 0.003 | **0.776** | 0.60 | H0: dUE $\nrightarrow$ ILR | 0.001 | 0.97 |
| | **[2.76]** | [0.04] | **[11.97]** | | | | |

**(b) GDP growth (dGDP)**

| | Const. | $dGDP_{t-1}$ | $ILR_{t-1}$ | $R^2$ | *Causality tests:* | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|---|
| $dGDP_t$ | **0.013** | **-0.371** | **-0.007** | 0.18 | H0: ILR $\nrightarrow$ dGDP | **12.13** | **0.00** |
| | **[6.80]** | **[-4.16]** | **[-3.48]** | | | | |
| $ILR_t$ | **0.200** | -5.167 | **0.752** | 0.61 | H0: dGDP $\nrightarrow$ ILR | 3.46 | 0.06 |
| | **[3.40]** | [-1.86] | **[12.06]** | | | | |

**(c) Consumption growth (dCONS)**

| | Const. | $dCONS_{t-1}$ | $ILR_{t-1}$ | $R^2$ | *Causality tests:* | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|---|
| $dCONS_t$ | **0.013** | **-0.199** | **-0.007** | 0.08 | H0: ILR $\nrightarrow$ dCONS | **7.68** | **0.01** |
| | **[5.72]** | **[-2.10]** | **[-2.77]** | | | | |
| $ILR_t$ | **0.170** | -1.538 | **0.767** | 0.60 | H0: dCONS $\nrightarrow$ ILR | 0.37 | 0.54 |
| | **[2.79]** | [-0.61] | **[12.01]** | | | | |

**(d) Output gap (OG)**

| | Const. | $OG_{t-1}$ | $ILR_{t-1}$ | $R^2$ | *Causality tests:* | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|---|
| $OG_t$ | **0.247** | **0.960** | **-0.325** | 0.97 | H0: ILR $\nrightarrow$ OG | **17.26** | **0.00** |
| | **[3.65]** | **[52.97]** | **[-4.15]** | | | | |
| $ILR_t$ | **0.171** | -0.006 | **0.757** | 0.58 | H0: OG $\nrightarrow$ ILR | 0.16 | 0.68 |
| | **[2.92]** | [-0.41] | **[11.18]** | | | | |

**Table 15** Illiquidity ratio of firm size groups, unemployment rate and GDP growth

Results from an unrestricted VAR(1) model for the change in the unemployment rate ($dUE_t$) and liquidity for small ($ILR_t^{small}$) and large ($ILR_t^{large}$) firms proxied by the Amihud illiquidity ratio. The number of endogenous lags is determined by the lowest number of lags suggested by the Schwartz and Akaike Info Criterion. The period is from first quarter 1980 to fourth quarter 2007. Note that the unemployment rate is the actual unemployment for the respective month. Numbers in brackets are t-values for the estimates and * and ** denote significance at the 5% and 1% level respectively. The three last columns shows the results from the Granger causality tests.

**(a) Unemployment change**

| | Const. | $dUE_{t-1}$ | $ILR_{t-1}^{small}$ | $ILR_{t-1}^{large}$ | $R^2$ | *Causality tests (H0)* | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|---|---|
| $dUE_t$ | **-0.114** | -0.087 | **0.084** | -0.079 | 0.07 | $ILR^{small} \nrightarrow dUE$ | **6.30** | **0.01** |
| | **[-1.99]** | [-0.90] | **[2.51]** | [-0.17] | | $ILR^{large} \nrightarrow dUE$ | 0.03 | 0.86 |
| $ILR_t^{small}$ | **0.293** | -0.181 | 0.645 | 3.121 | 0.60 | $dUE \nrightarrow ILR^{small}$ | 0.74 | 0.39 |
| | **[2.34]** | [-0.86] | [8.78] | [3.14] | | $ILR^{large} \nrightarrow ILR^{small}$ | **9.84** | **0.00** |
| $ILR_t^{large}$ | **0.011** | **-0.016** | **0.001** | 0.81 | 0.73 | H0: $dUE \nrightarrow ILR^{large}$ | 1.75 | 0.19 |
| | **[1.49]** | **[-1.32]** | **[0.22]** | [14.35] | | H0: $ILR^{small} \nrightarrow ILR^{large}$ | 0.05 | 0.83 |

**(b) GDP growth**

| | Const. | $dGDP_{t-1}$ | $ILR_{t-1}^{small}$ | $ILR_{t-1}^{large}$ | $R^2$ | *Causality tests (H0)* | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|---|---|
| $dGDP_t$ | 0.014 | -0.393 | -0.003 | -0.011 | 0.24 | $ILR^{small} \nrightarrow dGDP$ | **11.26** | **0.00** |
| | [7.78] | [-4.49] | [-3.36] | [-0.85] | | $ILR^{large} \nrightarrow dGDP$ | 0.73 | 0.39 |
| $ILR_t^{small}$ | 0.364 | -5.777 | 0.627 | 2.962 | 0.60 | $dGDP \nrightarrow ILR^{small}$ | 0.71 | 0.40 |
| | [2.64] | [-0.84] | [8.61] | [2.95] | | $ILR^{large} \nrightarrow ILR^{small}$ | **8.72** | **0.00** |
| $ILR_t^{large}$ | 0.006 | 0.691 | 0.001 | 0.819 | 0.73 | $dGDP \nrightarrow ILR^{large}$ | 3.22 | 0.07 |
| | [0.77] | [1.79] | [0.19] | [14.51] | | $ILR^{small} \nrightarrow ILR^{large}$ | 0.04 | 0.85 |

**Table 16** Relative spread, unemployment rate and other financial variables

The first part of the table shows the estimation results from an unrestricted VAR(1) model for the quarterly change in unemployment ($dUE_t$), the illiquidity ratio (ILR), the average dividend price ratio (D/P) for the firms listed at the Oslo Stock exchange, the term spread between the yield on a 10 year government bond and the 3 month rate. Finally we also include the equally weighted market return for firms listed on the Oslo Stock Exchange ($r^{OSE}$). The number of endogenous lags is determined by the lowest number of lags suggested by the Schwartz and Akaike Info Criterion. The period is from first quarter 1980 to fourth quarter 2007. Note that the unemployment rate is the actual unemployment for the respective month. Numbers in brackets are t-values. The second part of the table shows the Granger causality tests between the variables. The null hypothesis is that the variables in the first row *do not* Granger cause the dependent variable in column 2 to 6. The table shows the $\chi^2$ statistic with the associated p-values.

| | const. | $dUE_{t-1}$ | Term $spread_{t-1}$ | $D/P^{OSE}_{t-1}$ | $r^{OSE}_{t-1}$ | $RS_{t-1}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| $dUE_t$ | **-0.695** | -0.174 | 0.007 | 0.029 | 0.008 | **15.324** | 0.17 |
| | **[-3.54]** | [-1.76] | [0.36] | [0.73] | [0.03] | **[3.84]** | |
| Term $spread_t$ | 0.313 | -0.011 | **0.488** | 0.303 | 2.150 | -26.626 | 0.40 |
| | [0.32] | [-0.02] | **[5.27]** | [1.49] | [1.46] | [-1.32] | |
| $D/P^{OSE}_t$ | 0.449 | 0.019 | 0.009 | **0.841** | 0.112 | -1.458 | 0.71 |
| | [1.67] | [0.14] | [0.34] | **[15.30]** | [0.28] | [-0.27] | |
| $r^{OSE}_t$ | -0.052 | 0.011 | -0.005 | **0.031** | 0.142 | 0.570 | 0.06 |
| | [-0.75] | [0.32] | [-0.76] | **[2.21]** | [1.38] | [0.40] | |
| $RS_t$ | **0.011** | -0.001 | 0.000 | -0.001 | **-0.012** | **0.808** | 0.70 |
| | **[3.35]** | [-0.31] | [0.08] | [-1.63] | **[-2.29]** | **[11.58]** | |

| *Granger causality tests:* | Dependent variable | | | | |
|---|---|---|---|---|---|
| | dUE | Term spread | $D/P^{OSE}$ | $r^{OSE}$ | RS |
| dUE | | 0.00 | 0.02 | 0.11 | 0.10 |
| p-value | | 0.98 | 0.89 | 0.75 | 0.76 |
| Term spread | 0.13 | | 0.12 | 0.58 | 0.01 |
| p-value | 0.72 | | 0.73 | 0.45 | 0.94 |
| $D/P^{OSE}$ | 0.54 | 2.21 | | **4.86** | 2.67 |
| p-value | 0.46 | 0.14 | | **0.03** | 0.10 |
| $r^{OSE}$ | 0.00 | 2.14 | 0.08 | | **5.25** |
| p-value | 0.98 | 0.14 | 0.78 | | **0.02** |
| RS | **14.71** | 1.73 | 0.07 | 0.16 | |
| p-value | **0.00** | 0.19 | 0.79 | 0.69 | |

**Table 17** Illiquidity ratio, unemployment rate and other financial variables

The first part of the table shows the estimation results from an unrestricted VAR(1) model for the change in the unemployment rate ($dUE_t$), the illiquidity ratio (ILR), the average dividend price ratio (D/P) for the firms listed at the Oslo Stock exchange, the term spread between the yield on a 10 year government bond and the 3 month rate. Finally we also include the equally weighted market return for firms listed on the Oslo Stock Exchange ($r^{OSE}$). The number of endogenous lags is determined by the lowest number of lags suggested by the Schwartz and Akaike Info Criterion. The period is from first quarter 1980 to fourth quarter 2007. Note that the unemployment rate is the actual unemployment for the respective month. Numbers in brackets are t-values. The second part of the table shows the Granger causality tests between the variables. The null hypothesis is that the variables in the first row *do not* Granger cause the dependent variable in column 2 to 6. The table shows the $\chi^2$ statistic with the associated p-values.

| | const. | $dUE_{t-1}$ | Term spread$_{t-1}$ | $D/P^{OSE}_{t-1}$ | $r^{OSE}_{t-1}$ | $ILR_{t-1}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| $dUE_t$ | -0.209 | -0.126 | 0.005 | 0.025 | -0.229 | **0.200** | 0.12 |
| | [-1.70] | [-1.26] | [0.23] | [0.61] | [-0.78] | **[2.87]** | |
| Term spread$_t$ | -0.385 | 0.005 | **0.458** | 0.327 | 2.570 | -0.561 | 0.40 |
| | [-0.64] | [0.01] | **[4.70]** | [1.60] | [1.80] | [-1.64] | |
| $D/P^{OSE}_t$ | **0.462** | 0.055 | -0.005 | **0.848** | 0.138 | -0.105 | 0.71 |
| | **[2.86]** | [0.41] | [-0.19] | **[15.43]** | [0.36] | [-1.14] | |
| $r^{OSE}_t$ | -0.044 | 0.006 | -0.003 | **0.030** | 0.133 | 0.023 | 0.07 |
| | [-1.06] | [0.18] | [-0.38] | **[2.11]** | [1.32] | [0.94] | |
| $ILR_t$ | 0.276 | 0.032 | 0.006 | 0.002 | -0.557 | **0.705** | 0.51 |
| | [1.77] | [0.25] | [0.24] | [0.03] | [-1.49] | **[7.94]** | |

| *Granger causality tests:* | Dependent variable | | | | |
|---|---|---|---|---|---|
| | dUE | Term spread | $D/P^{OSE}$ | $r^{OSE}$ | ILR |
| dUE | | 0.00 | 0.17 | 0.03 | 0.06 |
| p-value | | 0.99 | 0.68 | 0.86 | 0.80 |
| Term spread | 0.05 | | 0.04 | 0.15 | 0.06 |
| p-value | 0.82 | | 0.85 | 0.70 | 0.81 |
| $D/P^{OSE}$ | 0.37 | 2.57 | | **4.43** | 0.00 |
| p-value | 0.54 | 0.11 | | **0.04** | 0.97 |
| $r^{OSE}$ | 0.61 | 3.22 | 0.13 | | 2.23 |
| p-value | 0.43 | 0.07 | 0.72 | | 0.14 |
| ILR | **8.21** | 2.70 | 1.31 | 0.89 | |
| p-value | **0.00** | 0.10 | 0.25 | 0.35 | |

**Table 18** Illiquidity ratio, GDP growth and other financial variables

The first part of the table shows the estimation results from an unrestricted VAR(1) model for quarterly GDP growth ($dGDP_t$), the illiquidity ratio (ILR), the average dividend price ratio (D/P) for the firms listed at the Oslo Stock exchange, the term spread between the yield on a 10 year government bond and the 3 month rate. Finally we also include the equally weighted market return for firms listed on the Oslo Stock Exchange ($r^{OSE}$). The number of endogenous lags is determined by the lowest number of lags suggested by the Schwartz and Akaike Info Criterion. The period is from first quarter 1980 to fourth quarter 2007. Note that the unemployment rate is the actual unemployment for the respective month. Numbers in brackets are t-values. The second part of the table shows the Granger causality tests between the variables. The null hypothesis is that the variables in the first row *do not* Granger cause the dependent variable in column 2 to 6. The table shows the $\chi^2$ statistic with the associated p-values.

| | const. | $dGDP_{t-1}$ | Term $spread_{t-1}$ | $D/P^{OSE}_{t-1}$ | $r^{OSE}_{t-1}$ | $ILR_{t-1}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| $dGDP_t$ | **0.008** | **-0.406** | 0.000 | 0.002 | 0.006 | **-0.006** | 0.21 |
| | **[2.26]** | **[-4.48]** | [0.09] | [1.25] | [0.70] | **[-2.50]** | |
| Term $spread_t$ | -0.381 | -7.481 | **0.442** | 0.381 | 2.607 | -0.807 | 0.41 |
| | [-0.65] | [-0.49] | **[4.43]** | [1.83] | [1.83] | [-1.88] | |
| $D/P^{OSE}_t$ | **0.466** | -4.592 | -0.001 | **0.854** | 0.146 | -0.118 | 0.72 |
| | **[2.94]** | [-1.11] | [-0.03] | **[15.15]** | [0.38] | [-1.03] | |
| $r^{OSE}_t$ | -0.061 | 2.042 | -0.001 | 0.027 | 0.131 | 0.047 | 0.11 |
| | [-1.51] | [1.94] | [-0.22] | [1.87] | [1.33] | [1.58] | |
| $ILR_t$ | 0.199 | -5.041 | 0.019 | 0.003 | -0.463 | **0.776** | 0.61 |
| | [1.81] | [-1.76] | [1.01] | [0.08] | [-1.74] | **[9.72]** | |

| *Granger causality tests:* | Dependent variable | | | | |
|---|---|---|---|---|---|
| | dGDP | Term spread | $D/P^{OSE}$ | $r^{OSE}$ | ILR |
| dGDP | | 0.24 | 1.23 | **3.75** | 3.10 |
| p-value | | 0.63 | 0.27 | **0.05** | 0.08 |
| Term spread | 0.01 | | 0.00 | 0.05 | 1.02 |
| p-value | 0.93 | | 0.97 | 0.83 | 0.31 |
| $D/P^{OSE}$ | 1.58 | 3.33 | | 3.49 | 0.01 |
| p-value | 0.21 | 0.07 | | 0.06 | 0.94 |
| $r^{OSE}$ | 0.49 | 3.34 | 0.14 | | 3.02 |
| p-value | 0.48 | 0.07 | 0.70 | | 0.08 |
| ILR | **6.22** | 3.55 | 1.05 | 2.50 | |
| p-value | **0.01** | 0.06 | 0.30 | 0.11 | |

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